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ORIGINAL RESEARCH

Optimal sizing of distributed generation units and shunt capacitors in the distribution system considering uncertainty resources by the modified evolutionary algorithm

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Abstract
Distributed generation units (DGUs) as auxiliary sources of power generation can play an effective role in meeting the load consumption of the distribution network, also have positive effects such as reducing loss and improving voltage. Moreover, capacitors by reactive power compensation produce positive effects similar to DGUs in the distribution networks. The idea of joint operation of DGUs and shunt capacitors (SCs) in the presence of demand response program (DRP) to derive maximum benefits from their installation is proposed in this paper. The time of use (TOU) mechanism is used as one of the demand response programs (DRPs) to alter the consumption pattern of subscribers and improve the performance of the distribution system. Objective functions include minimization of energy loss, operational cost, and energy not supplied (ENS). In general, the problem of determining the optimal capacity of DGUs and SCs is complex due to the demand variation. Also, considering the effect of uncertainty sources complicate the optimization problem. Hence, a modified shuffled frog leaping algorithm (MSFLA) is proposed to overcome the complexities of this problem. The proposed approach is tested on two 95, and 136-node test networks, and the results are compared with other evolutionary algorithms. According to the obtained results, after using the proposed approach in determining the optimal capacity of DGUs and SCs in the first system, the amount of energy loss, operational cost and ENS dropped by 11, 25.5 and 5% compared to baseline values. After applying the TOU mechanism in allocation of DGUs and SCs simultaneously in the second system by proposed method, the values obtained for the mentioned objectives reduced by 29, 65 and 7% compared to initial values.

Keywords Energy not supplied · Shunt capacitors · Distributed generation units · Uncertainty source · Modified shuffled frog leaping algorithm · Demand response program

List of symbols

$\varphi_{Pd}\varphi_{Ep}$	Occurrence probability of load demand and electricity price
C_{Ep} C_{Ep}	Numerical values extracted from probabilistic distributions for load demand and electricity purchase price
$P_{t,i}^{MDF}$	Modified demand of the ith feeder at time t
Ns	Number of scenarios
$P_{t,i}^{TOU}$ $P_{t,i}^{INI}$	Surge or drop in the demand for this mechanism and the initial demand values in ith feeder at time t without TOU mechanism
TOU ^{max}	Maximum speed of demand surge or drop in the TOU mechanism
μ	Mean value
σ	Standard deviation
$X_w X_b$	Worst and best frogs
$P_{DG,j}$	Active power of jth DG unit
$P_{Sub,s}$	Active power of sth sub-station
$Price_{DG,j}$	Purchase price of electricity from jth DG unit
$Price_{Sub,s}$	Purchase price of electricity from sth sub-station
$U_{i,j}$ $U'_{i,j}$	Repair time (hours per year) and the compensation time for the branches related to bus i

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$\lambda_{i,j}$ $d_{i,j}$	Failure rate and line length
N_{Sub}	Number of sub-stations
C	Constant value
$Y_{ij}\theta_{ij}$	Magnitude and branch admittance angle between buses i and j
KK_{max}	Number of current iteration and maximum iteration number
W	Inertia weight
$f_i^{min} f_i^{max}$	Lower and upper limits of *i*th objective function
μ_i	Fuzzy membership function of *i*th objective function
β_k	*k*Th weight of objective function
E^{pr}	Distribution function parameter
R_i	Resistance of the *i*th line
I_i	Current of *i*th line
N_{brch}	Number of branches
X	Vector of decision variables
X_G	Best frog between all memblexes
rand	Random number in [0,1]
D_{min} D_{max}	Minimum and Maximum displacement of *i*th frog
$V_{min} V_{max}$	Minimum and maximum allowable values of *i*th bus voltage
$Q_{C,i} Q_d$ $I_{f,i} I_{f,i}^{Max}$	Current amplitude at time t and the maximum current of *i*th feeder
$P_{DG}^{min} P_{DG}^{max}$	Minimum and maximum output power of *i*th DG unit
N_{Cap}	Number of capacitors
$t_{i,j} t'_{i,j}$	Average repair time and the average line recovery time between the *i*th and *j*th buses
P_j Q_j	Active and reactive power injected by the network in the *i*th bus
N_{Bus}	Number of buses
$V_i \delta_i$	Voltage magnitude and Voltage angel of the *i*th bus
m n	Number of non-dominated solution and objective functions
$W_{min} W_{max}$	Boundaries of inertia weight
N_{DG}	Number of DG units
$N_{\mu j}$	Normalized membership function of each for each member

1 Introduction

Distribution systems' operation strategies have changed dramatically in recent years due to the proliferation of DGUs. Development and integration of these units in distribution systems have exerted positive effects on voltage profile of buses, line current profile, and reliability. Hence, a great number of studies have explored the effect of DGUs to optimally operation distribution systems (Azizivahed et al. 2017, 2018). In addition, shunt capacitors (SCs) are used in distribution systems to improve network performance for a variety of purposes, such as enhancing the power quality and decreasing loss by injecting reactive power (Askarzadeh 2016). Hence, some studies have explored the separate effect of DGUs and SCs on the network's operation to augment the performance of the distribution systems.

The distribution network reconfiguration and DGUs allocation was solved using a genetic algorithm (GA) to reduce loss and harmonic distortion (Din et al. 2019). Taguchi performance analysis method was proposed for optimal DGUs allocation to diminish loss (Galgali et al. 2019). A particle swarm optimization (PSO) algorithm was proposed for optimal sizing of DGUs to decrease loss (Kumari et al. 2017). A new analytical method was presented to determine the optimal capacity and location of distributed generation units to decrease loss (Tah and Das 2016); this model obviates the need to consider the impedance matrix. A biogeography-based algorithm was presented for optimal sizing and placement of DGUs using the effective power factor model to minimize loss (Ravindran and Victoire 2018). A two-step method based on combination of sensitivity analysis and cuckoo optimization algorithm was used for optimal locating and sizing of SCs to reduce loss (Reddy and Prasad 2014). An artificial bee colony (ABC) method was proposed to allocate shunt capacitors in radial test system to enhance the voltage stability considering load variable (El-Fergany and Abdelaziz 2014). Two hybrid evolutionary methods were used for placement and sizing of SCs to minimize loss (Abdelaziz et al. 2016; Lotfi et al. 2016). A crow search optimization algorithm was introduced to determine the size and location of SCs in the network to reduce active loss and modifying the voltage profile (Askarzadeh 2016). Most of the above studies have considered the power loss and voltage profile as objective functions in solving the optimization problem in 33 and 69 bus test networks, and good results have achieved in reducing loss and improving the voltage profile. Also, they have been able to provide practical optimization algorithms to solve the considered optimization problem. But, these studies have neglected to consider the objective function of reliability in solving the optimization problem, which is very critical in the distribution network, failure to account for this point will result in frequent blackouts in the network and the distribution system instability. There is also no trace of the operational cost objective function related to the cost of grid power generation and distributed generation units. Moreover, these studies have considered the problem as a single-objective problem and have not presented a strategy for solving the multi-objective problem. In fact, the simultaneous effect of two objective functions in solving the problem is not seen. In the following, the references that have modeled the considered optimization problem in a Multi-objective framework, are examined.

A Multi-objective fire butterfly optimization was presented for optimal DGUs allocation to reduce loss, voltage deviation and pollution of DGUs (Elattar and ElSayed 2020). A hybrid PSO-incremental learning algorithm was suggested for placement and sizing of DGUs to reduce loss and improve the voltage profile (Grisales-Noreña et al. 2018). Two state-art-of methods including Non-dominated sorting genetic and ant lion optimization were proposed for locating and sizing of DGUs to reduce loss and voltage deviation (Liu et al. 2019; VC 2018). A population-based algorithm was proposed for the placement and sizing of SCs to decrease loss and enhance voltage stability (Al-Ammar et al. 2021). Honey-Bee mating (HBM) method was proposed to determine the capacity and optimal location of SCs in the distribution system to diminish loss and voltage deviation (Kavousi-Fard and Samet 2013). A two-step method that combines sensitivity analysis and ant colony optimization algorithm was suggested to determine the capacity and placement of SCs in the distribution network in an attempt to diminish loss and voltage deviation (Abou El-Ela et al. 2018). These studies have solved the multi-objective optimization problem using Pareto fronts and weighting factor methods. In addition to presenting novel and state-of-art algorithms in these studies, the presence of several new objective functions such as voltage stability and pollution is also seen in these studies. But similar to the studies examined in the previous paragraph, changes in electrical load and electricity price are not considered in solving the problem. Since the electrical load in real distribution systems is variable, dynamic planning is required for the optimal operation of the distribution network considering DGUs and capacitors. Moreover, some objective functions such as operational costs and energy loss must be calculated under the time-varying electrical load and electricity price.

Using DGUs and SCs simultaneously has additional advantages and capabilities for the distribution system than the separate presence of these units in the network. Hence, another group of studies has focused on the simultaneous effect of DGUs and SCs in the optimal operation of distribution network. An improved PSO-Simulated annealing algorithm was introduced to determine the capacity and placement of DGUs and SCs to reduce network loss and operational cost (Su 2019). The GA was proposed to determine the capacity and optimal location of DGUs and SCs with variable electrical load to diminish active loss (Das et al. 2019). An evolutionary algorithm based on decomposition was utilized for placement and sizing of DGUs and SCs in the network to reduce active and reactive loss (Biswas et al. 2017). The water cycle evolutionary algorithm was suggested for placement and sizing of DGUs and SCs to reduce network loss (Abou El-Ela et al. 2016). The PSO algorithm was presented for placement and sizing DGUs and SCs in the distribution network by considering the uncertainty of the electrical load in order to reduce active loss and strengthen voltage stability (Zeinalzadeh et al. 2015). Given the valuable work discussed above on the problem of optimal placement and sizing of capacitors and distributed generation sources, acceptable results are observed in reducing loss and operational cost in the simultaneous presence of DGUs and SCBs compared to the separate presence of these units in the distribution network. However, in most of these studies, the effect of uncertainty resources on solving the optimization problem has not been considered. As a result, the solution found for the problem could be far from the actual operating point of the system. Therefore, considering the effect of these resources on the optimal use of the network enables the network operator to have correct and accurate planning based on the real situation of the system. Another noteworthy point derived from the review of the above studies in this field is the inadequate attention allocated to the issue of demand response programs (DRPs). DRPs are usually implemented at the lowest cost and with the participation of consumers to improve the performance and reliability of the distribution network at certain times.

