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METHODOLOGIES AND APPLICATION

Optimal placement of different types of DG units considering various load models using novel multiobjective quasi-oppositional grey wolf optimizer

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Abstract
The optimal placement of Distributed Generation (DG) units in radial distribution system is one of the important ways for techno-economic improvements. The maximum technical benefits can be extracted by minimizing the distribution power loss as well as bus voltage deviation, whereas the maximum economical benefits can be procured by minimizing the total yearly economic loss which includes installation, operation and maintenance cost. So for the maximum techno-economic benefits, all three objectives should be simultaneously minimized by considering a multiobjective optimization technique. For optimal results, a Pareto optimal concept-based novel multiobjective quasi-oppositional grey wolf optimizer (MQOGWO) algorithm has been proposed. The performance of the proposed algorithm has been tested on IEEE-33 bus radial distribution system. In this analysis, various voltage-dependent load models such as constant power, constant current, constant impedance, residential, industrial and commercial load models have been considered at different loading conditions like light load, full load and heavy load. The effects of DG type on the system performance have also been analyzed to find the best optimal solution.

Keywords Distributed Generation · Yearly economic loss · Power loss · Voltage deviation · Multiobjective quasi-oppositional grey wolf optimizer

1 Introduction

Distributed Generation (DG) is one of the most significant trends in power systems used to meet the high-level energy demand. Its definition is not confined in a particular area as the concept involves varieties of technologies and impacts. Generally, it involves small-scale technologies for harnessing renewable and non-renewable energy sources (such as photovoltaic cell, fuel cell, and wind turbine). The DG can be classified into the four categories depending on the capacity of generation: a) micro-DG: size up to 5 kW, b) small DG: size varies from 5 kW to 5 MW, c) medium-sized DG: 5–50 MW and d) large-sized DG: 50 to 300 MW (Ackermann Andersson and Söder 2001). Since DG also supports active and reactive power compensation in distribution systems, it can eliminate the need for installation of spinning reserve plants (Rebours, and Kirschen 2005). The DG units located in the close proximity of the load stations can reduce the T&D losses, overall system costs that include the cost of long transmission and distribution lines, while improves the system voltage profile. Though all these benefits can be harnessed only via optimal placement and sizing of DGs in the radial distribution system (RDS) (Behera Dash and Panigrahi 2015 March). In this context, several researchers have proposed different techniques to harness maximum benefits of optimal DG placement (ODGP) in different scenarios.

For optimal allocation of DG in RDS, a teaching learning-based optimization (TLBO) technique has been

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implemented by Mohanty and Tripathy (2016), while Saha and Mukherjee (2018) have presented a novel chaos-integrated symbiotic organisms search (CSOS) algorithm to solve the same problem. In both the above-mentioned papers, ODGP problems are analyzed by considering the minimization of real power loss, improvement in voltage profile and voltage stability index (VSI) as three distinct objective functions which are optimized by weighting factor method. In both papers, authors failed to consider the economic point of view which is also one of the major aspects. A Pareto-based multi objective particle swarm optimization (MOPSO) technique is implemented by Zeinalzadeh Mohammadi and Moradi (2015) to find the optimal sizing and placement of DG units and shunt capacitor banks considering load uncertainty. They have considered only technical objectives like minimizing active power losses, improving the voltage stability and balancing currents in system sections but didn't considered the cost as an objective function. A group of authors in Abdel-mawgoud et al. (2018) have determined the optimal locations and sizes of DG in RDS via chaotic moth-flame optimization (CMFO) technique and real power loss sensitivity factor (PLSF) method to gain the maximum reduction in active power loss only. While by the authors Sujatha Roja and Prasad (2019), a similar objective (only minimization of active power loss) has been considered for multiple DG placements by genetic algorithm and particle swarm optimization method. A multi-objective framework using particle swarm optimization technique with fuzzy decision making approach has been presented by Kaur and Jain (2017) for multiple DG placement considering voltage-sensitive loads. Musa Gadoue and Zahawi (2014) presented a new algorithm using discrete particle swarm optimization (DPSO) for solving optimal DGs placement problems. A basic PSO technique was used by Aman Jasmon Bakar and Mokhlis (2013) for simultaneous minimization of power loss and maximization of voltage stability for ODGP problem. Another modified version PSO named as hybrid Nelder-Mead PSO (HNMPSO) technique has been implemented by Senthil kumar, Charles Raja, Srinivasan, and Venkatesh (2018) to find the optimal size of renewable DG by optimizing the area required for DG installation for minimizing power loss considering different load models. El-Ela El-Sehiemy and Abbas (2018) have shown optimal allocation and sizing of DG and capacitor banks by using water cycle algorithm (WCA) where the objective functions are minimization of power losses, total electrical energy cost, voltage deviation and emissions produced by generating sources while improving the VSI. A Quasi-Oppositional Swine Influenza Model Based Optimization with Quarantine (QOSIMBO-Q) has been used in a multi-objective function-based ODGP problem in distribution system (Sharma Bhattacharjee and Bhattacharya 2016). Here, the main objective was to minimize the power losses, with an improved voltage regulation. Several other techniques like biogeography-based optimization (BBO) (Ghaffarzadeh and Sadeghi 2016), bat optimization algorithm (Yuvaraj Devabalaji and Ravi 2018), clonal differential evolution (Madihah Junichi Hirotaka 2017), Hybrid Teaching–Learning-Based Optimization (HTLBO) technique (Quadri Bhowmick and Joshi 2018), stochastic fractal search algorithm (SFSA) (Nguyen and Vo 2018) and Stud Krill herd Algorithm (ChithraDevi Lakshminarasimman and Balamurugan 2017) have been proposed by several authors to solve similar ODGP problem considering various objective functions in different scenarios.

From the literature, it is seen that most of the authors either considered single objective function or multi-objective functions using weighted sum method, while a very few authors used Pareto-based multi-objective optimizations, but in that case they failed to consider the economic point of view of DG placements. It is also observed that the complexity increases significantly when the voltage-dependent load models (such as constant current, constant impedance, residential, and industrial and commercial loads) and different types of DGs are considered (El-Zonkoly 2010). To solve this type of complex ODGP problem in optimal way, a novel multiobjective quasi-oppositional grey wolf optimizer (MQOGWO) algorithm has been presented in this work. The objective of this work is to harness the maximum benefits of DGs by optimal placement and sizing of different types of DGs considering various types of load models at different loading conditions. The sizes and its locations in the RDS are optimally chosen by the proposed MQOGWO algorithm in such a way that all three major objectives like power loss, yearly economic loss, and voltage deviation can be simultaneously minimized.

2 System modeling

In this work, the main objective is to maximize the annual profit with minimal power loss as well as optimum bus voltage profile. The optimum economical and technical benefits have been analyzed by optimal placement of different types of DG units in radial distribution systems with different loading conditions. The different types of DG units have been mathematically implemented as described in section "DG modeling", whereas different loading conditions have been implemented as described in section "Load modeling".

2.1 DG modeling

Depending upon the availability and feasibility, different types of DGs of optimal sizes can be installed at proper locations in the network. For the mathematical implementation of different types of DGs, it can be modelled as follows:

2.1.1 DG as a "negative load" model

In this mode of operation, DG is assumed as a constant real power generator only. In this situation, the real power output from the DG at ith bus ($P_{\mathrm{DG},i}$) can be treated as a "negative load" of the specified bus. So, after placement of this type of DG at ith bus, the real load at ith bus ($P_{\mathrm{load},i}$) can be modified as

$$P_{\mathrm{load},i} = P_{\mathrm{load},i} - P_{\mathrm{DG},i} \tag{1}$$

2.1.2 DG as a "constant power factor" model

In this mode, DG is assumed as a generator which is operating at a constant power factor (*pf*). For the lagging power factor case, both real and reactive power of DG can be treated as "negative load" whereas for leading power factor case, the real and reactive power of DG can be treated as "negative load" and "positive load" model, respectively. The reactive power of DG at ith bus ($Q_{\mathrm{DG},i}$) can be calculated as

$$Q_{\mathrm{DG},i} = P_{\mathrm{DG},i}\tan(\cos^{-1}(pf_{\mathrm{DG},i})) \tag{2}$$

$P_{load,i}$ can be modified using Eq. (1), whereas $Q_{\mathrm{load},i}$ can be modified as follows:

$$Q_{\mathrm{load},i} = Q_{\mathrm{load},i} \pm Q_{\mathrm{DG},i} \tag{3}$$

where positive and negative signs can be used for leading and lagging *pf* operating mode of DG, respectively.

2.1.3 DG as a "variable reactive power" model

In this mode of operation, DG is assumed as a variable reactive power source. In this category, the induction generator-based DG like wind turbine is considered. The reactive power consumed by such a generator can be calculated as a function of real power generation as mentioned below (Yammani, Maheswarapu, and Matam 2016):

$$Q_{\mathrm{DG},i} = -Q_0 - Q_1 P_{\mathrm{DG},i} - Q_2 P^2_{\mathrm{DG},i} \tag{4}$$

where $P_{\mathrm{DG},i}$ can be calculated from the wind turbine power curve. The coefficients Q_0, Q_1, and Q_2 are provided by the manufacturer or can be calculated by experimentation. In this study, the value of Q_0, Q_1 and Q_2 are considered as 0.0004, 0.0395 and 182.34, respectively, which are taken from Teng (2008).

