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Multi-Objective Optimization of Distributed Generation Despite Energy Storage Systems for Optimal Management

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Abstract: The influence of distributed generation resources and energy storage units in distribution networks is increasing. Therefore, it is essential to examine their effect on network reliability. In this study, in order to present the optimal energy management strategy in the smart distribution network, the problem of multi-objective optimization of rearrangement of distribution feeders with the presence of distributed generation sources and energy storage units has been solved in a dynamic framework. Objective functions in this study include minimization of energy losses, redistributed energy and operating costs. In order to simultaneously optimize the reliability index and other objective functions, another optimal design for the production of distributed generation units, charging and discharging of energy storage systems as well as the topology of distribution network feeders is presented. In order to solve the multi-objective optimization problem in this study, a combination of particle social algorithms and frog mutation has been used. In order to show the ability of the method in providing an optimal energy management plan in a 95-bus network has been tested. In this paper, it is shown that the effect of distributed generation resources and energy storage units in solving the optimization problem leads to a reduction in losses, undistributed energy, and operating costs.

Keywords: rearrangement of distribution feeders, distributed generation sources, energy storage systems, multi-objective optimization.

1. INTRODUCTION

Distribution network operation strategies have changed significantly in the last decade due to the high penetration of renewable energy sources and energy storage along with automation systems [1-3]. The random nature of energy storage units poses a serious challenge to the power supply with high reliability. Accordingly, many studies have been conducted to provide a model for the optimal management of charge and discharge of energy storage units, because these units play a crucial role in the management of renewable energy sources in distribution networks. One of the most common energy management techniques in intelligent distribution networks is the rearrangement of distribution network feeders in the presence of energy storage units and distributed generation sources. The process of rearranging distribution feeders to change the topology of distribution feeders is done by switching management and due to operational limitations in distribution systems. The rearrangement problem of distribution feeders can be formulated as a nonlinear and convex problem. Therefore, mathematical methods are not suitable due to the limitations of objective functions and constraints of this problem such as discontinuity and derivation [4]. Accordingly, researchers have proposed optimization methods based on heuristic algorithms to solve this optimization problem, which is discussed below:

In [5], an improved gravitational search algorithm is proposed to solve the rearrangement problem of distribution feeders in the presence of distributed generation sources with the aim of improving transient stability, reducing losses, and operating costs. In [6], a combined algorithm of particle clustering and frog mutation is proposed to solve the problem of rearrangement of distribution feeders in the presence of distributed generation sources with the aim of improving voltage stability and reducing losses. An improved genetic algorithm with variable population has been proposed to solve the rearrangement problem in the distribution network with the aim of reducing losses [7]. In [8], the particle community coding optimization algorithm is presented in order to solve the rearrangement problem of distribution feeders by considering different models of distributed generation sources. The expansion of electrical energy storage units along with distributed generation sources in the distribution network has led to further studies on the optimal management of these resources. Many studies have been performed to obtain an optimal energy management plan for integrating electrical energy storage units with distributed generation sources in fixed topology distribution networks.

In [9-11], the optimal energy management strategy is proposed by integrating a large scale of distributed generation resources in the distribution network in order to reduce operating costs. In [1], the colonial competition algorithm is proposed to provide optimal energy management in the distribution network in the presence of distributed generation sources and energy storage units with the aim of reducing operating costs. The combined particle and gray wolf community algorithm has been introduced in order to present the optimal energy management strategy in the distribution network with the presence of distributed generation sources and energy storage units [12]. Considering the previous work in the previous paragraphs related to the problem of rearrangement of distribution feeders, it is clear that the electric charge is considered in the fixed problem-solving interval. As a result, we have an optimal arrangement for the study interval, but in real distribution networks, due to the change in the electrical load of the network per hour, solving the optimization problem by considering a constant load is not acceptable. In [13], an improved hybrid particle and wolf community algorithm is proposed to solve the problem of dynamic rearrangement of distribution feeders in the presence of distributed generation sources with the aim of improving reliability and reducing energy losses. An improved hybrid particle assembly and frog mutation algorithm are proposed to solve the problem of dynamic rearrangement of distribution feeders and capacitive switching in the presence of distributed generation sources and energy storage units [14]. In [15], the ant colony algorithm is proposed to solve the problem of dynamic rearrangement of distribution feeders and switching of capacitor banks in the presence of distributed generation sources. In a high-penetration distribution system, distributed generation resources using a random program to model the intermittent behavior of resources have the uncertainty of a common and practical solution for the operation of the distribution network. In addition, solving the problem of dynamic rearrangement of distribution feeders with the integrated presence of distributed generation sources and energy storage units has also not been considered considering the uncertainty of distributed generation sources in previous studies related to energy management. Accordingly, the model presented in this study includes the following aspects:

- Dynamic rearrangement of distribution feeders,
- Provide an optimal plan for energy management in the presence of integrated distributed generation resources with energy storage units,
- Respond to demand at an appropriate level of network reliability due to the uncertainty in the output power of distributed generation sources and the purchase price of energy.

