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Optimization methods for power scheduling problems in smart home: Survey

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ABSTRACT

Optimizing the power demand for smart home appliances in a smart grid is the primary challenge faced by power supplier companies, particularly during peak periods, due to its considerable effect on the stability of a power system. Therefore, power supplier companies have introduced dynamic pricing schemes that provide different prices for a time horizon in which electricity prices are higher during peak periods due to the high power demand and lower during off-peak periods. The problem of scheduling smart home appliances at appropriate periods in a predefined time horizon in accordance with a dynamic pricing scheme is called power scheduling problem in a smart home (PSPSH). The primary objectives in addressing PSPSH are to reduce the electricity bill of users and maintain the stability of a power system by reducing the ratio of the highest power demand to the average power demand, known as the peak-to-average ratio, and to improve user comfort level by reducing the waiting time for appliances. In this paper, we review the most pertinent studies on optimization methods that address PSPSH. The reviewed studies are classified into exact algorithms and metaheuristic algorithms. The latter is categorized into single-based, population-based, and hybrid metaheuristic algorithms. Accordingly, a critical analysis of state-of-the-art methods are provided and possible future directions are also discussed.

1. Introduction

In the power sector domain, the "Age of Electricity" started in 1896 when hydroelectric power from Niagara Falls was transmitted to Buffalo City, USA. By the end of World War II, the "Atomic Age" began. This period focused on technologies for building and installing power plants that use nuclear power to generate electricity with the lowest cost. At present, we have entered the "Energy Age," wherein the demand for energy is increasing due to the multitude of appliances that require a huge amount of power to operate. Old power grids are

Abbreviations: ACO, Ant Colony Optimization; AFSA, Artificial Fish Swarm Algorithm; BBO, Biogeography Based Optimization; BFOA, Bacterial Foraging Optimization Algorithm; BPSO, Binary Particle-Swarm Optimization; CMP, Capacity Market Program; CP, Critical Period; CPP, Critical Peak Pricing; CSA, Crow Search Algorithm; CSOA, Cuckoo Search Optimization Algorithm; DLC, Direct Load Control; DR, Demand Response; DSM, Demand-Side Management; EB, Electricity Bill; EDE, Enhanced Differential Evolution; EDRP, Emergency DR Program; EDTLA, Enhanced Differential Teaching-Learning Algorithm; EHO, Elephant Herding Optimization; EMC, Energy Management Controller; EP, Electricity Price; ESS, Electricity Storage System; EWA, EarthWorm Optimization Algorithm; FBAT, Flower Pollination BAT; FGA, Flower Pollination Genetic Algorithm; FPA, Flower Pollination Algorithm; FTLBO, Flower Pollination Teaching Learning-Based Optimization; G-DSM, Generic Demand-Side Management; GA, Genetic Algorithm; GHSA, Genetic Harmony Search Algorithm; GTLBO, Genetic Teaching Learning-Based Optimization; GWD, Genetic Wind Driven; GWO, Grey Wolf Optimizer; HBG, Foraging and Genetic Algorithm; HEMS, Home Energy Management System; HGPO, hybrid GA-PSO; HSA, Harmony Search Algorithm; HSH, Hybrid BFOA and HSA; I/C, Interruptible/Curtailable; IBR, Inclining Block Rates; ILP, Integer Linear Programming; LOC, Length of Operation Cycle; MFO, Moth-Flame Optimization; MILP, Mixed Integer Linear Programming; NSA, Non-Shiftable Appliance; OSR, Optimal Stopping Rule; OTP, Operation Time Period; PAR, Peak-to-Average Ratio; PIO, Pigeon Inspired Optimization; PSC, Power Supplier Company; PSPSH, Power Scheduling Problem in The Smart Home; PSO, Particle-Swarm Optimization; RES, Renewable Energy Source; RTP, Real-Time Price; SA, Shiftable Appliance; SBA, Strawberry Algorithm; SG, Smart Grid; SSO, Social Spider Optimization; TG-MFO, Time-constrained Genetic-Moth Flame Optimization; TLBO, Teaching Learning-Based Optimization; TOU, Time-of-Use; TS, Tabu Search Algorithm; UC, User Comfort; WDO, Wind-Driven Optimization; WTR, Waiting Time Rate

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currently facing this major challenge because of the primitive nature of their infrastructure that fails to fulfill the user requirements [1].

To overcome such challenge, researchers have become more interested in smart grids (SGs) instead of the old power grids to be able to meet the user requirements [2].

SGs are next-generation power grids that can improve efficiency, safety, control, and reliability by upgrading management and distribution systems of old power grids. The key to these improvement is bi-directional communication between power supplier companies (PSCs) and their users; such communication allows PSCs to send power flow to users and obtain their feedback [3]. The feedback allows PSCs to anticipate the power consumption of users in upcoming periods. In addition, SGs are incorporated with new technologies, such as advanced software for data management and intelligent controllers, to enhance the delivery network [4].

SGs can update their distribution systems to become more efficient by deploying renewable energy sources (RESs) to generate power. RESs play a pivotal role in reducing reliance on fossil fuels to generate power. Accordingly, RESs decreases carbon emission and its impacts on the environment [5].

The primary objectives of SGs are to make a power system efficient, reduce power demand during peak periods, and minimize the cost of power production. Optimizing the power consumption of users plays a lead role in achieving the objectives of SGs. Reducing their electricity bill (EB) is the major benefit gained by users in optimizing their power consumption [6]. The power consumption of users can be optimized by scheduling their smart appliances operating time in their smart homes and shifting the load from peak to off-peak periods using the dynamic pricing scheme discussed in Section 4.2. This optimization problem is called the power scheduling problem in a smart home (PSPSH). PSPSH is formulated as an optimization problem to find the best schedule for smart appliances from all feasible schedules. Therefore, several optimization algorithms have been adapted to handle PSPSH [7–9].

Research in PSPSH began 10 years ago. Several surveys have been conducted during this period [4,5,10,11]. PSPSH has been classified and surveyed in different ways. The authors of [4] conducted a survey based on objective functions, including the maximization of social welfare, minimization of electricity cost, minimization of aggregated power consumption, minimization of aggregated power consumption and electricity cost, and minimization of aggregated power consumption and maximization of social welfare. In Ref. [5], the authors conducted a survey based on user interactions, optimization approach, and time scale.

In this survey, the methods used to address PSPSH are classified into two classes; (i) exact algorithms and (ii) metaheuristic algorithms. The latter is classified into local search-based, population-based, and hybrid metaheuristic algorithms, which are discussed in Section 5.

Several papers on this subject have been published within the last 10 years by renowned publishers, such as IEEE, Springer, Elsevier, MDIP, and others. The numbers of publications about PSPSH are provided in Fig. 1, with the distribution based on the publisher.

The structure of this survey is as follows. In Section 2, SG is defined in terms of communication, security, and optimization. The illustration of the features, goals, and system model of SGs is also provided in this section. An overview of a smart home is presented in Section 3. A smart home is defined to show its impact on PSPSH. In addition, a smart home system is modeled and described. A comprehensive definition of PSPSH and its constraints are provided in Section 4. PSPSH formulation, motivational schemes (e.g., dynamic pricing schemes) used in PSPSH to motivate users to schedule their smart home appliances, and the datasets used in most of the literature are also discussed. In Section 5, the optimization methods used to handle PSPSH are summarized to present their objectives, contributions, and gaps. Lastly, this survey is concluded with a comprehensive summary in Section 6.

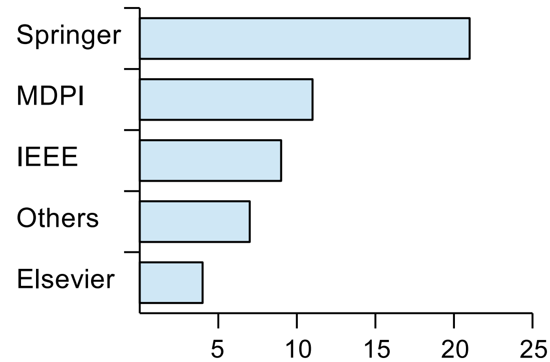

Fig. 1. Number of publications about PSPSH per publisher.

2. Smart grid (SG)

The term (grid) traditionally refers to an electrical system that supports various electrical operations, such as electricity distribution, transmission, generation, and control [3].

SGs are considered the next-generation power grids; they were introduced to overcome the limitations and inefficiency of traditional power grids [5]. SGs provide new technologies to improve power distribution systems, power delivery efficiency, and system safety and reliability [3,12,13].

2.1. Definitions of smart grid

SG has been defined differently in various literature.

US Department of Energy [14] defined the SG as:

"A smart grid uses digital technology to improve reliability, security, and efficiency (both economic and energy) of the electric system from large generation, through the delivery systems to electricity consumers and a growing number of distributed-generation and storage resources".

According to James Momoh [15] the SG was defined as:

"The smart grid is an advanced digital two - way power flow power system capable of self - healing, and adaptive, resilient, and sustainable, with foresight for prediction under different uncertainties. It is equipped for interoperability with present and future standards of components, devices, and systems that are cyber - secured against malicious attack".

Briefly, SG is defined as a power grid that provides bi-directional communication between PSCs and users in smart homes. Through SGs, PSCs obtain feedback from users and apply it to control and optimize the usage of available power to achieve high performance in power delivery and meet the power requirements of users.

