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TOPICAL REVIEW

Home Energy Management Systems: A Review of the Concept, Architecture, and Scheduling Strategies

BINGHUI HAN[1], YOUNES ZAHRAOUI[2], MARIZAN MUBIN[1], SAAD MEKHILEF[3,4], (Fellow, IEEE), MEHDI SEYEDMAHMOUDIAN[3], (Member, IEEE), AND ALEX STOJCEVSKI[3]

[1]Power Electronics and Renewable Energy Research Laboratory (PEARL), Department of Electrical Engineering, Faculty of Engineering, University of Malaya, Kuala Lumpur 50603, Malaysia
[2]FinEst Centre for Smart Cities, Tallinn University of Technology, 19086 Tallinn, Estonia
[3]School of Software and Electrical Engineering, Faculty of Science, Engineering and Technology, Swinburne University of Technology, Victoria, VIC 3122, Australia
[4]Department of Electrical Engineering, College of Engineering, Universiti Tenaga Nasional, Selangor 43000, Malaysia

Corresponding authors: Marizan Mubin (marizan@um.edu.my) and Saad Mekhilef (smekhilef@swin.edu.au)

ABSTRACT Growing electricity demand, the deployment of renewable energy sources and the widespread use of smart home appliances provide new opportunities for home energy management systems (HEMSs), which can be defined as systems that improve the overall energy production and consumption of residential buildings by controlling and scheduling the use of household equipment. By saving energy, reducing residential electricity costs, optimizing the utilization rate and reliability of utility companies' power systems, and reducing air pollution for society, HEMSs lead to an enhancement in the socioeconomic development of low-carbon economies. This review aims to systematically analyze and summarize the development trends and challenges of HEMSs in recent years. This paper reviews the development history of the HEMS architecture and discusses the characteristics of several major communication technologies in the current HEMS infrastructure. In addition, the common objectives and constraints related to scheduling optimization are classified, and several optimization methods in the literature, including various intelligent algorithms, have been introduced, compared, and critically analyzed. Furthermore, experimental studies and challenges in the real world are also summarized and recommendations are given. This paper reveals the trend from simple to complex in the architecture and functionality of HEMSs, discusses the challenges for future improvements in modeling and scheduling, and shows the development of various modeling and scheduling methods. Based on this review, researchers can gain a comprehensive understanding of current research trends in HEMSs and open up ideas for developing new modeling and scheduling approaches by gaining insight into the trade-offs between optimum solutions and computational complexity.

INDEX TERMS Demand response, home appliances, home energy management system, optimization, renewable energy resources, smart grid.

ABBREVIATIONS

RERs	Renewable energy resources
GHG	Greenhouse gas
AMI	Advanced metering infrastructure
BHC	Bidirectional high-speed communication
SG	Smart grid
DR	Demand response
HEMS	Home energy management system
DERs	Distributed energy resources
HESS	Home energy storage systems
NILM	Non-intrusive load monitoring
BEMSs	Building energy management systems
EMS	Energy management system
EVs	Electric vehicles
PV	Photovoltaic

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HAN	Home area network
LP-WAN	Low-power wide-area network
BES	Battery energy system
PAR	Peak-to-average ratio
HVAC	Heating, ventilation and air conditioning
RCC	Resident comfort criteria
DRE	Distributed renewable energy
ESS	Energy storage system
LP	Linear programming
BILP	Binary integer linear programming
MILP	Mixed integer linear programming
NLP	Non-linear programming
MINLP	Mixed integer non-linear programming
SoC	State of charge
EES	Electrical energy storage
TOU	Time of use
RTP	Real time price
IBR	Inclining block rate
DP	Dynamic programming
GA	Genetic algorithm
PSO	Particle swarm optimization
BOA	Butterfly optimization algorithm
ABC	Artificial bee colony
NSGA-II	Non-dominated sorting genetic algorithm
DoD	Depth of discharge
AI	Artificial Intelligence
ANN	Artificial neural network
MAS	Multi-agent system
SVR	Support vector regression
MPC	Model predictive control

I. INTRODUCTION

Society is facing several problems such as energy shortage and environmental pollution caused by fossil fuels [1]. To solve the energy issues, the need for a reliable and secure energy supply that is independent of fossil fuels is an important goal for most countries [2]. Consequently, renewable energy resources(RERs), such as solar, wind, and biomass power are deployed at scale to provide dependable energy and mitigate greenhouse gas (GHG) emissions [3]. However, unlike traditional energy sources, the volatile and intermittent nature of the RESs in power systems may lead to unforeseen peaks in energy production, which affects the stability of the power grid [4]. To overcome these shortages, technologies including advanced metering infrastructure (AMI) and bidirectional high-speed communication (BHC) develop rapidly, which leads the power grid transiting from a traditional centralized grid to distributed smart grid (SG). Thus, to meet the changes in time-based electricity prices or other forms of financial incentives and to provide flexibility and reliability in SGs, demand response (DR), which is defined as changes in electricity usage by end users also diversified increasingly [5].

In addition, with the vigorous development of control and communication technologies, various electronic home entertainment, information, and communication equipment have gradually become an indispensable part of home life. People's life is becoming more and more convenient and intelligent, and living standards are also getting higher and higher. In the meantime, modern lifestyles also bring some disadvantages. For example, the widespread use of smart household appliances leads to a dramatic increase in household energy consumption [6]. Besides these, there are circumstances of wasting energy consumption or low energy consumption utilization rate in the community due to the lack of energy-saving awareness or the failure to pay attention to the working conditions of various electrical appliances in time of some residents [7]. Manual monitoring and control are not enough to achieve the goal of energy conservation in smart homes. Therefore, intelligent scheduling and control of kinds of home appliances have become an important direction for energy conservation in smart homes.

The technology to improve the energy production/ consumption condition of homes systematically by scheduling home appliances intellectually is called a home energy management system (HEMS) [6]. The HEMS can transfer or reduce energy costs by scheduling the use of household appliances, in addition, it enables the energy generated by distributed energy resources (DERs) to be stored and managed with home energy storage systems (HESS) [8], by improving the overall energy production and consumption conditions of a house. This is usually achieved by using an optimal scheduling algorithm to calculate the appropriate time to turn on or turn off a device by considering factors such as external information (e.g., updated grid prices or weather forecasts) and inner information (e.g., consumer preferences or home appliance historical usage data) [9].

Compared with manual operation, HEMSs have the advantage of automatically assessing electricity prices, household demand, the uncertainty of external environmental variables, and customizing appropriate household energy consumption plans to control the use of household appliances. Nowadays, HEMSs have become increasingly attractive for end-use customers, power companies, and society to ensure power control and management. By optimizing the energy consumption of customers' homes according to electricity price and their habits, HEMSs can save energy for society while reducing the electricity cost of their homes. Furthermore, HEMSs allow public utilities to analyze the future energy needs of customers to optimize the application of power and increase the reliability of power systems [10].

There are many surveys and review articles about HEMSs. A summary of the main relevant review articles on HEMSs between 2015 and March 2022 is presented in Table 1. Based on the different aspects of HEMSs, these research papers can be roughly divided into HEMS' architectures [11], [17], functionalities [11], [17], [19], infrastructures [11], [13], [20], modeling categorizations and approaches [6], [21] and kinds of optimization scheduling strategies [6], [11], [16], [21], [22] as well as HEMS applications in SG and DR [23] and interdisciplinary meta-reviews about HEMSs [24]. However,

TABLE 1. Existing review papers on different areas of HEMSs (2015-2022).

Ref.	Year	Description
[6]	2015	This paper reviewed challenges, methods, and impacts on the modeling frameworks of HEMSs
[11]	2016	This article presented a review of the architecture, functionalities, infrastructures, scheduling strategies, and RERs adoption of HEMS.
[18]	2016	This study investigated key functions and energy-saving effects of 276 published papers from 1976 to 2014 and 305 EMS cases related to building energy management systems (BEMSs).
[20]	2016	This work reviewed the concept and cases of BEMSs and the power line communication technology deployed in them.
[19]	2017	This paper introduced issues that occurred in achieving an actual NILM, by exploring its primary applications of it and proposed a new method i.e. advanced NILM.
[12]	2017	This article provided an in-depth review of charging infrastructure, charging technologies, international standards, applications, and energy management systems (EMSs) for electric vehicles (EVs).
[13]	2017	This study overviewed the categories of behind-the-meter EMS, the classification of loads, enabling technologies & standards, and a case study of the system implementation.
[23]	2017	This article presented the key characteristics, challenges, and models of energy management systems aggregators.
[14]	2018	This work summarized the architecture and communication infrastructure of micro-grid EMS, analyzed different categories of optimization methods, and provided executions in the real world.
[24]	2020	This paper presented a meta-review of the impacts, agents, and functionalities of smart HEMSs in enhancing energy benefits.
[15]	2021	This study investigated different forms of energy generation technologies, analyzed the quality of literature, and introduced future recommendations about smart HEMSs.
[16]	2021	This paper summarized and discussed management strategies and future challenges in the area of BEMSs.
[21]	2021	This article reviewed EMSs of islanded microgrids in terms of six main optimization aspects, along with the future trends.
[22]	2022	This study used a scientometric research methodology to present a 3-tier taxonomy of machine learning applications for functionalities of HEMS and BEMS.

according to the classification results, it can be found that except for the [11] published in 2016, which reviewed all aspects of HEMS in an overall manner, other review articles only cover some or even one aspect of HEMS. For example, reference [19] focuses on non-intrusive load monitoring (NILM), which is one part of the monitoring functionalities of HEMSs while [22] proposes a 3-tier taxonomy of machine learning applications in HEMSs. This result not only means that the review of HEMSs in recent years has become more and more refined due to the in-depth research but also indicates that the overall discussion of HEMSs needs to be reorganized and improved.

This paper aims to systematically analyze and summarize the development trends and challenges of HEMSs in recent years. Three main contributions are provided in this work. Firstly, the development history of the HEMS architecture is reviewed and updated along with the characteristics of major communication technologies in the current HEMS infrastructure. Secondly, since there are few review papers that mentioned about the collection of the optimization objective functions, this work classifies and collects the objectives functions and constraints of scheduling optimization. In addition, common used optimization algorithms are introduced, compared, and critically analyzed. Finally, the applications and challenges of HEMS are also summarized and research recommendations are given to help readers have a comprehensive understanding of current trends in the HEMSs.

The remainder of this paper is organized as follows. The architecture of HEMS including the development process, the description of every moduels, and the functionalities of HEMSs is introduced in Section II. Section III discusses the characteristics of major communication technologies deployed in the current HEMS infrastructure. Objectives functions, constraints, and optimization algorithms are classified, introduced, compared, and critically analyzed in Section IV. Section V describes and discusses the application and challenges faced in HEMS, along with the research recommendations. Finally, Section VI concludes the work.

II. ARCHITECTURE OF HEMS

The overall system structure of HEMSs is gradually formed since 1979 [25]. With the widespread installation of AMI and the development of SG, HEMSs develop from early analog systems with limited application to modern modular smart systems [10]. As shown in Table 2, the development process of HEMSs mainly focuses on three aspects, i.e., the improvement of the system architecture, the update of information transmission technologies, and the optimization of the scheduling strategy. In this section, the typical architecture of a HEMS is described, along with the main functionalities of the HEMS.

As an application on the end-user side of SG, a modern HEMS can be defined as a modular system with the ability to interact with household appliances and public utilities that organically integrate all power generation, consumption, and storage equipment in the home with a variety of intelligent technologies to ameliorate the power efficiency. The general architecture of a HEMS is presented in Fig. 1, which can be divided into five main components below:

A. CENTRAL CONTROLLER

In the literature, the central controller has been introduced in different technical terms such as smart controller [10], smart center [11], or central platform [9], which is the core component of a HEMS. To manage and optimize the energy usage of household appliances, it usually provides five major system management functionalities, including monitoring,

TABLE 2. The development process of HEMSs.

