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An Efficient Hybrid Method for Solving Security-Constrained Optimal Power Flow Problem

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Abstract: The optimal operation for different states such as normal and contingency cases of a power system has a very important role in the operation. Therefore, it is necessary to analyze contingencies in the system so as the most severe cases should be considered for integrating into the optimal power flow (OPF) problem and the security-constrained optimal power flow (SCOPF) becomes an important problem for considering in the power system operation. This paper proposes a combined pseudo-gradient based particle swarm optimization with constriction factor (PGPSO) and the differential evolution (DE) method for solving the SCOPF problem. The PGPSO-DE method is a newly developed method for utilizing the advantages of the pseudo-gradient guided PSO method with a constriction factor and the DE method. The proposed PGPSO-DE has been tested on the IEEE 30 bus system for the normal case and the contingency case with two types of the objective function. The results yielded from the proposed method have been validated via comparing to those from the conventional PSO, DE, and other methods reported in the literature. The comparisons for the results obtained from the proposed PGPSO-DE method have shown that it is very effective to solve the large-scale and complex SCOPF problem.

Keywords: Constriction factor; differential evolution; particle swarm optimization; hybrid method; pseudo gradient; security-constrained optimal power flow.

1. Introduction

The general problem of the optimal power flow (OPF) has a long time of development since the first introduction in 1962 [1]. The OPF problem is a very general optimization problem in the power system operation with many variables such as power generation outputs, bus voltages, switchable capacitor banks and tap changers of transformers and many constraints to be handled such as the active and reactive power balance and the upper and lower limits of active and reactive power outputs, the voltage at buses, the capacity of capacitor banks and steps of transformer taps [2]. Therefore, the OPF is actually a large-scale and complicated optimization problem in the power system operation because of many variables and constraints to be handled. Besides, OPF is a high non-linear characteristic problem due to the non-linear and non-smooth objective function of the power generation cost tightens with the complex system and generators constraints. Consequently, with the challenges of the OPF problem brought, over the last half-century, many researchers have contributed a lot in terms of effort and time to figure out

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approaches to solve this problem. These methods include the mathematical programming methods, meta-heuristic search methods, and hybrid methods.

Since the OPF problem had been early developed, it attracted several studies using different optimization methods from mathematical programming methods to metaheuristic methods. This problem has been solved by several mathematical programming methods such as linear programming (LP) [3], non-linear programming (NLP) [4], Newton based techniques [5], quadratic programming (QP) [6], and interior point (IP) methods [7]. These methods have shown that they are effective in solving this problem. However, the OPF problem was solved by these methods is simple with basic constraints. Moreover, these methods are only applicable to the OPF problems with the theoretical assumption that the problem is differentiable [8]. In fact, the OPF problem in modern power systems is always a nonlinear optimization problem and may be a non-differentiable one, thus it is an actual challenge for optimization methods for dealing with, especially the conventional methods. As a result, the mathematical programming methods may have difficulties when solving this problem, especially with large-scale and non-differentiable problems. Therefore, the development of a global optimization method for solving the non-differentiable OPF problems is a vital issue for the operation in modern power systems.

Due to drawbacks of the conventional methods, meta-heuristic search methods have been considered as one alternative promising option for solving the OPF problem with the advantages of obtaining near-optimum solutions without considering the problem is whether differentiable or not. Some of the mature meta-heuristic search methods which have been applied for dealing with the OPF problem such as symbiotic organisms search [9], firefly algorithm [10], evolutionary programming (EP) [11], bacteria foraging optimization algorithm (BFOA) [12], tabu search (TS) [13], and simulated annealing (SA) [14]. These meta-heuristic algorithms have shown they are effective for dealing with this kind of OPF problem. However, these methods can still suffer the local optimum solution with long computational time, especially for the large-scale problems. Therefore, these methods further need to be improved to efficiently deal with the complex and large-scale problems. To enhance the search ability of different methods, hybrid methods have been also developed enhance their search ability in dealing with the complex OPF problem such as a hybrid method of modified imperialist competitive algorithm (MICA) and teaching learning algorithm (TLA) in [15], a hybrid method of shuffle frog leaping algorithm (SFLA) and simulated annealing (SA) algorithm as in [16], and a hybrid method of particle swarm optimization (PSO) and gravitational search algorithm (SA) as in [17]. The advantage of the hybrid methods is the ability to reach a good solution quality for complex optimization problems. However, the main disadvantage of these hybrid methods is the suitable selection of many control parameters from the combined methods since there are many control parameters from the combined methods for selection and an inappropriate selection of control parameters may lead to a local solution for the considered problem.

