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A Model for Artificial Intelligence Supported Energy Management in Smart Campuses

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ABSTRACT

Rising energy consumption and inefficiencies in large-scale facilities, such as university campuses, present critical financial and environmental challenges. Traditional energy management systems rely on static strategies, failing to adapt to real-time variations in demand, which leads to unnecessary energy waste and increased operational costs. This study introduces an AI-driven integrated energy management framework that utilizes real-time data from IoT sensors to optimize energy consumption across key campus systems, such as lighting, ventilation, heating, air conditioning, renewable energy sources, information and communication technology infrastructure, and building energy management systems. By using artificial intelligence methods, the proposed system improves energy use across key campus operations such as heating, cooling, lighting, and communication systems. It analyzes real-time data from sensors to make smart decisions and adjust energy usage without affecting user comfort. Simulation results show that this approach can reduce total energy consumption by up to 59.125% on a mid-sized campus. This highlights the system's strong potential to lower energy costs and support sustainability goals through smarter, data-driven energy management. However, the system's effectiveness depends on high-quality sensor data, adaptive AI algorithms, and robust cybersecurity measures to protect the IoT-based infrastructure. The novelty of this work lies in its unified framework that integrates multiple AI models and optimization methods across all major campus subsystems, rather than addressing a single application domain as seen in most prior studies. The results highlight the transformative potential of Artificial Intelligence in sustainable energy management, demonstrating that smart campus implementations can significantly reduce costs, enhance efficiency, and set a benchmark for autonomous AI-driven energy optimization in facilities.

Keywords: Artificial intelligence, Deep learning, Energy management, HVAC, Smart campus.

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1. Introduction

Recent technological advancements, particularly in sustainability and efficiency, have significantly increased the importance of smart campus (SC) applications. Educational institutions are seeking eco-friendlier, cost-effective, and user-centric solutions to address the rising energy consumption within their campuses. In this context, energy management in campuses goes beyond mere cost reduction and necessitates a comprehensive approach that integrates user comfort, security, aesthetics, and operational efficiency. Systems supported by smart sensors and data collection technologies have become essential components in creating efficient, dynamic, and sustainable campus environments.

Energy management in large-scale campuses present a complex and multidimensional challenge, making manual control highly impractical. A lack of dynamic and intelligent oversight of energy-intensive systems such as building energy management systems (BEMS), Heating, Ventilation, and Air Conditioning (HVAC) systems, renewable energy systems (RES), Information and Communication Technology (ICT), lighting system (LS) and water management often results in unnecessary energy waste and elevated operational costs. At the same time, maintaining user comfort while optimizing energy use is essential for achieving a balanced and sustainable system. However, many existing solutions rely on static management strategies that fail to adapt to real-time changes, leading to significant inefficiencies. Traditional energy management approaches primarily focus on reducing energy consumption through single-dimensional solutions while overlooking critical factors such as user comfort, security, and system adaptability. The increasing energy costs and environmental concerns further emphasize the need for a more integrated and holistic approach. The absence of real-time data processing and quick decision-making capabilities further limits the responsiveness of current systems, highlighting the necessity for advanced, AI-driven energy management approaches.

This study aims to develop an AI-based integrated energy management system to optimize energy consumption and enhance sustainability in SCs Bajwa et al. (2024). Real-time data collected from various sensors, including temperature, humidity, light, and motion, are analyzed using advanced AI algorithms such as Artificial Neural Network (ANN), Reinforcement Learning (RL), and Convolutional Neural Network (CNN). These AI models dynamically optimize key energy-consuming systems including HVAC, lighting, and water management, ensuring a more efficient and sustainable campus environment. The model is simulated for a mid-sized campus and the potential energy savings are quantified. The main contribution of this study lies in the development of a unified AI-driven energy management framework that integrates multiple machine learning architectures (Multi-Layer Perceptron (MLP), CNN, RNN, RL) and optimization techniques (Genetic Algorithm (GA), Particle Swarm Optimization (PSO)) to control and optimize different energy-consuming systems within a smart campus. Unlike prior works that typically focus on individual components such as HVAC or lighting, this study proposes a holistic, real-time, sensor-integrated system capable of dynamic learning and control. The framework is validated through simulation on a mid-sized campus model, with quantified results in terms of energy savings and financial impact.

This study seeks to answer the following research question: Can a unified AI-driven energy management framework integrating multiple machine learning architectures and optimization techniques effectively optimize energy consumption across diverse campus systems in real-time while maintaining user comfort and operational efficiency? The hypothesis guiding this research is that such an integrated AI-based system will significantly reduce overall campus energy consumption and operational costs compared to traditional, single-system-focused methods, without compromising user comfort or system security.

2. Literature Review

The integration of SCs with sustainable management models represents a critical area of research, emphasizing energy efficiency, digital transformation, and data-driven decision-making. Chen (2024) examined optimization strategies for shared energy storage operators in multi-microgrid systems, exploring collaborative energy management approaches. Similarly, Bayramov et al. (2021) assessed household electricity generation from the perspective of energy independence, highlighting the social significance of alternative energy sources. Ma, G (2023) focused on the integration of digital technologies on smart campuses, analysing the impact of big data and AI-driven methodologies on campus management.

Building on these perspectives, Li (2023) explored the design and optimization of AI-based SC frameworks, emphasizing their potential to enhance campus experiences, improve efficiency, and promote sustainable practices. This research supports evidence-based decision-making in shaping future SC initiatives. In a related study, Nóbrega et al. (2022) examined the challenges and opportunities in education within the framework of sustainable development goals, demonstrating how SC models can be customized to meet the diverse needs of stakeholders and foster new educational paradigms.

Valks et al. (2021) highlighted the role of SC tools in optimizing space utilization and enhancing energy efficiency for students and staff. Their study underscores the impact of these tools on organizational decision-making processes and their broader implications for campus sustainability.

AI-driven management systems in SCs have demonstrated significant contributions across various domains, including energy efficiency, security, user experience, and infrastructure management. Existing studies in the literature primarily focus on reducing energy consumption, enabling dynamic system management, and implementing data-driven optimization processes. For instance, Wang and Zhang (2018) developed strategies to optimize energy management in real-time markets by employing RL techniques for energy storage arbitrage. Similarly, Kim and Lim (2018) investigated RL based energy management algorithms in smart energy buildings, emphasizing energy consumption reduction and supply-demand balance.

