IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received March 2, 2021, accepted March 6, 2021, date of publication March 10, 2021, date of current version March 19, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3065087

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

K. PARVIN[1], M. S. HOSSAIN LIPU[2], M. A. HANNAN[1], (Senior Member, IEEE), MAJID A. ABDULLAH[3], KER PIN JERN[1], R. A. BEGUM[4], MUHAMAD MANSUR[1], KASHEM M. MUTTAQI[5], (Senior Member, IEEE), T. M. INDRA MAHLIA[6], AND ZHAO YANG DONG[7], (Fellow, IEEE)

[1]Department of Electrical Power Engineering, College of Engineering, Universiti Tenaga Nasional, Kajang 43000, Malaysia
[2]Department of Electrical, Electronic, and Systems Engineering, Universiti Kebangsaan Malaysia, Bangi 43600, Malaysia
[3]Department of Electrical and Electronics Engineering Technology, The University of Hafr Al-Batin, Hafar Al-Batin 38524, Saudi Arabia
[4]Institute of Climate Change, Universiti Kebangsaan Malaysia, Bangi 43600, Malaysia
[5]School of Electrical, Computer, and Telecommunications Engineering, University of Wollongong, Wollongong, NSW 2522, Australia
[6]School of Information, Systems, and Modeling, University of Technology Sydney, Ultimo, NSW 2007, Australia
[7]School of Electrical Engineering and Telecommunications, UNSW, Sydney, NSW 2052, Australia

Corresponding author: M. A. Hannan (hannan@uniten.edu.my)

This work was supported in part by the Ministry of Higher Education, Malaysia through Universiti Tenaga Nasional under Grant 20190101LRGS, and in part by the UNITEN Bold Refresh Publication Fund 2021, under Project J5100D4103.

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 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

The associate editor coordinating the review of this manuscript and approving it for publication was Moayad Aloqaily.

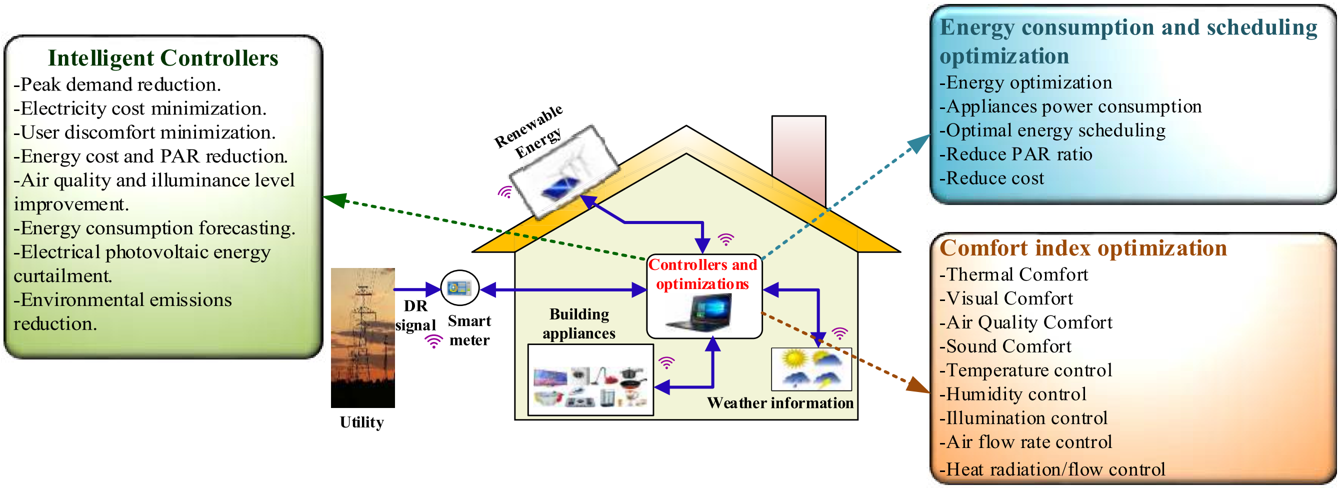

FIGURE 1. The structure of BEMS with intelligent controllers, energy consumption, scheduling and comfort index optimization.

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. Petro anu *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].

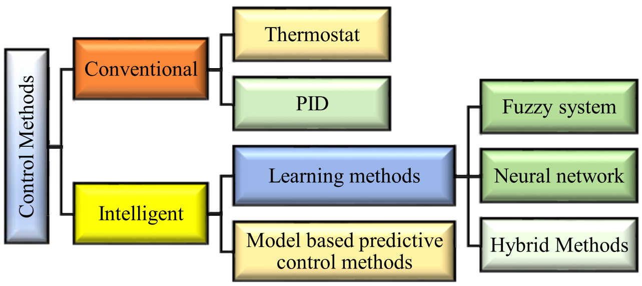

FIGURE 2. **Various Control schemes in BEMS.**

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,

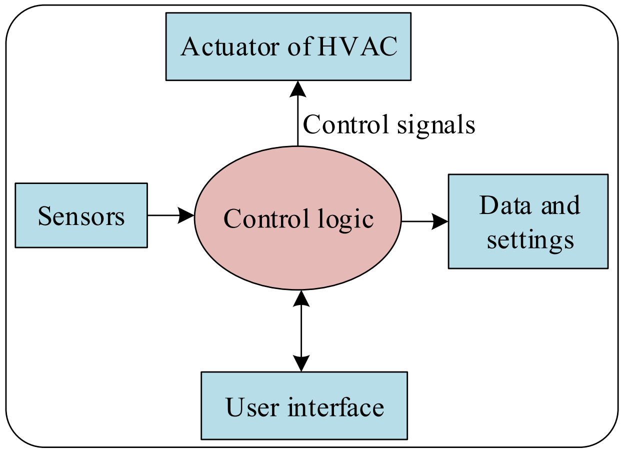

FIGURE 3. **The Structure of a typical thermostat.**

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).

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

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

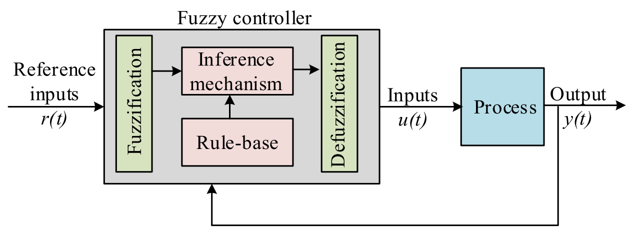

FIGURE 4. **An FLC integrated into a closed-loop control system.**

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 controlle'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].

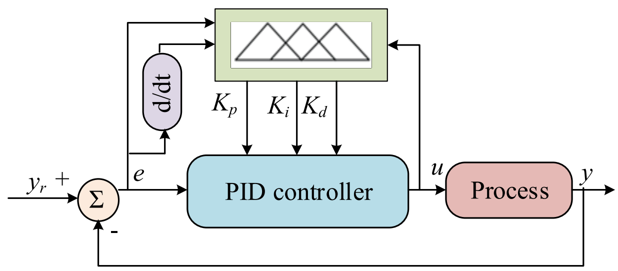

FIGURE 5. Fuzzy online gain tuned PID controller structure employed in BEMS.

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 (Tac),

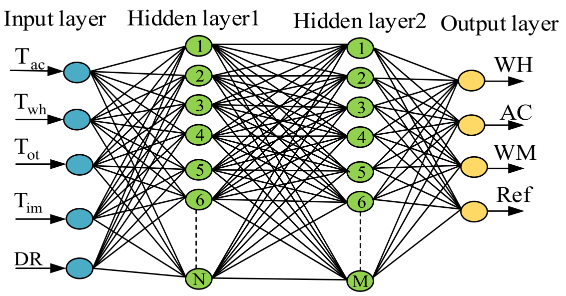

FIGURE 6. ANN-based controller used in demand-side management of residential buildings.

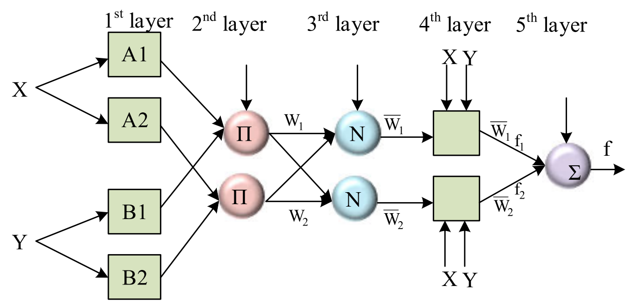

FIGURE 7. The configuration of ANFIS used in building energy management.

WH temperature (Twh), total power consumption (Tot), time of the system (Tim), 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.

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 thermostatic 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

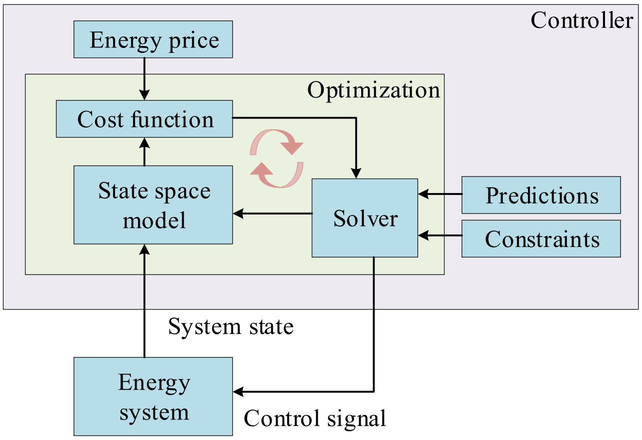

FIGURE 8. MPC concept towards build energy management.

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].

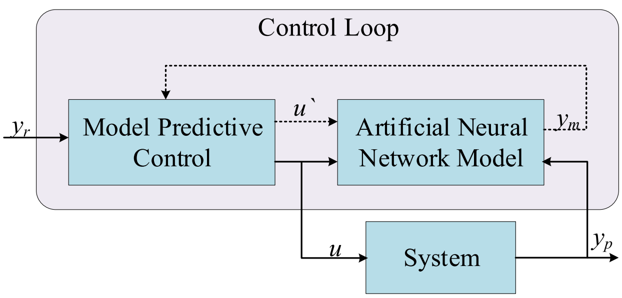

FIGURE 9. The block diagram of NN-MPC.

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]	▪ Low cost. ▪ Simple Operation.	▪ Low thermal conductivity. ▪ Low heat capacity.	▪ Peak demand reduction. ▪ Electricity cost minimization. ▪ User discomfort minimization.	The cooling electricity price reduces by 30%.
PID	[78]	▪ Simple structure. ▪ Easy execution. ▪ Quick response. ▪ Inexpensive.	▪ Inaccurate results if it is not properly tuned. ▪ Performance is not satisfactory in noisy and non-linear processes.	▪ Energy savings. ▪ Environmental emissions reduction.	Energy consumption decreases by 87%.
Fuzzy	[109]	▪ Reliable, efficient and customizable. ▪ Works efficiently in a non-linear system.	▪ It requires lots of data. ▪ Needs human expertise.	▪ Energy cost and PAR reduction ▪ Scheduling of home appliances.	The PAR minimizes by 25.45%.
PID-Fuzzy	[116]	▪ Fast and robust. ▪ Capability to work under a wider range of operating settings.	▪ Requires tuning of the fuzzy membership function.	▪ Air quality and illuminance level improvement. ▪ Thermal comfort enhancement. ▪ Energy consumption reduction.	Energy consumption drops by 25-30%.
ANN	[127]	▪ Works without detailed information on the system. ▪ Ability to detect complex relationships.	▪ It needs a large amount of quality data. ▪ It needs a long time for training operations. ▪ Needs expensive processing devices.	▪ Thermal comfort enrichment. ▪ Energy consumption minimization.	ANN achieves energy savings by 36.5 %
ANFIS	[182]	▪ Has a high degree of tolerance to uncertainty. ▪ Good generalization performance.	▪ Low interpretability of learned parameters. ▪ Strong computational complexity.	▪ Energy consumption forecasting.	ANFIS Obtains the correlation coefficient (R^2) above 0.96 in the testing data.
MPC	[139]	▪ Has improved transient response. ▪ It can control multiple variables within the boundary. ▪ Generic consideration of constraints.	▪ High computational load. ▪ High algorithm complexity. ▪ High number of control parameters.	▪ 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]	▪ Enhanced steady-state and dynamic performance	▪ Training efforts are usually high which require complex computation in a large scale system.	▪ 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,

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

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: Kalmal filter, ERL: Energy-Plus Runtime Language

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

In [184], a novel control algorithm is proposed for microgrids 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,

$$Min \sum_{t}^{NT} \sum_{t}^{NZ} p_t^{DAP} . \left(P_{t,z}^{FL} + P_{t,z}^{DL} + P_{t,z}^{RL} \right) + \sum_{t}^{NT} \sum_{t}^{NZ} p_{t,z}^{dp} \cdot \theta_{t,z}$$
$$+ \sum_{t}^{NT} \sum_{t}^{NZ} p_{t,z}^{lp} \left(E_{t,z}^{light} - E^{best} \right)^2 + \sum_{t}^{NT} \sum_{z}^{NZ} p_{t,z}^{tp} \cdot \Delta T_{t,z}^{tp} \quad (6)$$

