

## AI-Enhanced Power Management System for Buildings: A Review and Suggestions

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### ABSTRACT

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Modern power management systems are highly recommended for institutes to enhance power saving, as they effectively stratify their activities. These systems are essential to integrate intelligent methods, such as machine learning and deep learning, to make optimal decisions in managing consumed power and significantly minimize energy usage. In this review, we delve into the concept of smart energy management, focusing on three key areas: Wireless Sensor Networks (WSN), Building Information Modeling (BIM), and Artificial Intelligence (AI) techniques represented by deep learning (DL) and machine learning (ML) approaches. The primary objective of this review is to propose an optimized model for an energy management system based on a clustered WSN that collects the required information. Additionally, we explore how data from buildings' BIM systems can be effectively utilized to create an optimized method for managing power consumption using ML/DL techniques, specifically applicable to smart buildings. Implementing this solution can efficiently manage power consumption in institute buildings, leading to significant energy savings and reduced related costs.

## 1. INTRODUCTION

As new wireless technologies advance, it is worth to mention that Wireless Sensor Networks (WSNs) have become highly flexible and dynamic aspects that are being implemented in almost everywhere [1]. WSNs are gaining significant importance among institutions, innovators, and researchers due to their promising and creative applications in the context of reducing component cost which allows for widespread deployment [2]. They can be defined as networks of sensor nodes that can be wirelessly communicate in order to collect and transmit information about their surroundings. These sensors are frequently used to monitor humidity, temperature, smoke, pressure, circuit power and etc. These aspects' information is made available in real time [3]. After the data from these sensors is collected, it is analyzed by an integrated software product. The data collected and analyzed by the sensor nodes can be used for monitoring and decision-making, which allows reducing effort and managing resources in a more energy-efficient manner.

In recent years WSN is being implemented almost everywhere and one of the common fields to be integrated with is energy management systems where these systems are fed with real-time data from WSN nodes. Energy control systems have been implemented to monitor all incoming and outgoing network points economically, these real-time systems, allow for supervisory control and data acquisition. Because of advances in computational technology and power system modeling, applications can now be fed real-time data from those systems to provide operators with additional decision-making information. Natural evolutions in these applications enabled higher levels of automation in the decision-making process [4]. Building energy consumption reports for 30-45%

of global energy consumption, with electricity consumption accounting for a significant portion of building energy usage [5]. Smart energy systems help owners to increase energy efficiency in these buildings, both residential and commercial buildings could benefit from such systems in order to decrease energy consumption [6].

Currently, different techniques have been used in managing energy consumption in buildings as shown in Figure 1. which briefly describes the manual and smart methods in controlling energy. Energy management systems (EMSs) are vital for efficiently managing energy usage and minimizing wastage across different domains. Nevertheless, they do encounter specific constraints. A notable limitation involves their dependence on centralized data collection and processing, leading to potential delays, inefficiencies, and vulnerability to single points of failure. This is where WSNs step in to enhance EMS capabilities, with a focus on automating processes, resource management, ensuring occupant comfort, and promoting energy conservation. In WSN, sensors in smart buildings can collect data on the status of various environmental elements and generate smarter action which is capable of utilizing accessible resources more effectively while maintaining desired behavior. Monitoring elements including air conditioners, lights, computers, doors, windows, and so on empowers the concept of Building Management System (BMS) to arise, which is capable of effectively and automatically managing building elements and thus attempting to reduce overall building energy usage while preserving adequate levels of comfort [7].

Artificial intelligence (AI) has found its way into energy management decision-making process. AI systems have gained wide interest for solving many problems in energy systems including controlling, scheduling and forecasting.

These techniques can deal with difficult tasks in modern large-scale power systems to satisfy increasing load demand. On the other hand, individual load forecasting systems can be used in a variety of everyday applications, such as day-ahead residences forecasting which aids in the appropriate energy requirements from smart grids [8]. Energy forecasting methods, which predict a consumer's future energy consumption and demand from grids, are extremely useful in this regard. Proper energy production and utilization planning ensures efficient use in industries and households, as well as a stable amount of energy production at power plants [9].

In this research, three main areas are reviewed, which are the data representation in smart buildings by Information Building Modeling (IBM) systems, using WSN in extracting information that includes energy consumption, determining occupancy and other necessary information, and the employment of AI in controlling energy consumption and predicting it in buildings and related institutions. After that, a possible solution for presenting an optimized power consumption system based on AI is suggested.

The paper is structured as follows: Section 2 explains the systematic review methodology considered in deriving this research. Section 3 outlines the concept of smart building while subsection 3.1 introduce the integration of BIM with WSNs. While section 4 clarifies the impact of AI in energy management optimization. Section 5 represents the solution methodology to optimize energy management systems and finally Section 6 concludes the work.

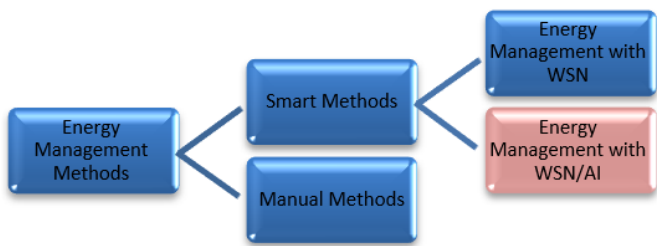


Figure 1. Energy management methods

## 2. SYSTEMATIC REVIEW METHODOLOGY

This section outlines the used methods in identifying, reviewing, and analyzing scientific literature related to energy management and control in smart buildings. This research considers a wide-ranging of peer-reviewed publications and conference papers available in well-known scientific journals for the review methodology. Google scholar, IEEE, Science Direct, research gate and ACM are among the databases that have been used in searching for the relevant literature. WSN, Smart Buildings, energy efficiency, IBM, Deep Learning, and Machine Learning among the keywords associated with energy management are adopted to find related studies in online databases. The extensive examination yielded numerous papers published in internationally recognized journals. The filtering standards are clearly described below to consider:

- Studies which present approaches gathering WSN with the concept of energy management in smart cities and specifically smart buildings as a part of Building Information Modeling (BIM).
- Research works that focus on the role of machine learning (ML) and Deep Learning (DL) in managing

energy consumption in smart buildings.