Besides the OPF problem, constraints that represent the operation of the system after contingency cases can be also integrated to allow dispatching the system in a defensive manner. In this case, the OPF problem has become more complex due to handling all the constraints in the normal case and contingency case to guarantee the system operating in an optimal manner. Therefore, this problem called a security-constrained OPF (SCOPF) is very complex and also important for study in the power system operation to maintain the economy and reliability of power systems. Recently, many studies have been proposed solution methods for solving this complex problem. A cross-entropy method [18] has been applied for dealing with the SCOPF problem, in which the corresponding SCOPF stochastic problem is defined first and the cross-entropy method is used to solve the new problem. The numerical result for the IEEE 57 bus and IEEE 3000 bus systems has shown that the cross-entropy method can find a near-optimum solution for the complex SCOPF problem with few solution evaluations. In [19], a method based on self-organizing hierarchical particle swarm optimization with time-varying acceleration coefficients (SOHPSO-TVAC) has been implemented for solving the complicated SCOPF problem. The result of this study has shown that the proposed method was effective in solving this problem. A contingency partitioning method based on the preventive-corrective SCOPF computation has been introduced by Xu *et al.* in [20]. In [21], a modified bacteria foraging optimization algorithm (MBFA) was applied to find the optimal operating condition of a power system with the purpose of the cost minimization of the wind-thermal generation system and reduction of the real power loss while satisfying the secure voltage for the operation. In [22], a fuzzy based harmony search algorithm (FHSA) based method has proposed to search for the optimal solution for the OPF problem for the security enhancement of power systems. In [23], the SCOPF problem was solved by using the adaptive flower pollination algorithm (APFPA) and the obtained results from the research have shown that this method has a potential for further researches in this direction. In addition, the SCOPF has been also solved by a hybrid canonical differential evolutionary particle swarm optimization (hCDEEPSO) method [24]. This method has shown its effectiveness via the test on large-scale systems and the comparison of the obtained results to those from differential evolutionary particle swarm optimization and mean-variance mapping optimization. In general, the SCOPF problem is a very nonlinear and complex one with a great challenge for methods to find the optimal solution.

In this paper, a new hybrid method based on the pseudo-gradient particle swarm optimization with a constriction factor and differential evolution (PGPSO-DE) [25] is implemented for dealing with the complex SCOPF problem considering the non-smooth fuel cost function including the quadratic fuel cost function and the fuel cost function with valve point loading effects of thermal generators. The main objective of the proposed method in this study is to explore the global search in the problem search space using the PSO with a constriction factor method guided by the pseudo-gradient and to exploit the local search in the problem search space using the DE method. The key advantage of the proposed approach is its search ability to obtain the near optimum-solution for large-scale optimization problems with complicated constraints by utilizing the search ability of each method of PGPSO and DE. The proposed PGPSO-DE method has been mainly validated on the IEEE 30 bus system and the obtained results from the method are verified with those from the conventional PSO, conventional DE, and other methods available in the literature.

The remaining organization of the paper is as follows. Section 2 presents the security-constrained optimal power problem. Section 3 provides the PGPSO-DE method and its application for solving the problem. Section 4 addresses the numerical results. Finally, the conclusion is given.

2. Mathematical Model of the Problem

The SCOPF problem is usually a nonlinear and large-scale and complicated optimization one where many variables and complicated constraints will be handled. The objective of the SCOPF problem is to find an optimal operating point so that the total cost of thermal generating units for both normal and contingency cases is minimized satisfying different constraints of the system, buses, and generators. In this paper, the constraints considered in the SCOPF include the real and reactive power balance at buses, upper and lower limits of real and reactive power outputs at generator buses, upper and lower voltage magnitude limits at generator and load buses, upper and lower limits of transformer tap settings, reactive power capacity limits of switchable capacitor banks, and maximum limit of transmission lines.