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^{tp} 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,

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

where P is an unknown vector where the values of R and C are determined using data collected from the zone, *k, N* and *Nz* denote the time step, number of measurements, number of thermal zones, respectively. T_{1j}^{m} and T_{1j}^{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,

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

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,

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

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

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,

$$\text{Cost}_T = \frac{\sum_{t=1}^{T} \sum_{a_i}^{An} \varepsilon (t) \times \zeta a_i (t) \times \zeta (t)}{\left(\sum_{t=1}^{T} \sum_{a_i}^{An} \zeta a_i (t) \times \varepsilon (t) \times \zeta (t) \right)_{\max}} \tag{11}$$

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

$$Minimze \omega_1 (Cost_T) + \omega_2 (W_T) \tag{13}$$

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

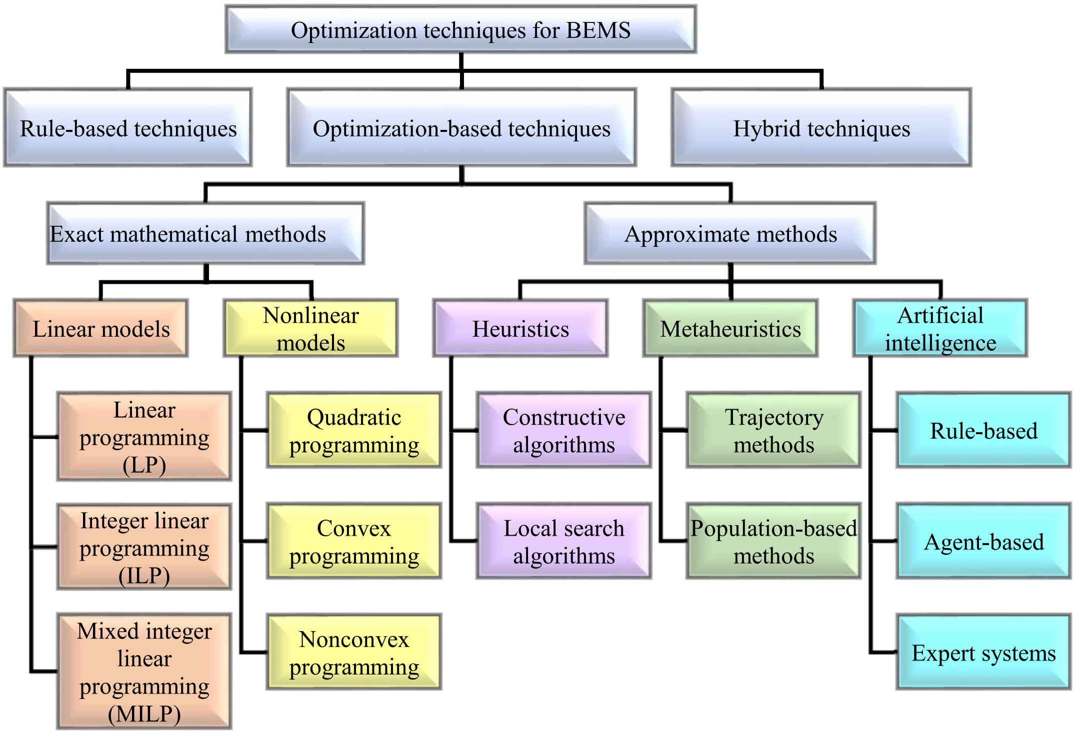

FIGURE 10. **Optimization techniques for BEMS.**

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 predefend 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].

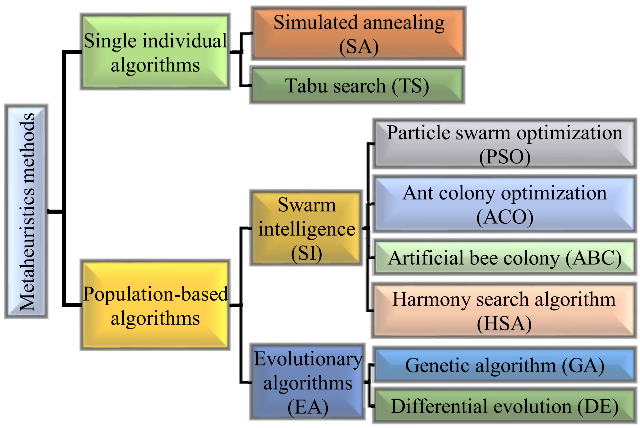

FIGURE 11. Metaheuristics optimization techniques implemented in BEMS.

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

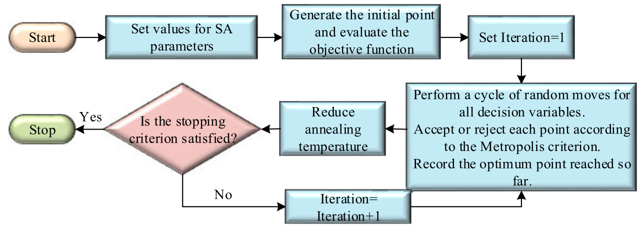

FIGURE 12. Flowchart of SA algorithm.

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]:

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

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

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].

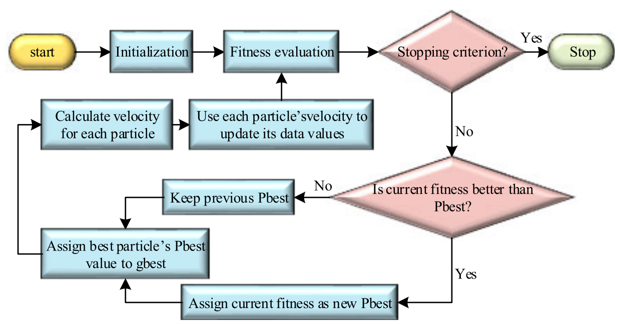

FIGURE 13. Flowchart of PSO algorithm.

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].

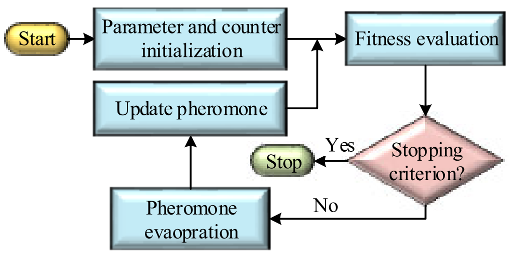

FIGURE 14. Flowchart of a typical ACO algorithm.

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 ABS 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 CO_2 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.

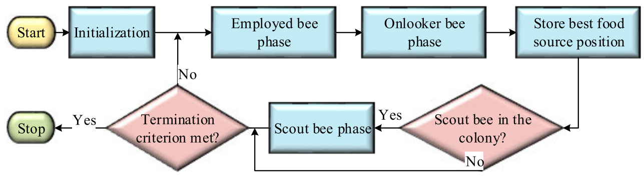

FIGURE 15. Flowchart of a typical ABC algorithm.

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.

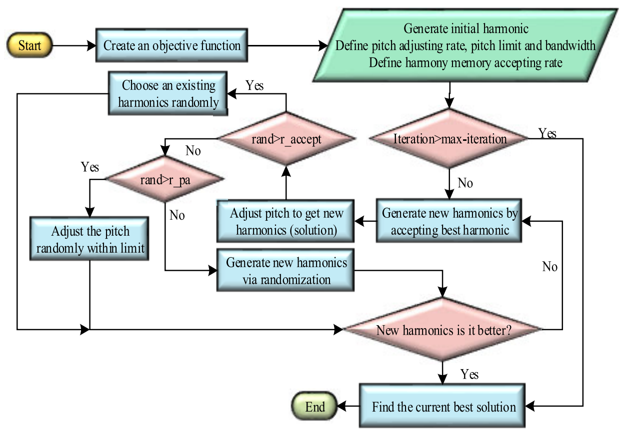

FIGURE 16. The basic structure of the HS algorithm.

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

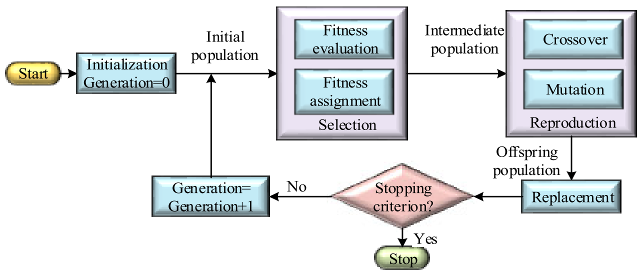

FIGURE 17. Flow chart for a typical GA optimization.

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].

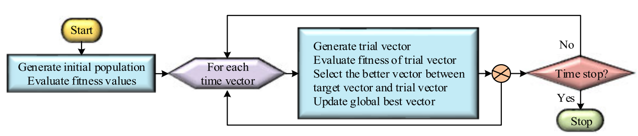

FIGURE 18. Flow chart for a typical DE algorithm.

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

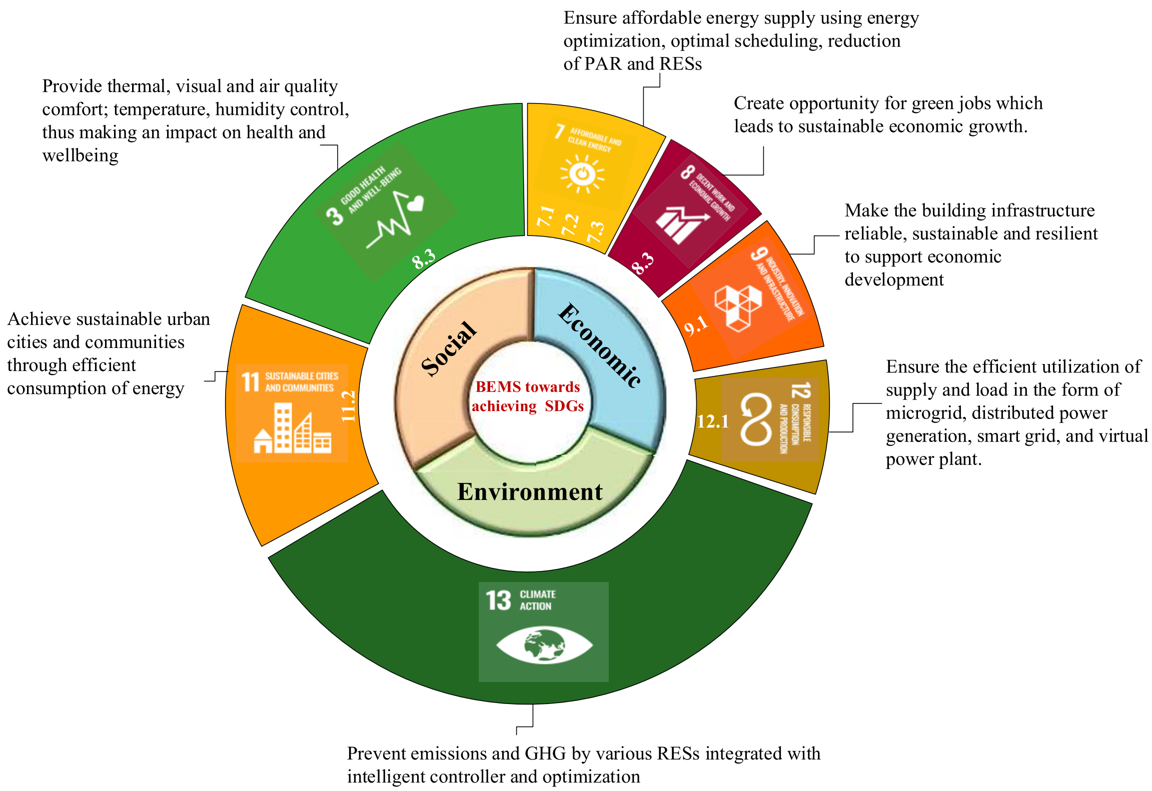

FIGURE 19. BEMS links to sustainable development objectives.

