Optimal Active Distribution Network Reconfiguration for Loss and Supply Cost Minimization Using Grey Wolf Algorithm

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Abstract – In this paper, a novel reconfiguration approach for distribution network incorporating distributed generation is introduced aiming to minimize power losses and energy supply costs. Given the temporally variable consumption of residential, industrial and commercial loads and the time-variant energy prices, an hourly reconfiguration scheme for an entire daily cycle is proposed. Also considering the privately-owned nature of distributed sources, the energy supply is carried out within a competitive market. The optimization is based on grey wolf algorithm (GWO), implemented in MATLAB software on an IEEE 33-bus test network. The simulation is done for four scenarios with respective objective functions for the evaluations of the results thereof. By comparing the obtained results it is concluded the configuration of network will be the unique for each of objective function. Finally, the effects of switching at different hours of day are compared in terms of loss minimization and supply costs against single daily switching scheme.

Keywords: Reconfiguration, Distribution network, Energy supply cost reduction, Power loss, Grey wolf algorithm

1. Introduction

Distribution network reconfiguration is an ideal inexpensive solution in which the states of grid breakers are regularly manipulated so as to achieve grid operation goals. Accordingly, reconfiguration improves the objective functions while taking account of network limitations [1]. In recent years, distribution grids have migrated from conventionally passive into active parts of the power system through utilization of distributed generation sources which bring about improved reliability and voltage profile as well as lower losses and energy supply costs. Given their common objectives, simultaneous application of reconfiguration and distributed generation will result in a significantly-improved network arrangement for DG operation and, therefore, a more optimal network operation. Several papers have focused on this subject each distinguished by their developed objective functions. In [2], a network reconfiguration approach based on bee colony algorithm is introduced aimed at minimized losses and improved voltage profile as well as load balance. The work in [3], employs mixed integer linear programming for distribution network reconfiguration problem in the presence of distributed generation with the attempt to minimize power losses and improve voltage profile. Besides reconfiguration, the work in [4] focuses on the optimal DG location aimed at minimized active power losses as well as improved voltage stability through CSA approach. The results indicate the high performance of simultaneous reconfiguration and DG placement. Network reconfiguration has also been employed in [5], through micro-genetic algorithm, to lower feeder losses and get better average interruption index. The authors of [6] have implemented reconfiguration using GA with a unique objective function incorporating power quality and reliability criteria in optimizing power losses, voltage deviation, average interruption frequency index and average energy not supplied. Further, the work in [7] focuses on reconfiguration in an active distribution system with the objectives of lower losses and optimized reactive power (VAR). The effect of DG penetration level with minimum, medium and maximum capacity are considered through big-M and linear division techniques. However, load diversity and time variations are not taken into account. Two different models of static and dynamic reconfiguration are considered in [8] to achieve lower losses and improved DG efficiency in an active network with nonlinear integer programming. The authors in [9] apply PSO algorithm to solve network reconfiguration problem and improve grid reliability and the energy-not-supplied indices. In [10], TFN technique and mixed big-bang multi-objective approach are employed for reconfiguration and DG location in an attempt to lower losses, operation costs and emissions and improve voltage stability index. However, the load type is ignored and a flat profile is assumed throughout the day. Reducing the energy loss and costs via capacitor placement

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Received:2020.07.15 ; Accepted: 2020.11.25

are the objectives sought through GA-based reconfiguration in [11]. The authors take account of different load types and employ a forecasting technique to model the daily load behavior. However, a constant energy price is considered throughout the day. In [12], maximum DG owner benefits and minimum utility costs are sought through distribution network reconfiguration though with constant load. A reconfiguration-based multi-objective optimization along with optimal sizing and placement of DGs is presented in [13] which attempts to minimize power losses, annual operation costs and gas emissions. Despite considering variations in load, wind velocity and solar radiation, energy price variations and load diversity are ignored.

Although objectives such as lower losses and improved voltage profile have been frequently addressed in the literature, the load type and load fluctuations have mostly been overlooked. As the network's technical objective, lower losses are always desirable though the costs and/or benefits are the main deciding factors in planning and optimizations.

In this paper, two main objectives of energy supply cost and power losses are addressed through reconfiguration of an active distribution network and the results are discussed. In order to make the approach more practical, the variations of different load types, e.g. residential, commercial and industrial, along with the 24-hour price variations are considered. Energy purchased by the utility from DG owners is based on contracts with hourly purchase intervals. The optimal reconfiguration problem is solved through GWO in a sample network to achieve the defined objectives.