Ref.	Authors	Years	Development process
[25]	Moen	1979	The first microprocessor-based solar energy management system was proposed.
[26]	Wise	1981	Sensors were regarded as sensing systems and an extension of a central processor.
[27]	Capehart *et al.*	1982	The first optimizing energy management algorithm to reduce the cost of electricity was introduced.
[28]	Bhatnagar and Rahman	1986	Knowledge-based algorithms were used for electric utility load forecasting.
[29]	Wacks	1991	Utility load management using home automation was proposed.
[30]	Kidd	1999	The management system was built based on the sensoring devices.
[31]	Kushiro *et al.*	2003	An integrated residential gateway controller was built for HEMS.
[32]	Inoue *et al.*	2003	A network architecture for HEMS with control/monitor capabilities was proposed.
[33]	Sierra *et al.*	2007	A fuzzy control approach with a man-machine interface was presented to improve indoor living conditions.
[34]	Karjalainen	2009	Thermal comfort based on thermostats in homes and office buildings was examined in Finland.
[35]	Han *et al.*	2011	Efficient HEMS based on ZigBee and the infrared remote control were proposed.
[36]	Pipattanasomporn *et al.*	2012	An intelligent HEM algorithm for DR analysis was proposed.
[37]	Di Giorgio and Pimpinella	2012	An event-driven intelligent control strategy was provided based on binary linear optimization.
[38]	Batista *et al.*	2012	Photovoltaic and wind energy systems were embedded in the HEMS.
[39]	Kim et al.	2012	A HEMS was implemented with mobile applications
[40]	Squartini *et al.*	2013	Data uncertainty is considered in the HEMS.
[41]	Boynuegri *et al.*	2013	A HEM algorithm for houses with renewable sources (PV, wind turbine, and battery bank) was provided.
[42]	Iimura *et al.*	2014	A real electrical energy-balanced solar house was built based on HEMS.
[43]	Frascarolo *et al.*	2014	An artificial lighting system has been experimented with and implemented to maximize visual comfort and conserves.
[44]	Huang *et al.*	2015	A generic gradient-based repair PSO algorithm was proposed for the DR of the HEMS.

logging, management, control, and alarm [10], [11], [54], as shown in Fig. 2.

TABLE 2. *(Continued.)* The development process of HEMSs.

[45]	Iwafune *et al.*	2015	PV generation forecast errors were considered in the HEMS model.
[46]	Cervera-Vázquez *et al.*	2015	User comfort of ground source heat pump systems was considered in the optimization.
[47]	Goubko *et al.*	2016	Consumer preferences were learned from the appliance usage data to measure the corresponding comfort levels.
[48]	Ruelens *et al.*	2017	The exogenous weather data forecast was provided based on a deep reinforcement learning algorithm.
[49]	Arabul *et al.*	2017	A fuel cell–battery–wind turbine–solar panel hybrid off-grid framework was provided in the HEMS.
[50]	Hemmati and Saboori	2017	An efficient HEMS working on a net-zero energy model was proposed.
[51]	Chaudhuri *et al.*	2019	A scalable method used with any comfort-prediction model was proposed.
[52]	Paveethra *et al.*	2020	An application of voice recognition was included in the wireless HEMS.
[53]	Dorahaki *et al.*	2022	A behavioral HEM model based on time-driven prospect theory was developed.

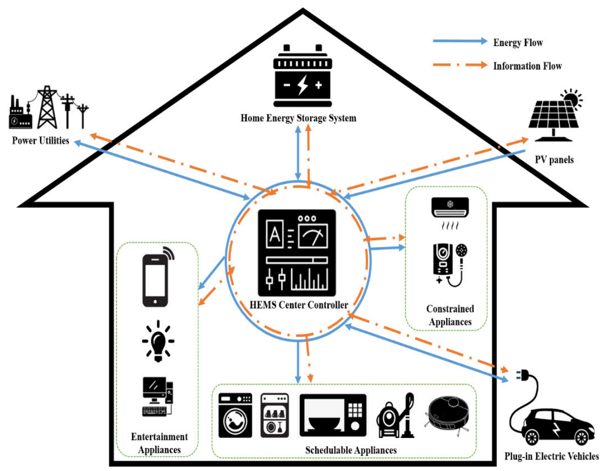

FIGURE 1. Typical architecture of a representative HEMS.

1) MONITORING

Monitoring is a functional module that monitors energy consumption in the HEMS and generates real-time information. This function can liberate the user's attention and automatically achieve the purpose of power conservation. The monitoring function of some HEMSs can be more powerful, such as providing a visual display service of their operating modes and/or the energy consumption status of each household appliance.

2) LOGGING

Logging is the process that collates and saves the data information of electricity consumed for each appliance

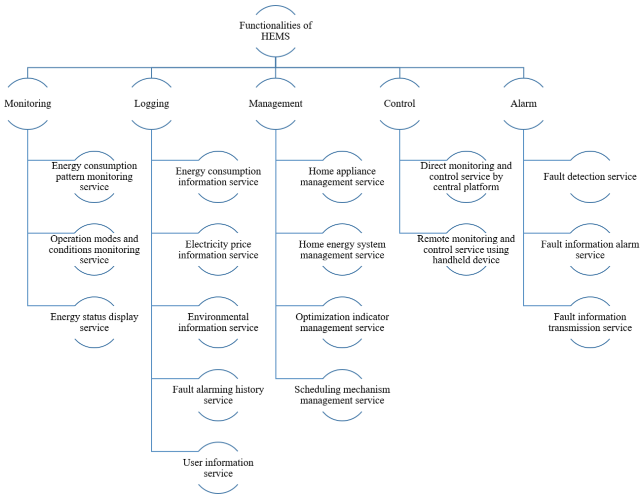

FIGURE 2. **Major functionalities of a representative HEMS.**

including DERs, plug-in electric vehicles (EVs), and energy conservation states. Moreover, the logging contains DR analysis for real-time electricity prices from the utilities, external environmental variables recording and analysis such as user behavior and weather condition, and fault alarming history.

3) MANAGEMENT

Management is the primary functionality of a HEMS to achieve some objectives such as energy saving, cost reduction, and environmental protection. Specifically, management aims to collect, collate, and analyze the information related to the usage of home appliances collected by smart meters, such as real-time power consumption, and combine it with given performance optimization indicators (electricity costs, living comfort, peak reduction, and greenhouse gas emissions, etc.) to calculate the most suitable scheduling mechanism for each household appliance, and finally, achieve the goal of energy optimization.

4) CONTROL

Control can be divided into direct control and remote control based on the method which is used to control the system. Direct control refers to the method of monitoring and controlling the system directly through the central controller or its central visual platform, whereas remote control signifies the method of monitoring and controlling the system through other accessible devices networked with the central controller such as PCs, laptops, and smartphones.

5) ALARM

Alarm, also known as fault detection, means that when the various electrical equipment involved in HEMS, such as DERs, HESS, and EVs, cannot work normally or various networks associated with HEMS, including water, electricity, and the Internet, are disconnected, the controller will detect the source of the error, activate the alarm device, and transmit the corresponding fault information, e.g. fault locations, types, etc. to the display devices.

In a summary, in a fully functional HEMS, the central controller is the component that complements the given objectives and meets user-defined specifications and preferences by processing usage data, forecasting uncertainties, and providing optimization strategy in a house. The description and the application of common objectives that have been used in HEMS can be seen in section IV.

B. SMART HOME APPLIANCES

As the terminal parts of HEMSs, smart home appliances are devices with monitoring, communication, and control capabilities with the center controller. Only when the home appliances were scheduled and operated at a proper time, the preset goals of HEMSs can be achieved ultimately. Since there are diverse appliances in each family, and the ownership rate, power consumption, and usage of different devices are also very different among families [55], to manage energy consumption effectively and efficiently, smart home appliances are usually classified before modeling and calculating. In this review, household appliances are divided into conventional appliances, smart appliances, and EVs according to whether the appliance requires a smart plug and can be used as emergency energy supply equipment [11], [56].

1) CONVENTIONAL APPLIANCES

Conventional appliances refer to traditional electrical devices without communication and automatic control functions. To successfully connect these appliances to the HEMS and obtain proper dispatch, these appliances need to be equipped with additional auxiliary communication and control equipment such as smart plugs, which have the ability to identify the attached appliance, record its energy consumption pattern of it, and recognize the behavior of users [56].

2) SMART APPLIANCES

Different from conventional appliances, smart appliances in this section refer to novel household electrical devices that are equipped with intelligent control and communication modules themselves but cannot provide emergency power supply for other loads. Smart appliances do not require extra smart plugs to connect to the HEMS, which is the embodiment of the continuous development of smart home technology and the basis for widespread residential energy management [11], [56].

3) ELECTRIC VEHICLES

EVs mentioned in the HEMS literature not only refer to EVs powered purely by electricity in rechargeable batteries, but also include various hybrid vehicles, in which electricity occupies part of the driving energy. An EV is a special kind of smart appliance due to the feature of the energy storage system. Generally, EVs in the HEMS are able to

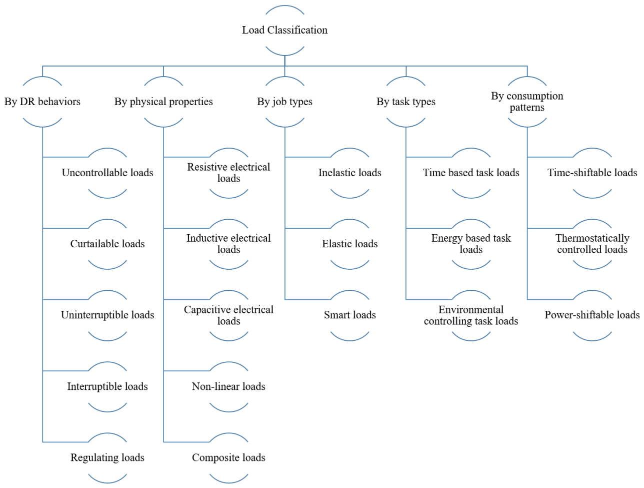

FIGURE 3. Classification principles for home appliances.

provide emergency power for other household loads [11]. Recently, EVs have fascinated great attention because of their important role in reducing global pollution, improving energy efficiency, promoting the stability of the grid system, and playing an important role in future DR applications [10], [12], [57], [60].

In addition to the classification mentioned earlier, Fig. 3 presents some other category methods for household appliances that are convenient for modeling and optimization. For example, home appliances can be classified into uncontrollable loads, curtailable loads, uninterruptible loads, interruptible loads, and regulating loads by their DR behavior [61] [6]. Principles like physical properties and job types were described and discussed in [13]. The authors in [62] categorized residential appliances in accordance with their task types to get the best feasible task activation plan. The appliances in the work [63] were simplified and classified into time-shiftable appliances, thermostatically controlled appliances, and power-shiftable appliances based on their consumption patterns.

C. SENSING AND MEASURING DEVICES

Sensing and measuring devices are the fundamental elements in the HEMS. The sensing and measuring devices can be wired, wireless devices, or both, these devices are responsible for collecting information from the surrounding environment such as the temperature, power consumption, and level of energy storage. The common sensor devices that have been used in HEMS are shown in Table 3. Other sensors include the sensors that can measure physical quantities such as humidity, current, voltage, and illuminance, and detect smoke, movement, or room occupancy [9], [64]. With the installation of AMI, the importance of novel sensing and measuring devices in HEMSs grows rapidly by serving as a BHC interface between the users and the utilities [65]. By collecting various usage data from utility services, smart sensing, and measuring devices enable the HEMS to manage real-time grid information for customer accounts to attain the objectives of the family and provide the utility opportunities to predict the load demand more accurately in the future, thus reducing power generation costs and loss.

TABLE 3. Sensors regularly used in HEMSs.

Sensors	Description
Magnetic	For perimeter security and door/window security.
PIR	For movement detection of objects.
RFID	For access control and device identification.
Ultrasonic	For detection of objects or persons.
Vibration	For perimeter security and vibration detection.
Video	For security and motion identification.

D. ENERGY GENERATION AND STORAGE DEVICES

In recent years, due to the inherent intermittence and randomness of RESs, individual households are becoming participants in RESs electricity generation with the independence and self-sufficiency feature of home microgrids. Currently, RESs are integrated into smart homes including solar photovoltaic (PV) [66], wind [67], biomass [68], geothermal energy [69], and so on [70]. In addition, hybrid energy systems such as solar-wind energy [49] and solar–wind–diesel energy [71] have also been complemented to provide a reliable and sustainable power supply for a family with a full set of modern home appliances and complete basic residential functions.

Due to the intermittence and randomness characteristics of RESs, the electricity generated by RESs integrated with homes is ensuring the continuity and stability of the power supply of home microgrids. Usually, the energy storage device in a smart home refers to a local battery with an energy management system, which offers an effective solution by providing energy storage for subsequent use and energy dispatch that trades energy with public utilities with a given profit when electricity generation exceeds local demand.

E. USER INTERFACE

The user interface is a kind of software that allows the provision of an interface between the controller, sensors, smart meter, and the appliances of the HEMS and has the function of displaying information. The purpose of this module is to enable users to operate HEMS according to their own preferences, and to ensure the quality of life of residents while monitoring and dispatching household energy consumption in real-time more conveniently and efficiently. The user interface software is designed to be a common model for friendly use to bring more interactive choices to residents. Early user interface software was designed to be installed on personal computers. In the past decade, due to the popularity and user-friendly nature of remote mobile and control devices, increasing in the number of user interface software has been designed to be applications for tablets and mobile phones and bring more interactive choices to residents [9].

