Market-based Method for Reconfiguration of Distribution Networks Using Mine Blast Algorithm (MBA)

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ABSTRACT:
Today, reduction of losses and operational costs is considered an important issue in power systems. Demand response program causes diminished consumption during peak hours and thus increased reliability and reduced costs. Reconfiguration of distribution networks are among the practical methods in reducing losses and costs as well as improving the voltage profile. In this paper, the reconfiguration of distribution networks is performed considering demand response potential and in the presence of distribution generated (DG) sources using a new optimization algorithm called mine blast optimization algorithm (MBA). For this purpose, reducing losses, improving voltage profile, and lowering operational costs of the network are also taken into account as objective function. The proposed method is applied on 33-bus radial network. Simulation has been performed using MATLAB software.

KEYWORDS: Mine Blast Optimization Algorithm (MBA), Reconfiguration of Distribution Networks, Demand Response, Reduction of Losses, Reduction of Costs.

1. INTRODUCTION

Losses are always present in power systems, whose major part is related to distribution network. Various methods have been adopted to mitigate the losses and naturally the operational costs in networks including capacitor placement, installing distribution generation (DG) sources, consumption management, replacing the network conductors and network reconfiguration. Among them, reconfiguration is the simplest and least expensive method to mitigate the losses.

Reconfiguration of distribution networks refers to opening a number of keys and closing the same number of keys, such that while keeping the radial structure and constraints of the system, the losses are also minimized [1]. Although reduction of losses is considered the key objective in reconfiguration of distribution networks, the issue of reconfiguration is also employed for other purposes including improving voltage profile, enhancing voltage stability, improving reliability, equalizing the demand of feeders, reducing operational costs, and the like [2].

One of the effective methods for reducing costs is usage of demand response program. Demand response refers to the ability of final users to improve the consumption pattern of electric energy to achieve suitable prices and improve the reliability of the network [3]. Generally, demand response aims to reduce electricity consumption during critical hours. The critical hours are when the price of wholesale market is very high or the system storage level is low due to incidence of unexpected events. Indeed, demand response is alteration of behavior in consuming energy on the part of demands [2]. The progressive growth of electricity consumption in recent years has changed usage of demand response sources into a vital issue for system operators. In general, the demand response can alter the form of electric energy consumption through demand management in the system such that the system peak declines and the consumptions transferred to non-peak hours. Accordingly, implementing the demand response program brings about various economic advantages and reliability.

There are many researches on distribution network reconfiguration with a variety of methods. In [4] optimization objective and constraints of the distribution network reconfiguration and overviews a variety of algorithms, including the heuristic, stochastic optimization and intelligent methods is presented.

Using of hybrid heuristic genetic algorithm [5], combination of cycle-break algorithm and genetic algorithms [6] or genetic algorithm [7] are a method for reconfiguration of distributed system. Moreover, using of multi-agent particle swarm algorithm [8], modified particle swarm algorithm (MPSO) [9], multi-objective discrete particles swarm algorithm with graph theory [10] and two group PSO [11] are another optimization method for reconfiguration. In [12] a distributed system with renewable energies and particle swarm optimization (PSO) algorithm is presented. a multi objective method for optimal network reconfiguration as well as reactive power dispatches of DGs is proposed in [13] to improve the network performances by using non-dominated sorting PSO.

A rule-based expert system with a colored Petri net (CPN) algorithm is developed in [14] for load balancing of distribution systems. In [15] a dynamic reconfiguration considering the load variation was proposed. A minimum spanning tree (MST) based on Kruskal's algorithm has been applied to find the optimal reconfiguration under multi times, with minimizing the total power loss as objective function. A new reconfiguration heuristic to reduce the total power loss and the maximum current of electrical radial networks based on the branch-and-bound strategy is presented in [16]. Using of evolutionary algorithms is another method for reconfiguration of network, such as [17] and [18] that latter reconfigured switch and tap-changer. Ref. [19] proposes the study and application of an algorithm based on Ant Colony Optimization, method covered in the paradigm of Swarm Intelligence, sub-discipline of Computational Intelligence.