As far as the solution method is concerned, it should be noted that optimal placement and sizing of DGUs and SCs in distribution systems is not linear and convex. Therefore, mathematical algorithms are not suited for solving this complex optimization problem due to their limitations. Evolutionary methods are used for solving engineering optimization problems due to their features such as simple implementation and low computational volume. Most of the research examined in this study have used evolutionary methods including NSGA II (Liu et al. 2019), GA (Din et al. 2019), and PSO (Kumari et al. 2017) for solving optimal placement and sizing DGUs and SCs in the distribution network. However, due to the random nature of these methods, they may encounter initial convergence in solving some complex optimization problems. Therefore, finding a suitable and practical optimization method is of paramount importance.

The main ideas presented in the paper are as follows:

- Providing a novel approach for optimal sizing of DGUs and SCs in the distribution network by considering the variable electrical load.
- Presenting a TOU mechanism as one of the DRPs for optimal sizing of DGUs and SCs in the network to modify the consumption pattern of subscribers.
- Considering the ENS index as a function of the reliability objective in this study and improving this index by allocating DGUs and SCs in the distribution system.

- Considering sources of uncertainty, including consumption power demand and electricity purchase price, for solving the considered optimization problem.
- Presenting a MSFLA to address the complexity of the optimization problem and to provide a new type of mutation operator in the proposed algorithm to enhance search-ability and population diversity.
- Utilizing the Pareto optimization approach based on the domination concept in the proposed algorithm to solve the multi-objective optimization problem and introducing two various criteria, Generational Distance (GD), Diversity Metric (DM) to evaluate Pareto solutions.

The primary goal of this study is to introduce an efficient approach to obtain the optimal sizing of DGUs and SCs, considering the resources of uncertainty and DRPs. Energy loss, operational cost, and ENS index are considered as objective functions in this research. Also, to demonstrate the capability of the proposed approach, two 95 and 136-bus test networks are utilized. Given the different objective functions in this study, the proposed algorithm uses a fuzzy strategy to save the set of non-dominated solutions in an external repository. This study is organized as follows. In Sect. 2, the problem formulation, including objective functions, constraints, uncertainty modeling and time of mechanism are presented. The optimization methodology and simulation results are described in Sects. 3 and 4. The Pareto solution analysis and conclusions are presented in Sects. 5 and 6.

2 Problem formulation

The optimization problem addressed in this paper is to find the optimal size of DGs and SCs for installation in radial distribution systems taking into account variable load and uncertainty of load and electricity price. The objective functions adopted in this study are to minimize energy loss, ENS, and operational cost. Objective functions are bounded by equality and inequality constraints. In the following, uncertainty sources modeling and time of use mechanism are presented in this section.

2.1 Objective function

In this study, the objective functions include minimization of energy loss, operational cost, and ENS index.

- **Energy loss**

  Distribution system energy loss is obtained from Eq. (1) (Lotfi et al. 2019)

$$f_1(X) = \sum_{i=1}^{N_{brch}} R_i |I_i|^2 \tag{1}$$

$$X = \left[P_{DG1}, P_{DG2}, \ldots .P_{DG,NDG}, Q_{Cap1}, Q_{Cap2}, \ldots .Q_{Cap,NCap}\right] \tag{2}$$

- **Operational cost**

  The operational cost in this study is derived from the following equation:

$$f_2(X) = \sum_{j=1}^{N_{DG}} Price_{DG,j}\, P_{DG,j} + \sum_{s=1}^{N_{sub}} Price_{Sub,s}\, P_{Sub,s} \tag{3}$$

- **Energy not supplied**

The ENS of the reliability objective function is derived from Eq. (4):

$$ENS_i = P_i \sum_{i,j\in V,\ i\neq j} (U_{i,j} + U_{i,j}) \tag{4}$$

where, $v = \{0.1. \ldots .(n-1)\}$ is the set of the nodes in the distribution network. The final equation to calculate the ENS of the network without considering the reference node is calculated from Eq. (5):

$$f_3(x) = \sum_{i=2}^{N_{Bus}} ENS_i \tag{5}$$

2.2 Constraints

In this section, some equality and inequality limitations for the optimization problem are provided that should be satisfied.

- **Load flow equations**

$$P_j = \sum_{i=1}^{N_{Bus}} V_i V_j Y_{ij} \cos\left(\theta_{ij} - \delta_i + \delta_j\right) \tag{6}$$

$$Q_j = \sum_{i=1}^{N_{Bus}} V_i V_j Y_{ij} \sin(\theta_{ij} - \delta_i + \delta_j) \tag{7}$$

- **Bus voltage range**

$$V_{min} \le V_i \le V_{max} \quad i = 1, 2, \ldots, N_{Bus} \tag{8}$$

- **Feeder current**

$$\left|I_{f,i}\right| \le I_{f,i}^{Max} \quad i = 1, 2, \ldots, N_{feeder} \tag{9}$$

- **DGs constraint**

$$P_{DG}^{min} \le P_{DG,i} \le P_{DG}^{max} \quad i = 1, 2, \ldots, N_{DG} \tag{10}$$

- **Shunt capacitor limit**

$$Q_{Cap,i} \le Q_d \quad i = 1, 2, \ldots, N_{Cap} \tag{11}$$

2.3 Uncertainty sources modeling

In this study, power demand and electricity purchase price are considered as uncertainty resources in the optimization problem. Uncertainty in the projected power demand and the purchase price of electricity formulated by the normal and log-normal distribution functions are expressed as follows:

$$f(x) = \frac{1}{\partial\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\partial^2}} \tag{12}$$

$$f_p(E^{pr},\mu,\sigma) = \frac{1}{E^{pr}\sigma\sqrt{2\pi}} exp(-\frac{(lnE^{pr}-\mu)^2}{2\sigma^2} \tag{13}$$

In this study, the scenario generation method is utilized to account for the uncertainty of system design parameters. In this method, using Monte Carlo simulation, a number of random modes are developed for the system variables using the probabilistic distribution function of system variables, then the occurrence probability of each mode is computed (Barani et al. 2018; Niknam et al. 2012). Equations (14, 15) reveal the samples extracted from the probabilistic distributions for power demand and the purchase price of electricity, respectively. The sum of probabilities must be equal to one, Eq. (16) shows how samples are combined to generate scenarios in which the sum of the probabilities of the generated scenarios is always equal to one (17).

$$\delta_{Pd} = \left\{\left(C_{Pd}^1, \varphi_{Pd}^1\right), \left(C_{Pd}^2, \varphi_{Pd}^2\right), \ldots .\left(C_{Pd}^n, \varphi_{Pd}^n\right)\right\}, \varphi_{Pd}^1 + \varphi_{Pd}^2 + \cdots + \varphi_{Pd}^n = 1 \tag{14}$$

$$\delta_{Ep} = \left\{\left(C_{Ep}^1, \varphi_{Ep}^1\right), \left(C_{Ep}^2, \varphi_{Ep}^2\right), \ldots .\left(C_{Ep}^n, \varphi_{Ep}^n\right)\right\}, \varphi_{Ep}^1 + \varphi_{Ep}^2 + \cdots + \varphi_{Ep}^n = 1 \tag{15}$$

$$S = \varphi_{Pd} \times \varphi_{Ep} \tag{16}$$

$$\sum_{S\in Ns} \delta_{Pd} + \delta_{Ep} = 1 \tag{17}$$

It should be noted that in this paper, to reduce computational complexities and accelerate program execution, the scenario reduction is employed using the backward technique (Barani et al. 2018; Niknam et al. 2012). This method, in addition to reducing the computational complexities of the problem and improving its speed, ensures the accuracy required for problem solving. Scenario reduction is a method for optimal selection of useful scenarios from a set of generated scenarios that not only shortens the execution time of the algorithm, but also considerably reduces the computational complexity of the problem. For this purpose, the backward reduction technic is used to reduce the number of scenarios. Suppose that the initial probability distribution Q is defined on the scenario set Ω. The problem of optimal reduction of set Ω can be expressed as follows:

$$K_D\left(S,S''\right) = \Pi s \times d\,(S, S'') \tag{18}$$

Define a subset of scenarios $\Omega s \subset \Omega$ and assign a new distribution to remaining scenarios so that the reduced probability distribution Q' defined on Ωs set is the nearest distribution to the main distribution Q in terms of probability distance. The Kantorovich distance can be expressed as follows:

$$d\,(S, S'') = \left(\sum_{i=1}^{H}(s_i - s_i'')^2\right)^{1/2} \tag{19}$$

In the above equation, S is a string scenario that has H subsets of s_i, $d\,(S, S'')$ is the distance between the two scenarios S and S''.

The scenario reduction algorithm is as follows:

- Collect the generated scenarios and determine the obtained scenarios probabilities so that the sum of scenario probabilities in each step is one.
- Calculate the vector distance matrix for each scenario pair, and compute the Kantorovich distance matrix by multiplying the probabilities of scenarios.
- Find the scenario with the lowest Kantorovich distance and mark it in the Kantorovich matrix.
- Choose a scenario with minimum Kantorovich distance and the scenario with the closest Kantorovich distance from that scenario.
- Eliminate the scenario with the lowest Kantorovich distance due to its low probability and closeness to the other scenario, and add its probability to the closest

scenario. By doing so, the sum of the remaining scenarios will always be one.

- Update the probability matrix with the new matrix.

