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Fuzzy logic-supported building design for low-energy consumption in urban environments

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HIGHLIGHTS

- Fuzzy logic experts manage uncertainty to improve the accuracy of findings.
- Foster collaboration for sustainable building design and urban planning.
- A longer prediction horizon enhances the accuracy and efficiency of forecasts.
- Design and build thoughtfully to enhance the quality of life in urban areas.

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ABSTRACT

Climate, building materials, occupancy patterns, and HVAC (heating, ventilation, and air conditioning) systems all interact in complex ways, making it difficult to design low-energy buildings. Thus, innovative architectural and engineering design strategies are required to meet the worldwide need to decrease building energy usage. To improve the calculation of energy consumption of buildings, this work introduces the FCR-BCS (fuzzy clustering rule-based building control systems), which integrates fuzzy logic concepts into computational simulations. FCR-BCS can contemplate real-world uncertainties and fluctuations using linguistic factors and approximate reasoning for more precise and trustworthy results in energy-efficient building design. This method's significance rests in its potential to significantly reduce energy use, advance sustainability, and improve urban residents' quality of life; architects and engineers can thus employ

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FCR-BCS to enhance the efficiency of HVAC systems and insulation. The outcomes of FCR-BCS simulation assessments show that it is capable of making buildings more energy efficient. The experimental outcomes demonstrate that the suggested model increases the sensitivity analysis by 99.4 %, energy efficiency analysis by 99.8 %, occupancy patterns analysis by 97.5 %, temperature profile analysis by 98.8 %, and energy consumption analysis by 99.6 % compared to other existing models.

Nomenclature

1D CNNs	One-Dimensional Convolutional Neural Networks
ANN	Artificial neural network
BMS	Building management system
BM-BWO	Boosted mutation-based black widow optimization
CO_2	Carbon dioxide
EH-WSNs	Energy-harvesting-based wireless sensor networks
EMS	Energy management system
F-EFPA	Fuzzy-enhanced flower pollination algorithm
F-GWOA	Fuzzy extended grey wolf optimization algorithm
FCR-BCS	Fuzzy clustering rule-based building control systems
FECS	Fuzzy-enhanced computational simulation
HESS	Hybrid energy storage system
HVAC	Heating, ventilation, and air conditioning
kW	Kilowatt
LED	Light emitting diode
LSTM	Long Short-Term Memory
MLP	Multilayer Perceptron
MWCNT	Multi wall carbon nano tube
PSO	Particle swarm optimization
RES	Renewable energy system
SDGs	Sustainable Development Goals
SRC	Steam Rankine cycle
T-AE-ESCA	Trust-aware energy-efficient stable clustering algorithm
WSN	Wireless sensor network

1. Introduction

Environmental preservation, efficient resource exploitation, and use of non-carbon energy sources are the key principles of sustainable development goals aiming to achieve net-zero and decarbonization strategies and seek to mitigate climate change [1–4]. Therefore, it should come as no surprise that environmental and energy policies revolve around improving the energy efficiency of the systems, since it has the potential to make a substantial contribution to sustainability [5,6], it is vital to conduct research that establishes a connection between these structures and the SDGs [7,8]. Given growing emissions and limited resources, the future sustainability of the environment and the significant potential of energy-efficient practices and renewable energy to reduce CO_2 emissions are critical issues, and these issues have been observed since the COVID-19 pandemic [9–11]. Green design or sustainable architecture sometimes referred to as green building, seeks to produce constructions that benefit the surroundings and people [12]. Using fuzzy-enhanced computational simulation (FECS), which efficiently manages uncertainty-developing buildings with minimal energy footprint has enormous potential [13,14]. Simplifying the modeling process, improving the interpretability of models, and increasing general acceptability inside the architectural and engineering community all depend on ongoing research [15]. Thus, low-energy building development has benefited much from the emergence of computational modeling techniques enhanced with fuzzy logic [16,17].

The FECS has shown promise in the domain of low-energy building design although it does suffer from a few challenges [18]. The occupant behavior, local weather, and equipment performance uncertainties, fuzzy logic excels in building energy calculations that rely on imprecise and unpredictable data are a few of the challenges [19]. Also, the real-time or near-real-time outcomes can be challenging when these fuzzy logic-based models are integrated into computational simulations due to increasing processing costs [20]. Calibration and validation of fuzzy-enhanced models can also present certain difficulties [21]. Many dynamic factors involved in these models, such as parameters, membership functions, and rule sets, must be fine-tuned to reflect actual building behavior [22]. Validating and collecting the massive amounts of data needed to keep these models precise [23]. Additionally, it may be difficult for non-experts to understand and trust the conclusions produced by complicated systems based on fuzzy logic. This leads to apprehension in the stakeholders owing to low interpretability [24]. Furthermore, the necessity for specialized expertise and software tools may cause opposition in the building design industry to use FECSs [25]. Some designers may be hesitant to adopt these methods in favor of simulations, preferring to stick to more conventional methods [26]. In addition, heating, ventilation, and air conditioning (HVAC) systems can be optimized using fuzzy logic controllers by considering variables such as occupancy, exterior temperature, and personal preferences for comfort [27]. These controllers can help to reduce costs by making real-time adjustments to HVAC settings. The difficulty, however, lies in creating reliable fuzzy rules and membership functions that do justice to the intricate interdependencies between variables [28]. Fuzzy-based predictive models employ past data to make predictions about building energy consumption in the future. The integration of fuzzy logic into energy simulation software for buildings has been shown to improve the precision of these programs [29,30]. User preferences, temperature comfort, and occupancy patterns are some of the fuzzy inputs that models consider [31]. By considering the building's materials, insulation, and design elements, fuzzy-based optimization techniques are used to create energy-efficient building envelopes [32,33].

