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Optimal scheduling of distributed generations in microgrids for reducing system peak load based on load shifting

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ABSTRACT

Demand Side Management (DSM) is one of the ways to create interaction between the MicroGrids (MGs) and increase consumer participation in management schemes. Different algorithms and strategies have been used to execute consumption management programs which often cover a limited number of loads in several specific types. In this paper, first, the load shift method, as an optimization problem to reduce system demand peak and subscriber's bills for various loads in smart MGs, is solved by Hybrid Particle Swarm Optimization algorithm with Sinusoidal and Cosine Acceleration Coefficient (H-PSO-SCAC). Then the study is aimed at measuring the effect of the proposed program on the generation and presence of MGs in the market for improving the level of social welfare. The results are performed on a Smart Grid (SG) consisting of three residential, commercial and industrial MGs which include different types of controllable loads. The results show that the highest percentages of peak load reduction after the implementation of the DSM program by (H-PSO-SCAC) algorithm for the three MGs are 23%, 19% and 19%, respectively. Also, the highest percentages of reduction in subscriber's bill for the three MGs are 16.8%, 19.2% and 20.5%, respectively. The proposed algorithm has performed much better in reducing bills and peak loads than most other methods such as Logarithmic Function (LF), Multi Agent (MA), Evolutionary Algorithm (EA), and Symbiotic Organisms Search (SOS). The findings show that the proposed program can reduce peak load, reduce subscriber's bills, save production costs, help balance the supply and demand, and improve the level of social welfare from the perspective of the distribution system operator.

1. Introduction

For many years, electrical energy has become an integral part of human life and all aspects of life, whether in the personal lives of individuals or in manufacturing, agriculture, and the like are closely related to this energy. In general, a smart grid (SG) can be defined as a set of power grid infrastructures with a widespread telecommunications network [1]. In fact, combining these infrastructures and coordinating their performance with each other in a systematic framework will lead to the creation of an Active Smart Distribution Network (ASDN) [2].

The smart network infrastructure has four categories: smart information infrastructure, communications infrastructure, protective infrastructure, and management infrastructure. The management infrastructure is the focus of this study. In the management infrastructure, a smart network supports a two-stage electrical and information flow. Therefore, it is suitable for the realization of management purposes. There are various management purposes for a smart network such as improving the energy efficiency, decreasing the operation costs, keeping the balance between production and consumption, controlling carbon pollutants, and increasing system efficiency.

The solution for all of the above-mentioned goals is usually having a consumption management program. Power companies provide these programs and consumers respond to them, and direct interactions with consumers make these programs possible. Consumption management programs may reduce extra costs of production, transfer, and distribution infrastructures [3]. There are many approaches and strategies for consumption management in the literature only some of which are provided here.

For instance, linear programming method has been used in [4] to implement the direct load control method and the profit-based DSM problem solving. In this reference, because the load is directly controlled, the consumer's satisfaction is ignored. Also, Ref. [5] provides an algorithm for point pricing and control of residential network loads, but this method focuses on direct load control. Also, in this case, in addition to ignoring consumer satisfaction, the DSM has been implemented only on residential loads in several limited types.

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Some reported management programs calculate the decrease rate of allowable loads for the control of next day and introduce a power market tender area to move the load peak [6]. For example, [7] provides a direct load control method for controlling water heaters and air conditioners in a residential network. The linear programming method has been used to implement the control process in the network. In this reference, while the DSM program is performed on a limited number of residential loads in two types, the load variation is much higher in the real network.

In [8], a new method is presented for implementing probabilistic coordinated energy management between a distributed network and connected micro-grids based on game theory. In [8] the variety of consumption patterns and load types is not considered for the consumers. Also, the game theory method has special complexities that make it difficult to implement in a SG infrastructure.

Moreover, Ref. [9] proposes the method of energy management in multiple micro-grids considering load constraints using a hybrid algorithm. Finally, the proposed method is simulated on multi micro-grids using GAMS and MATLAB software. In this study, only the profits of retailers and their satisfaction in the market were desired and the consumers were ignored.

Another category of methods used to run DSM is the Multi-Agent System. This method has been used to implement the DSM program in order to reduce peak load, flatten the load curve, and reduce operating system costs [10]. This method is very comprehensive and accurate, but in the system under study, the consumer model is fixed and there is no variety. In [11], the game theory method has been used to run the DSM program on the SG. In this method, the goal is to reduce the Peak to Average Ratio (PAR) and the energy cost, which is modeled by a logarithmic function. In this method, different types of consumers are considered, but the objective function only considers the priorities and the profit of the consumer. Meta-heuristic methods have also been used to implement DSM programs. [12] The genetic algorithm method is used to run the DSM on the SG. In this method, the smart network includes various residential, commercial and industrial loads. Genetic algorithm is an old and accurate method, but it can be trapped in local optimum to solve problems with complex target functions. Also, the existing objective function has only considered consumer satisfaction and nothing has been considered from the production side. Also, in [13], the symbiotic organisms search method is used to run the DSM program. In this method, the objective function is to flatten the load curve that has been implemented on a network including residential, commercial and industrial loads. In this case, different types of controllable loads for the network are considered, but the problems and priorities of the production side in the objective function are not considered. Consumption management using Mixed Integer Linear Program (MILP) method was reported to improve social welfare and increase distributors' profitability [14]. This method is one of the classic methods and is not suitable for performing complex problems.

Another important issue that should be noted is the high cost of generation, transmission, and environmental pollutants. Therefore, in [15], the problem of consumption management is solved by combining the fuzzy method and particle swarm to improve the profitability and efficiency of a distribution system. In this reference, only the profits and interests of the producers are considered. The variety of loads on the network was also assumed to be constant.

After the DSM issue in the SG, optimal production planning is also a major concern. This issue has been studied in different scientific references with different objective functions and methods. For example, in [16], fuzzy logic has been used to optimize MG planning and implement DSM programs. In this reference, the goal is to increase consumer satisfaction and reduce annual operating costs. In this case, the objective function is good and complete, but still there is no variation in the pattern of network loads. Also, in [17], the combination of fuzzy logic and Binary Particle Swarm Optimization (BPSO) algorithm has been used for optimal planning in the MG. In this method, the objective function has been to reduce network losses and operating costs. Regarding the objective function, however, consumer satisfaction and profit have not been considered.

Ref. [18] has used a combination of fuzzy training and multi-agent systems to manage the energy of a micro-grid separately from the grid. The load model was also assumed to be fixed in the MG and in the limited types. In this paper, the results show that the proposed method can provide the reliability and security of the feeding system in the island operation mode while maintaining the balance of production and consumption. Of course, in addition to meta-heuristic methods, other methods such as the game theory have been used to plan production in MGs. For example, in [19], a function is considered for planning which, in addition to reducing production costs, optimizes the bill and the consumer's satisfaction. This objective function is optimized by the game theory. In this case, no specific type of load is considered for the network. Although the game theory method can model different situations in the network, it has complexities in implementation. In some references, hierarchical methods are used to run DSM programs. For example, in [20], this method has been applied to DSM with the aim of increasing the level of social welfare of consumers and increasing the profit of the network. In this method, a fixed load curve for the network is assumed. Also, in [20], the objective function is optimized by the artificial immune algorithm. In [21], a hierarchical method based on the game theory has been applied to DSM in the SG. In this reference, an attempt has been made to balance the price and demand in the market by taking into account all the different constraints and relationships between providers and power consumers by the Stackelberg game. This reference focuses on pricing and relationships between market players, and does not address changes in network load patterns.

In summary, as described in each reference, in some studies, the DSM has been done only for a specific type and a limited number of loads. Also, in some other references, as mentioned, the fixed load model has been assumed. However, in a real network, there are various loads with different consumption patterns. Another gap that was observed in some of the references was that most of them considered only the satisfaction and interests of the consumer or only the satisfaction and profit of system operators. Few studies have considered the interests of the consumer and the operator simultaneously. On the other hand, another important issue in solving these problems is the method of problem solving. The method should be simple and accurate and should be able to get the optimal answer for the problem. However, in most studies, either complex methods have been used to solve the problem or the used method has not been accurate enough to solve the problem. Therefore, in this paper, to cover the gaps in the literature, a two-stage method for the simultaneous management of consumption and production in the SG with various loads was presented. In summary, the important innovations of this article are as follows:

- Solving the problem of consumption and production management simultaneously in a Multi Micro-Grid (MMG) including a wide variety of controllable loads in three types: residential, commercial and industrial.
- Providing a two-step approach to implementing a management plan and examining its impact on the market and the level of social welfare.

