Carbon reduction target: supporting the energy-environmental management studies (with a focus on consulting services)

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ABSTRACT

The energy and environmental consultant plays an important role in achieving building and industrial decarbonisation. Buildings and industry are responsible for about 65% of global energy use and related greenhouse gas emissions. However, traditional methods, such as manual energy audits and static benchmarking, cannot effectively handle the growing complexity of modern facilities and the large amount of operational data they generate. This research develops a data-driven framework specifically designed for energy and environmental consultants who conduct the necessary analytics and recommendations at the analysis level of interventions. The proposed approach follows the Technological Regenerative Innovation (TRI) framework, which combines three main components: Internet of Things (IoT) sensors for real-time monitoring, Big Data analytics for energy consumption prediction, and Explainable Artificial Intelligence (XAI) to provide clear and interpretable model outputs. The proposed aspects of the TRI framework were evaluated using case studies of industrial and commercial critical facilities, including an air handling unit at university(with different cleaning conditions), chiller plants for buildings (supermarkets & hospitals), steel industries undergoing decarbonisation, and a data centre cooling facility. The results show that ensemble machine learning methods achieve higher prediction accuracy than individual algorithms in several case studies, with performance varying depending on data availability. In addition, SHAP-based explanations improve model transparency and make the prediction process easier to understand, addressing a limitation of many commercial energy management systems. The findings also provide practical insights. The comparison of two similar air-handling units showed that regular HVAC maintenance can reduce energy consumption by 16–70% while improving heat-transfer efficiency and airflow. Furthermore, the proposed fishbone-based multidimensional performance indicator framework demonstrated that using multiple energy performance indicators provides a more accurate assessment of hospital energy consumption than relying on only a few indicators, for the 44 hospitals investigated. This finding requires further validation

and does not rule out the potential benefits of feature selection.

In critical industry like steel, combining energy usage and production data with machine learning assisted energy-flow allocation. It extended ISO 50001 practice across different case studies of steel mills, achieving promising predictive accuracy for specific energy consumption. Finally, extending the TRI framework to data-centre cooling introduced a regime-aware, temporal form of explainable AI, revealing that the influence of key operating variables shifts according to load conditions in ways that conventional global feature-importance analysis cannot detect. This analysis used a publicly available, physically grounded synthetic dataset comprising 3,498 hourly observations, rather than measurements from a live data-centre facility. Taken together, these contributions demonstrate that combining IoT-enabled monitoring, machine learning, and explainable artificial intelligence can move energy management from a reactive discipline toward a predictive, evidence-based one. The methodologies developed here were tested across offices, hospitals, HVAC systems, data centres, and steel manufacturing, demonstrating their potential for application across sectors. However, the complete TRI framework still misses the experimental validation as well as adaptive control and autonomous decision-making, as it requires further validation possibly with higher degree of involvement from an industry side.

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LIST OF ABBREVIATIONS

AHU Air Handling Unit

AI Artificial Intelligence

ANFIS Adaptive Neuro Fuzzy Inference System

BigData Big Data

C&I Commercial and Industrial

CNN Convolutional Neural Networks

EnPI Energy Performance Indicator

HVAC Heating, Ventilation and Air Conditioning

IoT Internet of Things

KPI Key Performance Indicator

LSTM Long Short-Term Memory

ML Machine Learning

MRMR Minimum Redundancy Maximum Relevance

RQ Research Question

SEC Specific Energy Consumption

SHAP SHapley Additive exPlanations

TRI Technological Regenerative Innovation

XAI Explainable Artificial Intelligence

XGBoost eXtreme Gradient Boosting

Chapter 1



Introduction

1 INTRODUCTION

1.1 Background

The Commercial and Industrial (C&I) sector has always been centre of attention in the climate debate. Worldwide, buildings account for roughly 40% of final energy consumption and about one-third of greenhouse gas emissions, a scale that makes them impossible to ignore in any serious decarbonisation strategy [1]. The European Union has responded with the Green Deal and the Climate Law, which set binding targets of a 55% reduction in net greenhouse gas emissions by 2030 and full climate neutrality by 2050 [2]. Meeting these commitments will require a thorough overhaul of how buildings are designed, operated, and maintained. Despite a change in pace lately, the EU has nevertheless shown a great vision and care for the protection of the Earth and its future generations.

Energy consultants sit at the sharp end of this transformation. Their work auditing, strategy development, monitoring, and verification directly shapes the effectiveness of the measures that building owners and industrial operators adopt. Yet the tools consultants have traditionally relied on, such as manual audits and static benchmarks, rarely keep pace with the dynamic nature of real building energy use [3]. Artificial intelligence (AI) and machine learning (ML) have emerged as a way to close that gap, offering data-driven prediction and optimisation that go well beyond conventional approaches.

This thesis is part of a PhD programme at the University of Pavia, conducted in partnership with Alens SRL, an energy-consulting company based in Pavia, Italy. The overarching aim is to strengthen the services that energy-environmental consultants provide by developing innovative processes and tools that merge sustainability thinking with data-intensive methods. Embedding the research in a real consulting firm ensures that the work remains anchored in practical problems, and that the solutions developed are not just theoretically elegant but genuinely useful in the field.

Carbon neutrality, balancing CO_2 emissions with equivalent removals, is now a central principle of energy policy everywhere [4].

Achieving it in the built environment goes beyond installing renewables, it also calls for the intelligent management of existing systems. AI and ML have proven particularly valuable here, capable of uncovering subtle relationships among diverse datasets, selecting appropriate Key Performance Indicators (KPIs), and assessing the technical-economic feasibility of efficiency measures with a precision that older methods could not match [5].

The past decade has seen a rapid expansion of AI/ML applications in building energy management. Simple regression models have given way to deep-learning architectures that handle increasingly complex challenges, from short-term load forecasting to whole-system control. Ensemble methods such as Random Forest and Gradient Boosting frequently outperform single-algorithm approaches in commercial and industrial settings [6, 7]. Despite these advances, the integration of such tools into everyday consulting practice remains patchy. Obstacles include concerns about model interpretability, inconsistent data quality, and uncertainty about how well a model trained on one building will transfer to another. The present work tackles these obstacles by examining multiple domains office buildings, hospitals, heating, ventilation and air-conditioning (HVAC) systems, and heavy industry (particularly steel manufacturing). Despite advances in energy monitoring and predictive modelling, a gap remains between collecting energy-related data, generating reliable predictions, interpreting model outputs, and translating analytical results into actionable decisions. These tasks are often addressed separately, making it difficult to establish a consistent workflow that connects energy-performance assessment with interpretable, evidence based recommendations. This thesis investigates how these elements can be brought together within one framework. The research draws on real operational data from several industrial and commercial applications, complemented by a publicly available, open access dataset for data-centre. Using operational data, new methods and frameworks are developed that can help organisations reduce their carbon footprint and make better energy decisions. The ultimate goal is to deliver practical, scalable tools that energy consultants can trust and apply in a wide variety of contexts.

1.2 Objectives and Scope

1.2.1 Motivation

First, most energy management systems in commercial and industrial buildings still operate on a reactive basis: they fix things after

they break and run on fixed schedules that ignore changes in building use. Even when extensive monitoring equipment is installed, the resulting flood of data often remains under-analysed because in-house teams lack the necessary skills, and external analytics services do not always integrate smoothly with existing workflows [3].

Second, benchmarking energy performance is especially difficult for certain building types. Offices can be compared using straightforward metrics like energy per square metre, but hospitals are a different matter. They operate 24 hours a day, require tight control of indoor air quality, and house a great deal of specialised, energy-intensive equipment. Existing indicator sets rarely capture these unique characteristics, making it hard to assess how a particular hospital is performing relative to others, or to pinpoint the most promising efficiency opportunities [8].

Third, deep decarbonisation of energy-intensive industries, steel above all, demands robust methods for allocating energy flows and tracking performance over time. Steel production alone is responsible for about 8% of global CO_2 emissions, and reaching net-zero by 2050 is expected to require a 93% reduction from current levels [9]. While the ISO 50001 energy management standard provides a useful framework, its effective implementation hinges on data-driven tools that can handle the complexity and variability of real industrial processes.

The main goal of this PhD is to develop, validate, and show data-based methodologies that strengthen the work of energy - environmental consultants in pursuit of carbon reduction. Specifically, the project sets out to:

1. Build a comprehensive Technological Regenerative Innovation (TRI) framework that brings together Internet of Things (IoT) sensing, BigData analytics, and Explainable Artificial Intelligence (XAI) for predictive energy management in commercial and industrial buildings.

2. Systematically review the state of the art in AI/ML applications for building energy management, identifying performance trends, methodological gaps, and directions for future research.

3. Quantify, through a year-long comparative field study, how maintenance interventions, in particular the cleaning of air handling units, affect HVAC energy consumption and system performance.

4. Design a multidimensional energy performance indicator framework for critical buildings(hospitals, data centers, supermar-

kets, etc.), enabling more precise benchmarking and clearer identification of efficiency improvements.

5. Establish data-driven procedures for energy flow allocation and decarbonisation road-mapping in energy-intensive industries, with a specific focus on steel manufacturing.

The research covers both the civil sector (commercial buildings, hospitals) and the industrial sector (steel), reflecting the cross-sectoral character of the carbon reduction challenge. The methodological approach combines data analytics, machine learning modelling, and performance benchmarking within a single, consulting-oriented framework. The research examines complementary aspects of the TRI framework across several studies rather than validating the entire framework in a single implementation.

1.3 Research Questions(RQs)

The gaps identified in the previous sections point to four interconnected questions that this thesis sets out to answer. Each question addresses a specific problem in energy and environmental management, and together they form the backbone of the research.

1.3.1 Research Question 1: Performance Indicators

What scientifically sound Energy Performance Indicators (EnPIs) can effectively predict and benchmark energy consumption across diverse critical facility types?

Traditional metrics such as energy use per square metre are easy to calculate, but they rarely capture the full picture for complex facilities. Hospitals, for example, run around the clock and depend on specialised equipment, while industrial plants have production cycles and process variables that simple indicators cannot represent. A single figure like kWh/m^2 says nothing about how occupancy, weather, or production volume actually drive consumption.

This question therefore asks whether multidimensional indicators, built from operational variables that matter in practice, can deliver more accurate forecasts and fairer comparisons across buildings of different types and sizes. The investigation covers:

- Critical facilities whose total energy consumption depends on several interacting variables
- Identify and evaluate the pros and cons of different Energy Performance Indicators (EnPIs)

- Data centres, where cooling power and IT load are key drivers of energy use
- Industrial steel manufacturing, where the indicator Wh/(Nm^3/ton) is evaluated against conventional alternatives
- A comparative analysis of indicator effectiveness
- Validation of the chosen indicators through machine-learning regression models.

1.3.2 Research Question 2: Explainable Artificial Intelligence

How can explainable artificial intelligence bridge the gap between complex machine-learning models and practical implementation in energy consulting?

Machine-learning models can predict energy use with impressive accuracy, yet many of them remain "black boxes": they output a number without showing how it was reached. Energy managers and consultants naturally hesitate to trust recommendations they cannot verify, and this lack of transparency has slowed the uptake of AI in everyday consulting work.

The question is whether AI and ML models, when paired with Internet of Things (IoT) monitoring, can support decision-making frameworks that are both accurate and transparent. The work focuses on:

- The Technological Regenerative Innovation (TRI) framework
- Data centre cooling systems, using K-Means clustering, XGBoost, and SHAP to predict cooling power consumption
- Data centre cooling systems, using K-Means clustering,
- Commercial and industrial chiller systems as case studies
- SHAP (SHapley Additive exPlanations) analysis to reveal which variables most influence predictions
- Integration and validation of IoT sensor data with big-data analytics.

1.3.3 Research Question 3: Predictive Maintenance

What is the quantifiable impact of routine cleaning and maintenance interventions on HVAC system energy efficiency and indoor environmental quality?

HVAC systems are among the largest energy consumers in commercial buildings, yet the actual savings from regular cleaning and maintenance are poorly documented. Much of the existing evidence is anecdotal rather than based on controlled measurement, making it hard for building owners to justify maintenance spending or to know what return they can expect.

This question tests whether a controlled experimental study, running over a full year and comparing maintained and unmaintained units, can produce reliable figures for the energy and air-quality benefits of maintenance. The study focuses:

- Side-by-side performance of cleaned and uncleaned Air Handling Units (AHUs)
- Changes in energy consumption, airflow, and thermal efficiency
- Indoor air quality, measured through volatile organic compound (VOC) levels
- Data collected across a complete annual cycle to capture seasonal variation.

1.3.4 Research Question 4: Framework Integration

Can industrial and commercial technologies enable the shift from experience-based to data-informed operational strategies in high-energy processes?

In many industrial plants, energy management still rests largely on the experience of individual operators. While practical knowledge is valuable, it can be inconsistent and may miss patterns that systematic data analysis would reveal. The challenge is to move from reactive, intuition-driven decisions to predictive strategies grounded in operational data.

This question explores whether process-specific indicators, combined with machine learning, can offer clearer insight than traditional metrics and whether this combination can support a genuine shift toward predictive energy management. The investigation includes:

- Energy analysis in commercial and industrial facilities like steel manufacturing
- Data centre energy systems, evaluating how analytical tools can improve cooling efficiency

- Identification of high-energy processes, with particular attention to compressed-air systems
- Development of a novel EnPI (Wh/(Nm^3/ton)) and comparison with the conventional kWh/Nm^3
- Comparison of machine-learning models, supported by rigorous data validation.

The four research questions structure the thesis, from energy-performance assessment and explainable AI to maintenance evaluation and the integration of these elements within the TRI framework. Each question is addressed through a dedicated study, and the findings are synthesised to assess the framework's applicability within the limits of the available evidence. The methodology used to answer them is set out in the next chapter.

1.4 State of the art overview

1.4.1 AI and ML for Building Energy Management

Applications of AI and ML in building energy management have grown substantially over the past decade. Hong et al. [5] reviewed machine learning across the entire building life cycle and noted progress in energy prediction, fault detection, and optimal control. Nonetheless, a wide gap remains between algorithm development and deployment in practical building management systems.

More recently, Liu and Chen [7] identified deep learning, reinforcement learning, and ensemble methods as the dominant techniques for energy optimisation. Their analysis showed that office buildings can achieve energy savings of up to 37% when AI-based control is applied to HVAC systems, whereas residential and educational buildings show lower but still meaningful savings (about 23% and 21%, respectively).

Many studies have compared the predictive performance of different algorithm families. Seyedzadeh et al. [10] found that support vector machines and artificial neural networks could predict building energy consumption with R^2 values typically between 0.80 and 0.95. Ensemble techniques have often delivered even stronger results. Panagiotou and Dounis [11] reported that Random Forest and XGBoost reached R^2 values as high as 0.96 for daily and weekly forecasts in commercial buildings, with error margins around 4-7%.

Deep learning has proven especially effective for capturing temporal patterns in energy time series. Kim and Cho [12] proposed a CNN-LSTM hybrid for residential load forecasting that has been

cited over 1,200 times and has served as a template for many subsequent studies. Long Short-Term Memory (LSTM) networks, in particular, can achieve mean absolute percentage errors as low as 2-4% for short-term predictions [13].

A persistent obstacle, however, is the opaque nature of many ML models. The lack of transparency erodes trust among energy managers. This has motivated growing interest in Explainable AI (XAI), with methods such as SHAP (SHapley Additive exPlanations) that attribute predictions to individual input features [14, 15].

1.4.2 Energy Performance Indicators and Benchmarking

Energy Performance Indicators (EnPIs) provide the most essential and quantitative backbone of energy analysis and energy management in any critical facility. It has been noticed that ISO 50006 classifies EnPIs at organisational, system, and process levels, giving facilities a proper flow, framework and structure to track, analyse, and compare performance over the time [16].

Buildings, particularly public buildings, present a unique challenge when evaluating energy performance. Previous studies have used indicators such as energy consumption per floor area, per bed, per patient, and per unit of healthcare service [17]. However, the lack of standard methods for calculating these indicators makes it difficult to compare results across different case studies and buildings. To improve energy prediction in hospitals, several researchers have applied machine learning techniques. For example, Panagiotou and Dounis [11] developed ANFIS and XGBoost models that achieved mean absolute percentage errors between 2.27% and 10.77%. Similarly, Timur et al. [18] reported that support vector machines performed better than linear regression, with prediction errors of 8.89% and 15.79%, respectively. While these studies show that data-driven methods can improve energy forecasting, they also point to the need for more consistent benchmarking approaches that allow meaningful comparisons across healthcare buildings.

1.4.3 HVAC System Optimisation and Maintenance

HVAC systems account for 30-45% of energy use in commercial buildings and up to 60% in hospitals. Although the link between good maintenance and energy performance is intuitively clear, quantitative evidence on the energy impact of specific maintenance actions has been scarce. Some studies have reported modest or even negative savings from cleaning coils and filters in small buildings, while others have documented airflow improvements of 10-46% fol-

lowing professional duct cleaning in larger systems [19]. The specific energy consumption (SEC), defined as energy per unit volume of air handled, has emerged as a useful metric for assessing air handling unit performance. This thesis contributes the first year-long controlled comparison of two identical AHU systems, one maintained, one not, operating under comparable conditions in [19]. The benefits of HVAC cleaning through a multi-climate field study, reporting reductions in energy consumption and improvements in supply airflow in [20].

1.4.4 Industrial Decarbonisation and Energy Management Systems

Industry contributes about one-quarter of global CO_2 emissions, with steelmaking being one of the hardest-to-abate sectors. Adoption of ISO 50001 has been shown to reduce energy intensity by roughly 26% in certified companies [21]. Machine learning is beginning to be used to improve industrial energy management: Moghadasi et al. [22] applied Gradient Boosting to a gas complex and achieved a 10.31% reduction in energy use, saving over 7,000 tonnes of CO_2 per year. Kanchiralla et al. [23] showed the applicability of ISO 50006-based EnPI hierarchies in the Swedish engineering sector. Still, the integration of ML tools with ISO 50001 frameworks in the steel industry remains largely unexplored, a gap that this thesis aims to fill.

1.4.5 Explainable AI for Energy Decision Support

For AI-driven energy management to be usable in practice, its recommendations must be interpretable. SHAP analysis, grounded in cooperative game theory, quantifies the contribution of each input feature to a given prediction [15]. In the context of this work, SHAP allows energy managers to see, for example, which chiller components drive overall electricity consumption, and to verify that the model's logic is consistent with physical expectations. That level of transparency is essential if consultants and their clients are to trust and act upon AI-generated insights.

The reviewed literature informs the methodological choices of this thesis. Rather than introducing new technologies, the research focuses on integrating IoT, machine learning, and explainable AI into a consulting-oriented energy-management workflow. The case studies evaluate how this integration supports energy-performance assessment, prediction, and interpretation across different applications.

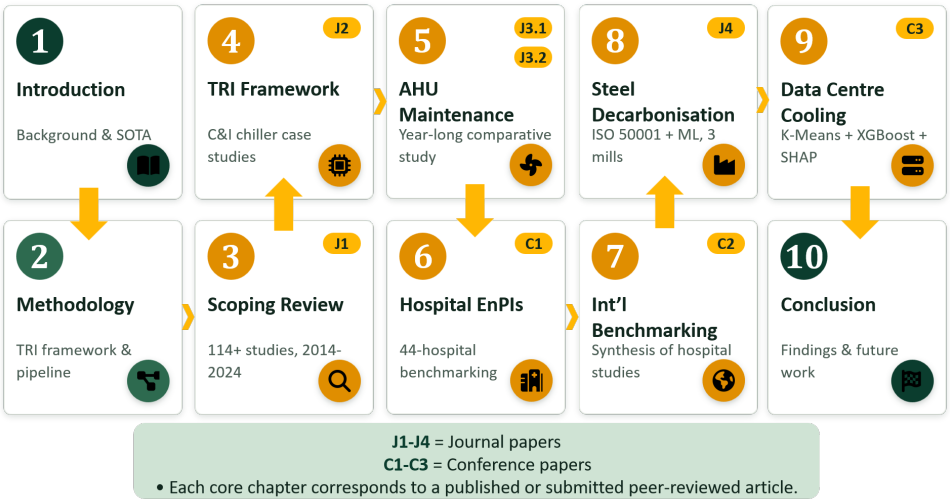

Figure 1.1: Thesis structure and the relationship between chapters and RQs.

1.5 Thesis Outline

This dissertation follows the thesis-by-publication format. Each core chapter corresponds to a paper that has been published in, or submitted to, a peer-reviewed journal or conference. The structure is shown in Figure 1.1, and the mapping between chapters(published research papers) and RQs is summarised in Table 1.1.

Table 1.1: Mapping of Published thesis chapters to RQs.

Chapter [-]	Title	RQ covered
3	Scoping review of AI/ML in building energy management (J1)	Overview
4	TRI framework for C&I energy management (J2)	RQ2, RQ4
5	Impact of AHU cleaning on HVAC performance (J3.1 and J3.2)	RQ3
6	Multidimensional EnPI framework for hospitals (C1)	RQ1
7	Benchmarking synthesis for hospital EnPIs (C2)	RQ1
8	Steel mill decarbonisation with ML-assisted energy allocation (J4)	RQ1, RQ4
9	Data centre cooling with regime-aware temporal XAI (C3)	RQ2, RQ4

The chapters are organised as follows:

Chapter 1 sets the scene for the entire thesis. It explains why energy and environmental consultants need better tools, defines the four RQs, reviews what others have done in this area, and lists the main contributions of this work.

Chapter 2 describes the research context and the overall methodology. It introduces the Technological Regenerative Innovation (TRI) framework and explains how the data-driven pipeline works across all case studies.

Chapter 3 corresponds to Paper J1 as shown in Figure 1.1, a scoping review published in *Energy Reports*. The paper focuses over one hundred studies from 2014 to 2024 that applied artificial intelligence and machine learning to building energy management. It identifies which algorithms work best for different forecasting horizons, how ensemble methods compare to single models, and what gaps remain in the literature. This review provides the scientific foundation for the rest of the thesis.

Chapter 4 corresponds to Paper J2, an extended conference paper submitted to a journal. This chapter presents the TRI framework in detail and tests its predictive intelligence and explainability components on two chiller systems, one commercial and one industrial. It uses SHAP analysis to show which operational parameters drive energy consumption, addressing **RQ 2 (1.3.2)** on explainable AI. The chapter also demonstrates how IoT sensing, big data analytics, and machine learning can be woven into a single framework, touching on **RQ 4 (1.3.4)** about shifting from experience-based to data-informed strategies.

Chapter 5 corresponds to Paper J3.1 and J3.2, published in *Energy and Buildings*. This chapter reports a year-long field experiment comparing two identical air handling units at the University of Pavia, one that was cleaned and maintained, and one that was left untouched. It quantifies the energy savings, airflow improvements, and thermal efficiency gains from maintenance interventions, directly answering **RQ 3 (1.3.3)** on predictive maintenance.

Chapter 6 corresponds to Paper C1, a conference paper. It develops a multidimensional energy performance indicator framework for hospitals, organised around a fishbone (Ishikawa) structure. The framework captures drivers such as weather,

occupancy, and medical equipment usage, and it is validated against data from forty-four hospitals. This work addresses **RQ 1 (1.3.1)** on performance indicators.

Chapter 7 corresponds to Paper C2, another conference paper. It synthesises international benchmarking studies for hospital energy performance indicators, showing how different metrics have been used across countries and healthcare systems. This chapter supports **RQ 1 (1.3.1)** by identifying which indicators allow fair comparison between hospitals.

Chapter 8 corresponds to Paper J4, published in *IEEE Transactions on Industry Applications*. It applies the ISO 50001 energy management standard to three steel mills, two in Italy and one in the United States, using machine learning to allocate energy flows and predict specific energy consumption. The chapter introduces a novel indicator, Wh/(Nm^3/ton), and compares it with conventional metrics. This addresses **RQ 1 (1.3.1)** on performance indicators and **RQ 4 (1.3.4)** on framework integration for industrial processes.

Chapter 9 corresponds to Paper C3, a conference paper accepted at IAS 2026. It extends the TRI framework to data centre cooling, combining K-Means clustering, XGBoost regression, and temporal SHAP analysis. The regime-aware approach reveals how the importance of cooling variables changes under different load conditions, answering **RQ 2 (1.3.2)** on explainable AI. The chapter also shows how the TRI framework scales to another sector, contributing to **RQ 4 (1.3.4)** on data-informed operational strategies. As this paper uses publicly available open access dataset, real operational data can help in validating this study.

Chapter 10 brings everything together. It discusses how the findings across all chapters fit into the broader picture of energy consulting, notes the limitations of the work, and suggests where future research could go.

The four RQs thread through the chapters as follows. **RQ 1 (1.3.1)** on performance indicators runs through the hospital studies in Chapters 6 and 7 and the steel mill study in Chapter 8. **RQ 2 (1.3.2)** on explainable AI is taken up by the chiller study in Chapter 4 and the data centre study in Chapter 9. **RQ 3 (1.3.3)** on predictive maintenance is covered entirely by the AHU experiment in Chapter 5. **RQ 4 (1.3.4)** on framework integration appears in the

TRI validation of Chapter 4, the steel mill application of Chapter 8, and the data centre extension of Chapter 9.

1.6 Research Contributions

The principal contributions of this thesis are:

1. **Decadal scoping review**: A systematic analysis of 114+ peer reviewed studies (2014-2024) that categorize algorithm performance across building types and forecasting horizons.

2. **TRI framework**: A novel integration of IoT sensing, BigData analytics (with Microsoft Fabric), and XAI (SHAP) for predictive energy management, addressing the disconnect between data collection and actionable insight. Adaptive control and autonomous decision-making remain proposed extensions and require separate experimental validation.

3. **Empirical AHU maintenance evidence**: The first year-long controlled experiment comparing identical maintained and unmaintained AHU systems, demonstrating energy savings of around 16.2% to 71.4% depending on the maintenance and cleaning intervention.

4. **Multidimensional hospital indicator framework**: A fish-bone (Ishikawa)-based framework that captures key drivers of hospital energy consumption and shows that a comprehensive indicator set outperforms reduced feature sets.

5. **Industrial energy allocation algorithm**: An Energy Use Significance Score methodology, validated on three steel mills, that enhances ISO 50001 with ML-based EnPI forecasting for specific energy consumption.

6. **Cross-sector applicability**: The application of data-driven energy management methodologies across commercial buildings, hospitals, HVAC systems, steel manufacturing, and data-centre cooling. The case studies show the adaptability of selected predictive and explainability methods to different operational settings. Their results provide a basis for further evaluation of the framework under larger-scale and longer-duration deployments.

1.7 List of Publications

This thesis is based on the following peer-reviewed publications, which form the core chapters of the dissertation as shown in figure 1.1 and the publications are grouped by type.

1.7.1 Journal Papers

1. **N. Ahmed**, Y. Ding, G. Canti, and N. Anglani, "Sustainable building's energy management with artificial intelligence and machine learning: A decadal scoping review (2014–2024)," *Energy Reports*, vol. 15, p. 109082, 2026. https://doi.org/10.1016/j.egyr.2026.109082
   (Forms Chapter 3 of this thesis)

2. **N. Ahmed**, G. Canti, G. Cassetta, Y. Ding, and N. Anglani, "A Data-Driven Framework for Energy Management in Commercial and Industrial Sector using IoT, Big Data, and XAI," in *Proc. IEEE Energy Conversion Congress and Exposition (ECCE)*, Philadelphia, PA, USA, 2025, pp. 1–8. https://doi.org/10.1109/ECCE58356.2025.11260078
   Extended journal version in review (IAS IEEE 2026). (Forms Chapter 4 of this thesis)

3. **N. Ahmed**, T. Facchinetti, M. Hernandez, and N. Anglani, "The impact of air handling unit cleaning on HVAC electricity consumption and system performance," *Energy and Buildings*, vol. 353, p. 116896, 2026. https://doi.org/10.1016/j.enbuild.2025.116896
   (Forms Chapter 5 of this thesis)

4. N. Ildiri, E. Biesiada, T. Facchinetti, N. Anglani, **N. Ahmed**, and M. Hernandez, "Impacts of HVAC cleaning on energy consumption and supply airflow: A multi-climate evaluation," *Energy and Buildings*, vol. 328, p. 115147, 2025. https://doi.org/10.1016/j.enbuild.2024.115147 *(Related to 2nd part of Chapter 5 of this thesis)*

5. R. Khalid, **N. Ahmed**, and N. Anglani, "Decarbonization of Steel Mills, how to Set-up an Effective Allocation of Energy Flows, aiming at Tracking Efficiency and Energy Savings assisted with Machine learning tools," *IEEE Transactions on Industry Applications*, vol. 62, pp. 2100–2112, 2026.
   (Forms Chapter 8 of this thesis)

1.7.2 Conference Papers

1. **N. Ahmed**, S. Bennati, and N. Anglani, "Multidimensional Energy Performance Indicators and Data Analytics Scientific Framework to Enable Effective Energy Management in Hospitals," in *Proc. IEEE 9th International Youth Conference on Energy (IYCE)*, 2024, pp. 1–6. https://doi.org/10.1109/IYCE60333.2024.10634953
   (Forms Chapter 6 of this thesis)

2. **N. Ahmed**, S. Bennati, and N. Anglani, "Energy Performance Benchmarking and Indicators: A Comprehensive Framework for scientifically sound Data-Driven and Energy Management Improvements in Hospitals," in *Proc. IEEE 8th International Energy Conference (ENERGYCON)*, 2024, pp. 1–6. https://doi.org/10.1109/ENERGYCON58629.2024.10488801
   (Forms Chapter 7 of this thesis)

3. **N. Ahmed**, G. Canti, and N. Anglani, "Extending Technological Regenerative Innovation Framework for Data Center Cooling Power Prediction with Regime Aware Temporal XAI," in *Proc. IEEE Industry Applications Society Annual Meeting (IAS)*, 2026, accepted.
   (Forms Chapter 9 of this thesis)

Author's contribution: Nouman Ahmed is the first author on all publications except J4, where he is the second author. He led the conceptualisation, methodology, data analysis, and writing for J1, J2, J3.1, J3.2, C1, C2, and C3. For J4, he contributed to the methodology, machine learning modelling, and manuscript preparation.

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Chapter 2



Research Context and Methodology

2 RESEARCH CONTEXT AND METHODOLOGY

2.1 Research Context

2.1.1 The Role of Energy Consulting in Carbon Reduction

Energy consultants are main actors in the shift toward carbon neutrality. They conduct energy audits, devise efficiency strategies, set up monitoring systems, and verify that interventions deliver the promised savings. The quality of their advice directly influences the effectiveness of the carbon reduction measures adopted by building owners and industrial operators [1]. In today's landscape, the profession faces mounting challenges: building energy systems are growing more complex, the volume of data from smart meters and IoT devices is expanding rapidly, and regulatory demands are becoming stricter. Traditional manual approaches can no longer keep pace. AI and ML offer a way to strengthen consultants' analytical capabilities, enabling them to handle larger datasets, uncover patterns hidden from manual inspection, and provide recommendations that are both more accurate and more actionable.

2.1.2 The Academic-Industrial Partnership Model

This PhD was conducted through a collaborative arrangement combining academic research at the University of Pavia, particularly within the Energy Laboratory (LABEN), with industrial engagement at Alens SRL and a six-month research period abroad at TECNUN, University of Navarra, Spain. The partnership brought several benefits.

First, there was direct access to real client data and live consulting projects, which kept the research grounded in genuine problems rather than idealised scenarios.

Second, new methods were tested immediately on active assignments, yielding quick feedback on their practical performance.

Third, the continuous exchange between university and industry helped develop a research style that values both rigour and applica-

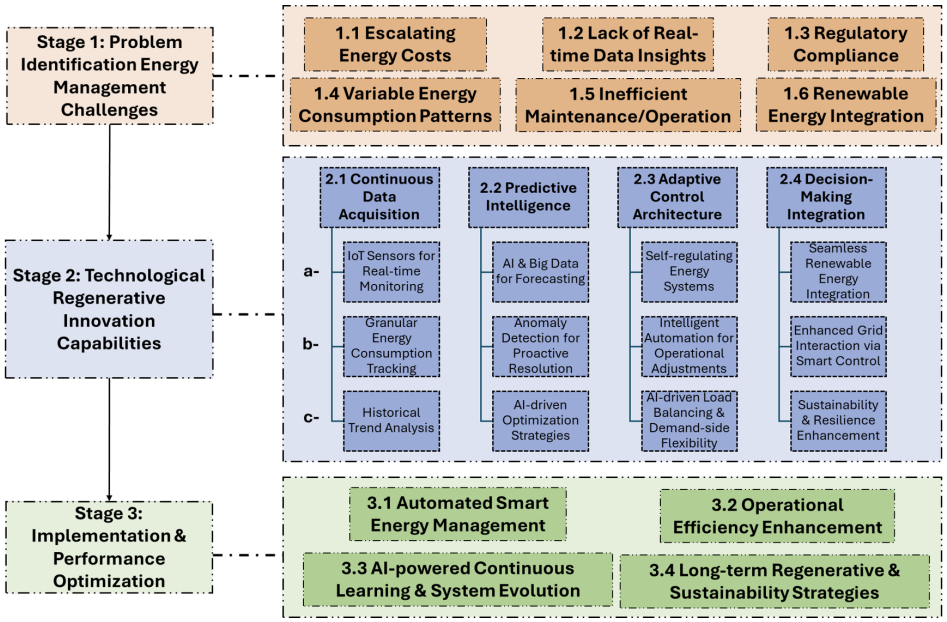

Figure 2.1: The Technological Regenerative Innovation (TRI) framework.

bility, a combination that is essential for producing solutions that energy consultants can actually use.

2.2 The Technological Regenerative Innovation (TRI) Framework

The TRI framework is one of the central methodological contribution of the thesis focusing specially on the TRI capabilities. Some elements including stage 2.1 and 2.2 of the framework are validated through case studies about commercial and industrial (C&I) facilities. The adaptive control and decision making are described as framework design elements but are not experimentally validated in this work due to implementation and resource limitations. The aim is to create systems that are not merely efficient but genuinely regenerative, encompassing concepts such as AI, smart monitoring, autonomous operation, and the adoption of renewable energy, all directed at reducing carbon emissions and improving infrastructure performance.

2.2.1 Stage 1: Problem Identification

The first stage catalogues the energy management shortcomings commonly observed in practice. Based on consulting experience,

six recurrent challenges stand out:

- **Rising energy costs**: escalating electricity and fuel prices that put growing financial pressure on building operators and industrial facilities.
- **Limited real-time insights**: monitoring infrastructure that generates large volumes of data but rarely converts them into predictive intelligence.
- **Regulatory compliance**: rapidly evolving energy efficiency regulations that demand sophisticated analytical skills.
- **Variable consumption patterns**: the increasing influence of renewables and fluctuating occupancy or production schedules.
- **Sub-optimal maintenance**: calendar-based routines that either waste resources (when done too often) or allow performance to degrade (when done too infrequently).
- **Renewable energy integration**: the additional variability introduced by solar, wind, and other distributed sources.

2.2.2 Stage 2: TRI Solution Framework

The core of TRI rests on four interconnected pillars:

Pillar 2.1: Continuous Data Acquisition

High-resolution IoT sensors capture energy and environmental parameters at multiple time scales, from minute-level to daily. The infrastructure brings together heterogeneous data sources, weather variables, equipment operational parameters, and contextual information, while flagging critical consumption periods for detailed analysis.

Pillar 2.2: Predictive Intelligence

AI and BigData analytics are applied to forecast system behaviour. Machine learning models, including Random Forest, Gradient Boosting, Support Vector Machines, and Neural Networks, are trained on historical records and continuously refined as new data arrive. This allows the system to adapt to seasonal shifts and evolving usage patterns without manual reprogramming.

Pillar 2.3: Adaptive Control and Optimisation

Predictions are turned into concrete operational actions: adjusting set-points, scheduling maintenance before failures occur, and solving multi-objective optimisation problems that balance energy savings, occupant comfort, and system reliability.

Pillar 2.4: Continuous Learning

Feedback loops and automatic model refinement ensure that the framework improves over time. As building use and external conditions change, the system self-tunes, keeping its recommendations relevant.

2.2.3 Stage 3: Outcomes and Benefits

Implementing the TRI framework yields measurable results: lower energy consumption and costs (with documented HVAC savings of up to 37% in office buildings), reduced carbon emissions, longer equipment life through predictive maintenance, and easier compliance with evolving regulations. Because the framework is modular, it can be adapted to a wide variety of building types and industrial settings, making it a practical asset for consulting firms.

2.3 Data-Driven Methodology Pipeline

Although the exact steps vary across application domains, all studies in this thesis follow a consistent multi-layer workflow.

2.3.1 Data Layer: Collection and Preprocessing

Data are collected from diverse sources, weather services, facility management systems, IoT sensors, and production logs, typically at multiple temporal resolutions. Preprocessing includes cleaning, normalisation, gap-filling, and outlier detection. Feature engineering transforms raw values into informative inputs: temporal features (hour, day, season), weather-related variables (temperature, humidity, solar irradiance), and operational descriptors (occupancy schedules, set-points, production volume). Feature selection techniques such as F-test, Minimum Redundancy Maximum Relevance (MRMR), and Relief for Regression are used to identify the most predictive variables.

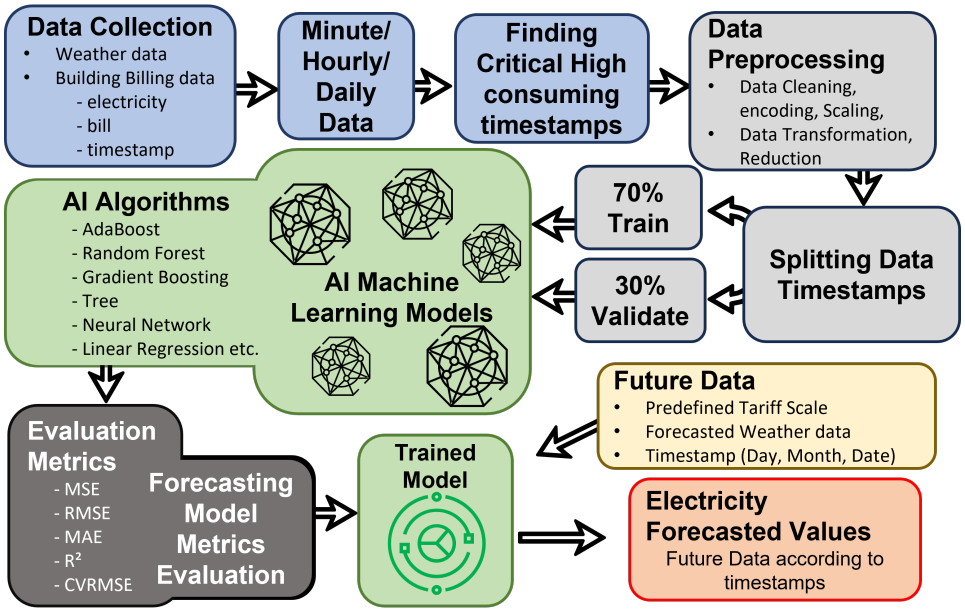

Figure 2.2: Generalized data-driven methodology pipeline for AI/ML analysis of C&I critical facilities.

2.3.2 ML Layer: Model Development and Validation

AI/ML Models are trained using a chronological train-test split (typically 70% training, 30% testing or 80% training, 20% testing split is used in some studies, depending on data availability to respect the temporal order of the data, with cross-validation applied where appropriate as shown in figure 2.2. Hyper-parameters are optimised via grid search and Bayesian methods. Performance is evaluated through multiple metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), R^2, and the Coefficient of Variation of RMSE (CV(RMSE)).

2.3.3 XAI Layer: Explainability and Interpretation

To overcome the black-box nature that often limits adoption in consulting, SHAP analysis is integrated into every modelling workflow. SHAP values quantify the contribution of each input feature to each prediction, providing both a global view of feature importance and local explanations for individual forecasts. This transparency helps energy managers verify that the models capture physically plausible relationships and builds the trust needed to act on AI-driven recommendations along with new Key Performance Indicators(KPIs) as shown in figure 2.3.

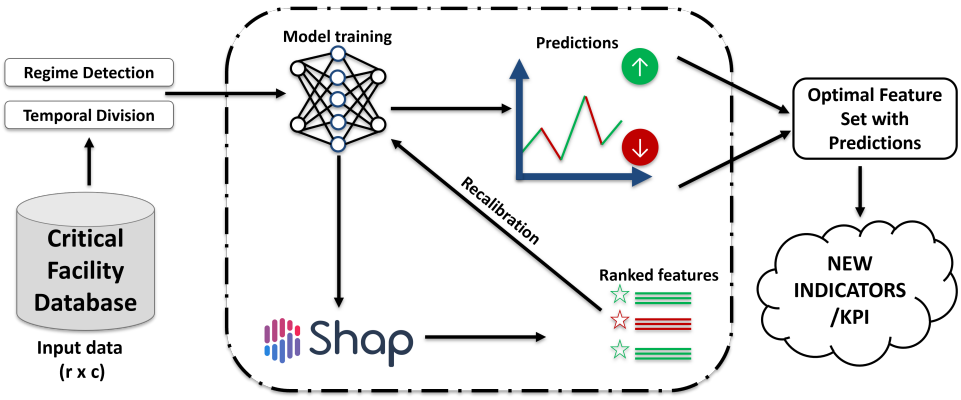

Figure 2.3: Data analysis flow of predictive intelligence within the TRI framework for target prediction. Model training produces predictions, and SHAP analysis ranks feature contributions within each context.

2.3.4 Output Layer: EnPIs, Benchmarking, and Decision Support

The final layer translates model outputs into formats that consultants can use directly. Energy Performance Indicators (EnPIs) are calculated in line with ISO 50006 and tailored to the specific sector, energy per bed or per square metre in hospitals, toe per tonne in steel mills. Benchmarking compares current performance against historical baselines and peer facilities. Decision support outputs include prioritised efficiency measures, predicted savings, and projected carbon reductions, all designed for inclusion in client reports and presentations.

2.4 Case Study Overview

The research papers presented in Chapters 3 to 9 comprise seven chapters, but the number of case studies are distinguished from the number of broad application categories. The research was validated through six complementary case studies:

1. **Commercial Building.** A 1,640 kW chiller system serving a university complex in Pavia, monitored via Power BI and Microsoft Fabric (14,999 hourly instances).

2. **Industrial Chiller.** A multi-circuit system in Northern Italy, with data from glycol circuits, evaporators, cold water networks, and evaporation towers (1,493 instances).

3. **AHU Comparative Study.** Two identical AHUs at the University of Pavia, one maintained (AHU-C) and one uncleaned (AHU-UC), monitored over a full year under comparable thermal loads.

4. **Hospital Benchmarking.** A dataset of 44 hospitals, combining energy consumption, building characteristics, operational parameters, and environmental conditions.

5. **Steel Mill Decarbonisation.** Three electric-arc-furnace mills (two in Italy, one in the US) differing in size, product mix, and operation, used to develop energy flow allocation and EnPI prediction models.

6. **Data Centre Cooling.** A small-to-medium data centre was used to evaluate the TRI framework using 3,498 hourly observations, combining K-Means, XGBoost, and SHAP to predict cooling power consumption and provide explainable, context-aware insights for cooling system operation.

2.5 Conceptual Links Between Papers

Each paper presented in this thesis focuses on a different application domain, they are all connected by a common objective: leveraging data-driven methods to improve energy management, support decision-making, and contribute to decarbonisation across commercial and industrial sectors.

The scoping review (Chapter 3) establishes the scientific foundation of the thesis by systematically analysing the evolution of artificial intelligence and machine learning techniques in building energy management, identifying both research trends and existing knowledge gaps [2]. The TRI framework paper [3]. (Chapter 4) proposes a methodology that integrates IoT, BigData, AI, and explainable AI into a regenerative energy management framework for commercial and industrial facilities . This framework serves as the conceptual backbone for the subsequent studies.

The AHU case study (Chapter 5) shows that effective energy management extends beyond predictive analytics alone. By quantifying the impact of maintenance on HVAC performance, it shows that physical maintenance and intelligent monitoring should work together to achieve sustainable energy savings [4]. Further, the multi-climate HVAC cleaning study, provides complementary research context for Chapter 5, which investigates the effectiveness of routine heating, ventilation, and air conditioning (HVAC) clean-

ing on energy consumption, indoor air quality and supply airflow patterns in different locations[5].

The hospital studies (Chapters 6 and 7) expand the framework to the healthcare sector by developing multidimensional Energy Performance Indicators (EnPIs) and benchmarking methodologies that enable fair comparisons between hospitals while providing practical decision-support tools for energy consultants and facility managers [6, 7].

The steel mill study (Chapter 8) further shows the flexibility of the proposed methodology by applying ML to one of the most energy-intensive industrial sectors. The study combines ISO 50001 principles with predictive analytics to improve energy performance assessment and support industrial decarbonisation strategies [8].

Finally, the data centre cooling study (Chapter 9) extends the predictive intelligence capability of the TRI framework by incorporating regime-aware explainable artificial intelligence. Rather than focusing solely on prediction accuracy, the study combines operating regime identification with temporal SHAP analysis to explain how the influence of key variables changes under different operating conditions. This provides transparent and context-specific insights that can support more informed operational decisions for cooling system management while strengthening the explainability component of the TRI framework [9].

Taken together, these studies show the evolution of the proposed methodology from a conceptual framework to practical applications across multiple sectors, including commercial buildings, healthcare facilities, heavy industry, and data centres. Despite addressing different case studies, they share a common philosophy of combining IoT-enabled monitoring, ML, explainable AI, benchmarking, and predictive analytics to support more intelligent, sustainable, and regenerative energy management.

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Chapter 3



Sustainable building's energy management with artificial intelligence and machine learning: A decadal scoping review (2014–2024)

3 SUSTAINABLE BUILDING'S ENERGY MANAGEMENT WITH ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING: A DECADAL SCOPING REVIEW (2014–2024)

Artificial Intelligence (AI) and Machine Learning (ML) have become important tools for improving buildings' energy management. This chapter is based on a published journal review paper that studies the recent progress of AI and ML applications in this field. The paper provides the scientific background of energy management with artificial intelligence and machine learning by reviewing existing research, identifying widely used methods, and highlighting current challenges. Based on a systematic review of studies published between 2014 and 2024, it evaluates the performance of different AI and ML techniques and identifies research gaps in model comparison, real-time data integration, benchmarking, and explainability. The findings establish the research context for this thesis and support the development of transparent, practical, and data-driven energy management frameworks presented in the following chapters.

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journal homepage: www.elsevier.com/locate/egyr

Review article

Sustainable building's energy management with artificial intelligence and machine learning: A decadal scoping review (2014–2024)

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ABSTRACT

Artificial Intelligence (AI) and Machine Learning (ML) are transforming energy management in buildings by enabling data-driven prediction, optimization, and real-time control. This scoping review synthesized the state of the art in this field over the past decade (2014–2024), based on a structured search of peer-reviewed studies. The review classified AI/ML applications, according to features like: forecasting horizons, algorithm families (classical ML, deep learning, hybrid/ensemble, reinforcement learning), building categories (residential, commercial, healthcare), and integration levels (standalone, IoT-enabled, microgrid-enabled). The analysis of 100+ comparative studies showed that ensemble and hybrid methods frequently outperform single algorithm methods, however, performance gains vary considerably depending on data quality, forecasting horizon, and building operational characteristics. Key challenges remain in data standardization, balance between model complexity and interpretability, privacy, and scalability from individual buildings to urban districts. Emerging opportunities were highlighted at the intersection of AI with digital twins, IoT, and transfer learning, which support small data contexts and real time adaptation. By bridging technical advances with practical challenges, this work aims at informing the scientific community, working towards intelligent, sustainable, and efficient energy management in buildings, by supporting with a clear classification of AI/ML techniques and their most promising applications across different building types.

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Nomenclature

AE	Autoencoders
AI	Artificial Intelligence
ANFIS	Adaptive neuro fuzzy inference system Learning
ANN	Artificial Neural Network
CNN	Convolutional Neural Networks
CRPS	Continuous Ranked Probability Score
DDM	Data-driven methods
DL	Deep Learning
DML	Distributed Machine Learning
DNN	Deep Neural Networks
DQA	Differential Quadrature Approach
DRL	Deep Reinforcement Learning
DT	Decision Trees
EKF	Extended Kalman Filters
FA	Firefly Algorithm
FCS	Fuzzy Control Systems
GA	Genetic Algorithm
GAN	Generative Adversarial Networks
GB	Gradient Boosting
GMM	Gaussian Mixture Model
GP	Gaussian Process
GPR	Gaussian Process Regression
GRU	Gated Recurrent Unit
GTO	Gorilla Troop Optimizer
KMC	K-means Clustering
LR	Linear Regression
LR-I	Linear Regression Interaction
LR-S	Linear Regression Stepwise
LSTM	Long Short-Term Memory
MACS	Multi-agent Control Systems
MLP	Multilayer Perceptron
MOPSO	Multi-objective Particle Swarm Optimization
PBML	Physics-based Machine Learning
PCA	Principal Component Analysis
PSO	Particle Swarm Optimization
QL	Q-learning
RC-T	Regression Coarse Tree
RF	Random Forest
RF-T	Regression Fine Tree
RL	Reinforcement Learning
RNN	Recurrent Neural Networks
RQ	Research Question
SA	Sensitivity Analysis
SARIMAX	Seasonal Auto Regressive Integrated Moving Average with eXogenous variables
SL	Supervised Learning
SUA	Stochastic Uncertainty Analysis
SVM	Support Vector Machines
TL	Transfer Learning
TSF	Time-series Forecasting
UL	Unsupervised Learning
WNN	Wide Neural Network

1. Introduction

Artificial Intelligence (AI) has become pivotal in transforming energy management, with over 25% of the research now focused on energy applications (Jin et al., 2020). From optimizing grid operations to reducing energy consumption in buildings, AI showed significant potential to address critical sustainability challenges while managing increasingly complex energy infrastructure facilities. Methods, from the machine learning (ML) domain and its broader field of AI, are

becoming very popular for energy system prediction and modeling. Often, they are used interchangeably but have distinct meanings. AI represented the broader concept of creating machines that can simulate human intelligence and decision making processes (Duan et al., 2019; Robinson et al., 2005). ML, as a subset of AI, specifically focused on algorithms that learn patterns from data without being explicitly programmed for every scenario (Sarker, 2021; Jordan and Mitchell, 2015). Deep learning, utilizing neural networks, represented a more specialized computational approach within ML that uses highly parameterized architectures to learn complex mappings from data (Dargan et al., 2020; Singaravel et al., 2018). For energy management applications, both prediction and forecasting serve crucial but distinct roles. Prediction typically involves estimating current or immediate future states based on available data inputs (such as real time energy demand prediction) (Hernandez et al., 2014; Rafique and Jianhua, 2018), while forecasting extended to longer term projections using historical patterns and trends (such as monthly or seasonal energy consumption forecasting) (Ugbehe et al., 2025; Chou and Tran, 2018). In practice, both AI and ML techniques can be applied to either prediction or forecasting tasks, with the choice depending on the specific algorithm capabilities and scopes, rather than the AI/ML categorization (Mukhamediev et al., 2022; Entezari et al., 2023). They have thus emerged as transformative technologies in energy management, too, encompassing a broad spectrum of applications aimed at optimizing energy generation, distribution, consumption, and their sustainability, not only in buildings (Hanafi et al., 2024; Ukoba et al., 2024). These techniques involve algorithms that can analyze complex datasets, predict energy demand and supply patterns, optimize the exchange with the grid or inside a microgrid, and enable more efficient resource allocation in general (Khan et al., 2023b; Kibria et al., 2018).

The integration of AI and ML in energy management marks a pivotal transformation in the approach to energy efficiency and sustainability in buildings, a way paved in the past by expert systems and first-generation neural network applications. As the use of energy in buildings accounted for approximately 39% of energy consumption in the United States and 40% in Europe, with corresponding CO_2 emissions of 38% and 36% respectively, the need for innovative energy management solutions has become increasingly urgent with this specific focus (Amasyali and El-Gohary, 2018; Ürge-Vorsatz et al., 2007; Arent et al., 2022).

AI and ML technologies offered promising advancements, their application presented both opportunities and challenges, that require a comprehensive review and a careful examination. Energy analysis using large amounts of data has become a promising solution, but it also brought its own challenges. These include issues with data quality, making sure the models work well in different situations, and ensuring that the results are easy to understand and interpret (Rashid and Kausik, 2024).

The prediction of energy consumption in buildings represented a multifaceted challenge, extending beyond technological capabilities. The intricate interplayed among physical properties of the built environment, environmental factors, building information, human elements, and operational considerations, created a complex prediction environment (Bibri and Krogstie, 2017). This complexity necessitates sophisticated analytical approaches capable of integrating diverse data types, while accounting for their interdependency.

Despite substantial progress in AI/ML applications for energy management, several critical gaps remain unaddressed, as current reviews often prioritized algorithmic approaches and their comparison, neglected the crucial interplay of the many variables affecting energy consumption (Tran et al., 2023). Most recent studies mainly focus on comparing different algorithms rather than looking at how variables work together. Li et al. (2024a) compared four different methods (data generation, incremental learning, transfer learning, and physics informed approaches) under data shortage scenarios using Long Short-Term Memory(LSTM), by directing the effort on comparing their performances in the prediction of hourly building's energy consumption, by evaluating how input variables (meteorological: dew point temperature, sea level pressure, wind speed, outdoor temperature, wind direction; temporal: hour, month, day of week; plus historical energy data) perform under three distinct data shortage scenarios (extreme: 1-week, heavy: 4-weeks, mild: 13-weeks) across five building types. Li et al. showed that the effectiveness of different variables changes dramatically depending on data availability. This scenario dependent variable performance analysis addresses a crucial gap: understanding not just which variables matter, but when and under what data conditions they contribute most to prediction accuracy. Ma and Yeung (2024) created multi channel conditional Generative Adversarial Networks (GANs) for HVAC's energy consumption forecasting across 11 office buildings and the method showed 17%–76% accuracy improvements compared to conventional methods (ARIMA, MLP) and deep learning benchmarks (CNN, LSTM, GRU). Their approach used eight inputs (five meteorological variables, two calendar features, plus historical energy data) but the study's contribution was centered on the architectural innovation of GANs rather than analyzing how these variables interdependently influence predictions leaving input variable interaction patterns and their context dependent importance unexplored. Laukkarinen and Vinha (2024) tested different tree based methods (Random Forest, XGBoost, LightGBM) for predicting indoor temperature of the building. These studies do not look enough at how different factors influence each other when predicting electricity use. Zhang et al. (2024) investigated in detail that building features like size, number of floors, and construction year in a particular area, were major factors, but they failed in catching how all these factors work together. Zhao et al. (2024) showed that, as the medical equipment way of usage affects deeply a hospital energy consumption, they indeed managed to cut the electricity bill by 15% by comparing 15 forecasting methods, nevertheless in their study they neglected how variables meteorological variables can be interwoven. However their study addressed a gap by incorporating how variables like medical equipment usage (CT, MRI scans), outpatient visits, and climatic factors are interwoven, which prior models had neglected. Understanding these connections could give better predictions and more useful information than just comparing algorithms. Additionally, there is insufficient analysis regarding e.g., optimal data types and volumes for various prediction scenarios, the impact of feature selection methodologies, Jain et al. (2014) and Ahmed et al. (2024b) and the effect of temporal granularity on prediction accuracy.

As the field evolves, new challenges and opportunities arise. Data standardization remains a critical hurdle, with an urgent need for consistent collection and formatting protocols. Privacy concerns, especially in residential sector, require a careful balance between collecting the data, needed for analysis, and respecting people's rights. Additionally, scaling up these models from single buildings to entire cities is a major challenge that researchers are working on addressing (Potdar et al., 2018).

1.1. Research Questions (RQ) addressed

Hence, the authors of this review work are interested in shading some lights on the following questions:

1. What were the most effective AI/ML models for different forecasting horizons in building's energy management?
2. How do hybrid models compare to single model approaches across diverse building types?
3. What role do key parameters like environmental and operational parameters play in prediction accuracy and which are the parameters mainly connected to forecasting energy analysis in buildings?
4. How can transfer learning address challenges related to data in energy prediction in buildings?
5. What are the key performance differences between traditional statistical methods and advanced AI techniques in energy forecasting?

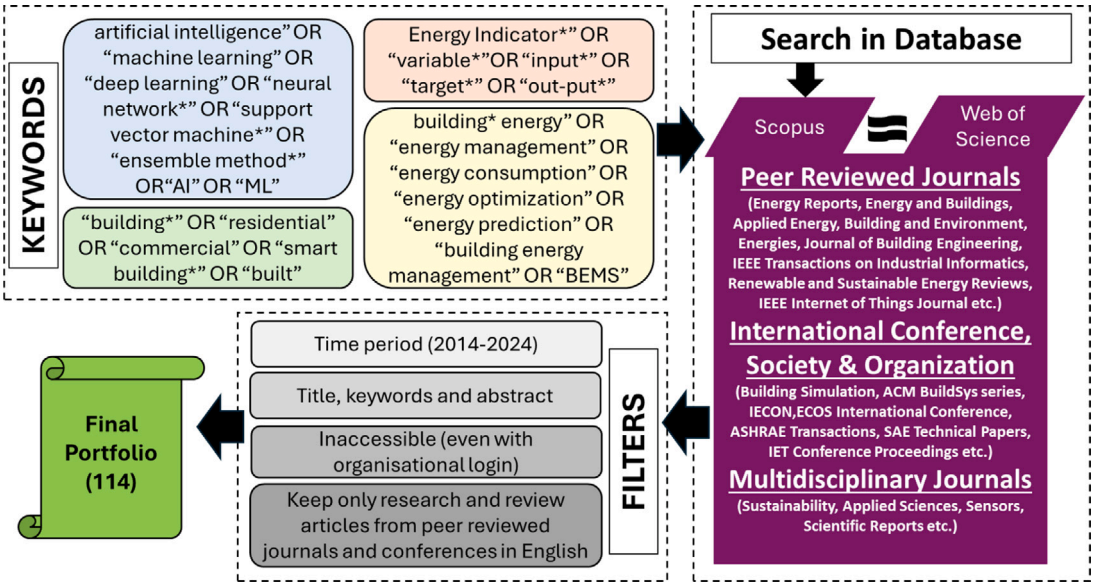

Fig. 1. Document selection and exclusion methods used in the literature review.

1.2. Review methodology

A systematic literature search was conducted largely in accordance with the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) guidelines. The literature search was performed exclusively on the Scopus database because of its extensive coverage of the interdisciplinary fields central to this study. Scopus indexed core publications, including the complete contents of IEEE Xplore, ScienceDirect etc, as evidenced by the representative sources in Fig. 1. The search strategies, detailed in Table 1, targeted peer-reviewed journal articles and conference proceedings published between January 2014 and December 2024.

This scope was chosen to prioritize a focused yet comprehensive analysis of the contemporary decade research landscape. The annual distribution of the resulting search showed the distribution of research content across Scopus academic database, with coverage of interdisciplinary research for peer reviewed article and conference papers publications, as visualized in Fig. 2. Blue bars represent journal articles (n = 1485), while green bars represent conference papers (n = 728). The graph showed steady growth from 36 publications in 2014 to over 437 in 2023, reflecting an impressive (more than ten-fold) increasing research interest in data driven energy analysis in buildings. The slight decline in 2024 may represent incomplete year data at the search date.

1.2.1. Search strategy and information sources

The last systematic search with the complete Scopus query strings as shown in Table 1 was conducted on September 15, 2025. We included studies that met the following criteria using Scopus filters:

- Population: Energy systems of Building (residential, commercial, healthcare, educational)
- Concept: Application of AI/ML methods for energy prediction, forecasting, optimization, or management
- Context: Studies providing sufficient technical detail on algorithms, datasets (size, temporal resolution, features), and performance metrics
- Publication type: Peer reviewed journal articles and conference papers
- Language: English
- Time period: 2014–2024

This search strategy ensured coverage of AI/ML applications for the current scope. All inclusion decisions were carefully reviewed and validated by the authors to ensure consistency and reliability in the selection process.

Table 1
Systematic search strategy performed on scopus with query design for review about AI/ML for building's energy management.

Search component	Search terms	Rationale
AI/ML technologies	"artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*" OR "support vector machine*" OR "ensemble method*" OR "AI" OR "ML"	Captures all major AI/ML approaches mentioned in research scope; includes both full terms and common abbreviations; uses truncation for variations
Energy applications	"building* energy" OR "energy management" OR "energy consumption" OR "energy optimization" OR "energy prediction" OR "buildin* energy management" OR "BEMS"	Focuses on specific energy management contexts relevant to buildings; includes system acronyms and application areas
Energy indicators	"Energy Indicator*" OR "variable*" OR "input*" OR "target*" OR "output*"	Targets studies discussing measurable energy parameters and modeling variables; aligns with quantitative focus
Building context	"building*" OR "residential" OR "commercial" OR "smart building*" OR "built"	Ensures building specific focus; excludes industrial or transportation energy applications; covers various building types

1.2.2. Selection process

A total of 2213 records were identified from the Scopus database. Of these, 366 records were removed prior to screening due to being non English, lacking full text availability, being articles in press, book series, or trade journal entries. The remaining 1847 records were screened based on title and abstract, leading to 865 records being excluded for clearly not meeting eligibility criteria (e.g., focused on industrial processes, lacked AI/ML application, or were purely review papers without primary analysis). Out of these, we could not access about 60 full texts despite the generous institutional access. We excluded approximately 430 studies that focused exclusively on smart grid systems and

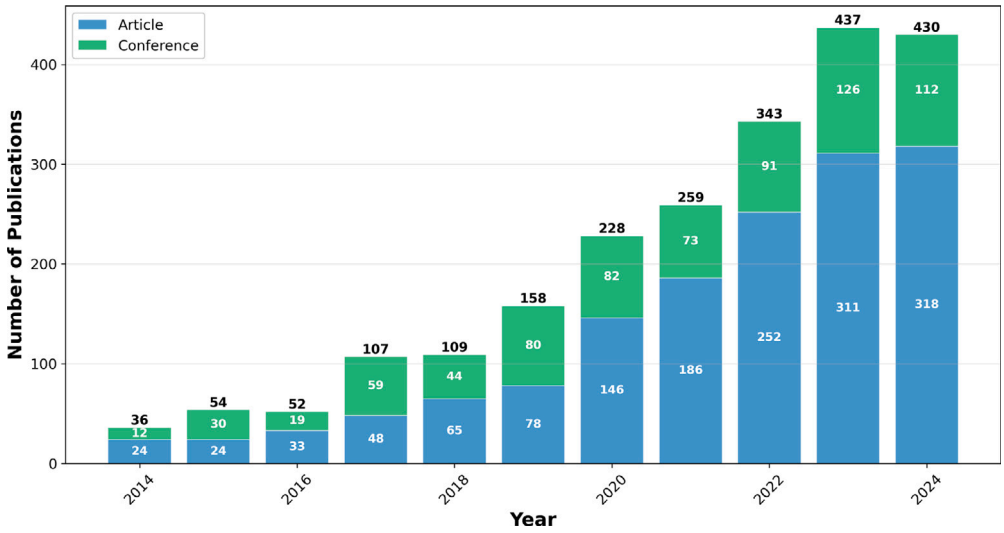

Fig. 2. Bar chart representation of total numbers of peer reviewed article and conference research papers published yearly in the past decade for 2014–2024 with respect to Scopus search using query terms specified in Table 1.

renewable energy systems without building analysis, purely theoretical algorithm development without empirical validation, industrial or transportation energy systems, or studies lacking quantitative performance evaluation. The screening process was conducted by Author 1 and 4, which represented a limitation as formal inter-rater reliability assessment was not performed. However, detailed inclusion/exclusion criteria were applied consistently throughout the selection process. All records were screened according to the defined search strategy, and the screening methodology, and a final set of included studies were reviewed and agreed upon by all authors.

Among the nearly 400 papers reviewed in detail, 286 were excluded due to insufficient methodological details, lack of building-specific focus, absence of performance metrics, duplication of results across multiple papers by the same authors, or preliminary studies that were superseded by more complete versions. This resulted in 114 papers, all included in the current analysis. Additionally, we identified 11 highly cited landmark papers (each with more than 400 citations, as of March 2024) that shaped the field's development, which we separately highlighted in Table 2 for historical context. The study selection process was summarized in the PRISMA flow diagram, as shown in Fig. 3.

