The impact of feeder reconfiguration on automated distribution network with respect to resilience concept

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Received: 6 March 2020 / Accepted: 26 August 2020 / Published online: 30 August 2020
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Abstract

Owners of power systems incur high costs and investments to transfer the electrical power to customers in the distribution network. Hence, the reliability of the distribution network is particularly important in the lives of customers. Natural disasters such as hurricane and earthquake or sudden faults may threaten the reliability of the distribution network. Therefore, the focus of this study is to provide a new formulation for the distribution system resilience and voltage security. To improve the mentioned objectives in the automated distribution system, the concept of distribution feeder reconfiguration (DFR) is used in this study. Due attention of distribution network resilience and voltage security issues, energy not supplied and voltage stability index along with power loss are considered as objective functions. According to the increase of distributed generators in the distribution network, the effect of these units is considered in the DFR problem. An improved particle swarm optimization is presented to solve the complex and non-convex DFR problem. The proposed algorithm is tested into two distribution systems including IEEE 33 and 70-node.

Keywords Resilience · Distribution feeder reconfiguration · Energy not supplied · Voltage stability index

1 Introduction

Developing the resilience of power grids versus natural disasters is the main problem for all countries. Recently, hurricanes, flooding, earthquake, and tsunami have resulted in very high economic and human casualties. More than 129 power lines were damaged by ice disaster in the south of China in 2008 and most of the power facilities were ruined in 13 provinces, causing power blackouts for about 14.66 million families [1]. In 2016, a tornado in the Jiangsu province of China caused power outages of 135,000 households [1].

An 8.8 Richter scale quake occurred in central Chile in February 2010 and a tsunami after an earthquake affected the seaside and crowded parts of the country. The major supplies crumbled, disconnecting electricity, gas, water,

phones caused the suffering of the people [2]. Most of the earthquake damages were due to power distribution networks, so that many large cities did not have electricity for several weeks. Therefore, to investigate the effects of natural disasters on the power grid and to assess the efficiency of the essential reactions against catastrophes, conception of resilience in the power grid was introduced and then the ability of the power grid to cope with natural disasters was assessed [3]. As the distribution grid has the adjoining association to the life of clienteles, the resilience of the distribution grid is mostly appeared by the ability to provision and recovery of dangerous loads under the distribution grid in the natural disasters [4]. The assessment of network resilience and investigating the impact of natural disasters on the distribution grids has a significance importance for protecting people's work and battling against natural

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catastrophes [4], fortunately with the integration of recent automation technologies in the distribution network, the process of identifying the location of the fault and separating the damaged segment takes less time than the normal networks, which also causes the power to return to the damaged location sooner.

In [5], the frequency of risky weather happenings and the level of damage from numerous risky climate events to the power grid resilience were analyzed. In [6], a new model was suggested to evaluate power grid resilience under the assumption that the transmissions line and substations were removed as individually or attacked simultaneously. A conceptual framework was presented in [7] for gaining vision into the power system's resilience, focusing on the extreme climate disasters impacts on the power system. In [8], a new framework was suggested to assess the resilience of the power system. Also, the impacts of wind and electrical load on the probability of transmission line failure were considered to the resilience evaluation. In [9], a framework was introduced to evaluate power transmission system resilience under typhoon weather conditions. The proposed framework estimated the transmission system resilience concerning the severity of the weather, location of the fault modules, renovation of resources, and emergency reaction policies. In [10], the concept of network resilience was defined as a combination of network ability to prepare service despite fault and the restoration time to service in the case of a fault. In [11], an optimal micro-grid design model was proposed to maximize power system resilience against weather events. In [2], a methodology was presented to determine the resilience of distribution network resilience against earthquake, the expected energy not supplied (EENS) of the distribution network was determined after the earthquake through sequential Monte-Carlo simulation. A method based on the Monte Carlo method was presented in [4] to assess distribution network resilience with a focus on the critical loads in severe weather events. A stochastic optimization model was suggested in [3] to design for distribution system infrastructure resilience to minimize overall grid costs. In [12], a new approach was proposed for resilient distribution system planning. Also, a genetic algorithm (GA) was implemented to obtain the distribution optimal size, feeder path, and lines. In [13], a stochastic mixed-integer program was presented to design a resilient distribution system grid against natural events, where the damage caused by natural disasters was modelled as a series of stochastic events.