- Research works that take into consideration the impact of ML and DL in forecasting or predicting approaches in smart grids energy management.

Papers are further reduced on the basis of research engine filter criteria such as publication date, paper type, and additional selection depending on abstract examining. Based on the mentioned filtering criteria, Figure 2 shows the flowchart of explaining the considered basic research areas that are combined with the exclusion criteria.

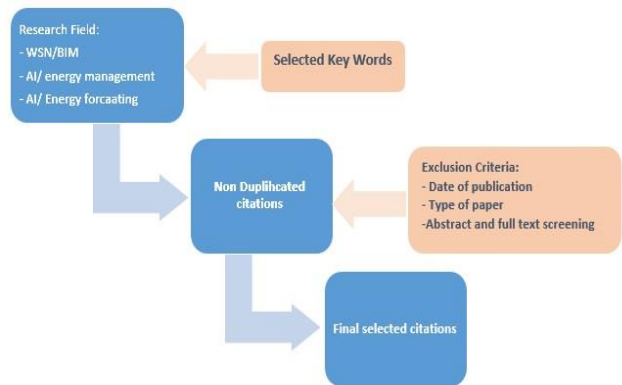


Figure 2. Flowchart of the adopted methodology

## 3. THE CONCEPT OF SMART BUILDINGS AND SMART BUILDING TECHNOLOGIES

The term of “smart” or “intelligent” of a residence or even a city has increased in popularity in the recent years. It can be noticed that the term smart is more recent than intelligent in the context of improving energy consumption [10]. The term "intelligence" in the smart city context state the spread of ICT in the infrastructure, technological development and electronic techniques, whereas "smartness" extends to the needs of individuals and community [11]. Smart Building Technologies (SBT) provides intelligent and integrated infrastructure solutions for buildings that provide comfort, energy efficiency, safety, and security. SBT provides customized individual solutions and services all through entire life cycle of a building by combining technological innovations experience. To construct a smart building there are four main components that needs to be integrated. The first component includes sensors which are devices that monitors the environment and collect the data to be further analyzed. The second component is an analytic software which helps to understand the data collection process by the sensors. The third component is a user interface for better interaction. Finally, connectivity solutions to communicate between the devices [12]. One of the main technologies to represent data within the concept of SBT is Building Information Modeling (BIM) which is a well-known investigated technology in the literature to represent the collected data from a smart building, an overview of this concept would be reviewed in the following subsequent section.

### 3.1 The integration of BIM and WSN in smart buildings

BIM is considered as a crucial component of any building's "digitalization" and could be used for energy-efficient restoration processes. It involves sensor data connected to

indoor/outdoor environment and energy-usage parameters of the building, to deal with data-acquisition functionality that are related to building information. The collection of data involves the deployment of comprehensive WSNs capable of capturing and transmitting real-time data to cloud toolkit [13]. The effectiveness of WSN/BIM monitoring management system could be noticed in managing what is described as smart cities. BIM could be used to detect energy consumption and enhancing project resource productivity by eliminating unnecessary waste [14]. The management of energy in BIM-based smart buildings has received a lot of attention. For example, BIM was used to integrate buildings, sensors and intelligent software components [15]. The guidelines are generated for facility managers based on data collected by indoor sensors to alert them for potential energy-saving actions.

In the study [16], wireless sensors were located to observe thermal properties as a reaction to server load spreading during runtime. Real-time data is collected and analyzed in relation to BIM, which captures both the conceptual and efficient properties which aimed to predict real-time thermal performance of the working environment. Another study suggested that using a Building Automation System (BAS) to control energy consumption in order to maximize building energy efficiency, in which the whole energy performance, operation costs, and environment were improved. In this context, BIM was one of the methods for visually representing, managing, and exchanging information about all aspects of a building [17]. A framework related to a real-time BIM-enabled energy controlling system for a metro rail station was proposed and it has been discovered that the proposed integrated BIM can reduce much than 25% of the cooling load [18]. The influence of occupancy-associated parameters on entire energy consumption in buildings occupancy-based management strategies were being examined [19], taking into consideration heating, air conditioning (HVAC) and lighting control.

In the study [20], an enhancement for the occupant comfort throughout office buildings was performed by combining environmental data collected by a WSN with human perception gathered by a feedback tool. The deployment of the WSN nodes is crucial for maximizing network lifecycle and minimizing the cost for the deployment of those nodes, this allows for improved measurement accuracy while lowering building energy usage and ensuring the comfort for indoor users. Zaimen et al. [21] suggested a conceptual strategy that relies on utilizing the BIM database to obtain accurate information on the target area. The suggested solution could be added as a plugin into BIM tools to enhance sensor integration in real time while accounting for node and obstacle heterogeneity. Similar to the study [21], Dahmane et al. [22] also took into consideration the deployment of the sensor nodes but they adopted ISOD (Indoor Sensor Optimal Deployment) framework which developed a multi-objective optimization

approach, exploited BIM information, including all the required properties of material and deployed the optimum WSN structure dynamically. Indoor energy could be preserved by utilizing BIM model with AI. Wan et al. [23] proposed an innovative hybrid digital twin-building data structures (DT-BIM) model. The proposed model uses artificial intelligence to discover resource shortages, assess requirements, make judgments, distribute resources, and update all database procedures. Wang et al. [24] proposed a novel efficient energy Building Digital Twins (BDTs) system using BIM model to discover the main techniques of Digital Twins. Data Fusion Algorithm (DFA) was developed by joining Backpropagation Neural Network (BPNN) along with the means of Dynamic Host Configuration Protocol (DCHP). The Indoor Environmental Quality (IEQ) related to building systems had a significant impact on the well-being and overall efficiency of the occupants.