The application of AI and ML algorithms in energy management is becoming increasingly widespread. For example, Islam (2024) explored P2P energy trading models and analyzed their potential impact on energy optimization. In another study, Kılıç (2024) proposed an LSTM-based intraday electricity price forecasting model for the West Denmark power grid, addressing the optimization of energy trading strategies. Additionally, Hu et al. (2023) introduced an innovative pricing-game strategy for community grids driven by virtual prosumers, enhancing economic efficiency in P2P energy markets.

Building upon this foundation, several recent studies have offered comprehensive overviews of how artificial intelligence supports energy sustainability and optimization. (Hou & Wang, 2023) conducted a large-scale bibliometric analysis of AI and big data applications in the energy sector, identifying key research trends, influential institutions, and prevalent technologies such as deep learning (DL) and RL in smart grids and forecasting systems. Szczepaniuk (2022) expanded on this by reviewing the technical deployment of AI algorithms—including machine learning, metaheuristic optimization, and fuzzy logic—in real-world energy scenarios such as load forecasting, fault detection, and grid cybersecurity. In parallel, Adewoyin et al. (2025) examined the broader role of AI in driving sustainable energy development, focusing on its contributions to renewable energy forecasting, peer-to-peer energy trading, and carbon mitigation. These studies collectively underscore the growing relevance of AI in enhancing energy system intelligence, reliability, and sustainability—further validating the strategic integration of AI-driven tools in SC environments.

While the reviewed literature demonstrates the effective application of various AI techniques to individual components within smart campuses, such as HVAC or RES, there is a notable lack of comprehensive frameworks that integrate multiple AI architectures for coordinated, campus-wide energy management. Most prior works focus on isolated subsystems and rely on static or offline optimization methods, limiting adaptability to real-time campus dynamics. Furthermore, many studies do not fully address the multidimensional nature of energy management, often overlooking critical factors like user comfort, security, and operational sustainability in their models. Financial impact assessments are also inconsistently reported, creating a gap between theoretical development and practical applicability.

This study aims to bridge these gaps by proposing a unified AI-driven energy management framework that integrates diverse machine learning models (MLP, CNN, RNN, RL) and optimization techniques (GA, PSO) to dynamically control multiple energy-consuming systems within a smart campus. The approach emphasizes real-time sensor integration and adaptive control to enhance both efficiency and user comfort. By simulating the framework on a mid-sized campus and quantifying energy savings alongside financial benefits, this work advances beyond previous studies by providing a holistic, practical, and validated solution for sustainable campus energy management.

Recent advancements in AI have introduced transformer-based models as powerful alternatives for energy forecasting and management. For example, Sreekumar et al. (2024) proposed a transformer-based framework for sustainable energy consumption forecasting, demonstrating its potential in capturing complex consumption patterns and supporting socioeconomic decision-making. Similarly, L'Heureux et al. (2022) applied a transformer-based model for electrical load forecasting, achieving higher accuracy compared to traditional neural networks by leveraging the transformer's ability to model long-range temporal dependencies. While these models show promising results, their high computational requirements and complexity may pose challenges for real-time deployment in embedded smart campus environments. Therefore, in this study, simpler yet efficient models such as MLP, CNN, and RNN are adopted, with future work planned to explore the integration of transformer-based approaches as hardware and data availability improve.

In summary, research on SC management encompasses various aspects, including energy efficiency, data security, user experience, and sustainable management strategies. However, existing solutions often prioritize energy consumption reduction while neglecting other critical factors in a holistic manner. As a result, this study aims to fulfil this gap by developing an AI-based energy management system that ensures multidimensional optimization, integrating energy efficiency with user comfort, security, and operational sustainability in SCs. A variety of artificial intelligence techniques have been applied across different domains of SC energy management, as summarized in Table 1, which provides an overview of commonly used AI methods, their respective applications, and reported energy savings in relevant studies.

Table 1. Overview of AI methods preferred in SC energy management

System	Used AI Technique	Yielded Saving	Reference Studies
HVAC	RNN, MFPC, Genetic Algorithm, MPC	3%-60%	(Klaučo et al., 2014), (Lee & Tsai,2020), (Purdon et al.,2013)
RES	FNN, SVM, DQN	25%-50%	(Mayer et al.,2016), (Yao & Steemers,2005)
BEMS	RL, MLP, DNN	5.7%-42.6%	(Salakij et al.,2016), (Yuce & Rezgui,2017), (Li at al.,2021)
LS	RNN, CNN, MACS	20%-70%	(Kolokotsa,2003), (Byun et al.,2013)
ICT	CNN, SON, LSTM	50%-65%	(Trinh et al.,2018), (Abbas & Arif, 2006)

3. Research Methodology

This section outlines the methodological framework employed in developing the AI-driven energy management system for SCs. The approach integrates various ML techniques, optimization algorithms, and real-time data processing to enhance energy efficiency, user comfort, and system adaptability.

3.1 Data Collection and Preprocessing

The proposed system relies on real-time data collected from multiple IoT sensors, including temperature, humidity, light, motion, and CO_2 sensors as shown in Figure 1. These sensors provide continuous data streams that are used to dynamically monitor and optimize energy consumption.

To ensure the accuracy and reliability of the data collected, the following preprocessing steps are applied:

- **Noise Removal:** Data filtering techniques are used to eliminate sensor noise and outliers.
- **Normalization:** Data values are scaled using Z-score standardization or min-max normalization.
- **Feature Extraction:** PCA is employed to reduce dimensionality and extract relevant features for model training.