2.4 Time of use mechanism

Demand response programs (DRPs) refer to a set of measures taken to modify energy usage pattern to boost system stability and hamper price rise, particularly at peak network loads. Participants in the DRPs are subscribers who, instead of reducing consumption, are responsible for modifying their energy usage patterns to diminish their costs, which ultimately results in lower electricity usage. In general, DRPs can be split into two sections: incentive programs and price-based programs (Azizivahed et al. 2019; Jahani et al. 2019).

In this paper, one of the DRPs called time of use mechanism (TOU) is used to alter the consumers' usage pattern to improve system performance. Mathematical modeling of the TOU mechanism is presented in (20)–(22). Based on this mechanism, the total modified energy cannot exceed a fixed value (assuming 15% of the base demand). Also, a balance must be struck between the increase and drop of overall power over a particular period.

$$\mathrm{P}_{t,i}^{\mathrm{MDF}} = \mathrm{P}_{t,i}^{\mathrm{TOU}} + \mathrm{P}_{t,i}^{\mathrm{INI}} \tag{20}$$

$$\left|\mathrm{P}_{t,i}^{\mathrm{TOU}}\right| \le \mathrm{TOU}^{\max} \times \mathrm{P}_{t,i}^{\mathrm{INI}} \tag{21}$$

$$\sum_{t=1}^{T} \mathrm{P}_{t,i}^{\mathrm{TOU}} = 0 \tag{22}$$

3 Multi-objective optimization strategy

In this section, original shuffled frog leaping algorithm (SFLA), modified shuffled frog leaping algorithm (MSFLA) and fuzzy clustering strategy are briefly presented.

3.1 Shuffled frog leaping algorithm

The SFLA was first introduced in 2003 by Eusuff et al. (2006). In this algorithm, each frog possesses information about a solution to a problem. The SFLA consists of the initial population of possible solutions to the problem. These solutions are actually a set of virtual frogs that are further divided into several groups. Each group of frogs has characteristics that can be influenced by the characteristics of frogs in other groups. In each group, the worst and best frogs are shown by X_w and X_b, respectively. The best frog between the groups is indicated by

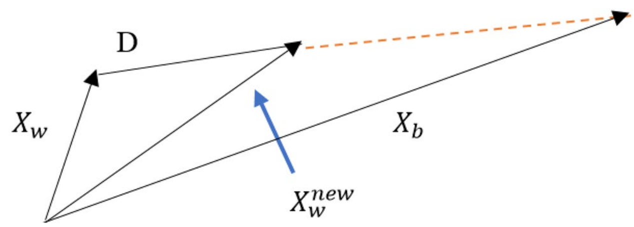


Fig. 1 Improvement of frog's position

Start

1. Generate initial random population (P) of frogs;
2. Calculate objective function;
3. Sort the frogs based on descending order of their fitness;
4. **For** i=1 to maximum iteration number;
5. Divide the P into M groups;
6. **For** each group;
7. Determine the best and worst frog;
8. **Repeat**
9. Modify the worst frog position by equations (23) and (24).
10. **Until** a specific number of iteration is satisfied
11. **End For**;
12. **End For**;
13. Shuffled the groups;
14. Sort the frogs based on descending order of their fitness;
15. Check if determination= true;

End;

Fig. 2 The pseudo-code of SFLA

X_G. The evolutionary process is performed by changing the position of the worst frog X_w in each group as follows:

$$\mathrm{X}_w^{\mathrm{new}} = \mathrm{X}_w + \mathrm{D}_i \tag{23}$$

$$\mathrm{D}_i = \mathrm{rand} \times (\mathrm{X}_b - \mathrm{X}_w) \tag{24}$$

$$-\mathrm{D}_{max} \le \mathrm{D}_i \le \mathrm{D}_{max} \tag{25}$$

After applying Eqs. (23, 24), if the new position of the worst frog is not improved, the evolutionary process is conducted by replacing X_G with X_b in Eq. (24). If the position of frogs cannot be enhanced, a new frog is randomly generated in the place of the worst frog in the above equations. Figures 1 and 2 show the movement of the worst frog toward the optimal position and the pseudo-code of the SFLA, respectively.

3.2 Modified shuffled frog leaping algorithm

The classic SFLA, where frogs with the worst fit adjust their position relative to the group or the best frog, deploy them along a line between X_b and X_w. This may lead the algorithm towards the wrong answers. For this reason, we present a new strategy to improve the performance of the MSFLA. Equation (26) is suggested for the *k*th repetition due to the limited search score.

$$D_i = \text{rand} \times C \times (X_b - X_w) \tag{26}$$

In the above equation C is a search acceleration factor that prevents algorithm to stagnate at a local optimum leading to its premature convergence (Elbeltagi et al. 2007). A review of previous studies reveals that the range of acceleration values between 1.3 and 2.1 ($1.3 < C < 2.1$) (Elbeltagi et al. 2007) provides the MSFLA with the best opportunity to find the global optimal with a minimum number of iterations. To have more control over Eq. (26), a weight W is added. It expresses the relationship between the local optimum point and the global optimum point in the frog leap process according to Eq. (27):

$$D_i = W \times \text{rand} \times C \times (X_b - X_w) \tag{27}$$

In the above equation, parameter W has a huge effect on the convergence behavior of the algorithm. A higher value of parameter W boosts the algorithm's ability to find the global point in the search space and undermines the ability to find the local point. The effect of the previous speed on the current speed of the algorithm can be controlled by modifying W according to Eq. (28).

$$W = W_{min} + \frac{(K_{max} - K) \times (W_{max} - W_{min})}{K_{max}} \tag{28}$$

Thus, the value of W will gradually decrease from W_{max} to the minimum value W_{min} in a linear iterative process. The search capacity in an algorithm iteration process is high and the algorithm will be able to search a large solution space and new areas will be constantly explored to find the solution. From the perspective of intermittent iteration, the algorithm progressively shrinks its search range to one area, thus increasing the convergence rate. The flowchart of the MSFLA is depicted in Fig. 3.

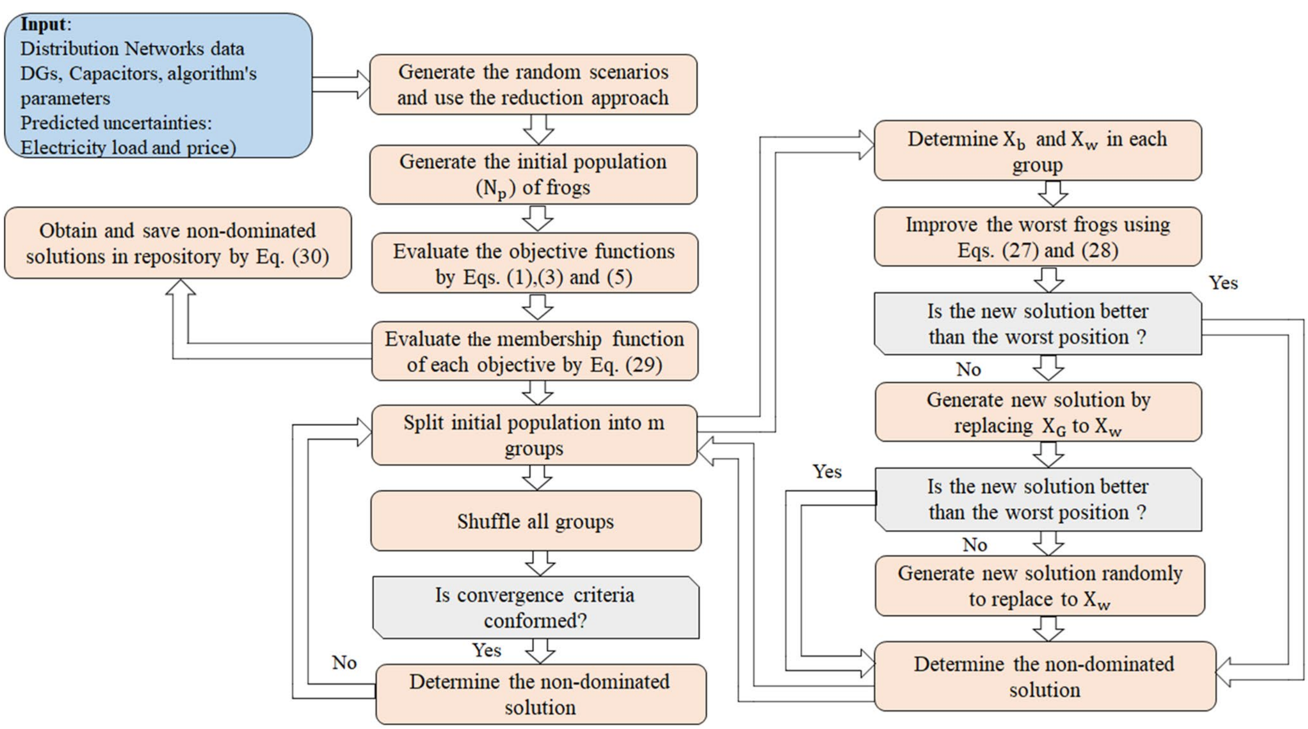


Fig. 3 Flowchart of the MSFLA

3.3 Fuzzy clustering strategy

In this study, the problem of Multi-objective optimization where there are contradictory objective functions is performed using a fuzzy optimization tool (Lotfi et al. 2019). The membership function is applied to have the same range for all objective function as follows:

$$\mu_i(x) = \begin{cases} 1 & f_i(X) \le f_i^{min} \\ 0 & f_i(X) \ge f_i^{max} \\ \frac{f_i^{max} - f_i(X)}{f_i^{max} - f_i^{min}} & f_i^{min} \le f_i(X) \le f_i^{max} \end{cases} \tag{29}$$

The normalized objective function (Lotfi 2020; Lotfi et al. 2019) is calculated for each individual as follows:

$$N_{\mu j} = \frac{\sum_{k=1}^{n} \beta_k \times \mu_{jk}(x)}{\sum_{j=1}^{m} \sum_{k=1}^{n} \beta_k \times \mu_{jk}(x)} \tag{30}$$

β_k is chosen based on the degree of priority from the point of view of operator. In this study, ($B_1 = B_2 = B_3 = 0.33$) for three-objective optimization and ($B_1 = B_2 = 0.5$) for two-objective optimization.