In the study [25], the author focused on merging BIM models, sensors, and specialized Internet of Things (IoT) hardware from microcontrollers into such a framework that enabled a seamless workflow for the monitoring, analysis, interpretation, and visualization of IoT-sourced data in a BIM context. The created system controlled variables like temperature, humidity, sunlight, and air quality in accordance with predefined comfortability levels to achieve best occupants experience. In addition to BIM methodologies and tools that may effectively support the management of all data and information, IoT sensors provided a significant amount of information on energy usage and internal environment of the building.

Desogus et al. [26] showed the research's goal and findings on evaluating the integration of BIM technique and IoT systems to achieve a dynamic and automated data exchange between sensors and Revit which is a BIM model. Moreno et al. [27] presented a BIM-FM prototype for a university building's operations and access to updated environmental data. The developed prototype made two contributions: two types of data are registered, first frequently obtained environment data and building records, also it could automate data feeding, modifying, and recovery processes, resulting in an enhanced environment both for BIM experts and non-expert users. In the same context regarding energy management, Shalabi and Turkan [28] presented a research for energy management by simulating approach, the study is represented by a framework built on the BIM that gathers the output data from building energy simulators, building energy management systems (BEMS) and computerized maintenance management systems (CMMS) in order to identify and locate building spaces that may require maintenance. Additionally, it allows managers to combine and view related data from numerous systems at single hub. Table 1 present a comparative assessment for studies related to BIM and how it can be represented with the help of WSNs.

**Table 1.** Comparative assessment for studies related to BIM and WSN (from 2020 to 2022)

| Author                      | Outcome   | Study Description   | Approach   |
|-----------------------------|---|---|--|
| Kontaxis et al. (2022) [13] | The study examined the design, technology and cost of WSNs capturing real-time information from BIM renewal toolkits. | It was constructed on real WSN systems at BIMERR pilot sites for capturing dynamic information for BIM and smart residence.     | Z-Wave Radio Access Technology (RAT) is made up from several Z-Wave sensors. The sensors communicate by means of the BIMERR Middleware through the Internet through a local Gateway. |
| Zaimen et al. (2020) [21]   | WSN design and a Novel BIM-based Method in Smart Buildings.   | Suggested a conceptual strategy that relied on utilizing the BIM database to obtain accurate. information on the target area in | Within the BIM tool, WSN placement is implemented as a plugin (add-on software). This plugin extracted smart building information from   |

|                                |   |   |   |
|--------------------------------|---|---|---|
|                                |   | real time. The presented solution could be installed as a plugin into BIM tools to enhance sensor integration in real time.   | the BIM database in real time, along with sensor limitations, and then determines the optimum sensor node placement. The end outcome will be visualized in a 3D model.  |
| Dahmane et al. (2020) [22]     | Framework based on BIM for Optimal WSN Deployment in Smart Buildings.   | Adopted ISOD framework which developed a multi-objective enhancement approach, use BIM database information, comprising all the physical material used in the obstacles, and design the best WSN configuration dynamically.<br>A new hybrid digital twin-building data modeling (DT-BIM) model is proposed. | The framework developed an algorithm (NSGA-II) to generate an optimum deployment in a WSN by resolving a multiple function which decrees sensors while maximizing their coverage areas.   |
| Wan et al. (2022) [23]         | Saving indoor energy by using a smart building's optimal design.  | With the help of artificial intelligence, this model identifies resource shortages, analyzes requirements, makes decisions, allocates resources, and updates all procedures in the database.  | GANN-BIM model was derived by incorporating ANN with Genetic Algorithm.   |
| Wang et al. (2022) [24]        | Energy saving design for buildings.   | Energy efficient Building Digital Twins (BDTs) were studied using BIM model to explore the key techniques of Digital Twins.   | Data Fusion Algorithm (DFA) was developed by joining Backpropagation Neural Network (BPNN) with the means of Dynamic Host Configuration Protocol (DCHP).  |
| Engenharia (2021) [25]         | BIM as an intelligent management tool.  | Sensors sent the parameters they measure to an ODS, like MySQL, The created system controls variables like temperature, humidity, sunlight, and air quality in accordance with predefined comfortability levels.  | Combining Online Database Services (ODS) and BIM systems (like Autodesk Revit) into a visualized platform (Microsoft Power BI).   |
| Desogus et al. (2021) [26]     | Allow building managers access to real-time statistics and information on energy usage and building conditions. | Visualizing internal building characteristics (such as temperature, brightness, etc.) with energy consumption metrics allows for evaluating the integration of BIM methodology with IoT systems.  | Integrating sensors with Revit BIM model along with visual programming platform.  |
| Moreno et al. (2022) [27]      | BIM Dynamic Data Feeding for Facility Management.   | This article offers a BIM prototype for a university building's operations and access to updated environmental data. It stored sensor data and automates data feeding, updating, and recovery processes, resulting in a user-friendly surroundings both for BIM experts and non-BIM users.                  | -Sensor devices were connected by Wi-Fi using Microsoft Azure® platform as an IoT solution.<br>- Data is stored in Microsoft Excel® spreadsheet.<br>- The DiRoots® plug-in is being used to obtain or update data in the Revit® building information model. |
| Shalabi and Turkan (2020) [28] | Managing energy by BIM energy simulation.   | The framework allowed BIM components to use data collected by other systems to found energy performance by comparing it to real energy performance, and also provide access to maintenance records and BEMS alarms that have happened in the building at the element level.                                 | -Data collected be BEMS.<br>- Energy simulation data results created by EnergyPlus™ based Design Builder software.  |
| Lin and Cheung (2020) [29]     | Establishing an environmental monitoring solution for parking areas in smart cities using WSN/BIM.              | WSN nodes were installed in a parking garage to collect carbon monoxide (CO), humidity and temperature data in real time in order to monitor the parking garage's environment.  | - NET micro framework for WSN nodes.<br>- Autodesk Revit, Autodesk Navisworks and Navisworks API foe BIM module.<br>- C# (.NET Framework) for processing of data.   |

#### 4. THE IMPACT OF ARTIFICIAL INTELLIGENCE ON ENERGY MANAGEMENT OPTIMIZATION

AI plays as a main role in energy management systems decision-making for different applications, such as wind turbines, solar power generation systems, and so on. AI techniques have grown in popularity for solving various problems in power systems such as control, planning, scheduling, forecasting, and so on. These techniques can deal with the most difficult tasks that applications in modern large energy systems face as more interconnections are added to meet increasing load demand. DL as an AI method has been triggered by a large amount of data generated by inexpensive sensors and web - based applications, as well as significant progress in data processing, primarily via Graphic Processing Units (GPUs) [30]. ML and DL could be implemented in many

areas related to energy, the main focus in this section will be on the studies considering management and forecasting approaches for energy in smart buildings.

