Smart Energy Management System for Minimizing Electricity Cost and Peak to Average Ratio in Residential Areas with Hybrid Genetic Flower Pollination Algorithm

Abdul Mateen[a], Muhammad Wasim[a], Abdul Ahad[a,b,*], Tehreem Ashfaq[c], Muddesar Iqbal [d,f,*] and Amjad Ali[e]

[a]*Department of Computer Science, University of Management and Technology, Sialkot Campus, Pakistan*
[b]*School of Software, Northwestern Polytechnical University, Xian, Shaanxi, 710072, P.R. China*
[c]*City, University of London, EC1V 0HB, United Kingdom*
[d]*Division of Computer Science and Informatics, School of Engineering, London South Bank University, London SE1 0AA, U.K*
[e]*Information and Computing Technology (ICT) Division, College of Science and Engineering (CSE), Hamad Bin Khalifa University, Doha, Qatar*
[f]*Renewable Energy Laboratory, Communications and Networks Engineering Department, College of Engineering, Prince Sultan University, Riyadh, 11586, Saudi Arabia*

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ABSTRACT

Demand Side Management (DSM) plays a significant role in the smart grid to minimize Electricity Cost (EC). Home Energy Management Systems (HEMSs) have recently been studied and proposed explicitly for HEM. In this paper, we propose a novel nature-inspired hybrid Genetic Flower Pollination Algorithm (GFPA) to minimize cost with an affordable delay in appliance scheduling. Our proposed GFPA algorithm combines elements of the Genetic Algorithm (GA) and Flower Pollination Algorithm (FPA) to create a hybrid approach. To assess the effectiveness of the proposed algorithm, we consider a scalable town consisting of 1, 10, 30, and 50 homes, respectively. The proposed solution finds an optimal scheduling pattern that simultaneously minimizes EC and Peak to Average Ratio (PAR) while maximizing User Comfort (UC). We assume that all homes are homogeneous in terms of appliances and power consumption patterns. Simulation results show that our proposed scheme GFPA performs better when applying Critical Peak Pricing (CPP) signal using different Operational Time Intervals (OTIs) and compared with unscheduled, GA, and FPA-based solutions in terms of reducing cost since they achieve on average 98%, 36%, 23%, and 22%, respectively. Similarly, PAR averages 98%, 36%, 59%, and 55%, respectively. While, UC comparing to GA and FPA, are around 88%, 48%, and 63%, respectively. Our proposed scheme achieves better results by applying Real Time Pricing (RTP) signals and different OTIs. As these schemes, i.e., unscheduled, GA, FPA, and GFPA, achieve cost on average 92%, 50%, 29%, and 28%, respectively. While PAR on average 94%, 39%, 62%, and 56%, and UC for GA, FPA, and GFPA on average 98%, 52%, and 49%, respectively. Overall, our proposed GFPA algorithm offers a more effective solution for minimizing EC with an affordable delay in appliance scheduling while considering PAR and UC.

1. Introduction

Smart grids present the vision of bidirectional communication systems by integrating advanced communication methodologies, control technologies, and sensing technologies at distribution and transmission levels. Some main characteristics and advantages of smart grids are that they are hack-less, self-healing, consumer-friendly, have the ability to cover all types of storage and generation options, show resistance to attacks, and have optimal assets with high power quality Yadav, Hrisheekesha and Bhadoria (2023). Modern grids are considered more environmentally, politically, economically, and technically advanced than old-age ones Rehman, Haseeb, Jeon and Bahaj (2022). With the immense increase in the world's population, the demand for electricity has greatly increased. Since the world's population has a direct relation to the demand for electricity, thus, this increase in demand for electricity creates problems like load shedding, frequency beads, and blackouts. In order to fulfill electricity demands, there are two possible options. First, increase electricity generation capacity. Second, schedule the load according to electricity generation capacity through Home Energy Management Systems (HEMSs). The first approach indicates new power sub-stations, while in the second approach, the consumer has to manage the load by exploiting load scheduling techniques. These techniques can manage the load between off-peak and on-peak hours.

Here are some of the difficulties related to Demand-Side Management (DSM) and HEMS and possible solutions to address them:**Lack of data:** A significant challenge in implementing DSM and HEMS is the lack of data on energy consumption patterns of individual households. This makes it difficult to develop accurate models and algorithms to optimize energy use. Possible solutions include the use of smart meters, data analytics, and machine learning techniques to collect and analyze data on energy consumption patterns. **Complexity:** Another challenge is the complexity of the energy system and the numerous variables that influence energy consumption patterns. DSM and HEMS require sophisticated algorithms and models to optimize energy use,

*Corresponding author: M. Iqbal, A. Ahad
ORCID(s):

which can be challenging to develop and implement. Possible solutions include the use of advanced optimization techniques, such as genetic algorithms, and machine learning algorithms, which can learn from data and improve over time. **Interoperability:** DSM and HEMS require communication between various devices, systems, and stakeholders. The lack of interoperability standards can make it challenging to integrate different components of the energy system, which can limit the effectiveness of DSM and HEMS. Possible solutions include the development of common standards for communication and data exchange, such as the OpenADR standard, which can facilitate interoperability between different energy system components. **Privacy and security:** DSM and HEMS require collecting and sharing sensitive data, such as energy consumption patterns and user behavior. This can raise privacy and security concerns, particularly if the data is not adequately protected. Possible solutions include the use of encryption and secure communication protocols to protect sensitive data and the development of privacy policies and guidelines to ensure that user data is collected and used transparently and ethically. **User engagement:** The success of DSM and HEMS depends on user engagement and participation. However, many users are not aware of the benefits of DSM and may not be willing to participate. Possible solutions include the use of incentives, such as rebates and discounts, to encourage participation, as well as the development of user-friendly interfaces and educational materials to inform and engage users about the benefits of DSM and HEMS.

DSM plays an important role in energy management for smart power generating systems which provides support for different functionalities in several areas, such as management and electricity market control, construction of infrastructure, decentralized energy management resources, and sustainability increase by decreasing the cost and level of carbon emission, control and influence of the load demand, and change in demand profiles. Energy management has also gained a key place in DSM. At every time step of the day, DSM informs the main controller about the available capabilities of load reduction and new load scheduling patterns. The main controller then makes decisions about shifting load from high peaks to low peaks. The applications of scheduling the appliances in smart grids have a noteworthy role and can be applied for one of the following reasons:

- Peak load management: Scheduling schemes can be used to manage peak loads in the power grid by scheduling the usage of electricity-intensive appliances during off-peak hours.
- Load balancing: Scheduling schemes can be employed to balance the load on the grid by scheduling the usage of various devices and appliances to ensure a consistent and stable load.
- Demand response: Scheduling schemes can be used to manage the demand for electricity during periods of high demand by scheduling the usage of appliances and devices to reduce overall demand.
- Energy conservation: Scheduling schemes can be employed to reduce energy consumption by scheduling the usage of appliances and devices during times when energy is least expensive or most abundant.
- Renewable energy integration: Scheduling schemes can be used to integrate renewable energy sources, such as solar and wind, into the grid by scheduling the usage of appliances and devices to align with periods of peak renewable energy production.

Overall, scheduling schemes play a crucial role in smart grid-demand side management by providing a means to optimize energy usage, balance loads, and integrate renewable energy sources, leading to improved efficiency, reliability, and sustainability of the power grid. We have used our scheme for load-balancing problem in demand side management.

In Zhou, Li, Chan, Cao, Kuang, Liu and Wang (2016), an overview of smart HEMS is presented, where the authors discuss the architecture of HEMS and its functional modules. DSM advocates consumers alter their demand for electricity. Demand Response (DR) progress is in the form of time-based charges or other economic inducements. DR reflects the most reliable solutions for decreasing peak-time demand and flattening the demand curve. It also offers several types of pricing signals including Peak Load Pricing (PLP), RTP, CPP, Time-Of-Use (TOU), Inclined Block Rate (IBR), and Day-Ahead RTP (DA-RTP). Minimizing the EC with scheduling is a challenging task in HEMS. Optimization for appliance scheduling problems is solved in various ways in the literature. Another important problem in Energy Management Systems (EMS) is UC, which is mainly neglected. In Althaher, Mancarella and Mutale (2015), Automated Demand Response (ADR)-based optimization scheduling is proposed for different appliances at the domestic level with the major aim to minimize EC while maximizing UC. Studies expose that most consumers wish to reduce their EC and do not want to compromise on their comfort. A massive amount of electricity is used in residential areas, and its consumption is growing rapidly. According to Evangelisti, Lettieri, Clift and Borello (2015), more than 65% of the produced electricity is wasted. Hence, with the advancement of smart grids, there is a better opportunity to save the maximum produced energy using any of the two mentioned techniques. This paper schedules the load demand for scalable towns consisting of one, ten, thirty, and fifty homes under the CPP and RTP pricing signals. The main contributions of this work are as follows:

- We propose a novel nature-inspired hybrid genetic flower pollination-based optimization and scheduling scheme (GFPA) for smart grid appliances while considering the different OTIs and PRs for appliances.
- The effectiveness of the proposed scheme is evaluated and compared with other state-of-the-art GA and FPA algorithms in terms of total EC, Peak to Average Ratio (PAR), delay time, and load.

- Simulation results show that the proposed scheme find optimal scheduling pattern that simultaneously minimizes EC and PAR while maximizing User Comfort (UC) by assuming that all homes are homogeneous regarding appliances and power consumption patterns.

The remainder of this paper proceeds as follows: Section II highlights the state-of-the-art. In Section III the system model, mathematical formulation, and pricing model are described. Then, the proposed scheme is discussed in Section IV. Section V presents the simulation results and discussions. Finally, Section VI concludes the paper and enlists future work.

2. Related Work

This section discusses the state-of-the-art related to algorithms and smart grid scheduling. Since the 1960s, the optimal power flow problem is a well-defined and the major concern of the optimal power flow is cost minimization. However, it is also concerned with additional constraints of the grid, like phase sensor, angle bound, and voltage. Although these approaches have a similar objective to minimize fuel cost. The optimal power flow distribution is well scrutinized for supporting and operating different topologies Huneault and Galiana (1991). With extension towards decentralization, negotiating agents are not yet comprehensively scrutinized on a per unit basis. The centralization approach is still used and has a long time and dominant impact on renewable energy resources. A power-generating resource greatly impacts benefits if optimization is done from an omniscient and global perspective. This is also true for optimal power flow. With the passage of time, distributed schemes attained more and more importance. Different works proposed decentralized and hierarchical structures. For example, combinatorial optimization, heuristic, and greedy algorithm approach. A solution that cannot be implemented is non-feasible and also worthless. So, constraint handling is an important aspect of the appliance scheduling problem. Modeling these constraints was never simple in past. Small, versatile, operating energy generators, controllable consumers, large power generating plants, complex, and non-linear constraints restrict operations and flexibility, which is offered to the scheduling algorithm for predictive planning. Taking these constraints can convert any solution into a feasible one. Many techniques and algorithms are proposed and implemented in the field of SG.

