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Research Article

A Day Ahead Electrical Appliance Planning of Residential Units in a Smart Home Network Using ITS-BF Algorithm

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The concept of energy management in smart homes has received increasing attention in recent years, particularly on issues such as creating a balance between user privacy and reducing energy costs. Accordingly, this article proposes a user-oriented multi-objective approach, which minimizes energy costs and maximizes consumer privacy. In addition, a home energy management system is suggested for smart homes to optimize the energy consumption pattern of appliances. On the other hand, considering challenges in energy management of smart homes, the concept of demand-side management (DSM) is introduced. The objective of the proposed method is to reduce energy consumption to lower consumers' electricity bills. Also, it improves user comfort (UC) in average waiting time conditions. In this research, a smart home equipped with an energy management system and smart home appliances that can inject electric power into the upstream network is considered the main system. This framework leads to a multi-objective optimization problem in which the two objectives mentioned above are considered two separate dimensions. To solve the problem, an ITS-BF Algorithm is used, which employs a random search to schedule home appliances and batteries based on the application of flexible devices in smart homes. The case studies show that the proposed method can considerably respect and satisfy users' privacy and reduce the energy cost to an acceptable level. Finally, the numerical results obtained from the simulation have been analyzed to evaluate the proposed method's efficiency. The simulation results show that an ITS-BF algorithm performs better than the existing methods in reducing costs and waiting time.

1. Introduction

The world has made amazing progress in developing new technologies and putting them to innovative use. Electricity is an important and necessary need in today's world. Also, home energy management is proposed to use energy efficiently with minimum cost and maximum user comfort (UC). Electricity is generated in power stations and distributed through different utility companies. In today's world, electricity crises in the form of blackouts, voltage drops, voltage instability, and frequency drops are major issues people face. Two different approaches are used to deal with these issues. First, electricity production is increased by

using renewable energy sources (RER) and replacing them with conventional ones, such as heat generators and fuel cells; second, applicant consumption is monitored, scheduled, and restricted with new techniques. Also, traditional networks cannot afford novel electricity demands with one-direction power flow and a lack of links and connections between different components. For this purpose, smart grids (SGs) have been introduced as updated power networks to provide a substructure for the emergence of the new power industry and prospective applicants. SG is a network that introduces a physical power system that connects information control and communication technologies to a customer satisfaction platform. This modern system provides

electricity for residential, commercial, and industrial zones while allowing two-way communication between consumers and generator units. There are various proposals for controlling the power demand of smart grids. The most popular one is engaging the applicant's behavior and consumption, also known as demand-side management (DSM). It is one of the most important parts of SG that balances load and supply by informing customers about the real-time energy market. Consequently, all applicants can take part in scheduling their devices and make rational decisions about their electricity usage patterns to reduce costs and increase network stability. The reason for choosing machine learning methods is their ability to receive and record information and have no linear characteristics, so in diverse environments they can offer great performance compared to linear methods.

The smart grid's attributes and objectives require energy consumption to be regulated so that costs and adverse effects on the upstream grid are reduced as much as possible. One indicator of minimizing these effects is reducing the Peak to Average Power Ratio (PAPR).

A BEMS is an integrated system that uses tools such as computers, network communications, and wiring to connect all the indoor subsystems of home appliances and other household devices. This system illustrates the increasing role of artificial intelligence in emerging big data technologies and extraordinary computing power. The new generation of artificial intelligence is rapidly expanding and has become an attractive research topic. With the increase in the volume of data and complexity in similar systems' management and calculations, most engaged researchers emphasize the fundamental role of artificial intelligence in the power of intelligent data analysis. In this way, smart home technology effectively focuses on managing consumption and optimizing it at home, in addition to increasing the level of comfort and security of residents by updating daily schedules and constructing high-quality lifestyles. The smart home management system, which first started in the United States, is one of the most fundamental technologies in smart home system design. These microcontrollers are used to monitor home appliances, lighting systems, and air conditioning equipment (heating and cooling) according to the defined conditions and functions. The intelligent building management system needs to learn the behavior and interests of residents to provide a favorable environment. In terms of creating an accurate model of the mentioned systems for evaluating controllers' performances, machine learning-based ones are fine as proper methods that require data processing, including classification and prioritization using the proposed algorithms. It is necessary to define a specific algorithm to combine the structural characteristics of information and store them in a database for large-scale public buildings. This database can be used to detect imperfections or errors in the obtained data and correct them.

1.1. Literature Review.

Based on the studies conducted in the last few decades, researchers have focused on optimizing energy consumption in the presence of diverse loads and using combinations of various technologies to reduce costs and improve the quality of delivered energy. The research focused on preparing a program for daily and weekly activities in the building; only linear methods for predicting the energy consumption of public buildings have been proposed and used, but the prediction accuracy is not provided [1]. The MavHome (Management of an Adaptable and All-Inclusive Home) project is a multi-stakeholder research project at Washington State University and the University of Texas. The main goal is to maximize residents' comfort and minimize operating costs [2]. In another study, the simulation of household electricity consumption is investigated. This model included household cooling, heating, ventilation, air conditioning, lighting, and electricity consumption. The results of the studies presented patterns of energy demand changes, load fluctuations, and variation between location configuration and household size [3–6].

This research presents household appliance planning and control techniques to implement demand-side management using a smart grid to control electricity consumption in houses and offices. The methods reduce the cost of energy consumption, and consumers are encouraged to program their devices' operation periods using load-carrying methods [7]. In a study, electrical energy consumption is investigated in a model of British domestic buildings to identify trends in energy consumption. This study also introduced a series of new analysis techniques to improve the understanding of household electricity consumption [8]. In France, the research laboratory (G-SCOP) has created a pattern of residents' behavior in different states every hour of the day and night to predict the possible state using a Bayesian network. These patterns are created by examining the European Union household energy consumption database [9]. In another study, they made a model for adjusting the house's temperature using smart thermostats. This model focuses on the entry and exit of the residents, and the considered database is created by monitoring a specific location for one month [1].

The methods used to design intelligent energy management programs can be categorized into artificial intelligence (AI) and classical mathematical methods. The suboptimal points are reached based on the local search of the problem's solution areas or using an expert's experience. [10] This category includes fuzzy control methods [11] and genetic algorithms [12]. These methods may get stuck at a suboptimal point. As these techniques are created based on experience, they are weak against changes and possibilities and may be affected by human errors. In contrast, classical methods are more complicated but provide optimal and reliable answers. For example, the mixed integer linear programming method has been used in [13] to optimize the production energy of distributed production resources and loads to reduce costs. In this article, the smart building is equipped with a distributed generation of wind and solar power, a storage battery, and electric vehicles that can be connected to the network. This article does not consider the important factor of common welfare and comfort. Furthermore, in [14], a general model for building energy management is used, which can optimize and compromise between user comfort and energy cost minimization. Also,

the main emphasis is on the increasing use of hybrid cars connected to the grid and its positive effects, such as the lack of fossil fuel consumption and the use of energy stored in the vehicle to meet demand for power in peak hours. It should be mentioned that charging the batteries of numerous cars is considered a major danger to the smart network.