2.2. Benefits and goals of smart grid

The SGs exhibit considerable advantages in distribution networks not only in changing the lifestyle of modern society but also in avoiding the shortcomings of old power grids. The major advantages that oblige PSCs to update old power grids and their distribution systems to SGs are summarized as follows [13,16]:

- Improve the quality and reliability of electrical power systems
- Enhance the efficiency and capacity of the electric power systems
- Reduce the overall cost of delivering power to users
- Reduce the EB of users by applying new approaches
- Enable new power sources to reduce carbon emission levels
- Reduce the consumption of fossil fuels in generating power
- Improve communication between PSCs and users

2.3. Features of smart grid

Achieving system efficiency and meeting power demands of users are the primary objectives of SGs. SGs have many features that help achieve their optimal use. These features are described as follows [16,17]:

- **Smart Meter**: a device that measures power consumption in smart homes and makes users aware of their power consumption. Meanwhile, it helps PSCs by providing information about user consumption to achieve load power balance. Therefore, the smart meter is the most critical mechanism in SGs.
- **Demand-side Management (DSM)**: it allows PSCs to encourage their users to modify their electric power consumption profile and reduce power consumption during peak periods or shift their consumption load from peak to off-peak periods to flatten their consumption curve using the demand response (DR) program. The DR program is in charge of providing dynamic pricing schemes (i.e., the price of electricity is changing throughout a time horizon) or other incentive schemes.
- **Bi-directional Communication**: two-way communication between PSCs and users to send power flow and receive information for control and feedback.
- **Integration of Distributed Generation Resources**: it maintains the balance of distributed energy resource systems during peak periods and engage RESs at points of appropriate interconnection.
- **Energy Storage Devices**: storage devices in SGs contribute significantly to reducing pressure on SG's distributed systems during peak periods by storing power during off-peak periods and then using the stored power during peak periods.
- **Distribution Automation**: a mechanism that helps and improves power system reliability by detecting faults and restoring power lines after interruptions from control centers.
- **Multiple Sensors**: sensors are equipped with a power line that helps pinpoint a problem's location.
- **Self-healing**: SGs can repair simple problems without technician intervention. For damaged infrastructure problems, SGs can send a full report regarding the problem to technicians.
- **Self-monitoring**: SGs are monitored automatically, and thus can manage power distribution systems and troubleshoot outages without technicians.

2.4. Traditional power grids versus smart grids

Many challenges affirm the incapability of traditional power grids to meet power demand of users effectively while SGs are advancing into a new level of distribution and power transmission. Table 1 compares between SGs and traditional power grids.

2.5. Smart grid system model

SG comprises PSC (data center), power generators, intelligent nodes, data network, energy network, and smart homes or buildings. The general infrastructure of SG is presented in Fig. 2.

The data network and energy network are key factors in SG that are regarded as its nervous system due to their function in connecting PSC with the other components of SG and exchanging data and energy between them. The intelligent nodes use remote monitoring to manage the distribution of power generated by power generators (e.g., solar plants, offshore wind farms, power-heat coupling units, and fossil fuel based power plants). PSC (data center) is typically operated to supervise transmission and distribution operations. These components of SG assume full responsibility for managing all operations accurately from power generation to power consumption [12].

3. Smart homes

A smart home is one of the technologies that serve residents. It incorporates residential houses with smart technology to improve the comfort level of users (residents) by enhancing safety and healthcare and optimizing power consumption. Users can control and monitor smart home appliances remotely through the home energy management system (HEMS), which provides a remote monitoring system that uses telecommunication technology [18].

HEMS comprises hardware and software that allows users to efficiently manage their power consumption by controlling smart home appliances operation time, as discussed in Section 3.2. Several studies have proposed different architectures for HEMS and discussed how HEMS provides benefits in terms of improving safety and healthcare and solving PSPSH to optimize power consumption and improve the efficiency of power systems [8–10,19].

3.1. Definition of smart home

A smart home has been defined in several ways based on its features.

Lutolf in Ref. [20] defined a smart home as:

> "The smart home concept is the integration of different services within a home by using a common communication system. It assures an economic, secure and comfortable operation of the home and includes a high degree of intelligent functionality and flexibility".

According to Alam in Ref. [18] a smart home is defined as:

> "An application of ubiquitous computing that is able to provide user

Table 1
Comparison between SGs and traditional grids.

Traditional grids		SGs	
Characteristic	Description	Characteristic	Description
Electromechanical technology	No communication between devices in a grid.	Digital technology	Facilitate remote control by improving communication between devices in a grid.
One-way communication	Communication between PSCs and their users one-way.	Two-way communication	Communication between PSCs and users is two-ways, i.e., from/to companies and users.
Centralized generation	Power is generated and distributed from main power plants to users.	Distributed generation	Power is generated and distributed from multiple power plants and substations to limit blackouts.
Few sensors	Power lines are equipped with few sensors. This condition increases the difficulty in determining a problem's location.	Multiple sensors	Multiple sensors are equipped with a power line that helps pinpoint a problem's location.
Manual restoration	Technicians are needed to repair the failures of a power system.	Self-healing	SGs can repair simple problems without technician intervention. For damaged infrastructure problems, SGs can send a full report regarding the problem to technicians.
Manual monitoring	A power distribution system is monitored manually.	Self-monitoring	SGs are monitored automatically, and thus can manage power distribution systems and troubleshoot outages without technicians.

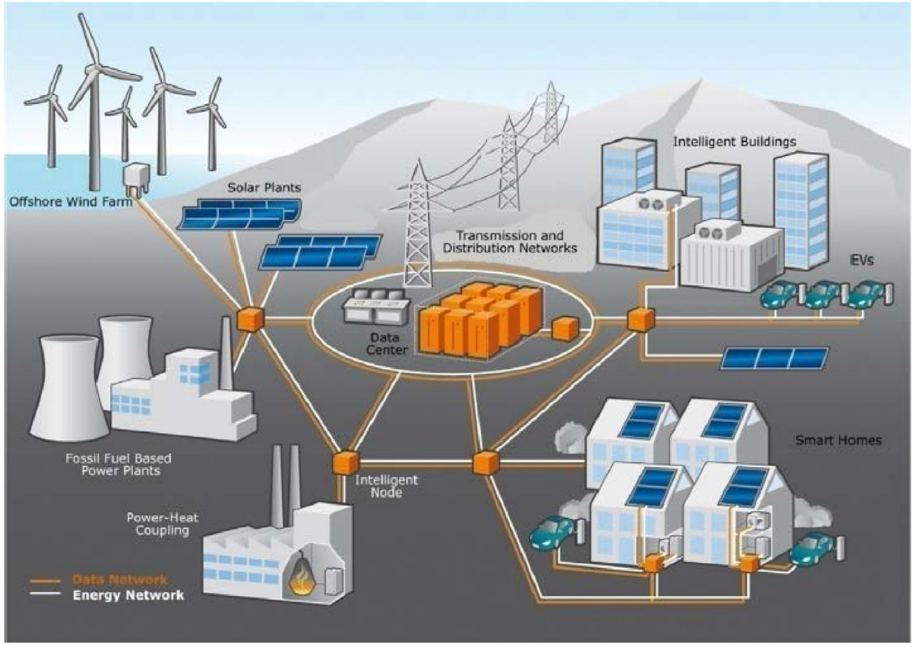

Fig. 2. General infrastructure of SG [12].

context-aware automated or assistive services in the form of ambient intelligence, remote home control or home automation".

Berlo et al. in Ref. [21] defined a smart home as:

"A home or working environment, which includes the technology to allow the devices and systems to be controlled automatically, may be termed a smart home".

Accordingly, a smart home can be defined as a place of residence incorporated with technologies, such as smart appliances, which are controlled remotely through HEMS to make the life of residents more comfortable and safe and to optimize power consumption.

3.2. Smart home model: home energy management system (HEMS)

As mentioned earlier, SG has three major parts, including PSC and generator component, the communication component, and the user component.

For the user component, a smart home should be equipped with HEMS, which comprises hardware and software, particularly the smart meter. This device is in charge of sending/receiving signals to/from the PSC. The PSC can send dynamic price signals through the data network to the smart meter. The smart meter will then send the dynamic price signals to the energy management controller (EMC) and return user feedback to the PSC. The EMC is considered the heart of HEMS. It is in charge of the connection and exchange of data among HEMS components through the home gateway. The EMC connects to smart home appliances through sensors installed in the appliances and to users using mobile applications. Fig. 3 shows the HEMS components.

The scheduling process in HEMS can start once HEMS receives the dynamic price signals from the PSC and the appliances scheduling information from the user, such as the valid scheduling periods for appliances, the time required by appliances to complete their operation cycle, and the power required by each appliance.

4. Power scheduling problem in smart home (PSPSH)

A comprehensive definition for scheduling was put forward in Ref. [22]:

"Scheduling is the allocation, subject to constraints, or resources to objects being placed in space-time, in such a way as to minimize the total cost of some set of the resources used".

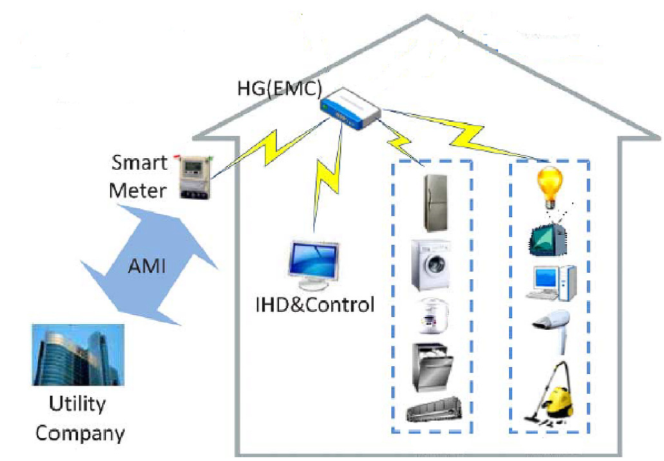

Fig. 3. HEMS components [7].

The primary purpose of creating a schedule is to organize people's lives, activities, and work without interruptions while still being able to perform on time. Scheduling problems are encountered in different fields or domains, such as the bus scheduling problem [23], flow shop scheduling problem [24], job shop scheduling problem [25], and power scheduling problem [7,9].

The power scheduling problem is a problem that involves allocating a set of machines (e.g., home appliances, industrial devices) to a time horizon in accordance with a set of constraints. PSPSH is a problem of scheduling the operations of smart home appliances at appropriate periods in a predefined time horizon in accordance with a set of constraints and a motivational scheme to reduce the values of EB and peak-to-average ratio (PAR) and improve the satisfaction level of users.

The motivational schemes motivate users to reduce their power consumption during peak periods by shifting the load to off-peak periods and balancing the power demand during a time horizon. Motivational schemes are developed by PSCs on the basis of a technique called DR, which is discussed in Section 4.2.

This scheduling problem should be implemented in accordance with several constraints, which are typically divided into two types [26]:

- **Hard Constraints.** This type of constraints must be essentially satisfied in the scheduling solution to be feasible. For example, each home appliance must be scheduled to operate at its allowable period.
- **Soft Constraints.** The satisfaction of soft constraints in the scheduling solution is not essential but desirable. For example, a home appliance may be scheduled to operate in the beginning of its allowable period to finish its operation as soon as possible.