In Rahim, Javaid, Ahmad, Khan, Khan, Alrajeh and Qasim (2016), authors proposed an energy management system based on the GA. The main contribution is to make the EC lower by reducing the PAR. Therefore, the EC and PAR are effectively low in the proposed scheme. However, they did not consider the UC. In Zhu, Tang, Lambotharan, Chin and Fan (2012), authors proposed an effective LP-based DSM model. The proposed model is used to minimize the utilization of power in day timings and this model efficiently deals with the distribution of demand between the min-peak hours and max-peak hours. The paper Balouch, Abrar, Abdul Muqeet, Shahzad, Jamil, Hamdi, Malik and Hamam (2022) proposes a novel approach for scheduling flexible loads in smart grids using reinforcement learning (RL) techniques. The RL algorithm is designed to learn the optimal scheduling policies for each flexible load in the grid based on the current state of the grid, including the availability of renewable energy sources and the current demand for energy. In Samadi, Wong and Schober (2015), the authors worked on categorizing load into three types: non-interruptible, fixed, and interruptible. In Abushnaf, Rassau and Górnisiewicz (2016), authors proposed a Predictive Demand Side Management (PDMS) model. Similarly, in paper Erdinc (2014), authors worked on a Non-dominated Sorting Genetic Algorithm (NSGA) to solve the problem of multi-objective optimization in the DSM.

Authors in Althaher et al. (2015) worked on the HEMS and optimize the operational time of appliances. The major concern is to reduce the computation cost and reduce the operational time of appliances. Similarly, in Bharathi, Rekha and Vijayakumar (2017), the authors also deal with cost reduction, pollution emission, and uncertainty problems in different types of energy sources. In DSM, the consumers reduce the EC and PAR by scheduling the home appliances from higher peak slots to lower peak slots or by fitting in the Renewable Energy Sources (RES). The DR and load management are the main functionalities that are emphasized in Zhou et al. (2016). In Rastegar, Fotuhi-Firuzabad and Zareipour (2016), authors proposed a load-balancing technique for residential, commercial, and industrial areas. They also compared the load consumption patterns with the GA-DSM and without GA. The result of their paper shows that the proposed model successfully obtains the desired objectives. However, they did not consider the PAR and UC. In Adika and Wang (2014), authors worked on appliance scheduling in a targeted residential area. Their major objectives are to reduce the PAR and cost. However, they did not consider the initial and maintenance cost.

In Manzoor, Javaid, Ullah, Abdul, Almogren and Alamri (2017), an efficient GA-based scheme is introduced to minimize the maintenance cost and PAR. However, the limitation of the work includes the large appliance delay and not considering the UC. A Queuing-based Energy Consumption (QEC) is used to monitor the different smart homes in SG Liu, Yuen, Yu, Zhang and Xie (2015). In Chen, Wang, Hodge, Zhang, Li, Shafie-Khah and Catalão (2017), authors overcome the power grid challenges. Their major contribution is to reduce peak formation. Moreover, in Rastegar and Fotuhi-Firuzabad (2014), authors worked on state of the art EMC for HEMS to reduce the peak formation. They also focused on electricity cost reduction and reduced the UC level with an acceptable limit. For this purpose, the authors used GA algorithms and Linear Programming. However, they did not consider the PAR. In Yousefi-khangah, Ghassemzadeh, Hosseini and Mohammadi-Ivatloo (2017), authors worked on a couple of different systems to optimize the increased price of short term arranging of a distributed system with the combination of Demand Grids (DGs). In

Ogwumike, Short and Denai (2015), authors proposed a manageable load model that is equally useful for direct and local control from a regular system of distributed energy resources optimization. Moreover, a load control algorithm is proposed to deal with the DSM Ye, Qian and Hu (2015). They worked on load scheduling and reduced the energy expense for the users.

In Nguyen et al. (2014), authors proposed a centralized optimization technique that helps minimize PAR and energy consumption. In Nigdeli, Bekdas and Yang (2016), authors worked on the tuning of Mass Damper (MD) using FPA. An MD is mostly used in a systematic building structure to reduce vibrations. It is a meta heuristic technique that can work even in a critical situation when the other mathematical equations are failed to perform. Moreover, In Aslam, Iqbal, Javaid, Khan, Aurangzeb and Haider (2017), authors used GA to schedule several homes. They used a hybrid GA version with the Cuckoo Search Algorithm (CSA). In Jayabarathi, Raghunathan, Adarsh and Suganthan (2016), authors used different techniques for a residential area. For multiple homes, smart meters are playing the role of a bridge for two-way communication between consumers and utility. Du *et al.* in Du, Jiang, Li, Counsell and Smith (2016), implement the Pareto technique for Multi-Objective Demand Side Scheduling (MODSS). The relationship between operational safety and the other two objectives, EC and delay, can be achieved by using the Pareto-optimal front. Some papers are compared in Table 1. This comparison is made on the basis of techniques, pricing schemes, objectives of each paper, achievements, and limitations.

Some other recent studies in this area include Ali, Tariq, Iqbal, Feng, Raza, Siddiqi and Bashir (2020); Sun, Cai, Guo, Ma, Zhang, Wang, Liu, Kang and Yang (2022); Ponnusamy, Kasinathan, Madurai Elavarasan, Ramanathan, Anandan, Subramaniam, Ghosh and Hossain (2021); Yahaya, Javaid, Alzahrani, Rehman, Ullah, Shahid and Shafiq (2020), which reviews recent advances in energy management techniques for smart grids, including demand response, energy storage, and renewable energy integration. Authors in Massaoudi, Abu-Rub, Refaat, Chihi and Oueslati (2023) provides a comprehensive overview of demand response programs in smart grids and their impact on grid stability and energy efficiency. Moreover, SG relies heavily on power electronics and electrical devices, which generate heat during operation. Efficient cooling and thermal management are essential for the reliable and safe operation of these devices Shahzad, Imran, Tahir, Khan, Akgül, Abdullaev, Park, Zahran and Yahia (2023). Communication between various components such as sensors, meters, and control devices is critical for efficient and effective operation in smart grid systems. Antennas play an essential role in enabling wireless communication between these components. Therefore, developing a high-performance planar antenna is important to smart grid applications Alibakhshikenari, Virdee, See, Shukla, Moghaddam, Zaman, Shafqaat, Akinsolu, Liu, Yang et al. (2022). The metamaterial-inspired T-matching network employed in the proposed antenna design can improve the impedance bandwidth of the antenna, leading to better transmission and reception capabilities Alibakhshikenari, Virdee, Shukla, Wang, Azpilicueta, Naser-Moghadasi, See, Elfergani, Zebiri, Abd-Alhameed et al. (2021b). This enhanced performance can improve wireless communication's reliability, stability, and efficiency in smart grid systems. As such, this paper's research findings could provide valuable insights into developing improved wireless communication technologies for smart grids Alibakhshikenari, Virdee, Althuwayb, Xu, See, Khan, Park, Falcone and Limiti (2021a).

An immense amount of energy is consumed by residential areas and this consumption is rising quickly. This massive amount of energy consumption is caused by different issues discussed above. During the distribution of energy, combined primary and secondary distribution, the loss in the frequency ratio is up to 70%. While the remaining 30% of energy is lost in transmission lines, Reddy, Reddy and Manohar (2016) is also called transmission loss. Nevertheless, the most common objectives of electricity management in HEMS are UC maximization, EC minimization, and PAR reduction. In this paper, to address the above mentioned issues, an efficient hybrid solution is proposed for HEMS. During hybridization, the whole FPA is used for the best results. After getting the solution of FPA, crossover and mutation from GA are applied for further improvement in the proposed solution. The proposed GFPA outperforms both of these scheduling techniques in terms of minimizing the PAR, maximizing UC, and, price minimization. This work compares the FPA, and GA with unscheduled EC and is considered a scalable town. Homes contain different appliances with TOU, OTI, and PR. Moreover, for each home of a scalable town, appliances are categorized into three categories: fixed appliances, non-interruptible appliances, and interruptible appliances presented in Table II and Table III Erdinc (2014).

3. System Model

This section discusses the system model, mathematical formulation, and pricing schemes. Moreover, the details about the categorization of appliances are also a part of this section. Electricity generation to consumption has basically four stages: i) generation, ii) distribution, iii) transmission, and iv) consumption. Further, electricity consumption can be divided into three different sectors: i) corporate, ii) residential, and ii) industrial. Many researchers have suggested different optimization techniques for the DSM. The proposed GFPA is introduced for reducing the EC with the scheduling of appliances. The GFPA is a hybrid technique that comprises the combination of the GA and the FPA. These techniques act as a catalyst in the process of finding a suitable and optimal solution amongst all possible solutions with limited resources. Their recommended solution might not be the best, but it will always assure you a solution that might be close to the best one.

Categorization of Appliances: Appliances are categorized into three different classes given below:

Table 1
Summary of state-of-the-art.

Techniques	**Pricing Schemes**	**Objectives**	**Achievements**	**Limitations**
GA Rahim et al. (2016)	RTP	Minimize the PAR and cost	Minimize the PAR	ignore the UC and unable to reduce the cost
LP Zhu et al. (2012)	TOU	Reduction in power utilization	Minimization in PAR and cost	Did not consider the UC
FDM and NSGA Samadi et al. (2015)	RTP	High energy for residential applications	Increase UC and efficient integration of RES	EC increases and ignore the maintenance cost
Small HEM Abushnaf et al. (2016)	TOU	Reduce the EC	Minimization in EC	Ignore the UC
DR and MOPSO program Bharathi et al. (2017)	DA-RTP and TOU	Pollution emissions and operational costs	Minimization in cost and emissions with RES	RES installation, maintenance cost and UC ignored
Deliberate two different systems to explore the incremental price Yousefi-khangah et al. (2017)	-	Multi-objective optimization agenda	Multi-objective optimization framework	Work for short term scheduling
Game theoretical approach Nguyen, Song and Han (2014)	DA-RTP	Less PAR and EC	Lessen PAR and EC	High communication overhead and fail to protect customer privacy
Manageable load modelling Ogwumike et al. (2015)	RTP	GSO for multiple object and constrains	New problem of Shift able load proposed	PAR and UC ignored
Algorithm for load control Ye et al. (2015)	-	Less load and power scheduling	Schedule different type of appliances	UC and PAR not considered
Queuing-based energy consumption monitoring for smart homes Manzoor et al. (2017)	-	Residential SG networks	Delay reduction and cost minimization	didn't consider PAR and RES
Efficient GA Based DSM Adika and Wang (2014)	DA-RTP and TOU	Covered commercial, residential and industrial areas	PAR reduce and cost minimize	Larger appliance delay and UC ignored
Delay and energy consumption analysis Liu et al. (2015)	RTP	Low duty cycle data rate, and energy consumption	Minimum energy consumption	Cannot consider PAR and delay
Power grid challenges Chen et al. (2017)	RTP	Residential energy management system for avoiding peak formations	PAR reduced and less cost	UC ignored
Smart charging and appliance scheduling Rastegar et al. (2016)	CPP	Residential Area	Cost Minimization, PAR reduction	Lack of initial installation and maintenance cost of batteries and UC
LP, GA, and Teaching Learning Based Optimization (TLBO) Rastegar and Fotuhi-Firuzabad (2014)	-	Cost minimization and UC maximization	Minimize electricity consumption cost	Do not bother PAR
Heuristic algorithms and Mixed Integer Linear Programming (MILP) Agnetis, De Pascale, Detti and Vicino (2013)	-	Optimization of load scheduling for energy consumption	Load balanced	Cost minimization is not considered
Multi-Input Multi-Output Model Derakhshan, Shayanfar and Kazemi (2016)	DA-forecasting	DA-EC and load forecasting price and load signal forecast	Price and load signal forecast	Real time forecasting is not considered
ILP and gray wolf optimization Pradhan, Roy and Pal (2016)	-	Applied to economic load dispatch problems	Dispatch load in off peak hours	Solved economic load dispatch problem