The rest of the paper is organized as follows. Section 2 presents problem formulation including the objective function and associated constraints. In section 3, the GWO approach is presented. The sample network along with the simulation results and discussion are given in section 4. Finally, the conclusions are drawn in section 5.

2. Problem formulation

Utility grids are committed to supply electrical energy to their customers regardless of the time and duration the energy is required. Since the energy usage by customers is not constant throughout day, the network losses resulting from the flow of energy flow will also have an uneven profile. Also, the energy purchasing price of the utility varies with the demand level. Therefore, the utility tries to supply the customers' demand with the lowest cost and minimum losses. To this end, the optimal network configuration and supply of the electricity from local markets and the associated cost minimizations demand an efficient modeling approach which is mathematically presented below.

2.1. Objective Functions

Due to low voltage and, therefore, high current, power losses in distribution systems are high. In fact, minimizing the losses has always been a main objective for distribution utilities. In this section, power loss minimization is presented as the primary objective function as:

$$F_{Eloss} = \min E_{Loss} = \sum_{t=1}^{24}\sum_{l=1}^{N} r_{l,t}\, I_{l,t}^{2} \quad (1)$$

Where E_{Loss} is the lost energy, $r_{l,t}$ is the resistance of branch l at time t and $I_{l,t}$ is the current of branch l at time t.

As previously mentioned, the second interesting goal for the utility is lowering, to the extent possible, the operation costs and supply of the customers' electricity at the least cost. This is considered as the second objective and expressed as:

$$F_{cost} = \min \sum_{t=1}^{24}\left(C_t^{DG} + C_t^{sub}\right) \quad (2)$$

Where F_{cost} is the supply cost of energy in the entire daily cycle and includes the cost of supply from DG sources C_t^{DG} and power market C_t^{sub}. C_t^{DG} is obtained as:

$$C_t^{DG} = \sum_{t=1}^{24}\sum_{m=1}^{N_{DG}}(\rho_{m,t}.\, E_{m,t}) \quad (3)$$

Where $\rho_{m,t}$ is the energy price purchased from mth DG at time t. Also, $E_{m,t}$is the energy delivered by the mth DG to the grid at time t calculated by:

$$E_{m,t} = S_{m,t} \times pf_{m,t} \quad (4)$$

In the above equation, '$S_{m,t}$ is the capacity and $pf_{m,t}$ is the power factor of the mth DG at time t.

Further, the price of energy purchased from power market (C_t^{sub}) at time t for an entire day is expressed as:

$$C_t^{sub} = \sum_{t=1}^{24}(\rho_{sub,t}.\, E_{sub,t}) \quad (5)$$

Where $\rho_{sub,t}$ is the energy price purchased from power market at time t and $E_{sub,t}$ is the amount of energy purchased during this period.

2.2. Problem constraints

2.2.1. Radiality constraint

For many reasons including simplicity and avoiding complex and costly protection system, distribution networks are designed and operated radially. During reconfiguration, some ring(s) may be created within the network. Therefore, in order to take into account the radiality, matrix A is defined as the bus propagation matrix. The network is radial only when the matrix determinant is +1 or -1. This constraint is mathematically modeled as:

$$\begin{cases} \det(A) = 1 \text{ or } -1 \;:\; \text{Radial system} \\ \det(A) = 0 \;:\; \text{Not Radial} \end{cases} \quad (6)$$

2.2.2. Branch capacity limitation

Power limitation of the distribution lines is highly significant for safe operation. The energy flow in each line for each hourly interval is limited by (7) to equal or less than the branch maximum capacity.

$$|S_{l,t}| \leq S_{l,t}^{max} \tag{7}$$

Where $S_{l,t}$ and $S_{l,t}^{max}$ are the actual and maximum power flow of line l at time t, respectively.

2.2.3. Grid voltage constraint

Distribution network voltage shall be maintained within an acceptable band for different load levels as expressed by:

$$V_{imin} \leq |V_{i,t}| \leq V_{imax} \tag{8}$$

Where $V_{i,t}$, V_{imin} and V_{imax} are the voltage of bus i at time t and the minimum and maximum voltage levels, respectively.