Solving the problem of multi-objective optimization of dynamic rearrangement of distribution feeders in the presence of distributed generation sources requires an accurate and powerful solution method. For this purpose, a combined optimization algorithm of particle assembly and frog mutation to deal with the complexity of the optimization problem is presented in this study. Particle clustering [16] and frog mutation [17-25] algorithms have minor drawbacks such as premature convergence or entrapment in local optimizations. For this purpose, a combination of two algorithms has been used in order to use the advantages of these methods to reduce their disadvantages.

2. DEFINING THE PROPOSED PROBLEM AND ITS FRAMEWORK

In this section, it is assumed that a company owns all the equipment and facilities of the distribution network, as well as the operation of the distribution network is the responsibility of this company. The operator of this company solves the problem of random optimization due to the uncertainties related to the output power of solar units and the purchase price of electricity from the market. Problem variables, objective functions, problem constraints, and uncertainty modeling are described below.

2.1. Problem variables

The variables of the multi-objective optimization problem are as follows:

$$X = \left[X_{SW}, X_{Tie}, X_{DG}, X_{ES}\right] \tag{1}$$

$$X_{SW} = \left[SW_1^t, SW_2^t, \ldots, SW_{Ntie}^t\right] \tag{2}$$

$$X_{Tie} = \left[Tie_1^t, Tie_2^t, \ldots, Tie_{Ntie}^t\right] \tag{3}$$

$$X_{P_{DG}} = \left[P_{Dg1}^t, P_{Dg2}^t, \ldots, P_{DgN_{Dg}}^t\right] \tag{4}$$

$$X_{P_{ES}} = \left[P_{ES1}^t, P_{ES2}^t, \ldots, P_{ESN_{ES}}^t\right] \tag{5}$$

X is the vector of the control variables of the problem. N_{dg} and N_{ES} the number of distributed generation sources and energy storage units, respectively. Tie_i Indicates the status of the i-th switch and its value is zero or one. SW_i and N_{tie} indicate the number of closed switches and the number of closed switches. $P_{Dg,i}^t$ and $P_{ES,j}^t$ the amount of active power is the i-th scattered production unit and the j-th energy storage unit at t-th time, respectively.

2.2. Objective functions

In this study, the objective functions include minimization of energy losses, redistributed energy and network operation costs.

Energy losses are calculated from Equation (6) [8]:

$$f_1(x) = \sum_{t=1}^{24} \sum_{i=1}^{N_{brch}} R_i \times \left|I_i^t\right|^2 \tag{6}$$

I_i^t and R_i are the impedance and the actual current of the line i-th at time t-th, respectively. N_{brch} Indicates the number of network lines.

The redistributed energy is calculated from Equation (8):

$$\mathrm{ENS}_i = P_i \sum_{i,j\in V, i\neq j} \left(U_{i,j} + U'_{i,j} \right) \tag{7}$$

In the above relation, V is the set of buses that are fed from a feeder. $U'_{i,j}$ and $U_{i,j}$ indicate the repair time (hours per year) and the time related to compensation (hours per year) of the branches related to bus i, respectively. $d_{i,j}$ and $\lambda_{i,j}$ failure rates and line lengths, respectively. $t'_{i,j}$ and $t_{i,j}$ the average repair time and the average recovery time of the line are between the i-th and j-th bus axes [9]. The final relation of the redistributed energy of the whole network is calculated by considering the reference node of Equation (8):

$$f_2(x) = \sum_{i=2}^{N_{Bus}} \mathrm{ENS}_i \tag{8}$$

The operating cost in this study is calculated from the following equation:

$$f_3(x) = \sum_{t=1}^{24} \left(\sum_{j=1}^{N_{DG}} \mathrm{Price}^t_{DG,j} P^t_{DG,j} + \sum_{s=1}^{N_{Sub}} \mathrm{Price}^t_{Sub,s} P^t_{Sub,s} + \sum_{k=1}^{N_{SW}} \mathrm{Price}^t_{Sw,k} \left| S^t_k - S^{t0}_k \right| \right) \tag{9}$$

$P^t_{Sub,s}$ and $P^t_{DG,j}$ the active power of scattered production is j-th and post-th at time t-th, respectively. $\mathrm{Price}^t_{DG,j}$ and $\mathrm{Price}^t_{Sub,s}$ the purchase price of electricity is from the scattered generation and the third post at the time of t, respectively.The cost of switching is $\mathrm{Price}^t_{Sw,k}$ at the time of t-th. N_{sub} and N_{sw} represent the number of switches and posts, respectively. S^{t0}_k and S^t_k represent the primary and secondary status of the km switch at t-th time, respectively.