According to the above modeling strategies of DG, it can be categorized by four different types as mentioned below:

- *Type I:* DGs that can inject only real power to the system or in other words, the DGs which are operating at unity power factor (upf) are categorized in this type. The good examples are PV cell, fuel cell, bio-gas, etc.
- *Type II:* This type of DG can inject both real and reactive powers to the line. So, the operating power factor (pf) of the DGs can be anything between (0,1) lagging pf. The synchronous machine is one of the examples of type II DG.
- *Type III:* In this type, DGs are selected that can inject only reactive power to the system. It means the operating pf of DGs would be zero. These types of DGs are generally used as var compensator. Some examples are SVC, switched capacitors, synchronous compensators, etc.
- *Type IV:* This type of DG can inject real power but consumes reactive power. Hence, the operating pf of DGs will vary between (0,1) in the leading zone. Wind turbines can be assumed as type IV DG.

2.2 Load modeling

In the standard IEEE distribution network system, it is assumed that both active and reactive loads on every bus are constant and independent. But in reality, scenarios are completely different. For analysis purpose, loads can be categorized as (i) static load models and (ii) dynamic or realistic load models. The optimal DG placement (ODGP) problem is generally considered for planning aspects which can be realized by static load models, whereas optimal operation of such system can be realized by dynamic or realistic load models as well as real-time power generations from DG units. In some cases, the dynamic load model can also be considered in the ODGP problem for long-term planning purpose. In this study, different types of static load modelling have been considered for simplified analysis on planning aspects. For the static load modelling, loads are assumed to be voltage dependent. Mathematically, it can be expressed as:

$$P_i = \gamma . P_{0i}\left(\frac{|V_i|}{|V_{0i}|}\right)^{\alpha} \tag{5}$$

$$Q_i = \gamma . Q_{0i}\left(\frac{|V_i|}{|V_{0i}|}\right)^{\beta} \tag{6}$$

where P_i and Q_i are real and reactive power at bus i after DG placement, whereas P_{0i} and Q_{0i} are their corresponding nominal or standard power before DG placement. Similarly, V_i and $V_{0\mathrm{i}}$ are voltages at bus i after DG and nominal voltage before DG, respectively. α and β are the exponents for real and reactive power, respectively, whereas γ indicates the multiplier for loading conditions. In this study, five different types of load models like constant power (CP) load, constant current (CC) load, constant impedance (CI) load, residential (RES) load, industrial (IND) load, and commercial (COM) loads have been considered. Different values of α and β are considered for different types of load models which are taken from Abdi and Afshar (2013) and also given in Table 1. The analysis has also been performed with three different loading conditions like light load (LL), rated or full load (FL) and heavy load (HL) condition and its corresponding γ values are considered to be 0.5, 1.0 and 1.2, respectively.

3 Problem formulation

For the maximum techno-economic benefits, three different objectives have been considered in this multi-objective ODGP problem. After DG placement, the minimization of power loss (P_L^{aDG}) and voltage deviation ($\mathrm{VD_{aDG}}$) have been taken as a technological enhancement, whereas minimization of yearly economic loss ($\mathrm{YEL_{aDG}}$) has been considered for maximizing economical benefits (Kumar Mandal and Chakraborty 2019). So, the overall objective can be presented mathematically as follows:

$$\begin{aligned} \text{minimize} \quad & [P_L^{\mathrm{aDG}}, \mathrm{YEL_{aDG}}, \mathrm{VD_{aDG}}] \\ \text{subject to} \quad & h(x) = 0,\ g(x) \le 0 \end{aligned} \tag{7}$$

Here, $h(x)$ and $g(x)$ represent equality and inequality constraints, respectively. Here, the main equality constraint is power balance equation, whereas line flow or thermal limit, bus voltage limit and penetration limit or DG capacity limit, etc. are considered as main inequality constraints which should be strictly followed.

The backward/forward sweep load flow analysis is performed for calculating total power loss (P_L) in the RDS. As described by Kumar Mandal and Chakraborty (2019), the P_L can be converted into the total yearly economic loss (*YEL*) for the further cost analysis. According to the authors, *YEL* before DG placement ($\mathrm{YEL_{bDG}}$) and *YEL* after DG placement including the cost of DGs ($\mathrm{YEL_{aDG}}$) can be calculated and re-presented as follows:

$$\mathrm{YEL_{bDG}} = P_L^{\mathrm{bDG}} \times C_e \times 8760 \tag{8}$$

$$\mathrm{YEL_{aDG}} = P_L^{\mathrm{aDG}} \times C_e \times 8760 + \frac{C_{\mathrm{DG}} \sum_{i=1}^{N_{\mathrm{DG}}} P_{\mathrm{DGi}}}{L_{\mathrm{DG}}} \tag{9}$$

where P_L^{bDG} signifies P_L before the DG placement, C_e indicates energy loss cost per kWh in \$, N_{DG} indicates the number of DG installed in RDS, C_{DG} represents the cost of power generated by DG per kW which include installation, operation, and maintenance costs of DG, and L_{DG} indicates the total life of DG in years. So, the total yearly savings (*TYS*) will be

$$\mathrm{TYS} = (\mathrm{YEL_{bDG}} - \mathrm{YEL_{aDG}}) \tag{10}$$

The voltage deviation (VD) at different nodes mainly depends on the loading condition of the system. During the heavy load condition, it suffers more and then creates the voltage dip problems, especially in the farthest or remote locations. After optimal DG placement, DG can tackle its nearby load demands and that helps to minimize the voltage dip phenomena. $\mathrm{VD_{aDG}}$ can be calculated by calculating the standard deviation (σ_{N-1}) of all the nodes voltage after the optimal placement of DGs. Mathematically, it can be represented as:

$$\mathrm{VD_{aDG}} = \sigma_{N-1} = \left(\frac{1}{N-1} \sum_{i=1}^{N} (V_i - \overline{V})^2 \right)^{\frac{1}{2}} \tag{11}$$

where $\overline{V}$ represents the average value of all the node voltages. The system having minimum value of $\mathrm{VD_{aDG}}$ showed the minimum voltage dip problems at all buses, and thus it is also taken as one of the objectives. After calculating all the three important objectives, a Pareto-based MQOGWO technique has been applied to minimize all the objectives simultaneously for selecting the best optimal point of operation.

4 Multiobjective quasi-oppositional grey wolf optimizer (MQOGWO) algorithm

The proposed MQOGWO algorithm is a novel and modified form of well known, tried and tested grey wolf optimization (GWO) algorithm. The GWO algorithm is a nature inspired meta-heuristic algorithm, and it was first proposed by Mirjalili, Mirjalili and Lewis (2014). It follows the leadership hierarchy and the hunting strategy of grey wolves for the optimization process. In the leadership hierarchy, alpha (α) wolf is considered as the main leader and decision maker of the group followed by beta (β) and delta (δ) wolves. The remaining all wolves are considered

Table 1 Load model exponent values

Types of load model	Exponent α	Exponent β
Constant power (CP)	0	0
Constant current (CC)	1	1
Constant impedance (CI)	2	2
Residential load (RES)	0.92	4.04
Industrial load (IND)	0.18	6
Commercial load (COM)	1.51	3.4

as omega (ω) wolves and they follow α, β and δ wolves. The main hunting strategies like searching of prey, encircling the prey, and then attacking on the prey are mainly guided by all three α, β, and δ wolves and ω wolves trail rest of three wolves for better optimum solution. The proposed MQOGWO algorithm also follows the similar concept of hunting strategies like GWO algorithm, but the major changes have been proposed in initialization process and in selection process. The proposed algorithm uses quasi-oppositional (QO) scheme instead of random generation scheme used in basic GWO for generating position vector of grey wolves in initialization process. This QO scheme for initialization can be implemented in basic GWO algorithm for more thrust from the beginning of searching prey and to obtain a better approximation of the current position vector of wolves.

4.1 Initialization based on quasi-oppositional scheme

For the QO scheme of initialization, firstly, both random estimated and its corresponding opposite estimated points are generated. Mathematically, the random estimated points ($P_{i,j}$) can be generated as follows:

$$P_{i,j} = P_{\min,i} + \sigma_{i,j}\cdot\left(P_{\max,i} - P_{\min,i}\right) \quad i = 1,\ 2\ldots D;\quad j = 1,\ 2\ldots \mathrm{NP} \tag{12}$$

Here, D represents the dimension of the problem; In other words, D is the decision variable of the problem under consideration; NP is the size of the population. $P_{\min,i}$ and $P_{\max,i}$ represent the minimum and maximum value of i^{th} decision variables, respectively. $\sigma_{i,j}$ indicates a random number within [0, 1].