- Implementing the proposed two-stage method in the form of an integrated optimization problem

Finally, this paper proposes a management strategy on networks consisting of three micro-networks: commercial, residential, and industrial with varying loads by the H-PSO-SCAC method to reduce subscriber's bills and improve social welfare in two steps implemented in accordance with Fig. 1.

In summary, the two-stage strategy outlined in Fig. 1 is as follows:

Stage 1:

- First, the controllable loads announce their request to participate in the DSM program to the Distribution System Operator (DSO).
- The DSO then executes the DSM program on each MG according to the requests and network conditions and modifies the MG load curve.
- After correcting the load curve of each MG, internal production planning is done for each MG.

Stage 2:

- In the second step, first the amount of surplus or power shortage of each MG is determined. This amount of required power or surplus is provided to the market.
- In the next step, the MGs will adjust their production planning according to the market's required power.
- Finally, the planning of the main network and MGs is done in the market and the amount of sales and Market Clearing Price (MCP) is determined.

In the following, we describe the production and demand management strategy along with their functions and constraints in Section 2. In Section 3, we explain the algorithm. Section 4 deals with explaining the study network. While in Section 5 we discuss the simulation results, in Section 6 we conclude the paper.

2. Production and consumption management strategy

2.1. Consumption management strategy

Consumption management programs have two strategies: load management and energy management. Load management aims at changing consumers' behavior, which is achievable in a smart network with smart infrastructures by reducing the load peak. The aim of energy management is to achieve efficient energy consumption, which means gaining maximum efficiency from minimum energy. In this study, consumption management is focused on load management. Load displacement method was studied in order to reduce load peak and consumer's cost for the smart network. Schematic of the DSM strategy is shown in Fig. 2.

As shown in Fig. 2:

Consumer:

- A number of controllable loads on the network first send a request to participate in the DSM program to a local server.
- The local server then checks the submitted requests and sends them to a central controller.

Network manager:

- The central controller executes the DSM program according to the load priorities and limitations, and sends control commands to the local server.
- According to the DSM program, the central planning controller is applied to controllable loads.

The consumption management program adjusts each load connecting time in a way that the final load profile matches the load profile provided by network manager considering the priority of consumer's tools.

2.1.1. Consumption management objective function and constraint

The objective function is the difference between the objective load profile and the final load profile after performing consumption management program as written in Eq. (1):

$$\text{Minimize} \sum_{t=1}^{N} (PLoad(t) - Objective(t))^2 \tag{1}$$

where *Objective (t)* is the objective load profile at time t and *PLoad(t)* is the final load profile after performing program at time t. *PLoad(t)* is obtained from Eq. (2):

$$PLoad(t) = Forecast(t) + Connect(t) - Disconnect(t) \tag{2}$$

where *Forecast(t)* is the anticipated consumption at time t, *Connect(t)* and *Disconnect(t)* are the dispatchable loads connected or disconnected at time t. Connected loads at time t (*Connect(t)*) have two parts: First, the dispatchable loads whose consumption times were transferred to time t from times before t, so their first consumption model impacts load time t. Second, the loads whose consumption time were not transferred to time t from times before t and their consumption times were transferred to times before time t, so their later consumption model impacts load t. Eq. (3) defines *Connect(t)*:

$$Connect(t) = \sum_{i=1}^{t-1}\sum_{k=1}^{D} X_{kit}.P_{1k} + \sum_{l=1}^{j-1}\sum_{i=1}^{t-1}\sum_{k=1}^{D} X_{ki(t-1)}.P_{(1+l)k} \tag{3}$$

where X_{kit} is the number of k tool kinds that were transferred from temporal step i to t, D is the number of tool kinds, P_{1k} and $P_{(1+l)k}$ are power consumptions at temporal steps 1 and $1+l$, and j is the overall consumption period for tool kind k. Similarly, *Disconnect* (t) has two parts: load reduction due to delay in equipment connection times that were initially supposed to start their consumption at temporal step t and load reduction due to delay in equipment connection times that were initially supposed to start their consumption after temporal step t. Eq. (4) defines *Disconnect (t)*:

$$Disconnect(t) = \sum_{q=t+1}^{t+m}\sum_{k=1}^{D} X_{ktq}.P_{1k} + \sum_{l=1}^{j-1}\sum_{q=t+1}^{t+m}\sum_{k=1}^{D} X_{k(t-1)q}.P_{(1+l)k} \tag{4}$$

where X_{ktq} is the number of dispatchable load of k kind that were delayed from time t to q, m is the maximum allowable delay time which is defined to be 12 h. Finally, fitness function was chosen to match final load curve algorithm with objective load curve and was defined as Eq. (5):

Max:

$$F_{DSM} = \frac{1}{1 + \sum_{t=1}^{24} (PLoad(t) - Objective(t))^2} \tag{5}$$

where F_{DSM} is the consumption management objective function. Note that in this study, load connection priority in each area providing more privacy was considered at times when consumer demands more load.

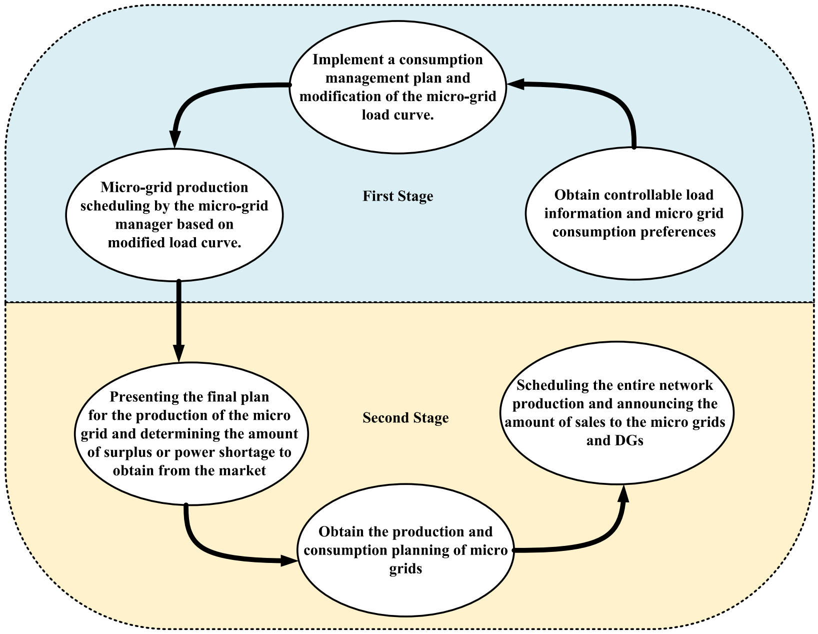

Fig. 1. Two-stage management strategy.

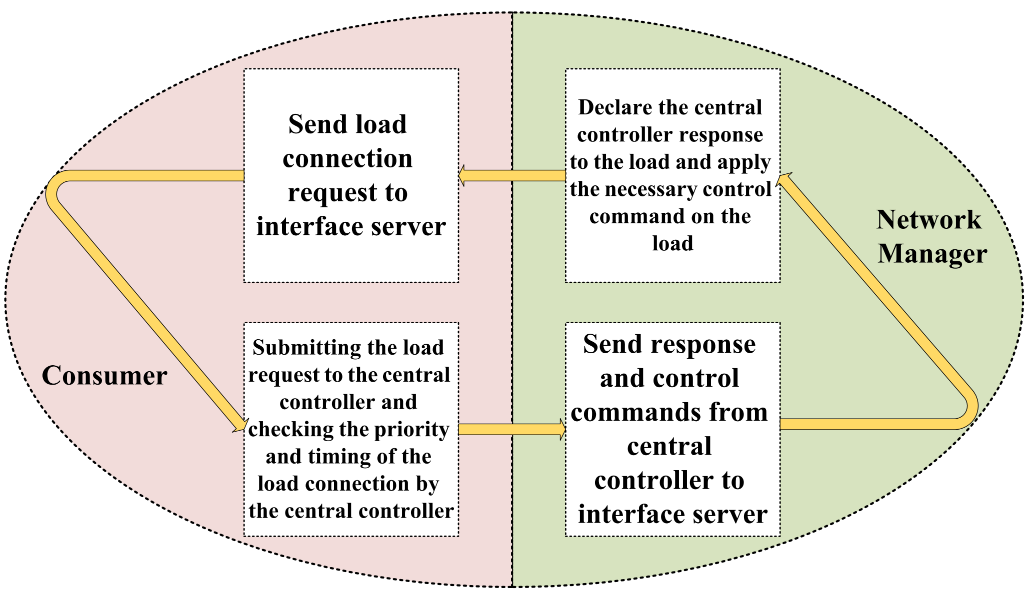

Fig. 2. DSM strategy.