The work presented in [20] is a step forward to define the reconfiguration problem closer to reality by considering the effect of harmonic loads. To solve this complicated combinatorial, non-differentiable constrained optimization problem, novel heuristic optimization techniques such as Shuffled Frog Leaping Algorithm (SFLA) and Imperialist Competitive Algorithm (ICA) are employed.

In this paper, reconfiguration of distributed network with DGs and considering of demand response program is proposed using MBA. The rest of this paper is organized as follows: problem modeling includes objective function, constraint introduction and load modeling is presented in section 2, backward/forward sweep power flow is illustrated in section 3, investigation of mine blast optimization algorithm is presented in section 4 and section 5 and section 6 are dedicated to simulation and paper conclusion, respectively.

2. PROBLEM MODELING

2.1. Objective Function

Every optimization problem has a mathematical function called objective function or cost function. The objective function of this problem includes reduction of losses and operational costs of the network.

2.1.1. The losses of the distribution network

Transmission of power through lines is always coupled with losses. The losses of the total power of the network in an hour are expressed as follows:

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

Where, P_{Loss}^t is the ohmic losses of the network in the t_{th} hour, R_i represents the Ohmic resistance of the i_{th} line, $|I_i^t|^2$ is the squared size of the current of i_{th} line at the t_{th} hour, and N_{branch} denotes the number of lines.

2.1.2. Operational costs

One of the main objectives of the problem is to obtain the optimal radial structure to minimize operational costs of the network. The function associated with the network operational costs can be stated as follows:

$$Cost = \sum_{t=1}^{T} (P_{grid}^t \times \lambda_{grid}^t) \tag{2}$$

Where, P_{grid}^t is the power received from the network and λ_{grid}^t represents the price of electricity purchased from the network at the t_{th} hour.

2.2. The Problem Constraints

Constraints are limitations considered in the problem, and are associated with the natural structure of the network.

2.2.1. Limitation of the voltage of buses

The allowable range of voltage changes in the network is limited, and standards usually consider slight changes around the nominal value as allowable. Accordingly, the voltage of buses should always lie within an allowable range:

$$v_i^{\min} \le v_i \le v_i^{\max} \qquad i=1, 2, \ldots, N_{bus} \tag{3}$$

Where, v_i is the voltage of i_{th} buss, v_i^{min} and v_i^{max} represent the minimum and maximum allowable voltage in the i_{th} bus, with N_{bus} representing the number of buses.

2.2.2. Limitation of the current of lines

The lines have a limited ability to pass the current, and passage of a current over this value can seriously damage the conductor. In order to prevent overload on the lines, the current of each branch should be lower than or equal to its maximum capacity.

$$\left| I_i \right| \le \left| I_i^{\max} \right| \qquad i=1, 2, \ldots, N_{Line} \tag{4}$$

Where, $|I_i|$ is the current of the i_{th} line, $|I_i^{max}|$ represents the maximum allowable current in the i_{th} line and N_{Line} denotes the number of lines.

2.2.3. The constraint of network radiality and feeding of all demands

The most difficult limitation for the network reconfiguration problem is the network's radiality limitation. Unlike other limitations, it is not possible to state this limitation as a mathematical equation and analytically. In this paper, using graph theory, isolated buses and loops were detected, after which if it is radial, the objective function corresponding to that solution is calculated. If the generated configuration is not radial, then a large number is considered as its corresponding objective function, so that this solution would be considered a bad solution, and accordingly will be regarded as low priority for selection. In this method, a matrix is defined whose rows are equal to the number of buses, while its columns are equal to the number of lines. Thereafter, in each row, if the bus corresponding to that row is connected to the lines corresponding to those columns, the columns become equal to 1, while the other members of that row will be zero. Following matrix development, in each row, the columns that were equal to 1 are counted and the obtained number is considered the order of that row. Thereafter, we remove any row whose order is one, while also eliminating the column in which the row is equal to one. The stages of row and column removal continue until reaching a null matrix, suggesting that the network is radial, otherwise it will be non-radial.

2.2.4. The constraint related to the demand response

this constraint is stated by the following relation:

$$DR_{\min}^{t} \le DR^{t} \le DR_{\max}^{t} \tag{5}$$

Where, DR_{max}^t and DR_{min}^t are the maximum and minimum values of demand reduction at the time of t.