While a multi-database approach could have identified additional niche studies, the breadth and quality of the literature captured through Scopus provided confidence that this review constitutes a representative and authoritative scoping of the field. The final collection of publications showed successful coverage of the key scholarly discussions from high impact sources. The selection criteria prioritized peer-reviewed journal articles and conference proceedings, specifically addressing AI/ML applications on buildings' energy systems. The articles were primarily collected based on their relevance to energy prediction and forecasting methodologies, the availability of detailed model descriptions, the presence of comprehensive dataset information, and the clear presentation of performance metrics. Studies were included if they provided sufficient technical details about the implemented algorithms, described the characteristics of the datasets used, and presented quantitative results with appropriate validation methodologies.

Given the diversity of study designs, datasets, and performance metrics across the reviewed literature, a formal risk of bias assessment was not conducted. Instead, studies with clearly reported methodologies, and comprehensive performance metrics were prioritized to ensure reliability and comparability. However, certain keywords and research areas were intentionally excluded from this review to maintain focus and scope. Terms related to smart city control applications, smart grid management, renewable energy without building integration, and

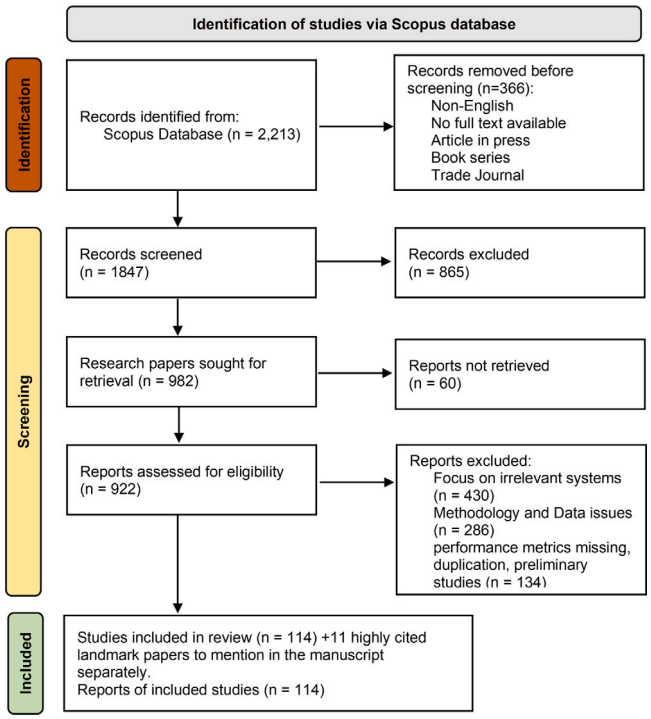

Fig. 3. Peer reviewed research paper selection process for this review paper following PRISMA flow diagram.

purely theoretical AI models without practical dataset information and analysis were not extensively covered. This review, while not claiming to be extensively exhaustive, presented the first decadal scoping review (2014 to 2024) of its kind in the energy. Priority was given to studies that provided sufficient information about data preprocessing techniques and performance comparison with baseline methods, where training and testing dataset details were explicitly mentioned, model hyperparameter were specified, and cross-validation or other robust evaluation techniques were employed.

The keyword co-occurrence network, visualized by using VOSViewer, provided a structured overview of the primary research themes within the literature on AI/ML for building's energy management, as shown in

Table 2
Top 11 relevant landmark articles having the highest citations in the field building's energy management at the date of September 15, 2025.

Author	Title	Citations
Kim and Cho (2019)	Predicting residential energy consumption using CNN-LSTM neural networks	1210+
Ahmad et al. (2017)	Trees vs. Neurons: Comparison between random forest and ANN for high resolution prediction of energy consumption in building	830+
Fan et al. (2017)	A short term building cooling load prediction method using deep learning algorithms	600+
Mocanu et al. (2016)	Deep learning for estimating energy consumption in building	540+
Jain et al. (2014)	Forecasting energy consumption of multi family residential buildings using support vector regression: Investigating the impact of temporal and spatial monitoring granularity on performance accuracy	520+
Wang et al. (2018)	Random Forest based hourly energy prediction of building	500+
Ahmad et al. (2018)	Predictive modeling for solar thermal energy systems: A comparison of support vector regression, random forest, extra trees and regression trees	470+
Candanedo et al. (2017)	Data driven prediction models of energy use of appliances in a low energy house	460+
Sajjad et al. (2020)	A Novel CNN-GRU-Based Hybrid Approach for Short Term Residential Load Forecasting	460+
Alhussein et al. (2020)	Hybrid CNN-LSTM model for short-term individual household load forecasting	410+
Cao et al. (2020)	Energy consumption prediction for residential buildings using deep learning and other machine learning techniques	400+

Fig. 4. The analysis showed five distinct, yet interconnected, thematic Color Coded Clusters:

- Green Cluster (Energy & Optimization): optimization, predictive control systems, controllers: Emphasizes control and optimization applications
- Yellow Cluster (Forecasting & Prediction): forecasting, prediction, support vector machine, random forests: Centers on predictive modeling techniques
- Red Cluster (Energy Systems in Building & Design): architectural design, cooling, HVAC, thermal comfort: Focused on energy system applications in buildings
- Blue Cluster (Advanced AI & Smart Systems): deep learning, reinforcement learning, smart grids, IoT: Represents emerging/advanced technologies
- Purple Cluster (Power & Consumption): electric power utilization, electricity consumption: Focused on power consumption analysis

This approach allowed us for both comprehensive coverage of the field and critical analysis of the methodological approaches employed across different studies, providing insights into current trends, challenges, and future directions in AI/ML applications for energy management in buildings and in net zero energy buildings. While both the technical complexity of the energy systems in the considered building types and the inner workings of AI algorithms are important, this review does not go into deep detail on those aspects. Instead, the focus is on giving a clear and informative overview of the types of AI and ML algorithms have been applied in building's energy management and discussing about the key parameters mainly connected to forecasting energy consumption in building and which the best techniques which correctly take them into account? which is the best granularity according to the scope of the prediction/forecast? Including too much detail on complex building modeling, energy system design or algorithm model architecture could shift the focus away from the main purpose of this review, which is to map out developments, highlight patterns, and provide insights into the broader use and impact of AI/ML models for the energy management of buildings' facilities in the past decade.

1.3. Positioning among existing reviews & our contribution

Several recent reviews have examined AI/ML in energy systems of building from different perspectives. Amasyali and El-Gohary (2018) provided a comprehensive overview of data-driven consumption prediction studies, while Fathi et al. (2020) focused specifically energy performance forecasting in urban buildings. Wang and Srinivasan (2015) examined ensemble prediction models, and Khalil et al. (2022) offered a systematic review of forecasting methods. However, these reviews either primarily emphasized algorithmic comparisons within specific building categories or focus on particular model families, without systematically examining how algorithm selection, forecasting horizons, and building characteristics interact across different sectors. This review extended existing overall work in three ways.

1. We create a clear, consistent way for organizing information that maps AI/ML applications across four dimensions simultaneously, forecasting horizons (short, medium, long-term), algorithm families (classical ML, deep learning, hybrid/ensemble, reinforcement learning), building categories (residential, commercial, healthcare), and system integration levels (standalone, IoT-enabled, microgrid-enabled).
2. We provide cross-sectoral performance synthesis, examining how ensemble and hybrid models perform relative to single-algorithm approaches across different building types.
3. We focus on emerging research on use of AI/ML on Microgrid Enabled Intelligent Buildings (MEIBs), an area receiving growing attention but limited systematic review. Studies in this domain reported potential energy reductions through AI-optimized coordination of distributed energy resources.

The paper is organized as follows: Section 2 presents a comprehensive literature review of AI/ML applications in energy systems for buildings, examining both single and hybrid model approaches, across different building types, to address research questions 1 and 2. Section 3 provides a systematic analysis of the main findings from selected

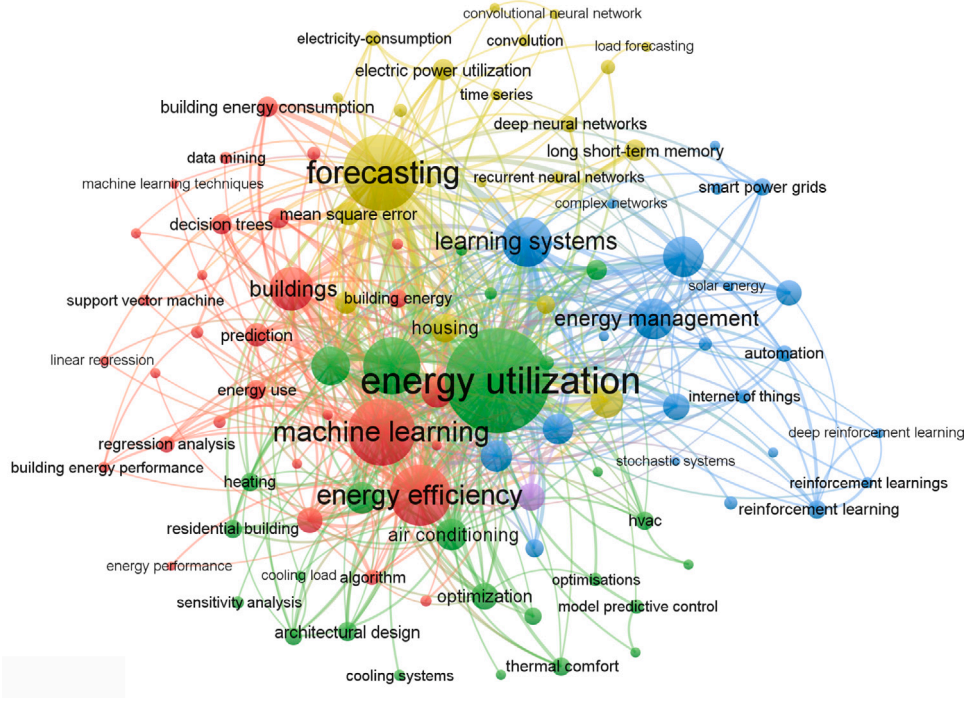

Fig. 4. Keyword co-occurrence network visualizing thematic structure of AI/ML building's energy management literature (2014–2024). Generated using VOSViewer analysis, where node size reflects keyword frequency and link thickness indicates co-occurrence strength. Green cluster (control applications) ; Yellow cluster (predictive modeling); Red cluster (building systems); Blue cluster (advanced technologies); Purple cluster (consumption analysis).

studies, by evaluating how environmental and operational parameters influence prediction accuracy across diverse building categories, specifically addressing research question 3 . This section also examined research question 5, through comparative analysis of traditional statistical methods versus advanced AI techniques in energy forecasting performance. The analysis of transfer learning applications and data related challenges (research question 4) was integrated throughout Sections 2 and 3, where hybrid models and ensemble approaches are discussed. Section 4 further addresses research question 3, by synthesizing key parameters identification across various studies and their impact on AI based energy analysis, thus providing a consolidated view of critical factors that influence model performance across different forecasting horizons and building types. Methodological limitations and future research directions addressing gaps are discussed in Section 5. The conclusion summarizes findings related to all research questions and discusses future research directions for more efficient and sustainable energy systems in buildings. Through this structured analysis framework, we systematically address each research question, while contributing to the understanding of current trends, where AI and ML show promise in ensuring more efficient, effective and sustainable energy systems for buildings. We also treat current limitations, while exploring future possibilities in energy management applications.

2. Literature review

The integration of AI and ML techniques has been used at different levels in the field of energy prediction and forecasting, while both terms are often used interchangeably, energy prediction and forecasting serve distinct purposes in energy analysis of buildings. This section synthesized findings from reviewed studies, organized by application domain and modeling approach. Rather than comprehensively describing each study, we focus on patterns, comparative performance, and methodological trends that address our research questions. Section 2.1 examines prediction and forecasting applications across building types. Section 2.2 discusses the evolution from single to hybrid modeling approaches. Section 2.3 addresses emerging applications in microgrid-enabled intelligent buildings, which represents a distinct but related research trajectory, focused on building-grid integration. Energy prediction involves estimating energy utilization or performance under specific conditions. This is performed by using current and historical data to understand immediate scenarios, such as determining a building's energy needs under particular occupancy or weather conditions. In contrast, energy forecasting focuses on projecting future energy patterns over time, incorporating temporal variables and historical trends to anticipate future consumption patterns, thus enabling more effective long term energy planning and management strategies.

These advanced methods like supervised and unsupervised learning, as well as advanced deep learning models like convolutional neural networks (CNNs), have shown strong potential. AI methods are powerful, choosing the right model depends on task specifics, data availability, and practical constraints and applying these tools effectively also requires solid knowledge of energy systems in buildings. Hua et al. (2022) showed that CNNs can effectively optimize prosumers energy scheduling by learning pricing patterns, significantly reducing computational time compared to traditional heuristic methods. Hybrid approaches, combining machine learning and deep learning, have consistently outperformed traditional ones, such as empirical trial, Multi-Objective Bayesian Optimization (MOBO) , the jPlus error method and the density functional theory (DFT), Palonen et al. (2013) and Tien et al. (2022), and have showed superior accuracy in forecasting energy utilization in various types of buildings, including healthcare facilities, commercial buildings, and residential structures. AI/ML models, as shown in pie-chart of Fig. 5, have been used for energy analysis over a decade, the most frequently used were: Artificial Neural Network(ANN) at 14.5% representing the largest share, Support Vector Machine (SVM) /Support Vector Regression (SVR) at 11.8% and Random Forest (RF) at 9.1%. Some moderately used models include: RL and Decision Tree(DT) each at 6.4%, DNN and PSO at 4.5% each. The less frequently used models were: CNN, Ensemble Models, and XGBoost each at 3.6% GP/GMM (Gaussian Processes/Gaussian Mixture Models) and DL at 2.7% each.

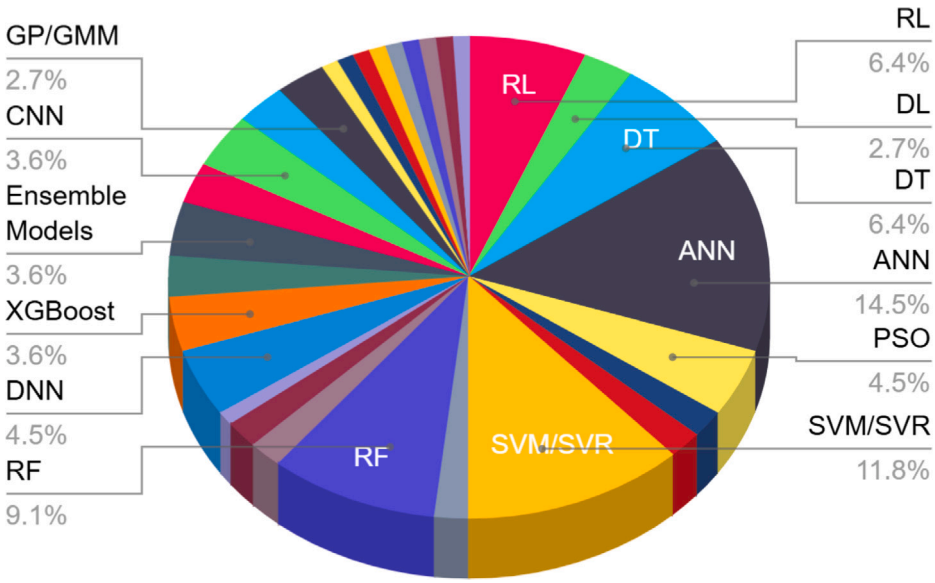

Fig. 5. Distribution of most AI/ML algorithm usage in building's energy applications across 114 reviewed studies (2014–2024), where percentages represent proportion of studies employing each algorithm class (categories not mutually exclusive, as many studies compared multiple approaches).

This distribution suggests that machine learning approaches like ANNs and SVMs were the most popular choices for energy analysis during this period, while more specialized or newer techniques like RL, DL and ensemble methods are gradually expanding their footprint in energy analysis applications in short, medium, and long term energy forecasting, by leveraging historical data, weather conditions, and building activity information.

2.1. AI/ML applications in energy prediction and forecasting for buildings

The application of AI/ML in energy systems of buildings has evolved from simple statistical models to sophisticated deep learning architectures capable of handling complex, multi-dimensional datasets. Modern AI/ML approaches in energy prediction has a better grasp of diverse data sources including weather patterns, occupancy schedules, building operational parameters, and real-time sensor measurements, to create comprehensive forecasting models. These techniques have showed particular effectiveness in addressing the challenges of energy systems in buildings, such as non-linear relationships between variables, temporal dependencies, and the need for real-time decision making. The integration of advanced ML algorithms with Internet of Things (IoT) infrastructure has further enhanced the capability to process continuous data streams and provide actionable insights for energy optimization.

The diversity of AI/ML approaches applied to energy prediction in building is extensive, encompassing various algorithm categories from traditional statistical methods to advanced deep learning architectures. Table 3 provides a comprehensive overview of different algorithm categories and their applications across the literature reviewed in this study, and it showed the breadth of the employed techniques. This section examined the current state of AI/ML applications in energy consumption prediction in buildings, focusing on model architectures, hybrid approaches, and their practical implementation across different building types, including residential, commercial, and healthcare facilities.

2.1.1. AI/ML models in energy prediction

AI/ML techniques have revolutionized energy prediction across various types of building, including healthcare buildings and residential structures. In healthcare facilities, Adaptive Neuro-Fuzzy Inference System (ANFIS) and backpropagation based models have proven particularly effective for electricity consumption prediction (Panagiotou and Dounis, 2022). The research compared eight different machine learning predictors using data from simulated healthcare facilities, for short term load forecasting, focusing on electricity and natural gas data for a year, with a granularity on 52,584 hourly time steps. The models include three backpropagation based ANNs, three metaheuristic optimized ANNs, an ANFIS, and an LSTM network. As anticipated, ANFIS and backpropagation based models showed the superior performance in handling complex nonlinear problems, with LSTM showing comparable results. The Levenberg Marquardt algorithm notably achieves the fastest convergence due to its hybrid approach that combines the stability of the gradient descent method with the speed of the Gauss Newton method, allowing for rapid error minimization during training.

A study on a building in Turkey proposes an innovative temperature forecasting approach using advanced machine learning models, specifically comparing Transformer Neural Networks with a hybrid CNN-LSTM architecture (Timur et al., 2020). The results highlighted the superiority of a transformer architecture in neural networks in which self attention mechanism helped to capture complex temporal and contextual dependencies in sequential data, making it suitable for accurately modeling and forecasting energy consumption patterns in buildings. The study Timur et al. (2020) used indoor temperature data for a one minute interval collected from multiple sensors, integrated with comfort feedback surveys from occupants, temperature (Mean, Max, Min) [°C], relative humidity [%], wind speed [m/s], historical consumption [MWh], months of year, duration of sunshine [h] and number of registered patients to obtain 1 month ahead electrical energy utilization output, measured in MWh/month for the upcoming month. The Transformer model showed superior performance with an R^2 score of 0.936 at one minute forecasting horizons, consistently outperforming the CNN LSTM model. Most notably, the system achieves a 50% reduction in energy utilization, while maintaining occupant comfort, particularly effective on a 60 min forecasting horizons. These results highlighted the potential for advanced AI techniques to revolutionize building's energy management, offering a practical solution to balance energy efficiency with occupant comfort for HVAC systems. The Xue et al. (2020) study specifically focused on energy utilization in a Norwegian hospital, with electricity being the main focus as it represented 55% of the total energy usage. The data analyzed included historical weather data and monitored energy utilization over 4 consecutive years, comparing different machine learning methods, finding that Random Forest and AdaBoost outperformed decision trees and

Table 3
Systematic categorization of artificial intelligence and machine learning techniques for energy consumption prediction in buildings: Literature distribution across algorithm models.

Algorithm category	Acronym	Paper references
Neural network models	ANN	Panagiotou and Dounis (2022), Timur et al. (2020), Kim et al. (2023), Olu-Ajayi et al. (2022), Boutahri and Tilioua (2024), Ardabili et al. (2019), Hwang et al. (2020), Fatehijananloo et al. (2024), FatehiJananloo et al. (2023), Ardabili et al. (2022), Seyedzadeh and Rahimian (2021), Dan and Phuc (2018), Park et al. (2024) and Vergés et al. (2024)
	LSTM	Panagiotou and Dounis (2022), Syed et al. (2021), Kim et al. (2023), Ardabili et al. (2019), Hwang et al. (2020), FatehiJananloo et al. (2023), Ardabili et al. (2022), Khan et al. (2023a) and Faiz et al. (2023)
	DNN	Nakai et al. (2021), Kim et al. (2023), Olu-Ajayi et al. (2022) and FatehiJananloo et al. (2023)
	MLP	Timur et al. (2020), Khan et al. (2023a), Safiyari et al. (2022) and Dalai et al. (2019)
	RNN	Kim et al. (2023) and Ardabili et al. (2022)
	CNN	Khan et al. (2023a), Faiz et al. (2023) and Ardabili et al. (2022)
Tree models	RF	Xue et al. (2020), Nakai et al. (2021), Cao et al. (2020), Olu-Ajayi et al. (2022), Boutahri and Tilioua (2024), Dan and Phuc (2018) and Zoubir et al. (2024)
	XGBoost	Cao et al. (2020), Boutahri and Tilioua (2024), FatehiJananloo et al. (2023) and Zoubir et al. (2024)
	GB and DT	Olu-Ajayi et al. (2022) and Zoubir et al. (2024)
Support vector machines	SVM/SVR	Timur et al. (2020), Olu-Ajayi et al. (2022), Boutahri and Tilioua (2024), Ardabili et al. (2019), Hwang et al. (2020), FatehiJananloo et al. (2023), Safiyari et al. (2022), Ardabili et al. (2022), Seyedzadeh and Rahimian (2021), Dan and Phuc (2018), Dalai et al. (2019) and Houchati et al. (2022)
Regression models	MLR	Timur et al. (2020), Olu-Ajayi et al. (2022), Dan and Phuc (2018) and Wang and Srinivasan (2015)
Optimization algorithms	GA, PSO, ABFIS	Panagiotou and Dounis (2022) and Ardabili et al. (2019)
Probabilistic models	GP/GMM	FatehiJananloo et al. (2023), Seyedzadeh and Rahimian (2021) and Li et al. (2024b)
Ensemble learning	Ensemble models	Nakai et al. (2021), Ardabili et al. (2019, 2022) and Wang and Srinivasan (2015)
	(RNN + KNN)	Kim et al. (2023) and Ardabili et al. (2022)

bagging methods(Bootstrap Aggregating), particularly when predicting lower levels of energy utilization. The models optimized through hyperparameter tuning to achieved high accuracy in the prediction of electricity consumption. The complex nature of hospital energy utilization patterns is challenging, and were affected by multiple variables, including weather conditions, occupancy rates, medical equipment usage, and operational schedules. Electrical power demand forecasting for a hospital building in Japan using actual measured data spanning approximately 4.5 years. DNN, RF, and GRU showed strong predictive performance. The researchers achieved the best results by creating ensemble models that combined different algorithms through weighted averaging, effectively compensating for individual model weaknesses, like for instance the DNN's slow response to sudden changes and LSTM's long computation times. A significant challenge was working with real measurement data, rather than idealized simulations, which introduced real world complexities and noise (Nakai et al., 2021).

The integration of diverse data sources has also enhanced prediction accuracy. Research has shown that combining ML techniques with weather conditions and building activity data leads to more precise energy utilization forecasts (Ruiz et al., 2017). This multi-source data integration approach captures a more comprehensive picture of energy needs. Additionally, a comparative study of ensemble learning models for healthcare facilities confirmed that ensemble models consistently outperform single model approaches in daily load prediction. China-based hospital building's data were used in forecasting daily and weekly electrical energy utilization. The granularity of the data was daily and weekly time series for energy load prediction. The study compared eight machine learning models, including single learning models (SVR) and ensemble learning models (e.g., Random Forest and XGBoost). The ensemble models outperformed single models in terms of prediction accuracy, with Mean Absolute Percentage Error(MAPE) values of 9.64% (RF) and 9.81% (XGBoost) on the test dataset. Ensemble models combine predictions from multiple learners to improve accuracy and robustness. For example, Random Forest aggregates predictions from decision trees, while XGBoost builds models iteratively to minimize errors. The study identified outdoor temperature, air pressure, and the operation status of the central air conditioning system as the top three factors influencing energy utilization. These features underscore the critical role of environmental and operational variables in energy modeling, hence it involved computational complexity and the need for extensive data pre-processing (Cao et al., 2020).

Across commercial buildings, like healthcare studies reviewed, several patterns emerged. For short-term forecasting (hourly to daily), ANFIS and backpropagation-based ANN models consistently showed strong performance, with MAPE values typically ranging from 6%–9% when predicting next-day electricity consumption (Panagiotou and Dounis, 2022; Nakai et al., 2021). LSTM networks achieved comparable accuracy (MAPE 7%–11%) but with significantly longer training times (Panagiotou and Dounis, 2022). For medium-term forecasting (weekly to monthly), ensemble methods showed clear advantages. Random Forest and XGBoost achieved MAPE values of 9.6–9.8% on hospital test datasets, compared to 11%–14% for single learners like standalone SVR (Cao et al., 2020). ANNs (using genetic algorithms or particle swarm optimization) underperformed expectations in healthcare applications (Panagiotou and Dounis, 2022), likely because hospital

energy patterns have sufficient regularity that gradient based optimization proves adequate, while metaheuristics' exploration capability offers limited added value. These findings suggest that for healthcare facilities, practitioners should consider ANFIS or standard ANNs for operational short-term forecasting, ensemble methods for medium term planning, especially with limited historical data, and careful evaluation before investing in computationally expensive optimization approaches.

2.1.2. Hybrid models and transfer learning

Hybrid models combine multiple different machine learning or deep learning architectures to leverage the strengths of each component while compensating for their individual weaknesses. Recent advancements in energy prediction have highlighted the effectiveness of hybrid artificial intelligence models. A significant example from the literature showed that hybrid deep learning model leverages bidirectional LSTM processing to analyze energy utilization patterns in both forward and backward directions, enabling it to capture complex temporal dependencies that might be missed by traditional unidirectional analysis. Data pre-processing plays a crucial role in such model's success, incorporating lag values as additional features and implementing robust cleaning techniques. The training process is optimized to balance computational complexity with accuracy, making the model practical for real world implementation while maintaining high performance levels when applied to smart buildings, outperformed other commonly used hybrid approaches in energy utilization forecasting (Syed et al., 2021). The model's superior performance came from its novel Hybrid Stacked Bi-directional Uni-directional Fully connected architecture that stacks uni-directional LSTM layers on a bidirectional LSTM base, enabling it to capture complex, long-term temporal dependencies from both past and future contexts within the training data. The field has also seen remarkable progress through the application of transfer learning (TL), which addressed one of the fundamental challenges in energy prediction: limited data availability. Transfer learning enables models to apply knowledge gained from one dataset or scenario to new, different situations. This approach has proven particularly valuable in the context of energy consumption prediction in buildings. The fundamental challenge of limited data availability in energy consumption prediction in building is addressed by transfer learning by enabling models trained on comprehensive datasets from prototype buildings and that to be adapted by buildings with insufficient historical data.

A noteworthy study implemented Long Short Term Memory (LSTM) networks in combination with transfer learning for predicting energy usage in hospital buildings (Kim et al., 2023), By processing temporal sequences of energy utilization data while accounting for both short term fluctuations and long term patterns. The practical implementation typically involve data pre-processing to handle historical energy utilization records, weather data, and building operational parameters; training using comprehensive datasets from prototype buildings; and transfer learning approaches to adapt these models to buildings with limited available data. The effectiveness of these techniques is measured through metrics such as CV(RMSE) and coefficient of determination, with models showing enhanced prediction accuracy even with limited datasets through transfer learning applications. The LSTM model processed temporal sequences through three gate mechanisms (forget, input, and output gates) that managed long-term and short-term memory of energy patterns. Input variables include outdoor weather conditions (temperature, humidity, solar radiation), historical internal heat gains (lighting and plug loads), and temporal features (time, month). Transfer learning enhanced predictions by reusing weights from source domain models trained on prototype hospital building data and fine-tuning them with limited target building datasets. It improved CV(RMSE) values (e.g., from 22.5% to 15.3%) and squared error values (from 0.90 to 0.95) compared to standard LSTM.

2.2. Systematic reviews of AI/ML in energy systems for buildings

2.2.1. Energy forecasting in residential and commercial buildings

In the residential sector, AI/ML models have shown promising results in early stage design optimization. A significant study developed an ML model capable of predicting annual energy consumption for residential buildings (Olu-Ajayi et al., 2022) using data from, January 1 to December 31, 2020. Metadata (floor area, property type, wall/window descriptions, number of rooms) and monthly averaged meteorological data (temperature, wind speed, pressure) were used to compare nine ML algorithms for predicting annual energy consumption (kWh/m^2), with Deep Neural Networks achieving the best performance ($R^2 = 0.95$, RMSE = 1.16). This development provided architects and designers with valuable AI powered tools to enhance energy efficiency during the crucial design phase. It can allow designers to use input key building features for forecasting annual energy consumption at early design stages, the model facilitated in this study informed decision making for design optimization before construction. This addressed the critical gap of predicting energy consumption before buildings are constructed.

Advancing further into practical applications, researchers proposed innovative IoT-based solutions that deployed ML models on edge devices. Dalai et al. (2019) presented a hybrid edge cloud architecture for next hour energy forecasting. Their three layer IoT microgrid setup comprised smart energy meters, Raspberry Pi 3 controllers as edge nodes(physically close to smart meters), and a cloud server. This framework strategically balanced computational tasks as the cloud handled the intensive training of machine learning models, while the edge devices performed real time inference for immediate predictions. The study evaluated four algorithms on a dataset of 25,000 hourly records and found that the LibSVM (SVM) algorithm achieved the highest prediction accuracy, as it was evidenced by its lowest MAE and RMSE and its highest correlation coefficient.

A reinforcement learning approach can be used for electricity consumption forecasting in buildings, using decision trees to identify contextual energy patterns and hybrid algorithm to dynamically select between K-Nearest Neighbors (KNN) and Artificial Neural Networks (ANN). Tested on 5-minute interval data(inputs: the weekday, the allocated period, the consumption, the light, and the CO_2), the method achieved up to 71.43% accuracy in building contexts, demonstrating that adaptive model selection improved prediction performance, the study examined the impact of decision tree depth and sensor data quality on accuracy, with higher exploitation rates enabling faster model switching for optimal forecasts. This framework provided a data driven solution for energy management in both buildings and industrial facilities (Ramos et al., 2022).

Commercial buildings have seen equally impressive advancements in ML applications, particularly in energy demand prediction and renewable energy integration. A notable two step approach integrated both meteorological data and heating/cooling facility information, achieving high accuracy in daily and monthly energy consumption predictions for commercial buildings (Hwang et al., 2020). In the realm of renewable energy, a study focusing on building integrated photovoltaic (PV) systems found that the Light GBM model showed superior performance in predicting hourly energy production compared to other ML models (Zoubir et al., 2024). Probabilistic forecasting has the potential of hybrid AI models for renewable energy integration. Enhanced model of CNN-BiLSTM-NGBoost framework for solar power forecasting, achieved a 15 to 60% improvement in forecast while reducing uncertainty quantification errors by 20 to 43%, deep learning feature extraction enhanced traditional methods, yielding both reliable probabilistic intervals and sharp predictions (NRMSE 10%) across diverse weather conditions (Song et al., 2025). Ajayi and Heymann (2021) developed a Marine Predators Algorithm (MPA) for optimizing data center energy management through AI-driven demand prediction and dynamic energy dispatch with solar PV integration. They used MPA to train an ANN for day ahead energy forecasting using environmental

parameters (ambient temperature, humidity, chiller output, and CRAC supply temperature) from a Cape Town data center. The optimized ANN model achieved superior performance across all metrics (MSE, RMSE, MAE, MAPE) compared to state of the art algorithms, with ambient temperature identified as the most influential factor (37.63%) on energy demand. The MPA based energy dispatch system prioritized solar PV over thermal generation while incorporating spinning reserves, demonstrating advanced optimization capabilities for sustainable data center operations.

Kim et al. (2020) developed a sequence to sequence LSTM model for electricity load forecasting in Variable Refrigerant Flow (VRF) systems used in buildings. The study used Pearson correlation and random forest methods for feature selection, combined with Bayesian optimization for hyperparameter tuning. The optimized model achieved coefficient of variation of root mean square error (Cv(RMSE)) values of 7%, 12%, and 17% for 1, 2, and 4 h ahead forecasts respectively, significantly outperforming the ASHRAE guideline of 30%. This approach enables accurate prediction of VRF system electricity utilization for optimal control and fault detection applications. Rasheed et al. (2022) developed an AI enabled bi-level optimization framework for probabilistic load demand scheduling with dynamic pricing and renewable resource integration by machine learning algorithms (ANN, NN, Gaussian Process) for real time load forecasting and formulated the optimization as optimal stopping problems using mathematical programming with branch-and-cut and branch-and-bound algorithms. The first level minimizes energy consumption and delay costs through optimal time slot selection, while the second level addressed dynamic pricing through genetic algorithm based stochastic optimization. Using solar home electricity data from Ausgrid, Australia, the algorithm achieved effective uncertainty handling and cost effective solutions while ensuring end user satisfaction through individualized pricing signals and load prioritization mechanisms.

A foundational review (Brito and Brito, 2022) emphasized the crucial role of ML models in forecasting energy consumption in building and enhancing overall energy efficiency. The paper concluded that ML/AI models are superior to conventional statistical methods for forecasting because they can handle nonlinear patterns in energy data, are more robust across different applications, and ultimately provide greater accuracy for improving energy efficiency and management. Building upon this foundation, subsequent reviews have developed detailed taxonomies of AI based models in energy systems, specifically categorizing their applications in predicting energy demand and consumption of buildings (Ardabili et al., 2019; Khalil et al., 2022). The field has further evolved with the emergence of ensemble prediction models, which combine multiple AI techniques. A significant review on this topic highlighted the potential of these hybrid approaches to improve forecast accuracy while also discussing their limitations and suggesting future research directions (Wang and Srinivasan, 2015). Specialized reviews have delved into specific sub fields within energy prediction. One notable review focused on ML applications in energy performance forecasting of urban buildings, identifying critical research gaps and emphasizing the need for more comprehensive studies on real time energy management systems (Fathi et al., 2020). Expanding beyond traditional energy consumption prediction, another review explored the innovative application of AI/ML techniques in predicting building material properties and optimizing their production processes, potentially leading to more energy efficient manufacturing methods (Stergiou et al., 2023).

Jing et al. (2022) developed a chaos theory based prediction model for shopping mall energy consumption using phase space reconstruction and back propagation neural networks. Shopping mall energy consumption exhibited chaotic characteristics through Lyapunov index analysis, then applied chaos theory to reconstruct phase space data for BP neural network training. The optimized hybrid Chaos-BP model achieved significant performance improvement with RMSE reduced from 12.4 to 1.89, incorporating confidence intervals for uncertainty quantification. This approach provided enhanced prediction accuracy for commercial building's energy management optimization compared to traditional BP neural networks.

2.2.2. Buildings thermal comfort

In the scope of thermal comfort, research has showed the feasibility of Transformer Neural Networks to concurrently optimize occupant satisfaction and reduce energy consumption in HVAC systems (Faiz et al., 2023). A comparative study evaluated Transformer networks against a CNN-LSTM model across multiple forecasting horizons (1, 15, 30, and 60 min). The models processed real-time sensor data encompassing air quality, power consumption, and thermal comfort parameters. Crucially, the study implemented a machine learning-based predictive control strategy, the trained Transformer model forecast optimal HVAC setpoints, and these predictions were executed in real-time via an infrared controller, forming a closed loop control system. The granularity of data and the prediction horizon significantly influenced performance, with the 60-minute horizon providing the best balance, achieving substantial energy savings (50%) while maintaining high occupant satisfaction. While other machine learning based predictive models have achieved similar dual optimization in smart buildings (Boutahri and Tilioua, 2024). The implementation typically involves IoT wireless technologies collecting occupant related data, electrical consumption and environmental parameters to develop thermal comfort predictive models. These advancements are supported by reviews highlighting the potential for significant energy savings through AI managed indoor climate conditions (Ngarambe et al., 2020).

Chen and Tsay (2022) in 2022 developed a comprehensive AI/ML framework for predicting building carbon emissions and thermal comfort in office buildings through systematic evaluation of sampling methods, feature selection, and machine learning algorithms. They used five sampling methods with ten ML algorithms, analyzing cumulative contribution rates (CCR) of 25 design parameters affecting building performance. Results showed that Sobol sampling achieved optimal prediction accuracy, while the best ML algorithm varied with feature reduction levels from artificial neural networks at 100% CCR to k-nearest neighbors at 50% CCR. Notably, reducing input parameters by 88% (using only three key factors: cooling, heating setpoints and infiltration rate) resulted in merely 6.1% decrease in R^2 value (0.918), indicating significant optimization potential for energy management systems with maintained thermal comfort prediction accuracy. Stoffel presented a data driven model predictive control (MPC) approach for energy systems of building that combined k-nearest neighbor extrapolation detection with a fallback PI controller to ensure safe operation when neural network predictions become unreliable. Ambient temperature, zone temperature, specific direct solar radiation, time of the day, day of the week heat pump simple and logistic modulation as the inputs and the electric power consumption of heat pump as the output with the time step of 15 min. Building Optimization Testing Framework was designed to test it and this approach reduced thermal discomfort by 86% compared to standard data-driven MPC when using limited initial training data. Continuous online learning expanded the valid operating domain by 40%, showing how safety mechanisms can enable practical implementation of adaptive building control systems and ensuring good thermal comfort (Stoffel et al., 2023). The healthcare sector presented additional complexities due to unpredictable energy demands from medical equipment and operational variability. Braithwaite et al. (2017) Comprehensive reviews have shown that AI models are particularly adept at handling these challenges in hospital energy management (Fatehijananloo et al., 2024), with systematic analyses confirming their utility and recommending the development of specialized models for healthcare settings (FatehiJananloo et al., 2023).

2.3. AI and ML in Microgrid Enabled Intelligent Buildings (MEIBs)

While, Sections 2.1 and 2.2 focused on prediction and optimization within individual building boundaries, this section addresses a distinct but related research area, where AI/ML applications for buildings operate as active participants in microgrids. This emerging domain was included because it represented the evolution of building's energy

Table 4
Overview of AI algorithms in energy analysis of microgrid enabled intelligent buildings.

Algorithm category	Acronym	Paper references
Reinforcement and deep learning	RL	Kumar (2024), Das et al. (2024), Sarajcev et al. (2022), Bassiliades and Chalkiadakis (2018), Dounis (2022), Wei et al. (2017) and O'Neill and Wen (2022)
	DRL	Du et al. (2022) and Wei et al. (2017)
	DL	Kumar (2024), Das et al. (2024), O'Neill and Wen (2022), Dimd et al. (2023) and Khan et al. (2024)
Tree models	DT	Das et al. (2024), Sarajcev et al. (2022), Dounis (2022), Balakumar et al. (2023) and Bassiliades and Chalkiadakis (2018)
	RF	Das et al. (2024), Sarajcev et al. (2022), Balakumar et al. (2023) and Qiao et al. (2023)
Neural networks	ANN	Asghar et al. (2023), Das et al. (2024), Bassiliades and Chalkiadakis (2018) and Dounis (2022)
	DNN	Dounis (2022) and Khashei et al. (2023)
Optimization algorithms	PSO	Wang et al. (2012), Bassiliades and Chalkiadakis (2018) and Wang et al. (2011)
	GA	Dounis (2022)
	MACS	Wang et al. (2012) and Wang et al. (2011)
	GTO	Wang et al. (2023)
	DQA	Hu et al. (2024)
Probabilistic and filtering	GRU	Wang et al. (2023) and Sarajcev et al. (2022)
	EKF	Bassiliades and Chalkiadakis (2018)
	GPR	Asghar et al. (2023) and Ahmed et al. (2024a)
Ensemble and hybrid models	WNN, RF-T, RC-T	Asghar et al. (2023)
Regression and classification	LR	Ahmed et al. (2024b), Asghar et al. (2023) and Das et al. (2024)
	SVM	Ahmed et al. (2024b), Das et al. (2024), Sarajcev et al. (2022) and Qiao et al. (2023)
Other techniques	GB/PCA/TSF/PML	Das et al. (2024)
	KMC	Dounis (2022)
	SUA	Zhou (2022)
	DML	Amini et al. (2020)
	DDM	O'Neill and Wen (2022)

management from standalone optimization toward coordinated building grid interaction. MEIBs differ from traditional smart buildings in two key ways.

- Incorporate bidirectional energy flows, buildings both consume and potentially generate or store energy that can be shared with the grid or neighboring buildings.
- Optimization objectives extend beyond individual building performance to include grid services like peak shaving, frequency regulation, and renewable energy integration. These characteristics introduce control complexities that traditional building-focused algorithms may not address.

The review includes MEIBs studies where buildings remain the primary analytical unit and AI/ML techniques optimize building parameters like consumption, production, storage etc, in response to grid conditions. It also encompasses broader microgrid control studies focused on distribution system management without specific building level optimization, as these fall outside our review scope. This scoping decision means that the MEIB analysis emphasized building integrated distributed energy resources, demand response strategies implemented at building level, usage of IoT, and AI/ML methods for coordinating building operations with grid signals.

The integration of AI and ML in MEIBs has gained significant attention for enhancing energy efficiency, stability, and overall management. Recent research has highlighted the significant potential AI/ML algorithms as shown in Table 4. Research mainly focused on optimizing energy management to monitor, control, and optimize the generation, distribution, and consumption of energy within smart buildings and microgrids with automation.

2.3.1. Energy management and automation in smart buildings and microgrids

Digital Twins(DTs) have proven effective in optimizing building's energy management and grid participation (Singh et al., 2024), DTs are like virtual copies of real buildings. They use real time data from sensors and Building Information Modeling (BIM) to create accurate simulations of how a building performs. These virtual copies help buildings work smarter with the energy grid by predicting energy needs and optimizing how energy is used. With 5G technology, data can be sent quickly between the energy systems in buildings and the digital platform, making everything faster and more efficient. By adding AI, Digital Twins can predict future energy use, make real time adjustments to systems, and manage energy demand more effectively. This makes buildings more energy efficient and responsive to grid needs. The integration of 5G technology has enhanced services in smart buildings (Singh et al., 2024; Mazhar et al., 2022). Singapore has integrated IoT, AI, and immersive technologies like virtual reality into smart energy systems in buildings, enhancing efficiency and user experience. For instance, the National University of Singapore's 5G enabled net zero energy building has AI driven facade inspections and VR based remote education, demonstrating the transformative potential of high speed, low latency networks, it showed how 5G has capacity to address urbanization challenges while serving as a model for global smart city development to achieve sustainable development goals (SDG) (Huseien and Shah, 2022).

Machine learning algorithms, including reinforcement learning and deep learning, have optimized energy harvesting from renewable sources, improving storage and distribution efficiency (Kumar, 2024). ML algorithms showed specific applications in building's energy management, particularly through GRU-GTO (Gated Recurrent Unit with

Gorilla Troop Optimizer) and Reinforcement Learning approaches. The algorithm operates by processing real time data from HVAC systems, with performance measured through metrics including latency (data transfer time), transmission rate (mbps), and Mean Square Error for training loss. The scope primarily covers smart building HVAC systems (Wang et al., 2023), reducing communication delay and computational time when implemented with LiFi protocol. Meanwhile, Reinforcement Learning applications show promise in adapting to changing environmental conditions, though challenges remain in scaling solutions across multiple buildings and establishing comparable performance metrics. The granularity of data collection varies from immediate system responses to longer term energy consumption patterns, with input data encompassing power loss, price management, and reactive power measurements (Wang et al., 2023; Alanne and Sierla, 2022). These studies scope was explicitly defined within the domain of reinforcement learning for HVAC energy management, following the functional categorization established by Alanne and Sierla (2022). The proposed GRU-GTO framework provided superior comparative insights against established models like RNN, CNN, LSTM, and ANN, showing definitive improvements in energy efficiency and load balancing accuracy as highlighted in Wang et al. (2023). Artificial Intelligence of Things (AIoT) referring to the integration of AI with Internet of Things devices to enable them to collect data, learn from them, and make intelligent, autonomous decisions have enabled real time decision making and automation, contributing to reduced energy consumption of HVAC and lighting, improved occupant comfort, and enhanced building security (Sleem and Elhenawy, 2023). Centralized energy management systems (EMS) using regression models have been explored to minimize grid power injection in high rise buildings, focusing on peak shaving and demand side management (Asghar et al., 2023; Himeur et al., 2023).

Hierarchical control system represent a traditional control approach structured across four layers, physical, information, control, and dispatch and AI optimization strategies have enabled real time responses between generation and load sides of microgrid systems (Wu et al., 2020).

Novel distributed machine learning paradigms using local resilience management systems (RMS) have enhanced decision making and resilience in power systems, the implementation is done through a network of RMS agents (microgrids/smart buildings) that share local operational data with neighboring RMS units to enable coordinated decision making. The system uses specific data points including battery power/capacity, generator size, load profiles, and state of charge information. The key insight is that distributed intelligence can replace centralized decision making, leading to more robust operations and enhanced resilience, if one RMS agent fails, the system can still maintain a feasible (though potentially sub-optimal) solution (Amini et al., 2020). Particle swarm optimization (PSO) has been used in multi agent systems to optimize energy use and enhance the intelligence of integrated microgrid enabled energy systems in buildings (Manic et al., 2016; Wang et al., 2012).

Lu et al. (2020) developed a home energy management system (HEMS) optimization model for smart households with photovoltaic energy storage systems (PESS), by categorizing household appliances into three groups based on usage patterns and formulated a mixed integer programming model to minimize peak load and electricity costs through optimal appliance scheduling. Using actual solar radiation data from Shanghai, the authors compared different PESS capacities and found that the optimal configuration (scheme 4) reduced peak load by 61.51% and electricity costs by 71.39% compared to baseline scenarios. The multi objective optimization approach provided uniform Pareto solutions, offering residential building users flexible scheduling options while supporting China's transition toward subsidy free photovoltaic systems.

However, despite these improvements, challenges still exist. These include difficulties in model interpretability, ensuring they work reliably, and scaling them up for larger applications, especially for deep learning models (Das et al., 2024; Sarajcev et al., 2022) Data privacy and cyber security across different platforms are critical concerns (Sleem and Elhenawy, 2023; Himeur et al., 2023). Future research directions include standardizing test cases for evaluating AI models in microgrid systems, improving model explainability, and developing advanced strategies for data management and cyber security (Baduge et al., 2022; Khaoula et al., 2022). Integration of AI with building management systems (BMS) and demand response programs (DRPs) offers potential for further enhancing energy efficiency and building stability (Farzaneh et al., 2021; Bassiliades and Chalkiadakis, 2018).

2.3.2. AI and ML applications in renewable energy and building control system

AI and ML techniques have shown promise in achieving carbon neutrality within buildings, offering superior performance to traditional physical models in terms of simplicity, accuracy, and computational efficiency (Zhou, 2022; Dounis, 2022). AI driven models have improved the robustness of renewable energy systems by improving security, reliability, and stability under uncertain conditions (Zhou, 2022; Dounis, 2022). AI models for assessing transient stability in microgrid systems have showed great potential in handling grid fluctuations (Sarajcev et al., 2022). Machine learning based forecasting models have been successful in predicting renewable energy generation and electric power consumption, with dynamic pricing models helping to minimize electricity costs (Sarajcev et al., 2022; Balakumar et al., 2023).

Machine learning has been widely adopted in optimizing HVAC control systems in intelligent buildings (Du et al., 2022; Wei et al., 2017). A practical RL approach for building control involves first training the RL agent to simulate like conventional rule based control strategies before deployment, reducing initial unstable exploration behavior by 93% compared to standard RL approaches. This hybrid approach achieved a 6.3% reduction in operational costs while maintaining thermal comfort, showing better performance than both pure rule based control and traditional RL methods. The imitation learning phase reduced required training time from over 400 days to just 100 days, making RL based control significantly more feasible for real world building applications (Dey et al., 2023). Deep Reinforcement Learning (DRL) studies have been particularly successful in reducing energy utilization and emissions associated with HVAC systems (Du et al., 2022; Wei et al., 2017). DRL based controllers provide significant demand response services, such as load shifting and peak shaving, contributing to energy savings (Du et al., 2022; Wei et al., 2017). The integration of multi agent control systems has shown promise in managing energy utilization while maintaining occupant comfort (Wang et al., 2012, 2011).

These advancements presented the potential of AI and ML in enhancing the efficiency and sustainability of both renewable energy systems and building control systems, paving the way for more intelligent and environmentally friendly buildings especially in hospital infrastructures. The reviewed papers show a clear and consistent trend toward the adoption of advanced AI and machine-learning methods for energy consumption prediction across residential, commercial, institutional, and healthcare facilities. Techniques such as hybrid deep-learning architectures, ensemble models, and feature-enhanced methods repeatedly show improved accuracy and robustness compared with traditional approaches. The breadth of applications from cooling load estimation to power demand forecasting highlighted both the versatility of these models and the growing emphasis on data driven strategies to enhance energy efficiency and operational management in modern buildings.

3. Comprehensive analysis and evidence-based findings

In analyzing the main findings of the selected studies, it has become evident that AI/ML applications are increasingly enhancing not only the prediction, but also the optimization of energy.

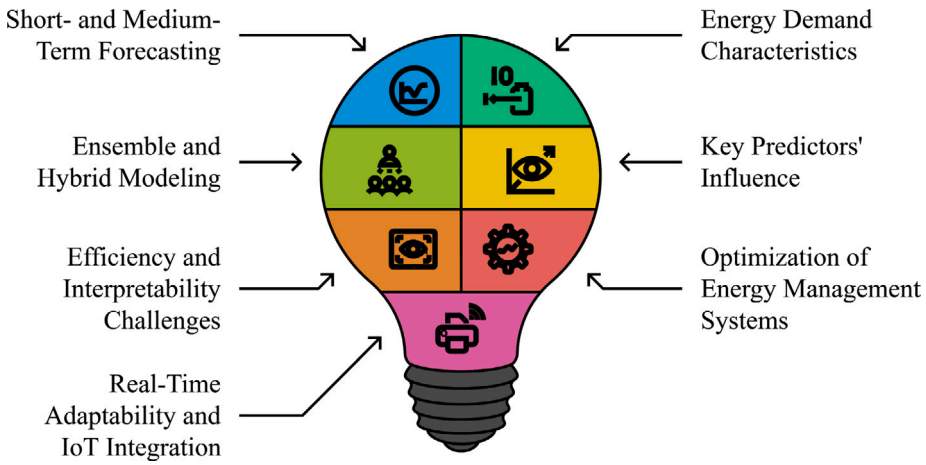

Fig. 6. Overview of AI applications with energy perspective by identifying key theme of the publications under study.

This comprehensive analysis categorizes insights under specific headings, each summarizing findings across relevant studies, as shown in Fig. 6, the visualization displays the central idea and thematic relationships, identified from the research papers. The central theme is short and medium term forecasting, which was achieved through techniques like advanced ensemble and hybrid modeling etc. These models are crucial for analyzing complex energy demand characteristics and determining the key predictors' influence. The ultimate goal is the optimization of energy management systems, a pursuit that faced challenges like improving the efficiency and interpretability of complex AI models, while ensuring their real time adaptability and IoT integration for processing real time data from smart devices.

Despite the promising capabilities of AI in energy management systems, several significant limitations and drawbacks require careful consideration. Primary challenges include data quality and availability issues, as energy systems require large, high-quality datasets for effective timing operations. However, organizations frequently encounter issues with missing or inconsistent data and they face substantial costs in data collection.

3.1. Model performance across different forecasting horizons (RQ1)

A synthesis of algorithm performances across reviewed studies showed distinct strengths and trade-offs among different AI/ML approaches. As summarized in Table 5, hybrid deep learning and ensemble methods consistently achieved the highest accuracy for complex, non-linear forecasting tasks, such as ultra-short-term solar PV prediction or building load balancing. While advanced deep learning models (e.g., DNN, LSTM) offered universal applicability and strong performance across horizons, they came with increased computational costs. In contrast, traditional statistical methods provide fast computation and interpretability but suffer from significantly lower accuracy, particularly in capturing dynamic or non-linear patterns. This comparative overview underscores that there is no single 'best' algorithm; rather, model selection should be guided by the specific forecasting horizon, data characteristics, and operational constraints of the application.

3.1.1. Ultra short-term forecasting (5–15 min)

Hybrid deep learning models showed superior performance for ultra-short-term forecasting, with CNN-BiLSTM-Attention-NGBoost achieving R^2 = 0.96 and Continuous Ranked Probability Score (CRPS) = 0.071–0.090 kW for solar PV systems (Song et al., 2025), representing 63.9% CRPS reduction over traditional quantile regression methods. Contextual reinforcement learning approaches achieved average rewards of 0.6–0.8 with 67%–71% accuracy for energy systems of building (Ramos et al., 2022). GRU-based models showed superior performance for HVAC systems, with GRU-GTO achieving 96–98.5% load balancing accuracy with reduced latency compared to RNN, CNN, LSTM, and ANN (Wang et al., 2023). These ultrashort-term predictions were critical for real-time operational control and demand response strategies in energy-intensive facilities.

3.1.2. Short-term forecasting (hourly to daily)

The comparative analysis of forecasting models for healthcare building load prediction showed varying levels of effectiveness across different approaches (Panagiotou and Dounis, 2022). ANFIS and backpropagation-based ANN models showed superior performance in short-term load forecasting, with ANFIS achieving MAPE = 2.27% with MSE = 537.71, outperforming metaheuristic-trained models (GA-ANN: MSE = 3064.0, MAPE = 7.1%) (Panagiotou and Dounis, 2022). Backpropagation-based approaches (Levenberg–Marquardt ANN: MSE = 613.95, MAPE = 2.78%) consistently exceed genetic algorithm variants by 40%–60%. While LSTM models showed satisfactory predictive capabilities with MSE = 787.18 and MAPE = 3.25% their performance did not surpass that of ANFIS and ANN implementations. This performance disparity highlighted the critical importance of selecting forecasting models based on specific application requirements, including the intended prediction horizon, data characteristics, and computational constraints within healthcare facility operations. Deep neural networks consistently outperform other approaches across building types, with DNN achieving R^2 = 0.95 and NMAE = 4.78% for residential buildings (Olu-Ajayi et al., 2022), while LSTM showed MAPE = 8.97% with CV = 12.7% for commercial buildings (Hwang et al., 2020). LightGBM achieves R^2 = 0.96 for building-integrated PV systems (Patsakos et al., 2022). Ensemble methods showed MAPE typically ranging from 5%–15% with R^2 > 0.90 across building types.

3.1.3. Medium-term forecasting (weekly to monthly)

For medium-term energy forecasting, SVM models delivered the best performance with a MAPE of 8.89% and R^2 of 94.90%, followed by MLP neural networks at 9.52% MAPE and R^2 of 93.61% (Timur et al., 2020). Key predictors like outdoor temperature, calendar variables, and historical energy consumption were instrumental for accurate forecasts. Seasonal variation significantly affected predictions, driven primarily by HVAC systems, while patient count showed negligible influence, underscoring the impact of environmental and operational factors over patient throughput (Timur et al., 2020). LSTM-based sequence-to-sequence models with Bayesian optimization achieved CV(RMSE) = 7%–17% for Variable Refrigerant Flow (VRF) systems (Kim et al., 2020), demonstrating 5%–12% improvement over grid search approaches. Chaos BP neural networks were characterized by the integration of chaos theory with a back-propagation algorithm, which

Table 5
Summary of forecasting and prediction algorithm performance across building's energy management studies. The table compares algorithm classes by key metrics (R^2, MAPE, CV(RMSE)), their best-suited applications, highlighting the trade-off between accuracy and complexity.

Algorithm class	References	Performance range	Best applications	Computation
Hybrid deep learning (CNN-BiLSTM-Attention, Chaos-BP)	Song et al. (2025), Kim et al. (2020), Jing et al. (2022) and Chen and Tsay (2022)	R^2: 0.95–0.96, MAPE: 2%–5%, CRPS: 0.07–0.09 kW	Solar PV, VRF systems, complex non-linear patterns, ultra-short-term forecasting	20%–85% improvement over single models; 3–10× training time
Advanced Deep Learning (DNN, LSTM, GRU)	Olu-Ajayi et al. (2022), Hwang et al. (2020), Kim et al. (2020), Stoffel et al. (2023), Panagiotou and Dounis (2022), Nakai et al. (2021), Syed et al. (2021), Kim et al. (2023), Dalai et al. (2019) and Ramos et al. (2022)	R^2: 0.90–0.95, MAPE: 4%–11%, CV(RMSE): 7%–17%	Universal applicability; short-to-medium term forecasting; temporal dependencies	Good balance of accuracy and deployability
Ensemble Methods (RF, XGBoost, LightGBM, GB)	Panagiotou and Dounis (2022), Nakai et al. (2021), Ruiz et al. (2017), Patsakos et al. (2022), Chen and Tsay (2022) and Olu-Ajayi et al. (2022)	R^2: 0.89–0.96, NMAE: 4%–7%, MAPE: 4.07–11.12%	Feature importance analysis, robust predictions, daily/weekly forecasting	15%–45% improvement over single models for short-term
Support Vector Machines (SVR, LibSVM)	Panagiotou and Dounis (2022), Timur et al. (2020), Olu-Ajayi et al. (2022), Hwang et al. (2020) and Dalai et al. (2019)	R^2: 0.80–0.94.90, MAPE: 6%–12%, Training MAPE: 8.10%	Small-medium datasets, monthly forecasting, edge computing	Moderate computational cost (2.28 s training)
Traditional Statistical (MLR, SARIMAX, Linear Regression, QR)	Panagiotou and Dounis (2022), Timur et al. (2020), Ruiz et al. (2017), Syed et al. (2021), Olu-Ajayi et al. (2022), Hwang et al. (2020) and Song et al. (2025)	R^2: 0.61–0.75, MAPE: 13%–39%, CRPS: 0.20–0.25	Baselines, interpretability, simple patterns	Fastest computation (0.13 s); 30%–65% lower accuracy than AI
Reinforcement Learning (Contextual RL, Online Learning)	Ramos et al. (2022) and Stoffel et al. (2023)	Average Reward: 0.6–0.8, Accuracy: 67%–71%	Contextual adaptation, online learning, real-time systems	Progressive improvement during operation
Fuzzy Logic (ANFIS)	Panagiotou and Dounis (2022)	MAPE: 2.27%, MSE: 537.71, R^2: 0.9885	Healthcare facilities with non-linear patterns	Best single-model accuracy for healthcare

Note: Different metrics reported reflect varying emphases in original studies. MAPE and NMAE measure relative error; R^2 measures explained variance; CRPS measures probabilistic forecast quality.

utilized phase space reconstruction to transform the univariate energy consumption time series into a multi-dimensional state-space representation. This method enabled the model to attain an RMSE of 1.89 for monthly commercial building prediction (Jing et al., 2022), representing an 85% improvement over conventional approaches. Random Forest and Decision Trees show strong performance, with DTR models achieving R^2 greater than 0.99 for weekly energy consumption forecasting in educational buildings (Asghar et al., 2023).

3.1.4. Long-term forecasting (seasonal to annual)

Advanced AI methods (DNN, gradient boosting) demonstrate superior seasonal stability due to their inherent capacity to capture complex nonlinear relationships and temporal dependencies in energy consumption patterns for long-term forecasting. DNN maintains $R^2 = 0.95$ with NMAE = 4.78% for annual residential forecasting (Olu-Ajayi et al., 2022), outperforming traditional methods by 20%–37%. DNN architectures with multiple hidden layers can learn hierarchical feature representations that automatically detect and adapt to seasonal variations in building energy usage. Gradient boosting with cumulative contribution rate analysis achieves $R^2 = 0.95$ for office building carbon emission predictions (Chen and Tsay, 2022). The gradient boosting algorithm achieved robust cross-seasonal performance through ensemble learning, where sequential weak learners iteratively correct prediction errors while the cumulative contribution rate analysis identifies the most influential parameters across different seasonal contexts. These methods inherently accommodate seasonal fluctuations by learning from sufficient historical data spanning multiple seasons, unlike traditional approaches that rely on fixed statistical assumptions. The 4 to 6% MAPE stability observed with AI methods compared to 27 to 40% variation in traditional approaches reflects their adaptive learning mechanisms that generalize well across changing environmental conditions (Hwang et al., 2020).

3.2. Hybrid and ensemble modeling advantages (RQ2)

Ensemble ML approaches such as XGBoost, Random Forest, and LightGBM consistently outperformed single-model approaches in predicting daily electrical loads in healthcare facilities. Ensemble models capitalized on daily data, resulting in more accurate predictions compared to weekly datasets, illustrating the value of fine-grained data in load forecasting. Specifically, XGBoost achieved training MAPE of 4.64% and testing MAPE of 11.12%, while Random Forest showed training MAPE of 4.07% and testing MAPE of 10.69% (Panagiotou and Dounis, 2022). Ensemble machine learning combining DNN, Random Forest, and GRU achieves prediction accuracies with average error below 1.55%, overcoming individual method limitations, such as delayed response to sudden changes (Nakai et al., 2021).

Moreover, hybrid ML frameworks combining deep learning with regression methods improved prediction accuracy in complex scenarios, particularly when predicting energy demands in hospitals. Hybrid deep

Table 6
Summary of studies on energy consumption and prediction models across building types.

Building type	Ref.	Key variables	Target variable	Granularity	Best algorithm	Metrics range
Healthcare/Hospital	Panagiotou and Dounis (2022), Timur et al. (2020), Nakai et al. (2021), Ruiz et al. (2017) and Kim et al. (2023)	Temperature, occupancy, day type, activity summaries	Daily/monthly energy (kWh)	Daily/Monthly	ANFIS, XGBoost	MAPE 2.27–10.77%
Residential	Syed et al. (2021) and Olu-Ajayi et al. (2022)	Appliance use, lag values, solar radiation	Household energy (Wh)	Sub-daily	Hybrid LSTM	MAPE 2.00–3.71%
Commercial/Office	Hwang et al. (2020), Kim et al. (2020), Chen and Tsay (2022) and Stoffel et al. (2023)	Temp, historical load, setpoints	Electricity demand (kW)	Hourly/Daily	LSTM, DNN	MAPE 4%–11%, $R^2 > 0.90$
Solar PV	Patsakos et al. (2022), Song et al. (2025) and Rasheed et al. (2022)	DNI, GHI, temp, historical PV power	PV output (kW)	5-min/Hourly	CNN-BiLSTM-Attention	$R^2$0.96, CRPS 0.07–0.09
VRF Systems	Kim et al. (2020)	Infiltration rate, setpoints, weather	Cooling/heating load	15-min	LSTM-seq2seq	CV(RMSE) 7%–17%
Data Center	Ajayi and Heymann (2021)	Ambient temp, chiller/CRAC temps	Energy demand (kW)	5-min/Hourly	ANN with weight analysis	MAPE 2.06–2.44%
Shopping Mall	Jing et al. (2022)	Ambient temp, RH, chiller output	Energy consumption (kW)	Hourly	Chaos-BP Neural Network	RMSE 1.89–3.5

learning, combining fully connected layers with bidirectional LSTMs, achieves MAPE = 2.00–3.71%, representing 72% improvement over single LSTM models (7.80% MAPE) for residential buildings (Syed et al., 2021). These findings align with broader research noting the accuracy and robustness of hybrid models for load forecasting [54].

CNN-BiLSTM-Attention-NGBoost reduced CRPS by 29%–40% compared to standalone NGBoost for solar PV systems (Song et al., 2025). Bayesian-optimized LSTM seq2seq improves CV(RMSE) by 5%–12% for VRF commercial systems (Kim et al., 2020). KNN combined with CNN-LSTM-Attention achieves R^2 = 0.95 with 88% parameter reduction for office buildings (Chen and Tsay, 2022). GRU-GTO showed superior performance with load accuracy of 98.5% versus 89.5% for ANN alone (Wang et al., 2023). However, not all hybrid combinations succeed. DNN alone attains R^2 = 0.95, notably outperforming ensemble stacking approaches (R^2 = 0.73) (Olu-Ajayi et al., 2022), indicating architectural design importance over simple model combination. Hybrid approaches showed 20%–85% improvements primarily when data exhibits non-linear chaotic characteristics, multi-scale temporal patterns exist, or feature engineering bottlenecks were addressed.