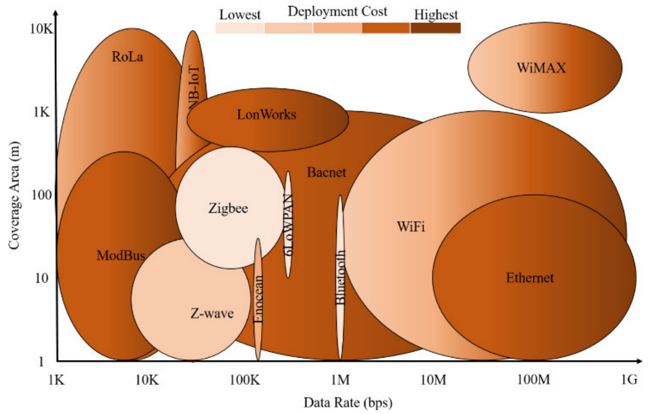

FIGURE 4. Communication technologies for HEMS.

III. COMMUNICATION OF HEMS

Within a home, an effective HEMS for whole-house energy management requires both external information (e.g., household activities, electricity prices, and weather forecasts) and appropriate communication with the corresponding devices [6], [9]. Therefore, an efficient communication system (wired or wireless) that shares demand-side information and optimizes the operation of home appliances locally is also required for a HEMS. Recently, the traditional electricity grid is changing to a smarter infrastructure, called the smart grid, which enables the energy management of homes at grid terminals by BHC. Subsequently, many communication schemes with hardware implementation emerged within the home area network(HAN).

A summary of most communication technologies that have been applied in HEMSs is shown in Fig. 4. Among them, wired technologies, such as Ethernet [72], [73], Bacnet [74], [75], LonWorks [76], and ModBus [76], usually have high data rates and reliability but also high deployment costs. On the contrary, wireless technologies, such as Zigbee [77], [78], WiFi [78], [79], Bluetooth [80], [81], Z-wave [82], [83], 6LoWPAN [84], [85], and Enocean [73], [86], etc., have low installation cost compared to wired technologies. In addition, wireless technologies do not require wiring and are easy to set up. Thus the installation of smart home appliances can be deployed without making major changes to home wiring, and are more convenient for maintenance and expansion, hence being better candidates for the HAN.

However, with the explosive usage of household appliances, wireless technologies are faced with small scalability, narrow coverage area, and signal interference problems due to the sharing of the frequency band (e.g., 2.4GHz for ZigBee, Bluetooth, and Wi-Fi). In addition, traditional long-distance wireless technologies like WiMAX [87] also have an extra monthly fee after the installation, which affects the promotion of this kind of technology. To solve these problems, new low-power wide-area network(LP-WAN) technology with sub-GHz frequency band and long-distance characteristics is getting more and more attention. LP-WAN has the advantages of low power consumption, wide coverage area, high stability, and strong anti-interference ability, which has great application potential in the field of HAN communication. At present, the application of LP-WAN mainly focuses on the two technical standards of LoRa [88], [89] and NB-IoT [89], [90], which have been used in large-sized houses such as villas and duplex buildings.

The communication protocols used in the communication system of the house can be selected based on the parameters including data rate, coverage area, deployment cost, power consumption, security, reliability, stability, and scalability [65]. Table 4 presents the advantages and disadvantages of wireless communication technologies used in HEMS. It is worth mentioning that compared with the technical details of the communication protocol used in the HAN, most HEMSs users usually pay more attention to deployment cost, installation simplicity, and maintaining the stability of the HAN. This may illustrate the phenomenon of the coexistence of various protocols in the market. Thus, multi-mode gateways containing multiple communication protocols have been one of the solutions to the compatibility problem under the coexistence of multiple devices and multiple protocols.

IV. OPTIMIZATION OF HEMS

Generally, HEMSs increase household energy utility efficiency by reducing or shifting the consumption of various home appliances. Since the reduction of load demand often leads to the discomfort of residents, which affects their participation in DR programs, the load-shifting method is more popular in residential buildings [9]. The typical schematic diagram of a HEMS is illustrated in Fig. 5. The consumption planning needs to rely on optimization and scheduling methods to find the best working hours for each household appliance. Therefore, the consumption operation of each appliance must be described for the formulation of optimization objectives, the choice of optimization methods, and the consequent calculation and operation constraints. This section describes the main optimization objectives, constraints, and methods applied to enhance the HEMS efficiency.

HEMSs reduce or shift the load demand by monitoring the consumption of home appliances and coordinating the operation of various devices to increase energy efficiency. Recently, the comfort of the residents is considered the most popular factor in residential buildings [9].

A. OBJECTIVES OF HEMS

Over the past decade previous, several studies focused to enhance the HEMS using traditional methods by reducing energy consumption, However, this reduction in energy cost may lead a discomfort for the users, which prevents residents from participating in the DR program [35]. Recently, the integration of RERs, ESSs, EVs, and DR, and the diverse applications of home appliances enable HEMS to acquire a broader architecture and functionality to deploy more effective energy

TABLE 4. Comparison of typical wireless communication technologies used in HEMS.

Reference	Technologies	Advantages	Disadvantages
[77], [78]	ZigBee	Self-organizing network; Small latency; High stability and reliability; Low energy consumption; High security.	Narrow bandwidth; Low transfer rate; Narrow coverage area; Poor wall penetration; Higher cost than Bluetooth; Interoperable protocols.
[78], [79]	Wi-Fi	Widespread popularity, Wide bandwidth; High transfer rate; Relatively simple configuration.	Network dependency High energy consumption; High cost; Low stability; Low security; Small scalability.
[80], [81]	Bluetooth	Widespread popularity, Low cost; High transfer rate; Quick connection with mobile phones.	Narrow bandwidth; Narrow coverage area; Low anti-interference ability; Low stability; Small scalability.
[82], [83]	Z-Wave	Low cost; Low energy consumption.	Low security and stability; Low reliability; Small scalability.
[88], [89]	LoRa	Low energy consumption; Wide coverage area; High stability; Strong anti-interference ability; Large scalability.	High cost; Low transfer rate.
[89], [90]	NB-IoT	Low energy consumption; Wide coverage area; High stability; Strong anti-interference ability; Large scalability.	High cost; Low transfer rate.

management. Fig. 6 presents the common optimization objectives and constraints used in the HEMS. These objectives are based on the types of home appliances and are subject to uncertain conditions such as weather, user behavior, electricity price, load consumption, and load diversity.

1) COST

Cost is the most common objective in the HEMS because it is the primary motivation for residents to use HEMSs to manage household appliances by minimizing the electricity

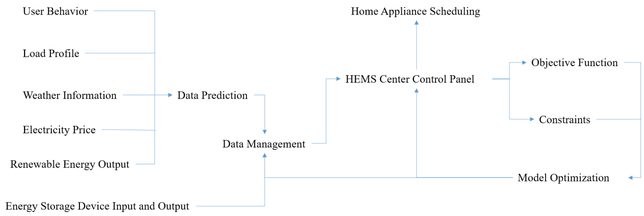

FIGURE 5. The typical schematic diagram of a HEMS.

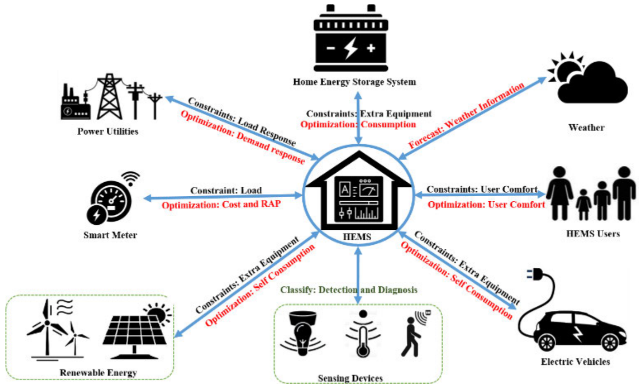

FIGURE 6. Objectives and constraints of a typical HEMS.

costs while considering available electricity prices and renewable micro-generation. As shown in Table 5, the objective of cost refers to any financial term related to energy management mainly including electricity costs minimization [63], [77], [98], [103], [79], [91], [97], the self-scheduling between the grid, renewable energy generators and loads [104], [105], retailer's profit maximization [102], total profit maximization [62], [106], [107], the start-up costs of the home system [108], and the maintenance cost [109].

2) LOAD PROFILING

Load profiling is one of the most common objectives that has been applied in HEMS in terms of changing the peak-to-valley structure and modifying the consumption method for electricity. It can make the household microgrid beneficial to not only the HEMS users but also the public utilities [110]. There are six different strategies of load profiling which are peak shaving, valley filling, strategic conservation, load shifting, strategic growth, and flexible load shape [13], [98], [111], [112] Compared with the first three strategies, load shifting, strategic growth, and flexible load shape provide more systematic and large-scale changes in load management. Table 6 represents the objective function of the load profiling, which mainly includes load peak minimization [98], [113], peak-to-average ratio (PAR) reduction [91], [103], [114], self-consumption [106] and energy balance [115].

3) USER COMFORT

Recent studies mainly focus on user comfort which is considered the primary focus of minimizing the energy

TABLE 5. Objective functions for minimization of cost.

Ref.	Objectives	Objective Functions	Description
[91]	Electricity cost minimization	$\sum_{\forall r \in R}\{\omega_r \cdot \sum_{\forall t \in T}\{\Delta\tau \cdot \lambda_t \cdot p_{r\|t}^{Grid}\}\}$ (1)	$r/\mathcal{R}$ and $t/\mathcal{T}$ are the index/total number of scenarios and time intervals, respectively, ω_r is the probability of scenario r, $\Delta\tau$ is the time step, λ_t and $p_{r\|t}^{Grid}$ are energy cost and grid power at time t.
[92]	Electricity cost minimization	$\sum_{i=1}^{NA}\sum_{t=1}^{NT}\rho_t^{Tariff}S_{i,t}P_i\Delta t$ (2)	t/NT and i/NA are index/total number of time intervals, and home appliances, respectively. ρ_t^{Tariff} is the cost under the tariffs, $S_{i,t}$ is the usage status variable (binary) of appliance i at time t, P_i is the rated power of appliance i, Δt is an operation time interval.
[77]	Electricity cost minimization	$\sum_{i=1}^{M}\Delta \times S_g \times P_g$ (3)	i/M is the index/total number of time slots, Δ is the time resolution, S_g and P_g are the electricity price sold by the grid and the power of the grid at time t, respectively.
[93]	Electricity cost minimization	$\sum_h C^h E_{grid}$ (4)	h is h-th time interval, C^h and E_{grid} are electricity price and energy purchased from the grid at h-th time interval, respectively.
[94]	Electricity cost minimization	$\sum_{j=1}^{n}c^{t_j}+\sum_{i=1}^{n}k_{f_i}$ (5)	i, j/n is the index/total number of home appliances, c^{t_j} is the electricity cost of j-th home appliance at time t, k_{f_i} is the discomfort level of the comfort aspect f of i-th home appliance.
[95]	Electricity cost minimization	$\frac{1}{\|S\|}\sum_{s\in S}C_T(s)$ (6)	s/S is an index/set of possible scenarios. $C_T(s)$ is the cost function.
[63]	Electricity cost minimization	$\sum_t(P_t^G \cdot \Delta t \cdot \lambda_t^{buy} + P_t^{V,G} \cdot \Delta t \cdot \lambda_t^{V,buy} + P_t^{B,G} \cdot \Delta t \cdot \lambda_t^{B,buy} - P_t^{PV,2G} \cdot \Delta t \cdot \lambda_t^{sell} - P_t^{V,2G} \cdot \Delta t \cdot \lambda_t^{V,sell} - P_t^{B,2G} \cdot \Delta t \cdot \lambda_t^{B,sell})$ (7)	t is the index of the time interval. P_t^G is the sum of the power purchased from the grid by all appliances excluding the power-shiftable appliances. $P_t^{PV,2G}$ is the power transfer from PV to the grid. $P_t^{B,G}$, $P_t^{V,G}$, $P_t^{B,2G}$, and $P_t^{V,2G}$ are power transfer of battery and vehicle from and to the grid, respectively, Δt is a time interval. λ_t^{buy} and λ_t^{sell} are electricity buying and selling prices. $\lambda_t^{B,buy}$, $\lambda_t^{V,buy}$, $\lambda_t^{B,sell}$, and $\lambda_t^{V,sell}$ are BES and EV electricity buying and selling prices, respectively.
[96]	Electricity cost minimization	$\sum_{\omega\in\Omega}\rho_\omega\big(\sum_{t=1}^{NT}\big(\pi_t^{G2H}P_{\omega,t}^{G2H} - \pi_t^{H2G}P_{\omega,t}^{H2G}\big)\Delta t\big) + \sum_{\omega\in\Omega}\rho_\omega\big(\sum_{i=1}^{NA}\sigma\big[DI_{\omega,i}^{+} + DI_{\omega,i}^{-}\big]\big) + \sum_{\omega\in\Omega}\rho_\omega\big(\sum_{i=1}^{NA}\sum_{t=1}^{NT}\big[STUP_{\omega,i,t}C_i^{ST} + SHDN_{\omega,i,t}C_i^{SD}\big]\big) + \sum_{\omega\in\Omega}\rho_\omega\big(\sum_{k=1}^{NK}IBR_k^{Tariff} \cdot Energy$	ω/Ω, t/NT, i/NA, and k/NK are the index/total number of scenarios, time intervals, home appliances, and energy consumption respectively, ρ_ω is the probability of scenario ω, π_t^{G2H} and π_t^{H2G} are traded electricity prices between home and grid at time t, respectively, $P_{\omega,t}^{G2H}$ and $P_{\omega,t}^{H2G}$ are delivered power from grid to home at time t, respectively, Δt is the operation time interval, σ is the

consumption cost and promoting user comfort for consumers' emotions and tendencies [53]. And the discomfort of users caused by unwanted interruptions, long waiting time, and strict usage timetable has an influence on the limited

