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# Smart building energy management and monitoring system based on artificial intelligence in smart city

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ABSTRACT

In the present scenario, the fastest-growing environmental concerns are energy management and monitoring. Inefficient energy recycling, energy consumption, energy utilization, and drain characteristic are smart building energy management challenges. Hence to examine the connection between smart city management policies and energy management, this research proposed an Artificial Intelligence Technique for Monitoring Systems in Smart Buildings (AIMS-SB) to manage energy consumption and produce and recycle energy required for a smart building. AIMS-SB helps to predict energy analysis, renewable energy production, and recycling evaluation based on prediction model strategies. AIMS-SB developed eco-design monitoring systems for smart buildings to optimize energy consumption, utilization, and drain characteristics. These efficient implementation strategies and methods for harnessing renewable energy help to improve the safety process, recycling, and reuse of our energy resources for smart building energy management. AIMS-SB provides viable solutions to the growing number of challenges associated with smart city energy management. Therefore, the system's findings demonstrate increased accuracy and efficiency compared to conventional methods.

## Introduction

The smartening and sustainability of cities are rapidly increasing across countries by developing innovations and technological improvements. The smart city intends to deal with resource escalation and high efficiency [1]. People's well-being, health, and productivity are directly identified by the performance of the light, climate, and other control systems and should not be ignored while optimizing energy loads. Hence, a strong understanding of all indoor elements interactions involving the building's electricity load and the public's comfort level is the groundwork for energy-efficient and sustainable building processes. This actively promotes sustainability and effectiveness and dramatically decreases consumption and utility costs. Networking and communication technologies in smart cities deal with energy supply, mobility and waste management, etc., generated by the growing population and urbanization. [2]. Energy requirements are abundant and complex in cities. Existing systems are improved and implemented in modern cities to provide solutions through an optimal approach [3]. For IoT-enabled smart cities, an optimized operational framework and efficient deployment of sensors should adopt the necessary conditions. Energy harvesting operations and energy-efficient solutions are two types of energy management classification in smart cities [4,5].

The Internet of things (IoT) interconnects advanced capability devices to interact with other devices, humans, and their physical environment to perform various tasks. [6]. Efficient energy management is tedious because of the demand for limited electricity resources. [7]. Smart monitoring system comes into existence through IoT technology by integrating energy management and control of monitoring systems. [8]. Energy consumption is reduced by the monitoring control and prevents the wastage of energy. Most monitoring control systems use photosensors, occupancy sensors, and motion sensors to automatically detect movement within a small area to save energy. [9,10].

In buildings, artificial intelligence (AI) techniques are implemented to achieve real-time management of energy consumption and efficient energy management activities. Building Automation Systems (BAS) have been widely used in industries and large-scale buildings in recent years [11]. Developing a smart building automation system with reliable, flexible, and adaptable is difficult [12]. Artificial intelligence-based smart building automation control (AIBSBAC) is used to improve safety, comfort, and energy consumption. [13]. For higher energy enhancement and optimum user comfort, AIBSBAC adjusts the guidelines through observations. [14,15]. Commercial building energy

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consumption is on the rise needed cutting-edge methods to manage and minimize this cost. The rising awareness of the need to reduce a building's overall energy has led to the adoption of Building Energy Management Systems. This research proposes a conceptual framework for Smart Energy Management Systems that integrates Artificial Intelligence Techniques to optimize energy analysis, renewable energy production, and recycling evaluation. Combinations of changes in weather data are used to produce patterns for controlling the energy consumption of buildings, which are then used to design the suggested control system. Consequently, the building's energy consumption may be modified by installing responsive controls for electrical lighting and modifying the operational schedule in reaction to climatic changes. Buddhahai et al. [16] proposed an energy prediction approach for non-intrusive load monitoring in home appliances. The multi-target classification approach does non-intrusive load monitoring. K-means clustering is used to divide the power data for applications. The area under the ROC Curve index determines the power states. The proposed model obtains appliance power state performance. The multi-target classification algorithm achieves better accuracy and F-score.

Zhou et al. [17] suggest using reinforcement learning artificial intelligence-based smart energy community management. Local energy pools are used to harvest excess energy from renewable resources. The MDP decision's model-free and ongoing task performance is obtained through the Markov decision process (MDP) and reinforcement learning algorithm. Numerical analysis is used to evaluate the performance of the proposed work. Yu et al. [18] designed deep reinforcement learning for smart home energy management. Markov decision process and deep deterministic policy gradient-based energy management algorithm are used to overcome HVAC and energy storage systems' problems. The real world determines the robustness and effectiveness of the proposed model traces experiments.

Rostirolla et al. [19] consider an elastic multilevel energy-saving model for smart cities. According to the demand, the resource turns on and off at each level, and the EICity model obtains cloud elasticity exploration. An energy monitor module controls energy consumption. Geolocation data are used to analyze the proposed work, reducing energy consumption. In [20], a multi-objective risk-based robust optimization approach to energy management is used in a smart residential building under combined demand and supply uncertainty. The proposed work minimizes the system's total cost, power supply, and emission cost. The robustness and flexibility of the framework are obtained by Decision Makers (DMs).

Lu et al. [21] modeled an optimal appliance scheduling model for home energy management in a smart household with a photovoltaic energy storage system. The proposed model reduces the load and cost of electricity, and single and multi-objective optimizations are achieved. HEMS solutions are facilitated by MATLAB software. Optimal scheduling for household appliances is obtained by PESS configuration. Optimal scheduling of multi-smart buildings' energy consumption considering power exchange capability is introduced in [22]. The case study is used to evaluate the power exchange capability effects. The proposed work reduces operation costs and energy consumption in a multi-smart apartment building. The global optimum solution is obtained by mixed integer programming (MIP), and optimization software used to solve the optimization problems is done by a general algebraic modeling system (GAMS).

