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Intelligent Controllers and Optimization Algorithms for Building Energy Management Towards Achieving Sustainable Development: Challenges and Prospects

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ABSTRACT Buildings account for a significant amount of energy consumption leading to the issues of global emissions and climate change. Thus, energy management in a building is increasingly explored due to its significant potential in reducing the overall electricity expenses for the consumers and mitigating carbon emissions. In line with that, the greater control and optimization of energy management integrated with renewable energy resources is required to improve building energy efficiency while satisfying indoor environment comfort. Even though actions are being taken to reduce the energy consumption in buildings with several optimization and controller techniques, yet some issues remain unsolved. Therefore, this work provides a comprehensive review of the conventional and intelligent control methods with emphasis on their classification, features, configuration, benefits, and drawbacks. This review critically investigates the different optimization objectives and constraints with respect to comfort management, energy consumption, and scheduling. Furthermore, the review outlines the different methodological approaches to optimization algorithms used in building energy management. The contributions of controller and optimization in building energy management with the relation of sustainable development goals (SDGs) are explained rigorously. Discussions on the key challenges of the existing methods are presented to identify the gaps for future research. The review delivers some effective future directions that would be beneficial to the researchers and industrialists to design an efficiently optimized controller for building energy management toward targeting SDGs.

INDEX TERMS Building energy management, controller, optimization, scheduling, sustainable development goals.

I. INTRODUCTION

Presently, buildings take the lead in consuming a substantial amount of energy, indicating about 40% of global energy

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consumption, which is responsible to release one-third of greenhouse gas (GHG) emissions [1], [2]. Another report demonstrates that buildings hold 49% of the total energy worldwide in which 60% of the energy is consumed for heating and cooling purposes [3], [4]. The poor management and ineffective control approach of appliances used in

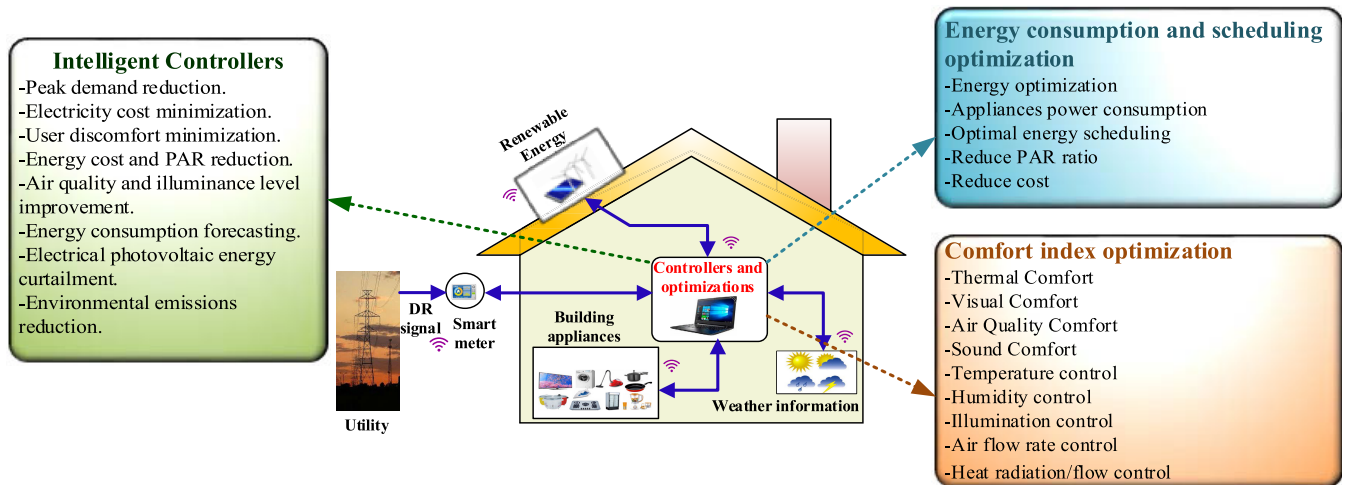


FIGURE 1. The structure of BEMS with intelligent controllers, energy consumption, scheduling and comfort index optimization.

the building may result in a significant loss of energy in a building's energy economy [5]. Hence, nowadays, the efficient utilization of energy in buildings and their impacts on global warming and climate change are the most challenging issues [6], [7]. Although a few efforts have been made by replacing the traditional appliances with energy-saving appliances or by applying simple strategies to reduce total energy consumption, yet the outcomes remain unsatisfactory [8], [9]. Therefore, the design of an enhanced building energy management system (BEMS) is becoming increasingly popular for monitoring and controlling a building's energy requirements [10]–[13]. BEMS integrates a set of operational processes to control energy effectively which in turn reduces the world energy consumption and carbon emissions significantly [14], [15].

A BEMS includes detection, communication, calibration, and even decision making. The overall architecture of a typical BEMS is shown in **Fig. 1**. The main components of BEMS are divided into five parts: Smart meter, sensing devices, information and communication technologies (ICT), smart appliances, and the core is the energy management controllers [16]. A smart meter keeps the record of the time-based data measurement and then transfers the data to the desired locations. Sensing devices detect different parameters such as current, voltage, temperature, motion, light, and occupancy [17]. ICT develops the connection between the sensor, devices, meters and monitoring or control unit. Smart appliances allow the devices to be monitored and controlled remotely using intelligent communication systems [18]. Sensing devices sense the desired parameters (e.g., illumination, temperature, and air quality) at different locations and send the signals to a centralized management system. Based on the sensed parameters, smart devices can be monitored, controlled, or scheduled to operate at required intervals [19]. Accordingly, optimization methods are applied to compute the optimal conditions satisfying the user needs

and system constraint. In this way, a maximum comfort level with optimal resource utilization is achieved [20], [21]. Moreover, renewable energy resources (RESs), such as photovoltaics (PV), batteries, and wind generators, are connected to the BEMS to provide energy to buildings during peak hours, thereby reducing the utility load on the electricity network [22], [23]. Through the use of intelligent control techniques, BEMS can be optimized to maximize energy efficiency and integrate RESs while reducing the cost of energy and maintaining the required user satisfaction levels [24], [25]. The advanced control methods not only achieve the desired comfort level but also reduce the operational and maintenance cost, thus improving the energy performance of the building [26], [27].

Researchers have been focusing to optimize the building energy performance with a target to minimize the energy cost and adverse environmental impacts [28], [29]. In this setting, BEMS can play a vital role to help end-users by optimizing overall energy consumption, energy cost, reduce peak demand and environmental impacts, without compromising comfort [30]. Numerous research works on various objectives, control schemes, optimization algorithms have made great efforts in developing an intelligent control system for efficient BEMS [31], [32]. However, achieving end-user satisfaction and comfort while maintaining the energy cost at the minimum level remains a challenge [33], [34]. Thus, the achievement of BEMS needs further investigation. In this context, this paper aims at reviewing the most efficient control and optimization algorithms in this discipline and concludes the optimized controllers for enhancement of BEMS efficiency.

A BEMS uses a centralized computer-controlled automation system that can monitor and control a small number of stations situated in the building aiming to reduce the energy cost, ensure safety and provide a comfortable environment [35], [36]. BEMS is connected to diverse systems in

a building through microprocessor-based wireless controllers to manage and optimize the operation of electrical equipment including lighting, humidity control, heating, ventilation, and air conditioning (HVAC) system, security systems and fire systems [37], [38]. Generally, BEMS is configured using the hardware, software, and communication protocols [39]. The hardware devices include various sensors, controllers, output devices and terminal interfaces. The sensor keeps a record of temperature, humidity, lighting level and then transmits the required information to the controllers. The controllers are the heart of the BEMS that receive the information from the sensors and then send instructions to the HVAC system. Then, the relays and actuators are used to follow the commands or requirements based on the decisions of the controllers. Afterward, exchange of information between each component and adjustment can be carried out using the user interface or terminal [39]. A work in [40] introduced a three-layered software infrastructure for HVAC systems in the building. The integration layer allows the interoperability of heterogeneous devices through the LinkSmart network and an interface called proxy by applying IEEE 802.15.4, ZigBee, UWB and EnOcean wireless sensor nodes. The middleware layer permits peer-to-peer (P2P) communication that helps to develop control schemes and rules to minimize energy consumption. The application layer manages event-based applications and provides feedback to end-users. Besides, BEMS can be integrated with various standards and internet protocols such as LonWorks, BACnet and ModBus [41].

BEMS with the application of advanced controller and optimization creates an opportunity not only in terms of saving energy, and carbon emissions reduction but also with regard to improve health and wellbeing, new innovation, infrastructure, job openings, and cost-effective energy supply. The impact of BEMS is critical for socio-economic and environmental perspectives which can be directly contributed to many objectives of sustainable development goals (SDGs). Thus, the role of BEMS is significant in achieving the current global challenges including reliable and affordable energy, energy efficiency, emission reduction, green jobs, economic growth, sustainable cities that can be correlated with the target of SDGs. Several notable articles have been published on BEMS. Mariano-Hernández [5] surveyed the literature related to different management strategies for BEMS highlighting demand-side management, model predictive control and optimization in residential and non-residential buildings. However, the authors did not highlight the different intelligent controls and optimization algorithms in detail. Molina-Solana [42] discussed the application of data science in BEMS concerning building energy load, operation, infrastructures, fault detection and economic evaluation. Nevertheless, the authors did not outline the methodological framework of optimization algorithms, controller schemes and related issues. Runge *et al.* overviewed the artificial intelligence (AI) [43] and deep learning techniques [44] to predict energy use in buildings, however, the control operation and optimizations in BEMS were not covered in detail.

Boodi *et al.*[45] focused on the intelligent BEMS emphasizing occupant comfort and different models. However, the authors did not explore the optimization objectives, constraints related to comfort index parameters, energy consumption and scheduling. Shakeri *et al.* [46] presented the BEMS considering the demand response programs, load management techniques, smart grid, different AI and optimization-based home energy management systems (HEMS). However, the authors did not provide the categorization of controllers and optimizations. Petroşanu *et al.* [47] investigated the machine learning models and sensor devices to achieve energy efficiency, enhanced sensing and optimized BEMS. Nonetheless, a detailed explanation of controllers and optimization of BEMS and relation with SDGs were not studied in detail.

To bridge the existing limitations, this review unveils new contributions with a detailed investigation of controllers and optimization in BEMS in connection with SDGs. The main contributions of this review are highlighted as follows:

- This work delivers a comprehensive review of the different control strategies towards efficient energy management in buildings with respect to classification, features, configuration, benefits, and drawbacks.
- This research critically examines the different energy management optimization techniques focusing on optimization objectives and constraints related to comfort management, energy scheduling, electricity expenses, and energy consumption. This work also includes the different frameworks, implementation processes, and applications of different metaheuristics optimization algorithms employed by different researchers.
- This work establishes the relationship of energy management in buildings with SDGs highlighting the influences of optimized control and efficient energy management towards future sustainability with regard to low carbon emissions, sustainable cities, green employment, cost-effective energy supply, and healthier living conditions.
- This research illustrates the scope, suitability, key issues and challenges of different control and optimization algorithms. The analysis, key findings, and recommendations would be helpful towards the development of efficient and sustainable energy management in buildings.