TABLE 5. ***(Continued.)*** **Objective functions for minimization of cost.**

		(8)	penalty factor, $DI^{+}_{\omega,i}$ and $DI^{-}_{\omega,i}$ are discomfort indexes, $STUP_{\omega,i,t}$, $SHDN_{\omega,i,t}$ C_i^{ST}, and C_i^{SD} are a start-up and shut-down variables (binary) and corresponding costs, respectively, IBR_k^{Tariff} and $Energy_{\omega,k}^{Tier}$ are stepwise tariff and energy consumption, respectively.
[97]	Electricity cost minimization	$\sum_{t\in\mathcal{T}}\left(\pi_t^{buy}P_t^{net}-\pi_t^{sell}P_t^{sell}\right)$ (9)	$t/\mathcal{T}$ is the index/total number of time intervals, π_t^{buy}, π_t^{sell}, P_t^{net} and P_t^{sell} are electricity price and energy traded with the grid at time t, respectively.
[98]	Electricity cost minimization	$\sum_{t\in\mathcal{H}}P_t\cdot\delta\cdot\left(\sum_{i\in\mathcal{S}^I}\left(L_i\cdot z_{i,t}\right)+\sum_{i\in\mathcal{S}^C}\left(L_i\cdot z_{i,t}\right)+\sum_{i\in\mathcal{S}^E}\left(L_i\cdot z_{i,t}\right)\right)$ (10)	$t/\mathcal{H}$ is the index/total number of time intervals, $\mathcal{S}^I$, $\mathcal{S}^C$, and $\mathcal{S}^E$ are set of interruptible appliances, non-interruptible appliances, and essential appliances, respectively, i is the index for the appliance, P_t is electricity price at time t. δ is the time granularity of each time slot. L_i and $z_{i,t}$ are rated power load and usage status variable (binary) of appliance i at time t, respectively.
[98]	Electricity cost minimization	$C^{day}-\delta\sum_{t\in\mathcal{H}}\left(L_t^{sol}P^{ss}-\frac{G_t+\lvert G_t\rvert}{2}P_t-\frac{G_t-\lvert G_t\rvert}{2}P^{dd}\right)$ (11)	$t/\mathcal{H}$ is the index/total number of time intervals, C^{day} is daily cost. δ is the time granularity of each time slot. L_t^{sol} and P^{ss} are the output load and subsidy of the PV at time

TABLE 5. ***(Continued.)*** **Objective functions for minimization of cost.**

			t, G_t, P_t, and P^{dd} are the total loads, electricity price, and the on-grid price at time t, respectively.
[99]	Electricity cost minimization	$\sum_{t=1}^{24}\left(\left(E_p^t * g_a^t\right)+\left(C_s^t * M_a^t\right)\right)$ (12)	t is an index of time intervals, E_p^t, g_a^t, C_s^t, and M_a^t are the electricity price, the power consumed from the grid, installation and maintenance fees of the PV system, and the power usage at time t, respectively.
[79]	Electricity cost minimization	$\sum_{n=0h}^{23h}\left(C_n\cdot E_c\cdot C_{dis}\right)$ (13)	n is an index of time intervals, C_n is the actual market hourly price, E_c is the energy consumed by the electric water heater per hour, and C_{dis} is the discomfort coefficient.
[100]	Electricity cost minimization	$(1-\alpha)\sum_{t=1}^{T}\sum_{i=1}^{I}P_i\cdot\left[C_t\cdot x_{i,t}-V_t\cdot y_{i,t}\right]\cdot\Delta t+\alpha\sum_{t=1}^{T}\sum_{i=1}^{I}z_{i,t}$ (14)	t/T and i/I are index/total number of time intervals, and home appliances, respectively, α is the weighting factor, P_i is the rated power of appliance i. C_t and V_t are the electricity price and the incentive offered at the time t respectively. $x_{i,t}$, $y_{i,t}$, and $z_{i,t}$ are usages, incentive, and inconvenience status variables (binary) of appliance i at time t, respectively.
[101]	Electricity cost minimization	$\sum_{t\in\mathcal{T}}\pi_tE_t^{net}+\epsilon\sum_{t\in\mathcal{T}}\left\lvert T_t^{in}-T^{set}\right\rvert$ (15)	$t/\mathcal{T}$ is the index/total number of time intervals, π_t and E_t^{net} is the tariff price and net energy consumption at time t, ϵ is the discomfort

participation in the DR programs of residents [116]. Different environment variables constitute the user comfort e.g., indoor temperature, outdoor temperature, humidity, etc. Therefore, to efficiently utilize the benefits of DR incentives while maintaining user comfort, there is a need to consider more

TABLE 5. ***(Continued.)*** **Objective functions for minimization of cost.**

			penalty index, T_t^{in} and T^{set} are the indoor and user-preferred temperature.
[102]	Electricity cost minimization	$\sum_{i=1}^{I}\sum_{t\in P_i} x_i(b_t+\sum_{j=1}^{J} p_{jt})$ (16)	*i/I* and *j/J* are the index/total number of time intervals, and shiftable loads, respectively, x_i is electricity price, b_t and p_{jt} are the power of non-controllable load and shiftable load *j* at time *t*, respectively.
[103]	Electricity cost minimization	$\sum_{i=1}^{I}\sum_{u=1}^{U} P(i,u) * C_a(u) + \sum_{u=1} s(u) * C_a(u)$ (17)	*u/U* and *i/I* are index/total number of time intervals, and home appliances, respectively, $C_a(u)$, *P(i,u)* and $s(u)$ are energy price, energy consumed by appliance *i*, and total power consumption in time *u*, respectively.
[102]	Retailer's profit maximization	$\sum_{i=1}^{I}\sum_{t\in P_i} x_i(b_t+\sum_{j=1}^{J} p_{jt}) - \sum_{t=1}^{T}\pi_t(b_t+\sum_{j=1}^{J} p_{jt})$ (18)	*i/I*, *t/T*, and *j/J* are the index/total number of sub-periods, time intervals, and shiftable loads, respectively, x_i and π_t are electricity price to consumers and on the spot market, b_t and p_{jt} are the power of non-controllable load and shiftable load *j* at time *t*, respectively, π_t is the energy price on the spot market at time *t*.
			ω/Ω, *t/NT*, *i/NA*, and *k/NK* are the index/total number of scenarios, time intervals, home appliances, and energy

TABLE 5. ***(Continued.)*** **Objective functions for minimization of cost.**

[104]	Self-scheduling	$\sum_{\omega\in\Omega}\rho_\omega\big(\sum_{t=1}^{NT}\big(\pi_t^{G2H}P_{\omega,t}^{G2H} - \pi_t^{H2G}P_{\omega,t}^{H2G}\big)\Delta t\big) + \sum_{\omega\in\Omega}\rho_\omega\big(\sum_{i=1}^{NA}\sigma_i\,[DI_{\omega,i}^{+} + DI_{\omega,i}^{-}]\big) + \sum_{\omega\in\Omega}\rho_\omega\big(\sum_{t=1}^{NT}\mu_t\,[DV_{\omega,i}^{+} + DV_{\omega,i}^{-}]\big) + \sum_{\omega\in\Omega}\rho_\omega\big(\sum_{i=1}^{NA}\sum_{t=1}^{NT}[STUP_{\omega,i,t}C_i^{ST} \cdot SHDN_{\omega,i,t}C_i^{SD}]\big)$ (19)	consumption respectively, ρ_ω is the probability of scenario ω, π_t^{G2H} and π_t^{H2G} are traded electricity prices between home and grid at time *t*, respectively, $P_{\omega,t}^{G2H}$ and $P_{\omega,t}^{H2G}$ are delivered power from grid to home at time *t*, respectively, Δt is the operation time interval, σ_i and μ_t are penalty factors of discomfort, $DI_{\omega,i}^{+}$ and $DI_{\omega,i}^{-}$ are discomfort indexes, $DV_{\omega,i}^{+}$ and $DV_{\omega,i}^{-}$ are indoor temperature index, $STUP_{\omega,i,t}$, $SHDN_{\omega,i,t}$ C_i^{ST}, and C_i^{SD} are a start-up and shut-down variables (binary) and corresponding costs, respectively, IBR_k^{Tariff} and $Energy_{\omega,k}^{Tier}$ are stepwise tariff and energy consumption, respectively.
[105]	Self-scheduling	$\sum_{\omega=1}^{N\omega}\rho_\omega\big(\sum_{t=1}^{NT}[\pi_t^{G2H}P_{\omega,t}^{G2H}\Delta t - \pi_t^{H2G}P_{\omega,t}^{H2G}\Delta t]\big) + \sum_{\omega=1}^{N\omega}\rho_\omega\big(\sum_{i=1}^{NA}\sigma[DI_{\omega,i}^{+} + DI_{\omega,i}^{-}]\big)$ (20)	$\omega/N\omega$, *t/NT*, and *i/NA* are index/total number of scenarios, time intervals, and home appliances, respectively. ρ_ω is the probability of scenario ω, π_t^{G2H} and π_t^{H2G} are traded electricity prices between home and grid at time *t*, respectively, $P_{\omega,t}^{G2H}$ and $P_{\omega,t}^{H2G}$ are delivered power from grid to home at time t, respectively,

parameters that directly affect the user. In order to improve the participation of DR projects, there are several methods to enhance user comfort by using HEMS for example maximizing the comfort factor, including the thermal comfort of heating, ventilation, and air conditioning (HVAC) system

TABLE 5. ***(Continued.)*** **Objective functions for minimization of cost.**

[106]	Total profit maximization	$\sum_{h\in H}(p_{sell}X_{pv\to gr}(h) - p_{buy}\left(X_{pv\to d_e}(h) + X_{gr\to hp}(h)\right) - C_{violation}(h))$ (21)	Δt is the operation time interval, σ is the penalty factor of discomfort, $DI^{+}_{\omega,i}$ and $DI^{-}_{\omega,i}$ are discomfort indexes. h/H is the index/set of time intervals, p_{sell} and p_{buy} are traded prices with the grid, $X_{pv\to gr}(h)$, $X_{pv\to d_e}(h)$, and $X_{gr\to hp}(h)$ are the electricity consumption functions, $C_{violation}(h)$ is a comfort violation function.
[62]	Total profit maximization	$\sum_i U_i(x) - \sum_j Cost_j(x)$ (22)	i and j are an index of tasks and appliances, $U_i(x)$ is the related utility function of task i under plan x, $Cost_j(x)$, is the cost function of activating appliance j under plan x.
[107]	Total cost minimization	$\sum_{y=1}^{Y}(C_y^1 + C_y^0)$ (23)	y/Y is the index/set of the planning year, C_y^1 and C_y^0 are installation and operation cost functions, respectively.
[109]	Equivalent annual cost minimization	$TC \times AIC - SV \times ASV + MC \times 365$ (24)	TC/AIC and SV/ASV are the investment cost, salvage value, and their index, and MC is the maintenance cost.
[108]	Running costs minimization	$\sum_{i=0}^{n}(Grid_i^{out}\cdot Cost_i^{buy} - Grid_i^{in}\cdot Cost_i^{sell})$ (25)	i/n is the index/total number of time intervals, $Grid_i^{out}$, $Grid_i^{in}$, $Cost_i^{buy}$ and $Cost_i^{sell}$ are energy consumption and prices traded with the grid.