This concept is limited by the following criteria:

The number of transferred tools cannot be negative as defined by Eq. (6).

$$X_{kit} > 0 \quad \forall i, j, k \tag{6}$$

According to Eq. (7), the number of transferred tools at a temporal step cannot be more than the number of permitted tools for controlling at that temporal step.

$$\sum_{t=1}^{N} X_{kit} \leq Ctrlable(i) \tag{7}$$

where *Ctrlable*(i) is the number of controllable loads of k kind at i time range and N is the overall number of time range [12].

Controllable load connection times can only be delayed; its limit is defined by Eq. (8):

$$X_{kit} = 0 \quad \forall i > t \tag{8}$$

Maximum allowable time to delay consumption for all tools is defined by Eq. (9):

$$X_{kit} = 0 \quad \forall (i - t) > m \tag{9}$$

2.2. Production management strategy

In this paper, the market clearing algorithm is used to model the competitive market. This algorithm is a method by which the market manager determines the winning supply and demand proposals as well as the market clearing price. The general method for clearing the next day electricity markets is the auctioning or pooling method.

In this method, consumers' proposals are organized in decreasing order and the supply is organized in increasing order in one price–power curve, and the point of intersection of these curves will determine the winners and the Market Clearing Price (MCP). The purpose of implementing this market in the current paper is to implement the Unit Commitment plan (UC) while considering the operational constraints of MGs and Distribution Generation's (DGs) on the basis of maximizing social welfare [22].

In the market implemented in this paper, the MGs and DGs commit as producers and the distribution grid loads (elastic loads) commit as the demand side with their proposals. Therefore, the generation management strategy has two stages: the first stage of internal MG planning and the second stage of overall planning of the main network and market execution [23].

2.2.1. Objective function and constraints of production management in MGs

The objective function in executing production planning from the viewpoint of the MGs is to maximize the profitability of MG manufacturers. This function for each MG is defined as the sum of the difference between revenue and costs over 24 h as given in Eq. (10).

Max:

$$F_{MG}=\sum_{t=1}^{24}\left\{Pload_{g,t}.\Pr_{Pload}\right\}-\sum_{t=1}^{24}\sum_{n=1}^{5}\left\{Costdg_{n,t}.Udg_{n,t}\right\} \tag{10}$$

where $Pload_{g,t}$ is the consumption of the MG g at the t hour which is the output of the consumption management program, Pr_{Pload} is the power–price per Hour t, $Costdg_{n,t}$ is the setup cost and operation of DG n*th* per Hour t calculated by Eq. (11), and $Udg_{n,t}$ is a binary variable that show presence or absence of DG in planning.

$$Costdg_{n,t}=\left\{c_n.Pdg_{n,t}^2+b_n.Pdg_{n,t}+a_n\right\}+\left\{STCdg_n.\left[1-Udg_{n,t-1}\right].Udg_{n,t}\right\} \tag{11}$$

a, b, c are coefficients of the unit cost function [22]. $STCdg_n$ is the cold or hot startup cost and $Pdg_{n,t}$ is the active power of n*th* unit per hour t.

The following restrictions must also be met:

Thermal units have the technical limitation of the lowest and highest amount of production expressed in Eq. (12):

$$P\min dg_n\leq Pdg_{n,t}\leq P\max dg_n \tag{12}$$

where Pmax and Pmin are respectively the minimum and maximum DG output powers.

At each time interval, the generation value must be equal to the sum of the loads of each MG according to Eq. (13):

$$\sum_{i=1}^{n}Pdg_i=\sum_{i=1}^{k}Pload_i+Ploss \tag{13}$$

$Pload_i$ is the load power in the network and *Ploss* represents the network losses.

The total maximum power of the units in the circuit (*Pmax* dg_k) shall be greater than, or equal to, the total load and spinning reserve. In other words, there should be a relationship for every hour (14):

$$\sum_{k=1}^{i}P\max dg_k\geq\sum_{i=1}^{k}Pload_i+\%10\times\sum_{i=1}^{k}Pload_i \tag{14}$$

In planning production, between 2 and 10 percent of the network load is usually considered as the Spinning Reserve. +10% is actually added for Spinning Reserve in Eq. (14).

2.2.2. Objective function and constraints of production management in the main grid and market

In the main grid, there are a number of local loads that supply the market demand with a step-by-step power–price curve. MGs also offer their surplus production under the three-step power–price curve as an offer to the watch market. Competitive electricity market among participants is performed by the market operator who, with the aim of maximizing social welfare, announces the amounts allocated to each participant after clearing the market. Finally, each MG will modify its hourly load and re-plan its production. The objective function of the market mechanism is to maximize social welfare from a Distribution System Operators (DSO) point of view. Social welfare as the sum of the difference between revenues and costs in 24 h is defined in Equation (15) [22].

Max:

$$F_G=\sum_{t=1}^{24}\sum_{l=1}^{5}\left\{Pload_{l,t}.\Pr_{Pload}\right\}-\sum_{t=1}^{24}\sum_{i=1}^{3}\sum_{stg=1}^{3}\left\{Pmg_{i,stg,t}.\Pr mg_{i,stg,t}.U_{i,t}\right\}-\sum_{t=1}^{24}\sum_{n=1}^{3}\left\{Costdg_{n,t}+\Pr dg_{n,t}.Pdg_{n,t}\right\}\times Udg_{n,t} \tag{15}$$

where $Pload_{l,t}$ is the Local load power of the main grid at hour t, Pr_{Pload} is the electricity price at time t, $Pmg_{i,stg,t}$ is the winning power of i MG in *stg* step at tth hour, $Prmg_{i,stg,t}$ is the market price won by MG at t hour and *stg* step. $U_{i,t}$ is the binary variable related to the presence or absence of a MG in the market, $Costdg_{n,t}$ is the cost of startup and operating DG nth per hour t, and finally $Udg_{n,t}$ is a binary variable that indicates the presence or absence of the main network DGs in programming. Also $Pdg_{n,t}$ and $Prdg_{n,t}$ are respectively the power and price won of the main grid DG at t hour. On the other hand, the constraints of this stage of management are as follows:

The power provided by the MGs in the market has a finite amount that is applied to each step of the price–power function and is expressed in accordance with Eq. (16).

$$0\leq Pmg_{i,stg,t}\leq P\max mg_{i,stg,t}.U_{i,t} \tag{16}$$

Where $Pmaxmg_{i,stg,t}$ is the maximum power that the MG is allowed to inject into the market.

At any time interval, the power value can be smaller than the sum of the loads of each micro-grid according to Eq. (17) because the goal here is operating the profit:

$$\sum_{i=1}^{n}PG_i\leq\sum_{i=1}^{k}Pload_i+Ploss \tag{17}$$

where $Pload_i$ is the load power in the main grid and *Ploss* is the grid losses. Other constraints for DGs of the main grid are considered similar to those for DGs in MGs. Finally, in the first step, the objective function (18), and in the second stage, the objective function (19) will be optimized.

$$Max: w_1.F_{DSM}+w_2.F_{MG} \tag{18}$$

$$Max: F_G \tag{19}$$

In Eq. (18), w_1 and w_2 as the weighting coefficients are related to the objective function of the consumption management and the internal planning of the MGs.

In this equation, F_{DSM} and F_{MG} are also the objective functions related to the consumption management and internal production management of the MGs. Moreover, F_G is the objective function of improving the level of social welfare from the perspective of the DSO. Finally, the flowchart of the management plan is shown in Fig. 3.

