Research Article

A new optimal energy management strategy based on improved multi-objective antlion optimization algorithm: applications in smart home

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Abstract

In recent years, energy demand has grown significantly relative to its production. The power companies have also offered a variety of schemes such as energy consumption management to meet this growing consumer demand. Energy consumption management is a set of strategies used to optimize energy consumption which includes a set of interconnected activities between the utility and customers to transfer the load from peak hours to off-peak hours. This reduces the electricity bill. This paper presents an optimal schedule for the consumption of residential appliances based on improved multi-objective antlion optimization algorithm to minimize the electrical cost and the user comfort. To prevent peaks, the peak-to-average ratio is considered as a constraint for the energy cost function. Also, two different tariff signals have been used to measure energy costs. The real-time pricing and critical peak pricing are considered as energy tariffs. The simulations results are compared with other meta-heuristic algorithms, including multi-objective particle swarm optimization, the second version of the non-dominated sorting genetic algorithm, and the basic antlion optimizer algorithm to show the superiority of the proposed algorithm. Final results show that using the proposed scheme reaches electricity bills less than 80%.

Keywords Energy demand · Energy optimization · Energy consumption · Improved antlion optimization · Multi-objective optimization algorithm

Abbreviations

IMOALO	Improved multi-objective antlion optimization
MOALO	Multi-Objective Antlion Optimization
MOPSO	Multi-objective particle swarm optimization
NSGAII	The second version of the non-dominated sorting genetic algorithm
PAR	Peak-to-average ratio
RTP	Real-time pricing
CPP	Critical peak pricing
DSM	Demand-side management
HEMS	Home energy management system

List of symbols

S	The set of shiftable appliances
t	Time slot
T	Number of time slots
DL	Energy consumed during a day
$\mathrm{HL}(t)$	Energy consumed at time slot t
s_i	On or off state of ith appliance
P_i	Power rate of ith appliance
$\mathrm{Price}(t)$	Energy price at time slot t
$\mathrm{Load}_{\mathrm{peak}}$	The most load consumed at a time at a certain time slot
$\mathrm{Load}_{\mathrm{avg}}$	The average load consumed during a day
$\mathrm{PAR}_{\mathrm{unscheduled}}$	PAR value for the unscheduled pattern
β	Penalty factor

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v	Violation
$time^{i}_{ideal}$	User's ideal time for the *i*th appliance
$time^{i}_{start}$	The starting time for the *i*th appliance

1 Introduction

Electricity is a very valuable source of energy, and the need for it is growing every day. Due to the limitations of traditional energy resources, two kinds of solutions have been considered for them: discovering alternative energy sources to generate more energy and making effective use of available resources. The second approach is more desirable and more economical [1]. Problems and challenges in increasing the capacity of electricity generation and increasing demand for electricity have led various countries around the world to seek an appropriate solution to optimize energy consumption [2]. The main challenges facing the traditional power grids today are the possibility of blackouts, lack of liquidity, the security of transmission lines, water crisis, and the environment. Since misusing or loss of energy and these grids cannot overcome these problems, using smart grids (SG) is a good idea for solving these kinds of problems [3]. SG includes a set of interconnected activities between the utility and consumers to rationalize electricity consumption so that the same efficiency in the field of electricity can be achieved with more efficiency and lower cost. Using SG, power consumption can be controlled through smart meters that create a two-way consumption between the consumer and the source [4]. Demand-side management (DSM) is one of the solutions to these problems, which has been introduced by electricity companies to control energy consumption by consumers [5–7]. The main goal of DSM is to create a balance between supply and demand for providing mainly two tasks: consumption reduction and efficiency improvement [8]. DSM includes productivity programs and demand response programs. In demand response programs, consumers are invited to participate in incentive schemes. These plans are based on changes in electricity prices. Therefore, consumers can change their consumption patterns accordingly. By doing so, their electricity bills will be significantly reduced [9, 10]. In traditional grids, utility manually sheds the consumer loads during peak hours to secure equipment on transmission lines. However, load shifting on the smart grids is done during peak hours to prevent peak load and damage to equipment. This is profitable for the company and the consumers and also increases network reliability [11]. Responding to such challenges requires meta-heuristic optimization algorithms that are highly capable of solving multi-objective optimization problems to manage energy consumption.

There are several related works in the literature, for example, genetic algorithms have been used in [12] to transfer power consumption from peak hours to off-peak hours to reduce power consumption. Of course, its application in the smart grid requires a calculation that must be done by cloud computing. It was said that this issue will be analyzed in the future.

An improved differential evolution algorithm was proposed in [13] to reduce energy cost, increase user comfort, and reduce PAR. Using renewable resources was also suggested to increase efficiency. However, their proposed algorithm still needed to be improved due to computational formulas.

A smart energy management system was introduced in [14]. The peak loads and the cost of electricity in a residential area were minimized by using multi-objective mixed-integer linear programming (MOMILP). Constraints included daily energy needs and consumer preferences. This system brought possible benefits to the company and the consumer.

In [15], a home energy management controller was proposed based on genetic harmony algorithm to reduce PAR and electricity cost and increase user comfort. To evaluate the performance of the proposed system, a single home and multiple homes with critical peak pricing signal and real-time pricing signals were considered.

A multi-period artificial bee colony (MABC) was used to increase productivity and reduce operating costs [16]. They used a real-time approach to manage the load. Management of energy consumption patterns in the residential area was possible to optimize various home appliances. It should be noted that in the proposed system, user convenience was not considered.

The community-based participatory energy plan was discussed in [17]. The authors examined the cost of consumer electricity bills and the smart grid. The main goal was to reduce PAR and electricity costs. This was done by connecting the consumer and the smart grid. The proposed plan was evaluated using the community-to-community plan in MATLAB. However, there was a compromise between user convenience and security.

In [18], micro-grid was introduced as an important part of the distribution system. The authors suggest the use of stand-alone hybrid renewable energy systems that are environmentally safe and economically efficient as a suitable solution for areas where electricity is not sufficiently available. They have presented technical and economic research for a residential area using the mentioned system. Their design included batteries, diesel, wind, and photovoltaics.

Achieving possible solutions in a shorter period to manage the demand side was identified as a challenge in [19]. Energy cost and user comfort have been considered as two important goals for load management, and to achieve these goals, a hybrid non-dominated sorting genetic algorithm has been used. However, the authors ignore the peak-to-average ratio.

In [20], a dragonfly meta-heuristic optimization algorithm is used to optimize the consumption of shiftable appliances taking into account the RTP pricing signal. Reducing energy costs and PAR and increasing user comfort are the goals ahead. By achieving these goals, network stability is also achieved.

However, different types of classic and bio-inspired solvers have been applied for determining the optimal solution of the problem, each of them has its shortcomings from premature convergence to their speed run and trapping in the local minimum.

In [18], an improved version of a meta-heuristic optimization algorithm called the improved emperor penguin optimization algorithm (IEPO) is used to optimize the performance of a cooling, heating, and combined power system.

The authors propose a multi-objective smart home energy management system for intelligently controlling small-scale load demand in [19]. Their objective is to reduce energy costs and reduce peak demand. They also use cooperative game theory to find the optimal Pareto solution to the multi-objective problem.

Meta-heuristic optimization algorithms have a very high ability to solve multi-objective optimization problems. It has been seen that these algorithms have better solutions for managing energy consumption. However, each of these algorithms has its disadvantages. We present an improved version of the MOALO algorithm to cover these disadvantages as much as possible.

This paper presents a home energy management system (HEMS) for achieving an optimal schedule for the consumption of residential appliances. This is done based on DSM in the smart grid. The improved multi-objective antlion optimizer algorithm as a new and efficient bio-inspired algorithm is proposed to reduce the cost functions. Then, the results are compared with three other algorithms including MOPSO, NSGAII, and MOALO. RTP and CPP are two electricity pricing scheme which is used in this study. In this paper, two objective functions are considered: electricity cost function with PAR constraint to reduce energy consumption and prevent the formation of peak load to increase grid efficiency and waiting time function to increase user comfort.

