Short-term Scheduling of Restructured Distribution Networks with Demand Response using Symbiotic Organism Search (SOS) Algorithm

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ABSTRACT:
Recently, power system restructuring, demand response (DR) program and using of distributed generation (DG) are important issues to enhance reliability, power flow continuity and power quality for costumers. In this paper, scheduling of distributed networks with DR program for a 24-hours optimization problem is modelled. The DR program is based on load side participation and in order to solve this optimization problem, a new algorithm called Symbiotic Organism Search (SOS) has been used. Objective functions are system losses and operation costs reduction. After exact definition of the problem, objective functions and constraints, proposed method for short-term scheduling is simulated on a 33-bus standard network with MATLAB software for different scenarios. Simulation results show that adoption of demand response programs with proposed method has desirable performance to reduce losses and costs.

KEYWORDS: Distributed Network, Symbiotic organism search algorithm, Short-term scheduling, Demand response, Distributed generation.

1. INTRODUCTION

All of the world's power systems had a vertical management structure before the 1990s. These electric power systems, which have been exclusively managed for more than a century, have recently experienced significant changes in their management structure, which is known as the restructuring of the electric power industry [1]. The power system restructuring affects the electric industry to transforms them from a vertical integrated unit to independent units. Each unit operates independently that is linked to others. In fact, in order to create competition and improve services, exclusive structure of the electric companies were separated to generation, transmission and distribution sections. In such situation, the customers can choose any electric company which sales power with higher reliability, higher quality and lower cost.

The issue of restructuring has raised new problems in power systems that, without solving them will not be able to take advantage of this transformation.

There is always a percentage of power losses in the system. In the traditional power systems, losses minimization was main purpose and in terms of costs, the total cost of final losses along with generation and transmission costs formed total costs of operation. However, in restructured power systems, each system component has a specific legal entity and is therefore independent of revenue and costs.

Recent advances in small power generation technologies have led power distribution companies to move towards network infrastructure changes to enhance the coordination of distribution networks with DG units. Also, with the use of DGs, effective activity in deregulated environments is possible which will have many benefits. Indeed, the use of DGs in distribution network is beneficial for both costumers and electric companies, especially in areas where centralized production is not feasible or there are imperfections in the transmission system [2].

On the other hand, without implementing consumption management programs, electricity markets suffered from a number of problems, including price volatility, transmission lines congestion, rising electricity prices in pick load and the need to install more power plants. Therefore, the market controllers quickly realized that solving mentioned problems was not possible without the costumer's involvement in the market, but it is not too easy, since for years the electricity has been provided to consumers easily and cheaply. Consequently, the task of markets is to encourage customers to change power consumption pattern which DR program as a subset of consumption management programs, give this incentive to customers [3].

The issues of DG controlling and load management in power systems are very important and great dimensions of this issue made it complex. Various methods have been proposed to solve this problem, including dynamic programming methods, Lagrangian relaxation, metaheuristic algorithms such as genetic algorithm, particle swarm optimization, hierarchical method, unit de-commitment method, exhaustive enumeration method, priority list, taboo search and simulating annealing method. Among the many studies in this field, a few can be mentioned.

In [4], a novel stochastic scheduling method which considers various types of demand response (DR) programs is presented. In this paper, all types of customers can participate in demand response programs which will be considered in either energy or reserve scheduling. Distributed equipment connected to the grid that is capable of participating in demand response can be programmed to process received RTP information and react autonomously based on user defined policies [5,6]. Faria [7] focused on demand response programs and distributed generation resources management by a virtual power player that aims to minimize operation costs under consumption shifting constraints. In [8] a cost minimization problem is formulated to intelligently schedule energy generations for microgrids equipped with unstable renewable sources and combined heat and power (CHP) generators. A stochastic programming framework for solving the scheduling problem is presented in [9]. Ruelens et al. in [10] proposed a batch reinforcement learning algorithm to schedule controllable loads such as water heater and heat-pump thermostat. The power and customer demand are supplied considering DR program and responsive load can vary in different time intervals. In [11] a short-term Energy Resource Management (ERM) methodology is performed. The ERM scheduling is formulated as an optimization problem that aims to minimize the operation costs from the point of view of a virtual power player that manages the network and the existing resources. The optimization problem is solved by a deterministic mixed-integer non-linear programming approach and by a heuristic approach based on genetic algorithms. In [12], a stochastic unit commitment problem which included the DR model based on the own price elasticity is presented. The problem was solved in two stages, where the first stage determined the unit commitment schedule in the event of generation outage and the second stage found the optimal final demand level and optimal real time power generation. Though the demand side can voluntarily reduce demand, the system operator exercises control during emergency situation. Kim et al. in [13] proposed a load scheduling algorithm based on Q-learning for a microgrid with time-of-use pricing scheme.