3.3. Energy demand characteristics across building types

Hospitals have unique energy demand profiles compared to other building types, with electricity accounting for 55% of total energy consumption surpassing district heating and cooling needs. This heightened demand stems from lighting, HVAC systems, and medical equipment usage. A study showed that Random Forest and AdaBoost models surpassed Decision Tree and Bagging methods, particularly in predicting periods of lower energy consumption, indicating these models' suitability for healthcare settings (Xue et al., 2020). Parameter importance varies significantly across user type. Data centers show temperature dominance at 37.63% influence, with chiller output temperature (22.15%) and Computer Room Air Conditioner(CRAC) supply temperature (21.73%) constituting 43.88% combined influence (Ajayi and Heymann, 2021). VRF commercial systems exhibit infiltration rate as most critical (27.0%), followed by heating/cooling setpoint (27.2%) and equipment intensity (>20%) (Kim et al., 2020). Office buildings demonstrate heating setpoint (20.1%), infiltration rate (16.1%), and cooling setpoint (12.8%) as primary drivers (Chen and Tsay, 2022).

The performance and optimal algorithm selection for energy prediction were highly dependent on building type, as each sector presented unique energy demand profiles and influential variables, depending on the specific equipment using energy (loads) and their intensity rate on the total consumption. Table 6 showed finding from key studies, illustrating how the best-performing model varies across healthcare, residential, commercial, and specialized systems like solar PV and VRF. For instance, healthcare facilities benefit from ANFIS and ensemble methods like XGBoost due to their non-linear operational patterns, while residential buildings record higher accuracy with hybrid LSTMs. Commercial and office buildings often achieved optimal results with deep learning models like LSTM and DNN, which effectively capture temporal dependencies in HVAC and lighting loads. This typology-driven analysis emphasized that effective energy modeling must account for sector-specific dynamics and equipment, rather than applying a one-size-fits-all algorithmic approach.

3.4. Environmental and operational parameter influence (RQ3)

3.4.1. Universal critical parameters

Temperature-related variables showed greater than 15% influence across all building types, because they directly affect HVAC equipment, which often accounted for a relevant share of the energy consumption. Historical consumption patterns prove essential for temporal dependencies. Building physical properties (total area, floor count) consistently show significance across categories. For educational buildings with PV integration, weather data (solar radiation, temperature) accounts for 60%–70% of prediction variance (Asghar et al., 2023).

3.4.2. Feature engineering impact

Temporal variables significantly enhance prediction accuracy in hospital energy forecasting. The inclusion of date-type variables distinguishing weekdays, weekends, and holidays improved model performance substantially, with R^2 increasing from 0.66 to 0.67 to 0.90 to 0.91 across multiple algorithms, while MAPE decreased from 16 to 17% to 8.37 to 9.32% for hospital buildings (Ruiz et al., 2017). These improvements represent substantial gains in hourly prediction accuracy, critical for operational energy management decisions. Similarly, incorporating activity variables specifically 13 hospital operational metrics enhanced Tree Ensemble Learner performance from R^2 of 0.9140 to 0.9434, with RMSE decreasing from 1143 kWh to 928 kWh per hour (Ruiz et al., 2017). The magnitude of these reductions is meaningful in hospital contexts, where hourly consumption typically ranges from several hundred to several thousand kWh depending on facility size and operational intensity. External temperature alone

proved insufficient for accurate predictions, with all three methods achieving R^2 values of only 0.65 to 0.69 and MAPE exceeding 15%. This limitation is particularly pronounced in hospital settings, where internal loads from medical equipment, lighting, and 24/7 operations dominate consumption patterns. However, the combination of outdoor mean temperature with calendar variables yielded accurate results, with seasonality exerting dominant influence due to HVAC systems representing the largest component of hospital electrical consumption.

These findings showed that effective energy forecasting requires multi-dimensional feature sets:

- temporal patterns capture operational schedules and occupancy variations
- meteorological variables account for climate responsive systems.

The optimal prediction granularity depends on forecasting objectives, hourly resolution is essential for real-time load management and peak demand reduction, whereas daily or weekly aggregations suffice for strategic energy planning and comparative benchmarking.

3.4.3. Feature reduction effectiveness

Feature selection demonstrates substantial efficiency gains without compromising predictive accuracy. In VRF system applications, Pearson correlation based filtering reduced the feature space from 6120 operational parameters to 494 variables, a 93% reduction by retaining only features with correlation coefficients greater than 0.3 relative to electricity consumption (Kim et al., 2020). This dramatic reduction was feasible because the original dataset contained high redundancy across multiple indoor units (100 units across 14 VRF systems), with many parameters representing repeated measurements of similar operational states. The retained features primarily captured outdoor unit operational characteristics (compressor status, refrigerant pressures and temperatures) and indoor unit control signals (electronic expansion valve positions, ON/OFF status), which proved sufficient for accurate load forecasting at hourly resolution. Similarly, cumulative contribution rate analysis in building energy prediction identified that merely 14 parameters account for 90% of performance variance, enabling 88% parameter reduction with only 6.1% R^2 degradation (Chen and Tsay, 2022). These findings consistently demonstrate that feature engineering contributes 35 to 50% accuracy improvements universally across algorithms, indicating that systematic data preparation, including correlation analysis, redundancy elimination, and variable importance ranking deserves equal emphasis to model selection in building energy forecasting workflows.

3.4.4. Building-specific insights

Operational schedules predicted better than occupancy counts for healthcare facilities. The number of patients remained steady over years with small deviations and showed no significant influence on medium-term electrical energy forecasting (Timur et al., 2020), suggesting operational schedule variables were more predictive than occupancy counts. For residential buildings, occupancy patterns reduce MAPE by 12%–18% when combined with weather data (Du et al., 2022; Balakumar et al., 2023). Solar radiation peaks in importance for PV-integrated systems, with 40% increase in PV forecasting accuracy when solar radiation data is included Asghar et al. (2023). For commercial HVAC systems, real-time sensor integration (temperature, humidity, CO_2) improves RL agent performance by 8%–12% (Singh et al., 2024).

3.5. Transfer learning for data scarcity challenges (RQ4)

The reviewed literature showed minimal explicit transfer learning applications, indicating a significant research gap but some studies employ true transfer learning are discussed below.

3.5.1. Healthcare building evidence

Transfer learning strategies with shortened simulation data achieved 45% accuracy improvement (CV(RMSE) from 20.2% to 11.05%) for heating period predictions using only 1-month datasets (Kim et al., 2023). Full and partial fine-tuning techniques both showed improved performance, with effectiveness varying by geographic location (11%–45% improvements across South Korean cities) (Kim et al., 2023). Specific improvements included: for Kangnung, CV(RMSE) improved from 20.2% (LSTM-only) to 11.05%; for Kwangju, CV(RMSE) improved from 13.86% to 10.26%, with R^2 increasing from 0.946 to 0.970; for Ulsan, CV(RMSE) improved from 13.97% to 10.25% with fine-tuning strategies (Kim et al., 2023). LSTM models achieved acceptable prediction accuracy even with 1-month simulated datasets through transfer learning technology (Kim et al., 2023).

3.5.2. Indirect transfer approaches

Clustering-based knowledge transfer using DTW-based facility type inference improved MAPE from 11.23% to 8.97% for data centers (Ajayi and Heymann, 2021), representing pattern matching rather than parameter transfer. Online learning with continuous retraining reduced extrapolation progressively for energy systems of building (Stoffel et al., 2023), addressing concept drift rather than data scarcity. Context-specific algorithm selection through decision tree identification achieves average reward convergence of 0.6–0.8 (Ramos et al., 2022).

3.5.3. Data scarcity solutions

Feature selection via Pearson correlation maintained accuracy with 93% feature reduction (Kim et al., 2020). Synthetic data generation through phase space reconstruction improved RMSE from 12.4 to 1.89 (Jing et al., 2022). Study (Olu-Ajayi et al., 2022) showed 85% performance degradation when dataset size decreases from 50,000 to 1000 instances, highlighting critical need for transfer learning solutions. True transfer learning remains underutilized despite clear evidence of severe performance degradation with limited data, representing a high-potential research direction for energy consumption forecasting in buildings, particularly for retrofit applications and newly constructed buildings lacking historical consumption data.

3.6. Traditional statistical vs. Advanced AI techniques (RQ5)

The comparative assessment of traditional statistical methods and advanced artificial intelligence techniques showed substantial performance disparities across multiple building types and forecasting horizons.

Table 7 presents a comprehensive synthesis of performance metrics from the reviewed literature, systematically comparing conventional approaches (linear regression, ARIMA, SARIMAX, quantile regression) with state-of-the-art AI methodologies (deep neural networks, long short-term memory networks, hybrid architectures, and ensemble methods). The comparative assessment revealed the following:

- Overall Performance: AI methods consistently outperformed traditional approaches by 30 to 65% across all building types and forecast horizons.
- Ultra-Short-Term Forecasting: AI showed the most pronounced advantage here, with hybrid deep learning models achieving a 63.9% reduction in error metrics for 5-minute solar PV predictions.
- Modeling Complex Systems: AI exceled at capturing non-linear dynamics. For example, LSTM models achieved low error rates for complex VRF systems, while chaos-BP neural networks provide an 85% RMSE improvement for monthly mall forecasts.
- Seasonal Stability: AI methods maintained stable performance year-round, showing only 4 to 6% seasonal variation in error, compared to 27 to 40% variation for traditional methods.

Table 7
Comparative performance of traditional algorithms and statistical methods and advanced AI techniques across building types and forecasting horizons.

Building type	Horizon	Traditional method	Metrics	Advanced algorithm	Metrics	Improvement	Ref.
Commercial	Daily	SARIMAX	MAPE: 27.16%	LSTM	MAPE: 11.24%	58.6% reduction	Hwang et al. (2020)
Commercial	Daily	Decision Tree	MAPE: 25.22%	LSTM	MAPE: 11.24%	55.4% reduction	Hwang et al. (2020)
Commercial	Monthly	SARIMAX	MAPE: 39.31%	DNN	MAPE: 27.59%	29.8% reduction	Hwang et al. (2020)
Residential	Annual	Linear Regression	R^2: 0.73, MAPE: 13.31%	DNN	R^2: 0.95, NMAE: 4.78%	30% R^2 improvement	Olu-Ajayi et al. (2022)
Residential	Annual	Decision Tree	RMSE: 25.19%	DNN	RMSE: 10.08%	60% reduction	Olu-Ajayi et al. (2022)
Solar powered building	5-minute	Quantile Regression	CRPS: 0.2486 kW	CNN-BiLSTM-Attention-NGBoost	CRPS: 0.0898 kW	63.9% reduction	Song et al. (2025)
Solar powered building	5-minute	Quantile Regression	NMAE: 12%–25%	Hybrid Deep learning	NMAE: 4.3–5.8%	52%–77% reduction	Song et al. (2025)
Hospital	Monthly	MLR	MAPE: 15.79%, R^2: 85.77%	SVM	MAPE: 8.89%, R^2: 94.90%	43.6% MAPE reduction	Timur et al. (2020)
Hospital	Monthly	MLR	Training: 0.13 s	MLP	Training: 0.55 s, MAPE: 9.52%	4× faster than SVM	Timur et al. (2020)
Hospital	Daily/ Weekly	Linear Regression	R^2: 0.6614, RMSE: 2269 kWh	Tree Ensemble Learner	R^2: 0.9434, RMSE: 928 kWh	42.6% R^2 improvement	Ruiz et al. (2017)
Hospital	Daily/ Weekly	Linear Regression	MAPE: 13.60–15.79%	SVR	MAPE: 8.10–10.77%	32%–41% reduction	Panagiotou and Dounis (2022)
Residential	Appliance level	Linear Regression	RMSE: 137.3 Wh, MAPE: 70.30%	Hybrid Deep Learning	RMSE: 5.44 Wh, MAPE: 2.00%	96% RMSE reduction	Syed et al. (2021)
VRF commercial	Hourly	Traditional (baseline)	Unable to capture non-linear dynamics	LSTM-seq2seq + Bayesian opt.	CV(RMSE): 7%–17%	Captures non-linearity	Kim et al. (2020)
Data center	5-min/hourly	Traditional (baseline)	Limited with high-dim. features	ANN with weight analysis	MAPE: 2.06–2.44%, Acc: 97.56%	Handles 6120+ features	Ajayi and Heymann (2021)
Shopping mall	Monthly	Conventional BP-NN	RMSE: 12.4	Chaos-BP Neural Network	RMSE: 1.89	85% improvement	Jing et al. (2022)
Building with IoT	1-hour ahead	Linear Regression	Training: 1.4 s	LibSVM	Correlation: 0.8765–0.9162	3.5× faster inference	Dalai et al. (2019)

- Feature Handling: AI techniques effectively managed high-dimensional data, with one study achieving 93% feature reduction while maintaining accuracy.
- Residential & Granular Forecasting: AI showed superior accuracy at both the whole-building level (achieving an R^2 of 0.95) and the appliance level (achieving a 96% RMSE reduction).
- Limitations & Context: Traditional methods maintain relevance where interpretability was essential or when minimal training time is the absolute priority, despite their lower accuracy.

Deep learning models, particularly ANNs and DNNs, displayed high accuracy in energy predictions, their computational demands and limited interpretability present challenges in practical applications. Ensemble and hybrid models have helped overcome some of these challenges. They deliver strong performance while maintaining a degree of transparency, which is important for making decisions in situations where understanding how the model works is critical. As models become more complex, balancing performance and ease of interpretation will be pivotal for their broader adoption (Boutahri and Tilioua, 2024; FatehiJananloo et al., 2023).

3.7. Optimization of energy management systems

The potential of AI in optimizing energy use, particularly through advanced HVAC management, is a recurring theme. Demand response strategies like peak shaving, load shifting, and dynamic pricing were particularly effective for high-demand environments like hospitals. These strategies help manage energy costs and minimize operational disruptions. Furthermore, multi-agent systems have showed the ability to balance energy needs with occupant comfort in real-time, which is crucial for maintaining optimal indoor conditions in healthcare facilities (Wang et al., 2012; Du et al., 2022; Balakumar et al., 2023). DRL combined with building simulation achieves 8%–15% energy savings compared to rule-based systems in commercial HVAC applications (Singh et al., 2024).

The integration of digital twins and AI-powered IoT systems is a promising area for real-time energy management in buildings. Ramos et al. (2020) used artificial neural networks (ANN) and support vector machines (SVM) for real-time load forecasting in office buildings using IoT sensor data with 5-minute intervals. The study influenced diverse sensor inputs over a 2.5 years dataset, incorporating temporal features like day/week information to enhance forecasting accuracy. Results showed that ANN outperformed SVM, achieving optimal performance with ten input features plus temporal variables while avoiding overfitting. The methodology supports intelligent energy management through high-frequency data collection and adaptive machine learning algorithms, exemplifying the integration of IoT sensors with AI-driven forecasting for real-time energy optimization in buildings. Studies emphasized that AI-enhanced IoT can optimize energy usage dynamically, adapting to changes in occupancy and environmental factors. Such systems could make buildings highly responsive, enhancing comfort while minimizing energy waste. Notably, smart hospital buildings are well-suited to leverage IoT for continuous energy optimization (Singh et al., 2024; Alanne and Sierla, 2022; Sleem and Elhenawy, 2023).

Current findings indicate gaps in cross-building model comparison, integration of real-time data for adaptable predictions, and enhanced understanding of complex models. The future of AI and ML in building's energy management will likely focus on refining hybrid models, enhancing digital twin technology, and integrating IoT systems for smarter, more adaptive buildings. Expanding the scope of studies to include different building types and climates could foster generalizable insights applicable to a broader range of building environments (Ardabili et al., 2022; Khalil et al., 2022; Fathi et al., 2020).

4. Key parameters consideration

Weather conditions and daily operational metrics emerged as critical predictors across studies. Predictive models leveraging outdoor temperatures, calendar dates, and prior energy usage showed significant accuracy improvements in medium and long term forecasting. The

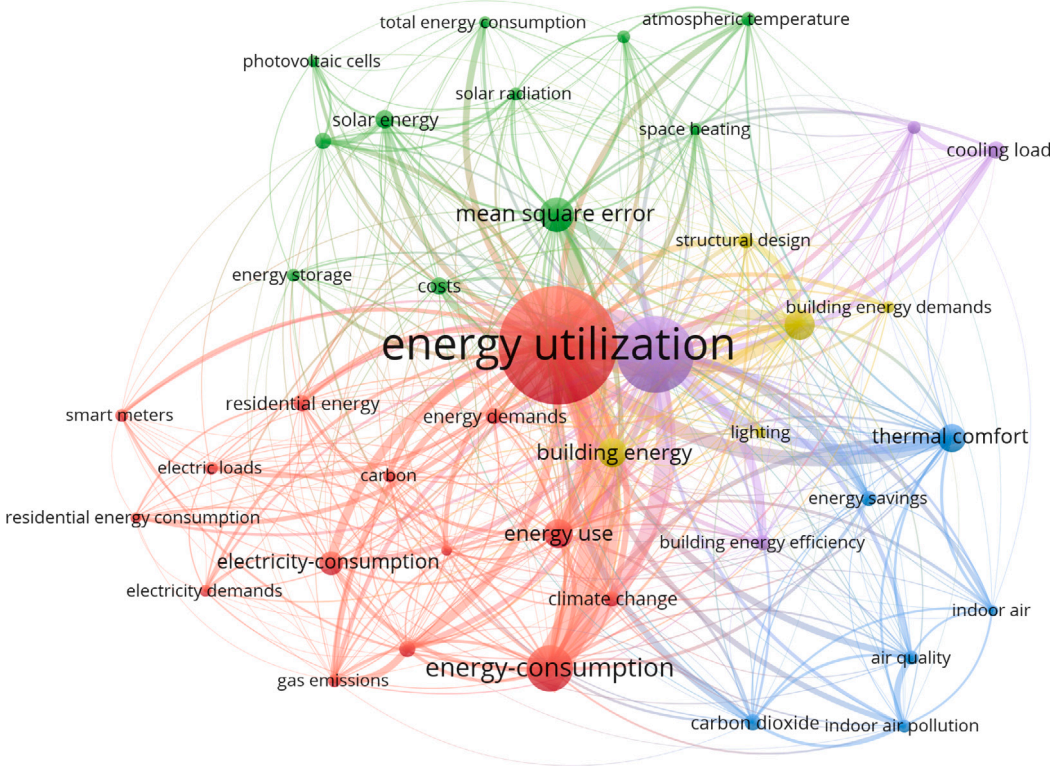

Fig. 7. Visualization of occurrence and linkage of key parametric features used in AI/ML energy modeling applications for building's energy management literature, thickness showing occurrence strength between variables using Vosviewer.

analysis of reviewed literature reveals that parameter importance and optimal granularity are intrinsically linked to the forecasting horizon and building type (addressing RQ3). For short-term forecasting (hourly to daily), real-time operational parameters such as HVAC status, occupancy patterns, and indoor air quality metrics (CO_2, temperature) show the highest predictive value, with studies showing 12%–18% accuracy improvements when these parameters are included (Ajayi and Heymann, 2021; Du et al., 2022; Balakumar et al., 2023). Conversely, medium to long-term forecasting (weekly to annual) benefits more from meteorological variables and temporal features, where outdoor temperature, solar irradiance, and calendar variables (seasonality, day type) account for 60%–70% of prediction variance (Ruiz et al., 2017; Asghar et al., 2023).

The optimal data granularity varies systematically with prediction objectives: sub-hourly resolution (5–15 min) is essential for real-time control applications and demand response strategies, particularly in healthcare facilities where medical equipment usage patterns require immediate response (Nakai et al., 2021; Wang et al., 2023). Hourly granularity provided the best balance for operational energy management and HVAC optimization, achieving CV(RMSE) values of 7%–17% for commercial systems (Brito and Brito, 2022). Daily and weekly aggregations suffice for strategic planning and comparative benchmarking, with ensemble methods achieving MAPE values of 9.6–11.2% at these resolutions (Tien et al., 2022; Olu-Ajayi et al., 2022). Notably, moving from daily to weekly datasets often reduces prediction accuracy by 15%–20%, suggesting that daily granularity represented a practical threshold for maintaining model performance while minimizing data collection overhead.

Literature also showed the interconnected nature of these predictive variables within AI and ML modeling frameworks as shown in Fig. 7. The network analysis showed a more comprehensive variable landscape centered around two dominant nodes: energy utilization and energy consumption, which serve as primary integration points for diverse predictor categories. The renewable energy cluster (green) encompasses solar energy, photovoltaic cells, and atmospheric conditions, validating the importance of weather variables while highlighting the growing integration of sustainable energy sources in predictive models. The energy systems in buildings cluster (purple) connects heating load, cooling load, and architectural design parameters, reinforcing the critical role of HVAC systems and building characteristics in energy forecasting. In healthcare buildings, where HVAC systems contribute substantially to energy demand, seasonality became a crucial predictor.

Cross-sectoral analysis reveals building-specific parameter hierarchies: healthcare facilities require operational schedule variables (weekday/weekend/holiday distinctions) over occupancy counts, improving R^2 from 0.66 to 0.91 (Olu-Ajayi et al., 2022). Data centers show temperature dominance at 37.63% influence, with chiller-related parameters constituting 43.88% combined effect (Rasheed et al., 2022). Residential buildings benefit most from appliance-level disaggregation and lag values when sub-daily forecasting is required (Brito and Brito, 2022). These findings suggest that effective parameter selection must align with building operational characteristics and forecast temporal scope, rather than applying universal variable sets across contexts.

Environmental quality variables (blue) including air quality, carbon dioxide levels, and thermal comfort demonstrate the expansion beyond traditional energy metrics to include indoor environmental factors that influence both energy consumption and occupant well being.

The residential and electrical systems cluster (red) bridges smart meters, electricity consumption, and residential energy patterns, supporting the observed accuracy improvements when incorporating operational metrics and usage history. The central positioning of mean square error indicates the prominence of model performance evaluation, while the interconnected structure facilitates the capture of complex relationships between weather conditions, energy systems in buildings, and energy outcomes that enhance forecasting accuracy. The studies covered a variety of energy datasets and modeling techniques in buildings:

- Input data: Energy consumption, weather, occupancy, building sensor data, design/operational parameters, specialized building/energy system data

Table 8
Summary of key parametric data driven energy consumption forecasting and prediction techniques in buildings.

Dataset	Input variables	Output variables	Modeling technique	Study
Simulated building/hourly	Electrical Plug Load, Time (Month, Hour), Outdoor Air Temperature (°C), Horizontal Solar irradiance(™'/m^2), Humidity (%)	Electrical consumption prediction (kWh/kW)	Neural networks, time series regression	Panagiotou and Dounis (2022), Kim et al. (2023) and Khan et al. (2024)
Time series data	Electrical Consumption (MWh), Number of Month of Year, Temperature (Mean, Max, Min) (°C), Relative Humidity (%), Wind Speed (m/s), Sunshine Duration (h), Number of Registered Patients Output	Month electrical energy consumption (MWh)	Statistical, machine learning models	Timur et al. (2020), Hwang et al. (2020) and Brito and Brito (2022)
Building sensor data	Temperature (°C), Precipitation (mm), Wind Speed (m/s), Atmospheric Pressure (hPa), Humidity (%), Solar Irradiance (W/m^2), Building Area (m^2), Number of Floors, HVAC Plug Load, Day of the Week	Electricity consumption prediction (kWh)	Machine learning	Xue et al. (2020), Fathi et al. (2020), Qiao et al. (2022) and Patsakos et al. (2022)
Building operational data	Date, Time, Day of the Week, Public Holiday Indicators, Temperature (°C), Total power consumption (kWh), High Precision Laser Dust Sensor (μm), Ozone Gas Detection Sensor (ppm), CO_2/TVOC Sensor (ppm), Dust Optical Sensor (V), Air Quality (CO, NH_3, NO, Gas Sensor (ppm)), Current Transformer (A), (Hz)	Thermal comfort and power consumption (kWh)	Neural networks	Nakai et al. (2021), Boutahri and Tilioua (2024), Fatehijananloo et al. (2024), FatehiJananloo et al. (2023) and Faiz et al. (2023)
Daily/hourly building weather data	Outdoor temperature (°C), Relative humidity (%), Wind speed (m/s), Barometric pressure (Pa), Precipitation (mm), Number of outpatients, Number of emergency patients, Number of inpatients, Day, (Weekday, Holiday), Operation status of HVAC	Weekly electricity consumption (kWh)	Time series, regression, machine learning	Cao et al. (2020), Ruiz et al. (2017), Syed et al. (2021), Ardabili et al. (2019), Zoubir et al. (2024), Houchati et al. (2022), Li et al. (2024b), Sarajcev et al. (2022) and Balakumar et al. (2023)
Building design, operational data	Time, Month, Hour, Temperature (°C), Humidity (%), Wind (m/s), Solar Irradiance (W/m^2), Sunshine (h), Surface, Wall area, Roof, Glazing, Building Area (m^2), Number of Floors, Electrical Plug Load, Total Power Consumption (kWh), HVAC Plug Load, Number of Occupants, CO_2 (ppm), Illumination (lux), Dust Optical Sensor (V), Air Quality (CO, NH_3, NO, Gas Sensor (ppm)), High Precision Laser Dust Sensor (μm).	Energy demand, performance prediction, heating and cooling load	Machine learning on multi agent systems	Cao et al. (2020), Ardabili et al. (2022), Seyedzadeh and Rahimian (2021), Dan and Phuc (2018), Wang and Srinivasan (2015), Ramos et al. (2022), Khalil et al. (2022), Mazhar et al. (2022), Kumar (2024), Wang et al. (2023), Sleem and Elhenawy (2023), Wu et al. (2020), Amini et al. (2020), Manic et al. (2016), Wang et al. (2012), Farzaneh et al. (2021), Bassiliades and Chalkiadakis (2018), Wei et al. (2017), Wang et al. (2011), Wang (2023) and Elbeltagi and Wefki (2021)
Building/energy data (thermal comfort, stability)	Air temperature (°C), Mean radiant temperature (°C), Humidity (%), Air velocity (m/s), Energy consumption (kWh), Interior temperature (°C), Outdoor temperature (°C), Illumination (Lux), Clothing insulation (Clo)	Performance metrics (comfort, stability)	Machine learning, control optimization	Khan et al. (2023a), Ngarambe et al. (2020), Singh et al. (2024), Asghar et al. (2023), Himeur et al. (2023), Das et al. (2024), Baduge et al. (2022), Khaoula et al. (2022), Zhou (2022), Dounis (2022), Du et al. (2022), O'Neill and Wen (2022), Hu et al. (2024), Javadian (2020) and Mosavi et al. (2019)

- Output variables: Energy consumption prediction/forecasting, energy demand, thermal comfort, building/system performance
- Modeling techniques: Neural networks, time series forecasting, regression, statistical models, machine learning, optimization, multi agent systems

A comprehensive review of the literature showed diverse applications of AI/ML in energy management, extending beyond basic consumption forecasting as show in Table 8. Recent research demonstrated a significant evolution in analytical scope, encompassing critical performance metrics such as thermal comfort optimization, grid stability enhancement, and seamless renewable energy integration. Energy consumption prediction, while remaining a fundamental focus, represented just one facet of current research endeavors. This diversity in methodological approaches reflects both the multi dimensional nature of energy management systems and the need for specialized solutions tailored to different operational contexts and objectives. The range of modeling techniques and data types utilized across studies underscores the sophistication required in modern energy management systems, particularly as buildings become increasingly integrated with smart grid technologies and renewable energy sources.

The datasets ranged from simulated building data to real world monthly/hourly energy, weather, and occupancy measurements. The modeling approaches included traditional time series and regression as well as more advanced machine learning and optimization techniques.

5. Limitations and future research directions

5.1. Methodological limitations

This review acknowledges several limitations. First, the literature search was conducted exclusively through the Scopus database. While Scopus provided comprehensive interdisciplinary coverage, a multi-database approach might have captured additional studies. Second, given the heterogeneity of study designs and metrics across reviewed literature, a formal risk of bias assessment was not conducted. Instead, we prioritized studies with clearly reported methodologies and comprehensive performance metrics. Third, the inclusion of highly cited

landmark papers (Table 2) may introduce citation bias(separate from the main 114-paper analysis), potentially under representing recent innovations with limited citation accumulation.

5.2. Future research directions

The review highlighted several overarching gaps that must be addressed to advance AI-based building's energy management. A primary need is for the development of standardized benchmark datasets and evaluation protocols, as current studies rely on heterogeneous data that hinder comparability. Research is also fragmented across building types and climates, limiting understanding of model generalization. Comprehensive cross-building and cross-climate studies are needed to assess how performance varies with construction characteristics, occupancy patterns, environmental conditions and typology of loads. Emerging domains such as microgrid-enabled intelligent buildings (MEIBs) require systematic evaluation. Priorities include standardized frameworks for assessing building grid interaction, common test cases for control algorithms, and research on scalability and privacy-preserving coordination across multiple buildings.

Practical deployment barriers require more attention as limited studies address real world implementation challenges including edge computing architectures, federated learning for privacy preservation, rapid response to sensor failures, and cost–benefit analysis compared to traditional rule-based systems. Collectively, addressing these gaps is essential for transitioning AI/ML approaches from experimental demonstrations to scalable, trustworthy, and real world ready solutions for sustainable building's energy management.

6. Conclusion

This scoping review examined the integration of Artificial Intelligence and Machine Learning in energy management systems for buildings. It focuses on prediction, optimization, and practical implementation challenges in the planning and monitoring of energy data. In general, the analysis of current literature highlighted major advancements in energy consumption forecasting. It also showed progress in system optimization across different building types. These advancements relied on data such as historical energy patterns, weather conditions, building information, occupancy data, and real time sensor measurements. They use methods ranging from statistical techniques to deep learning architectures.

Deep Reinforcement Learning has become a highly effective method for optimizing energy control systems and demand response services. It performs well because it learns control strategies through continuous interaction with the environment. It adapts to dynamic conditions without the need for manually programmed rules. DRL controllers have shown strong results in balancing energy efficiency and occupant comfort. They support real time energy management and improve occupant satisfaction. They also help maintaining energy efficiency and emission targets while enabling services such as load shifting and peak shaving. They achieved this by optimizing multiple objectives and learning from sequential decision making in complex environments. They can coordinate control points and adapt to varying occupancy patterns.

ANFIS and back propagation ANN models perform well in short term predictions, by providing strong accuracy for hourly and daily forecasts. SVM methods perform better in medium term predictions such as weekly forecasts. This difference exists because ANFIS and ANN capture non linear patterns in high frequency data, which are typical of short-term operational dynamics in energy systems in buildings where rapid fluctuations in occupancy, equipment usage, and immediate environmental conditions created complex temporal dependencies that require models capable of learning intricate non-linear relationships at high temporal resolution SVM handles variability in longer term data due to its stronger generalization ability.

Ensemble and hybrid methods outperform single model approaches. They are especially effective in complex environments like healthcare facilities.

Combining physical modeling with data driven approaches has become a major asset while managing energy data. Digital twins and AI based IoT systems show strong potential for real time energy optimization. Transfer learning helped to address the issue of limited data availability. As discussed in Section 5, several methodological limitations and research gaps remain, including:

- Data standardization continues to be a critical hurdle in widespread implementation
- Privacy concerns, particularly in residential settings, require careful consideration
- Scalability issues persist when extending from individual buildings to urban environments
- Deep learning models are often hard to understand, which makes it difficult for people to trust and use them in real world applications
- Limited cross building model comparison studies hinder generalization.

Future research should focus on improving model interpretability, while preserving performance. Also the need of standardized testing procedures emerged as a compelling one. Better integration of physical and data driven methods is needed. The successful use of AI and ML in building's energy management is essential for sustainable urban development. It offers significant opportunities to reduce energy use and environmental impact. As the field grows, balancing innovation with practical deployment will be essential for achieving meaningful savings and benefits.

CRediT authorship contribution statement

Nouman Ahmed: Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yuemin Ding:** Writing – review & editing, Supervision, Conceptualization. **Guido Canti:** Writing – review & editing, Validation. **Norma Anglani:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Project administration, Funding acquisition, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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Chapter 4



A Data-Driven Framework for Energy Management in Commercial and Industrial Sector using IoT, Big Data, and XAI

4 A DATA-DRIVEN FRAMEWORK FOR ENERGY MANAGEMENT IN COMMERCIAL AND INDUSTRIAL SECTOR USING IOT, BIG DATA, AND XAI

Commercial and industrial buildings generate large amounts of energy data, but many energy management systems still rely on fixed operating schedules and provide limited insight into how decisions are made. This chapter is based on a published conference paper that presents the Technological Regenerative Innovation (TRI) framework, which combines IoT, Big Data, and Explainable Artificial Intelligence (XAI) to support predictive energy management. The framework is demonstrated through case studies of commercial and industrial chiller systems, showing how transparent AI techniques improve the understanding of energy use and system behaviour. The contribution of the framework is its application oriented integration of data acquisition, predictive modelling, and explainability to support energy-management analysis. The individual technologies used within this structure are established methods. The case studies assess selected predictive and explainability capabilities and rather than interpreted as experimental validation of every proposed framework component. The proposed approach supports reliable and explainable decision-making, contributing to the overall objective of this thesis to develop practical, data-driven solutions for industrial and commercial energy management.

A Data-Driven Framework for Energy Management in Commercial and Industrial Sector using IoT, Big Data, and XAI

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***Abstract*—Traditional energy management systems in commercial and industrial (C&I) built environment rely on reactive maintenance and fixed operational parameters, leading to suboptimal energy efficiency and increased operational costs. This paper presents a data-driven framework integrating Internet of Things (IoT) sensors, Big Data analytics, and Explainable Artificial Intelligence (XAI) to provide a pblackictive analytics foundation for energy management in commercial and industrial(C&I) facilities. The proposed Technological Regenerative Innovation (TRI) framework, where "regenerative" denotes a self-reinforcing loop of data, pblackiction, and operational improvement, uses real time IoT enabled condition monitoring and Machine Learning(ML) with SHapley Additive Explanations(SHAP) analysis, delivering interpretable quantified insights into energy consumption patterns. TRI framework's effectiveness is validated using large-scale datasets of two case studies, (i) comprising 14,999 hourly samples for commercial case and (ii) 3,118 for industrial case. In these chiller system case studies, specifically ML models were used, one of these achieved R^2 values of 0.81 (commercial) and 0.85 (industrial). The corresponding CVRMSE values of 64.19% and 34.55% reflect inherent variability in hourly chiller operation where daily aggregated pblackictions show substantially lower relative error suitable for operational planning applications. The industrial case study presents critical operational parameters through SHAP analysis, identifying key parameters driving primary energy consumption. Through practical implementation, proposed TRI framework provides energy managers with transparency, ML based pblackictive tools and explainable insights through SHAP analysis, showing the pblackictive intelligence and explainability components as foundational enablers for future adaptive control capabilities.**

***Index Terms*—Artificial Intelligence, Big Data, Energy Management, Gradient Boosting, Internet of Things, Random Forest, Regenerative Innovation, SHAP**

This paper is an extended version of a paper that was presented at the 2025 IEEE Energy Conversion Congress and Exposition (ECCE), Philadelphia, PA, USA, 2025 [1].

I. Introduction

The global energy landscape is undergoing a fundamental transformation. Commercial and Industrial (C&I) facilities account for approximately 54% of global electricity consumption [2] and face increasing pressure to optimize energy efficiency while maintaining operational reliability, sustainability, and economic viability. Traditional energy management (EM) systems(systems operating on pblacketermined schedules with periodic manual checks and repairs only after equipment failures occur), relying on fixed settings, data accumulation without actionable analysis, and reactive maintenance, struggle to meet modern C&I demands.

Despite significant advances in digital technologies, current energy management systems in C&I sectors suffer from critical limitations that represent substantial research gaps. Existing energy management systems collect data, but pblackominantly operate on fixed operational parameters, leading to suboptimal energy utilization and unexpected equipment failures [3]. These systems rely on periodic interventions that fail to capture dynamic operational conditions and emerging inefficiencies. While IoT sensors and data collection systems are increasingly deployed, most C&I facilities lack pblackictive analytics that can translate raw data into actionable insights, resulting in missed opportunities for proactive optimization and preventive maintenance [4].

Current energy management approaches in C&I facilities can be categorized into four main paradigms, each with distinct strengths and limitations.

Traditional Maintenance-Based Approaches: Many C&I facilities, particularly smaller enterprises with limited budgets, continue using reactive or scheduled maintenance strategies. While cost-effective initially, these approaches fail to prevent

unexpected equipment failures and result in suboptimal energy utilization [3].

IoT-Enabled Monitoring Systems: Organizations deploy IoT sensors and data collection infrastructure to monitor equipment and energy consumption in real-time. However, despite having sensors in place, most facilities struggle to translate raw sensor data into pblackictive insights, as they lack in-house analytical capabilities or rely on fragmented external services [4].

Integrated Commercial Platforms: Companies based solutions such as Siemens Building X [5], ABB Ability Genix [6], Schneider EcoStruxure [7], and Johnson Controls Openblack [8] offer cloud-based monitoring, pblackictive analytics, and energy optimization capabilities. While these solutions provide useful dashboards and automation tools, most operate as closed systems, with little transparency into how pblackictions or recommendations are generated.This limits reproducibility and makes it difficult to quantify energy impacts or validate decisions in engineering terms. These solutions often operate as "black boxes", dashboards that providing recommendations without transparent reasoning ultimately limiting adoption and effectiveness of intelligent systems [9]. Despite their operational capabilities, these commercial platforms share a fundamental limitation from a research and engineering perspective as they are closed, proprietary systems. The model logic, training data, pblackiction mechanisms, and recommendation engines are not exposed to end users. An energy manager receives a recommendation without knowing what data triggeblack it or why a particular setpoint change is suggested, which creates a transparency deficit. It is basically a barrier to stakeholder trust, scientific reproducibility, and independent engineering validation. The Technological Regenerative Innovation (TRI) [1], [12] framework addresses this by using open ML tools and expressing SHapley Additive Explanations(SHAP) based contributions, allowing full auditability of pblackictions and their operational drivers. This distinguishes TRI from commercial solutions by making model decisions transparent and verifiable.

Component-Based Custom Solutions: Some organizations adopt individual components such as IoT sensors, Big Data analytics, or AI models from different service providers. However, these implementations lack explainable frameworks that integrate these technologies cohesively for comprehensive energy management [10]. Furthermore, traditional energy systems across all these approaches struggle to autonomously adapt to changing operational conditions, seasonal variations, and evolving usage patterns, requiring manual interventions that delay optimization responses [11].

Despite these diverse approaches, a critical gap remains in current energy management literature and practice: the absence of an integrated, transparent, and autonomous framework that bridges the divide between data collection and actionable intelligence while maintaining stakeholder trust.

The core missing element is not any individual technology, IoT sensors, analytics platforms, or AI algorithms are all widely available - but rather an open, transparent, and reproducible framework that:

- integrates these technologies cohesively with documented architectures using standard tools and standard ML libraries, rather than proprietary closed systems.
- provides quantitative, explainable decision-making processes (SHAP values) that enable stakeholder verification and engineering validation.
- further allows research communities to extend energy management strategies independently of vendor platforms by a comparative positioning of TRI against four leading commercial EMS platforms on transparency, explainability, and scientific reproducibility

Existing commercial solutions address parts of this challenge but lack transparency, while custom implementations lack the systematic integration needed for comprehensive energy optimization. This gap is particularly critical as C&I facilities face increasing pressure to show verifiable energy efficiency improvements to stakeholders while maintaining operational continuity.

This research addresses these gaps by proposing a novel Technological Regenerative Innovation (TRI) framework that transforms energy management from a "reactive" to a "pblackictive" (foundation) approach through intelligent integration of IoT, Big Data analytics, and Explainable Artificial Intelligence (XAI). Building on the concept of Regenerative Innovation introduced in [12] from a technology perspective, our proposed TRI framework focuses on digital, green, and renewable energy technologies to create sustainable and regenerative systems. It encompasses concepts such as AI, smart cities, autonomous systems , eco-friendly materials, and renewable energy adoption to blackuce carbon emissions and enhance infrastructure efficiency. A preliminary version of this framework was presented at the 2025 IEEE Energy Conversion Congress and Exposition (ECCE) [1]. This extended version significantly expands the SHAP-based interpretability analysis with mathematical formalism, adds a comparative positioning against four leading commercial EMS platforms (Section IV), and provides detailed methodological annotations for reproducibility. This paper validates the pblackictive intelligence and explainability components of TRI (Stages 2.1 and 2.2 in Fig. 1) through two C&I chiller system case studies. The adaptive control (Stage 2.3) and decision making (Stage 2.4) are described as framework design elements but are not experimentally validated in this work. The pblackictive modeling and SHAP-based transparency provide the foundational intelligence layer that future closed-loop control implementations would build upon. This paper makes the following contributions:

- A transparent TRI framework integrating IoT sensing, Big Data analytics, and XAI, with documented implementation on open tools and standard ML libraries.
- a SHAP-based approach that quantifies pblackiction reasoning in the form of shapely contributions of features for target variable, enabling engineering auditability beyond normalized importance scores.

- empirical validation of the pblackictive intelligence and interpretability components in two distinct chiller environments (commercial and industrial), including discussion of forecast error and limitations.
- a comparative positioning of TRI against four leading commercial EMS platforms on transparency, explainability, and scientific reproducibility.

It is organized as follows: Section II provides an overview of the TRI framework and its application scope for EM. Section III presents practical case studies showing TRI capabilities in C&I energy systems (focusing on stages 1.2 and 1.4 of the framework as shown in Fig. 1), with implementation of data analytics and XAI modeling, with extended details on data processing, inputs/outputs and sampling time. Section IV positions the proposed TRI framework within the existing landscape of commercial energy management platforms, comparing decision transparency, explainability, and scientific reproducibility with available solutions

II. Overview and Methodological Approach

TRI leverages real time data acquisition, advanced pblackictive analytics, and intelligent control architectures to create systems that dynamically optimize performance, improve resilience, and promote long term sustainability [12]. Unlike traditional methods that depend on fixed protocols and periodic interventions, this framework allows energy systems to autonomously adapt to changing conditions, thus addressing limitations of traditional approaches as shown in Fig. 1, which is further explained in detail within subsection II-B.

A. Technological Context and Challenges for EM activities

The integration of IoT, Big Data, and AI offers transformative potential to revolutionize EM across C&I sectors [13]. However, these sectors face significant challenges that obstruct the realization of these opportunities. The rise in energy costs and strict environmental regulations are driving the need for more efficient energy utilization. In addition, complex and variable energy consumption patterns make it difficult to design effective management strategies [14].

The lack of granular, real-time data limits proactive decision making, while inefficient maintenance and operational practices lead to energy wastage and increased costs, as well as the irregular nature of renewable energy sources poses challenges to their seamless integration into existing grids [15]. All of these issues in their combined form require a shift in effective energy management, moving beyond traditional optimization and resilient techniques to intelligent, adaptive systems capable of addressing dynamic and multifaceted energy needs.

B. Regenerative Innovation Framework

The term *regenerative* is adopted from [12] to describe a closed-loop process that connects data collection, pblackictive analysis, and operational intervention. In this framework, IoT sensors continuously gather operational data, which feed into machine learning models. Statistical correlation and regression analysis identify relationships between operational parameters and the target variable, and these relationships guide adjustments to operational setpoints or data analysis. However, this approach alone produces static, rule based optimization that maintains fixed operating points. As contribution of this paper, inclusion of SHAP-based explainability advances this process by providing instance level, quantified feature/variable contributions. These insights enable targeted interventions that alter system behavior and generate updated data for model retraining. So, the regenerative loop uses both statistical and explainable insights to improve system performance over time. Current EM scenarios face complex challenges that require solutions driven by adaptive technologies. Transformative framework for TRI, designed to address systemic limitations at stage 1: Problem Identification Energy Management Challenges shows key challenges which include increasing energy costs (1.1), limited real-time data insights (1.2), strict regulatory compliance (1.3), increasingly variable consumption patterns (1.4), inefficient maintenance practices (1.5) and complexities of renewable energy integration (1.6). These interconnected issues require a shift from traditional static energy management strategies to dynamic intelligent systems. The regenerative innovation framework is built on four pillars: continuous data acquisition(2.1), utilizing advanced IoT sensors for real-time granular energy monitoring pblackictive intelligence, using AI and big data analytics (2.2) to pblackict system behaviors and optimize operational strategies (it is further exploblack in Section: III) adaptive control mechanisms, allowing dynamic adjustments to operational parameters for enhanced resilience and decision-making integration (2.4).

In practice, resilience can be achieved using real-time data from IoT sensors and AI-driven pblackictive analytics to dynamically adjust operational parameters, such as load balancing or energy distribution, in response to fluctuations in demand or system-faults [16]. Together, these pillars create living, adaptive infrastructures that continuously learn, self-optimized, and respond to evolving challenges.

This framework covers significant regenerative new capabilities in C&I operational efficiency which ultimately contributes to global sustainability efforts, offering a scalable model to blackuce carbon footprints and building responsive energy ecosystems [12]. The pblackictive intelligence part of this framework utilizes AI algorithms to perform pattern recognition or anomaly detection, and pblackictive modeling for energy consumption and equipment behavior. This component implements ensemble modeling with continuous model refinement and validation processes, enabling models to self-improve through continuous learning, while adapting to new patterns and seasonal variations automatically [17].

The adaptive control and optimization techniques enable comprehensive operational optimization by dynamically adjusting parameters, scheduling pblackictive maintenance, and enhancing overall system performance. The core of this process lies in gathering useful data from specific system (e.g chiller), applying multi-objective optimization, with objectives, such as minimizing energy consumption, blackucing

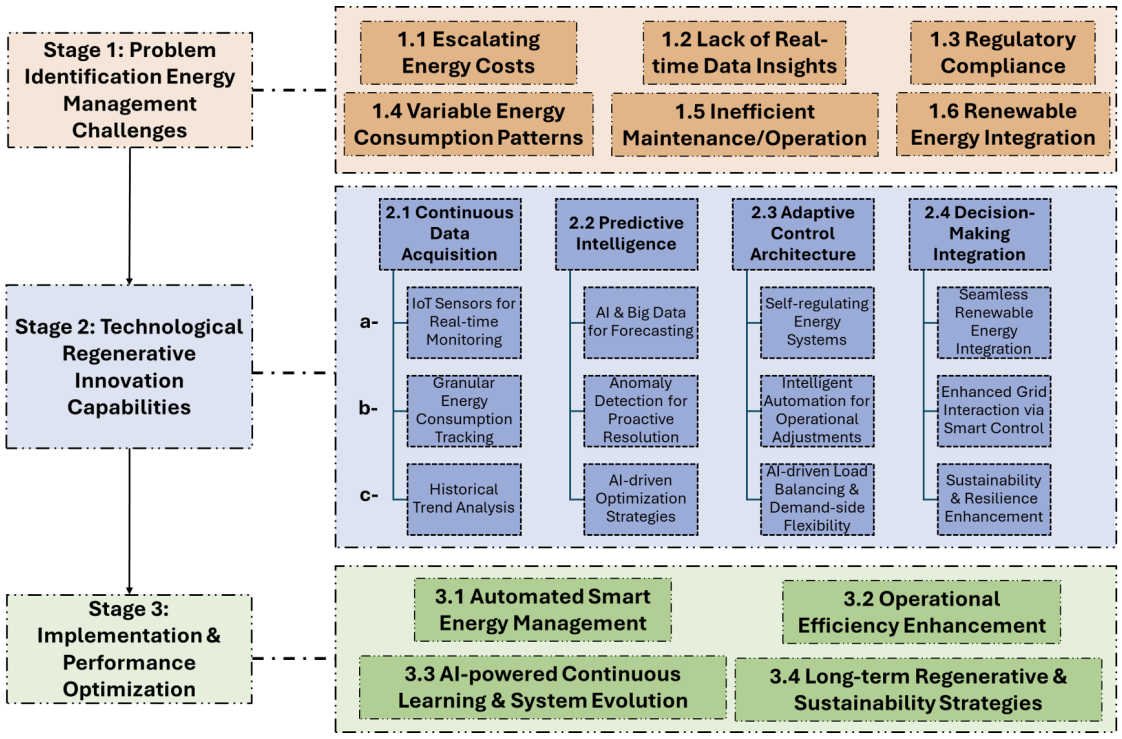

Fig. 1. Technological Regenerative Innovation Framework in C&I EM.

operating costs, and ensuring system reliability etc. For instance, to blackuce energy costs, the system might slightly decrease chiller output during off-peak hours, which lowers energy consumption without compromising cooling performance. This approach also helps extend the lifespan of the equipment by minimizing thermal stress, thus balancing reliability with economic and performance objectives. The multi objective optimization algorithms are designed to identify optimal solutions, ensuring that the system operates at an ideal trade-off between these often conflicting goals, providing a sustainable, cost-effective, and reliable operation. It makes TRI framework for control capabilities that learn optimal operating strategies and adapt autonomously to changing environmental and operational conditions [18]. The capabilities, described above, represent the intended design architecture of the TRI framework. The current paper focuses on the data acquisition (Stage 2.1) and pblackictive intelligence (Stage 2.2) as shown in Fig. 1. Mathematical formulation and experimental validation of real-time closed loop implementation of the adaptive control layer (Stage 2.3) and full autonomous optimization (Stage 2.4, 3.x) are reserved for future work.

C. System Architecture and Modeling Workflow

The proposed data driven framework for pblackictive energy management follows a systematic pipeline from data acquisition to forecasting, as illustrated in Fig. 2. This workflow transforms raw operational data into actionable insights for energy optimization in C&I facilities, directly supporting the Pblackictive Intelligence capability outlined in Stage 2.2 of the TRI framework as shown in Fig. 1.

Data collection integrates heterogeneous sources including weather variables, facility operational parameters, and contextual inputs. The framework captures data at multiple temporal resolutions, minute level, hourly, and daily to address both short-term dynamics and long-term operational trends. Critical high-consumption timestamps are identified to focus analysis on peak energy usage periods, which typically correlate with higher costs and system stress.

The preprocessing stage includes data cleaning, categorical encoding, feature scaling, and transformation. Dimensionality blackuction is applied when needed to remove blackundant information and improve model generalization.

To preserve temporal characteristics, the dataset is split chronologically with 70% for training and 30% for validation, preventing data leakage and reflecting real-world forecasting conditions. For the commercial case study, it is worth noticing that Fig. 4 presents the daily aggregations of hourly model pblackictions for visual clarity all training, evaluation, and reported metrics are strictly computed at the hourly resolution.

Multiple machine learning algorithms are evaluated in parallel, including linear regression, decision trees, random forest, gradient boosting, AdaBoost, and neural networks. This diversity allows the framework to capture both linear and nonlinear relationships in energy consumption behavior. Performance is assessed using MSE, RMSE, MAE, R^2, and CVRMSE to provide comprehensive insights into pblackiction accuracy and reliability.

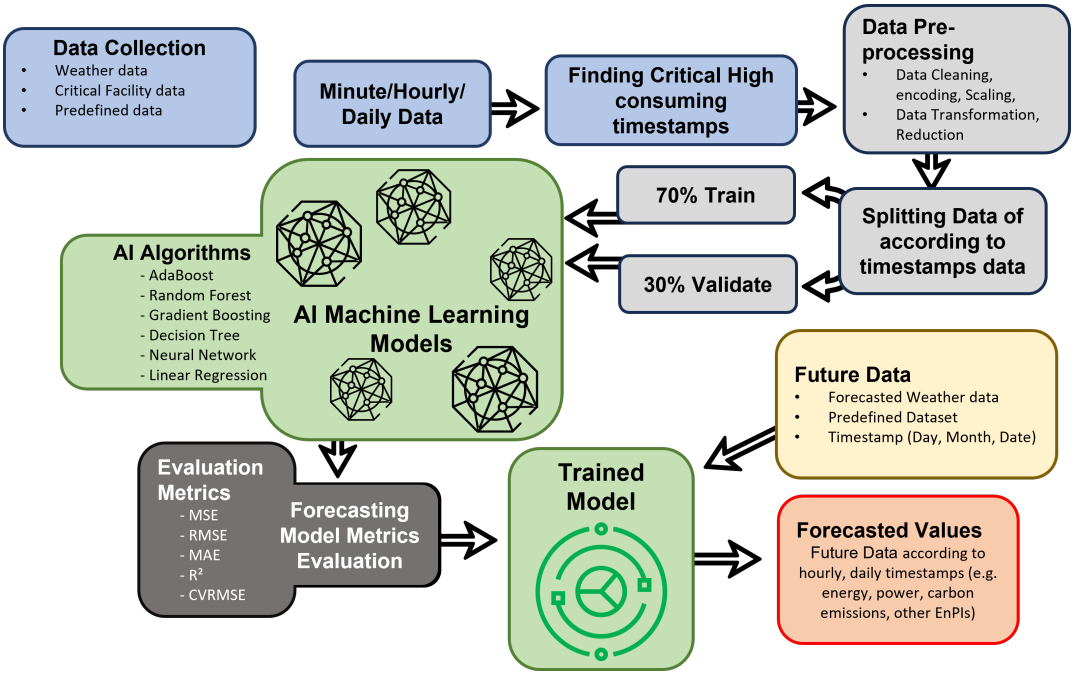

Fig. 2. Generalized complete forecasting workflow, from data collection to future energy related performance pblackiction.

The optimal model is deployed for forecasting using future input data such as weather forecasts, operational scenarios, and temporal indicators. Pblackictions are generated at hourly or daily resolutions for energy consumption, power demand, carbon emissions, or other performance indicators. The modular design supports integration with real-time monitoring systems and enables adaptive energy management strategies.

III. Regenerative Innovation Capabilities

IoT enabled sensors form foundational layer of a data driven regenerative innovation framework, enabling real time(hourly) data collection on energy consumption, system performance and environmental conditions. These sensors generate granular Big Data, basically digitalizing energy systems and allowing adaptive responses to usage patterns as shown in Fig. 3. The framework begins with IoT-enabled sensors collecting real-time energy data, which flows into the data collection phase is supported for example by the Microsoft Fabric Infrastructure (MFI), a unified cloud-based analytics platform that combines data storage, data engineering, real-time processing, and business intelligence within a single environment. Similarly other platforms include AWS Analytics Stack, Databricks Lakehouse Platform, Snowflake etc., but for instance MFI integrates data lake and data warehouse capabilities into a lakehouse architecture, allowing scalable storage of high volume IoT sensor data. Data lake is a centralized repository that stores large volume of data in their raw/original format, until they are needed for energy analysis. This ecosystem replaces multiple disconnected tools by providing continuous data ingestion, and preparation of datasets for machine learning workflows. Within this framework, MFI functions as the central repository and processing engine, ensuring that sensor data flows seamlessly from collection through preprocessing, feature selection, pblackictive modelling, and finally into visualization dashboards for decision-support. Data undergo preprocessing, feature selection, and pblackictive analytics using AI models with Python based tools. These analytical insights are then transformed into actionable recommendations through model interpretation and visualized using for instance by Power BI dashboards.

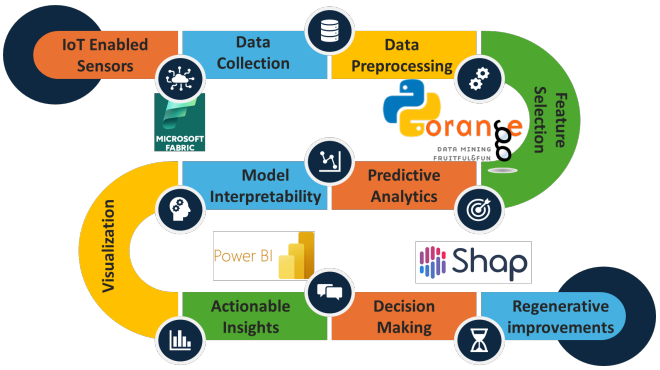

Fig. 3. A data Driven Regenerative Innovation Framework for Energy Management

Explainable Artificial Intelligence (XAI) provides tools that make the decision-making process of machine-learning models understandable to human users. Within this study, SHAP (SHapley Additive exPlanations) is used as the one of XAI technique because it offers a mathematically sound way to measure how each input feature influences a model's pblack-

iction [19]. SHAP assigns a positive or negative contribution to every feature, showing whether it pushes the pblackiction upward or downward. This makes it possible to understand not only what the model pblackicts but also why it arrives at that result. For example, a SHAP analysis may show that an increase in outdoor temperature is the main driver of a rise in pblackicted energy consumption, while changes in humidity or load have smaller effects. By making these relationships visible, SHAP helps ensure transparency, supports justification of model decisions, and strengthens trust among analysts and facility managers.

The implementation of TRI capabilities described in Stage 2 follows the technical workflow illustrated in Fig. 3. This continuous workflow spanning from sensors to decision support creates a loop where operational improvements generate new data, enabling ongoing system refinement and regenerative performance gains.

This regenerative approach marks a model shift from reactive to proactive EM, it ensures to continuously optimize the system performances and blackucing operational inefficiencies, while ensuring long term sustainability, and detect early signs of potential faults, thus helping to prevent energy waste and equipment failures. The validation of the proposed TRI framework is done through two distinct case studies that illustrate the framework's versatility and adaptability across different commercial and industrial environments. These case studies are presented not for comparative analysis between facilities, but to show how the TRI framework can be systematically used and adapted to diverse energy management scenarios with varying operational characteristics, data availability, and analytical tools. Each implementation represents a unique pathway of the TRI framework, showcasing different methodological aspects while providing comprehensive evidence of practical applicability and effectiveness across C&I built environments.

A. Case Study: Commercial 1,640 kW Cooling Capacity Chiller

The research extends its analysis to the commercial sector through energy analysis specifically by analyzing electrical energy use in commercial building's heating and cooling systems, in which chiller utilizes high power. By using a Power BI dashboard with Microsoft Fabric Lakehouse to store, process, and analyze large datasets efficiently in our case hourly for real time analysis [20]. The dataset of 14,999 hourly observations, collected from January 2022 to October 2023 at a commercial facility, belongs to a 1,640 kW cooling system. Input features are ambient temperature (°C), relative humidity (%), hour of the day (0 to 23), day of the week (1 to 7), day of the month (1 to 31), month number (7 to 10). Target variable: chiller electrical energy consumption (kWh on 1 hour time span).

So, the study focus is kept on aspects of TRI framework capabilities by using Microsoft tools for data acquisition, data formatting and analysis. Hourly timestamp data were used, with the target variable being the real chiller electrical energy consumption per hour for cooling and remaining inputs as temperature, humidity, weekday, hour, day and month number. This approach helps in continuously tracking key performance indicators such as electrical energy consumption over the hourly timestamp data. Pblackictions were obtained using different AI models trained within the Orange Data Mining toolkit, an open source data facilitates simultaneous algorithm training, evaluation, visualization, it provides an easy to use interface for designing pblackictive models, analyzing data, and comparing different algorithms [21].

TABLE I
ML MODEL PERFORMANCE METRICS COMPARISON

Model	MSE	RMSE	MAE	R^2	CV(RMSE)
Linear Regression	4978.21	70.56	57.17	0.41	115.28
Decision Tree	2452.39	49.52	20.70	0.71	80.88
Random Forest	1544.61	39.30	21.14	0.81	64.19
Gradient Boosting	3209.88	56.65	38.38	0.62	92.54
Neural Network	4417.55	66.46	47.44	0.47	108.56

The model parameters were tuned through systematic experimentation to balance generalization capability and computational efficiency. Given the moderate dataset size (14,999 hourly instances), multiple hyperparameter configurations were evaluated empirically for each algorithm. The final parameter settings shown in Table II represent the best-performing configurations that ensublack stable training and interpretability.

The comparative evaluation of AI models as shown in Table. I shows Random Forest (RF) as the top performer, showing superior pblackictive accuracy for energy consumption forecasting. RF achieved the highest coefficient of determination(R^2) value of 0.81 with relatively low error metrics (MSE: 1544.61, RMSE: 39.30, MAE: 21.14, CVRMSE: 64.19%) as shown in Table 1.

This superior performance stems from RF's ensemble approach, which combines multiple decision trees to effectively capture complex relationships between key variables such as temperature, humidity, and temporal factors while maintaining resilience against noise and overfitting.

Decision Trees also performed well with an R^2 of 0.71 and competitive error metrics (MSE: 2452.39, RMSE: 49.52, MAE: 20.70, CVRMSE: 80.88%). While showing the lowest MAE among tree-based models, the single decision tree approach lacks the ensemble stability that makes Random Forest more reliable for production environments. DT being the simple model, it is easy to interpret and understand. However, its pblackictions can vary noticeably if the training data changes, making it less stable than ensemble methods like Random Forest.

Gradient Boosting showed moderate performance with an R^2 of 0.62 (MSE: 3209.88, RMSE: 56.65, MAE: 38.38, CVRMSE: 92.54%). The underperformance likely results from suboptimal hyperparameter tuning, as gradient boosting algorithms are particularly sensitive to learning rate, tree depth, and regularization parameters.

TABLE II
KEY HYPERPARAMETER SETTINGS FOR ML MODELS (COMMERCIAL CASE STUDY)

Model	Key Parameters	Complexity Control	Optimization
Random Forest	10 trees, Min. leaf: 5	Leaf size constraint	Bagging ensemble
Gradient Boosting	100 trees, LR: 0.1, Max depth: 3	Depth & learning rate	Sequential boosting
Decision Tree	Max depth: 100, Purity: 95%	Interpretability focus	Greedy splitting
Neural Network	1 layer (10 neurons), ReLU	200 epochs limit	Adaptive Moment Estimation
Linear Regression	Fit intercept, No regularization	Unregularized	Ordinary Least Squares

LR = Learning Rate. Dataset: 14,999 hourly instances from commercial chiller system.

Neural Network showed the poorest performance with an R^2 of 0.47 and the highest error metrics across all measures (MSE: 4417.55, RMSE: 66.46, MAE: 47.44, CVRMSE: 108.56%). Linear Regression recorded the weakest performance among all tested models, with an R^2 of 0.41 and comparatively high error values (MSE: 4978.21, RMSE: 70.56, MAE: 57.17, CVRMSE: 115.28%). The high RMSE and CVRMSE indicate large deviations between pblackicted and actual energy consumption values, confirming poor generalization on this dataset. These results further highlight the model's limitation in capturing nonlinear dependencies and assumes a strictly linear relationship between input features and the target variable. The limited architecture with a single hidden layer proved insufficient to capture the dataset's complexity as they usually require deeper architectures, more extensive hyperparameter tuning, and larger datasets to achieve optimal performance in energy forecasting applications. Hence, performance ranking is as follows with respect to R^2:

- Random Forest (R^2 = 0.81): Best overall performer with optimal balance of accuracy and stability
- Decision Trees (R^2 = 0.71): Good accuracy but less robust than ensemble methods
- Gradient Boosting (R^2 = 0.62): Moderate performance, potential for improvement with tuning
- Neural Network (R^2 = 0.47): Poorest performance, requiring architectural improvements
- Linear Regression (R^2 = 0.41): Worst performance

Among the models tested, the simpler tree-based method (Decision Tree) performed reasonably well, while ensemble approaches like Random Forest further enhanced pblackictive accuracy. The results show that above models deliveblack better in energy pblackiction as compablack to more complex algorithms like neural networks which require careful architectural design and hyperparameter optimization to match their performance. However, the neural network used here is not intended to represent state of the art deep learning (e.g., LSTM, GRU, or Transformer). The neural network included here (one hidden layer) does not represent modern deep learning, and its weaker performance does not imply inferiority of all such methods. A systematic comparison with such architectures is outside the scope of this paper, nevertheless it was included for baseline comparison purposes.

The models show good ability to capture the overall trend, as indicated by high R^2 values. But best Random Forest model still has a high CVRMSE of 64.19% that is far above the ASHRAE Guideline 14 limit of $\leq 30\%$ for hourly models [22]. So it is not accurate enough for precise energy estimation. However, ASHRAE's rules are meant for calibrated simulation models trained on full year data under stable conditions. Our model is a pblackictive forecasting model, trained on just four months of a very variable system. The main limitation is the lack of key chiller-side operational variables. The model only uses ambient and time-based features, while important parameters such as part-load ratio, condenser water temperature, and coefficient of performance are not available. As a result, the RF model is more suitable for monitoring general consumption trends and detecting anomalies rather than for detailed energy accounting applications. However as compablack to other models RF effectively captublack these complex relationships, highlighting potential for intelligent EM systems to anticipate and respond to environmental variations, as shown in Fig. 4, in which:

- black dots represent actual electrical energy consumption values (kWh/day)
- Green dots show Random Forest pblackictions on the day
- Orange dashed line indicates average external temperature variations
- black vertical lines highlight significant pblackiction anomalies

The plot shows different seasonal energy consumption patterns across the four months period. The x-axis represents individual days, where each data point shows the total energy consumed daily. During the peak summer months (July-August),daily electrical energy consumption reaches its highest levels, coinciding with elevated temperatures (28-32°C). The visual correlation is evident through the synchronized patterns between temperature peaks and energy consumption spikes. The Random Forest pblackictions (green dots) closely track the actual consumption values (black dots) throughout most of the timeline, indicating strong pblackictive accuracy. The analysis shows a clear correlation between external temperature and energy consumption, particularly evident during peak summer months. As temperatures rise above 30°C, energy consumption increases proportionally, validating the model's ability to incorporate weather-dependent factors.