2 Problem statement

The DSM increases the reliability and stability of the SG performance while reducing energy consumption costs. This is the most important issue in the SG that needs special attention. In a smart home, the energy management system controls energy consumption by scheduling residential appliances [21]. In [22], a scheme has been proposed that reduces the cost of electricity consumption and, on the other hand, tries to increase consumer comfort. However, there is a trade-off between cost and consumer comfort. The DSM requires two-way communication of information between the consumer and the utility. This information includes the pricing signals set by the utility and the amount of consumer demand. The HEMS also plans the device consumption pattern based on the same information and user setting. The authors present a model of the HEMS in [23]. They suggested meta-heuristic methods for efficient energy consumption optimization accordingly to the RTP and IRB pricing signals.

Reducing the cost of energy consumption is the main goal of this study. Achieving this goal is possible using the DSM. Due to electricity tariffs, the cost of electricity consumption increases during peak hours. Therefore, consumption management reduces electricity bills by transferring the peak load of consumption from peak hours to off-peak hours. This increases the waiting time and thus reduces the user comfort, but this is not the only challenge ahead. Transfer of consumption load to off-peak hours causes peak formation during these hours, so the proposed solution should be able to establish a trade-off between reducing costs and increasing user comfort, as well as prevent peak load formation by reducing PAR.

3 Problem classification

3.1 Load categorize

There are several appliances in a home that is different in terms of power rating, performance, and operational time. In the proposed model, the appliances are divided into three categories of shiftable, non-shiftable, and fixed. Figure 1 shows a simple design of the proposed system model. According to this figure, there is two-way communication between the consumer and the utility. The operational time of shiftable appliances can shift at any time during a day. These appliances have a special role for the efficiency of the proposed design because by changing the operational time of these appliances from peak hours to off-peak hours, the cost of electricity and PAR can be significantly reduced, but this puts the user's comfort at risk. The issue of user comfort requires that these devices start operating at an ideal time in the user's view. Non-shiftable are those appliances whose operational time cannot be shifted. Fixed appliances are named because their operation length is unknown and also these devices start operation according to user demand. The details of

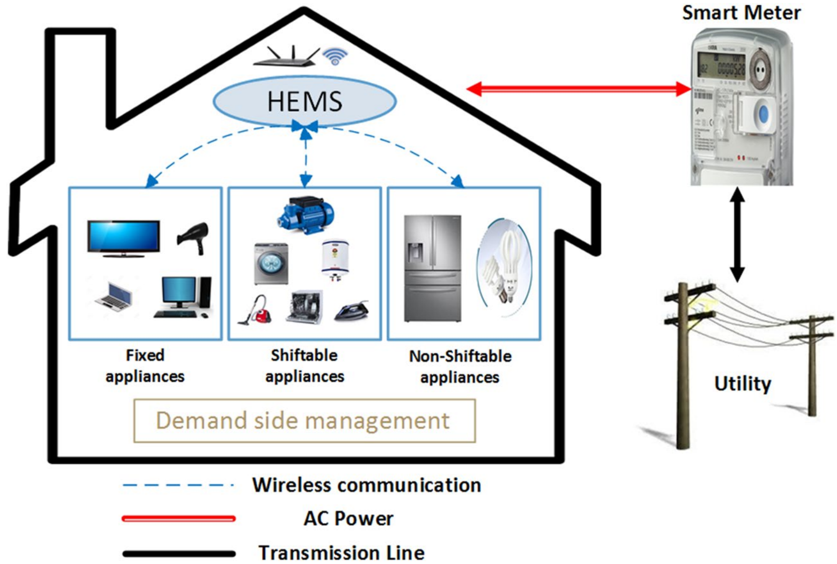

Fig. 1 The suggested method arrangement

Table 1 Appliances classification

Appliances	Load categorize	Operational time (hours)	Power rate (kW)	Ideal starting time
Water heater	Shiftable	10	2.6	–
Water pump		10	2	–
Vacuum cleaner		2	1.2	09:00
Dishwasher		3	2.5	22:00
Steam iron		1	1.2	06:00
Washing machine		2	3	17:00
Dryer		1	3.4	19:00
Refrigerator	Non-shiftable	22	0.3	–
Lights		7	0.4	–
Laptop	Fixed	2	0.1	–
PC		2	0.3	–
TV		5	0.3	–
Hairdryer		1	1.2	–
Blender		1	0.3	–

this category, with the power rate and operating time of each appliance, are given in Table 1.

3.2 Electricity tariff

The electricity company uses various electricity tariffs to calculate the daily electricity costs of consumers. TOU, DAP, RTP, and CPP are examples of these tariffs. In this paper, the RTP and CPP tariff is used to calculate the cost of energy. In the RTP method, pricing is determined based on customer demand, so the price of electricity is constantly changing throughout the day. It may even be different every few minutes. Using this pricing method requires smart meters to establish effective two-way communication between the consumer and the company. The CPP tariff, like the TOU, has fixed prices at various periods, but depending on the critical events that occur in the system, the price can change for at least a period. This pricing scheme is not economically suitable for consumers, but it can be used to significantly reduce the burden in times of crisis [20]. To reduce the consumption in critical hours of the year when electricity consumption is very high and the reliability of the system is at risk, using CPP seems to be a good solution. Therefore, it can be said that the purpose of CPP is to increase the reliability and the stability of the power grid. Figure (2) shows the CPP and RTP signals.

3.3 Cost functions

In this study, a home with a set of appliances is considered. Each day is divided into twenty-four-time slots. Each interval represents 1 hour. The proposed model works based on the schedule of shiftable appliances. The main objectives of this study are to reduce the electricity costs by scheduling energy consumption during off-peak hours and to reduce PAR to increase grid reliability in a way that increases the user's comfort as much as possible.

Shiftable appliances:

$$S \in [s_1, s_2, \dots, s_N], N = 7 \tag{1}$$

Time slots:

$$t \in T = [1, 2, \dots, T], T = 24 \tag{2}$$

where S shows the shiftable appliances, N is the number of shiftable appliances, and t is the number of the time slot.

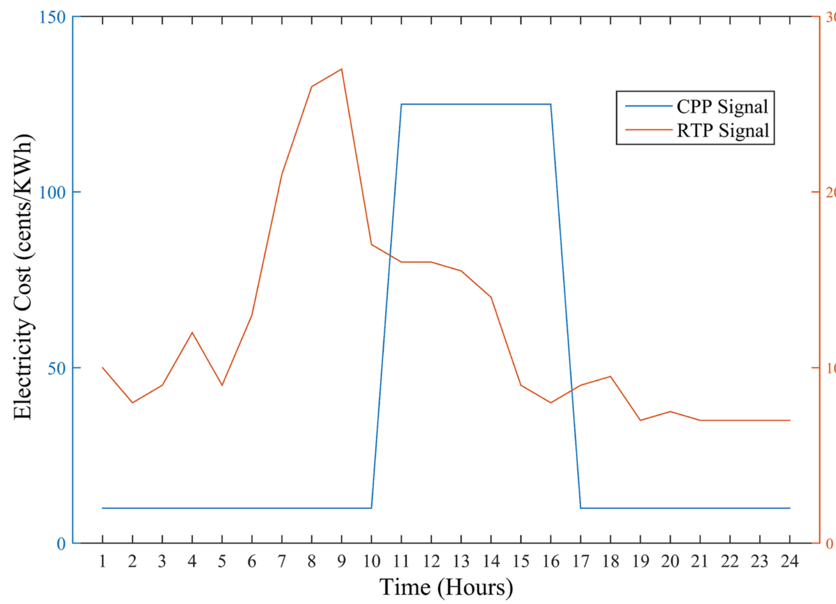

Fig. 2 Pricing signals [21]

Electricity costs are calculated using RTP and CPP pricing tariffs and energy consumption by the appliances. The energy consumed during a day is given as:

$$\mathrm{DL} = \sum_{t=1}^{T} \mathrm{HL}(t) \tag{3}$$

where DL shows the total load demanded during 1 day, $\mathrm{HL}(t)$ represents the energy consumed at time slot t, and T is the maximum of time slots.

Using the pricing signals, the daily energy cost is given as follows:

$$\mathrm{MinCost} = \sum_{t=1}^{T}\Big(\sum_{i=1}^{N} \left(s_i \times P_i\right)_t \times \mathrm{Price}(t)\Big) \tag{4}$$

where s_i indicates the on or off state of ith appliance, P_i represents the power rate of each appliance, and $\mathrm{Price}(t)$ is the energy prices at time t.