In this paper, a short-term scheduling of distributed networks with optimization based DR is presented. DR is based on load participation and a new optimization algorithm called SOS is used in this problem. After defining the appropriate model for the grid as well as objective functions, the optimization problem is simulated by MATLAB software. Different scenarios are considered on a 33-bus standard grid and results show that this method significantly reduces operation costs and power losses. The rest of this paper is organized as follow: section 2 is dedicated to problem modeling and defining of decision variables, objective functions and constraints. Backward/forward Power flow method and SOS algorithm introduction are presented in section 3 and 4, respectively. Simulation results are presented in section 5 for different scenarios and section 6 is dedicated to paper conclusion.

2. PROBLEM FORMULATION

2.1. Decision Variables

Decision variables include DR model and DG source placement. Demand side participation is one of the important resources that help the operator to schedule generation and consumption with lower cost and higher security. The loads can be divided into base load and changeable load. Base load is expected load based on historical data and its continuous feeding is essential. Changeable loads or responsive loads can reduce or shift into time for economic reasons and system reliability improving. Here, the DR means an incentive program to satisfy customers to reduce their consumption during critical hours.

DG sizing and placement are considered as another decision variables. The DG types is not important in this study and DGs sizing and placement are obtained [14].

2.2. Objective Functions

The objective function is a mathematical function whose inputs are the problem variables and the output is a number that represents the amount of input desirability. In this paper, the objective functions are minimizing the operation cost and power losses.

2.2.1. Minimizing of operation cost

Grid operation with lower costs is desirable. Optimal cost equation can be expressed as:

$$Cost = \sum_{t=1}^{T} (P_{grid}^{t} \times \gamma_{grid}^{t} + DR \times \gamma_{DR}^{t}) \quad (1)$$

Where, DR is responsive load value, γ_{DR}^{t} represents price paid to responsive load, P_{grid}^{t} is power purchased from the upstream network at t and γ_{grid}^{t} is price of electricity purchased at t.

2.2.2. Minimizing of Power Losses

As mentioned, grid losses are inevitable that must be reduce. The total power loss per hour is formulated as follows:

$$P_{Loss}^{t} = \sum_{i=1}^{N_{branch}} R_i \times \left| I_i^t \right|^2 \quad (2)$$

Where, R_i is resistive of i^{th} line, $|I_i^t|^2$ is squared magnitude current of i^{th} line at t and N_{branch} represents number of lines.

2.3. Constraints

2.3.1. Buses voltage limits

Busses voltage limits means stability margin of system voltage. According to defined limitation for buses voltage, following equation can be expressed:

$$V_{i,min} \le V_i \le V_{i,max} \qquad i=1, 2\ldots N_{bus} \quad (3)$$

Where V_i is bus voltage, $V_{i,min}$ and $V_{i,max}$ are minimum and maximum voltage of i^{th} bus, respectively and N_{bus} is the bus number.

2.3.2. Permitted line current flow

Thermal capacity is the most important limitation factor for transmission lines, cables or transformers to transfer power. The thermal capacity of the lines is simply determined based on current flow, so following equation can be used for current flow limitation:

$$|I_i| \le |I_{i,max}| \qquad i=1, 2\ldots N_{Line} \quad (4)$$

Where I_i is current of i^{th} line, I_{imax} is maximum allowed current for i^{th} line and N_{Line} is number of lines.

2.3.3. Demand response constraint

The DR takes place between a maximum and a minimum value which means highest and lowest loads reduction, so DR constraint is as follows:

$$DR_{min}^{t} \le DR^{t} \le DR_{max}^{t} \quad (5)$$

Where DR_{max}^t and DR_{min}^t are maximum and minimum load reductions at time t, respectively.