3. H-PSO-SCAC algorithm

One of the newest optimization algorithms introduced in 2018 is the Hybrid Particle Swarm Optimization algorithm with Sinusoidal and Cosine Acceleration Coefficient (H-PSO-SCAC) [24]. As is known, each particle in the PSO algorithm consists of three d-dimensional vectors. In the primary stage of the algorithm, particles are created with random positions and speeds. During the execution of the algorithm, the position and speed of each particle in the subsequent stage of the algorithm are created based on the information from the previous stage. Then, the equations that alter the speed and position of the particles are Eqs. (20) and (21).

$$V_i^d = V_i^d + c_1 \times r_1(pbest_i^d - X_i^d) + \\ + c_2 \times r_2(gbest_i^d - X_i^d) \tag{20}$$

$$X_i^d = X_i^d + V_i^d \tag{21}$$

where Eq. (20) updates the particle velocity and Eq. (21) updates the particle position. In these equations, r_1 and r_2 are random numbers in the interval [0, 1] with uniform distribution, and c_1 and c_2 are the learning coefficients. X_i^d and V_i^d are the position and velocity of the particles. *pbest* is the best previous position, and *gbest* is the best position of particle and particle groups.

However, some changes, as described below, were applied to the H-PSO-SCAC algorithm in order to achieve an improved search in this algorithm. Eqs. (22) and (23) represent the modified coefficients c_1 and c_2 [22].

$$c_1 = \xi \times \sin\left(\left(1 - \frac{M_j}{M_{\max}}\right) \times \frac{\pi}{2}\right) + \delta \tag{22}$$

$$c_2 = \xi \times \cos\left(\left(1 - \frac{M_j}{M_{\max}}\right) \times \frac{\pi}{2}\right) + \delta \tag{23}$$

The coefficients c_1 and c_2 are very effective in finding the optimal solution with high speed and accuracy. In this algorithm, the coefficients c_1 and c_2 were changed according to the sine and cosine sentences. This change, as noted in [22], causes the algorithm to quickly find the local optima. These values are obtained for the coefficients δ and ζ of the empirical form. In Ref. [22], after introducing the algorithm, many problems were solved and finally it was concluded that the best value for δ and ζ are 0.5 and 2, respectively. M_j is the current iteration number and M_{max} is the maximum iteration number.

Furthermore, in order to improve the performance of the algorithm in terms of finding the local optima, the search space of the problem, and the global optima, the variables were modified as in Eqs. (24) and (25):

$$X_i^d = X_i^d \times w_{ij} + V_i^d \times w'_{ij} + \\ + \rho \times gbest^d \times w_{ij} \tag{24}$$

$$w_{ij} = \frac{\exp(f(j)/u)}{1 + \exp(-f(j)/u)^{iter}} \\ w'_{ij} = 1 - w_{ij} \tag{25}$$

Table 1
Residential loads information.

Num	Num			Num
189	189	189	189	**189**
288	288	288	288	**288**
268	268	268	268	**268**
279	279	279	279	**279**
340	340	340	340	**340**
158	158	158	158	**158**
288	288	288	288	**288**
48	48	48	48	**48**
59	59	59	59	**59**
58	58	58	58	**58**
66	66	66	66	**66**
101	101	101	101	**101**
56	56	56	56	**56**
406	406	406	406	**406**
2604	2604	2604	2604	**2604**

Table 2
Commercial loads information.

Type Hrs3	Pattern(kW)			Num
		Hrs2	Hrs3	
–	156	–	–	**156**
–	117	–	–	**117**
–	123	2.5	–	**123**
–	77	–	–	**77**
–	99	2	–	**99**
–	93	3	–	**93**
3	56	3.5	3	**56**
1.5	87	1.75	1.5	**87**
–	808	–	–	**808**

Table 3
Industrial loads information.

Type Hrs6	Pattern(kW)						Num
		Hrs5	Hrs6		Hrs5	Hrs6	
–	39	–	–	39	–	–	**39**
–	35	25	–	35	25	–	**35**
–	16	30	–	16	30	–	**16**
50	8	50	50	8	50	50	**8**
100	5	100	100	5	100	100	**5**
–	6	–	–	6	–	–	**6**
–	109	–	–	109	–	–	**109**

where w_{ij} and w'_{ij} are the dynamic weighted acceleration coefficients of a particle that changes by Eq. (25). Also, u is the value of the original fitness function in the first iteration, *iter* is the current iteration number, $f(j)$ is the fitness function of the particle j, and ρ is a random number between 0 and 1 [24].

4. Study system

To show the effect of the method of load shifting, the described algorithm has been implemented on the SG with three levels of subscribers, i.e. residential, commercial and industrial subscribers, and each MG has one solar generation unit, one wind generation unit and five thermal generation units in which the information of the thermal [25], wind [26], and solar [27] units are in accordance with references, respectively. Three areas of load information are provided in Tables 1–3.

The Single-Line diagrams of the study network are shown in Fig. 4, and the technical information of this network is given in [28].

To observe the effect of consumption management planning on competitive markets, it is assumed that the MGs above are in a network consisting of five elastic loads and three DG [25]. Table 4 presents the parameters of the particle swarm algorithm with sine and cosine coefficients.

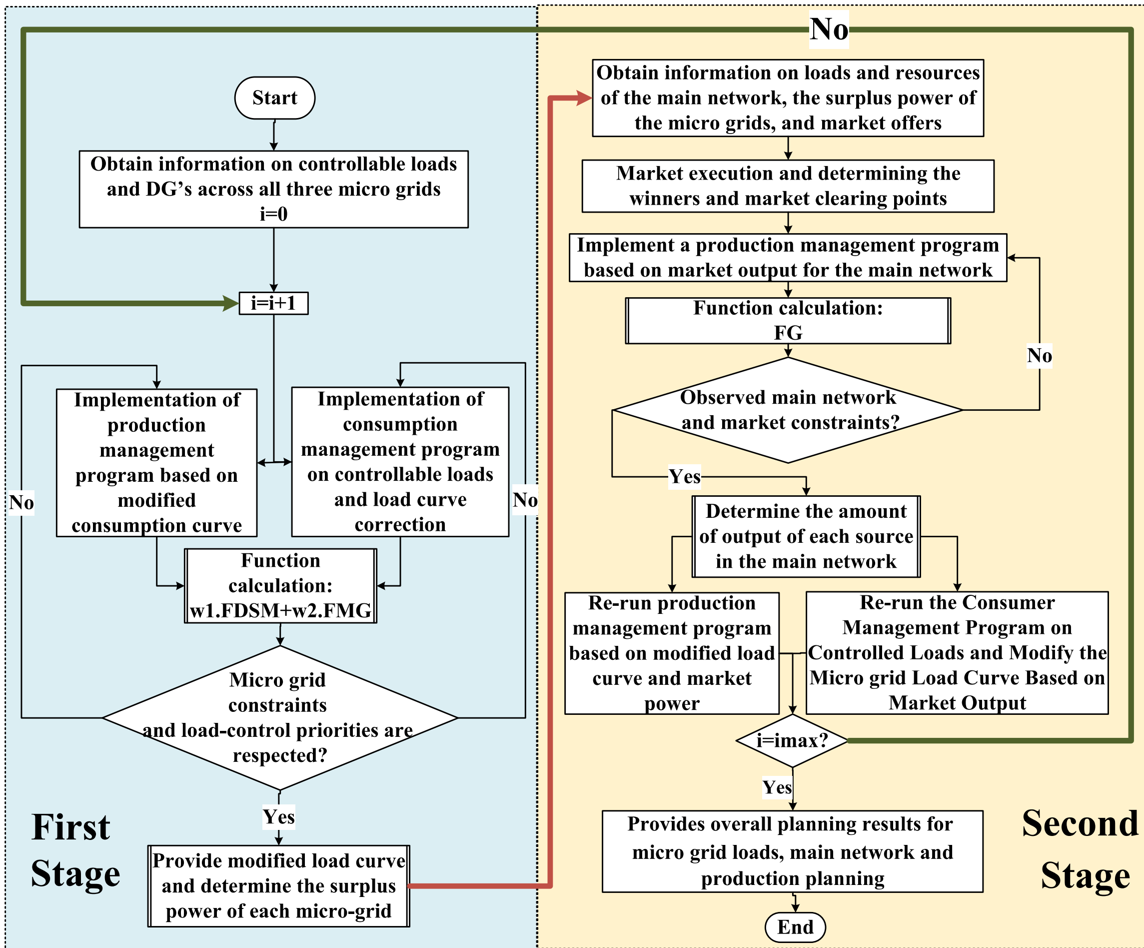

Fig. 3. Problem Solving Process.

Table 4
Parameters of H-PSO-SCAC Algorithm.