2.3. Problem constraints

The constraint on the radius of the network is calculated from Equation (10):

$$N^t_{branch} = N_{Bus} - N_{Source} \tag{10}$$

N_{Bus} ands in the network, respectively.represent the number of buses and substation N_{Source}

The constraint of load distribution equations is calculated from the relations (11) and (12):

$$P^t_j = \sum_{i=1}^{N_{Bus}} V^t_i V^t_j Y_{ij} \cos\left(\theta_{ij} - \delta^t_i + \delta^t_j\right) \tag{11}$$

$$(12)\; Q^t_j = \sum_{i=1}^{N_{Bus}} V^t_i V^t_j Y_{ij} \sin\left(\theta_{ij} - \delta^t_i + \delta^t_j\right)$$

P^t_j And Q^t_j the active and reactive capacities of the network are injected into the i-th bus at t-th time, respectively. δ^t_i And V^t_i the amplitude and angle of the voltage are i-th at time t-th, respectively. They represent the size and angle of branch admittance between the i and j axes, respectively.

Bus voltage range:

$$V_{min} \le V_i^t \le V_{max} \tag{13}$$

$$\left|I_{f,i}^t\right| \le I_{f,i}^{Max} i = 1, 2, ..., N_{feeder} \tag{14}$$

Transformer limitations:

$$\left|I_{trns,i}^t\right| \le I_{trns,i}^{Max}$$

(15)

$$i = 1, 2, ..., N_{transformer}$$

In fact, distributed generation sources in distribution systems are modeled as PV and PQ. In PV modeling, distributed generation sources must generate reactive power to maintain voltage in their range. In this study, PQ has been used to model dispersed production units [3-2].

In addition to the use of distributed generation sources in this study, the effect of energy storage units in solving the problem of dynamic rearrangement of distribution feeders has been considered. Simultaneous use of energy storage systems along with distributed generation sources improves reliability, improves voltage profiles, etc. in distribution systems. Proper operation management does not compromise network stability or reduce equipment efficiency [7, 1]. The following are the restrictions on energy storage units.

$$E_x^h = E_x^{h-1} + \sigma_{ch,x} P_{ch,x}^h \times \Delta h - \frac{1}{\sigma_{dis,x}} P_{dis,x}^h \times \Delta h \tag{16}$$

$$\Delta h = 1 hour, \quad x = 1, 2, ..., N_{ES}$$

(17) $E_x^{min} \le E_x^h \le E_x^{max}$

$$P_{ch,x}^h \le P_{ch,x}^{max} \tag{18}$$

$$P_{dis,x}^h \le P_{dis,x}^{max} \tag{19}$$

E_x^h is the energy value of x-th units at h time. $P_{ch,x}^h$ and $P_{dis,x}^h$ are the charge and discharge rates of the x-th unit at hm, respectively. E_x^{min} and E_x^{max} are the maximum and minimum energies of the x-th unit at time h, respectively. $P_{ch,x}^{max}$ and $P_{dis,x}^{max}$, respectively, represent the maximum charge and discharge of the x-th unit at h-th.

2.4. Uncertainty modeling

In this section, modeling sources of uncertainty, including the power of solar units and the purchase price of electricity is examined:

The beta distribution function in Equation (20) has been used to model solar radiation according to previous data.

$$f_b(s) = \begin{cases} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha).\Gamma(\beta)} . s^{\alpha-1} . (1-s)^{\beta-1} & 0 \le s \le 1, \alpha, \beta \ge 0 \\ 0 & \text{Otherwise} \end{cases} \tag{20}$$

$f_b(s)$ is a function of the beta distribution, α and β are determined based on past solar radiation data.

The log-normal distribution function in relation (21) has been used to model the purchase price of electricity according to previous data.

$$f_p\left(E^{pr},\mu,\sigma\right)=\frac{1}{E^{pr}\sigma\sqrt{2\pi}}\exp\left(-\frac{\left(\ln E^{pr}-\mu\right)^2}{2\sigma^2}\right) \quad (21)$$

E^{pr} The parameter is a function of the probabilistic distribution, σ and μ are the standard deviation and the mean, respectively. The scenario generation method has been used to model the uncertainty related to the parameters in this study [13]. In this method, like Monte Carlo, we generate random numbers according to the number of uncertainty parameters, then we calculate the amount of error and probability related to each of the sources of uncertainty using the roulette wheel corresponding to each of the generated random numbers. After generating the scenario, the high number of scenarios reduces the speed of problem-solving and increases the calculations. For this reason, it is necessary to reduce the set of main scenarios in such a way that the characteristics of the problem do not change drastically.