2.4. Load Modeling

To design a new distribution network or existing network development, the most important factor is loads dispersion and designed network must meet demands until its next development. Usually consumers are divided into household, commercial, industrial, agricultural, general and lighting groups. With respect to the load static features, three general model is proposed in power system studies which are constant power (powers are independent of voltage), constant current (powers are proportional to bus voltage) and constant impedance (powers are proportional to square bus voltage). In this paper, constant power model is considered.

3. POWER FLOW

Load flow studies are performed on power systems to understand the nature of the installed network. Load flow is used to determine the static performance of the system. It analyzes the power systems in normal steady-state operation [15]. Power flow methods in transmission networks such as traditional Newton Raphson method are quite less effective in the analysis of distribution systems due to radial structure and high R/X ratio in latter; also, by increasing the DG units penetration, the distribution network changes from a passive to an active grid [16]. Therefore, common power flow methods in distributed networks with DGs are not suitable and backward/forward sweep method based on current summation is used in this paper.

3.1. Backward/forward Sweep Method

The backward/forward sweep method is appropriate for radial construction and its effectiveness has already been proven. Simple structure, fast convergence and suitable for online and offline problems are as main advantages of this method [17]. Backward sweep starts from farthest point to source and load currents are obtained according to default or calculated voltage in previous iteration. After that, bus voltages calculate in forward sweep and convergence criterion must be examined.

3.1.1. Backward sweep

Power flow problem starts with backward sweep. In first iteration, all buses voltage are equal to source voltage (1 p.u.). In next iteration, buses voltage are calculated from previous step. With respect to buses voltage, the load current can be calculated as follows:

$$I_{L_i} = \left(\frac{P_i + jQ_i}{V_i} \right)^* \quad (6)$$

Where I_{Li}, P_i, Q_i and V_i are current, active power, reactive power and voltage of i^{th} load.

After that, it is necessary to calculate the current through lines starting from the farthest line relative to the reference line. For example, line j can be expressed as:

$$I_{L_j} = \sum_{j \in D} I_{L_i} \qquad i=1\ldots N \quad (7)$$

Where N is bus number, I_{Li} is current of j^{th} line and D is total lines which are connected to bus i. Consequently, backward sweep is finished and lines current are updated.

3.1.2. Forward sweep

In the forward sweep starting with source bus, whose voltage is known, and considering impedance and lines current, the voltage of i^{th} bus is calculated as follows.

$$V_i = V_{i-1} - Z_i I_{L_i} \qquad i=1\ldots N \tag{8}$$

Where V_i is voltage of i^{th} node, V_{i-1} is first node voltage at i^{th} line and I_{Li} is current of i^{th} line. Upon completion of this process, the forward sweep is finished and all busses voltage are updated.

3.1.3. Convergence criterion survey

After backward/forward sweep, the convergence criterion needs to be calculated as (9) to assess need for further iterations.

$$\Delta V_{max} = max\left|V_{i,old} - V_{i,new}\right| < \varepsilon \tag{9}$$

Where $V_{i,old}$ is voltage of i^{th} node in previous iteration, $V_{i,new}$ is voltage of i^{th} node in last iteration and ε is permissible voltage deviation value. If the above equation persists, the power flow will end; otherwise, iterations will continue. Fig. 1 shows flowchart of the backward/forward sweep method based on current summation.

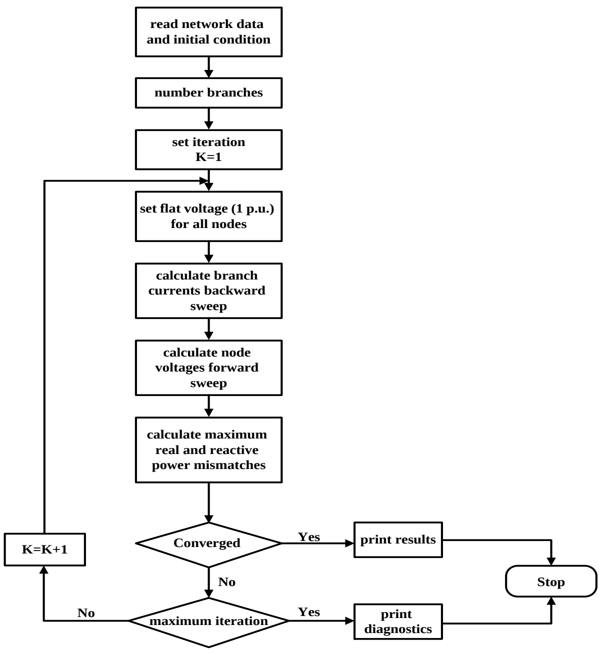

Fig. 1. Backward/forward sweep method flowchart.

