Received March 1, 2018, accepted April 16, 2018, date of publication April 30, 2018, date of current version May 24, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2831917

Review on Home Energy Management System Considering Demand Responses, Smart Technologies, and Intelligent Controllers

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This work was supported in part by Universiti Kebangsaan Malaysia under Grant DIP-2014-028 and in part by United Arab Emirates University under Grant G00001888.

ABSTRACT The increasing demand for electricity and the emergence of smart grids have presented new opportunities for a home energy management system (HEMS) that can reduce energy usage. The HEMS incorporates a demand response (DR) tool that shifts and curtails demand to improve home energy consumption. This system commonly creates optimal consumption schedules by considering several factors, such as energy costs, environmental concerns, load profiles, and consumer comfort. With the deployment of smart meters, performing load control using the HEMS with DR-enabled appliances has become possible. This paper provides a comprehensive review on previous and current research related to the HEMS by considering various DR programs, smart technologies, and load scheduling controllers. The application of artificial intelligence for load scheduling controllers, such as artificial neural network, fuzzy logic, and adaptive neural fuzzy inference system, is also reviewed. Heuristic optimization techniques, which are widely used for optimal scheduling of various electrical devices in a smart home, are also discussed.

INDEX TERMS Home energy management system, demand response, smart technologies, integrated wireless technology, intelligent scheduling controller.

I. INTRODUCTION

A home energy management system (HEMS) is becoming important due to concerns related to global warming and energy shortage; this system helps decrease the demand for electricity, especially during peak load times [1]. HEMS should not only be considered as a way to reduce greenhouse gas emission, but also to allow the automatic management of electricity in a house [2]. Various efforts, which include the control of various home appliances (such as water heaters, air conditioners (A/Cs), refrigerators, electric vehicles, lighting, and others), have been exerted to establish HEMS systems. HEMS can be installed in residential homes to help manage power supply by communicating with household appliances and utilities, monitor energy usage, and receive information (such as tariff prices) to reduce power consumption by scheduling the usage of household appliances [3], [4]. This system can also optimize the operational schedule of home appliances and simultaneously manage the distributed energy resources and storage [5]. The overall architecture of a typical HEM with demand response (DR) is shown in Fig. 1. A smart meter is commonly installed at home and constantly in communication with a smart grid via the Internet, which links customers and utilities [6].

The system consists of a personal computer (PC), which acts as a control center with software and communication protocols, such as WiFi, ZigBee, Bluetooth, and KNX. Wired or wireless communication is connected to the PC, which serves as a coordinator that receives/sends data from the utility to the smart home and controls signals to manage home appliances. Weather information is also accounted in HEMS by taking temperature readings inside/outside buildings, which can be used to determine the comfort level of

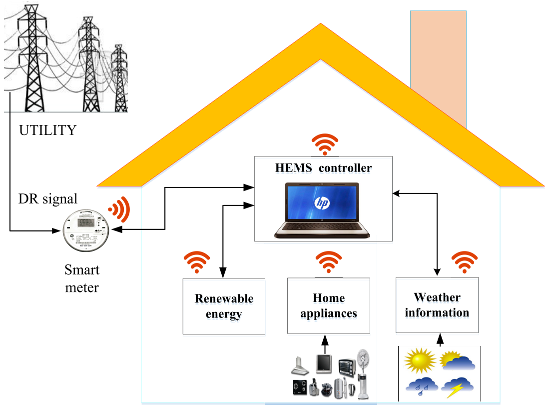

FIGURE 1. Architecture of home energy management system with demand response signal.

customers. Moreover, renewable energy resources connected to the HEMS system, such as photovoltaics (PV), batteries, and wind generators, provide energy to homes during peak hours, thereby reducing the utility load on the electricity network.

II. OVERVIEW ON HEMS

Previous and current works on HEMS systems are summarized in Table 1. Literature describes the evolution of HEMS from 1979 to 2017 as follows. The operation of energy management system was first based on a microprocessor [7]; its performance is improved, particularly with the advent of PCs in the 1980s. In 1982, an optimization algorithm for energy management was developed to reduce electricity cost by reducing demand and usage time [8]. A study [9] developed a computerized energy management system that considers operational size, geographical location, and various levels of energy management, such as the total number of applications and the basic, advanced, and total energy management.

A previous study [10] also developed a HEM system for residential application using a home automation communication network. Technologies, such as radio frequency, video technology, and ultrasonic sensors, were applied to track customers and locate missing objects [11]. An energy controller system was installed to manage the energy input/output of 20 residences in Japan by using a gateway for each home [12]. This gateway provides costumers with energy usage information and controls A/C and lights. Network architecture and power line communication have also been used for an energy management controller using home computers to control and monitor appliances [13]. The appliances connected to the home network are controlled by a compact appliance control interface, which is installed between home appliances and a network adapter. Furthermore, an intelligent algorithm based on game theory was integrated into the energy management scheme [14]. This algorithm was developed to track the activity of a single occupant and locate the status of various occupants within the same environment. Results showed that the algorithm can improve the

TABLE 1. Previous Works Related to Hems.