For this particular problem, DG sizes (S_{DG}) and their corresponding locations (L_{DG}) are considered as the elements of the randomly generated matrix of position vectors (P). These variables are arranged in the matrix in such a way that the upper half elements consist only of the size of DG units, whereas lower half elements consist only of their corresponding locations. Mathematically, it can be modelled as:

$$P = \begin{bmatrix} S_{\mathrm{DG1},1} & S_{\mathrm{DG1},2} & \cdots & S_{\mathrm{DG1,NP}} \\ \vdots & \vdots & \cdots & \vdots \\ S_{\mathrm{DG}n,1} & S_{\mathrm{DG}n,2} & \cdots & S_{\mathrm{DG}n,\mathrm{NP}} \\ L_{\mathrm{DG1},1} & L_{\mathrm{DG1},2} & \cdots & L_{\mathrm{DG1,NP}} \\ \vdots & \vdots & \cdots & \vdots \\ L_{\mathrm{DG}n,1} & L_{\mathrm{DG}n,2} & \cdots & L_{\mathrm{DG}n,\mathrm{NP}} \end{bmatrix} \tag{13}$$

Here, subscripts DG1, DG2, …, DGn indicate the DG numbers. So, $S_{\mathrm{DGn,NP}}$ and $L_{\mathrm{DGn,NP}}$ indicate the size and location of n^{th} DG unit, respectively, in NP^{th} population. For the penetration with n number of DG units, the size of this matrix will be ($2n \times$ NP).

Now, the generated random estimated points ($P_{i,j}$) are converted to its corresponding opposite estimated points ($\mathrm{OP}_{i,j}$) which are defined as the components of $P_{i,j}$. It can be represented as (Tizhoosh 2005):

$$\mathrm{OP}_{i,j} = P_{\min,i} + P_{\max,i} - P_{i,j} \tag{14}$$

This QO scheme was first proposed by Rahnamayan, Tizhoosh, and Salama (2007), and in that work they proved that quasi-oppositional points ($\mathrm{QOP}_{i,j}$) are more likely to be closer to the solution than its corresponding opposite estimated points. With the help of $P_{i,j}$ and $OP_{i,j}$, $QOP_{i,j}$ can be generated as (Rahnamayan, Tizhoosh & Salama 2007; Roy & Sarkar 2014):

$$\mathrm{QOP}_{i,j} = \mathrm{rand}(c_i, \mathrm{OP}_{i,j}) \quad \text{Where, } c_i = \frac{P_{\min,i} + P_{\max,i}}{2} \tag{15}$$

For the selection of best estimated populations among $P_{i,j}$ and $\mathrm{QOP}_{i,j}$, the fitness values for both the points are calculated and then consider the best among two points as the position vector of the corresponding grey wolf (X_j) as follows:

$$X_j = \begin{cases} QOP_j & \text{if } f\left(\mathrm{QOP}_j\right) \le f\left(P_j\right) \\ P_j & \text{else,} \end{cases} \tag{16}$$

The position vector of grey wolves ($\vec{X}$) is formed in such a way that $\vec{X} = \{X_1, X_2, \ldots, X_j\}$.

4.2 Social hierarchy

The fittest solution is assumed as α solution, and its position vector is assumed as X_α. Consequently, the second and third best solutions are named as β and δ solutions and their respective position vectors are assumed as X_β and X_δ, respectively. The rest solutions are assumed as ω solutions. The ω solutions follow α, β and δ solutions.

4.3 Encircling prey

The grey wolves encircle prey before hunting, and it can be mathematically modeled as:

$$\vec{D} = \left|\vec{C}.\vec{X}_p(k) - \vec{X}(k)\right| \tag{17}$$

$$\vec{X}(k+1) = \vec{X}_p(k) - \vec{A}.\vec{D} \tag{18}$$

where $\vec{X}_p(k)$ and $\vec{X}(k)$ indicate the position vector of the prey and the grey wolf, respectively, in the kth iteration. Here, 'k' varies from 1 to maximum allowed number of iteration, i.e., $\mathrm{IT}_{\max}$. Vectors A and C are the coefficient vectors and calculated as follows:

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a} \quad (19)$$

$$\vec{C} = 2\vec{r}_2 \quad (20)$$

where r_1 and r_2 are the random vectors in [0,1] and vector a decreases linearly from 2 to 0 over the course of iterations.

4.4 Hunting

Since all three α, β and δ solutions have better idea about the potential location of prey, the hunting process is guided by all three solutions. The positions of all the ω solutions are updated by following the positions of all three solutions. The mathematical model for hunting process can be formulated as:

$$\vec{D}_\alpha = \left|\vec{C}_\alpha.\vec{X}_\alpha - \vec{X}\right|,\ \vec{D}_\beta = \left|\vec{C}_\beta.\vec{X}_\beta - \vec{X}\right|,\ \vec{D}_\delta = \left|\vec{C}_\delta.\vec{X}_\delta - \vec{X}\right| \quad (21)$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_\alpha.\vec{D}_\alpha,\ \vec{X}_2 = \vec{X}_\beta - \vec{A}_\beta.\vec{D}_\beta,\ \vec{X}_3 = \vec{X}_\delta - \vec{A}_\delta.\vec{D}_\delta \quad (22)$$

$$\vec{X}(k+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (23)$$

where vectors A and C can be calculated using Eqs. (19) and (20), respectively.

4.5 Attacking prey (exploitation) and searching prey (exploration)

Since r_1 and r_2 are the random vectors in [0,1], so as per Eqs. (19) and (20), $C \in [0, 2]$ and $A \in [-a, a]$. Hence from Eqs. (17) and (18), it can be noticed that positive value of vector A forces the wolves to attack toward the prey and that is responsible for exploitations, whereas its negative value forces the wolves to diverge from the prey or search for another prey and that is responsible for explorations. The larger value of a in initial stage of iteration provides more thrust to the wolves for exploring the search space, whereas the smaller value of a in latter stage force the wolves to converge toward the prey.

4.6 Archive formation with Pareto optimal fronts

After updating the position vectors of grey wolves, fitness values of all the wolves have been calculated and then the non-dominated solutions have been selected. If the solution X_1 is not worse than the solution X_2 for all the objectives and it is strictly better than X_2 for at least one of the objectives, then the solution X_1 is said to dominate the solution X_2. Mathematically, it can be represented as (Kumar Mandal and Chakraborty 2019):

$$\forall m \in \{1, 2, \ldots, N_{\text{obj}}\} \rightarrow f_m(X_1) \le f_m(X_2) \wedge \exists n \in \{1, 2, \ldots, N_{\text{obj}}\} \rightarrow f_n(X_1) < f_n(X_2) \quad (24)$$

where N_{obj} is the maximum number of objectives to be considered and $f_m(X_1)$ indicates the value of mth objective function corresponding to X_1 solution. The solution X_1 is called non-dominated if and only if the above condition is strictly followed. The set of all non-dominated solutions is called Pareto optimal set or Pareto front. For the first time, create an archive which is nothing but a matrix that can store or retrieve non-dominated Pareto optimal solutions obtained so far. For the subsequent iterations, update the archive as follows:

- If the new non-dominated solution is dominated by anyone of the current archive member, then this solution is not allowed to enter in the archive.
- If the new solution dominates one or more solutions in the archive, then this new solution replaces the existing dominated solutions in the archive.
- And, if both new solution and the archive members are non-dominated, then just add the new member to the archive.

In most of the problems, the archive size becomes so large that it is very difficult to handle the archive matrix for further analysis. In that situation, the size of archive matrix can be truncated by clustering or crowding distance metric strategy.

4.7 Reduction of archive matrix by crowding distance metric

Crowding distance (Cr) metric is an iterative process used for the elimination of the most crowded points by penalizing those points. The lower value of Cr represents that the corresponding point is located in the most crowded area and hence that point is eliminated from the archive. This process is repeated until the archive size is reduced to its maximum allowable size or maximum number of Pareto fronts ($\text{PF}_{\max}$). The boundary points are very much important; therefore, Cr is not calculated for boundaries. The Cr of i^{th} Pareto front (Cr_i) can be calculated as (Modiri-Delshad & Rahim 2016):

$$Cr_i = \sum_{n=1}^{N_{\text{obj}}} \left(\frac{\left| f_{i+1}^n - f_{i-1}^n \right|}{B_n} \right) \quad (25)$$

where f_{i+1}^n and f_{i-1}^n indicate the nearby next and previous Pareto fronts to ith Pareto front along the nth objective in the archive. B_n indicates the maximum boundary gap for n^{th} objective.