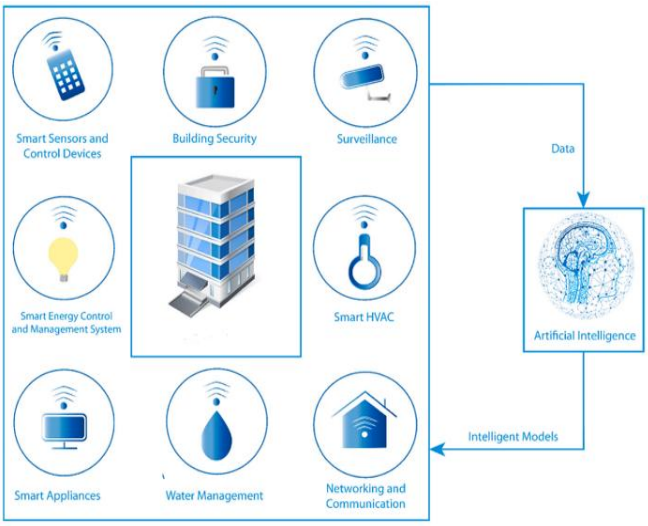

Figure 1: AI-driven smart campus energy management system (Baduge et al.,2022)

ML architectures are utilized to model and predict energy consumption, optimize system control, and adapt dynamically to changing campus conditions. Consequently, the case study prioritizes the AI technology most commonly used in each specific application area, rather than the one with the greatest theoretical energy-saving potential. The findings of the analysis are presented in Figure 2.

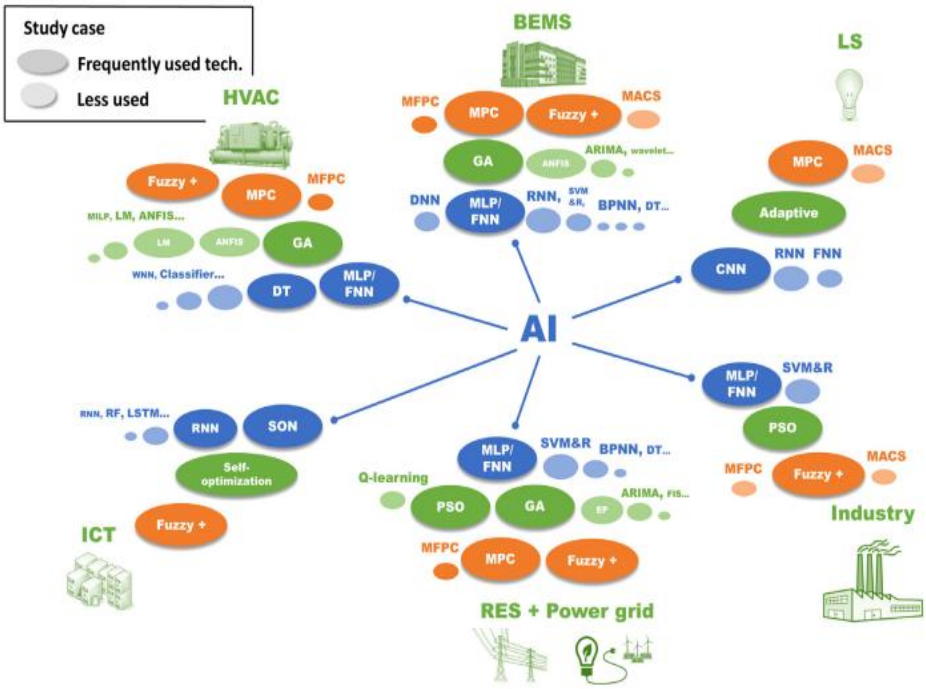

Figure 2: Artificial intelligence techniques used for learning, optimization, and control (Lee et al., 2022)

3.2 Machine Learning Methods

MLP and FNN are the most frequently used deep learning technologies in of time-series data. The neural structure is depicted in Figure 3. The neural structure of MLP/FNN can be expressed as in Eq. (1) (Lee et al., 2022; Jiang et al., 2020):

$$y = (W \cdot x) + b \tag{1}$$

where y represents the output data of the MLP/FNN, x is the input data, and b denotes the bias and W is the weighing function that is pre-trained using Eq. (2) (Jiang et al., 2020, Lee et al., 2022):

$$W_i \rightarrow W_i + \Delta W_i \tag{2}$$

where $\Delta Wi = \eta(ti - yi)xi, Wi$ is the current weight, ΔWi is the change (or update) that will be added to the current weight during learning, t is the target value, and η is the learning rate.

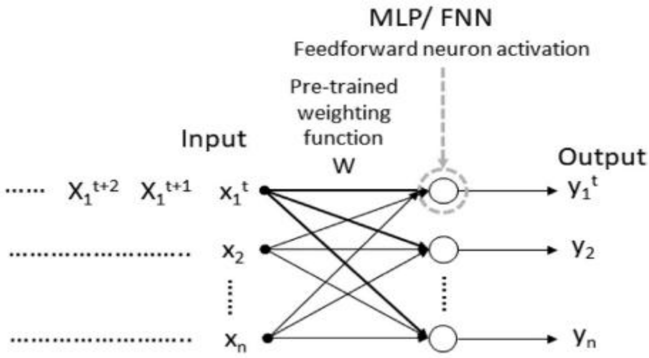

Figure 3: Neural structure of multilayer perceptron (Lee et al., 2022)

MSE sometimes referred to as the cost function, is what MLP/FNN training aims to minimize, as explained in Eq. (3):

$$MSE = \frac{1}{2} \sum_{k=1}^{n} (y_k - t_k)^2 \tag{3}$$

where y_k is the predicted output and t_k is the true target value for the k^{th} output node.

Additionally, the cost function can be defined using performance metrics such as the R^2 score, mean squared error (MSE) or mean absolute percentage error (MAPE). The forecast generated serves as the final output for control purposes. Supervised learning, combined with a MLP or feedforward neural network (FNN), can be used to develop operational models for energy conservation in stable and well-defined application domains such as factories, HVAC systems, RES, or BEMS.

RNNs, whose neural structure is described in Figure 4, can improve prediction accuracy when used in dynamic or unstable environments. The hyperbolic tangent activation function (tanh), which is defined in Eq. (4), plays a key role in enhancing the performance of RNNs (Lee et al., 2022).

$$h_{t+1} = (W_1 \cdot ht) + (W_2 \cdot x) + b \tag{4}$$

where h_{t+1}: The hidden state at the next time step t+1, which stores memory of past inputs.

ht: The hidden state at the current time step t, representing the network's memory.

x: The input vector at the current time step.

W_1: Weight matrix executed to the previous hidden state.

W_2: Weight matrix executed to the current input.

b: Bias term (adds flexibility to the transformation).

Both the current x value and the x value from the previous time step affect the RNN neural output y. Eq. (5) can be used to describe this (Lee et al., 2022):

$$y = (W \cdot x \cdot h_t) + b \tag{5}$$

y: The output of the RNN at the current time step.