II. CONTROL OPERATION OF BUILDING ENERGY MANAGEMENT SYSTEM

The main target of BEMS is to enhance the heating and cooling performance by limiting the energy involved in the production, use, and maintenance phases of buildings [48], [49]. The most effective strategy to reduce energy consumption during the use phase is to develop a robust control technique [50], [51]. Nevertheless, designing an effective control strategy is a key challenge [52], [53]. The control methods in BEMS are classified into two approaches; one is the

conventional method and the other is the intelligent method [54]–[56], as shown in Fig. 2. The conventional controllers are built using certain loops and mathematical models. They are widely used due to simple tuning and robustness. However, the performance of the conventional controller is not satisfactory in noisy and non-linear processes. Moreover, a certain extent of knowledge is required in conventional control while designing different models. On the other hand, intelligent controllers do not require system modeling and are designed based on certain rules or self-learning skills. They are promising due to their adaptability to operate under uncertainties [57]–[59]. In general, these methods are characterized by their robust computational skill, variable degree of complexity, fast response, enhanced stability and reliability, improved efficiency and higher energy savings [60], [61].

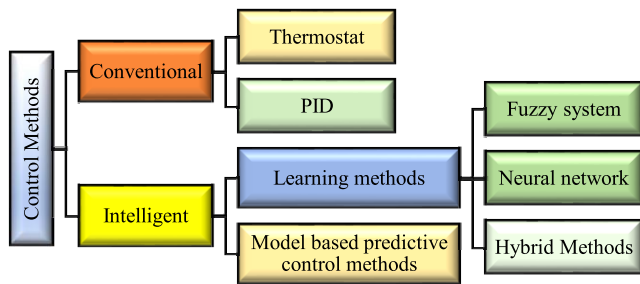


FIGURE 2. Various Control schemes in BEMS.

A. CONVENTIONAL CONTROL

Few conventional control systems have already been employed in BEMS such as thermostats, proportional-integral (PI) and proportional–integral–derivative (PID).

1) THERMOSTAT CONTROL

A thermostat is an instrument that maintains the temperature within the boundary set by the users [62], [63]. When the temperature exceeds the threshold limit, the thermostat cuts off the supply and accordingly restores the supply when the temperature drops under that required [64], [65]. Usually, the thermostats are used for heating or cooling to a set point temperature and can be installed in water heaters, ovens, refrigerators and HVAC systems [66], [67]. The internal configuration of a typical thermostat is shown in Fig. 3 [68].

The thermostat is employed in BEMS with respect to minimizing power fluctuations [69]; reducing cooling electricity cost [70]; controlling space heating [71]; improving thermal comfort [72], and increasing energy efficiency [73]. This method has the simplest control operations; nevertheless, the controlled devices always operate at full or at a default capacity when they are ON, thus, resulting in a large amount of power being consumed in each operation [74]. Besides, the ON-OFF operation may generate oscillations of the controlled temperature, which leads to wastage of energy in residential buildings. Sometimes, ON-OFF-based controllers cannot be effective in complex energy systems and hence,

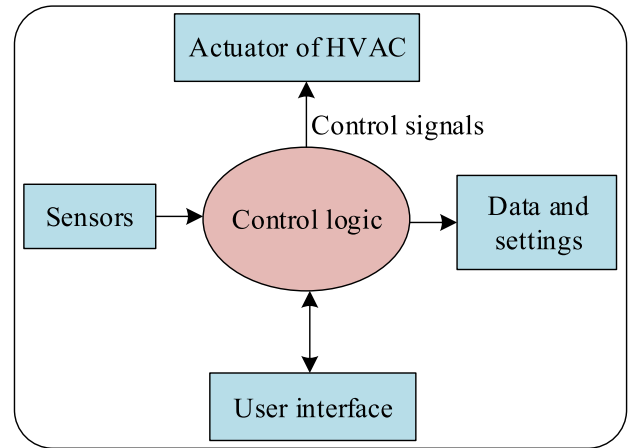


FIGURE 3. The Structure of a typical thermostat.

the appropriate control of variables and objectives cannot be fulfilled with only discrete ON or OFF values [75]. To tackle these issues, PID controllers are introduced in the subsequent subsections.

2) PID CONTROL

A PID control is considered as the most straightforward effective method in the control industry due to its three-dimension functionality to operate in both transient and steady-state responses [76]. A block diagram of the PID controller is shown in Fig. 4 [77]. The expressions of the transfer function in the “parallel form” and the “ideal form” can be written in (1) and (2).

$$G(s) = K_p + K_i \frac{1}{s} + K_d s \tag{1}$$

$$G(s) = K_p \left(1 + \frac{1}{T_i s} + T_d s \right) \tag{2}$$

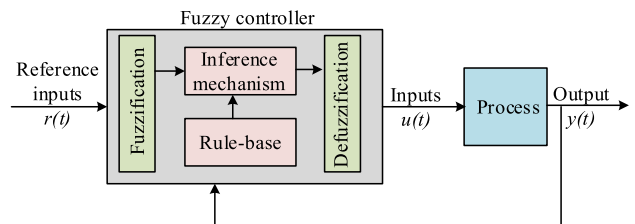


FIGURE 4. An FLC integrated into a closed-loop control system.

where K_p , K_i , and K_d denote the proportional gain, the integral gain, the derivative gain, respectively. T_i and T_d stand for the integral time constant, and the derivative time constant, respectively. The control output $u(t)$ of the PID controller in a continuous form can be shown as follows,

$$u(t) = K_p e(t) + K_i \int_0^t e(t) dt + K_d \frac{de(t)}{dt} \tag{3}$$

Generally, the inputs of PID controller are the reference point and controller output. In [78], the PID controller takes input

as the temperature difference between the surrounding air and the ground for cooling or heating the air to control the earth–air heat exchanger, leading to a reduction of energy consumption up to 87%. Besides, the PID controller has been successfully implemented in various sections in buildings such as light control [79] power tracking performance improvement [80] and vibration control [81] and energy consumption reduction [78]. Although P, PI, and PID are closed-loop/feedback control systems, their performance is not reasonable in noisy and non-linear processes due to the poor control performance, thus resulting in significant time delays [82]–[84]. The control technologies of PID have proven to become more efficient than thermostats; however, the selection of correct gains is still a demanding task [85], [86]. Thus, further exploration is required on predictive, optimal and adaptive techniques to improve the control performance of PID [15], [87]. To overcome the issues of PID controllers, intelligent control techniques explained in the following subsections have gained vital importance.

B. INTELLIGENT CONTROL

The intelligent control employed in BEMS with regard to advanced energy and comfort management control can be categorized as (i) Learning-based methods, including fuzzy systems [88], neural networks [89], fuzzy with conventional controls [90], and adaptive fuzzy neural network (ANFIS) systems [91], [92], etc.; (ii) the model-based predictive control (MPC) technique [93], [94]; and (iii) agent-based control systems [15].

1) FUZZY CONTROLLER

The fuzzy logic controller (FLC) is applied to numerous fields to solve the imprecise control problems using the computer. The performance of FLC is more accurate, robust and superior than the PID controller [95], [96]. The fundamental of fuzzy control is based on fuzzy logic theory, in which decisions are made by a set of “if-then” statements called the fuzzy rules [62], [97], [98]. These linguistic rules are generally written based on observations made by the controller’s designer and the system operators’ knowledge [99], [100]. The block diagram of a FLC integrated into a closed-loop control system is depicted in Fig. 4 [101]. As noticed in Fig. 4 that the FLC involves four steps including fuzzification, rule-base, inference mechanism, and defuzzification [102]–[104].

FLC has been successful in BEMS with the control of heating, cooling [105] and reduction of energy consumption [106]. Besides, FLC is more often used in temperature control [101], [107]. Moreover, FLC is applied in illumination management [108], thus leading to a decrease in energy consumption. Furthermore, the FLC employed in HVAC systems results in a significant drop in monetary cost, and peak to average ratio (PAR) [109]. Nevertheless, FLC has shortcomings in terms of selecting the appropriate parameter values [110]. Hence, FLC is often incorporated with optimization techniques such as genetic algorithm (GA),

particle swarm optimization (PSO) to improve the control performance in many sections of buildings such as power optimization, temperature control, and variable speed control.

2) PID-FUZZY CONTROLLER

The classical PID controller parameters are usually tuned only at a particular operating range with constant controller gains; however, the control parameters including the rise time, settling time and steady-state error of the system undergo drastic change if the operating range is changed [90]. The way forward could be to tune the PID controller online, which would improve the control system parameters under a wide operating range [111]. The configuration of the fuzzy online gain tuner is shown in Fig. 5 [112]. The structure is designed using the PID controller cascaded with a fuzzy controller [113]. The controller gains are adjusted online using the predictions of a fuzzy predictor, thereby improving the controller performance under all operating conditions [114]. The combination of the PID and fuzzy controller brings benefits to both control schemes, hence allowing to address the limitations in each control system [15].

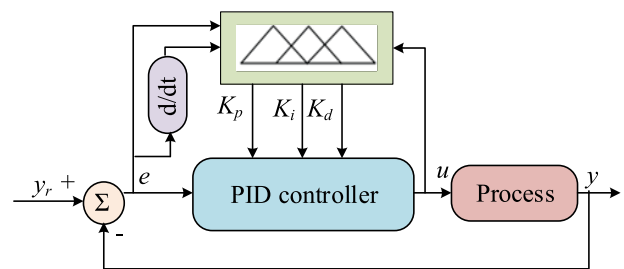


FIGURE 5. Fuzzy online gain tuned PID controller structure employed in BEMS.

This method is employed in energy optimization and comfort management in buildings [90]. The results indicate the better results of the fuzzy-PID controller than the simple On-Off controller, demonstrating its ability to successfully adjust the indoor temperature to its desired reference with lower fluctuations. Besides, the performance of Fuzzy-PID is excellent in controlling heating [85], HVAC systems [112], as well as achieving thermal comfort [115] and visual comfort [116].

3) ARTIFICIAL NEURAL NETWORK CONTROL

The artificial neural network (ANN) is a multi-dimensional information space that can learn information patterns. ANN exhibits strong computation intelligence, which can predict any complex and non-linear system [117]–[119]. ANN has the advantage to manage and control several types of problems with its improved learning ability and without depending on the mathematical functional relationship [120], [121]. ANN is employed in building energy management scheduling controller, [122], as shown in Fig. 6.

In the mentioned study, The ANN controller is structured using five inputs: room temperature (T_{ac}),

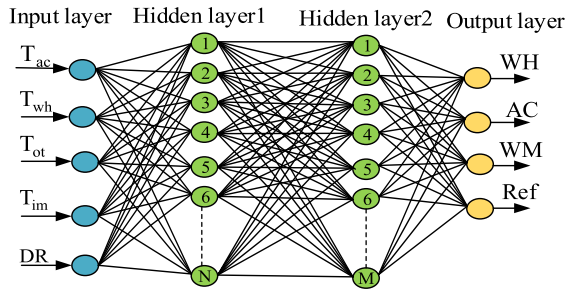


FIGURE 6. ANN-based controller used in demand-side management of residential buildings.