Reference	Description
[7]	Energy management system based on a microprocessor
[8]	Algorithm developed for energy management
[9]	Development of a computerized energy management system with four defined levels of energy management
[10]	Novel strategy for appliance control using a home automation communication network
[11]	Design of a ware home with video technology, radio frequency, and ultrasonic sensors
[12]	Energy controller system implemented to control air conditioners and lighting using a home gateway interface
[13]	Compact appliance control interface controller designed with home computers to control and monitor appliances
[14]	Optimal algorithm based on game theory for location and activity tracking of a single inhabitant
[15]	HEM controller for managing the energy consumption of appliances
[16]	Design of HEMS using infrared remote controls
[17]	Intelligent HEMS with simulated DR to reduce energy consumption and electricity cost
[18]	Smart HEM controller based on event-driven binary linear optimization
[19]	Advanced optimization for HEM that considers utility signals and comfort level
[20]	Energy management algorithm with renewable energy sources
[21]	Adaptable smart HEMS that considers the relationship between the power capacity of a network and energy usage
[22]	Smart HEMS based on real-time energy control by using rolling optimization to schedule the switching off of appliance during peak hours
[23]	A system that manages household energy without affecting the customer's preference settings
[24]	Intelligent energy management system that determines the optimal energy efficiency to minimize energy usage
[25]	Artificial bee colony as optimization algorithm to enhance the HEMS
[26]	An efficient core algorithm that schedules home load devices
[27]	A system that controls home appliances by using a smartphone
[28]	Implemented software and hardware systems to manage energy usage

comfort levels of occupants and reduce energy consumption. In 2006, the Whirlpool Corporation Company filed a patent, which describes a HEM controller that manages the energy consumption of appliances [15]. This invention provides an energy management system that can receive schedules of on-and off-peak time segments. An efficient HEMS using infrared remote (IR) controls was developed to control the lighting and power sockets in a room [16]. Nevertheless, the performance of IR control is limited because it cannot cover the entire distances between outlets and a central controller.

Advancement in HEMS began in 2012, when an intelligent HEMS with DR was developed to reduce energy consumption and electricity cost [17]. In this work, four home appliances, namely, A/C, water heater, electric vehicle, and clothe dryer, were controlled on the basis of priorities and comfort levels. A smart HEM controller based on event-driven binary linear optimization was designed to provide optimal electrical energy management in a residential area [18]. Other works used advanced optimization algorithms for HEM scheduling and considered the availability of adequately sized storage system, renewable resources, and dynamic electricity price to reduce the total energy costs in houses [19]. Additionally, a score role based on intelligent HEM algorithm was developed to control selected home appliances during a DR event by considering high-to-low power, utility signal, and the level of preset comfort [19]. Another work in Turkey presented a novel HEMS algorithm for a smart home with renewable energy resources [20]. The developed mechanism in this work uses multirate tariff, battery state of charge level, outlets through ZigBee, and renewable energy sources to schedule home appliances and reduce price tariffs. Renewable energy sources result in reduced electricity costs and energy demands. An adaptable smart HEMS was proposed to schedule home appliances by accounting for the relationship between the energy usage pattern and energy capacity of the network [21]. The system also considers various dynamic variables, which include weather condition, electricity tariff price, time of the day, and appliance status.

Several studies have considered the implementation of smart HEMS using real-time energy control approach to schedule home appliances. The DR tool allows appliances to participate in real-time energy control by adopting battery charging and PV system [22]. A fuzzy controller is utilized to determine the charging/discharging power of the battery, and rolling optimization is used to schedule energy consumption during off-peak periods. In a previous work [23], a HEMS system was implemented by managing household energy without affecting customer's preference settings. An intelligent energy management system, which uses an intelligent lookup table based on fuzzy logic and neural network, was also developed [24]. External sensors, environmental conditions, battery storage, prices, and customer behavior were selected as input to the system. The associative neural network was used to determine the optimal energy efficiency, which helps minimize energy consumption. A framework for HEMS was developed using an artificial bee colony as the optimization algorithm to improve the system by scheduling home appliances at a low-priced period [25]. An efficient core algorithm for HEMS that controls A/Cs and water heaters so as to reduce the total energy consumption of appliances is also presented in another study [26].

Several companies have designed intelligent HEMS to control energy consumption. For example, General Electric Co. designed a system that controls home appliances using smartphones. The system offers a strong support to customers by controlling and monitoring devices with a smartphone app [27]. Furthermore, Honda US has implemented a software and hardware system that controls, monitors, and optimizes electrical generation and appliance usage at home [28]. This home automation system uses solar PV and batteries to store energy that can be used during peak hours.