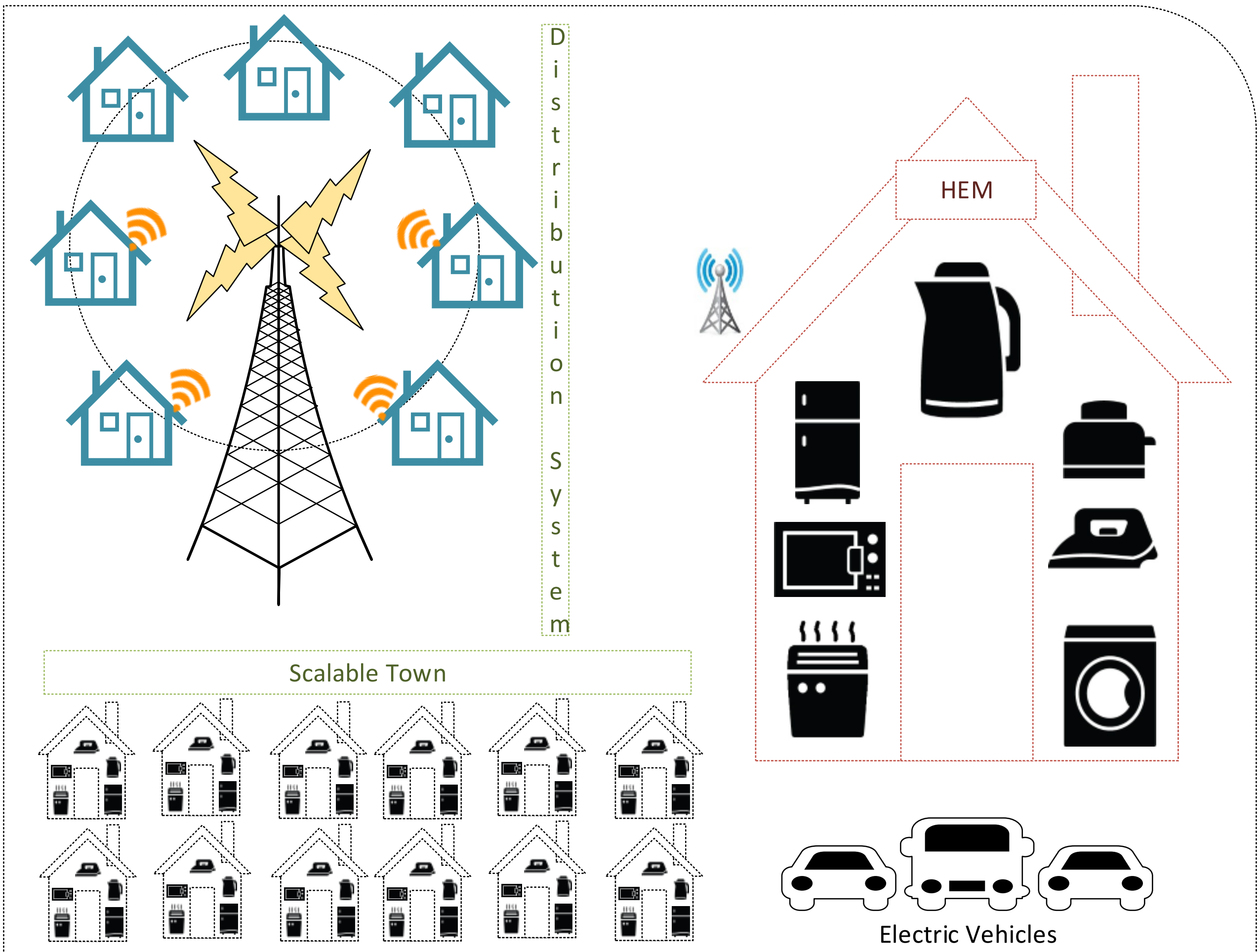


Figure 1: Proposed system model

- Fixed Appliances
- Non interruptible Appliances
- Interruptible Appliances

Fixed Appliances: Fixed appliances are those appliances that cannot be shifted from allocated time slots. D_{fa} represents the set of fixed appliances.
Non interruptible Appliances: These appliances can be shifted or moved from one epoch of time to the others. Nevertheless, once this category of appliances has gained the status of ON, these cannot be shifted or interrupted until their work is completed. Whereas D_{nsa} represents the set of this appliance category.
Interruptible Appliances: These appliances are also called shiftable appliances, as this type of appliance can be interrupted or moved at any time. D_{sa} is a set containing this type of appliance. D is a set of appliances containing all sub-categories of appliances (fixed, interruptible, non-interruptible). Further, Eq. (1) elaborates on this given statement.

$$D_{aps} = D_{fia} + D_{nsa} + D_{sa} \tag{1}$$

Where P is a set that contains PR of all appliances, such as P_{sa} is the PR of shiftable appliances, P_{nsa} is the set that contains PR of non-interruptible appliances and PR against the set of fixed appliances is denoted by P_{fa} Eq. (2).

$$P_{aps} = P_{fia} + P_{nsa} + P_{sa} \tag{2}$$

Mainly the focus is on achieving the objectives of minimum Cost Eq. (3), minimum PAR Eq. (4), and maximizing the UC Eq. (5). In order to achieve all these objectives, Load before and after scheduling is not compromised.

$$Obj_1 = min(Cost) \tag{3}$$

$$Obj_2 = min(PAR) \tag{4}$$

$$Obj_3 = max(UC) \tag{5}$$

PAR for unscheduled and scheduled schemes can be calculated by the ratio of the maximum load to the average load of each hour. Eq. (6) shows the calculation of the PAR as follows:

$$PAR = \frac{max(Load)}{avg(Load)} \tag{6}$$

Eq. (8), (9), (10), and 11) are used to calculate the total load consumption during 24, 48, 96, and 1440 time slots of a day receptively. Where D_t^{aps} represents the number of appliances and P_t^{aps} is the PR of each appliance. A load of each appliance can be calculated using the Eq. (7) given below:

$$Load = P \times app \tag{7}$$

$$T_{load} = \sum_{t=1}^{24} D_t^{aps} \times P_t^{aps} \tag{8}$$

$$T_{load} = \sum_{t=1}^{48} D_t^{aps} \times P_t^{aps} \tag{9}$$

$$T_{load} = \sum_{t=1}^{96} D_t^{aps} \times P_t^{aps} \tag{10}$$

$$T_{load} = \sum_{t=1}^{1440} D_t^{aps} \times P_t^{aps} \tag{11}$$

Total cost is calculated by the Eq. (12), (13), (14), and (15), where EP_t^{aps} is the electricity price signal and t is current time slot.

$$T_{cost} = \sum_{t=1}^{24} EP_t^{aps} \times P_t^{aps} \tag{12}$$

$$T_{cost} = \sum_{t=1}^{48} EP_t^{aps} \times P_t^{aps} \tag{13}$$

$$T_{cost} = \sum_{t=1}^{96} EP_t^{aps} \times P_t^{aps} \tag{14}$$

$$T_{cost} = \sum_{t=1}^{1440} EP_t^{aps} \times P_t^{aps} \tag{15}$$

$$D_{aps}^{status} = \begin{cases} 1, & the\ status\ of\ an\ appliance\ is\ ON \\ 0, & the\ status\ of\ an\ appliance\ is\ OFF \end{cases} \tag{16}$$

Single Home: In this scenario, the category of fixed appliances contains (Refrigerator, Telephone, and Television (TV)); the non-interruptible appliances category consists of (Lighting and Air Conditioner (AC)). At last, the category for interruptible or shiftable appliances contains (Desktop computer, Iron, Hair straightener, Printer, Dishwasher, Microwave, Oven, Toaster, Hair dryer, other fixed, Cooker hood, Washing machine and Kettle). In this particular, cost minimization for one home and multiple homes and a scalable town is considered. Different OTI for each type of appliance is also considered. Whereas the OTI and Length of Operation Time (LOT) vary from one problem to other. Nevertheless, the PR of each appliance is represented in TABLE 2.

Multiple Homes: By taking the scenarios of multiple homes, different PRs for each appliance are applied. Each home has the same appliance and may have different PRs for the same type of appliance. So, for this purpose, different PR for each appliance is taken into consideration. Each time scheduler takes one PR from predefined PRs. Predefined PRs against different appliances (Fixed, Non-interruptible and Interruptible) are given in Table 3.

3.1. Pricing Scheme

There are two types of pricing schemes that are implemented in this work. First, scheduling is done by using CPP and then by using an RTP signal. Details about CPP and RTP are given as below:

CPP: The CPP scheme applies at different time intervals, where very high peak prices are offered. It applies only when the demand for electricity is maximum. So, during these peak hours utility increases the price according to the user‘s demand for the load. Fig. 2 shows the CPP signal for each hour of the day. CPP is assessed for certain hours on event days (limited to 10-15 per year). Prices during these event days can be 3-10 times higher than the regular prices.

RTP: The RTP scheme provides information about the EC at any time. It changes from one hour to another and allows consumers to adjust their electricity usage. Fig. 3 shows the RTP signal during each hour of the day.

4. Proposed Methodology

In this section, we discuss the proposed scheme, in which to assess the DSM benefits, a modeling structure is used. The cost and the load are optimized by proper scheduling of each appliance by using the proposed GFPA scheduling technique. The FPA and GA are the parents of GFPA. These scheduling techniques are explained as follows:

Table 2
Categorization of appliances for a single home by taking one PR.