Simultaneous charging of batteries may cause a sudden overload of distribution equipment, especially if it occurs during peak consumption, which leads to congestion in the distribution system. Therefore, with proper planning, the destructive effects of these cars can be reduced to the lowest possible level [15]. The electricity prices at the time of use are a great factor in the optimal use of household loads with the presence of electric vehicles and energy storage devices [15]. Energy storage devices and electric cars have the possibility of energy interaction between the smart home and the distribution network. Nevertheless, the mentioned study did not consider the sources of distributed production. [16,17] examines manufactory production from the standpoint of IoT management. This approach greatly analyses and examines the need for components such as the cloud-based approaches to managing the output of factories as a particular service. Thus, similar to this research, providing such services through cloud technologies and IoT allows users to organize their products according to local goals. The main objective of this research is to implement an intelligent service to control the work schedule of electrical appliances in homes. Accordingly, the considered approach has been employed in various researchers' works, demonstrating their validity and the importance of the challenges raised in this research. To establish the Internet of Things, we can refer to [18] to cover various aspects of the challenges [19], create smart cities [20], and analyses the mutual role of the Internet of Things [21]. Regarding the role of service-oriented architecture in creating a platform to realize the ability to achieve this research's goals in the Internet of Things, we can refer to the analyses and approaches mentioned in [22]. Also, in [23], the importance of middleware in creating a platform for establishing IoTs by receiving assistance is discussed. Also, in [24], a comprehensive study for designing service-oriented middleware is introduced. Based on the literature review, many techniques have been proposed to optimize the home energy management system (HEMS). Most of these techniques are focused on reducing PAR and cost. In [25], the authors presented a price signal for dealing with DR at the time of use (ToU). The DR approach's goal is to plan and move the maximum load to the minimum load. In this work [26], the authors effectively considered the element of user satisfaction. While in [27], the authors introduced the framework for managing the load profile, which includes DSM. In addition, they mentioned that if a customer has any issues related to the priorities of the running equipment they have already set, they should send feedback. Similarly, the authors in [28] presented the results using experimental evolutionary techniques to achieve the minimum electricity bill regardless of user satisfaction. The research authors [29] proposed a general DSM model for residential users based on similar objectives of cost reduction, PAR reduction, and UC level increase. A Genetic Algorithm (GA) with Real Time Pricing (RTP) 2 has been used. The results show that UC has reached some classes in terms of time. In HEMS, two price signals are used: dynamic and static.

Dynamic price signals mainly influence DSM because it changes from time to time. The main goal of DSM is to obtain full UC with minimum cost. In this direction, many DSM techniques have been introduced in recent years. As in the article [30], wind optimization techniques (WDO) and ToU tariff prices are used to obtain minimum cost and maximum UC. In [31], a survey of different DR designs is provided that are classified into different categories. Various models for optimal control of DR strategies have also been presented. In [32], the authors proposed a cost-effective plan for load scheduling. The fractional programming (FP) approach is used along with the advanced RTP pricing tariff so that the user can manage his electricity consumption pattern by reducing the cost. The simulation results show that the proposed technique significantly leads to an economical energy consumption pattern. However, reducing the cost to a minimum is still a compromise, and UC and PAR have not been discussed in this work. On the other hand, while dealing with the OPF problem, the main goal is the optimal distribution of the generated power with the optimal settings of the control variables so that it can be solved with a specific objective function in the methodology [33]. The classic OPF problem is only based on the heat generator that mainly consumes fossil fuel. However, with the increase in energy demand and environmental concerns, RERs have been included to reduce the use of fossil fuels because they play an important role in carbon emissions and global warming. [34]. The use of green energy has rapidly increased the penetration of RERs in the power system. Integrating RERs such as wind turbines and photovoltaic solar panels (PV) is a complicated task because they have uncertainty in their production due to the dependence of these resources on the speed of the wind and solar radiation [35]. The authors address the problems of OPF and uncertainty in modeling wind, solar, and demand load. They suggested PDF include the average adjustment cost as an additional cost caused by the uncertainty of RERs. The battery storage system removes the uncertainty regarding RERs and stabilizes the electricity flow and different energy storage options. However, the writers ignored the calculations of heat generators. In [36], moment-to-minute changes have been used for load demand, photovoltaic solar panels (PV), and wind farms. Every 15 minutes, the OPF future is calculated for resource planning and dealing with uncertainty. However, the authors did not use multi-fuel options, the effect of point valve loading, heat generators' carbon emissions, or storage devices' use in their work. Applicant contribution is effective for load management by reducing PAR, minimizing cost, and increasing UC in terms of reducing waiting time. For this purpose, several innovative Tabu Search (TS), Bacterial Foraging Algorithm (BFA), and Real-Time Pricing (RTP) methods are used. GA is also used for the desired settings of electricity generation from the network. This study considers three emission reduction cases (production and discharge), voltage deviation, and fuel cost [37]. Three different scenarios have been considered to solve the energy management problem in smart homes with the following three objective functions:

The optimal time of indoor appliances by buffering the storage device is also presented in [38] to minimize costs as the objective of the optimization problem. Similarly, a household appliance participation algorithm for household load scheduling was introduced in [39] to reduce the cost of

electricity consumption. Beyond what has been stated in the demand-side management of smart networks, several methods in recent work have been used for household energy management and task scheduling. Creating local access to energy and smart home components, improving the house's energy efficiency, and monitoring and strengthening the house's environment and the residents' social welfare have been considered.

1.2. Contributions of the Study. For example, DR benefits both generators and consumers when there is a high load and the possibility of being turned off. On the other hand, consumers will benefit by reducing electricity costs with ease and comfort. In supply side management (SSM), optimal methods of generation and providing services with encouraging features are used, whereas in demand side management (DSM), consumers change their energy market usage behavior. In both concepts, the main goals are to reduce costs, improve the power system stability, and prevent noticeable peaks in daily consumption curves. For this purpose, there is a need to create an updated and improved energy management system (EMS) that governs electricity generation and consumption wisely. The importance of such a system is reflected through the assistance obtained, such as the maximum reduction of charges, the minimum PAR, and maximum user satisfaction, so that it can provide a solution for the security, reliability, and stability of the system. According to recent research, the main focus of this article can be summarized as follows:

This article introduces a new concept of demand-side management (DSM) that can improve user comfort (UC) in average waiting time conditions. The proposed plan uses the ITS-BF Algorithm technique, which can be more effective in reducing the costs, minimizing the waiting time, improving the UC level, and reducing the average waiting time for household interests in general compared to the existing plans. In addition to reducing the energy cost to a reasonable level, the proposed method can respect and satisfy users' privacy to a considerable extent.