##### 4.1 Use cases of ML and DL in energy management and control systems

From reviewing the articles in the field of energy management, it is obvious that ML and DL approaches have been widely investigated in the literature especially in recent years. Huang et al. [31] designed an optimal electricity management plan for intelligent buildings based on Deep Reinforcement Learning (DRL). They created a Q-learning-based energy model after modeling the electrical devices. The simulation results revealed that the improved strategy enhances the intelligent building while achieving rational and

efficient energy allocation. Jalal and Al-Rubayi [32] presented a study to develop a Smart Building Control System (SBCS) to reduce energy usage in a building by utilizing daylight sensors, occupant control, weather variations, load consumption, and changes in solar power. The energy consumption was reduced by 56% in the summer and 65% in the winter. Benavente and Ibadah [33] evaluated energy efficiency in buildings by analyzing and comparing different ML classifiers. The results of the study stated that it is necessary to have a detailed definition of the problem to be resolved, besides that, its mandatory to have prior analysis for the dataset used for both training and evaluating in order to have better results.

In the study [34], a ML model was used to calculate unmeasured variables brought on by a sparse array of sensors. They utilized of a six-month data collection gathered from a Japanese smart building. Results obtained demonstrated a precise estimation of interior measures that is appropriate for the best control of the HVAC system. Elbes et al. [35] constructed the indoor layer location algorithms utilizing long short-term memory neural networks (LSTM) for estimation, resulting in a fully tiered architecture for power management. Identifying information and the current location of persons inside the building are all necessary to accomplish energy efficiency. In the study [36], the K-Nearest Neighbor (KNN) approach is presented. The proposed strategy, according to simulation findings, reduced errors to less than 2 m by 40% when compared to other methods. Yang et al. [37] proposed a building model with adaptive machine learning for applications in building automation and control. The system had a dynamic ANN that uses online building operation data to update the building model on a regular basis utilizing an adaptable machine-learning-based building dynamics modeling technique. Additionally, the system employed a multi-objective functionality that enhance both energy consumption and thermal comfort. In the study [38], a deep reinforcement learning (DRL)-based controller was used to improve the energy usage for air-conditioning systems in relation to thermal comfort and quality of indoor air. The study produced an atmosphere with higher thermal comfort, 10% less CO<sub>2</sub>, and 45% better air quality.

Gao et al. [39] suggested DRL framework to create energy-efficient building indoor thermal comfort control techniques that could lower HVAC energy usage while keeping occupant comfort. They implemented a deep Feedforward Neural Network (FNN) and Deep Deterministic Policy Gradients (DDPG) to discover the best thermal comfort control strategy. In the study [40], a Deep Q-Learning was employed in conjunction with a DRL algorithm for optimizing energy consumption levels from air-conditioning, thermal comfort, and quality of indoor air (CO<sub>2</sub>) in a classroom with up to 72 occupants. When it was compared to air-conditioned with a stable temperature of 25°C, the DRL agent algorithm could save up to 43% on energy. The average energy savings with agent were around 19%. Nonetheless, the relating CO<sub>2</sub> level is reduced by approximately 24%.

In the study [41], a model was developed by applying the Gradient Boosting Machines algorithm (GBM) to predict the unit's energy consumption as an energy baseline. As a critical finding, the offline analysis revealed a great potential to save energy by 10.31% or 63,119 metric tons of yearly steam consumption. Diyan et al. [42] proposed a scheduling algorithm in smart homes based on human-machine interaction utilizing reinforcement learning. The suggested scheduling algorithm splited the day into different states. Each state performed various actions in each state in order to obtain the highest benefit. In terms of energy consumption and home user discomfort, the proposed system outperforms Least Slack Time (LST) based scheduling.

Lissa et al. [43] presented a study involving reinforcement learning for controlling the temperature of indoor and residential hot water, with the goal of lowering energy consumption by enhancing the use of energy production. The findings indicated that the presented DRL algorithm coupled with the dynamic setpoint saved 8% more energy than a rule-based algorithm, with savings reaching up to 16% over the summer period. Zhang et al. [44] suggested a DL based power control for uplink cell free massive multi-Input Multi-Output (MIMO) systems. Unsupervised learning, in which optimal power allocations are not required to be known, and thus has low training complexity. Haq et al. [45] tried to optimize energy consumption by applying reinforcement deep learning algorithm for observing home appliances with the goal of lowering energy consumption. The proposed method did not require any prior knowledge or information about various household electric appliances. The proposed method's efficiency and reliability were validated by simulation-based research results using real-time data.

#### 4.2 Role of forecasting in smart grids energy management

One of the most important tools for energy management systems is load forecasting. It is used for power balance in planning and management. Load forecasting has an important impact on operational efficiency. The load forecasting model should be able to predict electrical power demand accurately [46]. Computationally intelligent load forecasting techniques play an important role in reducing the energy crisis and contributing to environmental greenery. Forecasting could be classified into three different approaches: Statistical, DL and physical. Statistical forecasting methods analyze a collection of data points in a time series of the variable being studied. Future values of a specific variable could be predicted using the time series regression method. A different approach to forecasting is implemented through the use of algorithms that simulate learning processes, primarily through the use of Neural Networks (NN). Finally, Physical forecasting methods attempt to numerically simulate the physical processes that define the system in order to forecast its future state. In the case of buildings, physical processes usually include interactions with both the internal and external environments [47].