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 CO_2 emissions by 13 % through scheduling and peak shifting. A work in [295] also reveals that CO_2 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, CO_2 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.	▪ It can incorporate many cost functions. ▪ Achieves global optimal solutions.	▪ 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.	▪ Flexible and fast convergence speed. ▪ Delivers good quality solutions.	▪ 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.	▪ Requires fewer parameters to adjust. ▪ Simple execution. ▪ High efficiency and fast convergence speed.	▪ 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.	▪ Has guaranteed convergence. ▪ Adaptability to changes in new solutions.	▪ 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.	▪ Needs a few control parameters. ▪ Has a strong global search ability. ▪ Has both exploration and exploitation capability.	▪ 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.	▪ It needs less adjustable parameters. ▪ Easy execution. ▪ Fast convergence.	▪ 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.	▪ Easy implementation. ▪ Performs a parallel search into multiple regions.	▪ 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.	▪ Needs fewer parameter settings. ▪ Ability to handle multidimensional complex problems.	▪ 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	3 GOOD HEALTH AND WELL-BEING	SDG 3: Good health and well-being	3.9: Minimize diseases caused by pollution	▪ 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]
	11 SUSTAINABLE CITIES AND COMMUNITIES	SDG 11: Sustainable cities and communities	11.3: Enhance inclusive and sustainable urbanization and management.	▪ The concept, design, and technology of BEMS can be used to make sustainable urban cities and communities through efficient consumption of energy.	[276], [277]
Economic	7 AFFORDABLE AND CLEAN ENERGY	SDG 7: Affordable and clean energy	7.1: Ensure universal access to affordable, reliable and modern energy services	▪ 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.	[100,106,110, 112,113,165–168]
			7.2: Increase substantially the share of renewable energy in the global energy mix	▪ BEMS can be integrated with various RESs that has proven to become more cost-effective than fossil fuel alternatives.	
			7.3: Global rate of improvement in energy efficiency	▪ A smart building can deliver efficient, sustainable and modern energy with the deployment of demand response, energy efficiency, energy storage, and distributed generation.	
	8 DECENT WORK AND ECONOMIC GROWTH	SDG 8: Decent work and economic growth	8.3: Promote development-oriented policies that support productive activities, decent job creation.	▪ 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]
	9 INDUSTRY, INNOVATION AND INFRASTRUCTURE	SGD 9: Industry, Innovation, and Insfrustrute	9.1: Develop quality, reliable, sustainable and resilient infrastructure to support economic development	▪ 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]
	12 RESPONSIBLE CONSUMPTION AND PRODUCTION	SDG 12: Responsible consumption and production	12.1: Implement a framework of programs on sustainable consumption and production.	▪ 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	13 CLIMATE ACTION	SDG 13: Climate action	13: Take immediate measures to address the effects of climate change.	▪ 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 airflow 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.

REFERENCES

[1] J. Lizana, R. Chacartegui, A. Barrios-Padura, and J. M. Valverde, "Advances in thermal energy storage materials and their applications towards zero energy buildings: A critical review," *Appl. Energy*, vol. 203, pp. 219–239, Oct. 2017.

[2] C. K. Mytafides, A. Dimoudi, and S. Zoras, "Transformation of a university building into a zero energy building in Mediterranean climate," *Energy Buildings*, vol. 155, pp. 98–114, Nov. 2017.

[3] F. Harkouss, F. Fardoun, and P. H. Biwole, "Multi-objective optimization methodology for net zero energy buildings," *J. Building Eng.*, vol. 16, pp. 57–71, Mar. 2018.

[4] Y. Sun, G. Huang, X. Xu, and A. C.-K. Lai, "Building-group-level performance evaluations of net zero energy buildings with non-collaborative controls," *Appl. Energy*, vol. 212, pp. 565–576, Feb. 2018.

[5] D. Mariano-Hernández, L. Hernández-Callejo, A. Zorita-Lamadrid, O. Duque-Pérez, and F. Santos García, "A review of strategies for building energy management system: Model predictive control, demand side management, optimization, and fault detect & diagnosis," *J. Building Eng.*, vol. 33, Jan. 2021, Art. no. 101692.

[6] T. Karlessi, N. Kampelis, D. Kolokotsa, M. Santamouris, L. Standardi, D. Isidori, and C. Cristalli, "The concept of smart and NZEB buildings and the integrated design approach," *Procedia Eng.*, vol. 180, pp. 1316–1325, 2017.

[7] J. Utracki and M. Boryczka, "A multi-agent approach to the optimization of intelligent buildings energy management," *Procedia Comput. Sci.*, vol. 176, pp. 2665–2674, 2020.

[8] J. Zhu, Y. Shen, Z. Song, D. Zhou, Z. Zhang, and A. Kusiak, "Data-driven building load profiling and energy management," *Sustain. Cities Soc.*, vol. 49, Aug. 2019, Art. no. 101587.

[9] H. Mehrjerdi and R. Hemmati, "Energy and uncertainty management through domestic demand response in the residential building," *Energy*, vol. 192, Feb. 2020, Art. no. 116647.

[10] K. Parvin, M. A. Hannan, A. Q. Al-Shetwi, P. J. Ker, M. F. Roslan, and T. M. I. Mahlia, "Fuzzy based particle swarm optimization for modeling home appliances towards energy saving and cost reduction under demand response consideration," *IEEE Access*, vol. 8, pp. 210784–210799, 2020.

[11] C. Srivastava, Z. Yang, and R. K. Jain, "Understanding the adoption and usage of data analytics and simulation among building energy management professionals: A nationwide survey," *Building Environ.*, vol. 157, pp. 139–164, Jun. 2019.

[12] H. Doukas, K. D. Patlitzianas, K. Iatropoulos, and J. Psarras, "Intelligent building energy management system using rule sets," *Building Environ.*, vol. 42, no. 10, pp. 3562–3569, Oct. 2007.

[13] D. Lazos, A. B. Sproul, and M. Kay, "Development of hybrid numerical and statistical short term horizon weather prediction models for building energy management optimisation," *Building Environ.*, vol. 90, pp. 82–95, Aug. 2015.

[14] H. Shareef, M. S. Ahmed, A. Mohamed, and E. Al Hassan, "Review on home energy management system considering demand responses, smart technologies, and intelligent controllers," *IEEE Access*, vol. 6, pp. 24498–24509, 2018.

[15] P. H. Shaikh, N. B. M. Nor, P. Nallagownden, I. Elamvazuthi, and T. Ibrahim, "A review on optimized control systems for building energy and comfort management of smart sustainable buildings," *Renew. Sustain. Energy Rev.*, vol. 34, pp. 409–429, Jun. 2014.

[16] A. Zairi and M. Chaabene, "A review on home energy management systems," in *Proc. 9th Int. Renew. Energy Congr. (IREC)*, Mar. 2018, pp. 1–6.

[17] F. Farmani, M. Parvizimosaed, H. Monsef, and A. Rahimi-Kian, "A conceptual model of a smart energy management system for a residential building equipped with CCHP system," *Int. J. Electr. Power Energy Syst.*, vol. 95, pp. 523–536, Feb. 2018.

[18] W. Feng, Z. Wei, G. Sun, Y. Zhou, H. Zang, and S. Chen, "A conditional value-at-risk-based dispatch approach for the energy management of smart buildings with HVAC systems," *Electr. Power Syst. Res.*, vol. 188, Nov. 2020, Art. no. 106535.

[19] D. Zhang, N. Shah, and L. G. Papageorgiou, "Efficient energy consumption and operation management in a smart building with microgrid," *Energy Convers. Manage.*, vol. 74, pp. 209–222, Oct. 2013.

[20] S. Salimi and A. Hammad, "Optimizing energy consumption and occupants comfort in open-plan offices using local control based on occupancy dynamic data," *Building Environ.*, vol. 176, Jun. 2020, Art. no. 106818.

[21] I. Ullah and D. Kim, "An improved optimization function for maximizing user comfort with minimum energy consumption in smart homes," *Energies*, vol. 10, no. 11, p. 1818, Nov. 2017.

[22] Y. Luo, L. Zhang, Z. Liu, J. Yu, X. Xu, and X. Su, "Towards net zero energy building: The application potential and adaptability of photovoltaic-thermoelectric-battery wall system," *Appl. Energy*, vol. 258, Jan. 2020, Art. no. 114066.

[23] F. Sehar, M. Pipattanasomporn, and S. Rahman, "An energy management model to study energy and peak power savings from PV and storage in demand responsive buildings," *Appl. Energy*, vol. 173, pp. 406–417, Jul. 2016.

[24] L. A. Hurtado, P. H. Nguyen, W. L. Kling, and W. Zeiler, "Building energy management systems—Optimization of comfort and energy use," in *Proc. 48th Int. Universities' Power Eng. Conf. (UPEC)*, Sep. 2013, pp. 1–6.

[25] A. Ahmad and J. Y. Khan, "Real-time load scheduling, energy storage control and comfort management for grid-connected solar integrated smart buildings," *Appl. Energy*, vol. 259, Feb. 2020, Art. no. 114208.

[26] M. Han, R. May, X. Zhang, X. Wang, S. Pan, D. Yan, Y. Jin, and L. Xu, "A review of reinforcement learning methodologies for controlling occupant comfort in buildings," *Sustain. Cities Soc.*, vol. 51, Nov. 2019, Art. no. 101748.

[27] Z. Liang, D. Bian, X. Zhang, D. Shi, R. Diao, and Z. Wang, "Optimal energy management for commercial buildings considering comprehensive comfort levels in a retail electricity market," *Appl. Energy*, vol. 236, pp. 916–926, Feb. 2019.

[28] Y. Wang and C. Wei, "Design optimization of office building envelope based on quantum genetic algorithm for energy conservation," *J. Building Eng.*, vol. 35, Mar. 2021, Art. no. 102048.

[29] B. Liu and D. Rodriguez, "Renewable energy systems optimization by a new multi-objective optimization technique: A residential building," *J. Building Eng.*, vol. 35, Mar. 2021, Art. no. 102094.

[30] A. Costa, M. M. Keane, J. I. Torrens, and E. Corry, "Building operation and energy performance: Monitoring, analysis and optimisation toolkit," *Appl. Energy*, vol. 101, pp. 310–316, Jan. 2013.

[31] Y.-H. Lin, M.-D. Lin, K.-T. Tsai, M.-J. Deng, and H. Ishii, "Multi-objective optimization design of green building envelopes and air conditioning systems for energy conservation and CO_2 emission reduction," *Sustain. Cities Soc.*, vol. 64, Jan. 2021, Art. no. 102555.

[32] A. Ciardiello, F. Rosso, J. Dell'Olmo, V. Ciancio, M. Ferrero, and F. Salata, "Multi-objective approach to the optimization of shape and envelope in building energy design," *Appl. Energy*, vol. 280, Dec. 2020, Art. no. 115984.

[33] K. Bamdad, M. E. Cholette, S. Omrani, and J. Bell, "Future energy-optimised buildings—Addressing the impact of climate change on buildings," *Energy Buildings*, vol. 231, Jan. 2020, Art. no. 110610.

[34] M. Emami Javanmard, S. F. Ghaderi, and M. S. Sangari, "Integrating energy and water optimization in buildings using multi-objective mixed-integer linear programming," *Sustain. Cities Soc.*, vol. 62, Nov. 2020, Art. no. 102409.

[35] M. Manganelli, G. Greco, and L. Martirano, "Design of a new architecture and simulation model for building automation toward nearly zero energy buildings," *IEEE Trans. Ind. Appl.*, vol. 55, no. 6, pp. 6999–7007, Nov. 2019.

[36] V. Marinakis and H. Doukas, "An advanced IoT-based system for intelligent energy management in buildings," *Sensors*, vol. 18, no. 2, p. 610, Feb. 2018.

[37] A. Vosughi, M. Xue, and S. Roy, "Occupant-location-catered control of IoT-enabled building HVAC systems," *IEEE Trans. Control Syst. Technol.*, vol. 28, no. 6, pp. 2572–2580, Nov. 2020.

[38] P. Aparicio-Ruiz, E. Barbadilla-Martín, J. M. Salmerón-Lissén, and J. Guadix-Martín, "Building automation system with adaptive comfort in mixed mode buildings," *Sustain. Cities Soc.*, vol. 43, pp. 77–85, Nov. 2018.

[39] M. A. Hannan, M. Faisal, P. J. Ker, L. H. Mun, K. Parvin, T. M. I. Mahlia, and F. Blaabjerg, "A review of Internet of energy based building energy management systems: Issues and recommendations," *IEEE Access*, vol. 6, pp. 38997–39014, 2018.

[40] I. Khajenasiri, J. Virgone, and G. Gielen, "A presence-based control strategy solution for HVAC systems," in *Proc. IEEE Int. Conf. Consum. Electron. (ICCE)*, Jan. 2015, pp. 620–622.

[41] C. B. Jones and C. Carter, "Trusted interconnections between a centralized controller and commercial building HVAC systems for reliable demand response," *IEEE Access*, vol. 5, pp. 11063–11073, 2017.

[42] M. Molina-Solana, M. Ros, M. D. Ruiz, J. Gómez-Romero, and M. J. Martin-Bautista, "Data science for building energy management: A review," *Renew. Sustain. Energy Rev.*, vol. 70, pp. 598–609, Apr. 2017.

[43] J. Runge and R. Zmeureanu, "Forecasting energy use in buildings using artificial neural networks: A review," *Energies*, vol. 12, no. 17, p. 3254, Aug. 2019.

[44] J. Runge and R. Zmeureanu, "A review of deep learning techniques for forecasting energy use in buildings," *Energies*, vol. 14, no. 3, p. 608, Jan. 2021.