The PAR is defined as the ratio of the maximum load consumed by a consumer over a specified time slot during a day and the average total load during the same day. As PAR increases, the reliability of the grid decreases, and its stability is compromised. However, reducing PAR not only increases the stability of the grid, but also reduces the cost of electricity to consumers, and therefore, both the consumer and the utility benefit from the implementation of such schemes. Mathematically, it is computed as follows:

$$\mathrm{Load}_{\mathrm{peak}} = \max_{t\in T}(\mathrm{HL}(t)) \tag{5}$$

$$\mathrm{Load}_{\mathrm{avg}} = \frac{\sum_{t=1}^{T} \mathrm{HL}(t)}{T} \tag{6}$$

where $\mathrm{HL}(t)$ represents the energy consumed at time slot t and T is the maximum of time slots.

According to Eqs. (5) and (6), PAR is given as:

$$\mathrm{PAR} = \frac{\mathrm{Load}_{\mathrm{peak}}}{\mathrm{Load}_{\mathrm{avg}}} = \frac{\max\limits_{t\in T}(\mathrm{HL}(t)) \times T}{\sum_{t=1}^{T} \mathrm{HL}(t)} \tag{7}$$

where $\mathrm{Load}_{\mathrm{peak}}$ represents the most load consumed at a certain time slot, and $\mathrm{Load}_{\mathrm{avg}}$ represents the average load consumed during a day.

The unscheduled pattern reduces the cost of energy consumed by transferring the peak load consumed from peak hours to off-peak hours, but the peak load consumption may occur during off-peak hours. To prevent this from happening, the following constraint is considered:

$$\mathrm{constraint} : \mathrm{PAR} < \mathrm{PAR}_{\mathrm{unscheduled}} \tag{8}$$

where $\mathrm{PAR}_{\mathrm{unscheduled}}$ is the PAR value for the unscheduled pattern.

We apply this constraint as a multiplicative penalty function to the electricity cost function. Therefore, the electric energy cost function changes as follows:

$$\mathrm{MinCost} = \left(\sum_{t=1}^{T}\Big(\sum_{i=1}^{N} \left(s_i \times P_i\right)_t \times \mathrm{Price}(t)\Big) \times (1 + \beta \times \tanh(v)\right) \tag{9}$$

where β is the penalty factor, and here, $\beta = 10$; also v is the violation and the tanh (.) the function is used to bound the violation between [0,1] The violation is defined as follows:

$$v = \max\left(\frac{\mathrm{PAR}}{\mathrm{PAR}_{\mathrm{unscheduled}}} - 1, 0\right) \tag{10}$$

In Eq. (10), if PAR is greater than $\mathrm{PAR}_{\mathrm{unscheduled}}$, then the violation is positive. Otherwise, the violation is considered zero.

User comfort is defined based on consumer waiting time. Table 1 shows the user's ideal time to start the shiftable appliances. Reducing the cost of energy consumption and PAR increases the waiting time and endangers the user's comfort. Therefore, by reducing the waiting time, user comfort can be increased. The waiting time is calculated as follows:

$$\mathrm{WaitingTime} = \frac{\sum_{i=1}^{N} \left|\mathrm{time}^{i}_{\mathrm{ideal}} - \mathrm{time}^{i}_{\mathrm{start}}\right|}{N} \tag{11}$$

where N represents the number of shiftable appliances, here $N = 7$, $\mathrm{time}^{i}_{\mathrm{ideal}}$ is the user's ideal time for the ith appliance, and $\mathrm{time}^{i}_{\mathrm{start}}$ is the starting time for the ith appliance.

4 Algorithms

Optimization or programming in mathematics, economics, management, and engineering refers to selecting the best member from a set of achievable members. In the simplest form, an attempt is made to select the data from an achievable set and calculate the value of a function of its maximum and minimum value. Classical or analytical methods such as linear programming (LP) [22] seek to solve problems accurately. Therefore, they include differentiation to find the optimal answer. The main advantage of this type of optimization algorithms is to ensure the optimal answer, but they are difficult to use in problems of high complexity or large problems or with a discrete function. Although heuristic optimization algorithms do not guarantee the achievement of the most optimal and accurate answer and provide answers close to the exact answer, they can solve complex and difficult problems. The convergence speed of such algorithms is very high and they are applied in all fields of engineering.

The problem presented in this paper is a nonlinear and complex discrete problem, so it cannot be solved using classical methods. Therefore, we have proposed the improved multi-objective antlion optimization algorithm to achieve an optimal scheme for residential appliances in a way that reduces the cost of electricity, PAR, and waiting time.

4.1 Basic ALO algorithm

Before explaining the multi-objective version of the ALO algorithm, the base version of this algorithm must be provided. The ALO algorithm is based on the hunting mechanism of antlions and the principles inspired by their interaction with ants. In this algorithm, there are two populations: ants and the antlions. The main responsibility of the ants is to explore the search space using random walking. The antlions maintain the best position obtained by the ants and update their position as the ant's position improves. There is also an elite antlion in this search space that affects the movement of ants, regardless of its distance to other ants. If any of the antlions finds a better position than the elite, it will be replaced. After reaching the condition of stopping, the position of the elite antlion is selected as the final optimal response [23]. To model the interactions between ants and antlions, we first consider the ants to move in search space; then, the antlions are allowed to hunt. The random movement of ants is modeled according to the following equation:

$$X(t) = \left[0, \mathrm{cumsum}\left(2r\left(t_1\right) - 1\right), \mathrm{cumsum}\left(2r(t_2) - 1\right), \ldots, \mathrm{cumsum}\left(tr\left(t_n\right) - 1\right)\right] \tag{12}$$

where cumsum is the cumulative sum, n represents the maximum number of iteration, t shows the step of random walk, and $r(t)$ is a stochastic function that is calculated as follows:

$$r(t) = \begin{cases} 1 \text{ if rand} > 0.5 \\ 0 \text{ if rand} \le 0.5 \end{cases}, \text{rand} \in [0, 1] \tag{13}$$

Since any search space has its limitations, the range of variables in Eq. (13) cannot be used directly to update the position of ants. For the ants to walk randomly, their movement is normalized according to Eq. (14):

$$X_i^t = \frac{\left(X_i^t - a_i\right) \times \left(d_i^t - c_i^t\right)}{\left(b_i - a_i\right)} + c_i^t \tag{14}$$

where a_i represents the minimum random walk of the ith variable and b_i is the maximum random walk, d_i^t is the maximum of tth variable at tth iteration, and c_i^t indicates the minimum of ith variable at tth iteration. Antlion pits are simulated as Eq. (15):

$$\begin{cases} c_i^t = \text{Antlion}_j^t + c^t \\ d_i^t = \text{Antlion}_j^t + d^t \end{cases} \tag{15}$$

In this equation, Antlion_j^t represents the jth antlion at tth iteration. A roulette wheel is used to model the ability of ants to hunt. When an ant is trapped in a pit, the antlion throws stones at the edges of the pit. Its mathematical model is as follows:

$$\begin{cases} c^t = \frac{c^t}{I} \\ d^t = \frac{c^t}{I} \end{cases} \tag{16}$$

In Eq. (16) I is a ratio and is defined as follows:

$$I = 10^w \frac{t}{T}, W = \begin{cases} 2 \text{ when } t > 0.1T \\ 3 \text{ when } t > 0.5T \\ 4 \text{ when } t > 0.75T \end{cases}, \begin{matrix} 5 \text{ when } t > 0.9T \\ 6 \text{ when } t > 0.95T \end{matrix} \tag{17}$$

where t is the current iteration, T describes the maximum number of iteration, and W stands for a fixed value.

The last step of hunting takes place when the ant is immersed in the sand. Then, the position of the antlion should be updated relative to the position where the ant hunted to increase the chances of a new hunt. The following equation describes this action:

$$\text{Antlion}_j^t = \text{Ant}_i^t \text{ if } f\left(\text{Ant}_j^t\right) < f\left(\text{Antlion}_j^t\right) \tag{18}$$

Elitism is a feature of evolutionary algorithms that allows the best solution obtained to be maintained during the optimization process. In the ALO algorithm, the best antlion obtained at each step is stored and considered as an elite. The following equation shows the elite simulation:

$$\text{Ant}_i^t = \frac{R_A^t + R_E^t}{2} \tag{19}$$

where R_A^t is a random walk around the antlions by the roulette wheel in the tth iteration, and R_E^t describes also a random walk around the elite in the tth iteration.