In the general mathematical model, the SCOPF problem is established as follows:

$$\text{Min } F(U, X) \tag{1}$$

satisfying all the considered constraints of the system in the normal case as:

$$h(U, X) = 0 \tag{2}$$

$$g(U, X) \le 0 \tag{3}$$

and all the considered constraints of the system in the contingency case as:

$$h(U^S, X^S) = 0 \tag{4}$$

$$g(U^S, X^S) \le 0 \tag{5}$$

where $F(.)$ is the fuel cost function of thermal units; U is vector containing state variables; X is a vector containing control variables; $h(.)$ contains the equality constraints, $g(.)$ contains the inequality constraints; and S contains the set of outage lines.

The considered SCOPF problem above is formulated in detail as follows:

$$\text{Min } F = \sum_{i=1}^{N_g} F_i(P_{gi}) \quad (6)$$

where $F_i(P_{gi})$ whether represents the fuel cost function for thermal generating unit i modeled by a quadratic function as

$$F_i(P_{gi}) = a_i + b_i P_{gi} + c_i P_{gi}^2 \quad (7)$$

or consider the valve point loading effects represented by a non-smooth and non-differentiable function as follows:

$$F_i(P_{gi}) = a_i + b_i P_{gi} + c_i P_{gi}^2 + |\, e_i \times \sin(f_i \times (P_{gi,\min} - P_{gi}))\,| \quad (8)$$

where, P_{gi} is the power generation output of thermal unit i, $P_{gi,min}$ is the minimum power generation output of thermal unit i, and a_i, b_i, c_i, e_i and f_i are the fuel cost coefficients.

The considered constraints of the problem for the normal and contingency cases are described as follows:

- *Active and reactive power balance constraints at buses*: The balance of active and reactive power outputs should be satisfied at every bus in the system as follows:

$$P_{gi} - P_{di} = |V_i| \sum_{j=1}^{N_b} |Y_{ij}|\,|V_j| \cos(\delta_i - \delta_j - \theta_{ij}),\ i = 1, 2, \ldots, N_b \quad (9)$$

$$Q_{gi} - Q_{di} = |V_i| \sum_{j=1}^{N_b} |Y_{ij}|\,|V_j| \sin(\delta_i - \delta_j - \theta_{ij}),\ i = 1, 2, \ldots, N_b \quad (10)$$

where Q_{gi} represents the reactive power output of thermal unit i, P_{di} and Q_{di} represents the demand of real and reactive power outputs at bus i, respectively; N_b is the total number of buses in the system; $|V_i|\angle\delta_i$ and $|V_j|\angle\delta_j$ represent the voltage at buses i and j; respectively, and $|Y_{ij}|\angle\theta_{ij}$ is an element in admittance matrix Y_{bus} at row i and column j.

- *Power output limits at generation buses*: The real and reactive power outputs at generation buses are limited between their lower and upper boundaries.

$$P_{gi,\min} \le P_{gi} \le P_{gi,\max},\ i = 1, 2, \ldots, N_g \quad (11)$$

$$Q_{gi,\min} \le Q_{gi} \le Q_{gi,\max}, ,\ i = 1, 2, \ldots, N_g \quad (12)$$

where $P_{gi,max}$ is the maximum active power output of thermal unit i, $Q_{gi,max}$ and $Q_{gi,min}$ are the maximum and minimum reactive power outputs of the thermal generating unit at bus i, and N_g is the total number of generators in the system.

- *Voltage limits at buses*: The voltage magnitude at generator and load buses is limited within their lower and upper boundaries.

$$V_{gi,\min} \le V_{gi} \le V_{gi,\max};\ i = 1, 2, \ldots, N_g \quad (13)$$

$$V_{li,\min} \le V_{li} \le V_{li,\max};\ i = 1, 2, \ldots, N_d \quad (14)$$

where V_{gi} represents the voltage magnitude at generator bus i; V_{li} represents the voltage magnitude at load bus i; $V_{gi,min}$ and $V_{gi,max}$ represent the minimum and maximum voltage magnitudes at generator bus i, respectively; $V_{li,min}$ and $V_{li,max}$ represent the minimum and maximum voltage magnitudes at load bus i, respectively; and N_d is the total number of load buses.

- *Capacity limits of switchable capacitor banks:* The reactive power capacity for switchable capacitor banks is in their lower and upper boundaries.

$$Q_{ci,\min} \le Q_{ci} \le Q_{ci,\max},\ i = 1, 2, \ldots, N_c \quad (15)$$

where Q_{ci} represents the reactive power output generated by switchable capacitor bank connected at bus i; $Q_{ci,min}$ and $Q_{ci,max}$ represent the minimum and maximum reactive power outputs from switchable capacitor banks; and N_c is the total number of buses having connected switchable capacitor banks.