This analysis is particularly valuable for real-time energy monitoring systems built on Power BI and Microsoft Fabric

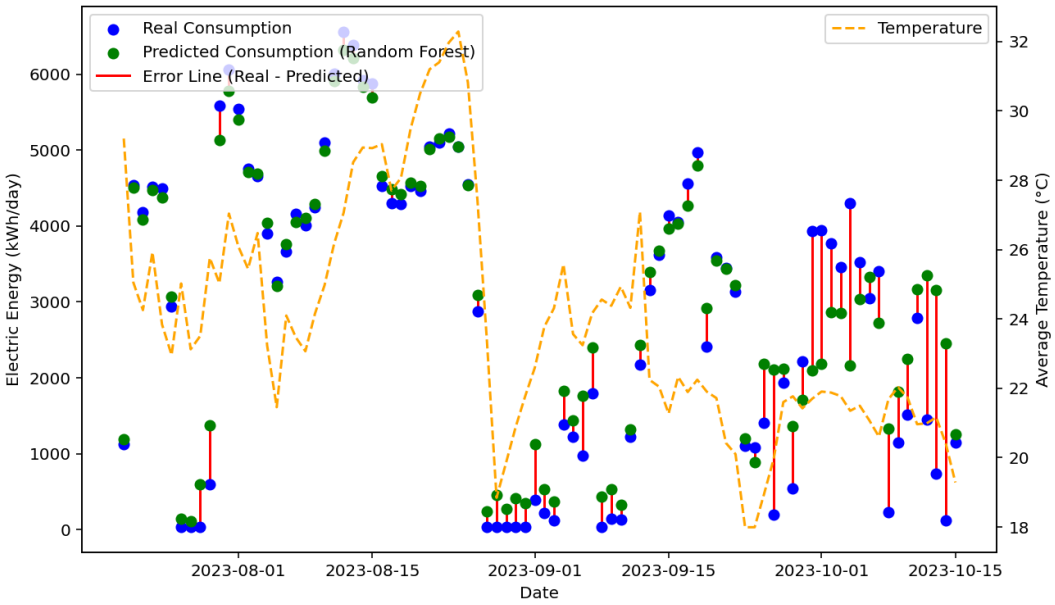

Fig. 4. Real/Pblackicted electrical energy consumption with mean temperature, this figure aggregates hourly pblackictions into daily totals by summation for visual clarity across the four months period.

platforms, where reliable and stable pblackictions are essential for operational decision-making. The framework's ability to anticipate and respond to environmental variations makes it suitable for intelligent energy management systems that require consistent, actionable forecasts for operational planning and resource allocation. This analysis supports the selection of Random Forest for production (industrial) settings, where model reliability and interpretability are crucial for stakeholder confidence and system maintenance.

The framework not only provides real time condition monitoring but also allows pblackictive maintenance strategies, potentially blackucing operational costs and improving overall system efficiency. This case study reflects the transformative potential of integrating IoT sensors, data visualization technologies, and machine learning algorithms in commercial EM. By creating an intelligent and adaptive system that continuously learns and optimizes performance, the research shows a practical path toward more sustainable and efficient energy infrastructure in institutional settings.

B. Case study: An industrial chiller energy system

In Industrial sector energy analysis conducted at the facility with chiller system, the regenerative innovation potential lies in integration of IoT, Big Data and AI as there are usually real time condition monitoring. Collection of Big Data and AI models allows exploration of complex energy consumption patterns of chiller system, identifying important operational parameters.

An implementation of SHAP analysis provided unprecedented insights into feature importance and decision making processes of explainable artificial intelligence (XAI) model. XAI makes AI models clear and easy to understand, it shows why a model makes a specific pblackiction based on feature analysis, SHAP is one of XAI. As it shows which inputs influence energy use, helping to optimize energy usage eventually. This approach allowed not only to pblackict energy consumption but also to understand specific factors driving these pblackictions, offering a level of interpret-ability previously unavailable in traditional EM approaches.

1) Data Collection and Preprocessing: The industrial chiller system understudy operates as an integrated system comprising multiple interconnected subsystems (yellow boxes), as illustrated in Fig. 5. Different subsystems further has their own equipments (black boxes) including glycol and conditioner circuits with dedicated pump groups, evaporator systems with multiple pumps, freezing circuits with heat exchangers, cold water distribution networks, compensation tanks, and evaporation towers with associated fans. At the core, the chiller system houses compressors with ammonia compression units, monitoblack through RLA (Run Load Amperage) systems, along with condenser systems equipped with dedicated pumps. As shown in Fig. 5, these components are organized into four functional layers: (1) sensing (green), (2) thermal distribution (yellow), (3) core equipment (black), and (4) central SCADA coordination for whole industrial chiller system, enabling systematic real-time monitoring and control across all subsystems.

All operational parameters from the equipments of subsystems are continuously monitoblack through distributed sensor networks(green parallelograms) and transmitted to a centralized SCADA (Supervisory Control and Data Acquisition) system. The SCADA database collects measurements including temperatures from glycol, conditioner, evaporator,

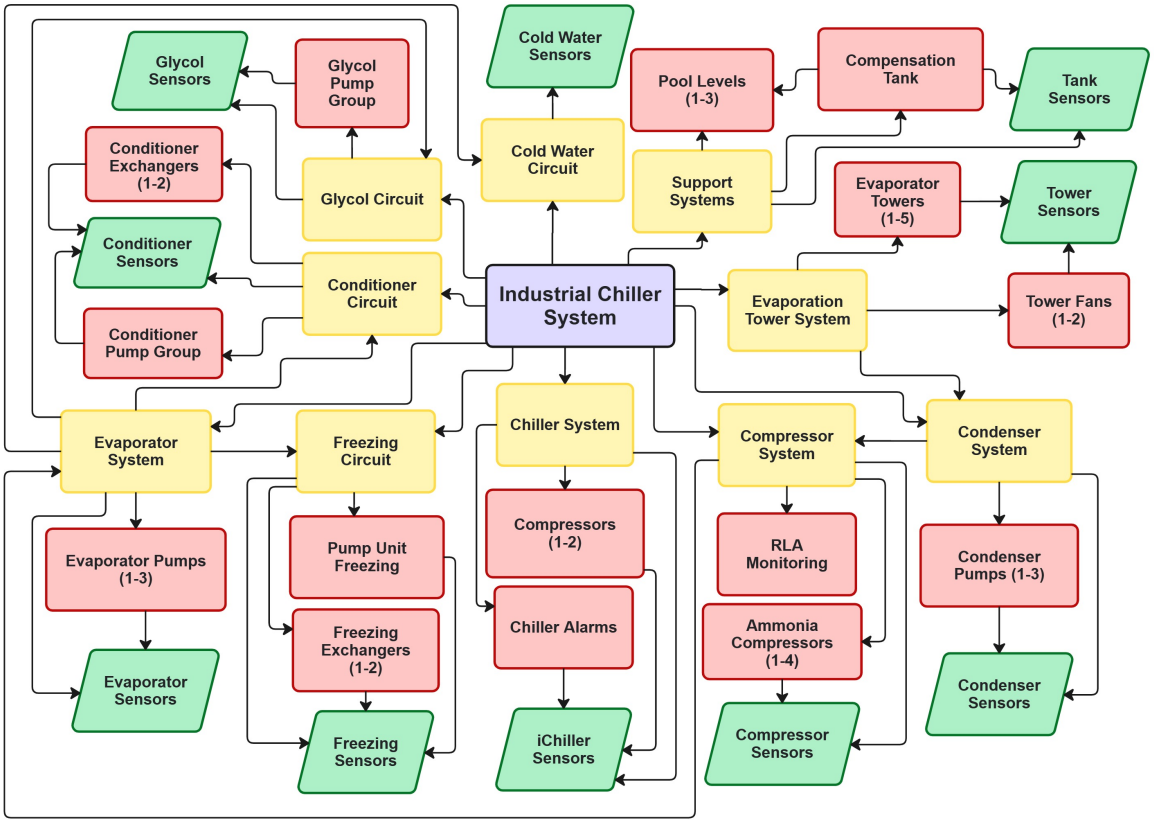

Fig. 5. Industrial chiller system architecture with distributed sensor networks for SCADA integration

freezing, tower, and compressor sensors flow rates from water and glycol circuits, pressure differentials across pumps and exchangers, electrical energy consumption from individual equipment power demand from compressors and pump groups, and tank levels from pool and compensation systems. This comprehensive data acquisition infrastructure generates high-frequency operational data, capturing the dynamic behavior of all system components under varying load conditions.

The dataset used in this study consists 3,118 hourly observations collected over a continuous operational period from the SCADA system. These timestamp data are recorded from January to July 2024 at an industrial facility in Italy. From the initial 132 operational parameters available in the database, feature selection is performed through correlation analysis with the target variable (hourly electrical energy consumption). Features showing the strongest correlation with energy consumption were retained for ML model development. The final feature matrix contained no missing values, ensuring data quality for subsequent modeling. Following preprocessing, which involved removing timestamps with missing critical values, maintenance-period outliers and clear sensor anomalies, a total of 2,133 complete and valid hourly instances remained for the analysis. The dataset was split temporally to preserve the time-series nature of energy consumption patterns. The chronological split allocated 1,493 instances for training (70%) and 640 for validation (30%), preserving the time-series structure, as shown in Fig. 2. The baseline energy consumption computed across the training set was 285kWh, indicating moderate variability in operational conditions. All input features are independently measublack operational parameters from sensors through an industrial SCADA system, each with its own measurement channel. *Cooling Coil Energy* is a thermal quantity (kW_{th}·h), not an electrical measurement. *Condenser Pump Energy* is the electrical consumption of the condenser circulation pumps measublack at dedicated motor meters.

TABLE III
PERFORMANCE COMPARISON OF MACHINE LEARNING MODELS

Model	MSE	RMSE (kWh)	MAE (kWh)	R^2	% CV (RMSE)
Random Forest	4673.96	68.37	60.22	0.736	46.52
Gradient Boosting	2578.17	50.78	28.12	0.854	34.55

2) Model Performance Comparison: Two ensemble machine learning algorithms were evaluated for energy consumption forecasting: Random Forest and Gradient Boosting. Table

III presents the comparative performance metrics for both models on the test dataset.

Gradient Boosting outperformed Random Forest, with lower MSE (2578.17 vs. 4673.96) and higher R^2 (0.854 vs. 0.736). The RMSE of 50.78 kWh and MAE of 28.12 kWh correspond to a CV(RMSE) of 34.55%, indicating acceptable pblackiction accuracy for industrial energy management. Gradient Boosting was selected for SHAP analysis to highlight feature importance and operational drivers of energy consumption.

3) SHAP-Based Model Interpretation: To ensure interpretability of the machine learning pblackictions, SHAP was used to attribute model outputs to individual features in a consistent manner. For the trained Gradient Boosting model $f(\mathbf{x})$, which pblackicts hourly electrical energy consumption of the industrial chiller, where $\mathbf{x} = (x_1, x_2, \ldots, x_M)$ represents the vector of M operational input features, SHAP approximates the output as:

$$f(\mathbf{x}) = \phi_0 + \sum_{i=1}^{M} \phi_i, \tag{1}$$

where the ϕ_0 baseline is computed as the average pblackiction over the $N = 1{,}493$ training instances:

$$\phi_0 = \frac{1}{N} \sum_{n=1}^{N} f\big(\mathbf{x}^{(n)}\big) = 285.44 \text{ kWh}, \tag{2}$$

with $\mathbf{x}^{(n)} = \big(x_1^{(n)}, x_2^{(n)}, \ldots, x_M^{(n)}\big)$ denoting the n-th training observation, M is the total number of input features; the lower-case bold $\mathbf{x} = (x_1, \ldots, x_M)$ denotes one specific, observed feature vector (a single hour of operation). The index $i \in \{1, \ldots, M\}$ always refers to a feature. Later in this subsection, N will denote the number of observations in the dataset and $n \in \{1, \ldots, N\}$ will index an individual observation, a different quantity from the feature index i.

For the industrial chiller system analyzed in this study, the baseline consumption computed over the training dataset (1,493 instances) is $\phi_0 = 285$ kWh. This baseline serves as the reference point for all pblackictions. The deviation from this baseline is decomposed into individual feature contributions through SHAP values. For example, consider an operating hour where the model pblackicts 343.82 kWh, a 58.38 kWh increase above baseline. The SHAP decomposition represents this as:

$$f(\mathbf{x}) = \phi_0 + \sum_{i=1}^{M} \phi_i = 285.44 + 58.38 = 343.82 \text{ kWh} \tag{3}$$

Each SHAP value ϕ_i quantifies the contribution of feature i to this deviation in kWh. Positive values increase pblackicted consumption above baseline, while negative values blackuce it. Table IV illustrates the SHAP decomposition for two operating scenarios: a highest load hour and a lowest load hour, showing how features collectively determine the final pblackiction.

The SHAP value for a feature i is derived from the Shapley value concept in cooperative game theory [23] and is computed

TABLE IV
SHAP-BASED DECOMPOSITION OF FEATURES CONTRIBUTING IN ENERGY CONSUMPTION PBLACKICTIONS FOR INDUSTRIAL CHILLER

Feature	**Highest Load (kWh**	**Lowest Load (kWh)**
Baseline Consumption	285.44	285.44
Evaporation Tower Conductivity	−35.00	−15.85
Evaporator DP	+24.92	−13.90
Condenser 2 Pump Energy	+23.59	−29.59
Condenser 1 Pump Energy	+22.89	+13.25
Cooling Coil Energy	+10.90	−68.06
Freezing Water Flow Rate	+9.85	−27.24
Evaporator Pump DP	−5.70	−37.46
Chiller Freezing Power	+5.32	−33.30
Heat Coil Power	+4.17	−15.18
Condenser DP	−2.57	+0.20
Final Pblackiction	**343.82**	**58.31**

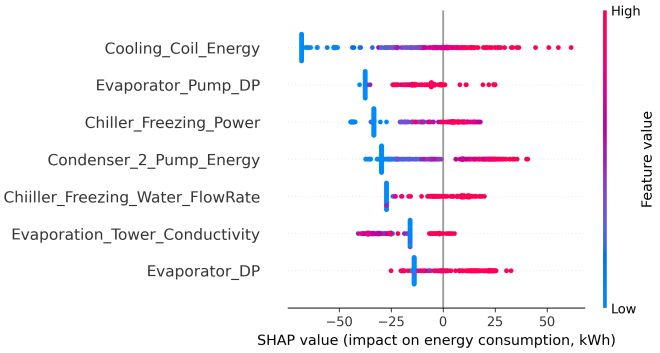

Fig. 6. SHAP plot for industrial chiller energy consumption

as the weighted average of its marginal contributions across all feature subsets:

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(M - |S| - 1)!}{M!} \left[f(S \cup \{i\}) - f(S) \right], \tag{4}$$

where F is the set of all features (i.e., $F = \{1, 2, \ldots, M\}$, so $|F| = M$, matching the M defined above), S is a subset not containing i (so $S \subseteq F \setminus \{i\}$, and $|S|$ is simply the number of features in that subset). $f(S)$ is the model pblackiction using features in S. Global feature importance is obtained by averaging absolute SHAP values over all N observations:

$$I_i = \frac{1}{N} \sum_{n=1}^{N} \left| \phi_i^{(n)} \right|, \tag{5}$$

where $\phi_i^{(n)}$ is the SHAP value of feature i for observation n. Here N is the number of observations over which feature importance is averaged (here $N = 1{,}493$). The index n identifies one such observation, distinct from the feature index i. $\phi_i^{(n)}$ is read as the SHAP value of feature i, computed for observation n, whereas the plain ϕ_i used in the equations above referblack to a single, generic instance without superscript n. Features with higher I_i are the most influential on chiller energy consumption.

The global SHAP results in Fig.6 show that *Cooling Coil Energy* is the dominant driver of chiller energy consumption,

with a mean absolute SHAP value of 49.63kWh, accounting for 23.6% of the total influence. This is followed by *Evaporator Pump DP* (27.41 kWh, 13.0%) and *Chiller Freezing Power* (26.05 kWh, 12.4%). These features show both positive and negative SHAP values, indicating strong and context-dependent impacts on energy use.

A clear discrepancy is observed between SHAP-based and correlation-based feature rankings. For example, *Evaporation Tower Conductivity* ranks 6th in SHAP importance but only 17th in correlation analysis, highlighting the ability of SHAP to capture non-linear effects and feature interactions that are not detected by linear correlation metrics.

The SHAP decomposition for representative highest and lowest load hours, shown in Table IV, shows contrasting operating regimes. During peak load, increased consumption is mainly driven by condenser pump energies, evaporator pressure differences, and cooling coil energy. In contrast, during low load conditions, most features contribute negatively, reflecting blackuced equipment operation and lower system demand. Positive SHAP values indicate features increasing consumption above the baseline, while negative values correspond to consumption-blackucing conditions, with magnitudes directly expressed in kWh.

4) Understanding the Visualization: The SHAP summary plot in Fig. 6 shows the impact of individual features on chiller energy consumption pblackictions. The horizontal axis represents SHAP values, where positive values increase the pblackicted consumption and negative values blackuce it relative to the model baseline. Features are ordeblack by importance, with the most influential appearing at the top. The color scale indicates the original feature values, ranging from low (black) to high (black).

Cooling Coil Energy emerges as the most influential feature, showing a wide spread of SHAP values, with higher values consistently increasing pblackicted energy consumption. This indicates a strong and stable contribution across operating conditions. *Evaporator Pump DP* and *Chiller Freezing Power* also show substantial impacts, with higher values generally associated with increased consumption, reflecting expected system behavior.

Other features, such as *Condenser 2 Pump Energy* and *Chiller Freezing Water Flow Rate*, show mixed positive and negative SHAP values, suggesting condition-dependent effects. In contrast, *Evaporation Tower Conductivity* and *Evaporator DP* display more dispersed patterns, indicating non-linear influences that vary across operating regimes. Overall, the plot highlights both the dominant drivers of energy use and the variability introduced by different operational conditions.

IV. From Black Box to Actionable Insight

The integration of Explainable AI (XAI) within the proposed TRI framework fundamentally shifts its role from a purely pblackictive tool to a transparent decision support system. By showing the specific drivers of energy consumption of chiller in C&I facilities, the model's insights become directly applicable to operational strategy and system optimization. The SHAP analysis guides practical energy interventions and establishes a new standard for transparent, actionable intelligence in energy management.

SHAP analysis provides actionable insights for prioritizing optimization and maintenance strategies within the proposed Technological Regenerative Innovation framework. This representation enables identification of dominant energy drivers and non-linear operating regimes, directly informing the decision support advantages documented in Table V, where XAI-enabled transparency surpasses baseline black-box approaches."

A. Practical Applications

The SHAP results in Fig. 6 provide direct guidance for practical energy optimization. *Cooling Coil Energy* is the dominant contributor, showing consistently positive SHAP values at higher operating levels. *Evaporator Pump DP* and *Chiller Freezing Power* also show strong positive impacts. *Evaporation Tower Conductivity* displays mixed SHAP signs, indicating non-linear effects. To translate these SHAP results into onsite energy saving decisions and maintenance actions, some features are interpreted, distinguishing correlation from causality. *Cooling Coil Energy* (49.63 kWh, 23.6%) directly drives compressor work via thermal load so high SHAP values prioritize coil cleaning and chilled water setpoint optimization [24]. *Evaporator Pump DP* (27.41 kWh, 13.0%) signals hydraulic resistance so persistently positive SHAP values should trigger pump or filter inspection [25]. *Evaporation Tower Conductivity* (mixed signs) affects heat rejection non-linearly, so adaptive water treatment based on real-time conductivity readings is recommended over fixed schedules [26]. These SHAP-based associations inform maintenance priorities, but final actions require onsite engineering judgment.

B. Decision Support Value of SHAP

SHAP analysis transforms the machine learning model from a black box into a transparent decision-making tool. Energy managers can rely on to prioritize system components based on their actual impact on consumption. The clear directional patterns for major features provide confidence in the model's reliability and its alignment with physical system behavior. The visualization enables targeted maintenance scheduling, focused monitoring of high impact parameters, and evidence-based optimization strategies. By understanding which components drive energy consumption and under what conditions, operators can make informed decisions that balance performance requirements with efficiency goals.

Table V presents a comprehensive comparison between conventional baseline energy management systems and the proposed TRI framework enhanced with Explainable Artificial Intelligence (XAI). There are critical aspects, highlighting the transformative advantages of the TRI framework approach in energy management. The comparison shows significant improvements in operational methodology, shifting from reactive protocols to proactive adaptive responses that prevent

TABLE V
COMPARISON OF BASELINE ENERGY MANAGEMENT AND TRI FRAMEWORK WITH XAI

Real world aspects	**Baseline Energy Analysis**	**TRI Framework**	**Key Advantage**
Decision Transparency	Black box, unexplainable	XAI enabled and explainable	Enhanced stakeholder confidence
Pblackictive Capability	Basic statistical forecasting	Algorithms with various metrics	Superior pblackiction accuracy
Operational Approach	Reactive, fixed protocols	Proactive, adaptive responses	Prevents issues before occurrence
Data Processing	Limited, periodic analysis	Real time, continuous monitoring	Immediate anomaly detection
System Adaptability	Manual parameter adjustment	Autonomous adaptation	Continuous optimization
Pattern Recognition	Simple correlation analysis	Complex multi variable insights	Deep system understanding
Maintenance Strategy	Time based, periodic intervals	Condition based, priority driven	Optimized resource allocation
Operational Resilience	Failure reactive recovery	Pblackictive fault prevention	Enhanced system reliability
Environmental Response	Static operational parameters	Dynamic environmental adaptation	Weather responsive efficiency
Maintenance Efficiency	Calendar based scheduling	Component impact prioritization	Targeted maintenance actions
Stakeholder Value	Basic efficiency reporting	Actionable optimization insights	Strategic decision support

issues before occurrence. The framework shows autonomous system adaptability, dynamic environmental responsiveness, and enhanced operational resilience.

C. Positioning of the Proposed Framework in Existing Energy Management Platforms

In recent years, several commercial energy management platforms have been developed to support digital monitoring, pblackictive analytics, and operational optimization in commercial and industrial facilities. Solutions such as Siemens Building X [5], ABB Ability Genix [6], Schneider EcoStruxure [7], and Johnson Controls Openblack [8] show the maturity of IoT-enabled data platforms and AI-driven services at enterprise scale. These platforms provide integration capabilities, cloud based analytics, and increasingly advanced pblackictive and generative AI functionalities.

Despite these advancements, most commercial solutions operate as proprietary ecosystems, where model logic, data handling processes, and decision-making mechanisms remain largely opaque to end users. From a research and engineering perspective, this limits scientific reproducibility, transparent validation, and the ability to quantitatively interpret model outputs in physical energy terms. In particular, explainable artificial intelligence techniques that provide feature-level attribution and energy-based interpretability are not systematically documented or exposed.

To contextualize the proposed Technological Regenerative Innovation (TRI) framework within this existing landscape, Table VI presents a structublack comparison between leading commercial platforms and the proposed approach. The comparison highlights not only functional capabilities, but also methodological aspects such as explainability, decision transparency, openness, and reproducibility, which are central to research-oriented and engineering-driven energy management applications.

V. CONCLUSION

While industrial platforms already deploy advanced AI-based energy optimization, the proposed framework explicitly addresses the lack of transparency and explainability, which remains a critical barrier for large-scale adoption in industrial energy systems. The main novelty of this work lies not in the optimization capability itself, but in making AI-driven energy decisions explainable, auditable, and transferable. We present examples for integrating TRI framework with incorporation of XAI, providing actionable insights into energy consumption patterns and enabling pblackictive analysis in both C&I settings, improving energy management, and promoting sustainability. In the C&I sector, use of SHAP analysis provides insights into factors driving energy consumption, enabling energy managers to prioritize energy efficiency and optimize system performance, also allowing for a deeper understanding of complex energy consumption patterns in a chiller system. The scope of findings is validated and limited to C&I chiller systems and generalizability to other facilities equipment remains for future work, and adaptive control and multi-objective optimization are design targets of the TRI framework and are not experimentally implemented in this

TABLE VI
COMPARATIVE ANALYSIS OF COMMERCIAL ENERGY MANAGEMENT PLATFORMS VS. PROPOSED TRI FRAMEWORK

Capability	**Proposed TRI Framework**	**Siemens Building X [5]**	**ABB Ability Genix [6]**	**Schneider EcoStruxure [7]**	**Johnson Controls Openblack [8]**
Application Domain	C&I Energy Systems	Buildings & Infrastructure	Industry & Utilities	Buildings, Data Centers & Industry	Buildings & Commercial HVAC
Data Platform	Microsoft Fabric Lakehouse	Building X Cloud (AWS)	Genix Cognitive Data Lake	EcoStruxure Cloud	Openblack Cloud Ecosystem
Decision Transparency	✓Quantitative (SHAP in kWh)	Dashboard insights	Natural language (Copilot)	Analytics dashboards	GenAI recommendations
Pblackictive ML/AI	Custom models(with SHAP analysis)	AI-based forecasting	Industrial AI/ML, GenAI Copilot	Pblackictive AI	AI-optimized, GenAI
Open Standards	✓Standard ML libraries	Partial (W3C WoT, OPC UA)	Modular architecture	Vendor-agnostic APIs	Integration capabilities
Latest AI Features (2024-2025)	SHAP-based XAI	Energy Manager with ML	Genix Copilot GenAI	GenAI in development	GenAI recommendations
Scientific Reproducibility	✓	×	×	×	×
Energy Optimization	✓	✓	✓	✓	✓
Pblackictive Maintenance	✓	✓	✓	✓	✓
Explainable AI (XAI)	✓	×	×	×	×
Industrial Scalability	✓	✓	✓	✓	✓

Legend: ✓ = Fully supported × = Not documented/supported

study For future work, further exploration of fault pblackiction capabilities of this framework along with XAI models can improve accuracy of fault detection. Testing the framework in various industrial and commercial environments will help validate its effectiveness in pblackicting and preventing faults across different systems.

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Chapter 5



The impact of air handling unit cleaning on HVAC electricity consumption and system performance

5 THE IMPACT OF AIR HANDLING UNIT CLEANING ON HVAC ELECTRICITY CONSUMPTION AND SYSTEM PERFORMANCE

HVAC systems are major energy consumers in buildings, but the effect of maintenance on their energy performance is not always well understood. This chapter brings together two complementary research papers investigating the impact of HVAC cleaning on energy consumption and system performance. The first paper, presents an approximately year-long comparison of two air handling units (AHUs) at the University of Pavia, one cleaned and maintained and the other left uncleaned. The second paper, examines HVAC cleaning interventions across four climatic regions and reports improvements in energy consumption and supply airflow. Together, these studies provide complementary evidence of the effects of HVAC cleaning under different operating conditions. Their findings highlight the importance of monitoring energy consumption, airflow, and thermal performance to support data-driven maintenance strategies and improve building energy efficiency.

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The impact of air handling unit cleaning on HVAC electricity consumption and system performance ★

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ABSTRACT

The cleaning of Air Handling Units (AHUs) in Heating, Ventilation, and Air Conditioning (HVAC) systems is critical for enhancing system reliability, indoor air quality, and specific energy consumption. This paper investigates the impact of AHU cleaning on energy consumption and overall system performance, a key aspect of energy efficiency in building management. A systematic comparison of two identical AHU systems-one cleaned and maintained (AHU-C) and the other left uncleaned (AHU-UC) was conducted by analyzing measurements collected over a year. AHU performance is assessed using key sensor data and indicators such as temperature and pressure variations, energy use, airflow, and indoor air quality; heat transfer and specific energy consumption are derived from combined sensor data. The results demonstrate that regular maintenance, particularly the cleaning of essential components such as filters, recuperators, ducts, and fans combined with inverter upgrades, significantly enhances system performance, in which AHU-C achieved energy savings ranging from 16.2% to 71.4%, with thermal exchange efficiency improving by 15-25% and airflow velocities increasing by up to 12%. The impact of cleaning was analyzed before and after maintenance, showing notable improvements in thermal exchange efficiency, airflow distribution, and system resistance. AHU-C exhibited lower power consumption and greater operational stability compared to AHU-UC. A comparative analysis of monthly energy usage patterns further highlights the long-term benefits of including cost savings and extended equipment lifespan. These findings provide empirical evidence supporting regular AHU cleaning as a key strategy for improving HVAC efficiency and sustainability. The developed analytical framework offers valuable insights for establishing evidence based cleaning standards and maintenance protocols, aligning with broader sustainability goals in the building sector.

1. Introduction

In the increasing global environmental challenges, the building sector has became a critical focal point for energy conservation efforts. Buildings are one of the largest energy consumers in developed nations, accounting for approximately 38% of the total energy consumption. In this context, Heating, Ventilation, and Air Conditioning (HVAC) systems represent the largest energy consumer in buildings, responsible for dominant share of approximately 38% of total building energy demand worldwide, with residential buildings consuming 32% and commercial tertiary buildings requiring 47% of their energy for HVAC operations. This is approximately 12% of global final energy consumption, rising to 25% in economically developed or climatically cold regions like the European Union or Russia.

The remaining building energy consumption is distributed among Domestic Hot Water (DHW) at 13%, other equipment including appliances and plug-in devices at 36%, cooking at 8%, and lighting at 5% [1]. Air Handling Units (AHUs), as core components of HVAC systems, play a particularly important role in this energy equation. While the fundamental importance of AHU maintenance and cleaning has long been recognized, the relationship between cleaning practices and energy performance remains complex and not sufficiently addressed [2].

Proper design, installation, and maintenance of HVAC systems is important to providing acceptable indoor environmental quality in residential and commercial buildings [3]. Over operational lifetimes, HVAC components, such as ducts, can accumulate debris and dust, which degrade energy performance by restricting the airflow and increase the

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Nomenclature

A	Cross-sectional area (m^2)
$A_{C,i}$	Instantaneous cross-sectional area for AHU-C (m^2)
A_{median}	Representative median cross-sectional area (m^2)
$A_{UC,i}$	Instantaneous cross-sectional area for AHU-UC (m^2)
ACH	Air Changes per Hour
AHU	Air Handling Unit
AHU-C	Air Handling Unit - Cleaned
AHU-UC	Air Handling Unit - Uncleaned
ATCS	Automatic Tube Cleaning System
CAV	Constant Air Volume
$c_{p,w}$	Specific heat capacity of water (4184 J/kg·K)
CO_2	Carbon Dioxide
COP	Coefficient of Performance
DHW	Domestic Hot Water
EER	Energy Efficiency Ratio
HVAC	Heating, Ventilation, and Air Conditioning
IAQ	Indoor Air Quality
IoT	Internet of Things
$\dot{m}_w$	Water mass flow rate (kg/s)
PM	Particulate Matter
Q	Heat transfer rate (W)
Q_{actual}	Actual volumetric flow rate (m^3/s)
Q_{rated}	Rated volumetric flow rate (m^3/s)
SEC	Specific Energy Consumption (Wh/m^3)
T	Temperature (°C)
T_{in}	Inlet temperature (°C)
T_{out}	Outlet temperature (°C)
ΔP	Pressure drop (Pa)
V	Air velocity (m/s)
$\dot{V}_w$	Volumetric flow rate (L/min)
VOC	Volatile Organic Compound
ρ_w	Water density (1000 kg/m^3)

exposure to pollutants such as particulate matter (PM) or volatile organic compounds (VOCs).

Professional air duct cleaning services have emerged, but benefits for energy efficiency and Indoor Air Quality (IAQ) remain largely unclear [4,5]. The contamination of HVAC components degrades the system's performance by increasing airflow resistance and fouling heat transfer surfaces. While some studies suggest that duct cleaning can help restoring HVAC's airflow, heat exchange efficiency and reducing indoor pollutant levels, other investigations show that benefits are often temporary [6].

The study leverages a unique experimental setup where both AHUs serve similar building zones and operate under comparable conditions, creating an ideal controlled environment to investigate cleaning and maintenance impacts. The systems are equipped with identical components, including supply and return fans, heating and cooling coils, filters, and control systems, ensuring direct comparability of performance metrics.

Although AHU-C underwent comprehensive cleaning and maintenance procedures following industry best practices, AHU-UC continued its normal operation without additional cleaning interventions (except inverter replacement, which was done for both), allowing a systematic analysis of the effects of cleaning and maintenance on energy performance (primary focus) and indoor air quality (IAQ).

The investigation is based on a data collection with a time resolution of 10 min over a complete annual cycle, capturing seasonal variations and diverse operational conditions. The granular monitoring approach encompasses key parameters, including energy consumption, airflow rates, pressure differentials, and thermal performance indicators. The methodology first establishes baseline performance characteristics through a detailed analysis of AHU-C post-maintenance, followed by a comparative analysis between the two systems to quantify the direct and indirect effects of cleaning on energy efficiency [7].

This research aims to advance the understanding of AHU cleaning impacts through several novel contributions. First, it provides empirical evidence of energy performance variations between maintained and non-maintained systems under similar operating conditions. Second, it establishes quantitative relationships between maintenance interventions and energy consumption patterns, addressing a significant gap in the current literature. We believe that the findings of this study have broader implications for building energy management practices, maintenance scheduling optimization, and life-cycle cost analysis of HVAC systems. By quantifying energy-saving potentials of proper maintenance procedures, this research can contribute to the development and refinement of industry standards, particularly for national and international organizations.

The use of high-resolution temporal data and systematic comparison methodology provide valuable insights that can help establish evidence-based cleaning standards and maintenance protocols [7]. Furthermore, the comprehensive dataset and performance analysis framework developed in this paper can serve as a foundation for creating digital twin models specifically focused on AHU cleaning and maintenance optimization [8]. Such digital twins could enable predictive maintenance strategies and real-time performance optimization, representing a significant step toward smart building operations [9]. The methodology and results presented here contribute to the ongoing efforts to reduce energy consumption in the building sector, which is in line with the Sustainable Development Goals (SDGs) [10]. Moreover, they provide stakeholders with concrete tools for implementing and validating maintenance practices.

The paper structure is shown in Fig. 1, outlining an overview of the paper in a logical flow chart: progressing from the context of AHU cleaning and associated research gap, to a methodology involving monitoring of identical AHUs. It highlights findings based on comparative analysis and implications involved and concludes with future directions. The paper is organized as follows: In Section 2 we provide an analysis of related works and the state of the art. The system model and the composition of the considered plant are described in Section 3. The evaluation approach is presented in Section 4. Section 5 analyses the impact of AHU pre- and post-cleaning, while a comparative analysis is carried out in Section 6. Finally, Section 7 concludes the paper.

2. Literature review

The relationship between Air Handling Unit (AHU) cleaning and maintenance with building performance is a critical area of international need in building energy management due to different operating conditions all over the world [11]. This review examines the current understanding of how maintenance practices affect energy consumption, system efficiency, and indoor environmental quality.

2.1. Evolution of understanding component cleanliness impact

Past research in AHU cleaning focused primarily on basic cleaning practices, but research has since evolved to encompass sophisticated analysis of component-specific impacts. A landmark study that was conducted in a 34-floor New York City building provided compelling evidence of the benefits of maintaining clean air-handler components [12]. The research, focused on two specific air handlers (SF-8 and SF-9), shows that proper maintenance not only improved energy efficiency but also enhanced critical building parameters such as dehumidification and comfort levels. The study's findings were particularly significant as they established a clear link between maintenance practices and multiple aspects of building performance [3]. However, the relationship between cleaning and energy efficiency is not as straightforward as initially believed. Subsequent research has revealed

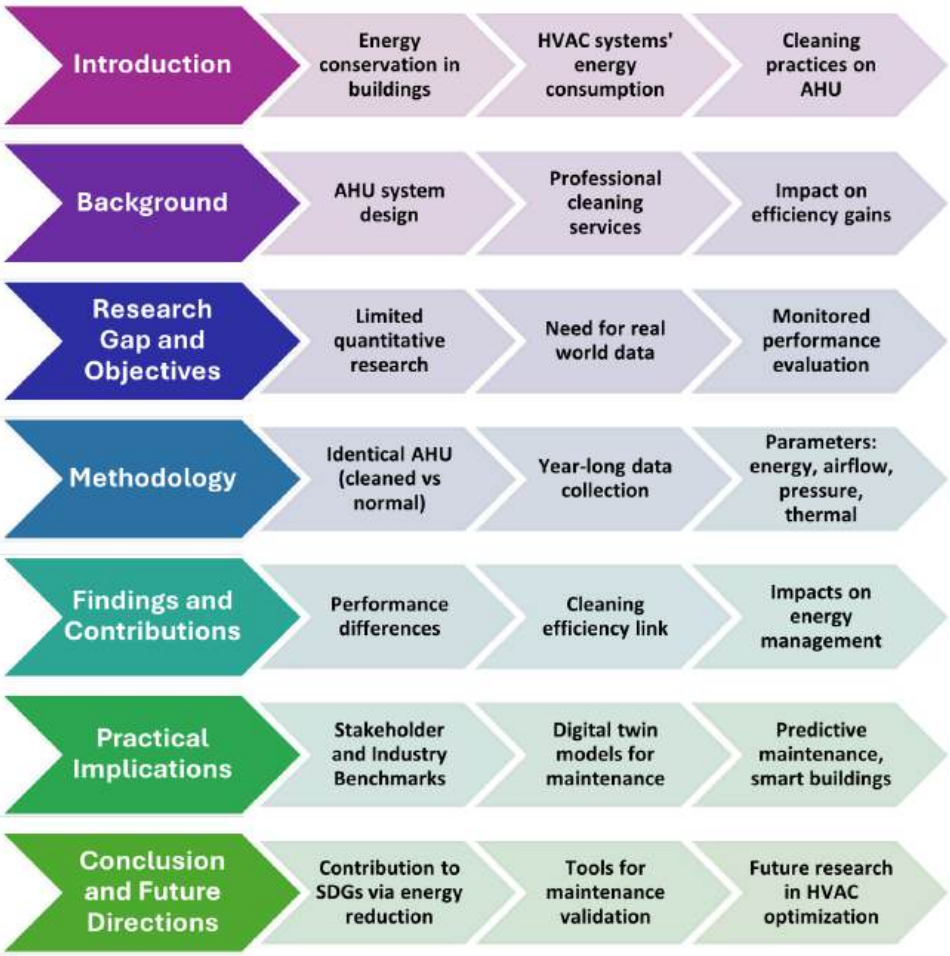

Fig. 1. The structure and a logical flow chart of the article.

important nuances in how building type affects maintenance outcomes. A parametric study examining constant air volume HVAC systems found that cleaning coils and filters yielded negligible energy savings in residential buildings and, surprisingly, negative savings in small commercial buildings [4]. This finding challenged the conventional wisdom that all cleaning interventions necessarily lead to energy improvements, suggesting that maintenance strategies need to be tailored to specific building contexts. The research examining the fundamental relationship between ventilation rate, air cleanliness, and energy consumption in unoccupied operating rooms demonstrated that a reduced ventilation rate of 6 ACH successfully maintained concentrations of particulate matter and airborne bacteria below required cleanliness standards while achieving a 70% reduction in annual energy costs compared to a 30 ACH rate. This work advances the understanding of how system operation parameters directly impact core performance outcomes; however, its findings are limited to unoccupied rooms and do not address the impact of component cleanliness (e.g., filter loading, coil fouling) on achieving these results at lower airflow rates [13]. In a comprehensive analysis [14] the energy and indoor air quality implications of high-efficiency filters in 15 commercial rooftop HVAC units were analyzed through the relationship between filter pressure drop, system performance, and particle removal effectiveness. In units without variable speed drives, higher filter pressure drop reduced airflow and fan power during fan only operation, creating potential savings, but increased total energy use during cooling (2-4%). Conversely, in units with fan speed control, the higher pressure drop consistently increased fan power (11-18%) to maintain airflow. Although the study provided valuable insights into filter efficiency trade-offs and included analysis of filter conditions, it did not examine how regular cleaning and maintenance of other HVAC components such as coils, ducts, and fans might interact with filter performance to influence overall system energy consumption and air quality outcomes [14].

2.2. *Experimental evidence and system performance*

A comprehensive study analysing packaged air-to-air HVAC systems shows the impact of dust through careful measurement of multiple performance parameters. The researchers collected data under four distinct conditions, systematically varying the cleanliness of heat exchanger coils and filters. Their findings show significant correlations between component cleanliness and system efficiency, as measured through air flow rates, cooling mode Efficiency Ratio (EER) and Coefficient of Performance (COP), power consumption, and thermodynamic parameters [5]. The complexity of maintenance optimization has been further explored by research conducted in Thailand's commercial buildings. This study made a significant contribution by quantifying the potential cost savings of optimized maintenance schedules.

The researchers found that increasing the cleaning frequency of filters and cooling coils from 28 to 54 times per year could reduce energy costs by 20%. This finding was particularly significant as it provided concrete guidance for maintenance scheduling while acknowledging the importance of considering local factors such as seasonal variations and staffing constraints [15]. A study [16] across four different climate zones shows that systematic HVAC cleaning can yield substantial energy savings while improving system performance. The research revealed that cleaned systems achieved fan energy reductions of 41

-60% while delivering 10-46% higher airflows compared to uncleaned counterparts. These findings were particularly notable in larger systems, where greater duct areas showed stronger correlations with improved airflow rates after cleaning interventions. The study also highlighted that smaller systems derived more significant benefits from coil cleaning due to enhanced heat exchange efficiency.

A case study [17] analysed potential benefits of installing Automatic Tube Cleaning System (ATCS), which uses circulating sponge balls to prevent biofilm and scale fouling in chiller condenser tubes, resulted in a 24.5% to 26.5% reduction in normalized chiller energy consumption. It directly links a specific mechanical cleaning technology to quantifiable, major improvements in system efficiency and energy savings, providing strong support for such interventions. A key finding was that the savings were contingent on consistent maintenance, as a lapse in servicing the ATCS led to a temporary reduction in its effectiveness. A model based study was done presenting a critical analysis that challenges the universal application of cleaning as an energy-saving measure, it concluded that Constant Air Volume (CAV) systems for the typical fouling levels (0-10% flow reduction) found in residential and small commercial buildings, cleaning coils and filters results in negligible or even slightly negative energy savings. The model shows that in small commercial buildings, cleaning often increases energy consumption because it raises the flow rate, which in turn increases the intake of outside air that must be conditioned and boosts fan power. The research provided important insights into the complex relationship between system cleaning and energy performance, particularly highlighting that duct sealing and insulation consistently outperform cleaning for energy savings, the study was limited to constant air volume systems and did not investigate the impact of cleaning frequency, cleaning methods, or the interaction between different component cleaning strategies on overall system performance and longevity [18].

2.3. Advanced technologies and system integration

In the literature, research has expanded beyond traditional maintenance approaches to examine the role of advanced air cleaning technologies. Studies have shown that gas-phase air cleaners can achieve ventilation energy reductions ranging from 1.9% to 18%, though these savings are highly dependent on system boundary conditions [19]. This research stream has opened new possibilities for integrating energy efficiency with indoor air quality improvements. The impact of sustained contamination on heat-recovery units has been quantified through both field measurements and laboratory testing. Research has documented that contaminant accumulation can lead to a 12% increase in pressure drop and an 8.1% decrease in thermal exchange efficiency [20]. These findings have significant implications for maintenance planning and energy management strategies. The field has advanced significantly with the development of sophisticated models for predicting particle loading rates on HVAC components. Current research considers multiple variables including outdoor particle distributions, indoor emission sources, HVAC airflows, and filtration efficiencies [21]. These models represent a significant step forward in maintenance planning, enabling more precise scheduling of interventions based on actual system conditions rather than fixed time intervals. Blondeau in 2020 conducted comprehensive testing of six commercially available in-duct air cleaning devices using different technologies. Their analysis revealed that only three of the six technologies were effective, with a combined mechanical and activated carbon filter system proving most comprehensive for multiple pollutants and an electrostatic precipitator being highly effective for particles while just two demonstrated acceptable energy effectiveness for low-energy buildings. The study focused solely on new equipment performance and did not investigate how system cleanliness or maintenance intervals affect the long-term efficiency and energy consumption of these advanced air cleaning technologies [22].

2.4. Research gaps

- Current research lacks comprehensive quantitative research about the direct relationship between AHU cleaning practices and energy performance under actual operational conditions.
- The literature shows a significant gap in comparative studies using identical AHU systems operating under similar conditions.
- The current body of literature on AHU cleaning and energy performance is notably finite. Among these, most are limited to short-term assessments, often ignoring seasonal variations and long-term operational trends.

The research gaps are addressed in this paper through a comparative analysis of two identical AHU systems, designated as AHU-C as shown in Fig. 2 and AHU-UC, installed at the locations with specific coordinates 45.201965, 9.138326 at University of Pavia, Italy, monitored approximately for whole year.

3. System model and components

The comprehensive evaluation for the impact of professional air duct cleaning on AHU performance and indoor air quality, a rigorous data collection from sensors was done which installed at different levels of AHU. The study was conducted in a controlled AHU facility situated at University of Pavia, Italy, outfitted with an extensive array of sensors and monitoring systems strategically installed across various AHU components. In Fig. 3 the system of AHU under study is presented. Both AHU systems operated continuously for approximately one year under identical conditions without maintenance interventions, allowing representative contamination accumulation. At the scheduled annual cleaning and maintenance interval, AHU-C received comprehensive professional cleaning, while AHU-UC was deliberately left uncleaned, this approach isolates the impact of the annual cleaning intervention by comparing two systems, differing only in maintenance treatment. The emergence of advanced IoT-based monitoring systems has enabled more precise quantification of maintenance impacts on system performance, providing new opportunities for detailed analysis of cleaning interventions [16].

The performance evaluation methodology is based on quantitative analysis of key operational parameters measured before and after cleaning interventions. These parameters were logged for almost whole year, data was obtained through continuous monitoring, cleaned from anomalies and outliers as discussed in Section 4.3 and comparative analysis was performed between cleaned (AHU-C) and uncleaned (AHU-UC) systems operating under identical conditions.

The methodology involved a two-phase approach, with measurements taken before and after the duct cleaning process. For the research on the impact of air duct cleaning on AHU performance and indoor air quality, a comprehensive instrumentation and monitoring system was employed to measure various parameters across different components of the AHU. Theoretical understanding suggests that maintaining clean AHU leads to improved energy efficiency and indoor air quality, comprehensive empirical evidence comparing maintained versus unmaintained systems under identical conditions remains limited. Building energy analysts often face difficult decisions regarding maintenance and cleaning resource allocation, particularly when operating multiple AHU systems within the same facility.

This paper presents a systematic comparison between two identical AHU systems operating simultaneously at the University of Pavia, Italy, providing a unique opportunity to quantify the impact of professional cleaning and maintenance interventions. The AHUs are designated as AHU-C and AHU-UC, and their composition is reported in Fig. 3. The two AHU systems feature an identical set of components, which compose the AHU and are organized in the same way within the AHU itself.



Fig. 2. Building block (a) served by 2 similar AHUs (b) at the University of Pavia.

3.1. Performance evaluation equations and metrics

The quantitative assessment of AHU performance is based on several key direct sensors data and performance indicators. The primary performance indicators include temperature variations, pressure drop variations, energy/power consumption, air flow velocity, indoor air quality but heat transfer and specific energy consumption was only measured using data of different sensors.

3.1.1. Heat transfer rate

The thermal energy transfer rate for water based heat exchangers calculated as:

$$Q = \dot{m}_w \cdot c_{p,w} \cdot |T_{in} - T_{out}| \tag{1}$$

where Q is the heat transfer rate (W), $\dot{m}_w$ is the water mass flow rate (kg/s), $c_{p,w}$ is the specific heat capacity of water (4184 J/kg·K), T_{in} and T_{out} are the inlet and outlet water temperatures (°C), respectively. For practical implementation with flow measurements in L/min:

$$Q = \dot{V}_w \cdot \frac{1}{1000} \cdot \frac{1}{60} \cdot \rho_w \cdot c_{p,w} \cdot |T_{in} - T_{out}| \tag{2}$$

where $\dot{V}_w$ is the volumetric flow rate (L/min) and ρ_w is the water density (1000 kg/m^3).

3.1.2. Specific energy consumption analysis

The fan cross-sectional area for each AHU was determined using the rated volumetric flow rate and measured air velocity:

$$A_{C,i} = \frac{Q_{rated,C}}{V_{C,i}} \quad \text{and} \quad A_{UC,i} = \frac{Q_{rated,UC}}{V_{UC,i}} \tag{3}$$

where $A_{C,i}$ and $A_{UC,i}$ are the instantaneous cross-sectional areas (m^2), i denotes the time instant, $Q_{rated,C} = 1.958$ m^3/s and $Q_{rated,UC} = 1.903$ m^3/s are the rated volumetric flow rates for AHU-C and AHU-UC respectively, and $V_{C,i}$ and $V_{UC,i}$ are the measured air velocities (m/s) at time instant i. To minimize measurement uncertainties, the median cross-sectional area was adopted as the representative area:

$$A_{median,C} = \text{median}(A_{C,i}) \quad \text{and} \quad A_{median,UC} = \text{median}(A_{UC,i}) \tag{4}$$

The instantaneous volumetric flow rate was calculated using the representative median area:

$$Q_{actual,C,i} = A_{median,C} \times V_{C,i} \quad \text{and} \quad Q_{actual,UC,i} = A_{median,UC} \times V_{UC,i} \tag{5}$$

The specific energy consumption (SEC), defined as the energy required per unit volume of air handled, was calculated as:

$$SEC_{C,i} = \frac{P_{C,i}}{Q_{actual,C,i} \times 3600} \quad \text{and} \quad SEC_{UC,i} = \frac{P_{UC,i}}{Q_{actual,UC,i} \times 3600} \tag{6}$$

where $SEC_{C,i}$ and $SEC_{UC,i}$ are the specific energy consumptions (Wh/m^3), $P_{C,i}$ and $P_{UC,i}$ are the instantaneous fan power consumptions (W), and the factor 3600 converts the flow rate from m^3/s to m^3/h. The generalized form of specific energy consumption can be expressed as:

$$SEC_i = \frac{P_i}{A_{median} \times V_i \times 3600} \tag{7}$$

where SEC_i is the specific energy consumption (Wh/m^3), P_i is the fan power consumption (W), A_{median} is the representative cross-sectional area (m^2), V_i is the air velocity (m/s), and the subscript i denotes the time instant. This metric enables quantitative comparison of fan energy efficiency between cleaned and uncleaned AHU systems under varying operational conditions.

3.1.3. Pressure drop analysis

The pressure drop across components indicates system resistance and energy losses:

$$\Delta P = P_{upstream} - P_{downstream} \tag{8}$$

Changes in pressure drop (ΔP) before and after cleaning are used to quantify airflow resistance improvements. The remainder of this section describes the various components of the AHUs, including the sensor devices [23] that were installed in the AHU system to monitor its functioning.

To ensure data reliability and enable accurate detection of cleaning-induced improvements, high-precision instrumentation was employed throughout the monitoring system. The complete specifications of all measurement equipment are presented in Table 1.

3.2. Supply and return fans

The fan is an important component responsible for circulating air through the AHU and the duct system as shown in Fig. 3 at locations number 7 and 11. Monitoring the fan's performance is important to analyze the impact of air duct cleaning on airflow, pressure, and energy efficiency. To achieve this, the following sensors were installed at fan unit.

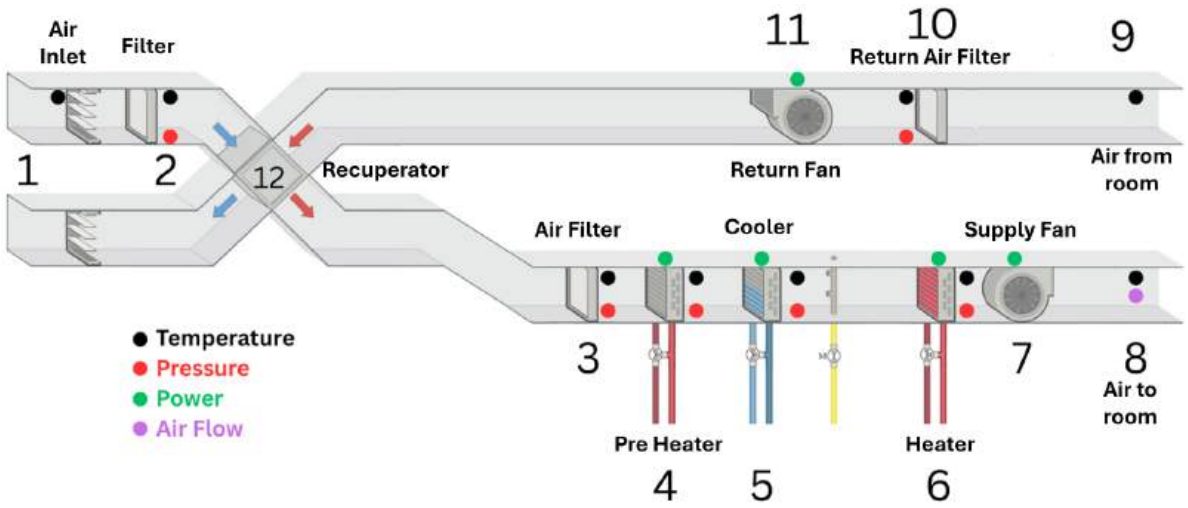

Fig. 3. Components and process flow of the AHU systems considered in this study with sensors location.

Table 1
Accuracy and specifications of measurement equipment used in the AHU monitoring system.

Component	Parameter	Sensor Type	Accuracy	Range/Additional Info
Fan Unit	Power Consumption	Three-phase Power Meter	±0.5%	0.02–200 A; Resolution: 0.1 kW
	Airflow Rate	Airflow Sensor	±2%	Uncertainty: ±2% of reading
Heat Exchanger (Air-side)	Temperature	PT1000	±0.1°C at 0°C	4–95°C; Uncertainty: ±0.15°C
	Differential Pressure	Diff. Pressure Sensor	±1% FS	±500 Pa; Uncertainty: ±5 Pa
Heat Exchanger (Water/Refrigerant)	Temperature	PT1000	±0.1°C at 0°C	4–95°C; Uncertainty: ±0.15°C
	Flow Rate	Ultrasonic Flow Meter	±1%	Modbus; Pressure loss <25 kPa
	Pressure	Pressure Sensor	±0.25% FS	Up to 16 MPa
	Thermal Energy	Heat/Cool Meter	Class 2	0.1–9,999,999.9 kWh; 24-month storage
Dampers & Filters	Differential Pressure	Diff. Pressure Sensor	±1% FS	±500 Pa; REMOTAIR wireless
	Temperature	PT1000	±0.1°C at 0°C	4–95°C; Uncertainty: ±0.15°C
Indoor Air Quality	CO_2 Concentration	Digital Air	±50 ppm	400–1500 ppm
	VOC Level	Quality Multi	±50 ppm	0–2000 ppb
	Temperature	Sensor	±0.5°C	−20°C to 60°C
	Relative Humidity	REMOTAIR®	±3% RH	0–100%; 24 V DC power

Power consumption sensors. This sensor measured the electrical power consumed by the fan motor at the supply and return sides, providing information about the energy efficiency of the fan operation. The three-phase power meters used for fan monitoring have an accuracy of ±0.5% of reading and are capable of measuring power consumption with a resolution of 0.1 kW. The measurement range covers 0.02-200 A current and operates at 200Amps maximum capacity, specified for the inductive energy meter model.

Airflow sensors. Airflow sensor, was installed after the fan to measure the airflow rate. This measurement allows for the quantification of changes in airflow capacity and distribution after duct cleaning, which impacts indoor air quality and system performance. Airflow measurements were conducted with an uncertainty of ±2% of reading across the operational range, allowing precise quantification of volumetric flow rate changes before and after cleaning interventions.

3.3. Cooling and heat exchanger coils

Pre/Post-heating heat exchangers are responsible for heating the supply air to maintain desired temperature level, for transferring thermal energy between the air stream and a secondary fluid (water) as shown in Fig. 3 at location number 4, 5 and 6. Cooling and Dehumidification Coil is responsible for cooling and dehumidifying the supply air to maintain desired temperature and humidity levels. Monitoring the performance of the heat exchanger coil is important to evaluate the impact of duct cleaning on heat transfer efficiency and indoor air quality.

Temperature sensors (Air). Air temperature measurements allow for the calculation of temperature differential across the cooling or heating coils. Changes in temperature differential show variations in heat transfer efficiency due to factors such as airflow resistance or absolute thermal resistance. Improved heat transfer efficiency after duct cleaning results in larger temperature differentials, indicating better cooling or heating performance. Platinum resistance temperature sensors (PT1000) with an accuracy of ±0.1°C at 0°C were used for air temperature measurements. These sensors operate within the temperature range of 4°C to 95°C with a measurement uncertainty of ±0.15°C across the operational range.

Differential pressure sensors (Air). A differential pressure sensor measures the pressure drop across the cooling or heating coils. A high pressure drop shows resistance to airflow, potentially caused by dust accumulation. A decrease in pressure drop after duct cleaning indicates a reduced airflow resistance, leading to improved airflow distribution and energy efficiency. Differential pressure sensors with a measurement range of ±500 Pa and an accuracy of ±1% of full scale were installed across heat exchanger coils. The measurement uncertainty for pressure drop calculations is ±5 Pa, providing sufficient resolution to detect cleaning-induced performance changes.

Temperature sensors (water/refrigerant). The temperature of the secondary fluid (water or refrigerant) at the inlet and outlet of the cooling or heating coils is important to measure. These measurements, combined with flow rate and pressure data, allow for the calculation of heat transfer rates and energy balances. Changes in fluid temperature differential show variations in heat transfer efficiency improved airflow after duct cleaning. Water temperature measurements utilize the same PT1000 sensors with identical accuracy specifications, ensuring consistent temperature differential calculations for heat transfer rate determinations.

Flow meters (water/refrigerant). Changes in flow rate impact heat transfer rates and overall cooling or heating capacity. Improved flow distribution after duct cleaning enhances the overall efficiency of these components. Ultrasonic flow meters with Modbus communication protocol were employed for water flow measurements. These instruments provide flow rate measurements with an accuracy of ±1% of reading and operate with a maximum pressure loss of less than 25 kPa, ensuring minimal system interference.

Pressure sensors (water/refrigerant). The pressure of the secondary fluid provides information about the performance of the hydraulic system and potential flow restrictions. Changes in pressure drop across the cooling or heating coils show variations in flow resistance. A decrease in pressure drop after duct cleaning shows improved flow distribution and reduced energy consumption for fluid circulation. Water-side pressure measurements are conducted using sensors with a maximum operating pressure of 16 MPa and measurement accuracy of ±0.25% of full scale, providing reliable data for hydraulic system performance analysis.

Energy analyzer (water/refrigerant). Monitoring the heat energy consumption of the secondary fluid is important for analyzing energy efficiency and heat transfer. A reduction in power consumption after duct cleaning shows improved system performance and reduced energy costs. By analyzing these various parameters before and after the duct cleaning process, it becomes possible to quantify the improvements in cooling and heating performance, energy efficiency, and overall system operation. The collected data are used to optimize the system, to identify potential issues, and to develop strategies for maintaining optimal performance over time. Heat/cool meters with ultrasonic measurement technology provide energy consumption data with Class 2 metrological accuracy. These instruments measure thermal energy accumulation from 0.1 kWh to 9,999,999.9 kWh with data storage capabilities for up to 24 months, enabling comprehensive energy analysis over extended periods.

3.4. Dampers and filters

Dampers and filters are important components of the AHU system as shown in Fig. 3 at location number 2, 3 and 10, playing a important role in maintaining indoor air quality (IAQ) and controlling airflow distribution. The sensors installed to analyze these components are listed below.

Differential pressure sensors. Differential pressure sensors were installed across the filters to measure the pressure drop. Filters accumulate particulate matter over time, the pressure drop increases, indicating higher resistance to airflow. A decrease in pressure drop after duct cleaning signify reduced airflow resistance, potentially leading to improved energy efficiency and better airflow distribution. Filter monitoring utilizes differential pressure sensors with a measurement range of ±500 Pa and accuracy of ±1% of full scale. The proprietary REMOTAIR motherboard with Computer-On-Module and SD memory card enables continuous data logging and wireless communication via IEEE 802.11 b/g/n network with WPA2/PSK encryption for secure data transmission to AWS cloud servers.

Temperature sensors. Temperature sensors on the filters provides valuable information into their performance and the impact of duct cleaning. Filters accumulate particulate matter and debris over time, the resistance to airflow increases, leading to a temperature rise across the filter. By monitoring the temperature differential between the upstream and downstream sides of the filter, it is possible to detect when the filter becomes excessively loaded or clogged. Clogged filters impede heat transfer between the air stream and the heating or cooling coils, reducing the overall system efficiency. Temperature sensors at the filters help identify any changes in heat transfer patterns before and after duct cleaning, indicating potential improvements in energy efficiency. Monitoring temperature patterns across the filters can reveal deviations from expected behavior, which may indicate air leaks or filter bypass. Filter temperature monitoring employs the same PT1000 temperature sensors used throughout the system, maintaining measurement consistency and enabling accurate temperature differential analysis across filter assemblies.

3.5. Additional sensors

The installation of additional sensors to measure carbon dioxide (CO_2) levels and VOC levels at the outlet of AHU/inlet of room duct and Inlet of AHU/Outlet of Room Ducts within the facility provides valuable information. Carbon dioxide levels are often used as an indicator of occupancy and ventilation effectiveness. Reductions in CO_2 levels after duct cleaning show improved ventilation effectiveness and air exchange rates, contributing to better indoor air quality. Volatile Organic Compound (VOC) are a class of gaseous pollutants that originate from various sources, including building materials, cleaning products, and outdoor air. Monitoring VOC levels at the air stream inlet and outlet locations provides information into the system's ability to remove these pollutants effectively using a cleaned filter. Indoor air quality sensors measure CO_2 concentrations with an accuracy of ±50 ppm and VOC levels with a resolution suitable for detecting cleaning-induced air quality improvements. These measurements provide quantitative assessment of ventilation effectiveness and pollutant removal efficiency before and after duct cleaning interventions.

3.6. Operating parameters

The two AHUs have very similar operating parameters. Their similarity was the main reason to select such systems for the present investigation, in order to be able to compare their behavior under two different cleaning conditions. The operating parameters of the AHUs are reported in Table 2. As can be seen in the table, almost all the relevant parameters are the same in the two systems. There is a slight difference in the amount of air handled by the systems, since the buildings served by the systems are slightly different. The voltage and current values in Table 2 are given for both delta and star (Y) motor connections, where the first value represents the delta configuration and the second represents the Y configuration.

4. Evaluation methodology

All sensor data were acquired at 10-min intervals and stored locally. Data validation procedures included range checking, rate-of-change limits, and statistical outlier detection. Measurements falling outside acceptable ranges or exhibiting unrealistic variations were flagged and excluded from analysis to maintain data integrity. The wireless monitoring system operated with encrypted connectivity, ensuring reliable data transmission and security throughout the measurement duration. The system's operation begins as shown in Fig. 3 at the air inlet at location 1, where fresh outside air enters and passes through an initial filter, then moves through a recuperator/cross-flow heat exchanger, marked in the figure by the X-shaped intersection with blue and red arrows, where incoming and outgoing air streams exchange thermal energy for improved

Table 2
Detailed AHU-UC and AHU-C specifications.

Specification	Unit	AHU-UC	AHU-C
Airflow			
Supply Air	m^3/h	10,500	9,300
Return Air	m^3/h	6,850	7,050
Supply Fan			
Power	kW	7.5	7.5
Speed	rpm	2,900	2,900
Voltage	V	400/690	400/690
Current	A	14.4/8.4	14.14/8.14
Power Factor	–	0.88	0.89
Return Fan			
Power	kW	4	4
Speed	rpm	1,440	1,440
Voltage	V	400/690	400/690
Current	A	4.4/2.6	8.4/4.8
Power Factor	–	0.81	0.82

efficiency. The air then undergoes a series of treatments through key components: a secondary filter for additional air cleaning, a preheater for initial temperature adjustment, a cooler for temperature and humidity control, and a heater for final temperature regulation. Two essential fans drive the system: the Supply Fan as shown in Fig. 3 at locations number 7, which pushes the treated air into the building's distribution network, and the Return Fan as shown in Fig. 3 at locations number 11, which pulls used air back through a Return Air Filter at position 10 for either recirculation or exhaust through the Air Outlet, creating a continuous cycle of air treatment and distribution that maintains optimal indoor air quality.