2.5. Multi-objective problem strategy and a proposed algorithm

In this section, the proposed multi-objective problem strategy and algorithm are presented. In a multi-objective problem where the goals are in conflict with each other, the problem is formulated as follows [8, 3]:

$$\mathrm{Min} f\left(x\right)=\left[f_1\left(x\right),f_2\left(x\right),...,f_n\left(x\right)^T\right],G_i\left(x\right)\leq 0,H_i\left(x\right)=0 \quad (22)$$

$G_i\left(x\right)$ and $H_j\left(x\right)$ are equal and unequal constraints, respectively. n and x are the numbers of objective functions and the vector of the optimization variables, respectively. The pareto optimization method works for multi-objective problems based on mastery. The x_1 and x_2 vectors prevail when the following conditions are met [8, 3]:

$$\forall i\in\left\{1,2,...,N_{obj}\right\},\quad f_i\left(x_1\right)\leq f_i\left(x_2\right) \quad (23)$$

$$\exists i\in\left\{1,2,...,N_{obj}\right\},\quad f_i\left(x_1\right)< f_i\left(x_2\right) \quad (24)$$

Since the objective functions are not in the same range, fuzzy sets are executed to replace each objective function with a value between (0 and 1). f_i^{min} and f_i^{max} represent the upper and lower bounds of the objective function. These values are calculated separately using the optimization of each objective function. The value of the normalized membership function for each member in the set of answers is obtained from Equation (25) [9]:

$$N_{\mu j}=\frac{\sum_{k=1}^{n}\beta_k\times\mu_{jk}\left(x\right)}{\sum_{j=1}^{m}\sum_{k=1}^{n}\beta_k\times\mu_{jk}\left(x\right)} \quad (25)$$

m and n are non-dominant solution numbers and objective functions, respectively. Expresses the weight k-th of the objective function and the value is selected by the operator based on the degree of importance of each objective function. The particle clustering algorithm is used in many optimization problems due to its simple execution and high speed. The main problem of this algorithm is early convergence and it may be solved quickly in solving a problem, but the answer is a local optimal problem. One of the advantages of the frog jump algorithm compared to other algorithms is the simplicity and minimal storage space of this algorithm. The reason for using a combination of particle clustering algorithms and frog mutations is to use the advantages of both algorithms to reduce their disadvantages. The following is a step-by-step hybrid algorithm for solving the multi-objective optimization problem:

1. Production of the initial population as follows:

$$\text{Initial} - \text{population} = \begin{bmatrix} \\ X_1 \\ X_2 \\ \vdots \\ X_N \end{bmatrix} \tag{26}$$

2- Calculation of objective functions for all particles based on relations (6, 8, and 9).
3- Calculate the membership function for each objective function based on the relation (24).
4. The normalized value for all particles is calculated from (25).
5. Using the Pareto optimization method in order to obtain the normalized objective functions from the previous step and store the non-dominant answers in the set of considered answers.
6. Dividing particles in K sets based on decreasing fit.
7. Specify and in the set of particles.
8. At this stage, information is exchanged between all collections. To do this, all sets are combined and reclassified, all non-dominant solutions are extracted from existing particles, and stored in the set of answers.
9. Calculation of objective functions for particles based on relations (6, 8, and 9).
10. Calculate the membership function for each objective function based on the relation (25).
11. Calculate the normalized value for all particles in Equation (26).
12- Convergence condition study, in this study, the maximum number of repetitions has been used.

3. SIMULATION RESULTS

To solve the problem of optimizing the rearrangement of distribution feeders in a dynamic framework, the 95-bus test network [9] has been used. The study period for solving the proposed problem is 24 hours. In this section, the combined algorithm of particle clustering and frog mutation is used for single and multi-objective optimization and its results are compared with the algorithms of colonial competition [14] and grenade launcher [15]. In the 95-bus test system, 4 distributed generation units (diesel generators) with a capacity of 1000 kW are used in 6, 10, 25, 34, and 45 buses. 3 solar units with a capacity of 3000 kW along with 300 kW energy storage units have been installed in Buses 41, 85, and 88. The cost of purchasing electricity from distributed generation units and the cost of switching is 0.042 $ per kilowatt and $ 0.041 per switch, respectively. 30 scenarios have been used to model the considered uncertainties. Figures (1) and (2) show the load profile and electricity price in 24 hours. The number of energy losses, operating costs, and undistributed energy before the make-up are 315969.55 kW, 1401651.91$, and 315.56 kWh per year, respectively.