Distributed generators (DGs) severely affect the operation of a distribution system such as improving the power quality, system reliability, and reducing the system loss [14, 15]. In [16], a new approach was suggested to re-establish critical loads from the power blackouts in distribution

network afterward catastrophes through by dividing a distribution grid into micro-grids considering DGs. In [17] a resilience distribution network planning (RDNP) was proposed to enhance the resilience of distribution network against natural events in the presence of DGs. In [18], an optimal scheme was presented for optimal sizing and optimal location of batteries and photovoltaic units to maximize distribution network resilience. In [19], a new model based on the temporal-spatial natural disaster was presented to enhance power system resilience considering DGs.

The reconfiguration process concept is altering the distribution feeders' structure to optimize the subject of a certain objective to fulfill a set of limitations [20, 21]. Distribution feeder reconfiguration (DFR) is an optimization problem that performed by managing the state of switches including sectionalising and tie-switches in a distribution network to search a radial operating configuration without forming any part of the network as an island [20]. Generally, the DFR approach for specific objectives is performed in the distribution network such as improving reliability [14, 21], network security [20], transient stability [22] and minimizing investment cost [23], active loss [14, 20, 21, 23, 24], operational cost [25].

Solving the DFR problem in the distribution network is very complicated to enhance the resilience of the distribution network and voltage stability, because there are combinations of candidate switching in distribution systems that need to be managed to evaluate objective functions in the system and meet constraints, and gets more complicated by considering the effect of DGs in solving DFR problem. So, providing a strong method that can tackle with the DFR problem complexity is very important.

Evolutionary algorithms are well-known methods that have been used in recent years to solve many non-convex and nonlinear optimization problems compared to other methods. One of the population-based optimization methods derived by the group life of birds and fish is the particle swarm optimization (PSO) algorithm [26]. This algorithm has been utilized in various engineering optimization problems due to its features such as simplicity and low computational volume. Also, it has some weaknesses such as: premature converge or trapped into local optimal in some cases. To this end, a new categorizing model is proposed in improved particle swarm optimization (IPSO) algorithm to overcome premature convergence and increase search capability.

The proposed problem in this study is a multi-objective optimization problem and necessities a means to optimize all objective functions at once. In this regard, a new method is presented to obtain Pareto-fronts based on dominance in solving a multi-objective optimization problem. To verify the suitability of the proposed algorithm, it is

applied to the two test system including 33 and 70-node distribution networks. The simulation results indicate the proposed algorithm's ability to solve the optimization problem.

In this regard, the great features of this study are as follows:

- The DFR approach is proposed to enhance the resilience of the distribution system and voltage security.
- Presenting a new formulation to assess the distribution grid resilience.
- Considering the voltage stability index (VSI) in the DFR problem to enhance the voltage stability of the distribution grid.
- Presenting an efficient and strong method, IPSO algorithm to solve the DFR problem in the single and multi-objective frameworks.
- Considering the impact of DGs on objective functions and changing network topology.

The study is organized as follows. Sections 2 and 3 provide problem formulation including objective functions, limitations, and the proposed approach. Section 4 presents the simulation results in two sections. Conclusions are provided in Sect. 5.

2 Problem formulation

The objective functions in this study including power loss, ENS, and VSI as well as constraints of the proposed problem are investigated in this section.

2.1 Objective functions

Minimizing power loss, ENS, and maximizing VSI are the considered objective functions in this study.

2.1.1 Power loss

$$f_1(X) = \sum_{j=1}^{N_{branch}} R_j \times I_j^2, \quad (1)$$

$$X = [\overline{Tie}, \overline{SW}, \overline{P_{dg}}], \quad (2)$$

$$\overline{Tie} = [Tie_1, Tie_2, \dots, Tie_{N_{tie}}], \quad (3)$$

$$\overline{SW} = [SW_1, SW_2, \dots, SW_{N_{SW}}], \quad (4)$$

$$\overline{P_{Dg}} = [P_{Dg1}, P_{Dg1}, \dots, P_{DgN_{DG}}], \quad (5)$$

where X is the control variables vector, R_j and I_j are resistance and current of the j th branch, respectively. N_{branch} and N_{tie} are the number of branches and tie-switches, respectively. Tie_i and SW_i are the state of the i th tie switch and sectionalizing switch number, respectively. P_{Dgi} and N_{Dg} are the active power output of the i th DG and number of DG, respectively.