In the energy field, several machine learning techniques and algorithms such as the grasshopper optimization algorithm [34,35], response surface optimization [36,37], multi-objective grey wolf optimization [38,39], multi-objective particle swarm optimizer [40,41], and others [42,43] have been being used for optimization and prediction purposes. Fuzzy logic has been instrumental in the evolution of several approaches and algorithms [44]. Most suited to enable load balancing, fault tolerance, and reliable communication, the fuzzy-enhanced flower pollination algorithm (F-EFPA) was developed by Mittal et al. [45]. It showed improved energy efficiency, stability, and durable performance than other clustering algorithms, as shown by both analytical and simulated data. To aid in load balancing, fault tolerance, and reliable communication, Mittal et al. [46] Introduced the fuzzy extended grey wolf optimization algorithm (F-GWOA) to enhance the performance parameters of wireless sensor networks (WSNs). The fuzzy logic system chooses the most relevant and optimal cluster heads using boosted mutation-based black widow optimization (BM-BWO) [47]. Also, the trust-aware energy-efficient stable clustering algorithm (T-AE-ESCA) was developed by Mittal. et al. [48] to extend the performance parameters of WSN. Hanet al. [49] suggested an adaptive hierarchical-clustering-based routing protocol for energy-harvesting-based wireless sensor networks (EH-WSNs) to ensure continuous coverage of the designated area. While energy-harvesting technology can extend the lifetime of WSNs, an energy-efficient routing protocol is still required for EH-WSNs due to the unavailability of nodes during the energy-harvesting phase. In general, the modeling or optimization algorithms may accomplish targets continuously by utilizing data-harvesting technology. It does help in maintaining performance for an extended period than the conventional routing protocol and with a higher probability of success in prediction and optimization [50,51]. Afzal et al. [52] and Chandran et al. [53] suggested multilayer perceptron neural network-assisted models for the prediction of building energy consumption. The hyper-parameters of the multilayer perceptron model were fine-tuned and optimized by combining them with eight meta-heuristic algorithms using the hybridization approach. Each hybrid model's performance is examined using statistical analysis. The findings show that the chosen optimizers are generally good at producing correct results. Ali et al. [54] and Arun et al. [55] proposed the data-driven machine learning approach for urban building energy performance prediction and retrofit analysis. Urban building energy performance analysis is the last phase in the five-step process that begins with data collecting and continues with archetype creation, parametric modeling based on physics, modeling using machine learning, and finally, analysis of the results. The proposed technique is piloted on the residential building stock in Ireland and using parametric modeling of 19 selected critical factors for four residential building archetypes, it produces a synthetic building dataset of one million structures. Furthermore, using an ensemble-based machine learning methodology improves the model's performance, increasing its accuracy to 91 % from 76 % using the conventional approach. Artificial Neural Networks (ANNs) are also useful techniques for optimization and prediction processes, they can be applied in several sectors such as energy, fuels, industrial manufacturing, health, education, society, and others [56–62]. Indeed, research on the major performance features of solar chimney power plants was proposed by Cuce et al. [63] and Arun et al. [64] using ANNs and computational fluid dynamics. Changing the collector radius and chimney height while keeping certain inclination degrees affects the performance of the system. For example, the inclined design can surpass the power output in the reference scenario by means of a collector radius of 73.2 m and a chimney height of 155.68 m, therefore attaining over 49.233 kW. While it does not completely vanish, the effect of a taller chimney on power output reduces at a certain point. The study shows that a more notable rise in power generation emerges from altering the chimney height and collector radius. To power electric motorcycles, Zahedi et al. [65] and Qayyum et al. [66] suggested a hybrid system. A battery life model is crucial to estimate the frequency of replacements over a decade. Ultracapacitors integrated into the hybrid energy storage systems (HESS) improve power specs by boosting acceleration and regenerative braking capabilities. Over a decade, this lowered system costs due to fewer replacements needed and longer battery life due to reduced battery current. Despite having an initial cost of $833 more than traditional energy storage systems, the research found that HESS setups with the optimum size provide better power specs and a 10-year comparable cost of $3466 cheaper.

Assessing and contrasting objective and subjective thermal comfort in a Malaysian green office building was suggested by Lakhiar et al. [67] and Zhao et al. [68]. The predicted mean vote and other well-established thermal comfort models were used in this research to assess the interior environment alongside occupant surveys. While the objective data aligned with thermal comfort requirements, subjective thermal sensation votes indicated it was colder than anticipated. Inside, it was noticeably chillier than everyone had expected. This research highlights the limitations of traditional thermal comfort models, particularly in tropical environments. The findings suggest prioritizing occupant-centered design for environmentally friendly structures in tropical regions. To enhance the effectiveness of pressure vapor phase soldering ovens, Havellant et al. [69] and Hezam et al. [70] used temperature-based process monitoring. For vapor phase soldering ovens, a gauge-type pressure sensor with fused temperature measurement can track variations in vapor pressure. It functions as an Internet of Things-enabled node for data recording and subsequent control. The author detected and minimized the idle time by around 60 s, 15–20 % of the overall soldering cycle time, by fusing the hydrostatic pressure measurements with the temperature information. The oven's yield is increased by 15–20 %, the system's power consumption is reduced by 15–20 %, and the time above the liquidus of the solder is reduced by around 35 % as a result [71]. To optimize mixed convection heat transfer utilizing deep learning with a multilayer perceptron, Dong et al. [72] and Reza et al. [73] introduced the MWCNT-water nanofluid. To train the ANN-Multilayer Perceptron (MLP), a complete dataset was obtained using 48 simulations. Step two included producing an extra 700 data points with exceptional precision using the trained ANN. This approach allowed the authors to efficiently explore the parameter space, aiding in understanding and optimizing the system's behavior. The best possible values for the variables that maximize the Nusselt number were found using the ANN-based method. Predicting and controlling thermal deformation

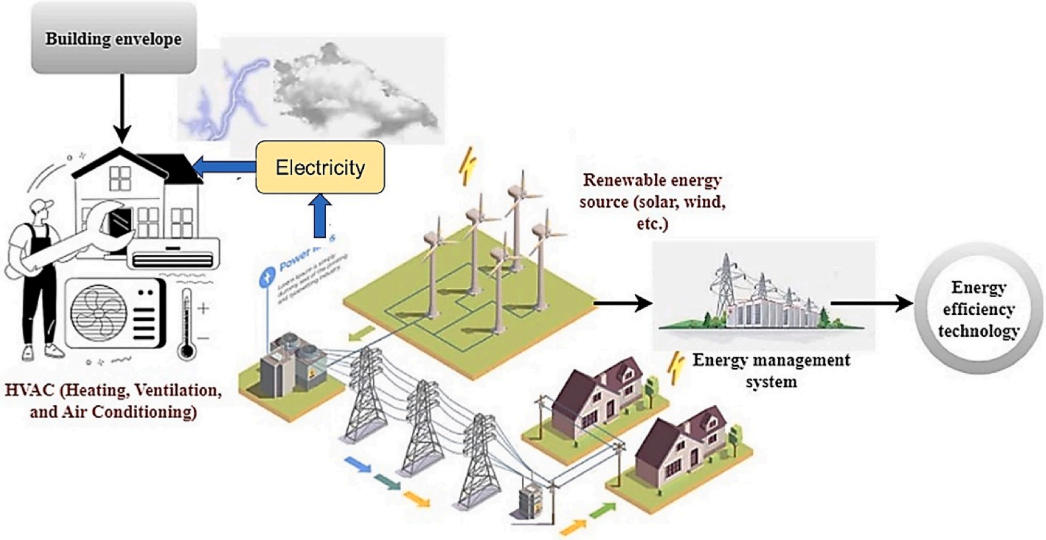


Fig. 1. Schematic representation of energy management system.

in machine tools was proposed by Chu et al. [74] using machine learning and feature analysis. The study found that Gaussian Process Regression provided the best results among the several machine learning models tested for Z-axis deformation prediction. Anomaly detection in temperature sensors was addressed using Long Short-Term Memory (LSTM) networks and One-Dimensional-Convolutional Neural Networks (1D-CNNs) to enhance system resilience and dependability. This method provides an in-depth response to the problem of thermal deformation in machine tools, improving the industry's accuracy and productivity.

FCR-BCS are promising developments for low-energy buildings, excelling in load balancing, error management, and consistent communication maintenance. FCR-BCS has better performance in energy economy, stability, and network longevity than other clustering techniques. Encouragement of sustainability in the built environment is yet another main goal of our work. Reducing urban area environmental effects depends on sustainable building design. The main contribution of the paper is.

- Designing Fuzzy Clustering Rule-Based Building Control Systems (FCR-BCS) to manage the complexity and unpredictability of building energy systems, enhancing energy efficiency.
- Using FCR-BCS and fuzzy logic principles to develop sustainable buildings, reduce waste and pollution, and promote sustainable development in the building and planning sectors.
- Demonstrating that eco-friendly structures enhance urban dwellers' quality of life and the environment. Improved insulation and efficient HVAC systems increase indoor comfort and reduce energy costs.

The rest of the paper is structured as follows: Section 2 details the proposed method, section 3 discusses the experimental outcomes, and Section 4 concludes the research paper.

2. Proposed method

The proposed method uses fuzzy logic within computational simulations to optimize building designs for low-energy consumption. Integrating fuzzy logic allows the method to account for unpredictable factors and human behavior patterns, leading to more accurate and flexible energy-efficient solutions. This enhances sustainability and reduces energy expenditures. Together referred to as the building envelope, Fig. 1 shows the walls, roof, windows, and insulation of the structure. Minimizing heat transmission depends on the building's exterior design and construction, which also helps to preserve a comfortable interior environment. It comprises heating and cooling systems, energy-efficient ducting, heat recovery ventilation systems, and other equipment used to maximize energy consumption.