2. Model System

The offered system model is shown in Figure 1. A HEMS has been proposed to launch intelligent applications for reducing electricity, PAR, and waiting time. Smart homes can be considered a network that includes smart devices, SM, and energy management controllers (EMC). The applications used in a smart home are planned in EMS, and the planning is done by considering the consumption patterns of each user and the electricity price. In this technique, first price signals are received by SM from the instrument and then transferred to the EMC section. After prescribing the appropriate plan, the schedule is sent from EMC to SM to control the periods in which each device is allowed to work and consume electricity. For programming, utility companies share their SM, EMC, and information resources.

There are many loads in residential sites which are generally divided into two categories:

(I) Schedulable loads

(II) Constant loads

While loads such as refrigerators and stoves are considered constant loads, vacuum cleaners, washing machines, and clothes dryers are examples of schedulable loads that provide the most electricity in a household. They consume and behave differently in response to changes in electricity prices over time [3].

3. Formulation

An energy management scenario is considered that can be implemented in central control equipment. All intelligent electrical equipment is controlled and programmed by the central control of the smart home network. The objective function presented in (1) is:

$$\text{Objective Function Min} = \frac{\text{SP}}{\text{LF}}. \tag{1}$$

SP represents the cost of operating a smart home, and LF represents the load factor.

SP is defined as the difference between the cost of purchasing energy from the upstream grid (C_{EP}) with the profit from the sale of upstream grid energy (C_{ES}) and the profit from participation in the consumption reduction program (C_{DM}).

$$\text{SP} = C_{EP} - C_{BS} - C_{DM}, \tag{2}$$

$$\text{LF} = \frac{\text{average of load}}{\text{Peack of load}}. \tag{3}$$

Increasing the load factor can include reducing the peak consumption or increasing the average consumption by filling the valleys of the overall load profile.

Replaceable appliances in this study include water pumps, vacuum cleaners, dishwashers, and water heaters (category A). However, they are interrupted and transferred to other time intervals after setting the working time. As mentioned earlier, many devices do not have this feature due to necessity and cannot be adjusted. The user sets the active time of these devices, so incentive plans are considered so that users have a passion for using these devices optimally. An air conditioner, a refrigerator, and a stove are suitable examples of these devices (Category B). The device is represented by $\forall i \in \{I, D, B\}$ and X_i represents the power consumption. The daily electricity consumption of each household appliance is calculated based on (1).

$$X_i = \sum_{t=1}^{t} \left(\sum_{i \varepsilon \{I,D,B\}} p_i \times \sigma_i(t) \right), i\varepsilon\{I, D, B\}. \tag{4}$$

The total cost of all devices at t interval is calculated based on (2).

$$\varsigma_i = \sum_{t=1}^{t} \left(\sum_{i \varepsilon \{I,D,B\}} p_i \times \delta(t) \times \sigma_i(t) \right), i\varepsilon\{I, D, B\}, \tag{5}$$

where T is the whole-time gap, P_d is the home appliance electricity rates, and $\delta(t)$ is Electricity price. The device's state is in a specific time gap calculated based on (3).

$$\sigma_i(t) = \begin{cases} 0, & \text{if appliance is off,} \\ 1, & \text{if appliance is off.} \end{cases} \quad (6)$$

Therefore, the total energy consumption and total cost per day are calculated and provided in Table 1:

3.1. Central Energy Storage System (Battery).
for managing storage system an objective function should be described as follows, which is presented in (7):

$$PC = \sum_{H=1}^{144} Tr_H \left(FE_h + \sum_J E_j I_{jh} + \left(\frac{1}{\eta^B}\right) \right.$$
$$\left. \left(E^{Bp} I_h^{Bp}\right) - \eta^{\dot{B}} \left(E^{Bn} I_h^{Bn}\right) \right). \quad (7)$$

$$PC = \sum_{h=1}^{144} Tr_h \left(FE_b - \sum_J E_J I_{Jh} + \left(\frac{1}{\eta^B}\right) + \left(E^{BF} I_h^{BP}\right) + \left(\frac{1}{\eta^B}\right) \left(E^{Pp} I_h^{PP}\right) \eta^B \left(E^{Bn} I_h^{Bn}\right) - \eta^B \left(E^{Bn} I_h^{Bn}\right). \quad (11)$$

This energy can be sold to the grid if the energy discharged from the storage system is greater than the amount consumed in the house. The energy transferred to the grid for sale to companies is limited to the maximum allowable energy.

$$E_h^T \le \eta^B, \quad (12)$$

$$E_h^T = \eta^B \left(E^{BF} I_h^{BP}\right) + \eta^P \left(E^{BF} I_h^{BP}\right) - \left(\frac{1}{\eta^B}\right)$$
$$+ \left(E^{BF} I_h^{BP}\right) - \sum_J E_J I_{Jh} - FE_h. \quad (13)$$

3.2. Distributed System Stores Energy in Bars.
With the advent of high-efficiency electronic equipment and their applications in smart loads in the smart home, the central battery can be used for some loads in a distributed manner. These distributed batteries can be controlled separately. The ultimate goal in the presence of batteries distributed in loads is described as (14).

$$PC = \sum_{H=1}^{144} Tr_H \left(FEE_h + \sum_J E_j E_{jh} \right). \quad (14)$$

Obviously, the battery cannot be charged and discharged at the same time:

$$E^{Bp} + I_h^{Bp} \le 1. \quad (8)$$

The amount of battery discharge in each period should be less than the amount of stored energy so:

$$E^{Bn} I^{Bn} \le E_0^B + \sum_{m=1}^{h-1} \left(E^{Bp} I_m^{Bp} - E^{Bn} I_m^{Bn}\right). \quad (9)$$

The maximum battery charge per period is limited by its capacity:

$$E_0^B + \sum_{m=1}^{h} E^{Bp} I_m^{Bp} - E^{Bp} I_m^{Bp} \le E^{\max B}. \quad (10)$$

Another objective function for optimizing a smart home that includes PHEV and central batteries is introduced in (11).