2.1.2 Energy not supplies (ENS)

In this study, ENS as one of the resilience indexes which shows the total energy load not distributed during outage [27]. The main goal of this paper is to minimize ENS by solving the DFR problem. The ENS for radial distribution system in case of a possible fault in any line can be calculated as follows:

$$ENS = \sum_{b=1}^{N_{branch}} \left(\lambda_b t_b \sum_U P_u \right), \quad (6)$$

where U is the set of upstream buses that lost their supply if there is a fault on a b th branch. λ_b is the average number of fault occurred for the b th branch, t_b is the average repair time for the b th branch. The ENS of the whole distribution system is obtained regardless of the reference bus as follows:

$$f_2(x) = \sum_{i=2}^{N_{BUS}} ENS_i. \quad (7)$$

2.1.3 Voltage stability index (VSI)

Another of the purposes of this study is to enhance voltage security in the distribution system by solving the DFR problem. Security analysis should be performed in a distribution grid through assessing the VSI to maintain its stability after the disruption occurrence [28]. The VSI formulation in Eq. (8) can be calculated from the load flow results:

$$VSI_m = \left(|V_s|^2 - 4 \cdot (P_m X_m - Q_m r_m) \right)^2 - 4 \cdot (P_m r_m + Q_m X_m) \cdot |V_s|^2, \quad (8)$$

$m = 1, 2, \dots, N_{bus}$
 $m \neq s.$

The equivalent circuit of two nodes including m and s is shown in Fig. 1.

To achieve a steady operation state, VSI for all nodes should be larger than zero which is depicted in (11). N_{bus} is the number of buses.

Fig. 1 Equivalent circuit of two nodes in a radial system

$$VSI = [VSI(2), VSI(3), \dots, VSI(N_{bus})], \quad (9)$$

$$f_3(x) = \frac{1}{\min(VSI)} + \text{penalty factor}, \quad (10)$$

$$\text{penalty factor} = \begin{cases} 0 & VSI_m \geq 0 \\ \infty & \text{otherwise.} \end{cases} \quad (11)$$

The penalty factor (PF) is used to eliminate the unsteady decision variables during the optimization procedure.

2.2 Constraints

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

2.2.1 Distribution system radial topology

$$N_{branch} = N_{node} - N_{source}, \quad (12)$$

where N_{node} and N_{source} are the number of nodes and sub-stations, respectively. N_{branch} is the number of branches.

2.2.2 Load flow equations

$$P_i = \sum_{j=1}^{N_{bus}} V_i V_j Y_{ij} \cos(\theta_{ij} - \delta_i + \delta_j), \quad i = 2, 3, \dots, N_{bus}, \quad (13)$$

$$Q_i = \sum_{j=1}^{N_{bus}} V_i V_j Y_{ij} \sin(\theta_{ij} - \delta_i + \delta_j), \quad (14)$$

where P_i and Q_i are the net injected active and reactive powers of the i th bus. V_i and δ_i are the voltage magnitude and angle of the i th bus, Y_{ij} and θ_{ij} are the admittance magnitude and angle between i th and j th buses.

2.2.3 Bus voltage

$$V_{min} \leq V_i \leq V_{max}, \quad (15)$$

where V_{min} and V_{max} are the minimum and maximum boundaries of the voltage of the i th bus, respectively.

2.2.4 Feeders current

$$|I_{fdr,i}| \leq I_{fdr,i}^{Max} \quad i = 1, 2, \dots, N_{feeder}, \quad (16)$$

where current amplitude and a maximum current of the i th the feeder is indicated by $I_{fdr,i}$ and $I_{fdr,i}^{Max}$ respectively. N_{feeder} shows feeder number.

2.2.5 Transformers current

$$|I_{trns,i}| \leq I_{trns,i}^{Max} \quad i = 1, 2, \dots, N_t, \quad (17)$$

where current amplitude and a maximum current of the i th the transformer is presented by $I_{trns,i}$ and $I_{trns,i}^{Max}$ respectively. N_t shows the transformer's number.