$x \cdot h_t$: Represents a combined interaction between the current input xxx and the memory h_t

W: Weight matrix for producing the output from input and memory.

b: Bias term.

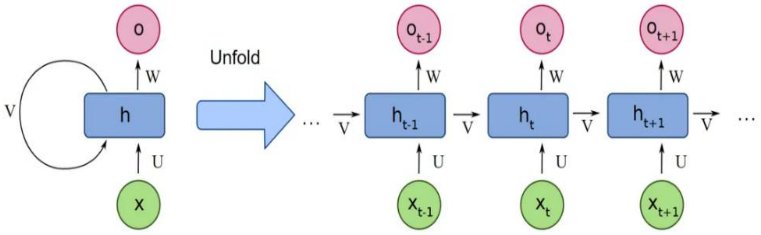

Figure 4: Recurrent neural activations (Analytics Vidhya, 2022)

Recurrent neural networks (RNNs) utilize both the chronological order and temporal dependencies within data to make accurate predictions, as shown in Equations (4) and (5). These models are especially effective for handling complex and fluctuating time-series data, such as weather patterns or ICT network performance. To further enhance prediction accuracy, advanced variants of RNNs—such as gated recurrent units (GRU) and long short-term memory (LSTM) networks—have been introduced. GRUs offer a more streamlined architecture than LSTMs, enabling faster computation. Although GRUs are more sophisticated than standard RNNs, the original RNN architecture has proven sufficient for managing energy consumption tasks.

In energy efficiency applications, the goal is not necessarily to achieve the highest prediction accuracy, but to develop models that can generalize across diverse operational scenarios. For this reason, RNNs were selected to model energy-saving systems.

Additionally, occupancy detection is a critical component in optimizing energy usage. Alongside time-series data from infrared sensors, occupancy systems may utilize thermal imagery or video streams—such as those used in LS control. CNNs are well-suited for processing this type of image or video data. The operating principle of a CNN is illustrated in Figure 5.

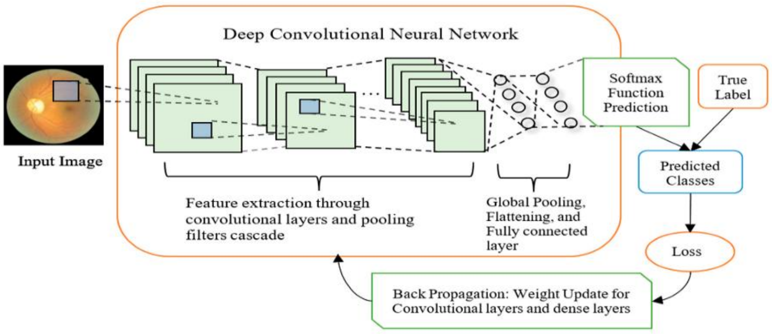

Figure 5: Convolutional neural network in image capture (Hu et al., 2019)

As depicted in Figure 5, the CNN begins with an initial layer composed of multiple feature extraction paths operating in parallel. Through convolution operations, it identifies critical patterns from the input data, which are then passed to a down sampling stage. Although the resulting feature maps are reduced in dimension, they retain essential characteristics due to shared weights and biases across the network. At this stage, the Rectified Linear Unit (ReLU) activation function is executed to initiate non-linearity, thereby enhancing the model's ability to learn complex patterns without compromising the integrity of the convolution process. Following ReLU, the data is fed into the pooling layer, which contributes to dimensionality reduction and directly supports the model's final decision-making process.

MLP, RNN, and CNN are three supervised learning methods, each suited for different types of data. MLP is ideal for analysing stable time-series data, while RNN excels in handling dynamic weather patterns or unpredictable communication signals. CNN, on the other hand, is particularly effective for processing visual data and content related to human perception, such as image signal analysis.

When working with outputs from a predefined numerical model, MLP or FNN proves to be the most efficient. However, in energy systems lacking a defined structure—where control is achieved through trial and error— RL techniques like DQN and Q-networking are the most appropriate. The operational framework of an agent performing trial-and-error-based control is depicted in Figure 6.

Figure 6 illustrates the operational framework of an agent-based trial-and-error control mechanism using Deep Q-Networks (DQN). Unlike supervised learning models such as MLP or FNN, which focus on predicting system states based on historical data, DQN is designed to learn optimal control policies via interaction with the environment. The agent observes the current system state, takes an action (e.g., adjusting HVAC settings), and receives feedback in the terms of rewards (such as energy savings or comfort improvements). Over time, this RL approach enables the agent to develop control strategies that adapt to dynamic and uncertain conditions without requiring explicit labeled datasets. This contrasts with supervised models that rely on pre-collected data for prediction but do not inherently make control decisions.

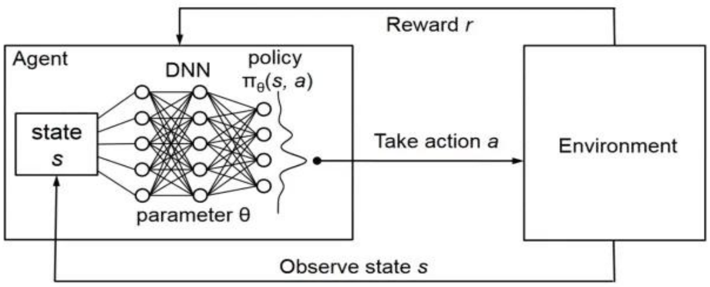

Figure 6: Mechanism of agent-based trial and error control (Jayakody, 2022)

Self-Organizing Networks (SON) represent a form of machine learning primarily designed to enable autonomous adaptation in communication infrastructures. This intelligent framework aims to streamline the rollout, fine-tuning, and fault recovery of mobile radio access systems. In this study, the focus is on enhancing the energy efficiency of ICT systems utilizing SON principles. As illustrated in Figure 7, SON extends beyond basic learning capabilities to support proactive maintenance and performance optimization.