2.2.4. Load flow constraint

In order to get the most suitable configuration, load flow constraint should be taken into account to safely and optimally decide on active and reactive power as well as voltage phase and amplitude and branch currents. Equations (9) and (10) represent the nonlinear load flow constraint.

$$P_{i,t} = |V_{i,t}| \sum_{k=1}^{N} |V_{k,t}| \left[g_{ik,t} \cos(\theta_{i,t} - \theta_{k,t}) + b_{ik,t} \sin(\theta_{i,t} - \theta_{k,t})\right] \tag{9}$$

$$Q_{i,t} = |V_{i,t}| \sum_{k=1}^{N} |V_{k,t}| \left[g_{ik,t} \sin(\theta_{i,t} - \theta_{k,t}) + b_{ik,t} \cos(\theta_{i,t} - \theta_{k,t})\right] \tag{10}$$

Where $P_{i,t}$ and $Q_{i,t}$ are the active and reactive powers of bus i at time t, respectively. Also, $V_{i,t}$ and $V_{k,t}$ are voltages of buses i and k at time t. The real and imaginary components of the admittance between buses i and k are denoted by $b_{ik,t}$ and $g_{ik,t}$, respectively. Finally, $\theta_{i,t}$ and $\theta_{k,t}$ are, respectively, the voltage phases of buses i and k at time t.

3. Grey Wolf Optimization Algorithm

Grey Wolf Optimization (GWO) was introduced in 2014 as a nature-inspired metaheuristic approach. Grey wolves have a hierarchical society and their social behavior is the underlying principle of this method.

Grey wolf leaders are categorized within four levels, namely α ,β ,δ and ω in order of their strength. Their hunting process consists of three stages of social hierarchy, prey encirclement and attacking the prey, as described below.

3.1. Social hierarchy

α, β and δ are respectively considered as the first, second and third best solutions and the rest of the wolves are categorized as ω.

3.2. Prey encirclement

The wolves take siege and surround the prey. This is formulated as [14]:

$$\vec{X}(t+1) = \vec{X}_P - \vec{A}.\vec{D} \tag{11}$$

$$\vec{D} = |\vec{C}.\vec{X}_P(t) - \vec{X}(t)| \tag{12}$$

Where t is the iteration number, $\vec{X}_P$ is the) prey coordinate vector and $\vec{X}$ is the spatial position of each grey wolf. $\vec{A}$ and $\vec{C}$ are the coefficient vectors as expressed in (13) and (14), respectively:

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a} \tag{13}$$

$$\vec{C} = 2.\vec{r}_2 \tag{14}$$

Where a is diminished linearly from 2 to zero through the iterations. $\vec{r}_1$ and $\vec{r}_2$ are stochastic vectors within the interval[14].

3.3. Attacking the Prey

Grey wolves are capable of estimating the prey location. After surrounding the prey, wolf groups α, β and δ are considered to have the best estimation of the prey location, i.e. the best solution. Other estimates are put into category ω. The associated relations are as follows[14]:

$$\vec{D}_\alpha = |\vec{C}_1.\vec{X}_\alpha - \vec{X}| \tag{15}$$

$$\vec{D}_\beta = |\vec{C}_2.\vec{X}_\beta - \vec{X}| \tag{16}$$

$$\vec{D}_\delta = |\vec{C}_3.\vec{X}_\delta - \vec{X}| \tag{17}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.(\vec{D}_\alpha) \tag{18}$$

$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_2.(\vec{D}_\beta) \tag{19}$$

$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3.(\vec{D}_\delta) \tag{20}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{21}$$

Due to the nonlinear and complex nature of the reconfiguration problem, the metaheuristic GWO technique is implemented in MATLAB software to solve the related objective function equations. The effect of each objective function in different scenarios will be evaluated on a sample test network.

4. Simulation Results

A standard 33-bus IEEE test system including 37 branches, 32 disconnects and 5 tie switches, as shown in Fig. 1, is considered for simulation and evaluation of the proposed method [15]. As indicated by different researches in the literature, the power loss of the network in its initial configuration is 202.71 kW. Also the minimum bus voltage belongs to bus 18 at 0.9131 P.U. which is below its allowed range.