4 Simulation result

In this section, 95 and 136-node test systems are employed to assess the ability of the MSFLA for solving the problem of determining the optimal capacity of DGUs and SCs in the distribution network. All simulations are done in MATLAB (ver. 2016a). The scenario reduction strategy with 50 scenarios is used to model the sources of uncertainty. Also, the sources of uncertainty in solving the optimization problem include consumption demand and electricity purchase price. The TOU mechanism as one of the DRPs is executed in all nodes of the two test networks, the idea of using TOU is to reduce the operational cost and improve the system performance by shifting the electrical loads from peak times to off-peak times. To compare and validate the results of the proposed method, gravitational search algorithm (GSA), Imperialist competitive algorithm (ICA), Non-dominated sort genetic algorithm II (NSGA II), and SFLA are utilized to solve the considered optimization problem. After the introduction of the first version of the Genetic Algorithm in 1993, in 2002, the proponents of this algorithm introduced an elitist mechanism based on the importance of defective queues called the NSGA II to provide diversity in Pareto-optimal solutions (Liu et al. 2019; Parvizi and Rezvani 2020). In order to shown the mechanism and ability of the proposed algorithms to solve the optimization problem, the values of the parameters related to these algorithms are depicted in Table 1. Moreover, three cases are simulated to solve the optimal sizing of DGs and SCs in each test network:

Table 1 Parameters of the proposed algorithms

Parameters	MSFLA	SFLA	ICA	NSGAII	GSA
Population size	1100	1100	1100	1100	1100
Number of group	5	5	–	–	–
Maximum iteration	100	100	100	100	100
Acceleration rate (C)	1.6	–	–	–	–
Mutation	–	–	–	0.9	–
Crossover	–	–	–	0.01	–

1- Only installation of SCs.
2- Only installation of DGs.
3- Installation of both DGs and SCs simultaneously.

4.1 95-node test system

This test system is depicted in Fig. 4, and the demand characteristic of this system is depicted in Fig. 5 (Lotfi et al. 2019). Five 1000 kW DGUs (diesel generators) are installed in buses # 6, # 10, # 25, # 34 and # 45 along with four 100 kVAr capacitors in buses # 10, # 24, # 34 and # 70. The cost of purchasing electricity from DGUs is $ 0.042 per kW. The cost of energy purchased from substations at high and low demand periods is $ 0.04465 per kWh and $ 0.0401 per kWh, respectively. The energy loss, operational cost, and ENS before installing DGUs and SCs are 31,869.54 kWh, $ 140,651.91, and 345.56 kWh/ year, respectively.

In this section, the optimization problem in the presence of separate and simultaneous DGUs and SCs in the single-objective framework is solved by various algorithms. The best, worst and average results along with the standard deviation (STD) of MSFLA, SFLA, ICA, GSA, and NSGA II algorithms for optimization cases 1 and 2 in 20 different experiments are depicted in Table 2. In order to provide more details of the results of methods used in 20 different experiments, Tables 3, 4, and 5 compares the single-objective optimization results obtained by different methods in 20 experiments for cases 1 and 2, respectively.

According to Table 2, it is clear that the proposed MSFLA converges to better results than other methods. Moreover, DGUs allocation has a significant role in reducing the objective functions compared to SCs allocation in the distribution test system. For example, the values of ENS and energy loss obtained by the MSFLA for case 1 are 304.46 kWh/year and 30,075.35 kWh, respectively. In case 2, these values have

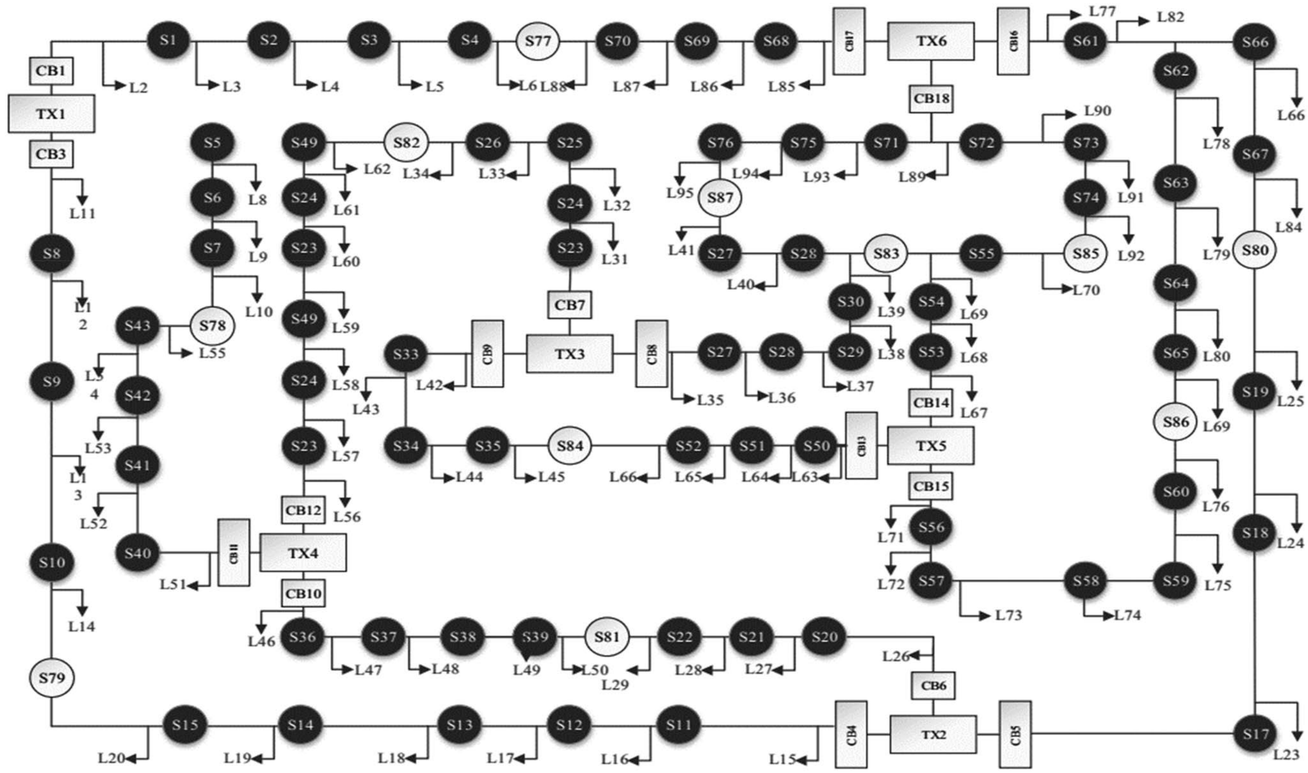


Fig. 4 Topology of the 95-node test system

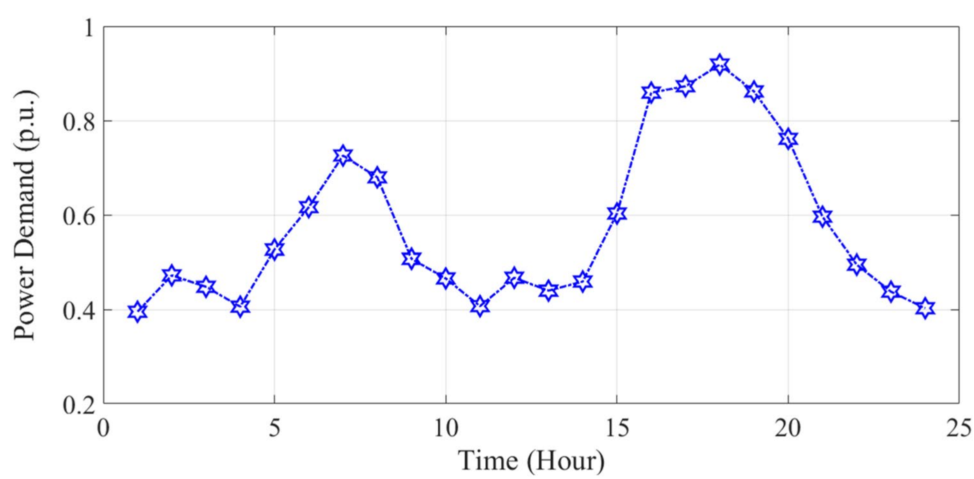


Fig. 5 Active demand for the 24-h interval

reached 294.31 kWh/year and 29,889.35 kWh, respectively. Also, the values of ENS, energy loss, and operational cost obtained from the MSLA for case 2 dropped by about 17%, 6.5%, and 5.5% compared to the initial values.

To illustrate the impact of DRP on objective functions assessment, the results of different objective function optimization attained by several algorithms for case 3 without and applying the TOU mechanism are listed in Table 6. Moreover, the optimal shame of active and reactive power generation of DGUs and SCs for optimizing energy loss is depicted in Table 7. According to Tables 2, 3, 4, 5 and 6, the following points can be taken.