4.2 MOALO algorithm

Solving a multi-objective problem requires a set of solutions that create the best trade-off between the objectives, called the Pareto optimal set. The MOALO algorithm provides an archive for storing optimal solutions. By selecting a solution from the archive, the ALO algorithm can improve its quality. A leader is selected from the archive and used to improve the diversity of the archive. The archive must have limitations and the final solution to improve the distribution must be selected from the archive. Niching is used to measure the distribution of solutions in the archive. In this method, the neighborhood of each solution up to a predefined radius is checked to obtain the number of solutions that exist in the neighborhood of each solution. This is considered as a distribution criterion. Two mechanisms are used to improve the distribution of solutions in the archive. Firstly, the antlions are selected from the solutions that have a smaller population in their vicinity. The following equation defines the probability of selecting a solution from the archive:

$$P_i = \frac{c}{N_i} \tag{20}$$

where c is the constant and must be greater than 1, and N_i is the number of solutions in the neighborhood of the ith solution.

Secondly, if the archive is full, the solutions that have a larger population in their vicinity should be removed from the archive and replaced by new solutions. The following equation indicates the probability of removing a solution from the archive:

$$P_i = \frac{N_i}{c} \tag{21}$$

where c is the constant and must be greater than 1, and N_i is the number of solutions in the neighborhood of the ith solution. Finally, the elite is selected from the archive using the roulette wheel and (19).

4.3 Improved MOALO algorithm

In this section, we propose an improved version of the MOALO algorithm (IMOALO) using opposition-based learning (OBL) and a self-adaptive population (SAP).

Table 2 Parameters of meta-heuristic algorithms

MOPSO [24]		NSGAII [25]		MOALO & IMOALO		Common parameters	
Parameters	Value	Parameters	Value	Parameters	Value	Parameters	Value
nRep	55	pCrossover	0.8	ArchiveMaxSize	100	time slot	24
W	0.45	nCrossover	80	Archive_X	0	VarMin	0
Wdamp	0.99	pMutation	0.5	Archive_F	1	VarMax	1
c1	0.5	nMutation	50	r	0.7	nPop	100
c2	0.5	mu	0.02	V_Max	0.2	MaxIt	350
nGrid	20	sigma	0.1	–	–	–	–

Table 3 Statistical data for the total cost

Total cost (cents)		meta-heuristic algorithms			
		MOPSO [24]	NSGAII [25]	MOALO	IMOALO
RTP	Min	785.15	746.95	746.45	779.45
	Max	2576.09	825.75	3760.95	3635.33
	Mean	1012.68	779.57	1310.20	1183.57
	Var	196,311.89	518.95	1,004,040.18	615,136.68
CPP	Min	1356	984.50	984.50	984.50
	Max	11,665.66	1929.50	2392.50	2224
	Mean	3916.31	1402.93	1359.23	1407.02
	Var	12,305,955.81	81,232.72	174,422.02	105,689.56

OBL helps to produce a more diverse initial population, while the SPA automatically selects the population size at each iteration. Algorithm 1 shows the pseudocode of the IMOALO algorithm.

4.3.1 Opposition based learning

The MOALO algorithm, like other meta-heuristic optimization algorithms, requires a random initial population. If this initial population is close to the optimal solution, MOALO has more hope of moving towards the optimal solution. However, the initial solution may be far from the optimal solution. Also, the worst-case scenario is that the initial solution is in the opposite direction to the optimal solution. In this case, the optimization process may require more time or the optimal answer may not be achieved. Therefore, to increase the productivity of the initial population of the MOALO algorithm, we use OBL, which is modeled as follows:

$$\overline{X_i} = X_{\max} + X_{\min} - X_i \tag{22}$$

where $\overline{X_i}$ shows the opposite location of X_i, and $X_{\max}$ and $X_{\min}$ indicate the upper and lower bounds. If $\overline{X_i}$ has better fitness than X_i, then $\overline{X_i}$ replaces X_i.

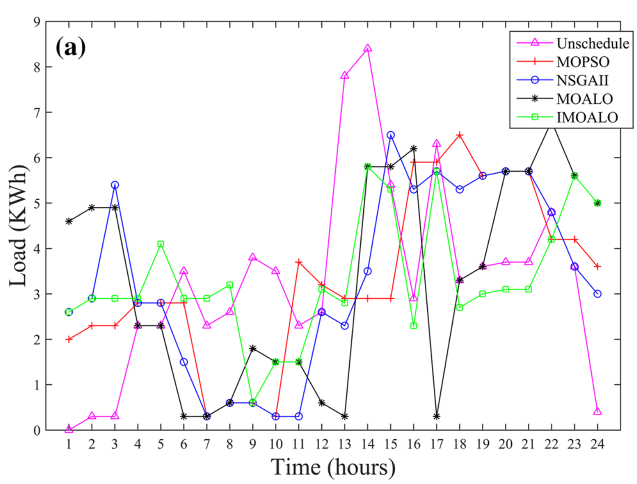

Fig. 3 Hourly load consumption **a** with RTP signal and **b** with CPP signal

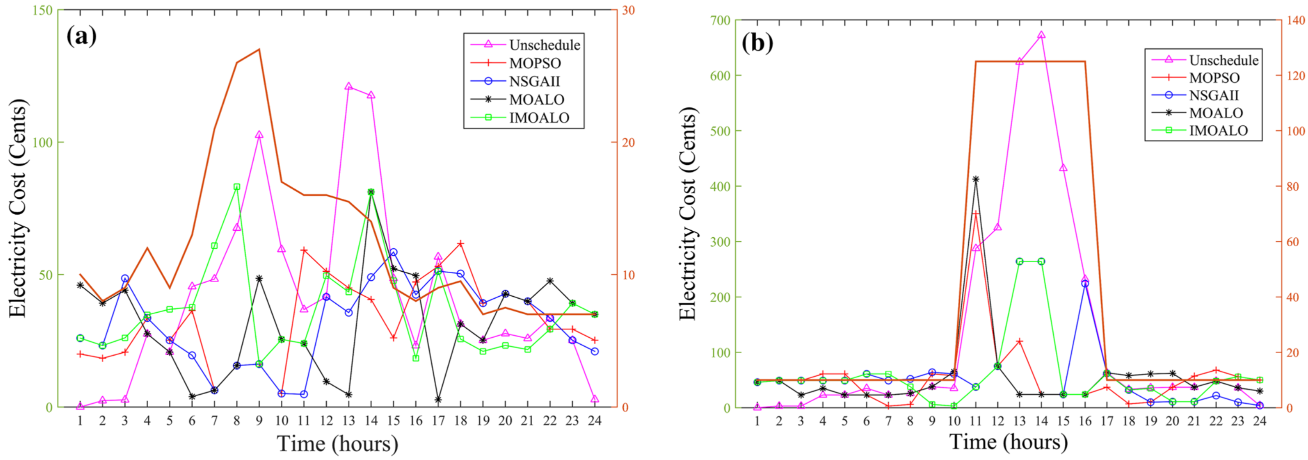

Fig. 4 Hourly electricity cost: **a** with the RTP signal and **b** with the CPP signal

4.3.2 Self-adaptive population

The MOGOA algorithm requires a control parameter to determine the population size. It should be noted that determining population size in specific optimization issues is a very difficult and challenging task. The self-organizing population does this automatically each time the algorithm is repeated. In the first, the initial population size is determined as follows:

$$pop = 10 * d \tag{23}$$

where d indicates the number of the variables. Then, in the next iteration of the main loop of the algorithm, the size of the new population is obtained as follows:

$$pop_{new} = round(pop + r * pop) \tag{24}$$

where r is a random number between $[-0.5, 0.5]$. It is a control parameter that changes the size of the population and is produced randomly with a uniform distribution. Depending on whether the sign r is negative or positive, the population size decreases or increases. When the new population size is larger than the size of the population in the previous iteration ($pop_{new} > pop$), then all members of the current population are transferred to the next iteration and the rest of the new population is produced according to elitism. But if the size of the new population is smaller than the population size of the previous iteration ($pop_{new} < pop$), then only the top members of the current population are moved to the next iteration and the rest are removed. And when the new population size is less than the problem dimension, the size of the new population equals the number of variables in the problem.