Type	Appliances	PR (kWh)	LOT
Fixed Appliances	Refrigerator	1.666	24 h
	TV	0.3	6 h 45 min
	Telephone	0.005	24 h
Non-Interruptible Appliances	Air Conditioner	1.14	7 h 15 min
	Lighting	0.1	6 h 15 min
Interruptible appliances	Desktop Computer	0.15	2 h 15 min
	Iron	2.40	30 min
	Hair Straightener	0.055	0 h
	Printer	0.011	0 h
	Dishwasher	1.32	30 min
	Microwave	1.20	0 min
	Oven	1.14	30 min
	Toaster	0.80	15 min
	Hair Dryer	1.80	30 min
	Other Fixed	0.05	24 h
	Cooker Hood	0.225	30 min
	Washing Machine	1.40	1 h
	Kettle	2.0	30 min

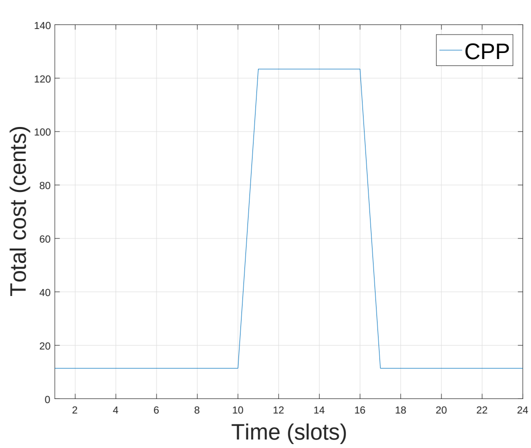


Figure 2: CPP signal

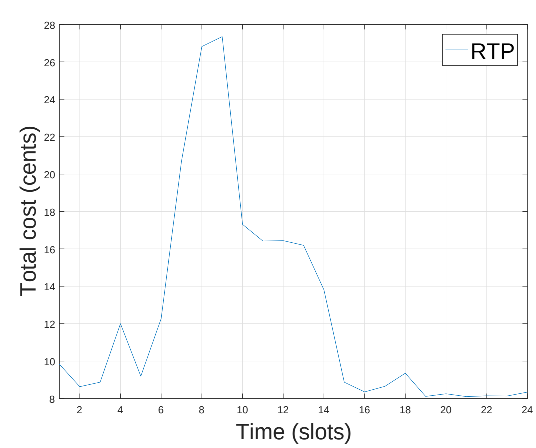


Figure 3: RTP signal

Table 3
Categorization of appliances for multiple homes by taking different PR.

Type	Appliances	PR (kWh)	PR (kWh)	PR (kWh)	LOT
Fixed Appliances	Refrigerator	1.666	1.75	2.0	24 h
	TV	0.10	0.3	0.15	6 h 45 min
	Telephone	0.083	0.005	0.09	24 h
Non-Interruptible Appliances	Air Conditioner	1.80	1.90	1.60	7 h 15 min
	Lighting	1.14	1.18	1.10	6 h 15 min
Interruptible appliances	Printer	0.011	0.016	0.020	0 h
	Hair Straightener	0.055	0.065	0.045	0 h
	Desktop Computer	0.15	0.13	0.17	2 h 15 min
	Oven	1.14	1.16	1.18	30 min
	Cooker Hood	0.225	0.200	0.220	30 min
	Iron	2.40	2.60	2.0	30 min
	Microwave	1.20	1.25	1.28	0 min
	Toaster	0.80	0.6	1.0	15 min
	Kettle	2.0	2.3	2.1	30 min
	Other Fixed	0.05	0.08	0.10	24 h
	Washing Machine	1.40	1.60	1.0	1 h
	Dishwasher	0.05	2.0	2.2	30 min
	Hair Dryer	1.32	1.36	1.4	30 min

GA: The GA is a nature-inspired algorithm based on Darwin's theory. In the middle 70s, John Holland invented this algorithm. This algorithm can be used for problems having a stochastic nature; which means that when changes are adopted. GA can also be defined as a search-based optimization technique that leads towards the optimal solution and works based on a genetic population like chromosomes Whitley (1994). Here, the meaning of this word optimization is "moving towards the best solution". However, this definition of optimization can vary from one type of problem to another. In the scenario of this paper, this optimization technique is used for PAR and cost reduction in the demand-side management of smart grids. Here, GA applies to a set of appliances to find the best solution for this population of appliances. And, also the process of elitism can be observed in this scenario where all other populations move towards the fittest or best solution (Algorithm 1). For further details, the paper Agnetis et al. (2013) can be read, where Agnetis *et al.* uses a heuristic approach for household energy consumption, timeliness, and climate comfort level.

GA Steps: We have multiple ways to choose the parents chromosomes, for them, any one of the following given procedures can be chosen.

- Fittest
- Roulette wheel
- Truncation selection
- Tournament
- Pick the best, by itself.

And, we chose the last one.
Crossover: There are mainly three types of crossover as following:

- Uniform crossover
- Two-point crossover
- One-point crossover

And here, we chose the two-point crossover.

Mutation: We have a choice of choosing one type of mutation process from its multiple. The following are the types of mutation:

- Inversion
- Deletion
- Insertion
- Substitution

FPA: Xin-She Yang developed FPA in 2012 Yang (2012), which is known as a nature-inspired heuristic algorithm. And, the idea of this algorithm has been taken from the process of pollination which takes place in flowers. We

Algorithm 1 GA

```
Data initialization
Set limits: upper and lower
for All appliances which belong to set A do
    for Generating population from i=1 to Maximum Pop Size do
        for Generating appliances from j=1 to Maximum App Size do
            Set of initial population generation
            Evaluation of each population's individual fitness
            while Generation < maximum_generation do
                Choose any two parents or chromosomes according to the given criterion
                for to generate randomness in the population of appliances do
                    Initially: crossover
                    Finally: mutation
                end for
                Got the best solution or ending criteria?
                Apply elitism
            end while
        end for
    end for
end for
Return: optimal values/solution
end
```

Algorithm 2 FPA

```
Data initialization
for all appliances belonging to set A
for Generating population from k=1 to Maximum Pop Size do
    Generating random population (flowers/appliances)
    for Generating appliances from m=1 to Maximum App Size do
        if Rand() > switch probability then
            For updation: use levy flight formula
        else
            Get population randomly
            Limits check
        end if
        Again generate random population
        For each individual: calculate fitness
    end for
    Get the local best
    Compare the current solution with the previous one
    if Current solution has less cost than previous one then
        Update solution
    end if
    Global best solution updated
end for
Return final best solution
end
```

know that the ultimate purpose of flowers is reproduction. So in our appliance scheduling problem, we choose this pollination algorithm to give an optimal solution (details of this process in Algorithms 2). Nonetheless, the author claims in his paper that this proposed FPA performs better than the other heuristic algorithms, i.e., GA and Partial Swarm Optimization (PSO). Further, FPA is one of the most recently developed algorithms. Its ultimate objectives are given as below:

- Optimal reproduction of the plants
- Survival of the fittest

There are two types of pollination that take place in FPA, i.e., biotic and a-biotic. About 10% of the plants belong to the category of a-biotic, while the other 90% of plants belong to the category of biotic. In global pollination (also called biotic), pollinators like bats, birds, and animals are used as a carrier of the pollens. In a-biotic (also known as local pollination), the process of water diffusion and wind-blown caused pollination. Algorithm 1 elaborates on the steps which are being used.

FPA Steps:

- Levy distribution formula for Global pollination
- Self or local pollination
- Use the reproduction process for the consistency of flowers in view of the likeness of two flowers used in pollination.
- For the selection of global and local pollination, control switching probability is used.

4.1. Proposed GFPA Algorithm

The GFPA is our proposed algorithm and is a hybrid or merger of FPA and GA. For hybridization, we take two steps: 1) crossover and 2) mutation from GA and insert into FPA (Algorithm 3). Basically, crossover and mutation are powerful features of GA. In GFPA, FPA is completely used to provide its best results. After finding the best results of FPA, crossover, and mutation are applied for more suitable results. A Hybrid of GA with FPA takes more time for convergence; however, it provides better results than parents. More details and comparisons of these scheduling schemes are discussed in section 5.

4.1.1. Findings by Hybridization

The proposed nature-inspired hybrid GFPA has several advantages:

Robustness: GFPA is robust and can handle different types of optimization problems, including both continuous and discrete optimization problems.

Global optimization: GFPA can effectively search the entire search space to find the global optimum solution. This

Algorithm 3 Proposed GFPA Algorithm

```
Data initialization
For all appliances belonging to set A
for Generating population from k=1 to MaximumPopSize do
    Generating random population (flowers/appliances)
    for Generating appliances from m=1 to MaximumAppSize do
        if Rand() > switch probability then
            For updation: use levy-flight formula
        else
            Get population randomly
            Limits check
        end if
        Again generate population randomly
        For each individual: calculate fitness
    end for
    Get the local best
    Compare the current solution with the previous one
    if Current solution has less cost than previous one then
        Update solution
    end if
    Update global best solution
    for Get population randomness do
        Apply crossover process
        Then mutation process
    end for
end for
Return best solution
end
```

is achieved by incorporating the exploration and exploitation capabilities of both GA and FPA.

Fast convergence: GFPA has a fast convergence rate due to the use of the flower pollination algorithm, which uses a random search strategy to quickly explore the search space.

Flexibility: GFPA is a flexible algorithm that can be easily adapted to different optimization problems by changing the optimization function and the parameters.

Scalability: GFPA can be applied to large-scale optimization problems due to its ability to parallelize the fitness evaluation process.

Overall, the GFPA algorithm is a promising optimization technique that combines the strengths of both GA and FPA, making it an effective and efficient optimization tool for solving complex optimization problems, e.g., scheduling in the current scenario.

5. Simulation Results and Discussions

In this section, details of the simulation results and discussions are presented. We perform simulations to show this work's productiveness and optimal scheduling for smart homes. The GA, FPA, and proposed GFPA are implemented for applying scheduling on smart homes. In the scenario of this paper, time slots are composed of 24, 48, 96, and 1440, starting from 12 pm to 12 pm. The simulation results presented in our paper cover different time slots ranging from 24 to 1440, which correspond to hourly and daily time scales. The reason for considering such a wide range of time slots is to evaluate the proposed algorithm's performance under various operating conditions and to demonstrate its scalability for different system sizes. Since the simulation results show that the proposed GFPA algorithm performs consistently well across different time scales, achieving significant cost reduction, PAR improvement, and UC enhancement. By considering different time slots, we have also shown that the algorithm can handle different load profiles and demand patterns, making it applicable to a wide range of scenarios. Simulation results are shown in Fig. 4 and Fig. 5.

RTP and CPP Signal for Single Home: Fig. 6 and Fig. 7 present the cost comparison. For performance evaluation, simulations are performed against different OTIs (e.g., 15, 30, and 60 minutes). Cost is calculated in terms of cents. For reduction in EC, appliances are scheduled. The basic goal of scheduling is to shift the load from high peak slots to low peak slots to reduce the electricity bill. Energy consumption schedules for implemented schemes are depicted in Fig. 4 and Fig. 5. The comparison of all applied schemes is shown in Table 4 and Table 5. Different PRs for each appliance are applied and instead of showing load in stairs for multiple homes. Only the total load for both schemes (CPP and RTP) is shown. However, the stair graph of load at each time slot can be shown by applying different OTIs. Fig. 4 and Fig. 5 show the load at each time slot by using CPP and RTP schemes.

