Energy Systems
https://doi.org/10.1007/s12667-019-00333-3

ORIGINAL PAPER

Multi-objective dynamic distribution feeder reconfiguration along with capacitor allocation using a new hybrid evolutionary algorithm

Hossein Lotfi[1] · Reza Ghazi[1,2] · Mohammad bagher Naghibi-Sistani[1,2]

Received: 1 September 2018 / Accepted: 6 March 2019

Abstract

Distribution feeder reconfiguration (DFR) and capacitor allocation are used in distribution systems to reduce power losses improve reliability and keep the voltage within acceptable limits. Distribution feeder reconfiguration is an important issue which can improve the network performance by changing the status of switches to satisfy some objective functions. The performance can be further improved by simultaneous application of capacitors. The DFR problem is intrinsically complex and nonlinear; combination with capacitor allocation the problem becomes more complex than before, hence a precise optimization method is required to solve the problem. In this paper a multi-objective framework is presented for DFR along with capacitor allocation problem over multiple time intervals as dynamic DFR considering distributed generation, energy storage systems and photovoltaic units. The common objectives of DFR problem in traditional distribution systems are power losses and voltage deviations. Usually less attentions have been paid to reliability and security of distribution network. In the present paper the operation cost, reliability and voltage stability index are considered as objective functions. A novel hybrid optimization method called is proposed to solve the problem. The proposed method is a combination of Improved particle swarm optimization and Modified shuffled leaping algorithms. The obtained results justify its superior performance in solving the proposed complex optimization problem.

Keywords Distribution feeder reconfiguration (DFR) · Energy not supplied (ENS) · Distributed generation (DGs) · Multi-objective optimization · Photovoltaic (PV) units · Energy storage systems (ESSs)

✉ Hossein Lotfi
Hossein_lotfi95@yahoo.com

1 Department of Electrical Engineering, Neyshabur Branch, Islamic Azad University, Neyshabur, Iran

2 Department of Electrical Engineering, Ferdowsi University of Mashhad, Mashhad, Iran

Published online: 02 April 2019

1 Introduction

Generally, distribution systems are designed in mesh type, but operated in radial, because many operations such as voltage control and protection are based on radial configuration. The distribution feeder reconfiguration (DFR) is performed by managing the open/close status of sectionalizing and tie-switches in order to optimize some objective functions while satisfying the operational constraints without islanding formation of any bus in distribution network. In modern distribution systems, the DGs, ESSs and electric vehicles (EVs) have taken an important position [1]. The integration of DGs and ESSs has a significant impact on the distribution network regarding the voltage profile of buses and branch currents [2]. If these devices are not properly managed the stability of system may encounter instability. The effects of DGs, EVs and ESSs on solving the DFR problem are considered in [7, 9, 10, 12–18, 20, 21]. In the following, the static and dynamic models of DFR problem and the modelling of DFR problem in this study and the method for solving the problem are presented. In [3], authors have presented a comprehensive survey on DFR problem including the characterised solution methods. In the static DFR framework, depending on the objective functions, the information about the load pattern and the electricity price, the DFR problem has solved. In this framework, the load pattern and electricity price are considered to be fixed. In [3–18], the DFR problem has been modelled as static framework. Static DFR problem is inherently a composite and non-differentiated complex optimization problem which is difficult to solve. During the past years, different mathematical methods have been used to solve the DFR problem [4–6]. For example, authors in [4] proposed the distance measurement technique (DMT). A new method based on brute force approach to solve the DFR problem to reduce power losses is provided in [5]. In [6], the DFR problem is modelled as an integer programming (IP) optimization to reduce the total power losses. However, these numerical methods cannot guarantee in presenting the global optimal solution because of having some constraints such as the continuity and derivability of the objective functions. Hence, these numerical and mathematical algorithms are not suitable candidates for solving the Multi-objective DFR problem. A literature survey shows that various evolutionary optimization algorithms have been used to solve the DFR problem [7–22]. In [7] a hybrid PSO-MSFLA is proposed to solve the DFR problem considering DGs in order to improve the reliability and security. In [8] an Invasive Weed Optimization (IWO) algorithm is provided to solve the multi-objective DFR problem in radial distribution systems. In [9] a Decimal coded Quantum PSO (DCQPSO) is presented to solve the multi-objective DFR problem considering DGs. Authors introduced a Social Spider Optimization (SSO) algorithm to solve the DFR considering Electric Vehicles (EVs) and Vehicle-to-Grid (V2G) [10]. In [11] a new hybrid Big Bang-Big Crunch algorithm (HBB-BC) is provided to solved the multi-objective DFR along with capacitor placement in balanced and unbalanced radial distribution systems. Authors presented a multi-objective Hybrid Big Bang-Big Crunch algorithm (MOHBB-BC) to solve the multi-objective DFR problem and allocation of DGs [12]. In [13] a heuristic approach according to uniform voltage distribution based constructive reconfiguration algorithm (UVDA) is proposed to solve the DFR problem and optimal DG sizing. In [14], an enhanced gravitational search algorithm (ESGA) is suggested to solve the DFR problem in presence of DGs. In [15], a PSO algorithm is suggested to solve a risk-based reconfiguration of electric distribution networks in presence of reward/penalty scheme considering load and generation uncertainty, Scenario theory (ST) was used for risk modelling. Authors suggested a GA to solve the DFR problem considering DGs in order to minimize the cost of purchased energy regarding hourly Locational Marginal Prices (LMPs) of wholesale market [16]. Authors presented a branch exchange (BE) method to solve the multi-objective DFR problem considering DGs in order to improve the power quality [17]. In [18] an enhanced Gravitational Search Algorithm (EGSA) is proposed to solve the multi-objective DFR problem considering DGs in order to improve the transient stability.

The survey on this subject shows that most of references have been used static framework to solve DFR problem which is not appropriate due to the time variation of the load pattern and electricity price, especially in smart grids [19]. Power systems encounter more uncertainties in both sides of generation and demand due to uncertainty in load patterns and electricity prices. A common approach is the development of operational problems such as economic load dispatch, optimal power flow and DFR over multiple time intervals regarded as dynamic DFR. In Dynamic DFR (DDFR) framework, the load pattern and electricity price are not constant over different time intervals. Therefore, the load pattern and electricity price are predicted for specified time interval, then DFR problem for this time interval is solved. In [20–22], the DFR problem has been modelled as Dynamic framework. In [20] Ant Colony Optimization (ACO) technique is presented for simultaneous dynamic scheduling of feeder reconfiguration and capacitor switching in presence of DGs considering uncertain and variant generation. Authors proposed a hybrid evolutionary algorithm which is combination of Grey Wolf Optimizer (GWO) and Improved PSO (IPSO) to solve the dynamic DFR problem considering DGs, Time varying electricity prices and different load levels [21]. In [22] the combination of dynamic programing and harmony search is presented for DFR problem to power loss reduction and reliability improvement.

In this study, the Distribution feeder reconfiguration along with capacitor allocation (DFR&CA) problem is solved as a dynamic optimization problem over multiple time intervals. For this purpose, the load pattern and electricity price related to next day are predicted. Then, feeder reconfiguration is implemented in distribution network related to next day by management of switches (sectionalizing and tie-switches) regarding different objectives and engineering and physical constraints.

Advantages of DFR&CA in dynamic framework compared to other works in the literature are as follows.

- Due to changes in the load pattern and electricity prices, solving the DFR problem in different time intervals is important due to cost reduction and management of electrical power resources. These matters are considered in the present work which are not taken into account in static framework.

- In this study, the hourly load and price changes are considered in dynamic DFR and capacitor allocation problem in 24 h related to next day while in previous works this problem is solved only over long period of time leading to significant error.

Many recent research works on the DFR problem have focused on different objectives such as reducing power losses, voltage deviation and operational cost, but less attention has been paid to reliability and network security. Therefore, improving distribution network reliability can be a major concern. For this reason, Energy Not Supplied (ENS) along with Voltage Stability Index (VSI) and operation cost are considered as objective functions. Solving the multi-objective DDFR&CA problem in radial distribution network requires an accurate and powerful optimization algorithm. To do so, a new hybrid algorithm based on combination of Improved Particle Swarm Optimization and Modified Shuffled Frog Leaping Algorithm (IPSO-MSFLA) is proposed to deal with the complexities of DDFR&CA as a non-linear and non-convex problem having many local optima. On one hand the PSO is widely used in power system optimization because of its simple implementation, on the other hand the SFLA compared with other evolutionary algorithms benefits from minimum storage requirement. By reviewing papers [7, 9, 15, 21], it is observed that these algorithms have been widely used to solve this problem. However, the both algorithms have some weaknesses such as; premature converge and convergence towards the global optimal in long time period, hence, a new initiative strategy is added to each in order to improve the population diversity and the search ability of algorithm such as: presenting a new mutation in MSFLA and changing the learning factors in IPSO algorithm. In the optimization of DDFR&CA problem the PSO, SFLA and IPSO-MSFLA algorithms are implemented to demonstrate the superiority of the proposed hybrid algorithm over PSO and SFLA algorithms.

Advantages of IPSO-MSFLA with respect to original PSO and SFLA algorithms are as follows.

- Improving the diversity of population and search ability of IPSO-MSFLA by splitting the initial population between IPSO and MSFLA. Then, each algorithm executes an optimization process to get the global best solution.
- The possibility of premature convergence or falling into local optimum in IPSO-MSFLA algorithm is reduced by modifying the mutation strategy in MSFLA and learning factors in IPSO
- Improving the accuracy and performance of IPSO-MSFLA algorithm by choosing the best global obtained from IPSO and MSFLA.

In this study, by considering VSI, ENS and operation cost as objective functions, it is imperative to tackle the problem as a multi-objective optimization problem. In this multi-objective problem, the proposed algorithm utilizes the concept of Pareto optimality. In addition, an external repository is considered to storage the Pareto solutions during the search process. Finally, a fuzzy decision making is used to find the best compromise solution.

In this regard, the following points are summarised.