Distributed multi-objective scheduling of power consumption is implemented by Nebel-Wenner et al. [23] for smart buildings. A database-driven does feasible power consumption and scheduling from the building model simulation. Self-consumption is used to optimize the simulation result. The flexibility used to get different targets from the smart buildings shows the advantages of the optimization process. An improved firefly algorithm based on genetic algorithm operators is suggested by Wahid et al. [24] for energy efficiency in smart buildings. Minimum energy consumption optimization and maximum user comfort management are obtained from the proposed model's performance compared with the FA, GA, ABC, and ACO algorithms. The efficiency of the firefly algorithm is obtained by statistical analysis.

Bourhanane et al. [25] proposed machine learning for energy consumption prediction and scheduling in a smart building. The CompactRIO implements the proposed model. A real-world testbed is used to test the proposed model. PV installation with SB electrical appliances is used to train and validate the proposed model. Accuracy is obtained from small data sets. The proposed model blueprint helps the researchers implement and investigate energy consumption scheduling and predicting through machine learning. Zhang et al. [26] considered artificial intelligence algorithm-based prediction of energy photovoltaic power generation. Photovoltaic power generation prediction influences the proposed method's different factors, and the relationship between the factors is analyzed. The comparative test and statistical graph analyze the performance of the proposed model. Web of object architecture on IoT environment (WISE) is used by Yu et al. [26] for smart home and building energy management. The proposed model is used to connect and cooperate with IoT applications and services automatically. Web-based IoT services and applications are obtained through WoO-based architecture. Service federation and composition are used to mash up various services in the network concept. Smart building energy prediction methodology based on WoO, optimal object attributed are selected.

Nowadays, the quantity of energy consumed in residential buildings by electrical appliances such as refrigerators, washing machines, freezers, dishwashers, vacuum cleaners, fans, air conditioning, heater, iron, etc., is very high. With the development of the global energy crisis and the growing trend towards energy preservation to attain energy sustainability, it is essential to establish a new program for energy

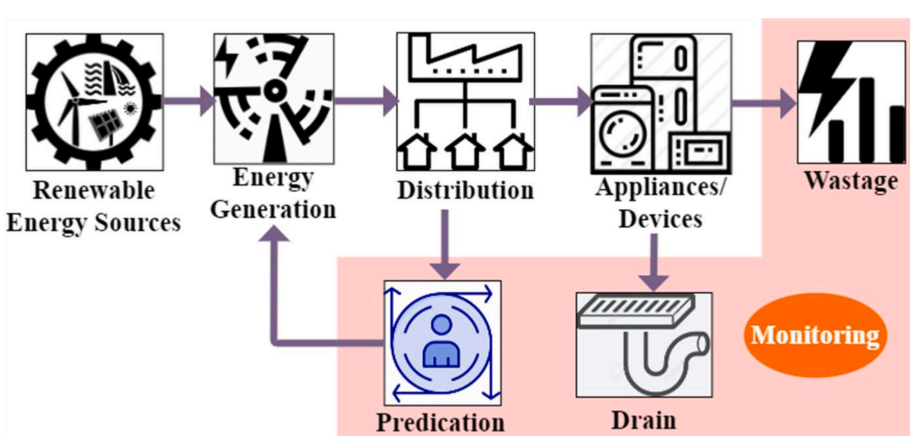


**Fig. 1.** Proposed Artificial Intelligence Technique for Monitoring Systems in Smart Buildings (AIMS-SB) Method's Process Flow.

management in residential areas. So, enhancing the energy performance of residential facilities has become necessary support for energy strategies. However, there has always been doubt among people regarding the influence of smart buildings on society. Therefore, investigations must be conducted to study the influence of smart buildings to improve awareness and make people more confident. Thus, an exploration of the influences of smart buildings has been discussed in this research. Based on the survey, there are several issues with existing methods in achieving high accuracy and efficiency in smart building energy management. Hence, this paper proposes the AIMS-SB method to manage energy consumption and produce and recycle energy required for a sustainable and smart building.

The contribution of the paper is

- Designing the AIMS-SB to manage energy consumption and produce and recycle energy required for a sustainable and smart building.
- Introducing efficient implementation strategies and methods for harnessing renewable energy help to improve the safety process, recycling, and reuse of our energy resources for smart building energy management.
- The experimental results have been performed, and the suggested AIMS-SB model enhances the accuracy and efficiency ratio compared to other existing methods.

## Research methodologies

In smart and sustainable buildings, energy management is necessary to distribute energy to the required appliances/ devices. Here, the energy is provided to the necessary devices that consume the energy and address the energy wastage. The AIMS-SB method is developed to deploy the AI for this energy efficiency, and a decision tree is introduced here. This work aims to address the wastage of energy and improve the accuracy level and efficiency of energy. In Fig. 1, the proposed method's process flow is illustrated.

### *Analysis of energy management and utilization*

This work balances energy distribution, management, and generation by deploying a decision tree. The classification is done by utilizing the decision tree and sorting out the waste of energy in smart cities. Energy waste uses non-productive resources, including electricity, water, and gas. Inefficient management and maintenance of energy-using equipment significantly contribute to energy loss. This has been predicted using AIMS-SB to manage energy consumption and management for a smart building.

$$\beta = \frac{1}{y_n} + \sum_{e}^{m} (y_0 * m_t) + (i_f/t_i) * [(g_s + f_r) + (y_0 * m_t)] + t_i \tag{1}$$

The analysis is done for the energy management in sustainable and smart buildings, Here, the energy drain is monitored and forwards the energy to the appliances that improve energy efficiency. The energy is termed as $e'$, forwarding of energy is referred to as $f_r$, and drain is denoted as $a'$, in this $[(g_s + f_r) + (y_0 * m_t)] + t_i$ the time is estimated for the energy forwarding.