This energy can be sold to the grid if the energy discharged from the energy storage equipment is greater than the consumption of the house.

$$E_j I_{jh} + \sum_b^j \frac{1}{\eta^b} \left(E^{Bp} I_h^{Bn}\right) - \eta^B \left(E^{Bn} I_h^{Bn}\right) = EE_{jh}, \quad (15)$$

$$EF_h + \sum_b \frac{1}{\eta^b} \left(E^{Bp} I_h^{Bn}\right) - \eta^B \left(E^{Bn} I_h^{Bn}\right) = FEE_h. \quad (16)$$

Also, this battery cannot be charged and discharged simultaneously as the central trays.

$$I_{bh}^{Bn} + I_{bh}^{BP} \le 1. \quad (17)$$

Furthermore, the discharge rate of the distributed batteries in each period should be less than their available charge:

$$E_{bh}^{Bn} I_{bh}^{Bn} \le E_{0b}^B + \sum_{m=1}^{h-1} \left(E_h^{Bn} I_{bm}^{Bp}\right) - \left(E_h^{Bn} I_{BM}^{Bn}\right). \quad (18)$$

The following equation estimates the capacity range of batteries;

$$E_{bh}^{Bn} + \sum_{m=1}^{h-1} \left(E_h^{Bn} I_{bm}^{Bp}\right) - \left(E_h^{Bn} I_{BM}^{Bn}\right) \le E_b^{\max B}. \quad (19)$$
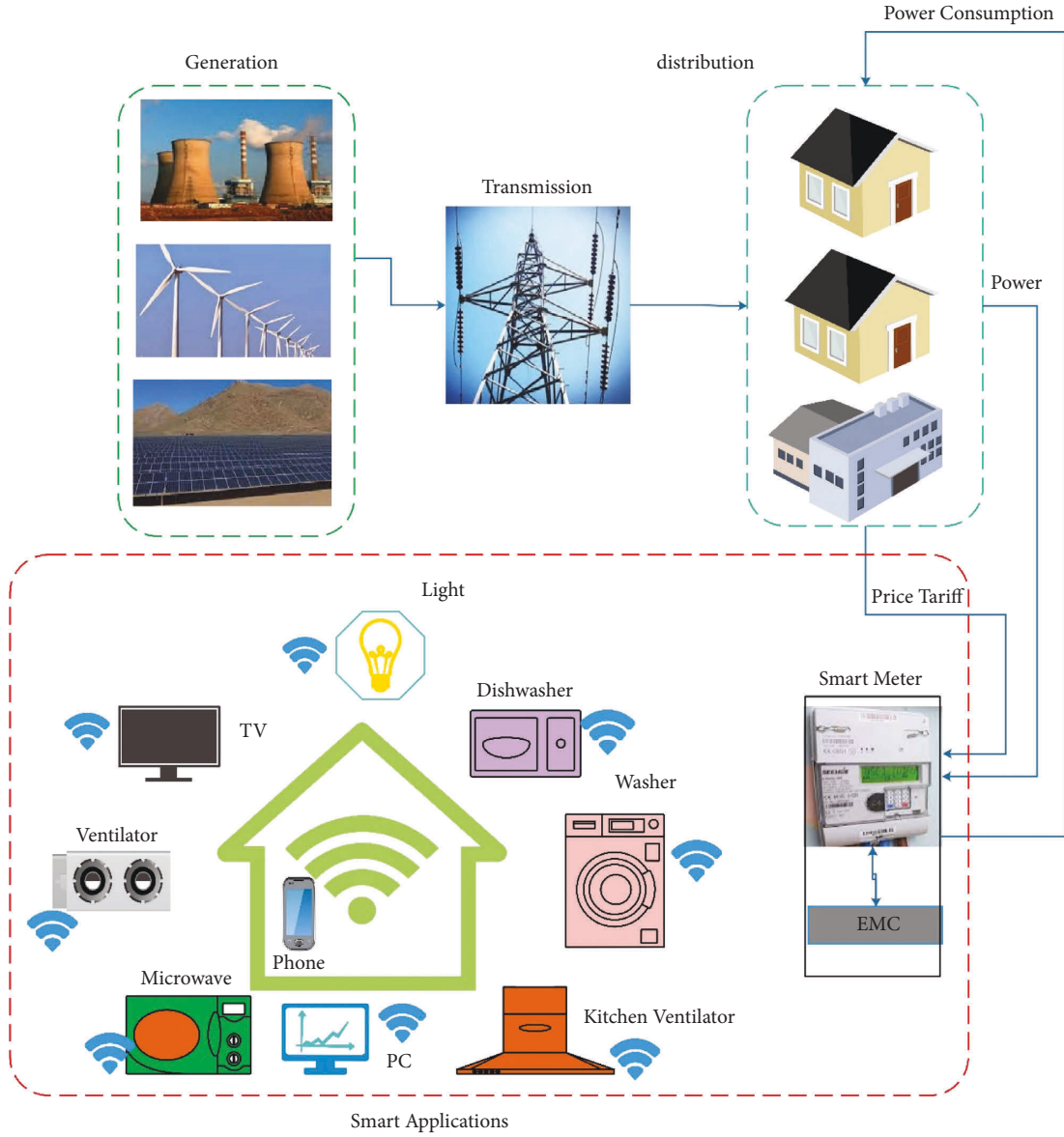
Figure 1: Proposed system model.

Finally, the following equation is shown to achieve the goal that should be optimized in the presence of PHEV and distributed batteries.

$$\text{PC} = \sum_{H=1}^{144} Tr_H \left(FEE_h + \sum_J EE_{JH} \left(\frac{1}{\eta^b} \right) \left(E^{Pp} I_h^{Pp} \right) + \left(\frac{1}{\eta^b} \right) \left(E^{Pp} I_h^{Pp} \right) - \eta^P \left(E^{Pn} I_h^{Pn} \right) \right). \qquad (20)$$

3.3. PHEV Displacement Modeling.

In this research, we use the Gauss-Markov displacement model to design the PHEV displacement model. Based on this model, each moving agent frequently examines its spatial position and updates its status whenever it reaches the boundary distance. In this study, PHEV is the moving factor that updates its location periodically and is frequently considered. Therefore, we use the displacement model to implement the PHEV movement pattern. PHEV speed depends on the time, which means the location of each PHEV at the time t depends on its location and velocity at the time $t-1$ is stated below:

$$v_t = \alpha v_{t-1} + (1 - \alpha)v + \sigma \sqrt{1 - \alpha^2} W_{t-1}. \qquad (21)$$

TABLE 1: Appliance parameters.

Type of appliance	Appliance	Daily use (hours)	Electricity rate (kWh)
Interchangeable appliance	Vacuum cleaner	0.7	6
	Water heater	5	12
	Water pump	1	16
	Dishwasher	1.8	5
Non-replaceable appliance	Washing machine	07	5
	Dryer	5	4
Basic appliance	Refrigerator freezer	0,255	18
	AC	1,5	15
	Oven	2,15	10

(i) $v_t = [v_t^x, v_t^y]$ Indicates PHEV speed at time t

(ii) $\alpha = [v_t^x, v_t^y]$ Indicates variance at different times

(iii) $\sigma = [v_t^x, v_t^y]$ Indicates standard deviation

(iv) $W_{t-1} = [W_{t-1}^x, W_{t-1}^y]$ The amount of random correlation in the Gaussian process

The displacement is evaluated in X and Y directions based on the following equation and model relations.

$$v_t^x = \alpha v_{t-1}^x + (1 - \alpha)v^x + \sigma^x \sqrt{1 - \alpha^2} W_{t-1}^x, \tag{22}$$

$$y = \alpha v_{t-1}^y + (1 - \alpha)v^y + \sigma^y \sqrt{1 - \alpha^2} W_{t-1}^y. \tag{23}$$

4. Optimization Techniques

4.1. Bacterial Foraging Optimization Algorithm. The Bacterial Foraging Optimization Algorithm (BFA) was introduced in 2002 [15] and is a relatively new model for solving optimization problems inspired by the social behavior of Escherichia coli (E. coli) that is present in the human intestine. For many organisms, finding food includes steps such as gathering members into certain groups and trying to find food and gathering and consuming it at the most optimal time while minimizing the risk of being attacked and injured by predators or assailant groups.