4.1. PSPSH model

A comprehensive formulation for the PSPSH model and objective functions are provided in this section. Different formulations have been provided in the literature, including complex and direct formulations. Therefore, a uniform, coherent, and simple formulation for PSPSH is presented in this section. The proposed formulation is described and defined for a single user. However, it can be easily adapted to multiple users.

4.1.1. Power consumption calculation

In PSPSH, the scheduling time horizon for the operating time of home appliances is typically divided into number of time slots (z-time slot per hour); therefore, the length of time slot t is formulated as

$$t = \frac{60}{z}, \tag{1}$$

The allowable scheduling time horizon T for home appliances to be scheduled is represented in Eq. (2):

$$T = [t_1, t_2, t_3, \ldots, t_n], \tag{2}$$

where t_1 is the first time slot in T, t_n is the last time slot in T, and n denotes the maximum number of time slots in T.

The power consumed by an appliance at each time slot is represented as follows:

$$\mathbf{PS} = \begin{bmatrix} ps_1^1 & ps_2^1 & \cdots & ps_m^1 \\ ps_1^2 & ps_2^2 & \cdots & ps_m^2 \\ \vdots & \vdots & \cdots & \vdots \\ ps_1^n & ps_2^n & \cdots & ps_m^n \end{bmatrix}, \tag{3}$$

where p_i^j is the power consumed by appliance i at time slot j. Appliance i belongs to appliances S vector. Vector S is represented as follows:

$$S = [s_1, s_2, \ldots, s_m], \tag{4}$$

where s_1 is the first appliance in S, s_m is the last appliance in S, and m denotes the maximum number of appliances in S.

As discussed in Section 3.2, users have to provide appliances scheduling information, such as the allowable periods for the appliances to be scheduled (Operation Time Period (OTP)) and the time required by the appliances to finish their operation cycle (Length of Operation Cycle (LOC)). OTP contains two vectors, namely, a starting period vector, such as $OTPs = (OTPs_1, OTPs_2, \ldots, OTPs_m)$, and an ending period vector, such as $OTPe = (OTPe_1, OTPe_2, \ldots, OTPe_m)$. Notably, $(OTPs_i < OTPe_i, \forall\, i \in \mathbf{S})$.

LOC is represented as a vector that contains the LOC for each appliance, such as $LOC = (l_1, l_2, \ldots, l_m)$. Furthermore, considering that the starting operation time for appliance i is St_i and the ending operation time for the same appliance is Et_i; therefore, $l_i = Et_i - St_i$. The St and Et vectors for all appliances are represented by Eqs. (5) and (6):

$$St = [st_1, st_2, \ldots, st_m], \tag{5}$$

$$Et = [et_1, et_2, \ldots, et_m], \tag{6}$$

The aforementioned time parameters (i.e., $OTPs$, $OTPe$, LOC, St,

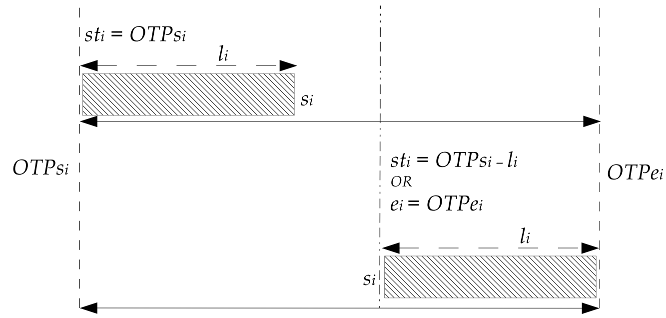

Fig. 4. Illustration of time parameters [7].

and Et) are illustrated in Fig. 4.

As mentioned earlier, the primary objectives of solving PSPSH and scheduling smart home appliances are EB and PAR minimization and user comfort (UC) level maximization. In the literature, UC level is evaluated on the basis of waiting time for smart home appliances. These objectives and parameters are formulated and discussed in the subsequent sections.

4.1.2. Electricity bill (EB)

Minimizing EB is one of the objectives of scheduling to reduce the cost of power consumed by users. The formulation for calculating EB through T is as follows:

$$Cost = \sum_{j=1}^{n} \sum_{i=1}^{m} p_i^j \times pc^j, \tag{7}$$

where pc^j is the price of electricity at time slot j. Electricity price (EP) must be received from the PSC and is generated on the basis of the DR program, as mentioned earlier.

4.1.3. Peak-to-average ratio (PAR)

PAR denotes the ratio of the maximum power demand to the average power demand. The value of PAR can be calculated using Eq. (8):

$$PAR = \frac{P_{max}}{P_{avg}}, \tag{8}$$

where

$$P_{avg} = \frac{\sum_{j=1}^{n} P^j}{n},$$

4.1.4. User comfort (UC) level

Maximizing the UC level is one of the objectives of PSPSH. The UC level can be evaluated on the basis of the waiting time rate (WTR) of the operation of appliances. Reducing WTR can improve the UC level because users typically prefer starting the operation of their smart home appliances without delay [7].

The UC level based on WTR is formulated for appliance i as follows:

$$WTR_i = \frac{st_i - OTPs_i}{OTPe_i - OTPs_i - l_i}, \quad \forall\, i \in \mathbf{S}, \tag{9}$$

Notably, the value range of WTR is between 0 and 1; the value is near 0 if the UC level is high and 1 otherwise.

The average WTR for all smart home appliances can be calculated using Eq. (10):

$$WTR_{avg} = \frac{\sum_{i=1}^{m} (st_i - OTPs_i)}{\sum_{i=1}^{m} (OTPe_i - OTPs_i - l_i)}, \tag{10}$$

4.2. Demand response (DR)

DR refers to user response to modifying electric power usage in the basis of dynamic EPs or other incentive methods to improve the efficiency and reliability of a power system. The DR technique has two types of programs, including incentive-based programs and time-based pricing schemes (dynamic prices) [6].

4.2.1. Incentive-based programs

Incentive-based programs include those that offer fixed or varying incentives to users to reduce their power usage during stressed or peak periods of a power system. Notably, users response to these programs is optional. However, several programs penalize users if they break the contract when events are declared. Incentive-based programs include interruptible/curtailable (I/C), direct load control (DLC), capacity market program (CMP), and emergency DR programs (EDRPs) [4].

1. ***Direct Load Control (DLC)***

This program permits PSCs to remotely turn off appliances in a smart home. Such control is feasible through switches placed within the premises of smart homes that allow PSCs to communicate directly with appliances. Incentive payments are given in advance to users who participate in DLC, to motivate them to maintain their power consumption within predefined thresholds [4].

DLC has been used in several studies, particularly in residential areas. For example, DLC was adopted in Ref. [27] to control two types of appliance in a smart home. These appliances were used in the simulation results to evaluate the DLC scheme in terms of reducing power demand during peak periods.

2. ***Interruptible/Curtailable (I/C)***

I/C is a program that offers advanced incentives, such as rate discount or bill credit, to motivate users to curtail part of their total power consumption to reduce load during peak periods [4]. However, several penalties will be imposed to users who do not respond to I/C terms and conditions. The authors of [28] presented several scenarios in the Iranian power system grid in 2007 using a numerical model to evaluate and analyze the impact of the I/C program.

3. ***Emergency DR Program (EDRP)***

EDRP motivate users to reduce their power consumption during peak periods by providing an incentive payment. The EDRP program has been applied to a New York electricity grid. Participants in this program can reduce their power consumption during emergency (peak) periods, and the EDRP will send them payment [4].

4. ***Capacity Market Program (CMP)***

CMP is offered to users who provide a predefined power consumption curve to predict the power required to be generated. In general, CMP participants will receive a notification one day before that they have to contribute to reducing power consumption [4,29]. Moreover, users receive incentive payment even if they are not asked to curtail their power consumption.

4.2.2. Time-based pricing schemes

Time-based pricing schemes allow users to choose periods of using home appliances in accordance with EPs without curtailing power consumption. Time-based pricing schemes (dynamic price) provide different prices in a day, with higher prices during peak periods due to high power demand. This situation obliges PSCs to use additional power plants to meet user requirements. However, PSCs provide low EPs during off-peak periods [6]. The goal of these schemes is to encourage users to shift their load from peak to off-peak periods to reduce power demand during peak periods. Time-based pricing schemes include time-of-use (TOU) price, real-time price (RTP), critical peak pricing (CPP) and inclining block rate (IBR).

1. ***Time-Of-Use (TOU)***

TOU is a dynamic pricing scheme that provides two different prices between off-peak and peak periods during a day. In addition, TOU has another form, which has three prices, including low-peak, mid-peak, and peak period prices [6]. The price curve of TOU is previously determined for a quarter of a year [9]. The TOU scheme was used in Ref. [8], where its major contribution was to schedule smart home appliances in accordance with the TOU pricing scheme to obtain a well-prepared schedule for appliances.

2. ***Critical Peak Pricing (CPP)***

CPP is a pricing scheme similar to TOU; it provides two different prices between off-peak and peak periods to balance power demand in case it is extremely high compared with other power demand periods [6]. For example, if power demand is very high at a specific period, then the cost of generating power will be very high as well due to the increasing number of power generators used to meet user requirements. Therefore, the cost of generating power exceeds the price values provided by TOU. CPP is declared only on days that are forecasted to have a very high power demand period, called a critical period (CP). In general, the CPP price curve is announced a day before CPP for 15 days in a year [30]. CPP plays a major role in balancing power demand in a day by generating very high EPs during CP, and users will typically prefer to shift their power demand out of CP. As proposed in Ref. [31], the CPP scheme is used to calculate EB, where EP during the off-peak periods is 250 cents/kW and 2500 cent/kW during CP.

3. ***Real-Time Pricing (RTP)***

RTP is a pricing scheme that provides EP that is nearest to the real generation price during a certain period [6]. EP provided in this pricing scheme changes dynamically every hour. Two types of RTP used by PSCs are day-ahead pricing and hourly pricing. For the day-ahead pricing scheme, PSCs provide EP to users 24 h beforehand. For hourly pricing, EP is provided every hour. Day-ahead pricing is more effective than hourly pricing because users are given sufficient time to schedule their power consumption [6]. Several studies have used RTP, particularly the day-ahead pricing scheme [9,32,33].