III. RESIDENTIAL DR PROGRAM IN HEMS

Recently, many researchers are showing interest in residential DR program, which is crucial in persuading residential customers to decrease their daily electrical consumption voluntarily by allocating available resources and managing load appliances [29], [30]. DR can be defined as changes in the electric usage of customers from their normal consumption patterns in response to changes in electricity cost over time or to incentive payments designed to induce low electricity usage during times of high wholesale market prices or suspected system reliability [31]. In Europe and the United States, DR programs have been widely implemented to adjust the timing, total electricity consumption, and instantaneous demand level [32].

In the DR program, customer response can be realized by three options, each of which considers cost and measures taken by the customer. In the first option, customers can decrease their electricity usage during critical peak periods when prices are high. This option imposes a temporary effect on comfort level. In the second option, customers may respond to high electricity prices by shifting their usage of certain household appliances from peak periods to off-peak ones. In the third option, a customer uses on-site distributed generation. In this case, the customer's electricity usage pattern changes [33]. Participating customers in DR programs can predict savings in electricity costs with reduction in their usage during peak periods [34]. According to the United States Department of Energy, residential DR programs can be classified into incentive- and price-based, as shown in Fig. 2 [35].

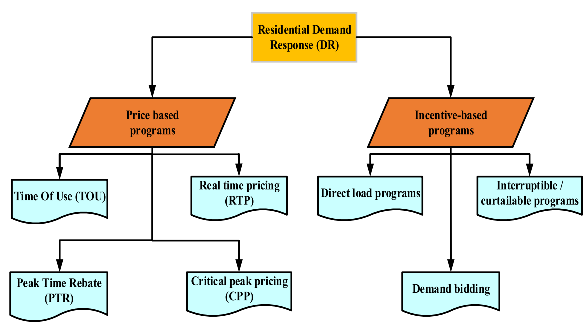

FIGURE 2. Categorization of residential demand response program.

A. INCENTIVE-BASED DR PROGRAM

An incentive-based DR program provides financial incentives to participating customers who aim to reduce and shift their consumption for their demand reduction during peak hours; a discounted rate is given to these customers in return for their participation in the program or bill credit payment [36], [37]. Incentive-based programs include direct load, interruptible/curtailable, and demand bidding programs. Direct load programs can remotely control customer appliances by transmitting signals that turn appliances off/on in a short notice based on a contract between the utility and the customers. Water heaters, A/Cs, and public lighting are common appliances that are remotely controlled using this type of program [38], [39].

In the load interruption/curtailment program, electricity prices are agreed upon between the utility and large industrial or residential customers, who switch off or shift their load to off-peak periods during emergencies. Reduction is achieved by transmitting demand-limiting signals from the utility, which benefits customers via incentive payments. This program helps the grid to stabilize during emergencies [33], [40]. The demand bidding program, also known as the buyback program, is based on customers' bids. Consumers bid for a specific load reduction in the wholesale electricity market, in which bidding is commonly conducted a day ahead [41]. Customers are free to select a bidding value in terms of the amount of energy reduction, and they will be rewarded if the actual amount of energy saving conforms to a certain requirement. In addition, no financial penalty is incurred if customer fails to reduce energy consumption according to the requirement [42].

B. PRICE-BASED PROGRAMS

Price-based programs include all tariff programs, where customers obtain financial benefits or discounts in return for their reduced electricity consumption at designated times. Price-based programs provide different electricity tariff prices and utilize a signal to help consumers obtain improved power [43], [44]. The consumers voluntarily modify the power consumption in their houses based on time-based electricity and follow the real-time cost of electricity by using tariff price programs, such as time of use (TOU) pricing, real-time pricing (RTP), or critical peak pricing (CPP) [45]. These programs offer different prices at various times of the day during off- and on-peak periods to indicate the ability of the utility to produce the required energy [46].

TOU is the most common residential electricity tariff, and it is currently used or considered for use in many utility companies worldwide. In TOU pricing, different electricity tariff prices are divided into time slots and various seasons of the year or hours of the day [47]. Power utilities can use TOU programs by setting the prices according to off-peak and peak time slots. In this case, electricity tariff prices are high during peak hours and low during off-peak hours to encourage consumers to shift their loads according to the increase in electricity prices. RTP is often called dynamic pricing, in which each hour of the year presents a different price; this price fluctuates by the hour for each time slot; such a case indicates the actual condition of the utility price of electricity [48]. Many utility companies are convinced that RTP programs, as the most efficient DR program, are flexible and highly acceptable in electricity markets [49]. CPP is designed to reward end users who voluntarily control and alleviate electricity demand usage or shift the usage of appliances to off-peak hours. CPP occurs a few times during the year, particularly summer when the demand for energy significantly increases; participating customers are notified of the increased prices [50], [51]. Several electricity retailers support CPP to benefit from significant load reductions during critical load periods. The peak time rebate pricing is a price-based program, in which consumers obtain a rebate that corresponds to the amount of their power consumption reduction [52].