By performing this monitoring phase, the wastage is addressed, and decreases, and the accuracy and the monitoring. It defines the energy from the previous state and forwards it to the necessary devices.

$$\beta(u_0) = \prod_{y_n} (m + i_f) * \left(\frac{a + m_t}{k_0/a}\right) + \left(\frac{e(y_0)}{r_e}\right) * \sum_{e'} (i_f - t_i) + (m_t + f_r/y_n) \tag{2}$$

The above equation (2) computed energy utilization for the number of devices in sustainable and smart buildings that deploy the energy necessary and move forward. Here, energy utilization is denoted as $u_0$, this allocation of energy is performed for the varying devices associated with the energy management system. The energy is balanced for the varying devices that utilize the energy requirement, and it is denoted as $\left(\frac{e' + m_t}{k_0/a'}\right)$. The energy is recycled to ensure energy efficiency in the smart city, and it is referred to as $r_e$, that deploys the utilization of energy.

In this energy, utilization is used to evaluate the efficiency of the appliances, and it is represented as $(m_t + f_r/y_n)$. Therefore, this prediction-based energy distribution helps solve several issues by creating a model to estimate energy usage in the cloud using AI services. The algorithm of the prediction model is proposed to use one of three methods: Support Vector Machine, Artificial Neural Network, or k-Nearest Neighbour, which helps to obtain data in the model training and testing processes as shown in the Equation.3

$$\mu = m(t_i) + \left(\frac{\sum_{e'} f_r}{r_e}\right) * \left(\frac{i_f/e(y_n)}{\beta}\right) + (v - p_s) * \prod_{u_0} m(m_t) + f_r \tag{3}$$

The prediction is made by equating the above equation (3); energy is forwarded to the smart building's required devices and improves the monitoring system. Here, the mapping is performed with the previous state, the identification is made for the varying devices, and it is represented as $\left(\frac{i_f/e'(y_n)}{\beta}\right)$.

The monitoring of energy is associated with the energy requirement in the devices and performs the prediction. The following equation detects the energy requirement and waste to enhance the monitoring system's efficiency.

$$\varnothing = \left.\begin{array}{l} \left(\frac{m_t}{y_0}\right) * \prod_{m'} e(a - m_t) + (\beta * k_0), \ \forall \ Requirement \\ \sum_{y_n}^{m_t} (e - f_r) + \left(\frac{v' * a'}{e'/r_e}\right) - t_i - (f_r + g_s), \ \forall \ Wastage \end{array}\right\} \tag{4}$$

In the above equation (4), energy detection is performed and classifies the requirement and wastage here; the energy is forwarded to the required devices and consumed reliably. Here, the first derivation is associated with the energy required for the devices. It is done by performing the prediction, and it is represented as $(a' - m_t) + (\beta * k_0)$.

In this process, the first derivation is associated with the requirement, which forwards the energy if there is any necessary energy, whereas the second derivation defines energy wastage. Here, the prediction is performed to detect the state of the devices, and it is represented as $\left(\frac{v' * a'}{e'/r_e}\right) - t_i - (f_r + g_s)$. Thus, the detection is performed $\varnothing$ to analyze the requirement and wastage.

### *Prediction of energy*

The energy prediction is made for the varying devices with the drain or energy requirement in the sustainable and smart building; the AIMS-SB method is proposed to address this issue. The following equation is used to monitor the energy requirement and waste by prediction methods and saves energy from waste.

$$m' = \prod_{a'} (i_f * e') + \left(\frac{m_t}{y_n/i_f}\right) - g_s(m_t) - \left(v' * \frac{d_s}{\beta}\right) + argmax[\partial + (e' - m_t)] \tag{5}$$

The above equation (5) monitors every state of appliances' energy requirement and usage in sustainable and smart buildings. Here, periodic monitoring is done that deploys the energy drain for the number of devices, and it is represented as $(i_f * e') + \left(\frac{m_t}{y_n/i_f}\right)$. The prediction is performed from the previous state of energy processing and utilizes the sustainable and smart buildings' energy in smart cities.

The classification instances for the varying appliances show a higher accuracy range that is low to high. The classification instances increase for the appliances that deploy from 20 to 80. Here, the appliances for 80 show higher classification instances compare to 20 appliances in the sustainable and smart buildings. In this processing, the AIMS-SB method

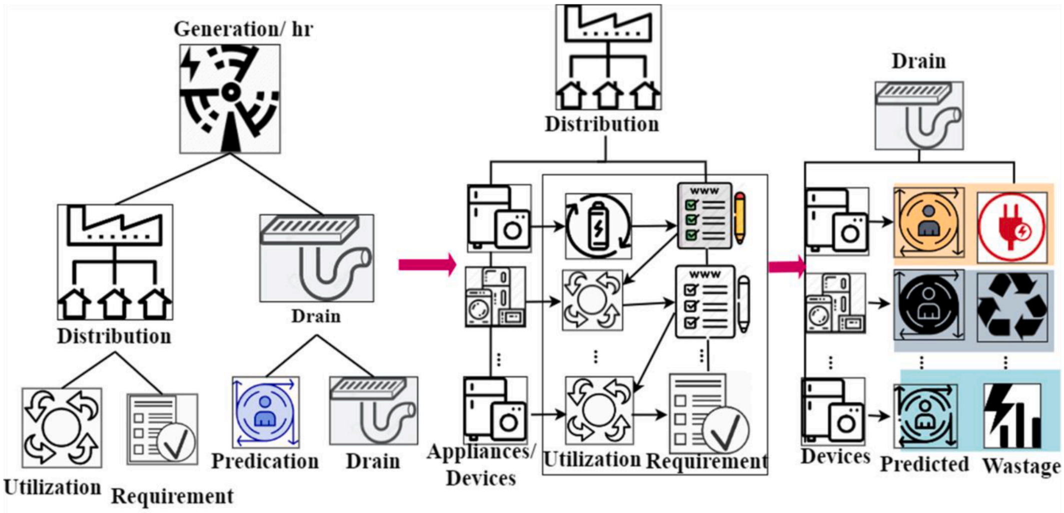


**Fig. 2.** Decision Tree for Energy Requirement and Wastage.

performs along with the decision tree. It is further discussed in the below sections as follows.