Number of populations	100
Number of iterations	600
δ	0.5
ζ	2

5. Results and discussion

5.1. Effect of DSM on consumption

By implementing the proposed management plan through the genetic algorithm, it can be seen that the final load profile is very close to the target load profile provided by the network administrator, and that the proposed method can cover a large number of controllable loads of various types. After implementing this method for the residential area, it was observed that the subscriber's bill was decreased from 2302.90 $ to 1915.1 $ per day, which is about 387.8 $ per day. This is equivalent to a cost reduction of 16.8% in the residential area. The graph related to the load profile for this area is shown in Fig. 5.

As shown in Fig. 5, the load curve in the residential MG has a large peak that is concentrated between 10 a.m. and 15 p.m. before DSM. But after DSM, the peak load has been corrected and spread during non-peak hours. Therefore, the amount of load during peak hours is greatly reduced. On the other hand, the amount of load during non-peak hours is increased. We can conclude that the peak load amount has decreased significantly, but in other hours the consumption rate has increased, leading to the increase of average consumption. Moreover, because the price of electricity during peak hours is high, reducing consumption during the peak will reduce the consumers' bills. Also, because the cost of production in the peak is usually high, by reducing the peak load in the residential network, the amount of internal production cost of the network is reduced by 16.37%.

The results for the commercial area are shown in Fig. 6. As is observed, the commercial area's equipment bill for one day has changed from 3626.60 $ to 2930.70 $, which represents a decrease in total costs of subscribers as much as 19.2%. This means that subscribers, besides having a higher average consumption with respect to the previous case, have saved about 695.9 $ of their own payment.

In commercial MGs, the number of loads are more than that of residential MGs, but their consumption period is longer. Therefore, as shown in Fig. 6, the MG loads were transferred from peak times between 4 and 12 to non-peak hours between 13 and 24 h. This reduces the peak load, increases the hourly load consumption, and increases the average consumption in the commercial MG. Therefore, because the price of electricity is lower during non-peak hours, as mentioned above, the cost of subscriber's bills has decreased by 19.2%. In this MG, because the period of consumption of subscriber loads is longer, the amount of reduction in the cost of subscribers' bills has increased more than that in the residential MGs. However, since there are fewer commercial MGs than residential MGs, the reduction in production costs is only 15.25%. In fact, the transfer of controllable loads from peak hours to non-peak hours has reduced production capacity during

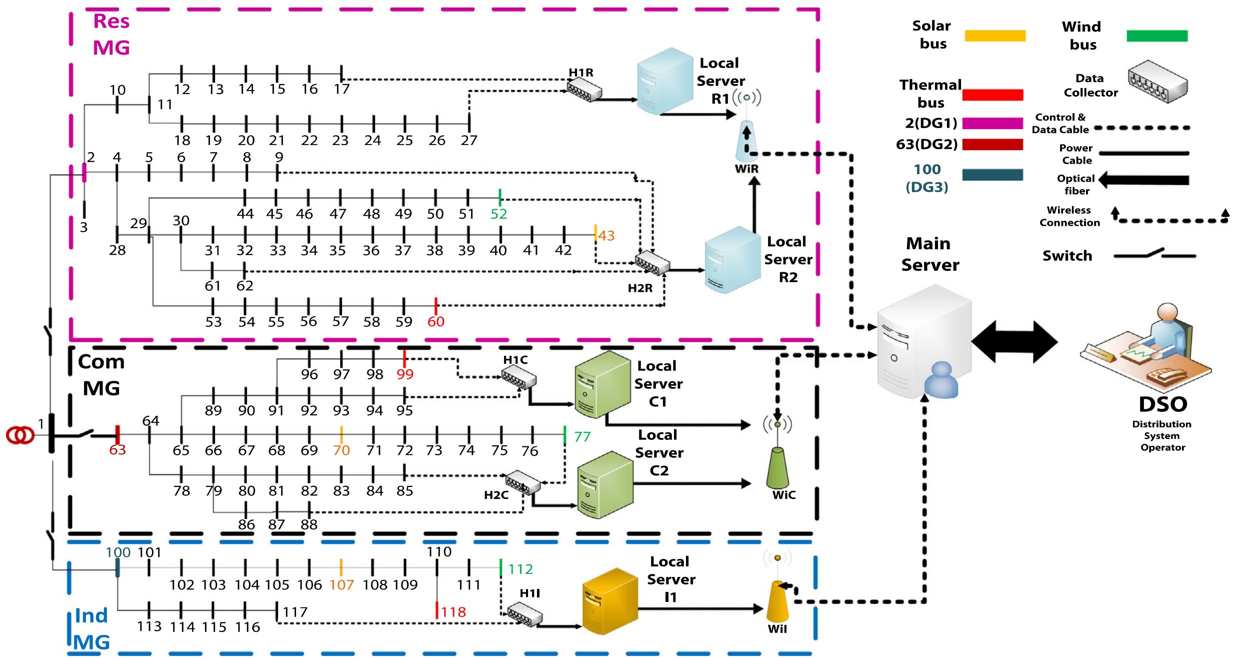

Fig. 4. IEEE 118-Bus Smart Distribution Network Diagram.

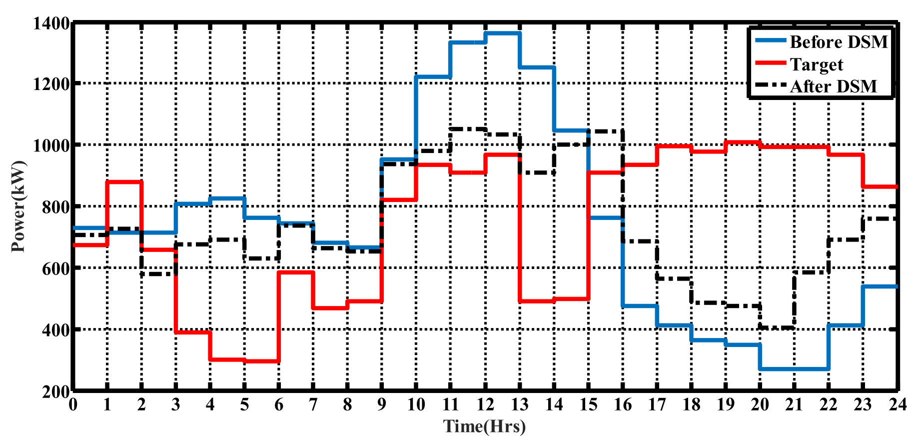

Fig. 5. Load profile for Residential MG.

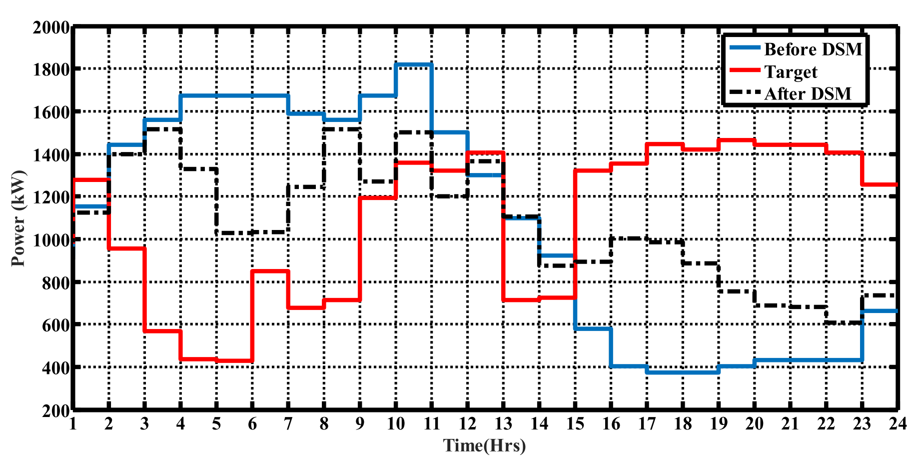

Fig. 6. Load profile for Commercial MG.

peak hours. On the other hand, because the cost of production is usually much higher during the peak, reducing production during peak hours reduces the costs of producers and saves costs for operators.

Table 5
Results of DSM programs with H-PSO-SCAC.

Area	Billing without DSM ($)	Billing with DSM ($)	Cost reduction (%)	Peak reduction (%)	Production cost reduction (%)
Residential	2302	1915	16.8	23	16.37
Commercial	3626	2930	19.2	19	15.25
Industrial	5712	4542	20.5	19	1.58

Table 6
Comparison of the percentage of peak reduction.