2.2.6 DGs power generation

$$P_{dg}^{min} \leq P_{dg,j} \leq P_{dg}^{max}, \quad (18)$$

where P_{dg}^{min} , P_{dg}^{max} are the minimum and maximum limitations of power generation at the j th DG, respectively.

3 Optimization approach and multi-objective strategy

In this section, improved particle swarm optimization (IPSO) algorithm and multi-objective strategy are briefly described.

3.1 Improved particle swarm optimization (IPSO) algorithm

The PSO algorithm is one of the evolutionary methods which is inspired by the group life of the birds and fishes [26, 29], each particle can be considered as a potential solution in the search space. The position and velocity of j th particle at t th iteration are updated as follows:

$$V_j^{t+1} = W \cdot V_j^t + c_1 \cdot r_1 (Pb_j^t - X_j^t) + c_2 \cdot r_2 (Gb^t - X_j^t), \quad (19)$$

$$X_j^{t+1} = X_j^t + V_j^{t+1}, \quad (20)$$

$$W = w_{max} - \frac{W_{max} - W_{min}}{iter_{max}} \cdot iter, \quad (21)$$

where c_1 and c_2 are positive constants, r_1 and r_2 are random numbers between zero and one. Pb_j^t and Gb^t represent the best personal fitness of j th particle and the best value between all personal fitness at t th iteration. W is the inertia weight, W_{max} and W_{min} represent the maximum and minimum of inertia weights. $iter$ and $iter_{max}$ are the current iteration and maximum iteration numbers [30, 31].

Like other population-based evolutionary algorithms, PSO suffering from premature convergence or trapping in local optima. For this purpose, an innovation is presented in the IPSO algorithm to solve the weakness. In the IPSO algorithm, particles are divided into several memplexes, then in each memplex, particles' velocity and position are updated according to (22)–(23). Finally, information is exchanged between all memplexes and the global best solution is extracted. The velocity and position of i th particle in j th the memplex is updated. In this algorithm, the velocity, position and inertia weight are shown by D , X , and W in Eqs. (22) and (23). The flowchart of the IPSO algorithm is shown in Fig. 2. Also, the steps of this algorithm for solving the multi-objective problem as follows:

$$D_{ij}^{k+1} = W \cdot D_{ij}^k + c_1 \cdot r_1 (X_{pbesti} - X_{ij}^k) + c_2 \cdot r_2 (X_{Gbest} - X_{ij}^k), \quad (22)$$

$$X_{ij}^{k+1} = X_{ij}^k + D_{ij}^{k+1}. \quad (23)$$

Step 1 Define the input data

Step 2 Convert the constraint multi-objective problem to an unconstrained one by the following equation:

$$J(x) = \begin{bmatrix} J_1(x) \\ J_2(x) \\ J_3(x) \end{bmatrix}_{3 \times 1} = \begin{bmatrix} f_1(x) + k_1 \sum_{j=1}^{N_{eq}} (h_j(x))^2 + k_2 \left(\sum_{j=1}^{N_{ueq}} (\text{Max}[0, -g_j(x)]^2) \right) \\ f_2(x) + k_1 \sum_{j=1}^{N_{eq}} (h_j(x))^2 + k_2 \left(\sum_{j=1}^{N_{ueq}} (\text{Max}[0, -g_j(x)]^2) \right) \\ f_3(x) + k_1 \sum_{j=1}^{N_{eq}} (h_j(x))^2 + k_2 \left(\sum_{j=1}^{N_{ueq}} (\text{Max}[0, -g_j(x)]^2) \right) \end{bmatrix}_{3 \times 1}, \quad (24)$$

$J_1(x)$, $J_2(x)$ and $J_3(x)$ are the values of the augmented $f_1(x)$, $f_2(x)$ and $f_3(x)$

K_1 and K_2 : penalty factors which are used to resolve constraints, the value of penalty factor in this study is 10,000. N_{eq} and N_{ueq} are the number of equality and inequality constraints, respectively, $h_j(x)$ and $g_j(x)$ are the equality and inequality constraints. Value of $J(x)$ is obtained as follows:

Fig. 2 The flowchart of IPSO algorithm

Distribution load flow is calculated based on tie and sectionalizing switches, DG units' active power, according to load flow results, values of $f_1(x)$, $f_2(x)$ and $f_3(x)$ are calculated and constraints are investigated. Then augmented objective functions are calculated according to results of functions and constraints. In other words, the penalty factor method is utilized to handle inequalities constraints. In this regard, each control vector which violates constraints will be fined by these penalty factors.

