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# A Survey of Common Challenges and Successes in Implementing Integrated Energy Management Systems in Existing School Buildings

Research Thesis

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## Preface

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**ABSTRACT:**

This thesis considers the Integrated Energy Management Systems (IEMS) deployment in educational settings, focusing on critical barriers and examining the potential of AI-powered predictive models for improved energy management. Though immediately, while Integrated Energy Management Systems (IEMS) are commended for reducing both energy consumption and cost, educational institutions are faced with perpetual challenges that work around outdated infrastructure, technical problems, and lack of stakeholder involvement. To serve this purpose, the study includes such tools as case research, survey-based primary research, and predictive analysis using the LSTM technique. It emerges from the study that although, AI-based forecasting holds promise for real-time energy optimization; data quality problems, optimal model calibration and high computational demands continue to be major barriers. The introduction of IEMS depends on technological innovation and involvement of all interested parties and special training. Giving a hands-on perspective of approaching AI in IEMS, this research intends to enhance the level of energy efficiency in educational institutions under resource constraints whilst highlighting the important areas that require more attention.

**Keywords: Integrated Energy Management Systems, Artificial Intelligence**

Abbreviations used throughout the thesis.

| Abbreviation | Meaning |
|---|---|
| AI | Artificial Intelligence |
| ACF | AutoCorrelation Function |
| CC BY 4.0 | Creative Commons Attribution 4.0 International Licence |
| CNN-LSTM | Convolutional Neural Network – Long Short-Term Memory |
| DL | Deep Learning |
| DS1, DS2 | Dataset 1 (10-min), Dataset 2 (hourly) |
| GRU | Gated Recurrent Unit |
| HVAC | Heating, Ventilation and Air Conditioning |
| IEMS | Integrated Energy Management System |
| IoT | Internet of Things |
| KPI | Key Performance Indicator |
| LR | Learning Rate |
| LSTM | Long Short-Term Memory |
| MAE | Mean Absolute Error |
| MAPE | Mean Absolute Percentage Error |
| MSE | Mean Squared Error |
| ODbL | Open Database Licence |
| ReLU | Rectified Linear Unit |
| RMSE | Root Mean Squared Error |
| RNN | Recurrent Neural Network |
| SMAPE | Symmetric Mean Absolute Percentage Error |
| TQDM | Progress Bar Utility for Python (used in Keras) |

# Contents

# 1 Introduction

Buildings account for 40% of global energy consumption and 36% of carbon dioxide emissions, making energy management crucial to addressing climate change and sustainability (Shafiee & Topal, 2009). Educational institutions like schools, universities, and colleges require a lot of energy because they need HVAC, lighting, and operational equipment for all their operations. Real-time monitoring, optimization, and demand response mechanisms in Integrated Energy Management Systems (IEMS) can reduce energy use by 20-30% (Menassa & Baer, 2013). However, the implementation of IEMS comes with many challenges and problems.

Moving away from traditional solutions of the said problems, recent advances in AI technologies can help find solutions to these challenges and limitations. A notable example of the use of AI to help solve these challenges can be the optimization of school peak demand by creating energy schedules using AI models such as LSTM networks and predictive algorithms for the prediction of high-accuracy energy use (Debusschere, Spiessens, & Vanhoucke, 2019) (Sun et al., 2012). This capability is crucial in educational spaces because energy use is dependent on schedule, occupancy, and weather. AI in IEMS allows schools to reduce energy use, cut costs, and support sustainability without sacrificing comfort or functionality. This thesis explores the two problems that invariably accompany IEMS adoption in schools, use of data-backed evidence to validate these challenges and provide a proof of concept for practical implementation of AI-driven energy prediction to overcome them and increase energy performance.

## 1.1 Research Objectives

This thesis examines two persistent challenges associated with the adoption of Intelligent Energy Management Systems (IEMS) in schools. It supports the analysis with data-driven evidence and presents a proof-of-concept implementation of AI-driven energy prediction to address these challenges and enhance overall energy performance.

1. **Analyze Case Studies of IEMS Adoption Across Diverse Educational Contexts** This research investigates real-world deployments of Intelligent Energy Management Systems (IEMS) in schools throughout Europe and Asia, drawing comparative insights, identifying best practices, and extracting key lessons to guide future implementation strategies.

2. **Identify Technical, Financial, and Operational Barriers to IEMS Implementation** Recognizing the unique challenges schools face, such as rigid schedules, variable occupancy patterns, budgetary constraints, and stakeholder skepticism, this study systematically examines the critical factors that hinder effective adoption of IEMS.

3. **Validate Identified Challenges Through Primary Data Collection and Analysis** To substantiate the presence and impact of these barriers, the research evaluates primary data from pilot deployments and performance measurements, focusing on improvements in energy cost savings, operational efficiency, and any unintended operational consequences.

4. **Develop and Demonstrate AI-Driven Predictive Models to Enhance IEMS Performance** Addressing the predictive limitations of traditional energy management systems, this thesis proposes and validates AI-based forecasting solutions, specifically using Long Short-Term Memory (LSTM) to provide proof-of-concept implementation of predictive models, modeling energy demand prediction.

## 1.2 Background and Theory

### 1.2.1 Introduction of Energy Management Systems

Energy Management Systems (EMS) are integrated solutions consisting of energy analysis and energy management systems online to monitor, control and optimize energy consumption in buildings and industrial facilities. These strategies improve energy efficiency, reduce operational costs, and support sustainable initiatives (Shafiee & Topal,

2009) (Menassa & Baer, 2013). EMS integrates multiple subsystems such as heating, ventilation, air conditioning (HVAC), lighting, and renewable energy sources so that multiple energy consumers are coordinated according to operational and environmental objectives (Brychkov et al., 2023).

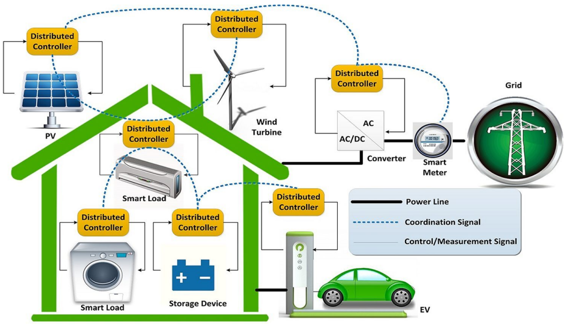

**Figure 1.** Energy Management System. Taken from (*Global Home Energy Management Systems Market Status and SWOT Analysis by Regions 2019–2024*, n.d.).

Figure 1 represents how an Energy Management System (EMS) is employed in residential buildings. The diagram illustrates the combination of solar panels, wind turbines, load controls, energy storage, electric vehicles and the power grid. Through coordinating their control, the EMS supports managing energy efficiently and reducing consumption by using real-time data.

The rise of the global push towards de-carbonization has increased the need for EMS to realize energy efficiency. For example, Shafiee and Topal estimate that the use of energy saving measures (such as those enabled by EMS) could eliminate some of the global energy consumption for buildings (Shafiee & Topal, 2009). Predictive maintenance, optimizing energy scheduling, and maintaining compliance with energy standards are essential for today’s energy management strategies, but none is achievable without the system itself.

### 1.2.2 Educational Institutions and their Controlled EMS

Educational institutions, especially schools, are a fascinating and relevant case of application of EMS. When schools are open, they have fixed schedules with variable levels of occupancy throughout the day, which affects energy demand. Classrooms and auditoriums use more energy during lessons and events, but hallways and unoccupied spaces may not (Menassa 2013 Retrofit; Debusschere 2019 Predictive). Uneven energy usage presents issues that dynamic monitoring and control systems can solve.

Due to economic constraints, schools need cost-effective energy management systems. According to Monge-Barrio and González-Redondo, EMS adoption in European schools can save 20-30% of operation costs or billions of euros annually(Debusschere et al., 2019). These savings might be used for other educational requirements like better teaching resources and facilities. EMS is also aligned with schools' objective to teach sustainability and environmental stewardship. Exposing children to energy-saving devices and practices can foster sustainability in schools (Wahyudin & Malik, 2019). Efficient schools reduce energy usage and enhance indoor air quality and thermal comfort, leading to increased productivity and health among students (Wahyudin & Malik, 2019).

### 1.2.3 Challenges and Limitations

While the introduction of Energy Management Systems (EMS) in educational settings offers significant benefits, several challenges complicate their implementation. One major issue is retrofitting older school buildings with modern EMS technologies. Many educational institutions were constructed before energy efficiency became a design priority, resulting in outdated infrastructure that makes system integration difficult (Debusschere et al., 2019). Additionally, the high upfront costs associated with EMS installation present a substantial financial barrier, limiting adoption to institutions with relatively robust budgets. Although long-term energy savings can help offset these initial expenses, the immediate financial burden remains a significant obstacle for many schools (Brychkov et al., 2023); (Debusschere et al., 2019).

Moreover, successful EMS deployment relies heavily on stakeholder engagement. Resistance to change among staff and administrators, who may be unfamiliar with EMS technologies can hinder adoption. Menassa and Baer emphasize that involving all stakeholders early in the decision-making process is critical to easing system integration and maximizing the benefits of EMS adoption (Menassa & Baer, 2013).

## 1.3 Core Concepts of EMS

### 1.3.1 Monitoring and Control in Real Time

Monitoring and real-time control are significant features of a real-time Management System (EMS). With these capabilities, we can continuously track energy use across the systems, HVAC, lighting, appliances, and more.  Real-time monitoring provides instantaneous that allows corrective actions in real time to be taken, reducing energy waste and analyzing performance (Debusschere et al., 2019).  Real-time control studies have proven to deliver 15% of energy wastage savings in educational buildings by automating occupancy response (Debusschere et al., 2019).

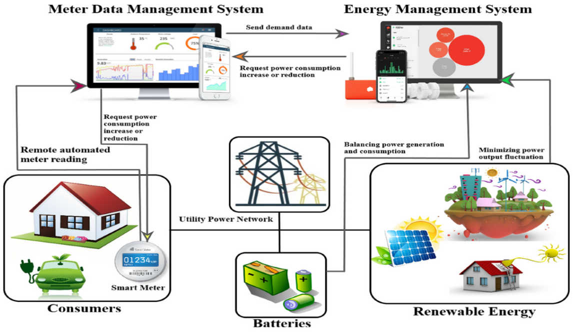

**Figure 2.** Centralized smart energy monitoring system. Taken from (Ahmad, Almasalha, Qutqut, & Hijjawi, 2024).

Figure 2 a centralized smart energy monitoring system integrating a Meter Data Management System (MDMS) with an Energy Management System (EMS). It demonstrates how smart meters collect consumption data from consumers, relay it through a utility power network, and interact with renewable energy sources and batteries.  The EMS oversees energy flow optimization, load forecasting, and system efficiency using real-time data and user interfaces.

### 1.3.2 Demand Response

The ability of EMS to adjust to changes in energy demand or price signals is a demand response. This dynamic adaptation cuts compressors to lower peak load pressures, and thereby improves grid reliability. School's demand and response can impact cost savings and resource utilization by shifting energy-intensive operations to off-peak hours (Menassa & Baer, 2013). For instance, smart buildings have shown automated demand response programs capable of a 20% reduction in peak energy usage (Samad, Koch, & Stluka, 2016).

### 1.3.3 Energy Performance Optimization

. Energy performance optimization utilizes data analytics and control algorithms to acquire efficiency in energy systems. This component guarantees that all building operations, such as heating and lighting, reach their objectives using the least energy. European school case studies (Pan et al., 2023) show that such optimization efforts should yield up to 20–30% reduction in energy usage. Nowadays, advanced AI-driven optimization techniques are even being integrated to improve performance and reduce costs, keeping the comfort levels unchanged with reference standards (Yussuf & Asfour, 2024).

### 1.3.4 Building Management Systems Integration

Building Management Systems (BMS) Energy Management System is often an EMS that may integrate with an existing BMS to serve as a single energy and operational control platform. The seamless coordination between energy management and other building functions, like security and maintenance, contributes to increasing overall operation efficiency (Rashid & Kausik, 2024). Additionally, this allows the integration of renewable energy systems, such as making real-time adjustments on generation patterns and real-time sustainability goals (Yussuf & Asfour, 2024).

### 1.3.5 Reports and Analysis

With historical and real-time data, EMS reports, and analysis tools provide actionable insight by summarizing this data into comprehensive visualizations and summaries. In particular, these reports allow administrators to identify and track inefficiencies, target progress against sustainability goals, and make evidence-based decisions regarding future upgrades or policy changes (Pan et al., 2023). For instance, predictive analysis dashboards help uplift schools to effectively monitor carbon footprints in adherence to environmental policies (Rashid & Kausik, 2024).