[45] A. Boodi, K. Beddiar, M. Benamour, Y. Amirat, and M. Benbouzid, "Intelligent systems for building energy and occupant comfort optimization: A state of the art review and recommendations," *Energies*, vol. 11, no. 10, p. 2604, Sep. 2018.

[46] M. Shakeri, J. Pasupuleti, N. Amin, M. Rokonuzzaman, F. W. Low, C. T. Yaw, N. Asim, N. A. Samsudin, S. K. Tiong, C. K. Hen, and C. W. Lai, "An overview of the building energy management system considering the demand response programs, smart strategies and smart grid," *Energies*, vol. 13, no. 13, p. 3299, Jun. 2020.

[47] D.-M. Petro anu, G. C ru a u, N. L. C ru a u, and A. Pîrjan, "A review of the recent developments in integrating machine learning models with sensor devices in the smart buildings sector with a view to attaining enhanced sensing, energy efficiency, and optimal building management," *Energies*, vol. 12, no. 24, p. 4745, Dec. 2019.

[48] V.-H. Bui, A. Hussain, Y.-H. Im, and H.-M. Kim, "An internal trading strategy for optimal energy management of combined cooling, heat and power in building microgrids," *Appl. Energy*, vol. 239, pp. 536–548, Apr. 2019.
[49] M. G. Yu and G. S. Pavlak, "Assessing the performance of uncertainty-aware transactive controls for building thermal energy storage systems," *Appl. Energy*, vol. 282, Jan. 2021, Art. no. 116103.
[50] S. Huang, Y. Lin, V. Chinde, X. Ma, and J. Lian, "Simulation-based performance evaluation of model predictive control for building energy systems," *Appl. Energy*, vol. 281, Jan. 2021, Art. no. 116027.
[51] A. Kathirgamanathan, M. De Rosa, E. Mangina, and D. P. Finn, "Data-driven predictive control for unlocking building energy flexibility: A review," *Renew. Sustain. Energy Rev.*, vol. 135, Jan. 2021, Art. no. 110120.
[52] H. Alkhatib, P. Lemarchand, B. Norton, and D. T. J. O'Sullivan, "Deployment and control of adaptive building facades for energy generation, thermal insulation, ventilation and daylighting: A review," *Appl. Thermal Eng.*, vol. 185, Feb. 2021, Art. no. 116331.
[53] D. Ibaseta, A. García, M. Álvarez, B. Garzón, F. Díez, P. Coca, C. D. Pero, and J. Molleda, "Monitoring and control of energy consumption in buildings using WoT: A novel approach for smart retrofit," *Sustain. Cities Soc.*, vol. 65, Feb. 2021, Art. no. 102637.
[54] C. Piselli, M. Prabhakar, A. de Gracia, M. Saffari, A. L. Pisello, and L. F. Cabeza, "Optimal control of natural ventilation as passive cooling strategy for improving the energy performance of building envelope with PCM integration," *Renew. Energy*, vol. 162, pp. 171–181, Dec. 2020.
[55] P. Huang, M. Lovati, X. Zhang, and C. Bales, "A coordinated control to improve performance for a building cluster with energy storage, electric vehicles, and energy sharing considered," *Appl. Energy*, vol. 268, Jun. 2020, Art. no. 114983.
[56] X. Jin, F. Qi, Q. Wu, Y. Mu, H. Jia, X. Yu, and Z. Li, "Integrated optimal scheduling and predictive control for energy management of an urban complex considering building thermal dynamics," *Int. J. Electr. Power Energy Syst.*, vol. 123, Dec. 2020, Art. no. 106273.
[57] Y. Chen and H. Tan, "Short-term prediction of electric demand in building sector via hybrid support vector regression," *Appl. Energy*, vol. 204, pp. 1363–1374, Oct. 2017.
[58] C.-H. Yang, K.-C. Lee, and S.-E. Li, "A mixed activity-based costing and resource constraint optimal decision model for IoT-oriented intelligent building management system portfolios," *Sustain. Cities Soc.*, vol. 60, Sep. 2020, Art. no. 102142.
[59] J. R. Vázquez-Canteli, S. Ulyanin, J. Kämpf, and Z. Nagy, "Fusing TensorFlow with building energy simulation for intelligent energy management in smart cities," *Sustain. Cities Soc.*, vol. 45, pp. 243–257, Feb. 2019.
[60] A. C. Tsolakis, I. Moschos, A. Zerzelidis, P. Tropios, S. Zikos, A. Tryferidis, S. Krinidis, D. Ioannidis, and D. Tzovaras, "Occupancy-based decision support system for building management: From automation to end-user persuasion," *Int. J. Energy Res.*, vol. 43, no. 6, pp. 2261–2280, May 2019.
[61] A. I. Dounis, "Artificial intelligence for energy conservation in buildings," *Adv. Building Energy Res.*, vol. 4, no. 1, pp. 267–299, Jan. 2010.
[62] A. C. Duman, H. S. Erden, Ö. Gönül, and Ö. Güler, "A home energy management system with an integrated smart thermostat for demand response in smart grids," *Sustain. Cities Soc.*, vol. 65, Feb. 2021, Art. no. 102639.
[63] H. Stopps and M. F. Touchie, "Managing thermal comfort in contemporary high-rise residential buildings: Using smart thermostats and surveys to identify energy efficiency and comfort opportunities," *Building Environ.*, vol. 173, Apr. 2020, Art. no. 106748.
[64] F. Nägele, T. Kasper, and B. Girod, "Turning up the heat on obsolete thermostats: A simulation-based comparison of intelligent control approaches for residential heating systems," *Renew. Sustain. Energy Rev.*, vol. 75, pp. 1254–1268, Aug. 2017.
[65] C. Wang, K. Pattawi, and H. Lee, "Energy saving impact of occupancy-driven thermostat for residential buildings," *Energy Buildings*, vol. 211, Mar. 2020, Art. no. 109791.
[66] N. Aste, M. Manfren, and G. Marenzi, "Building automation and control systems and performance optimization: A framework for analysis," *Renew. Sustain. Energy Rev.*, vol. 75, pp. 313–330, Aug. 2017.
[67] Z. Pang, Y. Chen, J. Zhang, Z. O'Neill, H. Cheng, and B. Dong, "How much HVAC energy could be saved from the occupant-centric smart home thermostat: A nationwide simulation study," *Appl. Energy*, vol. 283, Feb. 2021, Art. no. 116251.
[68] N. Yu, S. Salakij, R. Chavez, S. Paolucci, M. Sen, and P. Antsaklis, "Model-based predictive control for building energy management: Part II–Experimental validations," *Energy Buildings*, vol. 146, pp. 19–26, Jul. 2017.
[69] M. Xia, Y. Song, and Q. Chen, "Hierarchical control of thermostatically controlled loads oriented smart buildings," *Appl. Energy*, vol. 254, Nov. 2019, Art. no. 113493.
[70] P. C. Tabares-Velasco, A. Speake, M. Harris, A. Newman, T. Vincent, and M. Lanahan, "A modeling framework for optimization-based control of a residential building thermostat for time-of-use pricing," *Appl. Energy*, vol. 242, pp. 1346–1357, May 2019.
[71] A. Bruce-Konuah, R. V. Jones, A. Fuertes, L. Messi, and A. Giretti, "The role of thermostatic radiator valves for the control of space heating in UK social-rented households," *Energy Buildings*, vol. 173, pp. 206–220, Aug. 2018.
[72] W. Tian, X. Han, W. Zuo, Q. Wang, Y. Fu, and M. Jin, "An optimization platform based on coupled indoor environment and HVAC simulation and its application in optimal thermostat placement," *Energy Buildings*, vol. 199, pp. 342–351, Sep. 2019.
[73] H. Kazmi, J. Suykens, A. Balint, and J. Driesen, "Multi-agent reinforcement learning for modeling and control of thermostatically controlled loads," *Appl. Energy*, vol. 238, pp. 1022–1035, Mar. 2019.
[74] A. Fratean and P. Dobra, "Control strategies for decreasing energy costs and increasing self-consumption in nearly zero-energy buildings," *Sustain. Cities Soc.*, vol. 39, pp. 459–475, May 2018.
[75] R. Sangi, A. Kümpel, and D. Müller, "Real-life implementation of a linear model predictive control in a building energy system," *J. Building Eng.*, vol. 22, pp. 451–463, Mar. 2019.
[76] K. Lu, W. Zhou, G. Zeng, and W. Du, "Design of PID controller based on a self-adaptive state-space predictive functional control using extremal optimization method," *J. Franklin Inst.*, vol. 355, no. 5, pp. 2197–2220, Mar. 2018.
[77] M. A. Hannan, M. S. H. Lipu, P. J. Ker, R. A. Begum, V. G. Agelidis, and F. Blaabjerg, "Power electronics contribution to renewable energy conversion addressing emission reduction: Applications, issues, and recommendations," *Appl. Energy*, vol. 251, Oct. 2019, Art. no. 113404.
[78] S. E. Diaz-Mendez, C. Patiño-Carachure, and J. A. Herrera-Castillo, "Reducing the energy consumption of an earth–air heat exchanger with a PID control system," *Energy Convers. Manage.*, vol. 77, pp. 1–6, Jan. 2014.
[79] C. Copot, T. M. Thi, and C. Ionescu, "PID based particle swarm optimization in offices light control," *IFAC-PapersOnLine*, vol. 51, no. 4, pp. 382–387, 2018.
[80] B. Y. Zhao, Z. G. Zhao, Y. Li, R. Z. Wang, and R. A. Taylor, "An adaptive PID control method to improve the power tracking performance of solar photovoltaic air-conditioning systems," *Renew. Sustain. Energy Rev.*, vol. 113, Oct. 2019, Art. no. 109250.
[81] S. Thenozhi and W. Yu, "Stability analysis of active vibration control of building structures using PD/PID control," *Eng. Struct.*, vol. 81, pp. 208–218, Dec. 2014.
[82] K. Heong Ang, G. Chong, and Y. Li, "PID control system analysis, design, and technology," *IEEE Trans. Control Syst. Technol.*, vol. 13, no. 4, pp. 559–576, Jul. 2005.
[83] B. Yang, T. Yu, H. Shu, D. Zhu, F. Zeng, Y. Sang, and L. Jiang, "Perturbation observer based fractional-order PID control of photovoltaics inverters for solar energy harvesting via Yin-Yang-Pair optimization," *Energy Convers. Manage.*, vol. 171, pp. 170–187, Sep. 2018.
[84] M. Macarulla, M. Casals, N. Forcada, and M. Gangolells, "Implementation of predictive control in a commercial building energy management system using neural networks," *Energy Buildings*, vol. 151, pp. 511–519, Sep. 2017.
[85] G. Ulpiani, M. Borgognoni, A. Romagnoli, and C. Di Perna, "Comparing the performance of on/off, PID and fuzzy controllers applied to the heating system of an energy-efficient building," *Energy Buildings*, vol. 116, pp. 1–17, Mar. 2016.
[86] B. Paris, J. Eynard, S. Grieu, and M. Polit, "Hybrid PID-fuzzy control scheme for managing energy resources in buildings," *Appl. Soft Comput.*, vol. 11, no. 8, pp. 5068–5080, Dec. 2011.
[87] A. Shah, H. Nasir, M. Fayaz, A. Lajis, and A. Shah, "A review on energy consumption optimization techniques in IoT based smart building environments," *Information*, vol. 10, no. 3, p. 108, Mar. 2019.
[88] D. Kolokotsa, "Artificial intelligence in buildings: A review of the application of fuzzy logic," *Adv. Building Energy Res.*, vol. 1, no. 1, pp. 29–54, Jan. 2007.