WH temperature (T_{wh}), total power consumption (T_{ot}), time of the system (T_{im}), and demand response (DR) and four outputs namely, air conditioner (AC), water heater (WH), washing machine (WM) and refrigerator (REF). The designed ANN-based controller is used to control the ON/OFF of four selected electrical appliances; AC, WH, WM, and REF according to the consumer requirement, comfort management and preference of appliances.

Due to the superior performance and improved efficiency, ANN has been successfully utilized in different areas of BEMS including energy forecasting [123], energy cost [124], energy consumption [125], demand-side management [126] and thermal comfort [127]. However, ANN needs a large amount of quality data and may suffer from computation complexity such as being trapped in local minima, slow convergence speed and long training duration [110], [128] Recently, deep learning methods have received wide attention for the enhancement of energy forecasting in BEMS [129], [130].

4) ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

Adaptive neuro-fuzzy inference system (ANFIS) is one of the most used artificial intelligent algorithms which combines the advantages of ANN and fuzzy logic theory[91], [110]. ANN methods are excellent in data-driven processes while the fuzzy systems are outstanding in logic-based systems, thus, the integration of the two approaches offers benefits in data-driven and logical systems [131]. ANFIS controller exhibits improved learning performance, adaptability, and robustness which does not rely on mathematical modeling [91], [132]. However, the learning phase of ANFIS can be lengthy and computationally expensive [110]. The structure of ANFIS is designed using five layers, as depicted in Fig. 7. [133].

The effectiveness of the ANFIS controller is demonstrated in [134] highlighting its contributions in optimizing energy usage, electricity cost, and user comfort. ANFIS is also employed to develop an automated BEMS to find the best scenario for energy consumption. In [135], the ANFIS-based intelligent control method is proposed to monitor the legacy appliances, allowing the BEMS to handle both smart and non-smart home appliances.

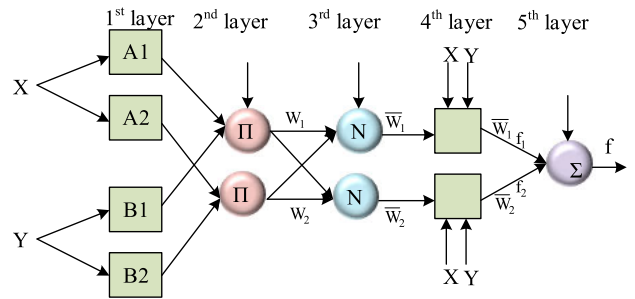


FIGURE 7. The configuration of ANFIS used in building energy management.

5) MODEL-BASED PREDICTIVE CONTROL

The control methodology of model predictive control (MPC) is based on the optimal control actions of a dynamical system and its predictions in future evolution [136], thus providing an advanced control strategy for complex building energy systems [75]. Most of the MPC is designed using the discrete linear models achieved by either developing linear autoregressive models with exogenous variables (ARX) models from empirical data or linearizing the state-space models around a certain steady-state point. Certain MPC formulations utilize physics-based models to generate the discretized forms of continuous model equations. The MPC can be integrated with the comprehensive model built-in EnergyPlus, TRNSYS, and Matlab Simulink to carry out the control performance and optimization in BEMS [137]. Besides a system model, predictive controllers require an optimizer to minimize some performance metrics, such as cost minimization or drive the system to a pre-defined setpoint trajectory [138]. The flow diagram of a typical MPC used in BEMS is depicted in Fig. 8 [139]. It is noticed that the structure is formed using a series of control signals for a defined prediction horizon, which is examined by the appropriate model and a distinct cost function.

MPC has been recognized as the most popular control approach for BEMS in the literature because of its ability to shift the loads from peak hours, adaptation to unexpected disturbances, and capacity to exploit the thermal mass of buildings considering energy price, weather, and occupancy predictions [93], [94]. Besides, MPC has strong points of being able to decrease energy costs by taking into account user comfort. In comparison with conventional control methods, MPC can handle constraints, uncertainties, dynamics and future system variable predictions [94]. A simulation study [74] compares MPC performance with both thermostat and PI controllers, demonstrating that MPC achieves the best results, contributing to a reduction in energy consumption and improving overall costs. In [140], MPC is proposed to design an intelligent building energy management system to reduce the energy consumption in consideration of the user's behavior, and the weather prediction. In [141], MPC is used to control the HVAC, battery storage system and renewable energy effectively in a multi-zone building to minimize the peak power demand while maintaining the

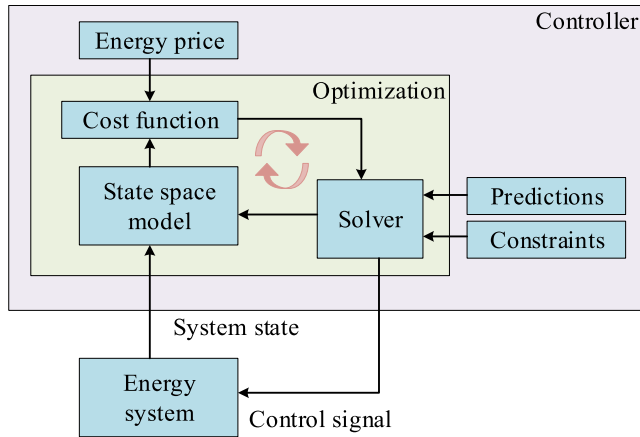


FIGURE 8. MPC concept towards build energy management.

thermal comfort of industry benchmarks. However, MPC has drawbacks in selecting a suitable model due to the costly installation [142]. Besides, the model development is a laborious task that could be time-consuming and even more complicated than the controller design itself [141]. Furthermore, the parameters tuning, choice of the cost function and the reformulation of the optimal control problem are some of the key challenges to be overcome [143].

6) NEURAL NETWORK-PREDICTIVE CONTROL

The neural network-predictive control (NN-PC) is designed using an estimator with ANN block and a dynamic optimizer with MPC block, as shown in Fig. 9 [144]. The operations of the NN-PC scheme start with the optimization of the measured data of a system to evaluate the control signal values [145]. Then, an optimal input signal is examined by reducing a specified performance standard [93]. After that, the first part of the optimal input signal executes until new measurements are accessible [146]. Finally, the control loop is repeated for the following period by a return to the first step [138], [144].

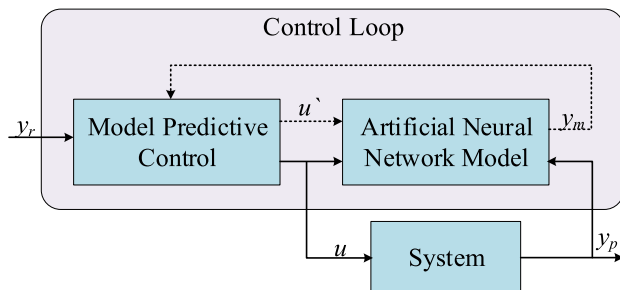


FIGURE 9. The block diagram of NN-MPC.

The idea of utilizing MPC to conserve energy in buildings derives from the principle of supervisory control. With the application of NN-MPC at the supervisory layer, the control objective is formulated to achieve one or more of the following:

- Minimum energy usage [147]–[152],
- Optimum thermal comfort [147], [149], [150], [152],
- Optimum indoor air quality (IAQ) at an acceptable level [153],
- Minimum operating cost [148], [151], [154], [155],
- Optimum visual comfort [152],
- Minimum retrofit cost [156], and
- Minimum thermal discomfort hours [156].
- Minimum operating cost [148], [151], [154], [155],

A comparison of various controllers employed in BEMS with their pros and cons is shown in Table 1.

III. OPTIMIZATION IN BUILDING ENERGY MANAGEMENT SYSTEM

The contributions of optimization in BEMS are significant for enhancing building energy performance [157]. A BEMS with optimization algorithms can perform many operations such as control the appliances by switching OFF or ON, air-conditioner temperature adjustment, refrigerator, electric water heaters, choose when to charge or discharge battery storage system and decide when to buy or sell electricity to the grid [158]. The BEMS is responsible not only to achieve the specific objectives stated above but also to accomplish consumer comfort and preference [147]. Nevertheless, such a situation results in management problems that can conflict with the objectives [159]. For instance, end-use wants to cut down the electricity cost on the condition that the quality of energy services would not be compromised, thus imposing limitations on the control operations [160]. Therefore, the development of a robust optimization algorithm is essential which can deliver the best results while ensuring all the constraints with regard to the electricity expenditures reduction and end-users dissatisfaction minimization [161], [162]. In other words, the objectives of optimization are related to two problems; one is a comfort management problem and the other is scheduling problems that are narrated in the following subsection.

A. OPTIMIZATION OBJECTIVES

The construction of the objective function is important in optimization to obtain the desired performance [163]–[165]. Generally, the objective function is chosen based on the requirements subject to satisfying the constraints of many variables [166], [167]. In BEMS, several things can be optimized [168]–[170]. Different works of literature have used different algorithms/methods to optimize energy management in the building [171]–[174]. Most of the studies focus on either comfort factors or economic factors for the formulation of the objective function [175]–[179]. Other factors include the minimization of the PAR in the load demand or the reduction of the production price [180].

1) COMFORT INDEX PARAMETERS

Researchers have employed many factors to achieve comfort management in buildings, as depicted in Table 2. Some

TABLE 1. Comparative analysis of different control methods used in BEMS.