To cut down on the amount of power that is used in buildings, energy-efficient lighting solutions, such as LED lights and smart lighting controls, are necessary. Offsetting this power used in a home or business using renewable energy sources, such as solar panels or wind turbines, may be an effective way to create clean energy [75,76]. An energy management system (EMS) is a combination of different building systems and sensors to monitor and regulate energy consumption. It adjusts the energy used depending on the number of people in the building, the current weather, and other variables by using the Taguchi approach. These technologies include various characteristics, including energy-saving home appliances, efficient construction materials, and smart thermostats. They have the potential to lessen the building's overall demand for energy [77,78]. Furthermore, to reduce the amount of energy that is used in buildings, it is essential to have effective communication and coordination between all the components used. In addition, data analytics and feedback loops play an important role in the process of continually optimizing energy use in accordance with real-time data

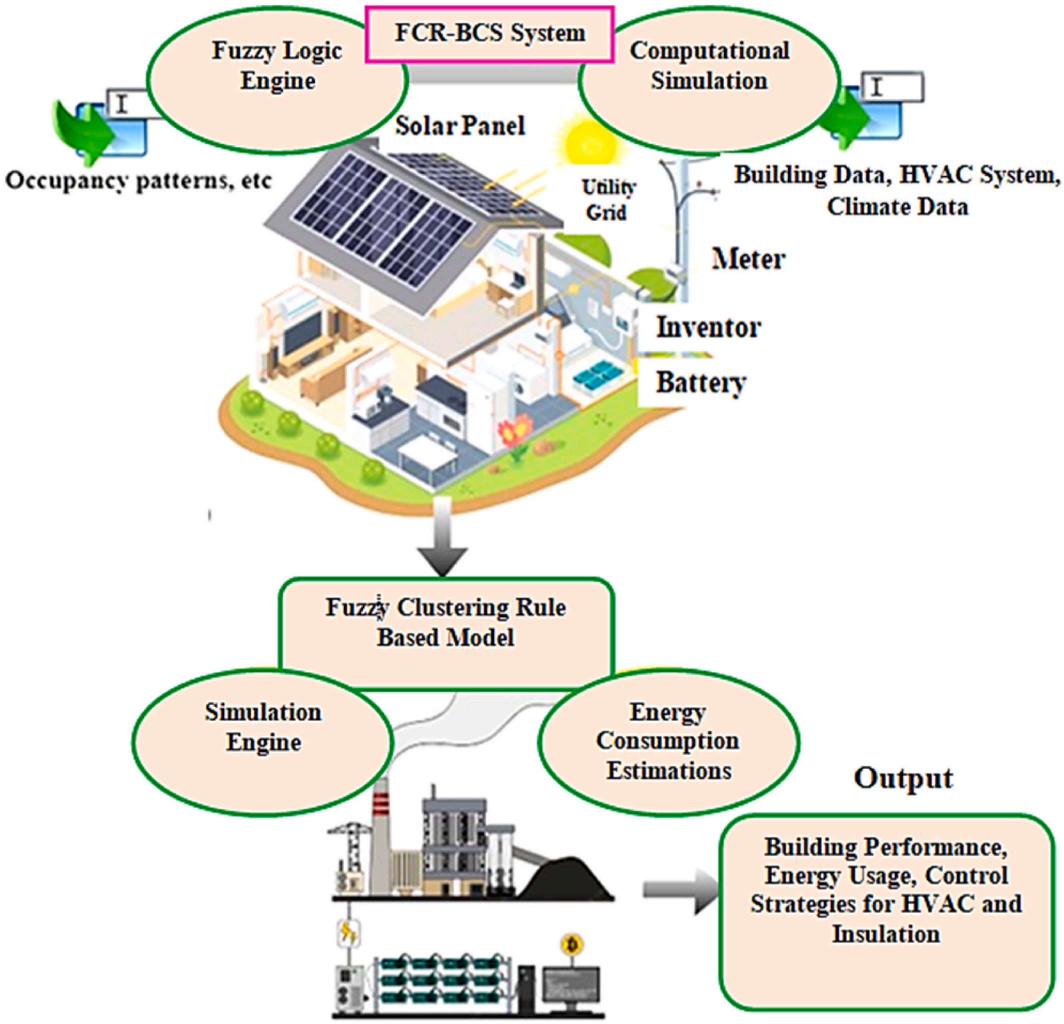


Fig. 2. Components of FCR-BCS.

and the preferences of individual users. In general, the equations for calculating energy efficiency and load (L) could be given in Appendix A.

2.1. Components of FCR-BCS

The components of FCR-BCS are shown in Fig. 2. It is an integral part of the larger FECS system. The FCR-BCS system is the basis for improving building energy efficiency that combines fuzzy logic with computer modeling. FCR-BCS plays a crucial role in achieving FECS's goals by representing and simulating the unpredictability of a building's energy systems using fuzzy logic. Fig. 2 shows how several factors like occupancy patterns, climatic data, HVAC system specifications, and building-specific data impact energy use. Correct operation of the simulation and fuzzy logic model depends on these values.

The Fuzzy Clustering Rule-Based Model is the primary part of the FCR-BCS. This model combines fuzzy logic with rule-based systems to account for complex relationships in the input data. Fuzzy logic accommodates various variables and approximate reasoning, effectively dealing with real-world uncertainties and fluctuations. The suggested FCR-BCS method's innovations include computing the variable dispatch threshold $V(th)$ in terms of a power-dependent factor, which allows for a reduction in the variance v of the load modifying the fuzzy circuits L_s due to load forecast and fc as inaccuracies. Since the energy storage system's dispatch power can follow the demand for load and the RES production variation. In this article, the FCR-BCS proposed method applies the AND as well as OR operations to classical functions to describe the fuzzy logical connectivity of a fuzzy set. The equations for calculating the above-mentioned parameters are given in Appendix B.

The importance of the FCR-BCS system in the context of reducing building energy use may be seen when its components are examined individually. Fuzzy logic makes it possible for the system to deal with the myriads of elements that influence a building's energy use. FCR-BCS is practical for architects, engineers, and facility managers, helping them manage the unpredictability of building