4.8 Selection of best compromised solution by fuzzy set theory

In the multi-objective scenario, it is not possible to choose a single optimal solution which can satisfy all the objectives simultaneously due to the conflicting nature of all the objectives. In that scenario, a single best compromised solution is chosen from the archive which consists of desired number of Pareto optimal fronts. A concept based on fuzzy set theory has been implemented to choose the best compromised solution. For implementing this concept, first of all a linear membership function is used to evaluate the Pareto fronts in the interval of [0,1]. Mathematically, it can be calculated as (Modiri-Delshad & Rahim 2016):

$$\mu_i^n = \begin{cases} 1 & f_i^n \le f_{\min}^n \\ \dfrac{f_{\max}^n - f_i^n}{f_{\max}^n - f_{\min}^n} & f_{\min}^n < f_i^n < f_{\max}^n \\ 0 & f_i^n \ge f_{\max}^n \end{cases} \quad (26)$$

where μ_i^n is a linear membership function of ith Pareto front for the nth objective. f_i^n indicates the ith Pareto front, whereas $f_{\min}^n$ and $f_{\max}^n$ are its minimum and maximum values for the nth objective function, respectively. After evaluation membership function of all the Pareto fronts for all objectives, all these Pareto fronts are normalized to a single objective with the help of normalized membership function (μ). The normalized membership function of ith Pareto front (μ_i) has been calculated as follows (Kumar Mandal and Chakraborty 2019):

$$\mu_i = \frac{\sum_{n=1}^{N_{\text{obj}}} (w_n.\mu_i^n)}{\sum_{i=1}^{PF_{\max}} \sum_{n=1}^{N_{\text{obj}}} \mu_i^n} \quad (27)$$

where w_n is the per-unit weighting factor of nth objective function. In this work, equal weights have been given to all objectives. After calculating μ for all the Pareto fronts, all these values are arranged in descending order. The order of μ reflects the priority order of the solution. That means the solution which has maximum value of μ is considered as the best compromised solution which is nothing but the best optimal solution considering all the objective functions. The complete flowchart of the proposed MQOGWO algorithm is presented in Fig. 1.

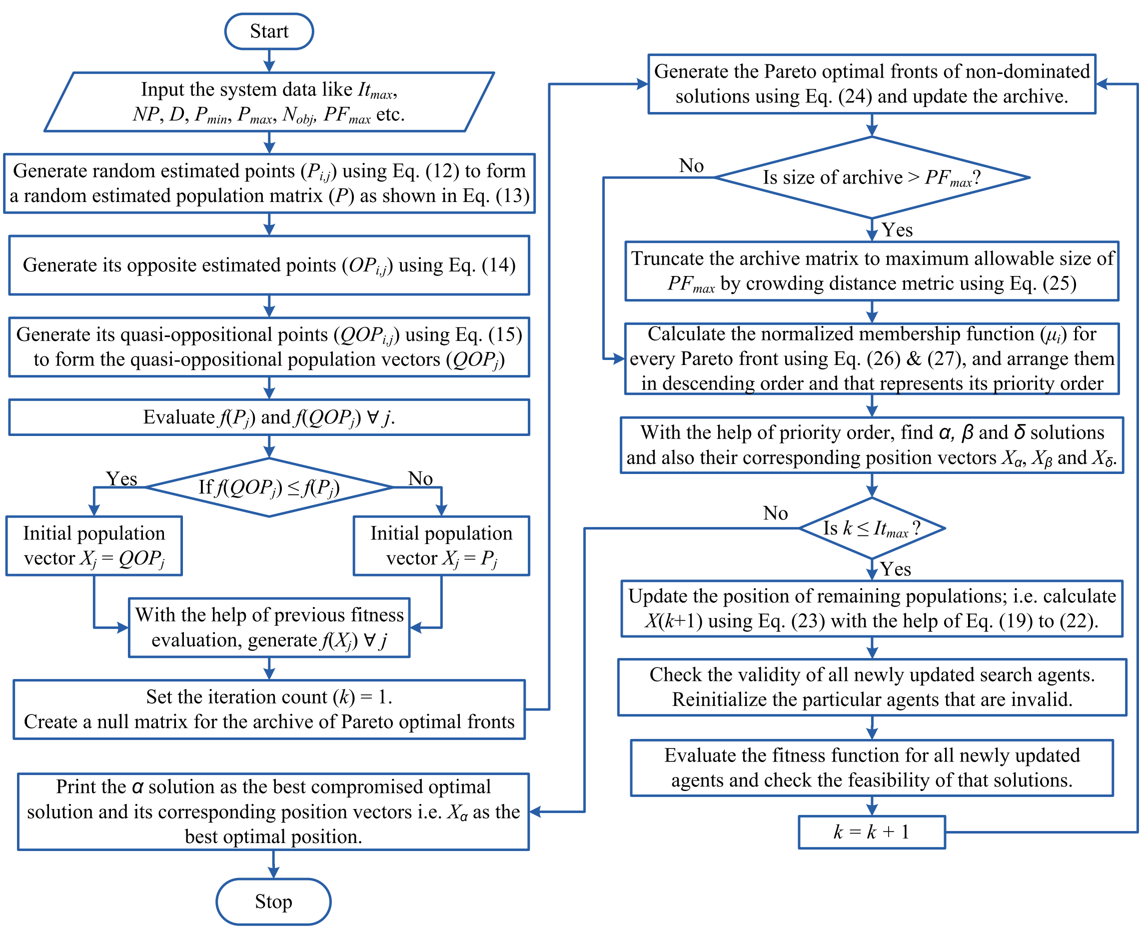

Fig. 1 Flowchart of the proposed MQOGWO algorithm

Table 2 Single objective case: Loss minimization

No. of DG	Methods	Location of DG (bus no.)	Size of DG (kW/kVAr)	Minimum bus voltage (p.u.)	Weakest bus	Real power loss (kW)	Active power from substation (kW)
Case 1: DGs operating at upf							
3	QOGWO	13	801.81/0.0	0.9687	33	72.784	841.674
		24	1091.29/0.0				
		30	1053.01/0.0				
3	OTCDE	13	801.80/0.0	0.9687	33	72.785	841.075
		24	1091.31/0.0				
		30	1053.60/0.0				
3	OCDE	13	801.84/0.0	0.9686	33	72.848	847.968
		24	1091.46/0.0				
		30	1046.58/0.0				
3	KHA	13	810.7/0.0	0.9610	18	75.412	–
		25	836.8/0.0				
		30	841.0/0.0				
3	SFSA	13	802.0/0.0	–	–	72.785	–
		24	1092.0/0.0				
		30	1053.7/0.0				
Case 2: DGs operating at 0.95 lagging pf							
3	QOGWO	13	830.21/272.88	0.9880	33	28.532	549.162
		24	1124.60/369.64				
		30	1239.56/407.42				
3	OTCDE	13	830.23/272.88	0.9880	33	28.533	549.093
		24	1124.65/369.66				
		30	1239.56/407.42				
3	SFSA	13	830.6/273.0	–	–	28.533	–
		24	1125.6/370.0				
		30	1239.6/407.4				
3	QOSIMBO-Q	13	830.3/272.9	–	–	28.5	–
		24	1123.9/369.4				
		30	1239.8/407.5				

5 Results and discussion

In this work, two different case studies have been performed for testing the performance of the proposed algorithm in both single-objective and in multiobjective environments. For the single objective case, only P_L^{aDG} is considered as the fitness or objective function which is required to be minimized. For both single objective and multiobjective cases, two different scenarios have been studied. In scenario-1, three numbers of type-I DGs have been taken, whereas same numbers of type-II DGs have been considered in scenario-2. For multiobjective case, at

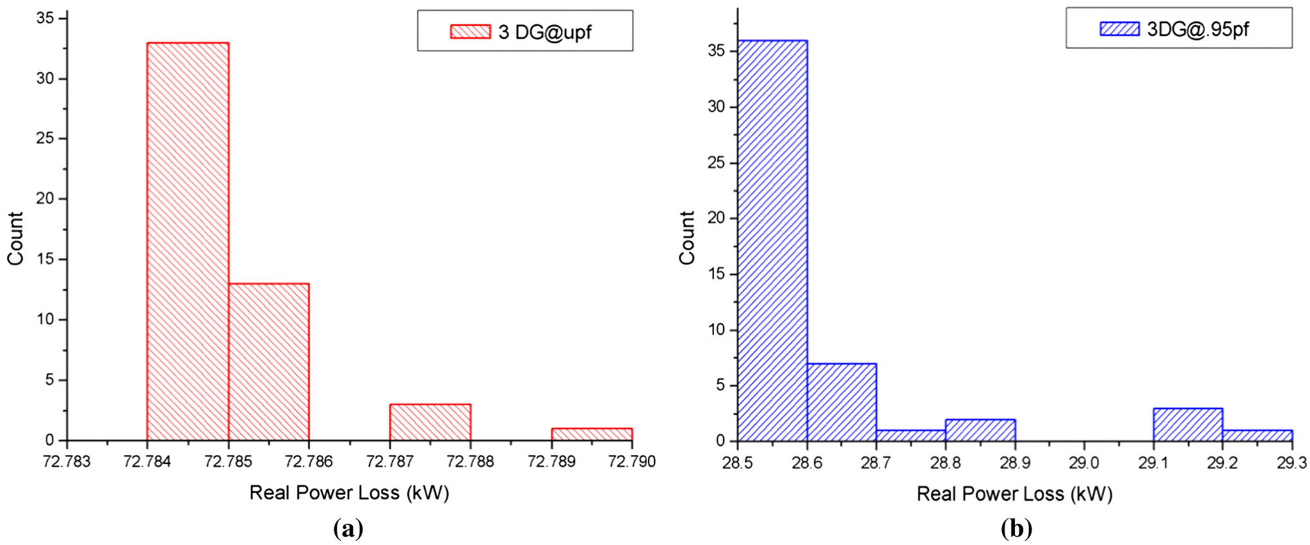

Fig. 2 Histogram plots of the 50 distinct trial results obtained by QOGWO algorithm under **a** DG@upf **b** DG@0.95pf