[89] M. S. Ahmed, A. Mohamed, H. Shareef, R. Z. Homod, and J. A. Ali, "Artificial neural network based controller for home energy management considering demand response events," in *Proc. Int. Conf. Adv. Electr., Electron. Syst. Eng. (ICAEES)*, Nov. 2016, pp. 506–509.
[90] A. Esmaeilzadeh, M. R. Zakerzadeh, and A. Y. Koma, "The comparison of some advanced control methods for energy optimization and comfort management in buildings," *Sustain. Cities Soc.*, vol. 43, pp. 601–623, Nov. 2018.
[91] E. I ik and M. Inalli, "Artificial neural networks and adaptive neuro-fuzzy inference systems approaches to forecast the meteorological data for HVAC: The case of cities for Turkey," *Energy*, vol. 154, pp. 7–16, Jul. 2018.
[92] F. Boithias, M. El Mankibi, and P. Michel, "Genetic algorithms based optimization of artificial neural network architecture for buildings' indoor discomfort and energy consumption prediction," *Building Simul.*, vol. 5, no. 2, pp. 95–106, 2012.
[93] J. Reynolds, Y. Rezgui, A. Kwan, and S. Piriou, "A zone-level, building energy optimisation combining an artificial neural network, a genetic algorithm, and model predictive control," *Energy*, vol. 151, pp. 729–739, May 2018.
[94] Y. Cao, J. Du, and E. Soleymanzadeh, "Model predictive control of commercial buildings in demand response programs in the presence of thermal storage," *J. Cleaner Prod.*, vol. 218, pp. 315–327, May 2019.
[95] G. M. Tamilselvan and P. Aarthy, "Online tuning of fuzzy logic controller using Kalman algorithm for conical tank system," *J. Appl. Res. Technol.*, vol. 15, no. 5, pp. 492–503, Oct. 2017.
[96] H. Zhang, A. Davigny, F. Colas, Y. Poste, and B. Robyns, "Fuzzy logic based energy management strategy for commercial buildings integrating photovoltaic and storage systems," *Energy Buildings*, vol. 54, pp. 196–206, Nov. 2012.
[97] A. Keshtkar and S. Arzanpour, "An adaptive fuzzy logic system for residential energy management in smart grid environments," *Appl. Energy*, vol. 186, pp. 68–81, Jan. 2017.
[98] A. Derrouazin, M. Aillerie, N. Mekkakia-Maaza, and J.-P. Charles, "Multi input-output fuzzy logic smart controller for a residential hybrid solar-wind-storage energy system," *Energy Convers. Manage.*, vol. 148, pp. 238–250, Sep. 2017.
[99] N. Kanagaraj, P. Sivashanmugam, and S. Paramasivam, "Fuzzy coordinated PI controller: Application to the real-time pressure control process," *Adv. Fuzzy Syst.*, vol. 2008, May 2008, Art. no. 691808.
[100] G. Peter, "Intelligent cost-oriented manufacturing applications to energy buildings using fuzzy experts," *IFAC-PapersOnLine*, vol. 52, no. 25, pp. 523–526, 2019.
[101] M. A. Hannan, Z. A. Ghani, M. M. Hoque, P. J. Ker, A. Hussain, and A. Mohamed, "Fuzzy logic inverter controller in photovoltaic applications: Issues and recommendations," *IEEE Access*, vol. 7, pp. 24934–24955, 2019.
[102] L. Ciabattoni, F. Ferracuti, M. Grisostomi, G. Ippoliti, and S. Longhi, "Fuzzy logic based economical analysis of photovoltaic energy management," *Neurocomputing*, vol. 170, pp. 296–305, Dec. 2015.
[103] S. Hu, C. Hoare, P. Raftery, and J. O'Donnell, "Environmental and energy performance assessment of buildings using scenario modelling and fuzzy analytic network process," *Appl. Energy*, vol. 255, Dec. 2019, Art. no. 113788.
[104] M. Pislaru, I. V. Herghiligiu, and I.-B. Robu, "Corporate sustainable performance assessment based on fuzzy logic," *J. Cleaner Prod.*, vol. 223, pp. 998–1013, Jun. 2019.
[105] M. Killian, B. Mayer, and M. Kozek, "Cooperative fuzzy model predictive control for heating and cooling of buildings," *Energy Buildings*, vol. 112, pp. 130–140, Jan. 2016.
[106] M. Killian and M. Kozek, "Implementation of cooperative fuzzy model predictive control for an energy-efficient office building," *Energy Buildings*, vol. 158, pp. 1404–1416, Jan. 2018.
[107] Y. Ma, P. Duan, Y. Sun, and H. Chen, "Equalization of lithium-ion battery pack based on fuzzy logic control in electric vehicle," *IEEE Trans. Ind. Electron.*, vol. 65, no. 8, pp. 6762–6771, Aug. 2018.
[108] R. Khalid, S. Abid, A. Zafar, A. Yasmeen, Z. A. Khan, U. Qasim, and N. Javaid, "Fuzzy energy management controller for smart homes," *Adv. Intell. Syst. Comput.*, vol. 612, pp. 200–207, Jun. 2018.
[109] R. Khalid, N. Javaid, M. H. Rahim, S. Aslam, and A. Sher, "Fuzzy energy management controller and scheduler for smart homes," *Sustain. Comput., Informat. Syst.*, vol. 21, pp. 103–118, Mar. 2019.
[110] Z. Pezeshki and S. M. Mazinani, "Comparison of artificial neural networks, fuzzy logic and neuro fuzzy for predicting optimization of building thermal consumption: A survey," *Artif. Intell. Rev.*, vol. 52, no. 1, pp. 495–525, Jun. 2019.
[111] G. Kannayeram, N. B. Prakash, and R. Muniraj, "Intelligent hybrid controller for power flow management of PV/battery/FC/SC system in smart grid applications," *Int. J. Hydrogen Energy*, vol. 45, no. 41, pp. 21779–21795, Aug. 2020.
[112] Y. Y. Ghadi, M. G. Rasul, and M. M. K. Khan, "Design and development of advanced fuzzy logic controllers in smart buildings for institutional buildings in subtropical Queensland," *Renew. Sustain. Energy Rev.*, vol. 54, pp. 738–744, Feb. 2016.
[113] P. H. Shaikh, N. B. M. Nor, P. Nallagownden, and I. Elamvazuthi, "Stochastic optimized intelligent controller for smart energy efficient buildings," *Sustain. Cities Soc.*, vol. 13, pp. 41–45, Oct. 2014.
[114] K. Premkumar and B. V. Manikandan, "Fuzzy PID supervised online ANFIS based speed controller for brushless DC motor," *Neurocomputing*, vol. 157, pp. 76–90, Jun. 2015.
[115] F. Calvino, M. La Gennusa, G. Rizzo, and G. Scaccianoce, "The control of indoor thermal comfort conditions: Introducing a fuzzy adaptive controller," *Energy Buildings*, vol. 36, no. 2, pp. 97–102, Feb. 2004.
[116] D. Kolokotsa, D. Tsiavos, G. Stavrakakis, K. Kalaitzakis, and E. Antonidakis, "Advanced fuzzy logic controllers design and evaluation for buildings' occupants thermal-visual comfort and indoor air quality satisfaction," *Energy Build.*, vol. 33, no. 6, pp. 531–543, Jul. 2001.
[117] M. Ilbeigi, M. Ghomeishi, and A. Dehghanbanadaki, "Prediction and optimization of energy consumption in an office building using artificial neural network and a genetic algorithm," *Sustain. Cities Soc.*, vol. 61, Oct. 2020, Art. no. 102325.
[118] X. J. Luo, "A novel clustering-enhanced adaptive artificial neural network model for predicting day-ahead building cooling demand," *J. Building Eng.*, vol. 32, Nov. 2020, Art. no. 101504.
[119] A. D'Amico, G. Ciulla, M. Traverso, V. Lo Brano, and E. Palumbo, "Artificial neural networks to assess energy and environmental performance of buildings: An Italian case study," *J. Cleaner Prod.*, vol. 239, Dec. 2019, Art. no. 117993.
[120] B. Yuce, H. Li, Y. Rezgui, I. Petri, B. Jayan, and C. Yang, "Utilizing artificial neural network to predict energy consumption and thermal comfort level: An indoor swimming pool case study," *Energy Buildings*, vol. 80, pp. 45–56, Sep. 2014.
[121] S. M. Dawoud, X. Lin, and M. I. Okba, "Hybrid renewable microgrid optimization techniques: A review," *Renew. Sustain. Energy Rev.*, vol. 82, pp. 2039–2052, Feb. 2018.
[122] M. Ahmed, A. Mohamed, R. Homod, and H. Shareef, "Hybrid LSA-ANN based home energy management scheduling controller for residential demand response strategy," *Energies*, vol. 9, no. 9, p. 716, Sep. 2016.
[123] A. L. Katsatos and K. P. Moustris, "Application of artificial neuron networks as energy consumption forecasting tool in the building of regulatory authority of energy, Athens, Greece," *Energy Procedia*, vol. 157, pp. 851–861, Jan. 2019.
[124] Q. Dong, K. Xing, and H. Zhang, "Artificial neural network for assessment of energy consumption and cost for cross laminated timber office building in severe cold regions," *Sustainability*, vol. 10, no. 2, p. 84, Dec. 2017.
[125] L. Ruiz, M. Cuéllar, M. Calvo-Flores, and M. Jiménez, "An application of non-linear autoregressive neural networks to predict energy consumption in public buildings," *Energies*, vol. 9, no. 9, p. 684, Aug. 2016.
[126] M. N. Q. Macedo, J. J. M. Galo, L. A. L. de Almeida, and A. C. de C. Lima, "Demand side management using artificial neural networks in a smart grid environment," *Renew. Sustain. Energy Rev.*, vol. 41, pp. 128–133, Jan. 2015.
[127] T. Chaudhuri, Y. C. Soh, H. Li, and L. Xie, "A feedforward neural network based indoor-climate control framework for thermal comfort and energy saving in buildings," *Appl. Energy*, vol. 248, pp. 44–53, Aug. 2019.
[128] A. Y. Abdelaziz and E. S. Ali, "Cuckoo search algorithm based load frequency controller design for nonlinear interconnected power system," *Int. J. Electr. Power Energy Syst.*, vol. 73, pp. 632–643, Dec. 2015.
[129] C. Fan, Y. Sun, Y. Zhao, M. Song, and J. Wang, "Deep learning-based feature engineering methods for improved building energy prediction," *Appl. Energy*, vol. 240, pp. 35–45, Apr. 2019.
[130] N. Somu and K. Ramamritham, "A hybrid model for building energy consumption forecasting using long short term memory networks," *Appl. Energy*, vol. 261, Mar. 2020, Art. no. 114131.

[131] S. K. Howell, H. Wicaksono, B. Yuce, K. McGlinn, and Y. Rezgui, "User centered neuro-fuzzy energy management through semantic-based optimization," *IEEE Trans. Cybern.*, vol. 49, no. 9, pp. 3278–3292, Sep. 2019.

[132] R. Soenoko, S. Wahyudi, and E. Siswanto, "Comparison of intelligence control systems for voltage controlling on small scale compressed air energy storage," *Energies*, vol. 12, no. 5, p. 803, Feb. 2019.

[133] W. Gao, H. Moayedi, and A. Shahsavar, "The feasibility of genetic programming and ANFIS in prediction energetic performance of a building integrated photovoltaic thermal (BIPVT) system," *Sol. Energy*, vol. 183, pp. 293–305, May 2019.

[134] Y. Ozturk, P. Jha, S. Kumar, and G. Lee, "A personalized home energy management system for residential demand response," in *Proc. 4th Int. Conf. Power Eng., Energy Electr. Drives*, May 2013, pp. 1241–1246.

[135] J. Chung, I. H. Choi, S. H. Yoo, M. T. Lim, H.-K. Lee, M.-K. Song, and C. K. Ahn, "Home-legacy device intelligent control using ANFIS with data regeneration and resampling," in *Proc. 15th Int. Conf. Control, Autom. Syst. (ICCAS)*, Oct. 2015, pp. 1294–1296.

[136] J. Wang, S. Li, H. Chen, Y. Yuan, and Y. Huang, "Data-driven model predictive control for building climate control: Three case studies on different buildings," *Building Environ.*, vol. 160, Aug. 2019, Art. no. 106204.

[137] A. Afram and F. Janabi-shari, "Theory and applications of HVAC control systems–A review of model predictive control (MPC)," *Building Environ.*, vol. 72, pp. 343–355, Feb. 2014.

[138] S. J. Cox, D. Kim, H. Cho, and P. Mago, "Real time optimal control of district cooling system with thermal energy storage using neural networks," *Appl. Energy*, vol. 238, pp. 466–480, Mar. 2019.

[139] S. Kuboth, F. Heberle, A. König-Haagen, and D. Brüggemann, "Economic model predictive control of combined thermal and electric residential building energy systems," *Appl. Energy*, vol. 240, pp. 372–385, Apr. 2019.

[140] C. Sa, K. Jens, and M. Bauer, "NEUROBAT–a self-commissioned heating control system," *Sensors Appl.*, vol. 2, pp. 1–25, Apr. 2001.

[141] E. Žáčeková, Z. Váňa, and J. Cigler, "Towards the real-life implementation of MPC for an office building: Identification issues," *Appl. Energy*, vol. 135, pp. 53–62, Dec. 2014.

[142] F. Behrooz, N. Mariun, M. Marhaban, M. Mohd Radzi, and A. Ramli, "Review of control techniques for HVAC systems—Nonlinearity approaches based on fuzzy cognitive maps," *Energies*, vol. 11, no. 3, p. 495, Feb. 2018.

[143] C. Romijn, T. Donkers, J. Kessels, and S. Weiland, "Real-time distributed economic model predictive control for complete vehicle energy management," *Energies*, vol. 10, no. 8, p. 1096, Jul. 2017.

[144] T. F. Megahed, S. M. Abdelkader, and A. Zakaria, "Energy management in zero-energy building using neural network predictive control," *IEEE Internet Things J.*, vol. 6, no. 3, pp. 5336–5344, Jun. 2019.

[145] Y. Chen, Z. Tong, Y. Zheng, H. Samuelson, and L. Norford, "Transfer learning with deep neural networks for model predictive control of HVAC and natural ventilation in smart buildings," *J. Cleaner Prod.*, vol. 254, May 2020, Art. no. 119866.