C. COMPARISON OF RESIDENTIAL DR PROGRAMS

A comparison of different DR programs in terms of advantages/disadvantages is shown in Table 2. The different residential DR programs shown in Table 2 help consumers save money, reduce electricity consumption, and decrease utility infrastructure investments. The electricity energy usage of customers participating in DR can be changed by the following methods; moving energy consumption to various periods of time, using an on-site standby generator for emergency backup to decrease dependence on the utility grid, and using load curtailment strategies to reduce energy consumption [53]. However, customers are discouraged from participating in the DR program by the uncertainties associated with the program, undefined quantity of load that the utility companies require for reduction at a DR event, difficulty in satisfying the expected comfort levels of end users, and the economic feasibility of participating in the program.

IV. INTELLIGENT HEMS FOR SMART HOMES

Smart home is an application of smart technologies in residential buildings that can provide many opportunities for energy saving and simultaneous reduction of greenhouse gas emission and energy consumption. Smart homes not only provide electrical energy savings, but also result in several benefits, such as security, increased comfort level, and improved home automation and energy management. Several enabling smart technologies result in the integration of intelligent HEMS with various functions inside homes, such as automatic control, connection to the utility by a smart meter, and minimized energy consumption [54]. With smart technologies, customers can control household appliances, optimize electricity consumption, and set a schedule for household appliances during critical peak hours based on the DR signals [55].

A. APPLICATIONS OF SMART TECHNOLOGIES FOR INTELLIGENT HEMS

In the context of intelligent HEMS, various research works have been carried out using smart technologies to develop hardware and control algorithms of the HEMS. In one study [56], a power socket for monitoring power consumption at a fixed time was developed; the socket turns off

TABLE 2. Comparison of residential DR programs.

Residential DR program	Response and activation period	Advantage	Disadvantage
Real-time pricing	Electricity prices vary daily at the customer's end.	End user can reduce the electricity cost with respect to the price change in a day or month.	Customers who want to reduce electricity bill should instantaneously respond.
Time of use pricing	Electricity prices vary hourly at the end users.	Tariff prices are high during on-peak and low during off-peak, thereby encouraging customers to shift loads to reduce cost.	Tariff displays one price change with respect to time for all customers, and following the prices is compulsory for end users.
Critical peak pricing	Electricity prices change any time at the customer's end.	End users receive notification for a short period to earn discount.	Customers should curtail or shift home devices for a certain period.
Direct load program	Prices change any time occur at the utility side.	The utility offers special discounts for shifting of appliances.	Utility should curtail or shift certain devices so as to balance power consumption with authorization from the customers.
Curtailable programs	Prices change any time at the customer's end.	Customers respond within a limited period to obtain discount rates.	Customers should curtail or shift home devices for certain periods of time.
Demand bidding	Prices change any time at the customer's end.	The utility offers special discount offers for shifting of appliances.	Customers should curtail or shift home devices for a certain period of time.

the supply when the monitored power is below the demand threshold. The power socket can be used with any type of domestic loads. A hardware HEMS was also developed and integrated with a rule-based algorithm and DR program in a laboratory [57]. The rule-based algorithm in the HEM control unit manages four loads based on priority and homeowner preference. Two-way communication between the loads and HEM control unit is implemented to report readings for current, voltage, and real power of the appliances. Furthermore, a machine learning algorithm, with sensing technology and communication, was implemented to design hardware prototype smart HEMS to help homeowners minimize the total electricity cost and intelligently manage loads [58]. An automatic on/off power switch socket is used to manage the domestic load energy consumption for energy management. A hardware architecture was developed for HEMS to control air-conditioning units using a smart thermostat [59]. Control was achieved by preprogramming the thermostat, which helps lower energy consumption during the DR period and improve temperature control. In addition, a hardware HEMS controller was developed in the laboratory of the University Politehnica, Bucharest [60]. The HEMS controller algorithm is used to obtain information regarding power consumption, turn on/off various residential appliances, and reschedule domestic loads to operate during off-peak times from home devices. User interface software with HEMS was implemented in an Android OS, which allows homeowners to access the load characteristics easily and remotely turn on/off the appliances. An effective hardware and control algorithm was also designed for HEMS to control selected home appliances automatically, which maintains the total energy consumption of home appliances below the set limits [61].