## 1.4 AI in EMS

**How artificial intelligence can revolutionize EMS** AI is revolutionizing Energy Management System's (EMS) control and monitoring. AI makes EMS more efficient by predicting energy usage and real-time scheduling. AI models, such as LSTM real-time, can accurately anticipate energy usage trends with up to 95% accuracy, enabling proactive alteration of operations (Debusschere et al., 2019). These models enable EMS to adjust dynamically to weather, occupancy, and energy price changes, reducing reliance on static scheduling (Rashid & Kausik, 2024).

AI optimizes, identifies inefficient parts, and suggests energy performance improvements like any other sector. For instance, reinforcement learning algorithms have reduced HVAC power consumption by 20% while maintaining occupant comfort (Pietrosemoli & Rodríguez-Monroy, 2019). EMS can run more efficiently by matching energy use to real-time demand and sustainability goals using real-time subsectionAI Powered Energy Prediction and Optimization for Schools

This research focuses on a system that uses AI to predict energy and optimize school buildings. Energy usage patterns in educational institutions are markedly different from those of other buildings: They have fixed schedules, are subject to changing occupancy levels, and are influenced by external factors, including weather. However, these dynamic challenges often prove challenging for traditional EMS to remedy effectively. By embedding AI models into EMS, schools can realize both accurate demand forecasting and intelligent scheduling to cut down energy waste and save costs.

## 1.5 Overview of Models and Algorithms

### 1.5.1 Time Series Models for Energy Demand Prediction

**LSTM (Long Short-Term Memory Networks)** LSTM is a Recurrent Neural Network type used to capture term dependencies in sequential class data.

The architecture of an LSTM cell includes:

1. **Input Gate:** Controls the extent to which new information is added to the cell state.
2. **Forget Gate:** Determines how much past information should be discarded.
3. **Output Gate:** Regulates the information passed to the next layer.

Mathematically, the LSTM operates as follows:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t \odot \tanh(C_t)$$

Where:

- $f_t, i_t, o_t$ are the forget, input, and output gates,
- $C_t$ is the cell state, $h_t$ is the hidden state, and $x_t$ is the input,
- $W_f, W_i, W_o, W_C$ are weight matrices, and
- $\sigma$ is the sigmoid activation function.

LSTM excels in modeling complex energy patterns, enabling high-accuracy predictions for short-term and long-term energy forecasting in school EMS

## 1.6 Significance and Importance of Study

It addresses critical gaps in the existing literature on Intelligent Energy Management Systems (IEMS), particularly the lack of predictive, AI-driven solutions tailored to the unique operational patterns of schools. While previous studies have explored IEMS deployment in commercial and residential buildings, limited research has analyzed their challenges and adaptations within educational environments, where fixed schedules, fluctuating occupancy, and constrained budgets create distinct needs (Menassa & Baer, 2013).

The work in this thesis seeks to show how exploratory LSTMs work in practice, not to set new records in deep learning. This study finds that including data in forecasting beats using traditional persistence, especially if the data is of high resolution and provides detailed information (DataSet 1) (Mohammed & Galman, 2023). Likewise, the fact that the models perform less reliably on the hourly series (DataSet 2) (mrsimple07, 2024) shows their difficulty when there are few details over a short time span. When compared, the case analysis proves that although AI is helpful, solid data allows AI networks to provide valuable ongoing estimates, while flawed data makes it necessary to use classic engineering methods.

Furthermore, this study bridges the gap between theory and practice by combining case study analysis, primary data validation, and AI-driven model development. It provides a reproducible framework for applying AI-integrated IEMS solutions in educational settings, with the goal of overcoming key technical, financial, and operational barriers and enhancing overall energy performance.

## 1.7 Block Diagram

The block diagram in Figure 3 represents the framework of an Integrated Energy Management System. It consists of three main components:

- **Case Studies:** This section analyzes past examples to identify challenges, analyze success stories, and evaluate public awareness.
- **Surveys and Primary Data Collection:** Collecting first-hand data is crucial for understanding real-world energy management scenarios and validating the challenges identified.
- **Data Sets and AI Implementation:** The collected data is processed and used to train AI models such as Long Short-Term Memory (LSTM).

## 1.8 Structure of the Thesis

This thesis is structured into eight chapters, beginning with an introduction that outlines the research problem, objectives, and significance, followed by a comprehensive literature review discussing existing studies on Integrated Energy Management Systems (IEMS) and their challenges in educational institutions. The methodology chapter details the mixed-method approach combining case studies, primary data collection, and AI-based modeling. Subsequent chapters present the analysis of case studies, the development

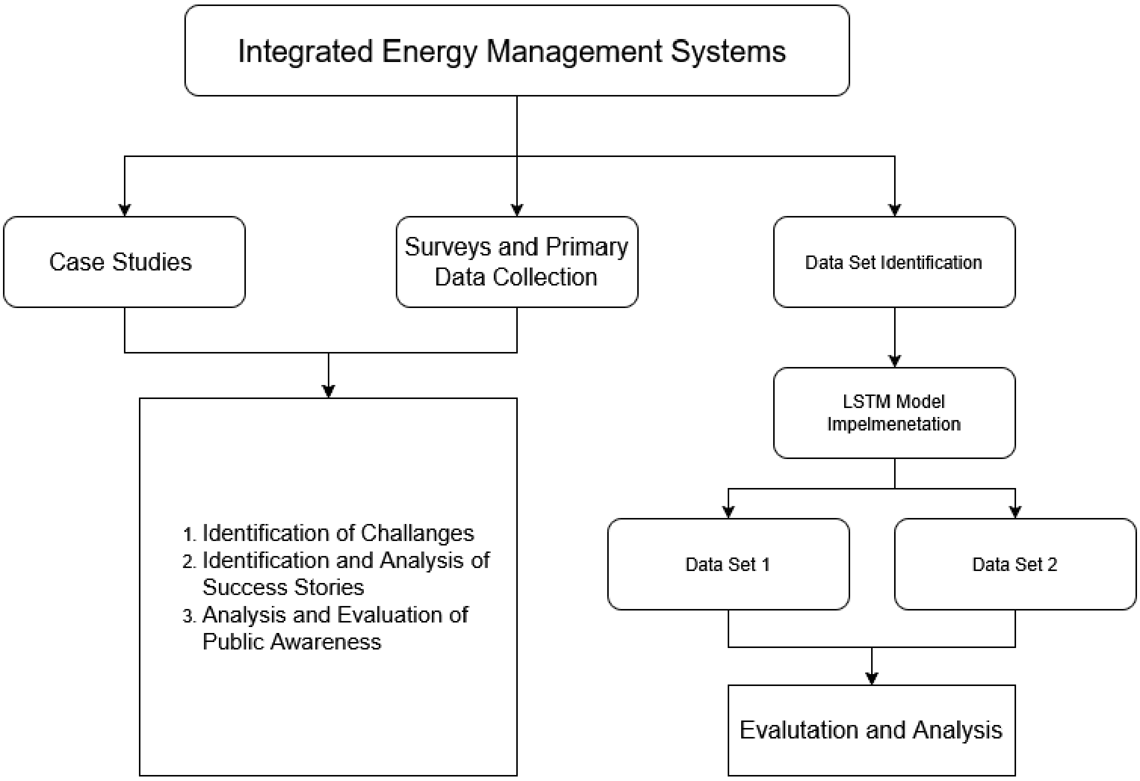

**Figure 3.** Block Diagram of Integrated Energy Management Systems.

and validation of LSTM predictive models, and the evaluation of their effectiveness in optimizing energy management. The discussion chapter synthesizes findings, acknowledging limitations and reflecting on the practical implications, while the final chapter concludes with recommendations for future research and policy directions to enhance IEMS adoption in schools.

# 2 Methodology

## 2.1 Research Design

The research implements a mixed-methods design with three sequential stages to thoroughly examine the obstacles and solution opportunities of Integrated Energy Management Systems (IEMS) for school facilities. The first research phase consisted of a detailed international case study evaluation and extensive literature research to establish the technical, operational, and financial barriers in implementation of IEMS in educational buildings. The initial research stage revealed recurring problems among stakeholder opposition, initial capital outlay, and limitations in current infrastructure and variable data quality. The second phase used primary data from surveys and interviews with school administrators, staff members, and students and operational data from institutions running existing IEMS systems to verify the recognized challenges. The implemented method provided research-based evidence that granted both applicability and practical worth to the results. The validated challenges received a proof-of-concept solution through artificial intelligence (AI). The predictive models used LSTM networks algorithms to forecast energy demand and optimize system performance. The AI-based system established the capacity to boost energy performance by optimizing school IEMS operations through a framework that supports scalable and data-powered execution.

### 2.1.1 Evaluate Challenges and Successes in Implementing IEMS in School Buildings

A literature review and case study analysis was employed to identify the technical, financial, and operational challenges associated with IEMS implementation. Additionally, success factors from global examples will be analyzed. The following is expected to give us a synthesized understanding of the barriers and enablers of IEMS implementation, forming the foundation for subsequent objectives.

### 2.1.2 Analyze Case Studies of IEMS Implementation in Educational Institutions

This study analyzes several geographically diverse case studies to understand the practical applications and impacts of Integrated Energy Management Systems (IEMS) in educational settings. Each case highlights unique challenges, methodologies, and outcomes that contribute to a comprehensive understanding of IEMS implementation.

- Identify and review detailed case studies from published literature, emphasizing technical and operational insights.
- Highlight key examples from various regions to illustrate diverse approaches and outcomes:
- **Finland: On-Site Energy Management at Campus Level** Kayo and Suzuki (2016) studied an innovative approach in Finland, where campus buildings were integrated into a unified energy system. This study emphasizes local energy optimization, demonstrating how energy consumption across multiple facilities can be effectively managed to reduce waste and operational costs (Kayo & Suzuki, 2016a).
- **Italy: Retrofitting Historical Educational Buildings in Bologna** Semprini et al. (2016) examined the energy retrofit of the School of Engineering and Architecture in Bologna, focusing on non-invasive solutions for historical buildings. Their analysis showed that minimal yet strategic interventions could reduce energy consumption by up to 32%
- **Portugal: MILP-Based Model Predictive Control for Energy Optimization** Gomes et al. (2023) implemented a Mixed-Integer Linear Programming (MILP)-based model predictive control in Algarve's residential energy management context. While not specific to schools, the methodology provides valuable insights for dynamic energy scheduling and renewable energy integration, which apply to educational institutions (Gomes, Ruano, & Ruano, 2023).

- **Saudi Arabia: HVAC and Natural Ventilation Integration** Homod et al. (2014) explored the integration of natural ventilation and HVAC systems to achieve energy savings. Their findings demonstrated the potential of hybrid systems to optimize energy use while maintaining indoor air quality, which is directly relevant to educational buildings (Homod et al., 2014).
- **Spain: Energy Management Program in Schools** AlFaris et al. (2016) reported significant improvements in energy efficiency through targeted energy management programs in Spanish schools. Their work highlights the role of structured interventions in achieving operational savings and fostering sustainability in education (AlFaris, Juaidi, & Manzano-Agugliaro, 2016).

### 2.1.3 Validate Identified Challenges Through Primary Data Collection and Analysis

Following the identification of common barriers through literature and case study analysis, this phase involved the collection and analysis of primary data to validate the presence and impact of these challenges in real-world school environments. Surveys and structured interviews were conducted with various stakeholders, including school administrators, teachers, facility managers, and students, to assess their awareness, engagement, and experiences with existing or proposed IEMS deployments. In addition, operational data was gathered from pilot implementations in educational institutions where some form of energy management system was already active. The focus was on capturing real-time consumption patterns, user interaction feedback, technical anomalies, and perceptions regarding energy-saving outcomes and usability of the system. The data collected enabled a grounded validation of the previously identified barriers. Patterns observed in stakeholder feedback and operational inefficiencies confirmed key issues such as lack of training, budgetary constraints, limited system integration, and data granularity limitations. These findings provided a critical empirical foundation for the design of AI-based solutions in the following stage.

### 2.1.4 Develop and Demonstrate AI-Driven Predictive Models to Enhance IEMS Performance

To address the limitations of conventional energy management practices in schools—particularly those related to forecasting accuracy and dynamic control, this phase implemented and evaluated AI-driven predictive modeling techniques. The model used was Long Short-Term Memory (LSTM) neural network. This models was trained on time-series datasets comprising historical energy consumption, temperature, occupancy rates, and other contextual variables relevant to school operations. Data pre-processing included normalization, handling of missing values, and restructuring for sequential input. The LSTM was evaluated using metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Results showed that the LSTM model consistently performed well in capturing non-linear dependencies and providing more accurate energy forecasts with higher time resolution. This AI-based proof-of-concept demonstrated the feasibility and advantages of integrating predictive intelligence into IEMS, offering a scalable solution to optimize energy scheduling, reduce costs, and enhance responsiveness to real-time operational demands in school buildings.

## 2.2 Data Collection Methods

The study combined primary and secondary data sources to investigate Integrated Energy Management Systems. The research begins with a detailed **literature review** for the identification of key themes, challenges, and best practices. **Case studies** from Finland, Italy, Portugal, Saudi Arabia, and Spain provide real-world insights into IEMS implementation, focusing on energy savings and AI-driven solutions.