TABLE 6. **Objective functions for power profiling.**

Ref.	Objectives	Objective Functions	Description
[113]	Load peak minimization	$\sum_{t=1}^{N_P}\left(\frac{1}{T}\left(P_{H\text{-}opt\text{-}pv_t} - P_{PEV\text{-}man\text{-}ref_t} - P_{PEV\text{-}woman\text{-}ref_t} - P_{AV}\right)^2\right)$ (26)	t/N_P is the index/total number of time intervals, T is equal to N_P, $P_{H-opt-pv_t}$, $P_{PEV-man-ref_t}$ and $P_{PEV-woman-ref_t}$ are the power of the house and the optimal reference power of two EVs, respectively, P_{AV} is the average power.
[98]	Load peak minimization	$\frac{H\cdot max_{t\in\mathcal{H}}(\sum_{i\in\mathcal{S}}(L_i\cdot z_{i,t}))}{\sum_{i\in\mathcal{S}}(L_i\cdot\lambda_i)}$ (27)	$t/\mathcal{H}$ and $i/\mathcal{S}$ are the index/total number of time intervals, and home appliances, respectively, L_i, $z_{i,t}$, and λ_i are the rated power load, the usage status variable (binary), and the number of operation time slots of appliance i at time t.
[98]	Load peak minimization	$\sum_{i\in\mathcal{S}^I}(L_i\cdot z_{i,t}) + \sum_{i\in\mathcal{S}^C}(L_i\cdot z_{i,t}) + \sum_{i\in\mathcal{S}^E}(L_i\cdot z_{i,t}) + L^{cha}c_t - l_t^{dis} - L_t^{sol}$ (28)	$\mathcal{S}^I$, $\mathcal{S}^C$, and $\mathcal{S}^E$ are sets of interruptible appliances, non-interruptible appliances, and essential appliances, respectively. i is the index for the appliance. L_i and $z_{i,t}$ are rated power load and usage status variable (binary) of appliance i at time t, c_t, L^{cha}, l_t^{dis}, and L_t^{sol} are the usage status variable (binary), rated charging and discharging a load of battery, and output load of the PV at time t.
[91]	PAR reduction	$\sum_{\forall r\in R}\left\{\omega_r\cdot\left(p_r^{Peak} - \underset{\forall t\in T}{avg}\left(p_{r\vert t}^{Grid}\right)\right)\right\}$ (29)	$r/\mathcal{R}$ and $t/\mathcal{T}$ are index/total number of scenarios and time intervals, respectively, ω_r, p_r^{Peak}, and $avg(p_{r\vert t}^{Grid})$ are probability, peak power and mean value of the grid power of space r, respectively.
[114]	PAR reduction	$\frac{max(E_{total}(t))}{\frac{1}{T}\sum_{t=1}^{T}E_{total}(t)}$ (30)	t/T is the index/total number of time intervals, and $E_{total}(t)$ is the function of the total daily energy consumption.

[91], [116], visual comfort of the lighting system [116], suitable load shifting [77], and quick response [93], and discomfort minimization including thermal discomfort of air conditioner and domestic hot water [117], waiting for time [91] and unreasonable load shifting [92].

Table 7 represents the different methods applied to enhance the comfort of the user by using HEMS.

TABLE 6. ***(Continued.)*** **Objective functions for power profiling.**

[103]	PAR reduction	$\frac{Load_{max}}{Load_{mean}} = \frac{Load_{max}}{\frac{\sum_N Load}{N}}$ (31)	N is the total number of time intervals.
[106]	Self-consumption	$\sum_{h \in H} X_{pv \to gr}(h) + C_{violation}(h))$ (32)	h/H is the index/total number of time intervals, $X_{pv \to gr}(h)$ and $C_{violation}(h)$ are functions of electricity and comfort violation, respectively.
[106]	Self-sufficiency	$\sum_{h \in H}(X_{gr \to d_e}(h) + X_{gr \to hp}(h) + C_{violation}(h))$ (33)	h/H is the index/total number of time intervals, $X_{gr \to d_e}(h)$, $X_{gr \to hp}(h)$, and $C_{violation}(h)$ are functions of electricity from the grid to the demand and heat pump, and comfort violation, respectively.
[115]	Grid-PV energy balance	$\delta(i) g_{GEV,i} + g_{Home,i} - P_{GPV,t,s}$ (34)	$\delta(i)$ is the binary variable of on/off state, $g_{GEV,i}$, $g_{Home,i}$ and $P_{GPV,t,s}$ are the capacity of the EV battery, load demand of the home, and power generated by the PV respectively.

TABLE 7. **Objective functions for maximization of user comfort.**

Ref.	Objectives	Objective Functions	Description
[91]	Thermal comfort maximization	$\sum_{\forall r \in R}\left\{\omega_r \sum_{\forall t \in T}\left\{\underbrace{\left\lvert \theta^{HVAC,sp} - \theta_{r\mid t}^{Air,in} \right\rvert}_{z_{r\mid t}}\right\}\right\}$ (35)	$r/\mathcal{R}$ and $t/\mathcal{T}$ are the index/total number of scenarios, time intervals, ω_r is the probability of space r, $\theta^{HVAC,sp}$ is the set-point temperature of HVAC, $\theta_{r\mid t}^{Air,in}$ and $z_{r\mid t}$ are indoor air temperature and dummy variable of the temperature of space r, at time t, respectively.
[116]	Thermal comfort maximization	$\delta(t) Q_{HVAC} - \frac{(T_{building} - T_{outside})}{R_{building}}$ (36)	$\delta(t)$ is the usage status variable (binary) of the HVAC system, Q_{HVAC} is the heat flow through the HVAC system, $R_{building}$ is the thermal resistance of the building, $T_{building}$ and $T_{outside}$ are the indoor temperature and outdoor temperature of the building, respectively.
[116]	Visual comfort maximization	$\eta(t)\kappa(t)E_{art} + E_{aux}$ (37)	$\eta(t)$ and $\kappa(t)$ are usage status variables (binary) of the lighting system, E_{art} is the illumination of artificial lighting, E_{aux} is the auxiliary illumination for nighttime or an emergency.
[117]	Thermal discomfort minimization	$\beta_a^+[T_{air}^{in} - T_{air}^{max}]_+^2 + \beta_a^-[T_{air}^{min} - T_{air}^{in}]_+^2$ (38)	β_a^+ and β_a^- are upper and lower weighting factors of air conditioner, T_{air}^{in}, T_{air}^{max}, and T_{air}^{max} are indoor, maximum,

4) OTHER OBJECTIVES

To improve the reliability of HEMS, reliance is placed on other objective functions such as energy loss, environmental impact, and social welfare. Energy loss is the energy that is lost in the process of delivering electricity from the power plant to the end user due to electrical resistance in the power lines and equipment. Since this energy loss is associated with the use of local production, most of the studies focused to obtain the optimal energy planning for HEMS to reduce the energy loss such as the authors in [107] proposed a novel strategy to reduce the power loss in the AC/DC converters. The environmental impact of energy consumption can be represented as an objective function for the optimization of HEMSs by reducing the level of GHG emissions. The mitigation of GHG emissions is slightly increasing by using clean energy [87] and imposing penalties on consumers based on the emissions rate [107]. Social welfare is a type of auction structure that allows users to bid on the electricity separately, with bidders receiving bids and allocating shares in proportion to the value of the bid. This bidding mechanism can maximize the overall benefits of the participating users, which is realized through an effective auction [96]. Therefore, the main optimization means to solve the problem of energy management by maximizing the total profit for the users. To achieve this, there have been many studies using different strategies such as in [118] proposed distributed load scheduling algorithms for a global incentive mechanism in residential networks to respond to and adjust loads. Table 8 represents the different objective

TABLE 7. ***(Continued.)*** **Objective functions for maximization of user comfort.**

[117]	Thermal discomfort minimization	$\beta_w^+[T_{dhw} - T_{dhw}^{max}]_+^2 + \beta_w^-[T_{dhw}^{min} - T_{dhw}^{in}]_+^2$ (39)	and minimum air temperatures, respectively. β_w^+ and β_w^- are upper and lower weighting factors of domestic hot water, T_{dhw}, T_{dhw}^{max}, and T_{dhw}^{max} are present, maximum, and minimum water temperatures, respectively.
[91]	Waiting time minimization	$\sum_{\forall r \in \mathcal{R}}\{\omega_r(\sum_{\forall k \in \mathcal{K}^{NI}}\{\Delta\tau(on_{r\|t}^k\tau - L^k)\}\})\}$ (40)	r/$\mathcal{R}$ and k/$\mathcal{K}^{NI}$ are the index/total number of scenarios and uninterruptible controllable home appliances, ω_r is the probability of space r, $\Delta\tau$ is the time step, $on_{r\|t}^k$ is usage status variable (binary) of appliance k, space r, at time t, τ is the time interval, L^k is the load of appliance k.
[91]	Waiting time minimization	$\sum_{\forall r \in \mathcal{R}}\{\omega_r \cdot (\sum_{\forall k \in \mathcal{K}^I}\{\Delta\tau \cdot (v_r^k - U^k - \delta^k + 1)\}\})\}$ (41)	r/$\mathcal{R}$ and k/$\mathcal{K}^I$ are the index/total number of scenarios and interruptible controllable home appliances, ω_r is the probability of space r, $\Delta\tau$ is time step, v_r^k and U^k are commitment status (binary) of appliance k, δ^k is usage status variables (binary) and time slots of the operating cycle of appliance k.
[92]	Discomfort cost minimization	$\sum_{i=1}^{NA}[DI_i^+ + DI_i^-]$ (42)	i/NA is the index/total number of home appliances, DI_i^+ and DI_i^- are discomfort index obtained before and after the scheduled time for appliance i.
[77]	User satisfaction maximization	$\sum_{j=1}^{N}\sum_{i=1}^{M} SA_n(t)$ (43)	i/M and j/N are the index/total number of time intervals and home appliances, $SA_n(t)$ is the user setting function at time t to control the appliance n.
[53]	End-User's satisfaction maximization	$\sum_s^{N_s}\sum_t^{N_t} w_s TDVF_{s,t}$ (44)	s/N_s and t/N_t are the index/total number of scenarios and time intervals, w_s and $TDVF_{s,t}$ are functions of decision weight and time discount value.
[103]	Resident comfort criteria (RCC) minimization	$\sum_{i \in Appliances} R^{RCC_i}$ (45)	i is the index of appliances, RCC_i is the comfort level of residents of appliance i.
[93]	Loads responsiveness Maximization	$\frac{1}{1+\sqrt{\sum_h\left(E_{grid}^h - \bar{E}\right)^2}}$ (46)	h is the h-th time interval, E_{grid}^h is traded energy with the grid at h-th time interval, and $\bar{E}$ is the average energy of the home.

functions that have been included to improve the reliability of HEMS.

5) SINGLE OBJECTIVE FUNCTIONS AND MULTI-OBJECTIVE FUNCTIONS

Table 9 lists the references related to single and multi-objective optimization. Among these articles, the single objective approach is presented in [51], [53], [62], [63], [79], [87], [94], [97], [99], [101], [104], [105], [109], [113], [115], [118], and [119]. The single objective formulations mainly include electricity costs minimization [63], [79], [94], [97], [99], [101], self-scheduling [104], [105], total profit maximization [62], maintenance cost minimization [109], load peak minimization [113], PAR reduction [114], energy balance [115], user's satisfaction maximization [53], energy consumption minimization [51], [119], and multi-home coordinated load scheduling [118].