3.2. Power Flow in Distributed Network with DG Sources

Distributed systems with DGs are similar to multi source network, so busses with DG are modelled as PQ or PV bus [16]. In this paper, DG units are controlled like a PQ bus and hence, they are considered as a negative load. The PQ bus are modeled as follows:

$$\begin{cases} P = -P_{DG} \\ Q = -Q_{DG} \end{cases} \tag{10}$$

4. SYMBIOTIC ORGANISM SEARCH (SOS) ALGORITHM

Optimization is a challenging area of study that has attracted increasing attention in recent decades [18]. Optimization find best solution which is depended on problem, limits and constraints. Recently, metaheuristic algorithms such as PSO and GA have more attractive and they are superior to traditional gradient-based approaches. The SOS algorithm is a recently developed population based algorithm introduced by Cheng and Prayogo in 2014 [18]. This algorithm is inspired from the symbiotic interactions that exist between two organisms in the ecosystem. Organisms in the real world rarely live in isolation due to dependence on other species for their survival [19]. This algorithm is based on organism behaviors with each other. Three types of symbiotic relationships are found in nature. They are mutualism, commensalism and parasitism. By performing these three phases, the SOS tries to move population, called an ecosystem of possible solutions, to promising areas of the search space during the search for the optimal solution [20].

The significant advantages of SOS algorithm over other metaheuristic algorithms include simple mathematical operations, easier to code, no usage of tuning parameters, robust and easy to realize and it needs lesser control parameters [21,22]. Operation details of these symbiotic interaction three phases are explained below.

4.1. Mutualism Phase

Mutualism refers to the relationship between two different species of organisms where both individuals get benefited. Let X_i be the organism corresponding to the i^{th} row of the ecosystem. A new organism X_j is chosen randomly from the ecosystem to relate with organism Xi. The new candidate solutions for X_i and X_j are determined based on the following equations.

$$X_{inew} = X_i + rand(0,1) \times (X_{best} - Mutual\_Vector \times BF1) \tag{11}$$

$$X_{jnew} = X_j + rand(0,1) \times (X_{best} - Mutual\_Vector \times BF2) \tag{12}$$

$$Mutual\_Vector = \frac{X_i + X_j}{2} \tag{13}$$

Where, rand (0, 1) is a vector of random numbers between 0 and 1, BF1 and BF2 are benefit factors that can be randomly 1 or 2, X_{best} is best member in i^{th} iteration and *Mutual_Vector* represents interaction between organism X_i and X_j. If the new organism's fitness is better than the previous fitness then organisms will be updated.

4.2. Commensalism Phase

Commensalism describes the symbiotic relationship between two organisms in which one benefits but the other neutral. In this phase, for each organism X_i another new organism X_j is randomly selected from the ecosystem. Now, the organism X_i tries to get benefit from the interaction and other organism X_j is neither benefits nor effects from this interaction. The new X_{inew} is calculated based on (14):

$$X_{inew} = X_i + rand(-1,1) \times (X_{best} - X_j) \quad (14)$$

Where, rand (-1, 1) is a random number in range of (-1, 1). If new organism is better than the previous one, it will be accepted, otherwise it will remain unchanged.

4.3. Parasitism Phase

Parasitism is a kind of symbiotic relationship where one organism is benefited and the other is, effectively, harmed. In this phase, one of the organisms selected randomly from the ecosystem X_i plays as a "*Parasite-Vector*". The *Parasite- Vector* is developed in the search space by replicating organism X_i, then altering the randomly selected dimensions by making use of a random number. The newly formed parasite competes for survival with the organism X_j. If X_j has lesser fitness when compared to the parasite, then the parasite kills the organism X_j and takes over its place in the ecosystem. Fig. 2 represents the SOS summary flowchart.