4. ***Inclining Block Rate (IBR)***

In the IBR scheme, EP increases with the total amount of electricity consumption. In other words, if the total electricity consumption exceeds a certain threshold in the total monthly/daily/hourly consumption, then EP will increase to a higher value. This scheme creates incentives for end users to distribute their load to different periods of the day to avoid high EP rates. Moreover, IBR helps in balancing loads and reducing PAR [34].

IBR has been adopted by Pacific Gas & Electric, Southern California Edison, and San Diego Gas & Electric Companies since the 1980s. These companies proposed two price levels for their users, where the second level is 15%–17% higher than the first price level [35]. Recently, several studies have combined IBR with RTP or TOU to flatten the load demand curve and reduce PAR [7–9].

4.3. Datasets

Smart home appliances should be equipped with several sensors for a wireless transceiver and for data processing. Different types of smart home appliances with varying properties are used in a smart home. Therefore, smart home appliances are classified on the basis of different criteria, such as operating mechanism and functions.

The smart home appliances in Refs. [7,9] were classified into shiftable appliances (SAs) and non-shiftable appliances (NSAs), where SAs are appliances that operate automatically (e.g., dishwasher and washing machine) and NSAs are those that manually (e.g., light and iron). In Refs. [8,36], smart home appliances were classified into fixed, elastic, and SAs. The operation of fixed appliances cannot be modified (e.g., lighting and fans), and that of SAs can be modified but without interruption (e.g., washing machine and clothes dyer). Elastic appliances can be shifted and interrupted (e.g., air conditioner and refrigerator). The authors of [37] used the same classification but with different names, such as unschedulable, user-dependent, and interactive schedulable. In Refs. [32,38], the authors classified appliances into two classes, including fixed appliances in the first class and shiftable and elastic appliances in the second class. The authors of [39,40] classified appliances into interruptible (e.g., space heater, heat pump), non-interruptible (e.g., dishwasher, clothes washer), and fixed appliances (e.g., furnace fan, fan). The authors of [33,41] categorized appliances into fixed, shiftable, and interruptible.

Notably, authors use their own classification and scheduling information for smart home appliances. Therefore, no standard classification and dataset are available for smart home appliances.

In this section, all available smart home appliances are presented and classified into SAs and NSAs due to the clarity of this classification, i.e., defining whether an appliance is operating manually or automatically is easy.

In Ref. [7], the authors used 10 types of SAs and 12 NSAs in the evaluation process. The SAs used are dishwasher, air conditioner, washing machine, clothes dryer, coffee maker, electric water heater, dehumidifier, microwave oven, electric vehicle, and refrigerator. The NSAs are lighting, attic fan, table fan, clothes iron, toaster, computer charger, vacuum cleaner, TV, hairdryer, hand drill, water pump, and blender.

The authors used an algorithm to schedule nine SAs and seven NSAs in Ref. [9]. The SAs are air conditioner, electric radiator, rice cooker, water heater, dishwasher, washing machine, electric kettle, humidifier, and clothes dryer. The NSAs used are lighting, computer, vacuum cleaner, TV, hairdryer, iron, and fan.

In Ref. [8], the authors used 13 types of smart home appliances and we classified them into SAs and NSAs. The SAs are washing machine, dishwasher, clothes dryer, air conditioner, refrigerator, water heater, space heater, and coffee maker. The NSAs are lighting, fans, clothes iron, microwave oven, and toaster.

The authors of [41] used eight SAs, namely, washing machine, clothes dryer, dishwasher, air conditioner, refrigerator, water heater, space heater, coffee maker, and six NSAs, namely, lighting, oven, blender, clothes iron, vacuum cleaner, and fan.

Most of SAs and NSAs used in the literature with their description are summarized in Tables 2 and 3, respectively.

5. Methods for power scheduling problem in smart home (PSPSH)

PSPSH is formulated as an optimization problem in which the primary objective is to schedule the operation time of appliances with the least EB cost in accordance with EP, PAR, and UC constraint [7].

Optimization problems involve finding the best solution(s) from all feasible solutions that can be addressed using optimization methods. Optimization methods are classified into exact and approximate methods [47]. Exact methods are efficient for low-scale optimization problems where they can obtain an optimal solution. By contrast, exact methods are unsuitable for solving high-dimensional optimization problems. Therefore, they are unable to efficiently solve PSPSH due to PSPSH complex, ragged, and huge search space [7,48]. Approximate methods are more efficient than exact methods in addressing PSPSH due to their performance in exploring high-dimensional search space. Approximate methods are divided into approximation and heuristic/metaheuristic algorithms (Fig. 5).

In this survey, the methods used to solve PSPSH are classified into (i) exact algorithms and (ii) approximate methods. For approximate methods, metaheuristic algorithms are considered in this classification which are classified into local search-based, population-based, and hybrid metaheuristic algorithms. Notably, heuristic algorithms are not surveyed in this review due to their unavailability, i.e., they have not been modeled previously in solving PSPSH.

5.1. Exact algorithms for PSPSH

Several exact algorithms have been modeled for PSPSH, including the integer linear programming (ILP) and mixed integer linear programming (MILP) algorithms.

A generic management methodology for minimizing the electricity cost of single and multiple houses that used ILP was proposed in Ref. [49]. The simulation results showed that power demand is supplied by considering electricity cost reduction and UC level.

The authors of [50] proposed a scheduling mechanism for home appliances using ILP. The proposed mechanism aimed to balance power consumption and reduce PAR value. Seven smart home appliances were used to evaluate the proposed mechanism and ILP for single and multiple homes. The simulation results showed the effectiveness of the proposed mechanism, particularly for multiple homes where it achieved more balanced power consumption.

MILP was modeled in Ref. [51] in terms of simultaneously minimizing total EB and improving UC. An approach was applied to a single home with a wind turbine, a photovoltaic system, and a storage battery. The TOU scheme was used to calculate the EB for five appliances. The simulation result proved that the proposed approach enables the residents of the smart home to live comfortably and economically. EB and the power consumed were reduced by up to 58% and 5%, respectively.

MILP was used for the scheduling process in Ref. [52] to reduce EB, PAR, and user discomfort. The result demonstrated the efficiency of the proposed approach in reducing EB. Moreover, energy could be exported to the national grid using a photovoltaic system when solar energy production was more than the users' demand.

An off-line HEMS was modeled in Ref. [53] to reduce EB, PAR, and user discomfort level. The proposed model comprised a central controller, smart appliances, and power generators and resources (e.g., backup battery, photovoltaic system). These components were connected using a communication network. The central controller controls the proposed model on the basis of MILP. The authors used six types of SAs and NSAs to evaluate the proposed model. In the simulation results, two scenarios were considered to evaluate the proposed model. EB was reduced in the first and second scenarios by 68.6% and 54.4%, respectively. The results proved the efficiency of the proposed model using MILP.

HEMS was proposed to schedule the operation time of home appliances using MILP in Ref. [54]. The primary objective of the proposed system was to maintain the UC level while reducing EB. Renewable energy generators and batteries were used to save power. The simulation results demonstrated the high efficiency of the proposed system compared with four state-of-art systems using their datasets and scenarios.

The authors of [55] analyzed the scheduling mechanism power consumed by home appliances. The objectives of this scheduling mechanism were to reduce EB for users and balance the power consumed throughout the time horizon. The authors modeled MILP to achieve the scheduling objectives for different simulated and real scenarios using the price tariff implemented in the Czech Republic. The simulation results showed the efficiency of the proposed model compared with the ripple control service used in the Czech Republic.

MILP was modeled in Ref. [56] to reduce EB and PAR value by

Table 2
SAs used in the most of the literature with their description.

No.	Appliances	Description
1	Space Heater	The space heater is typically used to heat a single or small area in the winter season. The space heater was used in Ref. [8] alongside with other 12 appliances in the evaluation of proposed HEMS using three metaheuristic algorithms. Other studies used a space heater in the experiential step, such as [39–42].
2	Heat Pump	A heat pump is an appliance in charge of transferring heat from a source to another place. The heat pump was used in the experimental section in Refs. [32,39] as one of the appliances used to evaluate proposed methods.
3	Portable Heater	A portable heater is a small space heater which is typically used when the main heating system is inadequate. The portable heater was used in Refs. [32,39] alongside with heat pump and other appliances to evaluate proposed methods.
4	Water Heater	The water heater is one of the most popular home appliances. The water heater is typically used in the early hours of the morning of summer days, whereas it used several times in winter days [7]. The water heater was used in evaluation part of methods used in Refs. [7–9,32,33,39–45] due to its commonly used in homes.
5	Dish Washer	The dish washer is normally used in morning and evening every day to clean dishes [7]. In Refs. [7–9,32,33,39–45], the authors used the dish washer as one of the home appliances that used to evaluate the performance of proposed methods.
6	Refrigerator	The refrigerator is the most common home appliance, which is usually used to keep food fresh [7]. The refrigerator had a high effect on the method used in Ref. [7] due to its operation time, as it was operated at all times of the considered time horizon, whereas in Ref. [46], the refrigerator was operated for half of the considered time horizon. In addition, the authors of [8,32,33,39,40,42–44] used the refrigerator with other home appliances to evaluate the performance of proposed methods.
7	Clothes Washer	The clothes washer has typically three operations, including wash, rinse, and spin. The clothes washer was used in Ref. [9] alongside with other eight types of SAs in the evaluation of the adapted algorithm. In Ref. [7], the clothes washer was also used in the evaluation of a new objective function using a metaheuristic algorithm. Other studies used a clothes washer in the experiential step, such as [8,32,33,39–41,43–46].
8	Clothes Dryer	The primary use of the clothes dryer is to dry wet clothes, and it is typically used after the clothes washer finished its operation [7]. The authors of [7–9,32,33,39–46] used the clothes dryer with other home appliances for evaluation in the experimental part.
9	Room AC	The primary purpose of the room AC is to transfer warm air from a space area and replace it with cold air [7]. Several studies used the room AC in their experiment part, such as [7–9,32,33,39,40,42–46].
10	Central AC	The central AC typically has the same functions of the room AC but for a large area (i.e., not only one room). The central AC need high power rating to be operated, wherein [32,39], the power rating of the central AC was more than the room AC by up to 67%.
11	Coffee Maker	The coffee maker is usually used to make coffee every morning and evening [7]. Several studies used the coffee maker in the simulation results, such as [7,8,33,41,43,44].
12	Electric Radiator	The authors of [9] considered the electric radiator as a SA that can be operated morning and evening. In Ref. [45], the electric radiator considered to operate twice per day regardless of the duration of the operation.
13	Humidifier	The primary purpose of the humidifier is to reduce the proportion of water in the air. The humidifier has a low power rating when it was used in Refs. [7,9,43–45] with 0.05 kW power rating.
14	Water Cooler	The water cooler is in charge of cooling and dispensing water using a refrigeration system. Usually, the water cooler used for long periods, wherein [46], the water cooler was operated for around 15 h.