According to these biological interpretations, BFA is formulated into the following basic steps [16]: Chemotactic 1 (rotation and swimming) is a process in which the bacterium directs its movement according to certain chemical signals in its environment. It is very important for a bacterium to climb the food accumulation and avoid harmful substances simultaneously. The bacterial position in the (j+1) chemotactic step is calculated from the position of the previous step and the step length $C(i)$ (as a step length unit) multiplied by the random direction $\phi(i)$:

Therefore, the total energy consumption and total cost per day are calculated by the following equations.

$$\theta^i(j+1, k, l) = \theta^i(j, k, l) + C(i) \times \phi(i). \tag{24}$$

$\phi(i)$ is a random direction for describing immersion calculated from Equation (25):

$$\phi(i) = \frac{\Delta(i)}{\sqrt{\Delta^T \Delta(i)}}, \tag{25}$$

so that $\Delta(i) \in R^D$ is produced randomly in the range $[-1,1]$. The cost of each situation is calculated by (26):

$$J(i, j, k, l) = J(i, j, k, l) + Jcc\left[\theta\theta^i(j, k, l)\right]. \tag{26}$$

In (26), the cost of position $J(i,j,k,l)$ with the effect of attraction and repulsion force between the bacteria in the population that Jcc has been changed. If the cost of location i of the bacterial species in $j + 1$ of the chemotactic step shown in $J(i,j,k,l)$ is better (less) than the location θi (j,k,l) in step j. So, a bacterium takes a step of $C(i)$ in the same direction to reach the maximum possible number of steps. ($[\![N]\!]\_S$).

Congestion 2 is a partial type of movement made possible by flagella and allows bacteria to pass through quickly and between the surfaces of a dense environment.

for example, suppose N_{reis} the number of reproductive stages, to reproduce, the bacteria with the minimum health will die; these are the bacteria that could not collect enough food during the chemotactic stages and will be replaced by an equal number of healthy bacteria. As a result, the population size will remain constant. The healthiest bacteria (those with enough food value and the lowest value of the cost function) are divided into two bacteria in an asexual way and take the place of the dead bacteria. The level of health can be calculated with different methods. Here, a method that considers the total amount of food received in each chemotactic as a health criterion is used:

$$J_{health}^i = \sum_{j=1}^{N_e+1} J(i, j, k, l). \tag{27}$$

4.1.1. Elimination-Dispersal. Changes in the environment can affect the behavior and population of bacteria. Therefore, when a change occurs in the environment, either slowly (for example, food consumption) or suddenly (for example, an increase in temperature), all the bacteria in one area may die or spread to other parts of the environment. Such movements have destructive effects on all previous chemotactic processes. While they may also have good effects, this change may move affected bacteria to a nutrient-rich area. These events lead to the definition of Elimination-Dispersal. Under such conditions, Ned is the number of occurrences of Elimination-Dispersal, and for each occurrence of each bacterium in the population, the probability ped is set so that at the end, the number of bacteria in the population remains constant (if one bacterium is deleted, another bacterium A random event will be played) [16].
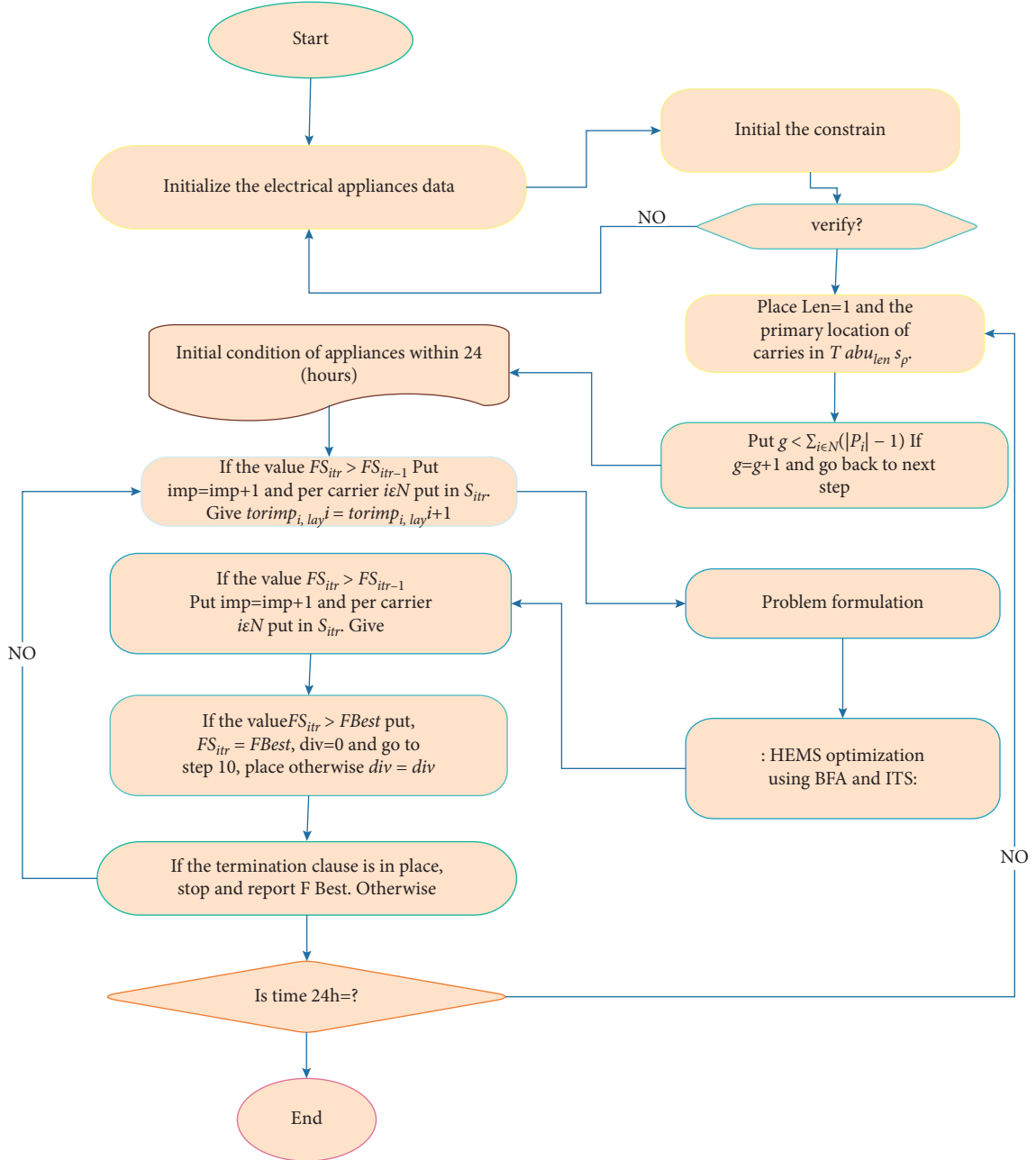
FIGURE 2: The Proposed protocol flowchart based on BFA and ITS.