One system (AHU-C) went through comprehensive cleaning and maintenance procedures while the other (AHU-UC) continued normal operation without additional cleaning and maintenance interventions. This experimental design allows for direct comparison while controlling for environmental variables and operational conditions. Both systems were extensively monitored through an array of sensors that measure important parameters such as temperature, pressure differentials, air velocity, VOC concentrations, and energy consumption at 10-min intervals throughout both the winter and summer seasons.

In the first phase, baseline data was collected with the AHUs operating under normal conditions, representing the pre-cleaning state. After the initial data collection, professional duct cleaning services were employed to thoroughly clean all AHU components following industry best practices and guidelines. Particular attention was paid to ensure a comprehensive cleaning process, targeting areas prone to accumulation of debris, contaminants, etc. Following the duct cleaning procedure, the second phase of data collection started, with the AHU operating under the same conditions (irrespective of environmental changes) as the pre-cleaning phase. These post-cleaning data allowed for a direct comparison with the baseline measurements, allowing the quantification of any changes or improvements resulting from the duct cleaning process.

4.1. Pre-cleaning baseline monitoring

Comprehensive baseline data was collected to establish pre-cleaning conditions while the AHU operated under normal circumstances. This baseline dataset served as a reference for assessing the initial state of the system and the IAQ levels prior to any cleaning intervention.

4.2. Post-cleaning monitoring

Immediately following the cleaning procedures, the monitoring campaign resumed under identical operational conditions to the pre-cleaning phase. This facilitated a direct comparison between pre- and post-cleaning datasets, isolating the impact of the cleaning intervention while minimizing potential confounding variables.

4.3. Data cleaning and formatting

The data collected came from multiple sensors and monitoring instruments from different manufacturers and monitoring service providers. This step involves combining and standardizing the data in a consistent format suitable for analysis. The University building's occupancy patterns and operational schedules differ between weekdays and weekends, so it is often beneficial to separate the data accordingly. Sensor measurements occasionally produce unrealistic or outlier values due to various factors, such as sensor malfunctions, environmental interference, or data acquisition errors. In some cases, sensors record zero values due to technical issues or data acquisition errors. These zero values introduce biases or distortions in the analysis.

To evaluate the impact of AHU cleaning, where data from various sensors are collected at 10-min intervals, the following data analysis steps were implemented and as shown in Fig. 4:

- Merging data from different sources into a single dataset with aligned time stamps.
- Removing any duplicates or erroneous data points identified through quality control checks.
- Identifying and separating the data into weekday and weekend subsets.
- Focusing the primary analysis on the weekday data, which represents typical building operations and occupancy levels.
- Weekend data analyzed separately to investigate potential deviations from normal conditions.
- Aligning the data to ensure consistent analysis periods across different days or weeks.
- Implementing range checks or statistical methods to identify unrealistic values.
- Identifying instances where sensors recorded zero values.
- Excluding these zero values from the analysis, as they not represent actual measurements.
- Alternatively, applying imputation techniques to replace zero values with appropriate estimates, if necessary.

By implementing these data processing steps, the analysis accounts for potential sources of error, inconsistencies, and biases within the collected data. This ensures a more reliable analysis of the impact of AHU cleaning on various performance parameters and indoor air quality measures. The cleaned and filtered data was then subjected to various statistical analyses and data visualization techniques. These analyzes help quantify changes in performance metrics, energy consumption, indoor air quality parameters, and other relevant variables before and after the AHU cleaning process, allowing for a comprehensive evaluation of the effectiveness of the cleaning intervention.

5. Pre- and post-cleaning impact on AHU-C

5.1. Cleaning and maintenance procedures

The comprehensive cleaning and maintenance interventions were conducted by a company based in Pavia, Italy, following industry best practices and manufacturer guidelines. The filters replacement was done for both AHU before cleaning procedures were implemented for AHU-C, while AHU-UC served as the control reference. The professional cleaning interventions followed an approach targeting all major AHU components. The specific procedures implemented are described below:

- Recuperator Cleaning (June 16th, 2023)
- Ductwork Cleaning (June 26-30th, 2023)
- Heat Exchanger Coil Cleaning (July 07 & 14, 2023)
- Fan and Internal Component Cleaning (July 21st, 2023)

The comprehensive analysis of AHU-C's performance before and after cleaning and maintenance interventions provides crucial insights into



Fig. 4. Cleaning and formatting data from real time sensors.

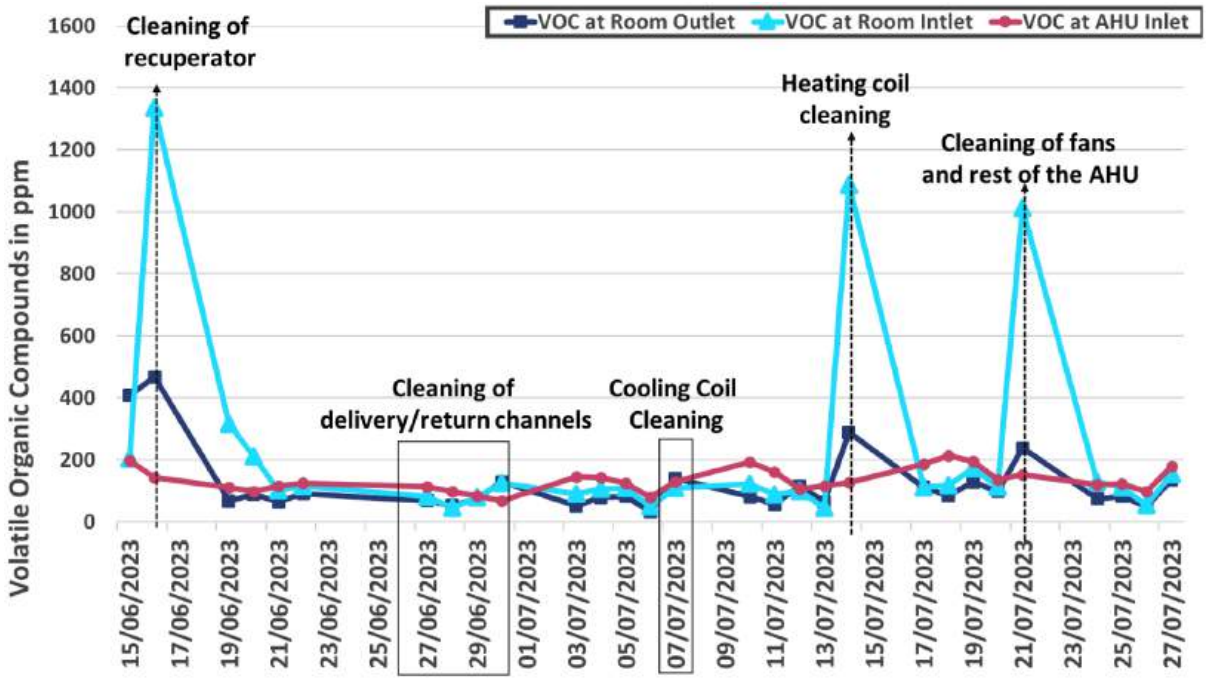

Fig. 5. Timeline of the cleaning activities and the trend of VOC in ppm over the time.

the direct impacts of cleaning procedures on system efficiency. This section presents a detailed analysis of the collected data, in order to assess such impact on system efficiency. By establishing clear pre- and post-cleaning behavioral patterns, this investigation aims to quantify the immediate and sustained effects of cleaning procedures on AHU operations. The cleaning activities were carried out over different periods of time to analyze the impact of the cleaning and the relationship between the cleaning activities carried out on various components of AHU-C and the observed trends in VOC concentrations at different points within the system. The cleaning activities targeted specific parts of the AHU, including the recuperator described in Section 5.3, fans inverter in Section 5.4, ducts in Section 5.5, coils in Section 5.6, fans and filters in Section 5.7.

5.2. Impact of cleaning on VOC in air

The analysis of VOC data has a distinct pattern, as shown in Fig. 5. The outdoor air entering the AHU consistently exhibits the highest levels of VOCs, reflecting the ambient air quality conditions. As the air stream passes through the AHU, a notable reduction in VOC concentrations is observed. This decrease is attributed to air filtration and treatment processes within the AHU, which are designed to remove a significant portion of airborne pollutants, including VOCs. The effective removal of VOCs by the AHU highlights its crucial role in improving indoor air quality by mitigating the impact of outdoor air pollution. Remarkably, the lowest levels of VOC are consistently detected in the air returning from occupied spaces. This finding suggests that indoor sources of VOCs, such as building materials, furnishings, cleaning products, and occupant activities, contribute relatively less to the overall VOC load compared to outdoor air. Despite indoor sources may still be present, their impact appears to be overshadowed by the higher levels of VOCs in the outdoor air supply.

The observed trend is attributed to several factors. First, the AHU's air filtration and treatment processes effectively remove a portion of the VOCs present in the outdoor air supply before it enters the occupied spaces. Additionally, the dilution effect provided by the continuous supply of fresh outdoor air helps to minimize the accumulation of indoor-generated VOCs within the occupied spaces. Furthermore, the lower VOC levels in the return air may also be influenced by adsorption and deposition processes occurring within the indoor environment. Certain building materials and surfaces act as sinks for VOCs, effectively removing them from the air through adsorption or deposition mechanisms. It is important to note that while the trend suggests a lower contribution of indoor sources to the overall VOC load, the potential impact of specific indoor sources should not be overlooked, as some VOCs may pose health concerns even at low concentrations or through prolonged exposure.

This observed pattern underscores the importance of proper ventilation and air filtration systems in maintaining acceptable indoor air quality, particularly in environments where outdoor air pollution is a significant concern. By effectively removing a substantial portion of outdoor-originated VOCs and diluting indoor-generated pollutants, the AHU plays an important role in creating a healthier indoor environment for occupants.

The data reveal noticeable spikes in VOC concentrations in the supply air immediately following cleaning activities performed on various components of the unit. These transient peaks, occurring in the air supplied to the occupied spaces, need further analysis. One potential cause

is the disturbance and re-suspension of accumulated particulates and contaminants during the cleaning process. Over time, various surfaces within the AHU, such as the recuperator, ducts, coils, and fans, accumulate dust, debris, and other pollutants, including VOCs adsorbed onto these surfaces. During cleaning activities, the physical agitation and removal of these accumulated materials may release adsorbed VOCs back into the airstream, leading to a temporary elevation in their concentrations. Additionally, certain cleaning agents or procedures themselves may introduce VOCs into the AHU system. For instance, the use of chemical cleaners or solvents during the cleaning process could contribute to the observed VOC peaks if the residual vapors or off-gassed compounds are not adequately removed or neutralized before restarting the system. It is also possible that the cleaning activities dislodge and aerosolize previously settled particulates and contaminants, which subsequently desorb VOCs into the airstream, contributing to the observed peaks. The magnitude and duration of these VOC peaks are important factors to consider. Transient spikes that quickly dissipate may pose a lower risk compared to prolonged or sustained elevated levels of VOCs. However, even short-term exposures to certain VOCs potentially have adverse health effects, particularly for sensitive individuals or those with pre-existing conditions.

5.3. Cleaning of the recuperator

The impact of the recuperator cleaning was analyzed by monitoring the temperature difference across the heat exchanger before and after the maintenance event. Notably, the observed change in temperature difference varied across air streams originating from different rooms within the building. On June 16, 2023, a significant maintenance event took place, involving the cleaning of the recuperator within the AHU. This maintenance activity aimed to address the potential accumulation of contaminants on the heat transfer surfaces, which impairs the recuperator efficiency over time.

This variation suggests that factors specific to each room, such as the initial air temperature, contaminant levels, or air flow characteristics, may have influenced the extent of the cleaning impact. One of the key observations following the recuperator cleaning was an increase in the temperature difference across the cross-flow heat exchanger, as shown in Fig. 6. The temperature difference was taken between the temperature at locations 3 and 2 for the recuperator as shown in Fig. 3. The cleaning improves heat transfer efficiency achieved by removing accumulated dirt, debris, or other contaminants from the heat transfer surfaces during the cleaning process. The accumulation of contaminants on the recuperator surfaces creates a coating of dust, increasing the absolute thermal resistance and inhibiting effective heat exchange between the incoming and outgoing air streams. By removing these deposits through the cleaning process, the thermal resistance was reduced, allowing for more efficient heat transfer and a larger temperature difference across the heat exchanger. In addition to the observed changes in temperature difference, the analysis also revealed a decrease in air velocity within the AHU system. This reduction in air velocity was attributed to the replacement of the fans' inverters, which occurred concurrently with the recuperator cleaning event. The inverter replacement likely impacted the power delivery to the fans, resulting in a decrease in their rotational speed and, consequently, a lower air flow rate through the AHU. However, it is noteworthy that the magnitude of the temperature difference increase varied among air streams originating from different rooms. Additionally, the variation in the cleaning impact among different air streams emphasizes the need for a comprehensive understanding of the factors influencing contaminant accumulation and heat transfer dynamics within the AHU system.

5.4. Installation of efficient inverters

The modification involving the replacement of inverters associated to the fans in the AHU systems on June 19, 2023, had significant implications for the overall performance and energy efficiency of the unit. Inverters play an important role in controlling the speed and power output of electric motors, including those driving AHU fans. By regulating the frequency and voltage supplied to the motor, inverters modulate the rotational speed of the fan blades, enabling precise adjustment of airflow rates and energy consumption based on system demand and operating conditions [24].

The replacement of the inverters introduced new operational characteristics and specifications, which resulted in a reduction in power consumption and fan speed as shown in Fig. 7. It is calculated by taking the average power consumption of the fan before and after the change, the plotted values show daily average percentage. The average values were taken from the working hours in which usually AHU is operating from 6 am to 7 pm. Fig. 8 illustrates the average fan energy consumption before and after the inverter change, highlighting significant energy savings across all fans. The data reveal percentage reductions ranging from 16.2% to 71.4%, with the most substantial decrease observed in the Return Fan AHU-UC, which showed a 71.4% reduction in the energy usage. This reduction is attributed to the enhanced energy efficiency and improved control mechanisms of the new inverters.

The decision to replace the inverters was driven by several factors, each with its own set of implications and potential benefits.

- Improved Energy Efficiency: Newer inverter technologies offer superior energy efficiency, enabling better control and optimization of motor performance. The reduction in fan power consumption aligns with energy conservation goals and contributes to lower operational costs as shown in Fig. 8.
- System Modernization: The cleaning and maintenance requires equipment upgrade or modernization initiative within the AHU system. Advanced inverter models provide enhanced features, improved reliability, and better compatibility with other system components [25].
- Performance Optimization: The new inverters were likely selected to address specific performance issues or compatibility challenges with the existing AHU configuration, ensuring optimal operation and resolving any inefficiencies associated with the previous inverters.

The reduction in fan power and the consequent decrease in airflow rate have important implications for the AHU's operation and performance. Careful monitoring and analysis of the AHU's performance post-modification are necessary to ensure that the desired outcomes, such as energy savings and improved control are achieved without compromising occupant comfort or indoor air quality.

5.5. Cleaning of delivery and return channels

Cleaning the delivery channels (ducts) have a significant impact on the overall performance of the AHU system. The duct conditions before and after cleaning are shown in Fig. 9. Pre-cleaning inspection revealed significant dust and debris accumulation on interior surfaces (top), while post-cleaning inspection confirmed thorough removal of contaminants (bottom). This cleaning directly contributed to the measured improvements in airflow velocity and system pressure losses.

Dust and other contaminants accumulate in the ducts, leading to reduced airflow, increased pressure drop [26], and potential heat transfer inefficiencies. After cleaning delivery channels as shown in green color of Fig. 10:

$$T_{oa} = 0.9(T_{ia}) - 1.9 \quad (9)$$

$$R_a^2 = 0.88 \quad (10)$$

Before cleaning delivery channels as shown in red color of Fig. 10:

$$T_{ob} = 1.2(T_{ib}) - 10.64 \quad (11)$$

$$R_b^2 = 0.71 \quad (12)$$



Fig. 6. Impact of cleaning of the recuperator on temperature difference and velocity(where background of pink and green color shows the time period before and after the cleaning respectively).

Based on the visuals shown in Fig. 10, the equations represent the relationship between the air temperature at location 9 as T_i and 8 as T_o as shown in Fig. 3. This relationship is analyzed before and after cleaning the delivery channels (ducts) between the AHU and the room. The slope (m) of the equation represents how much the return air temperature (T_o) changes relative to the supply air temperature (T_i). A slope closer to 1 indicates a more efficient system where return air temperature is better maintained.

- Before cleaning, m = 1.2, suggesting that the return air temperature was more affected by heat losses or gains.
- After cleaning, m = 0.9, indicating improved efficiency in maintaining air temperature.

The y-intercept (c) represents the theoretical return air temperature when the supply air temperature is 0. A more negative intercept may indicate higher heat gains or losses.

- Before cleaning, c = -10.64, suggesting significant temperature deviations.
- After cleaning, c = -1.9, indicating better thermal stability.

For clarity, these values are summarized in Table 3, it presents a clearer comparison, reinforcing how cleaning the delivery channels led to a more stable and efficient system.

The y-intercept represents the theoretical return air temperature when the supply air temperature is 0. A more negative y-intercept could show higher heat gains or losses in the system. The y-intercept became less negative after cleaning (-1.9 compared to -10.64 before cleaning), which also suggests improved efficiency in maintaining the air temperature after cleaning the delivery channels.

The R^2 value shows the goodness of fit of the linear model. A higher value (closer to 1) suggests a better fit of the linear model to the data.

Table 3
Comparison of slope and Y-intercept before and after cleaning.

Parameter	Before Cleaning	After Cleaning
Slope (m)	1.2	0.9
Y-Intercept (c)	–10.64	–1.9
R^2 **Value**	0.71	0.88

The R^2 value increased from 0.71 before cleaning to 0.88 after cleaning, indicating that the linear model better represents the relationship between supply and return air temperatures after cleaning the delivery channels.

Based on these observations, the performance of the AHU system appears to have improved after cleaning the delivery channels between the AHU and the room. The slope became closer to 1, indicating more efficient temperature transfer, the y-intercept became less negative, suggesting reduced heat gains or losses, and the R^2 value increased, indicating a better fit of the linear model. Dust and debris on the duct surfaces act as insulation, reducing the heat transfer between the supply air and the duct walls. Cleaning the ducts improves heat transfer efficiency, leading to better temperature control and energy savings. With improved heat transfer efficiency and airflow, reduced pressure drop, and enhanced heat transfer, the overall efficiency of the AHU system is improved, leading to energy savings and potentially extending the lifespan of the equipment.

5.6. *Cleaning of cooling coils*

The cleaning of the cooling coils within the air handling unit on July 7, 2023 had a significant impact on the heat exchange process and

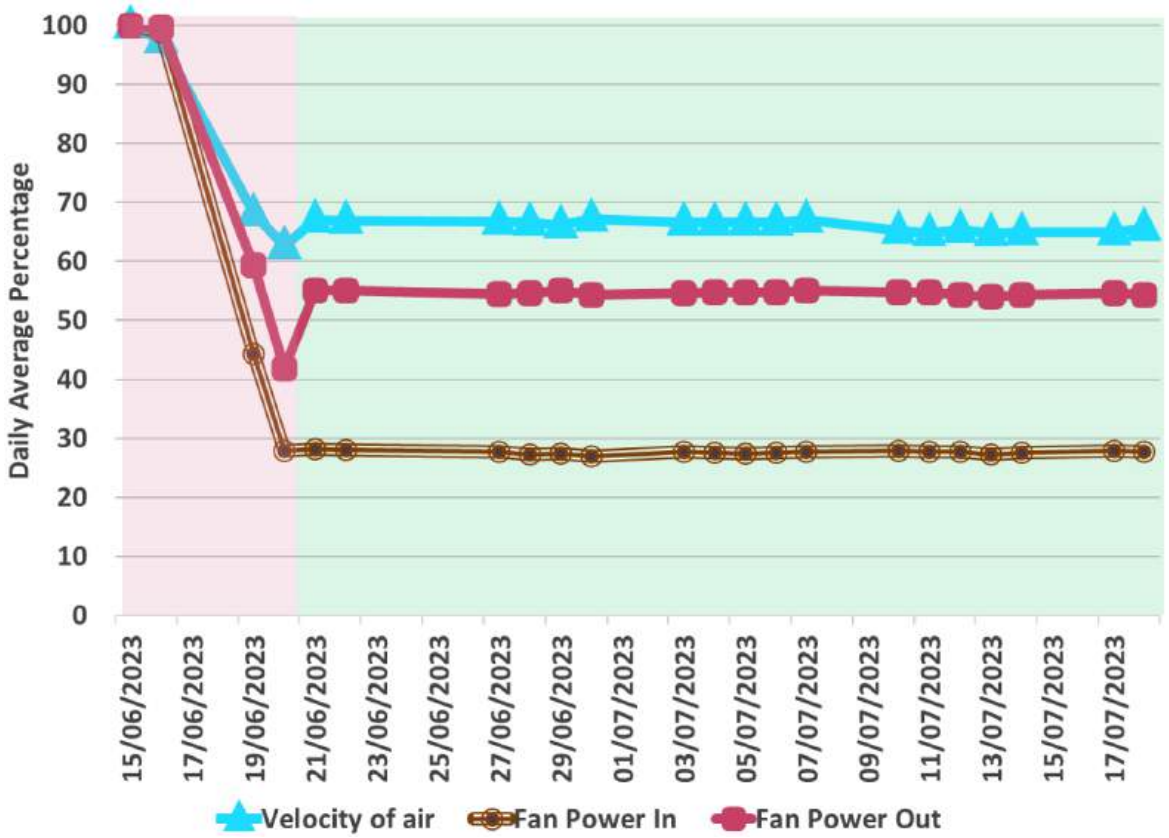

Fig. 7. Impact of inverters replacement for inlet and outlet fans of AHU-C, presenting averaged percentage of fan power consumption along with air flow (where background of pink and green color shows the time period before and after the installation of new inverter respectively).

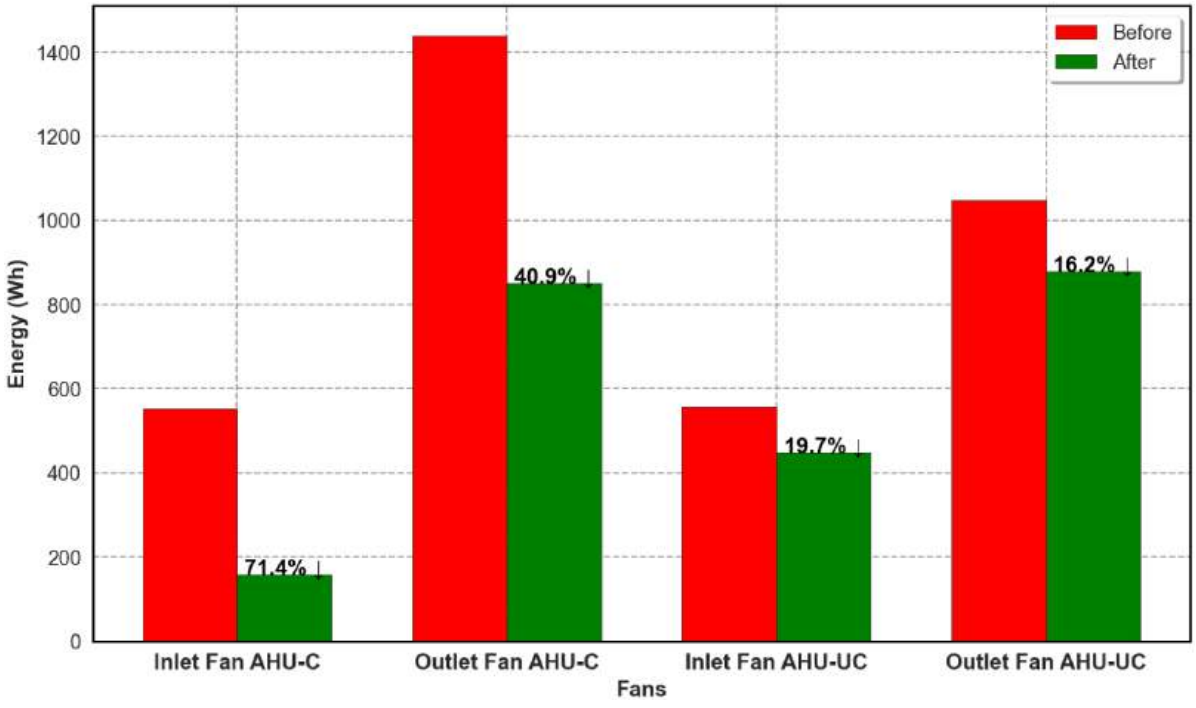

Fig. 8. Average fan energy consumption before and after inverter change in both AHU's inlet and outlet fans.



Fig. 9. Condition of the duct before and after the cleaning intervention.

overall system performance. Fig 11 illustrates the condition of the cooling coil before and after the cleaning intervention. The pre-cleaning state (left side) shows significant accumulation of dust, debris, and biological contaminants across the fin surfaces. The post-cleaning condition (right side) demonstrates complete restoration of the coil surface, with clear fin spacing and unobstructed air passages.

The maintenance event involved a thorough cleaning of the cooling coils, removing any accumulated dust, debris or fouling that could impede heat transfer.

After the cleaning, a notable increase was observed in the temperature difference between the water outlet and water inlet of the cooling coil as well as the cooler power as shown in Fig. 12. This temperature differential is a key indicator of the coil's heat transfer effectiveness. A higher temperature difference suggests that the cleaned coils were able to extract more heat from the air, resulting in enhanced cooling capacity. The removal of fouling layers improved the conductive heat transfer between the water and coil surface. With the coils operating at higher effectiveness, more heat was extracted from the air stream, necessitating an increased cooling load and consequently higher power consumption to meet the increased cooling demand. Cleaning the coils not only improved the heat transfer capacity of the water acting as the refrigerant inside the coils but also enhanced the heat transfer capacity of the air flowing across the cooling coils. The removal of fouling layers eliminated insulating barriers, allowing for more efficient convective heat transfer between the coil surface and the air stream as shown in Fig. 13. This enhanced air-side heat transfer is evidenced by the increasing trend in the air heat transfer rate observed after the cleaning process.

The figure presents a compelling visualization of the improved air-side heat transfer performance achieved after the thorough cleaning of the cooling coils. The air heat transfer rate, a key parameter quantifying the convective heat exchange between the coil surface and the air stream, is plotted against the outdoor air temperature.

This upward shift in the air heat transfer rate trend line after cleaning can be attributed to the enhanced convective heat transfer conditions at the air-coil interface. The removal of dusts eliminated insulating barriers, allowing for improved thermal contact between the coil surface and the air stream. Consequently, the convective heat transfer coefficient increased, facilitating more efficient heat exchange between the coil and the air.

Furthermore, the figure demonstrates that the magnitude of the air heat transfer rate improvement is not constant, but varies with outdoor air temperature. At lower outdoor air temperatures, the relative increase in air heat transfer rate appears more pronounced compared to higher outdoor air temperatures. This behavior can be explained by the interplay between convective and conductive heat transfer mechanisms within the cooling coil.

The observed increase in air heat transfer rate after coil cleaning not only translates to improved cooling capacity but also has implications for energy savings. By enhancing the air-side heat transfer, the system requires lower air flow rates to achieve the desired cooling output, potentially leading to energy savings and improved operational efficiency. Implementing a proactive coil cleaning schedule helps to sustain peak heat transfer performance, improve indoor environmental quality, and maximize overall system efficiency and energy savings in long run.

5.7. Cleaning of fans and rest of AHU

The cleaning of the fans and some rest of the air handling unit took place on July 21, 2023. The analysis shown in Fig. 14 reveals a comprehensive impact on air velocity across the AHU. Prior to the maintenance event, air velocity readings were relatively low, indicating potential buildup of dirt or contaminants on the fan. However, after the comprehensive cleaning process, the air velocity increased notably up to 12% without additional power input, which is evident from the graph.

Despite the fan power remaining constant before and after the cleaning, the improved air velocity suggests that the cleaning effectively removed obstructions and restored the system's ability to distribute air more efficiently. This outcome underscores the importance of regular maintenance and cleaning protocols to maintain an optimal performance of HVAC systems.

It is worth noting that the outdoor temperature during the observed period did not exhibit any substantial fluctuations that could have influenced the air velocity readings. Therefore, the increase in air velocity can be primarily attributed to the benefits of the cleaning process, which mitigated any flow restrictions within the air handling unit and associated duct work. The results highlight the positive impact of proactive maintenance strategies on system performance.

6. Comparative analysis

This section covers the systematic comparison between AHU-C and AHU-UC, with AHU-C representing the cleaned system and AHU-UC serving as a baseline reference for normal degradation patterns. This experimental design allows for a direct comparison, since both systems were extensively monitored through an array of sensors that measure critical parameters such as temperature, pressure differentials, air velocity, VOC concentrations, and energy consumption at 10-min intervals throughout both the winter and summer seasons.

6.1. Monthly energy consumption trend

Fig. 15 presents the violin plot of monthly energy consumption patterns for the two Air Handling Units (AHU-UC and AHU-C) from April 2023 to March 2024.

For AHU-UC (upper subplot), the energy consumption shows significant variation and interesting distributional patterns across the months.

The plot for AHU-UC in April and June shows high variability in daily energy consumption, with a wide distribution range spanning from low to high values, and the median closer to the upper end, suggesting most days had higher use while some had much lower. The most notable feature is observed in June 2023 (2023-04), where the unit displays the widest distribution range, with multiple density concentrations as can be seen by the wider sections of the violin plot, because of the change

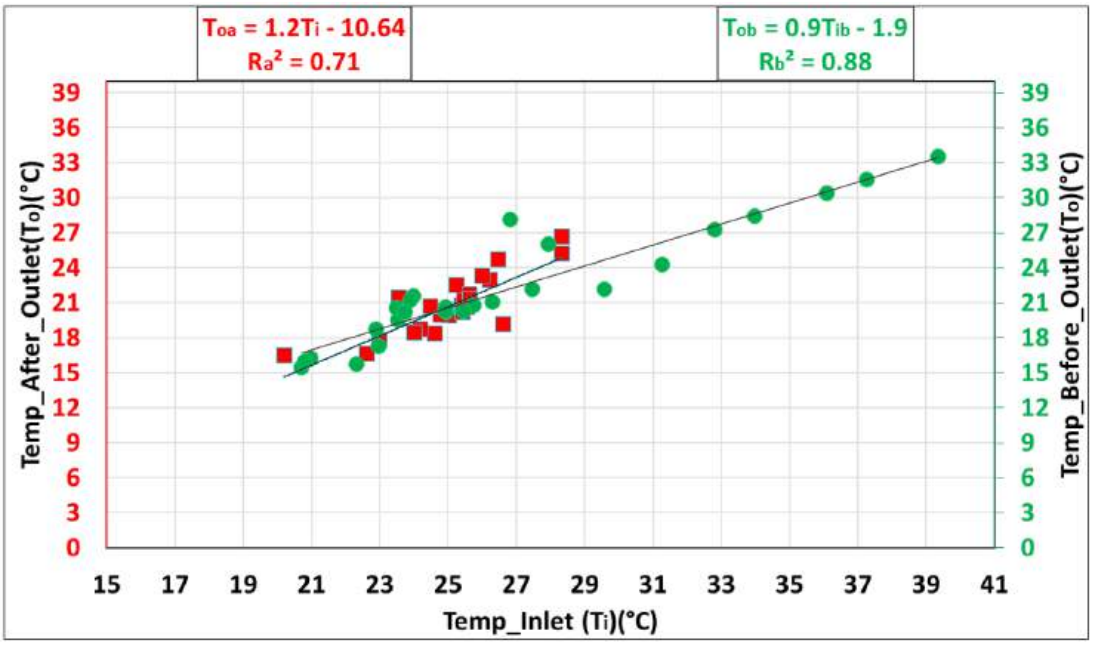

Fig. 10. Impact of cleaning delivery channels (duct) on how return air temperature changes relative to the supply air temperature, before and after cleaning.



Fig. 11. Condition of the cooling coil before and after the cleaning intervention.

of the inverters and impact of cleaning. This suggests a highly variable operation during this period. Moving into the summer months (May-June 2023), the distribution becomes somewhat more concentrated but still maintains considerable spread, with primary consumption falling between 20-40 kWh. As we progress through the year, there is a general trend toward more consistent operation, as evidenced by the narrowing of the violin plots from July 2023 onward. The median consumption (represented by the dashed lines within each plot) appears to stabilize around 30-35 kWh for most of the last months. The winter months (December 2023 to March 2024) show relatively similar distributions, suggesting more standardized operation patterns during this period.

For AHU-C (bottom subplot), the pattern is notably different from AHU-UC, particularly in terms of magnitude and variability. The initial month, between April and June 2023, shows a similar wide distribution to AHU-UC, but subsequent months demonstrate a marked decrease in both energy consumption and variability. After June 2023, in which the maintenance cleaning had been done, the energy consumption appears to stabilize at significantly lower levels, typically ranging between 5-15 kWh, with much narrower distributions compared to AHU-UC.

A key observation is that AHU-C appears to operate more efficiently or with lower demand than AHU-UC, as evidenced by its consistently lower energy consumption patterns in most months. The narrower violin plots in AHU-C from June 2023 onward suggest more consistent and controlled operation compared to AHU-UC, which maintains wider distributions showing more variable operation throughout the year. This comparison clearly demonstrates the significant impact of maintenance cleaning on AHU performance. The cleaned AHU-C shows a reduction in energy consumption compared to the uncleaned AHU-UC. This case study provides strong evidence for the importance of regular maintenance of the AHU in optimizing energy efficiency and operational stability in HVAC systems.

Both units show some negative values in their early operation periods, particularly in April 2023, which is an indication of energy sensor calibration issues in the initial phase of sensors installation. The overall trend for both units suggests a movement toward more stable operation patterns as the year progressed, although AHU-UC maintains higher and more variable energy consumption throughout the period.

6.2. *Impact of AHU cleaning on power consumption*

The analysis of the power consumption patterns for two Air Handling Units (AHUs), labeled C and UC, provides valuable insights into the benefits of regular maintenance and cleaning on energy efficiency. The radar plot as shown in Fig. 16 illustrates the power consumption of the two AHUs across different time intervals of the day, over the course of a year, from 2023-07 to 2024-03.

Recalling that AHU-C underwent a cleaning, while AHU-UC was not cleaned during this period, the key findings emerging from the analysis are as follows:

- Reduced Power Consumption: The power consumption of the cleaned AHU-C is consistently lower than that of the uncleaned AHU-UC, especially during peak hours from 8 AM to 6 PM. The maximum power consumption of AHU-C is 5000W in the working hoop, which is less than the maximum of 5100W of AHU-UC.
- Improved Efficiency: The cleaning of AHU-C appears to have improved its overall efficiency, resulting in lower power consumption throughout the day. This suggests that regular maintenance and cleaning of AHUs can be an effective strategy to optimize energy usage and reduce operational costs.

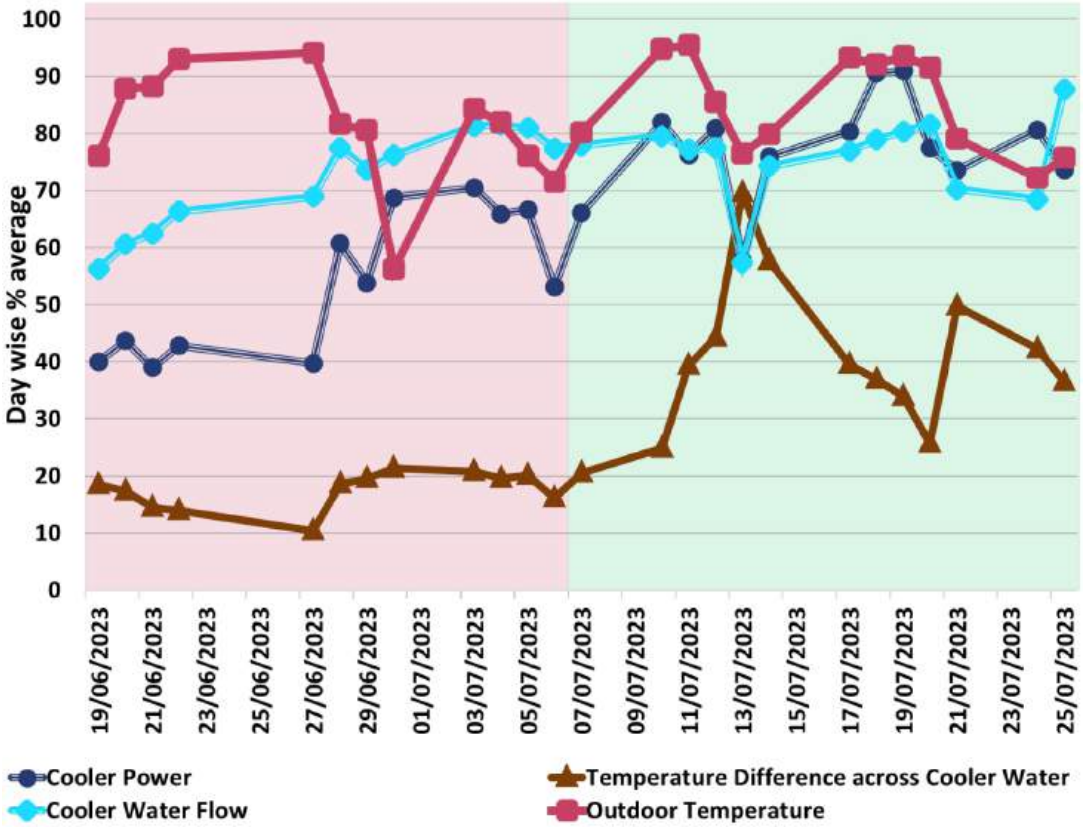

Fig. 12. Impact on cooling power, cooler water flow and temperature difference between the water outlet and water inlet of the cooling coil(where background of pink and green color shows the time period before and after the cleaning of cooling coil respectively).

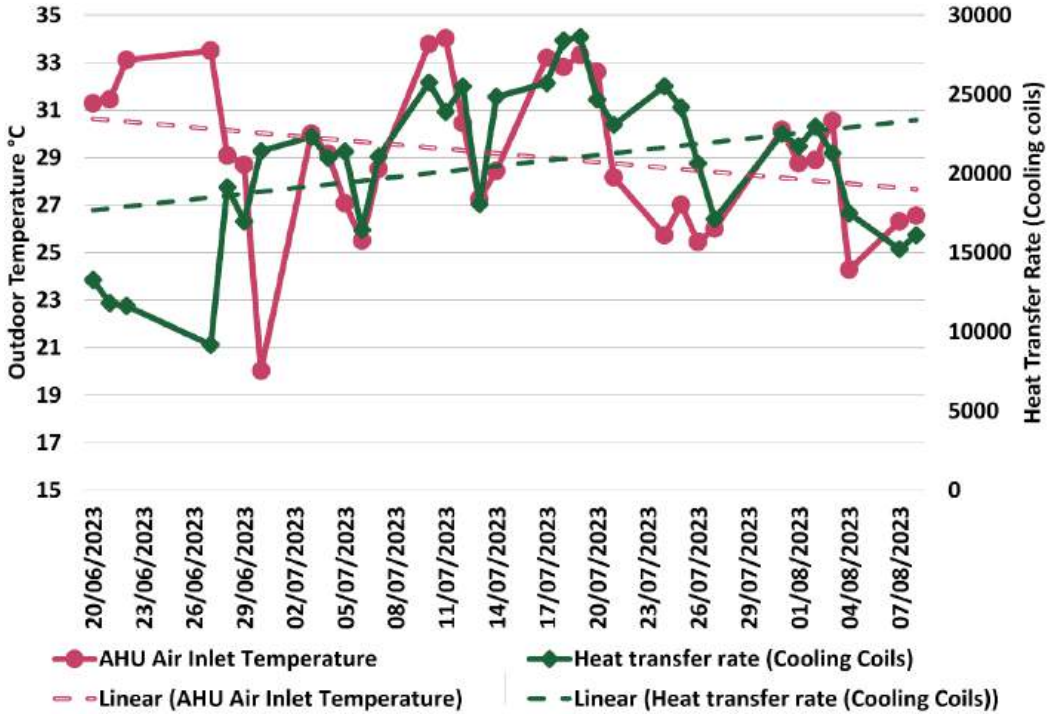

Fig. 13. Impact on air heat transfer rate of the air due to the cleaning of cooling coil.

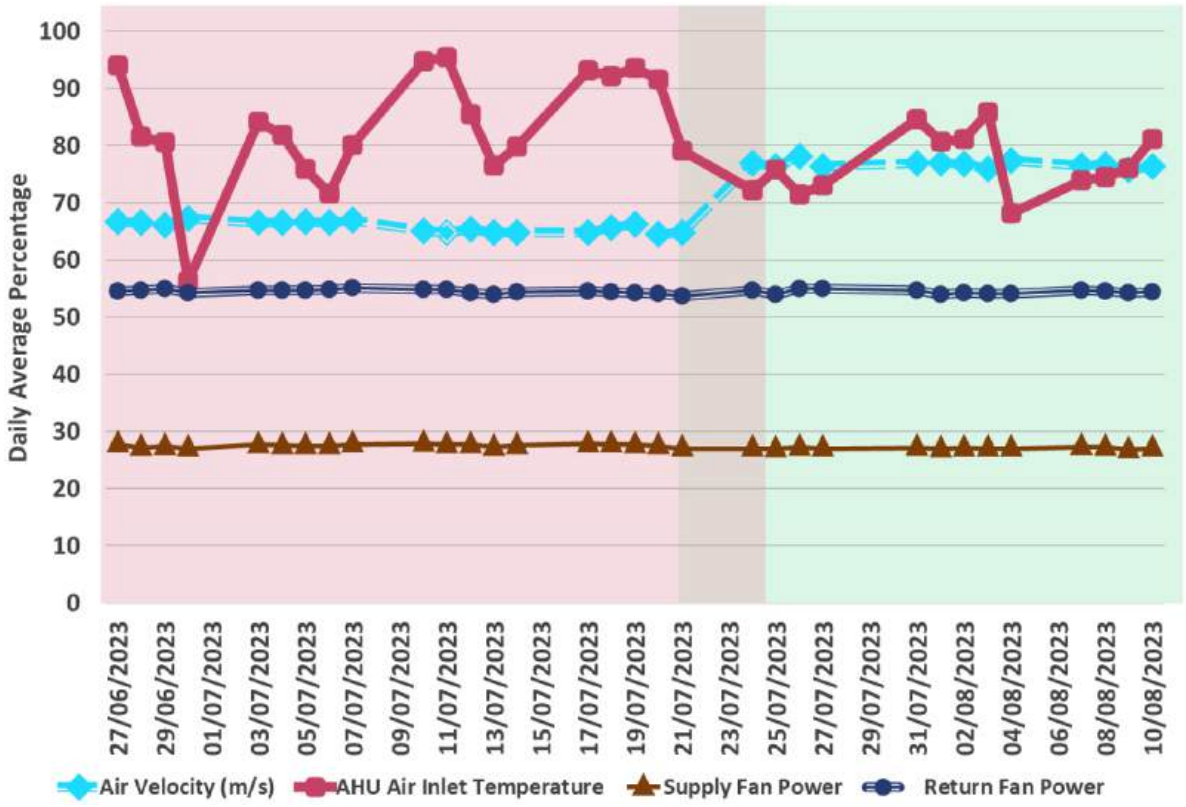

Fig. 14. Impact on air velocity due to the cleaning of the fans and rest of AHU(where background of pink and green color shows the time period before and after the cleaning respectively).

- Power Consumption Starting from 0 AM: Another notable observation is that the power consumption of both AHUs starts from 0 AM in some of the months, indicating the importance of monitoring and managing the HVAC system's operation even during non-working hours in university to maintain optimal efficiency.

University building energy managers can leverage these insights to develop more effective energy efficiency programs and make informed decisions regarding the maintenance and upkeep of their HVAC infrastructure.

6.3. Impact of AHU cleaning on air flow velocity

We used scatter plots, line plots, and heatmaps for each AHU, to analyze the impact of cleaning on the energy efficiency and operational performance of AHUs under varying airflow conditions.

6.3.1. AHU-C (cleaned)

Scatter plot analysis. The scatter plot in Fig. 17, top left, reveals a tight cluster of data points, with a power consumption ranging between 4800W and 5050W for air velocities 3.2-4.0 m/s. This range of air velocity corresponds to the lower air supply volume of AHU-C (9,300 m^3/h). This clustering suggests a linear and predictable relationship between air velocity and power consumption.

Line plot analysis. The line plot in Fig. 17, top center, illustrates a consistent power consumption profile as air velocity increases. The narrow confidence band indicates minimal variability, reinforcing the reliability of AHU-C's performance. Notably, power consumption slightly decreases at higher air velocities, potentially due to optimized fan operation in the cleaned system. The line is relatively smooth, indicating a stable and predictable system performance. This demonstrates the impact of cleaning on achieving steady-state operational conditions.

Heatmap analysis. The heatmap in Fig. 17, top right, for AHU-C provide an analysis of specific energy consumption (Wh/m^3), calculated by following the procedure done in Section 3.1.2. AHU-C, which was cleaned, demonstrates lower specific energy consumption values across all velocity bins, ranging from 0.62 to 0.85 Wh/m^3, this indicates reduced airflow resistance. Most bins are concentrated around 0.75 scale or lesser value, showing a predominance of lower power consumption values, indicated by the light blue colors. This uniformity reflects the energy efficiency of AHU-C post-cleaning, where the airflow system operates with minimal resistance.

6.3.2. AHU-UC (uncleaned)

Scatter plot analysis. The scatter plot in Fig. 17, bottom left, displays a broader dispersion of data points, with power consumption fluctuating between 4800 W and 5250 W for air velocities ranging from 6.75-8.75 m/s. This higher velocity range corresponds to AHU-UC's larger supply air volume (10,500 m^3/h). This wide dispersion indicates an inconsistent relationship between air velocity and power consumption. The irregular clustering and increased variability highlight the operational inefficiencies caused by the uncleaned system. This suggests a less consistent relationship between air velocity and power consumption, potentially due to increased system inefficiencies or equipment degradation over time.

Line plot analysis. The line plot in Fig. 17, bottom center, exhibits sharp increases in power consumption at higher air velocities, with significant fluctuations and a wide confidence band. The line is less linear, demonstrating a less consistent relationship between air velocity and power consumption. This variability is attributed to the increased system resistance due to dirt and obstructions in the duct work, which forces the fan to exert additional effort to maintain airflow, thereby consuming more power. These spikes represent instability and show that the system is

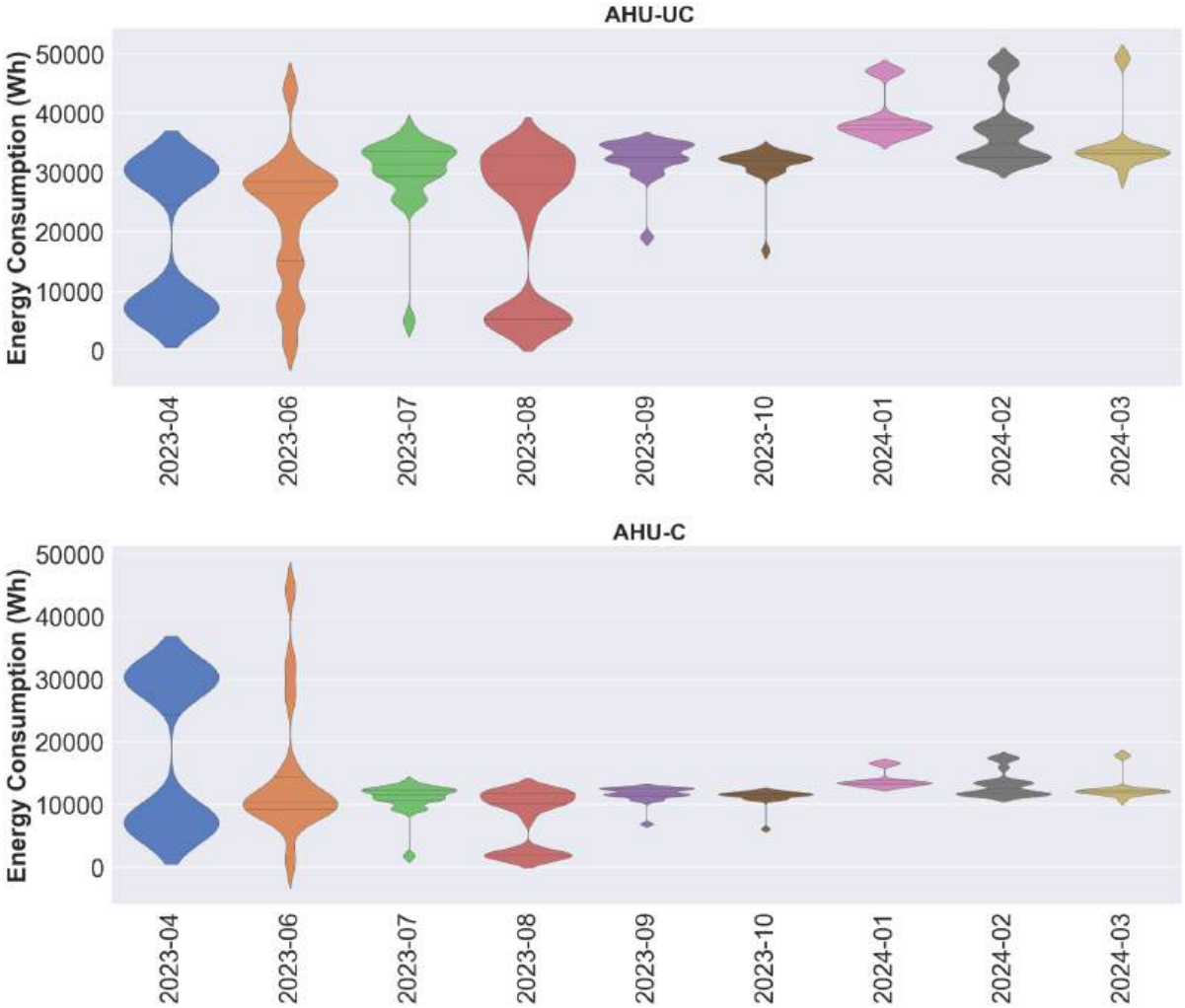

Fig. 15. Comparison of monthly energy consumption of cleaned and uncleaned AHU supply fan.

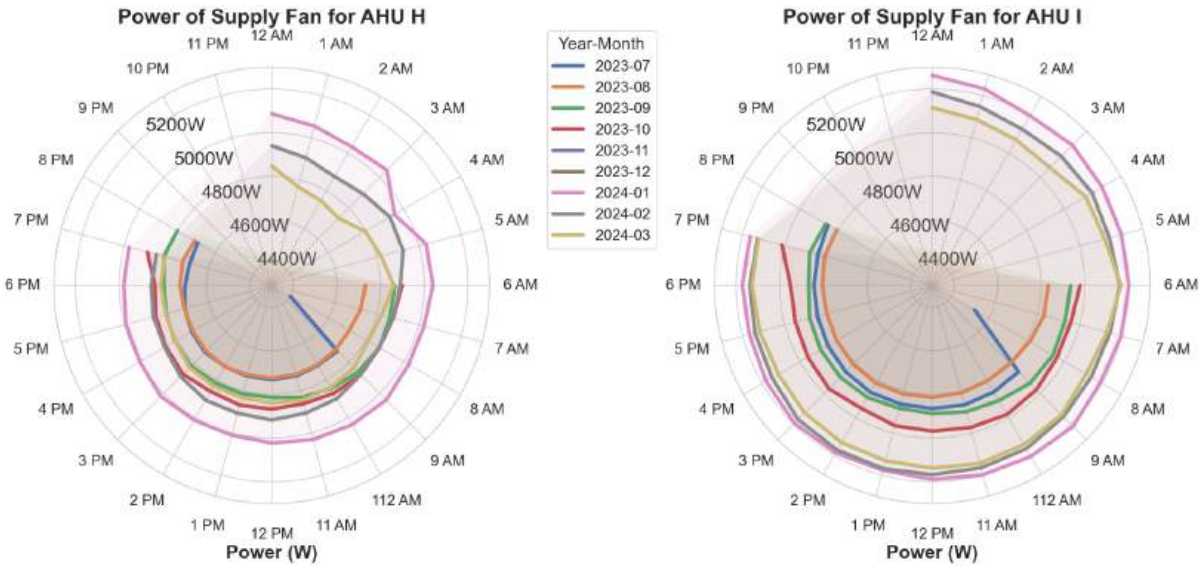

Fig. 16. Power consumption of AHU across different hours and months.

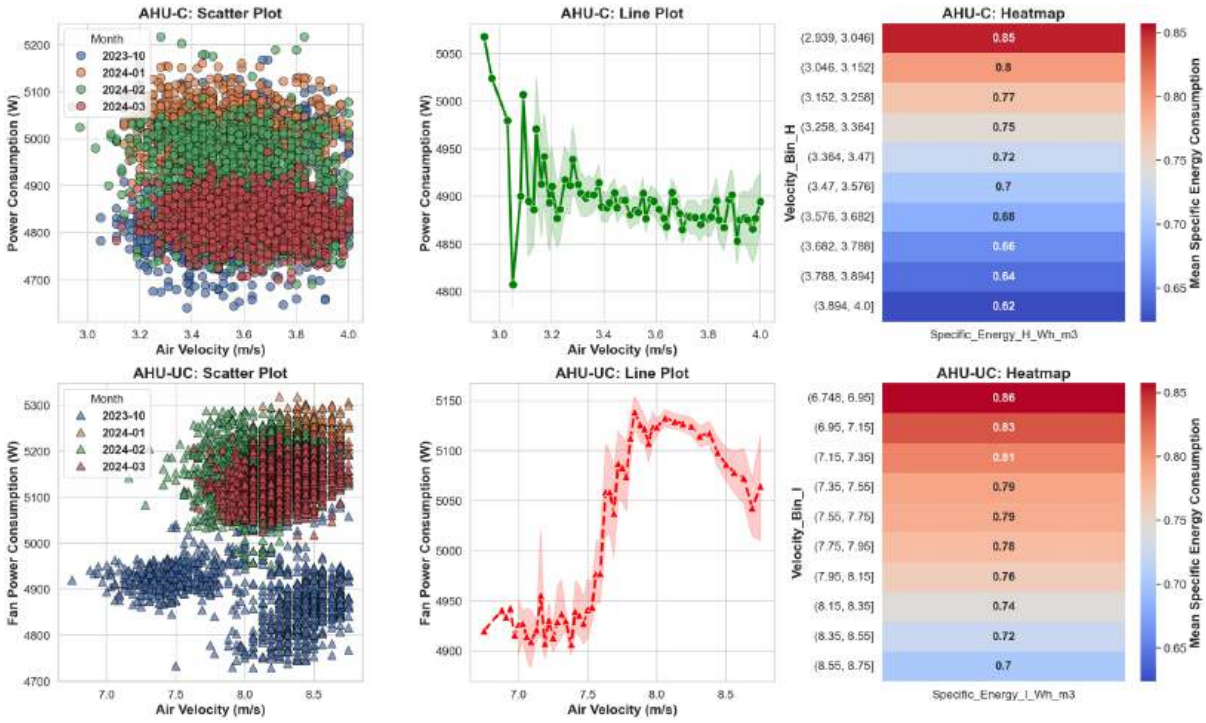

Fig. 17. Power consumption of supply fan with respect to air flow velocity of AHU-C and AHU-UC.

operating under strain. This irregular pattern suggests that the uncleaned AHU-UC is operating less efficiently compared to the cleaned AHU-C.

Heatmap analysis. The heatmap in Fig. 17, bottom right, both for AHU-C and AHU-UC provide a comparative analysis of specific energy consumption (Wh/m^3), calculation done using explanation in Section 3.1.2, across different air velocity bins, highlighting the impact of cleaning on energy efficiency. AHU-UC exhibits higher specific energy consumption values, ranging from 0.70 to 0.86 Wh/m^3. The higher energy consumption in AHU-UC suggests that accumulated dirt or obstructions may be increasing resistance, thereby requiring more energy to maintain airflow. AHU-UC displays a wider range of power consumption values, with more areas heat of heatmap, indicating higher consumption across the air velocity spectrum. This non-uniformity indicates inefficiencies resulting from a lack of regular cleanliness, which disrupts airflow uniformity and increases energy demand. The consistent trend of lower energy consumption in AHU-C enhances the importance of regular maintenance. The higher air velocities in AHU-UC are in a direct correspondence of its larger supply air volume (10,500 m^3/h) compared to AHU-C (9,300 m^3/h). However, the cleaning status of each AHU greatly influences the energy efficiency at these velocities.

AHU-C, despite operating at lower air velocities, the cleaned state allows for optimal performance with minimal variability, ensuring consistent power consumption across its operational range. AHU-UC, the higher air velocities amplify the inefficiencies caused by dirt and blockages, leading to increased power consumption and greater variability in performance.

7. Conclusion

Comprehensive empirical analysis of the impact of Air Handling Unit (AHU) cleaning on HVAC system performance and energy analysis is presented in this paper. By analyzing two identical units; one systematically cleaned (AHU-C) and the other left untreated (AHU-UC), it is demonstrated that proactive cleaning significantly leads to measurable improvements in system operation and energy savings.

Key findings highlight substantial reductions in energy consumption, with AHU-C consistently exhibiting lower power usage, particularly during peak operational hours. Following cleaning interventions such as component cleaning and inverter upgrades, energy savings ranged from 16.2% to 71.4%, underscoring the efficiency gains achieved through targeted cleaning. Specific improvements include:

- Recuperator and Cooling Coil cleaning: Enhanced thermal performance, increasing temperature differentials and improving air-side heat transfer rates by 15-25%, reducing thermal resistance and optimizing system efficiency.
- Airflow Restoration: Duct and fan cleaning improved airflow velocities by up to 12% without additional energy input.
- Indoor Air Quality Improvements: Regular cleaning effectively reduced pollutant levels, particularly Volatile Organic Compounds (VOCs), although transient spikes were observed during cleaning due to contaminant dislodgement.
- Long-Term Operational Stability: AHU-C demonstrated more consistent energy consumption patterns, whereas AHU-UC exhibited greater variability due to accumulated contaminants.

The findings of this study offer empirical evidence that integrating routine AHU cleaning into HVAC maintenance protocols is a cost-effective strategy to enhance energy efficiency, prolong equipment lifespan, and maintain optimal indoor environmental conditions. While this research was conducted in a single facility over a limited timeframe, future studies could expand on these insights by examining the long-term effects of varying cleaning frequencies and assessing their impact across different AHU configurations. These results provide valuable guidance for building managers and HVAC professionals, enabling data-driven decisions to optimize system performance and support sustainable building operations.

The approach demonstrated in this paper serves as a reference for future studies on HVAC system optimization, particularly in educational and institutional settings where energy efficiency improvements yield significant environmental and economic benefits.

CRediT authorship contribution statement

Nouman Ahmed: Writing - original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation; **Tullio Facchinetti:** Writing - review & editing, Validation, Supervision, Resources, Project administration, Methodology, Data curation, Conceptualization; **Mark Hernandez:** Writing - review & editing, Validation, Methodology; **Norma Anglani:** Writing - review & editing, Validation, Supervision, Funding acquisition, Formal analysis, Conceptualization.

Data availability

The data that has been used is confidential.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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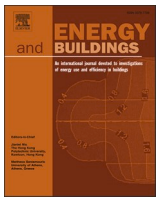



Impacts of HVAC cleaning on energy consumption and supply airflow: A multi-climate evaluation

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ABSTRACT

Energy-efficiency interventions are crucial for sustainable building operations to accommodate emerging indoor air quality (IAQ) criteria into their engineering life cycles. While several studies have addressed building energy consumption and IAQ considerations separately, few provide integrated analysis of these aspects in response to building hygiene practices. In response, this study evaluates the effectiveness of routine heating, ventilation, and air conditioning (HVAC) cleaning on energy consumption and supply airflow patterns in non-residential public buildings. This study juxtaposes HVAC energy consumption and ventilation performance before, during and after routine HVAC cleaning, across buildings situated in four different climate zones, while operating in cooling mode. Each site had nearly identical HVAC systems serving similar architectural features and occupational loads; these were segregated into an intervention (cleaned HVAC system) that could be compared to an otherwise identically operating HVAC (control system), which was not cleaned. Following prescriptive cleaning, HVAC systems exhibited significant energy consumption reductions and delivered higher airflows compared to their uncleaned counterparts. On average, intervention systems saved between 41 % and 60 % on conveyance (fan/blower) energy, with one exception, and supplied 10 % and 46 % more airflow compared to their uncleaned counterparts. This research demonstrates how a new generation of low-cost HVAC system monitors can compile Internet of Things (IoT) archives to show immediate energy consumption benefits associated with cleaning HVAC components and their associated ductwork serving relatively high occupancy commercial and educational spaces.

1. Introduction

Building operations consume nearly one-third of total global energy output, accounting for a significant contribution to CO_2 emissions worldwide [1]. In the United States, commercial and residential buildings account for about 40 % of domestic energy consumption [2]. Such energy consumption trends in the building sector are expected to continue due to population growth, urbanization, increases in high-density building developments, rising comfort demands, and emerging indoor air quality (IAQ) concerns [3]. Furthermore, emerging guidelines for improving ventilation and indoor air quality [4-7] are expected to increase building energy consumption budgets in the foreseeable future.

In the context of building services, HVAC-associated energy consumption is significant, accounting for nearly 50 % of total energy usage in U.S. commercial and public buildings [8]. Given this substantial contribution, enhancing HVAC performance can lead to significant societal energy savings [9]. HVAC systems continuously manage thermal energy transfer while mixing and replenishing fresh air through occupied spaces. Energy is primarily consumed for heating, cooling, ventilation, air filtration, distribution, as well as by supporting auxiliary components such as chillers, boilers, backup fans, and variable frequency drives (VFDs). These systems employ various components and mechanisms to manage indoor environmental conditions.

HVAC systems are often operated to manage thermal comfort while maintaining indoor air quality through conditioning and (re)circulating filtered fresh air to occupied spaces. Given the amount of time people spend indoors, building environments can significantly impact occupant comfort and respiratory exposure; thermal management and indoor air

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quality are identified as one of the primary factors influencing the comfort, wellness, and productivity of building occupants [10-12]. Ducted HVAC systems with integrated filters help reduce the indoor load of ambient particulate matter (PM) in the environments they serve. Depending on the design and operation of these systems, in-line filters can further reduce the PM load associated with occupant shedding and indoor particle resuspension [13]. However, in some cases, the HVAC system itself can become both an acute and chronic source of PM and volatile organic carbon (VOC) emissions [14-16].

Conventional HVAC operations result in the gradual accumulation of particulate matter (PM) on the surfaces of different HVAC components [17,18], often reducing the energy efficiency of these systems over time; both heat transfer inhibition and cumulative airflow drag are responsible for this phenomenon [19,20]. While the PM fouling of any single HVAC component may lead to minor energy efficiency losses, the energy impacts can become significant when considering cumulative losses across all HVAC components, especially in larger buildings with expansive ductwork [21]. Moreover, design factors, faulty installation, operational paradigms and inadequate maintenance of HVAC system components can contribute to increased respiratory PM exposures, some of which can influence allergenic and hypersensitive responses from building occupants [22,23]. For instance, soiling of ductwork downstream of cooling coils and other areas that experience relatively high humidity or large humidity swings, often support microbiological deposition and activity, which can lead to negative operational and maintenance outcomes, including corrosion, odors, compromised insulation, and potential respiratory pathogen sources [24].

1.1. Review of Relevant literature

While numerous studies emphasize the importance of HVAC operation and maintenance for improving building energy performance [25-27], there is a lack for research investigating the effectiveness of building hygiene practices, in particular HVAC cleaning, on immediate and long-term energy savings potential for higher occupancy buildings. Since the U.S. Environmental Protection Agency (EPA) released the 1997 position paper on residential duct cleaning [28], only a limited number of studies have systematically examined the potential impacts HVAC system component cleaning can have on energy consumption patterns—a few of which included any accompanying IAQ survey.

Zhai and Johnson examined the effects of pressure drops within HVAC systems—caused by filter fouling, duct obstructions, and leakage—on fan energy consumption [29]. Using full-scale laboratory experiments, the authors observed that increased pressure drops, particularly from fouled filters, can raise energy consumption by up to 45.5 % when duct leakage is also present. To simulate increased pressure from fouling, the study introduced materials like linen sheets and wooden objects within the ductwork to mimic dust and obstructions, while foam board particles were added to elevate pressure drops across the filter. In a related study, Wilson et al. [30] examined the energy savings associated with cleaning coils and filters in constant air volume HVAC systems within single-family residential and small office buildings. Using a validated computer model to simulate varying levels of fouling in multiple climates, they found that while fouling affects both air conditioner and furnace energy use, anticipated energy savings are minimal for single-family residential buildings and may be negative for small office buildings based on fouling levels reported in the literature. They also emphasize the importance of regular cleaning and proper maintenance of constant air volume HVAC systems that introduce outside air for ventilation, to ensure that the systems maintain their designed ventilation rates.