Step 3 Generate the initial population of particles.

Step 4 Evaluate the objective functions for the whole population.

Step 5 Calculate the membership functions of each objective and normalized objective function for all particles according to (26)–(27).

Step 6 Apply the Pareto method to obtain normalised objective function of the previous step and save non-dominate solutions in the repository.

Step 7 Divided particles (p) into q memplexes, each memplex comprises of (p/q) particles

Step 8 Determine X_{pbest} and X_{gbest}

Step 9 Update the i th particles in j th memplex according to (22)–(23). This approach performs for all memplexes

Step 10 Memplex shuffle, at this step, all memplexes are mixed and restored to exchange information among memplexes. From the existing particles, all the non-dominated solutions are extracted and saved in the repository.

Step 11 If the convergence criterion is satisfied, the optimization process is finished, otherwise back to Step 8. The maximum iteration number is selected as the stopping criterion.

3.2 Multi-objective optimization methodology

In solving the multi-objective problem, there are non-dominated solutions instead of an optimal solution. This method (Pareto) works based on the concept of dominance [32, 33], the vector X_1 dominates vector X_2 if:

$$\forall i \in \{1, 2, \dots, N_{obj}\}, \quad f_i(X_1) \leq f_i(X_2), \quad (25)$$

$$\exists j \in \{1, 2, \dots, N_{obj}\}, \quad f_j(X_1) < f_j(X_2). \quad (26)$$

Since the values of the objective function ranges are different in this study, so fuzzy decision making is used [32, 33] to have the same ranges for each objective function as follows:

$$\mu_i(x) = \begin{cases} 1 & f_i(X) \leq f_i^{min} \\ 0 & f_i(X) \geq f_i^{max} \\ \frac{f_i^{max} - f_i(X)}{f_i^{max} - f_i^{min}} & f_i^{min} \leq f_i(X) \leq f_i^{max}, \end{cases} \quad (27)$$

where f_i^{min} and f_i^{max} are obtained through optimizing each objective function separately [32, 34].

The normalized objective function is determined for each individual in the repository as follows:

$$N_{\mu j} = \frac{\sum_{k=1}^n W_k \times \mu_{jk}}{\sum_{j=1}^m \sum_{k=1}^n W_k \times \mu_{jk}}, \quad (28)$$

where m and n represent the number of non-dominant solutions and objectives, respectively. W_k is the weight of k th objective function.

4 Simulation results

It should be noted that the IPSO algorithm is used to solve the DFR in the presence of DGs in the standard test systems including IEEE 33 and 70-bus. All simulations are performed in the MATLAB R2016 software on a core-i5 processor laptop and 4.0 GB of RAM. Parameters of the IPSO are: the initial population is 400, the maximum iteration number is 200 and the number of the memplex is 5. In two case studies, simulation results obtained by the proposed IPSO algorithm are compared with evolutionary methods including particle swarm optimization (PSO), gravitational search algorithm (GSA), and grey-wolf optimization (GWO).

4.1 33-bus test network

This test system is a 12.66 kV distribution system consisting of the two-feeder substation, 32 nodes, and 5 tie-switches [35]. This test system is depicted in Fig. 3. In this study, two 300 kW DGs are installed on buses 7 and 14 and two 500 kW DGs are located on buses 24 and 30. The initial values of the VSI, ENS, and power loss before the DFR are 1.495 p.u., 382,201 kWh/year, and 202.67 kW, respectively.

4.1.1 Single-objective optimization

The results of the single-objective optimization obtained by IPSO, PSO, GSA, and GWO algorithms for ENS, and VSI in 30 runs are shown in Tables 1 and 2. According to the results in Tables 1 and 2, it is clear that IPSO has achieved better results than other algorithms. The ENS and VSI values obtained by the proposed IPSO algorithm are dropped by about 10% and 15% compared to the initial values before the DFR.