Fuzzy logic is often integrated into SON to improve processes such as signal handover, coverage reliability, and overall network service quality. In this research, SON is classified as an artificial intelligence methodology. Due to its ability to self-adapt without requiring labeled datasets, SON aligns with unsupervised learning approaches, similar to deep neural networks (DNNs). These systems operate without explicit output labels and are capable of autonomously identifying patterns and generating operational insights. As shown in Figure 7, SON's neural structure allows it to dynamically interact with system components, thereby enhancing the learning process and enabling deeper adaptive capabilities..

Figure 7 depicts the neural structure and adaptive mechanism of a Self-Organizing Network (SON) applied to energy efficiency optimization in ICT systems. Unlike supervised learning models that require labeled data for training, SON functions as an unsupervised learning approach that autonomously detects patterns and adapts system parameters without explicit supervision. By continuously interacting with network components, SON dynamically adjusts configurations such as signal handover and coverage settings, improving overall service quality and energy efficiency. This proactive and self-adaptive capability enables SON to maintain optimal performance in complex, evolving environments, distinguishing it from traditional AI models that rely on static datasets.

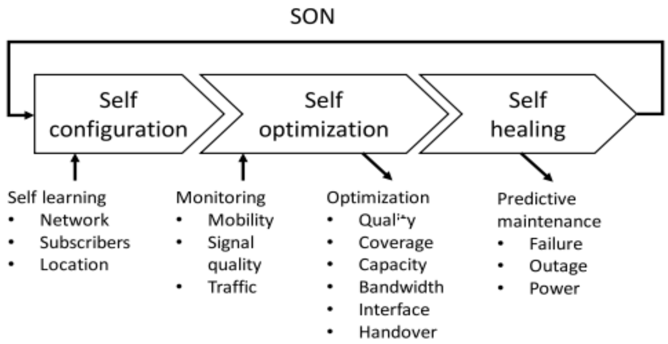

Figure 7: Self-organizing network energy efficiency optimization (Lee et al., 2022)

The choice of machine learning models in this study was guided by a combination of domain-specific requirements, data characteristics, and computational constraints. MLP and FNN were selected for HVAC and RES subsystems due to their proven efficiency in modelling stable, well-structured time-series data with relatively low noise and high periodicity—common traits in HVAC scheduling and solar energy prediction. These models also ensure fast inference times and lower training complexity, which are critical for real-time applications. RNNs, on the other hand, were used in subsystems such as BEMS and ICT where temporal dependencies are more complex, and inputs are subject to fluctuation or non-stationarity (e.g., occupancy, weather data, network traffic). Although more sophisticated models like transformers or GRU/LSTM could be used, RNN was preferred due to its lower computational burden and sufficient accuracy for the problem scale. CNNs were used for LS systems where image and motion data are primary inputs, leveraging their superior performance in spatial pattern recognition. The model-subsystem matching was thus informed by the type and behaviour of the input data, desired response time, and the need for system interpretability and generalizability.

For short-term forecasts, GA or PSO can be used to increase accuracy. Prediction performance is much enhanced when an ANN is used alone. A larger training dataset helps ANN achieve even higher accuracy for long-term forecasts longer than a year. These results imply that prediction accuracy increases with the length of the data gathering period. Thus, long-term data collecting should be a part of the most successful AI optimization strategy.

However, when extensive datasets are not available, GA or PSO can serve as viable alternatives. A comprehensive analysis indicates that PSO is more effective for optimizing multiple devices, whereas GA is better suited for controlling a single device. Additionally, for complex optimization problems, a hybrid multi-objective GA may also be considered.

4. Theory and Calculation

This study presents a comprehensive approach to developing AI-driven energy management systems in SCs. The proposed model integrates decision-making, anaylsis, and real-time data collection processes to optimize energy consumption and contribute to sustainability goals. While existing literature primarily focuses on energy efficiency or specific system components, this study provides a holistic framework that incorporates user comfort, security, and operational efficiency. A notable strength of the proposed system is its capacity to autonomously manage energy through the processing of data from

IoT sensors using advanced AI algorithms. This enables dynamic adaptation to changing campus conditions. Figure 8 illustrates the distribution of energy consumption and savings following the implementation of the AI-based optimization model. It includes detailed calculations across different energy-consuming systems, corresponding savings percentages, and the overall cost reduction achieved.

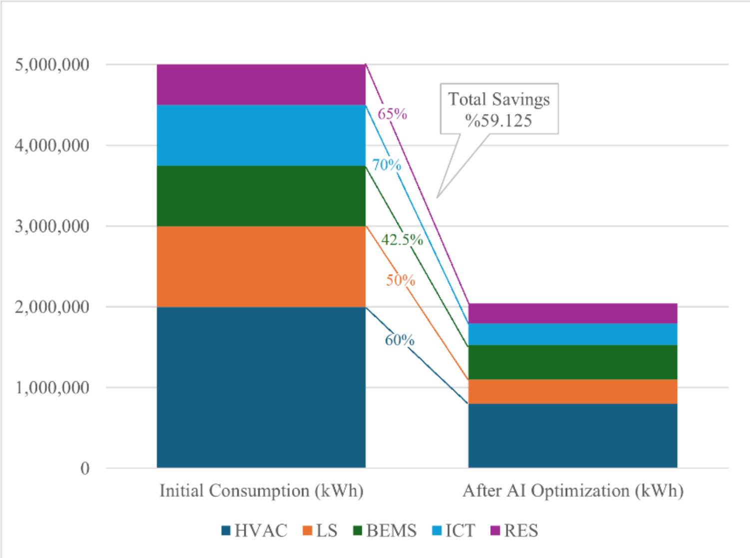

Figure 8: Theoretical energy savings in a mid-sized smart campus after AI-based optimization

4.1 Energy Consumption and Savings Per System

Smart campuses exhibit varying energy consumption across different systems. This section examines the key components of campus energy consumption and the impact of AI-based optimizations on energy savings in each system.