*Decision tree*

The decision tree is used to classify the energy requirement and wastage and forward the necessary energy to the prediction method's devices. The root node is the energy management, and the leaf node indicates the requirement and wastage of energy; based on this, the energy is forwarded promptly. Fig. 2 illustrates the decision tree for energy requirement and wastage classification.

If any leaf node satisfies the condition, energy forward to the drain or necessary device falls under the distribution process. The following equation (6) generates the classification method to evaluate the decision tree approach.

$$h_x = \begin{cases} \sum_{k_0}^{\mu}(e'*u_0) + \left(\frac{v'*\varnothing}{y_n}\right)*m' + (d_s*e') \\ = \left(\frac{e' + m_t/\varnothing}{i_f}\right)*\prod_{f_r}(e' + \mu) - g_s \end{cases} \tag{6}$$

The classification is done to identify the requirement and wastage of energy associated with energy utilization by performing prediction. The classification is done by deploying the prediction method and evaluating the requirement and wastage of energy associated with the energy utilization method. The classification that indicates the distribution of energy, to the necessary devices. In this approach, the detection is performed for energy usage, and wastage provides the necessity promptly and monitors the accuracy level.

In decision tree the requirement and wastage define the leaf node related to the balancing factor, and the energy is acquired from the

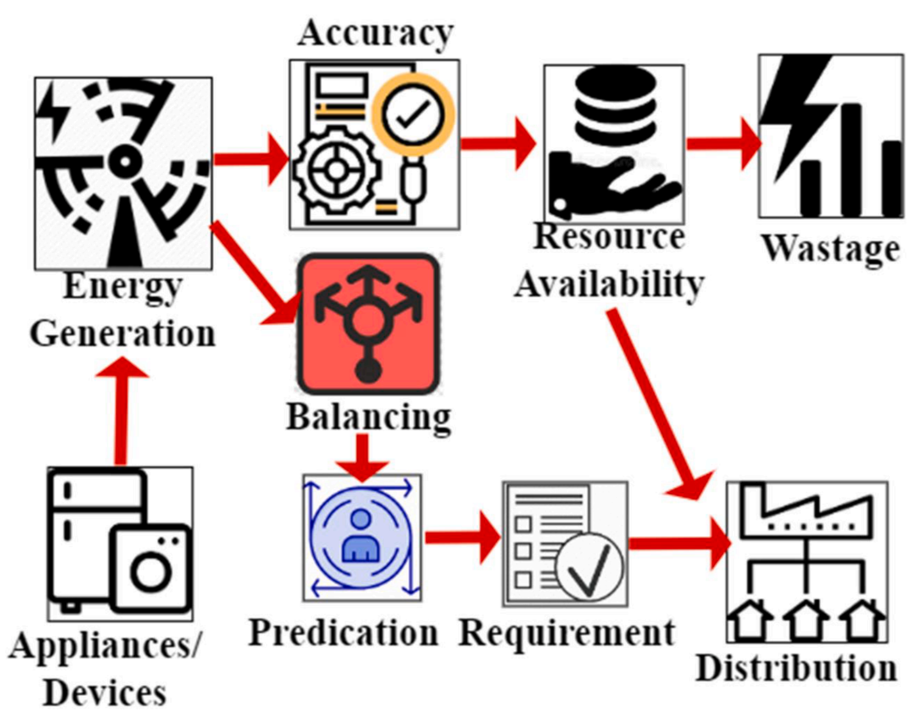


**Fig. 3.** Energy Distribution—Post Classification.

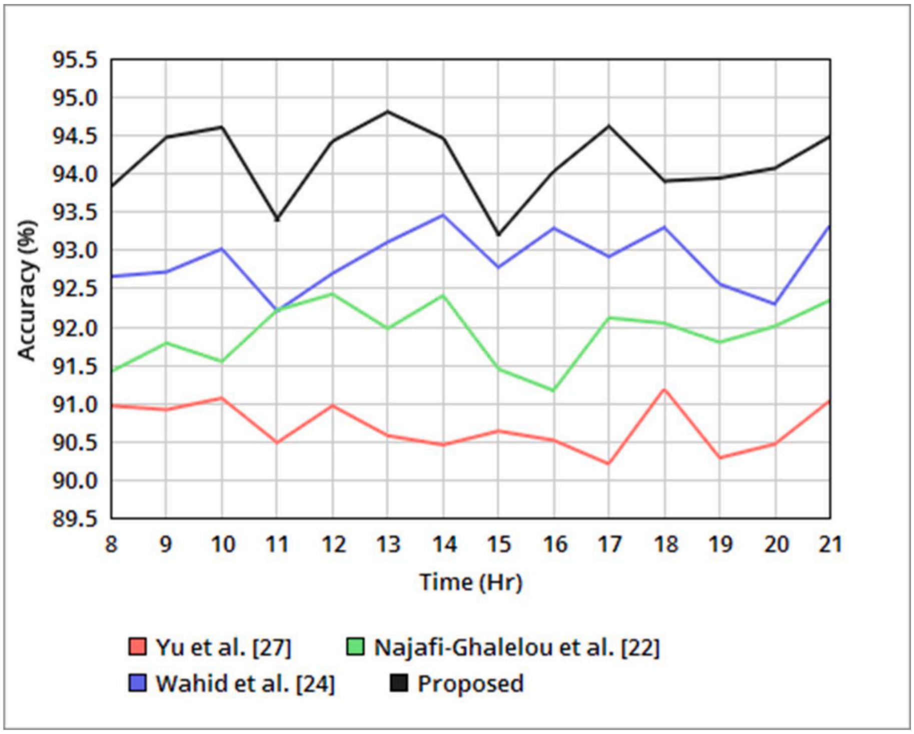


**Fig. 4.** Accuracy Comparison with Existing Methods.

renewable energy source from the smart city. Here, the energy is forwarded to the required devices for this periodic identification is performed, and it is denoted as $\left(\frac{e'+m_t/\varnothing}{i_f}\right)$. This classification is done on AI's sustainable and smart buildings and provides efficient energy transmission. The following equation is used to evaluate the energy drain and avoid wastage for this energy recycling to address this issue.