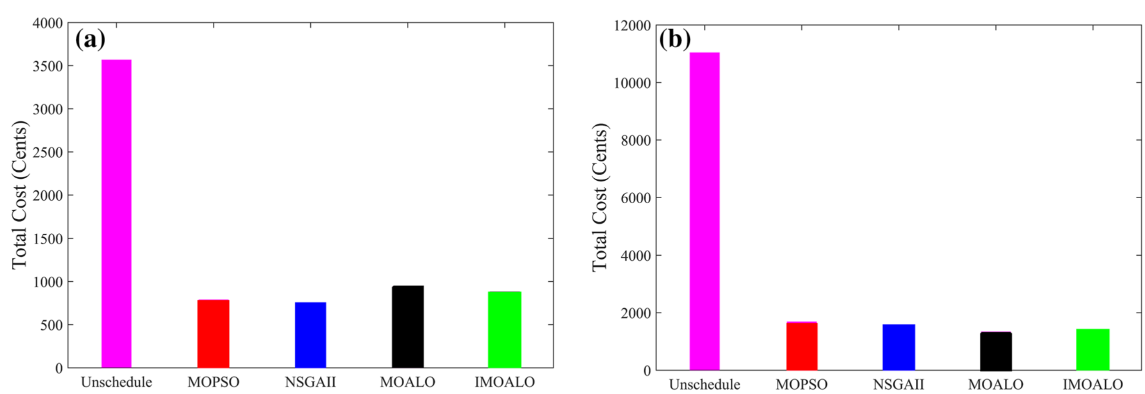

Fig. 5 Total cost per day **a** with an RTP signal **b** with a CPP signal

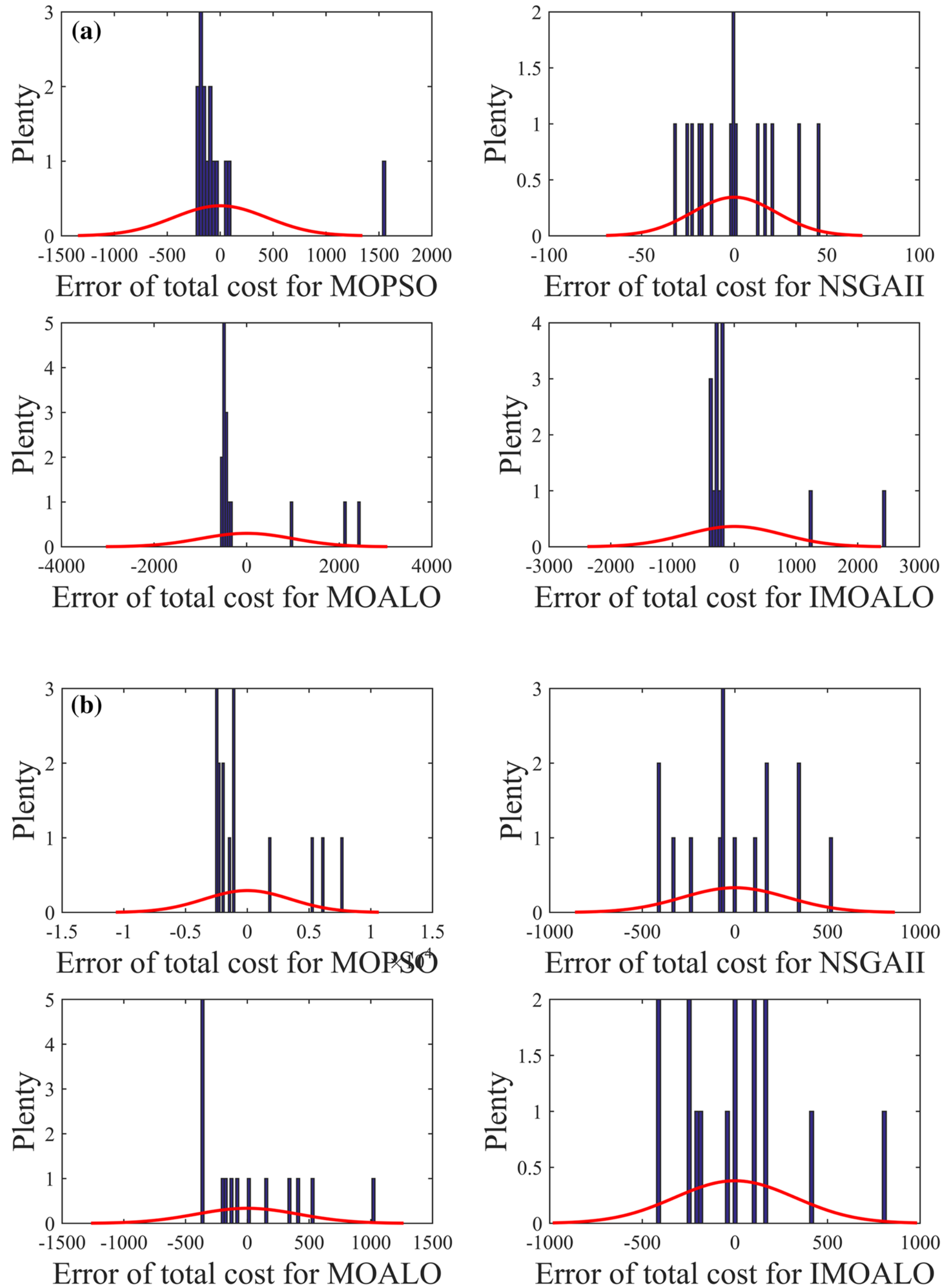

Fig. 6 Histogram plot for the total cost **a** with RTP signal **b** with CPP signal

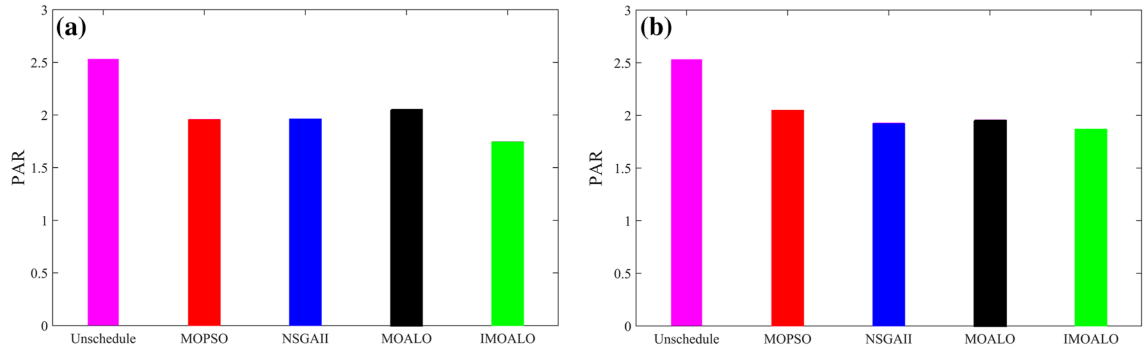

Fig. 7 PAR reduction **a** with an RTP signal **b** with a CPP signal

Algorithm 1: The Improved Multi-Objective Antlion Optimizer algorithm.

Initial parameters of MOALO
Initial the primary population of Ants
Calculate the opposite positions of each ant using Eq. (22)
Replace them if the ant's opposite position has better fitness.
while the end condition is not met
  Determine the new population size using Eq. (24)
  If $pop_{new} > pop_{old}$
    Calculate the position of new members using elitism.
  end
  If $pop_{new} < pop_{old}$
    Remove the failed members from the population.
  end
  for every ant
    Select a random antlion from the archive
    select the elite using the Roulette wheel from the archive
    Create a random walk and normalize it
    Update the position of Ants
  end
  Calculate the objective values of all Ants
  Update the archive
  If the archive is full
    Delete some solutions using the Roulette wheel from the archive to accommodate new solutions
  end
end
return archive