The campus energy consumption is divided into five major systems which collectively account for 100% of the campus's total energy use (Advanced Energy Management Company, 2024), (Australian Government Department of the Environment and Energy, 2024):

1. HVAC: 40% of total energy consumption.
2. RES: 10%.
3. BEMS: 15%.
4. LS: 20%.
5. ICT: 15%.

After implementing AI-based optimizations, the energy savings for each system are as follows:

1. HVAC: 60% savings.
2. RES: 50% savings.
3. BEMS: 42.5% savings.
4. LS: 70% savings.
5. ICT: 65% savings.

Table 2 presents a comprehensive overview of various AI technologies implemented in different smart campus systems, detailing the types of data utilized, learning models applied, optimization techniques employed, control strategies used, and their overall impact on energy savings. The table categorizes all applications such as HVAC, RES, BEMS, LS, and ICT, illustrating how AI-driven approaches enhance efficiency. To ensure clarity, the abbreviations used in the table are defined as follows: MPFC is a control strategy that dynamically adjusts system performance based on predictive modelling and occupant feedback; FNN is a type of ANN where data flows in one direction without cycles; MLP is a class of feedforward neural networks with multiple layers for DL. A summary figure highlighting some of the most successful cases of AI applications for energy saving has been included in Appendix A (Figure 10).

Table 2. Artificial intelligence technologies in smart campus systems

			AI Technology			Effect	
System	**Reference Study**	**Data Type**	**Learning**	**Optimization**	**Control**	**Energy Saving**	**Other Benefit**
HVAC	(Purdon et al., 2013)	Text Data	Occupant feedback, Classifier	-	MFPC	60%	-
RES	(Mayer et al., 2016)	Time series data, Text data	White box model, FNN	MLP	MPC	50%	Cost saving 50%
BEMS	(Salakij et al., 2016)	Time series data, Text data	Building model, MLP		MPC	42.60%	Prediction MAPE up to 6.3%
LS	(Kolokotsa, 2003)	Time series data	RNN	-	Adaptive MPC	70%	-
ICT	(Sinclair et al., 2013)	Map/image data	CNN	-	Handover management	65%	-

Figure 9 illustrates the architecture of the AI-driven smart campus energy management system, highlighting its multi-layered structure and key components. The system integrates diverse energy sources—including power generation, RES, and thermal storage—to enhance overall energy efficiency. It manages equipment and facilities such as HVAC, lighting, and auxiliary infrastructure through sensors, actuators, and smart control devices.

The framework consists of three primary layers:

- The control layer, comprising the energy management system, cloud computing, and building automation.
- The communication layer, employing Bluetooth, ZigBee, Wi-Fi, and 5G technologies.
- The sensing layer, which collects real-time data via smart meters, environmental sensors, RFID, cameras, and GPS.

By leveraging AI and IoT technologies, the system enables demand-side energy management, maximizes power generation, and minimizes energy costs, all while maintaining user comfort, safety, design efficiency, and optimized maintenance. The integration of these components supports a thorough and adaptive energy-saving strategy, contributing to a more sustainable and intelligent campus environment (Farzaneh et al., 2021).

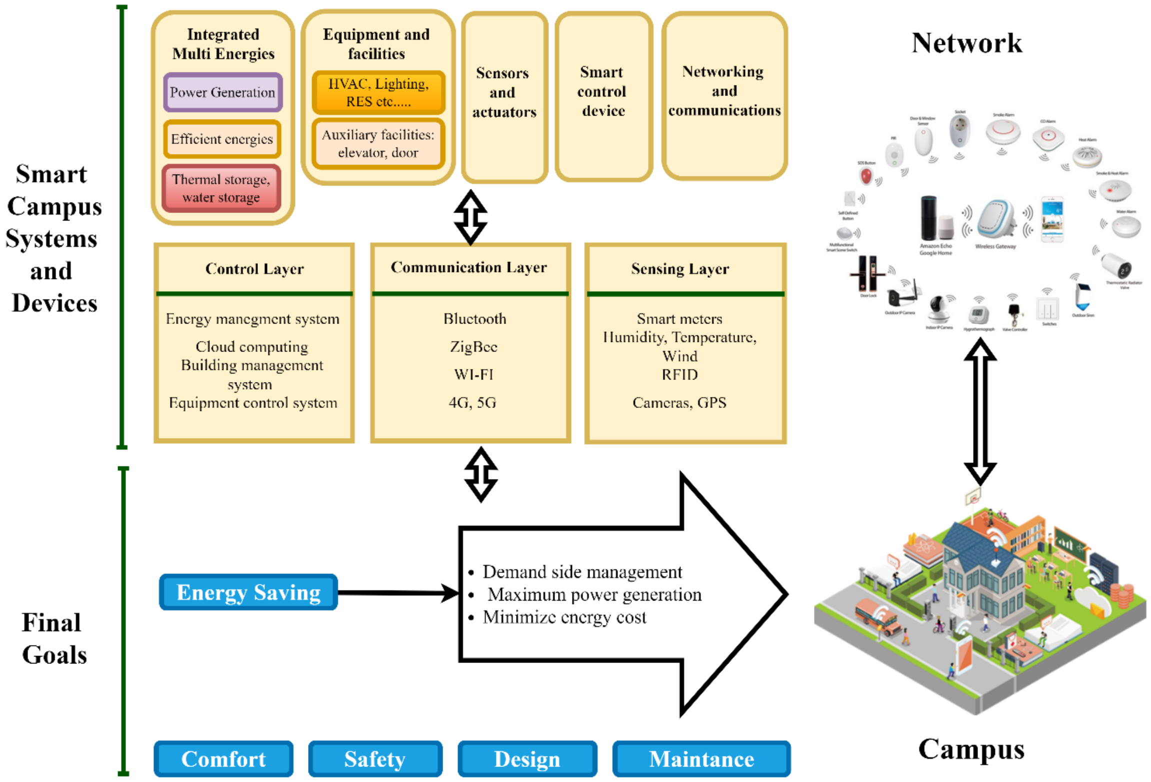

Figure 9: Technology infrastructure required for energy management in smart campus

5. Results and Discussion

The calculations were conducted in a smart campus environment, with an estimated area ranging between 33,000 and 100,000 square meters, depending on its energy efficiency. Benchmarks for smart campuses with advanced energy management systems suggest that energy consumption per square meter typically falls within 50 – 150 kWh/m² per year (Almasri et al., 2024), where higher efficiency systems—such HVAC, BEMS, RES, LS, and ICT infrastructure contribute to lower energy intensity. Given the total energy consumption of 5,000,000 kWh/year, the estimated campus area is calculated as in Eq. (6) (Ruliyanta et al. 2022):

$$Campus\ Area = \frac{Total\ Energy\ Consumption\ (kWh/year)}{Energy\ Intensity\ (kWh/m^2/year)Total} \tag{6}$$