- *Tap changer limits of transformers:* The transformer tap changers are limited in their allowable upper and lower boundaries.

$$T_{k,\min} \le T_k \le T_{k,\max}, \; k = 1, 2, \ldots, N_t \tag{16}$$

where T_k represents the tap changer of transformer k; $T_{k,max}$ and $T_{k,min}$ represent the maximum and minimum values of transformer tap changer i, respectively; and N_t is the total number of transformers having tap changer.

- *Capacity limit of transmission lines:* The transparent power flow in all transmission lines is limited by their maximum capacity.

$$S_l \le S_{l,\max}, \; l = 1, 2, \ldots, N_l \tag{17}$$

where S_l is the transparent power flow in transmission line l, $S_{l,max}$ is maximum capacity limit of transmission line l, and N_l is the total number of transmission lines in the system.

In this problem, the control variable vector for the problem is represented as:

$$X = [P_{g2}, P_{g3}, \ldots, P_{gN_g}, V_{g1}, V_{g2}, \ldots, V_{gN_g}, Q_{c1}, Q_{c2}, \ldots, Q_{N_c}, T_1, T_2, \ldots, T_{N_t}] \tag{18}$$

in which, P_{g1} is used as the slack bus of the system in this study.

Also, the state variable vector for the problem is represented as follows:

$$U = [Q_{g1}, Q_{g2}, \ldots, Q_{gN_g}, V_{l1}, V_{l2}, \ldots, V_{lN_l}, S_{l1}, S_{l2}, \ldots, S_{N_l}] \tag{19}$$

3. Application of PGPSO-DE to the Problem

A. Particle Swarm Optimization Method

The particle swarm optimization (PSO) method was developed in 1995 [26] for simulating the social behavior and a swarm representing the organized movement of a school of fish or a flock of birds for their food. The general advantage of the PSO method is very simple and it is very easy to implement to several different optimization problems in engineering fields. In the PSO algorithm, a swarm (population) includes individuals (particles) typically represented by two parameters of position and velocity, in which a particle can move from a position to other ones with a certain velocity. However, to guarantee the intake of the swarm, the position and velocity of all particles are usually adjusted not to exceed their allowable limits defined the considered problem.

Suppose that a population in a swarm with N_p individuals (particles) and each individual d (d = 1, 2, …, N_p) has a position X_{id} and a corresponding velocity V_{id} where i = 1, 2, …, N is the dimension of the problem containing in the particle's position. The position of each individual d in the swarm is determined by:

$$V_{id}^{(n+1)} = \omega \times V_{id}^{(n)} + c_1 \times rand_3 \times (Pbest_d - X_{id}^{(n)}) + c_2 \times rand_4 \times (Gbest - X_{id}^{(n)}) \tag{20}$$

and the corresponding velocity of individual d is updated by:

$$X_{id}^{(n+1)} = X_{id}^{(n)} + V_{id}^{(n)} \tag{21}$$

where ω is the inertia weight parameter, n is the current iteration, c_1 is the individual cognitive factor, c_2 is the social cognitive factor, $Pbest_d$ is the best position of individual d up after n iterations, and $Gbest$ is the best individual's position among the particles in the swarm.

To enhance the convergence and stability of PSO, a constriction factor has been introduced in 1999 by Clerc and Kennedy [27]. For the PSO method with the constriction factor, there is a modification of the velocity for particles which are calculated as follows:

$$V_{id}^{(n+1)} = \chi\left(\omega \times V_{id}^{(n)} + c_1 \times rand_3 \times (Pbest_d - X_{id}^{(n)}) + c_2 \times rand_4 \times (Gbest - X_{id}^{(n)}\right) \tag{22}$$

where the constriction factor from the above equation χ is determined by:

$$\chi = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|}; \; \varphi = c_1 + c_2, \; \varphi > 4 \tag{23}$$

On the other hand, the position updating for particles can be enhanced by using a pseudo-gradient concept [28]. The pseudo-gradient is an alternative manner for determining whether the current movement direction of the individual of the search space in the non-differentiable problem is good or not. The pseudo-gradient at a point $g_p(x)$ for the minimization a function $f(x)$ is determined as follows [29]. Consider a point x_k moving to another one x_l in the search space of the problem, there will be two possibilities happening for this movement:

i) If $f(x_k) \geq f(x_l)$: It indicates that the individual has a right movement and should continue to move following this direction. Therefore, the values of pseudo-gradient at the considered point l will be set to a non-zero, that means $g_p(x_l) \neq 0$.

ii) If $f(x_k) < f(x_l)$: It indicates that the individual should not continue to move on this way and needs to change to another one which may be better. Consequently, the values of pseudo-gradient at the considered point l will be set to zero, that means $g_p(x_l) = 0$.