Intelligent methods have been used by HEMS to minimize the cost of energy consumption using real-time control, stochastic scheduling, and real-time monitoring [62]. In real-time control, HEMS controls the selected devices. In stochastic scheduling, stochastic dynamic programming is used to compute the total cost of energy consumption and select a set of home devices to control. Finally, in real-time monitoring, the controllable household loads are displayed in real-time, and the loads are scheduled according to the load characteristics. Nevertheless, the implemented intelligent algorithm is complex, with a large computational burden and low speed. A bespoke software for the HEMS to switch devices on/off and monitor power consumption was also developed [63]. This software runs in Linux on a Raspberry PC, and it is written in JavaScript, Python, and HTML. A graphical user interface for HEMS was designed and created on a PC via a communication protocol, which can display, process, and gather data usage power with real-time remote control on home appliances. This system aims to inform end users regarding their energy consumption habits by relaying this information to them.

A major feature of smart technologies for HEMS is that they integrate storage and renewable energy resources into energy consumption. In [64], an embedded system that integrates storage energy resources and PV to a smart home was developed. The system manages an intelligent home energy requirement by installing photovoltaics (PV) and batteries. A PV generator with a grid connected inverter is used in the HEMS, and it applies a self-learning feedback mechanism to create an intelligent power consumption management system [65]. The interaction of PV with other smart appliances results in increased comfort, reasonable strategy for customer economy, and power balance.

B. SMART SENSORS IN HOME APPLIANCES AND COMMUNICATION PROTOCOLS

Various types of wireless sensor technology have been used to link home appliances with HEMS. Smart residential home appliances can be integrated to a wireless control network, such as ZigBee, Bluetooth, and WiFi, to receive signals remotely or automatically from a utility inside a smart home [66], [67]. The standard IEEE 802.11 is one of the most common wireless technologies present in smart homes [68]. Wireless communication between a PC and a smart outlet is the key to intelligent home automation and building control [69].

Information and communication technologies are essential in HEMS for designing an optimal scheduling controller and strategies for energy management. An intelligent HEMS using ZigBee based on IEEE 802.15.4 standard has been developed to provide intelligent services for customers with air-conditioning systems, heating, and two-way communication networks [70]. A wireless communication platform-based protection and monitoring systems for residential buildings were developed using a ZigBee wireless sensor [71]. An intelligent cloud HEMS using ZigBee communication was used for intelligent power and environmental monitoring devices and intelligent cloud management servers in smart homes [72]. This system can reduce the average total power consumption by 7.3 %. A ZigBee wireless sensor based on HEMS that monitors the energy consumption of residential loads and lights was also designed [73]. HEMS gathers the energy consumption data for each home appliance and controls the load via scheduling to reduce energy cost. An intelligent controller for HEMS using ZigBee wireless protocol is also utilized to control home appliances automatically based on dynamic tariff by considering customer preferences [74]. The controller provides manual or automatic options for controlling various appliances. Furthermore, ZigBee wireless protocol for power sensor nodes is used in remote power measurement and turning on/off of electric appliances [75]. Results showed that using ZigBee communication network in this system enables the accurate monitoring of energy usage.

A novel energy management approach based on low energy Bluetooth for communication between home appliances in HEMS was developed. The approach takes into account different storage devices, energy sources, electrical home appliances, and communication protocols [76]. Simulation results showed that the proposed approach is effective in minimizing peak load demand and electricity bills. However, the applicability of Bluetooth is limited due to several factors, such as high complexity, low communication range (10 m), limited network size, and power consumption exceeding that of ZigBee technology [77]. Developments in information and communication technology, such as power line communication, wireless sensor networks, and WiFi, have exponentially improved home energy management evolution [78]. Nevertheless, WiFi consumes additional power, thereby making it expensive in a complex infrastructure where it needs additional components, such as routers, in the network. A low-cost and efficient solution to monitor and control residential loads using a WiFi smart plug was proposed [79]. The WiFi communication is established in the smart outlet using an IP address. An intelligent HEMS system based on a WiFi sensor network was adopted to control electricity in a household [80]. The microcontroller-based Arduino platform and WiFi network are used to monitor the power consumption of different home appliances and remotely control multiple devices to minimize energy consumption. A comparison of the three types of wireless protocols used in wireless sensor networks for HEMS is summarized in Table 3.

TABLE 3. Comparison of different wireless protocols.