Firstly, the solution found by the MSFLA outperforms than other evolutionary methods. Secondly, the amount of objective functions including energy loss, ENS, and operational cost obtained from the MSLA have dropped by 11%, 25.5%, and 5% compared to the initial values, which shows the effectiveness of the simultaneous allocation of DGUs and SCs than the separate allocation of these units in the test network. Thirdly, applying the TOU

Table 2 Results of Cases 1 and 2 for different objective functions

Objective function	Algorithms	DGs installation		Capacitors installation	
		Best solution	Standard deviation	Best solution	Standard deviation
Energy loss (kWh)	ICA	30,209.65	38.69	30,451.31	38.25
	SFLA	30,129.95	37.89	30,339.56	36.59
	NSGA II	30,078.65	37.15	30,319.89	36.45
	GSA	30,059.45	36.46	30,289.56	35.69
	MSFLA	29,889.35	35.15	30,075.45	34.89
Operational cost ($)	ICA	133,746.56	44.96	133,541.46	45.36
	SFLA	133,729.54	43.65	133,509.33	44.96
	NSGA II	133,701.25	43.15	133,491.25	44.85
	GSA	133,686.54	42.89	133,479.15	44.15
	MSFLA	133,669.26	42.16	133,445.45	43.65
ENS (kWh/year)	ICA	310.35	4.36	317.25	4.69
	SFLA	306.45	4.19	313.65	4.39
	NSGA II	303.25	3.89	314.32	4.28
	GSA	299.35	3.68	309.35	3.96
	MSFLA	294.31	3.25	306.46	3.65

Table 3 Results of minimizing ENS by different methods for case 1

Algorithms	ENS (kWh/year)			
	Best solution	Mean	Worst solution	Standard deviation
ICA	310.35	314.23	319.86	4.36
SFLA	306.45	309.37	314.79	4.19
NSGA II	303.25	306.68	311.51	3.89
GSA	299.35	302.79	308.41	3.68
MSFLA	294.31	296.54	301.39	3.25

Table 5 Results of minimizing ENS by different methods for case 2

Algorithms	Energy loss (kWh)			
	Best solution	Mean	Worst solution	Standard deviation
ICA	317.25	321.68	327.48	4.69
SFLA	313.65	317.89	322.39	4.39
NSGA II	313.32	317.15	321.74	4.28
GSA	309.35	312.56	317.25	3.96
MSFLA	306.46	309.35	313.85	3.65

Table 4 Results of minimizing energy loss by different methods for case 2

Algorithms	Energy loss (kWh)			
	Best solution	Mean	Worst solution	Standard deviation
ICA	30,209.65	30,244.52	30,291.25	38.69
SFLA	30,129.95	30,174.56	30,229.14	37.89
NSGA II	30,078.65	30,128.56	30,165.25	37.15
GSA	30,059.45	30,904.87	30,141.56	36.46
MSFLA	29,889.35	29,939.51	29,979.45	35.15

program has reduced the objective functions in this study. For instance, values of energy loss, ENS, and operational cost dropped by 12.5%, 30%, and 5.5% compared to the initial values, respectively. Also, comparing the results of the objective functions between non-execution and execution of the TOU program reveals the effect of the DRP on improving the results of the objective functions. For example, the value of objective functions for energy loss, ENS, and operational cost dropped from 28,563.21 kW, 276.51 kWh/year, and $ 133,661.31 to 28,365.21 kW, 262.13 kWh/year and $ 133,586.15, respectively.

Finally, the highest and lowest total active power generation of DGUs is at 6 pm, and 11 am with 4368.72 kW and 1006.47 kW, respectively. Also, the highest and lowest active power generation of these units in 24 h belong to units 1 and 5 at 8 pm and 3 am with 979.74 kW and 103.54 kW, respectively. Moreover, the highest and lowest values of the total reactive power generation of SCs are observed at 4 pm, and 3 am with 347.94 kVAr and 67.78 kVAr, respectively. Similarly, the highest and lowest reactive power generation of SCs in 24 h are observed in units 4 and 1 at 3 pm, and 3 am with 93.79 kVAr and 10.13 kVAr, respectively.

Figures 6 depicts the convergence curve of the operational cost objective function gained by utilizing the five algorithms including MSFLA, NSGA II, SFLA, GSA, and ICA for 95-node test system. Given this figure, it is clear

Table 6 Results of Case 3 for different objective functions

Methods	Objective functions	Before applying TOU	After applying TOU
ICA	Energy Loss (kWh)	29,395.65	28,785.65
	ENS (kWh/year)	282.45	279.45
	Operational cost ($)	133,749.83	133,681.52
SFLA	Energy Loss (kWh)	29,115.65	28,689.65
	ENS (kWh/year)	279.89	274.89
	Operational cost ($)	133,725.41	133,667.45
NSGA II	Energy Loss (kWh)	28,869.56	28,450.22
	ENS (kWh/year)	279.35	273.25
	Operational cost ($)	133,695.56	133,641.25
GSA	Energy Loss (kWh)	28,826.54	28,566.54
	ENS (kWh/year)	278.54	271.54
	Operational cost ($)	133,689.25	133,635.45
MSFLA	Energy Loss (kWh)	28,563.21	28,365.21
	ENS (kWh/year)	276.51	262.13
	Operational cost ($)	133,661.26	133,586.15

Table 7 The optimal output of DGUs and SCs obtained by MSFLA for energy loss optimization

L.L	DGUs output (kW)					SCs output (kVAr)			
	DG1	DG2	DG3	DG4	DG5	Cap1	Cap2	Cap3	Cap4
1	344.417	303.621	312.809	344.285	270.647	13.200	22.054	27.256	24.604
2	371.738	327.322	326.406	173.057	240.817	38.857	12.279	11.793	23.076
3	138.096	322.940	182.808	378.779	103.571	10.139	17.197	17.043	23.404
4	374.013	217.668	303.911	204.995	201.137	33.247	13.700	20.595	19.190
5	289.708	296.643	296.529	158.979	148.655	34.519	15.517	34.636	25.255
6	329.262	351.356	348.784	375.325	538.285	56.061	37.199	30.462	45.323
7	383.549	511.814	335.699	484.813	393.365	32.533	42.518	31.291	54.529
8	464.064	309.550	449.509	441.987	458.560	41.993	31.490	35.070	53.845
9	387.252	183.077	387.923	205.498	149.695	17.796	37.081	29.473	29.330
10	389.467	113.851	202.116	349.249	280.595	34.002	38.344	31.952	21.358
11	147.284	129.140	275.580	275.579	178.891	22.942	24.726	29.432	34.347
12	391.178	347.037	167.144	264.917	296.224	37.319	24.678	23.528	25.985
13	387.150	308.449	325.380	375.158	306.764	15.455	20.132	26.410	20.522
14	245.613	195.130	176.529	185.752	324.445	17.914	37.002	18.890	38.170
15	900.140	975.111	752.979	878.600	725.271	57.277	68.462	87.235	93.797
16	570.943	517.223	849.538	876.865	541.911	56.803	55.560	59.448	77.508
17	710.881	719.372	945.452	690.223	614.488	93.465	89.013	84.339	81.124
18	957.868	690.779	979.646	783.911	956.669	78.985	69.487	59.176	79.352
19	896.104	882.758	773.608	537.927	576.189	77.493	62.085	68.424	60.387
20	979.746	897.600	569.312	526.975	912.908	57.248	70.196	81.281	65.062
21	827.870	593.436	574.647	765.399	769.171	92.652	54.823	89.011	73.546
22	110.714	246.929	177.252	333.750	398.840	28.662	13.959	12.434	16.915
23	354.739	233.676	352.215	380.203	123.453	20.529	38.262	37.882	35.329
24	380.198	293.894	176.285	138.972	232.803	25.397	38.684	33.271	15.843

L.L. load level

that the MSFLA is converged to the optimal solution earlier compared to other methods.

Comparing the values of the objective functions in Table 2 exhibits that the objective functions of this study are inconsistent with each other. In other words, not all

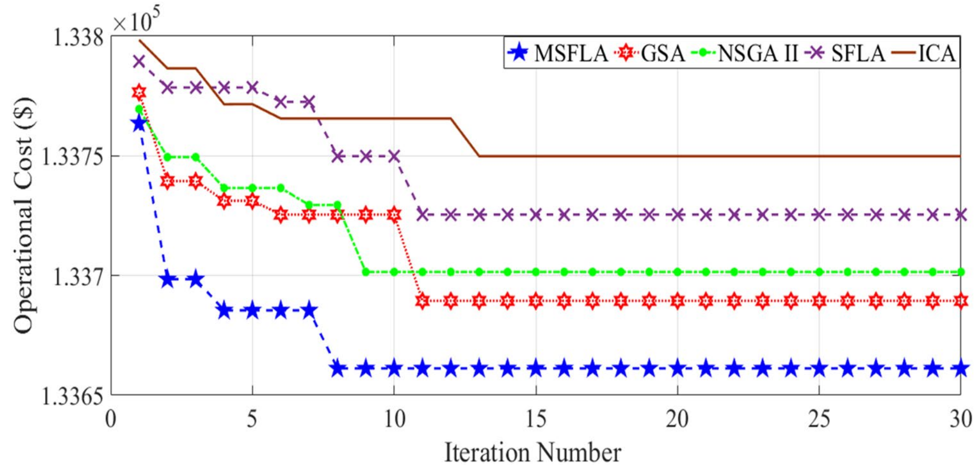


Fig. 6 Convergence curve of the operational cost for case 3 related to 95-node system