The multi-objective method is considered [77], [91], [92], [93], [98], [103], [106], [108], [116], [117]. In [77], the authors present a multi-objective to minimize the electricity

TABLE 8. ***(Continued.)*** **Objective functions for others.**

Ref.	Objectives	Objective Functions	Description
[107]	Total loss minimization	$\sum_{y=1}^{Y}\sum_{sc=1}^{SC}\rho_{sc}\cdot\sum_{s=1}^{S}\omega_s\cdot\sum_{t=1}^{T}\left(\sum_{l\in A_{eq}^{+}}^{L}A_{eq,l}V_{l,t,s,sc,y}\ \sum_{l\in A_{eq}^{-}}^{L}A_{eq,l}V_{l,t,s,sc,y}\right)$ (47)	*y/Y, sc/SC, s/S, t/T,* and *l/L* are index/sets of the planning year, scenario, season, time, and branch, respectively, ρ_{sc} is scenario probability, ω_s is days of a season, A_{eq}^{+} and A_{eq}^{-} are input and output branches sets, $A_{eq,l}$ is equipment branch matrix, $V_{l,t,s,sc,y}$ is the power flow of branches.
[91]	BES degradation minimization	$\sum_{\forall r\in\mathcal{R}}\left\{\frac{\omega_{r\cdot\Delta\tau}}{2\cdot\varepsilon^{-BES}}\cdot\sum_{\forall t\in\mathcal{T}}\left\{p_{r\mid t}^{BES,ch}+p_{r\mid t}^{BES,dch}\right\}\right\}$ (48)	r/ $\mathcal{R}$ and *t/T* are index/total number of scenarios and time intervals, respectively, $\Delta\tau$ is the time step, ε^{-BES} is energy stored in battery energy storage (BES), $p_{r\mid t}^{BES,ch}$ and $p_{r\mid t}^{BES,dch}$ are a power of BES in the charging/discharging mode of space *r*, at time *t*, respectively.
[119]	Fuel consumption minimization	$\sum\left(\left(F_0Y_{gen1}+F_1P_{g1}\right)\right)_{gen1}+\left(\left(F_0Y_{gen2}+F_1P_{g2}\right)\right)_{gen2}$ (49)	F_0 and F_1 are the intercept coefficient and the slope of the diesel generator fuel curve, Y_{gen1} and Y_{gen2} are rated generator capacity of two diesel generators, respectively. P_{g1} and P_{g2} are the electrical output powers of two diesel generators, respectively.
[51]	Energy consumption minimization	$\frac{E(T_a^{*},f^{*})-E_{ref}}{E_{ref}}\times 100\%$ (50)	T_a^{*} and f^{*} are optimal air temperature and operating frequency, respectively, $E(T_a^{*},f^{*})$ and E_{ref} are energy consumption at the optimal state (T_a^{*},f^{*}) and reference state, respectively.
[108]	Green factor maximization	$\frac{\sum_{i=0}^{n}\left(PV_i-Loss_i-Grid_i^{in}\right)}{\sum_{i=0}^{n}L_i}$ (51)	*i/n* is the index/total number of time intervals, PV_i , $Loss_i$, L_i , and $Grid_i^{in}$ are energy produced, lost, used, and sold to the grid.
[87]	Carbon emissions reduction	$E_c\cdot\frac{1}{\eta}(\alpha C+\beta NG+\gamma P)$ (52)	E_c is the energy consumed. η is conversion efficiency with a default of 0.34. $\alpha,\beta, and\ \gamma$ are carbon release factors with defaults of 112, 66, and 49, respectively. *C, NG,* and *P* are consumed fuel fractions.
[118]	Multi-home coordinated load scheduling	$\sum_{t=1}^{T}F_t^{RT}\left(\hat{L}_t^{Toal}\right)+\alpha\sum_{t=1}^{T}\sum_{h=1}^{H}J_h\left(L_{h,t}\right)$ (53)	*t/T* and *h/H* are index/total number of time intervals, and homes, respectively, $\hat{L}_t^{Toal}$ and $L_{h,t}$ are consumption of total homes and from the network, α is the scaling factor, $F_t^{RT}(\cdot)$ and $J_h\left(L_{h,t}\right)$ are functions of real-time cost and electricity cost of each home, respectively.

cost and maximize user satisfaction. In the work of [98], the authors describe a multi-objective framework of electricity cost and load peak minimization and compare the bill and load peak reduction efficiency between the home-equipped photovoltaic energy storage system and the home without a photovoltaic energy storage system. Customer's electricity cost minimization and retailer's profit maximization are discussed in [102]. The authors use a multi-objective framework in [103] to minimize electricity cost, PAR, and resident discomfort. A multi-objective optimization framework has been considered in [91] to minimize the electricity cost, PAR, waiting time, and BES degradation separately and maximize thermal comfort. In [92], the authors present the minimization of electricity bills and user discomfort costs. Electricity cost and load responsiveness are combined in multi-objective optimization in [93]. Electricity cost is minimized while load responsiveness is maximized. Langer and Volling [106] propose a multi-objective optimization methodology to maximize total profit while keeping the house self-consumption and self-sufficiency. Total cost (installation and operation cost) and total loss of the AC/DC converters are minimized in the work of [107]. A multi-objective problem to minimize running costs and maximize the green factor is proposed by [108]. In [116], the author presents a multi-objective approach to maximize thermal comfort and visual comfort in a smart home. Thermal discomfort of the air conditioner and domestic hot water is discussed in [117].

B. CONSTRAINTS OF HEMS

The constraints are fundamental in realizing the overall behavior of the appliances in the HEMS, including interdependence, and interaction with other agents and devices

TABLE 9. References with objectives.

Ref.	Equations	Single/multi-objective
[51]	(50)	Single-objective
[53]	(44)	Single-objective
[62]	(22)	Single-objective
[63]	(7)	Single-objective
[77]	(3) and (43)	Multi-objective
[79]	(13)	Single-objective
[87]	(52)	Single-objective
[91]	(1), (29), (35), (40), (41), and (48)	Multi-objective
[92]	(2) and (42)	Multi-objective
[93]	(4)and(46)	Multi-objective
[94]	(5)	Single-objective
[95]	(6)	Single-objective
[96]	(8)	Single-objective
[97]	(9)	Single-objective
[98]	(10), (11), (27), and (28)	Multi-objective
[99]	(12)	Single-objective
[100]	(14)	Single-objective
[101]	(15)	Single-objective
[102]	(16) and (18)	Multi-objective
[103]	(17), (31), and (45)	Multi-objective
[104]	(19)	Single-objective
[105]	(20)	Single-objective
[106]	(21), (32), and (33)	Multi-objective
[107]	(23) and (47)	Multi-objective
[108]	(25) and (51)	Multi-objective
[109]	(24)	Single-objective
[113]	(26)	Single-objective
[114]	(30)	Single-objective
[115]	(34)	Single-objective
[116]	(36) and (37)	Multi-objective
[117]	(38) and (39)	Multi-objective
[118]	(53)	Single-objective
[119]	(49)	Single-objective

for optimization and scheduling problems. The constraints in the HEMS can be divided into three groups load constraints, user comfort, and additional constraints. The users can set the constraints and also make it easier to update or adapt to changes. With the scenarios, specifying what the system should do, on one hand, and the constraints restricting them on the other, the objective is thus to ensure that no specified scenario can lead to violation of a constraint.

1) LOAD CONSTRAINTS

Load constraints are applied in the HEMS to set optimal load schedules based on device information, user settings, and pricing mechanism which mainly refer to commonly used appliances like air conditioners, washing machines, and water heaters, are modeled. Due to the lack to obtain information on the consumption curve for some electrical appliances, and considering the computational efficiency, the established model also needs to be simplified, therefore the average constant consumption profile is applied to model the load, as described in the study [93] and [104]. In other studies, the classification method has been applied to categorize load constraints by the pattern of the appliances [101], loads are classified into four types according to the equipment patterns utilization, and the study in [120] has divided the load constraints into three categories according to appliance characteristics.

2) USER COMFORT CONSTRAINTS

The existing findings on comfort are inconsistent and often based on experimental setups not applicable to conditions resulting from load shifting in residential buildings. Furthermore, prevailing sophisticated concepts for the structure of comfort activation have limited applicability to the residential sector, since simple and inexpensive control is required. Therefore, the comfort constraints are applied to easily adaptable to a large diversity of dwellings. User comfort constraints aim to increase consumer comfort iteratively up to a level that minimizes the electricity bill below a specified one to improve comfort [94] and reduce inconveniences [79], [96], [104], [106].

3) OTHER CONSTRAINTS

Other constraints include the external household equipment except for the normal smart appliances, which compressed different distributed renewable energy (DRE) such as PV panels and wind turbines, the energy storage system (ESS), and plug-in EVs. These kinds of constraints can be summarized into characteristic limitations [104], technology limitations [93], operation mode limitations [104], [113], [119], algorithm-based constraints [77], and GHG emission penalty [107].

C. OPTIMIZATION METHODS USED IN HEMS

After designing and modeling the HEMS using proper objectives and the corresponding constraints, the optimal scheduling of home appliances can be achieved by applying the optimization approach in HEMSs. Typically, the optimization approach can be divided into mathematical methods and intelligent methods according to the objective function and the set constraints of the HEMS. In the following subsections, the critical review of common optimization approaches used is presented.

1) MATHEMATICAL METHODS

The mathematical optimization method is the most commonly used classical optimization method. Basically, mathematical optimization is a deterministic optimization method that can deal with optimization systematically by selecting input values to obtain the optimal scheduling. Several approaches based have been applied in the literature such as Linear Programming, Non-linear Programming, and Dynamic programming.

a: LINEAR AND NONLINEAR PROGRAMMING METHODS

Linear Programming (LP) is the simplest form of mathematical optimization and has become the most important method due to its lower computational burden and the availability of commercial and non-commercial problem solvers such as CPLEX [121] and GLPK [9]. For optimization and implementation in HEMS, binary integer linear programming(BILP) and mixed integer linear programming (MILP) is still the most predominant method since it contains discontinuable variables in modeling for additional flexibility, which requires objectives and constraints represented by a linear relationship.

On other hand, non-linear programming (NLP) and mixed integer nonlinear programming (MINLP) is used for optimization problems where the objectives and/or constraints are all nonlinear. Compared with LP, NLP is more powerful, but the computational burden is greater. The comprehensive analysis of HEMSs based on LP and NLP approaches is summarized in Table 10. Most of the previous studies have focused on electricity cost optimization in HEMSssuch as in [100]. However, many studies are still limited to simulation experiments rather than real experiments using NLP, MINLP, LP, and NLP. Moreover, the modeling of some appliances is complicated such as the battery degradation, SoC levels, and the charging/discharging status.

b: DYNAMIC PROGRAMMING METHODS

In the optimization scheduling methods applied to HEMSs, the disadvantage of the deterministic optimization methods above is that these approaches do not consider uncertain factors such as residential electricity demand, power generation, and grid electricity prices. Although the problems of HEMS can be solved using the LP or NLP, However, the optimal solution is complicated to obtain, especially when the uncertain future realization matches the forecast.

Dynamic programming (DP) is proposed to solve large and complex optimization problems through recursion [123], [124]. The DP can simplify and decompose large and complex problems into smaller and simpler sub-problems and recursively solves the problems by storing the optimal solutions to the sub-problems.

Table 11 lists the contributions and limitations of HEMS based on dynamic programming approaches. Compared with LP and NLP methods, the DP-based HEMS approach considers the uncertainty of PV power, load demand, battery degradation, and weather conditions. However, the limitations of the DP approach are the designing and modeling of smart loads, PV, and BEE systems.

2) NATURE-INSPIRED META-HEURISTIC METHODS

Nature-inspired meta-heuristic algorithms refer to a class of optimization algorithms that imitate the development of natural phenomena or the behavior patterns of organisms and have randomization and local search characteristics [129]. For example, a genetic algorithm (GA) was proposed based on the law of "survival of the fittest" in the biological evolution mechanism of nature [103], [108], [130]. particle swarm optimization (PSO) was proposed based on the simulation of biological group social behaviors [93], [102], [113]. The butterfly optimization algorithm(BOA) was derived from the foraging process of butterflies [77]. The artificial bee colony (ABC) algorithm was inspired by the honey collection process of bees [131].

TABLE 10. Critical analysis of HEMS based on LP and NLP methods.