- The multi-objective DDFR&CA problem in radial distribution network is modeled considering three objective functions including operation cost, VSI and ENS.
- The effects of DGs, ESSs and PVs on different objective functions are investigated simultaneously
- A new hybrid algorithm based on combination of the improved Particle Swarm Optimization and Modified Shuffled Frog Leaping Algorithm (IPSO-MSFLA) is proposed.
- A new method for calculating the VSI is presented; the advantage of this strategy over other methods is that it can be implemented in mesh and radial networks.

Rest of this paper is organized as follows. Sections 2 and 3 describe formulation of the problem including objective functions, constraints and background theory. In Sect. 4 IPSO, MSFLA and IPSO-MSFLA algorithms are introduced. Section 5 presents a multi-objective solution methodology. Section 6 renders the simulation results in two parts. Pareto solution analysis and conclusions are presented in Sects. 7 and 8, respectively.

2 Problem formulation

In this section the objective functions along with the DDFR&CA problem formulation are provided.

2.1 Objective functions

Due to the importance of reliability and network security in this study, improvement of VSI and reduction of ENS in addition to operation cost are considered as the main objective functions.

2.1.1 Operation cost

$$f_1(X) = \sum_{\mathrm{t=1}}^{\mathrm{T}} \left(\sum_{\mathrm{j=1}}^{\mathrm{N_{dg}}} \mathrm{Price}^{\mathrm{t}}_{\mathrm{DG,j}} \mathrm{P}^{\mathrm{t}}_{\mathrm{DG,j}} + \sum_{\mathrm{s=1}}^{\mathrm{N_{sub}}} \mathrm{Price}^{\mathrm{t}}_{\mathrm{Sub,s}} \mathrm{P}^{\mathrm{t}}_{\mathrm{Sub,s}} + \sum_{\mathrm{k=1}}^{\mathrm{N_{sw}}} \mathrm{Price}_{\mathrm{Sw,k}} \left| \mathrm{S}^{\mathrm{t}}_{\mathrm{k}} - \mathrm{S}^{\mathrm{t0}}_{\mathrm{k}} \right| \right), \tag{1}$$

$$X = \left[\overline{Tie}\ \overline{SW}\ \overline{P_{dg}}\ \overline{Q_{Cap}}\ \overline{P_{ES}} \right], \tag{2}$$

$$\overline{Tie} = \left[Tie^T_1, Tie^T_2, \ldots Tie^T_{N_{tie}} \right], \tag{3}$$

$$\overline{SW} = \left[SW^T_1, SW^T_2, \ldots SW^T_{N_{tie}} \right], \tag{4}$$

$$\overline{P_{Dg}} = \left[P^T_{Dg1}, P^T_{Dg2}, \dots P^T_{Dg_{N_{Dg}}}\right], \tag{5}$$

$$\overline{Q_{Cap}} = \left[Q^T_{Cap1}, Q^T_{Cap2}, \dots Q^T_{Cap_{N_{Cap}}}\right], \tag{6}$$

$$\overline{P_{ES}} = \left[P^T_{ESS1}, P^T_{ESS2}, \dots P^T_{ESS_{N_{ESS}}}\right], \tag{7}$$

where $P^t_{DG,j}$ and $P^t_{Sub,s}$ are the active power outputs of the jth DG and sth sub-station at the tth time interval, respectively. $Price^t_{DG,j}$ and $Price^t_{Sub,s}$ are the electricity price of jth DG and sth sub-station at the tth time interval, respectively. $Price_{Sw,k}$ is the switching cost. N_{dg} and N_{sw} are the number of DG and switches, respectively. S^t_k and S^{t0}_k are the new and original states of kth switch at the tth time interval, respectively. Where X is the vector of control variables, Tie^t_i is the state of the ith tie-switch at the tth time interval. SW^T_i is the sectionalizing switch number that forms a loop with Tie^t_i. N_{tie} and N_{sw} are the number of the tie switches and number of switches, respectively. $Q^T_{Cap,r}$ and $P^T_{ESS,g}$ are the reactive power of the rth capacitor and active power of charge/discharge of the gth ESS at the tth time interval, respectively. N_{cap} and N_{ESS} are the number of Capacitor and the number of ESS, respectively.

2.1.2 Energy not supplied (ENS)

ENS is one of the most significant reliability indices that represents the behaviour of the system and reflects the expected unsupplied energy of system due to faults over the period of study [23, 24]. The ENS at each node can be calculated as follows:

$$ENS_i = P_i \sum\nolimits_{i,j \in V\ i \neq j} (U_{i,j} + U'_{i,j}), \tag{8}$$

Consider a distribution network with N_B nodes, $N_B > 1$ and node 0 as the source of this network. Assume that all nodes except the source have an active power P_i (kW), where $V = \{0, 1, 2, \dots, N_B - 1\}$ is the set of node in distribution network.$U_{i,j}$ is service unavailability related to the reparation time of all branches connected to the node i and $U_{i,j}$ is service unavailability related to the restoration time of all branches connected to the node i. $U_{i,j}$ and $U_{i,j}$ are defined as follows: $\lambda_{i,j}$: failure rate (fail/km-year),$t_{i,j}$: average reparation time (h/fail), $t'_{i,j}$: average restoration time (h/fail), $d_{i,j}$: length of line (km):

$$U_{i,j} = \lambda_{i,j} \times d_{i,j} \times t_{i,j}, \tag{9}$$

$$U'_{i,j} = \lambda_{i,j} \times d_{i,j} \times t'_{i,j}. \tag{10}$$

Finally, The ENS of whole distribution network is calculated without considering the reference node as follows:

$$f_2(x) = \sum_{i=2}^{N_{BUS}} ENS_i. \tag{11}$$

2.1.3 Voltage stability index (VSI)

In distribution networks, various factors, such as excessive power overloads, inappropriate performance of the transformer, and many other factors, cause voltage instability in each of the network points [24, 25]. One aim in this research is to improve the voltage stability of network through the DFR. Security analysis can be done in a distribution system by assessing the voltage stability index (VSI) to maintain stability following disturbances. In this paper the voltage stability is defined based on Thevenin equivalent. The Thevenin equivalent for all nodes of network is shown in Fig. 1.

With respect to the load flow technique, Eqs. (12) and (13) are obtained, and leading to Eq. (14):

$$I(j) = \frac{V_{th} - V_j}{R_{th} + jX_{th}}, \tag{12}$$

$$P(j) - jQ(j) = V_j \times I(j), \tag{13}$$

$$P(j) - jQ(j) = V_j \times \frac{V_{th} - V_j}{R_{th} + jX_{th}}. \tag{14}$$

The Eq. (15) can be calculated from Eq. (14):

$$\begin{aligned} &\left|V_j\right|^4 - \left|V_{th}\right|^2 - 2P(j)R_{th} - 2Q(j)X_{th} \cdot \left|V_j\right|^2 \\ &+ \left(P^2(j) + Q^2(j)\right) \cdot (R_{th}^2 + X_{th}^2) = 0. \end{aligned} \tag{15}$$

After establishing $B^2 - 4C \geq 0$ constraint for Eq. (15), the VSI will be defined as Eq. (16):

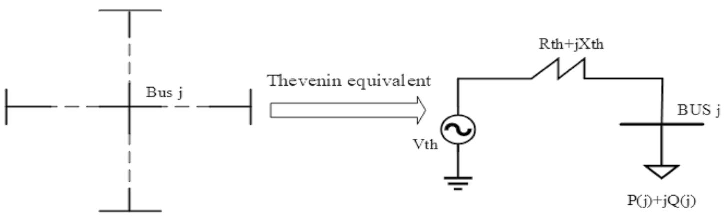

Fig. 1 Thevenin equivalent system of bus *j*

$$\mathrm{VSI(j)} = \left(\left|V_{th}\right|^2 - 2P(j)R_{th} - 2Q(j)X_{th}\right)^2 - 4 \\ \cdot\left(P^2(j) + Q^2(j)\right) \cdot (R_{th}^2 + X_{th}^2), \quad j = 2, 3, \ldots, N_{bus}. \tag{16}$$

In order reaching to a stable operating condition, VSI for all buses should be greater than zero, also N_{bus} is the number of buses:

$$\mathrm{VSI} = \left[\mathrm{VSI}(2), \mathrm{VSI}(3), \ldots, \mathrm{VSI}(N_{bus})\right], \tag{17}$$

$$\mathrm{bvsi(i)} = \begin{cases} 0 & \mathrm{VSI(i)} > 0 \\ 1 & \mathrm{VSI(i)} \le 0 \end{cases}, \tag{18}$$

$$\mathrm{bvsi} = \left[\mathrm{bVSI}(2), \mathrm{bVSI}(3), \ldots, \mathrm{bVSI}(N_{bus})\right], \tag{19}$$

$$\text{penalty factor} = M \times \mathrm{sum(bVSI)}. \tag{20}$$

The $f_3(x)$ function is defined as Eq. (*21*). The penalty factor is performed to remove the unstable decision variables during optimization process. M is a large number, for example in this study the value of M is 10^5:

$$f_3(x) = \frac{1}{\min(\mathrm{VSI})} + \text{penalty factor}. \tag{21}$$

2.2 Constraints

To solve the DDFR&CA problem, some equality constraints described in Sects. 2.2.1 and 2.2.2 must be satisfied, as physical limits. Also some inequality constraints described in Sects. 2.2.3–2.2.8 must be satisfied, as engineering limits.

2.2.1 Radial structure of the network

$$N_{branch}^{t} = N_{bus} - N_{source}, \tag{22}$$

where N_{bus} and N_{source} are the number of buses and number of substations, respectively. N_{branch}^{t} is the number of braches at the tth time interval.

2.2.2 Distribution power flow equations

Power flow equations must be satisfied throughout the optimization process. These equations can be expressed as follows:

$$P_i = \sum_{j=1}^{N_{bus}} V_i V_j Y_{ij} \cos\left(\theta_{ij} - \delta_i + \delta_i\right) \quad i = 2, 3, \ldots, N_{bus}, \tag{23}$$

$$Q_i = \sum_{j=1}^{N_{bus}} V_i V_j Y_{ij} \sin\left(\theta_{ij} - \delta_i + \delta_i\right), \tag{24}$$

where P_i and Q_i are the net injected active and reactive powers at the ith bus. V_i and δ_i are the amplitude and angle of voltage at ith bus, Y_{ij} and θ_{ij} are the amplitude and angle of branch admittance between ith and jth buses.