	MA [10]	LF [11]	EA [12]	SOS [13]	[H-PSO-SCAC]
Residential	17.7	25.85	18.3	24.22	23
Commercial	17.55	17.41	18.3	16.58	19
Industrial	13.61	15.12	14.2	15.79	19

Table 7
Comparison of the percentage of cost reduction.

	MA [10]	LF [11]	EA [12]	SOS [13]	[H-PSO-SCAC]
Residential	6.1	13.03	5	16.86	16.8
Commercial	6.4	15.11	5.8	19.17	19.2
Industrial	10.5	15.44	10	19.84	20.5

The results for the industrial area are shown in Fig. 7. The cost of industrial equipment without the demand-side management strategy is 5712 $ for one day, while it is 4544.22 $ by using demand-side management strategy, which resulted in a reduction of 20.5% in the subscribers' cost and a saving of about 1169.78 $ for this area.

Of the three MGs studied, the industrial MG has the lowest number of controllable loads, but its loads have the longest consumption pattern. Like the previous two MGs, by transferring controllable loads from peak times to non-peak times in this MG, the load curve is flattened, the peak load is reduced, and the amount of consumption during non-peak times is increased. The shift of consumers from peak times to non-peak times and the flattening of the load curve have led to an increase in average consumption while the amount of load has decreased during peak times. Therefore, this change will cause the consumption of the subscribers to be transferred to the hours when the price of electricity is cheaper and the cost of the subscribers' bills will be reduced. In this MG, because the consumption pattern and the level of consumption of controllable loads were much higher than in other MGs, the reduction in the cost of consumer bills was also higher than other MGs. However, since the number of controllable loads was much lower than the same in the previous two MGs, the cost of power generation in this MG decreased by only 1.58% after DSM. On the other hand, because the consumption pattern of controllable loads was longer and their power level was higher, the subscribers' bills were reduced by 20.5%.

Finally, because the price of electricity is cheaper during non-peak hours and the production of power is more expensive during peak hours, the implementation of the DSM program further reduces the cost of consumer bills for loads with longer consumption patterns and higher consumption levels. On the other hand, the large number of loads reduces the cost of power generation for the operator. For this reason, the highest reduction in production costs was observed in residential MGs. In industrial MGs, however, we had the highest reduction in consumer bills after implementing the DSM.

Also, the simulation results in Table 5 show that DSM is suitable and cost-effective for both the consumers and the manufacturing companies. In the tested case, according to Table 5, each consumer will save 16 to 20 percent on their costs, and the manufacturing companies will make significant savings with optimized planning, with Residential areas being larger than the others.

The general findings of this study, together with the results of other studies, are given in Tables 6 and 7. The results show that H-PSO-SCAC is a strong method in terms of consumption management solution, load peak and consumer bill reduction compared with other suggested algorithms such as LF, MA, EA, and SOS.

On the other hand, by comparing the results in Tables 6 and 7, it can be seen that the proposed algorithm in many areas has been able to perform better than other methods in reducing bill costs and reducing consumption peak. Figs. 8 and 9 illustrate this better.

Fig. 10 shows that load factor was increased using H-PSO-SCAC management program, which suggests increased network efficiency. In other words, the average energy consumption was increased rather than the peak.

The results in Table 5 show that after implementing the management plan on the consumption side of the residential MG, about 16.37% could be saved on the production costs. Also, commercial and industrial MGs reduced their thermal generation costs by 15.25% and 1.58%, respectively. The lower percentage of cost reduction in the industrial MG is due to the higher consumption level, the larger number of consumers in this area, and the pattern of consumption.

5.2. Effect of DSM and renewable resources on production of MGs

In this section, we will first discuss the effects of DSM and renewable sources such as wind turbines and solar panels on the production of MGs. While Fig. 11 shows the production planning of residential MGs without DSM and renewable resources, Fig. 12 illustrates the same with DSM and renewable resources.

As can be seen from the comparison between Figs. 11 and 12, after the implementation of DSM and the installation of renewable resources in the residential MG, the purchasing power of the main network has been significantly reduced. Table 8 shows the numerical results of this comparison.

According to the results of Table 8, the implementation of the DSM program and the installation of renewable DGs in residential MGs have reduced the cost of producing thermal units and purchasing power from the main network. The cost and amount of power purchases from the main network will decrease by 91.5% and 88.3% in residential MGs, respectively, after the implementation of DSM and the installation of renewable DGs.

Similarly, for commercial MGs, Figs. 13 and 14 show the effect of implementing the DSM program and installing renewable resources on MG production.

Comparisons between Figs. 13 and 14 show that the installation of renewable resources and the simultaneous implementation of the DSM program in the commercial MG also greatly reduces the amount of power purchased from the main network, especially during peak times. As before, Table 9 summarizes the results of this comparison.

As can be seen from Table 9, after the implementation of the DSM and the installation of renewable resources in the network, the cost and amount of purchasing power from the main network has decreased by 82.97% and 84.64%, respectively. The results in

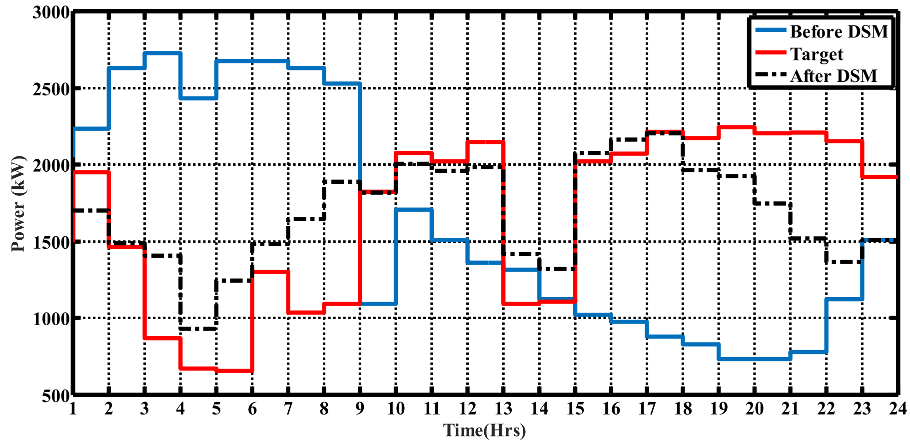

Fig. 7. Load profile for industrial MG.

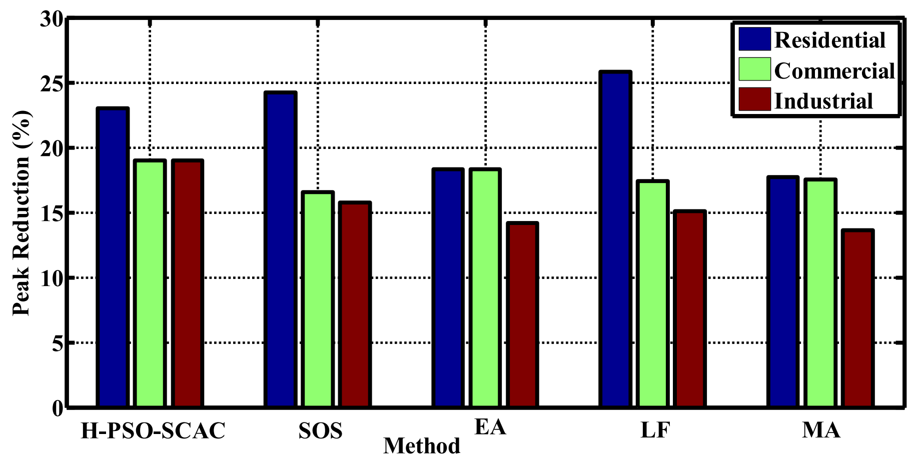

Fig. 8. Peak reduction percentage comparison.