The FPA, The GA, and the proposed GFPA are applied on different OTIs, (i.e., 15, 30, and 60 minutes). From the results, we can analyze that the PAR has a direct relation with the price As a greater PAR has a higher cost and vice versa. This can also be seen from Fig. 6 that the proposed GFPA, FPA, and GA in every OTI have lesser PAR compared to unscheduled. So we can conclude from these results that the proposed GFPA performs better than the FPA and the GA in terms of PAR. This is because our proposed technique shuffled interruptable or shiftable appliances from one slot to other and turned them on during a beneficial time in order to avoid generating higher peaks. The further details for PAR can easily be understood from Fig. 6 and Fig. 7

RTP and CPP Signal for Multiple Homes: Scheduling is done for multiple homes by taking real-time scenarios. Each home has the same appliance with different PRs. So, random PR for each appliance is chosen, in order to make this scenario real. The difference between cost, PAR, and average waiting time for 10, 30 and 50 homes is shown in Fig. 8, by applying the CPP signal. The comparison of all applied schemes for multiple homes against 60 minutes OTI is shown in Table 6 and Table 7. The values of PAR, cost and delay are changed in every iteration, as different PRs are used for the same appliance of every home. Appliances are scheduled according to the RTP scheme, the results are shown in Fig. 9.

Table 4
Comparison of different OTIs against CPP signal for a single home

Technique	OTI 60 minutes			OTI 30 minutes			OTI 15 minutes			OTI 1 minutes		
	PAR	Cost	Delay	PAR	Cost	Delay	PAR	Cost	Delay	PAR	Cost	Delay
Unsch.	5.41	3093.8	-	4.77	2530.30	-	4.65	2263.10	-	3.72	3961.10	-
GA	2.01	1135.60	11.43	2.02	1044.70	11.49	1.81	1066.68	11.48	1.54	2138.60	10.11
FPA	3.25	720.90	6.22	2.91	659.90	7.87	3.21	651.70	6.03	2.45	1217.90	5.32
GFPA	3.04	711.10	8.20	2.82	653.90	8.06	2.73	644.70	8.81	2.22	1204.90	5.09

Table 5
Comparison of different OTIs against RTP signal for a single home

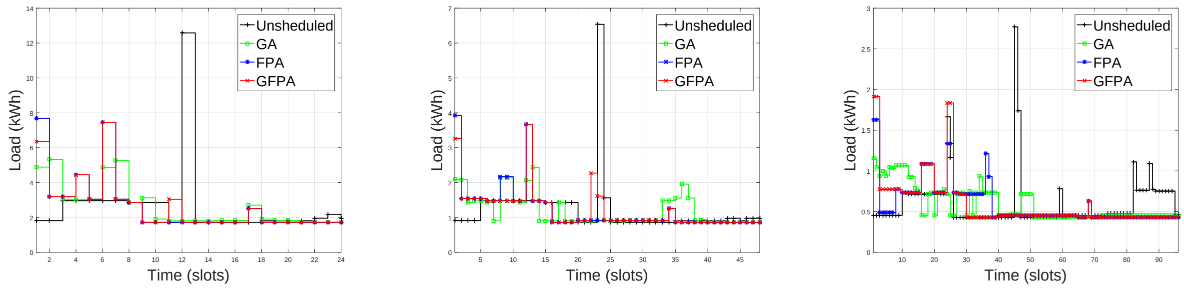
Technique	OTI 60 minutes			OTI 30 minutes			OTI 15 minutes			OTI 1 minutes		
	PAR	Cost	Delay	PAR	Cost	Delay	PAR	Cost	Delay	PAR	Cost	Delay
Unsch.	4.75	429.18	-	4.69	796.57	-	5.20	869.02	-	3.70	1442.90	-
GA	2.02	341.52	11.22	2.01	695.71	6.66	1.80	745.84	7.67	1.63	1343.20	10.31
FPA	3.01	241.37	6.22	3.25	476.79	5.22	3.21	529.62	4.90	2.52	1337.60	5.33
GFPA	2.81	230.37	8.2	3.04	466.79	5.31	2.73	515.62	7.41	2.21	1329.60	5.09

1-minute OTI for Single Home: One-minute OTI is applied over a single home. There are 1440 time slots for each appliance to be turned on. Any appliance can be turned on during a suitable time slot, assigned by the scheduling schemes. However, before scheduling these slots are user-dependent instead of the proposed scheme. Results for a single home are shown in Fig. 10 and Fig. 11. Total load is shown in (Fig. 10 (d) and Fig. 11 (d)), while load at a specific time slot is shown in (Fig. 14 (a) and Fig. 14 (b)).

1-minute OTI for Multiple Home: One-minute OTI is also applied over multiple homes. According to this OTI, there are 1440 time slots for each appliance. Every appliance can be turned on at any suitable time slot by the scheduling schemes. For multiple homes, scheduling is done for scalable towns comprised of 10, 30, and 50 homes successfully. Our algorithms scheduled all 18 appliances from on-peak to off-peak hours. When the CPP signal is applied, it produced the results as shown in Fig. 12 and against the RTP signal, results are shown in Fig. 13. The total load is shown instead of showing the load for each time slot. This is due to the reason that the load before and after scheduling must be the same. If energy consumption before scheduling is high, then EC will be high and the load is not properly scheduled by the scheduling schemes. By applying the RTP signal and by taking one-minute OTI over a single home, produce the following energy consumption sequence as shown in Fig. 14 (a). Similarly, by applying the CPP signal over a single home and by taking a one-minute OTI, produce the following energy consumption pattern as shown in Fig. 14 (b).

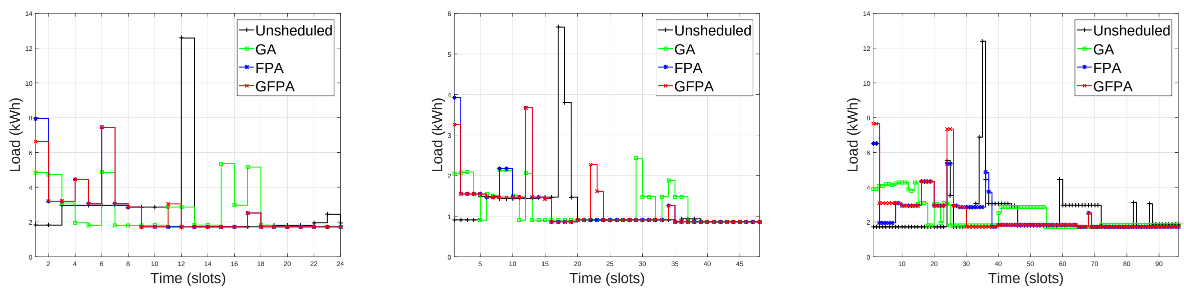
5.1. 60-minute OTI for Single Home

60-minute OTI is applied over a single home and according to this OTI, there are 24 time slots for each appliance to be turned on. Fig. 6 Fig. 7, TABLE 4, and TABLE 5 present the cost, PAR and waiting time comparisons and pictorial presentation, respectively. **60-minute OTI for Multiple Home:** 60-minute OTI is also applied over multiple homes



(a) OTI 60 minutes (b) OTI 30 minutes (c) OTI 15 minutes

Figure 4: Load against different OTIs by applying CPP signal for a single home.

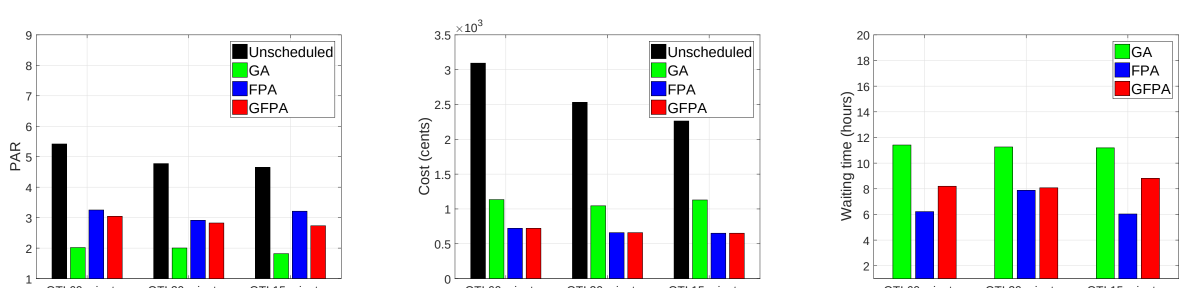


(a) OTI 60 minutes (b) OTI 30 minutes (c) OTI 15 minutes

Figure 5: Load against different OTIs by applying RTP signal for a single home.

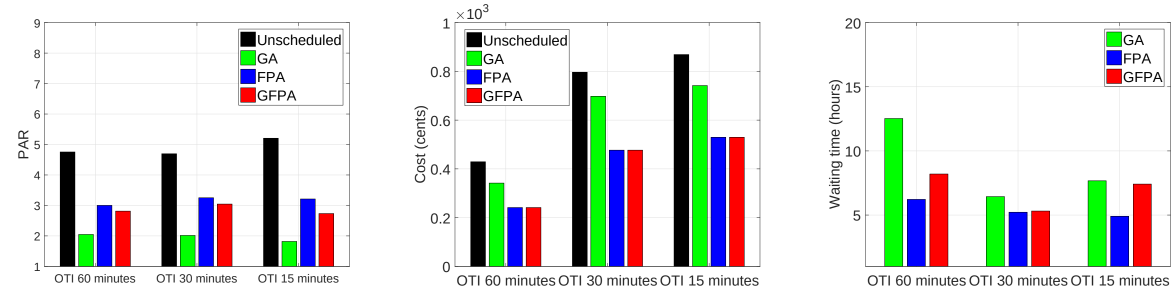
and according to this, there are 24-time slots for each appliance. The scheduling schemes can turn every appliance on at any suitable time slot. Moreover, appliances are scheduled according to the RTP and CPP signals in these schemes. The results are shown in Fig. 9 and Fig. 8, and compared in Table 6 and Table 7.

The choice of the OTI in simulation results is an important consideration in evaluating the effectiveness of the proposed algorithm. The OTI refers to the time interval at which the electricity price changes and it affects the granularity of the scheduling decision. Moreover, the 1-minute OTI represents a more granular level of pricing information, while the 60-minute OTI represents a less frequent update of the pricing information. We evaluated both OTIs to assess the performance of the proposed algorithm under different conditions. Additionally, the focus on using these specific OTIs are due to a couple of reasons. Firstly, the 1-minute OTI provides a more detailed view of the pricing information, which may be useful in determining the optimal scheduling pattern for appliances. Secondly, the 60-minute OTI represents a more practical scenario, as it is more likely to be used in real-world applications. Therefore, evaluating the performance of the proposed algorithm under both conditions provides a comprehensive assessment of its effectiveness.