A high-efficiency campus (consuming approximately 50 kWh/m²/year) corresponds to a larger area of 100,000 m², as it utilizes advanced energy management systems such as HVAC, BEMS, RES, LS, and ICT, which reduce energy consumption per unit area. Conversely, a lower-efficiency campus (with an energy intensity of 150 kWh/m²/year) is estimated to be 33,333 m², indicating higher energy use per square meter due to less optimized infrastructure and control mechanisms:

- High efficiency (~50 kWh/m²/year): 100,000 m²
- Lower efficiency (~150 kWh/m²/year): 33,333 m²

As presented in Table 3, AI-based optimization significantly improved energy efficiency across various systems, leading to a 59.125% overall reduction in total energy consumption. In absolute terms, energy consumption dropped from 5,000,000 kWh to 2,043,750 kWh per year, resulting in a significant decrease in operational costs. The financial impact is also notable, with total energy costs decreasing from $341,623 to $139,639, leading to annual savings of $201,985 as shown in Table 3 with Unit Energy Cost (2.5 ₺/kWh) (Energy Exchange Istanbul (EXIST), 2025).

These results highlight the transformative potential of AI-driven energy optimization in smart campuses. By integrating IoT-based monitoring, real-time data analytics, and adaptive control strategies, the system not only reduces energy waste but also enhances sustainability, cost-efficiency, and operational resilience.

Table 3. Simulation results for annual energy consumption of a mid-size campus.

System	Energy Usage Ratio	Initial Consumption (kWh)	Maximum Potential		
			After AI optimization (kWh)	Savings (kWh)	Savings (Percentage)
HVAC	40%	2,000,000	800,000	1,200,000	60%
RES	10%	500,000	250,000	250,000	50%
BEMS	15%	750,000	431,250	318,750	42.5%
LS	20%	1,000,000	300,000	700,000	70%
ICT	15%	750,000	262,500	487,500	65%
Total	100%	5,000,000	2,043,750	2,956,250	59.125%
Unit Energy Cost (₺/kWh)		2.5	2.5	2.5	-
Total Cost (₺)		12,500,000	5,109,375	7,390,625	-
Total Cost ($)		341,623	139,639	201,985	-

After implementing AI-based optimizations, the campus achieved a total energy savings of 59.125%, translating into an annual financial saving of ₺7,390,625. The most significant reductions came from HVAC and lighting system optimizations, which substantially decreased energy consumption while maintaining comfort and functionality.

Optimizing major energy-consuming systems—HVAC, lighting, ICT, RES, and BEMS—demonstrated remarkable energy savings. The findings show that AI-driven strategies led to a 60% reduction in HVAC energy usage, making it the most impactful optimization area since HVAC accounts for 40% of total energy consumption. Similarly, lighting systems, which make up 20% of total consumption, achieved 70% savings, underscoring the effectiveness of AI in dynamically managing illumination. ICT and RES also showed notable reductions of 65% and 50%, respectively, while BEMS achieved 42.5% savings, highlighting the system's efficiency in optimizing building-wide energy usage.

From a financial standpoint, AI-driven energy management resulted in substantial cost reductions. Before optimization, the total annual energy expenditure of the campus was ₺12,500,000. After implementing the AI model, this figure dropped to ₺5,109,375, yielding an annual savings of ₺7,390,625. These results reinforce the economic viability of AI-based energy management solutions, demonstrating their potential for both financial and environmental sustainability.

The total energy savings were calculated based on known savings percentages from the literature for each subsystem. These percentages were applied to actual energy usage data from your campus to estimate the final savings. The approach represents a best-case scenario. So, the 59.125% total energy saving was derived by aggregating estimated savings from individual systems (HVAC, LS, ICT, etc.) based on prior published AI implementations, then scaled to the energy profile of our university campus. These estimates assume ideal performance of AI models and infrastructure.

However, the system's success heavily depends on sensor data accuracy and the adaptive learning capabilities of AI algorithms. Noise or missing values in sensor data could negatively impact model performance, leading to suboptimal energy optimization. To mitigate these risks, robust data preprocessing and cleaning techniques must be applied to ensure the reliability of real-time energy data. Additionally, evaluating the system's adaptability across different campus environments is crucial for scalability and long-term efficiency.

Security and data privacy are also critical concerns in the widespread adoption of AI-driven energy management. The integration of IoT devices introduces potential vulnerabilities to cyberattacks, necessitating strong encryption methods and authentication mechanisms to protect sensitive energy consumption data. Moreover, the impact of AI-driven adjustments on user experience must be carefully assessed. A user-friendly and intuitive system interface is essential to ensure seamless adaptation to energy-saving measures without compromising comfort.

The simulation results highlight the transformative potential of AI-based energy management in optimizing energy consumption, reducing costs, and advancing sustainability initiatives within SCs. By addressing the limitations of previous research, the proposed system introduces a multidimensional management model that balances energy efficiency, user comfort, security, and operational sustainability.

The study also has some limitations. The calculated savings represent the maximum potential of the proposed model based on results reported in the literature. However, real-world implementation may yield lower performance than this theoretical maximum. To minimize the gap between ideal and practical outcomes, further research should focus on enhancing the robustness of AI algorithms, developing fault-tolerant mechanisms for handling incomplete data, and strengthening cybersecurity measures to improve system resilience. Additionally, broader evaluations across diverse campus environments are necessary to validate the system's adaptability and effectiveness on a larger scale.

AI-based energy management systems rely heavily on real-time sensor data, making data quality and cybersecurity critical. Poor data quality due to faulty or spoofed sensors can lead to incorrect model predictions and energy waste. To mitigate this, future implementations should include sensor validation mechanisms, redundant sensing, and data fusion techniques to enhance reliability. On the cybersecurity side, threats such as data tampering, unauthorized access, and denial-of-service attacks must be addressed using secure communication protocols, device authentication, and AI-driven anomaly detection systems. The integration of blockchain or edge-based security modules could further protect decentralized IoT environments

6. Conclusions

Energy management on smart campuses has become a crucial challenge due to rising energy demands, sustainability targets, and the increasing complexity of modern infrastructure. Conventional energy management approaches often struggle to adapt to dynamic environmental conditions, resulting in inefficiencies and excessive energy consumption.