Table 4 Results of optimizing VSI with DGs by different algorithms in 30 runs

Algorithms	VSI (p.u.)				Open switches	Switching number	DGs output (kW)			
	Best	Mean	Worst	STD			Bus7	Bus14	Bus24	Bus30
GSA	1.205	1.222	1.236	0.026	S33, S13, S8, S32, S37	6	297.7	295.9	500	497.5
GWO	1.186	1.183	1.214	0.019	S6, S34, S11, S32, S37	6	300	300	500	500
PSO	1.191	1.204	1.222	0.022	S7, S34, S11, S32, S37	6	299.7	300	395.9	500
IPSO	1.173	1.178	1.189	0.01	S7, S13, S9, S32, S37	8	299	300	500	500

4.1.2 Multi-objective optimization

Since the objective functions in this study conflict with each other and other words do not improve each other, providing a suitable solution to satisfy all three objective functions for solving the multi-objective DFR (MODFR) problem is one of the important challenges of this paper. For this reason, the Pareto-fronts for different objective functions obtained by the IPSO algorithm are shown in Fig. 4a, b. According to Fig. 4a, the minimum values

of VSI and ENS are 1.216 p.u. and 185,360 kWh/year, respectively. The optimal values of ENS and VSI in the best-compromise solution (which is highlighted in red) are 1.272 p.u. and 186,219.21 kWh/year, respectively. The difference of less than 2% between the value of each objective function in the best-compromise solution and its optimal value in the Pareto-front indicates the ability of the IPSO algorithm in solving the MODFR problem. Table 5 illustrates the best compromise solution and the control variables such as DGs outputs and switches

Fig. 4 Pareto front for different objective function using IPSO in the 33-node test system

Table 5 Best compromise solution and control variables related to the MODFR problem

Algorithms	DGs output (kW)				Power loss (kW)	ENS (kWh/year)	VSI (p.u.)	Open switches	Switching number
	Bus7	Bus14	Bus24	Bus30					
GSA	159.02	290.36	494.29	477.52	86.45	186,051.82	1.266	S33, S12, S35, S15, S27	6
GWO	300	300	499.98	498.77	85.68	185,309.12	1.244	S33, S14, S35, S16, S28	6
PSO	300	300	500	500	86.65	186,456.54	1.249	S33, S12, S8, S36, S27	6
IPSO	300	300	498.16	499.98	83.75	184,625.31	1.211	S33, S14, S11, S17, S28	8

Fig. 5 Single-line 70-node test system

status obtained by the IPSO and other algorithms for simultaneous optimization of all three objective functions. According to the Table 5, it is evident that the values of ENS, VSI, and power loss in the best-compromise solution obtained by IPSO algorithm are dropped from 382,201 kWh/year, 1.495 p.u. and 202.67 kW to 185,360 kWh/year, 1.272 p.u and 83.75 kW compared with initial values before the DFR.

4.2 70-bus test network

The 70-node test system is an 11 kV distribution network [36] is depicted in Fig. 5 which has two substations, four feeders, and 70 buses. This distribution system consists of seven DGs with 300 kW capacity at buses 9, 16, 24, 33, 43, 54 and 66. The initial values of the VSI, ENS and power loss before the DFR are 1.479 p.u., 1.130700×10^6 kWh/year and 227.53 kW, respectively.

4.2.1 Single-objective optimization

Tables 6, 7, 8 and 9 illustrate the results of single-objective optimization along with control variables obtained by IPSO and other evolutionary methods for ENS and VSI considering DGs on the 70-node test system. Their best, mean, worst solution and the standard deviation related to the ENS objective optimization without DGs effect obtained by GSA, GWO, PSO and IPSO algorithms are (1.554145×10^6 , 1.553654×10^6 , 1.553894×10^6 and 1.552782×10^6), (1.555215×10^6 , 1.554645×10^6 , 1.547915×10^6 and 1.553568×10^6), (1.557968×10^6 , 1.557514×10^6 , 1.557578×10^6 and 1.555794×10^6), and (1509.42 , 1438.34 , 1463.75 and 1319.25) kWh/year, respectively. These values related to VSI objective optimization without DGs effect obtained by GSA, GWO, PSO and IPSO algorithms are (1.316, 1.298, 1.305 and 1.295), (1.344, 1.325, 1.331 and 1.308), (1.358, 1.338, 1.343 and 1.332), and (0.034, 0.023, 0.029 and 0.018) p.u., respectively.