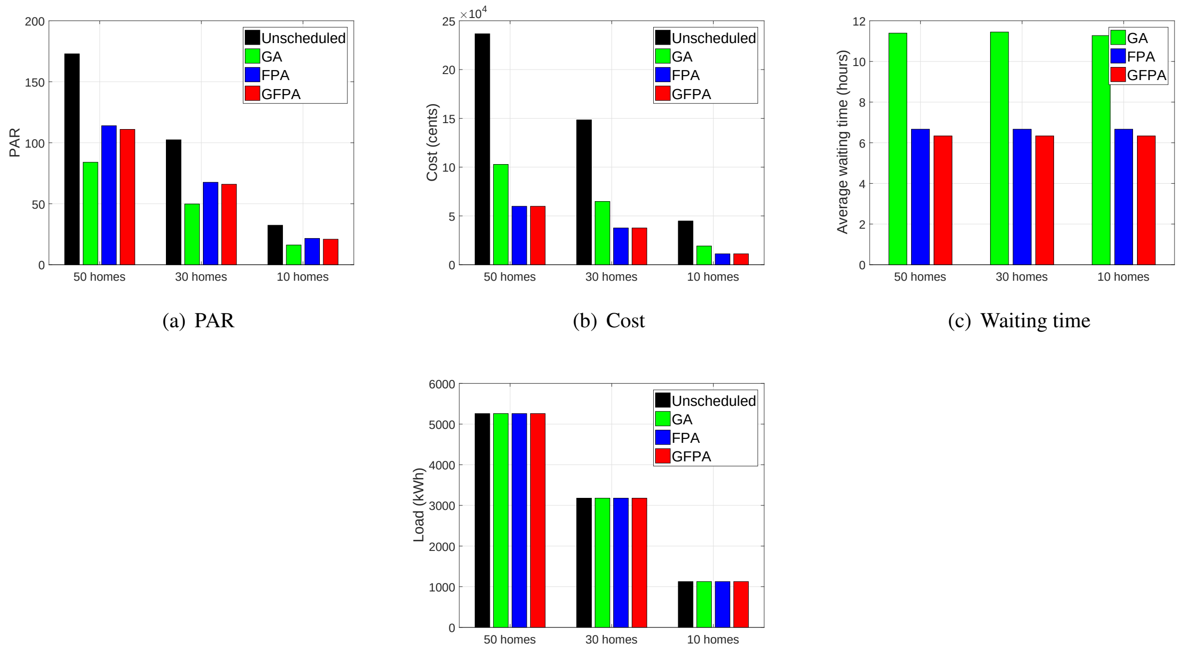
(a) PAR (b) Cost (c) Waiting time

Figure 6: PAR, cost and waiting time against different OTIs by applying CPP signal for a single home.



(a) PAR (b) Cost (c) Waiting time

Figure 7: PAR, cost and waiting time against different OTIs by applying RTP signal for a single home.



(a) PAR (b) Cost (c) Waiting time

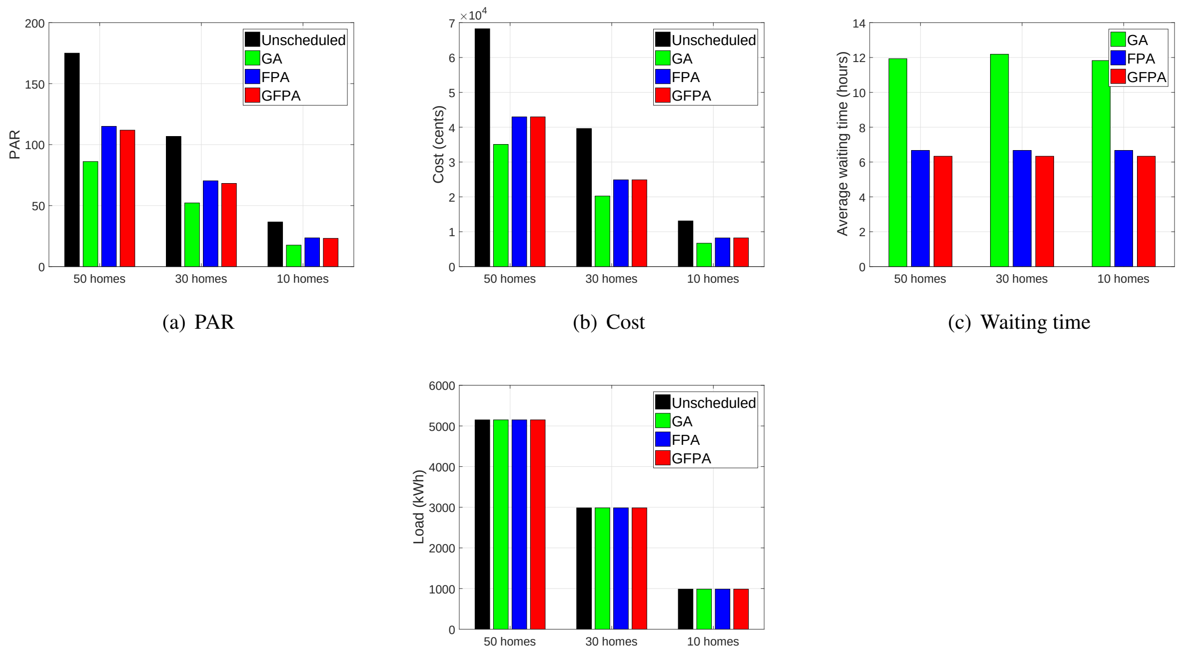
(d) CPP Load

Figure 8: PAR, cost, waiting time and load against 60-minute OTI by applying RTP signal for multiple homes.

5.2. Results Comparison

Different scenarios are discussed in this paper for tackling the issue of the appliance scheduling problem. For example, by taking bigger OTI, waiting time for consumers is increased. Similarly, the remaining time is wasted if some appliance stops before completing its total running time. To avoid this wastage of remaining time- so this paper has used different OTIs. So in this scenario, consumers can choose any OTI as per their comfort for scheduling. Nevertheless, the delay against each given OTIs is shown in Fig. 6 (c) and Fig. 7 (c). If we discuss total cost, GFPA, FPA and GA also performed better. Our proposed optimization schemes reduced the cost slot by slot (1, 15, 30 and 60 minutes) and as a result, the hourly cost is minimized, which means minimization of daily, monthly, and yearly costs and so on. Fig. 6 (b) and Fig. 7 (b). depicts the comparison between the costs of GFPA, FPA, GA and unscheduled costs. Another notable thing is that the cost pattern of our proposed scheduling schemes is quite optimal compared with the unscheduled load. The consumer's comfort has decreased by shifting the load. However, this shift benefits the consumers in terms of cost reduction. As a consumer tolerates changes in the energy consumption pattern and shifts the load, the utility will provide more cost-reduction benefits.

Performance Trade-off: The term trade-off refers towards a compromise between waiting time and cost. As if a consumer sacrifices his comfort, he actually wants less electricity cost. And, If the consumer cannot wait for the suggested time slot of Algorithms and turn on appliances at any time seeing his comfort, then he must have to pay for more electricity consumption. From the above, we can derive that there is an indirect relationship between delaying time and cost. So, consumers can choose any option from



(a) PAR

(b) Cost

(c) Waiting time

(d) Load

Figure 9: PAR, cost, waiting time and load against 60-minute OTI by applying RTP signal for multiple homes.

Table 6
Comparison of different techniques against RTP signal for multiple homes

Technique	50 homes			30 homes			10 homes		
	PAR	Cost	Delay	PAR	Cost	Delay	PAR	Cost	Delay
Unscheduled	171.1974	69502	-	103.5179	41329	-	30.7278	15364	-
GA	84.9811	35745	11.8736	51.1788	21283	11.770	15.9904	7968	11.8202
FPA	113.2659	43798	6.667	68.2608	26031	6.676	20.5924	9734	6.672
GFPA	110.2384	43553	6.33	66.2024	25033	6.333	20.0571	9694	6.343

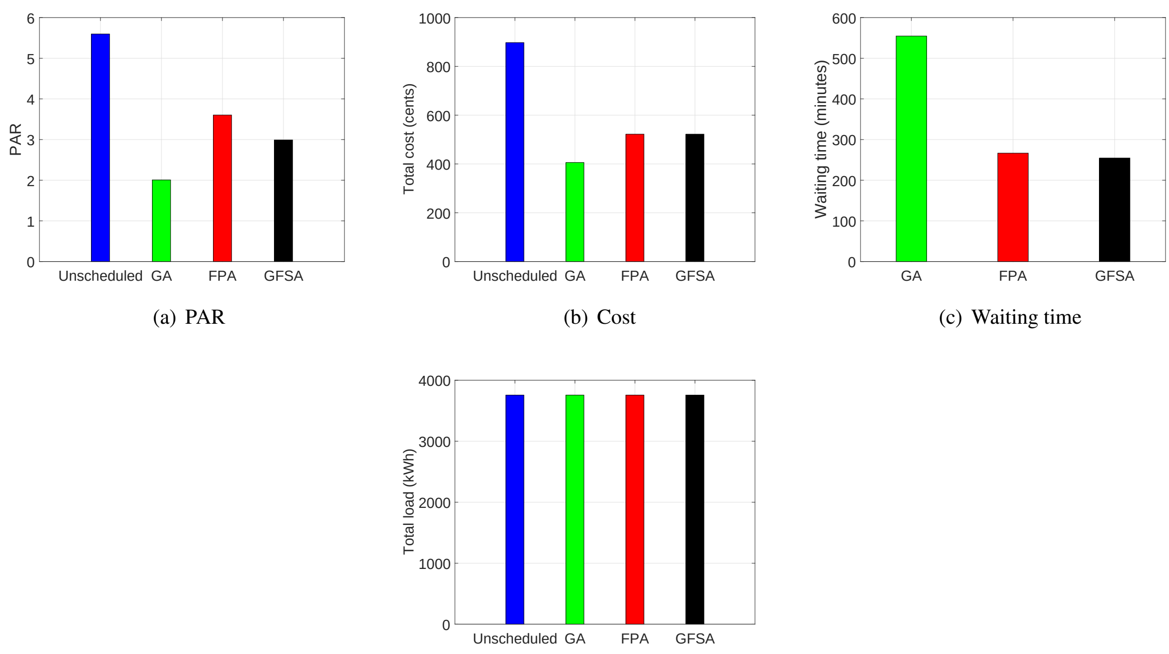
them, either less comfort or less cost. UC and EC of consumers are compared by applying GFPA, FPA and GA with an unscheduled load. It can be observed that our proposed GFPA performs better as costs are minimal in all cases. Conversely, it takes an average amount of PAR and waiting time compared to GA and FPA.

Feasible Regions: A region where all possible solutions lies in accordance with fitness function is known as feasible region. In this paper, we focus on minimizing PAR and EC. However, EC is mainly based price and consumption. We can only shift the load from off-peak to on-peak and can minimize the electricity price. During the calculation of EC, four parameters are considered.