This study proposes an AI-driven energy management system designed to optimize major energy-consuming components such as HVAC, lighting, BEMS, RES, and ICT. The system effectively manages energy distribution by dynamically manage resources depending on real-time demand, optimizes consumption patterns by identifying inefficiencies and adjusting operational schedules, and enhances overall efficiency by integrating renewable energy sources into the grid. The model successfully predicts energy consumption trends, automates decision-making processes, and ensures optimal utilization of available resources. Comprehensive performance analyses were conducted to evaluate the impact of AI-based optimization on energy savings, cost reduction, and carbon footprint mitigation. The results demonstrate that the proposed system achieves a total energy savings of 59.125%, translating into an annual cost reduction of ₺7,390,625 significantly lowering the SC's carbon footprint. The results highlight the critical role of AI-driven solutions in improving energy efficiency and operational sustainability in SCs. By offering a comprehensive framework, it serves as a valuable reference for future research in this domain.

Future research can focus on evaluating the adaptability of the proposed system to various campus structures and building types while integrating larger datasets and advanced algorithms to enhance model accuracy. Additionally, robust encryption techniques should be implemented to strengthen IoT security and mitigate cybersecurity risks. To improve user experience, personalized energy management scenarios can be developed, ensuring seamless adaptation to user behaviour. To systematically address the challenges of AI-driven energy management on smart campuses, future research will follow a phased roadmap. In the short term (1–2 years), pilot studies will be conducted on varied campus types to validate system performance and collect real-world data. Mid-term goals (3–5 years) include scaling the system to larger and more complex infrastructures, improving model robustness, and advancing Technology Readiness Levels (TRL) from laboratory validation (TRL 4) toward real environment demonstration (TRL 6). Long-term efforts (5+ years) aim for full-scale deployment, including integration with advanced cybersecurity measures and the development of personalized energy management tailored to occupant behaviour. Scalability metrics will guide optimization for diverse campus contexts. However, some limitations remain. The system's effectiveness depends on the quality and availability of sensor data, which may vary across campuses. Computational and integration challenges could affect real-time deployment.

7. Declarations

7.1 Competing Interests

There is no conflict of interest in this study.

7.2 Authors' Contributions

Abdalhadi MANASSRA: Developing ideas or hypotheses for the research and/or article, organizing and reporting the data, taking responsibility for the explanation and presentation of the results, taking responsibility for the literature review during the research, taking responsibility for the creation of the entire manuscript or the main part.

Gürkan IŞIK: Developing ideas or hypotheses for the research and/or article, planning the materials and methods to reach the results, organizing and reporting the data, taking responsibility for the explanation and presentation of the results, taking responsibility for the creation of the entire manuscript or the main part, reworking not only in terms of spelling and grammar but also intellectual content or other contributions.

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Appendices

List of Abbreviations

AI	Artificial Intelligence
ANN	Artificial Neural Network
b	Correction Coefficient
BEMS	Building Energy Management System
CNN	Convolutional Neural Network
CO_2	Carbon Dioxide
DL	Deep Learning
DNN	Deep Neural Network
DQN	Deep Q-learning Network
FNN	Feedforward Neural Network
GRU	Gated Recurrent Unit
GA	Genetic Algorithm
h_t	Recurrent neuron activation function
HVAC	Heating, Ventilation and Air Conditioning
ICT	Information & Communication Technology
IoT	Internet of Things
kWh	Kilowatt Hour
LS	Lighting System
LSTM	Long Short-Term Memory
MACS	Multi-Agent Control System
MAPE	Mean Average Percentage Error
MFPC	Model Free Predictive Control
ML	Machine Learning
MLP	Multi-Layer Perceptron
MSE	Mean Square Error
P2P	Peer to Peer
PCA	Principal Component Analysis
PSO	Particle Swarm Optimization
R^2	R-squared Value
ReLU	Rectified Linear Unit
RES	Renewable Energy System
RL	Reinforcement Learning
RNN	Recurrent Neural Network
SC	Smart Campus
SON	Self-Organizing Network
SVM	Support Vector Machine
t	Target Value
W	Weighting Function
x	Neuron Input
y	Neuron Output
η	Learning Rate

Appendix A: Some of The Most Cases of Successful Application of AI For Energy Saving

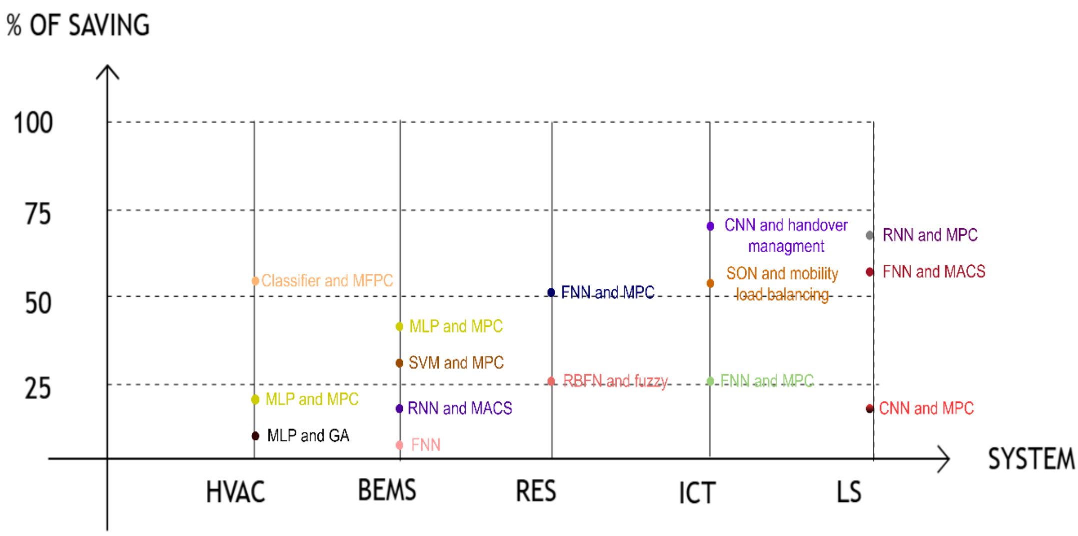

Figure 10: Some cases of successful application of ai for energy saving