Table 6 Results of optimizing ENS with DGs by different algorithms in 30 runs

Algorithm	ENS (kWh/year)				Open switches	Switching number
	Best	Mean	Worst	STD		
GSA	708,910.71	711,445.21	713,965.24	1358.6	S52, S9, S71, S68, S66, S45, S73, S77, S25, S15, S80	16
GWO	706,130.71	708,086.52	709,955.45	1268.5	S70, S71, S72, S68, S74, S47, S40, S77, S25, S15, S80	10
PSO	707,964.59	709,903.45	711,869.56	1288.2	S52, S8, S72, S67, S66, S46, S45, S77, S25, S15, S80	16
IPSO	704,185.32	705,408.41	706,653.15	1166.5	S52, S8, S72, S68, S66, S47, S45, S77, S25, S15, S80	16

Table 7 Results of optimizing VSI with DGs by different algorithms in 30 runs

Algorithm	VSI (p.u.)				Open switches	Switching number
	Best	Mean	Worst	STD		
GSA	1.273	1.293	1.323	0.039	S50, S29, S9, S77, S72, S73, S68, S80, S36, S15, S62	14
GWO	1.257	1.276	1.307	0.026	S50, S29, S8, S77, S72, S73, S66, S62, S38, S15, S80	14
PSO	1.263	1.282	1.305	0.029	S52, S71, S72, S24, S65, S62, S38, S77, S29, S13, S80	14
IPSO	1.221	1.214	1.258	0.019	S70, S8, S48, S80, S68, S31, S62, S39, S77, S78, S15	14

Table 8 The amount of active power generated by DGs in the 70-bus system for ENS optimization

Algorithms	Generated active power by DGs (kW)						
	DG1	DG2	DG3	DG4	DG5	DG6	DG7
GSA	300	300	300	300	300	300	300
GWO	300	300	300	300	300	300	300
PSO	300	300	300	300	300	300	300
IPSO	300	300	300	300	300	300	300

Table 9 The amount of active power generated by DGs in the 70-bus system for VSI optimization

Algorithms	Generated active power by DGs (kW)						
	DG1	DG2	DG3	DG4	DG5	DG6	DG7
GSA	246.45	269.67	300	165.23	293.44	286.84	182.51
GWO	222.59	283.43	185.66	191.70	286.15	299.40	300
PSO	192.52	277.90	273.50	167.95	251.61	300	300
IPSO	300	300	169.75	300	262.05	300	300

According to the results of Tables 6 and 7 along with results without DGs effect, the following points are highlighted.

The proposed IPSO algorithm has reached to better results than other algorithms, and once again, the ability of the IPSO algorithm to solve the complex DFR problem in the absence and presence of DGs is proved. According to the mentioned tables, it is obvious that the values of ENS and VSI obtained by IPSO are decreased from 1.130700×10^6 kWh/year and 1.479 p.u. to 704,185.32 kWh/year and 1.221 p.u. in comparison with initial values before the DFR.

4.2.2 Multi-objective optimization

The main focus of this section is to provide an approach to meet all the objective functions for solving the DFR problem. For this reason, the DFR problem is solved in a multi-objective framework. The Pareto-fronts for simultaneous optimization of different objectives are depicted in Fig. 6a, b. Also, the best compromise solution along with control variables such as DGs outputs and switches status obtained by IPSO and other algorithms are shown in Tables 10 and 11. According to Fig. 6a, b, it is obvious that the optimal value for each objective function in the

best-compromise solution (which is shown by red color) is close to its optimal value in the Pareto-front, which demonstrates the ability of the IPSO algorithm to solve the multi-objective problem in the 70-node test system.