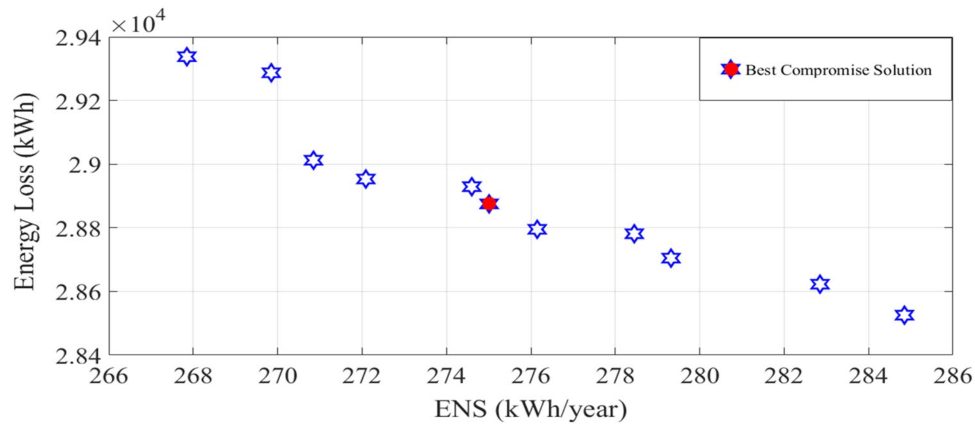


Fig. 7 Pareto-front for optimizing energy loss, and operational cost

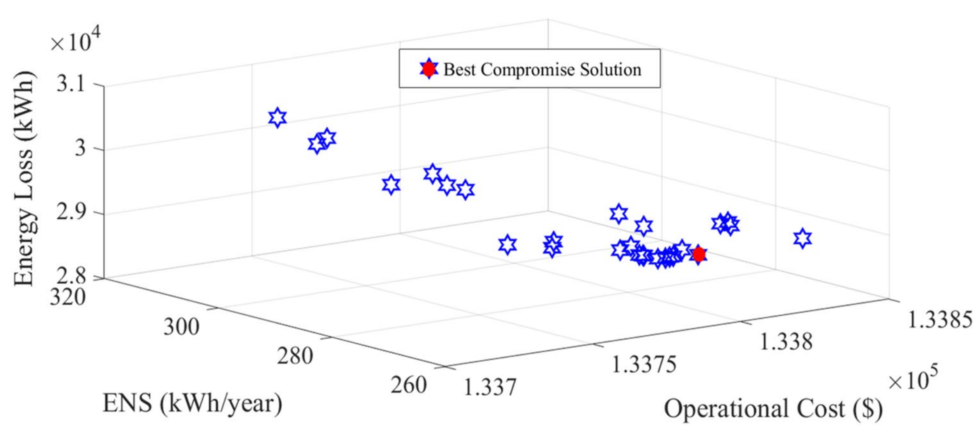


Fig. 8 Pareto-front for optimizing ENS, energy loss, and operational cost

three objective functions improved at the same time. As a result, the problem of Multi-objective optimization cannot be solved with the concept of single-objective. Therefore, we use Pareto optimization strategy to satisfy all objective functions. Figures 7 and 8 show the Pareto optimal fronts related to the optimization of two and three-objective obtained from the MSFLA. Moreover, the best compromise solution of each front is shown in red.

According to Figs. 7 and 8, it can be concluded that the difference between value of objective functions in best compromise response with their optimal values is not much different, which it shows the ability of the proposed method to solve the Multi-objective optimization problem. Besides, the value of objective functions in best compromise response related to Fig. 8, including loss, ENS, and operational cost

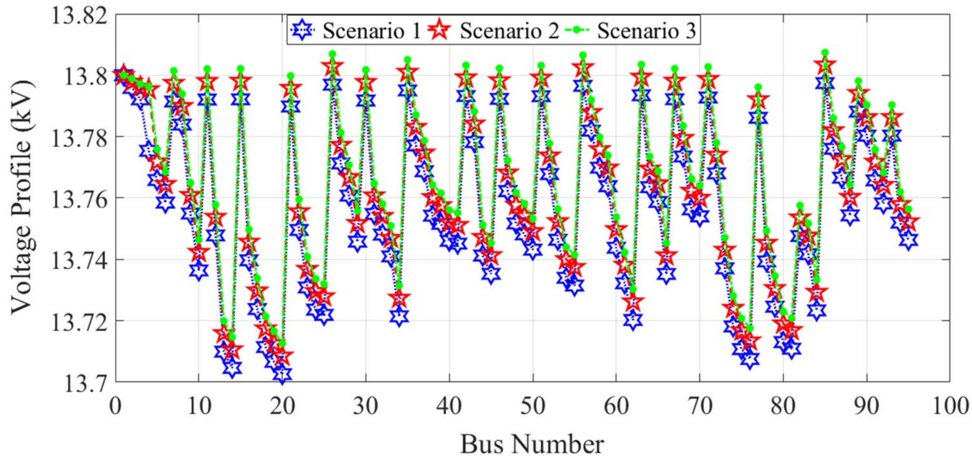


Fig. 9 Voltage profile of 95-node test system at 6 pm

declined by 11.5%, 24%, and 5% compared to the initial values.

Figure 9 exhibit the effects of DGUs, SCs, and DRP on the profiles of voltage in the distribution test system at 6 pm. To this end, three scenarios are defined to illustrate the effect of DGUs, SCs, and DRP on the voltage profiles of the two test systems. Scenario 1 is defined based on the initial network conditions, and scenarios 2 and 3 are based on the simultaneous presence of DGUs, SCs, and TOU mechanism, as well as the simultaneous presence of DGUs and SCs in both test networks, respectively. Voltage profile improvement in Fig. 9 indicates that the simultaneous presence of DGUs, SCs, and DRP exerts more significant effect on improving the voltage profile than the simultaneous presence of DGUs and SCs in solving the optimization problem.

4.2 136-node test system

This test system (López et al. 2016; Lotfi and Ghazi 2020) covers ten distributed units of 300 kW (diesel generator) in buses # 5, # 22, # 24, # 5, # 79, # 81, # 99, # 102, # 114 and # 126. Also, four 100 kVAr capacitors have been installed in buses # 10, # 20, # 34, # 70. Load profile and electricity price in 24 h are shown in Figs. 10 and 11. The purchase price of electricity from DGUs is $ 0.0425 per kWh. The energy loss, operational cost, and ENS before installing DGUs and SCs are 2155.64 kW, $ 14,549.91, and 43.53 kWh /year, respectively.

In this section, the problem of optimal sizing of DGUs and SCs in a single-objective form is solved by different evolution algorithms. Table 8 lists the results of objective functions optimization obtained from the MSFLA and other methods for cases 1 and 2, the optimization results are obtained from 20 separate experiments. Also, to further explain the results of the optimization methods in 20 different experiments, Tables 9, 10 and 11 compares the single-objective optimization results obtained by different methods for cases 1 and 2, respectively. Table 12 draws a comparison between the results of the different objective functions by several methods for case 3 in the absence and presence of DRPs. The optimal scheme of reactive and

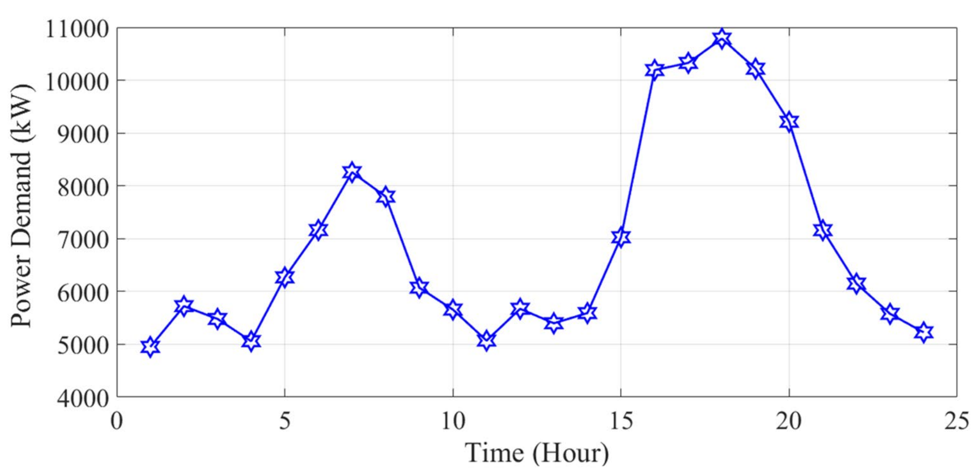


Fig. 10 Active demand profile of the136-node system

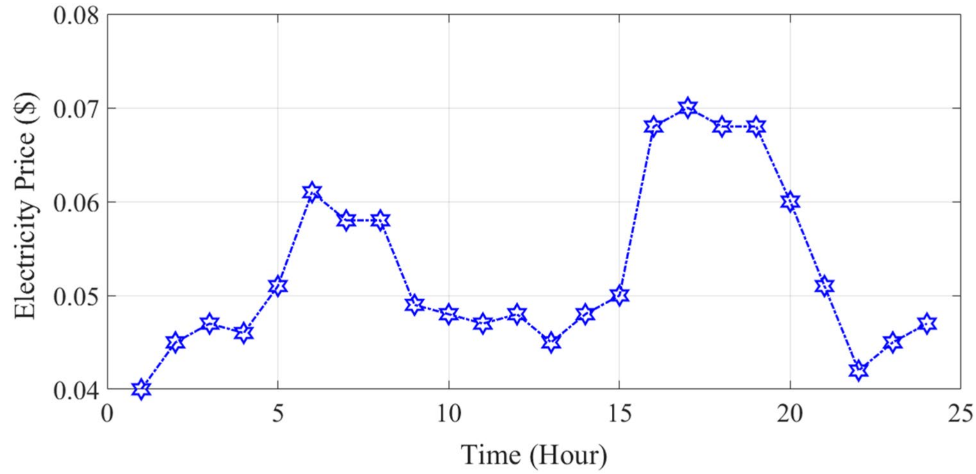


Fig. 11 Electricity price profile of the136-node system

Table 8 Results of Cases 1 and 2 for different objective functions

Objective function	Algorithms	DGs installation		Capacitors installation	
		Best solution	Standard deviation	Best solution	Standard deviation
Energy loss (kWh)	ICA	2079.49	39.85	2099.31	39.25
	SFLA	1991.32	37.66	2039.56	36.89
	NSGA II	1959.56	36.23	2019.89	36.45
	GSA	1929.69	34.85	1968.19	33.65
	MSFLA	1871.15	32.15	1899.21	32.84
Operational cost ($)	ICA	14,165.46	36.25	14,105.53	35.75
	SFLA	14,105.33	33.86	13,945.65	32.96
	NSGA II	14,069.56	32.69	13,925.25	32.16
	GSA	14,025.15	31.56	13,889.26	31.36
	MSFLA	13,951.45	28.12	13,845.13	28.65
ENS (kWh/year)	ICA	36.25	3.32	38.19	4.29
	SFLA	35.65	3.15	37.17	4.15
	NSGA II	34.69	2.96	36.31	4.89
	GSA	33.35	2.89	35.45	3.65
	MSFLA	31.52	2.65	34.49	3.15

Table 9 Results of minimizing energy loss by different methods for case 1

Algorithms	Energy Loss (kWh)			
	Best solution	Mean	Worst solution	Standard deviation
ICA	2079.49	2118.68	2159.46	39.85
SFLA	1991.32	2031.24	2069.36	37.66
NSGA II	1959.56	1996.25	2034.65	36.23
GSA	1929.69	1971.36	2012.42	34.85
MSFLA	1871.15	1907.45	1939.56	32.15

Table 10 Results of minimizing operational cost by different methods for case 1

Algorithms	Operational cost ($)			
	Best solution	Mean	Worst solution	Standard Deviation
ICA	14,165.46	14,201.14	14,239.21	36.25
SFLA	14,105.33	14,138.79	14,175.36	33.86
NSGA II	14,069.56	14,102.39	14,133.29	32.69
GSA	14,025.15	14,053.25	14,088.56	31.56
MSFLA	13,951.45	13,984.23	14,019.52	28.12

active power generation of SCs and DGUs for optimizing the operational cost are depicted in Tables 13 and 14.