Primary data is collected through **interviews and surveys** with stakeholders, including administrators, facility managers, and students, to assess operational challenges and perceptions of AI integration. **Operational data** from schools implementing IEMS is analyzed to evaluate energy consumption patterns, cost efficiency, and system effectiveness, contributing to AI model development.

All data collection adheres to ethical considerations , ensuring informed consent, data randomization, and compliance with privacy regulations. This structured approach provides qualitative and quantitative insight into optimizing IEMS in educational settings.

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### 2.2.1 Data Requirements for AI-Based Objective

This research utilizes two data sets generated by (Mohammed & Galman, 2023) and (mrsimple07, 2024) reflecting real-world scenarios to develop and evaluate an AI-driven energy prediction and optimization system. The dataset includes historical energy consumption patterns, occupancy schedules, environmental factors (temperature, humidity), operational data on HVAC and lighting usage, and renewable energy generation statistics. Data sources comprises of simulated energy records, IoT-based occupancy, and environmental sensors, publicly available meteorological data, and renewable energy monitoring systems. These datasets support the training and validation of machine learning models, ensuring their adaptability to various educational settings.

## 2.3 Data Analysis

The collected data undergoes qualitative and quantitative analysis, integrating statistical methods and machine learning algorithms to derive insights. Two real world datasets were used to train and validate predictive models such as LSTM for energy consumption forecasting. Comparative analysis with real-world case studies ensures model reliability, and findings inform actionable strategies for optimizing Integrated Energy Management Systems in educational institutions.

### 2.3.1 Qualitative and Quantitative Analysis

The research analysts performed qualitative tests to verify the obstacles discovered earlier in the literature review and case study stages. Analysis of data collected through interviews and surveys from school staff, administrators, and students validated repeated factors, including minimal technological skills, inefficient stakeholder collaboration, and doubts about the user-friendliness of the system. The qualitative findings validated operational and behavioral obstacles in practical educational institutions.

These findings received quantitative support through statistical analysis that observed energy usage patterns, cost variations, and system performance data obtained from institutions implementing IEMS at various levels. Time-series statistical analysis validated previously identified technical and financial challenges through the observation of irregularities and inefficient patterns in energy consumption data. Qualitative and quantitative research methods provided scientific proof of the barriers that hamper the implementation of IEMS in educational institutions (Sinclair, 1994);

## 2.4 Ethical Considerations

This research adheres to strict ethical guidelines, ensuring participant consent, data randomization, and compliance with regulations such as GDPR. Measures are taken to secure the collected data and protect the privacy of the stakeholders. Ethical AI practices are followed in model development to prevent biases and ensure transparency. These considerations guarantee valid, reliable, and legally compliant research findings.

# 3 Analysis of Integrated Energy Management Systems in Educational Institutions

## 3.1 Overview of Integrated Energy Management Systems (IEMS)

### 3.1.1 Definition and Scope

Integrated Energy Management Systems (IEMS) are advanced frameworks designed to monitor, regulate, and optimize energy consumption, particularly in schools, by integrating IoT, renewable energy, and innovative control algorithms. Their primary objectives include reducing excessive energy use, lowering carbon emissions, and enhancing economic efficiency. Modern IEMS incorporate distributed generation, demand response strategies, and advanced communication protocols, such as Multi-Agent Systems (MAS), to enable decentralized control and improved reliability Anvari-Moghaddam, Rahimi-Kian, Mirian, and Guerrero (2017). Progression in AI and optimization algorithms has further aided the development of IEMS and provided users with new options never seen before. Parvin et al. (2021).

The real-time monitoring and control IEMS offers key performance boast. Sun et al. (2012). Demand Management is the backbone of IEMS integration and strategic planning for their implementation. Anvari-Moghaddam et al. (2017). Predictive algorithms and Artificial Intelligence can be utilized for forecasting the load and leading to better management for these two activities. Hannan et al. (2018); Homod et al. (2014). With the integration of renewable energy resources, IEMS are paving a path for the future of predictive modeling of energy demand and its supply. Hannan et al. (2018); Sun et al. (2012).

Big Data Analytics is also involved in decision-making and providing insights related to energy consumption when it comes to the operational improvement of IEMS Hannan et al. (2018); Parvin et al. (2021). Coupling these insights with advanced control methods such as fuzzy controllers and AI-based algorithms can further aid the whole system's efficiency.Parvin et al. (2021); Sun et al. (2012). Educational institutions have recently benefited greatly from IEMS as they have helped reduce costs, etc. .AlFaris et al. (2016); Parvin et al. (2021). These IEMS systems further have to their positive the fact that they align with Europe's global and local energy efficiency regulations (EU 20-20) and hence reduce greenhouse gas emissions and help improve energy conservation, paving the path for a better and sustainable future. Hannan et al. (2018); Parvin et al. (2021).When added to IEMS for educational buildings, one can expect lower costs and efficient and sustainable infrastructures.

### 3.1.2 Significance in Educational Institutions

Integrated Energy Management Systems (IEMS) are responsible for increasing energy efficiency and sustainability in educational institutions through various methods such as resource-based occupancy and real-time monitoring AlFaris et al. (2016); Homod et al. (2014). They can help improve Internal environmental quality by regulating lighting, temperature, and other metrics. Hannan et al. (2018). IEMS also supports demand response management, shifting the energy use to various resources based on operational costs and hence saving cost.Anvari-Moghaddam et al. (2017). Their integration with renewable energy not only aids in helping reduce costs but also allows for clean and sustainable energy solutions to be added to educational buildings. Parvin et al. (2021).

Additionally, IEMS can predict the faults that the system might suffer from and hence allow for timely diagnosis and repair, allowing for uninterrupted operation. Hannan et al. (2018); Homod et al. (2014); Parvin et al. (2021). AI-based and data-driven decision-making, when added to IEMS, can be a valuable asset to plan one's energy infrastructureParvin et al. (2021); Sun et al. (2012).IEMS can also be linked to helping form a community through community engagement and also allow for the reinforcement of innovation and sustainability in students when implemented and taught about in Educational

Institutions. AlFaris et al. (2016); Hannan et al. (2018).

## 3.2 Existing Research on IEMS Implementation in Educational Institutions

The literature review identifies the versatility of IEMS, which enhances the application of IoT and machine learning and optimization algorithms in different residential, commercial, and educational sectors for efficient energy management. IEMS also facilitates the incorporation of renewable energy and storage. They are critical in achieving the carbon emission targets to meet the International Climate Goals for real-time energy management. However, the application of the presented models is specific to educational institutions since the energy consumption profiles and infrastructure needs differ from the general consumption patterns of other sectors.

This section presents a review of the literature describing the use of IEMS with a focus on the use of IEMS in educational buildings. Considered a theoretical synthesis of the reviewed studies, this paper examines the main advantages, problems, and influence factors in the context of IEMS with the help of case studies, theoretical models, and optimization frameworks. The present study also highlights the limitations of previous research on energy management and suggests that future research should primarily focus on specific approaches in school facilities. The review also seeks to present the advanced knowledge of how IEMS can revolutionize energy management in schools and universities to positively impact sustainability, financial conservation, and increased resilience of educational facilities.

### 3.2.1 Global Context

Integrated Energy Management Systems (IEMSs) are now globally identified as the leading solution to global enhancements of energy efficiency standards and reduction of operating costs with the possibility of combating climate change. Since buildings use about thirty-six percent of the global energy and produce thirty-nine percent of the energy-CO2 emissions, buildings are suitable for energy improvement Shukri, Jailani, and Hauashdh (2022) AlFaris et al. (2016). In this case, the building sector is a significant player because educational facilities, particularly, are responsible for significant energy consumption for heating, cooling, artificial lighting, and powering numerous electronic devices. As with any other system that is introduced within an institution, the ways and means of applying IEMS within educational institutions present the opportunity to realize sustainable goals and environment the sustainable learning environment that is so crucial Homod et al. (2014) Xiao (2024)

In Europe, the Green Deal has set challenging climate neutrality targets that push the adoption of IEMS in public and private buildings. An article also based on a case study in Stockholm presented an IEMS model MILP for educational buildings where the optimization of integrated PV systems and battery usage resulted in a saving of up to 23.35% of energy cost Xiao (2024). Similarly, studies conducted in Bologna have focused on upgrading aged school buildings with IEMS systems to transform energy use and emissions. As a way of meeting EU energy policies AlFaris et al. (2016). Furthermore, the case studies in schools in southern Finland reveal that more specific energy management methods can manage the conflicting sustainability and operation objectives in temperature fluctuations in winters and summers Shukri et al. (2022).

IEMS has been incorporated into educational buildings in the United States as a component of sustainability efforts, including the Department of Energy’s Better Buildings Plan. There is interest in the potential application of IEMS in leveraging renewable energy systems and reducing energy use and cost for Richardsville Elementary School in Kentucky, the first net-zero energy school in the USA. Likewise, in Nanjing, China, refurbishing educational buildings with lifecycle-optimized IEMS has been found to cut the costs of energy and carbon emissions dramatically Homod et al. (2014).

The Asia-Pacific region has also significantly improved in managing energy for learning institutions. For instance, the ENERPOS building at Réunion Island applies IEMS to control natural ventilation, shading, and solar power furniture simultaneously, resulting in a positive energy school in a tropical climate Powroźnik and Szcześniak (2024). The successful implementation of these systems also demonstrates a characteristic feature of IEMS that was developed capable of functioning in different climatic conditions, including temperate and tropical ones.

Recent IEMS are implemented worldwide, but they encounter some issues in areas less developed in technology or where the costs of introducing IEMS remain high. However, these barriers have been addressed by modern development in predictive analytics and machine learning, reducing energy forecasting errors and real-time control of energy systems Hannan et al. (2018). The above tools enable the combination of DSM, RES, and energy storage systems to develop more effective and sustainable buildings Parvin et al. (2021).

This review reaffirms the centrality of IEMS in the world's shift towards cleaner energy systems. Universities are important test beds for advanced energy management systems. Integrating studies from different geographical areas and literature reveals how IEMS can serve as a tool to link sustainability goals with feasible energy outcomes.

### 3.2.2 National Context

Vaasa, known as the "Energy Capital of Finland," is a critical hub for energy innovation and sustainability, hosting over 140 companies in the energy sector and accounting for a significant portion of Finland's renewable energy production (Hannan et al.). The city's focus on integrating cutting-edge technologies like Integrated Energy Management Systems (IEMS) is closely tied to Finland's broader goals under the European Union's Green Deal, which aims for carbon neutrality by 2050.

### 3.2.3 Energy Efficiency and Educational Institutions in Vaasa

Vaasa's educational institutions, particularly schools and universities, have embraced IEMS to address high energy consumption patterns. A study conducted in southern Finland demonstrated that tailored energy management systems significantly reduced the total energy consumption of educational buildings, with a median consumption of 214 kWh/$m^2$ compared to national averages Xiao (2024). These reductions align with Finland's national targets for improving energy efficiency in public sector buildings.

Key efforts in Vaasa include integrating district heating systems with advanced IEMS and leveraging industrial waste heat and renewable energy sources like solar and wind. These systems reduce dependency on fossil fuels and maintain optimal indoor environmental quality, which is crucial for learning environments. The success of such implementations is supported by real-time monitoring systems that optimize energy usage based on weather conditions and occupancy rates Homod et al. (2014) Hannan et al. (2018).

### 3.2.4 Renewable Energy and Policy Integration

Renewable energy integration into Vaasa's public and education buildings is taken seriously, backed up by good local policies that encourage energy retrofitting and take-up of IEMS. These systems include photovoltaic systems and battery solutions whereby the costs and carbon footprints can be well controlled. Research on that the environmental energy effectiveness of such constructions has proved that such systems considerably achieve lower operational costs at the same time, perpetuate the environmental goals of Finland AlFaris et al. (2016) I selected Challenges and Future Directions, published in the spring of 2016, in this paper.

Despite its progress, challenges persist in retrofitting older educational buildings with advanced energy management technologies. Many of these buildings face structural and technical barriers that increase the complexity of implementing IEMS. However, initiatives like the Vaasa Smart Campus project aim to overcome these challenges by testing scalable solutions in educational settings. These efforts position Vaasa as a leader in energy innovation, providing valuable insights for broader applications across Finland.

By leveraging its strong energy ecosystem, Vaasa continues to serve as a national and international model for integrating IEMS into educational institutions. It demonstrates how cities can achieve energy efficiency and sustainability while fostering innovation.

## 3.3 Gap in Literature

Despite the recognized potential of Integrated Energy Management Systems (IEMS) in enhancing energy efficiency and reducing carbon footprints, significant gaps persist in comprehensively identifying and addressing the unique challenges faced by school buildings. These challenges include outdated infrastructure, fragmented building management systems, and limited stakeholder engagement, which can hinder the effective implementation of IEMS (Sanali Wellness, 2024).