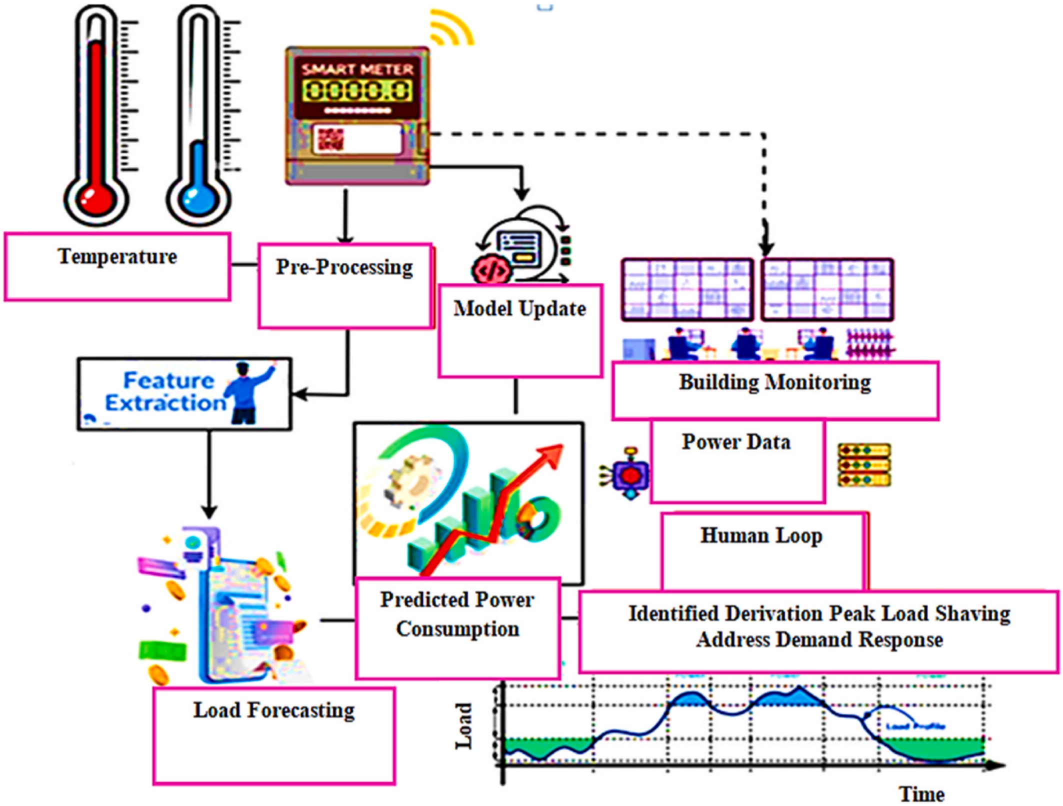


Fig. 3. Process flow of the proposed model.

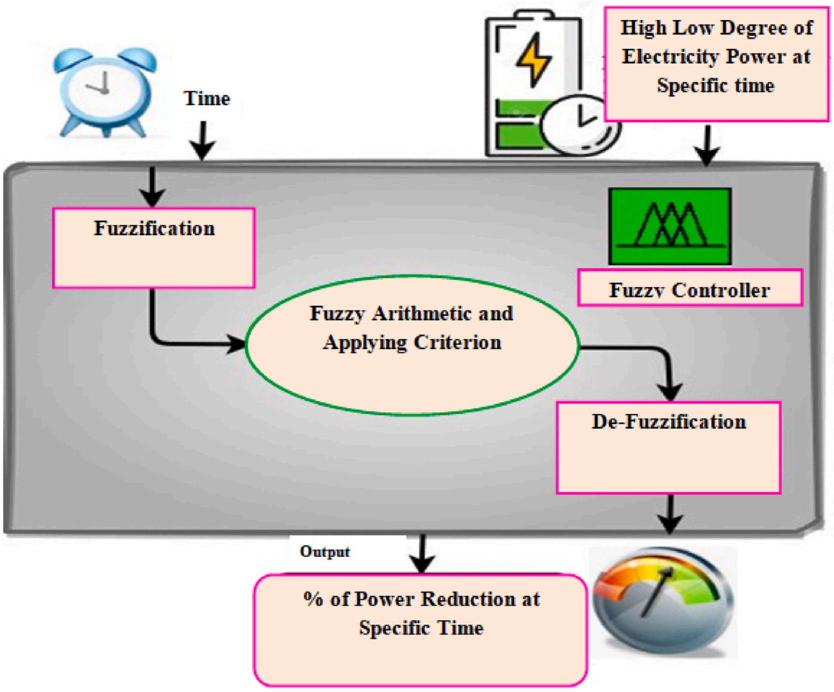


Fig. 4. Fuzzy control system.

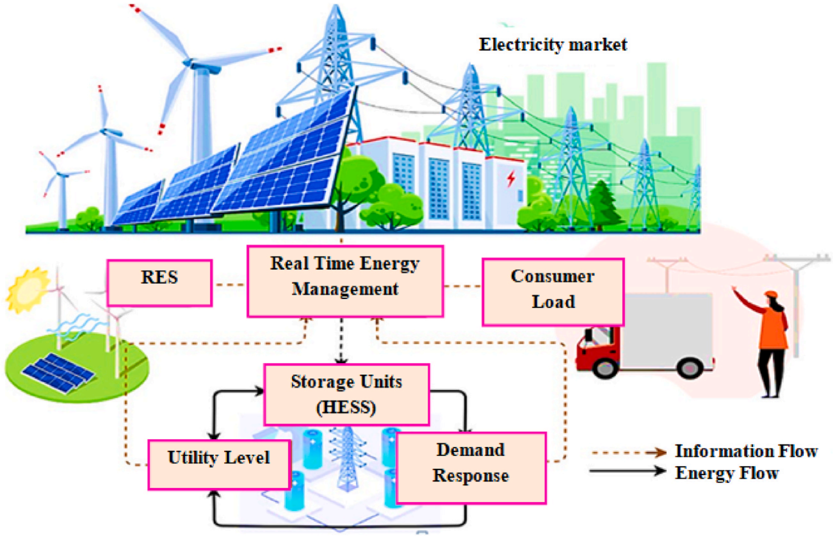


Fig. 5. Organizational framework for energy management.

operations and occupant behavior.

2.2. *Process flow of the proposed model*

Fig. 3 depicts the layout of the proposed model as it indicates a pre-processing stage in which the initial data from the smart meter is refined using novel methodologies. The characteristics most pertinent to the present work are used to train models with varying prediction horizons.

The prediction models are revised regularly to account for variations in power usage due to factors such as degradation, building age, etc. Based on the load forecasting results, the inference engine allows a building administrator or automatic control mechanism to take the necessary steps toward responsible energy management. The study's main contribution is the development of effective methods for high-resolution, short-term (one day ahead), intermediate-term (one week ahead), and long-term (one month ahead) forecasting. The study also presents a unified, powerful system for modelling energy consumption data and analysing occupancy patterns, which accounts for variations in power use throughout the week, including weekends and holidays, in a single model. Furthermore, the study emphasizes the use of a fuzzy controller, complete with a detailed block diagram, to manage electricity flow during specific periods, optimizing power utilization while minimizing fluctuations.

2.3. *Fuzzy control system*

A fuzzy controller controls the electricity demand and its fluctuation throughout the day. To happen this, the system requires a time feed that specifies a particular moment or time range as data for analysis. The data is necessary and mandatory for predicting daily electricity use, as power needs might fluctuate significantly at different times of the day. Fig. 4 indicates the present and future electrical load based on past data and conditions. Depending on the parameters set by the system, the demand is classified as high, medium, or low. In the fuzzification phase, hard-and-fast inputs like time and electrical power are recast as language variables with a degree of uncertainty. To account for the unpredictability and imprecision of the data, fuzzy sets are developed to reflect the range of power consumption possibilities. The controller does arithmetic operations to these fuzzy variables using fuzzy logic. It takes the fuzzy inputs and uses them to decide based on rules or criteria. Fuzzy if-then statements are a common way to indicate the rules that guide when and how much power should be used. The power savings requirement is output as a fuzzy set by the fuzzy logic system. Using defuzzification can get a clean result that lines up with a real-world power reduction value. Examples of common defuzzification techniques include the centroid, weighted average, and maximal membership principle [79].

The mean power during this average movement time is the dispatch power of the battery allows the battery to operate in a low-discharging mode and is utilized to smooth the relatively constant part of the load demand [87]. The output indicates the proportion of power savings required at that moment. It is an unambiguous signal that can be used to change electricity production or distribution by the power management system. This data can be relayed to relevant parts of the power system so that adjustments can be made. The value of the percentage of power reduction at a specified time regulates electricity production, distribution, or consumption. It can trigger actions like changing generating output, transferring loads, or redistributing power to meet the current electrical demand without overloading system. A fuzzy controller's block diagram includes multiple steps, from input data gathering to output control for time-of-use electricity power management. To minimize power usage and ensure the electrical grid's reliability, fuzzy logic is crucial in making judgments based on imperfect data. This method can make power management more flexible and responsive, improving energy efficiency and lowering expenses. The equations for explaining this model could be given in Appendix C.