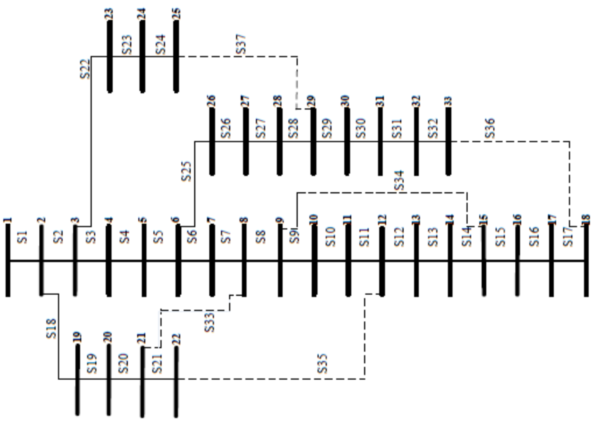

Figure 1: IEEE 33 bus-Network [15]

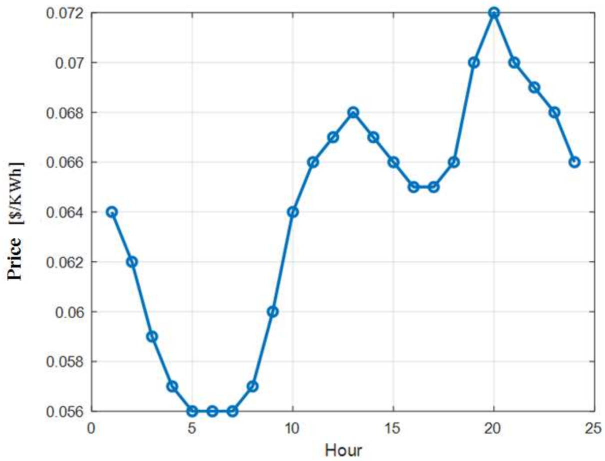

Figure 3: Hourly energy price [17]

For simulation purposes, three DG sources are considered at buses 14, 18 and 31 each with a fixed capacity of 500 kVA and PF=0.8. Also, three different load categories, namely residential, commercial and industrial are assumed whose profiles are given in Fig. 2. Also, load coefficients in 24 hours a day are considered different according to Fig. 2 [16]. It is also assumed that the network operator is allowed to perform switching operations only once during the day.

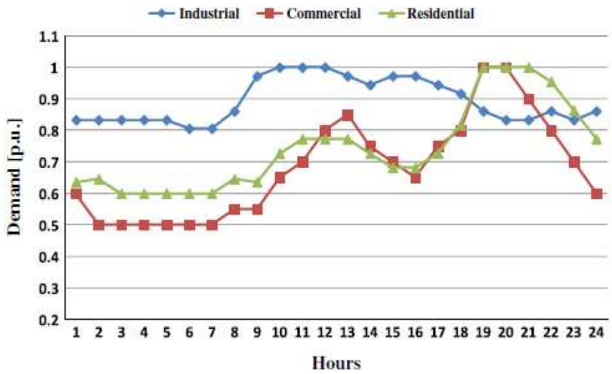

Figure 2: Mean daily load profile for different consumer categories [16]

As shown in Fig. 2, different behaviors are witnessed in different load categories. The demand level for each load category is depicted as a fraction of its daily peak level. Thus, the peak period for commercial and residential loads is during hours 19 and 20 and that of industrial consumers is from hours 9 to 12 a.m.

The utility purchases the required power from power market on an hourly basis. The hourly energy price is illustrated in Fig. 3[17]. In addition, the purchasing price from DGs at all periods is considered constant at 0.05 $\frac{\$}{\text{kWh}}$.

4.1. Results Validation

In order to validate the proposed approach and evaluate the GWO performance for the reconfiguration problem, the power loss minimization objective is primarily addressed and the results are compared to those of reference [18], as given in Table 1.

Table1: Validation of proposed reconfiguration approach: power loss minimization objective

		Result of reconfiguration	
Validation of method	Initial (Peak Load)	Proposed method	PSO [15]
Open switches	33-34-35-36-37	7-9-14-32-37	8-14-28-32-33
Power Loss [kW]	202.6	139.5	139.5

Based on Table 1, the proposed reconfiguration approach using GWO algorithm helps reduce the power loss from the initial 202.6 kW to 139.5 kW. The 31% decrease is similar to the result in [18] and thus validates the efficient performance of the grey wolf technique.

4.2. Scenarios

In this section the reconfiguration problem takes two objective functions, namely power loss reduction and least energy cost, into account. Also, the effect of DGs in the objective functions are assessed through considering two scenarios of reconfiguration with/ and without DGs in the network.

Given the results presented in Table 2, reconfiguration without taking account of DGs (scenario 1) leads to 31.7 percent reduction in power losses. Also, the energy purchased from the grid and their related costs have reduced 1.2 percent and 6.4 percent, respectively. Hence, the proposed loss-oriented reconfiguration framework has significantly achieved the optimization goals.