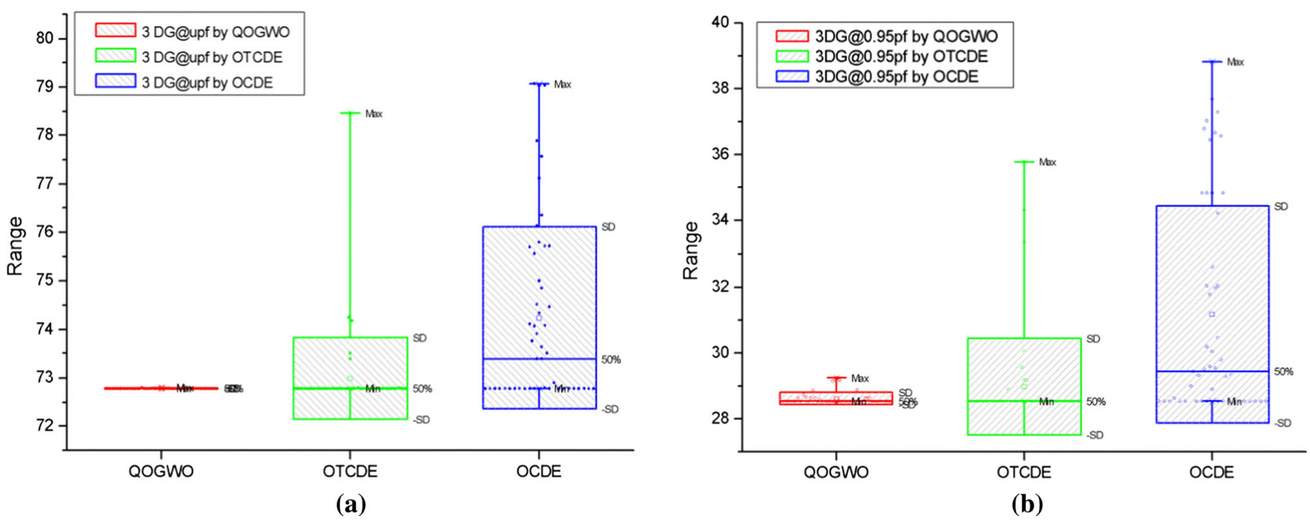

Fig. 3 Box-and-Whisker plots of the 50 distinct trial results obtained by different algorithms under **a** DG@upf **b** DG@0.95pf

the same time five different types of load models at different loading conditions have also been considered to analyze the effects of load variations on system performance. It is considered that the sizes of DGs may vary from 10 to 80% of total load demands, whereas all the nodes voltages should be between 0.95 p.u. to 1.05 p.u. (Rao and Sivanagaraju 2012). The total DG life is assumed to be 10 years. The cost of power generated by DGs including capital investment, installation, operation and maintenance cost is taken as \$ 30.00 per kW. The energy loss cost per kWh is considered to be \$ 0.05 (Rao and Sivanagaraju 2012). In this case study, NP, IT_{max}, and PF_{max} are taken to be 50, 500 and 50, respectively.

The effectiveness of the proposed MQOGWO algorithm has been tested on the standard IEEE 33-bus RDS, and its corresponding data are taken from Kumar and Jayabarathi (2012). In this standard test system, the total connected load demands are 3.715 MW and 2.3 MVAr, whereas its substation base voltage and base MVA are 12.66 kV and 100 MVA, respectively. The connected loads in this standard system are assumed as the loads at full load condition. By performing the load flow analysis on standard test system, it is seen that 210.987 kW and 143.128 kVAr power loss has occurred during the distribution process. This power loss is converted to its equivalent $\mathrm{YEL}_{\mathrm{bDG}}$ which is equal to \$92,412.502. Bus number 18 is found to be highly sensitive bus because its voltage falls to 0.9038 p.u. which is the lowest among all buses.

Table 3 Multiobjective case with constant power (CP) load model

Loading condition	DG location (bus no.)	DG size (kW)	DG size (kVAr)	Minimum Bus Voltage (p.u.)	Weakest bus no	power loss (kW/kVAr)	Total yearly economic loss ($)	Total yearly saving ($)
Case 1: DGs operating at upf								
LL	Without DG penetration			0.9540	18	48.787/33.049	21,368.694	NA
	14	396.54	0	0.9850	33	17.658/12.302	12,110.455	9258.239
	24	523.21	0					
	30	539.04	0					
FL	Without DG penetration			0.9038	18	210.987/ 143.128	92,412.502	NA
	13	801.02	0	0.9686	33	72.787/50.672	40,678.149	51,734.399
	24	1079.49	0					
	30	1051.91	0					
HL	Without DG penetration			0.8822	18	314.490/ 213.479	137,746.404	NA
	14	1054.85	0	0.9681	33	108.124/ 75.605	58,542.869	79,203.535
	24	1249.94	0					
	30	1423.44	0					
Case 2: DGs operating at 0.866 lagging pf								
LL	Without DG penetration			0.9540	18	48.787/33.049	21,368.694	NA
	13	376.14	217.190	0.9958	8	3.825/3.078	6059.310	15,309.384
	24	488.17	281.878					
	30	597.02	344.730					
FL	Without DG penetration			0.9038	18	210.987/ 143.128	92,412.502	NA
	13	756.86	437.025	0.9921	8	15.352/12.413	15,667.397	76,745.152
	24	1012.65	584.722					
	30	1211.61	699.605					
HL	Without DG penetration			0.8822	18	314.490/ 213.479	137,746.404	NA
	13	906.12	523.210	0.9900	8	22.232/17.906	20,327.676	117,418.728
	24	1178.10	680.256					
	30	1445.80	834.831					

5.1 Single objective case: minimization of P_L^{aDG}

In this case study, only one objective P_L^{aDG} is considered as objective function and type-I and type-II DG with operating power factor of 0.95 are chosen for comparative performance analysis with other state-of-the-art algorithms. For performing the task of single objective minimization, some steps that are mentioned in Sects. 4.6, 4.7 and 4.8 of the proposed MQOGWO algorithm have been omitted and made some needful changes. It can also be performed easily by just putting the value of N_{obj} from 3 to 1 for this case. This proposed algorithm for single objective case is named as QOGWO algorithm. Table 2 shows the optimal results obtained by this technique. Table 2 also shows the results obtained by techniques like novel opposition-based tuned-chaotic differential evolution (OTCDE) technique (Kumar Mandal and Chakraborty 2020), opposition based chaotic differential evolution (OCDE) (Kumar Mandal and Chakraborty 2019), krill herd algorithm (KHA) (Sultana and Roy 2016), SFSA (Nguyen and Vo 2018), and QOSIMBO-Q (Sharma Bhattacharjee and Bhattacharya 2016). By analyzing these results, it can be noticed that the proposed algorithm is able to produce the better results compared to other above-mentioned techniques. In scenario-1, the power loss obtained by QOGWO algorithm is 72.784 kW which is slightly better than 72.785, 72.848 kW, 75.412 kW, and 72.785 kW that are the losses obtained by OTCDE, OCDE, KHA, and SFSA algorithms, respectively. Similarly in scenario-2, the loss reduces to 28.532 kW after placement of 3 numbers of type-II DG which is slightly better than the loss obtained by recently proposed OTCDE, SFSA and QOSIMBO-Q algorithms.