2.4. Organizational framework for energy management

Energy management of an integrated energy storage system, including an energy storage device and an ultra-capacitor, is proposed in the research to reduce load demand. Each data point undergoes a two-stage management procedure. The initial stage is to fairly divide the load-reducing work between the two devices in light of the load-varying circumstances. The second stage uses the associate in information technology (AIT), which can be controlled in real-time, to manage the ultra-capacitor's energy to minimize the surplus load's demand. The proposed strategy is evaluated in this analysis using data collected directly from RES generators. The findings demonstrate that this approach can successfully reduce peak demand and maximize RES self-consumption with no need for exact forecasted loading and RES data. The suggested method offers variable power control, and the simulation results indicate its improvement over the usual method of utilizing the Particle Swarm Optimization (PSO) algorithm. RES, demand for electricity, the storage system, and other grid-dependent variables make up the micro-grid system structure seen in Fig. 5. A Hybrid Energy Storage System (HESS) is used to test the validity of the suggested energy management algorithm.

These guidelines summarize the anticipated connections between the inputs and the outputs (energy consumption). The energy efficiency study assesses the effectiveness of the fuzzy logic system in maximizing energy usage, which entails contrasting the anticipated energy use. FECS leverages fuzzy logic to enhance accuracy in building design simulations, accounting for variable factors and human behavior. This innovative approach aids in creating more energy-efficient buildings, promoting sustainability, and mitigating energy consumption in structures, thus reducing overall operational costs. Fuzzy logic allows the system to accurately predict and simulate the uncertainties in the building's energy systems [80]. This is a massive benefit since real-world scenarios often include inaccurate data and changeable aspects that can't be adequately modeled using binary logic. Fuzzy logic's ability to consider human behavior patterns enables adaptive design. Occupant behavior may significantly affect a building's energy use. Therefore, the ability to quickly and easily make adjustments is essential for maximizing energy efficiency.

Reduced energy expenses for building owners and occupants may be achieved with this strategy by optimizing building designs for low energy usage. As the cost of electricity rises, this becomes more crucial. Energy efficiency reduces carbon emissions and promotes environmental sustainability, supporting global climate change initiatives. Taking an interdisciplinary approach to sustainable building design and urban development is made possible by the method's adaptability and the fact that it can be used in various contexts, such as architecture, engineering, construction management, and urban planning.

Implementing systems based on fuzzy logic may be difficult and time-consuming, requiring expert-level expertise. Architects, engineers, and facility managers may benefit from training on utilizing and incorporating these tools. High-quality and reliable data, such as occupancy patterns, climatic data, and building-specific information, are essential for successful implementation. Collecting and updating this information may take a lot of time and energy. Software, hardware, and training may be needed to integrate fuzzy logic and computational simulation systems into building design and operation. Smaller firms and projects may find these prices prohibitive. Fuzzy logic systems also respond to language variables and rules. A lack of expertise in setting up a system might lead to erroneous results due to poorly specified variables or regulations. A limited prediction horizon may affect the approach's efficiency. Because building energy systems are constantly changing, short-term forecasts may be more reliable than long-term ones.

Promote adaptable design to maximize energy efficiency by catering to the specific demands of various building types and occupant behaviors. Sustainability in the environment: highlight how cutting down on carbon emissions and saving power has helped. Discussing the approach's adaptability and capacity to bridge gaps across various professional disciplines is essential to developing cooperation for environmentally responsible building design and urban planning. Recognize the difficulty but stress the long-term advantages, arguing that the barrier can be surmounted with sufficient investment in training and experience. Emphasize the significance of data quality and management, implying that future improvements in data gathering technologies may help to reduce this constraint. While there may be some up-front expenses, it's important to stress that the long-term energy savings and environmental advantages more than makeup for them. Ensure domain experts properly set up fuzzy logic systems to reduce the possibility of erroneous findings. Users should consider the predictive horizon and supplement it with other long-term planning tactics to get the most out of this method. Applying fuzzy logic model-based energy optimization techniques may reduce building energy usage [81]. This entails minimizing energy consumption without sacrificing ease or usefulness by modifying the input variables and system configurations for effective output. In summary, FECS with FCR-BCS represents a significant leap forward in the quest for sustainable and energy-conscious building design. While it requires careful planning and investment, the potential benefits of energy efficiency, cost reduction, and environmental impact make it a compelling choice for architects, engineers, and urban planners committed to a greener and more sustainable future. In general, energy management algorithm used for a HESS aiming to test the validity could be given in Appendix D.

3. Results and discussion

The data are taken from the building energy efficiency prediction Kaggle dataset [82]. Building energy efficiency regulations are getting tighter, and climate change is becoming a major problem in the modern world. To keep up, it's important to know how buildings use energy and to have a good idea of the energy load when designing a building. Machine learning offers an alternate strategy for time-consuming and money-consuming conventional energy calculation methods. With a total of 768 samples, the dataset includes 8 features and 2 targets related to residential structures. Buildings vary in size and shape yet share the same volume. Each of the 18 building shapes uses the same materials for that aspect. When environmental sustainability and economic efficiency are equally

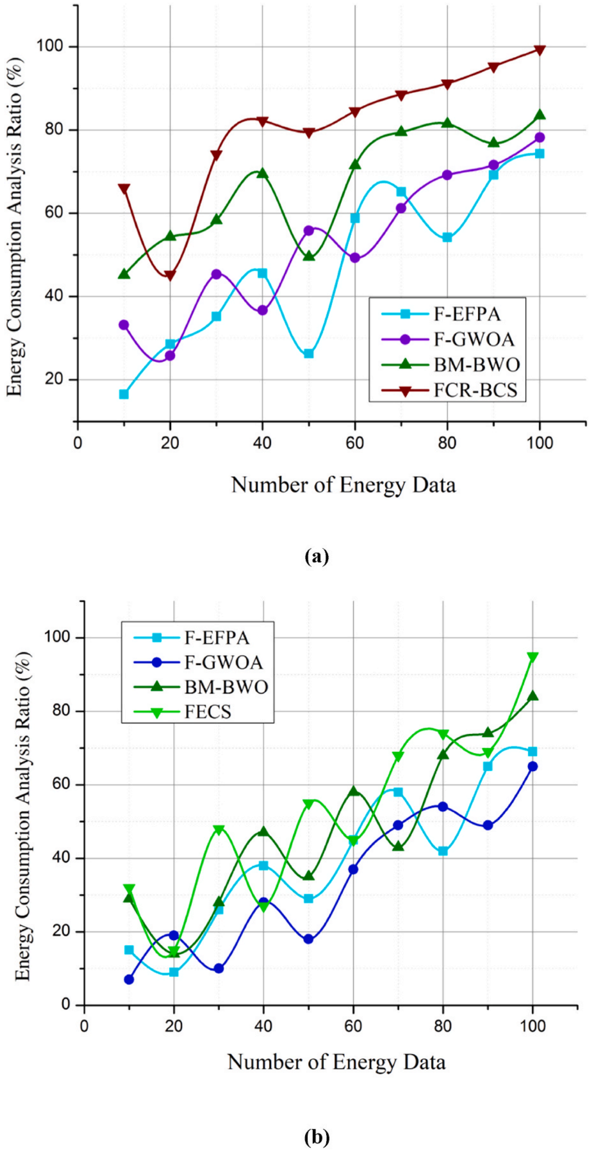
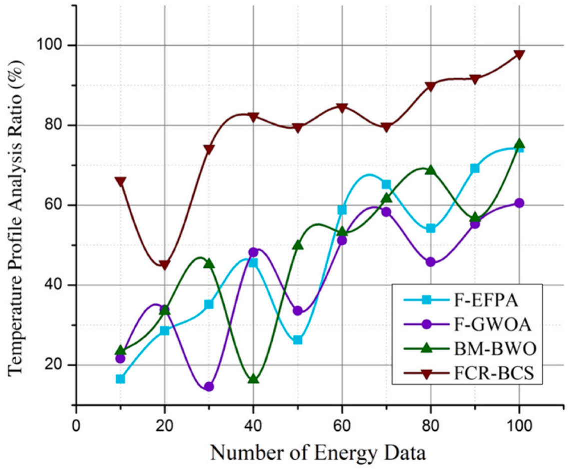


Fig. 6. (a) Energy Consumption analysis is compared with FCR-BCS; (b) Energy consumption analysis is compared with FECS.