Next, in order to evaluate the effect of DGs, the reconfiguration technique is applied to the 2nd scenario. With the default location of DGs, as in section 4, the reconfiguration leads to daily energy losses to decrease a remarkable 84.55 percent from its initial value down to 430.04 kWh. Also in this scenario, the total energy purchased by the utility from the power market and DGs is $3848.54. This is indeed a 20.31 percent reduction from the purchase cost in the initial network configuration. By comparing the first and second scenarios, it is observed that the combination of reconfiguration and utilizing DGs units can significantly reduce losses and, therefore, the purchase energy and the related cost.

Table 2: Results of Reconfiguration with / without DGs

	Initial Network	*With Reconfiguration*							
		Energy Loss				*Cost of purchased Energy*			
	-	Scenario 1 No DG	Δ(%)	Scenario 2 With DG	Δ(%)	Scenario 3 No DG	Δ(%)	Scenario 4 With DG	Δ(%)
Open switches	33-34-35-36-37	13-32-10-28-7	-	8-26-36-34-7	-	28-32-9-33-13	-	7-9-14-17-37	-
Energy Loss [kWh]	2783.70	1900.08	-31.7	430.04	-84.5	1962.85	-29.4	761.3	-70.3
Total Energy[kWh]	72351.4	71467.78	-1.2	69997.7	-3.2	71530.55	-1.1	72020.14	-0.4
Energy Cost ($)	4829.35	4516.8	-6.4	3848.5	-20.3	4472.8	-7.3	3829.4	-20.7

When the main objective function of the reconfiguration is the reduction in the costs of energy supply to the consumers, the results indicate (scenario 3) that the reconfiguration leads to 29.4 percent reduction in daily energy loss. The switching of breakers 28, 32, 9, 33, 13 has reduced the amount of purchased energy and its cost 1.1 percent and 7.3 percent, respectively.

Finally, the reconfiguration of the active distribution network in scenario 4, with the main objective of reducing energy costs, has resulted in 70.3 percent reduction in energy losses during a 24-hour cycle. The optimal reconfiguration, obtained by opening breakers 7, 9, 14, 17, 37, resulted in the least cost reduction (0.4%) compared to other scenarios. However, the energy cost imposed to the utility is the best among all 4 cases with a 20.7% saving compared to the initial configuration with no DGs.

Considering the results of all 4 scenarios, it can be said that reconfiguration itself can have positive impacts on the energy losses as well as energy purchase quantity and cost. When combined with DG utilization, however, it can more significantly reduce the mentioned losses and costs. Also, given the results of scenarios 2 and 4, it is observed that the solution, i.e. the new network configuration, is unique for each type of problem and scenario. Thus, when the loss minimization is the primary objective, scenario 2 has the highest reduction of 84.5 percent and when priority is given to the cost reduction, scenario 4 with 20.7% cost reduction yields the best result.

It should be noted that the voltage constraint should be observed across all scenarios with voltage of all buses being within 0.95 and 1.05 P.U. For this purpose, the voltage profile for all buses at the peak hour of 19 is illustrated in Fig. 4 for scenarios 2 and 4.

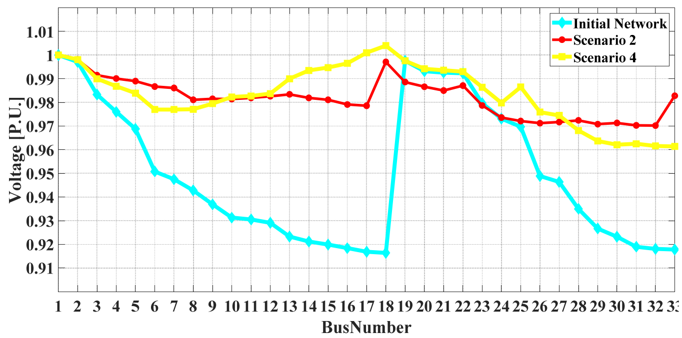

Figure 4: Voltage profile for network buses at hour 19

Table 3: Results of continuous reconfiguration with two objectives of power loss and energy purchase cost minimization