[146] H. Huang, L. Chen, and E. Hu, "A neural network-based multi-zone modelling approach for predictive control system design in commercial buildings," *Energy Buildings*, vol. 97, pp. 86–97, Jun. 2015.

[147] P. M. Ferreira, A. E. Ruano, S. Silva, and E. Z. E. Conceição, "Neural networks based predictive control for thermal comfort and energy savings in public buildings," *Energy Buildings*, vol. 55, pp. 238–251, Dec. 2012.

[148] H. Huang, L. Chen, and E. Hu, "A new model predictive control scheme for energy and cost savings in commercial buildings: An airport terminal building case study," *Building Environ.*, vol. 89, pp. 203–216, Jul. 2015.

[149] A. Kusiak, G. Xu, and Z. Zhang, "Minimization of energy consumption in HVAC systems with data-driven models and an interior-point method," *Energy Convers. Manage.*, vol. 85, pp. 146–153, Sep. 2014.

[150] X. Wei, A. Kusiak, M. Li, F. Tang, and Y. Zeng, "Multi-objective optimization of the HVAC (heating, ventilation, and air conditioning) system performance," *Energy*, vol. 83, pp. 294–306, Apr. 2015.

[151] A. Garnier, J. Eynard, M. Caussanel, and S. Grieu, "Predictive control of multizone heating, ventilation and air-conditioning systems in non-residential buildings," *Appl. Soft Comput.*, vol. 37, pp. 847–862, Dec. 2015.

[152] W. Kim, Y. Jeon, and Y. Kim, "Simulation-based optimization of an integrated daylighting and HVAC system using the design of experiments method," *Appl. Energy*, vol. 162, pp. 666–674, Jan. 2016.

[153] A. Kusiak, F. Tang, and G. Xu, "Multi-objective optimization of HVAC system with an evolutionary computation algorithm," *Energy*, vol. 36, no. 5, pp. 2440–2449, May 2011.

[154] A. E. Ruano, S. Pesteh, S. Silva, H. Duarte, G. Mestre, P. M. Ferreira, H. R. Khosravani, and R. Horta, "The IMBPC HVAC system: A complete MBPC solution for existing HVAC systems," *Energy Buildings*, vol. 120, pp. 145–158, May 2016.

[155] Y. M. Lee, R. Horesh, and L. Liberti, "Optimal HVAC control as demand response with on-site energy storage and generation system," *Energy Procedia*, vol. 78, pp. 2106–2111, Nov. 2015.

[156] E. Asadi, M. G. D. Silva, C. H. Antunes, L. Dias, and L. Glicksman, "Multi-objective optimization for building retrofit: A model using genetic algorithm and artificial neural network and an application," *Energy Buildings*, vol. 81, pp. 444–456, Oct. 2014.

[157] C. Mokhtara, B. Negrou, N. Settou, B. Settou, and M. M. Samy, "Design optimization of off-grid hybrid renewable energy systems considering the effects of building energy performance and climate change: Case study of Algeria," *Energy*, vol. 219, Mar. 2021, Art. no. 119605.

[158] Z. Yong, Y. Li-Juan, Z. Qian, and S. Xiao-Yan, "Multi-objective optimization of building energy performance using a particle swarm optimizer with less control parameters," *J. Building Eng.*, vol. 32, Nov. 2020, Art. no. 101505.

[159] B. T. Cao, M. Obel, S. Freitag, P. Mark, and G. Meschke, "Artificial neural network surrogate modelling for real-time predictions and control of building damage during mechanised tunnelling," *Adv. Eng. Softw.*, vol. 149, Nov. 2020, Art. no. 102869.

[160] R. Sendra-Arranz and A. Gutiérrez, "A long short-term memory artificial neural network to predict daily HVAC consumption in buildings," *Energy Buildings*, vol. 216, Jun. 2020, Art. no. 109952.

[161] A. Soares, A. Gomes, C. H. Antunes, and C. Oliveira, "A customized evolutionary algorithm for multiobjective management of residential energy resources," *IEEE Trans. Ind. Informat.*, vol. 13, no. 2, pp. 492–501, Apr. 2017.

[162] K. B. Masouleh, "Building energy optimisation using machine learning and metaheuristic algorithms," Queensland Univ. Technol., Brisbane, QLD, Australia, Tech. Rep. 120281, 2018, doi: 10.5204/thesis.eprints.120281.

[163] M. Roccotelli, A. Rinaldi, M. P. Fanti, and F. Iannone, "Building energy management for passive cooling based on stochastic occupants behavior evaluation," *Energies*, vol. 14, no. 1, p. 138, Dec. 2020.

[164] B. Bass, J. New, and W. Copeland, "Potential energy, demand, emissions, and cost savings distributions for buildings in a utility's service area," *Energies*, vol. 14, no. 1, p. 132, Dec. 2020.

[165] Y. Liu, Y. Wang, and X. Luo, "Design and operation optimization of distributed solar energy system based on dynamic operation strategy," *Energies*, vol. 14, no. 1, p. 69, Dec. 2020.

[166] G. Serale, M. Fiorentini, A. Capozzoli, D. Bernardini, and A. Bemporad, "Model predictive control (MPC) for enhancing building and HVAC system energy efficiency: Problem formulation, applications and opportunities," *Energies*, vol. 11, no. 3, p. 631, 2018.

[167] E. O'Dwyer, L. De Tommasi, K. Kouramas, M. Cychowski, and G. Lightbody, "Prioritised objectives for model predictive control of building heating systems," *Control Eng. Pract.*, vol. 63, pp. 57–68, Jun. 2017.

[168] S. Martínez, P. Eguía, E. Granada, A. Moazami, and M. Hamdy, "A performance comparison of multi-objective optimization-based approaches for calibrating white-box building energy models," *Energy Buildings*, vol. 216, Jun. 2020, Art. no. 109942.

[169] J. Liu, X. Chen, H. Yang, and Y. Li, "Energy storage and management system design optimization for a photovoltaic integrated low-energy building," *Energy*, vol. 190, Jan. 2020, Art. no. 116424.

[170] J. J. Robertson, B. J. Polly, and J. M. Collis, "Reduced-order modeling and simulated annealing optimization for efficient residential building utility bill calibration," *Appl. Energy*, vol. 148, pp. 169–177, Jun. 2015.

[171] Y. Sun, X. Luo, and X. Liu, "Optimization of a university timetable considering building energy efficiency: An approach based on the building controls virtual test bed platform using a genetic algorithm," *J. Building Eng.*, vol. 35, Mar. 2021, Art. no. 102095.

[172] A. T. Nguyen, D. Rockwood, M. K. Doan, and T. K. Dung Le, "Performance assessment of contemporary energy-optimized office buildings under the impact of climate change," *J. Building Eng.*, vol. 35, Mar. 2021, Art. no. 102089.

[173] R. Foroughi, S. Asadi, and S. Khazaeli, "On the optimization of energy efficient fenestration for small commercial buildings in the united states," *J. Cleaner Prod.*, vol. 283, Feb. 2021, Art. no. 124604.

[174] Q. Wen, G. Liu, W. Wu, and S. Liao, "Genetic algorithm-based operation strategy optimization and multi-criteria evaluation of distributed energy system for commercial buildings," *Energy Convers. Manage.*, vol. 226, Dec. 2020, Art. no. 113529.

[175] D.-K. Bui, T. N. Nguyen, A. Ghazlan, N.-T. Ngo, and T. D. Ngo, "Enhancing building energy efficiency by adaptive Façade: A computational optimization approach," *Appl. Energy*, vol. 265, May 2020, Art. no. 114797.

[176] Y. Zhang, X. Zhang, P. Huang, and Y. Sun, "Global sensitivity analysis for key parameters identification of net-zero energy buildings for grid interaction optimization," *Appl. Energy*, vol. 279, Dec. 2020, Art. no. 115820.

[177] B. Si, Z. Tian, X. Jin, X. Zhou, and X. Shi, "Ineffectiveness of optimization algorithms in building energy optimization and possible causes," *Renew. Energy*, vol. 134, pp. 1295–1306, Apr. 2019.

[178] J. Liu, M. Wang, J. Peng, X. Chen, S. Cao, and H. Yang, "Techno-economic design optimization of hybrid renewable energy applications for high-rise residential buildings," *Energy Convers. Manage.*, vol. 213, Jun. 2020, Art. no. 112868.

[179] R. A. Kishore, M. V. A. Bianchi, C. Booten, J. Vidal, and R. Jackson, "Optimizing PCM-integrated walls for potential energy savings in U.S. buildings," *Energy Buildings*, vol. 226, Nov. 2020, Art. no. 110355.

[180] A. Basit, G. Ahmad Sardar Sidhu, A. Mahmood, and F. Gao, "Efficient and autonomous energy management techniques for the future smart homes," *IEEE Trans. Smart Grid*, vol. 8, no. 2, pp. 917–926, Mar. 2017.

[181] S. Ali and D.-H. Kim, "Optimized power control methodology using genetic algorithm," *Wireless Pers. Commun.*, vol. 83, no. 1, pp. 493–505, Jul. 2015.

[182] C. Deb, L. S. Eang, J. Yang, and M. Santamouris, "Forecasting energy consumption of institutional buildings in Singapore," *Procedia Eng.*, vol. 121, pp. 1734–1740, 2015.

[183] C. D. Korkas, S. Baldi, and E. B. Kosmatopoulos, *Grid-Connected Microgrids: Demand Management via Distributed Control and Human-in-the-Loop Optimization*, vol. 2. Amsterdam, The Netherlands: Elsevier, 2018.

[184] C. D. Korkas, S. Baldi, I. Michailidis, and E. B. Kosmatopoulos, "Occupancy-based demand response and thermal comfort optimization in microgrids with renewable energy sources and energy storage," *Appl. Energy*, vol. 163, pp. 93–104, Feb. 2016.

[185] F. Wahid and D. H. Kim, "An efficient approach for energy consumption optimization and management in residential building using artificial bee colony and fuzzy logic," *Math. Problems Eng.*, vol. 2016, Jun. 2016, Art. no. 9104735.

[186] M. Fayaz and D. H. Kim, "Energy consumption optimization and user comfort management in residential buildings using a bat algorithm and fuzzy logic," *Energies*, vol. 11, no. 1, p. 161, 2018.

[187] N. Nassif, "Modeling and optimization of HVAC systems using artificial neural network and genetic algorithm," *Building Simul.*, vol. 7, no. 3, pp. 237–245, Jun. 2014.

[188] N. Delgarm, B. Sajadi, F. Kowsary, and S. Delgarm, "Multi-objective optimization of the building energy performance: A simulation-based approach by means of particle swarm optimization (PSO)," *Appl. Energy*, vol. 170, pp. 293–303, May 2016.

[189] M. Collotta, A. Messineo, G. Nicolosi, and G. Pau, "A dynamic fuzzy controller to meet thermal comfort by using neural network forecasted parameters as the input," *Energies*, vol. 7, no. 8, pp. 4727–4756, Jul. 2014.

[190] A. Marvuglia, A. Messineo, and G. Nicolosi, "Coupling a neural network temperature predictor and a fuzzy logic controller to perform thermal comfort regulation in an office building," *Building Environ.*, vol. 72, pp. 287–299, Feb. 2014.

[191] H. F. Scherer, M. Pasamontes, J. L. Guzmán, J. D. Álvarez, E. Camponogara, and J. E. Normey-Rico, "Efficient building energy management using distributed model predictive control," *J. Process Control*, vol. 24, no. 6, pp. 740–749, Jun. 2014.

[192] P. H. Shaikh, N. B. M. Nor, P. Nallagownden, I. Elamvazuthi, and T. Ibrahim, "Intelligent multi-objective control and management for smart energy efficient buildings," *Int. J. Electr. Power Energy Syst.*, vol. 74, pp. 403–409, Jan. 2016.

[193] J. Lim and G. Yun, "Cooling energy implications of occupant factor in buildings under climate change," *Sustainability*, vol. 9, no. 11, p. 2039, Nov. 2017.

[194] S. Ali and D. H. Kim, "Building power control and comfort management using genetic programming and fuzzy logic," *J. Energy Southern Afr.*, vol. 26, no. 2, pp. 94–102, 2015.

[195] L. Klein, J.-Y. Kwak, G. Kavulya, F. Jazizadeh, B. Becerik-Gerber, P. Varakantham, and M. Tambe, "Coordinating occupant behavior for building energy and comfort management using multi-agent systems," *Autom. Construct.*, vol. 22, pp. 525–536, Mar. 2012.

[196] Y. Gao, S. Li, X. Fu, W. Dong, B. Lu, and Z. Li, "Energy management and demand response with intelligent learning for multi-thermal-zone buildings," *Energy*, vol. 210, Nov. 2020, Art. no. 118411.