Table 3
NSAs used in the most of the literature with their description.

No.	Appliances	Description
1	Lighting	The lighting appliance was used in Ref. [7] alongside with other 11 NSAs in the evaluation step using a metaheuristic algorithm. Other studies used a lighting appliance in the experiential step, such as [8,9,33,40–42].
2	Furnace Fan	The furnace fan was operated for up to 8 h in Refs. [32,39], and used with other 11 appliances to evaluate proposed methods.
3	Fan	The authors of [9] considered the fan as NSA with very low power rating. In Refs. [7,8], the fan used a higher power rating than the used in Ref. [9]. Several studies used the fan with different power rate in the experiential step, such as [32,33,39].
4	Iron	Iron is one of the most popular home appliances, which is used to remove clothes creases. Several studies used the iron in their experiment part, such as [7–9,40–42,46].
5	Toaster	The toaster appliance was used in Ref. [7] as NSA in the evaluation step of the proposed method. Also, the toaster was used in the dataset in Refs. [8,33] to evaluate the performance of proposed methods.
6	Computer Charger	Computer charger is one of NSA that was used in Refs. [7,9,40,42] to evaluate the performance of proposed methods.
7	Vacuum Cleaner	The vacuum cleaner was used in Refs. [7,9] alongside with other NSAs in the evaluation step using a metaheuristic algorithm. Other studies used a vacuum cleaner in the experiential step, such as [40–42].
8	TV	The TV is the most popular home appliance due to its functionality that is offered to users. The authors of [7,9,40,42] used the TV in the experimental section of their studies.
9	Hair Dryer	The hair dryer is typically used for a short time, wherein [9], the hair dryer was used for no more than 5 min. Also, hair dryer was used in Refs. [7,40,42] as one of the appliances used to evaluate proposed methods.
10	Hand Drill	The hand drill is not a popular appliance in homes due to its limited functionality. In Ref. [7], the hand drill was used with other 11 NSAs and 10 SAs to evaluate the used method.
11	Water Pump	The water pump is one of the most widespread and oldest appliances. The water pump has different types with various power rating. The authors of [7] used the water pump with a high-power rating up to 2.5 kW, wherein [46], the power rating used for the water pump is only 0.8 kW.
12	Blender	The authors of [7] considered the blender as NSA with very low power rating. In Ref. [41], the blender used a higher power rating than the used in Ref. [7] by up to 75%.
13	Electric Stove	Usually, the electric stove needs relatively high-power rating to be operated. The electric stove was used by the authors of [40,42] as one of the appliances used to evaluate proposed methods.
14	Pool Pump	The pool pump is the primary machine in the swimming pool filtering system. The pool pump was used in the experiential step in Refs. [40,42].
15	Electric Vehicle	The electrical vehicle has a battery which used instead of the fuel. The batteries of the electrical vehicle typically need a high-power rating [7]. In Refs. [7,42], the battery of electrical vehicle consumed a high power compared with the other appliances, whereas the authors of [40] used lower power rating battery in the evaluation part.
16	Microwave Oven	The microwave oven is typically used for a short period with a relatively high-power rating [7,8,33].
17	Rice Cooker	TA rice cooker is a kitchen appliance designed to cook or heat rice. The rice cooker was used in Refs. [9,45] as one of the appliances used to evaluate proposed methods.
18	Electric Kettle	The electric kettle needs relatively high-power rating to be operated, wherein [9,45,46], the electric kettle was operated using a 1.5 kW power rating.
19	Oven	The oven is one of the most home appliances that need a very high power rating to be operated, where the authors of [41] used an oven with the 3 kW power rating, and in Ref. [46], the oven was consumed 2 kW power rating.

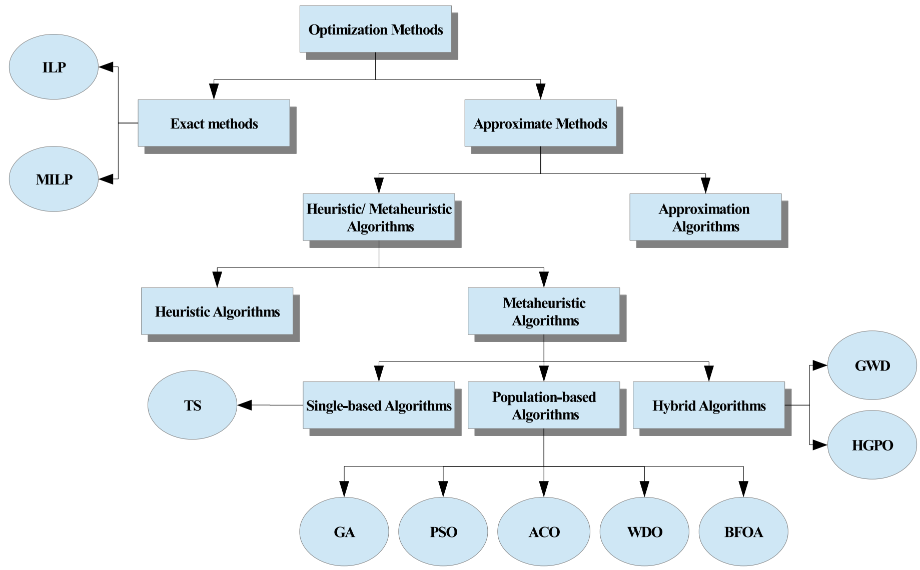

Fig. 5. Optimization methods.

balancing power demand in the time horizon for five home appliances. The authors used RESs to create a better schedule. The simulation results showed that the best solution was achieved using RESs. EB was reduced by 38% without using RESs and by 47% using RESs.

5.2. Metaheuristic algorithms for PSPSH

Metaheuristic algorithms are more efficient than exact algorithms in addressing optimization problems due to their efficiency in exploring a search space to find the optimal solution [57].

Therefore, several metaheuristic algorithms have been successfully applied to address PSPSH, such as genetic algorithm (GA) [8,9], particle swarm optimization (PSO) [8,58], ant colony optimization (ACO) [8], wind-driven optimization (WDO) [36], bacterial foraging optimization algorithm (BFOA) [38], and tabu search (TS) algorithm [58]. Metaheuristic algorithms are classified into single-based, population-based, and hybrid metaheuristic algorithms.

5.2.1. Single-based metaheuristic algorithms

A few numbers of single-based algorithms have been adapted to solve PSPSH. In general, single-based algorithms begin by generating a single solution and attempting to enhance it throughout iterations. The authors of [58] proposed efficient load management using the TS algorithm and the harmony search algorithm (HSA) to minimize EB, PAR, and user discomfort level. The RTP scheme was used with 13 home appliances, including SAs and NSAs, in the scheduling process within 24 h. However, TS proved its superiority to HSA in reducing EB and PAR. It obtained better reduction than HSA for EB and PAR by up to 10% and 11%, respectively. However, HSA achieved better UC than TS by up to 43%.

5.2.2. Population-based metaheuristic algorithms

Several population-based algorithms have been adapted for PSPSH. Among which, GA, BFOA, HSA, and PSO are the most prominent.

The authors of [9] combined RTP with IBR to balance power demand in a day and avoid any blackout resulting from high power demands during specific periods. The authors proposed a general architecture for HEMS in a smart home. Moreover, they formulated a multi-objective function that considered EB and UC level. GA was adapted to schedule the power consumption of 16 operations of SAs and eight operations of NSAs within 120 time slots (24 h) for 90 days. The simulation results showed the high performance of the proposed approach using GA in achieving the objectives compared with the unscheduled mode. The proposed approach reduced EB and PAR by up to 26% and 35%, respectively, whereas UC level was reduced due to the trade-off between EB reduction and UC improvement.

A new power scheduling model called generic DSM (G-DSM) was proposed using GA in Ref. [59]. The authors scheduled eight SA operations and seven NSA operations within 24 time slots (24 h). RTP was combined with IBR for 60 days. The objectives of the proposed model were to minimize EB and PAR and maximize UC. The simulation results showed the efficiency of the proposed model in achieving the objectives for single and multiple smart homes. The proposed model reduced EB for single and multiple smart homes by 39.39% and 45.85%, respectively, and PAR value by 17.17% for single and 52.24% for multiple smart homes. In terms of UC maximization, the proposed model reduced the UC level due to the trade-off between EB and UC.

In Ref. [60], GA was adapted to schedule electricity usage in smart buildings. The RTP scheme was implemented for the proposed scheduling. The proposed scheduling problem was formulated as a real-time task scheduling problem to demonstrate its complexity. The experimental results showed the efficiency of the algorithm in reducing EB under various building conditions. EB was reduced by up to 34.4%.

In Ref. [8], HEMS was designed to obtain an optimal schedule for achieving PSPSH objectives, including EB, PAR, and user discomfort reduction in accordance with the TOU price scheme combined with IBR. PSPSH was formulated as a multiple knapsack problem. Moreover, the authors formulated a multi-objective function that considered EB and UC level. GA, binary PSO (BPSO), and the ACO algorithm were adapted and evaluated using 13 home appliances, including SAs and NSAs, within 24 time slots (24 h) for one day. GA performed more efficiently than BPSO and ACO in achieving the objectives. EB was reduced by 48.79%, 40.43%, and 28.26% for GA, BPSO, and ACO, respectively, compared with the unscheduled mode. EB reduction and UC maximization exhibited an inverse relationship. However, GA performed considerably better than the others in minimizing the trade-off effect.

A load-shifting technique based on SG for a large number of appliances in the residential, commercial, and industrial sectors was proposed in Ref. [61]. GA was adapted to obtain an optimal schedule for appliance operating time in accordance with the RTP scheme to reduce EB and PAR. The simulation results showed the robust performance of the proposed approach in optimally achieving the objectives. EB and PAR were reduced by 5% and 18.3%, 5.8% and 18.3, and 10% and 14.2% for the residential, commercial, and industrial sectors, respectively.