Parameters	WiFi	Classic Bluetooth	Zigbee
Standard	IEEE 802.11	IEEE 802.15.1	IEEE 802.15.4
Data rate	11,54 Mbps	1 Mbps	20, 40, and 250 kbps
Frequency band(s)	2.4 and 5 GHz	2.4 GHz	868/915 MHz, 2.4 GHz
Power consumption	Very high	Low	Very low
Complexity	High	High	Low
Transmission range	> 100 m	10 m	10–100 m
Network topology	Point to hub	Ad hoc, small networks	Ad hoc, peer-to-peer, star, or mesh

The current wireless standards, such as WiFi and Bluetooth, are evidently limited in their applicability and unsuitable for use in online wireless monitoring and controlling residential loads because they require additional application layer gateway when connected to the Internet [81], [82]. ZigBee wireless sensors are used as a wireless communication media for home energy monitoring because they feature suitable communication range, low data rate, low power consumption, low complexity, provision of support to a large number of nodes in the network (up to 65,535), easy removal or addition of nodes in the network, and a powerful mesh network; consequently, the failure of one node exerts no effect on the remaining network [83], [84].

V. APPLICATIONS OF SCHEDULING CONTROLLER TECHNIQUES IN THE HEMS

HEMS can help reduce the overall energy consumption by scheduling home appliances without affecting customers' comfort level. Home loads are commonly scheduled by minimizing the power demand during peak load and reducing electricity cost via dynamic hourly electricity tariff [85]. With the use of an optimal scheduling controller, participating customers in DR programs can reduce electricity bills when they reduce their electricity usage during peak periods and shift peak time load to off-peak time [86]. Optimal scheduling strategies include the turning on/off of schedulable home appliances, such as A/Cs, water heaters, washing machines, clothe dryers, and electric vehicles, and nonschedulable home appliances, such as television, lights, printers, ovens, computers, and microwaves at any time [87]. Various scheduling control approaches have been utilized to create optimal appliance scheduling of energy usage by taking into account rule-based, artificial intelligence (AI), and optimization techniques.

A. RULE-BASED SCHEDULING CONTROLLER

Rule-based algorithm has been used in many systems for behavioral application by specifying conditions. The Rete algorithm is used in HEMS to control energy via smart taps in a network [88]. The loads are distributed to smart taps for data collection and rule processing. Similarly, a rule-based method with energy on demand has been used to manage electrical appliances by creating if/then rules based on high-to-low priority appliances [89]. A rule-based algorithm shifts loads to low-price periods and curtails the utilized loads. The algorithm can subsequently manage different types of load appliances and multiple operators, provide a suitable solution to decrease energy cost, and control price fluctuation under real-time pricing [90]. The rule-based algorithm for HEMS that considers DR application has also been developed so as to control home appliances [91]. Notably, the rule-based approach for scheduling home appliances presents several shortcomings, such as unsuitability for extensions, because it cannot rely on rules to extend the system. This approach is also unable to deal with large data, especially DR strategies, which makes controlling home appliances in real time difficult.

B. HEM SCHEDULE CONTROLLER USING AI TECHNIQUES

Recently, various AI techniques have been used to implement home appliance schedule controllers for residential consumers in smart houses. These AI-based HEM schedule controllers are based on artificial neural network (ANN), fuzzy logic control (FLC), and adaptive neural fuzzy inference system (ANFIS). An AI controller consists of software programming that mimics human thinking [92]–[94]. ANN, which is an information processing algorithm that models nonlinear systems and simulates the human brain, has been utilized as an intelligent controller to control home appliances [95]. ANN-based solutions can be used instead of simulation tools to create a fast solution for problems in control and prediction. An ANN-based advanced thermal control method in domestic buildings has also been developed to generate highly convenient thermal environments [96]. Results showed that the ANN control method can improve thermal comfort in domestic buildings. In one study [97], ANN was used with genetic algorithm for weekly appliance scheduling with optimized energy consumption in a residential sector to reduce energy demand during peak periods and maximize the usage of renewable sources. Moreover, another study [98] used PSO-based ANN to improve its operation by selecting the optimum number of neurons in each hidden layer and learning rates. The authors proposed a new hybrid lightning search algorithm (LSA)-based ANN to predict the optimal on/off status of home appliances [99]. The LSA optimization was hybridized with ANN to improve the ANN performance by selecting the optimum values of neurons in each hidden layer and learning rate, which enhances the accuracy of ANN. In [100], a distributed algorithm-based ANN was used in reducing the total energy price and operation delay for energy demand by obtaining accurate energy management decisions. The ANN technique can effectively manage energy consumption by controlling the household's electricity usage.