The new position of each particle is updated based on the determined pseudo-gradient by the equation as follows:

$$X_{id}^{(n+1)} = \begin{cases} X_{id}^{(n)} + g_p(X_{id}^{(n+1)}) \times |V_{id}^{(n+1)}| & \text{if } g_p(X_{id}^{(n+1)}) \neq 0 \\ X_{id}^{(n)} + V_{id}^{(n+1)} & \text{otherwise} \end{cases} \tag{24}$$

Therefore, the PSO method in this paper is a pseudo-gradient guided PSO with an integrated constriction factor is applied for combining in the proposed method.

B. Differential Evolution Method

The population based DE method is also a simple one developed in 1995 by Storn and Price [30] for solving different optimization problems in engineering fields. In the DE method, there are generally three steps for generating a new population which are mutation, crossover, and selection steps.

• *Mutation step*: In this stage, a base individual is added by a difference of other individuals to create a new one so as the search space of the problem can be explored. In this research, the mutation scheme DE/rand/1 is used as follows:

$$X_{id}^{'(n)} = X_{r1d}^{(n)} + F \times (X_{r2d}^{(n)} - X_{r3d}^{(n)}) \tag{25}$$

where $r1$, $r2$, and $r3$ are random numbers differently selected in the range [1,N_p]; $X_{id}^{'(n)}$ is the new individual created by other random individuals; and F is the mutation in the range [0,1].

• *Crossover step:* When the mutation stage is completed, this step referred to as the recombination one is applied to increase the population diversity by using the perturbed individuals. The objective of this step is to mix good individuals from the parent generation together with the newly created offspring generation. A trial individual is created as:

$$X_{id}^{''(n)} = \begin{cases} X_{id}^{'(n)} & \text{if } rand_5 \leq CR \text{ or } d = D_{rand} \\ X_{id}^{(n)} & \text{otherwise} \end{cases} \tag{26}$$

where $rand_5$ is a random number with normal distribution in the range [0,1]; D_{rand} is a random integer in the range [1,N_p]; and CR is the crossover rate value selected in the range [0,1].

• *Selection step:* This step is to decide that whether a new individual can be selected for use in the next generation or not based on the comparison between the fitness value from that individual and that from the previous generation. The individual with better fitness value is chosen for carrying out the next generation.

C. The Proposed Hybrid PGPSO and DE Method

Although both PGPSO and DE methods are effective methods and widely used for solving different optimization problems in different fields, they still suffer some drawbacks when applied to complex and large-scale problems such as low solution quality and long computational time. The advantage of the PGPSO method is good in the exploration while the advantage of the DE method is good in exploitation. Therefore, a hybrid of PGPSO and DE methods is to utilize the advantages of both of them. The proposed PGPSO-DE method is appropriate for dealing with large-scale and complicated optimization problems.

The main steps of the hybrid method are for solving an optimization problem as follows:

- *Initialization:* A population with *Np* individuals is firstly randomly initialized in their allowable limits defined by the limits of the considered problem.
- *Generating the first new generation:* A new generation is first created using the initialized one by application of the mechanism of position update of individuals from the PGPSO method and the newly generated population will be evaluated via the fitness function to choose the better one for carrying out the next generation.
- *Generating the second new generation:* A new generation is created in this stage using the three main mechanisms of the DE method and the obtained new population is also evaluated using the fitness function to select the better individuals for carrying out the next iteration.

D. Application of the Hybrid PGPSO and DE Method

The steps for application of the proposed PGPSO-DE for solving the SCOPF problem are as follows:

Step 1: Choose the control parameters for PGPSO and DE methods including the population size with N_p individuals; the maximum allowable number of iterations N_{max}; the individual coefficient c_1 and social cognitive coefficient c_2; scale factor R for the velocity of individuals in the PGPSO method; and mutation fact F and crossover ratio CR applied in the DE method.