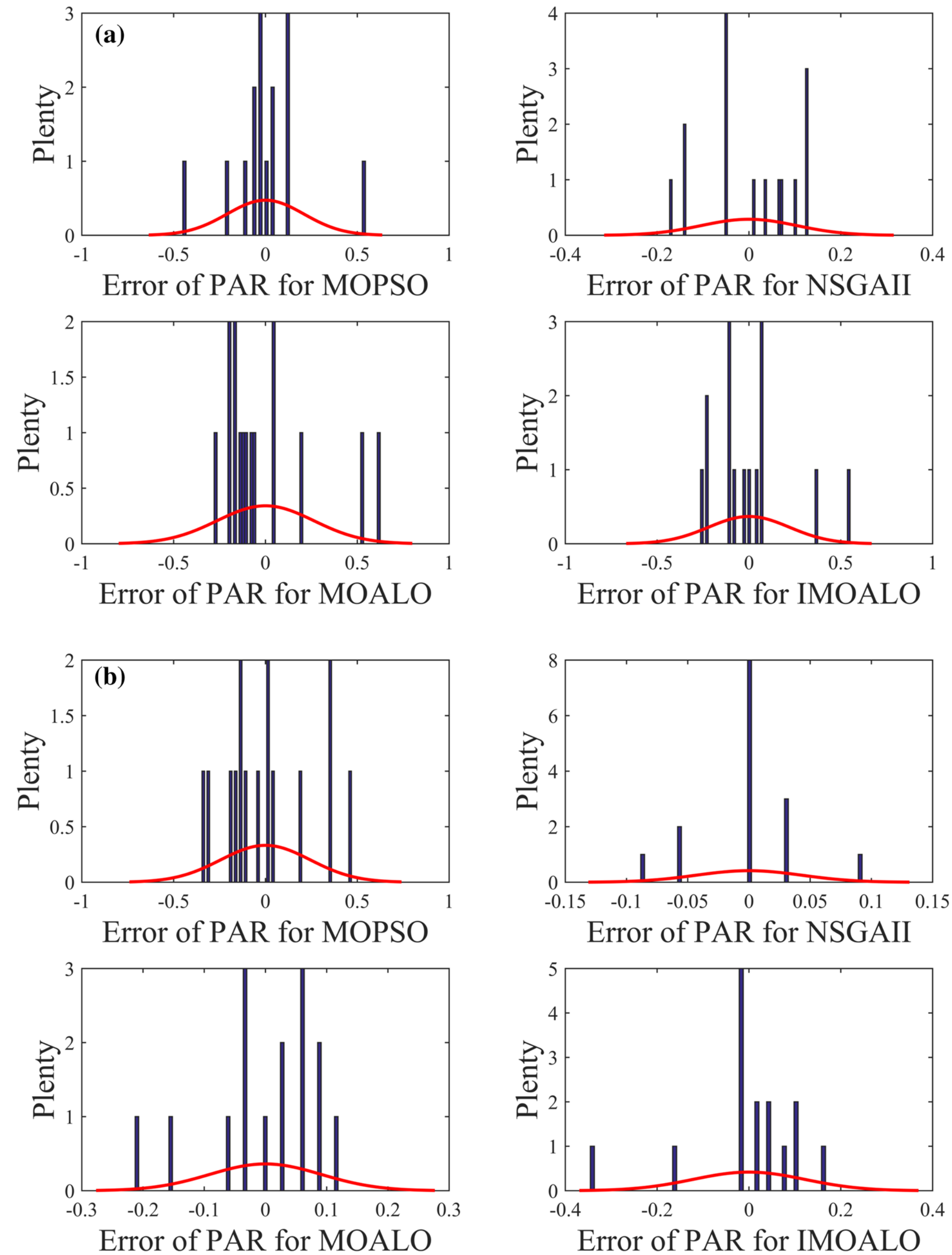

Fig. 8 Histogram plot for PAR **a** with an RTP signal **b** with CPP signal

5 Simulation and results

In this section, we review the results of the optimization algorithms. As stated in the previous sections, the main purpose of this paper is to provide an optimal residential scheduling scheme to reduce electrical costs to increase consumer profitability and reduce PAR to increase power grid efficiency and stability; consumer waiting time is also reduced to increase user comfort. In the proposed scheme, a home with different appliances in terms of energy consumption and operational time is considered. RTP and CPP signals are used as the electricity tariff, which is a good solution for increasing the reliability and stability of the power grid. The proposed MOALO meta-heuristic algorithm was simulated in MATLAB software Ver.2015a using a processor installed with Intel® Core™ i7-4500U CPU @ 1.8 GHz 2.4 GHz and installed memory Ram 8 GB on Windows platform. The other three algorithms MOPSO [24], NSGAII [25], and MOALO have also been simulated to confirm the accuracy of the results of the proposed algorithm by comparing their results. Table 2 presents the parameters of meta-heuristic algorithms. To ensure fairness between the proposed IMOALO algorithm and other meta-heuristic algorithms, each algorithm is run fifty times

Table 4 Statistical data for PAR

PAR		Meta-heuristic algorithms			
		MOPSO [24]	NSGAII [25]	MOALO	IMOALO
RTP	Min	1.47	1.68	1.71	1.71
	Max	2.46	1.98	2.61	2.52
	Mean	1.92	1.85	1.99	1.97
	Var	0.04	0.01	0.06	0.04
CPP	Min	1.68	1.83	1.68	1.53
	Max	2.49	2.01	2.01	2.04
	Mean	2.03	1.92	1.89	1.88
	Var	0.05	0.0018	0.08	0.01

with the same initial population. Table 3 shows the data obtained from this simulation, which includes the total cost and PAR for each meta-heuristic algorithm.

We assumed a home in which electrical appliances are divided into three categories: shiftable, non-shiftable, and fixed appliances. The proposed scheme for shiftable appliances has been implemented. A comparative analysis is performed for the schedule obtained from the proposed algorithm and other meta-heuristic algorithms, and the following results show that the proposed algorithm has a good performance to achieve the above objectives. Figure (2) shows the RTP and CPP signals used in this scheme.

Under these tariffs, the cost of electricity consumption during peak hours increases sharply. The purpose of this increase is to encourage consumers to reduce consumption during peak hours. As shown in Fig. (2), the cost of electricity consumption during off-peak hours is less than 20 cents for CPP tariff, while at 11 to 16 h, which is peak hours, the cost of electricity has increased by more than 120 cents. Therefore, the consumer has to pay a lot of money during peak hours. Also, the power grid equipment suffers a lot of depreciation. The hourly load consumption of scheduled and unscheduled patterns for CPP and RTP tariffs is shown in Fig. (3).

According to Fig. (3), the unscheduled pattern has a peak in the period of 13 and 14, which is equal to 7.5 and 8.5 KW, respectively, and are formed during peak hours. the proposed IMOALO algorithm has a good performance in terms of shifting loads to off-peak hours using both RTP and CPP signals. For this algorithm, the total load consumed during peak hours is about 14 kW and 11 KW using RTP and CPP, respectively, while the load demand during peak hours for the unscheduled pattern is 25 KW and 28 kW using RTP and CPP, respectively. Thus, IMOALO has been able to reduce demand during peak hours by more than 45% and 60% for RTP and CPP signals, respectively, compared to the unscheduled pattern. Also, this algorithm has been able to distribute the load demanded by the consumer in a balanced way outside the peak hours, and fortunately, we do not see a peak in the time slots during the peak hours for the pattern optimized by IMOALO. Also, the peak of scheduled patterns is less compared to unscheduled patterns. Other meta-heuristic algorithms also perform better than unscheduled. Figure (4) illustrates the hourly electricity cost along with a plot of the RTP and CPP signals.

The results in Fig. (4) shows that each algorithm tries to schedule the cost in off-peak hours and the electricity cost of the patterns scheduled by the MOALO, NSGAII, MOPSO, and IMOALO algorithms are much less than the unscheduled pattern. Also, according to Fig. (4b) the proposed IMOALO algorithm costs much less than the other three algorithms. The unscheduling during 13th and 14th give a peak of more than 100 and 600 cents for RTP and CPP signals, respectively. This peak has been reduced by up to 50% by MOPSO, NSGAII, and MOALO algorithms using the CPP signal, while the proposed IMOALO algorithm has reduced this peak close to zero. The total cost of electricity per day using RTP and CPP signals for the patterns scheduled by the optimization algorithms and the unscheduled pattern is estimated in Fig. (5).