The authors of [62] addressed the same issue for the residential, commercial, and industrial sectors using GA as well. However, their primary objective was to evaluate the proposed approach on the basis of EB and PAR reduction under different scenarios, including two residential sectors, two commercial sectors, and five industrial sectors. The experimental results showed the efficiency of the proposed approach in achieving the objectives.

To maintain the balance of power consumed throughout a time horizon, a threshold limit was proposed in Ref. [63]. The authors adapted a multi-objective evolutionary algorithm to overcome this issue by considering minimum EB and user discomfort. In the simulation results, 10 types of appliances were used to evaluate the proposed approach. During the scheduling processes, several appliances will automatically switch off if power usage exceeds the threshold limit. Furthermore, the proposed approach proved its efficiency in achieving the objectives. It reduced EB by up to 13% with a minimum effect on the trade-off between EB and UC level.

GA and the strawberry algorithm (SBA) were adapted to address PSPSH in Ref. [42]. These algorithms were used to schedule 15 home appliances, including SAs and NSAs, within 24 time slots (24 h) to minimize EB and PAR and improve UC level in accordance with the TOU price scheme. The experimental result demonstrated the efficiency of GA, which outperformed SBA in achieving the objectives. GA reduced EB and PAR by 1.1% and 8.8%, respectively, and improved UC by up to 10% compared with SBA.

BPSO and GA were adapted in Ref. [64] to reduce EB and PAR. The TOU pricing scheme was considered in the scheduling process to calculate total EB for the operations of 10 SAs and NSAs for a day. BPSO demonstrated its efficiency when it reduced EB better than GA by 4.

An efficient HEMS was proposed in Ref. [19]. This system was considered to obtain appropriate scheduling for home appliances to minimize EB and electricity demand during the peak periods. Two metaheuristic algorithms were adapted in this paper, including PSO and GA, to schedule 20 home appliance. The simulation results showed that the PSO obtained significant cost reduction with acceptable load curve.

The grey wolf optimizer (GWO) was adapted in Ref. [7] to address PSPSH. A multi-objective optimization approach was proposed to obtain an optimal schedule in terms of the simultaneous reduction of EB, PAR, and user discomfort. UC level was determined on the basis of two parameters, namely, *WTR* and a new parameter related to the availability of power for use by NSAs at any period. A total of 39 operations for SAs and 12 for NSAs under seven scenarios were used to evaluate the proposed approach. A combination of RTP and IBR was considered due to IBR's performance in dispersing power consumption throughout the time horizon to avoid any overload of power demand in a specific time slot. In the simulation results, the GWO solution was first compared with the GA solution using the dataset defined by the authors. GWO exhibited and yielded better results than GA. GWO and GA reduced EB and PAR by 6.6% and 22%, and 4.3% and 13.3%, respectively. Second GWO was compared with 19 state-of-the-art algorithms using the recommended consumption profiles of these algorithms and their evaluation criteria. GWO nearly outperformed the compared algorithms in minimizing of EB and PAR.

In Ref. [43], GWO was adapted to reduce EB and PAR and improve UC level. A new formulation for a smart battery was proposed to improve the quality of the solution by storing power during peak period and use the stored power at off-peak periods. The IBR scheme was considered and combined with the RTP to balance and disperse power demand of 38 SAs. The simulation results proved the efficiency of the proposed smart battery in achieving the objectives. In addition, the performance of GWO was compared with GA to show its efficiency in the scheduling process. GWO reduced EB and PAR better than GA by 4.6% and 17%, respectively, with maintaining UC level. Therefore, GWO outperformed GA in achieving PSPSH objectives.

The authors of [36] proposed a new mathematical model to obtain an optimal schedule for home appliances using WDO. The primary objective of the proposed approach was to minimize EB and PAR and maximize UC level. Min-max regret-based knapsack problem was used to improve the schedule. In simulation results, the authors implemented the TOU pricing scheme to evaluate the proposed approach using six types of home appliances. The results showed the efficacy of the proposed approach compared with PSO. EB and PAR obtained by the WDO were better than the obtained by the PSO by up to 10% and 8%, respectively.

A multi-objective optimization model was solved using a multi-objective genetic algorithm by schedule the home appliances in Ref. [65]. The objectives of the proposed approach was to improve satisfaction level of users and reduce EB. Total EB of power consumed by six home appliances was calculated on the basis of the RTP scheme. The simulation results proved the efficiency of the proposed approach in reducing EB and improving UC level simultaneously. The proposed approach reduced EB by 23% with the minimum trade-off effect between EB and UC level compared with the unscheduled mode.

A HEMS was integrated with Electricity Storage System (ESS) in Ref. [66]. GA, cuckoo search optimization algorithm (CSOA), and crow search algorithm (CSA) were adapted to minimize EB, peak load, and home appliances waiting time. The RTP and the CPP schemes were implemented to schedule 12 appliances, including SAs and NSAs. The CSOA performed better than CSA and GA in reducing EB under both pricing schemes with and without the integration of ESS. EB using CSOA was reduced by 13.06% and 23.30% without and with ESS compared with the unscheduled mode using RTP, respectively, and 23.41% and 38.97% using CPP for the same cases. The reduction of EB using RTP without and with ESS was 11.98% and 22.30% using CSA, and 11.93% and 22.34% using GA, respectively. EB was reduced using CPP by 23.12% and 36.76% using CSA without and with ESS, and by 22.83% and 35.29% using GA without and with ESS, respectively. For PAR reduction, CSOA outperformed CSA and GA as well, where CSOA reduced PAR value by 6.82% compared with GA and 7.02% compared with CSA using RTP scheme, and up to 4% compared with GA and up to 3% compared with CSA using CPP. In terms of WTR reduction and UC improvement, the CSOA obtained the minimum trade-off effect between EB and WTR.

PSPSH was addressed using flower pollination algorithm (FPA) and HSA in Ref. [67]. The CPP scheme was implemented as a pricing curve in the evaluation process. The primary purpose of this study was to schedule power consumption of 16 SA operations and reduce total EB and PAR and evaluate the behavior of waiting time during the scheduling process. In the simulation results, FPA performed better than HSA in terms of EB and PAR reduction. The FPA and HSA reduced EB by 11% and 2%, respectively, and PAR value by 23% and 21%, respectively. However, HSA outperformed the FPA in reducing the trade-off effect between EB and UC level.

HSA and earthworm optimization algorithm (EWA) were adapted in Ref. [68] to reduce EB and PAR by shifting load of home appliances from peak to off-peak periods. The TOU was used as pricing scheme for bill calculation of power consumed by six appliances for a day (24 time slots). In the simulation results, the EWA reduced EB and PAR by up to 17% and 6.8%, whereas HSA reduced EB and PAR by up to 12% and 9%. The results showed that EWA outperformed HSA in reducing EB, whereas HSA performed better than EWA in terms of PAR reduction. In addition, HSA reduced the trade-off effect between EB and UC considerably better than the EWA.

In Ref. [69], the authors adapted GA and EWA to address PSPSH. The primary objective of the adaptation was to reduce cost, PAR, and WTR of 13 SA operations and two NSA operations. In simulation results, EB was reduced by 35% and 20% using GA and EWA compared with the unscheduled mode, respectively. Moreover, GA outperformed EWA in reducing PAR value as well, where GA reduced PAR by 50% and EWA by 40%. In terms of UC maximization, both algorithms almost showed the same results.

The elephant herding optimization (EHO) algorithm was adapted in

Ref. [70] to reduce EB, PAR, and user discomfort level. The TOU pricing scheme was used to calculate cost of power consumed by 12 SAs and NSAs. In the simulation results, EHO demonstrated its efficiency in achieving the objectives compared with enhanced differential evolution (EDE) and the unscheduled mode. EHO reduced EB to 21.95% of the unscheduled mode, whereas EDE reduced it to 24.39%. In addition, EHO reduced WTR considerably better than EDE. However, EDE performed better than EHO in terms of PAR reduction, where it reduced PAR value by 15% compared with EHO.

The artificial fish swarm algorithm (AFSA) and GA were adapted in Ref. [71] to optimally reduce PAR, user discomfort and cost of power consumed by seven appliances, including SAs and NSAs, in accordance with the RTP scheme. The simulation results showed that the two adapted algorithms reduced cost, PAR, and user discomfort efficiently. However, AFSA obtained a better schedule than GA. AFSA reduced EB and PAR by 11% and 8% compared with GA. Besides, AFSA solution showed a better trade-off effect between EB and UC than GA.

The pigeon inspired optimization (PIO) and EDE were adapted in Ref. [72] to address PSPSH. The authors implemented the CPP scheme as pricing tariff. The PIO achieved better schedule than EDE in terms of PAR and WTR reduction, where the PIO reduced PAR value and WTR by 3% and 23% more than the obtained by EDE, respectively. However, EDE performed better than the PIO in reducing EB by up to 38%.

HEMS was designed on the basis of BFOA and social spider optimization (SSO) algorithm in Ref. [33]. This design aimed to reduce cost of power consumed by 12 appliances within 24 h in accordance with the RTP scheme. Besides, the proposed design aimed to reduce PAR value and user discomfort level. The BFOA showed better result in terms of EB reduction by reducing it by up to 18.41%, whereas SSO reduced EB by 10.83%. SSO outperformed BFOA in reducing PAR and user discomfort, where SSO reduced PAR by 1% better than the BFOA with minimum trade-off effect between EB and UC level.

GA and biogeography-based optimization (BBO) were adapted to reduce EB value and PAR and improve UC in Ref. [39]. Power consumption of 16 operations of smart home appliances was used to evaluate the adapted algorithms in accordance with the CPP. The simulation results showed that BBO outperformed GA in terms of EB and PAR reduction by 2% and 4%, respectively. UC level was divided into three different categories on the basis of appliances types. BBO outperformed GA in one category, whereas GA got better UC in the others.

A massive number of studies were conducted to address PSPSH using metaheuristic algorithms. Therefore, a summary of most of these studies is provided in Table 4 to show their main points.