2.2.3 Bus voltage limit

$$V_{min} \le V_i^t \le V_{max}. \tag{25}$$

Bus voltage magnitudes must be kept at acceptable range, where V_{min} and V_{max} are the minimum and maximum acceptable voltage value of the ith bus, and V_i^t is the voltage magnitude of the ith bus at the tth time interval.

2.2.4 Feeder limit

$$\left|I_{f,i}^t\right| \le I_{f,i}^{Max} \quad i = 1, 2, \ldots, N_{feeder}, \tag{26}$$

where $I_{f,i}^t$ and $I_{f,i}^{Max}$ are the current amplitude at the tth time interval and its maximum current of the ith feeder, respectively. N_{feeder} is the number of feeders.

2.2.5 Transformer limit

$$\left|I_{t,i}^t\right| \le I_{t,i}^{Max} \quad i = 1, 2, \ldots, N_t, \tag{27}$$

where $I_{t,i}^t$ and $I_{t,i}^{Max}$ are the current amplitude at the tth time interval and its maximum current of the ith transformer, respectively. N_t is the number of transformers.

2.2.6 DGs constraints

In general, DG units in distribution network are modelled as PV or PQ nodes [1]. If DGs are considered as PV model, they should be able to generate reactive power to keep the voltage amplitudes within proper boundaries. In this study the DG units are modelled as PQ nodes.

2.2.7 Capacitor constraints

The minimum and maximum reactive power values of the capacitor are as follows:

$$Q_{cap}^{min} \le Q_{cap,i}^{t} \le Q_{cap}^{max}, \tag{28}$$

where Q_{cap}^{min}, Q_{cap}^{max} are the minimum and maximum values of generated reactive power of capacitor, respectively, and $Q_{cap,i}^t$ is the reactive power magnitude of the ith capacitor at the tth time interval.

2.2.8 ESSs constraint

In order to increase the efficiency and life of the ESSs, there are some restrictions that ESSs follow during a day [2]. These restrictions are as follows:

$$\mathrm{E}_{\mathrm{k}}^{\mathrm{h}} = \mathrm{E}_{\mathrm{k}}^{\mathrm{h}-1} + \sigma_{\mathrm{ch,k}} P_{\mathrm{ch,k}}^{\mathrm{h}} \times \Delta\mathrm{t} - \frac{1}{\sigma_{\mathrm{dis,k}}} P_{\mathrm{dis,k}}^{\mathrm{h}} \times \Delta\mathrm{t}, \tag{29}$$

$$\Delta\mathrm{t} = 1\mathrm{h},\ \mathrm{k} = 1, 2, \ldots \mathrm{NESS},\ \mathrm{h} = 1, 2, \ldots, 24, \tag{30}$$

$$\begin{aligned} \mathrm{E}_{\mathrm{k}}^{\min} \le \mathrm{E}_{\mathrm{k}}^{\mathrm{h}} \le \mathrm{E}_{\mathrm{k}}^{\max};\ \mathrm{k} = 1, 2, \ldots \mathrm{NESS} \\ \mathrm{h} = 1, 2, \ldots, 24, \end{aligned} \tag{31}$$

.

$$\mathrm{P}_{\mathrm{ch,k}}^{\mathrm{h}} \le \mathrm{P}_{\mathrm{ch,k}}^{\max};\ \mathrm{k} = 1, 2, \ldots, \mathrm{NESS},\ \mathrm{h} = 1, 2, \ldots, 24, \tag{32}$$

$$P_{\mathrm{dis},k}^{h} \le P_{\mathrm{dis},k}^{\max};\ k = 1, 2, \ldots, \mathrm{NESS},\ h = 1, 2, \ldots, 24, \tag{33}$$

where $\mathrm{E}_{\mathrm{k}}^{\mathrm{h}}$ is the amount of energy storage in the kth ESS at hth hour. $\mathrm{P}_{\mathrm{ch,k}}^{\mathrm{h}}$ and $\mathrm{P}_{\mathrm{dis,k}}^{\mathrm{h}}$ are the permitted rate of charge and (discharge) of kth ESS at hth hour, respectively. $\sigma_{\mathrm{ch,k}}$ and $\sigma_{\mathrm{dis,k}}$ are the efficiency of the kth ESS during charge and discharge, respectively. $\mathrm{E}_{\mathrm{k}}^{\max}$ and $\mathrm{E}_{\mathrm{k}}^{\min}$ are the maximum and minimum amount of the energy storage in kth ESS.$\mathrm{P}_{\mathrm{ch,k}}^{\max}$ and $\mathrm{P}_{\mathrm{dis,k}}^{\max}$ are the maximum charging and discharging rate of the kth ESS at hth hour.

3 Background theory

In the following the meta-heuristic algorithms i.e. PSO and SFLA are introduced.

3.1 Particle swarm optimization (PSO)

Particle swarm optimization is an evolutionary-based optimization algorithm inspired by the social behavior of bird's migration. In this algorithm, each particle represent a possible solution in the search space, and this particle has two parameters including position and velocity [26, 27]. velocity and position of ith particle are updated as follows:

$$\mathrm{v}_{\mathrm{i}}^{\mathrm{k}+1} = \mathrm{W}\mathrm{v}_{\mathrm{i}}^{\mathrm{k}} + \mathrm{c}_1\mathrm{r}_1\left(\mathrm{pb}_{\mathrm{i}}^{\mathrm{k}} - \mathrm{x}_{\mathrm{i}}^{\mathrm{k}}\right) + \mathrm{c}_2\mathrm{r}_2(\mathrm{gb}^{\mathrm{k}} - \mathrm{x}_{\mathrm{i}}^{\mathrm{k}}), \tag{34}$$

$$\mathrm{x}_{\mathrm{i}}^{\mathrm{k}+1} = \mathrm{x}_{\mathrm{i}}^{\mathrm{k}} + \mathrm{v}_{\mathrm{i}}^{\mathrm{k}+1}, \tag{35}$$

where x_i^k, v_i^k are the position and velocity of *ith* particle at *kth* iteration. c_1 and c_2 are are two positive constants, also as known social learning factor. r_1 and r_2 are random numbers between zero and one. pb_i^k is the best personal fitness of *ith* particle at kth iteration,gb^k is the best value among all the best personal fitness at *kth* iteration. W is the inertia weight, which usually decreases from 1 to 0 linearly according to Eq. (36):

$$W = W_{max} - \frac{W_{max} - W_{min}}{iter_{max}} \cdot iter, \tag{36}$$

iter is the current iteration number and $iter_{max}$ is the maximum iteration number.W_{max} and W_{min} are the minimum and maximum boundaries of inertia weight [28].

3.2 Shuffled frog leaping algorithm (SFLA)

The SFLA was introduced by Eusuff and Lanssey. This algorithm is inspired by the group life of the frogs, each frog in this algorithm represent a possible solution in the search space [29, 30]. In this algorithm, the initial population is divided into several memeplexes, the number of frogs in each memeplex is equal. Based on this categorization, there are two types of search techniques in this algorithm, the first technique is the local search, according to which the frogs in each memeplex exchange information, improve their position based on food (the best answer), and the second technique is the exchange of information between memeplexes, according to which, after each local search in the memeplexes, the information obtained is compared between the memeplexes, to implement this algorithm, first the initial parameters of the algorithm are initialized, and then the initial population with P frogs is generated randomly. The fitness of each frog is calculated and after sorting the population based on descending order, the total population is divided into m memeplexes, each of these memeplexes includes n members, then a local search for the mutation of the worst frogs is done toward the best frogs by Eqs. (*37*–*39*):

$$D_i = rand \cdot (X_b - X_w), \tag{37}$$

$$X_w^{new} = X_w + D_i, \tag{38}$$

$$-D_{min} \le D_i \le D_{max}, \tag{39}$$

where rand is a random number between zero and one. D_{min} and D_{max} are the minimum and maximum displacement boundaries of frog. The frog with best fitness in the entire population is shown as X_g. After applying the above changes, if the new frog has a better response than the worst frog in the group, is replaced. Otherwise, these actions are repeated with the replacement of X_b with X_w, if after applying the above changes, no suitable answers found, a new frog is generated randomly and it is replaced with the worst frog, this trend continues for the specified number of repetitions until the stopping criterion is reached.

4 Proposed approach

In the following the Improved Particle swarm optimization (IPSO), the Modified Shuffled Frog-leaping algorithm (MSFLA) and the IPSO-MSFLA algorithms are briefly introduced.

4.1 Improved particle swarm optimization (IPSO)

The learning factors c_1 and c_2 have a significant impact on determining the personal and global best solutions in original particle swarm optimization algorithm. In order to improve the performance of the original PSO algorithm, c_1 and c_2 are set as social parameters and shown in the equation below [31]:

$$C_j = 1 + \frac{1}{(1 + \exp(-\alpha \times F(g_{best}(k))^k} \quad j = 1, 2, \tag{40}$$

where $F(g_{best}(k))$ is the fitness of the global optimum solution at kth iteration. $g_{best}(k)$ cannot be selected according to the objective function fitness. The proposed method for calculating $g_{best}(k)$ is described in Sect. 5. α is inverse value of the best compromise objective value in the first iteration which is shown:

$$\alpha = \frac{1}{F\left(\left(g_{best}(1)\right)\right)}. \tag{41}$$

4.2 Modified shuffled frog leaping algorithm (MSFLA)

In original SFLA, only the worst frog in the memeplexes improves its position according to (42–43). This learning mechanism is inadequate for particles, especially that the better frogs have less learning chances. In addition, with this learning strategy, frogs in the memeplexes easily converge to local minimal. To avoid the above defects and improve the performance of the original SFLA, we will change the evolutionary process of frogs. In the new evolutionary process, all frogs participate in the evolutionary process, and frogs improve their position by learning from better frogs. Therefore, the leaping step of the ith frog is modified as:

$$\begin{aligned} D_i^{q+1} = c_1 \cdot r_1^q \cdot d_i^q + c_2 \cdot r_2^q \cdot \left(x_z^q - x_i^q\right), \\ i = 1, 2, \ldots, n, \end{aligned} \tag{42}$$

$$x_i^{q+1} = x_i^q + D_i^{q+1}, \tag{43}$$

where x_z^q is a randomly selected frog with better fitness than x_i^q. The better frogs generally maintain their movement while the worst mainly learns from better frogs. This strategy is useful to avoid falling to local minimum and to improve the SFLA performance. r_1 and r_2 are the random numbers between zero and one. c_1 and c_2 are the constant values. Now the steps in MSFLA can be provide as follows:

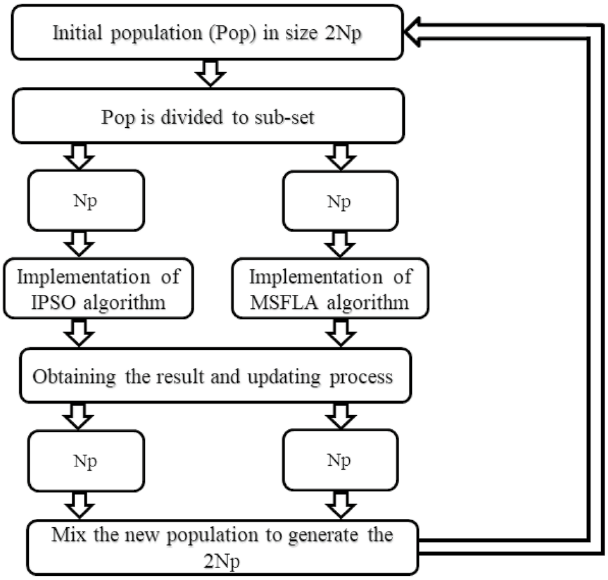

Fig. 2 The flowchart of hybrid algorithm

Step 1 Generate an initial population of the particles with randomly position and velocity.
Step 2 Calculate the objective function for all particles of population.
Step 3 Divide the particles into K memeplexes based on descending order of fitness value.
Step 4 Determine X_i and X_z in each memeplex.
Step 5 Update the position of ith frog based on equations (42-43).
Step 6 It should be noted that this procedure should be repeated for all memeplexes.
Step 7 Memeplex shuffle. at this step, in order to exchange information among all memeplexes, all memeplexes are combined together and restored again.
Step 8 Check the convergence criterion, If the convergence criterion is satisfied, the optimization process is finished, and the best frog (G_{best}) is selected as the final solution, otherwise return to Step 4.

4.3 Hybrid IPSO-MSFLA

The main idea of integrating the MSFLA and IPSO is to utilize the advantages of both algorithms. In order to implement a hybrid algorithm for solving the multi-objective DDFR&CA problem, $(2 \times \mathrm{Np})$ initial population are randomly generated. MSFLA and IPSO algorithms will start their optimization process with Np size population. The obtained new solutions are combined and divided again between two algorithms. Figure 2 shows the flowchart of the proposed hybrid algorithm.

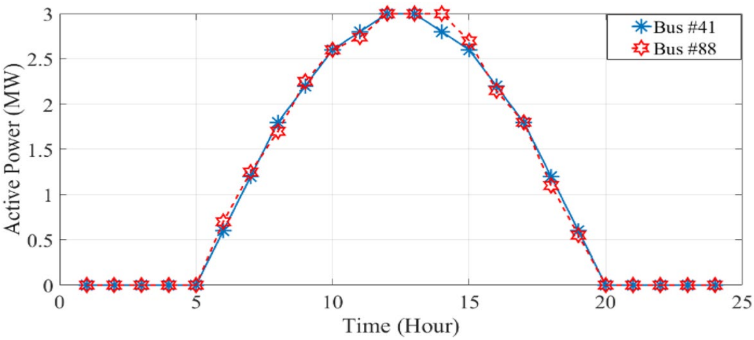

Fig. 3 Active power of solar PV units

5 Multi-objective optimization methodology

Multi-objective optimization refers to the simultaneous optimization of two or more conflicting objectives associated with specific constraints. Multi-objective optimization problems present a possibly high number of solutions rather than a single optimal solution [31]. The problem is described as follows:

$$\begin{aligned} &\mathrm{Min}\ \mathrm{f(x)} = \left[\mathrm{f_1(x), f_2(x), \ldots f_n(x)}\right]^{\mathrm{T}}, \\ &\mathrm{G_j(x)} \geq 0,\ \mathrm{H_i(x)} = 0, \end{aligned} \tag{44}$$

where $\mathrm{f_i(x)}$ is the ith objective function and $\mathrm{H_i(x)}$ and $\mathrm{G_j(x)}$ are equal and unequal constraints. n is the number of objective functions and x is the optimization variables vector.

5.1 Fuzzy model for multi-objective optimization

Since the objective functions are not precise and are not in the same range, so fuzzy sets are used to replace each objective function as a value between 0 and 1. A fuzzy set is generally shown by a membership function (μ_{i}) [32].The mathematical model for membership function as defined (*45*):

$$\mu_i(x) = \begin{cases} 1 & f_i(X) \leq f_i^{min} \\ 0 & f_i(X) \geq f_i^{max} \\ \frac{f_i^{max} - f_i(X)}{f_i^{max} - f_i^{min}} & f_i^{min} \leq f_i(X) \leq f_i^{max} \end{cases}, \tag{45}$$

where μ_{i} is the fuzzy set for ith objective function i.e. $\mathrm{f_i(X)}$. $\mathrm{f_i^{min}}$ and $\mathrm{f_i^{max}}$ are lower and upper bounds of the objective function. To solve multiple objectives problems, the fuzzy solution can be calculated as (*46*):

$$\mathrm{F(x)} = \min\{\mu_1(\mathrm{x}), \mu_2(\mathrm{x}), \mu_3(\mathrm{x})\}. \tag{46}$$

5.2 Pareto optimal solution

The Pareto optimal method is an appropriate approach to the multi-objective problem, which can be used to obtain a set of solutions rather than one [31]. This method works based on the dominance concept, the solution x_2 is dominated by x_1, when the following conditions are met:

$$\forall \mathrm{i} \in \{1, 2, \ldots \mathrm{N_{obj}}\}, \quad \mathrm{f_i}(\mathrm{x_1}) \le \mathrm{f_i}(\mathrm{x_2}), \tag{47}$$

$$\exists \mathrm{j} \in \{1, 2, \ldots \mathrm{N_{obj}}\}, \quad \mathrm{f_j}(\mathrm{x_1}) < \mathrm{f_j}(\mathrm{x_2}). \tag{48}$$

5.3 Fuzzy decision strategy

In this paper, an external repository is used to store all non-dominant solutions in each iteration. The solutions that are stored in this repository in all iterations are sorted based on the type of decision making strategy. During this process, the best Compromise solution is selected by choosing the top solutions in this collection [31] as follows:

$$\mathrm{N}_{\mu}(j) = \frac{\sum_{\mathrm{k}=1}^{\mathrm{n}} W_{\mathrm{k}} \times \mu_{\mathrm{fk}}}{\sum_{\mathrm{j}=1}^{\mathrm{m}} \sum_{\mathrm{k}=1}^{\mathrm{n}} W_{\mathrm{k}} \times \mu_{\mathrm{fk}}}, \tag{49}$$

where m is the number of non-dominant solutions, n is the number of objective functions, W_k is weight of the kth objective function. Value of W_k is selected by the operator based on the importance of the objective function.

6 Simulation results

6.1 Evaluation of the IPSO-MSFLA algorithm to solve the DDFR&CA problem

The proposed IPSO-MSFLA algorithm is used to solve the single and multi-objective DDFR&CA problems in absence and presence of DGs, ESSs and PV units in IEEE95-node test system [33]. The IEEE95-node test system consists of three DGs with capacity 1000 kW which are located at nodes #6, #25, #50, and four capacitors with capacity of 100 kVAr located at nodes #10, #20, #34, #70, two 3000 kW PV units installed on buses #41, #88 and their relevant 300 (kWh) energy storage units. The cost of sub-station is 0.041 $/kWh and the related costs of DG units are 0.042 $/kWh for all DGs and 0.041 $ for each switching. Figures 3 and 14 (see Appendix) show the single-line diagram of 95-node test system and active power generation of PV units. MATLAB programing code for the IPSO-MSFLA algorithm and the proposed objective functions are developed. The load profile for the 24-time intervals is shown in Table 1. According to the Fig. 3, it is clear that, the solar radiation is from 5 a.m. to 8 p.m., So the generated power is at this time interval. The maximum generated power value is from 10 a.m. to 3 p.m., which the maximum level of solar radiation is at this time interval. The maximum output power of each PV unit is 3 MW at the peak of the solar radiation, this pattern used in this study for each solar cell is extracted from in [2] but on a larger scale. The initial values of the VSI, operation cost and ENS before Distribution Feeder Reconfiguration are 1.0530 Pu, $141,998.91 and 348.56 kWh/year, respectively. Then, in order to better analyse single-objective optimization, the reduction amount of objective functions relative to the initial values before DDFR is presented as percentage format.

6.1.1 DDFR&CA problem without DGs, ESSs and PV units (case 1)

In this case, the DDFR&CA problem is solved without DGs, ESSs and PV units in the 95-node test system. The intension in this case study is first to evaluate the capability of the proposed algorithm in solving the DDFR&CA problem and second the effects of DGs, ESSs and PVs on different objective functions which are studied in the next section. The best obtained results from proposed IPSO-MSFLA algorithm for each objective are highlighted in Table 2. Tables 3 and 4 show the comparison between the results of the proposed IPSO-MSFLA and other algorithms to optimize operation cost and ENS in case 1. It should no noted that because there is no similar article for comparison, two hybrid algorithms i.e. Hybrid PSO-SFLA [6] and PSO-MSFLA [23] are selected amongst published papers and simulated to solve DDFR&CA problem. Tables 5 and 6 represent the optimal switching state and optimal capacity of capacitors within 24 h related to ENS optimization for case 1.