Table 4 Multiobjective case with constant current (CC) load model

Loading condition	DG location (bus no.)	DG size (kW)	DG size (kVAr)	Minimum bus voltage (p.u.)	Weakest bus no.	Power loss (kW/kVAr)	Total yearly economic loss ($)	Total yearly saving ($)
Case 1: DGs operating at upf								
LL	Without DG penetration			0.9557	18	45.581/30.837	19,964.576	NA
	14	369.55	0	0.9838	33	17.249/11.973	11,630.152	8334.424
	24	487.62	0					
	30	501.26	0					
FL	Without DG penetration			0.9114	18	182.479/ 123.448	79,926.005	NA
	13	764.81	0	0.9680	33	69.242/48.136	38,763.807	41,162.197
	24	1063.82	0					
	30	983.25	0					
HL	Without DG penetration			0.8936	18	262.862/ 177.823	115,133.597	NA
	14	1006.95	0	0.9667	33	101.723/ 70.965	55,189.586	59,944.011
	24	1218.20	0					
	30	1319.78	0					
Case 2: DGs operating at 0.866 lagging pf								
LL	Without DG penetration			0.9557	18	45.581/30.837	19,964.576	NA
	13	372.72	215.215	0.9957	8	3.810/3.065	6033.010	13,931.567
	24	485.68	280.440					
	30	596.39	344.366					
FL	Without DG penetration			0.9114	18	182.479/ 123.448	79,926.005	NA
	13	751.30	433.814	0.9919	8	15.226/12.299	15,556.992	64,369.012
	24	1012.38	584.566					
	30	1198.94	692.290					
HL	Without DG penetration			0.8936	18	262.862/ 177.823	115,133.597	NA
	13	895.07	516.830	0.9898	8	21.987/17.712	20,170.615	94,962.981
	24	1187.11	685.459					
	30	1431.32	826.470					

The robustness of the proposed algorithm can be analyzed by the histogram plots which are depicted in Fig. 2. It is plotted against 50 independent distinct trial runs. From the histogram plots under both operating power factor cases of DG units, it can be easily noticed that the deviation of the optimal results is very less, and most of the times, it can produce the optimal results. The robustness of the proposed algorithm as compared to other algorithms like OTCDE (Kumar Mandal and Chakraborty 2020) and OCDE (Kumar Mandal and Chakraborty 2019) can be noticed from the Box-and-Whisker plots which are presented in Fig. 3. In this plot, the variations of the results are pointed by small dots and circles, whereas small-square boxes and cross marks indicate its mean value and min–max points, respectively. The standard deviation (SD) and min–max points of the results are considered as the box range and whisker range, respectively. From these plots, it can be noticed that the least deviations in the results of both cases can be found by the proposed algorithm. So from these plots, it can be said that the proposed QOGWO technique is most robust technique followed by OTCDE and OCDE technique.

5.2 Multiobjective case: minimization of P_L^{aDG}, YEL_{aDG}, and VD_{aDG}

In this case study, all three objectives have been considered simultaneously to find the best optimized solution for the techno-economic analysis. This ODGP problem has been solved by the proposed MQOGWO algorithm considering different voltage-dependent load models instead of constant loads. The analysis has been further extended by

Table 5 Multiobjective case with constant impedance (CI) load model

Loading condition	DG location (bus no.)	DG size (kW)	DG size kVAr)	Minimum bus voltage (p.u.)	Weakest bus no.	Power loss (kW/kVAr)	Total yearly economic loss ($)	Total yearly saving ($)
Case 1: DGs operating at upf								
LL	Without DG penetration			0.9573	18	42.795/28.918	18,744.329	NA
	14	363.27	0	0.9837	33	16.836/11.675	11,364.667	7379.663
	24	485.45	0					
	30	481.40	0					
FL	Without DG penetration			0.9174	18	161.186/ 108.788	70,599.458	NA
	13	733.79	0	0.9677	33	65.909/45.756	36,983.812	33,615.646
	24	1048.09	0					
	30	923.37	0					
HL	Without DG penetration			0.9021	18	226.714/ 152.943	99,300.931	NA
	14	943.96	0	0.9651	33	95.384/66.358	51,830.250	47,470.681
	24	1197.71	0					
	30	1209.00	0					
Case 2: DGs operating at 0.866 lagging pf								
LL	Without DG penetration			0.9573	18	42.795/28.918	18,744.329	NA
	13	373.34	215.573	0.9959	8	3.782/3.052	6062.561	12,681.769
	24	499.18	288.236					
	30	596.11	344.205					
FL	Without DG penetration			0.9174	18	161.186/ 108.788	70,599.458	NA
	13	747.23	431.464	0.9919	8	15.096/12.192	15,474.756	55,124.702
	24	1015.01	586.085					
	30	1192.00	688.282					
HL	Without DG penetration			0.9021	18	226.714/ 152.943	99,300.931	NA
	13	885.48	511.292	0.9896	8	21.746/17.504	19,991.590	79,309.341
	24	1188.70	686.377					
	30	1414.71	816.879					

considering three different loading situations like LL, FL, and HL as well as two different types of DGs. The corresponding results for CP load model are shown in Table 3. Similarly, the results obtained by considering CC, CI, RES, IND, and COM types of load models are depicted in Tables 4, 5, 6, 7, and 8, respectively. In all the tables, the DGs that are operating at upf are considered in scenario 1, whereas scenario 2 considers the DGs with operating power factor of 0.866 lagging. It is worth mentioning that all the equality and inequality constraints are strictly followed during LL and FL situations. But during HL situation, no any valid solutions are found by following all these constraints. Since at rated load or FL the power flow across some few branches are already very close to their maximum rated capacity limits, these lines are not capable of handling 20% increased load demand. If we increased the load demand by 20%, then these lines will be failed and burned out. So for the analysis purpose, the line flow capacity limit constraints cannot be followed during the considered HL situation and hence omitted.

From Table 3, it is seen that the power loss before DG placement is comparatively reduced from the loss during FL condition, i.e., 210.987 kW/143.128 kVAr to 48.787 kW/33.049 kVAr during the LL condition, whereas it is increased to 314.490 kW/213.479 kVAr during HL condition. After optimal placements of 3 DGs in scenario 1, the losses are drastically reduced to 17.658 kW /12.302 kVAr, 72.787 kW/50.672 kVAr, and 108.124 kW/75.605 kVAr during LL, FL, and HL loading conditions, respectively. At the same time, the minimum bus voltages are improved and yearly economic losses are decreased drastically compared to the cases without DG penetration

Table 6 Multiobjective case with residential (RES) load model

Loading condition	DG location (Bus No.)	DG size (kW)	DG Size kVAr)	Minimum bus voltage (p.u.)	Weakest bus no.	Power Loss (kW/kVAr)	Total yearly economic Loss ($)	Total yearly saving ($)
Case 1: DGs operating at upf								
LL	Without DG penetration			0.9570	18	43.074/29.129	18,866.594	NA
	14	401.85	0	0.9854	33	16.292/11.349	11,406.977	7459.617
	24	501.46	0					
	30	520.44	0					
FL	Without DG penetration			0.9160	18	164.541/ 111.237	72,068.928	NA
	14	711.12	0	0.9673	33	60.972/42.385	34,733.005	37,335.923
	24	1052.36	0					
	30	912.27	0					
HL	Without DG penetration			0.9001	18	233.154/ 157.612	102,121.498	NA
	14	971.40	0	0.9649	33	87.443/60.936	48,295.711	53,825.787
	24	1171.66	0					
	30	1188.88	0					
Case 2: DGs operating at 0.866 lagging pf								
LL	Without DG penetration			0.9570	18	43.074/29.129	18,866.594	NA
	13	377.86	218.183	0.9961	8	3.771/3.048	6095.662	12,770.932
	24	503.77	290.886					
	30	599.62	346.231					
FL	Without DG penetration			0.9160	18	164.541/ 111.237	72,068.928	NA
	13	749.63	432.850	0.9917	8	14.990/12.102	15,380.872	56,688.056
	24	1014.41	585.739					
	30	1174.43	678.137					
HL	Without DG penetration			0.9001	18	233.154/ 157.612	102,121.498	NA
	13	889.63	513.688	0.9893	8	21.550/17.345	19,850.137	82,271.361
	24	1194.27	689.593					
	30	1386.58	800.636					

during all three loading situations. Similar trends with even better performance can be noticed in scenario 2. The better performance in every objective is due to the active as well as reactive power compensation by placements of lagging pf operated DGs in scenario 2. The maximum yearly economic benefits (as compared to without DG penetration case) of $117,418.728 can be extracted by the placement of type II DG during the HL situation, whereas maximum technical benefits (such as improvements in bus voltage profile and reduction in power loss) can be extracted by placement of similar type of DGs in LL situation. From this table, it can easily be noticed that total P_L and *YEL* are found to be lowest during LL situation in scenario 2, whereas highest during HL situation in scenario 1. Similarly, minimum bus voltage is found to be highest (0.9958 p.u.) during LL situation in scenario 2, whereas lowest (0.9681 p.u.) during HL situation in scenario 1.