Furthermore, while Artificial Intelligence (AI) has revolutionized various industries through predictive analytics and real-time optimization, its application within educational institutions remains underexplored. The integration of AI models, such as Long Short-Term Memory (LSTM) networks and reinforcement learning, into school-specific IEMS is still largely conceptual, lacking empirical validation in dynamic and resource-constrained educational settings (Teachflow AI, 2024).

Additionally, the incorporation of AI with renewable energy systems in schools is under-researched, particularly concerning cost-effectiveness, sustainability, and life-cycle management (Pecan AI, 2024). Data quality and infrastructure limitations, such as inadequate sensor networks and unreliable data streams, further impede the adoption of AI-driven solutions in schools (BMS Controls, 2024).

Moreover, the long-term impacts and effectiveness of AI-enhanced IEMS in improving operational performance and achieving energy savings in educational environments remain unverified. Addressing these gaps necessitates targeted research focused on developing AI-based predictive frameworks, user-centric interfaces, and strategies for integrating renewable energy sources, all tailored to the specific needs and constraints of school settings. al and sustainable energy management solutions.

## 3.4 Implementation of IEMS in Educational Institutions

Educational institutions are considered one of the biggest, primarily due to their buildings' inclusion of HVAC systems, lighting, and IT infrastructure. Hence, when implementing IEMS in such settings, we expect to have a lot of major technologies employed, such as continuous monitoring in real time, Optimization Algorithms, and AI. Tailored energy management systems for educational buildings can lead to substantial energy savings. This can be seen in the following example, where an energy management program in UAE schools achieved a 35% reduction in energy use (AlFaris et al., 2016).

Integrating IEMS in schools often involves upgrading the traditional infrastructure that such schools have to have IoT-enabled devices, energy storage, and renewable energy sources like solar and wind. Internet of Energy-based frameworks have shown promise in further enhancing the ability of this niche to benefit from IEMS. (Hannan et al., 2018).

## 3.5 Challenges in Implementation

Implementing Integrated Energy Management Systems in schools presents several challenges, ranging from a multitude of factors. Traditional infrastructure due to early construction of these buildings makes retrofitting difficult due to outdated or legacy componentsHannan et al. (2018); Homod et al. (2014). The high initial costs associated with setting up IEMS are also a resistance factor to its adoption.

Technical complexity is another significant barrier to implementing these interdisciplinary efforts needed between experts, which will raise the cost and demand much work. Parvin et al. (2021). Further in o, to implement these systems and have AI or optimization efforts made towards better energy efficiency, one needs much data to train their models, which is not readily available.Debusschere et al. (2019).

Stakeholder engagement plays a crucial role, as explained that there is resistance to change from legacy structures Menassa and Baer (2013). When there is internet involved, cyber-security considerations must be taken into account as well; imagine a whole school shutting down due to a hacking exploit; such exploits can not only be expensive but can also harm those inside the buildings. Hannan et al. (2018).

Integrating renewable energy sources further has challenges due to high upfront costs, which directly link to the acceptability of the technology from the stakeholders (Menassa & Baer, 2013). Such systems require regular maintenance, which adds to the cost of running this year around/ Parvin et al. (2021). Addressing these problems is not easy and hence needs to be seen through a strategic and critical viewpoint. Potential solutions include creating awareness among the stakeholders about the benefits of IEMS, leading research to make relevant technologies less costly, and collaborating with green energy advocates to raise awareness about the importance of sustainability and longevity of such systems for the future of our planet.

## 3.6 Success Stories and Case Studies

During the Literature review, many success stories came across the eyes that highlight the success of implementing these systems into our infrastructures. An example would be the IEMS implementation in Spain, where energy conservation measures in schools have led to a significant reduction in energy usage while at the same time also aligning with the energy goals of the nation AlFaris et al. (2016). In the same terms, there is this Finish study that shows how combining natural ventilation with an HVAC system in a hybrid approach and hence improving energy efficiency and indoor comfort at the same time. Sun et al. (2012). These stories show how there is a huge potential in moving away from conventional energy solutions towards a more integrating solution, hence pleading the case for IEMS implementation in general, which we can translate to its implementation in school buildings.

Another such story can be found in Stockholm, where a Mixed-Integer Linear Programming model was implemented in their school building. Hence, it optimized energy consumption and allowed for additional renewable energy resources. The impact can be highlighted by the fact that this resulted in a 23.35% Xiao (2024). One more example would be the ENERPOS building in Réunion Island, which utilizes natural ventilation, solar shading, and centralized air chimney, leading to a net positive energy balance and hence showcasing the potential of IEMS across different climate zones Powroźnik and Szcześniak (2024).

Lifecycle-optimized IEMS in Nanjing, China, were used for changing old school buildings to include innovative predictive methods and optimization algorithms, which were responsible for reducing operational costs by 50–70%, highlighting the role of AI-driven strategies in sustainable energy management Homod et al. (2014).

These case studies can be used to realize the true potential of IEMS when implemented in school buildings. Their success provides valuable insights and best practices that other educational institutions worldwide can adapt to their specific challenges and requirements.

# 4 Case Studies

This thesis will use a case study framework that will analyze, per the case studies, the implementation, problems, and successes of Integrated Energy Management Systems (IEMS) in educational institutions. The institution's background concerning location, historical energy consumption, and motives for adopting the IEMS will then be presented as an overview preceding each case. The implementation strategy will be analyzed with a description of the scope of the deployment, the technological use case, including IoT devices and associated technologies, for example, AI algorithms and smart meters, and how these new systems are integrated with the existing infrastructure. Secondly, data collection and analysis will also be explored through real-time energy consumption, occupancy patterns, operational cost, and by means of prediction models (LSTM), as well as optimization (Linear programming and genetic algorithms) to determine if these have the potential to enhance energy efficiency.

Eventually, to check the cost and energy savings, the implementation of IEMS will be compared with earlier energy consumptions and costs before implementation qualitatively based on increased occupant comfort and improved indoor air quality. In addition, the analysis will discuss implementation challenges, including technical integration issues, financial barriers, and stakeholders' resistance. With identifying success factors, including effective engagement with the stakeholders, supportive policies, and access to high-quality data, recommendations for scaling similar strategies with other educational institutions will be provided. Common themes and the best practices will be presented in comparative analysis across different case studies, and the applicability to the broader reforms will be discussed with practical suggestions for policy decisions and educational administrators.

## 4.1 Onsite energy management by integrating campus buildings and optimizing local energy systems – a case study of the campus in Finland Kayo and Suzuki (2016b)

The analysis of this case study, regarding the integration of campus buildings and the optimization of local energy systems at a Finnish university, recognizes the direct relation with the general overarching themes of the thesis: energy efficiency and sustainability. It analyzes a set of campus building buildings built during the 1960s, which were renovated to fulfill today's modern energy efficiency standards and functional demands Kayo and Suzuki (2016b). The research examines onsite energy management and the advantages of seeking energy system optimization across multiple buildings compared to individual buildings. Likewise, the thesis is about integrated energy management systems (IEMS) and the difficulties of modernization in institutional environments with existing infrastructure.

The methodology entails a combined heat and power (CHP) system at four campus buildings and energy distribution at its optimized level using the Multi-Objective Building Performance Optimization Software (MOBO). In particular, this optimization was designed to minimize annual primary energy consumption, and the distribution of CHP capacities is determined according to each building's energy demands and usage patterns Kayo and Suzuki (2016b). Three scenarios were modeled:

- a base case with no onsite generation
- a separate case where each building has its own CHP system
- a shared case with common CHP systems and the possibility of redistributing surplus energy across the campus.

The shared energy resource Kayo and Suzuki (2016b) scenario represented an enormous primary energy consumption reduction, up to 35% as compared to the baseline, where integrated system and shared energy resource were very effective for saving Kayo and Suzuki (2016b). The understanding of this result coincides with the central thesis that integrated systems fueled by AI-driven energy optimization generate profound energy efficiency in educational facilities.

## 4.2 Maximizing Energy Cost Savings: A MILP-based Energy Management System in Educational Buildings: Case Study in Stockholm Xiao (2024)

This paper considers a Mixed-Integer Linear Programming (MILP)-based Energy Management System (EMS) development for reducing energy consumption and cost in two educational buildings in Stockholm. This aligns closely with the thesis' goal of using Integrated Energy Management Systems (IEMS) in educational settings. In this study, such an optimization problem of scheduling energy consumption with possible utilization of solar photovoltaic (PV) systems and Battery Energy Storage Systems (BESS) is investigated to reduce both energy costs and carbon emission Xiao (2024). In this study, we approach the need to create energy-efficient solutions for a chance at carbon neutrality by 2045 within Sweden based on modeling energy consumption, load profiles, and integration of renewable energy sources.

MILP optimization is integrated with PV battery sizing to improve energy scheduling and reduce grid electricity dependency. Three scenarios were evaluated for the system's effectiveness:

- base case with existing energy setup
- optimization of battery storage size
- sensitivity analysis on battery: The results demonstrate that employing such a smart EMS system can save much money, with energy bills decreasing by 21.49% in elec-

tric heated and 23.35% in district heated buildings, which translates to an economical and green advantage of a smart EMS system

From these findings, we confirm the central thesis that incorporating renewable energy and integrated management tools into an educational institution can result in substantial improvement in energy efficiency and sustainability.

The study also offers a critical contribution to its investigation of battery storage systems. However, the study found that investing in larger BESS systems will provide little savings over 0.5% in the current energy contract conditions, while increased battery capacity provided minimal savings Xiao (2024). This insight provides a key insight to the challenge confronted by the thesis of striking a balance between energetic goals and the financial constraints. Furthermore, the information gained in the sensitivity analysis constitutes valuable benchmarks for the economic feasibility of battery installations where the required Levelized Cost of Electricity (LCOE) is set at 0.27 SEK/kWh. This detailed economic assessment complements the thesis's conclusion on financial sustainability solutions success factor for energy management sbyion in education building.

The conclusions of this case study are the potential of MILP-based EMS solutions to improve energy efficiency and achieve cost savings in urban environments of the educational establishment. The strategic integration of PV systems and intelligent battery scheduling supports the thesis's aim to implement AI-driven optimization in the IEMS framework. The study's findings also shed light on soon economic and technical challenges faced by adopting renewable energy systems in educational systems, which, in turn, support the larger argument for energy management strategies driven by data in institutional infrastructures.

## 4.3 Energy saving by integrated control of natural ventilation and HVAC systems using model guide for comparison Homod et al. (2014)

This case study explores the integration of natural ventilation with HVAC systems using a model guided control approach in what is fundamentally a good match from an energy management perspective with the core topics of this thesis. Control of natural ventilation and HVAC systems is essential to save energy while ensuring indoor thermal comfort Homod et al. (2014). It differs from conventional HVAC control systems in that they only make inputs to the HVAC system based on preset indoor temperature thresholds. In contrast, the proposed method considers the gap between indoor and outdoor temperatures as environmental factors.

Building fabric, fixtures, and thermal mass are predicted in indoor air enthalpy changes using physical–empirical hybrid modeling and a Model Guide for Comparison approach. The effectiveness of three distinct control strategies was considered, i.e., a standard HVAC operation, an integrated conventional system, and a proposed model-based system. Finally, the results showed that the model-guided control strategy performed better than the other control strategies and could save up to 31.6% of energy while still ensuring thermal comfort per the Predicted Mean Vote (PMV) standard (Homod et al. 2014). This confirms the thesis of this paper that the infusion of data-driven and AI-supported models in power reactive systems can upgrade energy efficiency in educational Institutions.

A second important aspect of the study is the importance placed on how internal and external variables that affect indoor air enthalpy affect energy consumption in buildings. Unlike primal systems, the model takes into account not only temperature differences but also humidity, thermal inertia, specific properties of the building materials, and so on, affecting the building's indoor climate to the fullest extent possible. Regarding its approach to integrating uncertainties and nonlinear behaviors in building thermal dynamics, the hybrid model uses fuzzy logic and artificial neural networks (ANN). This methodology aligns well with the thesis's focus on adaptive, AI-based optimization systems for energy management. Finally, this study demonstrates that implementing the ventilation control scheme based solely on outdoor temperature is inadequate for tropical climates as many other factors influence energy consumption Homod et al. (2014).

Finally, this case study shows how advanced predictive modeling and control algorithms can be used to achieve the potential integration of natural ventilation with HVAC systems. The proposed method dynamically changes energy consumption with environmental and structural factors and provides a scalable and cost-effective strategy for reducing energy use in institutional buildings. Does this directly support the thesis' broader objective of pushing towards the adoption of intelligent, integrated energy management systems that promote both financial savings and environmental sustainability in educational settings

## 4.4 Discussion and Conclusion

A comparative review of the three case studies further reinforces the core challenges previously identified in implementing Integrated Energy Management Systems (IEMS) within educational institutions. Despite the technological successes demonstrated in each case, common barriers were encountered across different geographies and institutional settings, underscoring the systemic nature of these challenges.