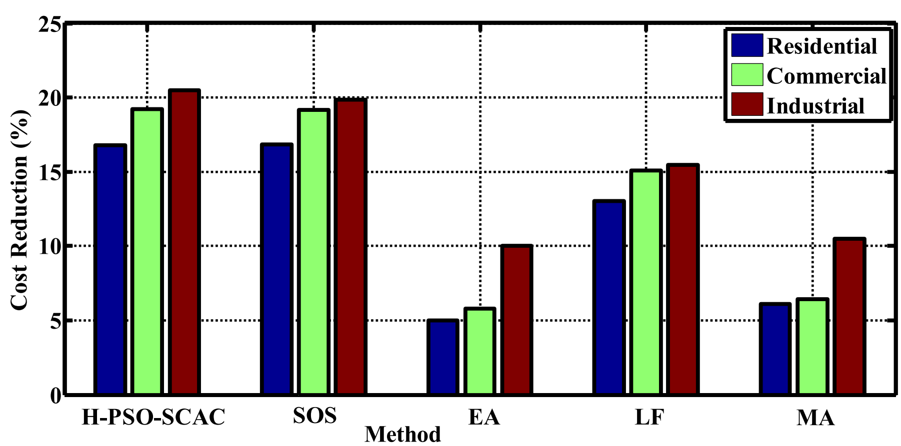

Fig. 9. Cost reduction percentage comparison.

Table 8
Comparison of the effect of DSM on the amount and cost of purchasing power from the main network in the presence of Renewable DGs for Residential MG.

Cost of purchasing power from the main network ($)		The amount of power purchased from the main network (kW)	
Without DSM & Renewable DG	With DSM & Renewable DG	Without DSM & Renewable DG	With DSM & Renewable DG
68652	5813.2	4560.5	530.7329

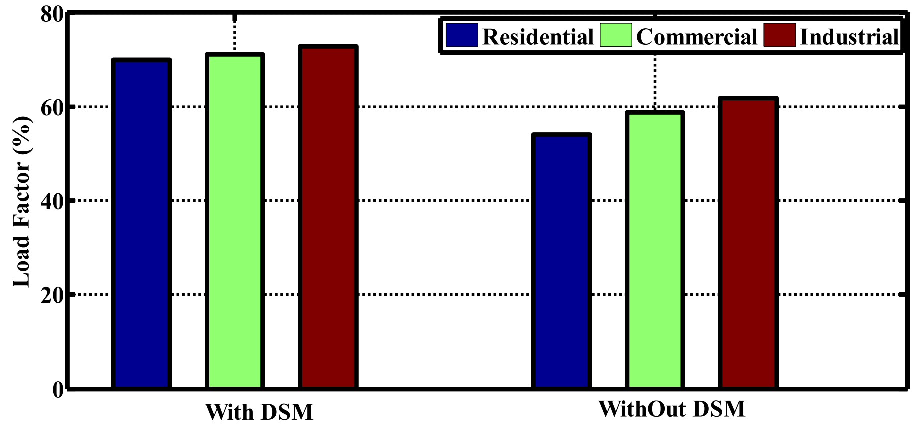

Fig. 10. Load factor change for three areas.

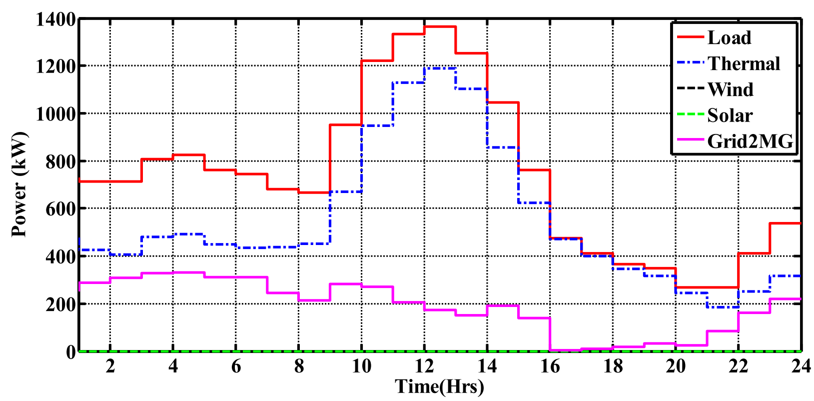

Fig. 11. Production planning Residential MG without DSM and renewable resources.

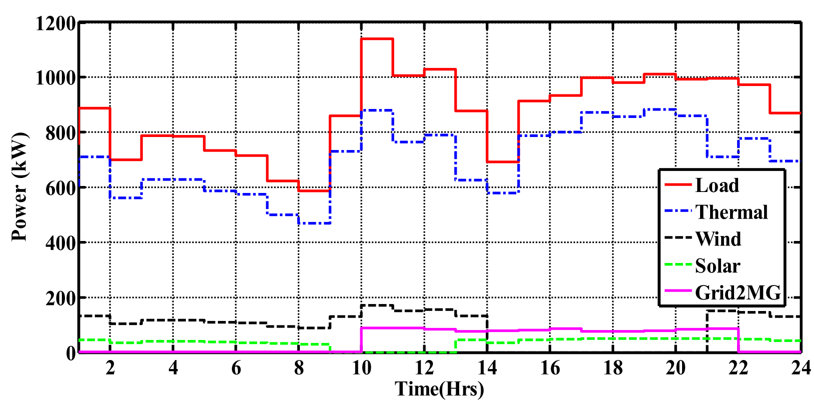

Fig. 12. Production planning in Residential MG with DSM and renewable resources.

Table 9
Comparison of the effect of DSM on the amount and cost of purchasing power from the main network in the presence of Renewable DGs for Commercial MG.

Cost of purchasing power from the main network ($)		The amount of power purchased from the main network (kW)	
Without DSM & Renewable DG	With DSM & Renewable DG	Without DSM & Renewable DG	With DSM & Renewable DG
81736	13913	4891.2	751.276

Table 9 show that the implementation of DSM programs in the presence of renewable resources for production in commercial MG can also save a lot of money. Finally, the effect of the presence of renewable resources on production planning for industrial MGs is shown in Figs. 15 and 16.

One of the major benefits of renewable resources is that they do not require fossil fuels. Therefore, their production costs are almost free. For this reason, as can be seen in Fig. 16, the presence of these resources allows the MG operator to provide most of the power required from these sources. Otherwise, according to Fig. 15, the operator will have to buy power at a high cost from the main network at peak hours. The numerical results of this comparison for industrial MGs are shown in Table 10.

As the results in Table 10 show, for industrial MGs, implementing DSM programs in the presence of renewable resources

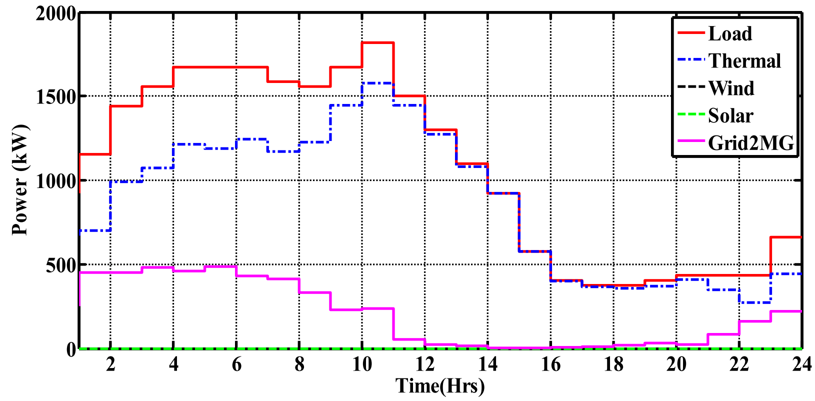

Fig. 13. Production planning in commercial MG without DSM and renewable resources.

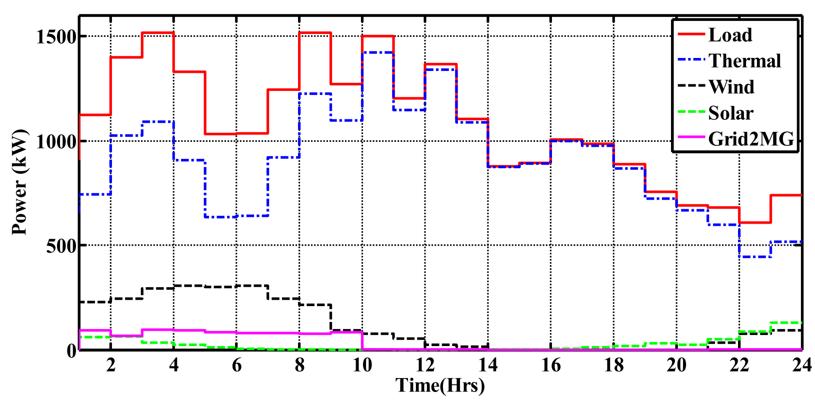

Fig. 14. Production planning in commercial MG with DSM and renewable resources.