In another study, Lin et al. [31] conducted an analysis of energy consumption patterns in United Arab Emirates buildings, with a specific focus on the operation and maintenance of building systems. Their findings indicate that, among other parameters, the cleanliness of air conditioning systems and the surface conditions of chillers are critical factors that significantly influence building energy consumption. In another study, Siegel and coworkers [32] critically examined particle deposition on evaporator coils and related effects of indoor particle and dust concentrations on coil fouling rates. Their results suggested that regular coil cleaning should be an integrated priority of residential air conditioning maintenance procedures to increase evaporator coil lifetimes and overall system energy efficiency. This observation likely extends to commercial HVAC hygiene as well.

While the quantity and thermodynamic properties of supply air have been the conventional focus of HVAC operations, the quality of air supplied to occupied spaces has received increased attention. Despite this, few studies have directly examined the effects of HVAC cleaning on indoor air quality. Ahmad et al. [22] looked at the effectiveness of three commercial HVAC duct cleaning processes in reducing airborne particulate matter (PM) and bioaerosols in residential homes. Results showed that during cleaning, PM and bioaerosol concentrations increased, suggesting that cleaning processes can disturb particle-associated pollutants. However, post-cleaning bioaerosol concentrations were significantly lower, indicating that cleaning has effectiveness on reducing subsequent respirable particle exposures over longer terms. In another study, Simbada et al. [16] analysed the bacterial DNA from HVAC filter dust collected in two university buildings. The results revealed the presence of potential pathogens, including the retention of antibiotic-resistant bacteria in HVAC systems, potentially posing health risk to occupants. They advised regular cleaning and disinfection of all HVAC systems to prevent potential pathogen accumulation and reduce occupants' potential respiratory exposures.

1.2. Contribution and research hypotheses

While existing literature highlights the potential of HVAC system management for enhancing energy savings, the actual effectiveness of HVAC system cleaning, and its influence on the interplay between energy consumption and indoor air quality should be considered [33]. Previous research has primarily relied on computer modelling and theoretical approaches to assess the effects of building hygiene practices on energy consumption, while an accompanying pool of actual field data are limited or not peer-reviewed if available. Studies often depend on controlled laboratory experiments, typically focusing on simulated cleaning processes for specific HVAC parts or components rather than on comprehensive, full-scale cleaning of ducts and other system elements. This approach may overlook key factors such as occupant activity, equipment aging, and actual duct conditions, including leaks—all of which can significantly impact HVAC performance. Additionally, previous studies on this topic have often focused on a limited sample of buildings, observed over relatively short durations within a single climate zone.

While existing literature predominantly focuses on residential and small office buildings, our study addresses medium-density commercial and public buildings. In response, this study demonstrates a scalable path to assess the effectiveness of HVAC system cleaning on energy consumption, concomitant with conditioned supply airflow monitoring, in medium-to-higher, non-residential buildings. By conducting our study in real-world settings, we aim to better capture actual building operation conditions and their effects on energy efficiency and supply airflow. A time-resolved examination of energy-related parameters and supply flow rates in buildings situated in four markedly different climate zones is reported— juxtaposing ventilation performance before, during and after staged HVAC cleaning using widely-accepted building hygiene practices. Each site chosen had nearly identical HVAC systems serving similar occupied areas, which were segregated into an intervention (cleaned system) for comparison with an otherwise identically operating control system that was not cleaned.

This report tests the hypotheses regarding the impact of building hygiene practices, specifically HVAC cleaning interventions, on energy consumption and indoor air quality as measured by supply airflow. We

propose that cleaned HVAC systems will consume less energy than their uncleaned counterparts while delivering higher airflow rates. We report some of the immediate energy consumption benefits associated with full-scale HVAC system cleaning in a variety of medium-to-higher occupancy building types across several climate zones (in cooling mode). While the absolute energy consumption benefits are relative to each site, we observed consistently improved ventilation performance patterns across all sites. This suggests that beneficial effects can be realized by cleaning all HVAC system components, but notably including the conveyance system itself (ductwork) and enhanced VAV operational stability.

2. Methods

2.1. Site selection and system Specifications

Given the significant impact of physical geography, urban effects and local climate conditions on HVAC system behaviour and its energy consumption [34], this study selected four groups of buildings across the United States and Europe, each representing conditions in a major climate zone with a significant population: In the United States, Johnson, Vermont represents the temperate northeast climate (Zone 6A: Cold–Humid); Pearl, Mississippi represents the sub-tropical southeast (Zone 2A: Hot–Humid); Boulder, Colorado, represents the arid mountain west (Zone 5B: Cool–Dry); and Pavia, Italy represents a temperate climate, 4A (Mixed–Humid) [35]. Studies have revealed that building type [36] and occupant activity [37] can affect HVAC system loads and dynamics. In this study, building functionalities span a diverse range of medium-to high occupancy settings, from an office building in Johnson, Vermont, to a daycare/gym facility in Pearl, Mississippi, as well educational spaces in Boulder, Colorado and Pavia, Italy. Fig. 1 displays locations of the buildings analysed in this study. Both occupied and unoccupied conditions were considered.

For this study, two nearly identical Air Handling Units (AHUs) were deliberately selected at each site for practical comparative analysis (control vs. intervention). The site selection was guided by the following criteria: first, they had to possess a minimum quantity of ducts with varying lengths and turns, in order to be generalized to an average medium-density service system duct system. Additionally, access to blueprints or simplified drawings of the HVAC system was required. It was also essential that the chosen systems did not incorporate variable speed fans, or if they did, the ability to operate them at a fixed speed for the duration of the study was mandated. Furthermore, a duplicate or a similar system in immediate proximity, serving a similar architectural space, was necessary for comparative analysis. Moreover, the systems had to be free of excessive nuances or variables like numerous reheat coils or inline restrictions. Finally, the location of these sites had to be dependable to ensure uninterrupted access throughout all scheduled phases of a cleaning response study. The cooling capacities of the HVAC systems ranged between approximately 10 tons (at the Vermont site) to 30 tons (at the Italy site).

To maintain consistency during this cleaning intervention study, any Variable Air Volume (VAV) controllers, where present, were deactivated (locked open). Ensuring that filter conditions did not impact the measurements in either control or cleaning intervention systems, any existing filters were replaced with new filters of the same type, before commencing cleaning protocols. Other key considerations encompassed formal facility manager engagements, scheduling all monitor installations, cleaning and subsequent operations in collaboration with building owners and managers. Furthermore, it was imperative that

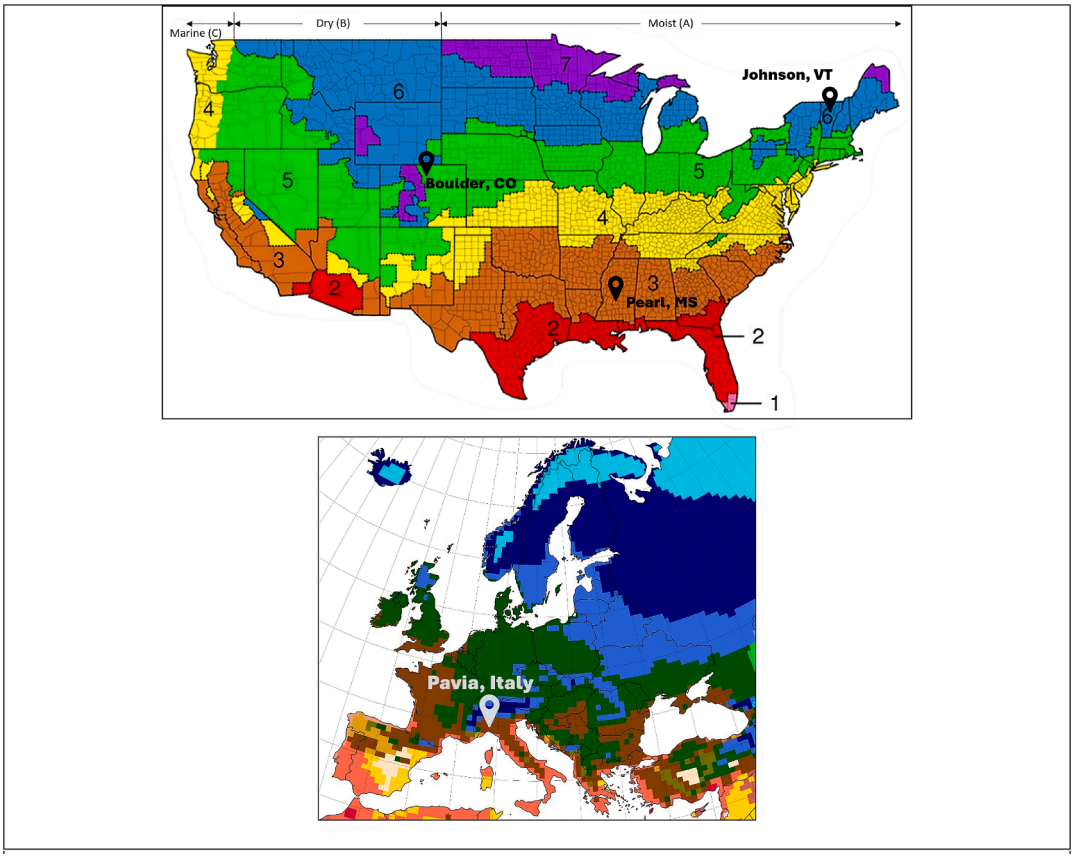

Fig. 1. Building sites participating in this study superimposed on a climate zone map as designated by ASHRAE [35]. Top: United States climate zones with three study sites including Boulder, Colorado (Zone 5b, Cold/Dry); Johnson, Vermont (Zone 6A, Cold/Humid); Pearl, Mississippi (Zone 3A Warm/Humid). Bottom: Europe climate zones, Pavia, Italy (Temperate/Warm).

cleaning contractors possessed the necessary training to install HVAC system energy monitors, sensors and accurately measure supply airflows at the registers. During the cleaning process, the supply and return duct systems, including registers, were thoroughly cleaned, ensuring that any dampers were left in their pre-cleaning positions. All HVAC system components, including fans/blowers, heat exchangers, and evaporator/condenser coils, were cleaned following industry standards [38]. The study timeline, along with a summary of climatic conditions at the building sites participating in this study, is listed in Table 1. Cleaning schedule staging and details for each site are available in the Supplementary Materials (A 1–A 4).

2.2. Data collection

The monitoring and data collection process was consistent and uniform for both control and intervention systems at each site. The following sensors were deployed in both intervention and control sides across at the four different sites (Fig. 2).

R&T-500 Series (T&D) sensors [39] were used at the Vermont and Mississippi sites for measuring energy (RTR-505-P) and pressure (RTR-505-mA, with 0.05 mA + 0.3 % of reading inaccuracy) values. Data from these sensors were accessed via the vendors' cloud server, T&D WebStorage Service [40]. Measurements from the sensors were reported at an hourly frequency.

At the Colorado site, a Dwyer Series 607 Differential Pressure Transmitter [41] was used to assess pressure drop, the Keyence FD-R Series Clamp-on Flow Meter [42] measured flow rate (temp accuracy = ±3 °C, flow accuracy = ±2 %), the Dwyer Series RHP Humidity and Temperature Transmitter [43] monitored humidity (±2 % inaccuracy) and temperature (±0.3 °C inaccuracy), and the WND series WattNode Wide-Range Modbus [44] served as the electric power meter (±0.5 % inaccuracy). Data from these sensors were accessed through the vendor's cloud server, Attune [45], with a data reporting frequency of every minute.

At the Italian site, the SmartDHOME [46] sensor family was utilized to measure energy consumption, providing real-time data monitoring capabilities through MyVirtuoso Home [47] software. The Ultrasonic Heat/Cool Meter was deployed to measure the flowrate and temperature of cooling water (±1 % inaccuracy). The energy consumption of fans (blowers) was measured using a three-phase inductive energy meter. For monitoring differential pressure, temperature, and relative humidity, as well as capturing real-time photos from the interior of HVAC system ducts and AHUs, REMOTAIR [48] sensors were utilized. Equipped with cameras installed in AHUs and ducts, REMOTAIR sensors captured photos multiple times per day, enabling the ongoing tracking of particle deposition conditions within the HVAC system.

At all sites, an industry standard method was used to measure and record the volumetric flow through each supply register using a four-quadrant measurement or flow hood. While the energy consumption and differential pressure within the HVAC systems were continuously measured, supply airflow was intermittently measured before, during, and after the cleaning process, with data recorded for both control and intervention systems. Measurements were conducted according to the National Environmental Balancing Bureau (NEBB) "Procedural Standards for Testing, Adjusting, and Balancing of Environmental Systems" [49]. Similar to the energy and air quality sensors, the supply airflow measurement process was consistent and uniform for both control and intervention systems at each site, ensuring the basis for stringent statistical comparisons.

Table 1
Table summarizing climatic zone and project timeline at the building sites participating in this study.

Location	Climatic condition	ASHRAE climate zone	Start date	End date
Johnson, VT	Temperate Northeast	6A: Cold – Humid	Jul 17, 2019	Sep 1, 2019
Pearl, MS	Sub-Tropical Southeast	2A: Hot – Humid	Jul 17, 2020	Oct 10, 2020
Boulder, CO	Arid Mountain West	5B: Cool – Dry	Aug 17, 2022	Oct 5, 2022
Pavia, Italy	Temperate	4A: Mixed – Humid	Jun 15, 2023	Aug 4, 2023

2.3. Data analysis

Both descriptive and inferential statistical methods were applied to analyse energy consumption and ventilation performance data. This analysis was structured to investigate the energy-related response of routine HVAC system cleaning, as well as to identify common patterns in system performance dynamics within these non-residential public buildings. Statistical analyses were conducted utilizing the R programming language within the RStudio environment [50], with visual presentations generated using R-compatible libraries [51].

The data analysis procedures were standardized across all locations. For the primary analysis, data collected from 8 am to 6 pm (local time zone) on regular working days were incorporated into the study. Sensor data from public holidays and system cleaning days were omitted from the analysis. Additionally, instances of technical malfunctions in either the control or intervention systems, such as refrigerant leaks, necessitated immediate attention from maintenance personnel, resulting in the shutdown of either the entire system or specific faulty components. Data collected on these days were also excluded from the analysis. Data from both the control and intervention (cleaned) systems were collected during all the different cleaning phases, which were consistently staged to isolate cleaning effects on the heat transfer equipment, conveyance system (ducts) and fans (blowers). Differential pressure across the HVAC system was continuously measured. Data obtained prior to cleaning served as foundational baseline(s).

Cumulative daily energy consumed by fans, blowers, and cooling equipment, alongside differential pressure values, were computed for both the control and intervention systems. The trends of these variables over the duration of the project were analysed using widely accepted statistical regression practices. A reporting model was constructed using the linear model function in base R to identify trends in energy consumption and ventilation performance variables [52]. This function formulates regressions with variance. In the context of this study, the regression model described linear relationships between the energy usage for cooling, air conveyance, and differential pressure (outcome variables) and the observation days across the project timeline (predictor variable). This model was individually fitted to the variables of interest in both the control and intervention systems, which were then compared.

To assess whether HVAC components in control and intervention systems at each site differ significantly, an analysis of covariance (ANCOVA) was conducted across the respective cleaning stages at each site. ANCOVA is a statistical technique that combines analysis of variance (ANOVA) with linear regression [53] for normally distributed data, which applies to the present study. In the context of examining regression variances between control and intervention systems, ANCOVA tests determined whether observed distinctions remain significant after accounting for covariates, thereby offering a more refined comprehension of the relationship between any independent and dependent variables. A significant interaction term between the experimental condition and the covariates indicates that the regressions for the control and intervention groups are not parallel, suggesting disparate relationships between the independent and dependent variables across the two groups. In this case, the ANCOVA fitted a linear model to predict energy consumption based on the observation day, system type, i.e., control or intervention, and the interaction between these two factors, i.e., observation day and system type. Eq. (1) shows an example of how the ANCOVA model was constructed in R for the value of interest:

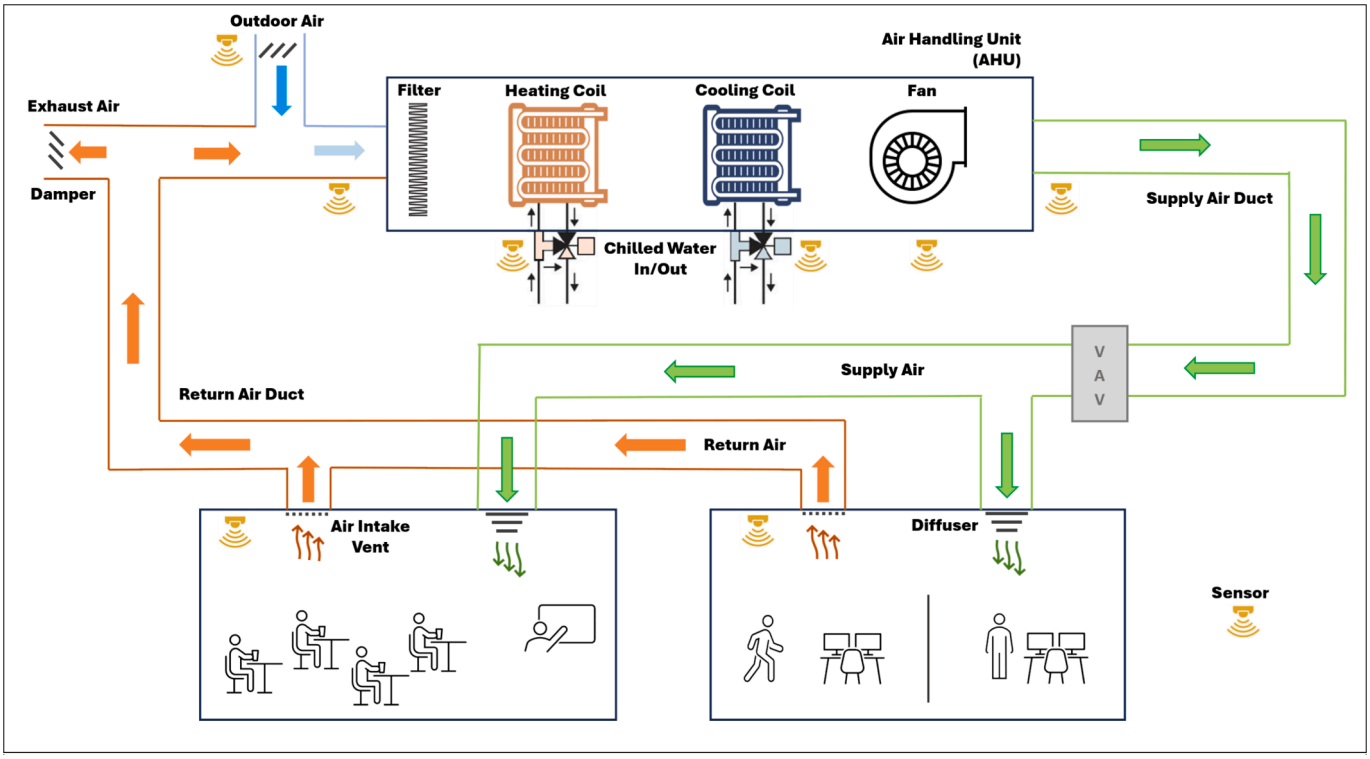

Fig. 2. Schematic of air handling units (AHU), sensor networks, duct work and occupied spaces of that typically observed in this study. Energy consumption sensors were installed on all fans and heat transfer equipment. Pressure sensors were installed in ductwork immediately upstream and downstream of the AHU. Thermodynamic sensors (T and RH) were installed in the occupied spaces and immediately adjacent to outdoor (fresh) air intake.

$$ANCOVAModel = LinearModel\left(\begin{array}{c} DependantVariable \\ ObservationDay + SystemType \\ +ObservationDay^{*}SystemType \end{array}\right)\# \tag{1}$$

The significance levels for the linear regression models were classified as follows: highly significant ($p < 0.001$), very significant ($p < 0.01$), significant ($p < 0.05$), marginally significant ($p < 0.1$) and not significant ($p \geq 0.1$). The p-value in this context indicates the probability of observing the difference in slopes between the control and intervention groups, assuming there is no true difference between them, with smaller p-values suggesting stronger evidence against the null hypothesis.

Additionally, we compared the daily energy required for air conveyance (i.e., fans and blowers) in both the intervention and control systems on each observation day, and adapted a method similar to that of Zhai and Johnson [29] to calculate the percentage of potential relative energy savings, as shown in Eq. (2):

$$PercentofRelativeEnergySaving = (Energy_{control} - Energy_{intervention})/Energy_{control} \tag{2}$$

To assess the impact of HVAC system cleaning on supply airflow, measurements from the control side were subtracted from those of the intervention side and plotted over the time for each project site. This enabled monitoring of how differences between intervention and control measurements changed throughout each cleaning phases. To better quantify the difference between the control and intervention systems following each stage of cleaning, we calculated the percentage increase in supply airflow rates using Eq. (3) [30]:

$$PercentofRelativeIncreaseinSupplyAirflow = (FlowRate_{intervention} - FlowRate_{control})/FlowRate_{control}\# \tag{3}$$

Changes in supply airflow at each stage of the cleaning compared to the previous cleaning stage was also studied to identify the cleaning stage that were most impactful as judged by supply airflow rates.

3. Results

The influence of routine HVAC system cleaning on energy use and supply airflow in public, non-residential buildings was studied. A detailed, time-resolved analysis was conducted on energy and airflow metrics in buildings grouped in the various climate zones is reported below. This section details the observed patterns in energy consumption, changes in supply airflow rates, and other overall impact of the HVAC cleaning practiced here. The structure of the Results and Discussion section is as follows: The impact of HVAC cleaning on energy consumption at each site is presented chronologically. Next, an analysis of supply airflow across all sites is provided. Other unanticipated benefits arising from the cleaning process, i.e., system stability, are then discussed.

3.1. Energy consumption

An overall reduction in energy consumption in fans and cooling energy was anticipated and quantified, primarily due to the decreased cooling loads resulting from the transition to cooler outdoor temperatures as the studies progress from summer to fall seasons at all sites. This expectation also applies to differential pressure reductions. The cleaning process commenced during the peak load of HVAC systems, coinciding with the peak of warmest season in each location. The sites and associated results are res described in the order studied, during summers of 2019, 2020, 2022 and 2023 (2021 was a study hiatus due to COVID-19 building shutdowns).

3.1.1. Johnson, VT

The analysis of the first location (2019), Vermont, examined the

cumulative daily energy consumption of the blower, cooling, and daily average differential pressure over the duration of this project. The daily energy use by blowers in both control and intervention systems, calculated based on the methodology in Eq. (2), indicates that daily relative energy savings ranged between 43 % and 50 %, with an average of 44 % over the study duration.

Parallel regression analysis of data from both the control and intervention systems suggests that although the cumulative daily energy consumption of the blower in the intervention system increased at a higher rate compared to the control system, the respective increases were not statistically significant. The relatively high p-values in both groups and the ANCOVA analysis indicated that routine HVAC system cleaning did not significantly impact the blower's energy consumption in this setting (Table 2).

For the energy consumption used for cooling by the main compressor, both the control and intervention systems exhibited negative slopes, indicating a decrease in energy consumption over the season observed. These data indicate that while there is a statistically significant decrease in energy consumption for cooling in both systems, which is consistent with the prevailing weather pattern, the routine cleaning of the HVAC system did not result in a significant consumption rate differences when comparing the control and intervention thermodynamic heat transfer performance. Additionally, the analysis showed a slight decrease in the daily averaged differential pressure in the cleaned system over time. However, no significant difference between the control and intervention systems was observed.

In summary, the primary system results from the Vermont office site location suggest that routine cleaning of HVAC systems did not significantly affect the energy consumption patterns of the conveyance or the cooling system, nor did it significantly impact the differential pressure in the system. The lack of significant energy performance differences between control and intervention systems implies that other factors may play a more crucial role. At the Vermont site, this manifest in differences in the number and duration of back up compressor recalls between the cleaned and control systems.

Here, both the control and intervention air conditioning systems featured a backup compressor, which were frequently brought into supplementary service to meet cooling demand. A notable observation following HVAC cleaning was the reduced startup frequency of backup equipment in the intervention (cleaned) side (Fig. 3). A comparison between the control and intervention systems revealed that the backup compressor in the intervention side was activated 47 % less frequently than its counterpart in the control side. This reduction in back-up system startup frequency could potentially extend equipment lifetime and reduce maintenance costs.

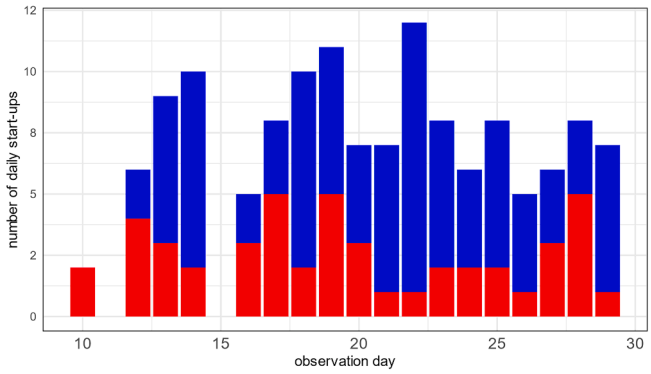

Fig. 3. Daily service recall frequency of back up air conditioning compressors supporting control (■) system and intervention system (■) in response to HVAC system cleaning in Johnson, VT office building.

Table 2
Table summarizing analyses of variance outcomes of selected energy consumption and differential pressure comparisons at the different sites. The significant codes used are as follows: *** indicates $p < 0.001$, ** indicates $p < 0.01$, * indicates $p < 0.05$.

Location	Parameter	System	Slope	Intercept	ANCOVA slope difference
Johnson, VT	Blower energy	Control	8.76	49706.08 ***	NS
		Intervention	14.10	27687.89***	
	Cooling energy	Control	−231.93*	23299.07***	NS
		Intervention	−231.36*	22036.38***	
	Cooling energy (backup)	Control	−48.30	4053.25***	*
		Intervention	−212.05***	5477.13***	
	Differential pressure	Control	0.00057	6.40***	NS
		Intervention	−0.0020	5.85***	
Pearl, MS	Blower energy	Control	1.73	528.63***	**
		Intervention	−6.58***	436.43***	
	Cooling energy	Control	−11.80*	1738.63***	*
		Intervention	−32.85***	1822.80***	
	Differential pressure	Control	−0.0041**	4.76***	*
		Intervention	−0.010***	4.73***	
Boulder, CO	Fan energy	Control	−0.95	4397.56 ***	***
		Intervention	33.17***	5208.38***	
	Fan energy (after hours)	Control	−4.73	3764.25***	***
		Intervention	−55.77***	6842.88***	
	Cooling energy	Control	−171.03***	6576.50***	*
		Intervention	−329.43***	17810.20***	
	Cooling energy (after hours)	Control	0.17	209.40**	***
		Intervention	−27.02***	2366.48***	
	Differential pressure	Control	0.00037	1.42***	***
		Intervention	0.011***	1.17***	
Pavia, Italy	Fan energy	Control	2592.6**	117184.1***	***
		Intervention	−38.09	57732.24***	
	Cooling energy	Control	−32.49	10821.42***	NS
		Intervention	−16.24	17407.68***	

Furthermore, considering the energy consumption of backup equipment (Supplementary Material, A 5), the comparison of power between the control and intervention systems revealed a significant energy consumption difference: the compressor on the intervention side demonstrated a substantially greater reduction in energy consumption compared to the control. These energy consumption patterns suggest that routine HVAC system cleaning may have a notable impact on the energy usage of backup compressors on these otherwise identical systems with similar architectural features and occupancy.

3.1.2. Pearl, MS

A similar analysis was done on the daily cumulative energy consumption of the blower and cooling systems, as well as the daily average differential pressure in the Pearl, Mississippi location. The intervention group included two blowers, while the control group had three blowers; additionally, both control and intervention HVAC systems were equipped with two compressors each. For the blower energy consumption, the intervention system exhibited a significant energy consumption decrease, while the control system showed no such performance changes

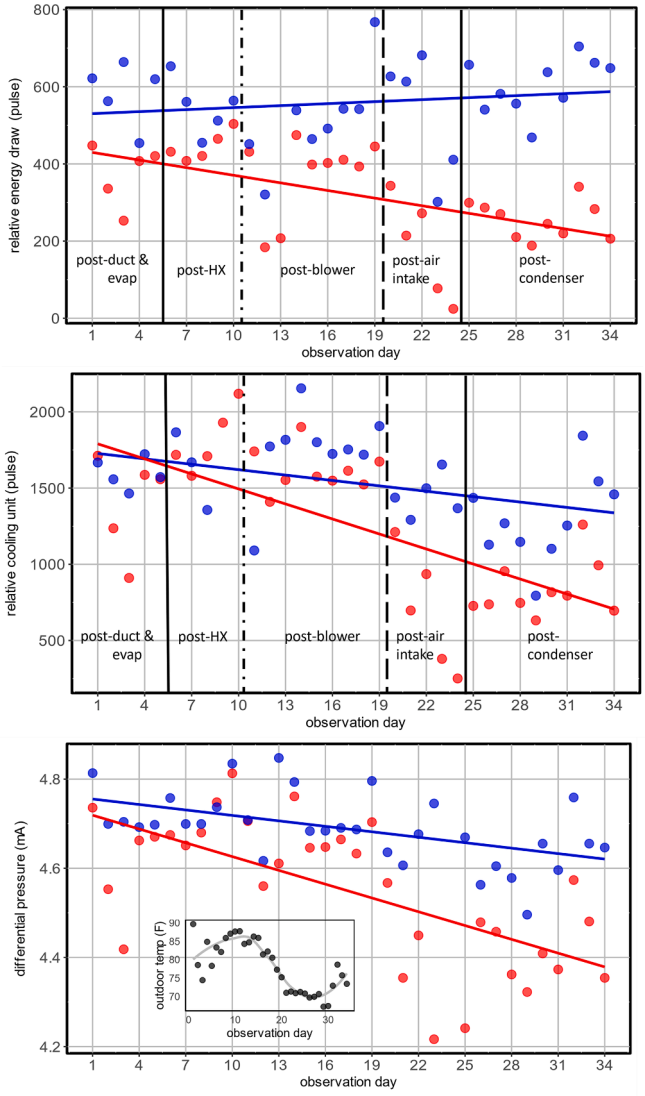

Fig. 4. Relative HVAC performance of control (-●-) system and intervention system (-●-) in response to stages of HVAC system cleaning in a Pearl, MS day care school building. **Top:** relative fan energy draw (normalized voltage pulses); **Middle**: relative cooling energy draw (normalized voltage pulses); **Bottom:** differential pressure across heat transfer equipment (normalized current (mA)); **Bottom inset**: outdoor temperature during observation period.

(Fig. 4). The daily energy use by blowers in both control and intervention systems, calculated with the methodology in Eq. (2), indicates that daily relative energy savings ranged between 4 % and 94 %, with an average of 41 % over the study duration. ANCOVA analysis also revealed a significant energy consumption difference between the control and intervention systems ($p < 0.01$), indicating that the routine HVAC cleaning resulted in a notable reduction in energy consumption (Table 2).

For the energy consumption patterns associated with the air cooling equipment, both systems showed significant decreases over time, consistent with the prevailing weather pattern; however, the intervention system demonstrated a steeper decrease compared to the control system. ANCOVA analysis confirmed a significant difference in slopes ($p < 0.05$), suggesting that routine cleaning led to a more pronounced reduction in cooling energy consumption.

In terms of daily average differential pressure (supply and outdoor air), both systems exhibited significant decrease over time, with the intervention system showing a steeper decrease compared to the control system. ANCOVA analysis indicated that routine cleaning resulted in a substantial reduction in differential pressure following individual stages of the cleaning process as well as the cumulative outcome.

The results from the Mississippi location demonstrate that routine cleaning of HVAC systems can significantly reduce energy consumption for both the blower and cooling systems, as well as lowering the differential pressure across this system.

3.1.3. Boulder, CO

In the analysis of the Colorado location, the daily cumulative energy consumption for the fan and cooling systems, as well as the daily average differential pressure, were examined for both the control and intervention systems. Cooling for this location was provided by a remote water-chiller system.

Concerning blower energy consumption, the intervention system demonstrated a significant increase over time and used between 20 % to 37 % less energy compared to control system on daily basis (Eq. (2). Meanwhile, the control system exhibited a non-significant decrease (A 6). Despite the increase in blower energy consumption, the intervention system showed a greater reduction in cooling energy consumption over time. Both systems showed significant decreases in terms of cooling energy consumption, consistent with the prevailing weather pattern, with the intervention system demonstrating a steeper decrease compared to the control system. ANCOVA analysis suggested that routine cleaning could be associated with a more pronounced reduction in cooling energy consumption at this location (Table 2).

Regarding daily average differential pressure, both systems exhibited significant increases over the study period, with the intervention system showing a much steeper increase compared to its control. Although the differential pressure (DP) of the intervention system remained lower than that of the control over an extended period, it increased toward the end of the cleaning phase and into the heating season (as indicated by outdoor air temperature data), allowing the system to provide conditioned air more effectively. An examination of supply air temperature and humidity revealed that the control system was unable to provide an appropriate temperature of conditioned air to the indoor spaces it served, while the cleaned system was capable of supplying air at desired conditions (A 7). This discrepancy may explain why the cleaned system consumed more conveyance (fan) energy compared to the control system, as the control system was unable to meet the load demand (A 8).

Unlike the other locations, the Colorado site HVAC systems remained fully operational during both occupied and unoccupied periods. Therefore, both occupied and unoccupied air conditioning data from the Colorado site was included for this aspect of the analysis. The HVAC system in Colorado featured integrated VAV controllers, which were initially deactivated ("locked open") during the primary study to maintain consistent airflow rates into the rooms. VAV terminal boxes modulate VAV damper positions to regulate both the supply airflow and

a "reheat" region to help better maintain local zone temperatures. Recent research indicates that VAV configurations can influence fan power cycles as well as cooling and heating energy consumption [25]. As a result, VAV boxes were initially deactivated during and after the cleaning process. However, once sufficient post-cleaning data was collected to compare sensor measurements between intervention and control systems, they (VAVs) were subsequently (re)activated and monitoring continued assess the system's performance in regular operational mode, i.e., with all VAVs activated.

Regarding fans energy and cooling, the intervention system at the Colorado site exhibited a steeper negative slope compared to the control (Fig. 5, A 8). The comparison of slopes between the control and intervention systems yielded significant differences. The intervention group, apparently benefiting from cleaning, displayed a substantially greater reduction in energy usage compared to the control system when considering the prevailing weather pattern. This finding underscores the potential efficacy of routine cleaning in improving energy efficiency considering both occupied and unoccupied hours.

3.1.4. *Pavia, Italy*

Similar analysis was done on the daily cumulative energy consumption of the blowers and cooling system in University of Pavia buildings. For blower energy consumption, the control system exhibited a significant positive slope, indicating an increasing trend in energy usage over this seasonal time. In contrast, the intervention system displayed a negative slope (Fig. 6). The comparison of slopes between the control and intervention groups yielded statistically significant differences considering the prevailing weather pattern during the end of the cooling season (Table 2). The differences in daily energy use by blowers in control and intervention systems at the Pavia site, calculated based on Eq. (2), shows that daily relative energy savings ranged between 39 % and 67 %, with an average of 60 % over the study duration (Fig. 6).

For the energy consumption used for cooling, both the control and intervention groups exhibited insignificant changes over time. While routine HVAC system cleaning demonstrated a significant reduction in blower energy consumption, its impact on cooling energy consumption was not significant (A 9). These findings highlight the importance of considering all system characteristics and environmental factors when evaluating the efficacy of cleaning interventions.

3.2. *Supply airflow*

In this study, a systematic method was used to measure and document the supply air from each supply register at each site (in cubic feet per minute, or CFM). Supply air measurements were obtained before, during, and after the cleaning process, with data recorded for both control and intervention systems. All sites had non-operable windows

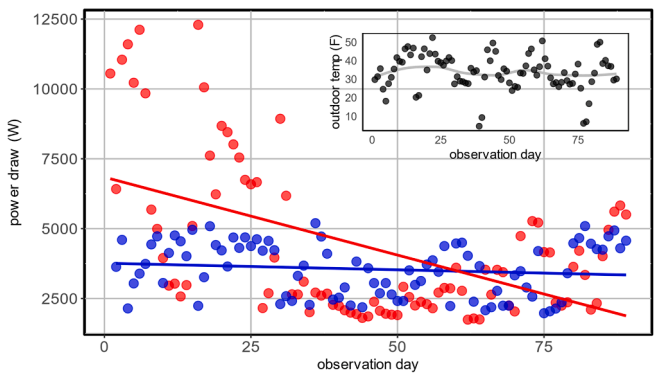

Fig. 5. Power draw of supply air HVAC fans operating in control (-●-) system and intervention system (-●-) in response to HVAC system cleaning in a Boulder, Colorado University classroom and office building. **Inset:** outdoor temperature during observation period.

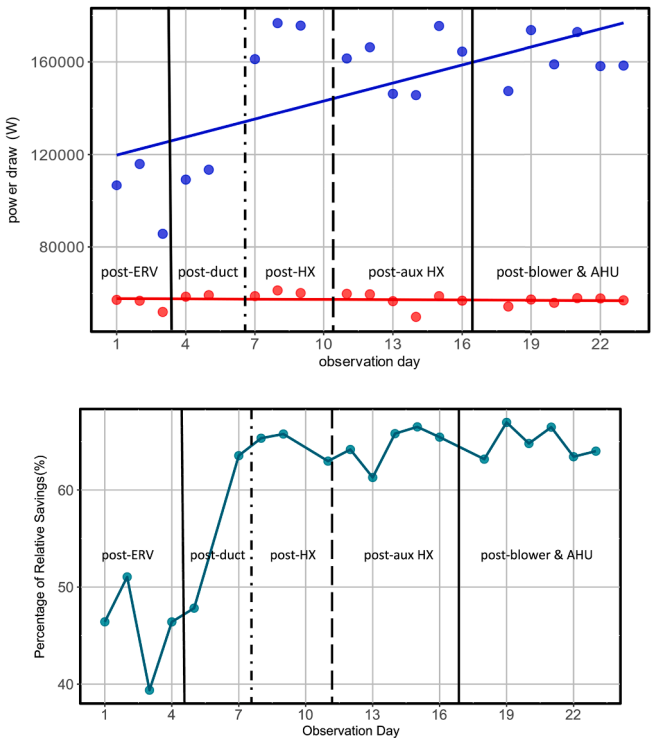

Fig. 6. Top: Power draw of supply air HVAC fans operating in control (-●-) system and intervention system (-●-) in response to stages of HVAC system cleaning in a Pavia, Italy, classroom and office building. **Bottom:** The percentage of relative energy savings over the duration of study.

and self-closing mechanical doors which were shut during these supply air measurements. Measurements were taken on the same days for both control and intervention systems. As shown in Fig. 7, the increase in supply airflow differences generally exhibits a positive slope, indicating the cumulative effect of cleaning on conditioned air flow to the occupied space. In all cases except one, the supply flow differences between control and intervention systems increased over time. Notably, the disparity in supply airflow rates between intervention and control systems rose by over 40 % in Colorado and Italy from pre-cleaning to post-cleaning. The Mississippi site showed a remarkable increase of 174 %.

Initially, the control system at the Mississippi site showed higher pre-cleaning measurements than the intervention system. However, as the cleaning progressed, the intervention measurements surpassed those of the control side. Further examination of the Mississippi site data shows (Fig. 8) that the intervention site had the dirtiest ducts among all the sites, despite having the shortest duct length and the smallest surface area cleaned. Notably, the evaporator coils in Mississippi were in better condition than those at other locations. The positive impact of duct cleaning on supply airflow rates at this site was evident in the data shown in Fig. 7.

In Vermont, both the ducts and coils were relatively clean. The primary issue was the presence of leaves and large debris in the air handling unit (AHU), which was located outside the building on the ground in the open air. An improvement in supply airflow was observed after cleaning the AHU box during the final stages of the cleaning process. This situation might also explain the minimal difference in energy savings between the control and intervention systems at this location, as the main obstruction was large debris rather than dust both in ductwork and cooling/heating equipment.

As judged by conditioned supply airflow, we were able to isolate a clear ventilation performance benefit in response to routine duct cleaning. The greatest change from the previous cleaning phase was an 89 % increase in conditioned supply airflow at the Italian site and 76 %

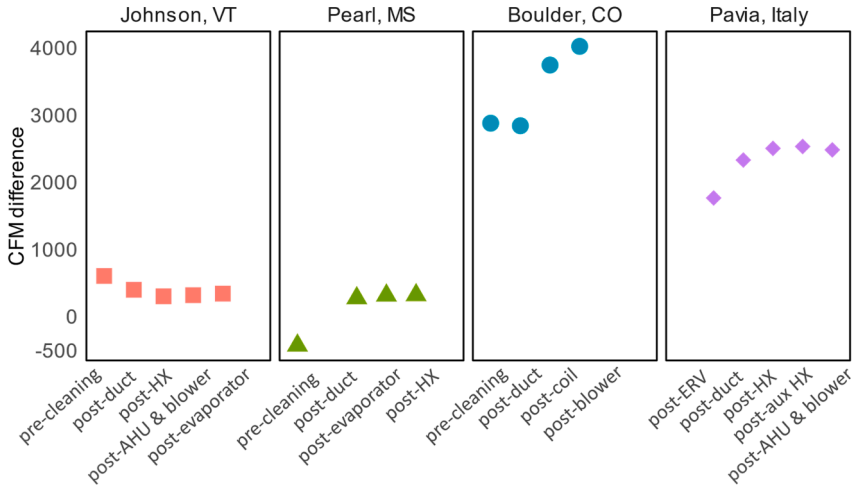

Fig. 7. Difference in supply air flow (ft^3/min) to occupied spaces in response to different cleaning stages at the respective sites: office building, Johnson, VT (■); day care school building, Pearl MS (▲); University classroom building, Boulder, CO (●) and University classroom and office building, Pavia, Italy (◆).

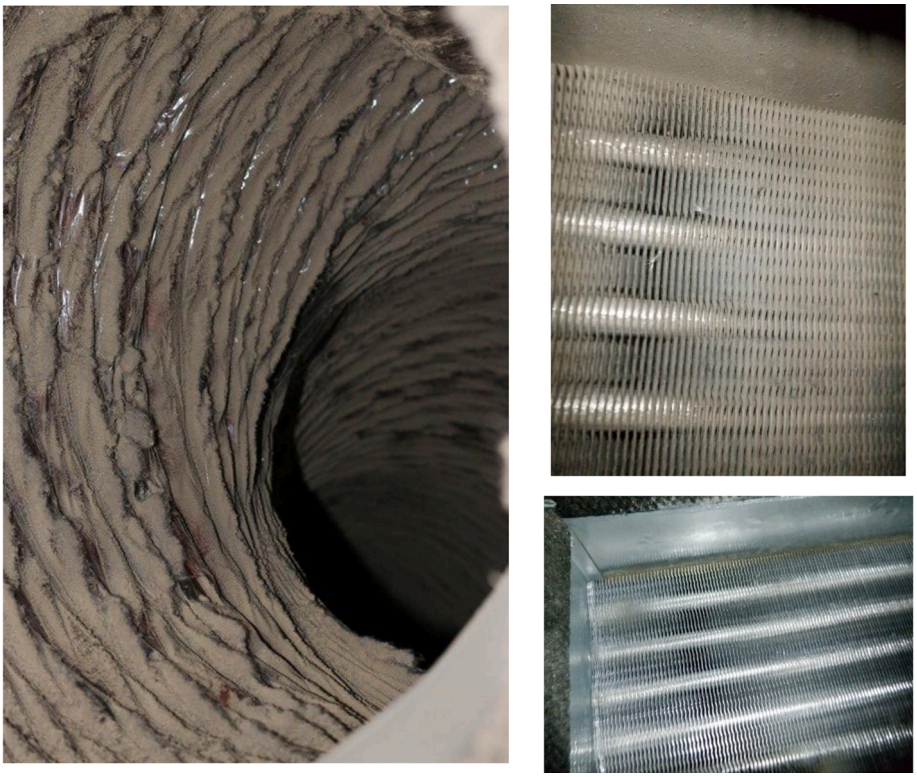

Fig. 8. Left: An image of the spiral duct taken before system cleaning at the study location in Pearl, MS. **Right:** A before (top) and after (bottom) system cleaning images of evaporator coils at the study location in Boulder, CO.

in Mississippi, following duct cleaning. In Italy, HVAC coils were not significantly dirty, however the ducts were visibly soiled, notably including large areas of dust accumulation. In Colorado, the most significant effect was observed after coil cleaning, with a 110 % increase in conditioned supply airflow compared to the previous phase, followed by a 20 % increase after blower cleaning. The coils in Colorado were visibly soiled (Fig. 8). Cleaning these coils led a notable increase in supply airflow compared to the control system, highlighting the importance of maintaining clean coils for optimal system performance.

A critical evaluation of conditioned supply airflow measurements shows that airflow rates consistently and significantly increased in cleaned systems compared to their uncleaned counterparts (Eq. (3). Across the different cleaning stages, the average relative increase in supply airflow (CFMs) were as follows: 46 % for the Italian site; 35 % for Colorado site; 19 % for Mississippi site; and 10 % for the Vermont site. Comparative analysis suggests that the larger cleaned duct area, correlates with a greater relative increase in supply airflow. The two sites with the largest improvements, Italy and Colorado, had the greatest duct surface areas cleaned and the highest duct surface-to-serving area ratios. They also had the largest cooling capacities. Details on duct length, duct surface area, area served by the HVAC system, and the cleaned surface-to-served area ratio for each project location are provided in Supplementary Material (A 10).

3.3. Complementary findings on system performance

Our study supports a conclusion that additional (unanticipated) benefits may be associated with HVAC cleaning process. Analysis of the system differential pressure at the Colorado site suggests system stability benefits can result from HVAC cleaning where VAV control is enabled. Fig. 9 illustrates system differential pressure when Variable Air Volume (VAV) boxes were subsequently activated following cleaning intervention; these results suggest improved stability resulted from HVAC cleaning. Notably, the occurrence and range of pressure fluctuations is markedly smaller in the intervention system operation where compared to the control group – a condition which remained apparent for several months after cleaning. This reduction in pressure variability can positively impact system control, particularly considering the influence of (large and capricious) pressure differences on various system components.

It is important to note here that those systems with the longer duct work reaches (Pearl, MS and Pavia, Italy (A-7)), benefited in large supply air flow increases, in response to isolating the duct work cleaning alone.

4. Discussion

Significant energy savings in larger buildings with medium-density occupancy could be realized and verified by implementing the coupled cleaning & monitoring approach described here. Due to differences in system characteristics across the four climatic locations—such as variations in ductwork size and equipment type— direct comparisons of energy savings and supply airflow improvements could not be applied here. However, despite this diversity, net energy consumption significantly decreased during and after HVAC system cleaning, though the degree of impact following each cleaning stage (fans, ducts, heat transfer equipment, etc.) varied by site. Only at one site did the blower energy increase in the intervention system; further analysis indicated that the associated control system was in poor condition, unable to perform adequately in supplying conditioned air at the desired set points.

Our analysis also indicated that larger systems, in terms of ductwork conveyance and cooling capacity, benefited more from cleaning than their smaller counterparts. Examination of all cleaned HVAC systems suggests that a larger cleaned duct area is associated with a greater relative increase in supply airflow. In smaller systems, the larger relative energy benefit is realized from coil cleaning, as cleaner evaporative coils enhance heat exchange efficiency by increasing the effective area for heat transfer. Additionally, clearing the limited flow passage area within coils can further improve flow rates.

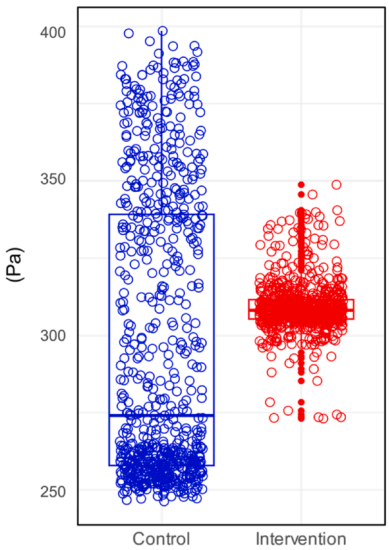

Fig. 9. Distribution of differential pressure (inches water) across filter/cooling coil complex operating in control (-○-) system and intervention system (-○-) in response to HVAC system cleaning in a Boulder, Colorado University classroom and office building with VAV systems engaged. Bottom line of boxes represents 25th percentile; center line of boxes represents 50th percentile; upper line of boxes represents 75th percentile.

Accurate and affordable energy consumption measurements are complex, particularly in larger systems. However, a new generation of IAQ and energy sensors, such as those employed here, now offer affordable detail to energy consumption patterns in response to building hygiene interventions beyond conventional BAS. Additionally, in cases where multiple faults are present within the HVAC system, implementing a maintenance schedule, such as HVAC system cleaning, may offer only potential for system performance diagnosis that was not previously available without on-site inspections [54]. The methods outlined in this study present an advance in leveraging modern monitoring IoT networks for demonstrating the efficacy of HVAC hygiene. Modern energy monitors are accurate and account for energy "losses and gains" in the specific context of short- and long-term seasonal weather changes. Future work can consider extending the post-cleaning data monitoring time to study the re-accumulation of dust (and biofilms) in-and-on HVAC components to better evaluate the longitudinal effects of cleaning.

At this time, we were unable to find a study in scope or design similar to that reported here. To meet rising societal expectations for indoor environment improvements, integrating strategies and analysis for the concomitant management of indoor air quality and maintenance of energy-efficient HVAC systems is essential. In this context, building hygiene costs, notably including periodic HVAC system cleaning, should be weighed in a comprehensive benefits analysis that considers longitudinal energy savings, improved ventilation performance and associated indoor air quality factors.

5. Conclusions

The advent of post-pandemic indoor air quality guidelines suggests that building hygiene will gain increased attention as systematic part of building maintenance portfolios. This study demonstrates how a new generation of affordable IAQ and HVAC system monitors can compile secure IoT archives into an evidence base that enables building mangers to leverage HVAC hygiene into operational scenarios that help optimize energy consumption to help maintain optimal supply airflow rates.

Here we analysed ventilation performance in response to HVAC cleaning in moderately aged buildings (less than 20 years) in four markedly different climates. This study shows that statistically significant improvements in HVAC energy consumption and conditioned air supply can be realized following staged, systematic cleaning of different HVAC systems during the peak of cooling season. On average, intervention systems saved between 41 % and 60 % in conveyance (fan/blower) energy (with one exception) and were able to supply 10 % to 46 % more airflow compared to their uncleaned counterparts. This study demonstrates that the cleaning of HVAC systems can yield significant co-benefits, including enhanced energy efficiency and improved supply airflow rate. These outcomes emphasize the role that facility managers can play in reducing the carbon footprint associated to their building operations. Policies mandating routine, rather than episodic HVAC system maintenance can facilitate the implementation of these measures.

It is important to note that HVAC cleaning can offer additional benefits beyond energy efficiency and fresh air delivery rates. Cleaned HVAC systems presented greater system stability in operational conditions, characterized by decreased fluctuations in system differential pressure. Moreover, the cleaned HVAC systems show decreased dependence on backup equipment, implying possible cost savings in longer-

term operational and maintenance expenses.

Maintaining adequately conditioned supply airflow is essential to ensure both comfort and appropriate indoor air quality [55]. We observed the important benefit of significantly increasing conditioned air flow in response to all stages of HVAC cleaning—notably including cleaning the ductwork itself. Lower airflow rates can lead to poor mixing conditions and uneven distribution of conditioned air, resulting in inadequate ventilation and spatial–temporal enthalpy inconsistencies. At the same time, studies have shown that higher airflow rates result in increased fan energy and total annual energy consumption [56]; thus, an optimum balance between minimum air quality considerations, room air mixing regimes and HVAC energy consumption is an important operational goal; indeed, routine HVAC hygiene may help achieve this goal. Only through thoughtful monitoring can such optimization be achieved and confirmed.

CRediT authorship contribution statement

Nasim Ildiri: Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Data curation. **Emma Biesiada:** Writing – review & editing, Methodology, Investigation, Data curation. **Tullio Facchinetti:** Writing – review & editing, Visualization. **Norma Anglani:** Writing – review & editing, Visualization, Data curation. **Nouman Ahmed:** Writing – review & editing, Data curation. **Mark Hernandez:** Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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- ALISEA S. r. l.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enbuild.2024.115147.

Data availability

Data will be made available on request.

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Chapter 6



Multidimensional Energy Performance Indicators and Data Analytics Scientific Framework to Enable Effective Energy Management in Hospitals

6 MULTIDIMENSIONAL ENERGY PERFORMANCE INDICATORS AND DATA ANALYTICS SCIENTIFIC FRAMEWORK TO ENABLE EFFECTIVE ENERGY MANAGEMENT IN HOSPITALS

Hospitals have complex energy demands because they operate continuously and require reliable heating, cooling, lighting, and medical equipment. This chapter is based on a published conference paper that presents a fish-bone (Ishikawa) framework for identifying the main factors that influence hospital energy use. The study groups these factors into infrastructure, operations, environmental conditions, and historical data, providing a structured approach for energy assessment. The framework is evaluated using data from 44 hospitals and regression analysis to examine the contribution of different energy indicators. The findings support the use of multiple indicators to improve energy benchmarking and decision-making, contributing to the overall objective of this thesis to develop practical, data-driven methods for energy management in healthcare buildings. Further validation using larger and more diverse hospital datasets and available indicators will help to determine whether the observed performance difference persists across different healthcare buildings.

Multidimensional Energy Performance Indicators and Data Analytics Scientific Framework to Enable Effective Energy Management in Hospitals

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***Abstract*—Hospitals have exceptionally high energy needs, but tracking insightful energy indicators can unlock major efficiency opportunities. As hospitals worldwide strive for sustainability, analysis based on multidimensional indicators that capture usage interdependencies is invaluable. The goal is to propose meaningful indicators helpful in analysis of hospital facilities in energy management. A key insight is that most hospitals likely remain far from optimized energy performance, despite their necessary high consumption. Significant potential exists for conservation and waste reduction through upgrades guided by energy efficient indicators and informatics. With robust data frameworks with scientific approaches is not yet common in healthcare, substantial room for efficiency improvements persists by adopting leading energy data practices. Accordingly, this paper presents an introduction to relevant energy indicators research for hospitals seeking to activate data-centric energy management. It serves both as a primer on the promise of leveraging advanced indicators for usage insights, and a preliminary approach in applying related techniques in a comprehensive energy optimization framework. With creative data use being new in healthcare, the concepts covered aim to ready hospitals to finally achieve long-possible energy savings according to Sustainable Development Goals. Advanced metrics can guide hospitals towards greener operations, cost savings, and climate-friendly care. Though hospitals present unique challenges, embracing innovations in energy intelligence promises to finally unlock decades of elusive savings via analytics-based sustainability.**

Keywords*—*energy management*, *energy indicators*, *energy intensity*, *regression learner*, *hospital*, *buildings

I. Introduction

Hospitals fall under the classification of commercial buildings where at least half of the total floor area serves non-residential, non-industrial, and non-agricultural purposes [1]. Due to stringent conditioning, heating, and power needs, these facilities are generally substantial consumers of both electric and thermal energy. Factors like air conditioning, hot water supply, and operation of co-generation systems comprised of diesel engines and gas turbines contribute to high consumption profiles [2]. Energy usage is influenced by a country's level of economic development, used as an indicator of the reliability of electricity provision to healthcare infrastructure [3]. Uninterrupted operation necessitates detailed understanding of hospitals' round-the-clock energy footprint, especially in developing nations where access to reliable power can be limited. Unfortunately, the diversity across hospital types complicates generalization of consumption patterns since facilities can vary significantly in terms of services offered, construction area, medical specializations, number of beds, and other operational attributes [4].

Hospitals inherently consume more energy than similarly sized office buildings and educational institutions due to their 24/7 operational demands for services like heating, cooling, ventilation, lighting, and powering medical equipment. Studies analyzing commercial building energy use have consistently found hospitals to be among the most energy-intensive building types. The environmental impacts from extensive energy use make healthcare a critical sector to address.

This study aims to systematize energy indicators and metrics hospitals can use to control total energy consumption and monitor progress over time. Collating data from various prior healthcare energy studies can also inform intelligent national and international bench-marking systems. Hospitals never close, requiring constant electricity, leading to excessive energy use and accompanying greenhouse gas emissions that worsen climate change. The healthcare sector accounts for nearly 5% of emissions in developed countries. Curtailing hospitals' carbon footprints is therefore essential for climate change mitigation.

Previous research papers have investigated hospitals' energy usage from several vantage points. Some have delineated the distribution of consumption across different medical equipment in various hospital categories like childcare, acute care, etc. [2]. Other studies have explored pathways to boost energy efficiency via load profiling, demand forecasting, and quantifying barriers to adoption of energy-saving technologies [2], [5], [6]. A range of electricity forecasting techniques have been applied, such as Laouafi et al.'s approach for short-term demand estimation under routine and abnormal conditions [7], and Bagnasco et al.'s neural network-based load modelling [8].

Overall, hospitals' electricity requirements have been assessed through lenses like techno-economic analysis for co-

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generation viability [9], multi-objective optimization of stable system configurations [10], and building energy simulations covering electricity, steam and hot water systems [11], [12]. The paper is structured as follows: Section II leverages a fish-bone diagram to visually map the multidimensional indicators affecting hospital energy usage. This enables root cause analysis of inefficiencies characterizes hospital energy loads based on macro and micro consumption patterns. Section III reviews commonly used research indicators for total energy consumption with analysis using comparison different machine learning algorithms comparison with four feature selection techniques are applied. Finally, in Section IV comparative R-squared and RMSE validation analysis provided insights into trade-offs between predictive accuracy and model simplicity providing a foundation for enabling effective energy management in hospitals for effective energy management that measurably improves efficiency and reduces emissions by ensuring sustainable development goals. In summary, the paper aims to systematize energy indicators that hospitals can track over time to control consumption and monitor efficiency progress with a broad framework for forecasting and characterizing hospital energy consumption using robust data-driven methods using multidimensional indicators affecting hospital energy usage.

II. Healthcare Buildings Energy Indicators

The term healthcare facility is broad, encompassing buildings or portions thereof that house hospitals, nursing homes, residential care facilities, clinics, medical and dental offices. Any buildings within industrial or commercial complexes used for medical purposes logically fall under the purview of this research. The heterogeneity inherent to hospital infrastructure - in terms of design, surroundings, regional climate, national development status, and governing regulations yields diverse energy consumption characteristics. Geshwiler et al. propose guidelines for new healthcare construction aimed at optimal conservation, with a focus on curbing HVAC system usage [13]. The U.S. Department of Energy advocates building energy models adhering to methods described by Harversons et al., involving baseline and as-designed models calibrated for climate zone and total floor area to determine ASHRAE 90.1 compliance for aspects like HVAC specifications and envelope parameters [14], [15]. Collectively, these influence equipment sizing for heating/cooling while flexibility in load distribution remains a critical design consideration.

Under infrastructure, to define indicators, parameters like hospital bed capacity, building construction time, and electrical systems can be assessed to gauge maintenance costs and upgrade needs. Operational aspects such as specialized depart-

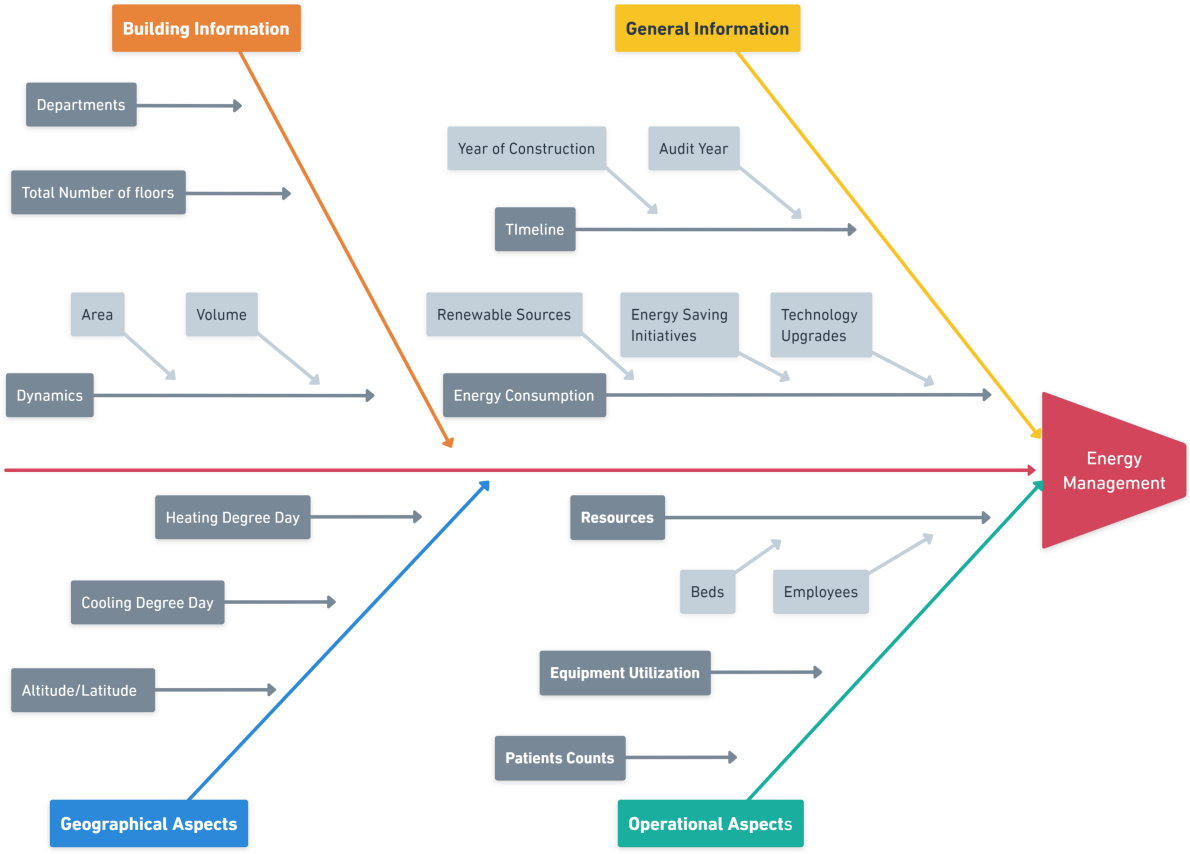

Fig. 1. Fish-bone info-graphic of multidimensional energy performance indicators interrelationships driving Energy Management in the Hospital

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mental requirements, equipment loads, and occupancy schedules provide insight on tailoring systems to actual demand. The fish-bone diagram provides a powerful visual tool for analyzing the myriad indicators affecting energy consumption within a healthcare facility. By delineating relevant categories such as infrastructure, operations, environment, and historical data, the technique enables systematic evaluation of root causes behind inefficient usage.

In essence, while safety remains paramount, healthcare facilities' unique mission necessitates electrical designs tailored to their specialized services, operating environments, geographic contexts, and stringent clinical standards - ranging from basic outpatient clinics to complex inpatient hospitals delivering round-the-clock acute care. By categorizing and graphically depicting various contributory elements, the fish-bone provides an intuitive info-graphic as shown in Fig. 1 for stakeholders to grasp the inherent complexities and interrelationships driving a facility's energy profile. Developed through collaborative inputs from diverse stakeholders, the fish-bone diagram builds holistic awareness of the complex interrelationships driving the facility's energy profile. Maintained dynamically, it aids data-driven prioritization of high-impact energy initiatives aligned with the hospital's specialized mission. The fish-bone thus serves as an invaluable visualization tool for pursuing continual gains in sustainability and efficiency in healthcare settings. Healthcare facilities' systems are fundamentally missioned to provide healing environments conducive to patient care and treatment across varying disease/disability severities. Design criteria for hospital buildings vary significantly based on the range of medical services delivered. For instance, the requirements of an inpatient ward differ vastly from those of a surgery suite or physician's office. 24/7 hospital operations managing non-ambulatory patients necessitate design standards entirely distinct from a medical office facility operating akin to conventional workplaces [17].