As compared to Table 3, very similar trends can be seen for all types of load models and that can be noticed from Tables 4, 5, 6, 7, and 8. The corresponding Pareto optimal fronts for all types of load models are shown in different section of Fig. 4. In every figure, the Pareto optimal fronts for all 6 different situations (each for LL, FL and HL situations for both scenarios) are plotted simultaneously. After optimal DG placements considering different load models, it is observed that the minimum power loss of 3.755 kW/3.031 kVAr is found in scenario 2 during LL situation with IND type load model, whereas it increased maximum up to 108.124 kW/75.605 kVAr in scenario 1 during HL situation with CP type load model. In every type of load models, the minimum power loss occurs during LL

Table 7 Multiobjective case with Industrial (IND) load model

Loading condition	Dg location (bus no.)	Dg size (kw)	DG size (kVAr)	Minimum bus voltage (p.u.)	Weakest bus no.	Power loss (kW/kVAr)	Total yearly economic loss ($)	Total yearly saving ($)
Case 1: DGs operating at upf								
LL	Without DG penetration			0.9569	18	43.104/29.166	18,879.355	NA
	14	365.68	0	0.9834	33	15.602/10.823	10,762.942	8116.413
	24	476.52	0					
	30	467.52	0					
FL	Without DG penetration			0.9153	18	167.792/ 113.617	73,492.725	NA
	14	720.15	0	0.9674	33	56.796/39.543	32,889.982	40,602.744
	24	1049.53	0					
	30	901.38	0					
HL	Without DG penetration			0.8988	18	240.518/ 162.929	105,346.810	NA
	14	998.31	0	0.9660	33	81.341/56.833	45,706.997	59,639.813
	24	1162.02	0					
	30	1199.51	0					
Case 2: DGs operating at 0.866 lagging pf								
LL	Without DG penetration			0.9569	18	43.104/29.166	18,879.355	NA
	13	373.63	215.741	0.9957	8	3.755/3.031	6037.878	12,841.477
	24	504.06	291.053					
	30	586.70	338.771					
FL	Without DG penetration			0.9153	18	167.792/ 113.617	73,492.725	NA
	13	746.93	431.291	0.9912	8	14.862/11.991	15,242.739	58,249.986
	24	1013.85	585.415					
	30	1150.34	664.227					
HL	Without DG penetration			0.8988	18	240.518/ 162.929	105,346.810	NA
	13	891.89	514.993	0.9891	8	21.318/17.175	19,717.376	85,629.434
	24	1199.50	692.613					
	30	1368.70	790.312					

situation in scenario 2 and then followed by FL in scenario 2, LL in scenario 1, HL in scenario 2, FL in scenario 1 and HL in scenario 1. Similarly in all types of load models, the *YEL* is found to be minimum during LL situation in scenario 2 followed by LL in scenario 1, FL in scenario 2, HL in scenario 2, FL in scenario 1 and HL in scenario 1, whereas the minimum bus voltage is found to be maximum during LL situation in scenario 2 followed by FL in scenario 2, HL in scenario 2, LL in scenario 1, FL in scenario 1 and lowest during HL in scenario 1. But it is seen that no any common trends are followed for *TYS* in all types of load models. The bus voltage profile for all types of load models considering all three loading situations in both scenarios are shown in Fig. 5. The minimum bus voltage trends for all types of load models can also be noticed from this figure. It is seen that bus number 18 was the weakest bus before DG penetration, whereas position of weakest bus changes to bus number 33 in scenario 1 and to bus number 8 in scenario 2 after DG penetration.

Figure 6 indicates the branch power flow profiles for all types of load models considering all three loading situations in both scenarios. From this figure, it is seen that the power flows from the branches 1 to 5 are comparatively very high without DG penetration and it reduces drastically after DG penetration for all types of load modelling during every loading situation. The reduction in power flows in scenario 2 is found to be more compared to scenario 1 because DG shares some of the active as well as reactive power load demands in scenario 2 whereas in scenario 1, it shares only active power load demand. So, it can be concluded that installing type-II DGs in the RDS are more

Table 8 Multiobjective case with commercial (COM) load model

Loading condition	DG location (Bus no.)	DG size (kW)	DG size (kVAr)	Minimum Bus voltage (p.u.)	Weakest bus no.	Power loss (kW/kVAr)	Total yearly economic loss ($)	Total yearly saving ($)
Case 1: DGs operating at upf								
LL	Without DG penetration			0.9573	18	42.492/28.720	18,611.423	NA
	14	403.01	0	0.9854	33	16.479/11.475	11,482.258	7129.164
	24	501.07	0					
	30	517.43	0					
FL	Without DG penetration			0.9175	18	159.501/107.708	69,861.394	NA
	13	732.60	0	0.9674	33	62.337/43.313	35,331.026	34,530.369
	24	1043.33	0					
	30	899.92	0					
HL	Without DG penetration			0.9024	18	224.235/151.369	98,214.987	NA
	14	925.19	0	0.9637	33	88.934/61.843	48,727.783	49,487.204
	24	1181.05	0					
	30	1151.95	0					
Case 2: DGs operating at 0.866 lagging pf								
LL	Without DG penetration			0.9573	18	42.492/28.720	18,611.423	NA
	13	371.60	214.569	0.9957	8	3.777/3.042	6020.770	12,590.652
	24	494.07	285.285					
	30	589.85	340.590					
FL	Without DG penetration			0.9175	18	159.501/107.708	69,861.394	NA
	13	742.98	429.010	0.9915	8	15.009/12.111	15,359.940	54,501.455
	24	1012.82	584.821					
	30	1172.86	677.230					
HL	Without DG penetration			0.9024	18	224.235/151.369	98,214.987	NA
	13	884.78	510.888	0.9893	8	21.592/17.371	19,858.295	78,356.692
	24	1188.93	686.510					
	30	1393.25	804.488					

beneficial than type-I DG during every loading situation for all types of load modelling.

6 Conclusion

In this work, a novel multiobjective quasi-oppositional grey wolf optimizer (MQOGWO) algorithm has been proposed and successfully implemented for the optimal placement of different types of DGs in the radial distribution system (RDS) considering different scenarios. The current optimal DG placement (ODGP) problem has been solved for extracting maximum techno-economic benefits. For maximizing technical benefits, power loss after DG placement (P_L^{aDG}) and bus voltage deviation (VD_{aDG}) have been considered as objective functions, whereas another objective function yearly economic loss (YEL_{aDG}) has been considered for maximizing economical benefits. Since all the above-mentioned objectives are contradictory in nature, so the best compromised solution, which can satisfy all these objectives to their maximum extent, is chosen for the optimal techno-economic benefits by formulating the Pareto-based multiobjective framework. For testing the effectiveness of the proposed algorithm, the problem has been further extended by considering different load models like CP, CC, CI, RES, IND, and COM during various loading situation like LL, FL, and HL. After successful implementation of the proposed MQOGWO algorithm in all the above-mentioned scenarios, it is seen that installing type-II DGs in the RDS are more beneficial than type-I DG during every loading situation for all types of load modelling. For comparative performance analysis, the proposed

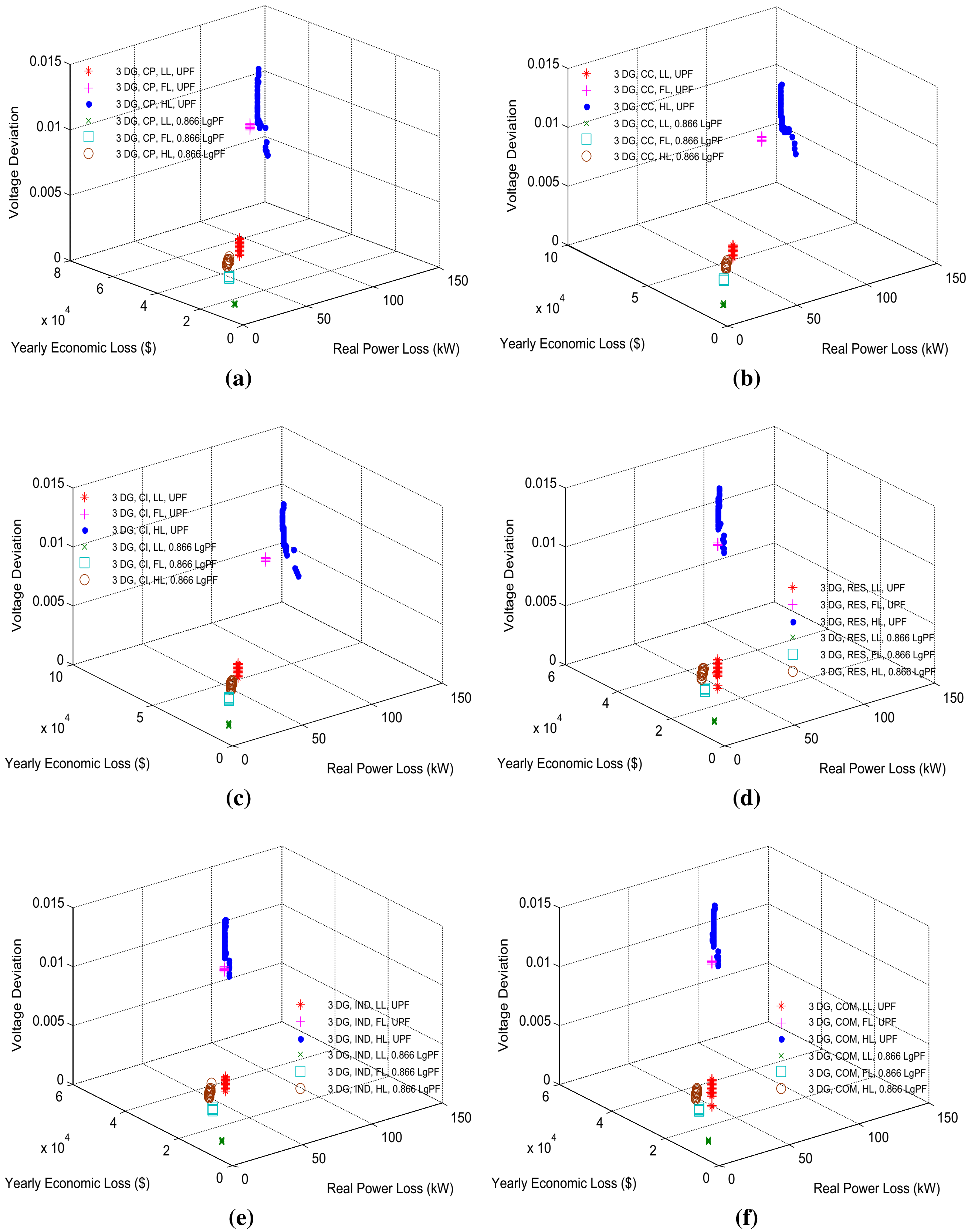

Fig. 4 Pareto-optimal fronts for **a** CP load model, **b** CC load model, **c** CI load model, **d** RES load model, **e** IND load model, **f** COM load model