**Table 2.** Comparison for the studies in terms of ML/DL approaches and the type of algorithm implemented in the studies

| Reference                 | Year | ML/DL | Algorithm Employed in the Study                         | Application       |
|---------------------------|------|-------|---|-------------------|
| Huang et al. [31]         | 2020 | DL    | DRL   |                   |
| Jalal and Al-Rubayi [32]  | 2022 | ML    | ANN   |                   |
| Benavente and Ibadah [33] | 2020 | ML    | SVC, DT, K-Neighbors, Logistic Regression, Gaussian NB, | Energy management |
| Kaligambe et al. [34]     | 2022 | ML    | XGBoost   |                   |
| Elbes et al. [35]         | 2019 | DL    | LSTN  |                   |

|                         |      |    |                            |                            |
|-------------------------|------|----|----------------------------|----------------------------|
| Afuosi and Zoghi [36]   | 2020 | ML | KNN                        |                            |
| Yang et al. [37]        | 2020 | ML | NARX ANN, MLP ANN          |                            |
| Valladares et al. [38]  | 2019 | DL | DRL                        |                            |
| Gao et al. [39]         | 2020 | DL | DRL, FNN                   |                            |
| Yu et al. [40]          | 2021 | DL | DRL                        |                            |
| Moghadasi et al. [41]   | 2021 | ML | GBM                        |                            |
| Diyan et al. [42]       | 2020 | DL | DRL                        |                            |
| Lissa et al. [43]       | 2020 | DL | DRL                        |                            |
| Zhang et al. [44]       | 2021 | DI | DNN                        |                            |
| Haq et al. [45]         | 2021 | DL | DRL                        |                            |
| Shan et al. [5]         | 2019 | ML | Ensemble learning          |                            |
| Huang et al. [8]        | 2019 | DL | CNN                        |                            |
| Han et al [9]           | 2021 | DL | LSTM                       |                            |
| Syed et al. [48]        | 2021 | DL | LSTM                       | Forecasting energy demands |
| Khan et al. [49]        | 2020 | DL | LSTM, CNN                  |                            |
| Eseye and Lehtonen [50] | 2020 | ML | EMD, ICA, SVM, BGA and GPR |                            |
| Ilager et al. [51]      | 2021 | ML | GBM                        |                            |

The vast majority of the studies investigated in the literature are based on DL-based sequential processes, like Long Short-Term Memory (LSTM), which is the most widely used in energy forecasting methods [9]. Hybrid DL models can contribute effectively for increasing the accuracy of prediction as clearly presented by Syed et al. [48]. The hybrid DL model was constructed by stacking fully connected layers and unidirectional LSTMs on bi-directional LSTMs. Another framework [49] which incorporate Convolution Neural Networks (CNNs) to extract the features from the data and fed it to LSTM to perform energy prediction. Shan et al. [5] proposed a model represented by ensemble learning to predict electricity consumption, the conducted research is based on real data taken from a hotel in Shanghai, China. The proposed model outperforms other models in term of generalization, accuracy and stability. In the study [8], a convolutional neural network-based (Load CNN) model with low training costs has been presented for individual resident next-day load forecasting. The model's prediction accuracy was on line with that of the most advanced models currently in use, making LoadCNN the very first load forecasting model to concurrently achieve high prediction accuracy and cheap training costs.

Eseye and Lehtonen [50] developed a novel hybrid ML approach to predict building heat consumption. Empirical Mode Decomposition (EMD), Support Vector Machine (SVM) and Imperialistic Competitive Algorithm (ICA) were all included into the proposed forecasting model. In order to identify the most crucial variables, a feature selection ML model integrating the Binary Genetic Algorithm (BGA) and Gaussian Process Regression (GPR) is also proposed. Ilager et al. [51] proposed a ML model for temperature prediction that uses gradient boosting. The experiment's findings demonstrated that the model consistently forecasts temperature with Root Mean Square Error (RMSE) value of 0.05 or a predicted values of 2.38°C, which is 6°C less than a competing theoretical model. Table 2 summarizes the previous mentioned studies in terms of ML/DL approaches and the type of algorithm implemented in the studies.

## 5. SOLUTION METHODOLOGY

Energy management has been addressed in many different ways, such as the use WSN/BIM, or AI techniques represented by ML/DL. Therefore, there is a crucial need for describing a methodology that best introduce an optimized system that can efficiently manage the energy in smart buildings. The

proposed system; which depends on the finding of this review, is represented in Figure 3, the highlighted boxes represent the contribution for this research. The optimized system could be described as the follows:

- Designing and implementing of a system based on clustered WSN for collecting the required information such as voltage and current consumption, determining occupancy and etc. The sensors used in this system are diverse. Some sensors can be mentioned such as motion, light, humidity, temperature, smoke and voltage sensors. The sensor nodes are distributed amongst the institute parts as well as the wireless communication systems. The suggested protocol for this system is Message Queuing Telemetry Transport (MQTT) because its lightweight design, efficiency, dependable message delivery, extensive connectivity capabilities, and robust bidirectional security.
- Building Information Modeling (BIM) utilizes data collected by sensors to create a comprehensive digital representation of a building. Throughout the structure, sensors gather important information on aspects like temperature, humidity, occupancy, and energy usage. This data is then fed into the BIM system, translating it into visual models and simulations. By integrating sensor data, BIM enables real-time monitoring, analysis, and optimization of building performance.
- Producing an optimized method for managing power consumption using ML/DL approaches.