Control Strategies	Refs.	Strength	Weakness	Purpose	Achievements
Thermostat	[70]	<ul style="list-style-type: none"> Low cost. Simple Operation. 	<ul style="list-style-type: none"> Low thermal conductivity. Low heat capacity. 	<ul style="list-style-type: none"> Peak demand reduction. Electricity cost minimization. User discomfort minimization. 	The cooling electricity price reduces by 30%.
PID	[78]	<ul style="list-style-type: none"> Simple structure. Easy execution. Quick response. Inexpensive. 	<ul style="list-style-type: none"> Inaccurate results if it is not properly tuned. Performance is not satisfactory in noisy and non-linear processes. 	<ul style="list-style-type: none"> Energy savings. Environmental emissions reduction. 	Energy consumption decreases by 87%.
Fuzzy	[109]	<ul style="list-style-type: none"> Reliable, efficient and customizable. Works efficiently in a non-linear system. 	<ul style="list-style-type: none"> It requires lots of data. Needs human expertise. 	<ul style="list-style-type: none"> Energy cost and PAR reduction Scheduling of home appliances. 	The PAR minimizes by 25.45%.
PID-Fuzzy	[116]	<ul style="list-style-type: none"> Fast and robust. Capability to work under a wider range of operating settings. 	<ul style="list-style-type: none"> Requires tuning of the fuzzy membership function. 	<ul style="list-style-type: none"> Air quality and illuminance level improvement. Thermal comfort enhancement. Energy consumption reduction. 	Energy consumption drops by 25-30%.
ANN	[127]	<ul style="list-style-type: none"> Works without detailed information on the system. Ability to detect complex relationships. 	<ul style="list-style-type: none"> It needs a large amount of quality data. It needs a long time for training operations. Needs expensive processing devices. 	<ul style="list-style-type: none"> Thermal comfort enrichment. Energy consumption minimization. 	ANN achieves energy savings by 36.5 %
ANFIS	[182]	<ul style="list-style-type: none"> Has a high degree of tolerance to uncertainty. Good generalization performance. 	<ul style="list-style-type: none"> Low interpretability of learned parameters. Strong computational complexity. 	<ul style="list-style-type: none"> Energy consumption forecasting. 	ANFIS Obtains the correlation coefficient (R ²) above 0.96 in the testing data.
MPC	[139]	<ul style="list-style-type: none"> Has improved transient response. It can control multiple variables within the boundary. Generic consideration of constraints. 	<ul style="list-style-type: none"> High computational load. High algorithm complexity. High number of control parameters. 	<ul style="list-style-type: none"> Electrical photovoltaic energy curtailment. Thermal energy generation with domestic hot water storage and floor heating. 	Operational cost reduces by 11.6 % compared to the PID controller.
NN-MPC	[147]	<ul style="list-style-type: none"> Enhanced steady-state and dynamic performance 	<ul style="list-style-type: none"> Training efforts are usually high which require complex computation in a large scale system. 	<ul style="list-style-type: none"> Energy consumption minimization Thermal comfort maximization. 	Energy savings in HVAC systems is estimated to be more than 50%.

authors have tried to find comfort for thermal, visual, air quality, and sound; others have tried to optimize the temperature, humidity, illumination, airflow, and heat radiation. In [181], the fuzzy-based GA control strategy is proposed to enhance the comfort index, and minimize power consumption. The following equation is used to express the comfort index.

$$comfort = \beta_1 \left[1 - (e_T/T_{set})^2 \right] + \beta_2 \left[1 - (e_L/L_{set})^2 \right] + \beta_3 \left[1 - (e_A/A_{set})^2 \right] \quad (4)$$

where “comfort” presents the overall comfort level ranging from 0 to 1. β_1 , β_2 and β_3 are user-defined comfort; e_T , e_L and e_A are error difference between the actual value and the optimized value with regard to temperature, illumination, and air-quality, respectively; T_{set} , L_{set} , and A_{set} are the user

setting parameters of temperature, illumination, and air-quality, respectively.

In [183], a microgrid demand-side management (DMS) is proposed to control the heating, ventilation, and air conditioning (HVACs) in a building optimally by taking into account occupancy schedule, temperatures and solar radiation forecasts. A multi-objective function is formulated to optimize the energy cost and the thermal comfort, as shown in the following equation,

$$Tot(t) = \sum_{j=1}^N Tot_j(t) = \sum_{j=1}^N (kE_j(t) + (1 - k) C_j(t)) \quad (5)$$

where E_j and C_j are the energy score and thermal score of building j , respectively. k denotes the scaling factor where the range $0 < k < 1$ defines the trade-off between energy and

TABLE 2. Summary of different algorithms focused on optimization objectives related to comfort index parameters.

Refs.	Algorithms/ Method	Optimization objectives – Comfort index parameters								
		Thermal Comfort	Visual Comfort	Air Quality Comfort	Sound Comfort	Temperature	Humidity	Illumination	Air Flow	Heat Radiation/ Flow
[181]	GA, fuzzy controller, Kalman filter	✓	✓	✓	×	✓	×	✓	×	×
[185]	ABC, fuzzy controller	✓	✓	✓	×	✓	×	✓	×	×
[186]	BAT algorithm, Fuzzy controller	✓	✓	✓	×	✓	×	✓	×	×
[187]	GA, ANN	✓	×	×	×	✓	✓	×	✓	✓
[188]	MOPSO, WSM	✓	✓	×	×	✓	×	✓	×	×
[21]	GA, PSO, KF	✓	✓	✓	×	✓	×	✓	×	×
[189]	ANN, Fuzzy controller	✓	×	×	×	✓	×	×	×	×
[190]	NARX neural network, Fuzzy logic	✓	×	×	×	✓	✓	×	✓	×
[191]	DMPC	✓	×	×	×	✓	×	×	×	×
[192]	HMOGA, Fuzzy logic	✓	✓	✓	×	✓	×	✓	×	×
[193]	ERL	✓	×	×	×	✓	×	×	×	×
[194]	Genetic programming, fuzzy logic	✓	✓	✓	×	✓	×	✓	×	×
[195]	MDP	✓	×	×	×	✓	×	×	×	×

WSM: Weighted Sum Method, DMPC: Distributed Model Predictive Control, KF: Kalman filter, ERL: Energy-Plus Runtime Language

comfort. The values $k \rightarrow 0$ and $k \rightarrow 1$ are given importance toward thermal comfort and energy savings, respectively.

In [184], a novel control algorithm is proposed for micro-grids comprising buildings incorporated with renewable energy sources and energy storage units. The objective of the proposed model was to ensure thermal comfort by considering the energy generation and consumption with the occupant behavior. In line with this, scalable and robust demand response programs were designed using a local closed-loop feedback controller to reduce the energy cost and thermal discomfort of the microgrid.

In [185], an improved energy management strategy is developed using a fuzzy-based artificial bee colony (ABC) algorithm to optimize illumination, temperature, and air quality. Likewise, in [186], effective energy management in a residential building is proposed using the BAT algorithm optimizing temperature, illumination, and air quality. After,

FLC computes the dissimilarities between the environmental parameters and optimized parameters to deliver energy to the actuators. In [187], an intelligent energy management and control strategy are introduced based on ANN and GA algorithms to improve the indoor environment quality by optimizing the HVAC system. In [188], a methodology for building optimization energy is designed using a multi-objective particle swarm optimization (MOPSO) method to examine cooling, heating, and lighting electricity consumption. In [21], an improved optimization function is developed using GA, and PSO to maximize user comfort. In [189], a combined neuro-fuzzy model is established to regulate the ON or OFF operation of the HVAC system. In [190], the authors proposed a coupling model using a nonlinear autoregressive with exogenous input (NARX) neural network and fuzzy logic to control the HVAC system. NARX neural

network model considers indoor temperature, outdoor temperature, air relative humidity, and wind speed to develop an indoor temperature forecast in the past state and accordingly fuzzy logic uses the indoor temperature forecast to drive the controller in the present state. In [192], an intelligent multi-objective control system for buildings is proposed using a hybrid multi-objective genetic algorithm (HMOGA) and a fuzzy controller. The results show that the HMOGA achieves the indoor building environment comfort with 8.1% improvement of comfort index. In [195], a multi-agent comfort and energy system (MACES) model is suggested based on Markov decision problems (MDP) considering occupant preferences, occupant schedules, actual thermal zones, and temperature. The comfort results indicate an improvement of 5 % in the proposed model in comparison to other control techniques. In [196], a machine learning model based optimized building energy management scheme is proposed for multi-thermal-zone buildings concerning

HVAC system to reduce energy consumption and electricity cost while achieving human comfort. The objective function to minimize the building energy cost can be written as follows,

$$\begin{aligned}
 &Min \sum_t^{NT} \sum_t^{NZ} p_t^{DAP} \cdot (P_{t,z}^{FL} + P_{t,z}^{DL} + P_{t,z}^{RL}) + \sum_t^{NT} \sum_t^{NZ} p_{t,z}^{dp} \cdot \theta_{t,z} \\
 &+ \sum_t^{NT} \sum_t^{NZ} p_{t,z}^{lp} (E_{t,z}^{light} - E^{best})^2 + \sum_t^{NT} \sum_z^{NZ} p_{t,z}^{ip} \cdot \Delta T_{t,z} \quad (6)
 \end{aligned}$$

where P defines the energy, DAP , FL , DL and RL stand for day-ahead price, fixed load, regulatable load and deferrable load, respectively. E^{light} is the light illuminance, ΔT is the temperature limit, θ is workload parameter, p^{dp} , p^{lp} and

p^p denote overload penalty price, visual penalty price and thermal penalty price, respectively; t, z represent time slot and NZ building thermal zone number, respectively.

In [197], an optimized control strategy for BEMS is proposed to coordinate renewable power generation, battery storage system and HVAC aiming to reduce the peak load demand while satisfying thermal comfort. A MPC was applied to regulate HVAC demand while taking into account renewable generation status, battery state of charge and building thermal dynamics and related constraints. An optimization problem is formulated using the following equations,

$$\min_{P=\{R,C\}} \frac{1}{N} \sum_{k=1}^N \sum_{j=1}^{N_z} (T_{ij}^m(m) - T_{ij}^e(k)) \quad (7)$$

where P is an unknown vector where the values of R and C are determined using data collected from the zone, k, N and N_z denote the time step, number of measurements, number of thermal zones, respectively. T_{ij}^m and T_{ij}^e represent the measured zone air temperature and estimated zone air temperature a time step k , respectively.

In [198], the authors applied the particle swarm optimization (PSO) and internet of things (IoT) platform to zero energy buildings aiming to achieve a comfortable visual environment through the utilization of the natural light while enhancing the indoor air conditioner energy consumption (ACEC). In [199], human comfort including thermal comfort and visual comfort-based control strategy was proposed to reduce the energy consumption in buildings effectively during peak hours. The thermal comfort was evaluated based on six key indicators such as the metabolic rate of the occupant, clothing, relative humidity, mean radiant temperature, indoor air temperature and air velocity. The two key features of the thermal condition including predicted mean vote (PMV) and the predicted percentage of dissatisfied (PPD) can be expressed using the following equations,

$$\begin{aligned} PMV &= [0.303 \exp(-0.036M) + 0.028] L \\ PPD &= 100 - 95 \exp\left(-0.03353PMV^4 - 0.2179PMV^2\right) \end{aligned} \quad (8)$$

where M and L denote the metabolic rate and thermal load of the human body, respectively.

In [200], the authors discussed the influence of low-cost sensing toward efficient energy management and indoor air quality (IAQ) in building highlighting the key challenges and prospects. In [201], the authors focused on the assessment of the IAQ, building energy consumption and changing air flow rate connecting to HVAC systems. The results illustrated a substantial amount of energy saving, indicating 50% reduction in air flow rate resulted in a decrease of 45.2% energy consumption with only slight variations in IAQ.