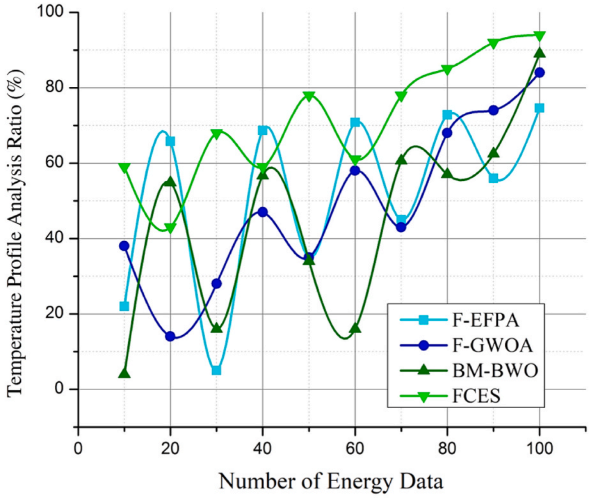
important today, efficient building management and energy conservation have never been more important. These objectives can be advanced using FCR-BCS. The FCR-BCS uses cutting-edge methods to examine energy efficiency, energy consumption, occupancy patterns, and sensitivity to many factors that affect a building's performance.

3.1. Energy consumption analysis

FCR-BCS analyzes energy consumption to maximize energy efficiency. This method takes a holistic view of a building's energy consumption trends, considering various factors for analysis. Indoor climate, humidity, occupancy, lighting, and HVAC system settings are only a few building parameters that are measured and pre-processed first. Using linguistic variables and membership functions, FCR-BCS models the uncertainty in data using fuzzy logic. These models build complex correlations between inputs and energy use, enabling continuous simulation and evaluation in real time. The impact of varying characteristics and regulations on energy consumption can be studied systematically using simulations of various situations and control systems. The FCR-BCS optimization algorithms adjust the controls' rules and settings to reduce energy use without compromising the building's occupants' comfort or the efficiency of its machinery. Visualizing tools like graphs and charts facilitate energy consumption statistics presentation, which helps stakeholders comprehend the consequences of different methods on energy efficiency [83]. FCR-BCS is equipped with devices for constant monitoring and feedback to maintain its energy-efficient operations over time. Ultimately, this analytical procedure provides



(a)



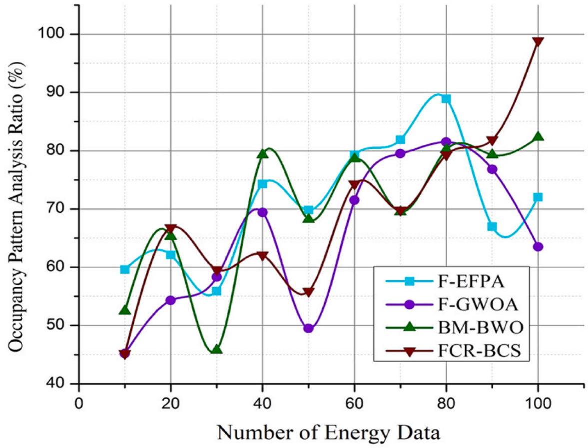
(b)

Fig. 7. (a) Temperature Profile Analysis is compared with FCR-BCS; (b) Temperature Profile Analysis is compared with FECS.

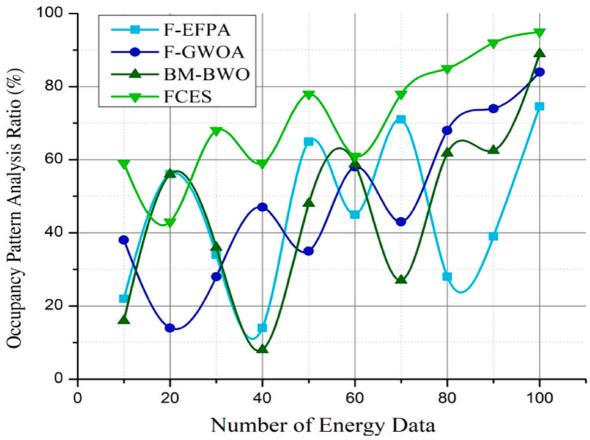
building owners, operators, and designers with the information they need to make educated decisions, enhance energy performance, and decrease operational costs, all of which contribute to more environmentally and socially conscious construction methods. From Fig. 6a and b, it can be observed that FCR-BCS performs 99.6 %, and FECS produces 90.3 %. A similar trend for an increase in Achieving Energy Consumption Analysis could also be reported in published works [83,84].

3.2. Temperature profile analysis

FCR-BCS relies on accurate temperature profiles for optimal performance of the HVAC, lighting, and other systems they control. FCR-BCS uses these profiles to make instantaneous judgments about heating and cooling to preserve comfortable temperatures inside while reducing energy use. Both indoor and outdoor temperature ranges are included in these profiles. As a result of factors such as occupancy and equipment heat output, indoor temperature profiles accurately depict the actual thermal conditions within the building spaces. The outdoor temperature profile is vital information for HVAC systems to heat and cool a structure. These temperature profiles are graphically displayed by FCR-BCS using line charts or color-coded heat maps. These visualizations are helpful for both building operators and designers, showing how internal and exterior temperatures change over time. FCR-BCS may dynamically alter HVAC settings, control blinds or shading devices, and decide whether to activate heating or cooling systems based on monitoring and analyzing temperature profiles. To keep indoor temperatures within tolerable ranges even when extreme weather is present, FCR-BCS may employ load shedding and other energy-saving measures. In addition, FCR-BCS can maintain its energy efficiency without



(a)



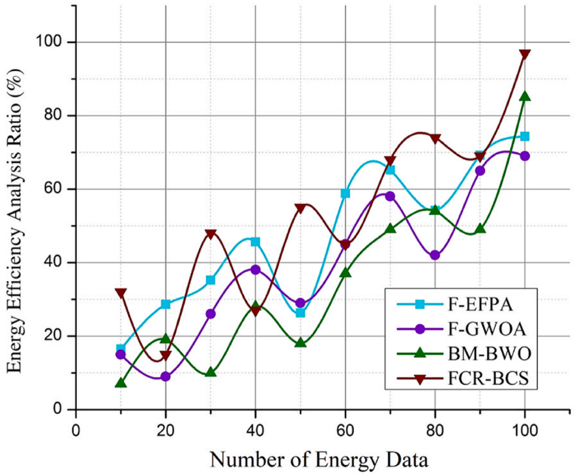
(b)

Fig. 8. (a) Occupancy patterns analysis is compared with FCR-BCS; (b) Occupancy patterns analysis is compared with FECS.

