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Optimizing Operation Scheduling in a Microgrid Considering Probabilistic Uncertainty and Demand Response Using Social Spider Algorithm

Amir Mortazi, SeyedAmin Saeed*, Hamidreza Akbari

Department of Electrical Engineering, Yazd Branch, Islamic Azad University, Yazd, Iran, amin.saied@iau.ac.ir

Abstract

The production of electrical energy from renewable sources has become an efficient solution to deal with the lack of fossil fuels, and prevent the emission of greenhouse gases and global warming. Due to the existence of different loads in terms of feeding priority, consumers can help the microgrid control center in optimizing the use of the microgrid and supplying energy to critical loads by providing the amount of load that can be interrupted or moved at different prices. Consumer pricing can reduce operating costs, especially when market prices are high. At the same time, with this method, consumers can economize on unimportant loads. In this paper, the effect of consumer pricing on the use of microgrids is analyzed considering the types of consumers and load priorities. In addition, the economic impact of applying production adequacy restrictions, i.e. meeting the demand of a special part of the microgrid load by local production in case of microgrid islanding, is evaluated. The demand response program is achieved with the objective function of maximizing social welfare. on the other hand, the operation is principally concerned with flattening the load curve as much as possible. The flatter the load curve, the better the capacity installed in the network, and as a result, it postpones the development of generation and transmission. In this regard, an attempt is made to operate the microgrid in the presence of demand response, so that while increasing social welfare, the load curve is flat at an acceptable level. With these goals, the problem is formulated as a multi-objective objective function based on nonlinear programming GAMS optimization software used to solve the problem, and ε constraint will be used for multi-objective optimization.

Keywords: Optimization, Operation Scheduling, Demand Response, Probabilistic Uncertainty, Social Spider Algorithm.
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1. Introduction

In recent years, providing solutions for optimal management of consumption, due to the increase in the use of renewable energy sources as electricity production units in modern networks, has gained momentum [1]. Demand response programs (DRP) as an essential part of demand side management (DSM) have always been one of the best ways to attract the participation of customers in modifying the consumption pattern. In general, the implementation of DR programs goes through electricity retail pricing. One of the factors affecting these prices in modern distribution networks with high penetration of renewable energy sources is the uncertainty of the production of these distributed generation units (DG's) [2-3]. Therefore, in the smart energy network, large consumers can use various sources to supply their energy needs, such as the electricity market, power plants under their ownership, including thermal power plants, and renewable energy sources such as wind turbines and solar power plants, and supply a part of the energy demand through bilateral contracts. A large consumer can participate in demand response programs, yet by examining the amount of consumer participation in demand response programs and the amount of pre-signed contracts, it is clear that consumers cannot always act based on the signed contracts. Hence, the modelling uncertainty for this source is negligible. The plan adopted by a large consumer to supply its energy needs depends on the extent of price reduction in the presence of uncertainties in the complex smart grid market [4-6].

In [7], in addition to creating a new price optimization framework in the real-time pricing (RTP) method, an optimal combined tariff plan has been proposed and reviewed that is more compatible with the pricing principles than the RTP pricing method. To increase the validity of the proposed framework and the new pricing method presented, the uncertainty related to renewable products as well as all the limitations related to the operation of the microgrid in real conditions such as load spreading have been considered. In [8], a method is presented to evaluate the effect of demand response in microgrids. In addition, several cases are simulated to better understand the problem. Also, the combined optimization algorithm including the gray wolf optimization (GWO) algorithm and the shark smell optimization algorithm has been used to solve the multi-objective objective function under different constraints [9]. In this regard, to check the uncertainty in the production of renewable energy sources, the Monte Carlo method has been employed to generate scenarios. The objective function of the problem considered in this research includes network losses, production cost, and reliability index and voltage stability. In [10], a comprehensive energy management model for operating a modified 33-radial bus distribution system, considering smart homes, is presented. In the proposed model, smart home customers can participate in a demand response program and the welfare index of customers is considered the main condition. Moreover, in the mentioned model, the uncertainties of the amount of load demand, the amount of production of renewable resources, and the price of electricity are accommodated by the Monte Carlo method.

This study aims to determine the optimal demand response program to reduce the power of the active power market and the cost of electricity at the same time as reducing power losses, in the presence of load uncertainty, from the point of view of the independent operator of the system [11]. In [12], the total price of electricity from the direct independent operator is calculated as the sum of the costs paid to producers in proportion to the price of electricity in the production bus and the cost paid to customers for their participation in the demand response program. In [13], the use of microgrids equipped with renewable resources and power storage resources has been investigated. Due to the increase in greenhouse gas emissions, the use of renewable resources, especially wind and solar resources is growing. One of the important characteristics of renewable resources is uncertainty in power generation, which is an inherent characteristic of these resources. The presence of these sources in the power system makes the operation of the power system face uncertainties, making it necessary to operate the microgrid and the amount of cost reduction has been investigated, which is due to the use of the microgrid demand response program in the state separated from the upstream network. In [14], the use of an incentive-based demand response program, in the presence of wind resources and the uncertainties of these resources are discussed to manage congestion in the power network. In the simulation part, the particle swarm optimization (PSO) algorithm is adopted for the optimization operation.