2) ENERGY CONSUMPTION AND SCHEDULING INDEX PARAMETERS

The minimization of power consumption, energy price, PAR and optimal scheduling considering different electricity tariff rates are the most frequently used objective functions in BEMS, as listed in **Table 3**. In [202], the authors proposed a demand-side management scheme using teacher learning-based optimization (TLBO) and enhanced differential evolution (EDE). The energy cost is calculated using day-ahead pricing, real-time pricing, and critical peak pricing. The results prove that the proposed model outperforms other state-of-the-art schemes with respect to PAR reduction and energy cost. In [203], residential load scheduling is introduced using a hybrid optimization algorithm including GA and binary PSO (BPSO). The developed model is evaluated using day-ahead and critical time pricing reflecting a significant reduction in energy price while maintaining minimum user discomfort. In [204], a HEMS is established based on GA, crow search algorithm (CSA) and cuckoo search optimization algorithm (CSOA) considering real-time pricing and critical time pricing. The proposed model demonstrates effectiveness in achieving electricity bills and PAR reduction. In [205], efficient energy management for the residential area is suggested using flower pollination algorithm (FPA) and bacterial foraging optimization algorithm (BFOA). The results indicate an alleviation in energy cost and PAR. In [206], an optimized HEMS combined with renewable RES and energy storage system (ESS) is proposed based on GA, bacterial foraging optimization (BFO), wind-driven optimization (WDO), BPSO, and hybrid GA-PSO (HGPO) algorithms. The report illustrated that a reduction of 19.94% and 21.55% was noted in energy bills and PAR respectively with the combination of RES and ESS. In [207], various machine learning models were used including decision trees, Gaussian naive Bayes and K-Neighbors to analyze the building energy efficiency. Besides, the performance of different classifiers is compared and analyzed. In [208], a novel methodology was developed to evaluate the performance of buildings based on an interpretable machine learning model. In [209], a support vector machine (SVM) was utilized to predict the building energy consumption using various inputs such as global solar radiation, temperature relative humidity and household consumption level. In [210], a feed-forward multilayer perceptron (MLP) neural network was employed to forecast the maximum and minimum points in the estimated demand profile in buildings. In [211], a deep learning algorithm was applied to predict the building energy consumption under different time resolution and time horizons. In [212], the authors introduced reinforcement learning to improve energy efficiency of buildings, indicating 10% energy savings in HVAC applications and 20% savings for water heaters.

In [213], the grid integrated solar photovoltaic (PV) based microgrid energy management system (EMS) is designed consisting of buildings with diverse occupancy patterns. A multi-objective optimization-based EMS was developed

TABLE 3. Summary of different algorithms focused on optimization objectives related to energy consumption and scheduling.

Refs.	Algorithms/ Method	Optimization objectives – Comfort index parameters								
		Thermal Comfort	Visual Comfort	Air Quality Comfort	Sound Comfort	Temperature	Humidity	Illumination	Air Flow	Heat Radiation/ Flow
[181]	GA, fuzzy controller, Kalman filter	✓	✓	✓	×	✓	×	✓	×	×
[185]	ABC, fuzzy controller	✓	✓	✓	×	✓	×	✓	×	×
[186]	BAT algorithm, Fuzzy controller	✓	✓	✓	×	✓	×	✓	×	×
[187]	GA, ANN	✓	×	×	×	✓	✓	×	✓	✓
[188]	MOPSO, WSM	✓	✓	×	×	✓	×	✓	×	×
[21]	GA, PSO, KF	✓	✓	✓	×	✓	×	✓	×	×
[189]	ANN, Fuzzy controller	✓	×	×	×	✓	×	×	×	×
[190]	NARX neural network, Fuzzy logic	✓	×	×	×	✓	✓	×	✓	×
[191]	DMPC	✓	×	×	×	✓	×	×	×	×
[192]	HMOGA, Fuzzy logic	✓	✓	✓	×	✓	×	✓	×	×
[193]	ERL	✓	×	×	×	✓	×	×	×	×
[194]	Genetic programming, fuzzy logic	✓	✓	✓	×	✓	×	✓	×	×
[195]	MDP	✓	×	×	×	✓	×	×	×	×

AFSO: Artificial Fish Swarm Optimization, DSM: Demand-side management, MILP: Mixed Integer Linear Programming, RNN: Recurrent Neural network, SVM: Support Vector Regression, RBF: Radial Basis Function, RFR: Random Forest Regression, EOA: Earthworm Optimization Algorithm, EA: Earliglow Algorithm, BPNN: Back Propagation Neural Network, HSA: Harmony Search Algorithm, TLBO: Teacher Learning Based Optimization

to optimize the energy cost and thermal comfort by considering intermittent characteristics of solar PV and occupancy scheduling. The case study developed in EnergyPlus proved the effectiveness of the proposed method with regard to changing energy demand intelligently and automatically using occupants’ information and behavior.

In [214], an effective HEMS through power scheduling for the smart home is designed using earliglow algorithm (EA). The results demonstrate that the proposed model reduces electricity price by 43.25% and 13.83% under the critical peak pricing and time of use market prices, respectively. The objective function is developed using electricity cost and energy consumption as expressed in the following equations,

$$Minimize \sum_{a=1}^N \sum_{t=1}^T (X_{a,t}^{app} (t) \times \wp \times E_{a,t}^{Price}) \quad (9)$$

$$P^{consumption} \sum_{t=1}^T \sum_{a=1}^N \wp \times X_{a,t}^{app} (t) \quad (10)$$

where $X_{a,t}^{app}$ denotes for the state of the load as OFF or ON (0 = OFF and 1 = ON), \wp denotes the power rating of the individual load, presents the electricity bill at any time duration t , a denotes the total number of loads in a household, and $P^{consumption}$ denotes the shiftable and non-shiftable load energy consumption.

In [215], An optimized home energy management controller is developed using a genetic harmony search algorithm (GHSA) aiming decrease electricity price and average waiting time. Two tariffs, namely real-time pricing and critical time pricing are employed to examine PAR and electricity expenses. The objective function can be expressed using the

following equations,

$$Cost_T = \frac{\sum_{t=1}^T \sum_{a_i}^{An} \varepsilon (t) \times \zeta a_i (t) \times \zeta (t)}{\left(\sum_{t=1}^T \sum_{a_i}^{An} \zeta a_i (t) \times \varepsilon (t) \times \zeta (t) \right)_{max}} \quad (11)$$

$$W_T = \frac{\sum_{t=1}^T W_{avg} (t)}{\left(\sum_{t=1}^T W_{avg} (t) \right)_{max}} \quad (12)$$

$$Minimize \omega_1 (Cost_T) + \omega_2 (W_T) \quad (13)$$

where $\varepsilon (t)$ is the electricity tariff at time interval t ; $\zeta a_i (t)$ is the energy consumed by the appliances at time interval t . The first term of Eq. (13) represents the minimization of cost and the second term denotes the average waiting time of the load. Two equal weights, ω_1 and ω_2 are assigned to both terms of the objective function amounting to 0.5.

In [216], an optimal energy trading in building microgrid is proposed integrating the optimization of electric vehicles and batteries in the day-ahead electricity market aiming to maximize the profit, reduce the power demand and decrease the renewable energy curtailment during peak hours. In [217], an optimization-based scheduling and bidding strategy for day-ahead bi-directional electricity trading in BEMS is introduced achieving optimal operation of building loads and distributed energy resources as well as a considerable reduction in energy cost and user inconveniences. In [218], a SynergyChain model-based decentralized and blockchain-assisted Peer-to-Peer (P2P) energy trading model is suggested

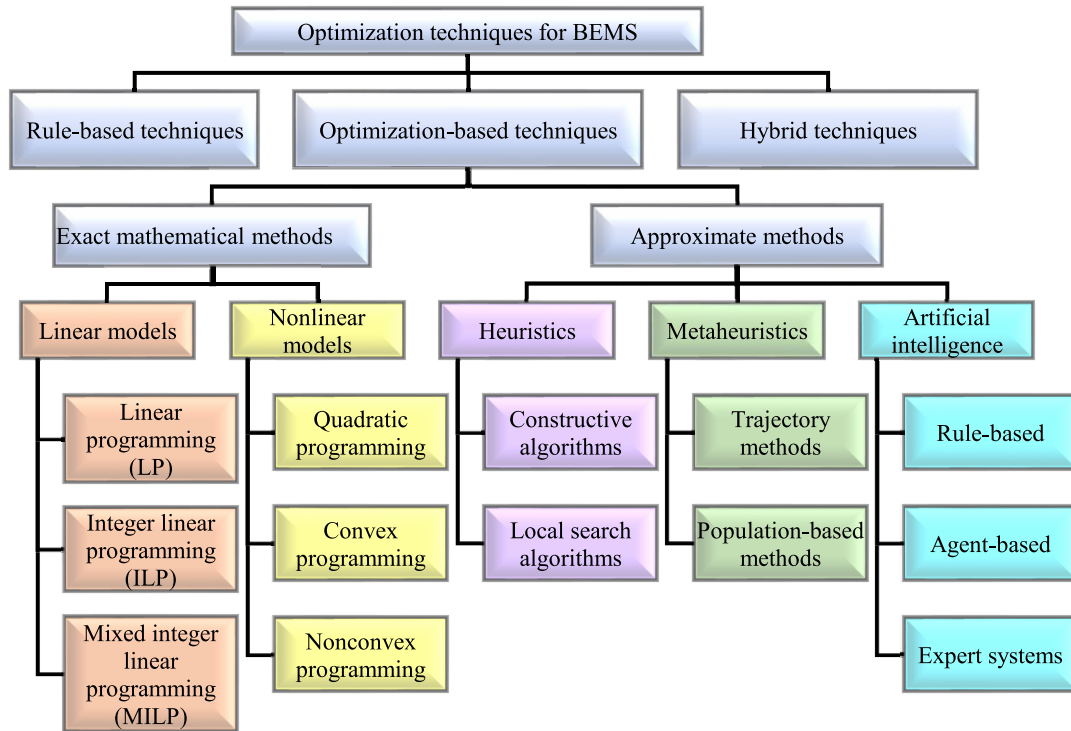


FIGURE 10. Optimization techniques for BEMS.

resulting in 39.7% improvement in energy consumption performance and 18.3% enhancement in the overall profitability of the system. In [219], blockchain-based distributed energy-trading models and smart contracts are proposed to provide a secure transaction for P2P energy trading and promote energy conservation integrated with renewable and edge energy products.

B. OPTIMIZATION CONSTRAINTS

The constraints are chosen to impose the limit of variables of any system so that updated values or positions always locate inside the boundary region while the optimization algorithm tries to achieve the desired objective function [220]–[222]. Commonly, the constraints are assigned to the maximum or minimum bounds of variables. For instance, in BEMS, constraints with respect to user comfort are generally allocated to maximum or minimum margins of temperature [223], [224]. In [225], the authors consigned temperature and peak power constraints to maximize user comfort in a building power management scheme. In [226], the authors selected the battery and scheduling constraints to minimize the daily electricity expenses. Besides, user preference constraint, energy requirement constraint and timing constraint are grouped in [227] for scheduling optimization of a smart home appliance. Energy constraint is defined in such a way so that load demand does not exceed the pre-defined limit [228], [229]. Timing constraints, on the other hand, are put to ensure uninterrupted operation, sequential processing or operation according to user time preferences.