Comparison of results for the various objective functions in Table 2, the conflict between the various objective functions is clear. For example, the ENS value is 339.842 (kWh/year), when the objective is cost minimization. The optimal value of ENS is 326.323 (kWh/year), when the objective is ENS minimization. The difference between objective functions shows that three objective functions are in contradiction so, they do not improve all together. However, in the multi-objective optimization using the Pareto-optimality concept in the proposed IPSO-MSFLA algorithm, a good compromise between the objective functions can be made to obtain the optimal solution for two or three objective functions. In this section Pareto-optimality concept is used to solve the multi-objective DDFR&CA problem in the absence of DGs, ESSs and PV units. All two and three-dimensional Pareto-optimal solutions for different objective functions are shown in Figs. 4, 5, 6 and 7 in order to prove the ability of the proposed IPSO-MSFLA algorithm in solving DDFR&CA problem. Referring to Figs. 4, 5, 6 and 7, it is clear that, the best obtained value for each objective function in all Pareto-fronts is somewhat close to its corresponding optimal value (Table 2) when each objective function is optimized individually. Therefore, the ability of the proposed IPSO-MSFLA to solve the multi-objective optimization problem is proved. To illustrate the superiority of the proposed IPSO-MSFLA algorithm, the single-objective results for operation cost and ENS optimization obtained by the proposed algorithm and other algorithms are listed in the Tables 3 and 4.

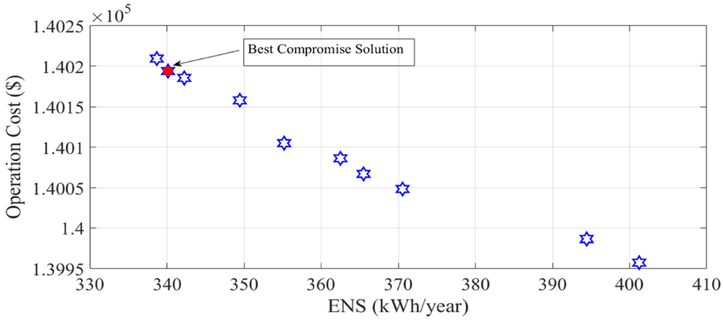

Fig. 4 Two-dimensional Pareto-front for operation cost and ENS

Table 1 The load profile for different time intervals

BUS	1	2	3	4	5	6	7	8	9	10	11	12
1	1	1	1	1	1	1	1	1	1	1	1	1
2–14	1	1	1	1.25	1.25	1.25	1.5	1.5	1.5	1.75	1.75	1.75
15–29	0.25	0.25	0.25	0.5	0.5	0.5	0.75	0.75	0.75	1	1	1
30–45	1	1	1	0.75	0.75	0.75	0.5	0.5	0.5	0.25	0.25	0.25
46–62	1	1	1	1.25	1.25	1.25	1.5	1.5	1.5	1.75	1.75	1.75
63–76	0.25	0.25	0.25	0.5	0.5	0.5	0.75	0.75	0.75	1	1	1
77–95	1	1	1	0.75	0.75	0.75	0.5	0.5	0.5	0.25	0.25	0.25
BUS	13	14	15	16	17	18	19	20	21	22	23	24
1	1	1	1	1	1	1	1	1	1	1	1	1
2–14	1.5	1.5	1.5	1.25	1.25	1.25	1	1	1	0.75	0.75	0.75
15–29	1.25	1.25	1.25	1.5	1.5	1.5	1.75	1.75	1.75	1.5	1.5	1.5
30–45	0.5	0.5	0.5	0.75	0.75	0.75	1	1	1	1.25	1.25	1.25
46–62	1.5	1.5	1.5	1.25	1.25	1.25	1	1	1	1.25	1.25	1.25
63–76	1.25	1.25	1.25	1.5	1.5	1.5	1.75	1.75	1.75	1.5	1.5	1.5
77–95	0.5	0.5	0.5	0.75	0.75	0.75	1	1	1	1.25	1.25	1.25

These results are obtained by 15 dependent trials for each algorithm. It is obvious that the proposed hybrid algorithm provides a better solution than others. According to Table 2, it is clear that the value of the VSI obtained from the IPSO-MSFLA algorithm is reduced about 2.1% than the initial state. Also, according to Tables 3 and 4 the ENS and operation cost are reduced about 5% and 1.51% than the initial state. In the initial state, feeder reconfiguration has not been implemented in the test network. The operation cost saving obtained from the proposed hybrid algorithm is about $ 2130

Table 2 Best solution obtained by the proposed IPSO-MSFLA algorithm for different objective functions for Case 1

Objective functions	ENS (kWh/year)	Operation cost ($)	VSI (Pu)
ENS (kWh/year)	329.312	140,188.31	1.0492
Operation Cost ($)	339.842	139,865.14	1.0459
VSI (Pu)	348.414	140,268.49	1.0304

Table 3 Results of proposed IPSO-MSFLA and other algorithms for operation cost for 15 Trials

Algorithm	Operation cost ($)			
	Best	Worst	Standard deviation	Reduction (%)
PSO	140,290.22	140,480.41	58.42	1.21
SFLA	140,209.43	140,381.24	56.15	1.26
Hybrid PSO-SFLA [23]	140,130.51	140,277.57	53.18	1.30
PSO-MSFLA [7]	140,009.42	140,145.52	51.89	1.42
IPSO-MSFLA	139,865.14	139,985.21	49.18	1.51

Table 4 Results of proposed IPSO-MSFLA and other algorithms for ENS for 15 Trials

Algorithm	ENS (kWh/year)			
	Best	Worst	Standard deviation	Reduction (%)
PSO	342.475	355.214	5.49	2
SFLA	338.214	349.126	5.25	3
Hybrid PSO-SFLA [23]	335.651	343.258	4.98	4
PSO-MSFLA [7]	333.545	339.426	4.57	4.5
IPSO-MSFLA	329.312	333.415	4.15	5

6.1.2 DDFR&CA problem with DGs, ESSs and PV units (case 2)

In this case, the proposed IPSO-MSFLA algorithm is implemented to solve a single and a multi-objective DDFR&CA problem in presence of DGs, ESSs and solar PV units in IEEE95-node test system. The best obtained results for each objective function are highlighted in Table 7. Tables 8 and 9 show the comparison between the results of the proposed IPSO-MSFLA algorithm and other algorithms for ENS and operation cost optimization in Case 2, respectively. Tables 10 and 11 represent the optimal switching state within 24 h related to ENS and operation cost optimization for Case 2. Tables 12 and 13 represent the optimal capacity of capacitors and DGs outputs within 24 h related to ENS and operation cost optimization for Case 2. Figure 8 represent the optimal ESSs outputs within 24 h related to ENS optimization

Table 5 The optimum switching scheme obtained from the proposed IPSO-MSFLA algorithm in ENS optimization for case1

L.L	Open reconfiguration switches										
	Sw1	Sw2	Sw3	Sw4	Sw5	Sw6	Sw7	Sw8	Sw9	Sw10	Sw11
1	4	7	8	22	25	35	66	65	74	32	28
2	4	43	79	20	26	35	67	65	85	87	30
3	4	40	15	81	45	35	61	64	85	71	83
4	77	43	15	81	82	33	19	56	74	32	83
5	77	5	15	39	26	84	16	58	72	71	27
6	4	40	15	39	49	51	19	65	72	76	30
7	4	78	15	81	82	33	19	56	74	87	27
8	69	41	15	39	82	52	19	60	74	31	30
9	4	43	15	39	49	35	19	65	55	87	29
10	77	78	15	21	82	33	67	65	53	32	30
11	4	7	15	39	49	35	19	60	74	71	30
12	4	5	15	81	49	52	67	86	74	71	83
13	4	78	79	22	82	84	67	65	74	32	83
14	77	78	10	22	49	84	66	65	72	87	30
15	4	41	15	22	49	35	80	65	72	75	83
16	77	43	79	39	26	52	67	65	85	87	27
17	77	78	15	39	82	35	19	65	53	76	83
18	77	43	79	39	26	52	67	65	74	71	83
19	4	43	15	39	26	35	19	65	74	87	83
20	77	41	15	20	26	52	66	56	74	71	30
21	68	7	15	81	26	52	19	60	74	71	30
22	4	43	15	39	49	35	19	65	85	32	83
23	4	5	79	81	49	84	66	65	85	32	30
24	4	7	15	22	26	35	80	65	72	31	30

LL Load Level

for Case 2, also Fig. 9 represent the optimal ESSs outputs within 24 h related to operation cost optimization for Case 2.

It is clear from Table 7, the control settings correspond to the ENS is reduced while VSI of the system and operation cost are increased. Therefore, it is necessary to solve the multi-objective DDFR&CA problem for this case. All two and three-dimensional Pareto-optimal solutions for different objective functions using proposed IPSO-MSFLA algorithm are shown in Figs. 10, 11, 12 and 13. These figures show that the proposed IPSO-MSFLA algorithm can handle this optimization problem regardless of its complexity and number of objective functions.

As shown in Figs. 10, 11, 12 and 13, the proposed IPSO-MSFLA algorithm can find several non-dominant solutions for each optimization case. A best compromise solution is chosen from the solution of the Pareto front, and part of the solution can be ignored. In other words, an optimal solution is chosen to optimize two or

Table 6 The optimum capacity of capacitor obtained from the proposed IPSO-MSFLA algorithm in ENS optimization for case1

L.L	Capacitor switching (kVAr)			
	Cap1	Cap2	Cap3	Cap4
1	71	95	100	100
2	100	100	100	100
3	100	100	100	100
4	20.5	87	100	100
5	100	100	100	93.5
6	22	100	80.5	100
7	99.5	96.5	99	100
8	100	79.5	83	24
9	100	100	95.5	100
10	100	98.5	100	100
11	100	40	96	100
12	100	100	100	94.5
13	5	99.5	20.5	100
14	98	71	14.5	100
15	89.5	100	100	100
16	96	100	5	58
17	82.5	100	100	100
18	97	86	100	99.5
19	14.5	100	100	100
20	100	100	63.5	100
21	62.5	100	99.5	100
22	100	100	97	100
23	96	100	100	100
24	100	48	100	100