The approach presented in [15] to solve the problem is to use demand response programs to reduce the cost of power supply by the owners of wind farms. In the presented method, the owners can purchase a part of their committed power from consumers through demand response programs to avoid possible fines if the speed or intensity of the wind decreases. Therefore, every wind farm can make up for its production deficit by concluding a contract with a part of the customers and avoiding heavy fines imposed by the power production contract due to non-production of power. Therefore, in this article, with the presented approach, the appropriate location and capacity of demand response have been determined to lower power generation costs from the perspective of the wind farm owner. In [16], the use of a smart grid equipped with renewable resources and power storage resources, as well as the effect of adding cars in the presence of renewable resources, has been investigated. They investigated the use of the demand response program as a tool to manage the uncertainty of clean energy sources and reduce the amount of unsupplied power, and the amount of cost reduction due to the use of the demand response program. The authors in [17] present the simultaneous and coordinated power market of production and ancillary services based on the placement of DG units in based on security constraints to face the uncertainties of wind power and load forecasting. Case studies conducted on a standard network show the effectiveness of this method in the face of wind and load uncertainties. In [18], the error resulting from the prediction of wind speed and solar radiation is modeled by probability density functions and a probabilistic planning model is proposed to optimize the performance of the smart microgrid in the short term to minimize the cost of operation and pollution with the presence of renewable resources. To elaborate, the use of demand response programs by domestic, commercial and industrial participants is suggested to cover the uncertainty of production power from renewable sources [19]. For the implementation of demand response programs, an incentive payment program has been proposed in the form of price and energy quantity proposals packages that are collected by demand response providers. In [20], the issue of network development planning in the presence of distributed production resources and the participation of the demand response program is modeled. The presented model, using Monte-Carlo and Hurwitz methods [21], considers the uncertainties caused by price elasticity, load forecasting and the production of scattered production resources in planning. On the other hand, according to the base load price as a variable with a limited fluctuation range, the presented model has accommodated necessary incentives to encourage the investor to follow upstream policies. The authors in [22] present an approach related to the cooperation between the renewable grid and the main grid, which is responsible for supplying the variable load demand through the energy management system. For this purpose, advanced management is introduced in a renewable grid, in the mode connected to the main grid, which can create an optimal exploitation strategy to minimize energy costs and maximize the output power from renewable sources, considering uncertainty. In the proposed method, the need for the reservation to compensate for the predicted renewable errors by demand response and distributed generation units is presented.

According to the relevant research, the effect of change in demand response and probabilistic uncertainty method has not been investigated, neither has. the constraint of epsilon, which can lead all optimizations to a more accurate answer. More specifically, the market clearing price in this work is determined in the day-ahead market. Although participation in these programs is optional, participants must respond to requests and distribute instructions. Participating in this program does not require physical contribution and only interval measurement is sufficient. The reduction in demand is measured against a pre-defined baseline. If a participant fails to reduce the demand from the baseline as planned, the penalty during the planned reduction period is greater than the day-ahead price and the real-time price. In most electricity markets, consumers have a more limited role than producers. The active participation of consumers in the electricity market can bring many benefits, which can be mentioned as follows:

- Consumers who can shift their load from expensive hours to cheap hours will reduce the cost of their energy consumption.
- Shifting the load will flatten the daily load curve and reduce the total cost of energy production.
- Consumers who do not adjust their consumption level in response to the price of electricity also benefit from it, because the reduction of the total cost of energy production leads to a reduction in the price of electricity.
- Producers' ability to exercise market power decreases.

On the other hand, the more flexible the loads become, the lower the producers' profit is. Therefore, it is necessary to pay attention to the behaviour of consumers and to model how consumers respond to the hourly prices of electric energy. Consumers temporarily reduce their consumption when faced with a sudden increase in electricity prices; but, in the long run, when faced with periodic fluctuations in electricity prices, they are willing to shift their consumption in a way that reduces their costs. If the consumers want to play an active and effective role in the electric energy market, the market clearing mechanism should be designed to consider the price-sensitive offers of the consumption side and load shifting of the consumers. These give consumers a chance to apply restrictions on their hourly and daily energy consumption; accordingly, producers can apply restrictions for the operation of their units every hour and day. It is worth mentioning that the optimization problem is going to be solved using social spider algorithm (SSA).

The sections of the present article are organized as follows: the problem formulations for market clearing price mechanism, priceable and flexible consumers within price sensitivity are elaborated in Section 2. A brief description of SSA is represented in Section 3. The simulations and discussion in several case studies are presented in Section 4 and finally, the conclusions are drawn in Section 5.

2. Problem Formulation

In this section, the market clearing mechanism in which consumers are allowed to submit proposals is discussed. The day-ahead market includes production and consumption pricing and its goal is to maximize social welfare. Therefore, the market operator must perform a multi-round optimization to determine the optimal production and consumption schedules as well as the market clearing price π^t in each period. It is assumed that the final producer unit is used to balance the market. A "side payment" is added to the marginal cost of that producing unit to determine the market clearing price π^t. This side payment allows the final producing units to meet the no-load cost (a fixed cost borne by the producing units regardless of their production level) and a start-up cost (a fixed cost borne by the producing unit when synchronization suffers), to compensate again.

This encourages manufacturers to bid their true cost. Since these costs are assumed to be fixed. Participating in the day-ahead market allows consumers to adjust their activities (for example, planning their industrial production) when the market is balanced. The number of consumers who can essentially respond to price signals issued closer to real time is probably much smaller. In this formulation, for the simplicity of the model, the congestion of the transmission network is ignored and it is assumed that ancillary services such as revolving storage are traded in another market. Similarly, if the amount of production or consumption of the participants in the market deviates from the determined optimal value, this difference is adjusted in the balancing market, which is separate from the day-ahead market.

The objective function is to maximize social welfare, which means the difference between the value of purchased electrical energy for consumers and the cost of producing this energy. Social welfare is defined as follows:

$$\max \sum_{t=1}^{T}\left(GS^{t}-OC^{t}\right) \tag{1}$$

Where the first term is the consumer's gross surplus GS^t and the second term is the operating cost OC^t in the interval t and T is the number of hours of the optimization period. In continuation, manufacturers provide proposals that include operating costs and related restrictions. Therefore, the operating cost is modeled as follows:

$$OC^{t}=\sum_{i=1}^{I}\sum_{b=1}^{B}MC^{i,b}P_{seg}^{i,b,t} \tag{2}$$

Where, I is the number of producing units; B represents the number of parts of the manufacturer's offer curve; $MC^{i,b}$ is the marginal cost of producing the ith unit in the bth part of the supply curve; and finally, $P_{seg}^{i,b,t}$ represents the production power of the ith unit in the bth section of the supply curve at time t.The restrictions on the operation of the production units are considered as follows:

$$P_{seg}^{i,b,t}\leq P_{offer}^{i,b}\cdot u_{G}^{i,t} \tag{3}$$

$$P^{i,t}=\sum_{b=1}^{B}P_{seg}^{i,b,t} \tag{4}$$

$$P^{i,t}\geq \underline{P}^{i}\cdot u_{G}^{i,t} \tag{5}$$

Where, $P_{offer}^{i,b}$ proposes power of the ith unit in the bth part of the bidding curve; $u_G^{i,t}$ is a state variable of the ith unit at time t (1: on, 0: off); $P^{i,t}$ shows production power of the ith unit at hour t and $\underline{P}^{i}$ is the minimum production power of the ith unit. Since not necessarily all consumers have the ability or the motivation to adjust the level of consumption based on the price, a part of consumption remains completely inflexible. Figure (1) shows the consumer pricing used in this model.