2.3. Load Modeling

In studies of power systems, three models including constant power, constant current, and constant impedance have been proposed for modeling. In this paper, the constant power model is considered to model the demand behavior.

2.4. The Model of Buses with Distributed Generation

In the presence of distributed generation (DG) sources in distribution networks, this network loses its radial state and will convert to feed from several points or continuously. The DG units which are controlled as PQ buses are introduced into the model as negative load:

$$\begin{cases} P = -P_{DG} \\ Q = -Q_{DG} \end{cases} \tag{6}$$

3. BACKWARD/FORWARD POWER FLOW

The typical methods of power flow used in transmission networks are different from those of distribution networks. This is because distribution networks have a radial structure and high R/X ratio. Furthermore, by enhancing the diffusion coefficient of DG sources, the distribution network turns from a passive network to an active one. In this paper, backward/forward sweep power flow based on current summation has been used in a distribution network. Simple structure and fast convergence are two important advantages of this method.

3.1. Backward Sweep

in the first iteration, the voltage of all buses is considered equal to the voltage of source. Considering the known value of voltage of buses, the current of loads can be calculated as follows:

$$I_{L_i} = \left(\frac{P_i + jQ_i}{V_i}\right)^{*} \tag{7}$$

Where, I_{L_i}, P_i, Q_i, and V_i represent the current, active power, reactive power, and voltage of i_{th} load, respectively.

After calculating the current of loads, the current passing through the lines should be calculated by starting from the farthest line in relation to the reference bus. For example, for the j_{th} line we have:

$$I_{L_j} = \sum_{j \in D} I_{L_i} \qquad i=1, 2, \ldots, N \tag{8}$$

Where, N denotes the number of system buses, I_{Lj} Shows the current passing through the j_{th} line, and D is the set of lines connected to the i_{th} bus. Accordingly, the backward sweep is terminated, and the current of all lines is calculated or updated.

3.2. Forward Sweep

in forward sweep, by starting from the reference bus (whose voltage is known), and considering the impedance and current passing through each line, the voltage of the i_{th} bus is calculated as (9):

$$V_i = V_{i-1} - Z_i I_{L_i} \qquad i=1, 2, \ldots, N \tag{9}$$

Where, V_i is the voltage of the i_{th} node, V_{i-1} shows the voltage of the initial node of i_{th} line, Z_i represents the impedance of the i_{th} line, and I_{L_i} Indicates the current passing through the i_{th} line. As this process is completed, the forward sweep is terminated, and the voltage of all buses will be updated.

3.3. Investigating the Convergence Criterion

after performing the backward/forward sweep, the convergence criterion should be calculated to check whether further iterations are required or not.

$$\Delta V_{max} = \max \left| V_{i,old} - V_{i,new} \right| < \varepsilon \tag{10}$$

Where, $V_{i_{old}}$ is the voltage of the i_{th} bus calculated in the previous iteration, $V_{i_{new}}$ Shows the voltage of i_{th} node calculated in the current iteration, with ε representing the extent of allowable deviation of the voltage. If (10) holds true, flow of current is terminated. Otherwise, the procedure of iteration of calculations should continue.

4. MINE BLAST ALGORITHM (MBA)

Reconfiguration of distribution networks is a nonlinear hybrid optimization problem with wide dimensions including a number of constraints. Considering the large number of keys in distribution networks, there are various states in opening and closing the keys in the network, further complicating the problem. To solve such a problem, robust and efficient optimization methods are required.

Today, optimization algorithms are easily used in different problems including linear, continuous, or discrete problems. The optimization algorithms including MBA suitably optimized the reconfiguration problems.

4.1. Fundamental Concepts

The main idea of this algorithm is based on blast of a mine, in which the collision of shrapnel shell resulting from the blast with the adjacent mines causes their exclusion. To better understand the situation, consider a mine field, and assume that we want to clear all of its mines. Thus, our objective is to find the mines and also determine the mines that have them maximum potential of blasting. In this view, it is in the optimal point of X^*, and can incur the maximum level of damage (minimization or maximization of f(x) per any X^*).