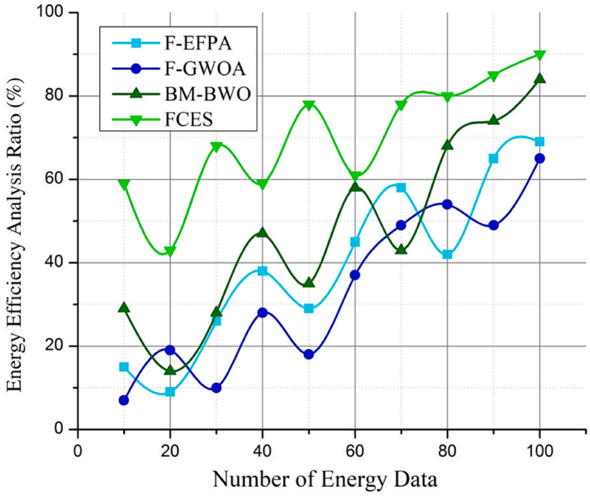
sacrificing occupant comfort by adjusting to varying climatic circumstances, anticipating temperature swings, and reacting to abrupt changes thanks to the information provided by temperature profiles, a similar trend for an increase in Achieving Temperature Profile Analysis that reported by Refs. [85,86]. FCR-BCS's capacity to maximize building energy performance and decrease operational costs, eventually contributing to sustainable and ecologically responsible building management practices, relies on its proactive and adaptive temperature control. It is evident from Fig. 7a that FCR-BCS performs 98.8 %, while FECS produces 91.4 % as depicted in Fig. 7b.

3.3. Occupancy patterns analysis

The occupancy patterns of a building have a significant impact on the management and optimization of the facility's energy systems, making them an essential component of FCR-BCS. To maximize savings on energy costs without sacrificing comfort for building occupants, FCR-BCS tracks and analyses occupancy patterns to adjust lighting, HVAC, and other systems as needed. These recurring configurations illustrate how people's presence in a building change across time and space. A similar trend for an increase in Achieving Occupancy Patterns Analysis was reported by Refs. [87,88]. They can differ significantly in residential regions, public buildings, and business establishments. The proposed FCR-BCS's array of sensors, occupancy detectors, and BMS can monitor occupant presence and activity in real time. Graphical tools such as occupancy profiles, heat maps, and bar charts depict occupancy patterns. These diagrams show how many people enter and leave a building at different times of day, week, or year. When FCR-BCS knows when and where a building is generally inhabited or empty, it may modify the temperature, lighting, and other features accordingly. For instance, FCR-BCS may lower lighting settings, adopt setback temperatures, or optimize ventilation rates during periods of low occupancy to preserve energy without sacrificing comfort or safety. When the inverse is accurate, and a building's rooms are filled with people, its lighting and climate control systems can adjust to their needs immediately. Fig. 8 depicts the FCR-BCS that can use



(a)



(b)

Fig. 9. (a) Energy efficiency analysis is compared with FCR-BCS; (b) Energy efficiency analysis is compared with FECS.

occupancy data for proactive system modifications and the system can forecast future occupancy patterns. FCR-BCS relies on occupancy patterns as an input, allowing it to optimize building energy systems in a way that coincides with inhabitants' actual presence and behavior. Energy savings, operational efficiency, and improved occupant satisfaction are some of how FCR-BCS helps the environment by proactively reacting to occupancy trends. From Fig. 8a it is evident that FCR-BCS performs 97.5 %, and FECS produces 93.6 % based on the occupancy pattern as depicted in Fig. 8b.

3.4. Energy efficiency analysis

FCR-BCS relies on energy efficiency studies to maximize building performance while reducing power usage. FCR-BCS uses fuzzy logic-based models and complex algorithms to assess and improve energy efficiency. From Fig. 9, this analysis systematically evaluates the facility's energy consumption habits, control methods, and the effect of varying building characteristics on energy efficiency. FCR-BCS evaluates the impact of varying temperature set points, lighting levels, occupancy patterns, and HVAC operations on energy consumption by simulating various scenarios and control setups. It employs optimization algorithms to determine the most effective control methods to find a happy medium between passenger comfort and decreased energy consumption. The analysis of energy efficiency helps businesses save money by reducing their energy use and carbon footprint, a similar trend for an increase in Energy Efficiency Analysis [89,90]. Because of its central role in accomplishing these goals, FCR-BCS is necessary for green building management and design. As a result, FCR-BCS performs 99.8 % as shown in Fig. 9a, and FECS produces 92.5 % in terms of energy efficiency

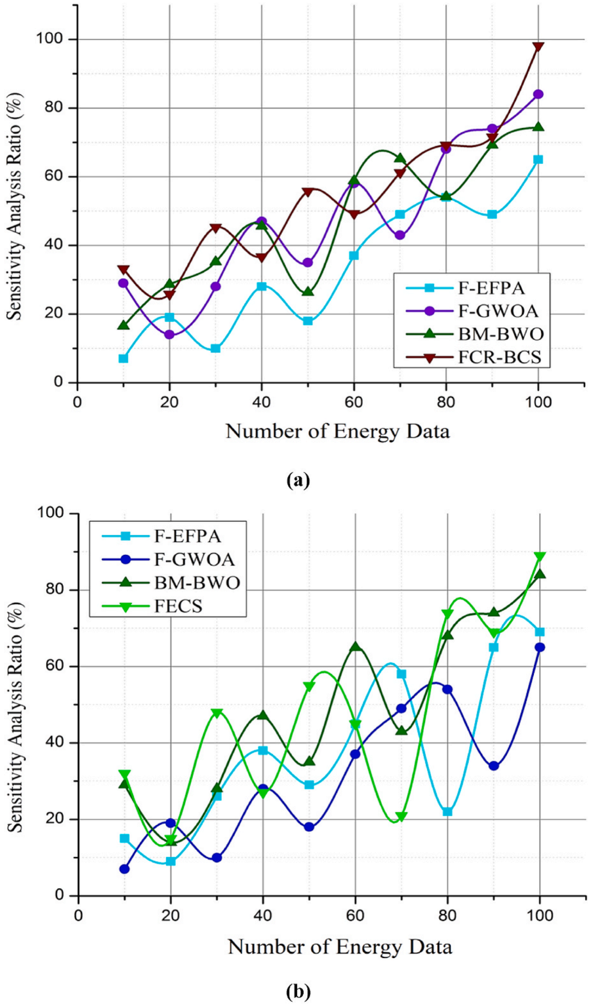


Fig. 10. (a) Sensitivity analysis is compared with FCR-BCS; (b) Sensitivity analysis is compared with FECS.

of the building as depicted in Fig. 9b.

3.5. Sensitivity analysis

Fig. 10 shows the sensitivity analyses for FCR-BCS and FECS in comparison with others. In FCR-BCS the sensitivity analysis determines how certain variables change the system's operation and power consumption. Adjusting insulation, heating and cooling temperatures, lighting schedules, and other inputs to see how they affect energy use and other metrics over time. FCR-BCS does a sensitivity analysis to determine which characteristics significantly affect the building's energy performance. With this knowledge, optimization efforts can be prioritized, focusing on the variables that will substantially impact energy savings. It further suggests where to focus efforts when upgrading or retrofitting.

In the end, sensitivity analysis equips users of FECS to make data-driven decisions, fine-tune control techniques, and zero in on actions with the most significant potential to improve energy efficiency without sacrificing occupant comfort. It is evident from Fig. 10a that FCR-BCS performs 99.4 %, and FECS produces 91.2 % in terms of fuzzy sensitivity analysis as depicted in Fig. 10b. A similar trend for an increase in sensitivity analysis was reported by Refs. [91,92]. Indeed, FCR-BCS is revolutionary because it changes how we think about green building management. These systems enable decision-makers to make data-driven choices by analyzing energy consumption, temperature profiles, occupancy patterns, energy efficiency, and sensitivity, all of which lead to lower energy costs and a brighter future for construction and facility management from an ecological and societal perspective.