In [180], the power consumed by the mixture of real-time and scheduled appliances is taken as constraints to be held lower than a target value at any time frame to ensure that demand does not rise considerably in peak hours

IV. OPTIMIZATION ALGORITHMS

Several research works have been carried out on different optimization algorithms for BEMS, as shown in Fig. 10. The metaheuristics optimization algorithms have strong points in terms of low memory and flexible time requirements in comparison to other algorithms [230]. Thus, these algorithms have been widely used in BEMS optimization.

A. METAHEURISTICS OPTIMIZATION ALGORITHMS

The metaheuristic optimization algorithm is based on the procedure of randomization and local search, which leads to the optimization and path of global search [231]. The classification of metaheuristics optimization algorithms implemented for BEMS is shown in Fig. 11. Single individual algorithms only evaluate one potential solution at a time, while the population-based algorithms can deliver a set of potential solutions simultaneously to move toward goals [232].

1) SINGLE INDIVIDUAL ALGORITHMS

a: SIMULATED ANNEALING

Simulated annealing (SA) is a famous heuristic optimization technique, which is inspired by metallurgy annealing. In SA, the crystalline solid is iteratively heated and cooled down slowly until it achieves its minimum lattice energy state [233].

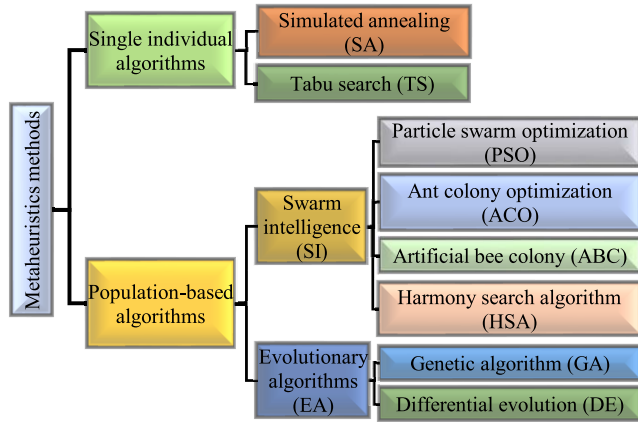


FIGURE 11. Metaheuristics optimization techniques implemented in BEMS.

Likewise, the SA algorithm produces a new potential solution to the problem according to a predefined criterion at each virtual annealing temperature [234]. The approval of the new state is then based on the fulfillment of the metropolis criterion, and this process is repeated until convergence takes place [233], [235]. A common flow diagram of SA is shown in Fig. 12 [236]. SA is applied in BEMS optimizing electricity costs and user satisfaction [237]. Furthermore, SA is applied in optimal energy management [238], thermal building optimization [239] and utility bill calibration [170].

b: TABU SEARCH

Tabu search (TS) concentrates on the local exploration of search space to achieve the optimal solutions iteratively. TS exhibits memory adaption, which supports to obtain the searching approach in a flexible way from the search space. The first move of TS comes from the initial position that finds the best neighborhood and assists to search for the optimal solution. The located neighbors either are present in the tabu list or absent from the list but hold true to fulfill the conditions. On these terms, if TS is incapable to obtain a better result, the different approaches are utilized to discover more search spaces. The aforementioned steps are continued until a stopping condition is satisfied [240]. In [241], TS is employed to develop a home energy management controller aiming to lessen appliances’ power consumption, PAR while satisfying user comfort level.

2) POPULATION-BASED ALGORITHMS

The population-based algorithm stores the entire set of solutions, where each solution is corresponding to a distinct point within the search space being repeatedly updated and moved toward a near-optimal solution [242]. Population-based methods are widely employed to address the wide range of optimization problems in BEMS.

a: PARTICLE SWARM OPTIMIZATION

Particle swarm optimization (PSO) algorithm is a well-known population-based optimization technique which uses

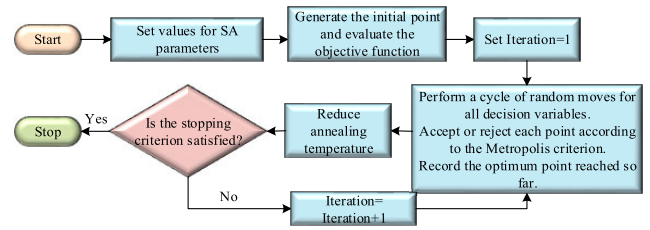


FIGURE 12. Flowchart of SA algorithm.

the characteristics and movement of a group of bird or fish to search for food [26]. In stochastic optimization, the PSO method identifies the optimal solution to a formulated problem through an iterative process. An objective function is defined to evaluate the random number of particles in the problem search space at their present locations [243]. The best results are achieved through the updated velocity and position of particles which can be formulated as follows [206]:

$$V_i^{k+1} = w V_i^k + c_1 r_1 (P_{Pbest,i}^k - X_i^k) + c_2 r_2 (G_{best} - X_i^k) \tag{14}$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{15}$$

where V_i^{k+1} is the updated velocity vector of the i^{th} particle, X_i^{k+1} is the updated position of the i^{th} particle, r_1 and r_2 denote two random numbers in the range [0,1], c_1 and c_2 are the learning factors and w refers to inertia or momentum weight factor. $P_{Pbest,i}$ is the best previous experience of i^{th} particle that is recorded and G_{best} is the best particle among the entire population. The execution process of PSO is illustrated in Fig. 13. [188].

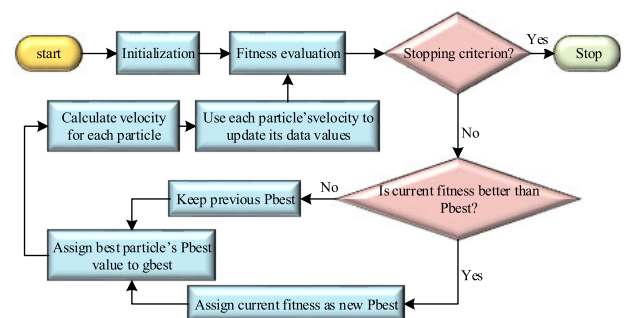


FIGURE 13. Flowchart of PSO algorithm.

The PSO method is used in BEMS to optimize energy prices, energy transfer to the utility grid, and user comfort level [244]. PSO is also used in the energy management of a residential building with a target to avoid peak formations while focusing on reducing electricity bills and maintaining user satisfaction levels [245]. Similarly, the authors employed PSO to reduce the energy consumption and electricity cost of a sustainable building while maintaining user comfort at a high potential value [246].

b: ANT COLONY OPTIMIZATION

Ant colony optimization (ACO) is developed using the behavior of an ant in a path that is formed using the deposition of pheromones by the previous ants [247]. The ants use the pheromone deposition for communication as well as for the identification of the most followed path which often leads to the optimal solution. However, the amount of pheromone relies on the travel length and individual cost which suggests that lower cost is associated with the shortest path (near-optimal path) and the greater quantity of pheromone traces [248]. ACO is superior with regard to the enhanced convergence in comparison to GA, PSO, and SA methods [249]. The overall process of ACO is illustrated in Fig. 14 [236].

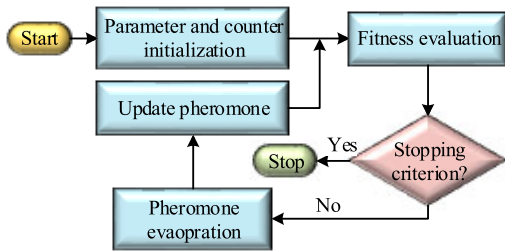


FIGURE 14. Flowchart of a typical ACO algorithm.

c: ARTIFICIAL BEE COLONY

The principle of an artificial bee colony (ABC) is based on the natural foraging act of honey bees [250]. The implementation process of the ABC algorithm is illustrated in Fig. 15 [251]. The ABC is more advantageous than other optimization methods with respect to simplicity, and flexibility, and robustness. Moreover, ABC requires a few control parameters and can be integrated with other optimization techniques to develop a hybrid system [252].

The ABC optimization method is used in [253] to execute the DR schemes integrated with renewable energy sources for residential buildings. In [185], the authors combined the fuzzy logic and ABC algorithm to improve user satisfaction, thermal illumination while reducing energy cost and CO₂ concentration. In [252], an effective energy management and control system are developed with ABC algorithm for a residential building to enhance energy efficiency and user comfort.

d: HARMONY SEARCH ALGORITHM

The fundamental of harmony search algorithm (HSA) is based on reproducing the music improvisation process, where a perfect state of harmony is searched by the musicians with their instrument pitches [254]. Three corresponding components need to be formalized to get an optimal result, one is the memory allocation of harmony, and the other is the randomization and adjustment of pitch. It is similar to the steps of improvisation of a skilled musician, plays any famous piece of music, then plays something similar to a known music piece and accordingly composes new or random notes.

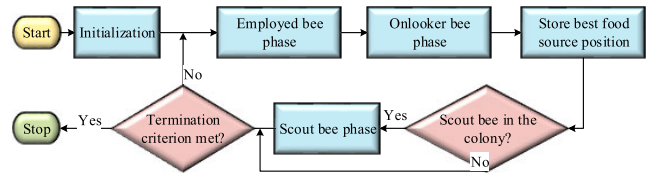


FIGURE 15. Flowchart of a typical ABC algorithm.

With this process, harmonic checking is performed to ensure a better solution [255], [256]. The implementation process of the HSA is shown in Fig. 16 [257].

HSA is used in [258] for appliances scheduling in a smart home aiming at achieving four objectives: cost saving, PAR reduction, waiting time minimization, and consumer comfort maximization. The HSA is also utilized in [259] for scheduling energy storage systems in renewable energy, in which time of use is in conjunction with the demand charge policy to assess the electricity expenditures. In the mentioned study, the authors compared HSA with GA and concluded that the proposed technique performed better than GA.

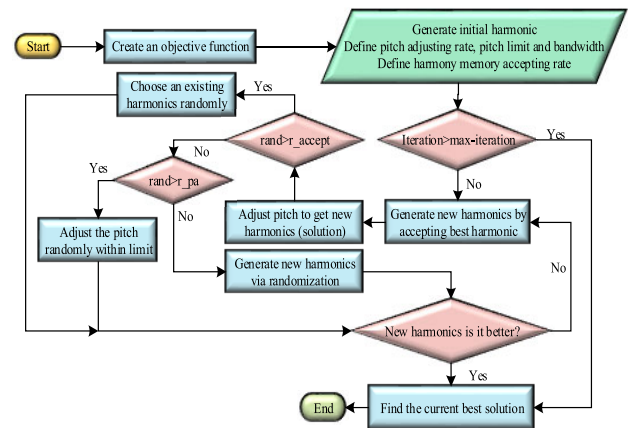


FIGURE 16. The basic structure of the HS algorithm.

3) EVOLUTIONARY ALGORITHMS

An evolutionary algorithm (EA) is based on the mechanisms that are inspired by the social behavior of species or biological evolution such as reproduction, mutation, recombination, and selection [260]. The EA uses the stochastic search procedures to reach the near-optimum solutions to large-scale optimization problems, for which the conventional metaheuristic algorithms may not deliver satisfactory outcomes.

a: GENETIC ALGORITHM

Genetic Algorithm (GA) is another notable intelligence-based optimization technique employed in BEMS. The implementation process of GA is illustrated in Fig. 17 [261].