The huge extent of damage resulting from each shrapnel shell in a region can represent presence of other mines, which may have greater or lower explosive power. Every shrapnel shell has a specific direction and distance, and can cause explosion of mines by colliding with them. The extent of damage resulting from explosion of each bomb is considered the eligibility level of the objective function in the location of that mine.

4.2. The Presented Method

the presented MBA method is initiated with a set of initial points, which are the first struck points. These initial points are represented by X_0^f, with f=1,2,3,…, Which can be determined by the user. Nevertheless, the presented algorithm can select the locations of the initial points randomly and using the upper and lower limit values of the problem of interest. This algorithm needs a primary population consisting of independent agents, which is developed through an initial blast and thoughts generation of a number of independent agents (shrapnel shells). The number of these agents in the initial population (N_{pop}) is considered as the number of shrapnel shells (N_s). This algorithm employs the values of upper and lower limits which are determined based on the problem of interest. It then generates the strike point using a small random value as follows:

$$X_0 = LB + rand \times (UB - LB) \tag{11}$$

Where, X_0, LB, and UB represent the generated initial points, lower limit, and upper limit of the problem, respectively. rand is a uniform random number between 0 and 1. Although across all of the optimization simulations implemented in this study, an initial strike point will be very effective and efficient, more initial points can also be utilized, causing increased dimensions of the primary population and thus elevated number of objective function assessments (computational cost). Assume that X is the current location of a mine, which is expressed as follows:

$$X = (X_m) \qquad m=1, 2, 3, \ldots, N_d \tag{12}$$

In this relation, N_d shows the dimensions of the search space and is equal to the number of independent variables. Assume that N_s shrapnel shells have been produced in response to mine blast, which also causes blast of another mine in the location of X_{n+1}:

$$X^f_{e(n+1)} = X^f_{e(n+1)} + \exp\left(-\sqrt{\frac{m^f_{n+1}}{d^f_{n+1}}}\right) X^f_n \qquad n=0, 1, 2, 3, \ldots \tag{13}$$

Where, $X^f_{e(n+1)}$, d^f_{n+1}, and m^f_{n+1} represent the location of the mine blasted in response to strike of shrapnel shell, the distance, and direction (slope) of the shrapnel shells shot in each iteration, respectively. The location of the blasted mine $X^f_{e(n+1)}$ is defined as follows:

$$X^{f}_{e(n+1)} = d^{f}_{n} \times rand \times \cos(\theta) \qquad n=0, 1, 2, \ldots \qquad (14)$$

Where *rand* shows a random number with uniform distribution and θ indicates the angle of shrapnel shells, which is equal to a constant value, calculated by $\theta=360/N_s$. Equation (14) has been written regarding simulation of mine blast in the real world. The shrapnel shells (independent agents) which have variable distances in relation to the blast point and specific directions explored the search space in each iteration as 360° and based on certain values of θ and d_n^f to find the best optimal point. The θ value is set at $360/N_s$ so that a uniform search is performed throughout the entire solution space. This prevents accumulation of independent agents in a certain region of the search space.

The exponential term in (13) is employed to improve the obtained blast point, through being affected by the information associated with the previous solutions (X_n^f). The distance d_{n+1}^f and direction of m_{n+1}^f are defined as follows:

$$d^{f}_{n+1} = \sqrt{\begin{matrix}(X^{f}_{n+1} - X^{f}_{n})^2 \\ +(F^{f}_{n+1} - F^{f}_{n})^2\end{matrix}} \qquad n=0, 1, 2, \ldots \qquad (15)$$

$$m^{f}_{n+1} = \frac{F^{f}_{n+1} - F^{f}_{n}}{X^{f}_{n+1} - X^{f}_{n}} \qquad n=0, 1, 2, \ldots \qquad (16)$$

Where, F is the value of objective function per X. To calculate the initial distance for the shrapnel shell, the relation $d_0= (UB – LB)$ is used in each of the dimensions. The initial distance calculated by the algorithm is employed to search for the best solution within the range of $LB < d_0 < UB$, which is calculated by multiplying the initial distance by a random number (such as *rand* function in MATLAB software).