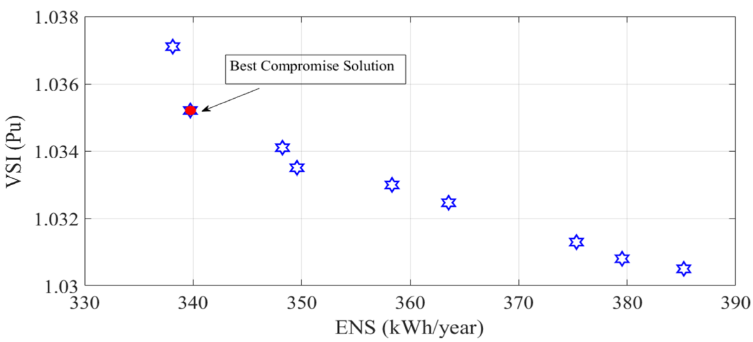

Fig. 5 Two-dimensional Pareto-front for VSI and ENS

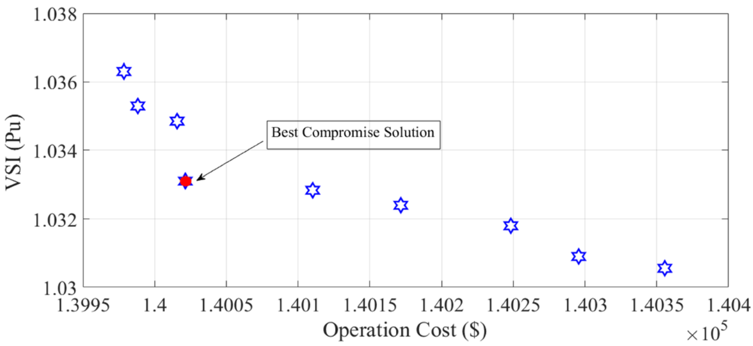

Fig. 6 Two-dimensional Pareto-front for VSI and operation cost

three objective functions. However, the system operator can apply his/her personal preference in choosing any one of solutions. Tables 8 and 9 show the optimum values for ENS and operation cost in presence of DGs, ESSs and PV units employing PSO, MSFLA and IPSO-MSFLA algorithms. The best, worst, average results along with the standard deviation for PSO, MSFLA and IPSO-MSFLA algorithms in 15 dependent trials are identified.

The better results of the proposed IPSO-MSFLA algorithm are obvious from Tables 8 and 9. The comparison the results of case 2 with cases 1 shows that including DGs, ESSs and PV units in the test network, the ENS and VSI are reduced which are desired outcomes of this study. According to Table 7 the value of the VSI obtained from the IPSO-MSFLA algorithm is reduced about 2.3% than the initial state. Also, with refer to Tables 8 and 9, it is clear that the values of ENS and operation cost obtained from the IPSO-MSFLA algorithm are reduced by 9.5% and 1.26% than the initial state. In the initial state, feeder reconfiguration is not performed in the test network. The amounts of operation cost saving obtained from the proposed hybrid algorithm is about $ 1740

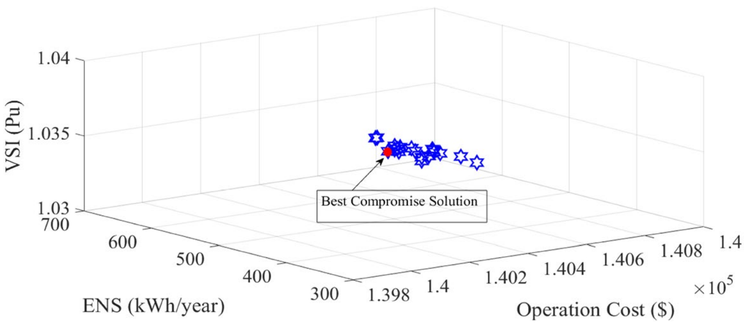

Fig. 7 Three-dimensional Pareto-front for VSI, ENS and operation cost

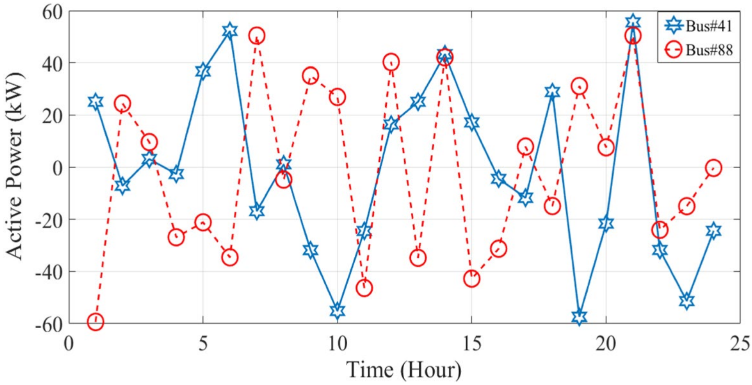

Fig. 8 Active power output of ESSs obtained from the proposed algorithm in ENS optimization for case 2

Table 7 Best solution obtained by the proposed IPSO-MSFLA algorithm for different objective functions in case 2

Objective functions	ENS (kWh/year)	Operation cost ($)	VSI (Pu)
ENS (kWh/year)	314.762	140,299.54	1.0465
Operation cost ($)	328.215	140,260.61	1.0423
VSI (Pu)	342.314	140,331.31	1.0294

Table 8 Results of proposed IPSO-MSFLA and other algorithms for ENS for 15 Trials

Algorithm	ENS (kWh/year)			
	Best	Worst	Standard deviation	Reduction (%)
PSO	331.372	350.235	6.55	4.9
SFLA	323.515	338.765	6.23	7.1
Hybrid PSO-SFLA [23]	321.563	333.743	5.89	7.9
PSO-MSFLA [7]	318.412	327.554	5.55	8.5
IPSO-MSFLA	314.762	321.778	4.85	9.5

Table 9 Results of proposed IPSO-MSFLA and other algorithms for operation cost for 15 Trials

Algorithm	Operation cost ($)			
	Best	Worst	Standard deviation	Reduction (%)
PSO	140,279.15	140,398.24	64.15	1.11
SFLA	140,269.88	140,385.56	58.45	1.14
Hybrid PSO-SFLA [23]	140,265.61	140,381.62	55.76	1.19
PSO-MSFLA [7]	140,263.45	140,378.84	53.14	1.21
IPSO-MSFLA	140,260.61	140,374.62	51.88	1.23

Table 10 The optimum switching scheme obtained from the proposed IPSO-MSFLA algorithm in ENS optimization for case2

LL	Open reconfiguration switches										
	Sw1	Sw2	Sw3	Sw4	Sw5	Sw6	Sw7	Sw8	Sw9	Sw10	Sw11
1	3	7	8	22	26	35	80	65	55	71	83
2	68	40	15	39	49	35	67	65	55	32	27
3	4	78	79	39	26	52	66	65	55	76	83
4	4	7	15	39	82	52	19	65	55	76	83
5	4	40	15	22	26	35	66	65	55	87	83
6	68	43	15	22	26	52	67	56	72	76	30
7	77	7	15	39	49	33	67	56	72	71	30
8	77	7	15	22	26	35	67	56	55	71	30
9	68	40	15	36	49	50	66	65	55	32	27
10	4	40	15	39	26	52	67	65	85	76	27
11	70	41	15	22	82	35	19	65	72	76	30
12	77	7	15	22	26	52	19	65	74	87	30
13	70	7	15	39	49	52	67	86	55	71	30
14	77	43	15	39	82	35	67	65	74	87	30
15	68	40	15	22	49	52	19	65	55	32	30
16	4	40	15	22	26	84	80	56	72	76	83
17	77	7	15	22	49	35	19	65	55	76	30
18	77	43	15	39	26	84	67	65	72	32	30
19	3	43	15	22	49	34	67	65	85	87	30
20	77	43	15	81	26	52	67	65	74	32	27
21	70	43	79	81	49	52	67	86	85	32	83
22	77	43	15	39	26	35	80	65	55	32	30
23	4	43	15	39	49	52	19	65	85	76	30
24	4	43	10	39	49	35	66	65	55	76	30

7 Pareto-solution analysis

In a multi-objective optimization problem in contrast to a single objective optimization, there is a set of Pareto solutions rather than an optimal solution. In this paper, two different indices i.e.: Diversification Metric (DM) and Generational Distance (GD) are used to validate the Pareto optimal front.

Diversification Metric (DM) For an *N*-dimensional optimization problem, if there is k number of points in the Pareto-front, the Centroid C_j for jth dimension is calculated as follows [7]:

$$C_j = \frac{\sum_{r=1}^{k} Y_{nr}}{k}, \tag{50}$$

$$n = 1, 2, \ldots, N_{obj}, \tag{51}$$

Table 11 The optimum switching scheme obtained from the proposed IPSO-MSFLA algorithm in OP-Cost optimization for case2

LL	Open reconfiguration switches										
	Sw1	Sw2	Sw3	Sw4	Sw5	Sw6	Sw7	Sw8	Sw9	Sw10	Sw11
1	69	42	15	81	26	35	19	65	55	75	30
2	70	7	79	22	49	35	80	58	72	87	83
3	68	7	15	37	49	35	19	65	55	87	83
4	68	42	15	81	49	52	19	60	55	32	30
5	4	7	15	22	49	35	66	60	55	76	30
6	70	7	15	39	26	84	80	65	72	32	30
7	70	43	15	81	49	84	19	60	55	32	83
8	69	43	15	39	82	52	80	60	55	32	30
9	69	43	15	22	26	84	19	86	55	32	30
10	68	78	15	39	49	84	19	58	55	87	27
11	68	43	15	22	26	35	19	62	55	32	30
12	68	43	15	22	26	52	19	62	55	32	30
13	69	43	15	39	26	35	19	60	55	32	27
14	70	7	79	22	82	84	19	60	55	32	30
15	70	7	15	81	49	35	19	86	55	76	28
16	68	7	14	39	49	35	19	60	55	87	27
17	70	78	13	39	49	84	19	60	55	76	30
18	4	43	79	39	82	35	80	60	74	87	30
19	4	43	15	38	82	35	19	60	55	32	30
20	70	43	79	81	26	35	80	60	55	32	28
21	4	7	15	22	26	35	19	60	72	32	83
22	70	7	15	22	82	52	19	60	85	87	30
23	69	43	15	22	82	52	19	65	55	76	83
24	70	43	15	39	26	84	19	86	55	87	30

LL Load level

where Y_{nr} is nth dimension of the rth point, finally the formulation DM is as follows, It is noted that more values for DM show that all generated arrays are close to each other:

$$DM = \sum_{n=1}^{N_{obj}} \sum_{r=1}^{k} (Y_{nr} - C_r)^2. \quad (52)$$

Generational distance (GD) GD measures how far is each solution in the non-dominated solutions set [7], and is modelled as follows:

$$GD = \frac{\sqrt{\sum_{s=1}^{n} E_s^2}}{k}, \quad (53)$$

where E_s is the Euclidean geometric distance between each of these non-dominant solutions and the closest number of Pareto-optimal collection. Therefore, the lower value for the GD parameter is more favourable.