First, GA uses a set of the randomly generated population called chromosomes to search for the best solution. The solutions are ranked based on the assessment of objective function. Then, the population advances through many operational stages including, reproduction, crossover, and mutation

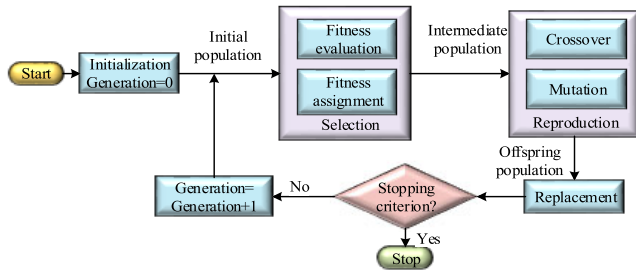


FIGURE 17. Flow chart for a typical GA optimization.

to upgrade the objective function and accordingly achieve the final best solution. These procedures continue until either the best offspring are not discovered or the condition of termination is fulfilled [262]. The strength of GA is that it can offer multiple solutions to problems, and can be easily executed in the simulation model [263]. However, GA has drawbacks in addressing multi-objective optimization problems accurately. Besides, GA has some weak points such as slow optimization response time and poor convergence due to the movement towards local optima rather than the global optimum of the problem [263].

Authors in [264]–[266] applied the GA method in BEMS for optimizing operating hours of appliances concerning electricity costs minimization, carbon emission reduction, power limits, and user preferences. In [138], GA is introduced to optimize the NN-PC controller effectively for thermal energy storage in the district cooling system. The superiority of GA over PSO and ACO in developing an energy management controller is reported in [245], showing an improved performance in terms of user comfort level maximization, electricity cost, and PAR minimization.

b: DIFFERENTIAL EVOLUTION

The differential evolution (DE) is introduced as a powerful tool associated with the evolutionary process to address non-linear optimization problems. After the population initialization followed by algorithm parameters, the weighted difference vector among the last two members of the previous population is used to generate the new population. Finally, the optimization solution is achieved through the mutation and crossover process. The DE procedure is shown in Fig. 18 [267].

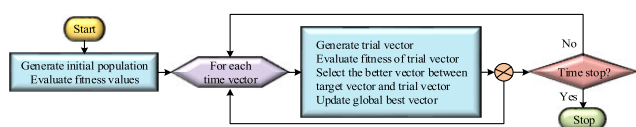


FIGURE 18. Flow chart for a typical DE algorithm.

DE algorithm is used in [268] to lower the power consumption and electricity cost. An enhanced DE is developed in [269], and its performance is compared to the HSA showing a better performance in terms of energy cost reduction.

c: OTHER ALGORITHMS

In addition to the optimization algorithms mentioned above, the literature shows that BEMS can be designed using other prominent optimization methods. Algorithms such as mixed integer programming algorithm (MIPA), integer programming, and dynamic programming are capable of managing energy efficiently, however, have drawbacks to control a large number of appliances [270]. These techniques also have demerits in dealing with multi-objective problems and their implementation in real-time due to their deterministic nature [271]. In [109], the bat algorithm (BAT) is integrated with the flower pollination (FP) algorithm to develop a new optimization algorithm named the BAT pollination algorithm. The developed algorithm is applied for scheduling home appliances to attain a considerable amount of reduced energy consumption, energy cost, and PAR. A building comfort management system based on mixed-integer quadratic optimization (MIQO) is proposed in [270]. In [271], a hybrid optimization algorithm including HSA and EDE is developed and applied for BEMS in the smart grid. The results indicate that the proposed method outperforms HSA and EDE with regard to cost and PAR. The detailed summary of each optimization algorithms with its positives and negatives is illustrated in Table 4.

V. BEMS TOWARD ACHIEVING SUSTAINABLE DEVELOPMENT GOALS

In 2015, the United Nations (UN) has presented 17 SDGs aiming to offer a common vision to have a proper life and peaceful environment for the planet and people [272]. We have found that BEMS affects three areas of sustainability including social, economic, and environment which have a strong relationship with 7 out of 17 SDGs, as shown in Table 5 and Fig. 19. We have explored several relevant studies to validate the relationship between BEMS and the target of SDGs. For instance, BEMS can provide thermal comfort [181], visual comfort [185], air quality comfort [186], temperature control [193], humidity control [190], lighting control [273], heat radiation [187] which can ensure good health and well-being that is linked to the target of SDG 3.9. Besides, BEMS can contribute to sustainable urbanization through the efficient operation of energy [274], [275] which is associated with the target of SDG 11.3. Moreover, BEMS can offer cost-effective energy supply [202], reduction of power consumption [276] through adopting energy optimization [277], optimal scheduling [278], reduction of PAR [215], energy efficiency [279], [280] and renewable energy generation [281], [282] that can be related to the target of SDG 7.1, 7.2 and 7.3. Also, manufacturing of the various components of BEMS including smart meter, sensing devices, smart appliances, the controller can create employment opportunities, thus linking to the target of SDG 8.3 [283]–[286]. BEMS can act as a sustainable model to promote economic growth [287]–[289] which can be linked to the target of SDG 9.1. The effective utilization of energy between supply and load can be achieved through the implementation

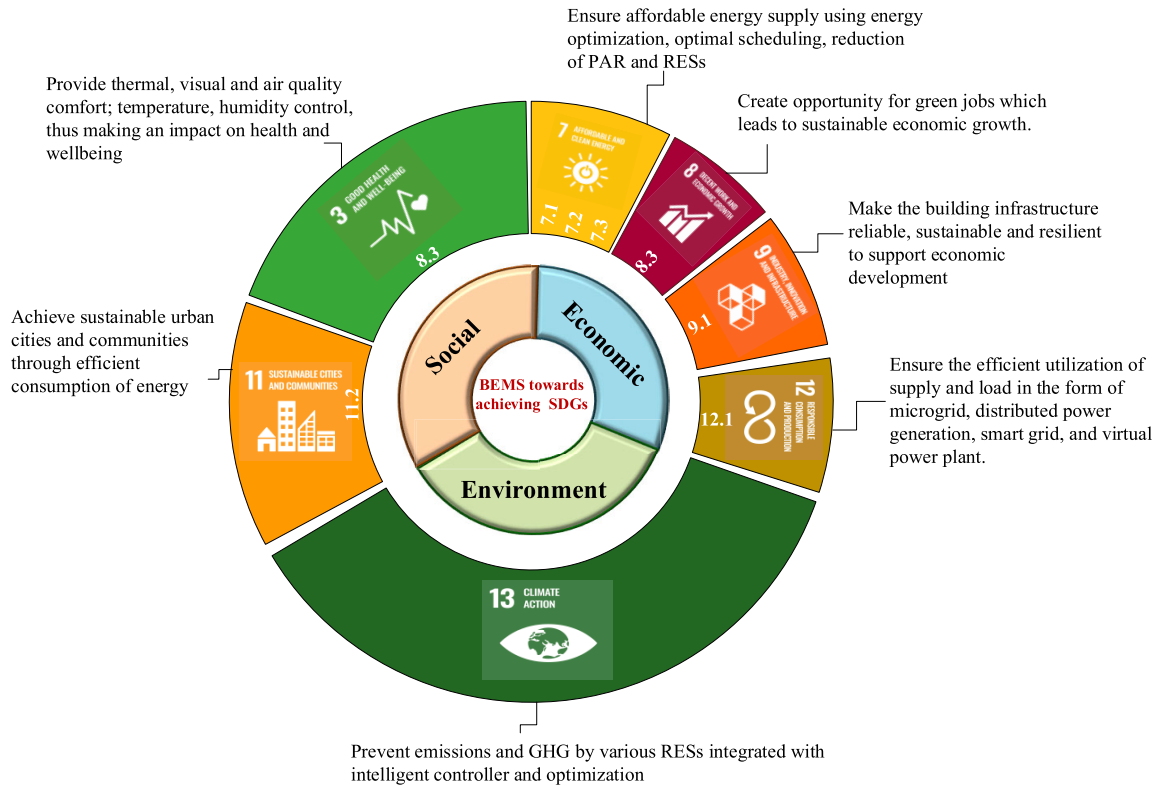


FIGURE 19. BEMS links to sustainable development objectives.

of microgrid [290], distributed power generation [291], smart grid [292], and virtual power plant [293] which is related to the target of SDG 12.1. Apart from social and economic insight, BEMS can also contribute to addressing negative environmental impacts that are linked to climate action in SDG 13. For instance, in [294], BEMS plays a vital role in reducing CO₂ emissions by 13 % through scheduling and peak shifting. A work in [295] also reveals that CO₂ emissions can be dropped by approximately 72%–78% by 2050 from the building sector by combining energy efficiency measures, electrification, and high renewable energy penetration.

Overall, the analyzed results show that the intelligent controllers and optimization algorithms of BEMS can achieve the SDGs efficiently related to cost reduction, CO₂ emission, and GHG reduction, reduce energy consumption, sustainable energy management, opening jobs, and ensure efficient energy utilization and production which contribute towards achieving the 7 out of the 17 SDGs as illustrated in Fig. 20. Thus, this study can increase the effort towards achieving SDG-2030 by controlling and optimizing the building energy consumption, therefore contributing to social benefits, economic growth and environmental protection.

VI. DISCUSSION, CHALLENGES AND PROSPECTS

With the movement towards enhancing the energy cost, thermal and visual comfort, the complexity in BEMS is more prominent than before. For achieving the desired performance, the control and optimization algorithms are

designed while taking into account all the constraints. The controllers can be constructed using different models such as energy tariff forecast models, weather forecast models and electrical appliances load profile models. Nevertheless, the model development needs laborious efforts and may not be accurate due to the unpredictable characteristics of different variables which results in poor performance in control operation. Hence, the existing control methods fail to deliver satisfactory solutions concerning occupant comfort and energy consumption.

The review has discussed various control strategies toward efficient energy management in buildings. The conventional controller like thermostat controller has low cost and simple operation but it has low heat capacity and thermal conductivity. PID controller is cost-effective and has easy execution, simple structure and quick response, however, it cannot deliver accurate results if PID parameters are not tuned properly. In contrast, intelligent control methods have become increasingly popular in controlling energy consumption and comfort management effectively in BEMS which result in significant energy cost reduction. However, they have some drawbacks. For instance, the fuzzy controller is efficient, customizable and works efficiently in a non-linear system, nevertheless it requires lots of data and human expertise. The PID-Fuzzy controller is robust and can operate under changing operational settings, nonetheless, it needs accurate tuning of the fuzzy membership function. ANN controller utilizes a self-learning algorithm for tuning parameters automatically that significantly reduces time and human effort to design an

TABLE 4. Comparative analysis of the commonly used optimization approaches in BEMS.