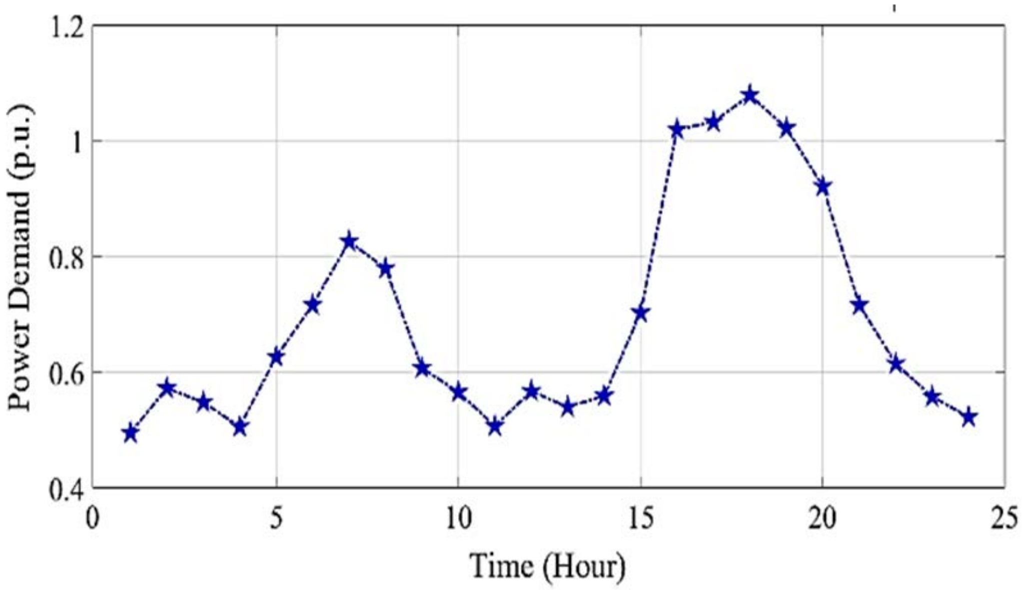

Figure 1.Load profile in twenty-four hours

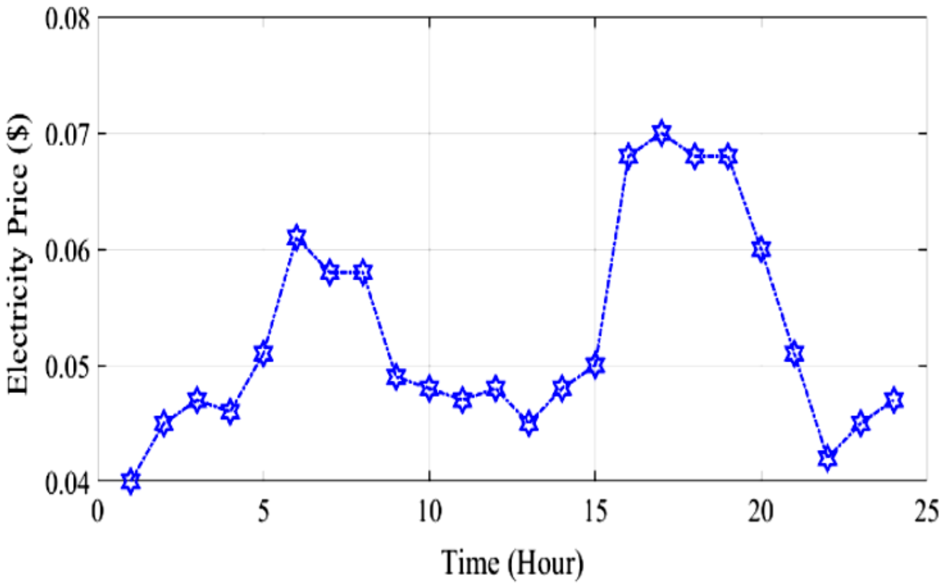

Figure 2. Electricity prices in twenty-four hours

3.1. Solving the problem of one-purpose optimization in the absence of distributed generation and energy storage units

The purpose of solving this section is to emphasize the ability of the proposed algorithm to solve the one-objective optimization problem. Tables (1) and (2) compare the results of different algorithms to optimize operating costs and undistributed energy. The results for all three algorithms are shown in 30 experiments.