According to Tables 8, 9, 10, 11 and 12, it is clear that the solution yielded by the MSFLA excels other algorithms. Moreover, the allocation of DGUs and SCs

Table 11 Results of minimizing energy loss by different methods for case 2

Algorithms	Energy Loss (kWh)			
	Best solution	Mean	Worst solution	Standard deviation
ICA	2099.31	2136.49	2176.25	39.25
SFLA	2039.56	2074.76	2112.39	36.89
NSGA II	2019.89	2140.68	2092.45	36.45
GSA	1968.19	1999.86	2033.65	33.65
MSFLA	1899.21	1974.65	2051.53	32.84

separately in the distribution network plays an important role in reducing the objective functions. The values of ENS, energy loss, and operational cost obtained from the MSLA for case 1 dropped by about 30%, 13%, and 5% compared to their initial values. These values obtained from the MSLA for case 2 decrease by about 38%, 15%, and 4.3% compared to their baseline values.

A comparison of the optimization results in the three cases indicates that the simultaneous allocation of DGUs and SCs has changed the value of objective functions of energy loss, operational cost, and ENS from 2155.64 kWh and $ 14,549.91 and 43.53 kWh/year to 1821.49 kWh, $ 13,958.45 and 28.46 kWh/year. Also, considering the TOU program and the effect of DGUs and SCS decreased the value of objective functions of energy loss, operational cost, and ENS by 29%, 7% and, 65% compared to the initial values. According to Tables 13 and 14, it is obvious that when optimizing the operational cost function, DGUs do not operate at their maximum power and the output power generation of these units has increased by 100 kW from 3 to 9 pm. Also, at 9 pm, the total maximum active power generation of DGUs reached its peak of 11,514.33 kW and the lowest total active power generation of DGUs belonging to 12 pm with 514.18 kW. Moreover, the highest and lowest reactive power generation of SCs have observed in units 4 and 2 at 8 pm, and 2 am with 97.62 kVAr and 26.94 kVAr, respectively. Also, the highest and lowest total reactive power of SCs have observed at 8 pm and 2 pm with 287.97 kVAr and 117.34 kVAr, respectively.

The convergence plot of MSFLA and other methods is shown in Fig. 12 for the energy loss objective function. This figure demonstrates that the proposed algorithm converges to the better results in less time with respect to other evolutionary algorithms.

To meet all the objectives of the problem simultaneously, the Pareto fronts related to the optimization of two and three-objective obtained from the MSFLA are shown in Figs. 13 and 14. According to Fig. 14, the value of objective functions of energy loss, operational cost, and ENS in best compromise response dropped by 16%, 7%, and 20% compared to the initial values. Another important point is that expanding the scale of the test network and increasing decision variables does not reduce the performance of the MSFLA.

Figure 15 displays the effect of DGUs, SCs, and DRP on voltage profiles in the 136-bus network at 6 pm. According to Fig. 15, it is clear that the improvement of the voltage profile in the simultaneous presence of DGUs, SCs, and TOU mechanism is more obvious than the simultaneous presence of DGUs and SCs in the test network.

5 Pareto solution analysis

The optimal Pareto fronts obtained should be evaluated to demonstrate the performance of the proposed method. For this purpose, two different criteria Generational Distance (GD) and

Table 12 Results of Case 3 for different objective functions

Methods	Objective functions	Before applying TOU	After applying TOU
ICA	Energy Loss (kWh)	1946.56	1819.12
	ENS (kWh/year)	38.69	34.21
	Operational cost ($)	14,165.46	13,789.64
SFLA	Energy Loss (kWh)	1898.54	1769.56
	ENS (kWh/year)	34.45	32.19
	Operational cost ($)	14,129.33	13,708.45
NSGA II	Energy Loss (kWh)	1876.59	1750.35
	ENS (kWh/year)	32.75	29.32
	Operational cost ($)	14,075.56	13,655.41
GSA	Energy Loss (kWh)	1861.29	1711.21
	ENS (kWh/year)	31.35	28.89
	Operational cost ($)	14,058.15	13,659.25
MSFLA	Energy Loss (kWh)	1821.49	1670.49
	ENS (kWh/year)	27.46	23.65
	Operational cost ($)	13,958.45	13,556.15

Table 13 The optimal output of SCs obtained by MSFLA for operational cost optimization

L.L	Capacitors Output (kVAr)			
	Cap1	Cap2	Cap3	Cap4
1	35.04	26.943	27.821	28.756
2	39.71	27.04	40.964	29.826
3	27.707	27.543	28.842	28.513
4	27.654	29.22	29.858	29.103
5	30.149	28.294	29.641	30.345
6	51.354	37.193	46.181	38.583
7	41.59	37.195	29.265	35.423
8	34.76	27.979	58.949	35.108
9	29.528	37.685	32.451	27.173
10	28.139	28.631	33.173	39.313
11	27.724	28.091	27.983	42.459
12	34.065	29.351	27.037	29.833
13	28.372	28.03	33.595	28.001
14	26.804	33.809	28.877	27.86
15	59.432	94.449	58.452	57.808
16	64.377	57.087	72.61	52.442
17	50.952	47.877	58.766	53.512
18	55.238	36.448	70.002	51.505
19	43.276	80.714	42.907	38.796
20	67.468	70.876	51.932	97.621
21	46.858	57.933	68.668	46.688
22	27.365	35.829	29.076	29.81
23	29.741	28.717	29.465	38.434
24	30.557	29.548	28.547	28.078

L.L. load level

Diversity Metric (D-Metric) (Lotfi et al. 2019) are presented as follows:

The ideal numerical value for GD criterion is zero, which indicates that all components are on the optimal Pareto front and are also close to each other. Moreover, a higher value for (D-Metric) criterion indicates that many of the components in the Pareto front are close together.

$$\mathrm{GD} = \frac{\sqrt{\sum_{s=1}^{n} E_s^2}}{k} \tag{31}$$

$$C_j = \frac{\sum_{r=1}^{k} Y_{nr}}{k} \tag{32}$$

$$\mathrm{DM} = \sum_{n=1}^{N_{obj}} \sum_{r=1}^{k} (Y_{nr} - C_r)^2 \tag{32}$$

Table 15 tabulates the best values of GD and DM indicators which helps readers to learn more about the powerful performance of the proposed algorithm for managing these cases. These values are achieved from solving multi-objective optimal allocation of DG sources and capacitors for two test systems. According to Table 15, it is obvious that the proposed MSFLA algorithm are able to handle Multi-objective optimization problems. Also, as shown by Table 15, it is clear that the criterions provided by the proposed MSFLA demonstrates the MSFLA algorithm's ability in solving the multi-objective problem.

6 Conclusion

Increasing the high penetration rate of distributed generation units (DGUs) in distribution networks and also considering the simultaneous effect of these units with shunt capacitors (SCs) in order to improve the performance of the distribution system, has created challenges such as reliability and economic issues for system operator. In this study, a novel approach called MSFLA is provided to obtain the optimal sizing of DGUs and SCs, considering the sources of uncertainty and demand response program. Compared with original SFLA, it expands local exploration scope and enhances the population diversity. Reduction of energy loss, operational cost, and ENS are defined as objectives in this study. The problem limitations include buses voltage, lines current and DGUs generation boundaries. The MSFLA uses the concept of dominance to obtain the Pareto-optimal solution in solving the presented Multi-objective optimization problem. The proposed method is tested on two 95 and 136-node test systems. The results which are achieved from the proposed method in comparison with the results of other evolutionary and state-of-art methods including SFLA, ICA, NSGA II, and GSA prove the claim that the proposed method has high accuracy and efficiency to solve single and Multi-objective problems regardless of the complexities and dimensions of the problem.