Hour	*Energy Loss Reduction*			*Cost Reduction*		
	Loss [kW]	Cost[$]	Open switch	Loss [kW]	Cost[$]	Open switch
1	10.43	129.40	7-10-16-21-28	16.75	126.57	7-10-16-25-37
2	7.47	118.03	7-10-15-21-27	13.85	110.67	7-10-15-21-28
3	7	110.78	7-10-15-21-27	13.90	105.14	7-10-15-21-28
4	7	110.45	7-10-15-21-27	13.90	103.27	7-10-15-21-28
5	7	109.20	7-10-15-21-27	13.90	102.46	7-8-11-16-28
6	7.32	110.44	7-10-15-21-27	13.14	101.49	7-8-11-16-28
7	7.51	110.45	7-10-15-21-28	13.04	101.49	7-8-9-17-37
8	7.8	120.05	6-10-15-21-28	15.04	115.84	7-10-29-34-37
9	8.75	127.95	6-8-11-16-28	14.74	118.97	7-10-29-34-37
10	13.9	155.74	7-8-9-15-37	18.61	146.81	7-10-29-34-37
11	16.68	168.51	7-8-10-16-37	21.33	159.17	7-9-14-17-37
12	21.6	183.37	7-8-9-16-37	27.74	176.90	7-9-14-17-37
13	25.71	189.57	7-8-9-16-37	27.89	166.85	7-9-14-17-37
14	18.1	170.69	7-8-9-17-28	23.64	161.18	7-9-17-27-34
15	15.75	160.97	7-8-9-17-37	21.99	152.60	7-9-17-27-34
16	13.19	147.46	7-9-17-27-34	19.21	136.31	7-8-9-16-37
17	18.17	163.85	7-8-9-16-37	20.64	159.81	7-8-9-16-37
18	24.1	175.68	7-8-9-16-37	29.68	163.47	7-9-14-17-37
19	39.44	240.44	7-10-29-34-37	47.26	235.12	7-9-14-17-37
20	39	232.50	7-8-9-17-37	47.02	229.37	7-9-14-17-37
21	29	217.16	7-8-9-17-37	42.29	207.29	7-9-14-17-37

From Fig. 4 it is observed that prior to the reconfiguration and DG utilization, i.e. when the initial configuration is applied; buses 6 to 19 and 26 to 33 have voltages below the acceptable limit at hour 19. With the reconfiguration, with both objectives of loss and cost reductions, the voltages are all within the allowed band. Since the profiles are related to the peak demand hour, it can be inferred that the voltages during all hours are within constraints.

4.3. Multiple Daily Reconfigurations

In this section, the restriction in the number of reconfigurations during the day is removed and the operator can apply the best configuration at each hour. Accordingly, Table 3 shows the results obtained by the proposed approach with the two objectives and considering DGs when the reconfiguration is regularly implemented throughout the day.

Based on Table 3, it can be observed that, for the loss-minimization objective, the number of switchings has significantly increased compared to the previous case. It can be seen that some breakers do not change state in adjacent time intervals. In most of the configurations for this objective function, breakers 7, 8, 9 and 10 are frequently opened. In addition, the total energy loss is 399.65 kWh which means a 40 kWh reduction compared to the result of scenario 2 (Table 2) when the reconfiguration was allowed once for an entire day. Also, the energy purchase cost has experienced a $93.39 decrease compared to scenario 2. Thus it is clearly seen that multiple reconfigurations with the objective of loss minimization can lead to better results than a single daily reconfiguration.

The increase in switching instances is also witnessed when the purchase cost reduction is the primary objective function. However, since the price changes are slow during the day, the number of switchings are lower than those when loss minimization is prioritized. With priority given to purchase cost minimization, no reconfiguration is required within some adjacent intervals. This is more the case when the load is relatively constant and at its off-peak levels. As predicted, the total cost with 24 daily reconfigurations is \$3567.35 which is \$262.05 lower than when just one daily reconfiguration is permitted. Thus, it can be concluded that for all types of objective functions, a dynamic reconfiguration scheme is more beneficial to the distribution utility.

5. Conclusion

In this paper, a novel approach based on GWO algorithm is introduced for reconfiguration of active distribution networks aimed to minimize both the power losses and the energy supply costs. The results on the test sample demonstrate that applying a suitable configuration on the active network leads to more optimal use of distributed generation sources including power loss reduction, improvement in voltage profile and lower energy supply costs for the consumers. The results further indicate that although the reconfiguration leads both power losses and supply costs to decrease, there is a unique resulting network configuration when each of these goals is prioritized. Thus, it can be confirmed that a configuration aimed at minimizing the power losses will not necessarily bring about the minimum supply costs and vice versa. Also, in this paper, the effect of a dynamic around-the-clock reconfiguration is assessed in comparison to once-per-day reconfiguration and concluded that the dynamic reconfiguration is more efficient in achieving the paper goals. The dynamic reconfiguration, however, may be limited in operation due to incurrence of additional costs related to circuit breaker degradation.

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