In addition, to conduct the exploration operation related to the space of interest within smaller or larger distances, exploration factor (μ) is also defined. This constant factor, which is used in the initial iterations of the algorithm, is compared with the index of number of iterations (k). If it is larger than k, then the exploration process begins. The relations associated with exploring the search space are as follows:

$$d^{f}_{n+1} = d^{f}_{n} \times (|randn|)^2 \qquad n=0, 1, 2, \ldots \qquad (17)$$

$$X^{f}_{e(n+1)} = d^{f}_{n+1} \times \cos(\theta) \qquad n=0, 1, 2, \ldots \qquad (18)$$

rand is also a pseudorandom number with normal distribution. During the exploration process, if the constraint related to μ is followed upon, the distance of each shrapnel shell is also modified using (17). Usage of square of a random number with normal distribution can allow for searching within smaller or larger distances in addition to better implementing the exploration process in initial iterations. Larger value for the exploration factor (μ) allows for exploring more remote areas (better exploration). Therefore, μ value determines the intensity of exploration. To enhance the capability of exploration and global search in the presented method, the initial distance of shrapnel shells is also diminished gradually. In this way, the mines are able to find the probable location of the global optimal point. Reduction of d_0^f value is performed as follows:

$$d^{f}_{n} = \frac{d^{f}_{n-1}}{\exp(k / \alpha)} \qquad n=0, 1, 2, \ldots \qquad (19)$$

In this relation, α and k are the constant degradation factor and number of iteration. Selection of α, which is determined by the user, depends on the extent of optimization problem complexity. The effect of α in reducing the distance of each shrapnel shell is adaptive and is done (19). Therefore, the entire lower limit to upper limit range of the problem of interest will be searched and explored.

4.3. Adjusting the User Related Components

improper selection of values of the algorithm components can result in low convergence rate, convergence to a local optimal solution, or achieving undesirable solutions.

- In simple or relatively complex optimization problems, selection of 10-15 shrapnel shells per each mine can be effective and practical. In more complex problems, however, larger number of shrapnel shells (Ns) is suggested, so that more blasts occur for better searching the solution space.

- The exploration factor (μ) is highly dependent on the extent of problem complexity, number of independent variables, constraints, and the search range (the distance between upper and lower limits). Typically, for problems with less than four variables and relatively complex functions, μ value is considered zero. Elevation of μ value can cause increased probability of entrapment in local optimal points.

- The degradation factor (α) is also dependent on the extent of complexity of problem, number of decision-making variables, and search range. When the search range (UB and LB) is wide, larger α values should be considered for better exploration. High values for α increase the probability of finding global optimal points, though it causes elongated computational time required.

4.4. Convergence Criterion

as with many meta-exploration algorithms, the best solution is calculated when termination conditions are in place. These conditions can be considered the number of iterations, working time of CPU or ε (which is a small value, and is defined as the allowable error between the two last solutions). The MBA will continue running until the above-mentioned termination criteria are not fulfilled any longer.

5. SIMULATION RESULTS

To indicate the efficiency of the proposed method, the reconfiguration problem is solved using MBA with the aim of decreasing losses and minimizing operational costs of the network, and considering the demand response. Simulation is performed in MATLAB for three different scenarios on a standard 33-bus radial distribution network, as shown in Fig. 1. The formation related to this network is also presented in [24].

The 33-bus distribution system has 37 branches, including 32 sectionalizers and 5 tie switches, with the latter shown with dotted line in Fig. 1. The sum of active and reactive loads installed is 3715 and 2300 kW, with the nominal voltage of the system being equal to 12.66 kV. The open switches of the system before reconfiguration are 33, 34, 35, 36, and 37, and the active losses are equal to 202.6 kW.

The price of energy for 24 hours a day in terms of $/MWh and hour load value per p.u. are indicated in Table 1. Furthermore, two response loads exist in bus 15 and 27, whose specifications are provided in Table 2.

Solving the reconfiguration problem by MBA is performed across three different scenarios: not considering the demand response with the aim of decreasing network losses, not considering the demand response with the aim of reducing operational costs, and considering the demand response with the aim of reducing losses during 24 hours a day.