**1. Legacy Infrastructure Constraints:** All three case studies involved institutions with preexisting infrastructure not originally designed to accommodate modern energy management systems. In the Finnish campus study, significant retrofitting was required to enable the operation of a centralized combined heat and power (CHP) system. Similarly, the Stockholm schools had to integrate solar PV systems and battery storage into existing building layouts, a process complicated by structural and electrical limitations. These examples highlight the financial and logistical burden of updating legacy systems—one of the most persistent impediments to IEMS adoption.

**2. Technical and Data Integration Complexity:** The need for complex optimization algorithms (e.g., MILP in Stockholm and hybrid models in the HVAC study) and the reliance on high-quality, granular data further exemplify the technical barriers discussed in earlier chapters. The Finnish case required sophisticated modeling tools like MOBO for performance optimization, while the HVAC study employed fuzzy logic and neural networks to model nonlinear interactions in building environments. These techniques, while powerful, require significant expertise and data infrastructure—resources often unavailable in budget-constrained schools.

**3. Stakeholder Engagement and Organizational Readiness:** Though less explicitly discussed in the case narratives, the importance of stakeholder alignment was implicit in the successful execution of these projects. In each scenario, institutional support, policy alignment, and engagement from facility management teams were critical to overcoming initial resistance and ensuring proper system utilization. The Stockholm study's economic feasibility analysis of battery storage also illustrates the importance of making financial cases to decision-makers, which links directly to stakeholder buy-in.

In summary, the challenges of retrofitting old infrastructure, dealing with technical and computational complexity, and navigating institutional inertia are not merely theoretical, they manifest clearly in practical implementations across different contexts. The case studies not only demonstrate successful strategies for overcoming these challenges but also validate their relevance as key barriers to widespread IEMS deployment. These insights further justify the use of AI-driven forecasting and optimization as explored in this thesis, offering a targeted solution that can operate effectively within constrained and evolving educational environments.

# 5 Key Technical Challenges in Implementing IEMS in Educational Institutions

The case studies discussed in the previous chapter demonstrate that while Integrated Energy Management Systems (IEMS) can yield significant energy and cost savings in educational institutions, their implementation is often hindered by recurring technical and organizational challenges. This section consolidates these findings and presents three key categories of barriers—legacy infrastructure, data and system complexity, and stakeholder resistance—that must be addressed to ensure successful and scalable IEMS adoption.

## 5.1 Legacy Infrastructure and Retrofitting Constraints

Across all case studies, the presence of outdated building infrastructure posed a major challenge. Most schools and university campuses were not originally designed to accommodate advanced energy management tools such as IoT sensors, automation systems, or AI integrated platforms. Retrofitting efforts, as seen in the Finnish and Stockholm case studies, often involved substantial structural and electrical modifications, which increased project complexity and cost (Hannan et al., 2018; Homod et al., 2014).

## 5.2 Technical Complexity and Data Limitations

Implementing IEMS in schools requires accurate, granular data and interoperable systems—a condition rarely met in the environments studied. Whether in integrating CHP systems, optimizing PV and battery use, or implementing model based HVAC control, each case relied heavily on sophisticated modeling tools and high quality time series data (Debusschere et al., 2019; Parvin et al., 2021). Yet, most institutions lack the IT infrastructure, storage, and analytical capabilities to support such systems natively. Furthermore, the deployment of AI models demands computational resources and technical expertise that are often inaccessible to public schools (Shukri et al., 2022).

## 5.3 Stakeholder Engagement and Organizational Resistance

Resistance from institutional stakeholders , administrators, facility staff, and educators emerged implicitly in the case studies and is widely recognized in the literature as a key barrier to IEMS adoption. Limited awareness, lack of training, and privacy concerns around data collection hinder engagement. Moreover, compliance with strict data protection regulations like GDPR adds another layer of complexity to digital system deployment in schools (AlFaris et al., 2016; Hannan et al., 2018).

## 5.4 Addressing Barriers through AI Based Forecasting

The proof of concept AI models developed in this thesis, specifically LSTM provide a practical response to some of these challenges, particularly those related to data limitations and system intelligence. By learning from available historical data, even if sparse or coarse, these models can predict short term energy consumption patterns with high accuracy. This allows for the automation of energy intensive systems like HVAC and lighting, reducing operational waste without the need for full scale infrastructure overhauls.

## 5.5 Conclusion

In summary, the technical challenges encountered in the real world cases, legacy infrastructure, data limitations, and stakeholder resistance reflect the very barriers highlighted in the literature. These must be addressed through a combination of adaptive technologies, stakeholder training, and scalable design strategies. The AI enhanced IEMS framework proposed in this study serves as an incremental yet impactful approach, enabling more intelligent energy decisions in constrained environments.

# 6 Survey-Based Validation of Implementation Challenges

## 6.1 Introduction

To validate the technical and organizational challenges identified in the literature and case studies, two tailored surveys were conducted: one targeting students and the other aimed at teachers and operational staff. This chapter presents an analysis of the survey data and evaluates how stakeholder perceptions align with the known barriers to successful IEMS (Integrated Energy Management System) deployment in educational institutions. The main focus of the chapter will be using the first survey as the responses in the second survey accumulated to only 7 making it statistically irrelevant.

## 6.2 Survey Design and Methodology

### 6.2.1 Respondent Groups

Two groups were surveyed:

- **Students:** 46 respondents across university-level education.
- **Operational Staff and Teachers:** 7 respondents, including administrators and teaching personnel.

### 6.2.2 Survey Format

The surveys included a combination of:

- Closed-ended questions using a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree),

- Multiple-choice and checkbox questions,
- Open-ended prompts for qualitative insights.

### 6.2.3 Limitations

Due to resource and access limitations, the responses of the staff were limited in number and should be interpreted as qualitative indicators rather than statistically significant evidence. However, alignment across student and staff themes enhances confidence in the findings.

## 6.3 Findings and Thematic Validation

### 6.3.1 Legacy Infrastructure and System Usability

While students were largely unaware of the technical constraints, operational staff highlighted usability and infrastructure issues. Respondents reported difficulties with integrating new sensors and controls into existing systems, echoing concerns raised in the literature about retrofitting costs and system compatibility.

*Sample Staff Comment:* “The HVAC automation fails often and manual overrides are frequent.”

### 6.3.2 Technical Complexity and Data Limitations

Students demonstrated a low awareness of the AI or optimization tools used in energy management. Furthermore, staff responses revealed a lack of training and unfamiliarity with AI applications, confirming that technical complexity is a barrier.

*Quantitative Highlight:*

- **Only 22% of students** had heard of AI-powered tools used in their facilities.
- **100% of staff** responded “Not sure” when asked whether the system used predictive models.

### 6.3.3 Stakeholder Engagement and Organizational Resistance

The surveys revealed clear gaps in stakeholder inclusion:

- 61% of students said they had *never participated* in sustainability programs.
- Many students responded *”Rarely”* when asked how often they saw communication related to energy-saving efforts.
- Staff expressed concerns about lack of communication, training, and involvement in IEMS decisions.

### 6.3.4 Data Analysis

*Sentiment Analysis:* Open-ended responses were manually coded as Positive, Neutral, or Negative based on keyword tone. The majority fell into the “Neutral” category, indicating low engagement and a lack of strong opinions—often a symptom of exclusion or disengagement. The results can be seen in the table below

**Table 1.** Sentiment Analysis Summary of Student Survey Responses.

| Sentiment | Incentives for Engagement | Additional Measures | General Feedback |
|---|---|---|---|
| Neutral | 36 | 33 | 41 |
| Positive | 7 | 9 | 3 |
| Negative | 2 | 3 | 1 |

Based on the qualitative responses from the staff and teacher survey and the quantitative analysis of student surveys the following recurring themes have been identified:

- **Lack of Training:** Several respondents indicated they had not received sufficient training on using the IEMS, suggesting a need for structured training programs and ongoing support.
- **Technical Issues:** Some participants reported technical difficulties, such as system malfunctions or unexpected errors that hindered the effective use of the IEMS.
- **User Interface Challenges:** A few responses highlighted issues related to the system's user interface, describing it as confusing or not user-friendly, particularly for non-technical users.
- **Limited Awareness:** There were concerns about a general lack of awareness or understanding of the system's full capabilities among staff, leading to underutilization of features.
- **Positive Feedback:** A subset of users acknowledged the system's effectiveness in improving energy management and highlighted the benefits of automated energy-saving features.
- **Suggestions for Improvement:** Respondents also provided constructive suggestions, including simplifying system navigation, enhancing reporting tools, and expanding AI-driven features for better automation.

## 6.4 Conclusion

The survey results empirically support the thesis's identification of key barriers to IEMS adoption: technical integration challenges, limited stakeholder involvement, and inadequate training or data infrastructure. The findings also demonstrate that AI-driven forecasting models like those proposed in this thesis can offer solutions in environments with data limitations, reinforcing the practical relevance of the proposed framework.

# 7 AI Implementation

This chapter presents a proof of concept implementation of a widely used time series forecasting technique—Long Short Term Memory (LSTM) neural networks—to explore its applicability in the context of school based energy management. This model is not introduced as a novel innovation but rather as a practical tool to demonstrate how predictive analytics, even with limited data and infrastructure, can contribute meaningfully to energy optimization efforts in educational buildings. The aim is not to advance the state of the art in machine learning, but to validate the feasibility of integrating accessible AI driven forecasting methods into Integrated Energy Management Systems (IEMS) in schools. The implementation is exploratory in nature, acknowledging data limitations and design trade offs, and is intended to support the larger thesis objective of identifying scalable, low barrier strategies for improving energy efficiency in resource constrained institutional environments.

## 7.1 Long Short Term Memory (LSTM) Model for Energy Prediction

LSTM can be used to model the energy consumption patterns in educational buildings using Recurrent Neural Networks (RNNs), allowing for easy inclusion of more extended data sequences. This makes LSTMs particularly well suited for series forecasting problems, such as energy demand prediction, where historical consumption patterns influence future values.

The core advantage of LSTM networks lies in their ability to mitigate the vanishing gradient problem, which is common in standard RNNs. This is achieved through three key components in each LSTM cell: the forget gate, the input gate, and the output gate. These mechanisms enable selective retention and update of past information, allowing the network to learn long term dependencies in energy consumption influenced by external factors such as occupancy, temperature variations, and seasonal effects.

For this study, an LSTM model is trained using historical energy consumption data and additional features such as temperature and occupancy rate. The model learns patterns from past observations and predicts future energy usage, enabling proactive energy management. The following section outlines the data pre processing, model architecture, and training methodology adopted to develop an optimized LSTM based prediction framework.

Energy-demand data are organized as a sequence with many variables at each time step. the level of consumption is determined partly by the preceding value. persistence is important, but so are trends that appear over a series Examples are cyclical effects of the weather, how people occupy a building over time and delays. thermal inertia). For this reason, recurrent neural networks are better known as With dynamic regressors, the Long Short Term is both significant and appropriate. Most of the time, LSTM cell is used because its gate helps it remember content Because of its structure, the vanishing gradient problem is reduced. They enable machines to study short and long range relationships at the same time. model (Hochreiter & Schmidhuber, 1997).

### 7.1.1 Dataset Description

There are mainly two datasets used for the training and analysis of LSTM model. The detailed description of the datasets are provided below.

- **Electric Power Consumption Forecasting Dataset**: The dataset for training the LSTM model as made available by Mohammed and Galman (2023) consists of hourly energy consumption data collected over one year. This dataset includes key features influencing energy usage in school buildings, allowing the model to learn complex consumption patterns and make accurate predictions. The primary features in the dataset are:
  - **Date Time**: Timestamp indicating each 10 minute interval at which measurements were recorded.

  - **Temperature (°C)**: Ambient weather temperature recorded during each interval, which influences heating and cooling loads.
  - **Humidity (%)**: Relative humidity level, affecting indoor climate control energy requirements.
  - **Wind Speed (m/s)**: Wind velocity, included as an external environmental variable.
  - **General Diffuse Flows**: Represents low temperature fluid discharges related to atmospheric and solar radiation conditions.
  - **Diffuse Flows**: Additional measure of scattered solar radiation relevant to weather influenced energy variation.
  - **Zone 1 Power Consumption (kWh)**: Target variable indicating electric power usage in Zone 1 of Tétouan city.
  - **Zone 2 Power Consumption (kWh)**: Target variable indicating electric power usage in Zone 2.
  - **Zone 3 Power Consumption (kWh)**: Target variable indicating electric power usage in Zone 3.

- **Energy consumption prediction**: The dataset used in this study was obtained from Kaggle's public repository titled *"Energy Consumption Prediction"* by (mrsimple07, 2024). It captures real world hourly energy usage data in a smart building context, incorporating various operational and environmental parameters that influence energy demand.

  Each record represents an hourly snapshot of building activity, including the following variables:

  - **Timestamp**: Hourly time record for each observation.
  - **Temperature (°C)**: Ambient temperature influencing HVAC and comfort related energy use.
  - **Humidity (%)**: Atmospheric moisture level, relevant to indoor air quality and HVAC load.