Optimization techniques	Objectives	Benefits	Drawbacks	Contributions	Ref.
SA	Energy management optimization.	<ul style="list-style-type: none"> It can incorporate many cost functions. Achieves global optimal solutions. 	<ul style="list-style-type: none"> Very sensitive to input parameters. Takes a long time to find a near-optimal solution. 	SA requires less computational efforts to estimate global optimum, indicating an optimization error of 0.03%.	[238]
TS	Energy consumption, PAR and comfort level optimization.	<ul style="list-style-type: none"> Flexible and fast convergence speed. Delivers good quality solutions. 	<ul style="list-style-type: none"> The result can be trapped in a local minimum in some cases. 	TS is efficient with respect to load curtailment, electricity expenses, PAR and waiting time.	[241]
PSO	Power and comfort level optimization.	<ul style="list-style-type: none"> Requires fewer parameters to adjust. Simple execution. High efficiency and fast convergence speed. 	<ul style="list-style-type: none"> Can converge prematurely. Hard to define the initial design parameters. 	PSO offers economic and comfort benefits when buildings are under the grid-connected and islanded operational stage.	[247]
ACO	Energy consumption optimization.	<ul style="list-style-type: none"> Has guaranteed convergence. Adaptability to changes in new solutions. 	<ul style="list-style-type: none"> Has a complex theoretical study. Convergence duration is uncertain. Probability distribution changes by iteration. 	ACO saves electricity costs by 11.4 %.	[248]
ABC	Energy efficiency and the users comfort optimization.	<ul style="list-style-type: none"> Needs a few control parameters. Has a strong global search ability. Has both exploration and exploitation capability. 	<ul style="list-style-type: none"> Search space is limited by initial solutions. 	ABC is dominant to PSO and GA in achieving the minimum value of the comfort index.	[252]
HSA	Renewable power-based energy storage charge scheduling optimization.	<ul style="list-style-type: none"> It needs less adjustable parameters. Easy execution. Fast convergence. 	<ul style="list-style-type: none"> Poor exploration in early iterations. Premature convergence. 	HSA is superior to GA under demand charge policy and time-of-use pricing scheme.	[261]
GA	Electricity bill and the end-user comfort optimization.	<ul style="list-style-type: none"> Easy implementation. Performs a parallel search into multiple regions. 	<ul style="list-style-type: none"> Slow convergence speed. It cannot always deliver satisfactory solutions. 	GA reduces the energy cost below 25% compared to the reference case.	[268]
DE	Energy consumption optimization.	<ul style="list-style-type: none"> Needs fewer parameter settings. Ability to handle multidimensional complex problems. 	<ul style="list-style-type: none"> Poor convergence. Can be easily dropped into local optimum. 	DE minimizes PAR by 38.41 %.	[271]




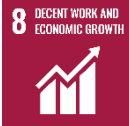



efficient BEMS. However, the ANN controller needs a long training duration and a large memory device for data storage. The ANFIS controller has good generalization performance and a high degree of tolerance to uncertainty, however, it has computational complexity issues and low interpretability of learned parameters. The MPC can control multiple variables within the boundary and has improved transient response, but it has a high number of control parameters and a high computational burden. The NN-MPC has improved steady-state and dynamic performance, nonetheless, it has complex computation in a large-scale system.

The optimization algorithms have been successful in addressing building optimization problems. However, the choice of an appropriate optimization algorithm in BEMS is an open issue to be investigated. SA can incorporate many cost functions and achieve global optimal solutions; however, it is sensitive to input parameters and takes a long time to find a near-optimal solution. TS has fast convergence speed but it has a local minimum trapping issue. PSO has simple

execution with fewer parameters adjustment and archives high efficiency and fast convergence speed, nevertheless, it can converge prematurely. ACO provides guaranteed convergence and has the adaptability to changes in new solutions, nonetheless, it has uncertain convergence duration and has a complex theoretical study. ABC has a strong global search ability but the search space is limited by initial solutions. HSA has an easy operation process and requires less adjustable parameters; however, it has premature convergence and poor exploration in early iterations. GA has an easy implementation, but it has shortcomings of slow convergence speed. DE requires fewer parameter settings and can handle multidimensional complex problems, nevertheless, it has drawbacks of poor convergence and local minima trapping issue.

In the context of the above discussions, an effective approach needs to be developed not only to address the shortcomings aforementioned but also to act effectively in multi-task control in BEMS for minimizing energy consumption and maximizing indoor environment quality (IEQ).

TABLE 5. The relationship between SDGs and BEMS.

Domain	SDG	Target	BEMS towards achieving SDGs	Existing studies to validate the relationship
Social	 SDG 3: Good health and well-being	3.9: Minimize diseases caused by pollution	<ul style="list-style-type: none"> The smart building incorporated with intelligent controller and optimization provides additional features, such as, enhanced thermal, visual comfort and temperature, humidity control and improved illumination which have a positive influence on health and wellbeing. A smart building can reduce substantial energy consumption and accordingly lessen emissions and pollution from buildings, thus improving the air quality and ensuring a healthy life of city inhabitants. 	[88–91,94,95, 98,162]
	 SDG 11: Sustainable cities and communities	11.3: Enhance inclusive and sustainable urbanization and management.	<ul style="list-style-type: none"> The concept, design, and technology of BEMS can be used to make sustainable urban cities and communities through efficient consumption of energy. 	[276], [277]
	 SDG 7: Affordable and clean energy	7.1: Ensure universal access to affordable, reliable and modern energy services 7.2: Increase substantially the share of renewable energy in the global energy mix 7.3: Global rate of improvement in energy efficiency	<ul style="list-style-type: none"> Affordable energy and the reduction of power consumption can be achieved with the implementation of different effective actions such as energy optimization, optimal scheduling, reduction of PAR which are associated with intelligent controller and optimization used in BEMS. BEMS can be integrated with various RESs that has proven to become more cost-effective than fossil fuel alternatives. A smart building can deliver efficient, sustainable and modern energy with the deployment of demand response, energy efficiency, energy storage, and distributed generation. 	[100,106,110, 112,113,165–168]
Economic	 SDG 8: Decent work and economic growth	8.3: Promote development-oriented policies that support productive activities, decent job creation.	<ul style="list-style-type: none"> The demand for smart building advances increasingly, and accordingly, the manufacture of various components of BEMS requires a lot of workforces, hence providing an opportunity for green jobs which leads to sustainable economic growth. 	[285]–[288]
	 SDG 9: Industry, Innovation, and Infrastructure	9.1: Develop quality, reliable, sustainable and resilient infrastructure to support economic development	<ul style="list-style-type: none"> The optimization and controller used in BEMS make the building infrastructure sustainable, resilient and adaptable in varying global climate conditions that promote economic progress. 	[289]–[291]
	 SDG 12: Responsible consumption and production	12.1: Implement a framework of programs on sustainable consumption and production.	<ul style="list-style-type: none"> The energy management in a smart building with appropriate controller and optimization confirms the effective utilization of supply and load, in the form of microgrid, distributed power generation, smart grid, and virtual power plant. 	[292]–[295]
Environment	 SDG 13: Climate action	13: Take immediate measures to address the effects of climate change.	<ul style="list-style-type: none"> The impact of carbon emissions and climate change can be mitigated using various RES integrated with the intelligent controllers in BEMS. The carbon emission can also be combated with the implementation of energy optimization techniques in BEMS in order to achieve optimal scheduling and reduced power consumption. 	[296]

In line with this, the review provides some useful suggestions in developing an efficient controller and optimization towards achieving sustainable building energy management, such as,

- A new control approach can be introduced by merging both conventional and advanced control methods in two possible ways. The first way could be to combine the

individual merits, and the second way could be to overlap the analogies.

- A new control strategy for advanced HVAC systems like a dedicated outdoor air system (DOAS) can be developed to achieve better performance in BEMS.
- More exploration is required to design model-independent control strategies in BEMS concerning model matching and parameter tuning.
- Further studies should be conducted on-air changing rate and indoor air pollutant levels in IEQ management for improving the energy efficiency of BEMS.
- Further examinations are required on IEQ control algorithm considering the occupancy level and variation of the air-conditioned zone.
- An in-depth investigation is required to obtain an accurate control response from an intelligent approach focusing on human behavior and occupant comfort.
- An advanced control process can be developed without the involvement of users with distinct information and experience.
- The performance of the IEQ could be enhanced with the self-learning and modifying capability using the closed-loop, and real-time learning skill.

VII. CONCLUSION

In recent decades, many research works concentrate on improving building energy performance, technology, control, cost, thermal comfort, and their impact on carbon emissions. The appropriate controller and optimization strategies can ensure the sustainable, resilient, and economic operation of building energy systems. Nevertheless, intelligent reasoning and coordination of control techniques, optimizing building energy, comfort management, including comfort demands, satisfaction, and behavior remain key challenges to achieve the desired goal. The impact of building energy management optimization on SDGs also needs to be evaluated because SDGs address global challenges related to a prosperous life, infrastructure, economic sustainability, employment, affordable cost, and climate. However, the countries with their different policies and reluctance approach towards SDGs are the main barriers to improving the existing scenarios.

This review presents detailed information and analysis of intelligent controllers and optimization in BEMS toward sustainable development. As a first contribution, the review comprehensively analyses the various controller schemes in BEMS, given importance to peak demand reduction, user discomfort minimization, energy cost and PAR reduction, environmental emissions decrease and scheduling of home appliances. Both conventional and intelligent controllers are outlined in terms of classification, characteristics, structure, advantages and disadvantages. The review reveals that intelligent controllers including fuzzy, fuzzy-PID, ANN, ANFIS, MPC and NN-MPC are more effective than the conventional controller in terms of accuracy, robustness, good generalization performance, enhanced transient response, improved steady-state and dynamic performance.

As a second contribution, this review delivers a detailed insight into various optimizations in BEMS concerning comfort objectives including thermal comfort, visual comfort, sound comfort, temperature, humidity, illumination and air-flow control. In line with these, various energy consumption objectives are presented highlighting energy optimization, appliances power consumption, optimal scheduling and cost reduction. This review also delivers the classification of optimization algorithms in BEMS denoting single individual algorithms and population-based algorithms. The various swarm intelligence and evolutionary algorithms are discussed with regard to methodological framework, execution processes, constraints, benefits and shortcomings. As a third contribution, this review investigates the key barriers and limitations of the existing building control schemes and optimizations related to computational complexity, implementation process, convergence speed and exploration capability. As a fourth contribution, the study reveals the strong connection of the 7 (out of 17) sustainable development objectives with the BEMS. The review discusses the significant role of BEMS in achieving the current global challenges including reliable and affordable energy, energy efficiency, emission reduction, green jobs, economic growth, and sustainable cities in connection with the target of SDGs.

The key information, results, analysis and suggestions obtained from this review could play remarkable roles in developing and executing advanced controllers and optimization in BEMS. Besides, this review can provide comprehensive knowledge and information to the academician, researchers and building engineers on various controllers and optimizations concerning operation, target, strength and weakness. Moreover, the vital contributions of the optimized controller of BEMS technology in achieving SDG objectives can provide inclusive insights about the deployment of advanced algorithms.

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