4. Conclusions

FECS emphasizing FCR-BCS, provides an attractive approach to addressing the worldwide problem of decreasing energy use in buildings. This novel method also recognizes the complicated interplay between weather, building materials, occupancy patterns, and

HVAC systems; it uses fuzzy logic to account for the unknowns in these relationships. This opens up a potentially fruitful path toward reducing energy use, increasing sustainability, and bettering the lives of city inhabitants. Construction management, city planning, building construction, and facility management are a few fields that could benefit from FCR-BCS. The experimental outcomes demonstrate that the suggested model increases the sensitivity by 99.4 %, energy efficiency by 99.8 %, occupancy patterns by 97.5 %, temperature by 98.8 %, and energy consumption by 99.6 % compared to other existing models. The use of this technology by architects and engineers can improve the efficiency of a building's heating, HVAC, and insulation systems.

By utilizing FECS, facility managers may optimize already-built facilities' energy management systems, cutting operational costs and environmental effects. In addition, these cutting-edge resources can be utilized by city planners to design greener streets and build more habitable metropolitan areas. FCR-BCS simulation studies provide empirical proof for the system's efficiency in boosting building energy performance. Future energy and construction systems shine as a ray of hope for the construction and city planning sectors in light of the urgent need for sustainable and energy-conscious solutions. It represents innovation and hopes that our cities may be revitalized one energy-efficient structure at a time. FECS essentially creates a path for a more environmentally conscious and sustainable future. However, one drawback of the suggested approach is that it becomes more difficult to manage and maintain as the number of input variables rises and the complexity of the rule base grows exponentially.

CRediT authorship contribution statement

Munusamy Arun: Writing – original draft, Software, Methodology, Investigation, Data curation, Conceptualization. **Cristina Efremov:** Writing – review & editing, Funding acquisition, Validation. **Van Nhanh Nguyen:** Writing – review & editing, Conceptualization. **Debabrata Barik:** Writing – original draft, Validation, Software, Resources, Methodology, Investigation, Data curation. **Prabhakar Sharma:** Writing – review & editing, Validation, Methodology. **Bhaskor Jyoti Bora:** Writing – review & editing, Methodology. **Jerzy Kowalski:** Writing – review & editing, Methodology. **Huu Cuong Le:** Writing – review & editing. **Thanh Hai Truong:** Writing – review & editing. **Dao Nam Cao:** Writing – review & editing, Conceptualization.

Declaration of competing interest

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

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Appendix A

Technologies for Energy Efficiency: These technologies include a wide variety of characteristics, including energy-saving home appliances, efficient construction materials, and smart thermostats. They have the potential to lessen the building's overall demand for energy.

$$\mu_g(al)^*op = \frac{\sum_{j=1}^{pv} \delta(cs_p) em_p(ad_g, L_{lp})}{ssd} \tag{1}$$

The genetic g algorithms $\mu_g(al)$ used to create the optimum approach op take into account the economy, however they may not be suitable for use in the actual world by applying Eq. (1).

In this paper, researchers offer a neural network-based predictive control system cs for load and PV output prediction p using fuzzy. The energy management $e\,m_p$ outcomes are influenced by small discrepancies between actual data and predictions as ad_g. Using predicted PV output and load L, a linear programming lp procedure is used to create storage system dispatch schedules ssd.

$$L = \frac{1}{cm} \sum_{j=1}^{pv} hd_s(g_e, ad_g) \tag{2}$$

The outcome of equations adds a feedback controller to monitor $\frac{1}{cm}$ the battery's charge status as part of the process of designing the hourly dispatch schedule hd_s. To reduce the cost of generated electricity g_e, a PSO-based mechanism is given in Eq. (2) that delivers the energy in a variable manner and with this approach, it is simple to obtain a local optimum L.

Appendix B

The suggested method's innovations include of computing the variable dispatch threshold th power pr, which allows for a reduction in the variance v of the load saving L_s due to forecast fc inaccuracies i. Since the energy storage system's dispatch power can follow the demand for load and the RES production variation, it can make the most efficient use of the accumulated power to moderate the load demand using Eq. (3).

$$V(th) = \sum_{j=1}^{pr} v(L_s) fc^i (g_e, ad_g) + \mu_g(al)^* op \tag{3}$$

In this article, our proposed method applies the AND as well as OR operations to classical functions to describe the fuzzy logical connectivity of a fuzzy set, yielding the above two Eqs. (4) and (5).

$$cs_p \cap ad_g = \sum_{i=1}^{j} \delta(hd_s) g_e \left(op, \mu_g \wedge fc^i \right) \tag{4}$$

$$cs_p \cup ad_g = \sum_{i=1}^{j} \delta(hd_s) g_e \left(op, \mu_g \vee fc^i \right) \tag{5}$$

Using the above-mentioned Eq. (6), users may identify the optimal variable responsible for ensuring fuzzy logical coherence.

$$\mu_{cs_p \cup ad_g}(a) = \mu_{Qcs_p}(op) + \mu_{ad_g}(op) - \mu_{cs_p \cap ad_g}(op) \tag{6}$$

Energy control $\forall_{ec}$ for a hybrid energy storage system, including a battery *b* and an ultra-capacitor *uc*, is proposed in this study in an effort to reduce load demand *ld*. Each data point *dp* undergoes two stages of treatment. In the beginning, must fairly divide the load-reducing *lr* work between the two machines by taking into account the load-variability *lv* requirements. The second stage can be controlled in real time, to manage the ultra-capacitor's energy to minimize the surplus load's demand *Sld*. In this analysis, researchers put the suggested strategy to the test by analyzing actual data using Eq. (7).

$$\left(\sum_{\forall_{ec} \left| m_{uc}^{b} \right| m_{dp}^{ld}} storage(ad_g)^* lv_{lr} \right) \leq stroage(cs_p)^* X_{Sld} \tag{7}$$

Appendix C

In this scenario, the battery's dispatch power for all type $\forall_{bd}$ is zero and the ultra-capacitor *uc* is the only source of power *p*. In addition, the steps involved in the ultra-capacitors dispatch power computation *pc* will be made apparent and illustrated in Eq. (8).

$$\sum_{\forall_{bd} \left| m_p^{uc} \right| m_p^{pc}} \frac{Per}{cp} = 1 \tag{8}$$

The average power during this average movement time is the dispatch power of the battery, as stated in Eq. (9), which allows the battery to operate in a low-discharging mode and is utilized to smooth the relatively constant part of the load demand.

$$\left(\frac{Puc}{cp} . (i - \Delta te) - \frac{Puc}{cp} (min) \right)_i \Rightarrow m_p^{uc*} m_p^{pc} > 1 \tag{9}$$

Appendix D

As the memory is built into the model by include self-regressive terms *sgt* as inputs in addition to the exogenous variables *evs*, this model is a subset of a recurrent neural network *rnn*. Contextual information *ct*, such as time of day, day of the week *dy*, and other aspects, will aid in capturing the immediate trends of the system, while these features will aid in preserving the long-term dynamics *D* of the time series shown in Eqs. (10) and (11).

$$sgt\left(\left(evs\left(m_p^{uc*} m_p^{pc} \right) \Rightarrow m_p^{pc} \right) - rnn\left(k_{dy}^{ct} \right) \right) \tag{10}$$

$$sgt\left(\left(evs\left(m_p^{uc*} m_p^{pc} \right) \Rightarrow m_p^{uc} \Delta te - rnn\left(k_{dy}^{ct} \right) \right) \right) \tag{11}$$

Pr_f is the power *Pr* forecast *f* for day *i* at time *step t*, where $nn(fv)$ is the function learned using the neural network, *fv* is the feature vector selected correctly for the multiple horizons *mh* of time, and *te* is the time step, as given in Eq. (12)

$$Pr_f(i, te) = nn(fv)^* mh^{te} \tag{12}$$

Data availability

The authors do not have permission to share data.

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