Ref.	Proposed methods	Contributions	Limitations
[100]	BILP	The experimental and numerical applications have shown that the results obtain from the BILP model for load scheduling are superior for scheduling and have lesser computation time than the MINLP model solution in [122].	The operation cost of the appliances is not considered.
[91]	MILP	Different objective functions based on MILP formulation have been introduced, including the electricity cost as the primary objective and PAR, thermal comfort, waiting time of both interruptible and non-interruptible appliances, and BES system degradation as alternative objectives.	The state of charge (SoC) of the BES system is modeled with limited rated values.
[92]	MILP	An effective HEMS model with different tariffs and an electrical energy storage (EES) system for the daily bill reduction of shiftable loads has been proposed.	The discomfort index was limited to a linear function proportional to the amount of load shifted before or after the consumer's desired time.
[104]	MILP	A self-scheduling strategy was proposed to ensure self-generation capability. The proposed model is based on a stochastic MILP model considering PV panels, an EES system, and three groups of loads.	Battery degradation is not considered.
[105]	MILP	A risk-oriented MILP model for deterministic and stochastic structures has been described for the self-scheduling and planning of the HEMS.	Uncertainties in load demand and battery degradation are not considered.
[119]	MILP	A MILP model of HEMS has been applied in an isolated hybrid PV/battery & diesel generator to minimize the operation cost.	The emission cost of diesel generators and operation mode of EVs on the stability condition have not been considered.
[63]	MILP	Day-ahead load scheduling based on the MILP model has been proposed to include the smart thermostat in a HEMS as an appliance and minimize the energy cost.	The operation mode of EVs on the stability of the microgrid has not been considered.
[96]	MILP	A self-scheduling strategy based on the stochastic MILP model was proposed to reduce the energy bill and evaluate the impacts of different tariffs including time of use (TOU), real-time price (RTP), and inclining block rate (IBR).	The over-consumption penalty is not considered.
		The authors developed a multi-objective MINLP model with both static and dynamic	Only SoC and

TABLE 10. ***(Continued.)*** **Critical analysis of HEMS based on LP and NLP methods.**

[107]	MINLP	frameworks for HEMS appliances, and a power-to-gas-based energy hub to minimize the total cost and total losses.	equipment degradation are considered in EES.
[62]	MINLP	An MINLP model based on task type and occupant preferences, considering the TOU tariff for HEMS has been proposed.	Only smart loads are considered.
[98]	MIP	A multi-objective based on MIP model aims to reduce the peak load and energy cost.	Battery degradation of the PESS is not considered.

Table 12 presents the analysis of HEMS based on nature-inspired meta-heuristic methods. Many objectives here were explored such as energy cost reduction, PAR improvement, free charging of EVs, and self-scheduling of offline mode. It is worth noting that more studies here take into account uncertainty information, such as weather conditions than the previously introduced mathematical optimization.

3) ARTIFICIAL INTELLIGENT METHODS

Artificial Intelligence(AI) is a subset of computer science that has become popular in recent years to solve optimization problems in HEMS. In HEMS, AI has significant applications allowing to make effective utilization of available data and assisting to make optimal decisions in complex practical circumstances for safer and more reliable control and less operation cost for the appliances that are connected with HEMS. The improvements in AI-based algorithms and computational capability with a large scale of data processing abilities are well enough to exploit the one operation in the HEMS to multiple controlling environments. Machine learning and artificial neural network(ANN) are the most important subsets of AI. This section presents the application of the AI method in HEMS using machine learning, ANNs, and multi-agent systems (MAS).

a: MACHINE LEARNING

Machine learning is one of the branches of AI, and can enhance the operation and control of HEMS. Generally, machine learning is classified into four types according to the method of learning namely: supervised, unsupervised, semi-supervised, and reinforcement learning. The operations of these categories including some examples of research work on their implementation in the HMES are shown in Table 13.

b: ARTIFICIAL NEURAL NETWORK

As discussed in the previous sections, several optimization objectives can be considered when modeling a HEMS. To optimize an objective function of the different appliances of a massively interconnected HEMS, it is important to solve large-scale linear/non-linear programming problems in real-time. However, the existing sequential algorithms may not be efficient when the computing time needed to obtain a solution depends on the type of the proposed problem, which may become complicated in real applications. A neural network presents inherent parallelism and thus can solve large-scale problems in real-time based on prediction. Generally, ANNs have been mainly used to predict user comfort [51], recognize

TABLE 11. **Critical analysis of HEMS based on DP methods.**

Ref.	Proposed methods	Contributions	Limitations
[125]	Approximate DP	An approximate DP-based integrative DR mechanism was proposed for the optimal scheduling of household appliances, ESS, and the V2G/V2H-enabled EV.	Some constraints have not been considered.
[123]	Differential DP	A HEMS framework based on a differential DP algorithm has been proposed in a smart home equipped with PV, BESS, and controllable appliances to optimize electricity bills and increase users' comfort factor.	Some appliances have not been considered.
[126]	DP	An LP-based prediction strategy of electrochemical BES management for residential photovoltaic systems was introduced combined with daily weather forecasts and load profiles.	Battery degradation was not considered.
[124]	Adaptive DP	An action-based heuristic DP method has been presented to solve the solar residential energy scheduling problem by classifying weather types and prioritizing different energy sources.	Battery degradation was not considered.
[127]	Approximate DP	An approximate DP method for HEMS connected with HVAC, water heater, and EVs was proposed to minimize household electricity costs and the discomfort of users. In this study, the authors considered different factors including the uncertainties of outside temperature, hot water demand, and uncontrollable loads.	The state of overcharge of the EV battery was not considered.
[128]	Multistep look-ahead algorithm	A new approximate DP called the multistep look-ahead algorithm was introduced to build the multi-objective HEMS framework including PV, ESS, deferrable loads, and thermal appliances to balance household electricity cost and thermal discomfort.	The operation cost of PV panels was not considered.

TABLE 12. Critical analysis of HEMS based on nature-inspired meta-heuristic methods.

Ref.	Proposed methods	Contributions	Limitations
[108]	GA	A multi-objective offline tree-based genetic algorithm for HEMS has been addressed with an adaptation to the real-implementation history data.	Load management is not covered in this paper.
[130]	Modified GA	An improved GA algorithm was proposed for a multi-objective HEMS model which considered weather information, user comfort, and the risky economic cost of a real house.	The proposed algorithm to solve the HEMS need to be improved.
[103]	NSGA-II	A non-dominated sorting genetic algorithm (NSGA-II) algorithm-based optimal power scheduling method in a smart home with energy storage was proposed to reduce multi-objective functions including the electricity bills, the comfort of residents, and the tariffs of RTP and IBR.	Battery degradation is not considered.
[113]	PSO	The authors proposed a universal two layers PSO model of the HEMS connected with PV and EVs considering load profile smoothing, electricity cost reduction, and free charging of EVs.	Uncertainties in PV power are not considered.
[93]	PSO and NSGA-II combined algorithm	A multi-objectives model for a PV- and ESS-integrated HEMS was implemented to reduce electricity cost and increase the load, by including an index called 'load responsiveness'.	The operational cost of PV and ESS are not considered.
[102]	Bi-level PSO optimization	Two Bi-level population-based algorithm was introduced to describe the constraints of the trade-off price between retailers and consumers considering user comfort for load operation.	The user's preferred appliance scheduling period is limited to a specific schedule
[77]	Improved BOA	An improved BOA method for a RERs and battery-embedded HEMS framework was proposed to reduce energy consumption costs and remain user satisfaction.	Some appliances have not been considered.
[131]	ABC	An ABC algorithm with adaptive properties was implemented to achieve the power generation balance and reduce the total electricity cost considering the tolerance for extreme cases, as well as the reliability and life cycle of the BES.	Uncertainties in PV power and load demand are not considered.

energy consumption patterns of household appliances [56], and speculate future load demands [120].

TABLE 13. Critical analysis of HEMS based on machine learning methods.

Ref.	Proposed methods	Contributions	Limitations
[132]	Asymmetric SVR	A new framework of support vector regression (SVR) with asymmetric characteristics for ESS is proposed to reduce the error of the predicted cost.	Energy loss for charging and discharging of ESS was not considered.
[47]	Bayesian learning	A Bayesian learning framework was proposed to learn consumer preferences and measure comfort levels using the data of appliance usage history.	More appliances can be considered.
[48]	Batch reinforcement learning	Incorporated the outdoor weather conditions prediction and a day-ahead timetable of the heat-pump thermostat in the HMES to obtain an accurate forecasting model.	More appliances can be considered.
[133]	Deep reinforcement learning	A novel deep reinforcement learning approach including a PV self-consumption optimization and a dynamic set-point definition for indoor temperature has been introduced. The objective of this study is to ensure the user's comfort, saving energy and load shifting.	Uncertainty of the PV plants is not considered.
[101]	Reinforcement learning and ANN	By combining the Q-learning method with an ANN, a reinforcement learning-based HEMS framework with the TOU pricing was proposed to decrease electricity costs while maintaining the user comfort level and operation characteristics of household appliances	Battery degradation is not considered.
[134]	Reinforcement learning and actor-critic methods	A novel deep reinforcement learning algorithm was proposed to optimize the cost of energy while maintaining the user comfort level and operation characteristics of appliances by combining reinforcement learning and actor-critic methods.	Battery degradation is ignored.

The developed neural networks for predicting the solutions, and implementing other control strategies neural network techniques for HMES are summarized in Table 14.

TABLE 14. Critical analysis of HEMS based on ANNs methods.

Ref.	Proposed methods	Contributions	Limitations
[51]	Single-layered feedforward ANN	A novel universal optimal air temperature framework based on single-layered feedforward ANN algorithm was presented to reduce the energy cost of the air conditioning and mechanical ventilation system while maintaining the user's thermal comfort.	Uncertainties in load demand were not considered.
[56]	Multi-layer feedforward ANN	A novel multilayer feed-forward ANN framework called Appliance Net was proposed to recognize the energy consumption patterns of household appliances connected to smart plugs.	More kinds of appliances can be considered.
[135]	ANN and adaptive neuro-fuzzy inference system	In this study, two methods namely ANN and adaptive neuro-fuzzy inference system have been used to analyze monthly data from Malaysia over seven years (2009-2016) for various factors such as changes in weather, climate, and load demand.	The average error of the ANN-based prediction method is much higher.
[120]	ANN and regression algorithm	A learning-based ANN framework was proposed to optimize energy for loads of major home appliances management to meet the power demand from the loads in real-life conditions.	Uncertainties in load demand were not considered.

c: MULTI-AGENT SYSTEM

MAS consists of multiple intelligent agents that acted to solve problems that may be beyond the capabilities of simple computations. Multi-agent systems create an effective approach for decomposing complex problems into many simplified sub-problems. By modeling each section as an autonomous agent, each agent pursues to promote its solution based on the maximizing individual [136], [137]. Over the last decade, MAS-based algorithms have been proven as effective solutions for HEMS and various types of load agents have been applied including agents for different household appliances, EV agents, energy storage agents, distributed generation agents, HEMS agents, and central coordinator agents. The classifications of the applications of the multi-agent system to HEMS are illustrated in Fig. 7. The summary of different MAS methods with their main contributions to HEMS is plotted in Table 15.

4) MODEL PREDICTIVE CONTROL METHODS

Model predictive control (MPC), also known as receding horizon control, is a promising approach that has recently been widely applied in different sectors such as power converters, microgrids, SG, control, and optimization in HEMS [141]. In this context, the optimal control behaviors or

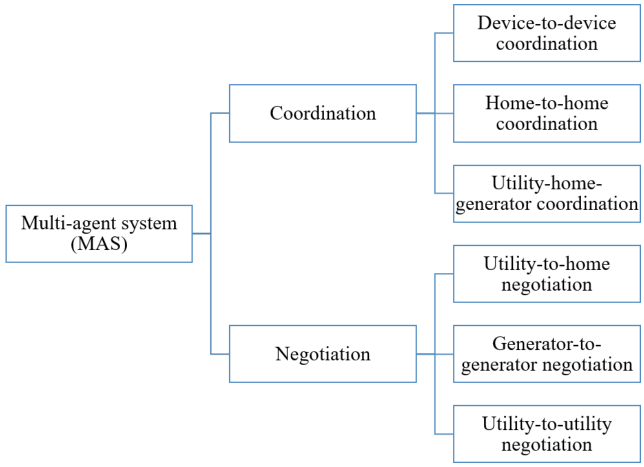

FIGURE 7. Categories of the applications of the multi-agent system to HEMS.

TABLE 15. Critical analysis of HEMS based on MAS methods.