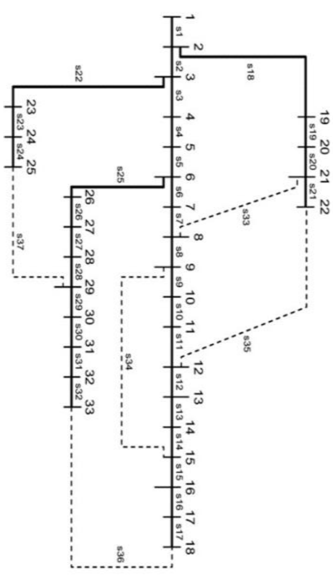

Fig. 1. The 33-bus network.

Table 1. The hour load in terms of p.u. and price of energy for 24 hours a day [22]

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. The specifications of the demand response installed in buses 15 and 27 [23]

Hour	bus 15		bus 27	
	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	-	-

5.1. The First Scenario

the final results obtained from applying the proposed method on the 33-bus network as well as their comparison with other papers are shown in Table 3. It is observed that the proposed method is converted to the global optimal solution, and the solution opting for the problem is the same as that of other papers. After the reconfiguration, the open switches include 7, 9, 14, 32, and 37. Furthermore, losses after the reconfiguration declined from 202.6 to 139.5.

Table 3. The final result of reduction of losses in the 33-bus network and its comparison with other papers.

Solving problem	Open switches	Losses (kW)
Initial	33 34 35 36 37	202.6
MBA	7 9 14 32 37	139.5
Ref. [24]	7 9 14 32 37	139.5
Ref. [25]	7 9 14 32 37	139.5

Fig. 2 shows the voltage profile for the 33-bus network. It can be observed that after the reconfiguration, the voltage profile of the system has improved considerably.

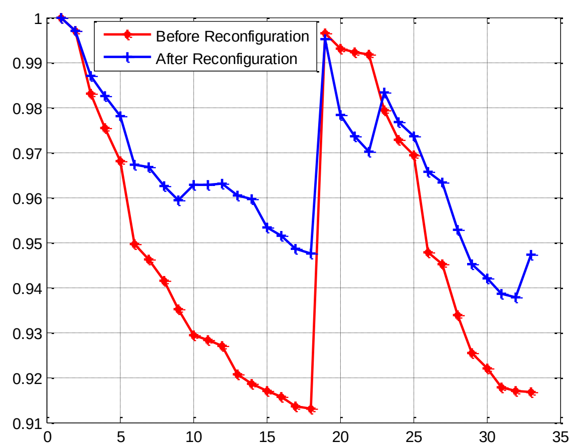

Fig. 2. The voltage profile of the 33-bus network.

The MBA convergence curve for the first scenario has been indicated in Fig. 3. MBA can be converged with a high rate to the global optimal solution.

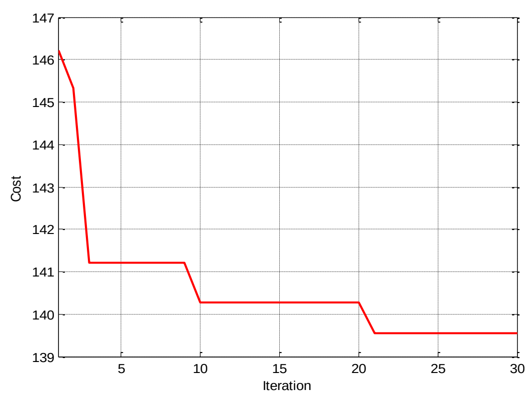

Fig. 3. MBA convergence curve.

5.2. The Second Scenario

the results obtained from this scenario indicate that along the hours when the network demand level is low or the electricity price is cheap, the costs obtained from the network are low. On the other hand, when the network demand level increases or electricity price becomes expensive, the network operational costs also grow. This can be explained based on cost function. During low demand hours, the power losses decline and the need to receiving power from the network diminishes. However, during peak hours, more power should be received from the network, thus enhancing the network costs.