FLC has been used in HEMS to control home electric appliances by minimizing energy consumption and electricity prices. FLC was designed by applying four steps, namely, fuzzification, defuzzification, rule base, and inference engine. FLC is simple to execute, and it can handle nonlinear and linear systems based on linguistic rules; furthermore, it requires no mathematical model [101]–[103]. FLC was developed for day-ahead scheduling of air-conditioning units to achieve optimal temperature scheduling in relation to outdoor temperature forecasts and electricity prices [104]. DR is applied via smart HEMS in a smart home environment. Simulation result displayed the ability of FLC in decreasing energy consumption and scheduling the operation of air-conditioning units. Appliance scheduling using FLC for smart homes was also implemented in a previous work [105]. The authors used fuzzy techniques to model user comfort and forecast prices to maximize comfort levels and minimize energy consumption in residences. A high-resolution model of electrical consumption for any residential dwelling using fuzzy logic inference system is also presented [106]. In this work, a PV plant is integrated in HEMS to reduce energy and electricity cost associated with home appliances' electricity consumption patterns. The appliance type and active occupancy serve as input to the fuzzy system, and the probability of each appliance starting within the next minute is considered the output. The developed FLC can control only a few types of home appliances without considering high-power consumption appliances. A real-time scheduling controller was implemented for residential appliances based on fuzzy logic in the HEMS [107]. In this study, four home appliances with battery and PV were considered in the system. Results showed that the FLC can reduce load demand by scheduling the operating times of home appliances and considering the energy supply from PVs and batteries. Researchers in [108] designed a FLC for HEMS to reduce energy consumption. However, the controller fails to account the users' comfort level and DR signals. Three control techniques, namely FLC, continuous relaxation, and mixed-integer linear programming, for scheduling home appliances were applied [109]. Three types of FLC, namely, task-related FLC, heat-related FLC, and FLC for the battery, were also used. The developed system is used to control and monitor energy storage devices, heating, and power consumption.

Another AI controller used for HEMS is the ANFIS, which is an intelligent controller that schedules and controls household load to reduce power consumption. The ANFIS structure presents many layers, and it requires no mathematical model [110]. An ANFIS-based controller in a smart house

TABLE 4. Comparison among artificial intelligence-based controllers for HEMS.

ANN Controller	FLC Controller	ANFIS Controller
1. Mathematical model is not required	1. Mathematical model is not required	1. Mathematical model is not required
2. Complex design and implementation	2. Easy design and implementation	2. Moderately complex design and implementation
3. Normal structure	3. Simple structure	3. Complex structure
4. Can achieve good performance if appropriate activation function, training data, and number of nodes are selected	4. Can achieve good performance if proper parameters in the rule-based algorithm and type of membership functions are selected	4. Can achieve good performance if suitable training data and type of membership function are selected
5. Requires learning process when designing the controller	5. Requires no learning process when designing the controller	5. Requires learning process when designing the controller

was implemented in [24]. The controller accounts for an intelligent lookup table and a fuzzy subsystem. The input is derived from output feedback, external sensors, and fuzzy subsystems. The proposed controller determines the optimal energy scheduling according to dynamic price without minimizing energy consumption. Nonetheless, the controller neglects other parameters, such as user preferences and DR strategies. An intelligent inference algorithm based on ANFIS for HEMS is also presented in [111]. This algorithm is used to increase the inference between the appliances that transmits the retraining schedule to the ANFIS. Results showed that the performance of the proposed ANFIS is better than that of classic ANFIS. Table 4 shows a comparison of the ANN, FLC, and ANFIS controllers for HEMS.

Literature showed that several limitations are associated with the use of FLC and ANFIS in scheduling controllers. For instance, FLC depends on appropriate variables in rule-based algorithms and membership functions. These variables are commonly determined on the basis of trial and error, which requires additional time. Challenges associated with the ANFIS controller include the large amount of data required and long training and learning times. Consequently, the ANN technique provides highly favorable features, such as excellent prediction, good performance in real-time operation, distinct ability to learn complex nonlinear functions through training, and creation of information received during learning.

C. HEM SCHEDULE CONTROLLER USING OPTIMIZATION TECHNIQUES

Generally, optimization is the determination of the most suitable solutions to problems after determining the objective function subjected to constraints. The objective function is often formulated on the basis of certain applications, and it can take the form of minimal error, minimal cost, optimal design, and optimal management. Various optimization techniques have been used to help end users create optimal appliance scheduling of energy usage based on different feed-in tariffs, pricing schemes, and comfort settings. Optimal energy consumption scheduling based on linear programming is used to minimize the electricity cost and waiting time for each home appliance that operates with a real-time pricing tariff [112]. An optimal approach based on game theory is used to determine the optimal consumption schedule for subscribers in a neighborhood to reduce electricity cost [113]. Moreover, the Lyapunov optimization technique is used to minimize the long-term expected cost of electricity for home appliances' energy consumption, which involves controllable loads, uncontrollable loads, and renewable energy [114].