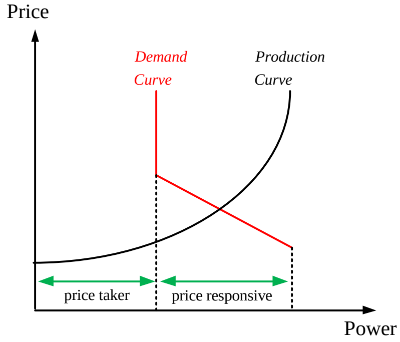

Fig. 1. Priceable and flexible consumer demand curve

Equation (6) describes how to calculate the consumer's gross surplus based on accepted offers and the marginal value of these offers. This relationship is limited to the consumers who adjust their consumption level based on the price, because it is assumed that the limit value of the priceable load is infinite. To simplify the model, it is assumed that the gross surplus of priceable loads is a fixed number and is not included in the optimization model:

$$GS^{t}=\sum_{k=1}^{K}\sum_{j=1}^{J}MB_{seg}^{k,j}\cdot D_{seg}^{k,j,t} \tag{6}$$

Where, K is the number of price-responsive consumers; $MB_{seg}^{k,j}$ is the marginal profit of the responsive consumer at the kth price in the jth section of the supply curve; and $D_{seg}^{k,j,t}$ donates the consumption load of the consumer responding to the kth price in the jth section of the supply curve at hour t. Since active consumer's pricing suggestions can be flexible, these suggestions can be a combination of the following:

– Volume-price order in each period
– Minimum energy consumption in each period
– Maximum energy consumption in each period
– Total energy consumption during the planning period
– Priced orders for inflexible loads

In the model used to settle the market, the features mentioned for the proposals can be expressed as constraints on the amount of load consumed in each period (7) and the amount of energy consumed in the entire planning period (8). The last constraint should be given unequally, as an offer from the consumption side is acceptable if it is not lower than the minimum offer from the producer. Otherwise, some of the load will not be supplied. These cases are modeled as follows:

$$u_D^{k,t} \cdot \underline{D}^{k,t} \le D^{k,t} \le u_D^{k,t} \cdot \bar{D}^{k,t} \tag{7}$$

$$0 \le \sum_{t=1}^{T} D^{k,t} \le E^{k} \tag{8}$$

$$D^{k,t} = \sum_{j=1}^{K} D_{seg}^{k,j,t} \tag{9}$$

$$D_{seg}^{k,1,t} \ge u_D^{k,t} \cdot \underline{D}^{k,t} \tag{10}$$

$$0 \le D_{seg}^{k,j,t} \le u^{k,t} \cdot \left(\bar{d}_{seg}^{k,j} - \bar{d}_{seg}^{k,j-1}\right) \tag{11}$$

$$\bar{d}_{seg}^{k,0} = 0 \tag{12}$$

Where, $u_D^{k,t}$ is the state variable of the consumer responding to the kth price at hour t (1: on, 0: off); $\underline{D}^{k,t}$ is the minimum consumption power of the responsive consumer at the price k at hour t; $\bar{D}^{k,t}$ is the maximum consumption power of the responsive consumer at the kth price in hour t; $D^{k,t}$ is the power consumption of responsive consumer at price k at hour t; E^k is the maximum energy required by the responsive consumer at the kth price during the planning period; and $\bar{d}_{seg}^{k,j}$ is the upper limit of the power offered by the responsive consumer at the kth price in the jth part of the supply curve. Another constraint is the stipulation of equality of production and consumption power:

$$\sum_{i=1}^{I} P^{i,t} = \sum_{k=1}^{K} D^{k,t} + \sum_{z=1}^{Z} D_T^{z,t} \tag{13}$$

Where Z is the number of price-sensitive consumers and $D_T^{z,t}$ represents the consumption power of the priceable consumer Z at hour t.

2-1- Demand response model

The load ratio that responds to price changes affects the load demand curve. As seen in Figure (2), the load contribution factor can be defined as the ratio of the flexible load to the total load.

$$LPF = \frac{D_R}{D_F} \tag{14}$$

The D_F parameter changes in each period due to the load change. On the other hand, LPF and π_L and π_H parameters remain constant during the planning period. Since consumers can shift their load from hour to hour, demand response can affect the price and load profile throughout the optimization period. On the other hand, if a consumer's price offer is too small, it may not be possible to move that part of the load. Thus, the benefits of load shifting should be evaluated considering these limitations. Common economic indicators such as consumer surplus can measure total consumption benefits, but these indicators cannot help to calculate the amount of profit obtained from the consumption of one-megawatt hour. For this reason, it is suggested here to calculate the average price during the planning period.

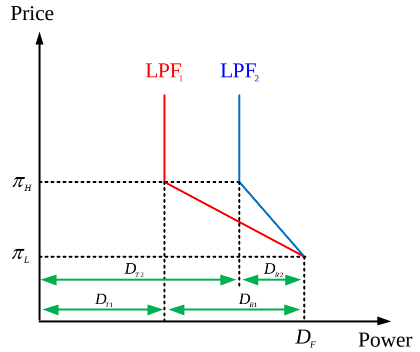

Fig. 2. Figure (2): The relationship between load participation coefficient and demand