4.2. ITS. In the tabu search algorithm, the neighborhoods around which the search has been done are kept temporarily and for a short period in a list called the forbidden list (Tabu). As a result, by creating a forbidden list, the creation of repeated neighborhoods will be prevented in a short period of time.

Two operators can be employed to improve the performance of the Tabu search algorithm: diversification and elitism. By accepting the worst answer, the diversification operator enlarges the search space and prevents getting stuck in local optima. The elite operator is used to select better answers and speed up the search process. In the proposed algorithm, according to the initial answer

for the initial location of the carriers, the value of the objective function is calculated from the allocation algorithm, and the location of the carriers is added to the forbidden list.

The neighborhoods of answers will be checked, and the best ones considering objective function values will be identified and added to the forbidden list. In this algorithm, the length of the forbidden list is considered fixed, and when the number of forbidden neighborhoods is greater than the length of the forbidden list, the first answer that enters the forbidden list is deleted. In other words, every neighborhood added to the forbidden list will remain on it until the number of repetitions is reached, and then it will be removed. In the

TABLE 2: Initial status of home appliance parameters (0 on −1 off).

| Type of appliance	Appliance	Initial condition of appliances within 24 (hours)
Appliance whit timing capability	Vacuum cleaner	[0 0 0 0 0 0 1 1 1 1 0 1 1 0 0 0 0 0 0 0 0 0 0 0]
	Water heater	[0 0 0 0 0 1 1 1 1 1 1 1 1 0 0 0 1 1 0 0 0 0 0 0]
	Water pump	[1 1 1 1 1 0 0 1 1 1 1 0 0 0 0 1 1 1 1 1 1 1 0 0]
	Dishwasher	[0 1 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 1 1 0 0 0]
Appliance whiteout timing capability	Washing machine	[0 0 0 0 0 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
	Dryer	[0 0 0 0 0 0 0 0 0 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0]
Basic appliance	Refrigerator freezer	[0 1 1 1 1 1 1 1 1 1 1 0 0 1 1 0 1 1 0 1 0 1 1 1]
	AC	[0 0 0 0 0 1 1 1 1 1 1 1 1 1 0 1 1 0 1 1 0 0 1 1]
	Gas oven	[0 0 0 0 0 0 1 1 1 1 1 1 1 0 0 0 0 1 1 1 0 0 0 0]
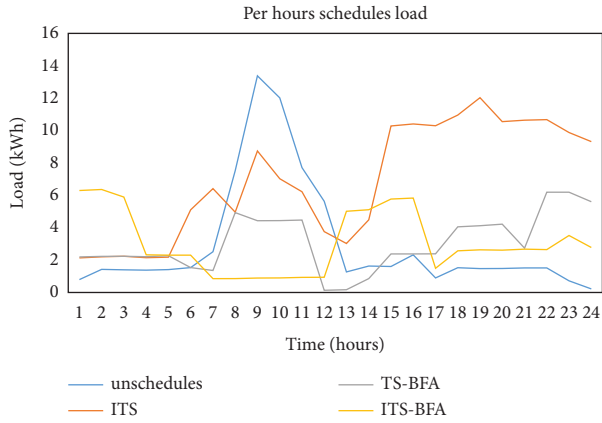
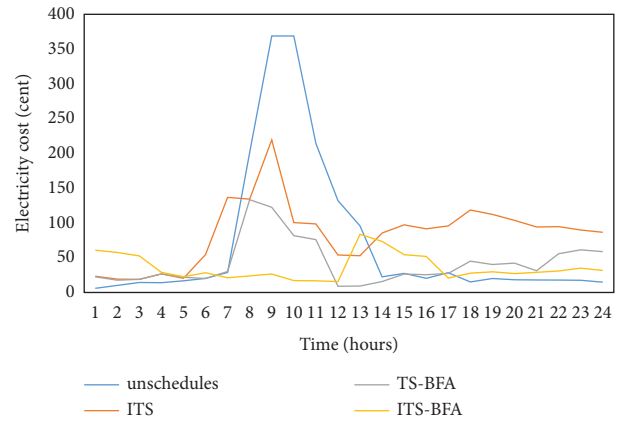FIGURE 3: Load during 24 hours.

FIGURE 4: Electricity cost based on TOU tariff during 24 hours.

beginning, the algorithm adds the best answer of each iteration to the forbidden list, regardless of whether it is improved or not, and continues searching around it. It also keeps the number of repetitions that did not improve the answer and the number of repetitions that improved the answer compared to the previous answer in two variables: div and imp. If there are still unimproved answers after inverted terminal repetition (ITR), if the div variable is more than imp, the diversification operator is executed; otherwise, the elite operator is executed.

The proposed protocol is implemented through the following steps (according to the flowchart in Figure 2):

The stop condition defines the time limit and describes the following steps as the process considered for the proposed algorithm.

Step 1: Place Len = 1 and sent the initial locations of carriers in $\text{Tabu}_{\text{len}}\, s_\rho$. For this place, the value FS_0 using the Limit function. Put: $G' = \varnothing, \text{NE} \equiv \varnothing, g = 1. FS_0 \equiv F\text{Best}$, itr = $1 g'' = 1$ Set all IoT and TI matrix values to zero. $g'' = g' + 1$ and $\text{Score}_g = 0$

Step 3: If $g < \sum_{i\varepsilon N}(|P_i| - 1)$ Put $g = g + 1$ and go back to step 2, otherwise go to step 4.

Step 4: Identify the highest value of objective function and neighboring value related to S_{ite-1} and set the values Pu tS_{itr} AND FS_{itr} respectively.