5.2.3. Hybrid metaheuristic algorithms

In Ref. [38], the authors proposed a hybrid version of GA and WDO called the genetic wind-driven (GWD) algorithm for PSPSH in a residential area. Four other algorithms, including GA, BPSO, BFOA, and WDO, were adapted to evaluate the performance of the proposed GWD in reducing demand during peak hours and shifting it to off-peak hours in accordance with the RTP scheme. The objectives of this study were to reduce EB and PAR and improve UC level using the power consumption of 12 appliances, including SAs and NSAs. A multi-objective function that included EB and user discomfort reduction was formulated. The simulation results were divided into scheduling for single and multiple smart homes. In a single smart home, the schedule of GWD was compared only with GA and WDO. GWD performed better than GA and WDO. EB was reduced to 60%, 62%, and 30% of the unscheduled solution using GA, WDO, and GWD, respectively. Moreover, GWD obtained the lowest PAR value up to 40% of the unscheduled solution. In terms of improving UC, the three algorithms exhibited the same effect on the trade-off between UC and EB. Therefore, the three algorithms had the same UC level. For multiple homes, the authors showed the performance of GA, BPSO, WDO, and BFOA for 50 homes. After scheduling the power consumed by 50 homes, the EB obtained by the algorithms was 35%, 50%, 61%, and 45% of the unscheduled solution for

Table 4
Summary of most of the studies used metaheuristic algorithms to address PSPSH.

NO.	Author	Method	Objectives	DR Scheme	Data	Simulation Results
1.	Hafsa [73]	PIO and EDE	EB and PAR minimization, UC maximization	TOU	6 appliances	EDE outperformed PIO in terms of EB by 7%, and WTR by 20%, whereas both algorithms obtained same PAR.
2.	Mashab [74]	HSA and BAT	EB and PAR minimization, UC maximization	CPP	11 appliances	HSA performed better than BAT in terms of EB by 11%, PAR by 20%, and WTR by up to 47%.
3.	Saadia [45]	BFOA and PIO	EB and PAR minimization, UC maximization	CPP	16 appliances	PIO outperformed BFOA in terms of EB and PAR reduction by 10% and 15%, respectively, while BFOA got better results in terms of UC maximization due to the trade-off between EB and UC.
4.	Hasan [75]	BFOA and SBA	EB and PAR minimization, UC maximization	RTP	12 appliances	BFOA outperformed SBA in terms of EB reduction by up to 5%, while SBA got better results in terms of PAR reduction by 19% compared with BFOA. UC level was divided into three different categories on the basis of appliances types.
5.	Bushra [76]	FPA	EB and PAR minimization, UC maximization	RTP	16 appliances	The results of FPA was compared with results of GA. FPA outperformed GA in reducing EB and PAR by up to 12.5% and 40%, respectively, while GA obtained better results in terms of UC maximization.
6.	Syeda [77]	GWO and BFOA	EB and PAR minimization, UC maximization	TOU	6 appliances	GWO outperformed BFOA in reducing PAR and user discomfort. BFOA achieved better results in terms of EB reduction, where BFOA reduced EB by 32% and GWO by 21% compared with the unscheduled mode.
7.	Anwar [40]	HSA and FA	EB and PAR minimization, UC maximization	CPP	16 appliances	HSA outperformed FA in terms of EB and user discomfort reduction, and FA got better results in terms of PAR reduction.
8.	Adnan [78]	HSA, FA, and BFOA	EB and PAR minimization, UC maximization	TOU	15 appliances	FA performed better than BFOA and HSA in terms of EB reduction, where the EB was reduced using FA by 14%, using HSA by 11%, and using HSA by 10% compared with the unscheduled mode. However, BFOA obtained a better solution in terms of PAR reduction. HSA obtained the best trade-off effect between UC and EB.
9.	Mahnoor [79]	GA and CSA	EB and PAR minimization, UC maximization	RTP	6 appliances	CSA obtained a better schedule than GA in terms of EB by 28% and PAR by 52%, while GA outperformed CSA in reducing the trade-off effect between EB and UC.
10.	Muhammad [80]	SBA and EDE	EB and PAR minimization, UC maximization	RTP	16 appliances	SBA outperformed EDE in terms of EB reduction by 30%, while EDE performed better in terms of PAR minimization and UC maximization than SBA.

GA, BPSO, WDO, and BFOA, respectively. However, BFOA outperformed the other algorithms in PAR reduction, while BPSO obtained the best UC level.

HEMS was integrated with RESs and ESS in Ref. [81]. GA, BPSO, WDO, BFOA, and a hybrid GA-PSO (HGPO) algorithm were adapted to reduce the power demand for 12 SAs and NSAs during peak periods in accordance with the RTP scheme. The results showed that the integration of RESs and ESS reduced EB and PAR by 19.94% and 21.55%, respectively. Moreover, the HGPO algorithm outperformed the other heuristic algorithms and further reduced EB by 25.12% and PAR by 24.88%.

In Ref. [82], the authors proposed HEMS to shift the load to off-peak periods and balance the load throughout a time horizon. The objective of the proposed system was to reduce EB and PAR and improve UC level. The authors used the day-ahead and hourly pricing schemes to schedule nine types of SAs and NSAs. In addition, the authors proposed real-time rescheduling to schedule appliances using the hourly pricing scheme, and formulated it as a knapsack problem. A hybrid version of GA and BFOA, called foraging and genetic algorithm (HBG) optimization, was proposed to optimally achieve the objectives. In the simulation results, TOU, RTP, and CPP were used to evaluate the proposed technique. The results demonstrated the efficiency of HBG and the proposed technique.

An energy management model with nearly zero energy building was proposed using GA, EDE, teaching-learning-based optimization (TLBO), and a hybrid version of EDE and TLBO, called enhanced differential teaching-learning algorithm (EDTLA), in Ref. [83] to manage energy consumption while considering UC level. The objectives of the proposed system were reducing EB, PAR, user discomfort level, and carbon emission. The proposed system was integrated with RES and ESS to improve the results. 12 types of home appliances were used to evaluate the proposed system and algorithms in accordance with the RTP scheme. The simulation results presented the performance of the integration using the proposed algorithm in achieving the objectives and reducing the level of carbon emission. The results showed that EB was reduced by up to 14.70%, 33.82%, 12.76%, and 36.02% using GA, TLBO, EDE, and EDTLA, respectively, compared with the unscheduled mode without the proposed integration. Meanwhile, EB was reduced by 36.76%, 64.70%, 52.94%, and 67.44% using GA, TLBO, EDE, and EDTLA, respectively, with the proposed integration. In terms of PAR reduction, the proposed algorithm integrated with RES outperformed the others. The value of PAR without the proposed integration was reduced by 17.30%, 30.76%, 15.38%, and 43.61% using GA, TLBO, EDE, and EDTLA, respectively, compared with the unscheduled mode. The proposed integration reduced PAR by 11.29%, 14.51%, 11.02%, and 29.41 using GA, TLBO, EDE, and EDTLA, respectively. To control carbon emission, the percentage of CO_2 was calculated. The CO_2 percentage of reduction using the proposed system was 40.35% for the unscheduled solution and 46.41%, 46.03%, 56.82%, and 54.94 using GA, TLBO, EDE, and EDTLA, respectively. Moreover, EDE obtained the best trade-off between EB and UC.

In Ref. [84], the authors proposed a new hybrid version of GA and HSA (genetic harmony search algorithm (GHSA)) to efficiently reduce EB, PAR, and user discomfort. The CPP and RTP pricing schemes were used to calculate EB for 10 types of appliances. In the simulation results, the performance and solutions obtained by the proposed algorithm were compared with GA, WDO, and HSA for single and multiple homes. GHSA outperformed the other algorithms in reducing EB and PAR. Using the RTP scheme, EB was reduced by 13.37%, 20.58%, 25.63%, and 29.86% using WDO, HSA, GA, and GHSA, respectively, for single home, and reduced by 50.54%, 25.91%, 31.31%, and 56.06% using WDO, HSA, GA, and GHSA, respectively, for multiple homes. Using the CPP scheme, EB for single and multiple homes were reduced by 31.52% and 41.94% using WDO, 36.05% and 40.82% using HSA, 39.65% and 44.04% using GA, and 46.19% and 54.04% using the proposed algorithm, respectively. The proposed GHSA obtained the best PAR for single and multiple homes using the two prices schemes. The value of PAR for single and multiple homes using RTP scheme was reduced by 38.32% and 47.77% using GHSA, respectively, whereas it was reduced using WDO by 13.97% and 43.09%, using HSA by 35.32% and 34.55%, and using GA by 25.54% and 43.45%, respectively. Using CPP, the value of PAR for single and multiple homes was reduced by 6.58% and 43.27% using WDO, 30.53% and 47.01% using HSA, 27.34% and 42.66% using GA, and 37.52% and 50.08% using the proposed GHSA, respectively. In addition, the proposed GHSA obtained the best trade-off effect between EB and UC for multiple homes, whereas it obtained the best trade-off using only the CPP for single home and HSA obtained the best using the RTP scheme.

A controller for HEMS on the basis of FA, GA, TLBO, and optimal stopping rule (OSR) theory were proposed in Ref. [85] to reduce the power consumption at peak periods and EB and improve UC level. Moreover, the authors proposed three versions of hybrid algorithms, including OSR-TLBO, OSR-GA, and OSR-FA, to enhance the quality of the solution and optimally achieve the objectives. The simulation results showed the high performance of the proposed hybrid versions in attaining the objectives for single and multiple homes.

The authors of [86] adapted BFOA and FPA to schedule 14 appliances within 24 h in accordance with the RTP and CPP schemes. The authors hybridized BFOA and FPA (HBFPA) to optimally obtain better schedule. The primary objectives were to reduce EB and PAR and improve UC level. The results proved that the proposed HBFPA outperformed the others in achieving the objectives under both pricing schemes for single and multiple homes.

The authors of [87] proposed a smart power system to share energy sources between users through HEMS. Four algorithms were intended to address PSPSH. These algorithms were flower pollination genetic algorithm (FGA), genetic teaching learning-based optimization (GTLBO), flower pollination teaching learning-based optimization (FTLBO), and flower pollination BAT (FBAT). The primary purpose of these hybridizations was to obtain an optimal schedule on the basis of EB and PAR without compromising UC level. The authors used six types of appliances to evaluate the proposed algorithms in accordance with the RTP scheme. In the simulation results, the proposed algorithms were compared with GA, TLBO, FPA, and BAT to show their performance in achieving PSPSH objectives. EB percentage of reduction obtained by the adapted and hybridized algorithms were 37.95%, 26.74%, 3.87%, and 12.32% using GA, TLBO, FPA, and BAT, respectively, and 39.17%, 40.75%, 25.23%, and 64.49% using GTLBO, FTLBO, FBAT, and FGA, respectively. For PAR reduction, GA, TLBO, FPA, and BAT reduced PAR value by 9.87%, 12.96%, 5.55%, and 2.46%, respectively, whereas GTLBO, FTLBO, FBAT, and FGA reduced it by 32.09%, 45.06%, 27.16%, and 33.95%, respectively. Notably, FGA obtained the best EB by lowering it by 64.49%, whereas FTLBO obtained the best PAR. In terms of UC maximization, BAT algorithm achieved the highest UC level by minimizing the trade-off effect between EB and UC.