$$i_f = \prod_{m'}^{e'} (v' - g_s) * \left(\frac{d_s + m_t}{k_0}\right) + \sum (u_0 - h_x) * (f_r + e'/r_e) \tag{7}$$

The identification of energy is made by evaluating the prediction method that maps the pursuing and previous state and forwards the energy to the necessary devices. It recycles the energy and forwards it to the devices, and it is represented as $(u_0 - h_x)*(f_r + e'/r_e)$. Thus, identifying the energy drain is monitored on time and addresses this issue by equating the above equation (7). The following division is formulated as energy distribution to the necessary devices related to the decision tree method.

*Energy distribution*

The energy is distributed to the necessary devices that utilize the energy from renewable energy sources by performing the prediction method. In this processing, the distribution is done by evaluating the decision tree; whether the device is necessary for the energy or not, the forwarding is carried out by deploying this in equation (8). A decision tree is introduced as part of the AI-deployed approach to improving energy efficiency based on utilization. The primary goals of this endeavor are to reduce energy waste and enhance energy efficiency and precision

$$d_s(e') = (m_t + y_0) - m' * \left(\frac{v'/a'}{f_r}\right) + \prod_{\varnothing} i_f * h_x - (m_t - g_s) m' - t_i \tag{8}$$

The energy distribution is evaluated by verifying whether the energy is required for the monitoring system; for this processing, prediction is performed. This approach evaluates energy-saving distribution, improves efficiency reliably, and addresses the energy drain and wastage. This energy distribution method addresses the energy drain and wastage; forwarding is performed by verifying the device's state. The energy distribution process post-classification is illustrated in Fig. 3.

Verification is performed for every state of devices in the sustainable and smart building to analyze the devices' state and promptly provide the energy. It is associated with a timely manner that is denoted as $h_x - (m_t - g_s)m' - t_i$. Thus, the energy distribution is evaluated in the above equation; then, energy management is computed below.

*Energy management*

The energy is provided to the sustainable and smart building for the monitoring system. This decision is made whether the energy is required for this processing or not. Based on this approach, the energy is forwarded to the required devices, and this prediction method's efficiency and accuracy level are evaluated. The largest end-use users of electricity are buildings and other structures. To maximize the effectiveness of available resources, energy consumption must be minimized based on the decision tree approach. Here, state-of-the-art cutting-edge methods and products help to reduce energy consumption in smart homes and buildings based on the appliance usage. Energy management is carried out for the necessary devices' distribution process, and here allocation is performed periodically.

Power is sent to the sensors and actuators of a smart building, enhancing its monitoring capabilities need to be linked based on accuracy, utilization, and efficiency. When the right amount of power is sent to the right appliances, energy waste is reduced, and precision is enhanced, which helps predict the system's energy distribution. It is estimated that the range for the drain identification method uses AI to validate the energy wastage and performance factor.

## Results and discussions

The performance of the proposed method is analyzed experimental setup with the following parameters. A building with 80 smart