[197] E. Biyik and A. Kahraman, "A predictive control strategy for optimal management of peak load, thermal comfort, energy storage and renewables in multi-zone buildings," *J. Building Eng.*, vol. 25, Sep. 2019, Art. no. 100826.

[198] Y. Zhang, Y. Zhong, Y. Gong, and L. Zheng, "The optimization of visual comfort and energy consumption induced by natural light based on PSO," *Sustainability*, vol. 11, no. 1, p. 49, Dec. 2018.

[199] H. Park, "Human comfort-based-home energy management for demand response participation," *Energies*, vol. 13, no. 10, p. 2463, May 2020.

[200] P. Kumar, C. Martani, L. Morawska, L. Norford, R. Choudhary, M. Bell, and M. Leach, "Indoor air quality and energy management through real-time sensing in commercial buildings," *Energy Buildings*, vol. 111, pp. 145–153, Jan. 2016.

[201] F. Mancini, F. Nardecchia, D. Groppi, F. Ruperto, and C. Romeo, "Indoor environmental quality analysis for optimizing energy consumptions varying air ventilation rates," *Sustainability*, vol. 12, no. 2, p. 482, Jan. 2020.

[202] N. Javaid, A. Ahmed, S. Iqbal, and M. Ashraf, "Day ahead real time pricing and critical peak pricing based power scheduling for smart homes with different duty cycles," *Energies*, vol. 11, no. 6, p. 1464, Jun. 2018.

[203] N. Javaid, F. Ahmed, I. Ullah, S. Abid, W. Abdul, A. Alamri, and A. Almogren, "Towards cost and comfort based hybrid optimization for residential load scheduling in a smart grid," *Energies*, vol. 10, no. 10, p. 1546, Oct. 2017.

[204] S. Aslam, Z. Iqbal, N. Javaid, Z. Khan, K. Aurangzeb, and S. Haider, "Towards efficient energy management of smart buildings exploiting heuristic optimization with real time and critical peak pricing schemes," *Energies*, vol. 10, no. 12, p. 2065, Dec. 2017.

[205] M. Awais, N. Javaid, K. Aurangzeb, S. Haider, Z. Khan, and D. Mahmood, "Towards effective and efficient energy management of single home and a smart community exploiting heuristic optimization algorithms with critical peak and real-time pricing tariffs in smart grids," *Energies*, vol. 11, no. 11, p. 3125, Nov. 2018.

[206] A. Ahmad, A. Khan, N. Javaid, H. M. Hussain, W. Abdul, A. Almogren, A. Alamri, and I. A. Niaz, "An optimized home energy management system with integrated renewable energy and storage resources," *Energies*, vol. 10, no. 4, p. 549, Apr. 2017.

[207] C. Benavente-Peces and N. Ibadah, "Buildings energy efficiency analysis and classification using various machine learning technique classifiers," *Energies*, vol. 13, no. 13, p. 3497, 2020.

[208] C. Fan, F. Xiao, C. Yan, C. Liu, Z. Li, and J. Wang, "A novel methodology to explain and evaluate data-driven building energy performance models based on interpretable machine learning," *Appl. Energy*, vol. 235, pp. 1551–1560, Feb. 2019.

[209] Z. Ma, C. Ye, H. Li, and W. Ma, "Applying support vector machines to predict building energy consumption in China," *Energy Procedia*, vol. 152, pp. 780–786, Oct. 2018.

[210] A. Ghofrani, S. D. Nazemi, and M. A. Jafari, "HVAC load synchronization in smart building communities," *Sustain. Cities Soc.*, vol. 51, Nov. 2019, Art. no. 101741.

[211] E. Mocanu, P. H. Nguyen, M. Gibescu, and W. L. Kling, "Deep learning for estimating building energy consumption," *Sustain. Energy, Grids Netw.*, vol. 6, pp. 91–99, Jun. 2016.

[212] K. Mason and S. Grijalva, "A review of reinforcement learning for autonomous building energy management," *Comput. Electr. Eng.*, vol. 78, pp. 300–312, Sep. 2019.

[213] C. D. Korkas, S. Baldi, I. Michailidis, and E. B. Kosmatopoulos, "Intelligent energy and thermal comfort management in grid-connected microgrids with heterogeneous occupancy schedule," *Appl. Energy*, vol. 149, pp. 194–203, Jul. 2015.

[214] O. Samuel, S. Javaid, N. Javaid, S. Ahmed, M. Afzal, and F. Ishmanov, "An efficient power scheduling in smart homes using Jaya based optimization with time-of-use and critical peak pricing schemes," *Energies*, vol. 11, no. 11, p. 3155, Nov. 2018.

[215] H. Hussain, N. Javaid, S. Iqbal, Q. Hasan, K. Aurangzeb, and M. Alhussein, "An efficient demand side management system with a new optimized home energy management controller in smart grid," *Energies*, vol. 11, no. 1, p. 190, Jan. 2018.

[216] A. T. Eseye, M. Lehtonen, T. Tukia, S. Uimonen, and R. J. Millar, "Optimal energy trading for renewable energy integrated building microgrids containing electric vehicles and energy storage batteries," *IEEE Access*, vol. 7, pp. 106092–106101, 2019.
[217] M. S. H. Nizami, M. J. Hossain, B. M. R. Amin, and E. Fernandez, "A residential energy management system with bi-level optimization-based bidding strategy for day-ahead bi-directional electricity trading," *Appl. Energy*, vol. 261, Mar. 2020, Art. no. 114322.
[218] F. Ali, O. Bouachir, O. Ozkasap, and M. Aloqaily, "SynergyChain: Blockchain-assisted adaptive cyberphysical P2P energy trading," *IEEE Trans. Ind. Informat.*, early access, Dec. 23, 2021, doi: 10.1109/TII.2020.3046744.
[219] M. Aloqaily, A. Boukerche, O. Bouachir, F. Khalid, and S. Jangsher, "An energy trade framework using smart contracts: Overview and challenges," *IEEE Netw.*, vol. 34, no. 4, pp. 119–125, Jul. 2020.
[220] N. Amani and E. Kiaee, "Developing a two-criteria framework to rank thermal insulation materials in nearly zero energy buildings using multi-objective optimization approach," *J. Cleaner Prod.*, vol. 276, Dec. 2020, Art. no. 122592.
[221] J. Zhao and Y. Du, "Multi-objective optimization design for windows and shading configuration considering energy consumption and thermal comfort: A case study for office building in different climatic regions of China," *Sol. Energy*, vol. 206, pp. 997–1017, Aug. 2020.
[222] A. Ebrahimi-Moghadam, P. Ildarabadi, K. Aliakbari, and F. Fadaee, "Sensitivity analysis and multi-objective optimization of energy consumption and thermal comfort by using interior light shelves in residential buildings," *Renew. Energy*, vol. 159, pp. 736–755, Oct. 2020.
[223] D. Lindelöf, H. Afshari, M. Alisafaee, J. Biswas, M. Caban, X. Mocellin, and J. Viaene, "Field tests of an adaptive, model-predictive heating controller for residential buildings," *Energy Buildings*, vol. 99, pp. 292–302, Jul. 2015.
[224] R. Halvgaard, P. Bacher, B. Perers, E. Andersen, S. Furbo, J. B. Jørgensen, N. K. Poulsen, and H. Madsen, "Model predictive control for a smart solar tank based on weather and consumption forecasts," *Energy Procedia*, vol. 30, pp. 270–278, 2012.
[225] D. L. Ha, S. Ploix, E. Zamai, and M. Jacomino, "A home automation system to improve household energy control," *IFAC Proc. Volumes*, vol. 39, no. 3, pp. 15–20, 2006.
[226] A. Barbato, A. Capone, G. Carello, M. Delfanti, M. Merlo, and A. Zaminga, "House energy demand optimization in single and multi-user scenarios," in *Proc. IEEE Int. Conf. Smart Grid Commun. (SmartGridComm)*, Oct. 2011, pp. 345–350.
[227] F. A. Qayyum, M. Naeem, A. S. Khwaja, A. Anpalagan, L. Guan, and B. Venkatesh, "Appliance scheduling optimization in smart home networks," *IEEE Access*, vol. 3, pp. 2176–2190, Jun. 2015.
[228] M. Wang, T. Zhang, P. Wang, and X. Chen, "An improved harmony search algorithm for solving day-ahead dispatch optimization problems of integrated energy systems considering time-series constraints," *Energy Buildings*, vol. 229, Dec. 2020, Art. no. 110477.
[229] M. Wang, H. Yu, R. Jing, H. Liu, P. Chen, and C. Li, "Combined multi-objective optimization and robustness analysis framework for building integrated energy system under uncertainty," *Energy Convers. Manage.*, vol. 208, Mar. 2020, Art. no. 112589.
[230] I. Mauser, "Multi-modal Building Energy Management," Karlsruhe Inst. für Technol. (KIT), Karlsruhe, Germany, Tech. Rep., 2017, doi: 10.5445/IR/1000070625.
[231] I. Ullah and S. Hussain, "Time-constrained nature-inspired optimization algorithms for an efficient energy management system in smart homes and buildings," *Appl. Sci.*, vol. 9, no. 4, p. 792, Feb. 2019.
[232] C.-M. Wang and Y.-F. Huang, "Self-adaptive harmony search algorithm for optimization," *Expert Syst. Appl.*, vol. 37, no. 4, pp. 2826–2837, Apr. 2010.
[233] P. Cao, Z. Fan, R. X. Gao, and J. Tang, "Harnessing multi-objective simulated annealing toward configuration optimization within compact space for additive manufacturing," *Robot. Comput.-Integr. Manuf.*, vol. 57, pp. 29–45, Jun. 2019.
[234] D. Aleksendrić and P. Carlone, "Composite materials–modelling, prediction and optimization," in *Soft Computing in the Design and Manufacturing of Composite Materials*. Amsterdam, The Netherlands: Elsevier, 2015, pp. 61–289.
[235] M. Schmidt and C. Åhlund, "Smart buildings as cyber-physical systems: Data-driven predictive control strategies for energy efficiency," *Renew. Sustain. Energy Rev.*, vol. 90, pp. 742–756, Jul. 2018.
[236] F. Kheiri, "A review on optimization methods applied in energy-efficient building geometry and envelope design," *Renew. Sustain. Energy Rev.*, vol. 92, pp. 897–920, Sep. 2018.
[237] M. Zillgith, D. Nestle, and M. Wagner, "Security architecture of the OGEMA 2.0 home energy management system," in *Proc. Int. ETG-Congr.; Symp. 1: Secur. Crit. Infrastruct. Today*, Nov. 2013, pp. 1–6.
[238] R. Velik and P. Nicolay, "Energy management in storage-augmented, grid-connected prosumer buildings and neighborhoods using a modified simulated annealing optimization," *Comput. Oper. Res.*, vol. 66, pp. 248–257, Feb. 2016.
[239] L. Junghans and N. Darde, "Hybrid single objective genetic algorithm coupled with the simulated annealing optimization method for building optimization," *Energy Buildings*, vol. 86, pp. 651–662, Jan. 2015.
[240] M. Bereta, "Regularization of boosted decision stumps using tabu search," *Appl. Soft Comput.*, vol. 79, pp. 424–438, Jun. 2019.
[241] S. Shafiq, S. Asif, I. Fatima, K. Yousaf, W. Safat, and N. Javaid, "An approach towards efficient scheduling of home energy management system using backtracking search optimization and tabu search," in *Proc. 32nd Int. Conf. Adv. Inf. Netw. Appl. Workshops (WAINA)*, May 2018, pp. 226–231.
[242] G. Li, W. Wang, W. Zhang, Z. Wang, H. Tu, and W. You, "Grid search based multi-population particle swarm optimization algorithm for multimodal multi-objective optimization," *Swarm Evol. Comput.*, vol. 62, Apr. 2021, Art. no. 100843.
[243] M. A. Hossain, H. R. Pota, S. Squartini, and A. F. Abdou, "Modified PSO algorithm for real-time energy management in grid-connected microgrids," *Renew. Energy*, vol. 136, pp. 746–757, Jun. 2019.
[244] J. Zhu, F. Lauri, A. Koukam, and V. Hilaire, "Scheduling optimization of smart homes based on demand response," in *Proc. IFIP Int. Conf. Artif. Intell. Appl. Innov.*, vol. 458, 2015, pp. 223–236.
[245] S. Rahim, N. Javaid, A. Ahmad, S. A. Khan, Z. A. Khan, N. Alrajeh, and U. Qasim, "Exploiting heuristic algorithms to efficiently utilize energy management controllers with renewable energy sources," *Energy Buildings*, vol. 129, pp. 452–470, Oct. 2016.
[246] L. Wang, Z. Wang, and R. Yang, "Intelligent multiagent control system for energy and comfort management in smart and sustainable buildings," *IEEE Trans. Smart Grid*, vol. 3, no. 2, pp. 605–617, Jun. 2012.
[247] K. Bamdad, M. E. Cholette, L. Guan, and J. Bell, "Ant colony algorithm for building energy optimisation problems and comparison with benchmark algorithms," *Energy Buildings*, vol. 154, pp. 404–414, Nov. 2017.
[248] C. I. Okonta, A. H. Kemp, R. O. Edopkia, G. C. Monyei, and E. D. Okelue, "A heuristic based ant colony optimization algorithm for energy efficient smart homes," in *Proc. 5th Int. Conf. Exhib. Clean Energy*, 2016, pp. 1–12.
[249] B. N. Silva and K. Han, "Mutation operator integrated ant colony optimization based domestic appliance scheduling for lucrative demand side management," *Future Gener. Comput. Syst.*, vol. 100, pp. 557–568, Nov. 2019.
[250] J. C. Bansal, S. S. Jadon, R. Tiwari, D. Kiran, and B. K. Panigrahi, "Optimal power flow using artificial bee colony algorithm with global and local neighborhoods," *Int. J. Syst. Assurance Eng. Manage.*, vol. 8, no. S4, pp. 2158–2169, Dec. 2017.
[251] S. Wang, J. Yang, G. Liu, S. Du, and J. Yan, "Multi-objective path finding in stochastic networks using a biogeography-based optimization method," *Simulation*, vol. 92, no. 7, pp. 637–647, Jul. 2016.
[252] F. Wahid, R. Ghazali, and L. H. Ismail, "An enhanced approach of artificial bee colony for energy management in energy efficient residential building," *Wireless Pers. Commun.*, vol. 104, no. 1, pp. 235–257, Jan. 2019.
[253] Y. Zhang, P. Zeng, and C. Zang, "Optimization algorithm for home energy management system based on artificial bee colony in smart grid," in *Proc. IEEE Int. Conf. Cyber Technol. Autom., Control, Intell. Syst. (CYBER)*, Jun. 2015, pp. 734–740.
[254] E. Valian, S. Tavakoli, and S. Mohanna, "An intelligent global harmony search approach to continuous optimization problems," *Appl. Math. Comput.*, vol. 232, pp. 670–684, Apr. 2014.
[255] I. A. Doush, M. Q. Bataineh, and M. El-Abd, "The hybrid framework for multi-objective evolutionary optimization based on harmony search algorithm," in *Proc. 1st Int. Conf. Real Time Intell. Syst.*, vol. 756, 2019, pp. 134–142.
[256] M. Fesanghary, M. Mahdavi, M. Minary-Jolandan, and Y. Alizadeh, "Hybridizing harmony search algorithm with sequential quadratic programming for engineering optimization problems," *Comput. Methods Appl. Mech. Eng.*, vol. 197, nos. 33–40, pp. 3080–3091, Jun. 2008.