The average market clearing price can be considered as the average market clearing prices in each period:

$$\pi_{avg} = \frac{1}{T}\sum_{t=1}^{T} \pi^{t} \tag{15}$$

But it is better to express the marginal cost of each group of participants in the market as a weighted average, whose general relationship is as follows:

$$\mu = \frac{\sum_{t=1}^{T} X^{t} \cdot Y^{t}}{\sum_{t=1}^{T} Y^{t}} \tag{16}$$

Where X^t is the set of costs or prices and Y^t weighting coefficients of consumed or produced energy in the relevant period. Thus, the average marginal cost for all price-responsive consumers can be calculated as the following weighted average:

$$\mu_R = \frac{\sum_{k=1}^{K}\sum_{t=1}^{T} \pi^{t} \cdot D^{k,t}}{\sum_{k=1}^{K}\sum_{t=1}^{T} D^{k,t}} \tag{17}$$

Similarly, the average marginal cost for price-sensitive consumers is obtained as μ_T. In addition, by placing the total consumption load in equation (17), the average marginal cost μ_D for all consumers can be obtained. The average marginal cost for producers can likewise be calculated as follows:

$$\mu_G = \frac{\sum_{i=1}^{I}\sum_{t=1}^{T} MC^{i,t} \cdot P^{i,t}}{\sum_{i=1}^{I}\sum_{t=1}^{T} MC^{i,t}} \tag{18}$$

Where $MC^{i,t}$ is the marginal cost of the ith producer at hour t. It is similarly possible to obtain the weighted average income of producers μ_P by placing the market clearing price π^t instead of the marginal cost in (18). The profit from the demand response for each consumer can be calculated as follows:

$$\lambda(LPF) = \mu(LPF = 0) - \mu(LPF) \tag{19}$$

Based on this general definition, the resulting changes in demand response to cost or income for different market participants can be shown as follows. Due to the balance between production and consumption, we have:

$$\mu_D = \mu_P \tag{20}$$

So

$$\lambda_D = \lambda_P \tag{21}$$

The relationship shows that the amount of profit from load shifting for flexible consumers is equal to the amount of income reduction of producers. The difference in the total profit of producers can be shown as follows:

$$\lambda_{TG} = \lambda_G - \lambda_P \tag{22}$$

This relationship indicates that producers benefit from load shifting when the reduction in operating costs due to load shifting is greater than the reduction in their income. The overall additional benefit that can be achieved on the consumer side (affordable and flexible) is calculated as follows:

$$\lambda_{TD} = \lambda_D \tag{23}$$

The overall additional benefit that can be achieved for both the producer and consumer can be obtained by adding the last two relations, which is equal to the change in total social welfare:

$$\lambda_{TA} = \lambda_D + \lambda_G - \lambda_P \tag{24}$$

As a result, we will have:

$$\lambda_{TA} = \lambda_G \tag{25}$$

It means that load-shifting spreads the amount of profit from reducing the operating cost of producers among all market participants. In the above equation, λ_R is the change in the cost of price-responsive consumers due to load shifting, λ_T shows the change in the cost of affordable consumers due to load shifting, λ_D represents the change in load demand cost, λ_G is the change in the operating cost of all producers, λ_P shows the change in total revenue for producers, λ_{TA} represents the change in the social welfare of all market participants, λ_{TD} is the change in total profit for all consumers, and λ_{TG} represents the change in total profit for all producers.

2-2- Overcoming uncertainty with a probabilistic approach

In the proposed stochastic method, the phenomenon of uncertainty is dealt with from a statistical point of view, in which probability density functions (PDF) are used. PDF is created for consumers' load according to the past collected data. To do this, every year is divided into four seasons and each season will be represented by a full day. So, every year is expressed by four days. Therefore, with 24 hours each day, there are a total of 96 ($4_{\text{seasons per Year}} \times 24_{\text{hour per day}}$) hours in each year. These 96 hours represent all the different moods in a year. Notably, in some references, the whole year is expressed by 12 days, each day representing one month. The number of days to express a year depends on the volume of calculations, the speed of processing and the data available in the past.

Assuming there are 96 hours in the whole year, if the data of the last n years are available in the desired location, for each hour, there are $90n$ ($n_{\text{years}} \times 30_{\text{days per month}} \times 3_{\text{months per season}}$) data for the consumers' load. For example, for 12:00 to 13:00 in the spring season, the data of the last n years of the same hour and on 90 different days of the spring season are collected. According to the measured data, the probability density function of consumer load is obtained for each hour. The probability density function of load is expressed by normal PDF.

In order to create yearly scenarios that include the combination of different events of consumers load, the probability density functions of the consumer load which are continuous are divided into four discrete intervals (four events). Assuming that the variables of consumer load are independent of each other, there are 16 (4 x 4) combined scenarios for each hour, where the probability of each scenario is equal to the probability of occurrence of each event. Therefore, there are 1536 ($16_{\text{scenario per hour}} \times 96_{\text{hour per year}}$) scenarios in the whole year. With these 1536 scenarios, we consider all possible situations that may occur in a whole year. In case of a great number of scenarios, we can reduce them using scenario reduction methods. Finally, we solve the optimization problem by obtaining the scenarios using the following objective function.

$$\min(\sum_s \rho_s f_s) \tag{26}$$

Where f_s is the objective function for the load values of the consumers in the specific scenario s, and the probability of that scenario is ρ_s corresponding to each one. The above objective function states that the priority (importance degree) of the objective function f_s for minimization is higher for scenarios with higher probability ρ_s. Here, weight has the same role for different scenarios in optimization.

2-3- Optimization

In this section, the method of modeling with a multi-purpose objective function using the multi-purpose programming method has been studied. In general, in solving optimization problems with a multi-objective objective function, there is no single solution that optimizes all the objective functions at the same time, and therefore, in such problems, a set of solutions is usually obtained for each of these solutions, the Pareto solution (It is called non-dominant answer). Each of the Pareto solutions is the optimal solution for one of the objective functions, but at least one of the other objective functions cannot be addressed by the optimal solution. To solve the problem of exploitation with the presence of demand response, the ratio of F1 and F2 should be optimized. The epsilon limit method has been employed to solve the problem. In this method, one of the objective functions is taken as the main objective function and other objective functions are considered constraints in the optimization problem.