Table 12 The optimum capacity of capacitor and DGs outputs obtained from the proposed algorithm in ENS optimization for case2

LL	Capacitors output (kVAr)				DGs output (kW)		
	Cap1	Cap2	Cap3	Cap4	DG1	DG2	DG3
1	97.5	94	99	43	960	985	970
2	99	97	97.5	96	1000	975	975
3	99	88	97.5	97	975	975	960
4	97.5	97.5	99	46	970	970	875
5	100	98.5	94	97.5	990	975	975
6	94	97	97	98.5	990	975	975
7	97.5	100	97.5	99.5	950	975	975
8	100	99	99	97.5	990	900	975
9	100	97.5	97.5	100	975	975	990
10	97.5	99	99	99	975	970	970
11	99.5	97.5	99.5	97.5	970	975	975
12	97.5	97.5	96	97	975	970	990
13	99	99	97	97	975	975	970
14	97.5	97.5	97.5	97.5	975	975	900
15	97.5	97.5	97.5	97.5	995	970	975
16	100	97.5	99.5	96	970	960	960
17	96	97	97.5	97.5	925	975	975
18	100	97.5	97.5	97.5	985	975	970
19	96	100	97.5	97.5	1000	995	990
20	99.5	97.5	35	96	990	970	960
21	100	97	99	99	1000	935	975
22	99	97.5	97	97.5	975	975	985
23	89.5	97	96	97.5	995	985	990
24	97	97.5	97.5	97.5	985	975	970

The obtained best values of GD and DM in two-dimensional Pareto-fronts related to Multi-Objective DDFR&CA problem are shown in Table 14, which are achieved by the proposed IPSO-MSFLA algorithm.

From Table 14, it is obvious that the proposed hybrid algorithm is able to handle multi-objective optimization problems very well.

8 Conclusion

In this study, a new hybrid evolutionary algorithm based on improved particle swarm optimization and modified shuffled frog leaping algorithm (IPSO-MSFLA) is presented for dynamic distribution feeder reconfiguration (DDFR) along with capacitor allocation (DDFR&CA) problem in the absence and presence of DGs, ESSs and PV units. The considered objective functions are: operation cost, ENS and VSI. Constraints of the problem are: preserving the radial structure of the network, limits for bus voltages, limits for line currents and capacity of transformers.

Table 13 The optimum capacity of capacitor and DGs outputs obtained from the proposed algorithm in OP-Cost optimization for case2

LL	Capacitors output (kVAr)				DGs output (kW)		
	Cap1	Cap2	Cap3	Cap4	DG1	DG2	DG3
1	8.5	9.5	5	5	50	50	1000
2	5	5	75	31.5	50	950	60
3	5	5	44	5	50	115	50
4	5	5	29	93	245	1000	50
5	5	97.5	5	5	50	50	120
6	51.5	5	5	5	50	425	50
7	5	67.5	61.5	5	65	990	955
8	5	100	5	5	50	50	50
9	91.5	5	6	94.5	50	50	50
10	5	9.5	96.5	75	50	50	50
11	9.5	5	9.5	5	75	50	400
12	5	5	9.5	5	50	50	50
13	7.5	5	9.5	5	50	50	50
14	75.5	5	5	5	50	50	635
15	5	5	89.5	5	420	65	50
16	5	5	10	100	115	50	50
17	5	5	5	5	50	50	95
18	5	9.5	15	5	50	95	530
19	98	100	5	9	200	50	985
20	69	13.5	5	100	50	50	965
21	5	5	5	8	50	95	685
22	5	5	23	5	50	50	930
23	5	17	9	5	50	50	50
24	5	6.5	5	5	65	50	50

LL Load level

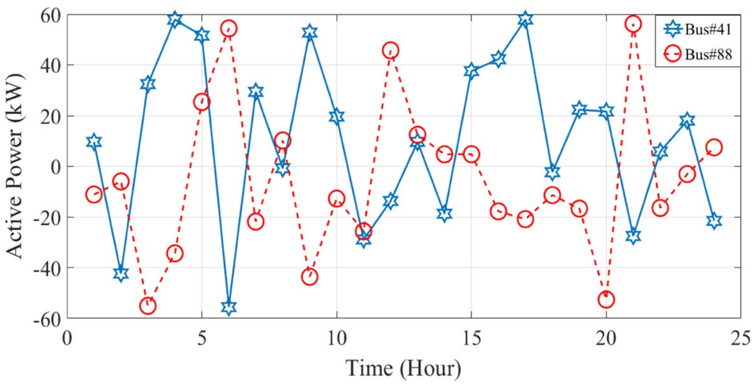

Fig. 9 Active power output of ESSs obtained from the proposed algorithm in Operation Cost optimization for case 2

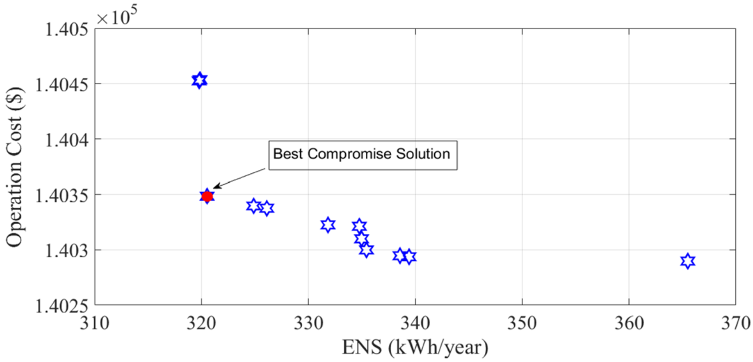

Fig. 10 Two-dimensional Pareto-front for operation cost and ENS

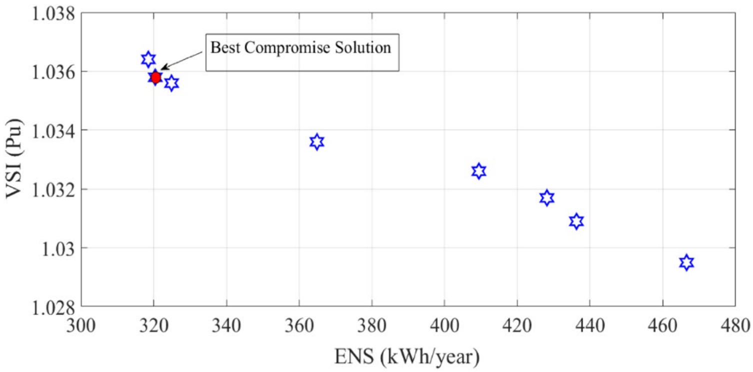

Fig. 11 Two-dimensional Pareto-front for VSI cost and ENS

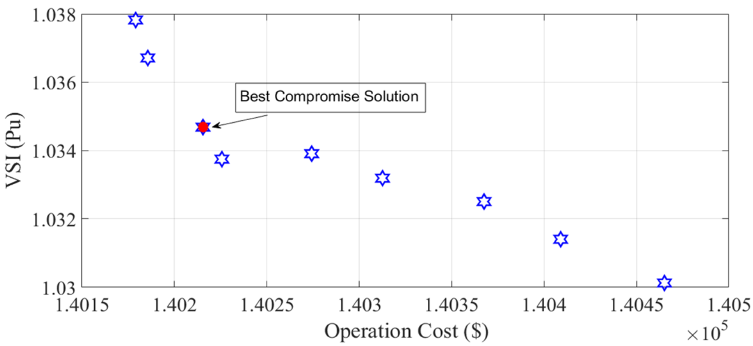

Fig. 12 Two-dimensional Pareto-front for VSI and operation cost

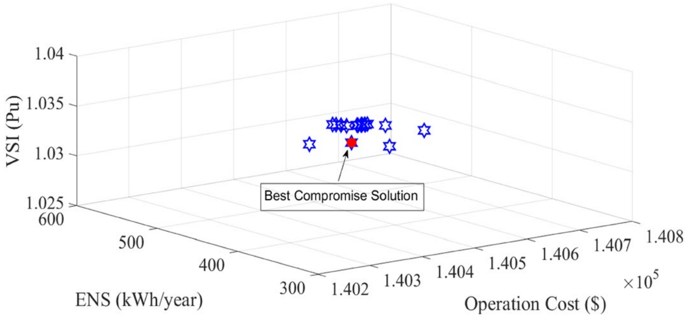

Fig. 13 Three-dimensional Pareto-front for VSI, ENS and operation cost

Table 14 Best GD and DM for Pareto-optimal solutions obtained by the IPSO-MSFLA algorithm

Dimensional of the problem	Indicators			
	GD (case 1)	GD (case 2)	DM (case 1)	DM (case 2)
ENS&operation cost	4.99	2.295	71,220.32	36,340.56
ENS&VSI	1.24	3.354	2291.523	30,457.42
Operation cost&VSI	8.842	7.111	89,977.52	17,838.43

With regard to multi-objective DFR problems, in the proposed hybrid algorithm the concept of Pareto optimality is utilized. The multi-objective DDFR&CA problem is solved with and without DGs, ESSs and solar PV units and the obtained results are provided through tables and figures. The obtained results from the proposed IPSO-MSFLA algorithm are compared with other algorithms in single-objective and multi-objective optimization considering different objective functions. The obtained results justify the superior performance of the proposed hybrid algorithm in solving such more complex optimization problem. Finally, the following results can be summarized from this paper.

- The proposed IPSO-MSFLA algorithm has a good performance to solve the DDFR&CA problem in IEEE95-nodes test system.
- The proposed IPSO-MSFLA algorithm can handle single and multi-objective optimization problems regardless of their complexity and scale.
- Application of DGs, ESSs and PV units leads to reduction in ENS objective and improvement in VSI objective function.
- DFR and capacitor allocation in distribution system will upgrade VSI and ENS indices. In addition, using the ENS along with the operation cost, the economic and reliable operation of system are provided.