In Ref. [41], HEMS was designed on the basis of a hybrid version of BFOA and HSA (HBH) to find the best schedule for 11 appliances. The obtained schedule evaluated on the basis of EB, PAR, and UC level. Seasonal TOU pricing scheme (summer and winter prices) was considered for calculating cost of power consumed by the appliances. Dynamic programming approach was used to coordinate the extensive data obtained from multiple homes. The proposed method was evaluated and compared with existing methods to measure its performance. The simulation results were divided into two parts, including summer and winter cases. In the summer case, EB of single home was reduced by 2.58%, 4.76%, and 2.68% using BFA, HSA, and HBH, respectively, before the proposed coordination, and reduced by 17.30%, 16.00%, and 13.39% after the coordination using the same algorithms. The EB of multiple homes was reduced by up to 3% for the three algorithms before the coordination, and 2.83%, 17.15%, and 13.27% after coordination using BFA, HSA, and HBH, respectively. The value of PAR of single and multiple homes using BFA, HSA, and HBH was reduced by 49.17% and 24.42%, 47.14% and 25.91%, and 49.79% and 24.60%, respectively, before the coordination. After the coordination, PAR was reduced by 43.25% and 23.36%, 42.08% and 28.25%, and 47.97% and 23.81% for single and multiple homes using BFA, HSA, and HBH, respectively. In the winter case, EB of single and multiple homes were reduced by 7.45% and 9.52%, 1.22% and 0.00%, and 2.26% and 1% using BFA, HSA, and HBH, respectively, before the proposed coordination, and reduced by 13.16% and 14.43%, 13.96% and 13.42%, and 11.86% and 14.65% after the coordination using the same algorithms. The value of PAR of single and multiple homes using BFA, HSA, and HBH was reduced by 43.23% and 26.05%, 41.83% and 35.11%, and 37.48% and 25.86%, respectively, before the coordination. After the coordination, PAR was reduced by 46.01% and 25.08%, 41.48% and 33.35%, and 35.34% and 24.55% for single and multiple homes using BFA, HSA, and HBH, respectively.

The authors of [88] adapted moth-flame optimization (MFO) algorithm and GA to address PSPSH using HEMS. To improve the schedule and achieve the objectives optimally, the authors hybridized the MFO and GA (time-constrained genetic-moth flame optimization (TG-MFO)). In addition, TG-MFO was combined with time constraints of appliances to get maximum UC level. Moreover, RESs and EES were integrated with the HEMS to obtain a better solution. In the simulation results, TG-MFO solution was compared with five metaheuristic algorithms, including GA, MFO, FA, ACO, and CSA. The proposed TG-MFO outperformed the others in accomplishing the objectives. In addition, the proposed TG-MFO showed better results for multiple users compared with the unscheduled mode.

5.3. Main algorithms for PSPSH: pros and cons

A large number of metaheuristic algorithms have been adapted for PSPSH, particularly population-based algorithms, as presented in Section 5.2. Fig. 6 shows the number of times each metaheuristic algorithm has been used to address PSPSH. The figure clearly shows that GA is the most adapted algorithm for PSPSH, having been adapted 25 times to address PSPSH. This large number of GA adaptation is attributed to its simplicity and suitability in addressing non-linear problems [8]. GA has two parameters that allow it to find a convenient schedule and balance exploration and exploitation throughout the iterations of the scheduling process. These parameters are crossover and mutation [9]. However, GA suffers from imbalance between exploration and exploitation; consequently, the optimal solution is not obtained in certain cases [7].

BFOA and HSA have been adapted seven times (Fig. 6), making them the second and third most popular algorithms used to address PSPSH. BFOA and HSA have elicited the attention of many PSPSH researchers because BFOA has flexible constraints and simple computational equations [38], while HSA has a robust and direct searching process [41]. However, BFOA exhibits an excellent ability to exploit a search space, while HSA has proven its efficiency in exploring a search space [41]. Therefore, both algorithms suffer from the imbalance between exploration and exploitation.

PSO has been adapted five times to address PSPSH. PSO is a robust population-based optimization algorithm with a good ability to solve optimization problems that have non-linear and non-differential functions [8]. Moreover, PSO can be implemented easily due to the simplicity of its mathematical equations. By contrast, PSO exhibits a high probability of getting stuck in local search due to its fixed parameters that restrict its movement between local and global optima, particularly in a deep and rugged search space, such as that of PSPSH [7].

5.4. Discussion

This study provides a comprehensive overview of PSPSH. PSPSH is a problem in scheduling the operations of smart home appliances at appropriate periods in a predefined time horizon in accordance with a dynamic price scheme or another incentive method to reduce EB and PAR and improve the satisfaction level of users.

Several methods have been adapted to obtain optimal scheduling, including (i) exact algorithms and (ii) metaheuristic algorithms. The latter is classified into local search-based, population-based, and hybrid metaheuristic algorithms. The best solutions are obtained by the hybrid metaheuristic algorithms [38,41,81,82].

Notably, several methods do not consider NSAs in the scheduling process, which results in unexpected power consumption once users operate these appliances [67,68]. Therefore, the power consumed by users may exceed the highest allowable power consumption limit (threshold) and lead to blackouts in smart homes. Meanwhile, other methods used NSAs as SAs in the scheduling operation, with the authors setting the time parameters for NSAs [59]. However, all NSAs are operated manually and nobody can tell in advance when and for how long users will use them. Therefore, setting time parameters for each NSA in advance seems impractical.

Most of these methods formulate the objective function as a single objective (EB reduction) in the evaluation process, while a few methods formulate the objective function as a multi-objective optimization function [8,42]. The multi-objective optimization function in these studies considers minimizing EB and improving UC level while disregarding the impact of PAR. However, this issue was addressed in Ref. [7], where the authors formulated the objective function as a multi-objective optimization function that considered EB and PAR

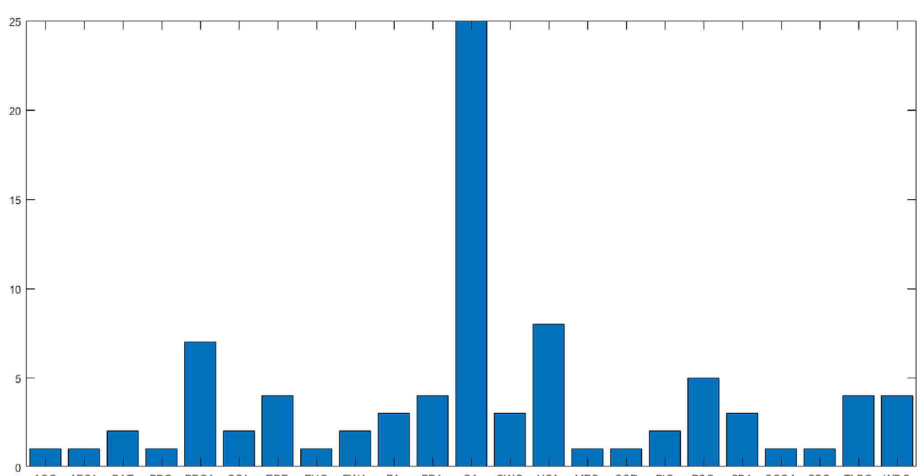

Fig. 6. Number of times each metaheuristic algorithm has been used to address PSPSH.

minimization and UC maximization.

Moreover, most of these methods use a small number of smart home appliances under one scenario, which leads to a limitation in the analysis and evaluation of algorithm performance [8,42].

6. Conclusion and future direction

This survey presented an overview of SGs, smart homes and their relation to PSPSH. A comprehensive definition of PSPSH and its elements and criteria, including objective functions, pricing schemes, and datasets, is provided and discussed. The state-of-the-art published to address PSPSH are reviewed and classified into exact, and metaheuristic algorithms. The latter is classified into local search-based, population-based, and hybrid metaheuristic algorithms. This review showed that the best solutions are obtained by hybrid metaheuristic algorithms. In addition, the review identified the gaps in the state-of-the-art of PSPSH and their unfavorable effects on the PSPSH solution.

Possible future directions can be considered to improve the quality of the PSPSH solution and obtain better or near-optimal schedule as follows:

- **Objective Function:** Very few studies have formulated the objective function of PSPSH as a multi-objective optimization function. These studies considered minimizing EB and improving UC level while disregarding the impact of PAR. However, the impact of PAR is beneficial in balancing power demand to avoid blackouts resulting from a high power demand during a short period. This issue has been addressed by only one study, and thus its results cannot be compared with those of other studies. Several studies can address this issue to obtain a better solution for simultaneously reducing EB, PAR, and user discomfort level.
- **External Power Resources:** New external power resources can be developed and used to contribute to improving the schedule, such as RESs and ESS. Notably, several studies have used these external power resources but without mathematical formulation for the optimization technique. Moreover, most of these studies have not used standard data for RESs, and thus their results are incomparable. However, these external power resources can be formulated mathematically and standard data obtained from official websites or analyses can be used to make studies and results more realistic and comparable.
- **Standard Datasets:** A standard dataset is one of the most critical issues being faced by authors in solving PSPSH. The datasets used to address PSPSH and evaluate the adapted algorithms differ from one study to another. This problem is due to the unavailability of standard datasets for PSPSH. This issue can be solved by proposing and publishing standard datasets and making them available for authors to facilitate comparison studies.
- **Improving the Behavior of the Adapted Algorithms:** As mentioned earlier, the best solutions for PSPSH are obtained using hybrid metaheuristic algorithms. In most studies, the authors combined two population-based metaheuristic algorithms to improve the results. However, the hybrid version of a metaheuristic algorithm with local-based or exact methods may obtain a better solution for PSPSH due to their effectiveness in enhancing the exploitation side of the algorithm and increasing its ability to find the local optimal solution at each iteration of the search.

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