Therefore, through the following relationship we can solve the multi-objective optimization problem with p as the objective function using the epsilon constraint method:

$$\begin{aligned} &\text{Minimize } F_1(x) \\ &\text{subject to } F_2(x) \le e_2, F_3(x) \ge e_3, \cdots, F_p(x) \le e_p \end{aligned} \tag{27}$$

To apply the epsilon limitation method, the range of changes in the objective functions F_2 to F_p should be determined and e_2 to e_p should be determined in these ranges. The most common approach to calculate these intervals is to use the final result table, which will be explained below.

Assume that the optimization problem has p as the objective function. Therefore, $p-1$ of the function should be considered a constraint. Basically, to prepare the final result table for $p-1$ objective function, first, the optimal value of each objective function is calculated separately. For the ith objective function, this value is called F_i^*. Then, for the solution that has optimized the ith objective function ($i=2,\ldots,p$) the value of other objective functions is calculated. Therefore, the ith row of the final table will be $F_p^i, \cdots, F_{i+1}^i, F_i^*, F_{i-1}^i, \cdots, F_2^i$. The final result is calculated in a similar way to the other rows of the table. The jth column of the mentioned table is the calculated value for the objective function F_j. The maximum and minimum value of this column will be the range of changes of the objective function F_j. Then, the range of changes in objective functions F_2 to F_p are divided into q_2 to q_p respectively. Therefore, a network of points $(q2-1),(q3-1),\ldots,(qp-1)$ is obtained. Considering the minimum and maximum values for the objective functions F_2 to F_p which are respectively $(q2+1),(q3+1),\ldots,(qp+1)$, thus the optimization problem turns into $(q2+1)\times(q3+1)\times\ldots\times(qp+1)$ sub-problems, which the answer of each of them must be obtained. Therefore, the problem will be modeled in the following closed form:

$$\begin{aligned} &\text{Minimize } F_1(x) \\ &\text{subject to } F_2(x) \le e_{2i}, F_3(x) \ge e_{3j}, \cdots, F_p(x) \le e_{pl} \\ &e_{2i} = Max(F_2) - \left(\frac{Max(F_2)-Min(F_2)}{q_2}\right)\times i \qquad i = 0,1,\cdots,q_2 \\ &e_{3j} = Min(F_3) + \left(\frac{Max(F_3)-Min(F_3)}{q_3}\right)\times j \qquad j = 0,1,\cdots,q_3 \\ &\vdots \\ &e_{pl} = Max(F_p) - \left(\frac{Max(F_p)-Min(F_p)}{q_p}\right)\times l \qquad l = 0,1,\cdots,q_p \end{aligned} \tag{28}$$

In the above problem, it is assumed that F_2 and F_p should be minimized and F_3 should be maximized. In the above problem, it is assumed that F_2 and F_p should be minimized and F_3 should be maximized. Correspondingly, $Min(.)$ and $Max(.)$ are the minimum and maximum values of the objective function. By solving each sub-problem, a Pareto solution will be obtained, or the problem may not be converged and a possible solution for the problem not be obtained. The more point the intervals of the objective function are divided into, the more Pareto solutions are obtained for the optimization problem with the multi-objective objective function; however, because of a larger number of calculations, the operation will take longer. For this purpose, there should be a trade-off between the number of each interval of the objective function and the calculation time. After solving all the sub-problems and obtaining all the Pareto solutions to the problem, the decision maker must choose one of the Pareto solutions as the final one among the obtained Pareto solutions according to the priorities and applications. For this purpose, a fuzzy approach with a linear membership function is employed for decision-making. The membership function of the fuzzy method is defined as equations (29) and (30):

$$\mu^k_{i \in \{Minimizing OF\}} = \begin{cases} 1 & F_i^k \le Min(F_i) \\ \dfrac{Max(F_i) - F_i^k}{Max(F_i) - Min(F_i)} & Min(F_i) \le F_i^k \le Max(F_i) \\ 0 & F_i^k \ge Max(F_i) \end{cases} \quad (29)$$

$$\mu^k_{i \in \{Maxmizing OF\}} = \begin{cases} 0 & F_i^k \le Min(F_i) \\ \dfrac{F_i^k - Min(F_i)}{Max(F_i) - Min(F_i)} & Min(F_i) \le F_i^k \le Max(F_i) \\ 1 & F_i^k \ge Max(F_i) \end{cases} \quad (30)$$

In these relationships, F_{ik} is the value of the objective function F_i in the kth Pareto solution and the membership function F_i in the kth Pareto solution. It indicates the degree of optimality of the objective function in the Pareto k solution. The overall membership function μ^k is called the Pareto solution k and is calculated as follows:

$$\mu^k = \frac{\sum_{i=2}^{p} w_i . \mu_i^k}{\sum_{k=1}^{M} \sum_{i=2}^{p} w_i . \mu_i^k} \quad (31)$$

where w_i is the weight coefficient of the ith objective function and M is the total number of Pareto solutions. The values of the weight coefficients are determined according to the importance of each objective function. The objective functions corresponding to the highest value of μ^k among all the solutions obtain the optimal value corresponding to multi-objective programming. In this article, the social welfare function is selected as the main objective function and the constraints corresponding to the ε values in each interval on the objective function of minimizing the load deviation from the average value are added to the model in the form of the following:

$$\sum_{t=1}^{T} \left(Dev_t^+ + Dev_t^- \right) \le \varepsilon \quad (32)$$

3. Social spider algorithm (SSA)

The searching behavior of a social spider can be described as the collective movement of spiders toward the location of a food source. The spider receives and analyzes the vibrations emitted in the search space to determine the potential direction of a food source. We use this natural behavior to perform optimization in the search space using the SSA method. In SSA, we consider the search space of the optimization problem as a multidimensional spider's search space. Each function in the search space represents a practical solution for the optimization problem, and each practical solution for the optimization problem in question is a position in the search space. The search space likewise acts as a medium for transmitting the vibrations produced by the spider. Each spider in the search space has a position and a quality (fitness), which indicates the potential of finding a food source at that location. The spider can move freely in the search space, but it cannot leave the search space. When a spider moves to a new location, it produces a vibration that spreads throughout the search space. A spider has information from a spider and others receive this vibrational information.