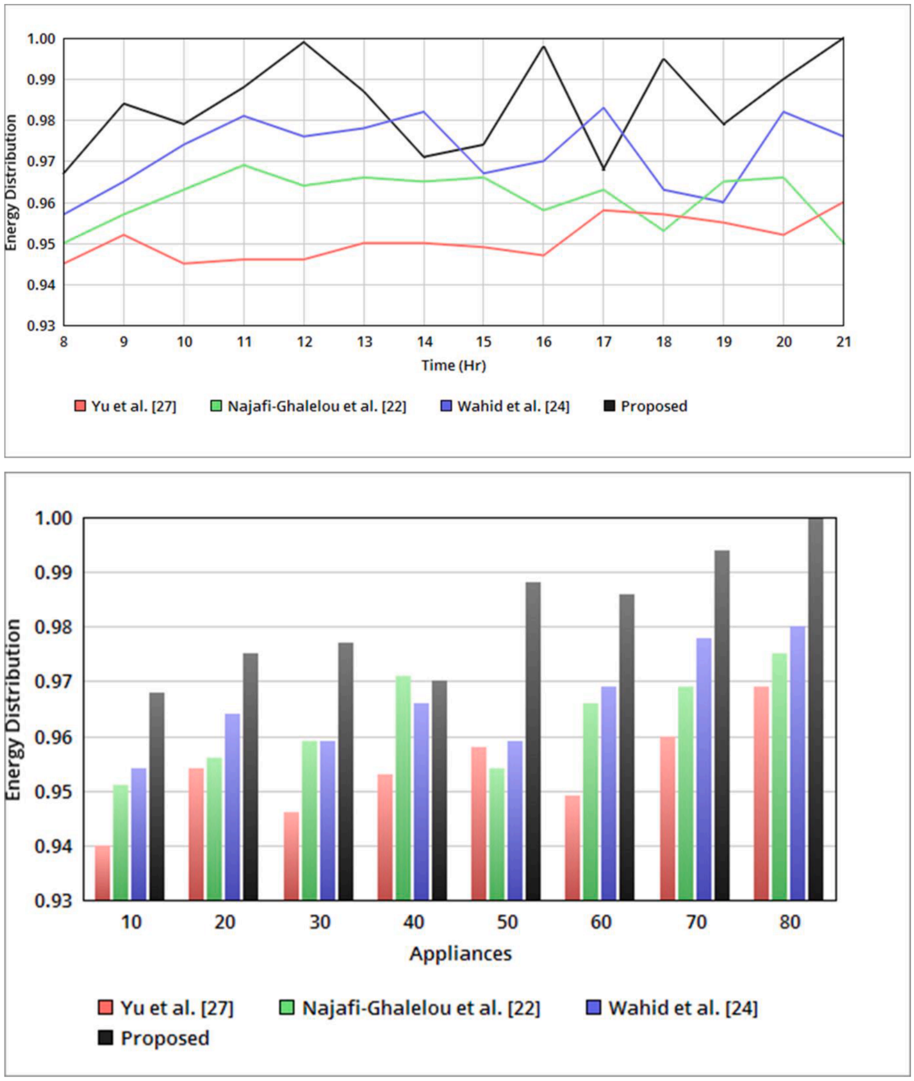


**Fig. 5.** Energy Distribution Comparisons with Existing Methods.

appliances controlled using two smart meters is considered for 13 h (8–21 h). In this process, the output of a 6*3KW renewable energy resource is utilized for energy generation. The utilization varies from 4 to 14KWH based on the operating appliances. The performance is verified using metrics accuracy, efficiency, energy distribution, utilization, and drain identification. Predictive and adaptive structures of appliance types with correspondingly wide ranges of energy needs are validated based on the forecast and actual practice. The utilization factor for the variable appliances' energy needs will rise if the forecast is enhanced based on energy requirement, distribution, and balance for different prediction factors.

For a comparative analysis, the methods proposed by Yu et al. [26], Najafi-Ghalelou et al. [22], and Wahid et al. [24] are considered.

*Accuracy*

The accuracy of the proposed work increased for the varying time calculated for hours and the number of devices. In this energy management, distribution and generation are used to forward the energy to the necessity, and it is analyzed by equating $\left[(g_s + f_r) + (y_0 * m_t)\right] + t_i$. By achieving this accuracy, the level is enhanced by identifying the energy utilization, denoted as $\left(\frac{e' + m_t}{k_0/a'}\right) + \left(\frac{e'(y_0)}{r_e}\right)$. Thus, the proposed work's accuracy level increased for varying times and showed a reliable energy distribution (Fig. 4).

*Energy distribution*

In Fig. 5, the energy distribution increases for varying times and appliances. It is done from renewable sources and forwarded to the required devices. The prediction is used to identify the device state of the energy distribution drain termed as $(v' - g_s) * \left(\frac{d_s + m_t}{k_0}\right)$. By performing this energy distribution, the wastage and energy requirements are evaluated promptly. Here, the identification is performed to define the appliance's state of monitoring in the system.

*Energy utilization*

The energy utilization for time and appliances shows a higher range than the other three methods. Here, the utilization is related to the distribution process that is done from the energy management. The previous state of processing is acquired and maps with the pursuing state and provides the resultant promptly, and it is represented as $(m_t + y_0) - m' * \left(\frac{v'/a'}{f_r}\right)$. The allocation of energy is derived to utilize the energy for the varying appliances, and it is denoted as $(f_r + m_t/\emptyset) - (r_e + k_0)$. Thus, the energy utilization for the proposed work shows a higher range of distribution and energy management (Fig. 6).

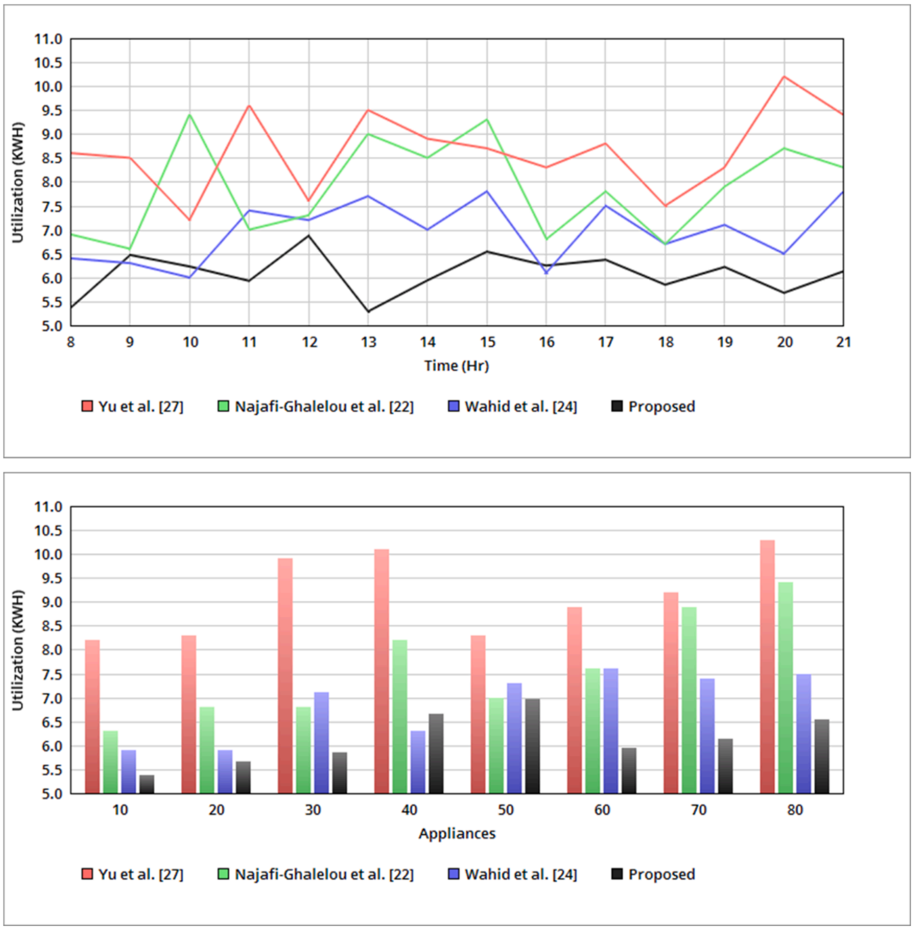


**Fig. 6.** Energy Utilization Comparisons with Existing Methods.

**Table 1**
Comparative analysis of time.

| Metrics | Yu et al. [26] | Najafi-Ghalelou et al. [22] | Wahid et al. [24] | Proposed |
|---|---|---|---|---|
| Accuracy (%) | 91.03 | 92.34 | 93.32 | 94.48 |
| Energy Distribution | 0.96 | 0.95 | 0.976 | 1 |
| Utilization (KWH) | 9.4 | 8.3 | 7.8 | 6.13 |