[257] J. H. Kim, "Harmony search algorithm: A unique music-inspired algorithm," *Procedia Eng.*, vol. 154, pp. 1401–1405, 2016.
[258] S. Muhammad Mohsin, N. Javaid, S. A. Madani, S. K. Abbas, S. M. A. Akber, and Z. A. Khan, "Appliance scheduling in smart homes with harmony search algorithm for different operation time intervals," in *Proc. 32nd Int. Conf. Adv. Inf. Netw. Appl. Workshops (WAINA)*, May 2018, pp. 51–60.
[259] Z. W. Geem and Y. Yoon, "Harmony search optimization of renewable energy charging with energy storage system," *Int. J. Electr. Power Energy Syst.*, vol. 86, pp. 120–126, Mar. 2017.
[260] A. Figueiredo, J. Kämpf, R. Vicente, R. Oliveira, and T. Silva, "Comparison between monitored and simulated data using evolutionary algorithms: Reducing the performance gap in dynamic building simulation," *J. Building Eng.*, vol. 17, pp. 96–106, May 2018.
[261] M. W. Ahmad, M. Mourshed, B. Yuce, and Y. Rezgui, "Computational intelligence techniques for HVAC systems: A review," *Building Simul.*, vol. 9, no. 4, pp. 359–398, Aug. 2016.
[262] A. Arabali, M. Ghofrani, M. Etezadi-Amoli, M. S. Fadali, and Y. Baghzouz, "Genetic-algorithm-based optimization approach for energy management," *IEEE Trans. Power Del.*, vol. 28, no. 1, pp. 162–170, Jan. 2013.
[263] M. Fadaee and M. A. M. Radzi, "Multi-objective optimization of a stand-alone hybrid renewable energy system by using evolutionary algorithms: A review," *Renew. Sustain. Energy Rev.*, vol. 16, no. 5, pp. 3364–3369, Jun. 2012.
[264] A. Soares, Á. Gomes, C. H. Antunes, and H. Cardoso, "Domestic load scheduling using genetic algorithms," in *Proc. Eur. Conf. Appl. Evol. Comput.* (Lecture Notes in Computer Science), vol. 7835. Berlin, Germany: Springer, 2013, pp. 142–151.
[265] Z. Zhao, W. Cheol Lee, Y. Shin, and K.-B. Song, "An optimal power scheduling method for demand response in home energy management system," *IEEE Trans. Smart Grid*, vol. 4, no. 3, pp. 1391–1400, Sep. 2013.
[266] A. Soares, C. H. Antunes, C. Oliveira, and Á. Gomes, "A multi-objective genetic approach to domestic load scheduling in an energy management system," *Energy*, vol. 77, pp. 144–152, Dec. 2014.
[267] V. Kachitvichyanukul, "Comparison of three evolutionary algorithms: GA, PSO, and DE," *Ind. Eng. Manage. Syst.*, vol. 11, no. 3, pp. 215–223, Sep. 2012.
[268] L. Tang, Y. Zhao, and J. Liu, "An improved differential evolution algorithm for practical dynamic scheduling in steelmaking-continuous casting production," *IEEE Trans. Evol. Comput.*, vol. 18, no. 2, pp. 209–225, Apr. 2014.
[269] Z. A. Khan, A. Zafar, S. Javaid, S. Aslam, M. H. Rahim, and N. Javaid, "Hybrid meta-heuristic optimization based home energy management system in smart grid," *J. Ambient Intell. Humanized Comput.*, vol. 10, no. 12, pp. 4837–4853, Apr. 2019.
[270] V. Rostampour and T. Keviczky, "Probabilistic energy management for building climate comfort in smart thermal grids with seasonal storage systems," *IEEE Trans. Smart Grid*, vol. 10, no. 4, pp. 3687–3697, Jul. 2019.
[271] J. Zhang, Y. Wu, Y. Guo, B. Wang, H. Wang, and H. Liu, "A hybrid harmony search algorithm with differential evolution for day-ahead scheduling problem of a microgrid with consideration of power flow constraints," *Appl. Energy*, vol. 183, pp. 791–804, Dec. 2016.
[272] J. D. Moyer and S. Hedden, "Are we on the right path to achieve the sustainable development goals?" *World Develop.*, vol. 127, Mar. 2020, Art. no. 104749.
[273] S. E. Diaz-Mendez, A. A. Torres-Rodríguez, M. Abatal, M. A. E. Soberanis, A. Bassam, and G. K. Pedraza-Basulto, "Economic, environmental and health co-benefits of the use of advanced control strategies for lighting in buildings of Mexico," *Energy Policy*, vol. 113, pp. 401–409, Feb. 2018.
[274] B. Li and R. Yao, "Urbanisation and its impact on building energy consumption and efficiency in China," *Renew. Energy*, vol. 34, no. 9, pp. 1994–1998, Sep. 2009.
[275] P. Sheng and X. Guo, "Energy consumption associated with urbanization in China: Efficient- and inefficient-use," *Energy*, vol. 165, pp. 118–125, Dec. 2018.
[276] A. Khan, N. Mushtaq, S. H. Faraz, O. A. Khan, M. A. Sarwar, and N. Javaid, "Genetic algorithm and earthworm optimization algorithm for energy management in smart grid," in *Proc. Int. Conf. P2P, Parallel, Grid, Cloud Internet Comput.*, 2018, pp. 447–459.
[277] M. Ali, S. Abid, A. Ghafar, N. Ayub, H. Arshad, S. Khan, and N. Javaid, "Earth worm optimization for home energy management system in smart grid," in *Proc. Int. Conf. Broadband Wireless Comput., Commun. Appl.*, 2018, pp. 583–596.
[278] A. Manzoor, F. Ahmed, M. A. Judge, A. Ahmed, M. A. Ul Haq Tahir, Z. A. Khan, U. Qasim, and N. Javaid, "User comfort oriented residential power scheduling in smart homes," in *Proc. Int. Conf. Innov. Mobile Internet Services Ubiquitous Comput.*, 2018, pp. 171–180.
[279] P. Rocha, A. Siddiqui, and M. Stadler, "Improving energy efficiency via smart building energy management systems: A comparison with policy measures," *Energy Buildings*, vol. 88, pp. 203–213, Feb. 2015.
[280] E. Annunziata, F. Rizzi, and M. Frey, "Enhancing energy efficiency in public buildings: The role of local energy audit programmes," *Energy Policy*, vol. 69, pp. 364–373, Jun. 2014.
[281] N. T. Mbungu, R. C. Bansal, R. Naidoo, V. Miranda, and M. Bipath, "An optimal energy management system for a commercial building with renewable energy generation under real-time electricity prices," *Sustain. Cities Soc.*, vol. 41, pp. 392–404, Aug. 2018.
[282] Z.-S. Li, G.-Q. Zhang, D.-M. Li, J. Zhou, L.-J. Li, and L.-X. Li, "Application and development of solar energy in building industry and its prospects in China," *Energy Policy*, vol. 35, no. 8, pp. 4121–4127, Aug. 2007.
[283] (2017). *World Green Building Council*. Accessed: Jan. 21, 2020. [Online]. Available: https://www.worldgbc.org/news-media/green-building—driver-decent-jobs-economic-growth
[284] M. S. Hossain Lipu, T. Jamal, and T. F. Karim, "An approach towards sustainable energy performance by green building: A review of current features, benefits and barriers," *Int. J. Renew. Sustain. Energy*, vol. 2, no. 4, pp. 180–190, 2013.
[285] (2020). *Benefits of Green Buildings*. Accessed: Jan. 21, 2020. [Online]. Available: https://www.worldgbc.org/benefits-green-buildings
[286] (2016). *Canada Green Building Council*. Accessed: Jan. 21, 2020. [Online]. Available: https://www.cagbc.org/News/EN/2016/20160210_News_Release.aspx
[287] C. Dipasquale, R. Fedrizzi, A. Bellini, M. Gustafsson, F. Ochs, and C. Bales, "Database of energy, environmental and economic indicators of renovation packages for European residential buildings," *Energy Buildings*, vol. 203, Nov. 2019, Art. no. 109427.
[288] E. Klumbyte, R. Bliudzius, and P. Fokaides, "Development and application of municipal residential buildings facilities management model," *Sustain. Cities Soc.*, vol. 52, Jan. 2020, Art. no. 101804.
[289] S. Copiello, "Economic parameters in the evaluation studies focusing on building energy efficiency: A review of the underlying rationale, data sources, and assumptions," *Energy Procedia*, vol. 157, pp. 180–192, Jan. 2019.
[290] O. Pisacane, M. Severini, M. Fagiani, and S. Squartini, "Collaborative energy management in a micro-grid by multi-objective mathematical programming," *Energy Buildings*, vol. 203, Nov. 2019, Art. no. 109432.
[291] W. Kim, S. Katipamula, and R. Lutes, "Application of intelligent load control to manage building loads to support rapid growth of distributed renewable generation," *Sustain. Cities Soc.*, vol. 53, Feb. 2020, Art. no. 101898.
[292] R. Tang, S. Wang, and H. Li, "Game theory based interactive demand side management responding to dynamic pricing in price-based demand response of smart grids," *Appl. Energy*, vol. 250, pp. 118–130, Sep. 2019.
[293] L. F. M. van Summeren, A. J. Wieczorek, G. J. T. Bombaerts, and G. P. J. Verbong, "Community energy meets smart grids: Reviewing goals, structure, and roles in virtual power plants in Ireland, Belgium and The Netherlands," *Energy Res. Social Sci.*, vol. 63, May 2020, Art. no. 101415.
[294] J. Louis, A. Caló, and E. Pongrácz, "Smart houses for energy efficiency and carbon dioxide emission reduction," in *Proc. 4th Int. Conf. Smart Grids, Green Commun. IT Energy-Aware Technol.*, 2014, pp. 44–50.
[295] J. Langevin, C. B. Harris, and J. L. Reyna, "Assessing the potential to reduce U.S. building CO_2 emissions 80% by 2050," *Joule*, vol. 3, no. 10, pp. 2403–2424, Oct. 2019.
[296] E. Georgopoulou, Y. Sarafidis, S. Mirasgedis, C. A. Balaras, A. Gaglia, and D. P. Lalas, "Evaluating the need for economic support policies in promoting greenhouse gas emission reduction measures in the building sector: The case of Greece," *Energy Policy*, vol. 34, no. 15, pp. 2012–2031, Oct. 2006.