3-1- Vibration

Vibration is a significant concept in SSA. It is one of the key features that differentiate SSA from other meta-heuristic processes. In SSA, two assets are utilized to describe a vibration, specifically the source location and the source intensity of the vibration. The source location is investigated by the meaningful space of the optimization problem, and then the intensity of vibration in the range $[0, +\infty)$ is defined. When each spider transfers to an innovative location, it produces a vibration at its present location. The position of spider a at time t is $L_a(t)$, or simply as L_a, if the time argument t will be defined later. Further, $V(L_a, L_b, t)$ is used to signify the vibration intensity detected by a spider at location L_b at period t and the source of the vibration is at location L_a. With these symbolizations, $V(L_a, L_b, t)$ is defined to characterize the intensity of the vibration made by spider s at the source location. This vibration intensity at the source location is connected with the fitness of its location $g(L_s)$, and thus the intensity rate is introduced as follows:

$$V(L_a, L_b, t) = \log\left(\frac{1}{g(L_s) - \Psi} + 1\right) \quad (33)$$

Where Ψ is a positively small persistent such that all conceivable fitness standards are superior to Ψ. As a procedure of energy, vibration weakens over distance. This animal portent is accounted for in the plan of SSA. The distance between spider x and y is assumed as $H(L_x, L_y)$ and we have:

$$H(L_x, L_y) = \left|\left| L_x - L_y \right|\right| \quad (34)$$

The standard deviation of all spider locations along each dimension is signified as ξ. With these descriptions, the vibration weakening over distance is calculated as follows:

$$V(L_a, L_b, t) = \frac{V(L_a, L_b, t)}{e^{\frac{\left|\left| L_x - L_y \right|\right|}{\xi \times q_a}}} \quad (35)$$

In the above formula, a user-controlled parameter $\xi \in (0, \infty)$ is shown which controls the weakening rate of the vibration intensity over distance. With larger parameters, there will be weaker attenuation imposed on the vibration. Then the locations are updated as below and then the algorithm will find the global best all over the search space:

$$V_s(t+1) = V_s + rand(.) \times (V_s - V_s(t-1)) + (V_s^f - V_s) \otimes \Re \quad (36)$$

Where, $\otimes$signifies element-wise multiplication and $\Re$ is a vector of random float-point numbers produced from zero to one uniformly, and $rand(.)$ denotes a random number in (0,1) interval. The optimization flowchart is depicted in Figure (3).

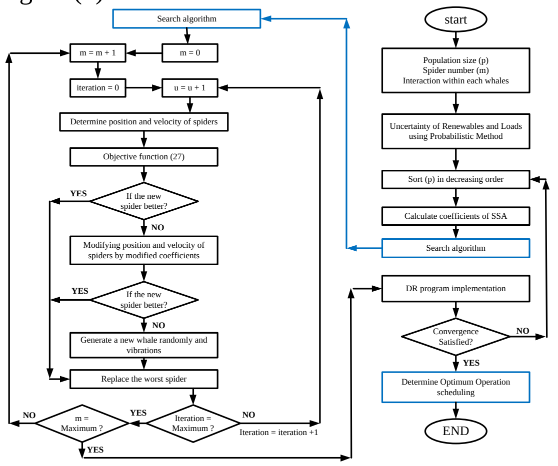

Fig. 3. The optimization flowchart for problem under consideration

4. Simulations

Briefly, the model of renewable energy resources is taken from [23-25] . Also, the other input parameters of microgrid, such as load profiles and mathematic formulation of renewable to generate power are extracted from [26-27]. In this regard, Figure (4) shows the effect of increasing consumer participation on the daily demand curve. As can be seen, the load demand is shifted from peak hours to low peak hours and fills the valleys of the curve. As the consumer participation factor increases, the daily demand curve approaches a flat curve.

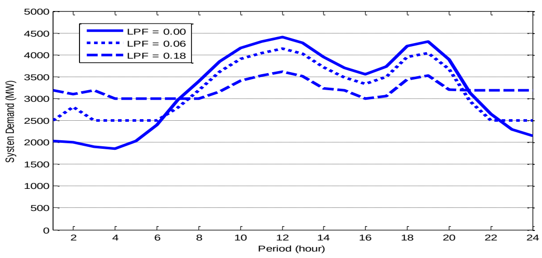

Fig. 4. system demand curve

Furthermore, in Figure (5), you can see the changes in daily demand during the optimization period, compared to the increase in the consumer participation factor. As shown in this figure, the changes in demand in the early hours of the day against lower price of electricity are larger than zero and negative in the hours when the price of electricity is high. In other words, consumption has increased during cheap hours and decreased in expensive hours.

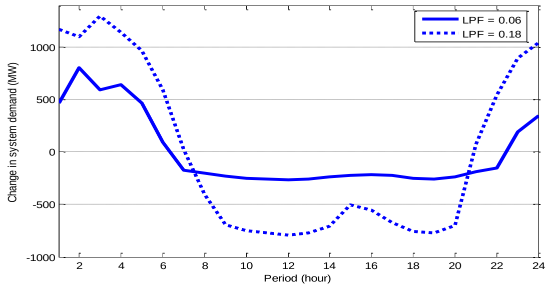

Fig. 5. System demand change curve

Figures (6) and (7) show the effect of increasing the load participation factor on the market clearing price. The decrease in load demand during peak hours has reduced the market clearing price. Furthermore, with the shift of the load to low consumption hours and the increase in consumption in these hours, the market clearing price has also increased in these hours.

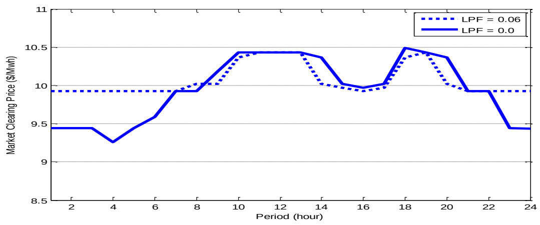

Fig. 6. Market clearing price

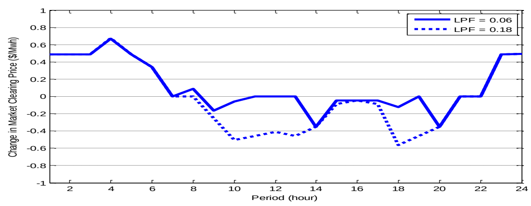

Fig. 7. Changes in the market clearing price

Figures (8) and (9) show the effective cost and profit from moving the load for flexible and affordable consumers. As can be seen, with a small increase in the consumer's participation coefficient, the effective cost of the flexible consumer is greatly reduced. Figure (9) similarly shows that the profit from increasing participation coefficient compared to the case without load displacement. The positivity of the priceable consumer's profit in most cases indicates the benefit of load shifting even for these consumers. To explain, with the shifting of the load, the clearing price of the market is reduced during the peak hours, which reduces the costs for all consumers.