Geographical location represents the primary determinant diversifying hospitals' electrical loads worldwide. Degree days quantify climate impacts per season, widely employed as an energy design guideline to forecast demand [18]. International standards governing medical electrical installations prioritize safety, particularly indirect contact protection. Standard IEC 60364-7-710 classifies medical areas into Groups 0, 1, and 2 based on contact between equipment and patients [19]. This IEC subset mandates requirements for electrical systems in healthcare settings to safeguard patients and staff, applicable to hospitals, clinics, practices, care centers, and workplace medical spaces [20]. Evaluating HVAC and lighting energy demands via standardized calculation protocols is now common practice for system planning and optimization in hospitals. However, a knowledge gap persists in understanding the electricity consumed by proliferating medical devices within increasingly complex clinical environments. As electrically-operated equipment grows ubiquitous, managing energy expenses has become a financial priority for modern healthcare operations [16].

III. Feature Selection Based on Data Analysis

Effective energy management in hospitals requires monitoring a multitude of influential parameters related to infrastructure, operations, and environmental factors as focused in previous section. This analysis leverages key indicators including:

- number of beds
- cooling degree days
- heating degree days
- year of construction
- number of employees
- total area & volume
- annual electricity consumption

data for regression modelling aimed at identifying significant drivers of hospital energy use in which data from data 44 hospitals is considered.

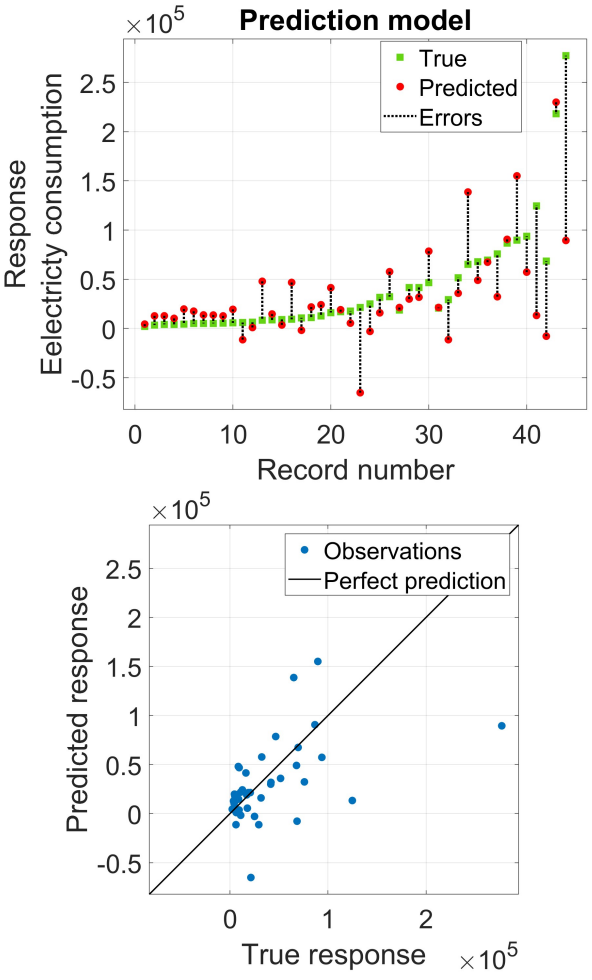

Fig. 2. Validation results with predicted and actual response of F test

Electricity consumption is modeled as the response variable, with the other indicators as potential explanatory predictors. [21] The data compiled provides crucial real-world insights into relationships between hospital scale, climate, occupancy,

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and electrical energy footprint. Regression analysis enables quantifying the relative impacts of these indicators on consumption patterns. The regression learner application in MATLAB is utilized for model development using four different feature selection methods - F test, Minimum Redundancy Maximum Relevance (MRMR), Relief for Regression (RReliefF), and no feature selection. This facilitates comparative analysis to determine the optimal combination of energy indicators as inputs to reliably predict electricity consumption. F test ranks predictors based on ANOVA F-statistics, MRMR applies mutual information theory for feature selection, RReliefF uses nearest distances, while no feature selection uses all features.

A. F Test

Indicators belonging to Geographical aspects, building information and operational factors served as the most predictive inputs as compared to the general information of hospital, since they have high individual correlation with electricity consumption. Validation results with predicted and actual response of MRMR are shown in Fig. 2

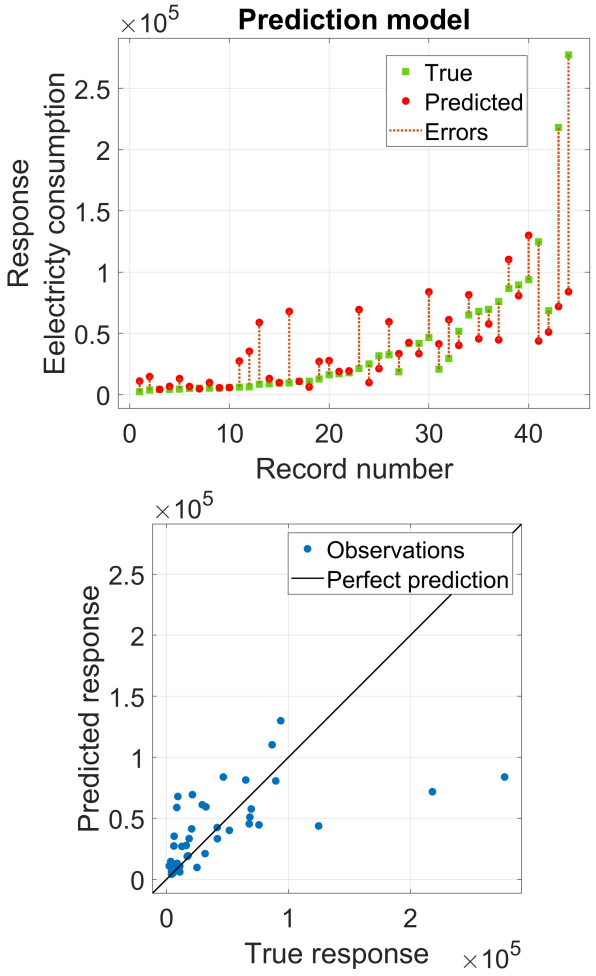

Fig. 3. Validation results with predicted and actual response of MRMR

B. Minimum Redundancy Maximum Relevance

It optimizes the mutual information between input variables and electricity consumption, while minimizing redundancy between selected features. This yielded a subset like building information including volume and area, operational aspects including the employee count and d year built by capturing non-linear relationships. Validation results with predicted and actual response of MRMR are shown in Fig. 3

C. RReliefF

It distinguishes electricity consumption patterns based on nearest neighbor distances calculated using the input variables. It picked indicators with maximizing between-class distances. Validation results with predicted and actual response of RReliefF are shown in Fig. 4

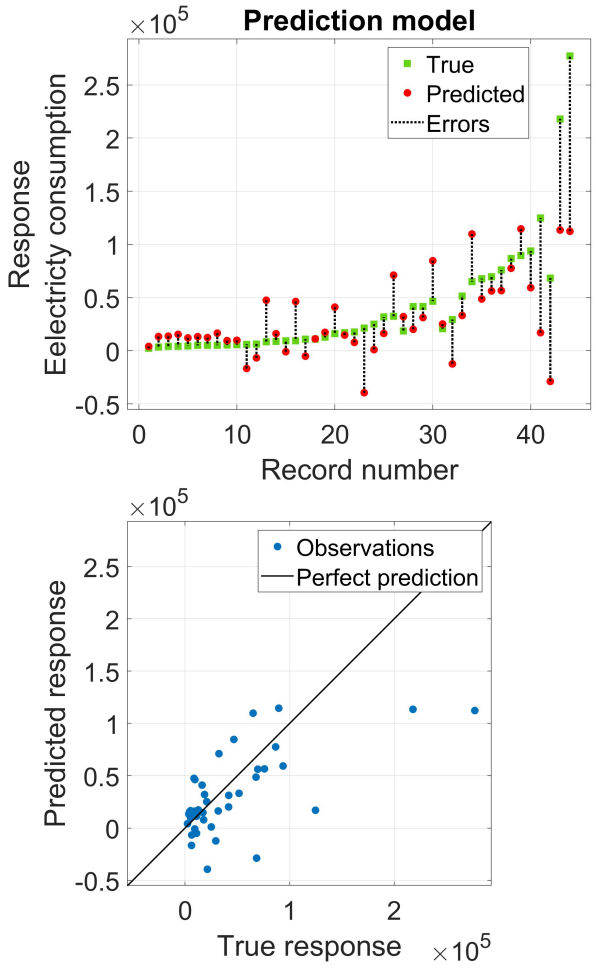

Fig. 4. Validation results with predicted and actual response of RReliefF

D. No Selection

Simply uses all provided features when training the regression model. By keeping all energy indicators as inputs, no selection maximizes preservation of potentially useful signals in the data. Even if some features contain redundancies, the

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model learns appropriate weighting of inputs through the training process. The danger of over-fitting is also reduced for this small data set. Validation results with predicted and actual response of no feature selection are shown in Fig. 5

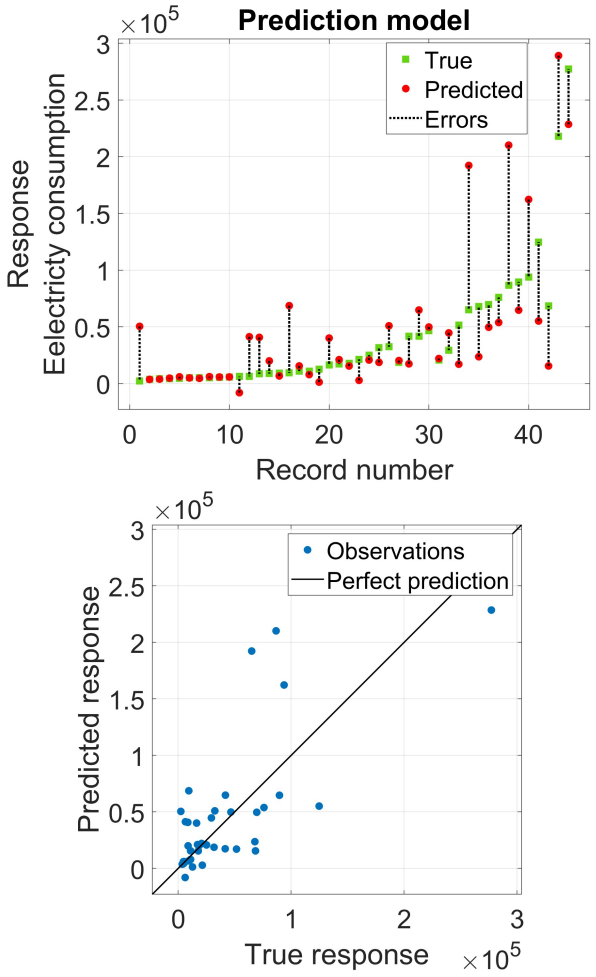

Fig. 5. Validation results with predicted and actual response of no feature selection

IV. Analysis based on root mean squared error and R-squared validation

The model used a key indicators and influential parameters related to infrastructure, operations, and environmental factors including number of beds, cooling degree days, heating degree days, year construction, number of employees, total area, volume, and electricity consumption with supervised regression algorithm to learn the relationships between the input variables and response as electricity consumption. The trained model then made predictions for hospitals in each selection criteria. A model able to predict electricity consumption solely from technical specifications enables simplified comparisons between the true and predicted values. The initial machine learning model implemented is trained on the dataset of 44 hospitals. Since this model only used 44 training examples, predictions may have significant errors uncovering the full complexity in each selection criteria.With a larger dataset covering a diverse range of hospitals, the model can learn how these different factors interact and influence electricity consumption patterns. It can identify intricate relationships and patterns that may not be evident in a small dataset. Additionally, a small dataset increases the risk of over-fitting, where the model learns the specific data present in the limited training of 44 hospitals.

A. Root mean squared error

Root Mean Squared Error (RMSE) provides a quantitative estimate of the deviation between a regression model's predicted values and actual observations. Lower RMSE indicates greater predictive accuracy. Examining the RMSEs for different feature selection techniques offers insights into model performance.The F test's higher RMSE of 43892 suggests its overall regression model, using features ranked by individual significance, has lower accuracy. MRMR and RReliefF's RMSEs of 43701 and 42549 are superior, demonstrating their ability to identify feature subsets yielding improved electricity consumption predictions.

Critically, no feature selection attains the lowest RMSE of 39102 as shown in Fig. 5 This implies that for this data, a model leveraging all available energy indicators as inputs can best capture the intricate relationships governing hospital electricity use. However, while lower RMSE is desirable, it alone does not guarantee the optimum approach. The predictive stability, complexity, and interpret-ability of selected features also warrant consideration. Still, the superior validation error indicates no feature selection empirically performs best in accurately forecasting energy consumption based on the given hospital data set. The no selection approach takes an "inclusive" strategy by retaining all provided energy indicators as inputs when training the regression model to predict electricity consumption. At first glance, this seems counter intuitive - we expect that feature selection should improve model performance by eliminating noisy or irrelevant variables.

B. R-Squared values

The R-squared indicates how well a regression model captures the variance in the response variable. Examining the R-squared values for different feature selection techniques provides useful insights. The F-test's R-squared of 0.38 suggests its selected features explain only 35% of the variance in electricity consumption, indicating substantial unexplained variability. In comparison, MRMR and RReliefF attain higher R-squared values of 0.4 and 0.41, demonstrating improved explanatory power from their chosen feature subsets.

No feature selection approach achieves the maximum R-squared of 0.5, implying that utilizing all available energy indicators accounts for 50% of the variance in electricity use. This aligns with the optimal RMSE obtained earlier for no selection. Comparative R-squared and RMSE analysis provides

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valuable practical insights into the trade-offs between predictive accuracy and model parsimony when developing data-driven hospital energy use models. But ultimately, selecting the right approach involves holistically assessing multiple factors beyond just validation error. Depending on the analysis goals, model simplicity and interpret-ability may take priority over maximizing variance explained. Additional metrics, cross-validation, and holistic performance assessment are advised before final model confirmation. All the inputs represent sensible energy indicators that likely have some degree of legitimate explanatory relationship with electricity usage in hospitals. Number of beds, cooling/heating degree days, total area, volume, employees, and year all provide relevant signals correlated to energy consumption patterns. In practice, rigorously evaluating different performance indicators and cross-validating robustness is advised before finalizing the optimal modelling strategy. Nevertheless, these initial results highlight that for certain problems, an inclusive modelling approach using all explanatory variables could prove more accurate than selective feature engineering. The variance reduction from feature selection may be outweighed by the reduced bias of using all available explanatory energy data. A cross-validation evaluation can definitively determine if no selection indeed gives superior test accuracy over other methods

V. CONCLUSION

This paper demonstrated a broadly generalized framework for leveraging multidimensional energy data to enable effective electricity assessment and management in healthcare facilities. The comparative analysis of four feature selection techniques provided valuable practical insights into balancing predictive accuracy. Using all available indicators with no selection empirically emerged optimal for the given hospital data based on lowest RMSE and highest R-squared validation. However, rigorous validation on unseen data remains essential before finalizing the modelling approach. While the complexity of hospital systems poses challenges, embracing data-centric techniques promises significant efficiency improvements towards sustainability. Further research should focus on delineating precise energy indicators, predictive models, and optimization algorithms tailored to the healthcare sector's unique demands. As hospitals worldwide strive for greener operations, data-driven energy intelligence will prove invaluable for unlocking elusive savings and reducing environmental impacts according to Sustainable Development Goals.

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Chapter 7



Energy Performance Benchmarking and Indicators: A Comprehensive Framework for scientifically sound Data-Driven and Energy Management Improvements in Hospitals

7 ENERGY PERFORMANCE BENCHMARKING AND INDICATORS: A COMPREHENSIVE FRAMEWORK FOR SCIENTIFICALLY SOUND DATA-DRIVEN AND ENERGY MANAGEMENT IMPROVEMENTS IN HOSPITALS

Hospitals consume large amounts of energy, but comparing their energy performance is difficult because of differences in building size, medical services, and operating conditions. This chapter is based on a published conference paper that develops a framework of energy performance indicators for hospitals. The study introduces a range of indicators that assess energy use from different perspectives, including building characteristics, occupancy, fuel type, and weather conditions. It also applies regression and machine learning techniques to analyse data from multiple hospitals and identify the main factors influencing energy consumption. The proposed framework provides a practical approach for improving energy benchmarking and supports the overall aim of this thesis by promoting data-driven energy management in healthcare facilities.

Energy Performance Benchmarking and Indicators: A Comprehensive Framework for scientifically sound Data-Driven and Energy Management Improvements in Hospitals

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***Abstract*— Hospitals are extremely energy-intensive facilities, but improved tracking and analysis of key energy indicators can enable better management of consumption, costs, and emissions. Multidimensional indicators provide greater visibility into the interdependencies between hospital infrastructure and operations. Energy usage intensity that adapts based on different operating conditions can reveal new efficiency pathways and opportunities using data analysis. This paper (i) synthesizes research on hospital energy use patterns, metrics, and indicators and (ii) it provides an overview on use of new indicator for a data driven tool aiming to collect a systematic set of benchmarks to support an effective energy management in hospital facilities. While hospital energy demands are high, tremendous potential to cut energy waste through technical strategies based on the specific energy indicators adoption remains untapped. New leveraging indicators act as pivotal elements for hospitals to institute systematic energy conservation programs including TEC (Total Energy Consumption) forecasting. Enhancing data collection and monitoring methods will further improve the efficacy of indicators. This paper serves as a background study and introduces to a selective literature helping to identify suitable energy indicators as part of a holistic approach to achieve more sustainable energy goals.**

Keywords—energy management, energy indicators, energy intensity, medical equipment, hospital, buildings,

I. INTRODUCTION

Hospitals routinely exhibit energy utilization intensities higher than similarly sized office buildings and educational institutions. This is largely due to their unique round-the-clock operational requirements for heating, cooling, ventilation, lighting, and medical equipment. Various analyses of commercial building energy usage have found that hospitals have significantly higher energy utilization intensities compared to other building typologies. According to the US Energy Information Administration (EIA), healthcare facilities had an average energy intensity of 545 kWh/m^2 in 2012, the second highest after food service buildings [1]. For 2018, the value was projected to be in the range of 457 kWh/m^2. Despite the decrease, this figure is still more than double that of a typical office building [2].

The data point about UK's National Health Service (NHS) facilities having TEC (Total Energy Consumption) of 350 kWh/ m^2 from a 2008 report by the Carbon Trust. The exact figure was calculated from study of 244 NHS sites across acute care, mental health, primary care, and other facilities [3]. Hospitals operate continuously without closure, necessitating constant power. Excessive energy usage consequently leads to heightened carbon dioxide and greenhouse gas emissions that accelerate climate change. Comparatively, the healthcare sector accounts almost 5% of greenhouse gas emissions in Developed Countries. Reducing hospitals' carbon footprints is therefore critical for mitigating climate change [4].

Extensive energy usage and emissions make the healthcare sector a critical participant in aggravating environmental harm, hence the purpose of this study is to discuss of a systematization of energy indicators and metrics which can help hospitals keep their total energy consumption (TEC) under control and monitor improvements over time towards stronger energy data management practices. Furthermore, the collection in a wide database of data coming from several studies on the sector, already performed for manifold reasons, can provide the basis for implementing an intelligent system of national and/or international benchmarks. We start the discussion from this collection and from the observations raised from its analysis, for the sake of proposing a scientifically sound methodology.

The work is structured as follows: Section II presents the characterization of load based on macro and micro energy consumption in hospitals and the background review of the mostly used energy indicators by the researchers focusing on hospital; TEC under different research across different analysis focus areas is discussed further in Section III. Finally, in Section IV leveraging energy indicators are proposed which can significantly enhance the quantity, quality, and insights from hospital energy data. This provides the foundation for an effective energy management program that drives measurable improvements in dependency of TEC and carbon emissions. Together with sensors, IoT integration, AI and ML can provide hospitals with intelligent data platform to deeply understand their energy use and identify impactful efficiency opportunities, once effective indicators are found.

II. CHARACTERIZATION ON ENERGY LOAD IN HOSPITALS

Hospitals have a diverse range of energy loads that can be characterized. Research indicates that HVAC systems account for the largest share of hospital TEC, ranging from 40-70% of total electricity use [5]. Medical imaging equipment including CT (computed tomography) and MRI (magnetic resonance imaging) scan represent major electricity loads, consuming up

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to 30% of total usage [6]. Additional major end uses are lighting (typically 10-20% of energy use), water heating (5-10%), and office equipment (3-5%) [7].

A. HVAC Load

HVAC energy consumption in hospitals is driven by ventilation requirements for infection control, strict temperature/humidity specifications.

B. Medical Equipment Loads

MRI/CT scanner energy consumption ranges from 0.5-30kWh per exam, with typical hospitals conducting 100-300 scans daily can curtail peak power draws from medical equipment by 20% or more of TEC [8]).

C. Lighting and Plug Loads

Lighting load reduction relies on occupant behaviour modification and use of high-efficiency LEDs, sensors, and smart lighting controls.

D. Hospital Building Equipment Load

Elevators, hot water, kitchens washers, dryer, mortuaries, battery charging, TVs, Data centres, servers, PC workstations, printers and other IT equipment, vending-machines curtail a lot of percentage of TEC for hospital laundries.

In summary, hospitals' vital services result in disproportionately intensive energy demands based on load characterization as shown in Fig. 1. But opportunities abound for hospitals worldwide to deploy innovative strategies that cut energy waste while meeting healthcare needs. Strengthened data collection and sharing capabilities can better inform next steps.

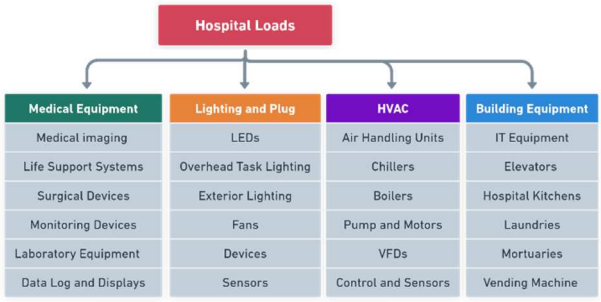

Fig. 1 Hospital Load Categorization

III. Key Metrics and Trends in Hospital TEC

Hospitals are major energy consumers, accounting for a significant portion of a country's e.g. USA, 545kWh/m^2 in 2012 [1] and 457kWh/m^2 in 2018 [2]. Hospital energy analysis has been a critical focus of concern. Improving energy efficiency in hospitals is therefore important goal to reduce energy costs and environmental impacts. Several regulations are available and numerous research work has been done focusing on different aspects hospital TEC as discussed below.

A. International Practices regarding TEC in Hospital

The International Organization for Standardization (ISO) has developed a standard - ISO 50006 and European Union has developed an EN 16247 that provides guidance on measuring energy performance and establishing performance indicators for hospitals and other healthcare facilities. The ISO 50006 and EN 16247 standard establishes a systematic approach for hospitals to manage their energy use. It defines relevant terms and principles related to energy management concept of Energy Performance Indicators (EnPIs). EnPIs allow healthcare facilities to monitor, analyse, and benchmark their energy performance over time and compare themselves to similar facilities. Some of the key EnPIs identified in ISO 50006 and EN 16247 for hospitals are:

- Energy use per unit floor area
- Energy use per number of beds
- Energy use per patient
- Energy use per unit of a healthcare service

B. Researcher Analysis of TEC in Hospitals

In the scope of hospital TEC, research has been done focusing on analysis about energy saving, different comparison, forecasting hospital energy load consumption etc. and several indicators were used by researchers as shown in Fig. 2. The use of several energy metrics corresponding to energy indicators of hospitals are discussed as follows based on research across different analysis focus areas:

A European study carried out in the Southwest of Spain [5] analysed energy use data from 55 healthcare centres in Spain to quantify savings potential. The centers ranged from 500-3500 m^2 in size. On average, air conditioning and heating accounted for 50% of energy use, lighting 30%, hot water 8%, and equipment 12%. TEC correlated with building size, averaging across all centers as shown in TABLE I.

TABLE I. Healthcare centers in Spain(2014)

Indicators	Energy Metrics and Other Measures
Total Energy Concumption	Range: ~50 to 250 kWh/ m2/year
Energy Avg. Distribution	HVAC: 50%
	Lighting: 30%
	Hot Water: 8%
	Equipment: 12%
Total Fuel Consumption in Extremadura	Diesel: 450 liters/m^2/year
	Natural Gas: 40,000 m^3/year
Water Consumption	Hot Water: 450 liters/m^2/year
Power Demand	Air Conditioning Units: 5 kW to 30 kW
Energy Savings	4.77 €/ m^2/year
	10,801 kWh/year
	385kg/ m^2/year CO2 reduction
Payback Periods	Average: 3.92 years across all upgrades

The study is concluded by reporting that a significant potential to improve energy efficiency in healthcare centres through technical and operational upgrades, especially HVAC, lighting, and building envelope is envisioned. A holistic approach is needed to optimize energy savings while maintaining healthcare service quality.

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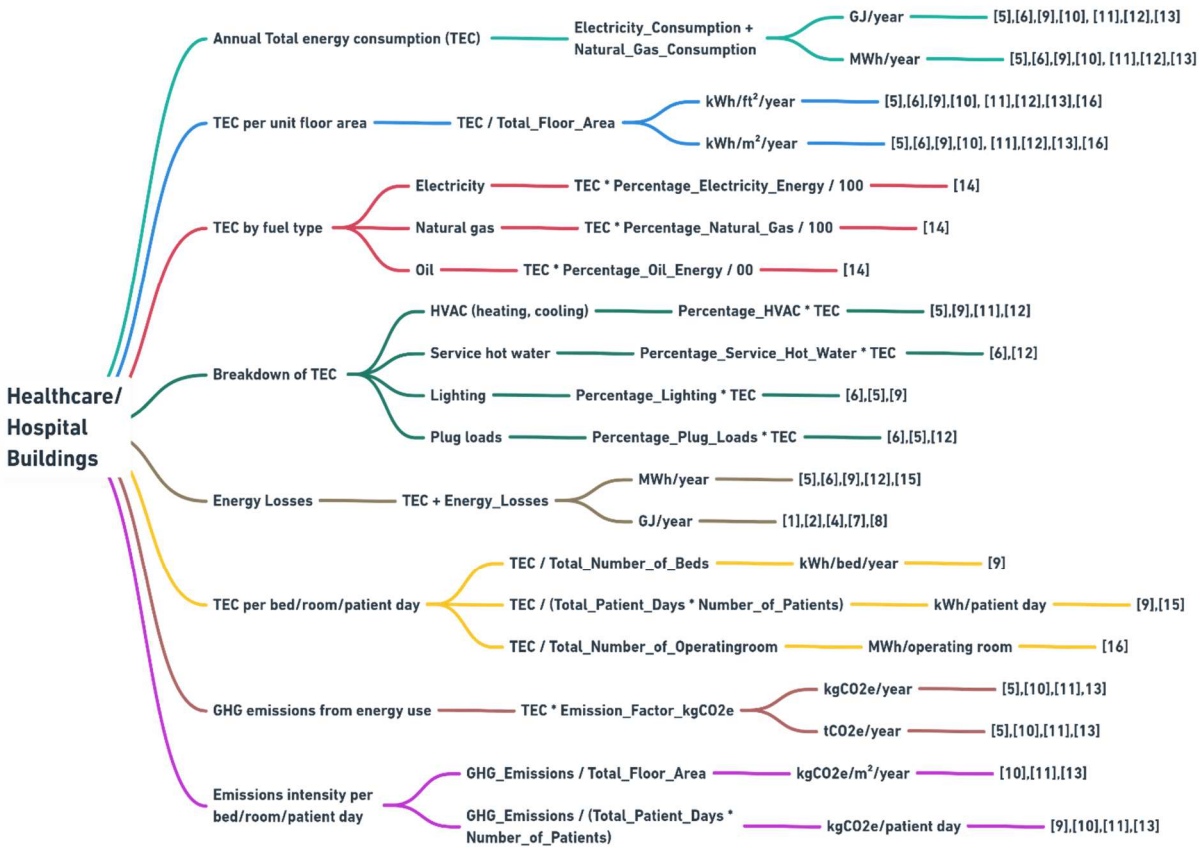

Fig. 2 Energy Indicators used in analysis of energy consumption of hospital buildings.

A study in Australia[9] analysed energy use in 3 healthcare buildings in tropical climate and discussed thermal comfort requirements of patients and staff have significant impact on system sizing and energy use. Total annual energy usage with several indicators is shown in TABLE II. The study provided a breakdown of energy end uses and identified priorities like lighting, equipment, and envelope improvements to reduce consumption in this building type and climate.

TABLE II. HEALTHCARE CENTER IN AUSTRALIA(2014)

Energy Indicators	Energy Consumption
Total Energy Concumption	Ranged from 167 to 306 kWh/ m^2/year
Energy Distribution	Electricity: 60-80% of total use
Water Consumption	Ranged from 0.4 to 1.4 m^2/year
HVAC and Lighting	Around 70% of electricity
Lighting Power Density	Ranged from 10 to 16.3 W/ m^2
Equipment Power Density	Ranged from 15 to 30 W/ m^2
Highest Intensity Areas	Dental: 320 kWh/ m^2/year, Renal: 488 kWh/ m^2/year
Envelope Contribution	Up to 45% of HVAC loads

A Canadian study [10] demonstrated how benchmarking with ENERGY STAR Portfolio Manager provides energy use intensity data to understand current consumption and set emissions reduction targets of Horizon Health Network, regional health authority Atlantic Canada. Monthly utility data is used to benchmark energy use and calculate associated greenhouse gas (GHG) emissions. In 2014, Canadian hospital energy intensity was 667kWh/m^2, with highest intensity of any building type. Since 2013, Horizon's Benchmarking approach has supported a 52,400 metric ton GHG reduction from their facilities details reported in TABLE III. Energy Star scores benchmark performance compared to similar buildings. Scores have increased across Horizon's facilities. The study showed that rigorous energy benchmarking has provided the data needed for Health Network to significantly reduce emissions from their healthcare facilities through informed energy management.

TABLE III. HEALTHCARE CENTER IN CANADA(2014)

Energy Indicators	Energy Consumption
Average Hospital TEC in Canada	667kWh/ m^2
Horizon's Baseline Average TEC	650kWh/ m^2
Horizon Hospital (after upgrades)	536kWh/ m^2
ENERGY STAR Scores	Increased from 50s-60s to 80s-90s
GHG Emissions Reduction	52,400 metric tons over 10 years
GHG Reduction at One Hospital	538 metric tons
Fuel Oil Use Reduction	Decreased by 44%
Certified Hospitals ENERGY STAR Scores	80-93 ENERGY STAR
Target for New Hospitals	558kWh/ m^2

A USA case study [11] examined upgrades to the central energy plant at a hospital in Texas. The hospital's existing steam boilers and chillers lacked sufficient capacity and redundancy with the addition of a new research building. A 4.3MW natural gas turbine cogeneration system was installed to provide electricity, steam heating, and emergency backup cooling. Cogeneration included heat recovery steam generator that captures waste heat to produce steam. Additional cooling towers, chillers, pumps and controls were added to enhance

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reliability and efficiency. Cogeneration provided over 8,000 hours of operation in first-year details reported in TABLE IV.

TABLE IV. HEALTHCARE CENTER IN USA (2014)

Energy Indicators	Energy Consumption
Electricity Use	1.5 GWh
Steam Production Capacity	99,500 lb/hr
Thermal Efficiency	30% to 88% with heat recovery
NOx Emissions	20.79 tons/year
CO2 Emissions	10,511 tons/year
Payback Period	2.16 years
Cost Savings	$1.85 million first year

The simple payback period was under 3 years, much faster than initial estimates of 3.5-4 years. NOx emissions decreased 71% and CO2 dropped 28% compared to separate heat and power systems. The study demonstrated how central plant upgrade with cogeneration significantly increased capacity, efficiency, emissions reductions, and cost savings for hospital.

One more Norwegian study [6] presents an analysis of equipment energy use in two Norwegian hospitals to understand how medical equipment contributes to hospital electricity consumption. It found that electricity use for fans, pumps, lighting, and medical equipment was up to 50% of total hospital energy use details reported in TABLE V.

TABLE V. HEALTHCARE CENTER IN NORWAY

Energy Characterization	Energy Indicators and Measures
Medical equipment, fans, pumps, and lighting energy use	Up to 50%
Average Equipment Power Intensity (Daytime)	90 (kWh/ m^2 per year)
Medical Biochemistry Lab	356 (kWh/ m^2 per year)
Large Medical Imaging Equip.	5.2 (kWh/ m^2 per year)
MRI Standby Power Consumption	17 kW
MRI Power Consumption (During Procedures)	154 - 175 kW
Small Medical Devices Energy Use	5000 hours at 0.3 kW each
Lighting Energy Intensity (Daytime)	Less than one-third of equipment
Waste Heat from Equipment	35 (W/ m^2)

It found a daytime energy intensity of around 90 kWh/ m^2 per year for equipment, much higher than the standard code value of 47 kWh/ m^2 per year used for hospital design. Imaging equipment like MRI and CT had high power draw and long standby times, making them major energy users. The paper recommended hospitals track equipment inventory, purchase energy-efficient models, implemen, and improve HVAC system design to account for equipment loads and recover waste heat. The study demonstrated that medical equipment is major and growing contributor to hospital energy use, and highlights ways to improve equipment energy efficiency through better tracking, design, technology, and management practices. A simulation-based study [12] compared three common hospital building to analyze the impact on energy performance. The study recommended investigating integration of spaces with simultaneous heating and cooling needs in future work.

A Chinese study [13] analyzed the total and per unit area TEC and carbon emissions for 22 hospitals in Tianjin, China. The paper also breaks down the TEC into major end use categories including heating, cooling, medical equipment, lighting, and others. The average TEC per unit area is calculated to be 348 kWh/ m^2year across all hospitals. For general hospitals it is 380 kWh/ m^2/year and for specialized hospitals it is 309 kWh/ m^2/year resulting into 145kgCO2/m^2/year. The heating system is found to be the biggest energy end use, accounting for 42% of total consumption. The focus of the study was on total and per unit area metrics and high-level end use breakdown for hospitals.

Previous researches on hospital energy use show focus on savings potential, consumption comparisons, and more. As summarized in Fig. 2 researchers have applied common energy metrics and indicators corresponding to the particular research questions and goals. But more standardization of TEC indicators would better align energy management, sustainable development goals and diversity of potential energy analytics approaches for hospitals.

IV. ANALYSIS ON THE KEY ENERGY INDICATORS IN HOSPITAL

Mitigating hospital TEC, carbon footprint and confront its role in climate change is necessary, with pro-active initiatives, hospitals can transform them into environmental sustainability agendas using ML and AI tools in forecasting data having more correlation. Careful tracking of energy use through key indicators allows hospitals to identify savings opportunities, set goals, and monitor progress over time. In form of percentage, use of different indicators corresponding to citied references and new proposed indicators are shown in Fig. 3.

ENERGY INDICATORS	%	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]
Energy Intensity by area	100.0	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Carbon Footprint/Emissions	40.0	✗	✗	✗	✓	✗	✗	✗	✗	✓	✓	✓	✓	✓	✗	✗	✗
TEC Percentage Breakdown	33.3	✗	✗	✗	✗	✓	✓	✗	✗	✓	✗	✓	✓	✗	✗	✗	✗
Analysis in Savings	31.3	✗	✗	✗	✗	✗	✗	✗	✓	✗	✓	✓	✗	✓	✓	✗	✗
TEC per Bed or Patients	26.7	✗	✗	✗	✗	✓	✗	✗	✗	✓	✗	✗	✓	✗	✗	✓	✗
Spatial Energy Mapping	18.8	✗	✗	✗	✗	✗	✓	✗	✓	✓	✗	✗	✗	✗	✗	✗	✗
TEC breakdown by NRES	6.3	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗
Energy Intensity by Volume	0	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
TEC per Employees	0	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
BED Occupancy	0	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
TEC wrt Degree Days	0	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
TEC breakdown by RES	0	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗

Fig. 3 Energy indicator percentage of usage in analysis of TEC

A. Granular Breakdown of end-use TEC:

Hospitals contain a diverse array of spaces, equipment, and systems that consume energy in different patterns. Granular end-use energy data involves collecting highly detailed breakdowns of energy usage by specific loads within a hospital facility. This provides an in-depth understanding of hospital energy use beyond high-level aggregate data. Temporal granularity shows daily/weekly/monthly usage profiles and opportunities for load shifting and demand management. This granular mapping of end-use energy helps hospitals identify the highest priority loads to target for energy efficiency and savings opportunities. Detailed submetering and monitoring provides insights into usage patterns of macro load as discussed in Section II. Interval data (15 min or hourly) provides basis for intelligent load scheduling, setpoint adjustment, and control strategies and enables optimal focus for maintenance, system upgrades, and intelligent operations.

B. Total Energy Consumption (TEC)

1) Energy Intensity by area

The TEC of a hospital is usually normalized by the gross floor area to calculate an EUI in kWh/ m^2/year. This accounts

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for hospital size and allows comparison of energy performance. EUIs are usually calculated for whole facility or individual departments to identify high energy density areas to prioritize for efficiency improvements.

2) Energy Intensity by Volume

Energy use can also be normalized by the volume of the building to determine an EUI in kWh/m^3/year. Volumetric EUIs account for hospital shape and height, useful for open spaces. Looking just at area misses energy use changes from height. The volume of occupied, cooled/heated space directly relates to energy demand. Volumetric EUI normalizes for shape differences in same areas. Internal Loads like HVAC occupy not just area their energy impact is proportional to volume. By factoring in emissions from the energy sources used, both volumetric and area based EUIs are easily extendable to calculate CO2 emissions intensities. This allows tracking of both energy and emissions performance annually in terms of tCO2e/ m^2/year and tCO2e/m^3/year .

C. Metric of Energy Consumption by Fuel Type:

Hospitals traditionally rely heavily on non-renewable energy sources (NRES) like electricity, natural gas, and fossil fuel-derived steam. Tracking consumption by energy source highlights the role of fossil fuels versus clean renewables in hospital emissions as displayed in Fig. 4.

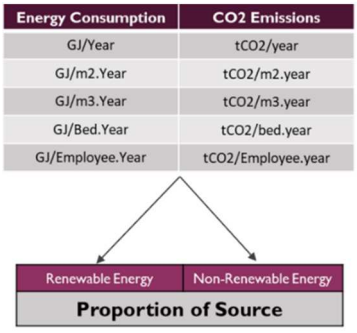

Fig. 4 Proportion of Energy Source

This data helps target reducing use of high-emission electricity and natural gas while increasing onsite solar and other renewables to significantly cut carbon footprints.

D. Localized energy density mapping

Energy density mapping involves spatially representing the energy usage intensity of different department within a hospital facility. This localization of energy loads helps identify high-priority zones for efficiency improvements.

1) Normalize by Employees/Patients

Hospital employees and patients are significant energy load consuming entities through their workspace usage, including lighting, computers, equipment, HVAC demands. For non-patient areas like offices and labs, the EUI can be calculated per employee (kWh/employee). This also represents the usage intensity relative to hospital population.

2) Normalize by Beds

The energy use intensity (EUI) of each department can be normalized per bed (kWh/bed) instead of per square footage. This accounts for varying service demands and occupancy.

3) Bed Occupancy

The maps can show how energy density changes based on daily bed occupancy rates in inpatient wards, ICUs, and other overnight facilities. Occupied beds draw more power.

E. Energy Consumption with respect to degree days(DD)

Analyzing local climate through DD provides insight into the load breakdown for hospitals in different global regions.

1) Heating DD

In colder climates with more heating DD, the heating load represents a larger share of total energy use. Heating systems like boilers and furnaces operate more extensively to maintain temperatures. Thermal insulation also becomes more crucial.

2) Cooling DD

In warmer regions with more cooling DD annually, cooling loads from air conditioning and ventilation dominate.

Hospital TEC is influenced by indicators mentioned above with complex interdependencies. By assessing the interactions and correlations between factors, driving hospital energy consumption using Machine Learning(ML) algorithms, models with greater predictive power can be developed to capture complex relationships between hospital electricity use and associated indicators like size, medical devices, heating degree days etc. These tools guide data-driven decision making to taper consumption and emissions.

V. A FRAMEWORK IN SUPPORT OF INDICATORS EVALUATIONS FOR HEALTHCARE SECTOR

Energy consumption has interdependencies between hospital infrastructure and operations. With the aim of moving first steps to implement a dependency of new indicators on the TEC to support data driven energy efficacy activities in the healthcare sector, TEC data of 34 hospitals was collected from a selected set of papers, all mentioned above, leveraging energy indicators served as predictor variables in a machine learning model, the machine learning outputs a forecast, by assessing interactions between influencing factors.

MATLAB regression learner's balance of simplicity, breadth of algorithms, and visualization capabilities likely makes it an appealing choice for experimenting with different regression approaches on the hospital energy data. The model used a supervised regression algorithm to learn the relationships between the input variables (number of beds/patients/ employees, DD, and hospital building volume) and output TEC, focused to explore different feature selection methods rather than finalizing an optimal predictive model. So maximizing training data was preferred, trained model then made TEC predictions for hospitals shown in Fig. 5, solely from technical specifications enabling simplified comparisons between true and predicted values.

The initial ML model implemented was trained on the dataset of 34 hospitals. Since this model only used 34 training examples, predictions may have significant errors uncovering the full complexity and variability in parameters that drive TEC, as visible in in Fig. 5 where true and the predicted response are reported with the margin of errors. The key action is of course to provide greater visibility into interdependencies between factors driving hospital TEC.

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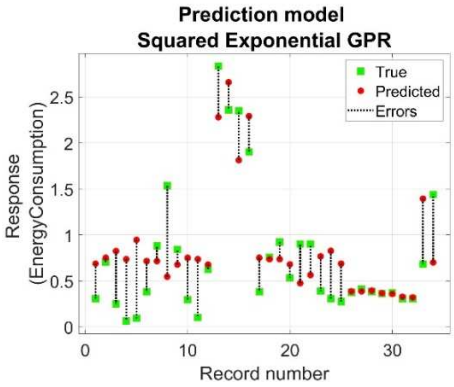

Fig. 5 Hospital TEC prediction response

The larger and more diverse dataset will allow the machine learning model to uncover more complex relationships and reduce the TEC prediction errors substantially. So, how can these models be used? For instance, during a new hospital design phase: the ML model allows rapidly assessing how different design parameters like shape, climate, employees etc. impact predicted energy use. Else? For setting meaningful KPI to achieve future goals.

These multidimensional indicators and granular form of TEC provides greater visibility into the interdependencies between hospital infrastructure and operations. They can reveal new efficiency pathways and grid interactive opportunities using smart data analysis. The rigorous analytical baseline from the model enhances measurement and verification of energy savings from efficiency measures. With large datasets, machine learning can discern TEC patterns and correlations not detachable by other less accurate forecasting techniques. In essence, the initial model shows promise for learning hospital energy dynamic EUI metrics but requires more training data to improve accuracy. Of course, by minimizing the prediction errors, the model can become a valuable tool for easily evaluating and comparing energy performance of hospitals, either in a design or in the maintaining/monitoring phase.

VI. Conclusion

This paper identifies more key energy indicators which enables hospitals to better understand their TEC patterns, identify savings opportunities, and continually improve efficiency over time, also by using ML tools. Granular end-use metering helps pinpoint the time of the load consumption behaviour focused usually across lighting, HVAC, medical equipment, computing, and other usage areas unique to hospitals. EUI metrics normalized by floor specifications having building volume, and number of beds/patients facilitates in data analysis and further examining the fuel mix highlights dependency on carbon-intensive grid electricity and natural gas versus lower-emission renewables. Spatial mapping of energy density connects usage to specific departments and activities. Leveraging indicators and implementation supporting indicator analysis provides data-driven guidance and analysis for better energy management and engagement initiatives based on the indicator's dependencies. The research synthesized in this review substantiates energy indicators as pivotal data variables for hospitals worldwide to institute systematic energy management programs. Continued advancement of hospital energy data collection, monitoring methods, and analytics platforms will further enhance efficacy of indicators. This paper provides a reference for applying indicators as part of a holistic approach for hospitals to achieve higher energy data management. Future works will compare the use of these techniques to more classical ones like Principal component analysis along with larger dataset to understand their potentials but also their weaknesses.

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Chapter 8



Decarbonization of Steel Mills, how to Set-up an Effective Allocation of Energy Flows, aiming at Tracking Efficiency and Energy Savings assisted with Machine learning tools

8 DECARBONIZATION OF STEEL MILLS, HOW TO SET-UP AN EFFECTIVE ALLOCATION OF ENERGY FLOWS, AIMING AT TRACKING EFFICIENCY AND ENERGY SAVINGS ASSISTED WITH MACHINE LEARNING TOOLS

Steel production is responsible for a significant share of global CO_2 emissions, making energy efficiency and decarbonisation important priorities. This chapter is based on a published journal paper that presents an ISO 50001-based framework for energy performance assessment in steel manufacturing. The study combines standard energy management practices with machine learning to identify major energy-consuming processes, define suitable Energy Performance Indicators (EnPIs), and evaluate energy-saving opportunities across three steel mills. It also compares different machine learning models for predicting energy performance, with the Support Vector Machine providing the best results. The proposed approach offers a practical and scalable method for improving energy monitoring, supporting energy management, and reducing emissions in steel production. The findings contribute to the overall thesis by demonstrating how data-driven methods can strengthen industrial energy efficiency and support reliable decarbonisation strategies.

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Decarbonization of Steel Mills, how to Set-up an Effective Allocation of Energy Flows, aiming at Tracking Efficiency and Energy Savings assisted with Machine learning tools

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***Abstract*—Achieving a net zero emission steel industry in the implementation phase requires strong methodologies, along with comprehensive data collection frameworks, to enable meaningful comparisons and to monitor progress. The exploration and application of machine learning tools at process level is an aligned step toward achieving such a goal. Starting from these claims, the paper presents the application of ISO 50001 to three steel mills, different in size and location, and it supports the creation of their baselines. Finding the energy saving opportunities, which are helpful in earning carbon credits, and implementing the framework for assessing the ongoing improvements, by the means of specific performance indicators (i.e. *toe/t* and €/t) for its energy intensive processes, are therefore a few contributions of this work. Machine learning techniques have been applied to air compressors dataset to investigate their expected specific energy consumptions and to find potential anomalies. The comparative analysis of various performance metrics (RMSE, MSE, MAE and R^2), applied to the energy performance indicators identified by the implementation of the ISO, offers a comprehensive evaluation and shows the superiority of support vector machine over other alternative algorithms. The proposed architectural framework is highly scalable, accommodating data availability ranging from yearly to monthly and daily levels also across different mills and processes. Thus, the novelty of this work is twofold. Methodologically it involves the application of ISO 50001, and practically, it applies a machine learning tool to an auxiliary service within the same mills to evaluate the robustness of the proposed architectural framework. The results show how powerful these tools are when combined and used for inter/intra assessments.**

***Keywords*—decarbonization, steel mills, machine learning, energy management, energy performance indicators, energy-intensive, IS0 50001, SVM**

I. Introduction

Steel is important for modern infrastructure, from buildings to vehicles. It is a growing sector and its CO_2 emissions are considerable, being 8% of the global emissions [1], hence it shall curb them by 93%, to reach net zero emissions by 2050 [2]. According to [3], in 2023, 1.92 tonnes of CO_2 were emitted and $\approx$ 21.27 GJ/t final energy was consumed. The benchmarking of meaningful energy performance indicators (EnPIs) is thus needed. Collection of data, identification, ranking, monitoring and defining baselines is necessary for setting up such EnPIs [4]. In [5] the taxonomy, based on the energy use of aluminum industry, is presented. It is an effective step in defining EnPIs. The method is also effective in allocating CO_2 emissions of foundries. A similar work has been presented for the food industry [6].

According to [7] energy audits are the starting tool for implementing energy management procedures. A comprehensive energy audit and management approach systematically identifies, evaluates, and prioritizes retrofit opportunities based on a holistic analysis of energy efficiency potential, economic viability, and environmental impact. ISO 50001:2018 [8] is an international standard that provides a framework for organizations to systematically improve their energy performances. It is applicable to all organizations and follows the Plan-Do-Check-Act (PDCA) cycle for continual improvement. The standard is designed to be integrated with other management systems to enhance energy efficiency and consumption.
The empirical study presented in [9] of Chinese manufacturing firms provides robust micro evidence that ISO

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50001 certification can significantly reduce energy intensity by approximately 26%. The research confirms the standard's effectiveness for industrial efficiency. The industrial case study in [10] demonstrates that machine learning (ML) can automate and enhance key technical requirements of ISO 50001, such as establishing baselines and identifying savings. By applying a Gradient Boosting model to an Iranian gas complex, they achieved a 10.31% energy saving (63,119 tons of steam) and reduced $7,027$ tons of CO_2 annually, proving that data-driven energy management system (EnMS) can deliver precise, actionable gains in efficiency.

ISO 50006 classifies EnPIs into three levels: (i) organizational, (ii) system, and (iii) process [11]. These levels were also applied in studies by Kanchiralla et al. on the Swedish engineering industry [12]. In another study, a focus on steel casting, the EnPIs are defined by considering specific energy consumption. Energy usage analysis is adhered to ISO 50006 guidelines. The authors took into account real time energy monitoring data, production data and regression-based analysis [13]. ML is an important tool in analyzing data and for industries -in general- but it can also help in setting up target for the EnPIs [14]. The authors of [15] used a tree-based pipeline optimization tool using a genetic algorithm to optimize the mechanical properties of the material and to measure the performance metrics. In [16], ML has been used for the evaluation of energy efficiency of the electric arc furnace (EAF) process. 42 features are taken into account to compute different metrics with different models. SHapley Additive exPlanations (SHAP) value is used to see the impact of the influential parameters on the output model. Additionally, in [17] the authors focused on the forecasting of wire mesh demand in steel industry. This precise forecasting can help steel wire mesh companies make informed decisions about inventory management. In [18] the authors introduce an innovative, comprehensive approach that integrates energy consumption, CO_2 emissions, and economic benefits to optimize a typical steel mill. Furthermore, this study examines the impact of energy structure, material structure, process parameters, and pricing on the energy-benefit indicator. As mentioned above, there is a growing interest in exploring measures for lowering energy consumption, reducing CO_2 emissions, and bringing high economic benefits to the iron and steel industry.

While prior studies affirm the value of ISO 50001 and demonstrate the potential of ML, there is a need for applied research that explicitly integrates the ISO 50001/50006 framework with advanced data analytics within the complex, multi-process environment of steel mills. This study positions the ISO standards not as a peripheral reference but as the essential scaffolding for our entire methodology, from initial energy auditing and significance scoring (Section II-B) to the development and comparison of EnPIs (Sections II-C & II-D). The machine learning application (Section II-E) is then deployed to enhance specific elements of this framework, such as the predictive baseline modeling.

The present study extends the work presented in [19] regarding the categorization of steel manufacturing process (SMP) for EAF based steel mills by analyzing EnPIs and identifying opportunities to apply ML tools for the validation. Overall, the work addresses the following research questions.

- How important is the categorization into different processes for setting up meaningful EnPIs?
- How will repetitive data collection and sharing over the year help maturing EnPIs for steel mills?
- How can ML be effective in setting up EnPIs in steel mills?
- What are the barriers and challenges in collecting data and applying the ML tool in the heavy industry?

This paper is structured as it follows. In Section II-B, the energy-intensive areas within the three mills are identified following the systematic guidelines of ISO 50001. In Section II-C interventions and energy-saving opportunities are compared for 3 mills. In Section II-D the comparison of EnPIs for the 3 mills is explained and performed. In Section II-E a ML model for the three mills has been developed for the air compressors' EnPI. A comparison of ML algorithms, in terms of performance metrics, is carried out to identify the best algorithm in Section III. Finally, the discussion and conclusion are presented.

II. Methodology

This study is carried out with the participation of 3 steel mills, 2 in Italy and 1 in USA. The purpose of the study is to help the decarbonization of the steel industry by (i) setting effective EnPIs, (ii) by collecting and sorting data for different critical processes and then (iii) applying different ML algorithms for the prediction of EnPIs in a business as usual scenario and in a scenario involving other mills where less information are available. The ML-assisted methodology implied the establishment of baselines, the setup of a granular analysis, the identification of strategic interventions and performance management. Each step is reported in detail in Fig. 1.

The authors proposed the model for the decarbonization in Fig. 5 of [19] but the cogency depends on the consistency of the samples: the greater the number of the mills participating, the more accurate the model becomes. This is the extension of that work, where the categorization of the steel manufacturing process was proposed. The methodology involves the following enhanced steps, each identifying the following subsections:

1) extension of the identification of the energy-intensive areas for another steel mill, based on the processes and functional areas;
2) proposal of interventions and comparison of economic benefits in terms of carbon savings and money for the 3 mills;

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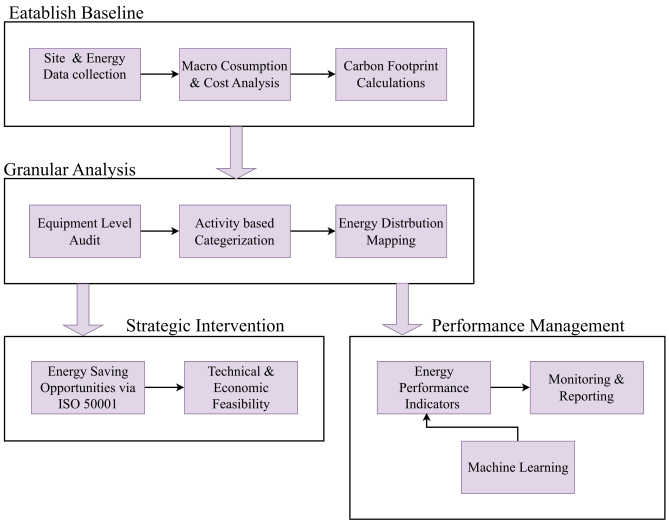

Fig. 1. Stepwise ML-assisted methodology for effective energy flow allocation and performance tracking in steel mills

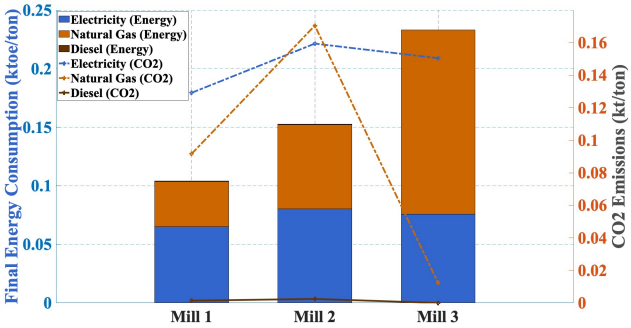

Fig. 2. Energy consumption and CO_2 emissions per ton of production in three steel mills

3) explanation and comparison of the EnPIs for 3 steel mills;
4) application of ML tools to compare and predict EnPIs for the compressed air system (ACO) facility.

A. Description of case study

The case study comprises 3 steel mills, 2 located in Italy and 1 in the United States. Production is mainly centered on stainless steels and specialty alloys, offered in the forms of blooms and billets, ingots, round, square, flat, hexagonal, and angle bars, wire rods, wire, reinforcement bars, and threaded rods. Data collection and energy audits were conducted over a five-month period at the US steel mill and a six-month period with the Italian energy consulting company to setup baselines and enable comparison across the 3 sites. Fig. 2 shows their energy consumptions and CO_2/t emissions. It is evident from the figure that mill 1 is more efficient in terms of energy consumption whereas mill 3 has a smaller carbon footprint (0.1 kt/ton). Initially, the manufacturing process is divided into m distinct processes, with each process involving n pieces of equipment. The energy consumption of each piece of equipment (including electrical, thermal, compressed air, hot and cold water, etc.) is assigned to the corresponding m-th process. Subsequently, each process is categorized into k different functional areas, based on the services it provides [19].

B. Energy intensive areas identification

Once the data have been collected and categorized, the energy intensive areas, based on the ISO 50001 guidelines, [8] are identified for the mill n.3 and compared with the data presented in [19] for mill n.1 and n.2. In that work, the authors presented the comparison of 2 mills, in this current work a third mill has been added to set baselines and identify areas for addressing energy saving opportunities. This method considers annual energy consumption of each process (A), monitoring system availability (B) and technical adequacy of user systems (C). The maximum score a process can attain is 54 and will be termed as *high energy significant area* (D). The criterion for assigning the scores is described in Algorithm 1.

Algorithm 1 outlines the procedure in a concise manner. The steps are self-explanatory and follow a logical progression. It takes into account energy use of each appliance/process/department in specific area, type of monitoring system, technological adequacy of the process/department, type of functional area and consumption share over functional area. As a result, Fig. 3 shows that the highest energy consuming area is PROD.TT and PROD.LAM (heat treatment and hot rolling), respectively, in the production process. There are also significant amounts of losses (reported as LOSS) in mill 3 followed by mill 2 and then mill 1. Fig. 3 is helpful to identify where savings and economic benefits can be achieved. This step is important for the identification, replacement or upgrade of an inefficient equipment. By looking at the scores, one can upgrade the system by installing the monitoring system for a specific process. ISO 50001 guidelines are used to find the energy intensive areas. To the author's knowledge this work presents a novel contribution by applying, for the first time in scientific literature, a procedure to identify energy significance areas of equipment and processes in steel mills. According to ISO 50001, energy planning should result in actions that consistently enhance energy performance in alignment with the established targets [20].

The comparison presented in Fig. 3 demonstrates that the method can be utilized for identifying energy intensity at the process/department/mill level. It also shows the unavailability of data for SMP, which hence urges the installation of a monitoring system, at a department level. A simple yet effective sensitivity analysis has been performed by using the tornado plots, as shown in Fig. 4. Such plot is used to visualize impact and risk [21]. The

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Algorithm 1 Energy Use Significance Score

Input: Incidence of energy uses in the functional area on the total in % (E), Monitoring System Type (S), Efficiency Level (C_1), Functional Area (K_{AF}), Consumption Share over Functional Area ($AF\%$)
Output: Significance Score (D)
Define:
A - Incidence of Energy Use
B - Monitoring System Availability
C - Technological Adequacy
Determine A based on E:
if $E > 25\%$ **then** $A \leftarrow 3$
else if $9\% \leq E < 25\%$ **then** $A \leftarrow 2$
else if $1\% \leq E < 9\%$ **then** $A \leftarrow 1$
else $A \leftarrow 0$
end if
Determine B based on S:
if S is only supply measurement, **then** $B \leftarrow 3$
else if S is occasional detailed gauge, **then** $B \leftarrow 2$
else $B \leftarrow 1$
end if
Determine C_1 based on efficiency:
if Very Efficient **then** $C_1 \leftarrow 1$
else if Average Efficiency **then** $C_1 \leftarrow 2$
else $C_1 \leftarrow 3$
end if
Compute $C_2 = K_{AF} \times AF\%_{\text{Score}}$
Define functional area weights:
$K_{AF} =$
if Main Activities **then** $K_{AF} \leftarrow 3$ Auxiliary Services $K_{AF} \leftarrow 2$
else$K_{AF} \leftarrow 1$
end if
Conditions for functional area consumption share score:
if $AF\% < 9$ **then** $AF\%_{\text{Score}} \leftarrow 1$
else if $9 \leq AF\% < 25$ **then** $AF\%_{\text{Score}} \leftarrow 2$
else $AF\%_{\text{Score}} \leftarrow 3$
end if
Compute $C = \frac{C_1+C_2}{2}$
Compute $D = A \times B \times C$
Classify D:
if $1 \leq D \leq 5$ **then** Low Significance
else if $6 \leq D \leq 11$ **then** Average Significance
else High Significance
end if
return D =0

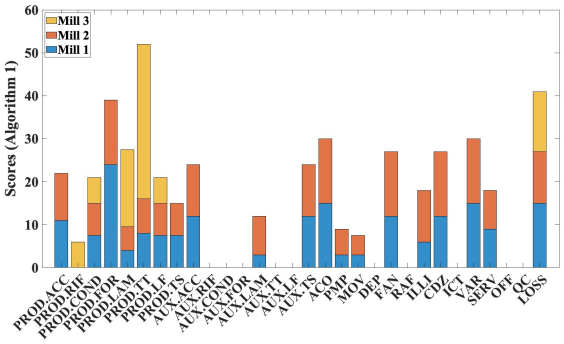

Fig. 3. Energy significant areas in 3 mills (Table III in Appendix for acronym) according to its score (Algorithm 1)

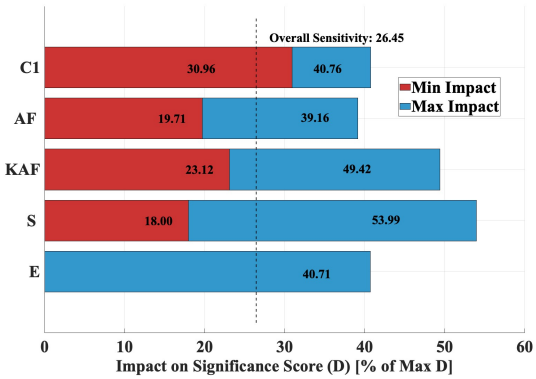

Fig. 4. Sensitivity analysis of energy use significance score

plot is the visualization of different input variables on the significant score D. Each bar shows a variable which is reported along the Y-axis. Blue bar shows the maximum effect whereas red bar shows the minimum effect that is when variable set to maximum and minimum respectively. The variables used to perform sensitivity analysis are incidence of energy use (E), monitoring system (S), functional area (K_{AF}), consumption share over functional area (AF) and efficiency level (C_1). The impact of each variable on significance score (D) is shown in decreasing order from bottom to top in Fig. 4. The longest bar shows the most sensitive variable, that is S in this case. While, the bar with the widest range, E, is the most influential, while determining D.

C. Interventions and energy savings opportunities

As a result of energy audits at each site, different energy saving opportunities are suggested. A one time investment of 5.342, 8.19 and 3.77 million EUR will result into 0.85, 0.98 and 0.51 million EUR/year savings in mill 1, 2 and 3 respectively. Figs. 5, 6 and 7 present different energy saving opportunities. Each figure shows investment, economic savings and payback period: each bubble size represents the CO_2 reduction, whereas the bubble color represents the payback period. As the color gets darker the payback

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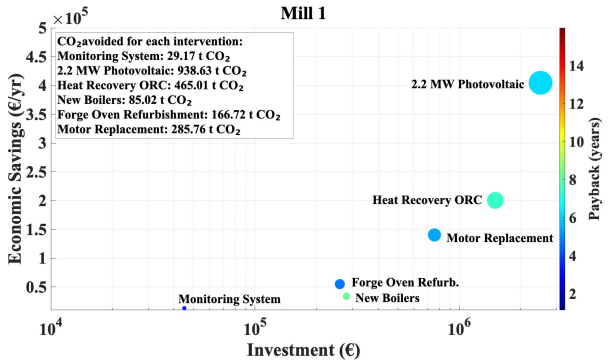

Fig. 5. Energy saving opportunities in Mill 1

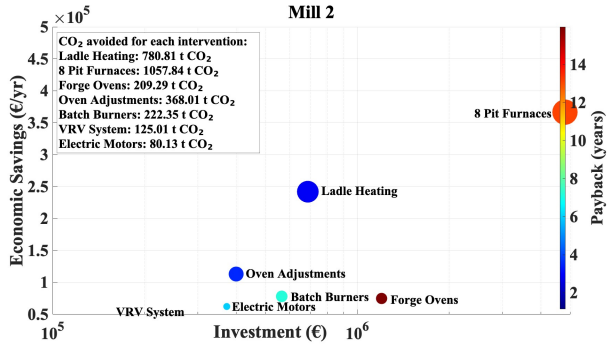

Fig. 6. Energy saving opportunities in Mill 2

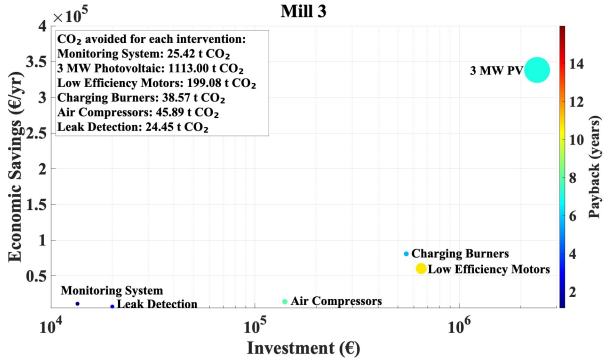

Fig. 7. Energy saving opportunities in Mill 3

time increases, whereas as the size of the bubble gets bigger, the avoided CO_2 emissions increase.