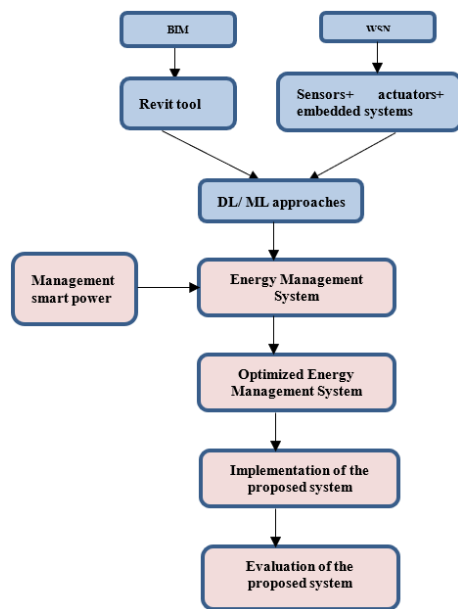
The basic idea for the suggested system can be shown in the diagram of Figure 4, it could be explained briefly as the following:

- Sensor nodes are connected to the local control unit.
- The local control unit collects the data and send it to the central control unit.
- The main job of the central control unit is to make a decision based on the readings from the sensors. A trained ML/DL model is placed in the central control unit to make the optimal decision.
- Local control unit receives the decision from the central unit and take the action for selecting one of the predefined power managements modes.
- Three energy management modes are outlined and classified as Shutdown, Selected, and Full. These

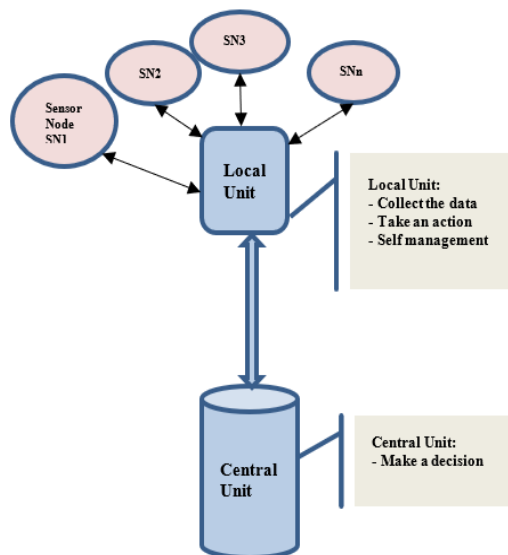
modes are determined based on the occupancy status within the building. The "Shutdown" mode is suitable for implementation when the building is unoccupied, in contrast to the "Full" mode, which is applied during peak occupancy. Meanwhile, the "Selected" mode is implemented when the building is partially occupied.

The reliability of the system is maintained as the following:

- Self-management is achieved by local unit if the central unit is not responding, the action in this case is not AI dependent decision but it could be performed in the traditional approaches; for example, setting up a threshold for a specific action.
- If the local unit is not responding, central unit could perform power management by selecting the chosen power mode.



**Figure 3.** Flow diagram for the proposed system methodology



**Figure 4.** Block diagram for the proposed system

## 6. CONCLUSION

Energy management was one of the important aspects that receive a lot of attention at the present time, many researchers have dealt with this topic, especially in the last few years. It was clear from the studies in the literature that the current trend was interested in including smart systems in the field of energy management in what is called smart buildings. In this review, the previous studies have been investigated and the main topics were clearly presented to suggest a suitable methodology and research areas for implementing an optimized smart energy management system. The suggested system expected to achieve high performance in terms of managing energy consumption in a smart and a reliable way.

The anticipation for this review is to encourage the adoption of suitable methodologies and research areas to implement optimized smart energy management systems. The desired outcome is for these systems to exhibit high performance in efficiently managing energy consumption in a smart and reliable manner. By fostering increased attention and interest in this field, its likely to drive advancements in energy management practices, ultimately contributing to more sustainable and energy-efficient building environments.

## REFERENCES

- [1] Rashid, B., Rehmani, M.H. (2016). Applications of wireless sensor networks for urban areas: A survey. *Journal of Network and Computer Applications*, 60: 192-219. <https://doi.org/10.1016/j.jnca.2015.09.008>
- [2] Chincoli, M., Syed, A.A., Exarchakos, G., Liotta, A. (2016). Power control in wireless sensor networks with variable interference. *Mobile Information Systems*, 2016: 3592581. <https://doi.org/10.1155/2016/3592581>
- [3] Wireless Sensor Network in a Data Center - AKCP. <https://www.akcp.com/blog/the-importance-of-wireless-sensor-network-in-a-data-center/>, accessed on Nov. 03, 2022.
- [4] Northcote-Green, J., Wilson, R.G. (2017). *Control and Automation of Electrical Power Distribution Systems* (Vol. 28). CRC Press.
- [5] Shan, S., Cao, B., Wu, Z. (2019). Forecasting the short-term electricity consumption of building using a novel ensemble model. *IEEE Access*, 7: 88093-88106. <https://doi.org/10.1109/ACCESS.2019.2925740>
- [6] Mariano-Hernández, D., Hernández-Callejo, L., Zorita-Lamadrid, A., Duque-Pérez, O., García, F.S. (2021). A review of strategies for building energy management system: Model predictive control, demand side management, optimization, and fault detect & diagnosis. *Journal of Building Engineering*, 33: 101692. <https://doi.org/10.1016/j.jobe.2020.101692>
- [7] Sembroiz, D., Careglio, D., Ricciardi, S., Fiore, U. (2019). Planning and operational energy optimization solutions for smart buildings. *Information Sciences*, 476: 439-452. <https://doi.org/10.1016/j.ins.2018.06.003>
- [8] Huang, Y., Wang, N., Gao, W., Guo, X., Huang, C., Hao, T., Zhan, J. (2019). Loadcnn: A low training cost deep learning model for day-ahead individual residential load forecasting. *arXiv preprint arXiv:1908.00298*. <https://doi.org/10.48550/arXiv.1908.00298>
- [9] Han, T., Muhammad, K., Hussain, T., Lloret, J., Baik, S.W. (2020). An efficient deep learning framework for