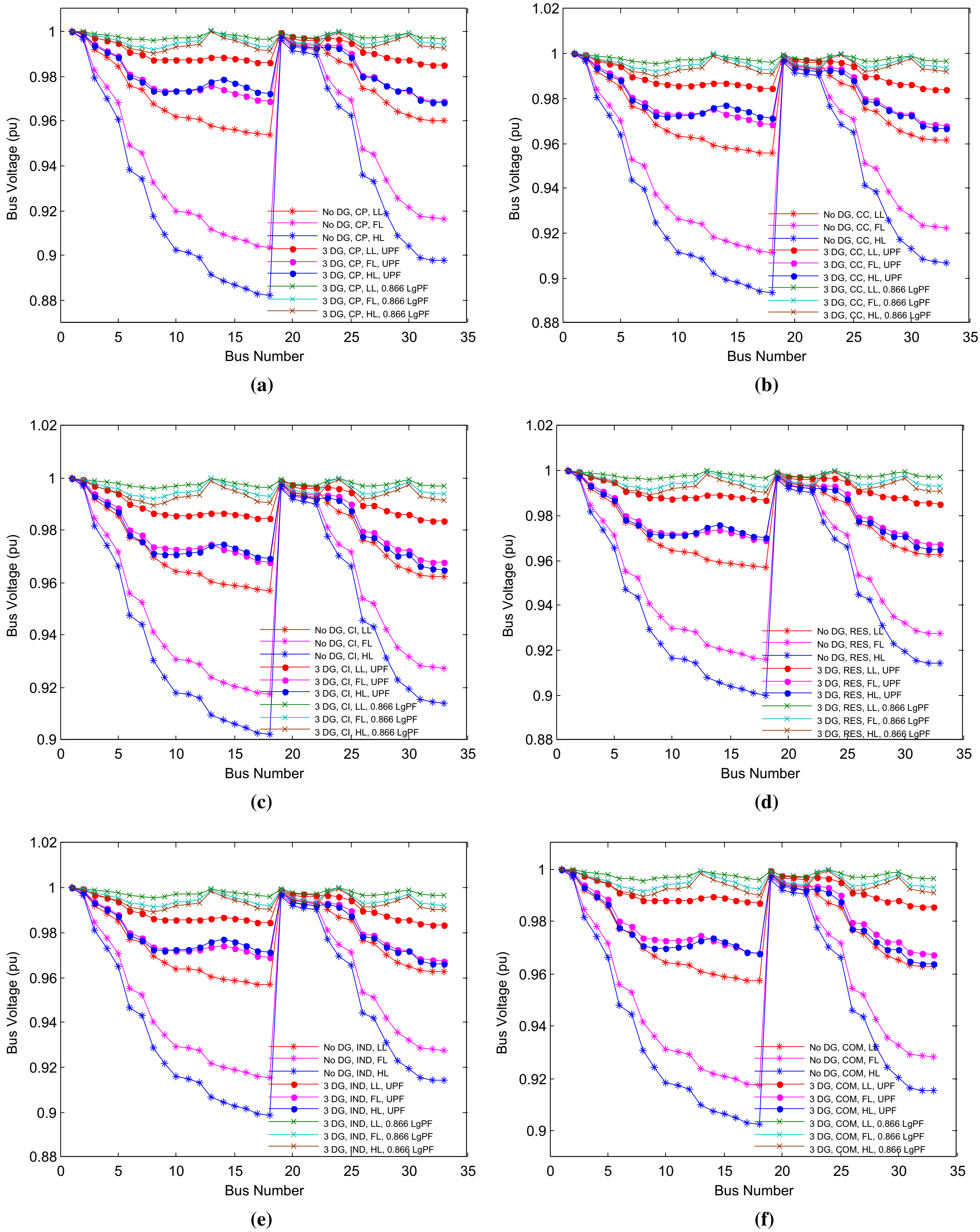

Fig. 5 Bus voltage profile for **a** CP load model, **b** CC load model, **c** CI load model, **d** RES load model, **e** IND load model, **f** COM load model

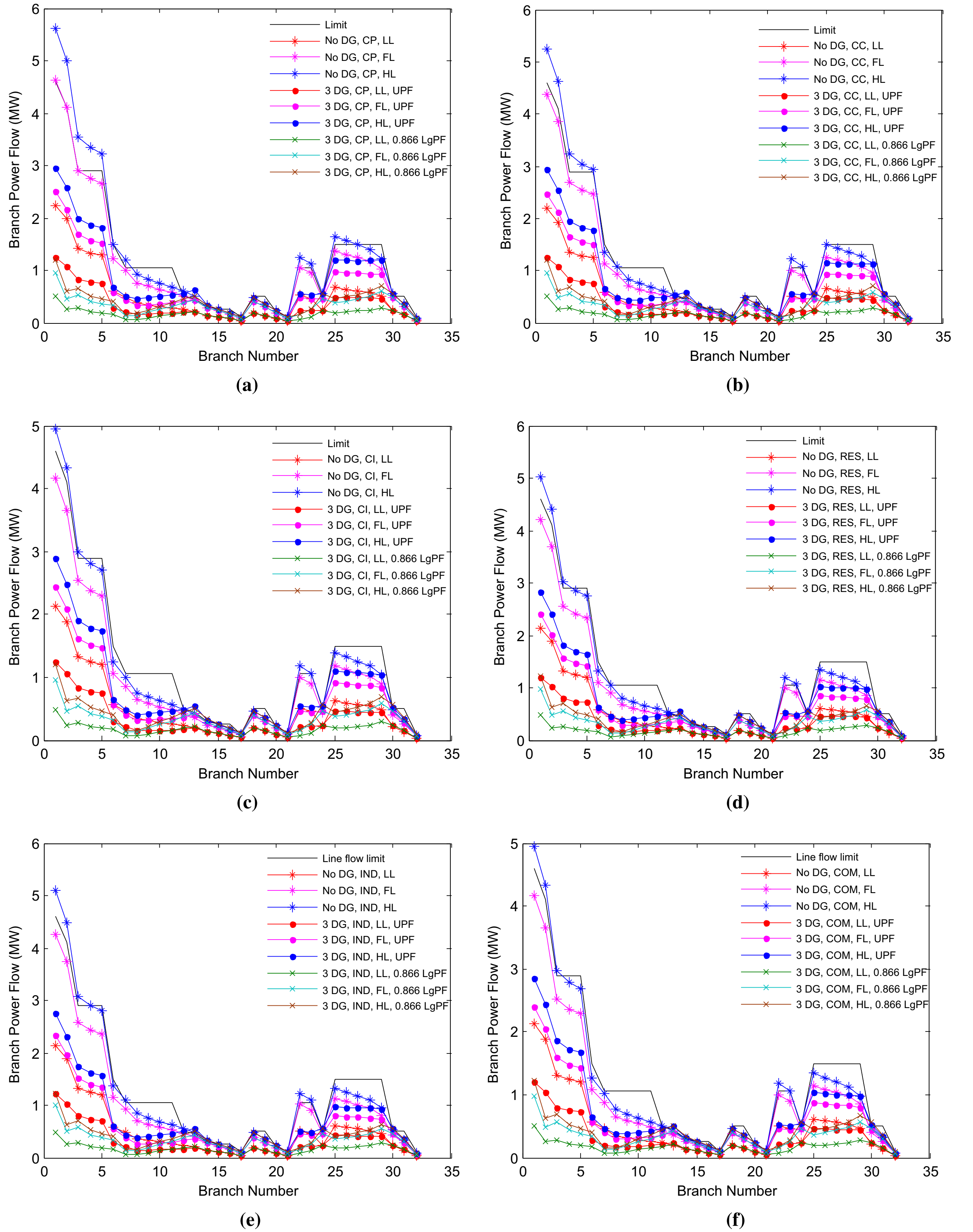

Fig. 6 Branch power flow profile for **a** CP load model, **b** CC load model, **c** CI load model, **d** RES load model, **e** IND load model, **f** COM load model

MQOGWO algorithm has been modified to QOGWO algorithm for minimizing single objective function. The performance of this QOGWO algorithm has been tested with other newly proposed meta-heuristic techniques, and it is found that it can produce the superior results and can prevent the premature convergence.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no any conflict of interest regarding the publication of this article.

Informed consent No human participants are involved to perform this research work.

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