Fig. 4 shows the network costs for the second scenario with and without MBA. The network reconfiguration has been successful in reducing costs across all the hours. Indeed, the reconfiguration has reduced the final cost by determining the most suitable topology for the network. Note that per all hours of the day, the optimal status of switches after the reconfiguration is equal to 37, 32, 14, 9, and 7.

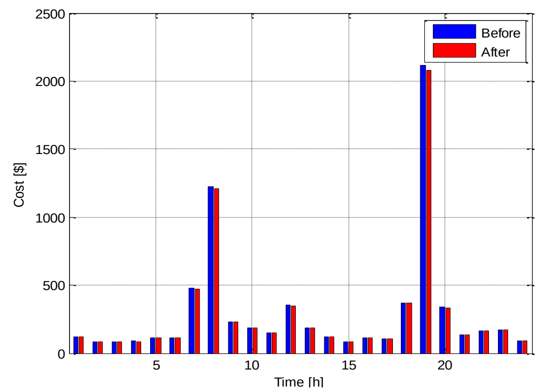

Fig. 4. The network costs in the second scenario.

Fig. 5 demonstrates the minimum system voltage for the states before and after the reconfiguration across different hours. For this purpose, in the two states and per each of the day hours, the bus with the minimum voltage is identified, and its voltage is considered as the minimum voltage of the system. Evidently, the minimum voltage of the system declines with increased demand, and vice versa.

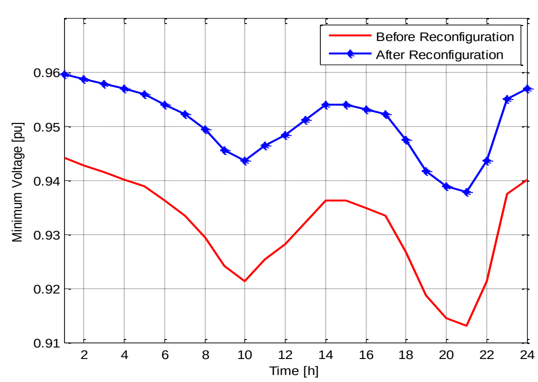

Fig. 5. The minimum voltage of the system for different states across different hours of the day.

5.3. The Third Scenario

the results of this scenario for 24 hours have been illustrated in Fig. 6. Based on the results of this scenario, it can be stated that when the demand level of the network is low, the network losses are also low. On the other hand, when the demand level increases, so do the network losses. In addition, network reconfiguration during different hours of the day have effectively caused reduction of network losses, which has been more evident in the presence of demand response. The optimal status of switches after the reconfiguration in this case, as with the second scenario, has been equal to 37, 32, 14, 9, and 7.

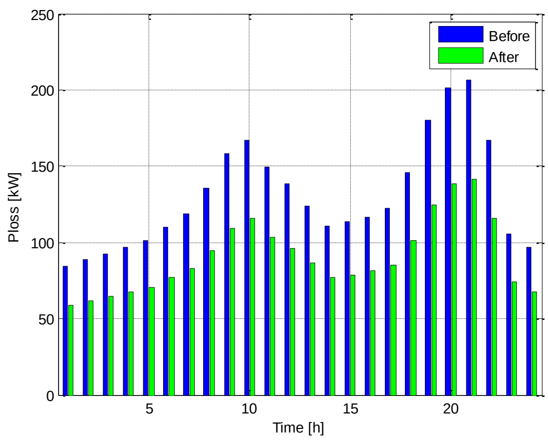

Fig. 6. The network losses in the third scenario.

6. CONCLUSION

In this paper, reconfiguration of distribution networks has been performed considering DR and using MBA. After suitable modeling of the problem, simulations have been done across three different scenarios. The results obtained from the simulation indicated that reconfiguration effectively leads to diminished losses, improved voltage profile, and declined operational costs of the distribution networks. Furthermore, comparison of the results obtained from MBA with other papers revealed that this algorithm converges to the global optimal solution. During low demand hours, the power losses decline, and thus the need to receiving power from the network also drops. However, during peak hours, more power should be received from the network, thereby increasing the network costs. It was observed that in the cases with presence of demand response, the network losses declined further.

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