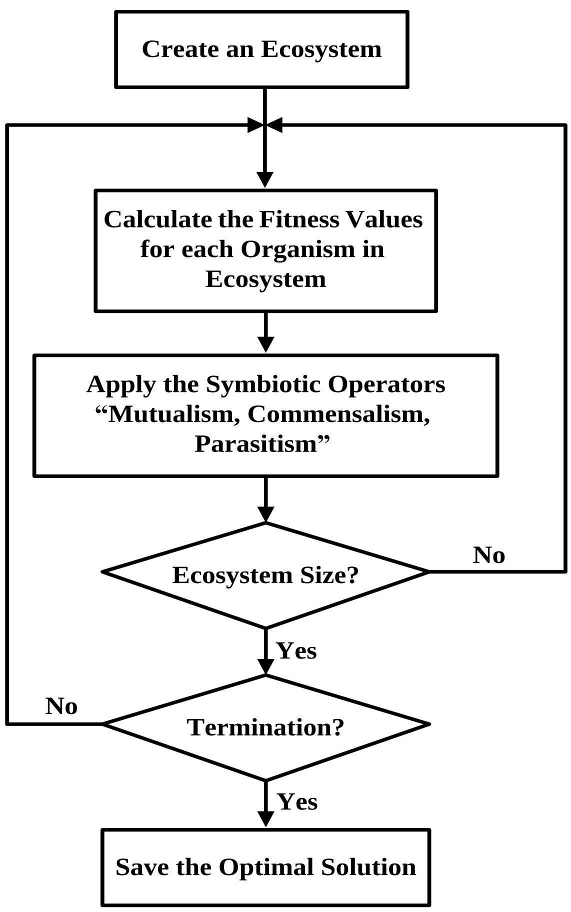

Fig. 2. The SOS flowchart.

5. RESULTS AND DISCUSSION

By introducing decision variables, objective functions, problem constraints and SOS algorithms, proposed optimization method is simulated by MATLAB software under different scenarios.

The proposed method is applied to a standard 33-bus radial distribution network. Configuration of 33-bus radial network is shown in Fig. 3 and its data is presented in [23]. Total active and reactive loads are equal to 3715 kW and 2300 kVar, respectively. System nominal voltage is equal to 12.66 kV and power loss is about 202.6 kW. Energy price and hourly load during 24-hours is shown in Table 1[24]. There is also two responsive load which are connected to bus 15 and 24 and their specifications are shown in Table 2 [4]. DGs size and place is presented in Table 3.

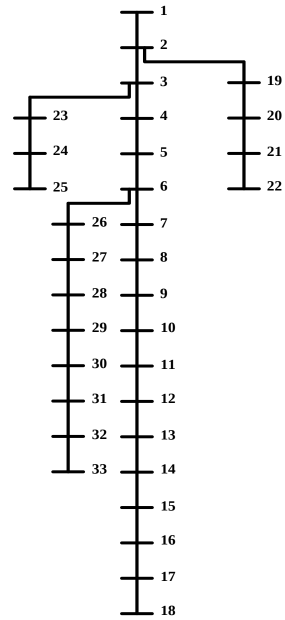

Fig. 3. The standard 33-bus system.

Table 1. Energy price and hourly load during a day.

Hour	Energy price ($/MWh)	Load (p.u.)	Hour	Energy price ($/MWh)	Load (p.u.)
1	47.47	0.6618	13	60.64	0.7941
2	31.64	0.6765	14	40.88	0.7500
3	31.65	0.6912	15	28.5	0.7500
4	32.6	0.7059	16	38.75	0.7647
5	40.78	0.7206	17	35.55	0.7794
6	38.64	0.7500	18	112.42	0.8529
7	158.95	0.7794	19	575.58	0.9412
8	384.14	0.8235	20	87.72	0.9853
9	67.27	0.8824	21	35.06	1.0000
10	52.29	0.9118	22	47.18	0.9118
11	44.59	0.8676	23	61.27	0.7353
12	108.49	0.8382	24	33.9	0.7059

Table 2. Responsive loads specification [4].