Step 5: If the value $FS_{itr} > FS_{itr-1}$ Put imp = imp+1 and per carrier $i\varepsilon N$ put in S_{itr}. Give $\text{torimp}_{i,lay^i} = \text{torimp}_{i,lay^i} + 1$

Step:6 If the value $FS_{itr} > F\text{Best}$ put, $FS_{itr} = F\text{Best}$, div = 0 and go to step 10, place otherwise div = div+ 1:

Step 7 If is div < ITR, go to step 10, otherwise if is the div < imp, go to step 8 and otherwise go to step 9

Step:8 Put imp = 0 and for $|G'|$ Allowed neighbor from NE, $\text{Score}_{y*} = \sum_{i\varepsilon N}\text{totimp}_{i,lay^i_y}$ As $y = 1, 2, \ldots.|G'|$ calculate. Highest score, Score_{y*} Specify. Neighboring it, NE_{y*} and the value of the target function, FNE_{y*} In order FS_{itr} And S_{itr} Put it and go to step 10.

Step:8 Put div = 0 and for $|G'|$ Allowed neighbor from NE, $\text{Score}_{y*} = \sum_{i\varepsilon N}\text{totimp}_{i,lay^i_y}$ As $y = 1, 2, \ldots.|G'|$ calculate. Highest score, Score_{y*} Specify. Neighboring it, NE_{y*} and the value of the target function, FNE_{y*} In order FS_{itr} And S_{itr} Put it and go to step 0.

Step:11 If the termination clause is in place, stop and report F Best. Otherwise $g = 1, g' = 1, \text{itr} = \text{itr} + 1, G' = \phi, \text{NE} = \phi$ And return to step 2.

4.3. HEMS Optimization Using BFA and ITS.

In order to optimize HEMS, the parameters of household appliances, along with their initial state (Table 2), are given as input to the hyper-innovative algorithms used in this research, i.e., BFA, ITS, and their combinations. Then, the initial efficiency level of each of these necessities in 24 hours is calculated based on the total energy consumption and the total cost per day by equations (25) and (26). Then, the innovative
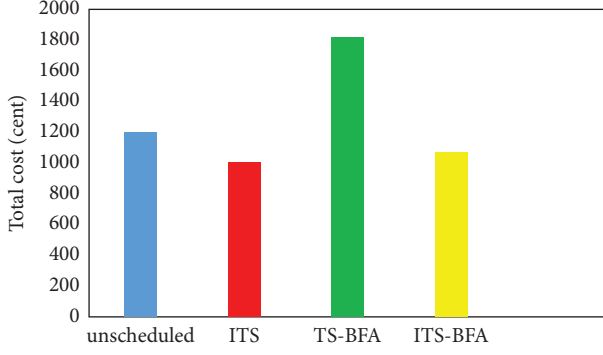
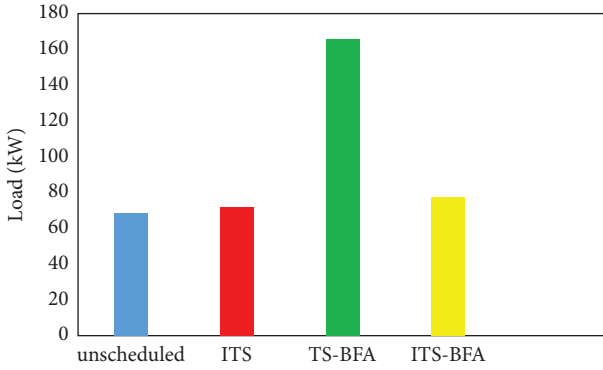FIGURE 5: Total cost of electricity for a 24-hour day.

FIGURE 6: Load before and after scheduling.

FIGURE 7: PAR value for all scheduling schemes.

FIGURE 8: Average waiting time for all scheduling plans.

algorithms follow their evolutionary process on these values until they reach the optimal state. The optimal situation to reduce energy consumption and minimize the total cost of consumption is to use the merit function of equation (27).

$$\mathrm{MIN} X_T + \varsigma_T. \tag{28}$$

5. Simulations and Results

The implementation and technological results of the proposed smart house using simulation in MATLAB are described in this section to study the proposed technique results of ITS compared with BFA and TS. A solitary house with nine devices to be programmed is intended, which are divided into three categories:

Set A: replaceable devices (water pumps, vacuum cleaners, dishwashers)

Set B: non-replaceable devices (for example, washing machines and drying machines that cannot be stopped during the working cycle)

Set D: impenetrable basic household appliances (for example, refrigerators and freezers, AC, stoves)

In TOU, prices are divided into several blocks of the day, and the price of each block is adjusted to a non-peak constant time and a peak time. The load is shown for 24 hours in Figure 1. The power of scheduling technology is less than the unscheduled scheme.
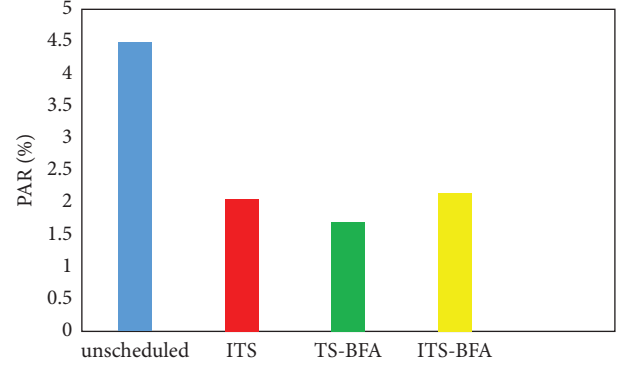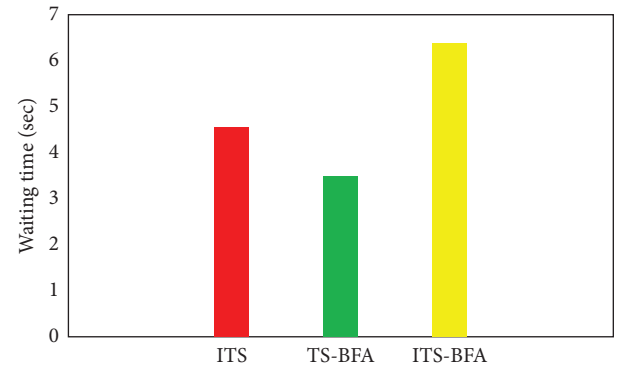
Figure 3 indicates that the maximum energy consumption for one day is 13,525 kWh of unscheduled kilowatt-hours, and for ITS, BFA-TS, and BFA-ITS is 6,126 kWh at 12,056 kilowatt-hours and 6,534 kWh, respectively. Total electricity consumption is relatively low for programming.

Figure 4 shows the electricity cost (per hour) of the proposed technique (ITS BFA) 's electricity cost (per hour) with unscheduled loads, ITS, and TS-BFA. According to the graph, taking the load from peak to time outside the courier is practical because the cost during peak intervals is lower than unscheduled loads. Also, the proposed combination was successful in cost-saving compared to ITS and TS-BFA.

For example, during peak hours such as 18 : 00 to 22 : 00, the proposed method has reduced consumption and final costs due to the high tariff.