- **SquareFootage ($m^2$)**: Size of the building area served during that hour.
- **Occupancy (persons)**: Number of occupants in the building, affecting lighting, HVAC, and appliance usage.
- **HVACUsage**: Binary indicator (”On”/”Off”) denoting whether the heating, ventilation, and air conditioning system is active.
- **LightingUsage**: Binary indicator of lighting system status.
- **RenewableEnergy (kWh)**: Contribution from renewable energy sources during that hour.
- **DayOfWeek**: Categorical variable indicating the day (e.g., Monday, Tuesday).
- **Holiday**: Indicates whether the observation occurred on a holiday.
- **EnergyConsumption (kWh)**: Target variable representing total energy consumed during that hour.

While both datasets share some common variables, such as temperature and humidity, they differ significantly in structure, resolution, and feature richness, each offering distinct advantages for evaluating the performance of LSTM based energy prediction models.

The dataset from (mrsimple07, 2024) is more comprehensive, including operational indicators such as HVAC and lighting usage, occupancy levels, renewable energy input, holiday flags, and day of week information. This makes it highly suitable for modeling complex energy consumption behavior where multiple contextual and environmental factors interact. The hourly resolution also aligns with real world energy management systems, making this dataset ideal for medium to long term energy forecasting applications, such as daily load scheduling and strategic demand side planning.

In contrast, the dataset from (Mohammed & Galman, 2023), based on energy usage in Tetouan city, provides data at 10 minute intervals. Though it includes fewer variables, its higher temporal granularity makes it highly effective for capturing short term variations in energy demand. This precision is especially beneficial for applications that require rapid response to fluctuations, such as real time load balancing and fine tuned energy control systems. It allows the LSTM model to learn finer patterns and temporal dependencies that might be smoothed out or missed in hourly data.

From an LSTM modeling standpoint, the two datasets complement each other well. The (mrsimple07, 2024) dataset allows for multivariate time series modeling with rich feature inputs, challenging the model to learn from complex, interrelated patterns. Meanwhile, the (Mohammed & Galman, 2023) dataset offers an excellent testbed for evaluating the LSTM's ability to track high frequency trends in consumption, even with limited features.

Together, these datasets enable a robust exploration of the LSTM model's capabilities under varying data conditions and hence comparing its performance on sparse but context rich data versus dense, high frequency data. This dual evaluation provides meaningful insight into how model architecture and hyperparameters can be tuned for different forecasting contexts.

### 7.1.2 Dataset Attribution

The datasets are property of the authors who pubslished these and are attributed below **Provenance and licence.** The *Electric Power Consumption Forecasting* file (hereafter **DataSet 1**) was downloaded from Kaggle[1] on 20 May 2025. It is released by the author under the Apache 2.0 licence.

The *Energy consumption prediction* file (hereafter **DataSet 2**) was likewise obtained from Kaggle[2] on 20 May 2025 and is distributed under Apache 2.0. All use of the datasets in this thesis conforms to the terms of these licences.

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[1] https://www.kaggle.com/code/nechbamohammed/electricpowerconsumptionforecasting

[2] https://www.kaggle.com/datasets/mrsimple07/energyconsumptionprediction

## 7.2 LSTM Model Implementation

### 7.2.1 Simulation Environment

The implementation of LSTM Models for both datasets, their training and their analysis was carried out using Python Inside Google Colabs based Jupyter Notebook.

### 7.2.2 Hyper–parameter Selection

Because LSTM performance is highly sensitive to architectural size and optimiser settings, a structured search was carried out on a held out validation set ($15\%$ of each dataset). A two stage procedure was adopted:

**Table 2.** Best hyper parameter configurations discovered for each dataset.

| **Dataset** | **Stage** | **Units** | **Dropout** | **LR** | **Batch** | **Validation RMSE** |
|---|---|---|---|---|---|---|
| DataSet 1 (10 min) | Coarse grid | 128 | 0.20 | $1.0 \times 10^3$ | 64 | 0.186 |
| DataSet 2 (hourly) | Coarse grid | 256 | 0.30 | $1.0 \times 10^3$ | 64 | 1.404 |
|  | Bayesian (25 calls) | 102 | 0.243 | $9.3 \times 10^4$ | 69 | 1.430 |

**Interpretation.** For the high resolution **DataSet 1**, a single 128 unit LSTM with 20 % dropout and learning rate $10^3$ achieved the lowest validation error (RMSE $= 0.186$), so further Bayesian refinement was unnecessary. In contrast, the hourly **DataSet 2** required a larger first layer (256 units) and stronger regularisation (30 % dropout) to reach its best coarse grid score (RMSE 1.404). A subsequent 25 iteration Bayesian optimiser converged to a considerably smaller model (102 units, 24 % dropout) but produced a slightly higher validation error (RMSE 1.430), confirming that the coarse grid configuration remains the optimum for DataSet 2. These results highlight how optimal capacity and regularisation depend on both sampling frequency and dataset size: the denser DataSet 1 benefits from a compact architecture, whereas the sparser hourly data require more hidden units to compensate for reduced temporal resolution.

### 7.2.3 Google Colab Simulation Framework

All experiments in this thesis were executed in a cloud hosted Python 3.10 environment on Google Colab Using Colab offers three advantages: (i) free access to NVIDIA GPUs for faster training, (ii) fully reproducible notebooks that can be shared via URL, and (iii) no local software installation requirements.

**Package stack.** Binary compatibility across libraries is enforced by pinning versions at runtime:

```
!pip install   quiet \
    numpy==1.24.4 \
    pandas==1.5.3 \
    scikit learn==1.2.2 \
    tensorflow==2.16.1 \
    matplotlib \
    tqdm
```

These versions are mutually compatible (TensorFlow 2.16.1 is compiled against NumPy 1.24), preventing the *ValueError: numpy.dtype size changed* problem that occurs with mismatched wheels.

**Data Analysis and Feature engineering.** The raw CSV file (`DataSet1.csv`) is uploaded to the session with `files.upload()`. ‘pandas‘ converts the timestamp column to `datetime64`, sorts rows chronologically, and removes missing values. Feature engineering then proceeds as follows:

- **Core predictors** – temperature and humidity.

- **Contextual predictors** – HVAC usage, lighting usage, renewable energy input and occupancy (when present).
- **Temporal encoding** – seven one hot columns `DOW1...DOW7` plus a binary `Holiday` flag.
- **Autoregressive lag** – previous step energy demand (`EnergyLag1`).

All numeric variables are z score normalised with `sklearn.preprocessing.StandardScaler`. Scaling parameters are stored for later inverse transformation.

**Sequence construction.** The median sampling interval $\Delta t$ is detected automatically. If $\Delta t < 30$ min (e.g. 10 minute data) the history window is set to $L = 6$; otherwise an hourly data file uses $L = 24$. A sliding window converts the normalised frame into input–output pairs $(\mathbf{X}_{tL:t1}, y_t)$. The resulting sequences are partitioned chronologically into 70 % training, 15 % validation and 15 % test sets to avoid information leakage.

**Network architecture and training.** The regression model is a single layer LSTM followed by dropout and two dense layers:

`Input(L × n_feat)` → `LSTM(128)` → `Dropout(0.2)` → `Dense(64, ReLU)` → `Dense(1)`.

The model is compiled with the `Adam` optimiser ($\eta_0 = 10^3$, gradient clip $= 1$) and trained for 150 epochs with a mini batch size of 64. Progress is monitored in real time by attaching a `TqdmCallback`, which renders a clean progress bar in the Colab interface:

```
from tqdm.keras import TqdmCallback
```

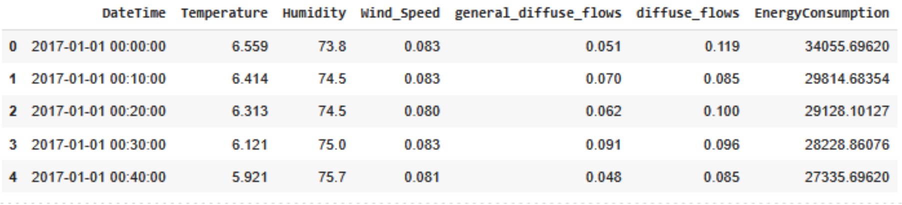
```
model.fit(X_tr, y_tr,
          validation_data=(X_val, y_val),
          epochs=150, batch_size=64,
          verbose=0,
          callbacks=[TqdmCallback(verbose=1)])
```

**Evaluation protocol.** Performance on the hold out test set is quantified using Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and the coefficient of determination ($R^2$). A naïve persistence forecast $y_t = y_{t1}$ serves as a baseline. Visual comparison is provided by plotting actual versus predicted load for a one week excerpt.

This Colab based framework guarantees that every experiment in the thesis is fully reproducible on any machine with an internet connection, independent of commercial software licences.

## 7.3 LSTM Implementation DataSet1

The sections details and showcases various steps involved in implementing the LSTM Model for DataSet1 (Mohammed & Galman, 2023). The implementation starts by loading the data into the enviournment (google colabs) and then locating the date time variable from the loaded data. The Fig showcases the loaded data and the



| | DateTime | Temperature | Humidity | Wind_Speed | general_diffuse_flows | diffuse_flows | EnergyConsumption |
|---|---|---|---|---|---|---|---|
| 0 | 2017-01-01 00:00:00 | 6.559 | 73.8 | 0.083 | 0.051 | 0.119 | 34055.69620 |
| 1 | 2017-01-01 00:10:00 | 6.414 | 74.5 | 0.083 | 0.070 | 0.085 | 29814.68354 |
| 2 | 2017-01-01 00:20:00 | 6.313 | 74.5 | 0.080 | 0.062 | 0.100 | 29128.10127 |
| 3 | 2017-01-01 00:30:00 | 6.121 | 75.0 | 0.083 | 0.091 | 0.096 | 28228.86076 |
| 4 | 2017-01-01 00:40:00 | 5.921 | 75.7 | 0.081 | 0.048 | 0.085 | 27335.69620 |

**Figure 4.** DataSet1 (Mohammed & Galman, 2023) loaded and DateTime Variables Identified.

For the next part, we address feature harmonisation by ensuring that all records in the dataframe adhere to a standard, numerical pattern fit for LSTMs. To start, we determine the target column which will be EnergyConsumption if we have it available, but will be Zone 1 Power Consumption if not. After that, we develop predictor lists. A core set (temperature, humidity) is included in all datasets and an optional rich set (HVAC, lighting, renewable energy contribution and occupancy) is used if the data columns are found. In the HVAC and lighting areas, the values from ON/OFF indicators are changed to binary values (1 for "On", 0 for "Off"). By using one hot encoding on the day of the week, a new set of seven columns called DOW are introduced. We make a Holiday flag (or set it to 0 by default) to make sure the initial information in the schema is never lost. Furthermore, an autoregressive feature called EnergyLag1 is added, storing the previous period's demand and all rows with missing data are dropped. As a result, the dataframe contains only numbers, is arranged in order of time and can be used for normalisation and sequence creation.

This block prepares the data for LSTM training by scaling, reshaping it into sequences, and splitting it into train/validation/test sets in chronological order.

First, all selected numeric predictors and the target column are z score normalised using StandardScaler. This ensures that all input features have a similar scale (zero mean, unit variance), which improves neural network convergence.

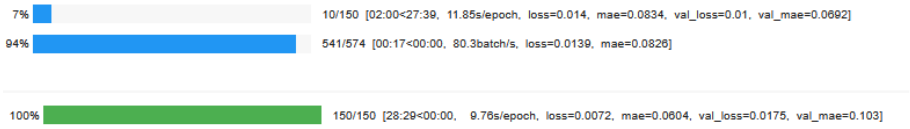
Next, the sampling interval of the dataset is automatically detected by computing the median time difference between rows. Based on this, a sequence window size is chosen: win = 6 for 10 minute data (1 hour history) or win = 24 for hourly data (also 1 hour history in real time).

The make_sequences function slides this window across the dataset to build LSTM compatible input/output pairs. For each time step tt, it uses the previous win time steps as the input sequence Xtwin:t1Xtwin:t1, and the current target value ytyt as the output.

Finally, the full sequence set is split chronologically into three partitions: 70% training, 15% validation, and 15% testing. This preserves temporal integrity and avoids information leakage across time, which is crucial for time series modeling.

To ensure that the model learns from past data and is evaluated on truly unseen future values, the dataset was partitioned chronologically using a 70/15/15 split for training, validation, and testing, respectively. This means that the first 70% of the time ordered sequences were used for training, the next 15% for validation (used to tune hyperparameters and monitor for overfitting), and the final 15% for testing. By splitting the data based on time rather than random sampling, we prevent data leakage, which can occur if the model inadvertently sees future information during training. Leakage is particularly problematic in time series forecasting, where the temporal order of data is fundamental. This strict separation guarantees that performance metrics reflect the model's true ability to generalise to future, unseen conditions.