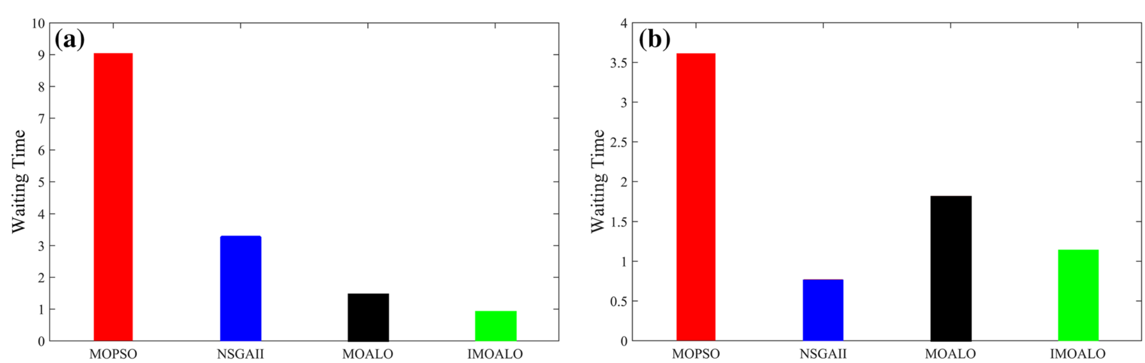

Fig. 9 Waiting time reduction **a** with an RTP signal. **b** With CPP signal

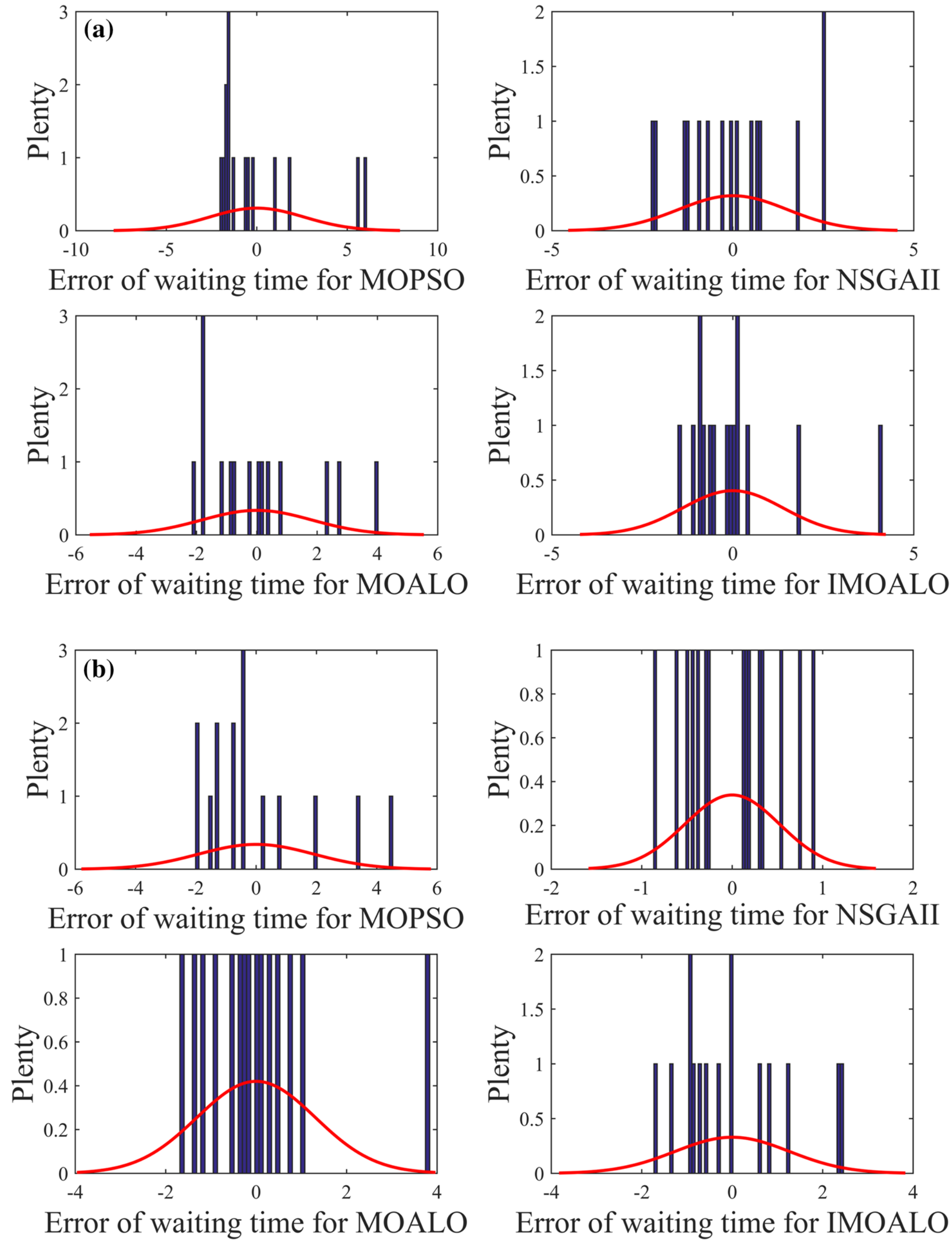

Fig. 10 Histogram plot for waiting time **a** with RTP signal **b** with CPP signal

According to the results in Fig. (5), the total electrical cost for the unscheduled pattern is 3500 and 11,000 cents using RTP and CPP signals, respectively. All the meta-heuristic algorithms used in this simulation have succeeded in reducing these costs and have performed similarly in this regard. All scheduled patterns have reduced the total cost by up to 75% and 80%, respectively, using RTP and CPP signals. These results show that the difference between the unscheduled pattern and other patterns is too much. According to Figs. 3 and 4, this difference is due to the fact that the energy consumed during peak hours by the unscheduled pattern is much higher than other patterns. For example, when using the CPP tariff, the load consumed by the unscheduled pattern during peak hours is about 28 kWh, while for other patterns, it is less than 10 kW. Besides, the proposed IMOALO algorithm has had the best performance when it uses the CPP signal as the electricity tariff. The proposed algorithm performed better than the MOALO algorithm when using RTP as the cost of electricity. Figure (6) shows a histogram of the total cost data in Table 3. Also, the minimum, maximum, mean, and variance values for the total cost are given in Table 3.

Figure (6) and Table 3 show that when reducing the total cost, the variance for the IMOALO algorithm is 615,136.68

Table 5 Statistical data for waiting time

PAR		Meta-heuristic algorithms			
		MOPSO [24]	NSGAII [25]	MOALO	IMOALO
RTP	Min	0.93	0.29	0.07	0.29
	Max	9.03	5.10	6.23	5.93
	Mean	2.97	2.54	2.21	1.80
	Var	6.80	2.25	3.34	1.94
CPP	Min	0.81	0.25	0.35	0.45
	Max	7.35	2.03	5.87	4.64
	Mean	2.82	1.11	2.03	2.18
	Var	3.66	0.27	1.71	1.59

and 105,689.56 using RTP and CPP, respectively, which is less than the variance obtained for the basic IMOALO algorithm. This indicates that IMOALO has a more robust performance than MOALO. Also, this value is 518.95 and 81,232.72 for the NSGAII algorithm, respectively, using RTP and CPP signals. Therefore, the NSGAII algorithm is much more robust than the other three algorithms. But, the minimum total cost for the IMOALO algorithm is 984.50 cents, which is less than the MOPSO algorithm and is equal to NSGAII. Also, the average value for the IMOALO algorithm has the same salvation as the other three algorithms. Therefore, the proposed algorithm performs better than other algorithms in reducing total cost. Figure (7) shows the performance of all scheduled and unscheduled models in terms of PAR reduction According to RTP and CPP signals.

According to Fig. (7), the PAR value for the unscheduled pattern is 2.5. All programmed patterns have been able to reduce this value well for both RTP and CPP cost signals. In the meantime, our proposed pattern has performed better than others. IMOALO not only reduces the PAR obtained in the MOALO scheme, but also the PAR obtained using this scheme is less than other schemes. IMOALO was able to reduce the PAR value by 35% and 30%, respectively, using RTP and CPP signals. A histogram of the PAR is shown in Fig. (8). Also, Table 4 presents the minimum, maximum, mean, and variance values for the PAR.

Table 4 shows that the variance for our proposed IMOALO algorithm is 0.04 and 0.01 using RTP and CPP signals, respectively, which is less than the variance obtained for MOALO and shows that the proposed algorithm is more robust than MOALO in terms of PAR reduction. The minimum PAR for the IMOALO algorithm is 1.53 using CPP, which is less than the value obtained for other algorithms. But when using the RTP signal, MOPSO got the lowest value, which is 1.47. Figure (9) presents the waiting time for each algorithm using RTP and CPP signal.