- Maximum price, minimum energy consumption
- Minimum price, maximum energy consumption
- Minimum price, minimum energy consumption
- Maximum price, maximum energy consumption

Table 7
Comparison of different techniques against CPP signal for multiple homes

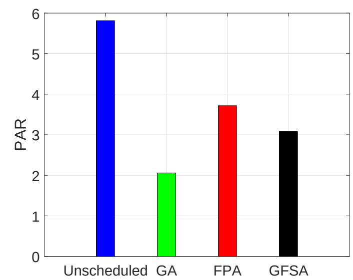
Technique	50 homes			30 homes			10 homes		
	PAR	Cost	Delay	PAR	Cost	Delay	PAR	Cost	Delay
Unscheduled	167.0688	243110	-	64.6343	146230	-	36.3286	44552	-
GA	82.5113	106970	11.255	49.1711	64250	11.290	17.2495	19026	11.266
FPA	111.0917	61800	6.667	66.2927	37180	6.676	23.7356	11186	6.667
GFPA	108.1676	61621	6.333	64.6343	37143	6.333	22.9717	11016	6.343



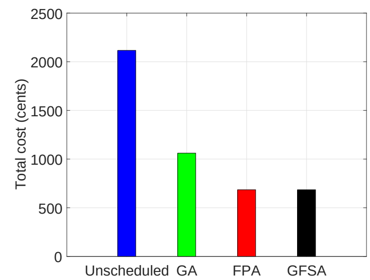
(a) PAR (b) Cost (c) Waiting time (d) Load

Figure 10: PAR, cost, waiting time and load against 1-minute OTI by applying CPP signal for a single home.

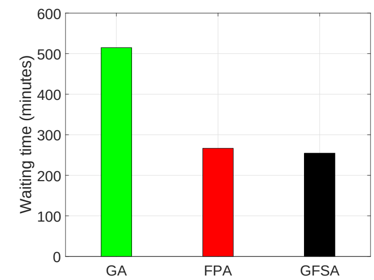
Feasible regions for this work are shown in Fig. 15 and Fig. 16. Thus, based on the above-given constraints, the cost of the scheduled load should be less or equal to the total unscheduled load. This key boundary point can be derived by multiplying the maximum and minimum loads with the maximum and minimum electricity price signals obtained from the utility. The feasible regions in Fig. 15 and Fig. 16 show the relationship between energy load and EC. The possible feasible regions (shaded with cyan color) against different OTIs are being shown by the Pointers (P1,..., P5). For more details, see Fig. 15 and Fig. 16. Feasible regions are taken upon the base of load and price amounts, while both of them can be maximum or minimum. Table 8 shows the different values against maximum EP, minimum EP, maximum load, and minimum load for the CPP scheme. Similarly, Table 9 shows the different values against maximum EP, minimum EP, maximum load, and minimum load for the RTP scheme.



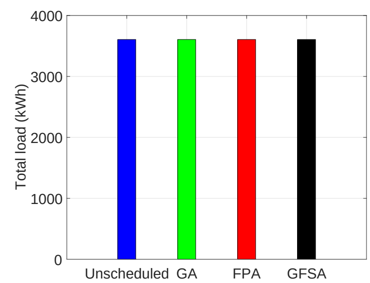
(a) PAR



(b) Cost

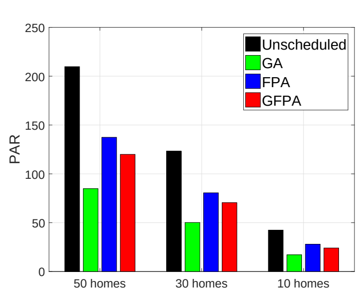


(c) Waiting time

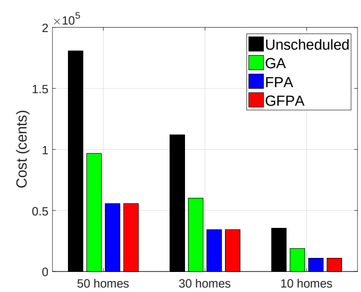


(d) CPP Load

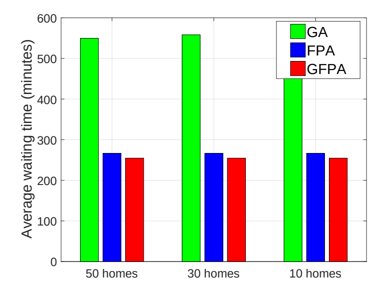
Figure 11: PAR, cost, waiting time and load against 1-minute OTI by applying RTP signal for a single home.



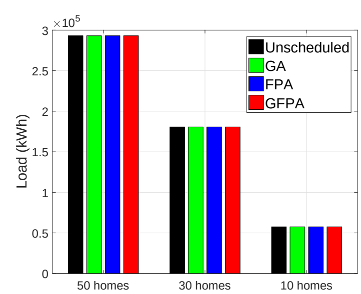
(a) PAR



(b) Cost



(c) Waiting time

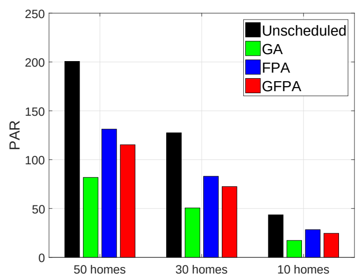


(d) Load

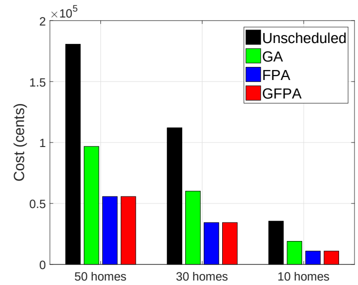
Figure 12: PAR, cost, waiting time and load against 1-minute OTI by applying CPP signal for multiple homes.

6. Conclusion and Future Work

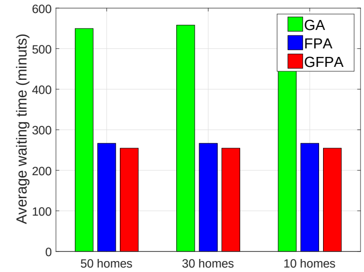
In this paper, we proposed a novel nature-inspired hybrid genetic flower pollination-based optimization and scheduling scheme for DSM in HEMSs. Our scheme achieves the goal of minimizing EC with an affordable delay in appliance scheduling, while simultaneously maximizing UC and minimizing PAR. Simulations were conducted on single and multiple homes, considering different OTIs and variable power consumption patterns. Our proposed scheme outperformed existing approaches, such as the FPA and GA, in terms of PAR, UC, and EC reduction. from simulation, our



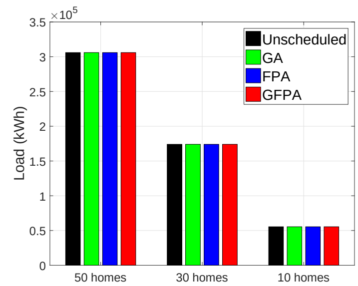
(a) PAR



(b) Cost

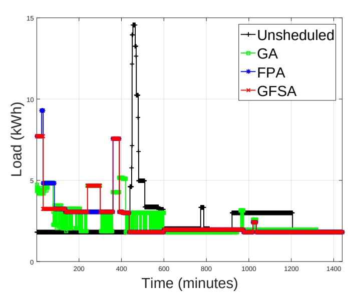


(c) Waiting time

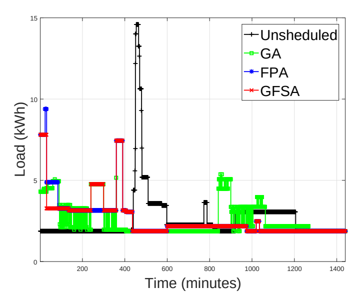


(d) Load

Figure 13: PAR, cost, waiting time and load against 1-minute OTI by applying RTP signal for multiple homes.



(a) CPP signal



(b) RTP sinal

Figure 14: Load against 1-minute OTI by applying RTP and CPP signal for a single home.

proposed scheme GFPA performs better when applying CPP signal using different OTIs and compared with unscheduled, GA, and FPA-based solutions in terms of reducing cost since they achieve on average 98%, 36%, 23%, and 22%, respectively. Similarly, PAR averages 98%, 36%, 59%, and 55%, respectively. While, UC comparing to GA and FPA, are around 88%, 48%, and 63%, respectively. Our proposed scheme achieves better results by applying RTP signals and different OTIs. As these schemes, i.e., unscheduled, GA, FPA, and GFPA, achieve cost on average 92%, 50%, 29%, and 28%, respectively. While PAR on average 94%, 39%, 62%, and 56%, and UC for GA, FPA, and GFPA on average 98%, 52%, and 49%, respectively. These findings suggest that our scheme has practical applications for improving the efficiency and sustainability of power grids. However, our scheme has some limitations, such as assuming homogeneous appliances and power consumption patterns. Future research directions include addressing these limitations and exploring more efficient techniques (that may be based on artificial intelligence) for reducing PAR, maximizing UC, reducing EC, and load shifting. Overall, our proposed scheme contributes to the development of DSM and HEMSs and promotes their adoption in real-world scenarios.

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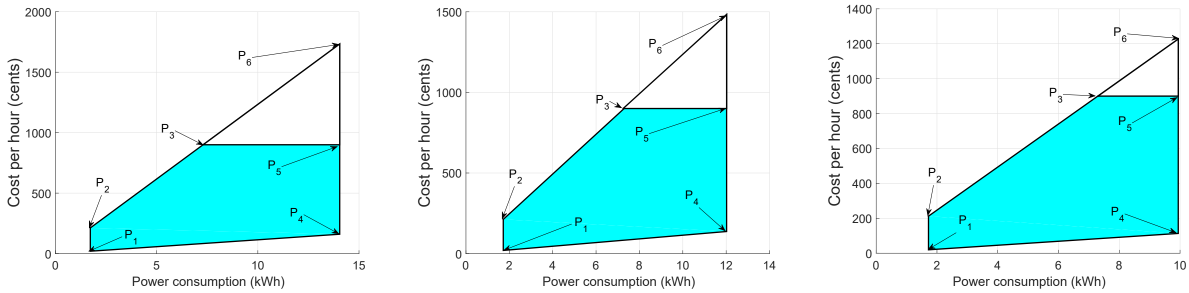
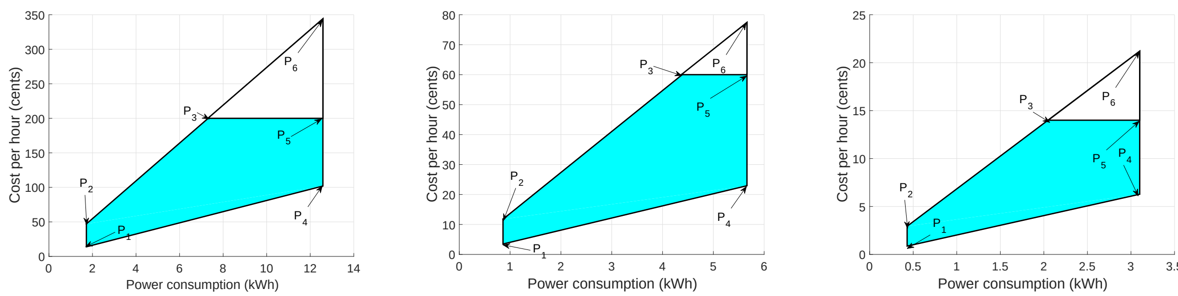
References

Abushnaf, J., Rassau, A., Górnisiewicz, W., 2016. Impact on electricity use of introducing time-of-use pricing to a multi-user home energy



(a) OTI 60 minutes (b) OTI 30 minutes (c) OTI 15 minutes

Figure 15: Feasible region against 60-minute OTI by applying CPP signal for a single home.