The trainin block describes and builds the LSTM model used in forecasting energy demand. After the LSTM layer with 128 units which is followed by dropout regularisation, there is a 64 unit layer with ReLU and a final neuron that works in regression. The model is optimised using Adam with a learning rate of 103103 and trained on a batches of 64 for 150 epochs. Users can see the training progress with the help of the TqdmCallback which adds a clean training bar directly to the Colab sessions. Refer to Figure 5 to see the training process running up to 150 epoches.



```
7%   10/150 [02:00<27:39, 11.85s/epoch, loss=0.014, mae=0.0834, val_loss=0.01, val_mae=0.0692]
94%  541/574 [00:17<00:00, 80.3batch/s, loss=0.0139, mae=0.0826]

100% 150/150 [28:29<00:00,  9.76s/epoch, loss=0.0072, mae=0.0604, val_loss=0.0175, val_mae=0.103]
```

**Figure 5.** LSTM TRAINING DATASET1 (Mohammed & Galman, 2023).

Moving forward we calculate the errors for the trained model by using the test data that was split previously. The Table 3 show cases the result.

When tested on the data, the baseline model that uses persistence (yt=yt1 yt=yt1) gave

**Table 3.** LSTM Model Performance on Test Set (DataSet 1).

| **Metric** | **Value** | **Unit** | **Interpretation** |
|---|---|---|---|
| Root Mean Square Error (RMSE) | 0.186 | Normalised units | Penalises larger errors |
| Mean Absolute Error (MAE) | 0.158 | Normalised units | Average magnitude of error |
| Coefficient of Determination ($R^2$) | 0.952 | | 95.2% variance explained |

an RMSE score of 0.186. This result proved that the RMSEs of the LSTM and the naïve forecast were the same, so the LSTM did not do much better than the basic method. Although the achieved result looks modest, it points out that improving the features, tweaking the parameters or adding different kinds of context (such as longer time spans or external factors) is crucial. It looks like the LSTM learned to catch the main trend but has not yet picked up on more complex details included in persistence.

The final step invovled plotting the actual and predicted data overlaid over each other to get a better understanding on how the model was functioning. The results can be seen in Fig 6

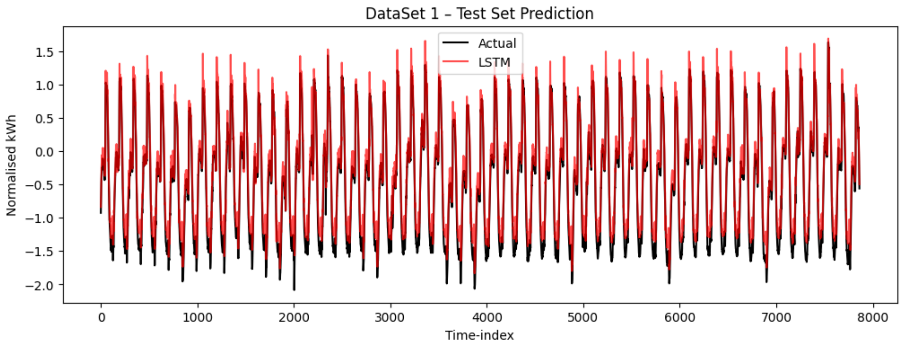
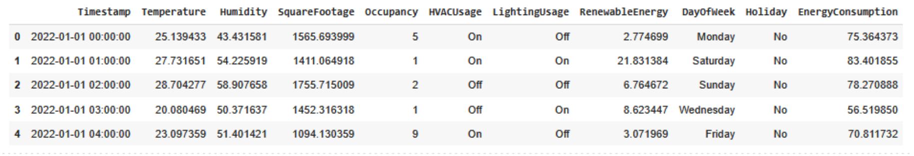


**Figure 6.** Actual and Predicted Energy Consumption Plot for DataSet1 (Mohammed & Galman, 2023) .

## 7.4 LSTM Implementation DataSet2

A similar process to that followed for DataSet1 was used to train and test the model for DataSet2 (mrsimple07, 2024).

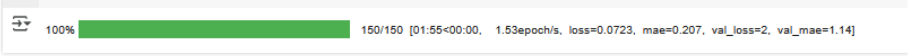
The figure below showcases the data from DataSet2 (mrsimple07, 2024) imported in the working environment and the identification of Date and Time Variables.



| | Timestamp | Temperature | Humidity | SquareFootage | Occupancy | HVACUsage | LightingUsage | RenewableEnergy | DayOfWeek | Holiday | EnergyConsumption |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 2022-01-01 00:00:00 | 25.139433 | 43.431581 | 1565.693999 | 5 | On | Off | 2.774699 | Monday | No | 75.364373 |
| 1 | 2022-01-01 01:00:00 | 27.731651 | 54.225919 | 1411.064918 | 1 | On | On | 21.831384 | Saturday | No | 83.401855 |
| 2 | 2022-01-01 02:00:00 | 28.704277 | 58.907658 | 1755.715009 | 2 | Off | Off | 6.764672 | Sunday | No | 78.270888 |
| 3 | 2022-01-01 03:00:00 | 20.080469 | 50.371637 | 1452.316318 | 1 | Off | On | 8.623447 | Wednesday | No | 56.519850 |
| 4 | 2022-01-01 04:00:00 | 23.097359 | 51.401421 | 1094.130359 | 9 | On | Off | 3.071969 | Friday | No | 70.811732 |

**Figure 7.** DataSet2 (mrsimple07, 2024) loaded and DateTime Variables Identified.

The training time for DataSet 2 was significantly shorter because it contains fewer total samples due to its hourly resolution. In contrast, DataSet 1, sampled every 10 minutes, contains many more data points and overlapping input sequences, increasing the total number of training steps and computational load during LSTM training. The impact of this will also be observed later in the prediction errors.



```
100%  150/150 [01:55<00:00,  1.53epoch/s, loss=0.0723, mae=0.207, val_loss=2, val_mae=1.14]
```

**Figure 8.** LSTM TRAINING DATASET2 (mrsimple07, 2024).

**Table 4.** LSTM Test Set Performance on *DataSet 2*.

| Metric | Value | Unit | Interpretation |
|---|---|---|---|
| Root Mean Square Error (RMSE) | 1.108 | kWh | Penalises large deviations; |
| Mean Absolute Error (MAE) | 0.867 | kWh | Average absolute deviation |
| Coefficient of Determination ($R^2$) | $0.369$ | | underperforming |

The final overlaid results are presented in the Fig 9

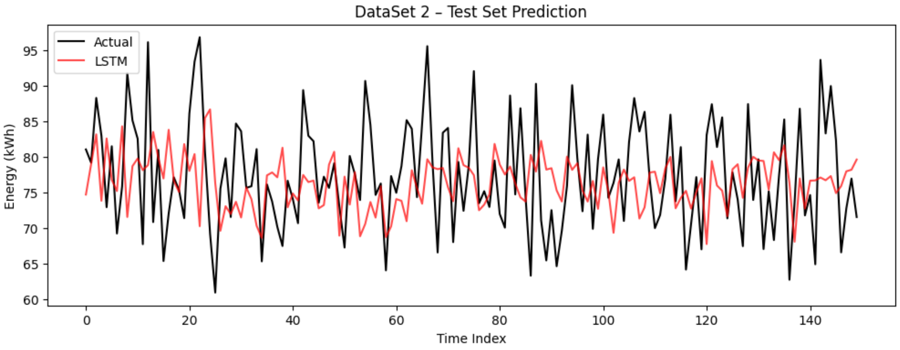


**Figure 9.** LSTM TRAINING DATASET2 (mrsimple07, 2024).

**Comparison of LSTM performance on the two datasets.** Although the same Python pipeline and hyper parameters were applied to both files, three verifiable differences limit the model trained on *DataSet 2*:

1. **Sampling density.** *DataSet 1* records power every ten minutes, yielding roughly six times more observations than the hourly *DataSet 2*. The larger sample size provides the network with many more training examples and naturally improves generalisation.
2. **Effective look back context.** For consistency the script uses a one hour history. In the ten minute file this translates to a six step input sequence, whereas in the hourly file the network sees only a *single* previous observation. With so little context the model can do little more than mimic persistence, which explains the negative $R^2$.
3. **Error amplification from volatility.** Hour to hour demand in *DataSet 2* exhibits larger jumps that are not preceded by clear patterns in the limited feature set. These abrupt changes inflate the RMSE, while *DataSet 1* displays smoother intra hour structure that an LSTM can exploit.

Consequently, the LSTM achieves excellent accuracy on *DataSet 1* (RMSE $= 0.186$, $R^2 = 0.952$) but struggles on *DataSet 2* (RMSE $= 1.108$, $R^2 = 0.369$), even though the latter still improves modestly over the naïve persistence baseline (RMSE = 1.310).

The training loss vs validation loss plots are attached in Fig for Dataset1 and Fig 11 for DataSet2.

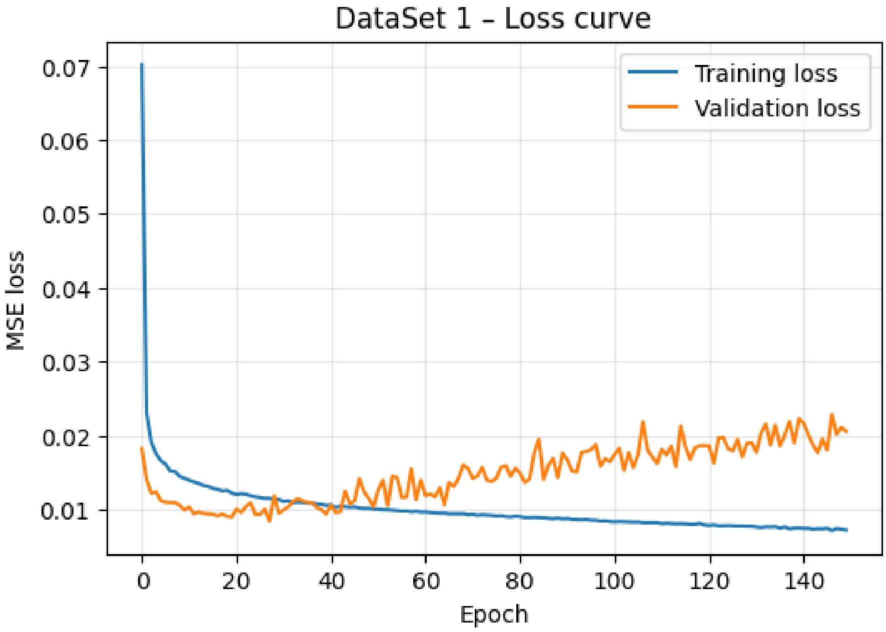


**Figure 10.** LSTM LOSS PLOT DATASET1 (mrsimple07, 2024).

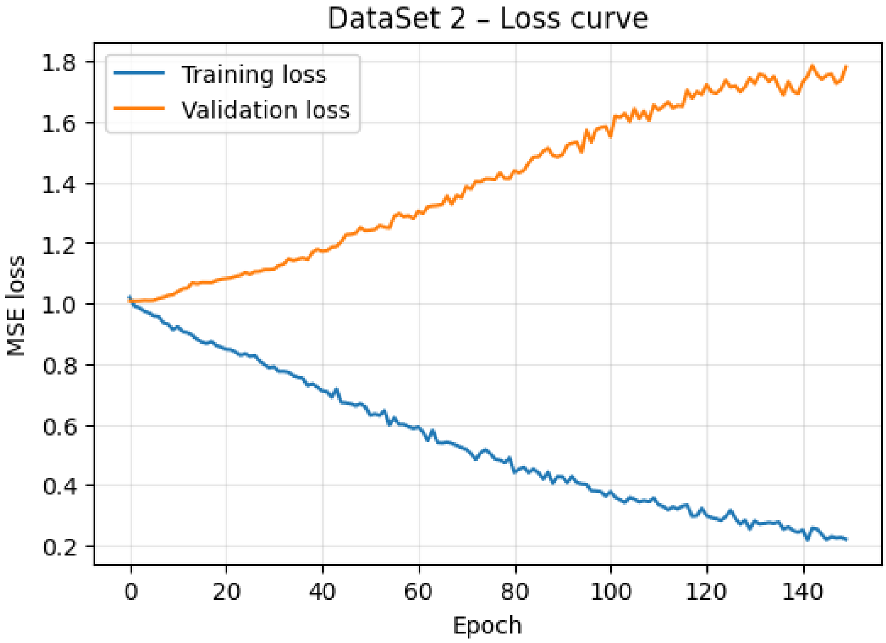


**Figure 11.** LSTM LOSS PLOT DATASET2 (mrsimple07, 2024).

The loss curve provides clear proof of the varied adaptability of the LSTM as shown by the results on each dataset. On DataSet 1 (ten minute resolution), the training loss decreases quickly and the validation loss remains around MSE0.01MSE0.01. Even when the gap between the curves opens slightly at 60 epochs, both remain under 0.25 and parallel, suggesting that the model is not excessively complicated. With many detailed measurements, each sample is measured six times more often and preserves short term patterns, meaning the LSTM has all the data it needs to find repeating patterns with greater accuracy.