Table 1. Optimization of operating costs in the absence of distributed generation and energy storage units

Algorithms	**Operating cost (dollars)**			
	The best	**Average**	**the worst**	**Standard deviation**
GEM	133683.23	133738.68	133801.48	45.23
ICA	133667.15	133727.52	133722.23	44.34
suggested method	133611.16	133644.35	133705.15	42.65

Table 2. Optimization of redistributed energy in the absence of distributed generation and energy storage units

Algorithms	**Redistributed energy (kWh per year)**			
	The best	**Average**	**the worst**	**Standard deviation**
GEM	308.65	315.84	324.85	6.95
ICA	299.45	305.55	314.52	5.65
suggested method	294.31	295.85	298.24	4.15

Comparing the results of Tables (1) and (2), it is clear that the proposed algorithm has achieved better results than other algorithms. According to the results of these tables, it is clear that the amount of energy is not distributed and the operating cost of the proposed algorithm is reduced by about 17% and 6% compared to the initial values. Figure (3) shows the convergence curve of operating costs. Given this figure, it is clear that the proposed algorithm converges to the optimal answer sooner than other algorithms.

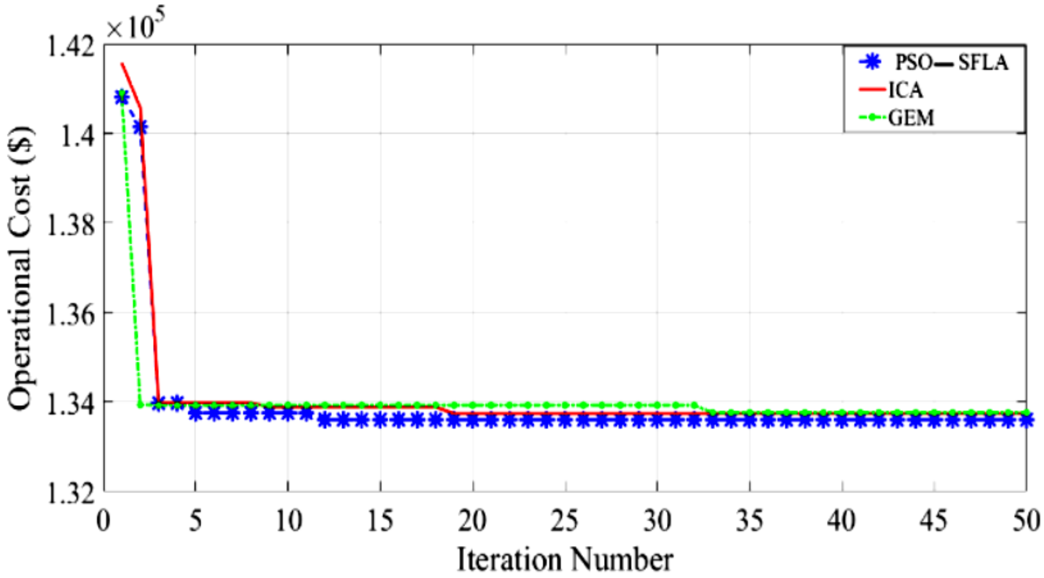

Figure 3. Convergence curve to optimize operating costs

3.2. Solving the problem of multi-objective optimization in the presence of distributed generation and energy storage units

In this section, the proposed algorithm is used to solve the problem of optimizing single and multiple objectives of dynamic rearrangement of distribution feeders in the presence of distributed generation sources and energy storage units. Table (3) shows the results of one-objective optimization for undistributed energy with all three algorithms. The optimal amount of redistributed energy from the hybrid algorithm is reduced by about 25% compared to the initial amount before the rearrangement.

Table 3. Optimization of redistributed energy in the presence of distributed generation and energy storage units

Algorithms	Redistributed energy (kWh per year)			
	The best	**Average**	**the worst**	**Standard deviation**
GEM	281.64	286.15	290.35	3.85
ICA	285.64	282.86	286.54	3.35
suggested method	276.15	279.68	282.15	3.24

Also, the optimal amount of energy losses and operating costs resulting from the combined algorithm are 28563.21 kW and 133664.14 $, respectively. Comparing the simulation results in this section with the preliminary results before the rearrangement and the results in the previous section, it is clear that the effect of distributed generation sources and energy storage units has not reduced distributed energy and energy losses.

In order to solve the two- and three-objective optimization problem, the Pareto optimal fronts obtained from the hybrid algorithm are shown in Figures (4) and (5). The optimal arrangement of switches, the output power of distributed generation units, and energy storage units obtained from the proposed algorithm for three-objective optimization are shown in Tables (4), Figures (6), and 7, respectively. According to Figure (7), the discharge and charging of energy storage units with negative and positive values are shown.