**Table 2**
Comparative analysis for appliances.

| Metrics | Yu et al. [26] | Najafi-Ghalelou et al. [22] | Wahid et al. [24] | Proposed |
|---|---|---|---|---|
| Efficiency | 0.936 | 0.944 | 0.958 | 0.965 |
| Energy Distribution | 0.969 | 0.975 | 0.98 | 1 |
| Utilization (KWH) | 10.3 | 9.4 | 7.5 | 6.55 |
| Drain Identification | 0.25 | 0.32 | 0.39 | 0.419 |

**Table 3**
Description.

| Parameter | Description |
|---|---|
| $\beta$ | Smart building analysis |
| $y_0$ | The appliance/device |
| $y_n$ | Number of devices |
| $i_f$ | Identification |
| $m_t$ | Energy requirement |
| $g_s$ | Energy Wastage |
| $e'$ | Energy |
| $f_r$ | Forwarding of energy |
| $a'$ | Drain |
| $t_i$ | Time |
| $m'$ | Wastage accuracy and monitoring |
| $u_0$ | Energy utilization |
| $k_0$ | Energy allocation |
| $r_e$ | Energy efficiency |
| $v'$ | Previous state |
| $\mu$ | Energy prediction |
| $d_s$ | Distribution of energy |
| $h_x$ | Classification |

The comparative analysis summary is tabulated in Tables 1 and 2 for time and appliances. AIMS-SB helps to foster a holistic approach to control and provide adaptive operational optimization, building energy management systems for an integrated building automation and energy management system. To gather data, analyze it, diagnose it, detect trends, and make decisions based on that data, the system may have numerous layers, from individual sensors and actuators to users' interfaces based on energy distribution and utilization. Building Energy Management Systems dynamically regulate the interior environment at low cost, ensuring the accuracy, efficiency, and welfare of building occupants by connecting buildings, systems, and people through service-oriented abstractions with drain identification (Table 3).

The above table shows that the proposed method improves accuracy by 6.75%, energy distribution by 11.4%, and reduces utilization by 7.11%.

The proposed method achieves 5.7% high efficiency, 7.6% high distribution, 7.55% less utilization, and 9.9% high drain identification.

Tables 1 and 2 show that energy usage is tracked and transferred to more efficient machines and compared based on time and appliance usage. In this case, the expected time for energy forwarding is predicted based on the forwarding of energy and drain identification. Hence the correlation is based on the energy usage tracked and transferred based on time and appliance usage using the prediction model.

## Conclusions

This paper introduced an artificial intelligence technique for monitoring systems in smart buildings. The proposed method aims to improve energy distribution efficiency for the monitoring systems by achieving fair utilization. Smart energy management relies on renewable sources for optimal allocation and device operations. In this process, the available energy is distributed for the appliances in order. Later, the required energy for seamless device operation is predicted based on the renewable energy source. This prediction helps to improve the energy distribution and accuracy of the devices. In this process, decision tree classifiers distribute and balance energy depending on the requirement and availability. The prediction-based energy distribution helps to improve drain identification, preventing device failures. This further augments the efficiency of operating devices and energy utilization. The performance verification shows that the proposed method improves accuracy, efficiency, distribution, and energy drain by optimizing utilization. Smart grids may facilitate the widespread use of real-time demand response in the future, and smart building technology is paving the way for this change.

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## CRediT authorship contribution statement

**Rajalakshmi Selvaraj:** Conceptualization, Supervision. **Venu Madhav Kuthadi:** Methodology, Investigation. **S. Baskar:** Writing – review & editing.

## Declaration of Competing Interest

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

## Data availability

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

## References

[1] Kamienski CA, Borelli FF, Biondi GO, Pinheiro I, Zyrianoff ID, Jentsch M. Context design and tracking for IoT-based energy management in smart cities. IEEE Internet Things J 2018;5(2):687–95. https://doi.org/10.1109/jiot.2017.2748037.

[2] Jegadeesan S, Azees M, Kumar PM, Manogaran G, Chilamkurti N, Varatharajan R, Hsu C-H. An efficient anonymous mutual authentication technique for providing secure communication in mobile cloud computing for smart city applications. Sustain Cities Soc 2019;49(101522):101522. https://doi.org/10.1016/j.scs.2019.101522.

[3] Golpîra H, Bahramara S. Internet-of-things-based optimal smart city energy management considering shiftable loads and energy storage. J Clean Prod 2020; 264(121620):121620. https://doi.org/10.1016/j.jclepro.2020.121620.

[4] Kumar N, Vasilakos AV, Rodrigues JJPC. A multi-tenant cloud-based DC nano grid for self-sustained smart buildings in smart cities. IEEE Commun Mag 2017;55(3): 14–21. https://doi.org/10.1109/mcom.2017.1600228cm.

[5] Hayashi, Yasuhiro, Yu Fujimoto, Hideo Ishii, Yuji Takenobu, Hiroshi Kikusato, Shinya Yoshizawa, Yoshiharu Amano, et al. 2018. Versatile modeling platform for cooperative energy management systems in smart cities. Proc IEEE. Instit Electr Electr Eng 106 (4): 594–612. 10.1109/jproc.2018.2809468.