Hour	bus 15		bus 28	
	Maximum reduction (kW)	Price ($/kWh)	Maximum reduction (kW)	Price ($/kWh)
8	15	6	12	14
9	9	7	24	9
10	5	4	5	12
13	7	10	-	-
14	7	50	-	-
15	21	60	16	12
16	7	8.5	19	8
17	10	6	25	60
18	4	10	18	60
19	15	20	10	30
20	28	30	18	10
21	10	30	21	6
22	3	30	8	20
23	6	30	-	-

Table 3. DG size and place in 33-bus system.

Bus	P (kW)
3	50
6	100
24	200
29	100

5.1. Scenarios

Short-term scheduling of distributed network with DGs and DR program by SOS algorithm is presented to reduce power losses and operation costs. Scenarios are as follow:

5.1.1. Scenario 1 (basic mode)

In this mode, operation cost and losses are calculated in the grid without responsive load as well as DG. Simulation results show that grid operation cost is $ 6915800 and power losses is equal to 3100.7 kW. These results are calculated for a simple grid, so they will reduce in following scenarios.

5.1.2. Scenario 2

In this mode, minimizing of operation cost during 24-hours a day is objective function. The grid with DG and responsive load is considered that optimization problem has been solved with SOS algorithm. The SOS algorithm population and maximum iteration are considered equal to 10 and 20, respectively.

Fig. 4 shows a day operation cost for scenario 2 compared with scenario 1. After applying DG and responsive load, operation costs are reduced in all hours. In second scenario, calculated value for grid operation cost is equal to $ 5912100 which is about 14.5% lower than the previous scenario (basic mode).

Comparison of total operation cost between first and second scenarios is shown in Fig. 5. As can be seen, in the second scenario the cost has reduced.

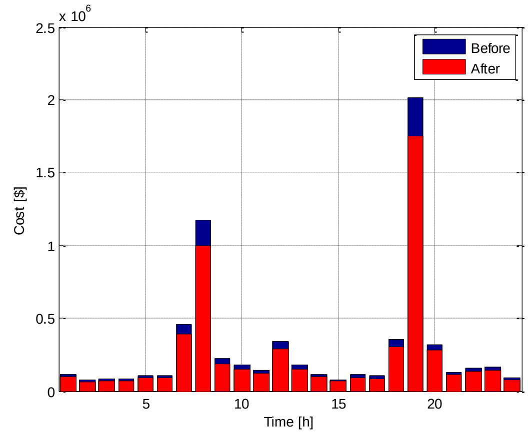

Fig. 4. 24-hours grid operation cost for scenario 2 in comparison with scenario 1.

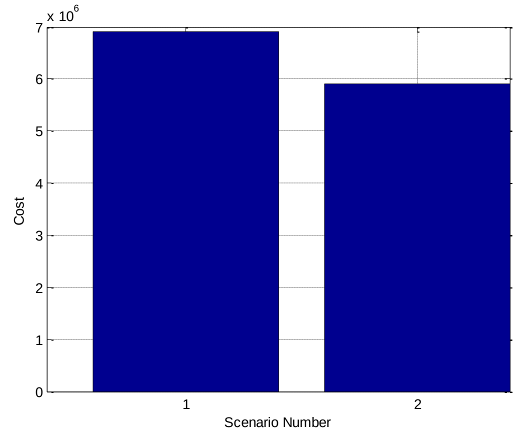

Fig. 5. Total operation costs for scenario2 and scenario1.

Fig. 6 shows status of the responsive loads during 24-hours for second scenario. This figure shows responsive load contribution in demand respond program. As an example, responsive load at bus number 15 propose 7 kW with 60 $/kW in 14th hour but this contribution was rejected in first scenario.

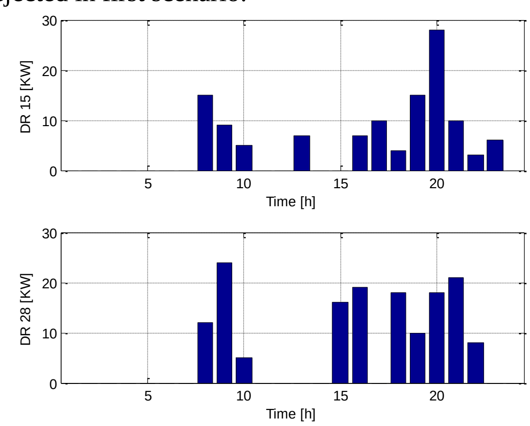

Fig. 6. Contribution of responsive loads during 24-hours for scenario 2.