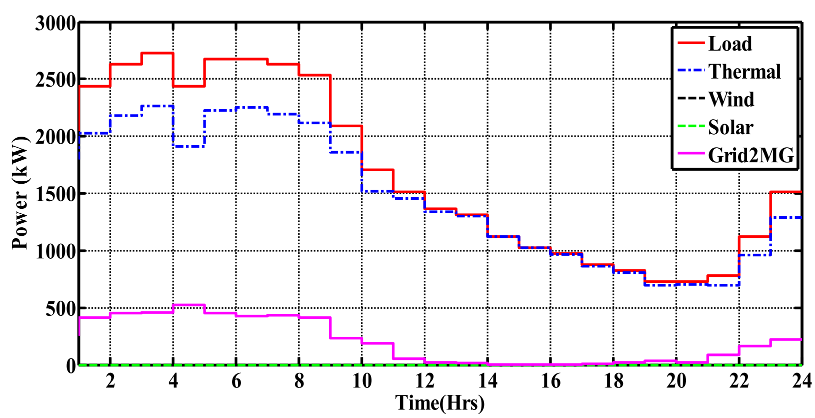

Fig. 15. Production planning in industrial MG without DSM and renewable resources.

Table 10
Comparison of the effect of DSM on the amount and cost of purchasing power from the main network in the presence of Renewable DGs for Industrial MG.

Cost of purchasing power from the main network ($)		The amount of power purchased from the main network (kW)	
Without DSM & Renewable DG	With DSM & Renewable DG	Without DSM & Renewable DG	With DSM & Renewable DG
82519	9467	4912	945.3608

can reduce the cost of purchasing power from the main network by 88.52% and reduce the amount of power from the main network by 80.75%.

As can be seen from the results of Tables 8 to 10, the implementation of DSM programs in the presence of renewable sources such as wind turbines and solar panels can greatly reduce the amount and cost of purchasing power from the main network. The presence of these resources saves significant costs in the operation of MGs.

5.3. Discussion on the effect of DSM programs on the market

Next, assuming that all purchases and sales have been held down after market clearing by auction with the unit price of the cleared market, Table 11 presents a summary of the profit levels

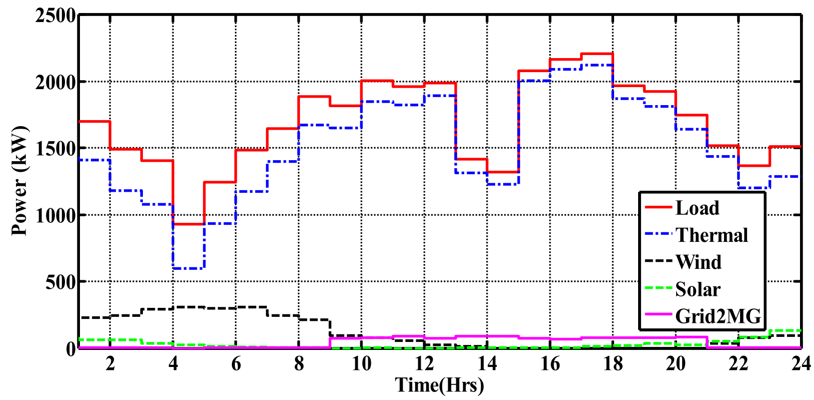

Fig. 16. Production planning in industrial MG with DSM and renewable resources.

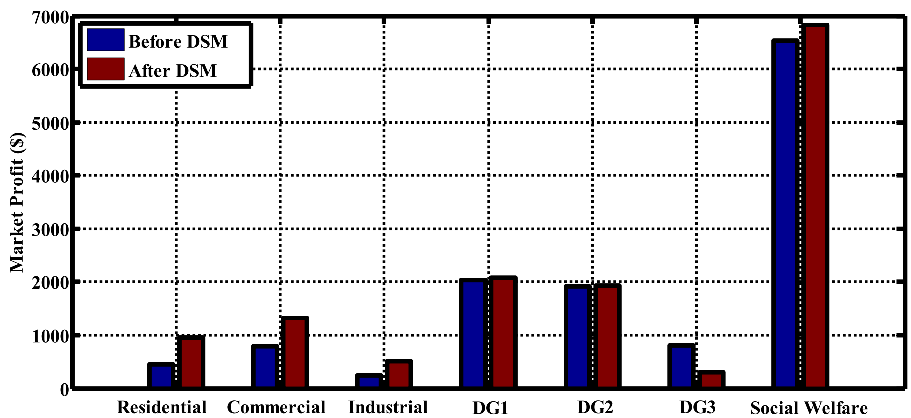

Fig. 17. Changes in the profits of MGs, DGs and social welfare in the market.

Table 11
Manufacturers profit.

	Before DSM	After DSM
Residential MG	456.7557	957.062
Commercial MG	789.4124	1326.512
Industrial MG	243.2046	506.83
DG1	2033	2077.918
DG2	1922.65	1936.073
DG3	805.5999	305.57
Social Welfare	6527.671	6832.917

of the participants in the market in numerical forms and in dollars in two different scenarios.

According to Table 8, after the implementation of DSM on MGs, because a large volume of power generation is reduced during peak hours, MGs can present their surplus power to the market. As can be seen in Table 11, the profit of MGs after DSM has increased because the amount of local production has decreased during peak hours. In this case, the MG can provide more power in the market and increase its profit at all times, especially during peak hours when electricity prices are more expensive. On the other hand, it should be noted that we do not have controllable loads in the main network, and the DSM runs only on MGs. Therefore, the DSM has no effect on the main network loads, increasing only the power provided by the MGs. In this case, DGs can compete with MGs which can offer more power at a lower price in the market. This depends entirely on the quadratic function of the DGs since the marginal price that DGs offer in the market is proportional to the derivative of this function. That is why in Table 11, DG 3 has failed to compete with other DGs and MGs in the market and has made less profit. DG 3 has not been able to provide the desired marginal price in the market according to its quadratic function, so it has won less market power. Therefore, DG 3 has a lower profit after DSM. In fact, by increasing the capacity of the MG in the market, the DGs will make less profit. By comparing the results given in Table 11, it can be inferred that after the implementation of the management plan, the overall profit of the residential and industrial areas has increased by about 52% and the overall profit of the commercial grid has increased by about 40%. Moreover, the level of social welfare for the operator has increased by 4.46%.

It is evident that when the system's load peak is reduced, the cost of operating the generators is also significantly reduced, resulting in a higher level of profitability and a level of social welfare index from the perspective of the operator. Fig. 17 illustrates the profits of micro-grids and DGs before and after DSM.

As shown in Fig. 17, after the implementation of the DSM program, the level of social welfare for the residential and commercial MGs as well as the DGs of the main network has increased. This demonstrates the effectiveness of DSM on the competition between Generation Company's (GENCOs) and MGs.

According to the results in Table 8 and Fig. 17, market execution in the network in question increases the profitability of the MG manufacturers while the proposed DSM is done on the network. However, for the networks with large loads such as the industrial MGs, there is no increase in profit because the volume of internal loads is so large that the manufacturers cannot play a role in the competition.

Also, the implementation of a two-stage program including DSM has increased the level of social welfare in the network from the perspective of the DSO, which is not seen in similar articles and is a unique innovation. On the other hand, using the H-PSO-SCAC algorithm to solve this problem was another innovation of this paper. Based on comparisons with other papers, it can be concluded that the proposed algorithm has provided better solutions.

6. Conclusion

This paper describes a two-stage management plan for the production and consumption sides at the same time. The applied plan is a powerful method based on load shifting, which is mathematically formulated as a minimization problem and implemented using the (H-PSO-SCAC). Simulations have shown that the described algorithm has the ability to commit a large number of controllable loads of different types, and to significantly reduce both the network's load peak and the operational costs. In addition, efficiency rate, system stability, and consumer satisfaction were enhanced using this strategy. Consumers were also encouraged to participate in the program, which has not been previously observed. Also, the implementation of the DSM program in MGs allows MGs to provide more electrical power in the market. Therefore, the profit of MGs, GENCOs and the level of social welfare are increased after the implementation of DSM.

CRediT authorship contribution statement

Javad Ebrahimi: Conceptualization, Methodology, Software, Investigation. **Mohammad Abedini:** Methodology. **Mohammad Mahdi Rezaei:** Supervision, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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