[6] Abdel-Basset M, Manogaran G, Mohamed M, Rushdy E. Internet of things in smart education environment: supportive framework in the decision-making process. Concurrency Comput: Practice Exp 2019;31(10):e4515.

[7] Ullah I, Baharom MNR, Ahmad H, Fazli Wahid HM, Luqman ZZ, Das B. Smart lightning detection system for smart-city infrastructure using artificial neural network. Wirel Pers Commun 2019;106(4):1743–66. https://doi.org/10.1007/s11277-018-5383-4.

[8] Huang J, Xing C-C, Shin SY, Hou F, Hsu C-H. Optimizing M2M communications and quality of services in the IoT for sustainable smart cities. IEEE Trans Sustainable Comput 2018;3(1):4–15. https://doi.org/10.1109/tsusc.2017.2702589.

[9] Rodriguez-Mier P, Mucientes M, Bugarín A. Feature selection and evolutionary rule learning for big data in smart building energy management. Cogn Comput 2019;11 (3):418–33. https://doi.org/10.1007/s12559-019-09630-6.

[10] Xu X, Li D, Sun M, Yang S, Shujiang Yu, Manogaran G, et al. Research on key technologies of smart campus teaching platform based on 5G network. IEEE Access: Practical Innov, Open Solutions 2019;7:20664–75. https://doi.org/10.1109/access.2019.2894129.

[11] Kadry S, Ghazal B. Design and assessment of using smartphone application in the classroom to improve students' learning. Int J Eng Pedagogy (IJEP) 2019;9(2):17. https://doi.org/10.3991/ijep.v9i2.9764.

[12] Gomathi P, Baskar S, Mohamed Shakeel P. Concurrent service access and management framework for user-centric future internet of things in smart cities. Complex Intellig Syst 2021;7(4):1723–32. https://doi.org/10.1007/s40747-020-00160-5.

[13] Jonban MS, Romeral L, Akbarimajd A, Ali Z, Ghazimirsaeid SS, Marzband M, et al. Autonomous energy management system with self-healing capabilities for green buildings (Microgrids). J Build Eng 2021;34(101604):101604. https://doi.org/10.1016/j.jobe.2020.101604.

[14] Yan B, Hao F, Meng Xi. When artificial intelligence meets building energy efficiency, a review focusing on zero energy building. Artif Intell Rev 2021;54(3): 2193–220. https://doi.org/10.1007/s10462-020-09902-w.

[15] Abdel-Basset M, Manogaran G, Mohamed M. RETRACTED: Internet of Things (IoT) and its impact on supply chain: a framework for building smart, secure and efficient systems. Future Gener Comp Syst: FGCS 2018;86:614–28. https://doi.org/10.1016/j.future.2018.04.051.

[16] Buddhahai B, Wongseree W, Rakkwamsuk P. An energy prediction approach for a nonintrusive load monitoring in home appliances. IEEE Trans Consum Electron 2020;66(1):96–105. https://doi.org/10.1109/tce.2019.2956638.

[17] Zhou, Suyang, Zijian Hu, Wei Gu, Meng Jiang, and Xiao-Ping Zhang, Artificial intelligence based smart energy community management: a reinforcement learning approach. CSEE J Power Energy Syst. 10.17775/cseejpes.2018.00840.

[18] Yu L, Xie W, Xie D, Zou Y, Zhang D, Sun Z, et al. Deep reinforcement learning for smart home energy management. IEEE Internet Things J 2020;7(4):2751–62. https://doi.org/10.1109/jiot.2019.2957289.

[19] Rostirolla G, da Rosa R, Righi JL, Barbosa V, Andre da Costa C. ElCity: an elastic multilevel energy saving model for smart cities. IEEE Trans Sustainable Comput 2018;3(1):30–43. https://doi.org/10.1109/tsusc.2017.2749880.

[20] Golpîra H, Khan SAR. A multi-objective risk-based robust optimization approach to energy management in smart residential buildings under combined demand and supply uncertainty. Energy (Oxford, England) 2019;170:1113–29. https://doi.org/10.1016/j.energy.2018.12.185.

[21] Lu Q, Zhang Z, Lü S. Home energy management in smart households: optimal appliance scheduling model with photovoltaic energy storage system. Energy Rep 2020;6:2450–62. https://doi.org/10.1016/j.egyr.2020.09.001.

[22] Najafi-Ghalelou A, Zare K, Nojavan S. Optimal scheduling of multi-smart buildings energy consumption considering power exchange capability. Sustain Cities Soc 2018;41:73–85. https://doi.org/10.1016/j.scs.2018.05.029.

[23] Nebel-Wenner M, Reinhold C, Wille F, Nieße A, Sonnenschein M. Distributed multi-objective scheduling of power consumption for smart buildings. Energy Inf 2019;2 (S1). https://doi.org/10.1186/s42162-019-0080-4.

[24] Wahid F, Ghazali R, Ismail LH. Improved firefly algorithm based on genetic algorithm operators for energy efficiency in smart buildings. Arab J Sci Eng 2019; 44(4):4027–47. https://doi.org/10.1007/s13369-019-03759-0.

[25] Bourhnane, Safae, Mohamed Riduan Abid, Rachid Lghoul, Khalid Zine-Dine, Najib Elkamoun, Driss Benhaddou. 2020. Machine learning for energy consumption prediction and scheduling in smart buildings. SN Appl Sci 2 (2). 10.1007/s42452-020-2024-9.

[26] Zhang SU, Wang J, Liu H, Tong J, Sun Z. Prediction of energy photovoltaic power generation based on artificial intelligence algorithm. Neural Comput Appl 2021;33 (3):821–35. https://doi.org/10.1007/s00521-020-05249-z.