Appendix

See Fig. 14

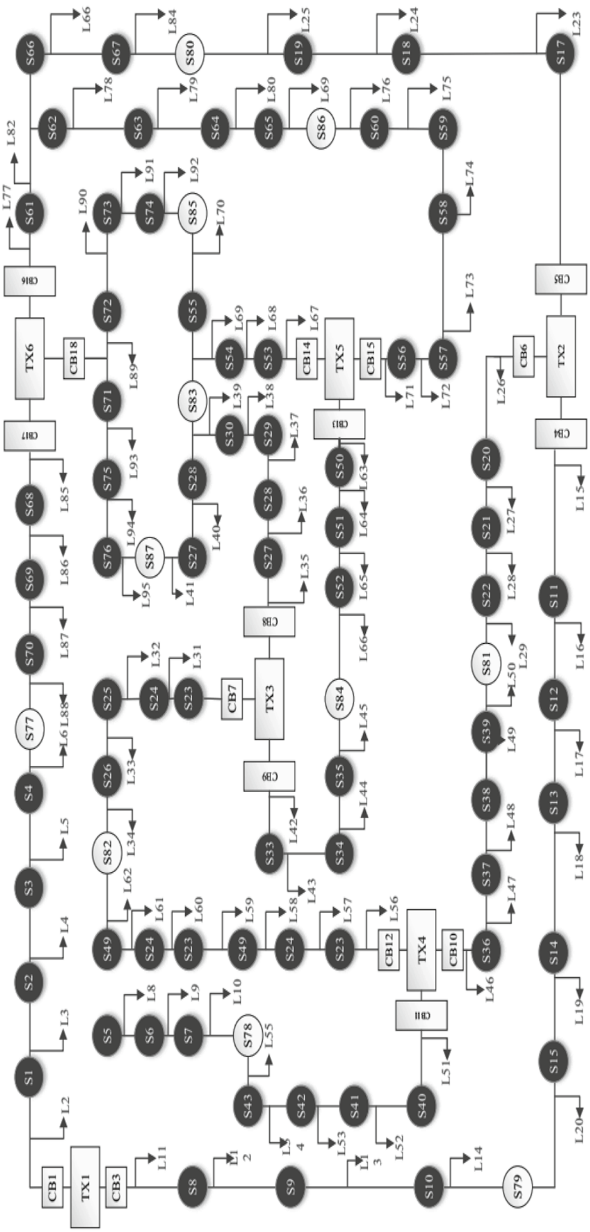

Fig. 14 One-line diagram of IEEE-95 bus test system

References

1. Niknam, T., Azad Farsani, E., Bahmani Firouzi, B.: A new tribe modified shuffled frog leaping algorithm for multi-objective distribution feeder reconfiguration considering distributed generator units. Euro Trans Electr Power **22**, 308–333 (2012)
2. Azizi Vahed, A., Naderi, E., Narimani, H., Fathi, M., Narimani, M.R.: A new bi-objective approach to energy management in distribution networks with energy storage systems. IEEE Trans Sustain Energy **9**(1), 56–64 (2017)
3. Mishra, Sivkumar, Das, Debapriya, Paul, Subrata: A comprehensive review on power distribution network reconfiguration. Energy Syst **8**(2), 227–284 (2017)
4. Kashem, M.A., Ganapathy, V., Jamson, G.B.: Network reconfiguration for load balancing in distribution networks. Proc Inst Electr Eng Gen Transm Distrib **146**, 563–567 (1999)
5. Morton, A.B., Mareels, I.M.Y.: An efficient brute-force solution to the network reconfiguration problem. IEEE Trans Power Deliv **15**, 996–1000 (2000)
6. Sarma, N.D.R., Rao, K.S.P.: A new 0-1 integer programming method of feeder reconfiguration for loss minimization in distribution systems. Electr Power Syst Res **33**, 125–131 (1995)
7. Azizivahed, A., Narimani, H., Naderi, E., Fathi, M., Narimani, M.R.: A hybrid evolutionary algorithm for secure multi-objective distribution feeder reconfiguration. Energy **138**, 355–373 (2017)
8. Rani, D.S., Subrahmanyam, N., Sydulu, M.: Multi-objective invasive weed optimization-An application to optimal network reconfiguration in radial distribution systems. Int J Electr Power Energy Syst **73**, 932–942 (2015)
9. Guan, W., Tan, Y., Zhang, H., Song, J.: Distribution system feeder reconfiguration considering different model of DG sources. Int J Electr Power Energy Syst **68**, 210–221 (2015)
10. Kavousi-Fard, A., Abbasi, A., Rostami, M.A., Khosravi, A.: Optimal distribution feeder reconfiguration for increasing the penetration of plug-in electric vehicles and minimizing network costs. Energy **93**, 1693–1703 (2015)
11. Sedighizadeh, M., Bakhtiary, R.: Optimal multi-objective reconfiguration and capacitor placement of distribution systems with the hybrid big bang-big crunch algorithm in the fuzzy framework. Ain Shams Eng J **7**, 113–129 (2016)
12. Esmaeili, M., Sedighizadeh, M., Esmaeili, M.: Multi-objective optimal reconfiguration and DG (Distributed Generation) power allocation in distribution networks using big bang-big crunch algorithm considering load uncertainty. Energy **103**, 86–99 (2016)
13. Bayat, A., Bagheri, A., Noroozian, R.: Optimal siting and sizing of distributed generation accompanied by reconfiguration of distribution networks for maximum loss reduction by using a new UVDA-based heuristic method. Int JElectr Power Energy Syst **77**, 360–371 (2016)
14. Narimani, M.R., AziziVahed, A., Azizpanah, R., Javidsharifi, M.: Enhanced gravitational search algorithm for multi-objective distribution feeder reconfiguration considering reliability, loss and operational cost. IET Gener Transm Distrib **8**(1), 1–15 (2014)
15. Miri Larimi, M., Haghifam, M.R., Moradkhani, A.: Risk-based reconfiguration of active electric distribution networks. IET Gener Transm Distrib **10**(4), 1006–1015 (2016)
16. Alemohammad, S.H., Mashhour, E., Saniei, M.: A market-based method for reconfiguration of distribution network. Electr Power Syst Res **125**, 15–22 (2015)
17. Ch, Y., Goswami, S.K., Chatterjee, D.: Effect of network reconfiguration on power quality of distribution system. Int J Electr Power Energy Syst **83**, 87–95 (2016)
18. Mahboubi-Moghaddam, E., Narimani, M.R., Khooban, M.H., Azizivahed, A., Javid Sharifi, M.: Multi-objective distribution feeder reconfiguration to improve transient stability, and minimize power loss and operation cost using an enhanced evolutionary algorithm at the presence of distributed generations. Electr Power Energy Syst **76**, 35–43 (2016)
19. Ghazi, Z., Doustmohammadi, A.: Fault detection and power distribution optimization of smart grids based on hybrid Petri net. Energy Syst **8**(3), 465–493 (2017)
20. Ameli, A., Ahmadifar, M.H., Shariatkhah, M.H., Vakilian, M.: A dynamic method for feeder reconfiguration and capacitor switching in smart distribution systems. Electr Power Energy Syst **85**, 200–211 (2017)
21. Azizivahed, A., Narimani, H., Fathi, M., Naderi, E., Safapour, H., Narimani, M.R.: Multi-objective dynamic distribution feeder reconfiguration in automated distribution systems. Energy **147**, 896–914 (2018)

22. Shariatkhah, M.-H., Haghifam, M.-R., Salehi, J., Moser, A.: Duration based reconfiguration of electric distribution networks using dynamic programming and harmony search algorithm. Int J Electr Power Energy **41**(1), 1–10 (2012)
23. Gitizadeh, M., AziziVahed, A., Aghaei, J.: Multistage distribution system expansion planning considering distributed generation using hybrid evolutionary algorithms. Appl Energy **101**, 655–666 (2013)
24. Dixit M, Kundu P, Jariwala R (2017) Integration of distributed generation for assessment of distribution system reliability considering power loss, voltage stability and voltage deviation. Energy Syst 1–27 (2017)
25. Aman, M.M., Jasmon, G.B., Bakar, A.H.A., Mokhlis, H.: A new approach for optimum DG placement and sizing based on voltage stability maximization and minimization of power losses. Energy **70**, 202–210 (2013)
26. Kennedy, J., Eberhart, R.: Particle swarm optimization. IEEE Int Conf Neural Netw **4**, 1942–1948 (1995)
27. Ganguly, S., Sasho, N.C., Das, D.: A novel multi-objective PSO for electrical distribution system planning incorporating distributed generation. Energy Syst **1**(3), 291–337 (2010)
28. Esmin, A., Lambert-Torres, G., Zambroni de Souza, A.C.: A hybrid particle swarm optimization applied to loss power minimization. IEEE Trans Power Syst **20**(2), 859–866 (2005)
29. Eusuff, M., Lansey, K., Pasha, F.: Shuffled frog-leaping algorithm: a memetic meta-heuristic for discrete optimization. Eng Opt **38**(2), 129–154 (2006)
30. Rajamohana, S.P., Umamaheswari, F.: Hybrid approach of improved binary particle swarm optimization and shuffled frog leaping for feature selection. Comput Electr Eng **67**, 1–12 (2018)
31. Niknam, T., Narimani, M.R., Aghaei, J., Azizipanah-Abarghooee, R.: Improved particle swarm optimization for multi-objective optimal power flow considering the cost, loss, emission, and voltage stability index. IET Gener Transm Distrib **6**(6), 515–527 (2012)
32. Niknam, T., Azad Farsani, E.: A hybrid self-adaptive particle swarm optimization and Shuffled Frog Leaping Algorithm for distribution feeder reconfiguration. Eng Appl Artif Intell **23**(8), 1340–1349 (2012)
33. Shaffiu A, Bopp T, Chilvaers I.: Active management and protections of distribution networks with distributed generation. Power Engineering Society General Meeting. IEEE; (2004)