5.1.3. Scenario 3

In this mode, minimizing of grid with DG as well as responsive load power losses during 24-hours a day is considered. Optimization problem is solved by SOS algorithm in which population and maximum iteration are considered equal to 10 and 20, respectively.

The responsive loads status during 24-hours a day for third scenario is shown in Fig. 7. Contribution of each responsive load is shown like previous scenario. As an example, responsive load at bus number 28 propose 25 kW circuit with 60 $/kW in 17th hour but this situation did not happen in second scenario (see Fig. 6) because contribution of this load is necessary to reduce power losses.

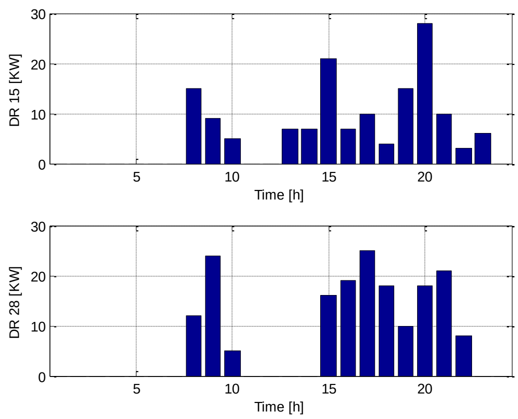

Fig. 7. Contribution of responsive loads during 24-hours for scenario3.

Fig. 8 shows comparison of grid power losses between scenarios 2 and 3. Power loss has been reduced in third scenario in the all hours.

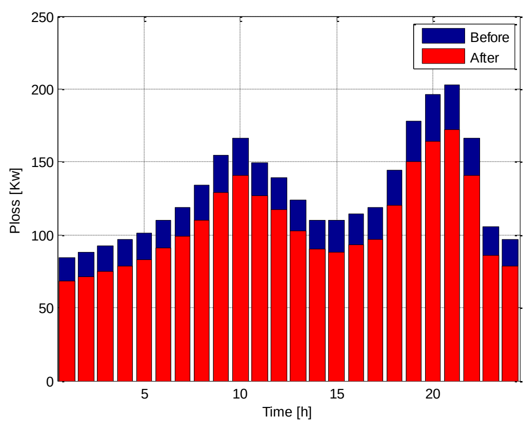

Fig. 8. 24-hours grid power losses for scenario3 in comparison with scenario2.

For a better comparison, grid losses in third scenario is compared with first scenario which is shown in Fig. 9. Third scenario loss is about 2573 kW which represents 17% decrease.

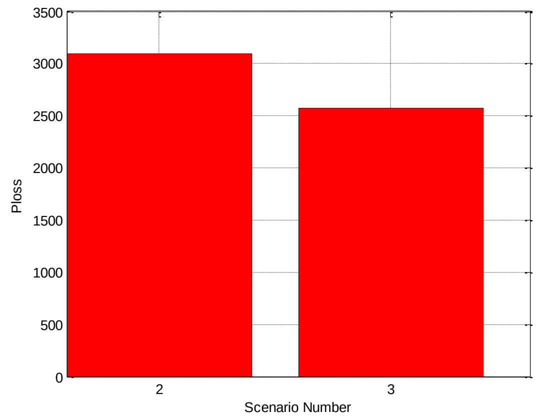

Fig. 9. Total power losses for scenario3 and scenario1.

6. CONCLUSION

Today, with respect to increased demand, the electric industry competitiveness and environmental issues, power losses and grid operation costs reduction are one of the main concerns of distribution network users. One of the most important and effective methods for reducing losses and costs in distribution networks is short-term scheduling. The purpose of this paper is to provide a short-term scheduling in the presence of DG as well as DR program in which SOS algorithm is used to optimize this problem.

Simulations are carried out by MATLAB software for three different scenarios. In firs scenario, the standard 33-bus network is in base mode without any DG or DR program. Second scenario is dedicated to grid optimization for operation cost in the presence of DG and DR program. Also, minimizing grid power losses with SOS algorithm in the presence of DG and DR program is studied in third scenario. Reduction of operation cost in scenario 2 and power losses in scenario 3 are about 14.5% and 17%, respectively. The results showed that SOS has the ability to find the optimal solution for problem.

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