- intelligent energy management in IoT networks. *IEEE Internet of Things Journal*, 8(5): 3170-3179. <https://doi.org/10.1109/JIOT.2020.3013306>
- [10] Al Dakheel, J., Del Pero, C., Aste, N., Leonforte, F. (2020). Smart buildings features and key performance indicators: A review. *Sustainable Cities and Society*, 61: 102328. <https://doi.org/10.1016/j.scs.2020.102328>
- [11] Albino, V., Berardi, U., Dangelico, R.M. (2015). Smart cities: Definitions, dimensions, performance, and initiatives. *Journal of Urban Technology*, 22(1): 3-21. <https://doi.org/10.1080/10630732.2014.942092>
- [12] The 4 Components that Make a Smart Building Ecosystem | Iota. <https://www.iotacomunications.com/blog/the-4-components-that-make-a-smart-building-ecosystem/>, accessed on Nov. 11, 2022.
- [13] Kontaxis, D., Tsoulos, G., Athanasiadou, G., Giannakis, G. (2022). Wireless sensor networks for building information modeling. *Telecom*, 3(1): 118-134. <https://doi.org/10.3390/telecom3010007>
- [14] Panteli, C., Kylili, A., Fokaides, P.A. (2020). Building information modelling applications in smart buildings: From design to commissioning and beyond a critical review. *Journal of Cleaner Production*, 265: 121766. <https://doi.org/10.1016/j.jclepro.2020.121766>
- [15] McGlenn, K., Yuce, B., Wicaksono, H., Howell, S., Rezgui, Y. (2017). Usability evaluation of a web-based tool for supporting holistic building energy management. *Automation in Construction*, 84: 154-165. <https://doi.org/10.1016/j.autcon.2017.08.033>
- [16] Wu, W., Li, W., Law, D., Na, W. (2015). Improving data center energy efficiency using a cyber-physical systems approach: integration of building information modeling and wireless sensor networks. *Procedia Engineering*, 118: 1266-1273. <https://doi.org/10.1016/j.proeng.2015.08.481>
- [17] Lee, D., Cha, G., Park, S. (2016). A study on data visualization of embedded sensors for building energy monitoring using BIM. *International Journal of Precision Engineering and Manufacturing*, 17: 807-814. <https://doi.org/10.1007/s12541-016-0099-4>
- [18] Bapat, H., Sarkar, D., Gujar, R. (2021). Application of integrated fuzzy FCM-BIM-IoT for sustainable material selection and energy management of metro rail station box project in western India. *Innovative Infrastructure Solutions*, 6: 1-18. <https://doi.org/10.1007/s41062-020-00431-7>
- [19] Salimi, S., Hammad, A. (2019). Critical review and research roadmap of office building energy management based on occupancy monitoring. *Energy and Buildings*, 182: 214-241. <https://doi.org/10.1016/j.enbuild.2018.10.007>
- [20] Ramsauer, D., Dorfmann, M., Tellioglu, H., Kastner, W. (2022). Human perception and building automation systems. *Energies*, 15(5): 1745. <https://doi.org/10.3390/en15051745>
- [21] Zaimen, K., Dollinger, J.F., Moalic, L., Abouaissa, A., Idoumghar, L. (2020). An overview on WSN deployment and a novel conceptual BIM-based approach in smart buildings. In *2020 7th International Conference on Internet of Things: Systems, Management and Security (IOTSMS)*, Paris, France, pp. 1-6. <https://doi.org/10.1109/IOTSMS52051.2020.9340226>
- [22] Dahmane, W.M., Dollinger, J.F., Ouchani, S. (2020, October). A BIM-based framework for an optimal WSN deployment in smart building. In *2020 11th International Conference on Network of the Future (NoF)*, Bordeaux, France, pp. 110-114. <https://doi.org/10.1109/NoF50125.2020.9249099>
- [23] Wan, Y., Zhai, Y., Wang, X., Cui, C. (2022). Evaluation of indoor energy-saving optimization design of green buildings based on the intelligent GANN-BIM model. *Mathematical Problems in Engineering*, 2022: 3130512. <https://doi.org/10.1155/2022/3130512>
- [24] Wang, W., Guo, H., Li, X., Tang, S., Xia, J., Lv, Z. (2022). Deep learning for assessment of environmental satisfaction using BIM big data in energy efficient building digital twins. *Sustainable Energy Technologies and Assessments*, 50: 101897. <https://doi.org/10.1016/j.seta.2021.101897>
- [25] Engenharia, E. (2021). BIM as a Smart Facility Management Tool of University Facilities. (Doctoral dissertation, Universidade do Minho (Portugal)).
- [26] Desogus, G., Quaquero, E., Rubiu, G., Gatto, G., Perra, C. (2021). Bim and IoT sensors integration: A framework for consumption and indoor conditions data monitoring of existing buildings. *Sustainability*, 13(8): 4496. <https://doi.org/10.3390/su13084496>
- [27] Moreno, J.V., Machete, R., Falcão, A.P., Gonçalves, A.B., Bento, R. (2022). Dynamic data feeding into BIM for facility management: A prototype application to a university building. *Buildings*, 12(5): 645. <https://doi.org/10.3390/buildings12050645>
- [28] Shalabi, F., Turkan, Y. (2020). BIM-energy simulation approach for detecting building spaces with faults and problematic behavior. *Journal of Information Technology in Construction*, 25: 342-360. <https://dx.doi.org/10.36680/j.itcon.2020.020>
- [29] Lin, Y.C., Cheung, W.F. (2020). Developing WSN/BIM-based environmental monitoring management system for parking garages in smart cities. *Journal of Management in Engineering*, 36(3): 04020012. [https://doi.org/10.1061/\(ASCE\)ME.1943-5479.0000760](https://doi.org/10.1061/(ASCE)ME.1943-5479.0000760)
- [30] Czum, J.M. (2020). Dive into deep learning. *Journal of the American College of Radiology*, 17(5): 637-638. <https://doi.org/10.1016/j.jacr.2020.02.005>
- [31] Huang, X.T., Zhang, D., Zhang, X. (2021). Energy management of intelligent building based on deep reinforced learning. *Alexandria Engineering Journal*, 60(1): 1509-1517. <https://doi.org/10.1016/j.aej.2020.11.005>
- [32] Jalal, B.M., Al-Rubayi, R.H. (2022). Energy management strategy with smart building control system to reduction electrical load using ANN. *Bulletin of Electrical Engineering and Informatics*, 11(6): 3188-3200. <https://doi.org/10.11591/eei.v11i6.4087>
- [33] Benavente-Peces, C., Ibadah, N. (2020). Buildings energy efficiency analysis and classification using various machine learning technique classifiers. *Energies*, 13(13): 3497. <https://doi.org/10.3390/en13133497>
- [34] Kaligambe, A., Fujita, G., Keisuke, T. (2022). Estimation of unmeasured room temperature, relative humidity, and CO<sub>2</sub> concentrations for a smart building using machine learning and exploratory data analysis. *Energies*, 15(12): 4213. <https://doi.org/10.3390/en15124213>
- [35] Elbes, M., Alrawashdeh, T., Almaita, E., AlZu'bi, S., Jararweh, Y. (2022). A platform for power management based on indoor localization in smart buildings using