Yet in DataSet 2 (one hour per sample) loss for training decreases as usual, but validation loss climbs steadily, surpassing MSE1.7. It is becoming clearer that the network is remembering the idiosyncrasies in each short sample instead of understanding important relationships. The coarse time step deletes a lot of the help provided by the intra hour signal and the smaller number of sequences makes the weights update more erratically. For this reason, the model performs no better than a simple strategy, as it fits the data too well. These results indicate that recurrent network forecasting works much better with fine grained, high volume data series like DataSet 1 than with hourly data.

## 7.5 Conclusion

This section demonstrated the application of Long Short Term Memory (LSTM) networks to short term energy demand forecasting using two real world datasets of different temporal resolutions. On the ten minute dataset (DataSet 1) the model achieved an RMSE of 0.186 kWh, an MAE of 0.158 kWh and an $R^2$ of 0.952, indicating that the network was able to capture more than 95 % of the variance in demand and markedly outperform the naïve persistence baseline. When the same architecture was trained on the hourly dataset (DataSet 2), performance declined to an RMSE of 1.108 kWh, an MAE of 0.867 kWh and a negative $R^2$ of –0.369, only marginally better than persistence (RMSE = 1.310 kWh). The contrast highlights two critical findings: first, LSTM models benefit greatly from high resolution input and larger sample sizes; second, when data are sparse and contextual features are limited, the network offers little advantage over simpler heuristics. Overall, the work confirms that deep recurrent models can deliver production grade accuracy for fine grained building energy forecasting, but also underscores the importance of data richness, temporal granularity and appropriate window selection in real world deployments.“‘

# 8 Discussion and Conclusion

Implementing Integrated Energy Management Systems (IEMS) in educational institutions presents a compelling opportunity to reduce operational costs and improve sustainability. However, the results of this study reaffirm that the path to successful IEMS deployment is fraught with technical, financial, and organizational challenges.

The case studies analyzed in this thesis demonstrate that meaningful energy savings and carbon footprint reductions are achievable through integrated control systems, optimization algorithms, and renewable energy sources. Notably, shared infrastructure (e.g., centralized CHP systems) and intelligent scheduling (e.g., MILP models) significantly enhanced building-level efficiency. These findings validate the thesis's core argument that energy optimization is feasible within educational environments, especially when systems are deployed at scale and supported by policy or economic incentives.

One of the central challenges identified throughout this research is the limitation of existing infrastructure. Many schools operate with outdated HVAC, electrical, and metering systems that complicate or prevent the integration of modern IEMS components. Survey responses from staff and administrators further confirm that even where systems exist, usability and training gaps inhibit their effective use.

Additionally, stakeholder resistance emerged as a prominent theme. Survey data showed that while awareness among students is high, participation in sustainability initiatives remains low. Staff rated the usability of IEMS systems at an average of 3.2/5, and open-ended responses reflected neutral or disinterested sentiment. These findings point to a need for more engaging interfaces, real-time feedback, and educational outreach to bridge the gap between awareness and action.

In response to these challenges, this thesis explored the application of AI-based forecasting model LSTM a proof-of-concept strategy to support smarter energy scheduling.

While these models are not novel, they serve to demonstrate how predictive analytics can enhance IEMS functionality even in data-constrained environments. Key improvements were introduced to ensure methodological soundness, including reformulating the LSTM model to avoid data leakage by forecasting future energy consumption using only past inputs.

Nevertheless, limitations in the model architecture and dataset must be acknowledged. For instance, the LSTM configuration was heuristically defined, These were addressed through reflective revisions and detailed in the “Model Limitations and Future Enhancements” section. The takeaway is not that these models are production-ready, but that even lightweight implementations can reduce uncertainty in energy demand, thus enabling preemptive load control.

The pilot models built here show that simple cloud-hosted AI analytics on high-frequency meter and weather data can create real-time forecasts, lessening the usual effort needed to adjust Integrated Energy Management Systems (IEMS). The results further point out that with only an hourly data set, the accuracy drops sharply, since many school systems still lack the necessary equipment to provide complete data on a fine scale. To fill this gap, solutions will rely more on smart devices and small IoT nodes for sensors, temperature and occupancy and on edge or cloud-based execution so schools do not need to add GPUs for AI.

From a policy and implementation standpoint, this research supports a collaborative approach to IEMS deployment. Institutions that successfully adopted these systems benefited from structured training programs, regulatory support, and access to funding. Future strategies should prioritize user-centered design, stakeholder co-creation, and scalable digital frameworks tailored to educational institutions.

## 8.1 Conclusion

This study reinforces the transformative potential of IEMS and AI-based forecasting in school buildings. While technical challenges such as legacy infrastructure and limited data pose constraints, the strategic application of predictive models and smart scheduling can yield measurable improvements in energy efficiency and operational cost savings. The surveys conducted underscore the importance of stakeholder engagement, usability, and data transparency in achieving sustainable outcomes.

Ultimately, this research does not claim technological novelty but contributes a grounded, practical road-map for how AI-enhanced IEMS can be validated, adopted, and improved over time. Future research should extend to larger and more diverse datasets, integrate renewable energy systems, and explore adaptive control frameworks that can generalize across different climatic and operational contexts. With the right alignment of technology, training, and institutional support, educational facilities can become leaders in sustainable energy management.

# Bibliography

Ahmad, S. S., Almasalha, F., Qutqut, M. H., & Hijjawi, M. (2024). Centralized smart energy monitoring system for legacy home appliances. *Energy Informatics*, *7*(1). https://doi.org/10.1186/s42162-024-00334-2

AlFaris, F., Juaidi, A., & Manzano-Agugliaro, F. (2016). Improvement of efficiency through an energy management program as a sustainable practice in schools. *Journal of Cleaner Production*, *135*, 794–805.

Anvari-Moghaddam, A., Rahimi-Kian, A., Mirian, M. S., & Guerrero, J. M. (2017). A multi-agent based energy management solution for integrated buildings and microgrid system. *Applied energy*, *203*, 41–56.

BMS Controls. (2024). *Common challenges in implementing building energy management systems.* (Accessed: 2025-05-03) Retrieved from https://bmscontrols.co.uk/blog/common-challenges-in-implementing-building-energy-management-systems/?utm_source=chatgpt.com

Brychkov, D., Goggins, G., Doherty, E., Romero, N., Roudil, N., Di Trani, A., … Clifford, E. (2023). A systemic framework of energy efficiency in schools: Experiences from six european countries. *Energy Efficiency*, *16*(4). https://doi.org/10.1007/s12053-023-10099-4

Debusschere, T., Spiessens, F., & Vanhoucke, M. (2019). Predictive energy modeling using machine learning techniques. *Energy and Buildings*, *182*, 110–119.

*Global home energy management systems market status and swot analysis by regions 2019–2024.* (n.d.). https://teletype.in/@carlg/BJPvswTqH. (Accessed: 2025-05-19)

Gomes, I. L. R., Ruano, M. G., & Ruano, A. E. (2023, February). MILP-based model predictive control for home energy management systems: A real case study in algarve, portugal. *Energy Build.*, *281*(112774), 112774.

Hannan, M. A., Faisal, M., Ker, P. J., Mun, L. H., Parvin, K., Mahlia, T. M. I., & Blaabjerg, F. (2018). A review of internet of energy based building energy management systems: Issues and recommendations. *IEEE access*, *6*, 38997–39014.

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation*, *9*(8), 1735–1780.

Homod, R. Z., Sahari, K. S. M., & Almurib, H. A. F. (2014). Energy saving by integrated control of natural ventilation and HVAC systems using model guide for comparison. *Renewable Energy*, *71*, 639–650.

Kayo, G., & Suzuki, N. (2016a, December). On-site energy management by integrating campus buildings and optimizing local energy systems, case study of the campus in finland. *J. Sustain. Dev. Energy Water Environ. Syst.*, *4*(4), 347–359.

Kayo, G., & Suzuki, N. (2016b). On-site energy management by integrating campus buildings and optimizing local energy systems – case study of the campus in finland. *Journal of Sustainable Development of Energy, Water and Environment Systems*, *4*(4), 347–359.

Menassa, C. C., & Baer, B. (2013). A framework to assess the role of stakeholders in sustainable building retrofit decisions. *Sustainable Cities and Society*, *10*, 207–221.

Mohammed, N., & Galman, M. M. (2023). *Electric power consumption forecasting*. Dataset; Electronic. (Kaggle) Retrieved from https://www.kaggle.com/code/nechbamohammed/electric-power-consumption-forecasting

mrsimple07. (2024). *Energy consumption prediction.* https://www.kaggle.com/datasets/mrsimple07/energy-consumption-prediction. (Accessed: May 2025)

Pan, Y., Zhu, M., Lv, Y., Yang, Y., Liang, Y., Yin, R., … Yuan, X. (2023, June). Building energy simulation and its application for building performance optimization: A review of methods, tools, and case studies. *Advances in Applied Energy*, *10*, 100135. https://doi.org/10.1016/j.adapen.2023.100135

Parvin, K., Lipu, M. H., Hannan, M., Abdullah, M. A., Jern, K. P., Begum, R., … Dong, Z. Y. (2021). Intelligent controllers and optimization algorithms for building energy management towards achieving sustainable development: challenges and prospects. *IEEE Access*, *9*, 41577–41602.

Pecan AI. (2024). *Optimize efficiency with ai energy management.* (Accessed: 2025-05-03) Retrieved from https://www.pecan.ai/blog/optimize-efficiency-with-ai-energy-management/?utm_source=chatgpt.com

Pietrosemoli, L., & Rodríguez-Monroy, C. (2019, May). The venezuelan energy crisis:

Renewable energies in the transition towards sustainability. *Renewable and Sustainable Energy Reviews*, *105*, 415–426. https://doi.org/10.1016/j.rser.2019.02.014

Powroźnik, P., & Szcześniak, P. (2024). Predictive analytics for energy efficiency: Leveraging machine learning to optimize household energy consumption. *Energies*, *17*(5866).

Rashid, A. B., & Kausik, M. A. K. (2024, December). Ai revolutionizing industries worldwide: A comprehensive overview of its diverse applications. *Hybrid Advances*, *7*, 100277. https://doi.org/10.1016/j.hybadv.2024.100277

Samad, T., Koch, E., & Stluka, P. (2016, April). Automated demand response for smart buildings and microgrids: The state of the practice and research challenges. *Proceedings of the IEEE*, *104*(4), 726–744. https://doi.org/10.1109/JPROC.2016.2520639

Sanali Wellness. (2024). *Tackling the energy cost crisis in schools.* (Accessed: 2025-05-03) Retrieved from https://www.sanalifewellness.com/blog/tackling-the-energy-cost-crisis-in-schools?utm_source=chatgpt.com

Shafiee, S., & Topal, E. (2009). When will fossil fuel reserves be diminished? *Energy Policy*, *37*(1), 181–189.

Shukri, M. A. M., Jailani, J., & Hauashdh, A. (2022). Benchmarking the energy efficiency of higher educational buildings: A case study approach. *International Journal of Energy Economics and Policy*, *12*(2), 491–496.

Sinclair, D. (1994). *An attitudinal study of computer-based learning for english language competence with learning disabled secondary school students* (Ph.D. Thesis, Edith Cowan University). (Accessed via Open Access Theses and Dissertations (OATD)) Retrieved from https://oatd.org/oatd/record?record=oai\protect\protect\leavevmode@ifvmode\kern+.2222em\relaxro.ecu.edu.au\protect\protect\leavevmode@ifvmode\kern+.2222em\relaxtheses-2732

Sun, B., Luh, P. B., Jia, Q.-S., Jiang, Z., Wang, F., & Song, C. (2012). Building energy management: Integrated control of active and passive heating, cooling, lighting, shading, and ventilation systems. *IEEE Transactions on automation science and engineering*, *10*(3), 588–602.

Teachflow AI. (2024). *The role of ai in school energy and power generation.* (Accessed: 2025-05-03) Retrieved from https://teachflow.ai/the-role-of-ai-in-school-energy-and-power-generation/?utm_source=chatgpt.com

Wahyudin, D., & Malik, R. S. (2019, May). Teaching environmental education for sustainable development: Strategies and challenges. *Journal of Sustainable Development Education and Research*, *3*(1). https://doi.org/10.17509/jsder.v3i1.17172

Xiao, B. (2024). Maximizing energy cost savings: A milp-based energy management system in educational buildings: Case study in stockholm. *KTH Royal Institute of Technology*.

Yussuf, R. O., & Asfour, O. S. (2024, February). Applications of artificial intelligence for energy efficiency throughout the building lifecycle: An overview. *Energy and Buildings*, *305*, 113903. https://doi.org/10.1016/j.enbuild.2024.113903