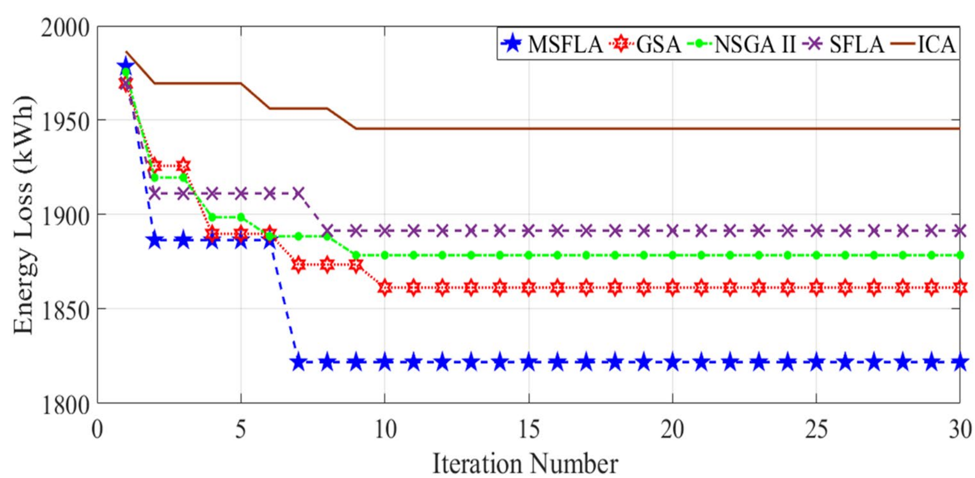
Simultaneous allocation of DGUs and SCs in the distribution network reduces energy loss, ENS, and operational cost. For example, the values energy loss, ENS, and operational cost obtained by MSFLA in the first system are dropped by 11%, 25.5%, and 5% compared to initial values. Considering the TOU program as one of the DRPs in allocation of DGUs and SCs simultaneously in the distribution network, while changing the consumption pattern of subscribers, improved the performance of the distribution system due to diminished energy loss and operational cost. Moreover, the values energy loss, ENS, and operational cost obtained by MSFLA in the second system are reduced by 29%, 65%, and 7% compared to the initial values. Also, the voltage profile in

Table 14 The optimal output of DGUs obtained by MSFLA for operational cost optimization

L.L	DGUs output (kW)									
	DG1	DG2	DG3	DG4	DG5	DG6	DG7	DG8	DG9	DG10
1	76.293	45.230	45.440	46.426	64.908	62.625	71.940	71.759	79.629	72.901
2	47.970	77.188	46.560	63.066	65.034	53.871	47.643	46.495	49.520	73.753
3	57.729	71.840	45.550	45.956	49.245	45.703	46.016	47.065	77.481	41.840
4	46.650	46.250	62.260	75.532	53.375	45.695	67.539	48.304	49.529	23.409
5	45.750	45.680	46.888	67.034	46.422	49.664	68.369	64.648	67.371	75.505
6	79.727	67.687	89.848	111.305	84.537	119.863	104.749	86.903	71.339	63.064
7	78.875	110.156	113.074	85.844	91.192	90.457	118.524	93.369	84.446	63.056
8	67.670	101.250	89.518	107.370	113.081	86.350	76.879	110.509	69.626	66.593
9	45.350	64.577	45.250	65.429	62.326	53.008	47.431	73.350	45.939	66.299
10	55.702	245.880	54.397	75.413	69.432	75.981	46.783	62.363	46.891	70.882
11	49.960	49.950	47.087	45.170	46.636	49.726	58.003	49.728	57.950	76.241
12	49.960	64.201	61.527	45.388	51.951	45.429	45.284	56.162	45.877	49.164
13	48.870	30.535	65.692	74.773	64.491	50.958	49.501	57.235	51.303	45.830
14	45.560	45.590	55.863	52.511	61.564	57.822	46.320	62.015	46.087	45.659
15	127.299	109.684	139.562	120.969	140.257	176.225	199.625	147.185	126.062	178.977
16	119.259	193.282	175.762	143.537	135.202	102.199	139.531	109.824	173.312	127.928
17	139.414	106.398	183.417	114.544	152.897	195.233	155.857	179.345	148.501	126.430
18	110.599	178.009	112.995	188.524	195.269	165.561	139.803	109.739	186.194	109.108
19	192.153	162.842	126.682	110.442	160.417	143.316	183.273	100.233	141.772	151.367
20	125.183	111.881	181.418	105.646	188.515	112.649	156.495	110.026	111.594	145.086
21	132.615	199.441	154.055	122.033	179.527	113.329	135.517	115.127	179.599	183.097
22	49.980	57.547	63.235	61.347	49.994	58.515	49.201	47.262	72.075	49.845
23	48.850	46.650	49.249	48.184	48.682	47.991	72.024	48.861	47.892	78.986
24	72.897	53.504	51.283	77.693	45.489	45.665	45.759	72.424	49.650	47.004

L.L. load level

Fig. 12 Convergence curve of the energy loss for case 3 related to the 136-node system



both test networks, considering DGUs, SCs, and DRP, has a more noticeable improvement compared to the presence of only DGUs and SCs in the distribution network.

Some suggestions for future studies of this research are as follows:

- Simultaneous scheduling of distributed generation units or shunt capacitors and FACTS taking into account the actual model of the electric load as well as its uncertainty.

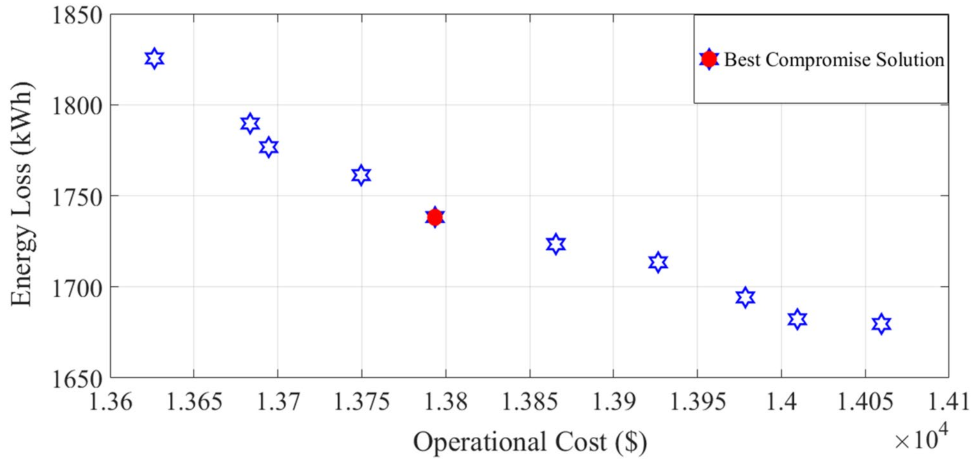


Fig. 13 Pareto-front for optimizing energy loss and operational cost

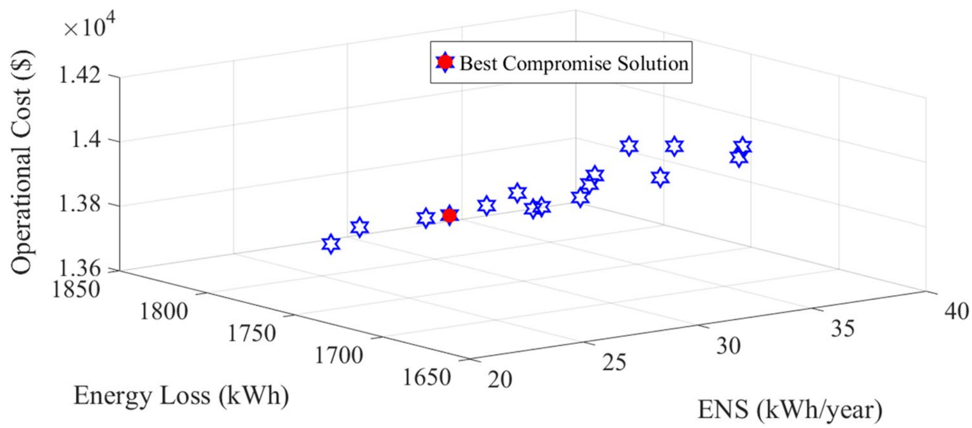


Fig. 14 Pareto-front for optimizing ENS, energy loss, and operational cost

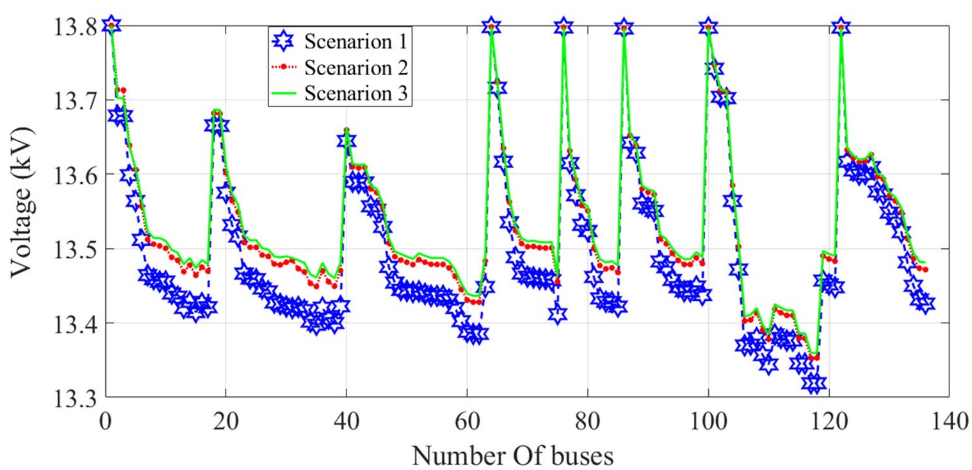


Fig. 15 Voltage profile of 136-node test system at 6 pm

Table 15 Obtained GD and DM for Pareto solutions by MSFLA for two systems

Problem dimensional	Criterions of MSFLA for test system 1		Criterions of MSFLA for test system 2	
	GD	DM	GD	DM
ENS& energy loss	25.45	54,109.12	29.85	55,905.52
ENS& operational cost	19.25	48,231.34	15.54	49,565.23
Energy loss and operational cost	16.73	39,416.46	18.42	38,596.56

- Integrating battery storage system with distributed generation units in the distribution network considering technical and operational constraints.
- Stochastic optimal planning of the distribution network with the sporadic nature of distributed generation units and electrical vehicles according to the optimal location of charging stations.
- Coordinated planning in the distribution network by simultaneously performing strategies of capacitor placement, dispatchable distributed generation units and distributed feeder reconfiguration.

Declarations

Conflict of interest The authors declare that there is no conflict of interest regarding the publication of this paper.

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