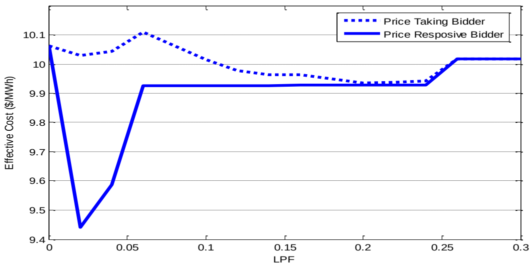

Fig. 8. Effective cost for flexible and affordable consumers

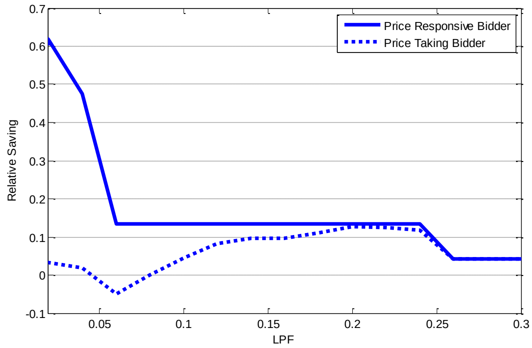

Fig. 9. Profit from load handling

Further, in Figure (10), the change is shown in the total social welfare due to the increase in the participation rate. As can be seen, in general, with the increase of this coefficient, the change in social welfare increases. Importantly, at the end of the range of the consumer participation coefficient, there is no change in social welfare, which is due to the constant marginal cost of producers. As it was observed in this modeling method, the participation of consumers in the movement of load increases the amount of social welfare, which is caused by the reduction of the cost of operation, hence this reduction in the operating cost can benefit all market participants. In other words, price-sensitive consumers who have not participated in demand response programs see a reduction in their costs. The reason for this is the reduction in the cost of electricity. It should be noted that with the excessive increase in the participation of consumers, the total price increases so much in non-peak hours that ultimately the overall profit of price-responsive consumers decreases.

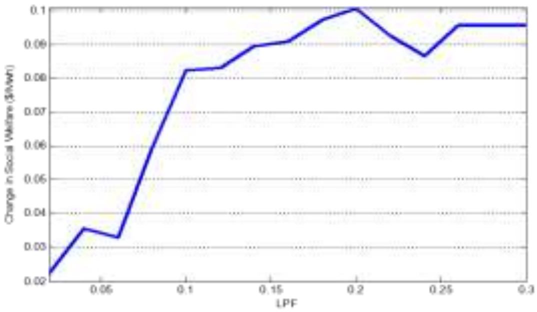

Fig. 10. Change in total social welfare

The next case study represents the effect of buying and selling power on the main grid. Since power is either sold/bought to/from the grid at each hour, the saved cost resulting from this task is obtained by calculating the total daily cost. Therefore, in addition to the load profile given in the previous section, the energy cost in the electricity market in a day is required (Table 1).

Table.1.
Cost of each kWh energy in the electricity market

Hour	*Load (kW)*	*Hour*	*Load (kW)*
1	0.033	13	0.215
2	0.027	14	0.572
3	0.020	15	0.286
4	0.017	16	0.059
5	0.017	17	0.086
6	0.029	18	0.059
7	0.033	19	0.050
8	0.054	20	0.061
9	0.215	21	0.181
10	0.572	22	0.077
11	0.572	23	0.043
12	0.572	24	0.037

To study the effect of buying/selling energy from/to the main grid, the renewable energy resources are eliminated. The parameter that should be determined as a result of adding the main grid is the capacity of the line connected to the grid. It is assumed that there is a load that varies at different hours, and there is the possibility to exchange power with the main grid. Using the proposed algorithm, some tests are carried out to determine the cost changes of the microgrid resulting from various capacities of the line connected to the grid. It can be concluded that as the capacity of the line connected to the grid increases, the energy exchange with the main grid is more likely to increase and the microgrid costs to decrease. When the capacity of the line connected to the grid is zero, or the main microgrid is isolated, the daily cost of the microgrid will be 5267.15$ and when the capacity of the line is 1100 kW, the daily cost of the microgrid 2431.05$, which saves 53.86% compared to the islanded mode. Figure (11) shows that cost reduction at the beginning of the curve is high. To elaborate, cost reduction is high at lower transmission line capacity compared to the independent mode and as the transmission line capacity is enlarged, the cost reduction decelerates, as. it is assumed that all DGs are on and operate between their minimum and maximum power range. Assume that we are at an hour when the power generation cost by DGs is cheaper than the cost of buying power in the main grid; therefore, according to the proposed algorithm, the DGs increase their power generation and sell the excess power to the main grid to save cost. But the maximum range of DGs' power generation does not allow us to generate a desirable amount of power. Thus, even if the line connected to the grid has the capacity, the DGs cannot generate such power. This also constrains buying power from the main grid at hours when the power generation cost of DGs is higher than the cost of buying power from the grid. Thus, increasing the capacity of the transmission line reduces costs to some extent, which is evident in the figure below.