- long short-term neural networks. *Transactions on Emerging Telecommunications Technologies*, 33(3): e3867. <https://doi.org/10.1002/ett.3867>
- [36] Afuosi, M.B., Zoghi, M.R. (2020). Indoor positioning based on improved weighted KNN for energy management in smart buildings. *Energy and Buildings*, 212: 109754. <https://doi.org/10.1016/j.enbuild.2019.109754>
- [37] Yang, S., Wan, M.P., Chen, W., Ng, B.F., Dubey, S. (2020). Model predictive control with adaptive machine-learning-based model for building energy efficiency and comfort optimization. *Applied Energy*, 271: 115147. <https://doi.org/10.1016/j.apenergy.2020.115147>
- [38] Valladares, W., Galindo, M., Gutiérrez, J., Wu, W.C., Liao, K.K., Liao, J.C., Lu, K.C., Wang, C.C. (2019). Energy optimization associated with thermal comfort and indoor air control via a deep reinforcement learning algorithm. *Building and Environment*, 155: 105-117. <https://doi.org/10.1016/j.buildenv.2019.03.038>
- [39] Gao, G., Li, J., Wen, Y. (2020). DeepComfort: Energy-efficient thermal comfort control in buildings via reinforcement learning. *IEEE Internet of Things Journal*, 7(9): 8472-8484. <https://doi.org/10.1109/JIOT.2020.2992117>
- [40] Yu, K.H., Chen, Y.A., Jaimes, E., Wu, W.C., Liao, K.K., Liao, J.C., Lu, K.C., Sheu, W.J., Wang, C.C. (2021). Optimization of thermal comfort, indoor quality, and energy-saving in campus classroom through deep Q learning. *Case Studies in Thermal Engineering*, 24: 100842. <https://doi.org/10.1016/j.csite.2021.100842>
- [41] Moghadasi, M., Izadyar, N., Moghadasi, A., Ghadamian, H. (2021). Applying machine learning techniques to implement the technical requirements of energy management systems in accordance with ISO 50001: 2018, an industrial case study. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, 1-18. <https://doi.org/10.1080/15567036.2021.2011989>
- [42] Diyan, M., Silva, B.N., Han, K. (2020). A multi-objective approach for optimal energy management in smart home using the reinforcement learning. *Sensors*, 20(12): 3450. <https://doi.org/10.3390/s20123450>
- [43] Lissa, P., Deane, C., Schukat, M., Seri, F., Keane, M., Barrett, E. (2021). Deep reinforcement learning for home energy management system control. *Energy and AI*, 3: 100043. <https://doi.org/10.1016/j.egyai.2020.100043>
- [44] Zhang, Y., Zhang, J., Jin, Y., Buzzi, S., Ai, B. (2021). Deep learning-based power control for uplink cell-free massive MIMO systems. In 2021 IEEE Global Communications Conference (GLOBECOM), Madrid, Spain, pp. 1-6. <https://doi.org/10.1109/GLOBECOM46510.2021.9685827>
- [45] Haq, E.U., Lyu, C., Xie, P., Yan, S., Ahmad, F., Jia, Y. (2022). Implementation of home energy management system based on reinforcement learning. *Energy Reports*, 8: 560-566. <https://doi.org/10.1016/j.egy.2021.11.170>
- [46] Panapongpakorn, T., Banjerdpongchai, D. (2019). Short-term load forecast for energy management systems using time series analysis and neural network method with average true range. In 2019 First International Symposium on Instrumentation, Control, Artificial Intelligence, and Robotics (ICA-SYMP), Bangkok, Thailand, pp. 86-89. <https://doi.org/10.1109/ICA-SYMP.2019.8646068>
- [47] Lazos, D., Sproul, A.B., Kay, M. (2014). Optimisation of energy management in commercial buildings with weather forecasting inputs: A review. *Renewable and Sustainable Energy Reviews*, 39: 587-603. <https://doi.org/10.1016/j.rser.2014.07.053>
- [48] Syed, D., Abu-Rub, H., Ghrayeb, A., Refaat, S.S. (2021). Household-level energy forecasting in smart buildings using a novel hybrid deep learning model. *IEEE Access*, 9: 33498-33511. <https://doi.org/10.1109/ACCESS.2021.3061370>
- [49] Khan, Z.A., Hussain, T., Ullah, A., Rho, S., Lee, M., Baik, S.W. (2020). Towards efficient electricity forecasting in residential and commercial buildings: A novel hybrid CNN with a LSTM-AE based framework. *Sensors*, 20(5): 1399. <https://doi.org/10.3390/s20051399>
- [50] Eseye, A.T., Lehtonen, M. (2020). Short-term forecasting of heat demand of buildings for efficient and optimal energy management based on integrated machine learning models. *IEEE Transactions on Industrial Informatics*, 16(12): 7743-7755. <https://doi.org/10.1109/TII.2020.2970165>
- [51] Ilager, S., Ramamohanarao, K., Buyya, R. (2020). Thermal prediction for efficient energy management of clouds using machine learning. *IEEE Transactions on Parallel and Distributed Systems*, 32(5): 1044-1056. <https://doi.org/10.1109/TPDS.2020.3040800>