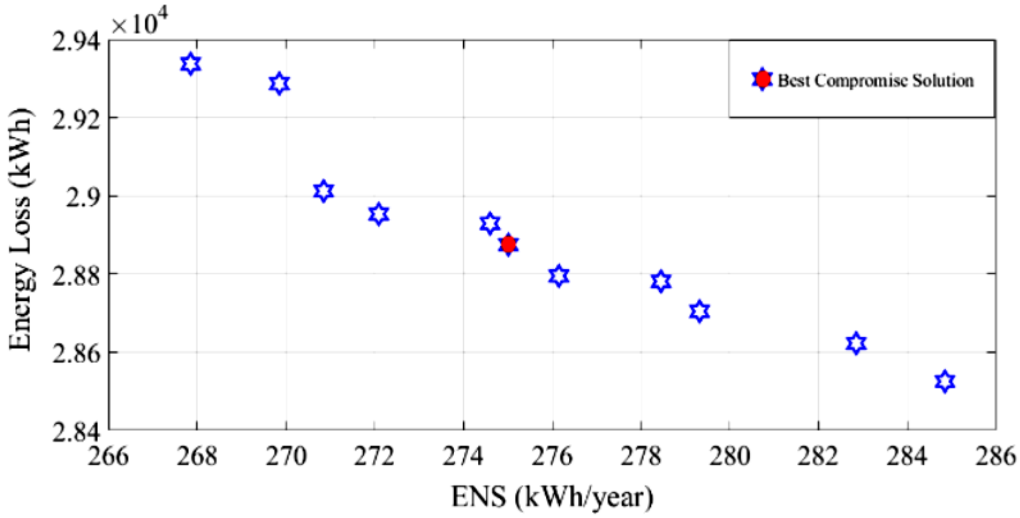

Figure 4. Pareto Optimal Front for the two-objective optimization problem

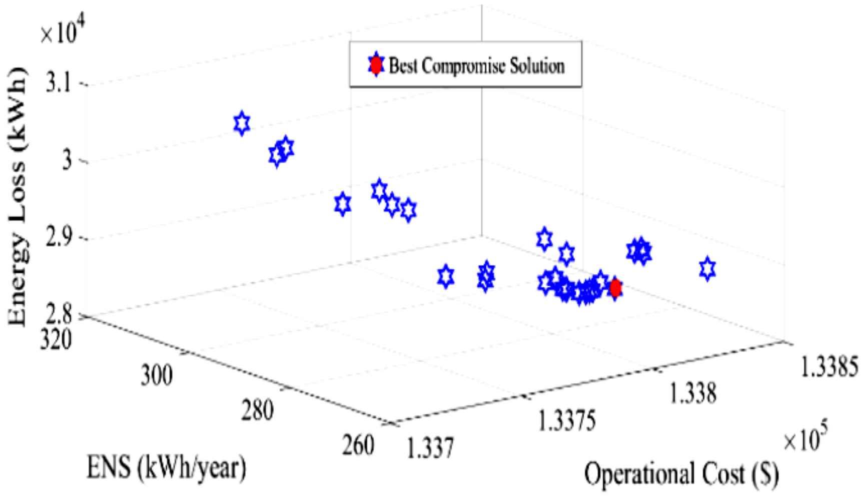

Figure 5. Pareto optimal front for the three-objective optimization problem

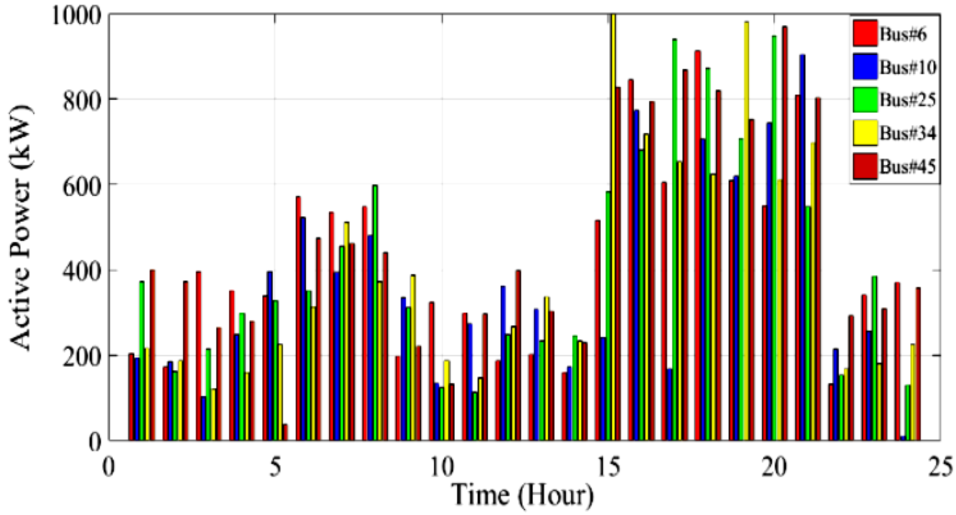

Figure 6. Production capacity of distributed generation units in twenty-four hours