Ref.	Proposed methods	Contributions	Limitations
[138]	MAS	The authors proposed a MAS-based load-shifting model in a cloud computing framework for energy planning between dynamic solar energy generation and energy demand.	Uncertainties in PV power are not considered.
[139]	MAS	A HEMS system combined with a real-time solar/hydrogen hybrid power generation system operated by the MAS has been implemented	Uncertainties in PV power are simplified.
[94]	Host-Parasite model-based MAS	A new MAS model used in HEMS based on the symbiotic interactions of host-parasite relationships in nature was proposed to improve user comfort. The proposed approach enables users to obtain a schedule of power reduction with low consumption, PAR, and cost.	ESS is not considered in case of extreme weather.
[140]	MAS-PSO combined algorithm	A HEMS based on MAS-PSO combined algorithm is applied to maintain the comfort level and minimum power consumption.	Uncertainties in load demand are not considered.

scheduled commands are determined according to predefined cost functions or objective targets under different constraints. Typically, the MPC approach has many advantages in HEMS applications such as: including different and complex constraints which can be involved in a simple formula, excellent dynamic performance with the robust control system, generating a simple straightforward signal for control, and open access is enabled to interface various solving algorithms, making complex optimization problems solvable and convenient. While the MPC approach has already been reported in different studies, they are seldom detailed from the perspective of HEMS. Besides, in HEMS, researchers need some challenges to enhance the MPC

TABLE 16. **Critical analysis of HEMS based on MPC methods.**

Ref.	Proposed methods	Contributions	Limitations
[106]	MPC	The MPC-based model was introduced for the HEMS in a single residential building including a modulating air-to-water heat pump, PV panel, battery, and thermal storage systems to optimize the floor heating and hot water supply.	Uncertainties in PV power were not considered.
[117]	MPC	A multi-objective MPC framework for user-centric HEMS, called Foresee, with was proposed. This study aims to reduce energy costs and carbon emissions and increase thermal comfort for users.	Uncertainties in load demand were not considered.
[142]	MIQP-MPC	In this study, a mixed-integer quadratic-programming MPC has been proposed to maximize the thermal comfort and the energy efficiency considering user weights and flexibility of the system by adding occupancy predictions.	Battery degradation was not considered.
[143]	MPC	An MPC-based two-layer HEMS framework is introduced to reduce the daily household energy costs, PV self-consumption, load transfer, and battery degradation costs.	The operation cost of PV panels was not considered

model with the consideration of different constraints and objective functions including the load-sharing accuracy, and circulating currents [108]. Table 16 summarized a different application of the MPC approaches that have been used in the HEMS.

5) OTHER METHODS

Besides the above approaches, several optimization methods including stochastic algorithms [95], [144], heuristic algorithms [80], [145], [148], fuzzy logic [49], [149], load-priority-based algorithms [150], [151], Load shedding algorithm [87], and backtracking search algorithm [152] have been proposed to improve the HEMS as given in Table 17. In these methods, not only the self-regulation of the system is considered, but also the multi-objective optimization of HEMS is more involved, and a variety of effective uncertainty quantification methods are used. However, much work still needs to be done in terms of battery modeling in EVs and ESSs, especially regarding battery degradation and maintenance costs increase due to the depth of discharge (DoD) of batteries.

TABLE 17. **Critical analysis of HEMS based on other methods.**

Ref.	Proposed methods	Contributions	Limitations
[144]	Stochastic optimization	A stochastic approach for the day-ahead operation of HEMS including batteries, PV, and electric water heaters has been applied to reduce operating costs while considering the cycling aging cost. Moreover, the authors generalized their approach to enhancing the battery-based applications in HEMS.	DR incentives and power losses are not taken into account in load balance.
[95]	Scenario-based stochastic algorithm	A scenario-based stochastic framework considering RTP, weather conditions, generation of RERs, and user preferences to use appliances have been proposed to optimize the electricity cost.	The DoD of the battery was not considered.
[152]	A binary backtracking search algorithm	A new binary backtracking search algorithm is proposed to promote the HEMS performance and achieve optimal load scheduling. The proposed HEMS model in this study includes air conditioners, water heaters, refrigerators, and washing machines.	All home appliances were considered to be controllable loads.
[87]	Load shedding algorithm	A load-shedding algorithm for HEMS has been developed to smooth peak demand and reduce GHG emissions.	User comfort was ignored.
[150]	Hopping algorithm	The authors proposed a novel hopping algorithm for energy planning of HEMS interconnected with PV/battery/utility to achieve optimal load scheduling and maintain user comfort based on load prioritization.	90% DoD might reduce lifecycle time and increase investment and replacement costs
[151]	Multiple users and load priority	Based on multiple inhabitants sharing a home and its appliances, this study proposed a HEMS algorithm that monitors and controls household appliances by a combination of energy pricing models including TOU, RTP, and IBR.	Energy losses were not considered.
[145]	Heuristic forward-backward algorithm	A heuristic forward-backward algorithm was proposed to minimize the energy cost and cut peak loads while maintaining the resident thermal comfort considering the thermal storage capacity and the electrical storage capacity.	The DoD of the ESS was not considered.
		An ECG-based heuristic	The

V. DISCUSSION ABOUT APPLICATIONS AND CHALLENGES

In recent years, household SGs have been widely accepted, DR programs such as TOU tariffs for residents have been implemented in many countries, and countries around the world have begun to conduct in-depth research on HEMSs to optimize the dispatch of household appliances, reduce energy consumption, and minimize greenhouse gas emissions. With

TABLE 17. ***(Continued.)*** **Critical analysis of HEMS based on other methods.**

[80]	ECG-based heuristic algorithm	model was developed to detect the human behavior pattern and monitor the energy flow of HEMS to reduce total consumption.	instability of load operation was not considered.
[146]	Arithmetic optimization algorithm	A novel multi-objective arithmetic optimization algorithm was implemented by a Raspberry Pi minicomputer to optimize the daily electricity cost, PAR, and user comfort.	The DoD of the ESS was not considered.
[147]	Pareto tribe evolution	A novel Nash equilibrium-based Pareto tribal evolution was proposed for multi-objective optimization of multiple HEMSs to determine the best trade-offs regarding consumer satisfaction, energy cost, and PAR of the load profile.	The DoD of the EV battery was not considered.
[148]	Cultural algorithm	A culture algorithm-based HEMS framework including wind turbines, BESS, load shedding options, and fuel cell vehicles was implemented considering capacity power rating and the charging/discharging mode of the BESS.	The DoD of the BESS was not considered.
[49]	Fuzzy logic	Fuzzy logic is proposed to enable off-grid operation for HEMS which is connected with different DERs such as fuel cells, batteries, solar panels, and wind turbines.	The operating parameters of all household appliances are fixed
[149]	Max-min fuzzy method	A multi-objective HEMS framework based on the max-min fuzzy method has been presented which considered the fluctuation of RES output power and load demand to optimize operating costs, emissions, and PAR while maintaining user comfort.	DoD was not mentioned.

the continuous consumption of energy and the intensification of environmental pollution, HEMS technology will become more and more important for occupants, utilities, and society.

In the real world, the promotion of AMI and the development of BHC technology further expand the architecture and functions of HEMS. However, unlike municipalities and public utilities, the choice of communication technology for individual residences mainly depends on coverage areas, data rates, and deployment costs due to their limitations. Therefore, wireless communication technologies such as ZigBee, Bluetooth, and Wi-Fi are better choices. On the other side, with the integration of DERs and HESS and the extensive application of EVs, the architecture and functions of HEMSs are becoming more and more livable. In addition to the wider scope of optimization scheduling, the optimization objectives and constraints that need to be considered in modeling are also increasing day by day.

Besides architecture and infrastructure challenges, HEMSs also face many challenges in experimental and numerical optimization. First, the ownership rate, power consumption, and usage of appliances diversify in each family. The devices considered in HEMS in the existing literature also vary significantly [55]. Therefore, it is important to classify and model the loads properly for future HEMS designs so that each HEMS can compatibly dispatch multiple unique devices. Second, the objectives assigned to HEMSs alter widely with multi-objective nature [55]. It is better to make a trade-off between multiple objectives. Last but not least, mathematical optimization methods are accurate in modeling and time-saving in the calculation. But also because of this, mathematical optimization algorithms have many limitations in modeling and it is difficult to solve some NP problems. The intelligent optimization algorithm can solve some NP problems, and some algorithms do not depend on the model, which makes algorithms more versatile. However, most intelligent optimization algorithms can only obtain approximate solutions, and some algorithms rely heavily on initial parameters. Thus, to manage the energy utilization of a house effectively and efficiently, it is best to choose an appropriate optimization algorithm according to the specific HEMS architecture.

As described in Section IV, these HEMS optimization methods in the current literature are mainly based on the achievement of optimizing different objective functions such as reducing the degree of electricity costs and the computational time complexity to evaluate their optimization performance. Robustness, sensitivity, and responsiveness are also evaluation standards in the literature. Experimental implementations of HEMS are also validated using various optimization methods, such as LP [100], GA [108], machine learning [47], and search algorithm [152].

VI. CONCLUSION

HEMSs improve the overall energy production and consumption of houses by optimizing and appropriately scheduling the use of household appliances, and their research and promotion can simultaneously benefit residential users, utilities, and society. This paper reviews the development history of HEMS architecture, discusses the characteristics of several major communication technologies in current HEMS infrastructure, reveals the trend of HEMS architecture and functions from simple to complex, and the better choice of wireless technology than wired technology. The summary of optimization objectives and constraints highlights that electricity cost reduction is still the most important objective in HEMSs, while recent studies are focusing on the maintenance of user comfort and user preferences, which have a direct impact on participation in DR energy conservation projects. The comparative and critical analysis of optimization methods shows the development prospects and potential of novel intelligent methods and combinatorial algorithms applied in HEMSs, which improve the modeling fidelity and optimization effects of various home appliances. It is noted that there is an increasing amount of research that begins to consider uncertainties such as home appliance ownership, user preference, weather conditions, PV power generation, and load demand in the optimization algorithms. However, efforts still need to be made including the impact of DoD selection on battery and grid performance, battery degradation cost, and the environmental impact of GHG emissions. The computational complexity of the methods and the robustness of the systems both in simulation and reality can also be considered in future research, which will have a long effect on the study of HEMSs. Finally, the discussions and recommendations of research applications and challenges about HEMSs recently can help readers have a comprehensive understanding of current research trends in HEMS, gain insight into the trade-off between optimal solutions and computational complexity, and lay a foundation for future research.

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BINGHUI HAN received the B.Eng. degree in measurement and control technology and instrumentation from Shenyang Ligong University, Shenyang, China, in 2014, and the M.Eng. degree in materials science from the Shanghai Research Institute of Materials, Shanghai, China, in 2018. She is currently pursuing the Ph.D. degree with the Power Electronics and Renewable Energy Research Laboratory (PEARL), Department of Electrical Engineering, University of Malay, Kuala Lumpur, Malaysia. Her research interests include energy management systems, building automation systems, renewable energy, and energy scheduling.

YOUNES ZAHRAOUI received the B.S. and M.S. degrees in chemistry from University M'hamed Bougara, Boumerdes, Algeria, in 2015 and 2017, respectively, and the Ph.D. degree from the British Malaysian Institute, Universiti Kuala Lumpur, Malaysia, in 2022. His research interests include motor drives, autonomous technologies, micro grid controls, energy management systems, hybrid renewable energy systems, micro grid systems, energy efficiency, building automation systems, artificial intelligence applications, and electric vehicle.

MARIZAN MUBIN was born in Kuala Lumpur, Malaysia, in 1977. She received the B.Eng. degree in telecommunication engineering from the University of Malaya, Kuala Lumpur, in 2000, the M.Sc. degree in communications and signal processing from the University of Newcastle Upon Tyne, U.K., in 2001, and the D.Eng. degree in electrical engineering from Tokai University, Japan, in 2006. She is currently a Senior Lecturer with the Department of Electrical Engineering, University of Malaya.

SAAD MEKHILEF (Fellow, IEEE) received the B.Eng. degree in electrical engineering from the University of Setif, Setif, Algeria, in 1995, and the master's degree in engineering science and the Ph.D. degree in electrical engineering from the University of Malaya, Kuala Lumpur, Malaysia, in 1998 and 2003, respectively. He is currently a Distinguished Professor with the School of Science, Computing and Engineering Technologies, Swinburne University of Technology, Melbourne, VIC, Australia, and an Honorary Professor with the Department of Electrical Engineering, University of Malaya. He has authored or coauthored more than 500 publications in academic journals and proceedings and five books with more than 32000 citations. His current research interests include power converter topologies, the control of power converters, renewable energy, and energy efficiency.

MEHDI SEYEDMAHMOUDIAN (Member, IEEE) received the B.Sc., M.Eng., and Ph.D. degrees in electrical engineering. He was a Lecturer and a Course Coordinator with the School of Engineering, Deakin University, Australia. He is currently a Senior Lecturer with the School of Science, Computing and Engineering Technologies, Swinburne University of Technology, Australia. His research interests include renewable energy systems, smart grids and micro grids systems, and the application of emerging technologies in green renewable energy development.

ALEX STOJCEVSKI received the bachelor's degree in electrical engineering, the master's degree in electrical and electronics engineering, and the Ph.D. degree. He is currently the Dean of the School of Science, Computing and Engineering Technologies, Swinburne University of Technology, Melbourne, Australia. He has held numerous senior positions in several universities across different countries. He has published more than 250 book chapters, journals, conference articles, and has given a number of internationally invited speaker presentations. His research interests include renewable energy and micro grids design.