(a) OTI 60 minutes (b) OTI 30 minutes (c) OTI 15 minutes

Figure 16: Feasible region against 60-minute OTI by applying RTP signal for a single home.

management system. International Transactions on Electrical Energy Systems 26, 993–1005.

Adika, C.O., Wang, L., 2014. Smart charging and appliance scheduling approaches to demand side management. International Journal of Electrical Power & Energy Systems 57, 232–240.

Agnetis, A., De Pascale, G., Detti, P., Vicino, A., 2013. Load scheduling for household energy consumption optimization. IEEE Transactions on Smart Grid 4, 2364–2373.

Ali, A., Tariq, S., Iqbal, M., Feng, L., Raza, I., Siddiqi, M.H., Bashir, A.K., 2020. Adaptive bitrate video transmission over cognitive radio networks using cross layer routing approach. IEEE Transactions on Cognitive Communications and Networking 6, 935–945.

Alibakhshikenari, M., Virdee, B.S., Althuwayb, A.A., Xu, K.D., See, C.H., Khan, S., Park, I., Falcone, F., Limiti, E., 2021a. Novel concentric hexagonal-shaped rfid tag antenna with t-shaped stub matching. IEEE Journal of Radio Frequency Identification 6, 112–120.

Alibakhshikenari, M., Virdee, B.S., See, C.H., Shukla, P., Moghaddam, S.M., Zaman, A.U., Shafqaat, S., Akinsolu, M.O., Liu, B., Yang, J., et al., 2022. Dual-polarized highly folded bowtie antenna with slotted self-grounded structure for sub-6 ghz 5g applications. IEEE Transactions on

Table 8
Feasible region values against CPP signal and different OTIs

Cases	OTI 60 minutes			OTI 30 minutes			OTI 15 minutes		
	Price	Load	Cost	Price	Load	Cost	Price	Load	Cost
Minimum load - Minimum price	11.40	1.721	19.61	11.40	0.86	9.80	11.400	0.430	4.904
Minimum load - Maximum price	123.40	1.72	212.37	123.40	0.86	106.18	123.40	0.43	53.09
Maximum load - Minimum price	11.40	12.58	143.42	11.40	6.53	74.49	11.40	2.76	31.57
Maximum load - Maximum price	123.40	12.58	1552.50	123.40	6.53	806.41	123.40	2.76	341.75

Table 9
Feasible region values against RTP signal

Cases	OTI 60 minutes			OTI 30 minutes			OTI 15 minutes		
	Price	Load	Cost	Price	Load	Cost	Price	Load	Cost
Minimum load - Minimum price	11.400	0.430	4.904	4.050	0.860	3.485	2.025	0.430	0.871
Minimum load - Maximum price	123.400	0.430	53.092	13.675	0.860	11.767	6.837	0.430	2.941
Maximum load - Minimum price	11.400	2.769	31.572	4.050	5.661	22.929	2.025	3.100	6.278
Maximum load - Maximum price	123.400	2.769	341.756	13.675	5.661	77.421	6.837	3.100	21.198

Antennas and Propagation 70, 3028–3033.

Alibakhshikenari, M., Virdee, B.S., Shukla, P., Wang, Y., Azpilicueta, L., Naser-Moghadasi, M., See, C.H., Elfergani, I., Zebiri, C., Abd-Alhameed, R.A., et al., 2021b. Impedance bandwidth improvement of a planar antenna based on metamaterial-inspired t-matching network. IEEE Access 9, 67916–67927.

Althaher, S., Mancarella, P., Mutale, J., 2015. Automated demand response from home energy management system under dynamic pricing and power and comfort constraints. IEEE Transactions on Smart Grid 6, 1874–1883.

Aslam, S., Iqbal, Z., Javaid, N., Khan, Z.A., Aurangzeb, K., Haider, S.I., 2017. Towards efficient energy management of smart buildings exploiting heuristic optimization with real time and critical peak pricing schemes. Energies 10, 2065.

Balouch, S., Abrar, M., Abdul Muqeet, H., Shahzad, M., Jamil, H., Hamdi, M., Malik, A.S., Hamam, H., 2022. Optimal scheduling of demand side load management of smart grid considering energy efficiency. Frontiers in Energy Research 10, 328.

Bharathi, C., Rekha, D., Vijayakumar, V., 2017. Genetic algorithm based demand side management for smart grid. Wireless personal communications 93, 481–502.

Chen, Q., Wang, F., Hodge, B.M., Zhang, J., Li, Z., Shafie-Khah, M., Catalão, J.P., 2017. Dynamic price vector formation model-based automatic demand response strategy for pv-assisted ev charging stations. IEEE Transactions on Smart Grid 8, 2903–2915.

Derakhshan, G., Shayanfar, H.A., Kazemi, A., 2016. The optimization of demand response programs in smart grids. Energy Policy 94, 295–306.

Du, Y., Jiang, L., Li, Y., Counsell, J., Smith, J., 2016. Multi-objective demand side scheduling considering the operational safety of appliances. Applied energy 179, 864–874.

Erdinc, O., 2014. Economic impacts of small-scale own generating and storage units, and electric vehicles under different demand response strategies for smart households. Applied Energy 126, 142–150.

Evangelisti, S., Lettieri, P., Clift, R., Borello, D., 2015. Distributed generation by energy from waste technology: A life cycle perspective. Process Safety and Environmental Protection 93, 161–172.

Huneault, M., Galiana, F.D., 1991. A survey of the optimal power flow literature. IEEE transactions on Power Systems 6, 762–770.

Jayabarathi, T., Raghunathan, T., Adarsh, B., Suganthan, P.N., 2016. Economic dispatch using hybrid grey wolf optimizer. Energy 111, 630–641.

Liu, Y., Yuen, C., Yu, R., Zhang, Y., Xie, S., 2015. Queuing-based energy consumption management for heterogeneous residential demands in smart grid. IEEE Transactions on Smart Grid 7, 1650–1659.

Manzoor, A., Javaid, N., Ullah, I., Abdul, W., Almogren, A., Alamri, A., 2017. An intelligent hybrid heuristic scheme for smart metering based demand side management in smart homes. Energies 10, 1258.

Massaoudi, M., Abu-Rub, H., Refaat, S.S., Chihi, I., Oueslati, F.S., 2023. Deep learning in smart grid technology: A review of recent advancements and future prospects. IEEE Access 9, 54558–54578.

Nguyen, H.K., Song, J.B., Han, Z., 2014. Distributed demand side management with energy storage in smart grid. IEEE Transactions on Parallel and Distributed Systems 26, 3346–3357.

Nigdeli, S.M., Bekdas, G., Yang, X., 2016. Optimum tuning of mass dampers for seismic structures using flower pollination algorithm. Int. J. Theor. Appl. Mech 1, 264–268.

Ogwumike, C., Short, M., Denai, M., 2015. Near-optimal scheduling of residential smart home appliances using heuristic approach, in: 2015 IEEE International Conference on Industrial Technology (ICIT), IEEE. pp. 3128–3133.

Ponnusamy, V.K., Kasinathan, P., Madurai Elavarasan, R., Ramanathan, V., Anandan, R.K., Subramaniam, U., Ghosh, A., Hossain, E., 2021. A comprehensive review on sustainable aspects of big data analytics for the smart grid. Sustainability 13, 13322.

Pradhan, M., Roy, P.K., Pal, T., 2016. Grey wolf optimization applied to economic load dispatch problems. International Journal of Electrical Power & Energy Systems 83, 325–334.

Rahim, S., Javaid, N., Ahmad, A., Khan, S.A., Khan, Z.A., Alrajeh, N., Qasim, U., 2016. Exploiting heuristic algorithms to efficiently utilize energy management controllers with renewable energy sources. Energy and Buildings 129, 452–470.

Rastegar, M., Fotuhi-Firuzabad, M., 2014. Outage management in residential demand response programs. IEEE transactions on smart grid 6, 1453–1462.

Rastegar, M., Fotuhi-Firuzabad, M., Zareipour, H., 2016. Home energy management incorporating operational priority of appliances. International Journal of Electrical Power & Energy Systems 74, 286–292.

Reddy, P.D.P., Reddy, V.V., Manohar, T.G., 2016. Application of flower pollination algorithm for optimal placement and sizing of distributed generation in distribution systems. Journal of Electrical Systems and Information Technology 3, 14–22.

Rehman, A., Haseeb, K., Jeon, G., Bahaj, S.A., 2022. Secure edge-based energy management protocol in smart grid environments with correlation analysis. Sensors 22, 9236.

Samadi, P., Wong, V.W., Schober, R., 2015. Load scheduling and power trading in systems with high penetration of renewable energy resources. IEEE Transactions on Smart Grid 7, 1802–1812.

Shahzad, A., Imran, M., Tahir, M., Khan, S.A., Akgül, A., Abdullaev, S., Park, C., Zahran, H.Y., Yahia, I.S., 2023. Brownian motion and thermophoretic diffusion impact on darcy-forchheimer flow of bioconvective micropolar nanofluid between double disks with cattaneo-christov heat flux. Alexandria Engineering Journal 62, 1–15.

Sun, Y., Cai, Z., Guo, C., Ma, G., Zhang, Z., Wang, H., Liu, J., Kang, Y., Yang, J., 2022. Collaborative dynamic task allocation with demand response in cloud-assisted multiedge system for smart grids. IEEE Internet of Things Journal 9, 3112–3124.

Whitley, D., 1994. A genetic algorithm tutorial. Statistics and computing 4, 65–85.

Yadav, R.K., Hrisheekesha, P., Bhadoria, V.S., 2023. Grey wolf optimization based demand side management in solar pv integrated smart grid environment. IEEE Access 11, 11827–11839.

Yahaya, A.S., Javaid, N., Alzahrani, F.A., Rehman, A., Ullah, I., Shahid, A., Shafiq, M., 2020. Blockchain based sustainable local energy trading considering home energy management and demurrage mechanism. Sustainability 12, 3385.

Yang, X.S., 2012. Flower pollination algorithm for global optimization, in: International conference on unconventional computing and natural computation, Springer. pp. 240–249.

Ye, F., Qian, Y., Hu, R.Q., 2015. A real-time information based demand-side management system in smart grid. IEEE Transactions on Parallel and Distributed Systems 27, 329–339.

Yousefi-khangah, B., Ghassemzadeh, S., Hosseini, S.H., Mohammadi-Ivatloo, B., 2017. Short-term scheduling problem in smart grid considering reliability improvement in bad weather conditions. IET Generation, Transmission & Distribution 11, 2521–2533.

Zhou, B., Li, W., Chan, K.W., Cao, Y., Kuang, Y., Liu, X., Wang, X., 2016. Smart home energy management systems: Concept, configurations, and scheduling strategies. Renewable and Sustainable Energy Reviews 61, 30–40.

Zhu, Z., Tang, J., Lambotharan, S., Chin, W.H., Fan, Z., 2012. An integer linear programming based optimization for home demand-side management in smart grid, in: 2012 IEEE PES innovative smart grid technologies (ISGT), IEEE. pp. 1–5.