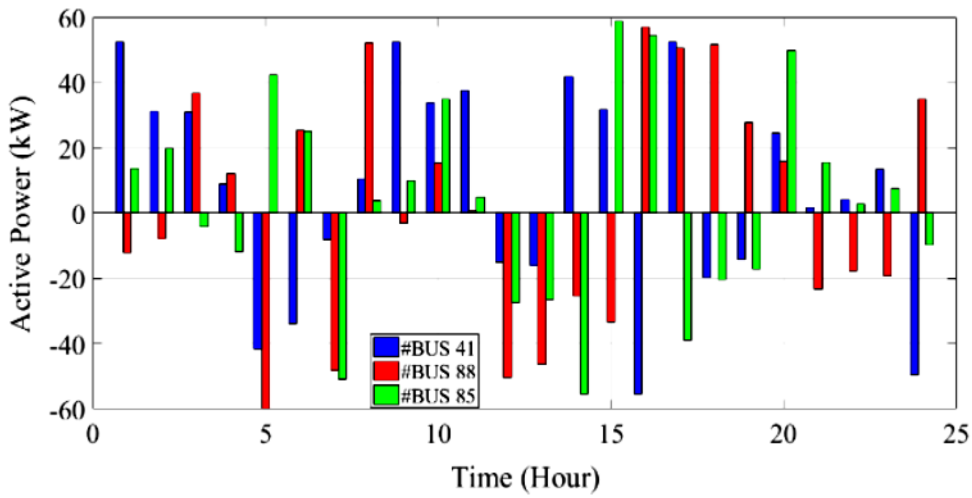

Figure 7. Production capacity of energy storage units in twenty-four hours

According to Figures (6) and (7), it is clear that the best value obtained for each objective function in response to the compromise (indicated in red) is very close to the optimal value of that function. The Pareto front is indicative of the ability of the proposed algorithm to solve the multi-objective problem. According to Figure (4), the optimal amount of undistributed energy and energy losses are 267.85 kW and 28586.356 kWh per year, respectively. The value of the two indicators mentioned in the compromise response is 274.35 kW and 28868.65 kWh per year, respectively. The difference between the optimal value of these indicators in the compromise response and their optimal values in the Pareto front is less than 2%.

Table 4. Optimal switching obtained from the proposed algorithm in twenty-four hours in order to optimize the three objectives

Load levels	Switches open										
	Sw1	Sw2	Sw3	Sw4	Sw5	Sw6	Sw7	Sw8	Sw9	Sw10	Sw11
1	70	43	15	39	26	35	80	86	85	32	30
2	4	43	15	22	82	84	18	86	85	31	30
3	4	40	15	22	49	35	66	86	85	71	30
4	77	43	79	22	82	35	80	86	85	32	30
5	68	43	15	81	82	52	19	86	54	87	30
6	4	43	15	81	82	84	80	65	55	32	30
7	4	78	13	81	49	84	80	57	55	32	30
8	4	78	15	39	26	52	67	86	85	32	30
9	70	78	79	81	82	84	19	86	85	32	83
10	70	7	15	81	26	84	19	86	55	71	30
11	4	43	15	22	26	35	19	86	85	32	27
12	4	78	79	81	26	35	19	86	72	87	30
13	77	78	79	81	26	84	19	86	55	71	30
14	68	7	15	22	49	84	19	86	72	32	30
15	70	43	15	39	26	33	19	86	85	87	29
16	77	7	79	39	49	84	19	86	85	32	83
17	77	43	15	39	82	35	80	86	55	71	30
18	77	43	15	81	82	35	19	65	55	87	30
19	77	43	15	39	26	35	19	86	85	32	83
20	77	43	79	39	82	84	19	86	74	87	30
21	4	7	15	21	49	52	67	60	85	87	30
22	77	43	15	22	82	84	19	86	72	32	83
23	4	43	79	39	82	35	80	60	85	32	29
24	77	78	15	22	26	84	19	86	85	32	29

4. CONCLUSION

The purpose of this study is to present the optimal energy management strategy in the distribution network. For this purpose, the issue of dynamic rearrangement of distribution feeders in the presence of distributed generation sources and energy storage units has been investigated. A combined algorithm of particle clustering and frog mutation is proposed to solve the optimization problem. Target functions include minimization of redistributed energy, energy losses, and operating costs. The important results of this study are as follows:

- The proposed algorithm is able to solve one- and multi-objective problems without considering their complexities.
- The effect of distributed generation resources and energy storage units in solving the optimization problem has led to a reduction in losses, undistributed energy, and operating costs.
- Considering undistributed energy as an indicator of reliability creates a safe and acceptable situation for the operation of the network.

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