A comparison of the values for power loss and ENS corresponding to single-objective optimization and the best-compromise solution obtained by the proposed IPSO algorithm are shown in Fig. 7a, b, respectively. From Fig. 7a, b, it is obvious that the power loss value for the best compromise solution (i.e. 707,135.5 kWh) is between two values (i.e. 704,185.3 kWh) and (i.e. 719,289.5 kWh) relevant to single-objective optimization considering power loss and ENS as separate objectives, respectively. Similarly, the ENS value for the best compromise solution (i.e. 126.45 kWh/year) is between two values (i.e. 118.67 kWh/year) and (i.e. 144.68 kWh/year) relevant to single-objective optimization considering ENS and power loss as separate objectives, respectively. These results once again confirm the strength of the proposed IPSO algorithm in solving the multi-objective problem.

The convergence curve of power loss optimization by GSA, GWO, PSO, and IPSO algorithms for the 70-node test system considering DGs are depicted in Fig. 8. According to Fig. 8, it is obvious that the IPSO algorithm converges

Fig. 6 Pareto front for different objective function using IPSO in the 70-node test system **Table 10** Best compromise solution along with the control variables related to the MODFR problem

Algorithms	Power loss (kW)	ENS (kWh/year)	VSI (p.u.)	Open switches	Switching number
GSA	139.65	707,584.75	1.415	S70, S8, S72, S68, S74, S46, S76, S77, S25, S79, S80	10
GWO	134.85	706,586.45	1.375	S70, S8, S72, S68, S74, S46, S76, S77, S25, S79, S80	8
PSO	132.15	709,589.65	1.329	S70, S71, S48, S67, S30, S46, S38, S77, S23, S15, S80	14
IPSO	125.55	704,365.75	1.319	S70, S8, S72, S68, S74, S46, S76, S77, S29, S79, S80	8

Table 11 The amount of active power generated by DGs in 70-bus network for MODFR problem

Algorithms	Generated active power by DGs (kW)						
	DG1	DG2	DG3	DG4	DG5	DG6	DG7
GSA	300	300	300	300	300	284.17	299.62
GWO	299	300	300	300	300	300	299.35
PSO	300	300	300	300	300	278.68	289.59
IPSO	299.72	300	300	298.53	300	300	299.82

Fig. 7 Comparing values for ENS and power loss in single and multi-objective optimization

Fig. 8 Convergence curve for power loss optimization related to 70-node test system

to optimal answer before than GSA, PSO and GWO algorithms.

5 Conclusion

This paper provides a multi-objective distribution feeder reconfiguration (DFR) approach as an effective and novel method to minimize the outages after fault occurrence and enhance the voltage security by managing the status of switches. Also, energy not supplied (ENS) and voltage stability index (VSI) are also considered as distribution system resilience and voltage security objectives, respectively. Moreover, the effect of distributed generators (DGs) is considered on evaluating objective functions in the considered DFR problem. This problem consists of minimizing ENS, power loss and maximizing VSI. Limitations of the problem are the grid's radial topology, the voltage of the buses, current of lines, transformers capacity and DGs power generation. To solve the considered DFR optimization, an improved particle swarm optimization (IPSO) algorithm is tested on 33 and 70-node test networks. Based on the simulation results in two case studies, the IPSO algorithm converges to an optimum solution compared to other heuristic methods such as gravitational search algorithm (GSA), particle swarm optimization (PSO) and grey wolf optimization (GWO). Thus, the simulation results prove the effectiveness of the IPSO algorithm compared to other algorithms such as GSA and GWO and PSO algorithms in solving the single and multi-objective problems regardless of their complexity and scale. Comparing numerical results shows that the DFR approach has a significant impact on enhancing VSI and reducing ENS. For example, the values of ENS and VSI obtained by IPSO algorithm in the first test system are reduced by approximately 11% and 13% compared to initial objective functions values. Moreover, investigating the effect of DGs in solving the DFR problem reduces ENS and power loss. For example, the values of ENS and VSI obtained by IPSO algorithm in the second test system are reduced by approximately 60% and 21% compared to initial objective functions values, these optimization results indicate that the objective functions in this study have been met.

Some suggestions for future studies related to the resilience studies are as follows. Usually, less attention has been paid to sources of uncertainty such as power demand and DGs power generation in resilience studies, so the answers obtained are far from the actual work point of the problem because the problem has not been evaluated in the real environment. Another idea for future studies is to use the FACTS devices to improve the distribution system power quality, which, has not been considered in most resilience studies. Finally, energy storage systems as backup units

along with DGs will play an effective role in reducing distribution network outages in future researches.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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