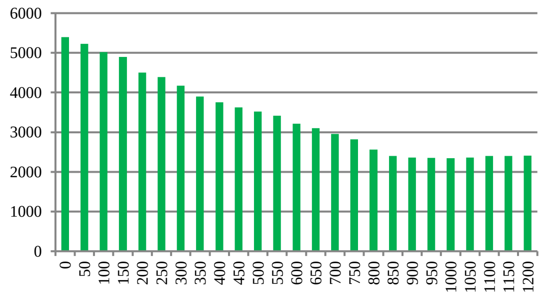

Fig. 11. Cost variations vs. capacity variations of the line connected to the grid

In this section, to demonstrate the comprehensiveness of the proposed method, a test is carried out in the presence of all elements to show the power exchange of different elements of the microgrid. In this test, we studied three scenarios for connecting the microgrid to the main grid and the power of the elements of the microgrids at different hours of the day. The tested system is a microgrid including 15 units, where the coefficients of the cost functions are given in [28]. The solar panels are used as renewable energy resources in the microgrid, where 4 of them are 90 kW panels given in Table 1. The system load is likewise the load given in Figure (12). For energy storage elements, a set of batteries with 1000 kWh capacity with an initial charge of 500 kWh is used with a maximum power exchange of 250 kW; in other words, the battery can be charged/discharged completely in 4 hours. The capacity of the line connected to the main grid is 750 kW.

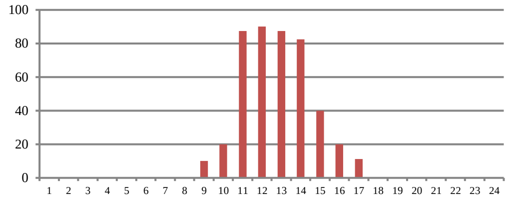

Fig. 12. Power generation of a 90 kW PV panel at different hours of the day

The error resulting from load prediction and renewable energy resources is considered to be 5%. Power exchange with the main grid imposes some costs and requires specific facilities and conditions. If we merely want to buy energy from the main grid, one-directional converters are required that pass energy only in one direction; if we exchange power with the main grid, more costly bidirectional converters are required. Consequently, exchanging power with the main grid, or buying and selling energy with the main grid required contracts and conditions that should be agreed upon with the main grid. According to the above discussion, connection to the main grid and power exchange with it is considered in three scenarios, which are given in the following:

A) The microgrid operates independently and exchanges no power with the main grid. In this scenario, there is no power exchange with the main grid; it is not required to store power in the energy storage elements. The power exchanged with the main grid and energy storage elements is zero.

B) The microgrid is only able to purchase energy from the main grid. At hours when the cost of buying energy is lower than its generation cost (beginning and ending hours of the day), electric power is purchased from the main grid, and at the middle hours when the cost of buying energy is high, no power is exchanged with the main grid. Since the battery has to store the energy bought from the main grid at cheap-energy hours, at the beginning hours, the energy bought from the main grid is stored in the battery such that the battery is charged completely. Since it is not possible to sell energy to the main grid, and the cost of generating energy by the DGs is considered to be constant, the battery is not discharged and its energy can be used when a failure occurs and the DGs are disconnected.

C) The microgrid can cooperate with the main grid in selling/buying electric power. In this scenario, at the beginning hours when the power should be bought from the main grid, the condition is similar to the second scenario. But in the middle hours when the energy cost increases, the energy stored in the battery is sold to the main grid. Since the cost of generating energy by the DGs is lower than the electricity market cost, the power generated by the DGs increases, and its excess power is sold to the main grid. The capacity of the line connected to the grid imposes some limitations. As the line capacity is considered to be higher, the revenue of selling energy to the main grid increases. In the final hours unlike the second scenario, since the battery's energy is discharged, some of the energy bought from the main grid is stored in the battery. The obtained results demonstrate the good performance of the proposed method. At higher possibility of power exchange with the main grid, the power fluctuations of the micro grid's elements at different hours increases, resulting in optimal microgrid performance and higher cost-effectiveness. In Table 2, the daily cost of a microgrid in three scenarios is given.

In Table 2, their methods and their cost effectiveness are compared. According to the table, not using elements indicated load supply using DGs only without renewable energy storage elements and the main grid. The results show that if the third scenario is used, 51.45% cost-effectiveness might be achieved. For fair comparison of various methods, the obtained results are compared with up-to-date customers and the results are given in Table 3. Correspondingly, it is seen that the proposed method benefits to other customers. The closest reference to the proposed method is [27], which has obtained an improvement of 25.6 %.

Table.2.
Comparison of the daily cost of a microgrid in three scenarios

Scenario	***No use of DGs***	***First scenario***	***Second scenario***	***Third scenario***
Daily cost ($)	5273.54	5016.42	4188.31	2549.89
Cost-effectiveness compared to when DGs are not used	0	4.87	20.58	51.64
Cost effectiveness compared to the first scenario	0	0	16.59	49.16

Table.3.
Comparing the improvement of the methods

Parameter	***Proposed method***	***[25]***	***[26]***	***[27]***	***[28]***
Daily cost	5273.54 $	6415.18 $	7325.84 $	6147.59 $	6498.62 $
improvement	51.64%	21%	13.75%	25.6%	21.1%

5. Conclusions

The results of this article showed that the participation of the price-responsive consumer reduces costs for other price-sensitive consumers in addition to reducing the energy supply costs for himself due to the shift of the load from high consumption and expensive hours to cheap hours and as a result of reducing the cost of energy in these hours. By defining consumer pricing for different load priorities, a new method of load management by the consumer was presented in this research. Load priorities can be defined in any quantity and at any price. Moreover, there are different methods of modeling priorities for consumers. In general, demand response improves market efficiency and operational reliability. If implemented correctly, it limits the electricity market's exposure to energy shortages and improves operational reliability with variable generation frequency. The design of demand response programs depends on the prevailing market conditions of a particular region. It can be concluded that exploitation has a much higher efficiency than the objective function of demand response by considering the objective function of demand response and flattening. A striking feature of the proposed method is its ability in modifying the generated power and compensating for the fault resulting from load and renewable energy resource prediction. In the proposed model, various simulations were carried out and the comparison results of energy management of the proposed algorithm with the direct search method and the multi-level direct search method indicate its superiority. In addition, the effect of the presence of various elements in the microgrid on the power generation cost of the microgrid was studied. The cost reduction with the addition of each element was studied on a system including multiple microgrids connected and connected to the main grid. Finally, the effect of the power transmission capacity of the lines between the microgrids on the power generation cost of the microgrid was studied, and the power generated by different elements at all hours of a day was shown.

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