The CO_2 avoided each year counts towards the sustainability and carbon credits for the mill itself. According to [22] the net carbon rates are 99.68 EUR/t of CO_2e on average in Italy in 2023. In mill 1, 6 potential interventions are found, with a potential CO_2 reduction of 1.9 kt/year. In mill 2, 7 potential interventions are found, bringing in a potential reduction of 2.8 kt/year. Similarly in Mill 3, 6 different interventions are responsible for 1.4 kt/year of CO_2 avoided. The share of CO_2 avoided with each energy saving opportunity is reported at the top left corner of Fig. 5, 6 and 7. Installation of solar system, monitoring system installation and up-gradation, installation of high efficiency motors, up-gradation of air compressors in different departments are some of the common interventions suggested in 3 mills. As a result, Table I shows a significant improvement as a % improvement in $EnPI_1$ and $EnPI_2$ after incorporating energy saving opportunities in all mills. The purpose is to enable internal prioritization within each distinct operational context. The marked differences in the clusters and values between the figures stem primarily from the mill characteristics outlined in Table IV. Therefore, the cross-mill comparison primarily demonstrates the application of a standardized decision support tool across diverse facilities, highlighting how common intervention types (e.g., PV, compressor upgrades) manifest with different economic and environmental returns depending on local conditions and this was expected.

D. Comparison of energy performance indicators

In this step the comparison of different EnPIs of the 3 mills at process level has been carried out, before the suggestion of interventions which are instead reported in Section II-C. The energy significant processes are steel making (mill 1 and 2), recasting (mill 1 and mill 3) , hot rolling (all 3 mills) , forging (mill 1 and mill 3) , cold drawing cell (mill 3 only). The EnPIs calculated and compared are specific energy consumption known as $EnPI_1$ in toe/t and specific energy cost referred as $EnPI_2$ in €/t. Table I summarizes the $EnPI_1$ and $EnPI_2$ before and after the interventions and % improvement for each mill and each process. It shows the $EnPI_1$ in mill 2 is higher in value as compared to mill 1 in steelmaking process whereas in hot rolling it is higher in value for mill 3. In overall plant production the $EnPI_1$ and $EnPI_2$ for mill 2 are higher in value if compared to others. The importance of EnPIs depends on facilitating the standardization of indicators of the mill [14].

It is essential to clarify the objective of the comparative analysis presented in this section. The direct comparison of EnPI values (e.g., toe/t, €/t) across the three mills is not intended to serve as a technological benchmark or to rank fundamentally different processes. Given the significant variability in plant configurations including drive technologies, furnace types, rolling stand designs, product mix, and operational schedules a direct comparison of absolute consumption figures between installations is not a meaningful indicator of relative equipment efficiency. Instead, this cross-facility comparison demonstrates the effective application of a standardized, ISO 50001/50006-based methodology to diverse operational realities. The observed variance in EnPI values validates the necessity of establishing site specific baselines. The primary utility of the analysis is to show that the same systematic procedure yields actionable insights for internal performance tracking within each unique context. Consequently, the most significant metric is the longitudinal percentage improvement

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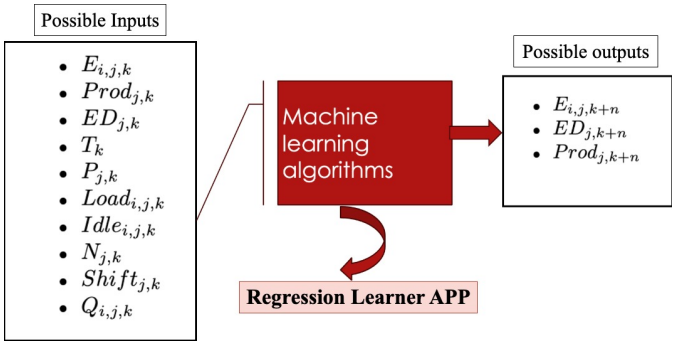

Fig. 8. Architectural framework for forecasting energy consumption and production (Acronym in the Table II)

for each mill against its own historical baseline (as shown in Table I), which provides a valid measure of progress independent of cross facility technological disparities. This shows the importance of benchmarking for an energy-intensive industry. Benchmarking is the first step for the effective decarbonization [23] for the energy intensive sectors e.g. chemical, iron and steel [19], cement, concrete and others.

E. Applying machine learning tool for the comparison and prediction of EnPIs for compressors

In steel manufacturing facilities, auxiliary services represent a substantial portion of overall energy consumption, warranting detailed investigation for energy optimization opportunities [24]. Among these auxiliary services, ACO have emerged as a significant focus area for energy performance optimization, with studies indicating that they consume approximately $3-5\%$ of a steel mill's total electrical energy consumption. Recent research has demonstrated that compressed air systems can account for $5-20\%$ of annual electricity costs in industrial facilities, highlighting their substantial impact on operational expenses [25]. This significant energy footprint has motivated detailed investigation into ACO efficiency and optimization strategies. Other critical auxiliary systems in steel manufacturing include pumping systems, purification units, ventilation infrastructure, water cooling networks, lighting installations, and localized air conditioning systems. However, ACO present particularly promising opportunities for energy efficiency improvements due to their ubiquitous presence and substantial energy consumption patterns. The establishment of appropriate EnPIs for compressed air systems requires consideration of multiple operational and technical parameters [14].

Fig. 8, presents the architectural framework of a machine learning model designed for EnPIs evaluation of compressors for the illustrated case studies. It comprises of 3 blocks: possible inputs, regression learner app and possible outputs. The possible inputs are described in Table II where each index is stated clearly followed by a possible sample time and description. The possible outputs can be $E_{i,j,k+n}$, $ED_{j,k+n}$, $Prod_{j,k+n}$. Where n is the next iteration (daily, hourly, monthly or yearly).

The dataset used in this study consists of yearly data collected from different mills m of compressors i in department j on a day k. However, the sampling period plays a crucial role in the accuracy and applicability of EnPIs. In this study, energy consumption and operational data are recorded on a yearly basis for each mill. While annual data provides a broad overview, it lacks finer granularity compared to monthly, weekly, or daily measurements, which could capture more detailed variations in compressor performance. This limitation must be considered when interpreting the results, as finer sampling periods could improve the precision of predictive models and allow for more dynamic energy optimization strategies. The model integrates 16 distinct input parameters to generate predictions for the specific energy consumption metric (Wh/Nm³/tons)/y. These input parameters encompass a comprehensive range of operational and technical variables, including fundamental technical parameters such as technology type, operating pressure (MPa), and power specifications (kW-Load, kW-Nominal, kW-Idle). Additionally, the model considers key operational factors, including flow rates, operating hours ($Idle_{i,j,k}$, $load_{i,j,k}$), and overall energy consumption (kWh/y). Given that the recorded data is on an annual scale, the derived EnPIs values represent averaged performance over the year, rather than reflecting short-term fluctuations in system efficiency. Future work will explore the impact of higher-frequency sampling (monthly/weekly/daily) to enhance predictive accuracy for the mills where the real time compressor data are missing. Additionally, it considers production metrics such as department tonnage $Prod_{j,k}$, specific energy consumption (Wh/Nm³)/y, and tons of oil equivalent (toe/y), along with contextual parameters including electrical consumption percentages (% of Elec-Dept, % of Elec-Mill) and air production contribution (% of Air-Prod). The dataset utilized for this model comprises observations from 29 compressors distributed across the 3 mills, providing a good foundation for cross-site performance analysis and prediction. This modeling approach facilitates the standardization of energy performance assessment across diverse mill operations while accounting for the multitude of operational and technical parameters that influence compressed air system efficiency. The model's structure enables effective prediction of the target variable (Wh/Nm³/tons) for a given $p_{j,k}$, which serves as a normalized measure of energy consumption in the compressed air system, making it particularly valuable for comparative analysis across different operational contexts.

III. Results and Discussions

This study extends the regression modeling approach presented in [14] to analyze EnPIs (Wh/Nm³/ton) for a third steel mill, validating the methodology's applicability

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TABLE I
EnPIs for Different Departments Before and After Interventions with Percentage Improvements

Department	**$EnPI_1$ (toe/t) -Before and After the Interventions**								
	Mill 1		**Mill 2**		**Mill 3**		**% Improvement**		
	Before	After	Before	After	Before	After	Mill 1	Mill 2	Mill 3
Steel Making	0.0978	0.0971	0.1270	0.1218	-	-	0.72	4.09	-
Recasts	0.2920	0.2896	-	-	0.1922	0.1895	0.82	-	1.40
Hot Rolling	0.0687	0.0670	0.1023	0.1023	0.1636	0.1612	2.48	0.00	1.47
Forging	0.0600	0.0599	-	-	0.1580	0.1580	0.17	-	0.00
Heat Treatment	0.0409	0.0409	-	-	0.0682	0.0672	0.00	-	1.47
Plant Production	0.1041	0.1030	0.1528	0.1466	0.0347	0.0342	1.06	4.05	1.44
Cold Drawing Cell	-	-	-	-	0.0682	0.0672	-	-	1.47
	$EnPI_2$ (€/t) -Before and After the Interventions								
Department	Before	After	Before	After	Before	After	Mill 1	Mill 2	Mill 3
Steel Making	82	81	104	100	-	-	1.22	3.85	-
Recasts	250	248	-	-	128	99	0.80	-	22.66
Hot Rolling	50	49	75	75	46	36	2.00	0.00	21.74
Forging	45	45	-	-	-	-	0.00	-	-
Heat Treatment	30	30	-	-	41	32	0.00	-	21.95
Plant Production	83	82	120	115	28.89	22	1.20	4.17	23.81
Cold Drawing Cell	-	-	-	-	7.76	6	-	-	22.68

TABLE II
Data for energy consumption, production, and other variables with indexing

Unit	**Indexing**	**Hourly**	**Daily**	**Monthly**	**Yearly**	**Description**
kWh	$E_{i,j,k}$	Yes	Yes	Yes	Yes	Daily energy consumption of compressor i in department j on day k
tons	$Prod_{j,k}$		Yes	Yes	Yes	Daily production of department j on day k
kWh	$ED_{j,k}$	Yes	Yes	Yes	Yes	Daily energy consumption of department j on day k
°C	T_k	Yes	Yes	Yes	Yes	Temperature on day k
Pa	$p_{j,k}$	Yes	Yes	Yes	Yes	Average daily operating pressure at department level j
h	$Load_{i,j,k}$	Yes	Yes	Yes	Yes	Loaded hours for compressor i serving department j on day k
h	$Idle_{i,j,k}$	Yes	Yes	Yes	Yes	Unload hours for compressor i serving department j on day k
#	$N_{j,k}$		Yes			Number of people in department j on day k
#	$Shift_{j,k}$		Yes			Shift hours for department j on day k
m^3	$Q_{i,j,k}$		Yes			Cumulative volume processed by compressor i, delivering to department j on day k

to a new site. The used dataset consists of operational data from 29 compressors (9 additional compared to [14], with more input features). To develop and compare regression models, MATLAB's regression learner was used, applying 5-fold cross-validation to ensure robust evaluation and minimize overfitting. In this process, the data set was divided into 5 equal parts, with each model trained on 80% of the data and validated on the remaining 20%, rotating the validation set over 5 iterations. The final performance of the model is determined by averaging the results in all folds, providing a reliable estimate of accuracy. Multiple regression models were analyzed to establish the relationship between operational parameters and energy consumption patterns. The study implemented and evaluated seven different machine learning algorithms: linear regression (LR), decision tree (Tree), support vector machine (SVM), ensemble methods, gaussian process regression (GPR), neural network (NN), and kernel-based methods. Fig. 9 compares the actual (green circles) and predicted (red squares) values of Wh/Nm^3/ton using an SVM model. The black lines represent the prediction errors, showing the difference between actual and predicted values. While the model performs quite well in the range 4-7 Wh/Nm3/ton, it struggles outside those ranges. The errors arise partly due to the limited dataset, as only yearly data are used for the compressor in the mill (according to availability), making it less granular. With a smaller dataset, the model struggles to capture finer trends, leading to few discrepancies between predictions and actual values.

The comparative analysis of various performance metrics provides a comprehensive analysis. The root mean squared error (RMSE) and mean squared error (MSE) serve as primary indicators of prediction accuracy, where lower values signify better model performance. The SVM model achieved the lowest error rates with an RMSE of 0.9859 and MSE of 0.9720, demonstrating superior predictive accuracy compared to alternative models as shown in Fig. 10, and 11 . These metrics are particularly significant as they penalize larger prediction errors more heavily, indicating that the SVM model consistently avoids substantial deviations in its predictions.

The coefficient of squared error (R^2) provides crucial insight into the model's explanatory power, measuring the proportion of variance in the dependent variable that is predictable from the independent variables. The SVM model achieved an R^2 value of 0.7808, significantly outperforming other algorithms. This indicates that approximately 78.08% of the variance in EnPI patterns is

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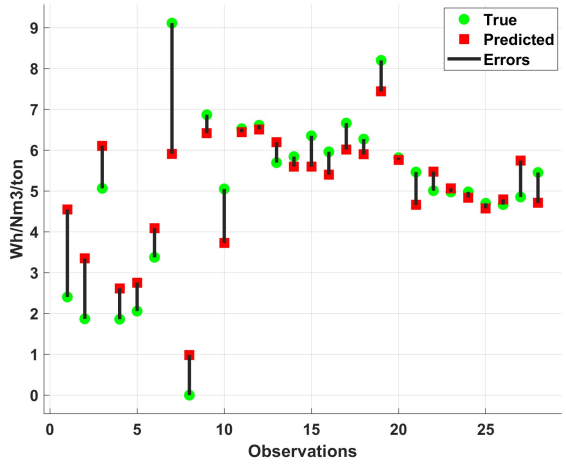

Fig. 9. Prediction vs. real 'Wh/Nm3/ton' by using regression learner APP (results for SVM)

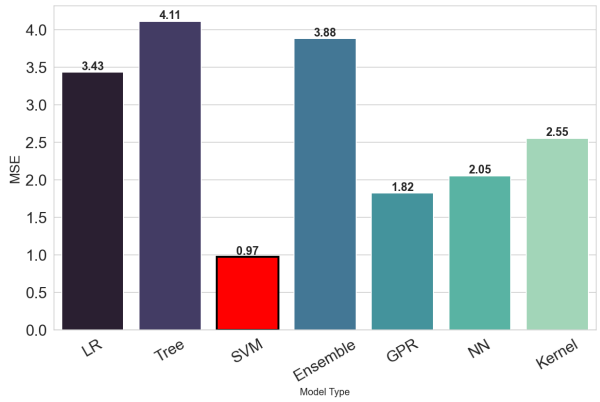

Fig. 10. Comparison of MSE values

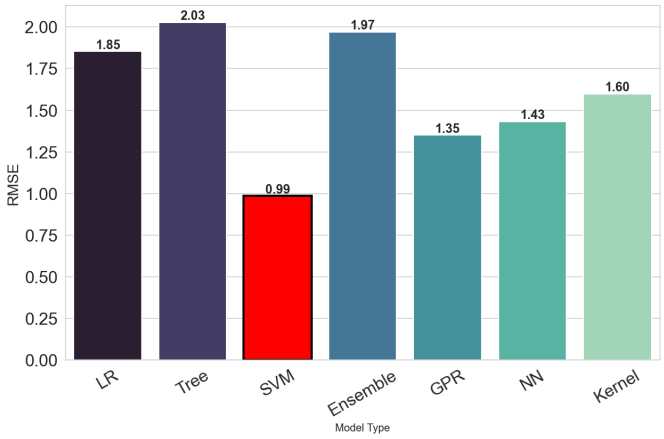

Fig. 11. Comparison of RMSE values

effectively captured by the model as shown in Fig 12.

The MAE offers a complementary perspective on model performance by measuring the average magnitude of errors

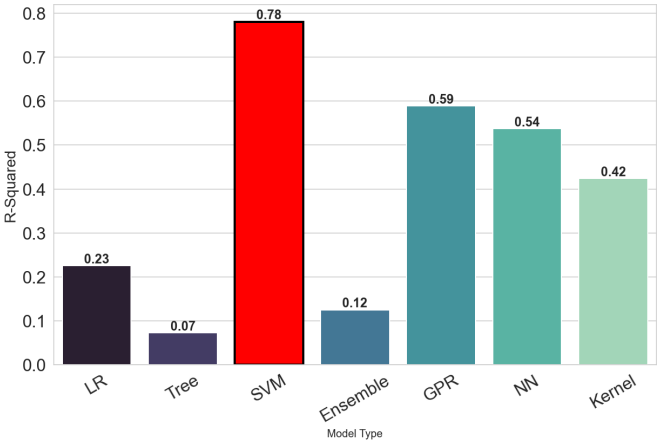

Fig. 12. Comparison of R-Squared values

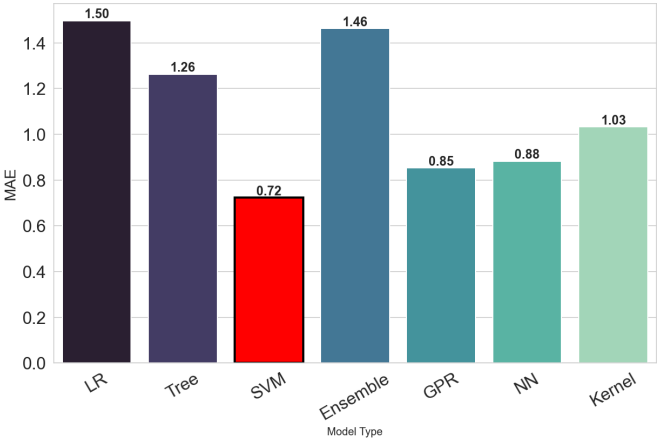

Fig. 13. Comparison of MAE values

in prediction, without considering their direction. The SVM model's MAE of 0.7233 was notably lower than other models, indicating superior accuracy in absolute terms as shown in Fig. 13. This metric is particularly valuable in industrial applications where the scale of prediction errors directly impacts operational decision-making.

The rRMSE provides a scale-independent measure of model performance, enabling meaningful comparisons across different operational contexts. The SVM model's rRMSE of 19.48% is the lowest, as shown in Fig. 14, among all the tested models, further confirming its superior predictive capabilities. This relative measure is especially relevant in cross-site applications, where absolute EnPI values may vary significantly due to differences in operational scale and conditions.

IV. Challenges and Conclusion

The contribution of this work is both methodological and practical. The step of applying ISO 50001 guidelines (*Algorithm: 1*) to 3 steel mills make it novel in methodological contributions. However, the implementation of

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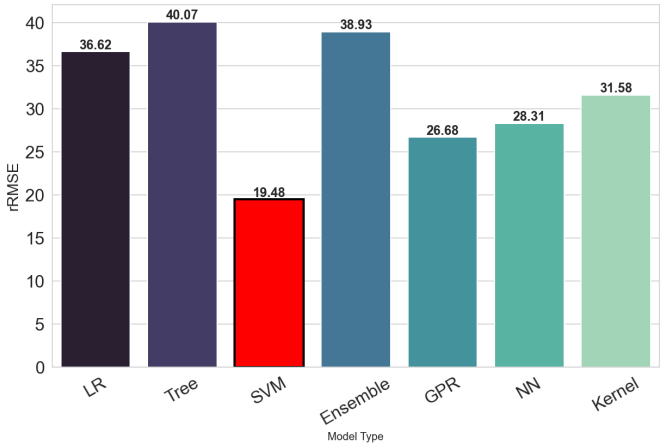

Fig. 14. Comparison of rRMSE values

the architectural framework proposed for the steel mill settings makes it unique for the applied contribution (Fig. 8).

At first, implementation of ISO 50001 was relevant because it made the user able to identify the energy significant area of a particular mill for a specific process or equipment, which is a crucial step forward to suggest possible interventions. For instance, in this case the identified energy intensive areas are: steel making, hot rolling, conditioning, forging and thermal treatment (for the main activities); air compression, ventilation and air conditioning (for the auxiliary services); losses and various utilities (for general services). A simple yet effective sensitivity analysis shows how the incidence of energy use and monitoring system are two crucial parameters in assessing the energy intensive areas.

At second, based on energy audits, assisted with ISO 50001, at 3 different locations, various energy saving opportunities have been identified and compared. Compact yet effective plots are presented to visualize the relationship between economic savings, investment, payback and avoided emissions.

At third, 2 important EnPIs, which are toe/t and €/t of mill 1, 2 and 3 are calculated and compared in Table I. Table I shows a significant improvement in terms of savings, both economic and environmental. Both EnPIs are important from an industrial standpoint for the continuous enhancement towards a net zero emission industry.

The fourth contribution of the paper is to propose and apply an architectural framework model for the forecasting of energy consumption for air compressors. The results show both the effectiveness and the importance of granularity. The model considered 16 distinct technical, and operational parameters of 29 compressors. The SVM emerged as the optimal model due to several key characteristics that align with the challenges of our limited dataset. SVM's inherent ability to effectively operate in high-dimensional spaces, while maintaining model stability with limited samples, proved instrumental in avoiding overfitting issues that often affect other algorithms in similar scenarios [26]. The relationship between energy consumption ($Wh/Nm^3/tons$) and its contributing factors exhibits complex, non-linear patterns that simpler models struggle to capture. Through its kernel methods, SVM successfully mapped these intricate relationships, outperforming both linear regression, neural network and tree-based approaches that assume simpler data structures. The robustness of SVM against outliers proved especially valuable in compressors industrial setting, where EnPIs data naturally exhibits significant variations due to diverse operational conditions, varying compressor efficiencies, and external factors. Unlike linear regression, which can be disproportionately influenced by extreme values through its squared error minimization approach, SVM's focus on maximizing the margin between data points provided more stable and reliable predictions across diverse operational scenarios. The primary challenge in this analysis was data availability, as results were computed from a dataset limited to a one-year time span. In general, the EnPIs can become more cogent once the model (Fig. 8) takes into account the data on a daily or monthly basis for one full year or more. At a site level, their strength also relies on providing baselines against which to assess the enhancement of site indicators over time. The ML model can be used for predicting production for future slots based on historical data, finding anomalies in the compressors, based on the analysis of results, and optimizing their energy efficiency while operating.

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Appendix

The appendix contains supplementary information that is referenced in the main document.

[1]Ingots, Blooms and Billets, Wire rod, Wire, reinforcing bars, threaded rods and chromium plated bars, forged, hot-rolled and cold finished-drawn bars, peeled/reeled and centerless ground in round, hexagonal, flat, square and angle profiles.

[2]Sm^3: Standard cubic meter. Standard conditions vary by industry: Petroleum industry (IPTS-15): 15°C, 101.325 kPa. Natural gas industry (ISO 13443): 15°C, 101.325 kPa. US customary: 60°F, 14.696 psi.

[3]Variable frequency drive

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TABLE III
STEEL MANUFACTURING PROCESSES AND THEIR RELATIONSHIPS TO EACH OTHER

Main activities (PROD)	**Auxiliary services (AUX)**	**General services (GEN)**
Steelmaking – ACC	Air compression – ACO	Lighting – ILLI
Casting – RIF	Purification – DEP	Losses – LOSS
Conditioning – COND	Ventilation – FAN	Maintenance of workshops – OFF
Forging – FOR	Handling system – MOV	Mensa, guesthouse, canteen – SRVC
Hot rolling – LAM	Pumping – PMP	Various utilities – VAR
Heat treatment – TT	Air conditioning – CDZ	Quality control – QC
Surface treatment – TS		IT and telecom equipment – ICT
Cold working – LF		Internal transport – TRNS

TABLE IV
SUMMARY OF TECHNICAL CHARACTERISTICS AND PRODUCTION CONDITIONS FOR KEY INSTALLATIONS ACROSS THE THREE CASE-STUDY MILLS

Technical and operational profile	**Mill 1**	**Mill 2**	**Mill 3**
Location	Italy	Italy	USA
Working days (days/year)	264	296	365
Main processes	ACC, COND, LAM, TT, TS, LF	ACC, COND, FOR, LAM, TT, TS, LF	RIF, COND, FOR, LAM, TT, LF
Main products[1]	Various grades	Various grades	Various grades
Annual production (kt/year)	$\approx$ 470	$\approx$ 193	$\approx$ 52
Electricity cost (€/kWh)	0.31	0.31	0.11
Natural gas cost (€/Sm^3) [2]	1.28	1.28	4.19
Diesel cost (€/kg)	1.24	1.24	n.a.
Baseline grid CO_2 intensity (kg/MWh)	370	371	371
Total energy consumption (GJ/year)	1372	884	418
Total CO_2 emissions (kt/year)	105	64	8.5
Compressor type (VFD) [3]	Mostly without VFD	Both with/without VFD	Mostly without VFD
Investment for interventions (€)	5 M	8.19 M	0.51 M
CO_2 avoided with interventions (kt/year)	1.69	2.84	1.45

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Chapter 9



Extending Technological Regenerative Innovation Framework for Data Center Cooling Power Prediction with regime Aware Temporal XAI

9 EXTENDING TECHNOLOGICAL REGENERATIVE INNOVATION FRAMEWORK FOR DATA CENTER COOLING POWER PREDICTION WITH REGIME AWARE TEMPORAL XAI

Data centres use a significant amount of electricity, and cooling systems account for a large share of this energy use. However, most existing cooling control methods respond only to current conditions and do not consider the different operating states or time-based changes that occur in real facilities. This chapter presents a published study that extends the Technological Regenerative Innovation (TRI) framework by applying a regime-aware and explainable artificial intelligence (XAI) approach to data centre cooling. The analysis uses a publicly available, open access dataset comprising 3,498 hourly observations from 1 January to 26 May 2025. The dataset provides a structured basis for examining regime-aware explanations but it does not constitute direct validation using measurements from a live data-centre facility. Its an evaluation of the proposed analytical approach on the specified dataset, with validation on real operational data remaining an important direction for future work. So, the study groups operating conditions into four meaningful regimes and develops an XGBoost model to predict cooling power with high accuracy. It then uses SHAP analysis to explain how the influence of key variables changes across operating regimes and over time. The findings show that some cooling variables have different effects under different operating conditions, which cannot be identified using conventional global feature importance methods. This provides more practical guidance for cooling management and further validates the TRI framework in the data centre sector, complementing its application across commercial, industrial, and healthcare environments.

Extending Technological Regenerative Innovation Framework for Data Center Cooling Power Prediction with regime Aware Temporal XAI

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***Abstract*—Data center (DC) cooling systems represent the single largest energy consumer in modern facilities making their efficient operation essential for reducing both operational costs and environmental impact. But existing energy management strategies remain reactive and do not account for operating state or time of day variability. This paper extends the Technological Regenerative Innovation (TRI) framework by introducing a regime aware and time based explainable artificial intelligence (XAI) approach for cooling power prediction. Using 3,498 hourly records spanning January to May 2025 from a small to medium facility, K-Means clustering identifies four operating regimes, namely Idle, Transition, Peak Load, and Thermal Stress, based on server workload and inlet temperature. The cooling power ranges from 0.33 to 1.11 kW, representative of a typical small to medium data center. Two high predictive machine learning (ML) models are used in this paper in which an XGBoost model strong predictive accuracy ($R^2 = 0.9730$, MAE $= 0.0209$ kW, RMSE $= 0.0261$ kW) on the cooling unit power consumption target as compared to Random Forest(RF) ML model. Beyond prediction accuracy, the principal contribution of this work is a regime temporal SHAP analysis that moves beyond conventional global feature importance by showing how the influence of individual variables changes across distinct operating contexts defined by regime and time. In particular, Chiller Usage shows regime dependent sign reversals, its SHAP contribution is negative under low-demand conditions and positive under high-demand conditions, reflecting a physically meaningful shift in its role. These results support actionable, context-specific guidance for cooling system operators.**

***Index Terms*—Data Center, Energy Management, Explainable AI (XAI), SHAP, Technological Regenerative Innovation, Operating Regime, Cooling Power Prediction**

I. Introduction

Data centers consume a growing share of global electricity, currently estimated at 1.1 to 1.5% of worldwide demand, with continued growth driven by AI workloads, cloud computing, and edge infrastructure [1]. Cooling systems account for roughly 45% of total facility power, making them a primary target for efficiency improvements [2]. In spite of this, most cooling control in practice remains reactive where actions are triggered by alarm conditions rather than anticipatory predictions, leaving significant energy savings unrealized.

Interpretability is a prerequisite for operational trust hence operators are unlikely to act on predictions from black-box models without understanding which variables are driving a particular recommendation and why [3]. The Technological Regenerative Innovation (TRI) framework [4] addresses this need by combining IoT sensing, predictive machine learning, and explainable decision support into a single management pipeline for commercial and industrial energy systems.

This paper further shows the TRI framework to the specific context of predictive modelling and interpretability of features involved in data center cooling through four contributions. First, K-Means clustering identifies four operating regimes that capture distinct physical states of the cooling system. Second, Random Forest and XGBoost models are trained globally and evaluated on a held out test set to confirm prediction accuracy. Third, a regime aware temporal SHAP analysis is carried out across four daily time periods, revealing non-monotonic and context dependent feature behavior that global importance rankings conceal. Fourth, physically grounded interpretations of the SHAP results are provided to give operators concrete scheduling and operational guidance.

Unlike existing studies that apply SHAP to building energy [5] or data center workload models [6] in a global, regime agnostic manner, this work systematically combines K-Means regime identification with time resolved SHAP analysis [7]. The regime temporal decomposition reveals sign reversals in key features that are entirely hidden in global importance rankings, which represents a methodological step beyond what has been reported for data center cooling explainability to date [8], [9].

The key novelty, compared with existing work, is the simultaneous decomposition of feature influence along both the regime axis and the temporal axis within the same XAI framework. Earlier studies either apply SHAP globally over all samples, or segment data by only one dimension (regime or time, not both). Combining the two dimensions reveals non-monotonic behavior that would otherwise remain hidden inside averaged importance scores. The remainder of this paper is organized as follows. Section II reviews related work on data

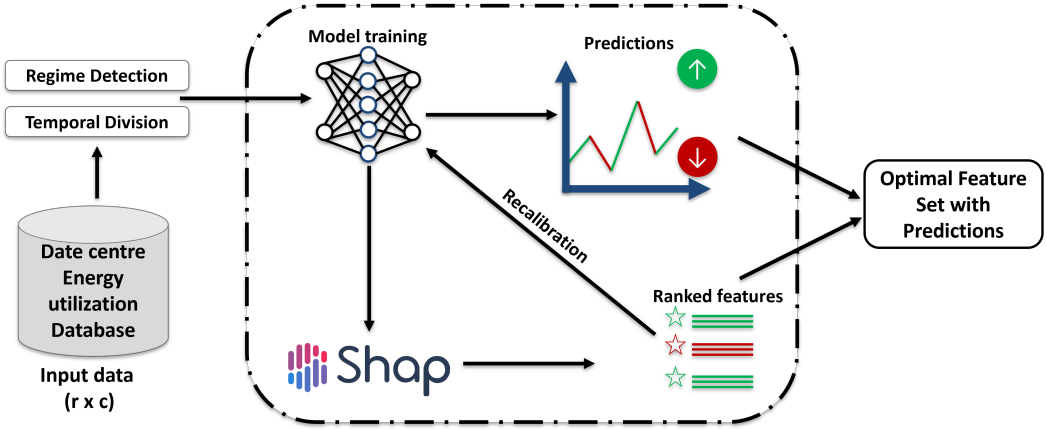

Fig. 1. Data analysis flow of predictive intelligence within the TRI framework for data center cooling power prediction. Raw sensor data enters the pipeline on the left. K-Means regime detection and temporal partitioning provide contextual slices. Model training produces predictions, and SHAP analysis ranks feature contributions within each context.

center energy prediction and SHAP-based explainability, and positions this study relative to existing approaches. Section III describes the dataset in detail, explains the K-Means regime identification procedure and the justification for selecting four clusters, and outlines the XGBoost training setup and the regime temporal SHAP formulation. Section IV presents the predictive model performance, the global SHAP feature ranking, and the regime aware temporal SHAP analysis, including the physical interpretation of sign reversals and the comparison between global and context-specific feature behavior. Section V summarizes the main findings and their operational implications for cooling system management, and outlines directions for future work.

II. Overview and Methodological Approach

A. Data Center Energy Prediction

Machine learning is widely applied to DC energy prediction tasks including Power Usage Effectiveness (PUE), cooling load estimation, and workload-driven modeling [6]. Masanet et al. [1] identified cooling as the main efficiency opportunity across large-scale facilities, while Dayarathna et al. [6] found that models trained without capturing changing operating states perform poorly under dynamic conditions. Deep learning improves prediction accuracy [9], but limited interpretability reduces operational adoption because engineers cannot verify whether model reasoning matches physical expectations.

Clustering has been used to segment operating conditions: Yang et al. [8] showed that regime conditioned models outperform a single global model for data center energy optimization. However, existing studies have not systematically combined regime detection with time-resolved SHAP-based explainability for data center cooling.

B. SHAP Explainability in Energy Systems

SHAP, introduced by Lundberg et al. [7], computes exact Shapley values for tree-based models in polynomial time, making it practical for large datasets. SHAP has been applied to residential building energy prediction [5] and industrial chiller management within the TRI framework [4]. A recent study on SHAP-assisted feature selection for data centers [10] showed that global importance rankings can mislead feature selection when operating conditions vary. The present work extends this observation to temporal and regime conditioned analysis, demonstrating that the direction of a feature's influence can reverse depending on the operating context.

The data analysis pipeline is illustrated in Fig. 1. Raw DC sensor data is preprocessed and split for model training and testing. Regime detection and temporal partitioning provide contextual slices, and SHAP is applied within each slice to produce ranked feature contributions.

III. Dataset and Methodology

A. Dataset Description

The dataset is a publicly available synthetic but physically grounded hourly record of a small to medium data center facility covering the period from January 1 to May 26, 2025, yielding 3,498 observations. The target variable is the *Cooling Unit Power Consumption* (kW). The raw input variables are as follows:

- server workload (%)
- inlet temperature(°C)
- outlet temperature (°C)
- ambient temperature (°C)
- Chiller Usage (%)
- AHU Usage (%)
- total energy cost ($)
- Temporal features

Two additional columns, namely Temperature Deviation (°C) and Cooling Strategy Action, were excluded from model inputs to prevent data leakage, as they are derived from or contemporaneous with the target. The cooling power ranges from 0.33 to 1.11 kW with a mean of 0.76 kW and standard deviation of 0.16 kW, reflecting a facility that operates across a broad range of load conditions over the five-month observation

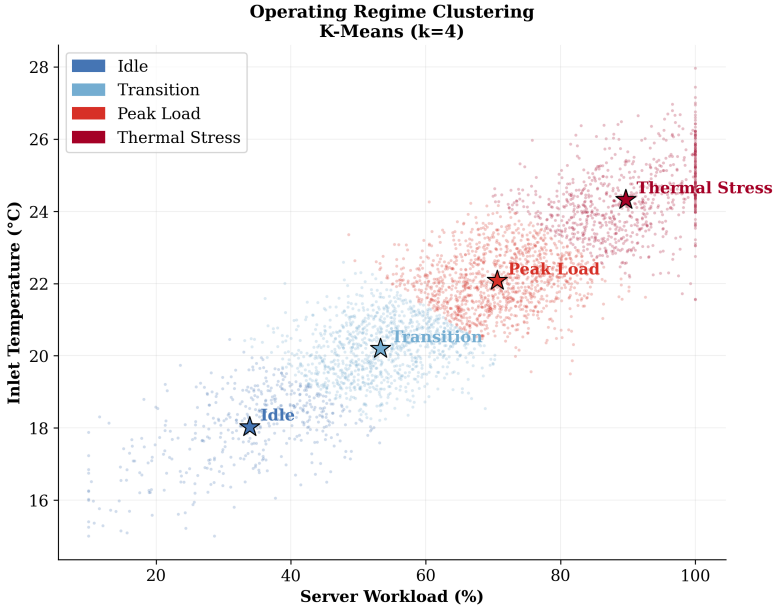

Fig. 2. K-Means operating regime clusters ($k = 4$) plotted against server workload (%) and inlet temperature (°C). Each point represents one hourly observation. Cluster centroids are marked with stars. The four regimes correspond to physically distinct operating states of the cooling system.

TABLE I
SUMMARY OF DATASET VARIABLES

Variable	Range	Units
Server Workload	10.0 to 100.0	%
Inlet Temperature	15.0 to 28.0	°C
Outlet Temperature	16.2 to 35.8	°C
Ambient Temperature	18.0 to 34.0	°C
Chiller Usage	20.0 to 100.0	%
AHU Usage	31 to 70.0	%
Total Energy Cost	0.03 to 0.16	$
Cooling Power (target)	0.33 to 1.11	kW

window, from low winter loads to higher late-spring loads. The 3,498 hourly records span a continuous time series with no missing values.

Table I summarizes the key input variables along with their ranges and units.

B. Feature Engineering

Temporal features were derived from the timestamp: hour of day, day of week, and month. Each was encoded using sine and cosine projections to preserve cyclic continuity. For example, hours 23 and 0 map to nearby points on the unit circle rather than to opposite ends of a linear scale. Segment labels (weekday/weekend, hour section) were retained in the data frame for SHAP slicing but were not passed as model inputs.

C. Operating Regime Identification

The following operating regime identification methodology is directly related to the present paper's regime-aware SHAP analysis. A K-Means clustering algorithm (k=4, n_init=10, random_state=42) is applied to two standardized features, Server_Workload(%) and Inlet_Temperature(°C). These two features were selected because they jointly capture the two primary dimensions of DC cooling demand, compute side heat generation (workload) and supply side cooling quality (inlet temperature). After clustering, regimes are semantically labeled by inspecting cluster centroid coordinates, the cluster with minimum Server_Workload is labeled Idle; the cluster with the highest joint (0.6×workload + 0.4×temperature) score is labeled Thermal Stress; the remaining highest-workload cluster is Peak Load; the remaining cluster is Transition. Table II summarizes the four regimes and their operational characteristics.

Segment labels for temporal analysis are added as metadata only and are not model features. Weekday/weekend is derived from day of Week, hour section assigns each instance to night (00–05), morning (06–11), afternoon (12–17), or evening (18–23). These labels are used exclusively for slicing the SHAP arrays post training.

The number of clusters was set to $k = 4$ to correspond directly to the four physically meaningful operating states of a data centre cooling system (Idle, Transition, Peak Load, and Thermal Stress). This choice is motivated by the clear physical separation expected between low workload low temperature, intermediate, high workload moderate temperature, and high workload high temperature conditions as shown in the cluster scatter plot provided in Fig. 2 and the resulting regime distribution across the full dataset is shown in Table III.

D. Predictive Models

The predictive models used in this study are configured as follows, which helps in the SHAP-based explainability

TABLE II
K-MEANS OPERATING REGIMES (4 CLUSTERS ON SERVER_WORKLOAD × INLET_TEMPERATURE)

Regime	Server Workload	Inlet Temp.	Operational Description
Idle	Low	Low-Moderate	Minimal compute activity; cooling demand low; chiller and AHU operating at baseline
Transition	Moderate	Moderate	Rising workload; cooling system ramping; intermediate thermal state
Peak Load	High	Moderate-High	Maximum compute utilisation; dominant cooling demand driven by server heat generation
Thermal Stress	Very High	High	Combined server heat + ambient thermal loading; highest cooling power required

TABLE III
OPERATING REGIME DISTRIBUTION (FULL DATASET)

Regime	Records	Share (%)
Idle	889	25.4
Transition	885	25.3
Peak Load	864	24.7
Thermal Stress	860	24.6

analysis. Random Forest used 600 estimators, a maximum depth of 18, minimum samples split of 6, minimum samples leaf of 4, and square-root max features. The high estimator count and relatively deep trees are appropriate for a regression target with smooth continuous variation driven by a small number of dominant features. XGBoost used 900 estimators, a maximum depth of 5 and a learning rate of 0.03. The combination of shallow trees with a high estimator count and regularization is XGBoost's canonical configuration for tabular regression [11].

Both models were trained on 80% of the data (2,798 observations) and evaluated on a held-out 20% test set (700 observations). The global model serves for overall SHAP analysis, while regime specific models capture instinct operating physics. Evaluation metrics are R^2, MAE, and RMSE, 5-fold cross-validation R^2 on the global model confirms generalization.

E. SHAP Analysis

The regime-aware temporal SHAP analysis follows a systematic procedure directly linked to this paper's core contribution. SHAP is applied to both trained models on the full test set, producing SHAP value arrays of shape (700 samples × 17 features). Global importance is computed as mean SHAP across all test samples. Regime-aware temporal analysis proceeds for each of the four regimes, a Boolean mask selects the test instances belonging to that regime. Within each regime mask, secondary masks are applied for Day_Type (Weekday/Weekend) and Hour_Section (Night/Morning/Afternoon/Evening). Mean absolute SHAP per feature is computed for each (regime, temporal_segment) combination, yielding 32 distinct importance profiles (4 regimes × 2 day types + 4 regimes × 4 hour sections). Signed SHAP (mean raw SHAP, not absolute) is additionally computed to reveal the direction of feature influence, whether a feature is pushing cooling power higher or lower within each context.

The hour sections used throughout the analysis are night (00:00 to 05:59), morning (06:00 to 11:59), afternoon (12:00 to 17:59), and evening (18:00 to 23:59).

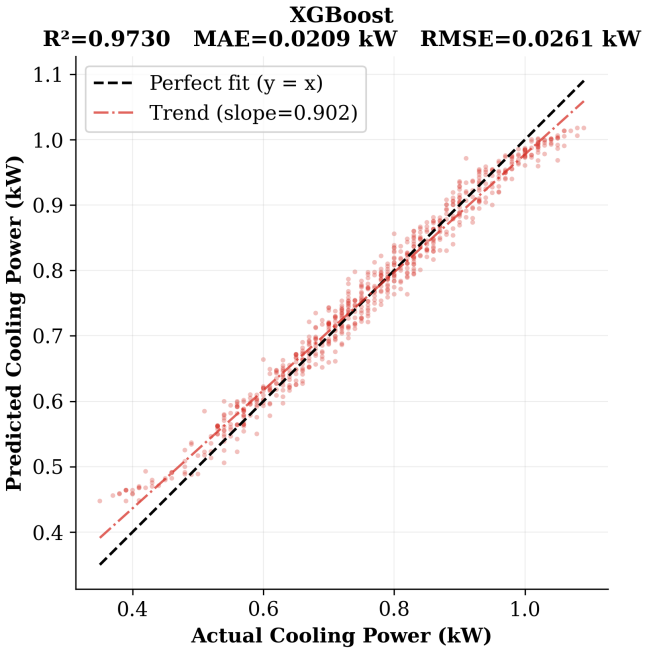

Fig. 3. Actual versus predicted cooling unit power consumption for the XGBoost model on the 700-sample test set. The dashed line shows a perfect 1:1 fit. The dash-dot line shows the fitted regression trend (slope = 0.902), indicating slight underestimation at the upper end of the power range.

IV. RESULTS AND DISCUSSION

A. Predictive Model Performance

Both models achieve strong predictive accuracy on the 700-sample test set. Table IV reports R^2, MAE, and RMSE. The XGBoost model reaches $R^2 = 0.9730$, confirming that the selected feature set appear as the dominant drivers of cooling power. The actual versus predicted scatter for XGBoost is shown in Fig. 3. A slight underestimation of the highest power values is visible (trend slope = 0.902), which reflects the well known smoothing tendency of gradient-boosted regression under extreme operating conditions.

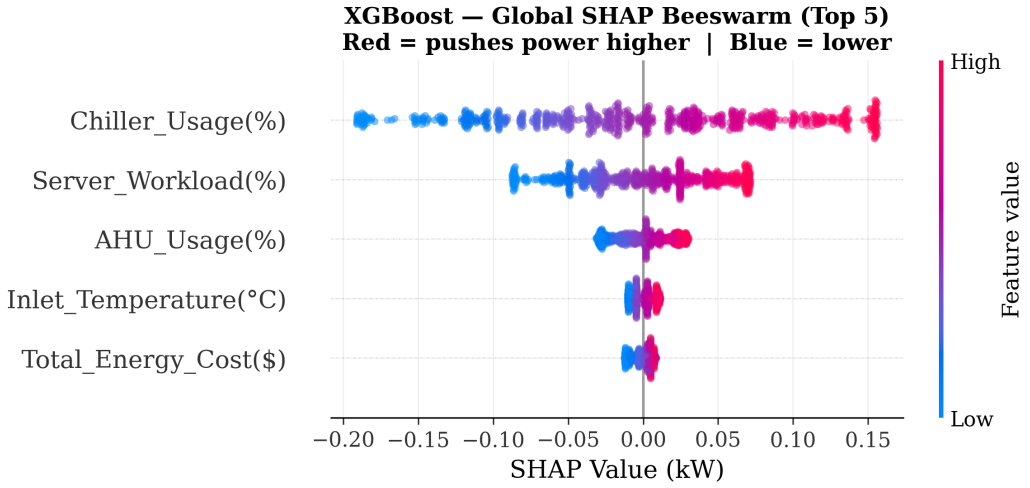

Fig. 4. XGBoost global SHAP beeswarm plot for the five most important features. Each dot is one test set prediction. Horizontal position shows the SHAP value in kW (positive = increases predicted cooling power; negative = decreases it). Color encodes the feature value: red = high, blue = low. Chiller Usage shows the widest spread, reflecting its dominant and variable role across all operating conditions.

TABLE IV
MODEL PERFORMANCE ON HELD-OUT TEST SET (700 SAMPLES)

Model	R^2	**MAE (kW)**	**RMSE (kW)**
Random Forest	0.9680	0.0231	0.0283
XGBoost	0.9730	0.0209	0.0261

Five-fold cross-validation was also performed, the XGBoost mean R^2 across folds was 0.9714 ± 0.0011, and the RF mean was 0.9680 ± 0.0014, confirming that results are stable and not specific to the random train-test split.

B. Global SHAP Feature Importance

Fig. 4 shows the XGBoost SHAP beeswarm plot for the five most important features across all test samples. Each dot represents one prediction; horizontal position encodes the SHAP value (positive values push predicted cooling power up relative to the baseline; negative values push it down); and color encodes the feature value (red = high, blue = low).

Chiller Usage ranks first and shows the widest lateral spread, confirming that it has the largest and most variable influence across all operating conditions. High chiller usage (red dots) pushes predictions toward higher cooling power, while low chiller usage (blue dots) is associated with negative SHAP values. Server Workload ranks second and shows a consistently positive effect, higher workload always increases predicted cooling demand. AHU Usage and Inlet Temperature follow, with similar directional consistency. Total Energy Cost appears as a proxy for time-of-day price signals, which correlate with demand cycles.

Fig. 5 shows the mean signed SHAP values for the top five features within each of the four regimes, broken down by the four daily time sections. Signed SHAP preserves the direction of each feature's average effect (positive = increases predicted cooling power - negative = decreases it) and therefore carries more physical information than mean absolute importance alone.

The most notable pattern is the sign reversal of *Chiller Usage* across regimes. In the Idle and Transition regimes, the signed SHAP for Chiller Usage is negative across all four time sections. This means that, relative to the global baseline, higher chiller activity in low-demand periods is associated with a reduction in predicted cooling power. A physically reasonable interpretation is that in these regimes the chiller is operating in a pre-cooling or free-cooling mode, where increasing chiller output reduces thermal stress before it develops, thus allowing the overall cooling unit to draw less power than the baseline average. In the Peak Load and Thermal Stress regimes, the sign reverses to positive where higher chiller usage is now associated with an increase in predicted cooling power, because the chiller is responding to active high-temperature conditions rather than anticipating them.

This regime conditional, non-monotonic behavior is completely visible in the global beeswarm plot as shown in Fig. 4, which aggregates all operating contexts into a single importance ranking. The sign reversal confirms that global SHAP importance is insufficient for facilities that transition between distinct operating states.

AHU Usage shows a weaker but directionally similar pattern. In Idle and Transition regimes it shows small negative SHAP values at night and slightly positive values during afternoon peaks. In Peak Load and Thermal Stress regimes its signed SHAP is consistently positive during Morning and Afternoon periods, reflecting the direct coupling between daytime compute loads and forced-air cooling demand.

Server Workload shows consistently positive signed SHAP in all regimes and time sections, with larger magnitudes

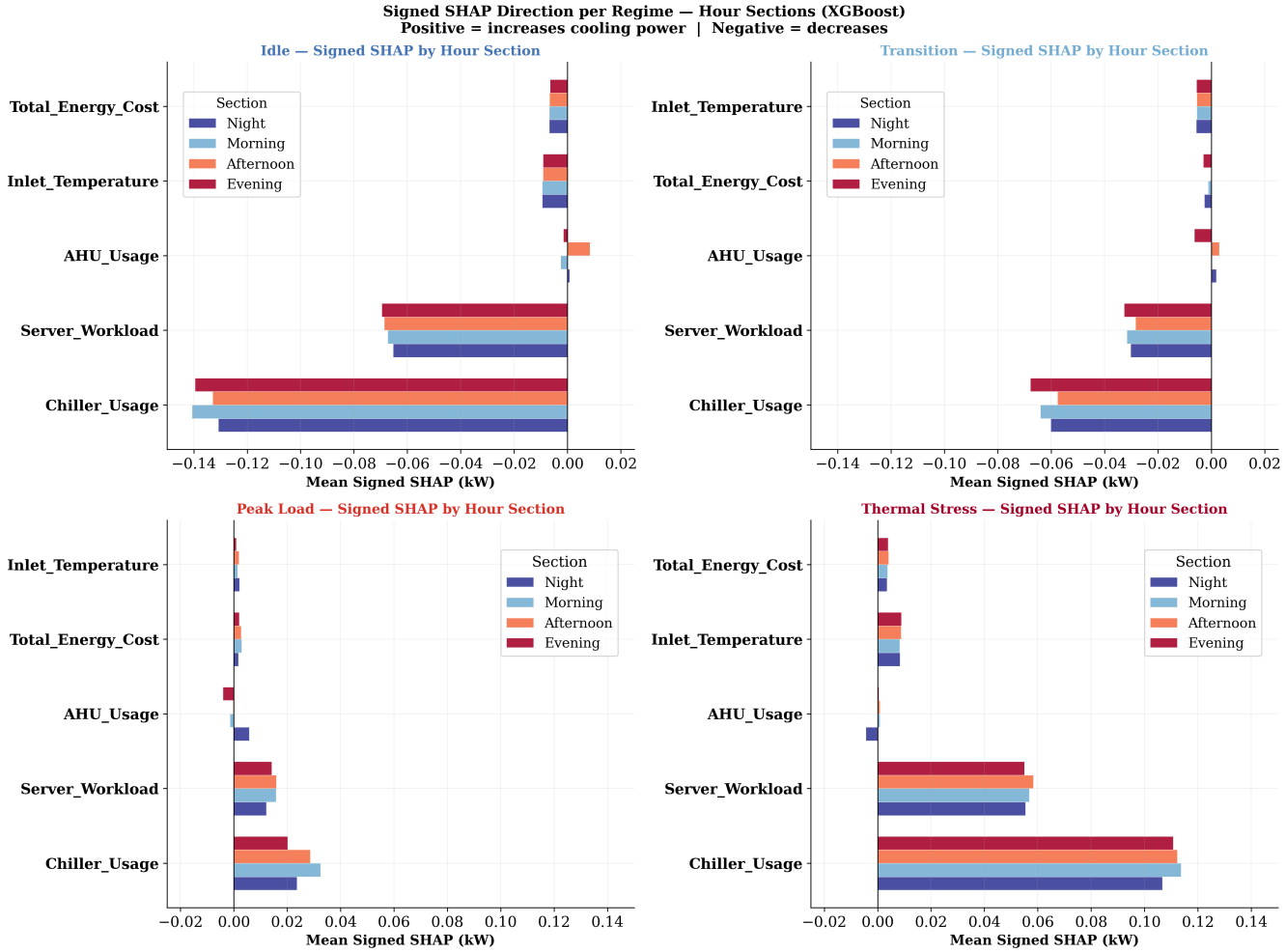

Fig. 5. Mean signed SHAP values for the five most important features, disaggregated by operating regime (rows) and daily time section (bar colors). Positive values indicate that the feature increases predicted cooling power relative to the baseline, negative values indicate a decrease. The sign reversal of Chiller Usage between low-demand (Idle, Transition) and high-demand (Peak Load, Thermal Stress) regimes is the key finding of this analysis.

during Morning and Afternoon in Peak Load and Thermal Stress. This is physically expected: higher compute activity always generates more heat that must be removed regardless of regime, and the effect is strongest when inlet temperatures are already elevated.

Inlet Temperature contributes positively to Peak Load and Thermal Stress across all time sections, and near-zero or slightly negative in Idle, where low ambient temperatures give the cooling system headroom. *Total Energy Cost* shows larger positive SHAP values during Morning and Afternoon periods in high-load regimes, reflecting the coincidence of peak electricity prices with peak cooling demand.

C. Operational Implications

The regime temporal SHAP results translate into concrete scheduling guidance for cooling system operators. During Idle and Transition regimes, the negative signed SHAP of Chiller Usage at night suggests that pre-cooling strategies are effective: running the chiller at moderate capacity during low-cost off-peak hours reduces predicted cooling demand during the subsequent morning ramp-up. Operators can schedule preventive chiller activation between 00:00 and 06:00 when electricity prices are low and inlet temperatures are at their daily minimum. During Peak Load and Thermal Stress regimes, positive SHAP contributions from Chiller Usage, Server Workload, and Inlet Temperature all compound simultaneously during afternoon hours. This confirms that afternoon periods (12:00 to 17:59) are the highest-risk windows for thermal stress, and that cooling resources should be fully committed rather than throttled on cost grounds. The AHU Usage positive contribution during these windows further supports running AHU at high capacity when server loads are elevated. The consistent positive contribution of Server Workload across all regimes and time sections confirms that workload-based predictive cooling control (activating cooling resources in anticipation of scheduled high-compute jobs) is always beneficial, regardless of time of day.

V. Conclusion

This paper presented a regime aware temporal XAI framework for data center cooling power prediction, extending the TRI approach to data center operations. The dataset contains 3,498 hourly observations from a single facility covering January to May 2025, with cooling power ranging from 0.33 to 1.11kW, representative of a small-to-medium data center. K-Means clustering with $k = 4$, selected based on WCSS elbow and silhouette analysis, identifies four operating regimes (Idle, Transition, Peak Load, Thermal Stress) that provide a physically meaningful context for SHAP interpretation. The XGBoost model achieves $R^2 = 0.9730$ (MAE $= 0.0209\,\text{kW}$, RMSE $= 0.0261\,\text{kW}$) on the 700-sample test set, with stable cross-validation scores confirming generalization. The central finding is that Chiller Usage shows a regime conditional sign reversal in its SHAP contribution: negative under low demand Idle and Transition conditions (where chiller activity anticipates rather than responds to thermal stress) and positive under high-demand Peak Load and Thermal Stress conditions (where it directly drives cooling power). This non-monotonic behavior is entirely hidden in global SHAP rankings and becomes visible only through regime temporal decomposition. AHU Usage shows a weaker but directionally similar pattern, while Server Workload maintains consistently positive SHAP across all contexts. These findings confirm that global feature importance is insufficient for facilities that transition between distinct operating states, and that regime aware explainability produces actionable guidance that global analysis cannot.

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Chapter 10



Discussion and Conclusion

10 DISCUSSION AND CONCLUSION

10.1 Discussion

This thesis set out to create practical, data-based methods that could strengthen energy and environmental consulting in support of energy and carbon-reduction management. Across seven connected studies, the results show how AI/ML and explainable analytics can be used in energy management in commercial buildings and heavy industry.

10.1.1 The TRI Framework as an Integrative Approach

The TRI framework made its main contribution by linking IoT data collection, machine learning prediction, and SHAP-based interpretation. This combination tackled a common problem: large volumes of data were being collected but not effectively turned into usable information for decision-makers. The framework was validated on commercial and industrial chillers, data centre cooling, and steel manufacturing, showing that it could adapt to different industrial and commercial environments. Particularly contribution of TRI lies in integrating established technologies into a common energy-management workflow rather than introducing IoT, machine learning, or SHAP individually. The case studies show how selected components connect data monitoring, prediction, and interpretation across different applications. However, the level of implementation and supporting evidence varies across studies, and the entire framework has not been experimentally validated.

High prediction accuracy alone was not enough for day-to-day energy management. The commercial chiller Random Forest model (R^2 = 0.81) and the industrial chiller Gradient Boosting model (R^2 = 0.85) confirmed that ensemble methods outperformed single algorithms, aligning with the scoping review evidence. Explainability was equally important. SHAP analysis pinpointed the variables that most influenced energy consumption, including Evaporation Tower Conductivity, which had been overlooked by conventional correlation. This ability to detect complex, nonlinear relationships

increased the transparency of the models. Because SHAP values were expressed in physical units (kWh), engineers and energy managers could understand how each factor contributed to a prediction, building confidence in the results. A comparison with commercial software platforms showed that, while these platforms offered similar predictive capabilities, they often lacked the transparency needed for scientific validation and engineering judgment.

10.1.2 Regime-Aware Explainability

The data centre cooling study added a temporal and contextual dimension to the framework. Instead of computing SHAP values across the whole dataset, feature importance was examined within individual operating regimes and time windows. This indicated, for example, that the effect of Chiller Usage reversed depending on conditions. During Idle and Transition periods, higher chiller usage reduced predicted cooling power, suggesting pre-cooling benefits. During Peak Load and Thermal Stress, however, higher usage increased cooling power. Standard global SHAP analysis could not have captured this shift. The practical implication is that cooling systems can be operated more efficiently by increasing chiller activity during off-peak hours, when electricity prices and outdoor temperatures are lower, thus easing the morning load ramp. The afternoon was consistently the period of greatest thermal risk, indicating when full cooling capacity must be available.

10.1.3 Empirical Evidence for Maintenance Interventions

The year-long comparison of two identical AHUs gave strong evidence that regular HVAC maintenance delivers measurable energy improvements. The cleaned AHU (AHU-C) achieved energy savings of 16.2% to 71.4%, thermal exchange efficiency gains of 15–25%, and airflow velocity increases of up to 12%. Cleaning the supply and return ducts improved the relationship between supply and return air temperatures, making heat transfer more stable. Cleaning the cooling coils enhanced heat exchange between the water and air sides, directly boosting cooling performance. Monthly data showed that AHU-C consumed less energy every month and exhibited smaller seasonal fluctuations, indicating that maintenance improved both efficiency and operational consistency. The multi-climate study also highlights the importance of evaluating HVAC cleaning through measured energy consumption and system-performance indicators. These results provide building owners and energy consultants with concrete evidence that regular AHU cleaning is a worth-

while investment and support the shift toward condition-based maintenance planning.The year-long comparison provides evidence of the benefits of the cleaning and maintenance interventions investigated. However, the results are specific to the two units and their operating conditions. Further studies across more units and facilities are needed to assess how these energy savings vary across systems.

10.1.4 Multidimensional Indicators for Buildings(Hospitals)

The hospital studies tackled the difficulty of benchmarking healthcare facilities, where many interacting factors drive consumption. A multidimensional Energy Performance Indicator (EnPI) framework, structured using the Ishikawa approach, organised influences into infrastructure, operations, environment, and history. Analysis of 44 hospitals indicated that models using all available indicators achieved the lowest prediction error (RMSE 39,102) and the highest R^2 (0.50), outperforming models with reduced feature sets. This suggests that removing variables can damage the model's ability to capture the complex interdependencies typical of hospitals. The moderate R^2 values also reflect the inherent unpredictability of hospital energy use, and larger, more diverse datasets would likely improve accuracy. International comparisons highlighted wide variations in energy intensity caused by differences in climate, building design, medical services, and operational practices, reinforcing the need for standardised, multidimensional benchmarking. However, the small sample size and moderate predictive performance limit the generalisability of these findings. The results do not rule out the value of feature selection, as its effectiveness may vary across datasets, models, and hospital characteristics.

10.1.5 Industrial Decarbonisation with Machine Learning

The steel mill study showed that blending ISO 50001 and ISO 50006 frameworks with machine learning can support industrial decarbonisation. An Energy Use Significance Score, which combined energy consumption, availability of monitoring systems, and technology suitability, helped prioritise where efficiency improvements would have the greatest impact. Sensitivity analysis showed that monitoring system availability had the strongest influence on the score, underlining the value of reliable data collection. Steel making, hot rolling, and conditioning were consistently identified as the most energy-intensive processes. The estimated CO_2 reduc-

tions and financial savings showed that machine learning can inform practical, high-impact decisions. For the compressor energy prediction, the SVM model captured nonlinear energy-consumption patterns effectively, and its predictive performance ($R^2 = 0.7808$) for the proposed unit($Wh/Nm^3/ton$). This positions SVM as a suitable tool for monitoring compressed air systems, detecting anomalies, and supporting continuous optimisation.

10.1.6 Limitations and Challenges

Several limitations should be kept in mind. In the commercial chiller case, the CV(RMSE) exceeded the ASHRAE Guideline 14 threshold for hourly models, mainly because key variables such as part-load ratio and condenser water temperature were missing. The model was therefore better suited to tracking general trends and detecting abnormal behaviour than to precise performance contracting. The industrial chiller model, built on only seven months of data, also had prediction errors above the recommended limit. SHAP explained relationships but did not establish causation, so engineering judgment remains essential before making operational changes based on the results. The hospital dataset of 44 facilities constrained the regression models' predictive power and may not have captured the full range of factors affecting consumption. Similarly, the steel mill compressor analysis used a single year of data, limiting its ability to represent seasonal and long-term changes. The data centre cooling model achieved high accuracy but relied on a five-month synthetic dataset, validation on real, longer-term operational data from different data centre configurations is needed. Additionally, adaptive control and multi-objective optimisation, though described in the TRI framework, were not experimentally validated in this work. Overall, the case studies provide evidence for the predictive, interpretability, and performance-assessment components of TRI examined in the individual studies. Differences in datasets, validation methods, and application contexts limit direct comparisons, while adaptive control remains unvalidated. Further research is needed to evaluate adaptive control and enhance the applicability of the framework across a broader range of applications.

10.1.7 Cross-Sector Observations

One of the strengths of this research was the successful application of the same core methodology across commercial buildings, hospitals, steel mills, and data centres. The consistent performance across these diverse settings confirmed that the TRI framework can

be adapted to different operational environments, data sources, and management needs. The scoping review findings further supported the case study results, with both showing that ensemble methods tend to outperform single algorithms in short-term energy forecasting and that explainability and data quality remain key challenges. Across building types and forecasting horizons, machine learning models consistently delivered higher accuracy than conventional statistical methods, reinforcing the case for their wider adoption in energy consulting.

Taken together, the studies address complementary aspects of the four research questions. Chapter 3 provides the scientific foundation for the research, while Chapters 6–8 investigate energy performance indicators and benchmarking (RQ1), Chapters 4 and 9 examine prediction and explainability (RQ2), and Chapter 5 evaluates the effects of maintenance interventions (RQ3). Chapter 4, together with Chapters 8 and 9, further contributes to RQ4 by examining how data-driven methods can support energy-management decisions in different operational contexts. These contributions are interconnected through the broader objective of translating operational data into reliable, interpretable information for energy and environmental consulting. However, each study addresses a specific application and validates only selected methodological components of TRI framework, their combined findings support the proposed TRI approach without constituting experimental validation of the entire framework.

10.2 Conclusion

This research developed and evaluated data driven methods to enhance energy and environmental consulting in support of carbon reduction across commercial and industrial sectors. By examining how IoT technologies, machine learning, and explainable AI can be connected within the TRI framework, the thesis addresses the gap between data collection and practical, evidence-based decision-making.

The findings support the applicability of selected TRI components, rather than providing complete experimental validation of the entire framework. Model performance varied across applications, while SHAP analysis helped interpret model predictions. The year-long comparison of two air-handling units showed improvements in energy consumption and system performance following maintenance, although the findings remain specific to the units and operating conditions studied. In the hospital study, the full set of energy-performance indicators outperformed the tested re-

duced sets for the 44 hospitals analysed, a finding that requires further validation. In steel manufacturing, machine learning supported energy assessment and compressor-energy prediction. The data-centre study further explored regime-aware temporal explainability using a publicly available synthetic dataset.

Several limitations were recognised, including restricted datasets, missing operational variables, and the absence of real-time closed-loop control trials. Future work should therefore pursue larger and more diverse datasets, improved feature engineering, and the implementation and testing of adaptive control strategies in live environments. Further research can assess the applicability of the discussed methods and framework across critical facilities and evaluate whether recommendations derived from explainability analyses lead to measurable operational improvements. Overall, the thesis shows the potential of combining IoT-based moni toring, machine learning, and explainable artificial intelligence, as data-driven methods to support energy-performance assessment, prediction, and interpretation across different applications. Further validation is needed to establish their generalisability and determine how the TRI framework can best support reliable and practical energy management decisions. The proposed methodologies offer practical open source tools for improving energy efficiency, lowering carbon emissions, and supporting robust, evidence based consulting across a wide range of commercial and industrial applications.