The figure shows the four differences in the total cost of electricity between ITS, TS-BFA, ITS-BFA, and unscheduled. It is clear from this figure that ITS-BFA has the lowest cost compared to unscheduled, ITS, and TS-BFA designs. In the case of Unscheduled, the total cost is 1250.1 cents, and the total cost of ITS, TS-BFA, and ITS-BFA is reduced by 1901.2, 850.4, and 790.8 cents, respectively. The cost of all scheduling plans is reduced. However, TS-BFA is the most expensive planning scheme compared to other methods. Figures 5 and 6 show the times before and after the scheduling.

Figure 7 compares PARs between unscheduled, ITS, TS-BFA, and ITS-BFA in 24 hours. PAR reduction positively influences the network's cost, load, and stability, so both

users and the power system can benefit. If the PAR value for Unscheduled is 4,5476 and the PAR values for ITS, TS-BFA, and ITS-BFA are reduced by 1.7977, 2.1559, and 1.1122, respectively, compared to Unscheduled, there were decreases in PAR in all scheduled programs, with TS-BFA experiencing the greatest decrease. Figure 8 easily shows the user (UC) according to the average waiting time duration. The average waiting time is when a user should wait for the device to turn on.

In this research, an individual house has been considered for simulation purposes. The tool set includes nine tools classified based on power rating and execution time. The simulation results show that the proposed combined optimization method based on ITS and BFA is more effective than other existing techniques in reducing the cost, improving the UC level, and minimizing the waiting room's average waiting time (PAR). The proposed programming has reduced the cost of the finished price of electricity without reducing the amount of power consumed by the subscribers, and in exchange for avoiding the creation of a peak during the cheap price hours, it did not create a problem for the electricity distribution company. In the end, it can be said that by using the proposed method and providing the least possible means of improvement, increasing demand in the domestic sector was limited, and the monthly electricity cost was reduced for the subscribers. In the future, other innovative algorithms can be used along with a combination of fuzzy techniques to increase the efficiency of load management in smart homes. In addition, we have focused on the issues of privacy protection and smart network security. This research can be expanded by using multiple houses and different price ranges.

6. Conclusion

Considering the importance of using new energies to reduce the consumption of fossil fuels, the optimal allocation of energy resources along with the optimal timing of smart home electricity consumption is one of the important topics of researchers' attention. This is an optimization problem, the purpose of which is to reduce the cost of electricity consumed by the smart home with the optimal timing of the smart home. The inputs of the problem include basic and technical information about the battery, hourly amounts of consumed power, hourly prices of electricity, and hourly amounts of essential and unnecessary loads. The variables of the problem, whose optimal value is considered as the output of the problem, are the amount of displacement of unnecessary loads, the amount of power produced or consumed by the battery, and the amount of power exchanged between the smart home and the network every hour of the day and night. The constraints of the problem include the maximum and minimum energy stored in the battery, the production-consumption balance in the smart home, the zero energy of the battery day and night, and the comfort of the house residents. Considering the number of inputs and the dynamic nature of the environment, optimizing the problem with an intelligent algorithm is

necessary. In this article, the mentioned issue is optimized by the ITS-BF Algorithm. Also, this article introduced a new concept of demand-side management (DSM), which can improve user comfort (UC) in the average waiting time conditions. Minimizing the waiting time, improving the UC level, and minimizing the average waiting time (PAR) for household goods and showing overall better performance than other methods were shown. In addition to the proposed method reducing the energy cost to a reasonable and acceptable level, it also significantly respects and satisfies users' privacy. In addition to the cases worked on in this article, for future research, other renewable sources and the supply of loads through CHP electricity and heat simultaneous production sources can be investigated in the cloud computing platform.

Abbreviations

FP: Fractional programming
OPF: Optimal power flow
RER: Renewable energy resources
PV: Photovoltaic
EMS: Energy management system
EMC: Energy management controllers
PAR: Peak-to-average ratio
PHEV: Plug-in Hybrid Electric Vehicle
ITR: Inverted terminal repetition
HEMS: Hierarchical energy management strategy
SH: Smart House
AC: Alternating current
b_j: Start the allowable interval of operation of the device j
g^P: Start the allowed period outside the PHEV house
c^P: End of allowed period outside PHEV
e_j: End of allowable period of operation of the device j
E_o^B: Initial charge of storage system (kWh)
E_o^P: Initial charge of PHEV battery
E_j: Energy consumption of device h in each period (kWh)
E^{Bn}: Battery charge rate (period / kWh)
E^{BP}: Battery charge rate ¢ (period / kWh)
$E^{\max}$: Maximum allowable energy received from the network (period / kWh)
$E^{\max B}$: Storage system capacity
$E^{\max P}$: PHEV battery capacity (kWh)
$E^{\max S}$: Maximum allowable energy for sale to the grid (kWh)
E^P: PHEV energy consumption outdoors (kWh)
E^{Pn}: PHEV battery discharge rate (period / kWh)
E^{Pp}: PHEV battery charge rate (period / kWh)
FE_h: Energy consumption of uncontrollable periodic appliances in loads h (kWh)
B_p: Mode of battery chargers distributed in loads
B_n: Discharge mode of distributed batteries in loads
EB_p: Chemical energy produced in batteries distributed in bars
EB_n: Chemical energy consumed in batteries distributed in bars
DSM: Demand-side management

UC: User comfort
ITS-   Improved Tabu Search- Bacterial Foraging
BF: Algorithms
SG: Smart Grids
PAPR: Peak to Average Power Ratio
HEMS: Home energy management system
TOU: Time of Use
DR: Demand Response
GA: Genetic Algorithm
RTP: Real Time Pricing
UC: Utility company
WDO: Wind optimization technique
h: Volume index
H: Planning time horizon
j: Controllable appliance index
E_h^T: Transmission energy between grid and house in period h (kWh)
I_j: The vector of the j device in the on or off position
I_{jH}:   Binary index of j device in period h
I_h^{Bp}:   Binary battery discharge indicator
I_h^{Bn}:   Binary battery charge indicator
I_h^{Pn}:   PHEV Charge Binary Discharge Indicator
I_h^{Pp}:   PHEV binary charge index
PC: Payment function
y_{jh}:   Binary index of device startup j
Z_{jh}:   Permanence indicator of device failure j
EE_{jh}:   The amount of surplus energy that network programmers receive
FEE_h: The amount of surplus energy that non-network programmers receive
Trh: Tariffs in the period h (¢ / kWh)
U_j: Number of operating cycles for the device j
η^B: Ac-dc conversion efficiency for storage system
$\eta^{B'}$:   Dc-ac conversion efficiency for storage system
η^P: Ac-dc conversion efficiency for PHEV battery
$\eta^{P'}$:   Dc-ac conversion efficiency for PHEV batteries.

Data Availability

Data will be available on request. For the data related queries kindly contact to Baseem Khan baseem.khan04@ieee.org.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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