The use of completely automatic DR is important toward achieving improved HEMS. An optimization approach was developed to minimize tariff for end users through effective operation of home appliances under different prices based on DR signals [115]. A mixed-integer nonlinear program optimization for scheduling household electrical appliances with an installed battery storage was developed in [116]. The HEMS was established under DR program using the time required to use the electricity tariff to minimize electricity costs. The optimization result showed that consumers can reduce energy cost by shifting energy consumption to off-peak times, which results in a 22% cost saving. Researchers in [117] also applied mixed-integer nonlinear programming for optimal scheduling of home electrical appliance, which accounts for energy saving and comfortable lifestyles. Optimal scheduling of home appliances using game theory has also been presented using electric vehicles and battery storage to reduce power consumption at home [118]. An autonomous demand-side management system based on game theory has also been developed. The algorithm is used to optimize the home appliances' energy consumption and manage residential loads by prioritizing appliances in terms of electricity cost reduction or customer comfort [119].

Recently, heuristic optimization techniques are extensively utilized to solve optimization problems. These techniques are stochastic algorithms that mimic the processes of natural phenomena, such as self-organization, natural evolution, and natural selection. Binary particle swarm optimization (BPSO) is used to create an optimal curtailment schedule based on a significant number of interruptible residential loads over 16 h [120]. This technique aims to produce a day-ahead schedule that minimizes the total electricity cost. Scheduling results showed that BPSO is an effective optimization technique for scheduling interruptible residential loads by generating schedules without influencing end user comfort. The PSO technique is also used to optimize desirable points during the appliances' operation time [121]. Weather conditions, user preferences, and appliance priorities are considered in this technique. The BPSO technique is also utilized for scheduling four controllable residential distributed energy resources and 29 interruptible appliances [122]. The objective function maximizes the net benefit of end users and reduces energy consumption. In [123], an optimal real-time schedule controller for HEMS was developed. This controller uses a new binary backtracking search algorithm as a schedule controller to control and schedule the operation of home appliances to off-peak time considering DR strategies. The proposed scheduling algorithm can reduce energy consumption during peak hours by approximately 9.7138%, with consideration of four appliances in every 7 h period.

Genetic algorithm (GA) with supervisory control and data acquisition was implemented to schedule residential loads with optimized energy consumption in the domestic sector and minimize electricity demand [122]. The system consists of variable loads and renewable energy sources, such as fuel cell, wind turbine, and PV. GA and mixed-integer nonlinear programming were compared under different scenarios; results showed that GA reduces energy better than that of mixed-integer nonlinear programming technique. Furthermore, a robust optimization and stochastic technique was used to schedule home devices and reduce electricity cost based on dynamic pricing [124].

Heuristic scheduling algorithm is also essential toward achieving optimal solutions. An efficient heuristic approach and optimization model was proposed to schedule and control residential smart home appliances and energy storage systems to obtain efficient energy management [125]. In [126], a wind-driven optimization technique was used to schedule home appliances by minimizing electricity cost and maximizing comfort level. Simulation results demonstrated that the wind-driven optimization technique reduces power consumption by 8.3% compared with that of PSO due to the optimal scheduling of residential loads. The BPSO technique was also developed for optimal scheduling of home appliances to reduce cost by categorizing appliances based on priority and DR program [127]. However, experimental results showed that the heuristic scheduling algorithm based on BPSO is relatively inefficient in terms of computational time, which makes it unsuitable for application in real-time scheduling. A dynamic residential load scheduling that optimizes scheduling of household appliances was also reported; this program allows customers to decrease electricity costs and minimize peak loads [128].

According to the literature, mathematical and heuristic optimization techniques can be both used to solve scheduling problems. The former can provide accurate solutions, but they are commonly time consuming when solving complex optimization problems. To overcome these drawbacks, heuristic optimization techniques are currently being extensively used. Nevertheless, the widely used heuristic optimization techniques, such as PSO, are limited with that they are relatively easily trapped in certain local minima, they are computationally complex, and they exhibit difficulty in selecting optimal control parameters. These factors all lead to unsatisfactory solutions. Finally, a significant barrier, which is represented by customers' awareness about smart technologies, should be considered to realize a proper intelligent HEM for interaction with customers.

VI. CONCLUSION

This paper first presented a description of the main components of a typical HEMS and subsequently provided a review regarding previous works on HEMS. DR strategies and techniques, such as the tariff program, were discussed in detail. Smart technologies for developing hardware and schedule controller algorithms for intelligent HEMS were also presented. Different types of communication protocols used for HEMS, such as WiFi, Bluetooth, and ZigBee, were discussed and compared. Artificial intelligent techniques used for developing a HEMS schedule controller based on rules, ANN, FLC, and ANFIS systems were also addressed. This paper also discussed mathematical and heuristic optimization techniques used to develop the optimal schedules and consequently minimize the energy consumption and shift operations of home appliances to off-peak times without affecting customer comfort. The effectiveness of various heuristic optimization techniques was also compared in terms of computational speed and complexity. The future trend in HEMS is towards the in cooperation of self-learning AI techniques in order to replace the user involvement in system settings.

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