According to Fig. (9), the MOPSO algorithm has the longest waiting time for both RTP and CPP signals, which are 9 and 3.6, respectively. Our proposed IMOALO algorithm has the best performance in terms of reducing the waiting time when using RTP as an electricity tariff. The waiting time for IMOALO is 1, which is 8 units less than the waiting time obtained by the MOPSO algorithm using the RTP signal. When using the CPP signal, NSGAII performs better than others. The waiting time for this pattern is less than one unit. Then, our proposed algorithm has a waiting time of 1.3 units. Figure (10) shows a histogram of the waiting time data in Table 3. Also, the minimum, maximum, mean, and variance values for the waiting time are given in Table 5.

According to Fig. (10) and the data in Table 5, when using the RTP tariff, the variance and the mean for our proposed plan are 1.94 and 1.8, respectively, which is less than the variance and the mean obtained for other plans and that means IMOALO performed better. But when using the

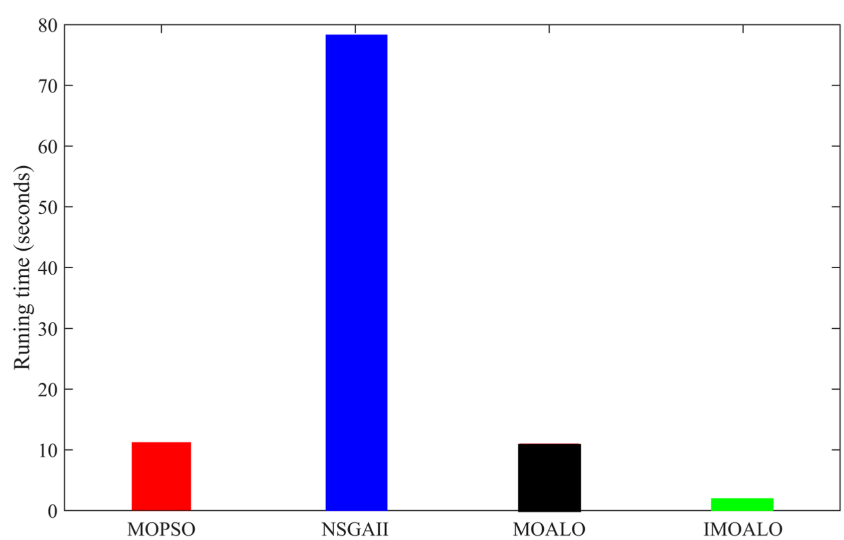

Fig. 11 The running time

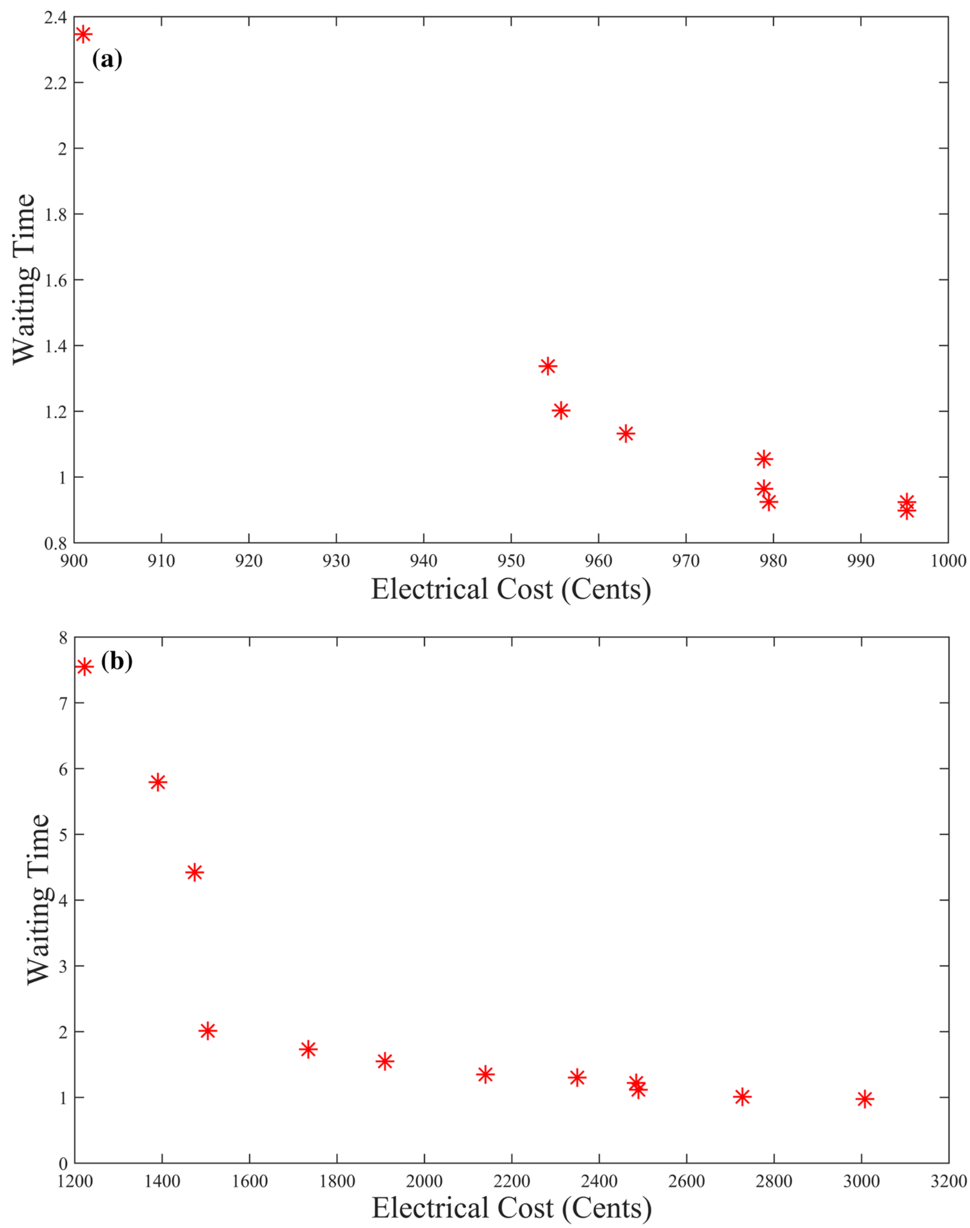

Fig. 12 Pareto optimal front obtained by the IMOALO algorithm. **a** With an RTP signal. **b** With CPP signal

CPP tariff, NSGAII has the lowest variance and the mean, which is 0.27 and 1.11, respectively. Figure (11) presents the running time for each algorithm.

According to Fig. (11), the NSGAII algorithm has the longest running time, which is more than 70 s, but this is not good. The running time for the proposed IMOALO algorithm and MOPSO and MOALO algorithms is less than 20 s, which seems appropriate. The IMOALO algorithm has the shortest running time. Figure (12) shows the Pareto optimal front for the proposed IMOALO algorithm.

According to Fig. (12), the repository obtained for the proposed IMOALO algorithm had 9 and 12 members, respectively, when using the RTP and CPP signals.

Based on the results presented in this section, the proposed IMOALO algorithm has performed well in designing an optimal residential schedule. This scheme can significantly reduce the total cost and PAR and increases the user comfort; therefore, the implementation of this plan will greatly reduce the electricity bill of consumers and also increase the stability of the power grid and reduce the maintenance costs that the company has to pay.

6 Conclusion

Optimal consumption and management of electricity help to reduce consumer demand. Demand-side management not only reduces electricity costs and increases consumer profitability, but also reduces network maintenance costs. In this paper, the IMOALO meta-heuristic algorithm is presented to optimize the consumption pattern of home appliances. The proposed scheme classifies the devices into three categories: shiftable, non-shiftable, and fixed. RTP and CPP signal is considered as electricity consumption tariff, which is a good solution to increase grid efficiency and stability. The simulation results are compared with MOPSO, MOALO, and NSGAII algorithms. The IMOALO algorithm has been able to reduce the daily cost of electricity by up to 75% and 80%, respectively, using RTP and CPP signals, and PAR by up to 35% and 30%, respectively, using RTP and CPP signals compared to the unscheduled pattern, which has performed better than other meta-heuristic algorithms. This algorithm also reduces the waiting time compared to other algorithms. Therefore, the results show that the use of the proposed plan can be an effective solution to deal with the growing consumer demand.

Compliance with ethical standards

Conflict of interest The authors declare no conflict of interest.

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