Step 2: Initialize an initial population

A population with N_p individuals where each individual contains the control variable vector is represented by a position X_{id}, where bus 1 is selected as the reference bus with $X_{id} = [P_{g2d}, P_{g3d}, ..., P_{gN_gd}, V_{g1d}, V_{g2d}, ..., V_{gN_gd}, Q_{c1d}, Q_{c2d}, ..., Q_{N_cd}, T_{1d}, T_{2d}, ..., T_{N_td}]$, in which $i = 1, 2, \ldots, N$ with $N = 2\times N_g + N_c + N_d$ -1 and $d = 1, 2, \ldots, N_p$.

Every individual in the population is firstly initialized as follows:

$$X_{id}^{(0)} = X_{id}^{\min} + rand_1 \times (X_{id}^{\max} - X_{id}^{\min}) \tag{27}$$

On the other hand, the initial velocity of each particle in the swarm is initialized as:

$$V_{id}^{(0)} = V_{id}^{\min} + rand_2 \times (V_{id}^{\max} - V_{id}^{\min}) \tag{28}$$

where X_{id}^{min} and X_{id}^{max} are the allowable lower and upper limits for position of individual d, respectively; V_{id}^{min} and V_{id}^{max} are the allowable lower and upper velocity limits of individual d, respectively; and $rand_1$ and $rand_2$ are the random numbers with the normal distribution in the range [0,1].

The maximum velocity of each individual d in the population is determined by setting to a scale ratio of the difference between the maximum and minimum limits of that individual:

$$V_{id}^{\max} = R \times (X_{id}^{\max} - X_{id}^{\min}) \tag{29}$$

and the minimum velocity of each individual d in the population is calculated based on the maximum velocity as:

$$V_{id}^{\min} = -V_{id}^{\max} \tag{30}$$

where R is the common scale factor for the velocity of all individuals.

Step 3: Evaluation of the initialized population:

Find the solution for the power flow problem corresponding to the initialized population and the result got from the solved power flow problem is used to evaluate the quality of the initialized population via the fitness calculation including the outage case:

$$FT_d^{(0)} = \sum_{i=1}^{N_g} F_i(P_{gi}) + K_{p0} \times (P_{g1} - P_{g1}^{\lim})^2 + K_{q0} \times \sum_{i=1}^{N_g} (Q_{gi} - Q_{gi}^{\lim})^2 + K_{v0} \times \sum_{i=1}^{N_d} (V_{li} - V_{li}^{\lim})^2$$
$$+ K_{s0} \times \sum_{l=1}^{N_l} (S_l - S_{l,\max})^2 + \sum_{s=1}^{N_o} \left(\begin{array}{l} K_p \times (P_{g1} - P_{g1}^{\lim,s}) + K_q \times \sum_{i=1}^{N_g} (Q_{gi} - Q_{gi}^{\lim,s})^2 \\ + K_v \times \sum_{i=1}^{N_d} (V_{li} - V_{li}^{\lim,s})^2 + K_s \times \sum_{l=1}^{N_l} (S_l - S_{l,\max,s})^2 \end{array} \right) \quad (31)$$

where K_{p0}, K_{q0}, K_{v0}, and K_{s0} are the penalty factors for the reactive power output at the slack bus, the reactive power output at generator buses, the voltage magnitude at load buses, and the transparent power flow in transmission lines for the normal case, respectively; K_p, K_q, K_v, and K_s are the penalty factors similar to the normal case applied to the contingency case; $P_{g1}^{\lim}$ is the real power limit of the generator connected to the slack bus; $Q_{gi}^{\lim}$ is the limits of reactive power output at generator buses i, $V_{li}^{\lim}$ is the voltage magnitude limit for load bus I; $P_{g1}^{\lim,s}$ is the real power limit of the generator connected to the slack bus in the contingency case with line s outage; $Q_{gi}^{\lim,s}$ is the reactive power limit at generator bus i in the contingency case with line s outage; $V_{li}^{\lim,s}$ is the voltage magnitude limit for load buses in the contingency case with line s outage; and N_o is the number of outage lines.

The limits of the corresponding state variables including the reactive power output at the selected slack bus, the reactive power output at generator buses, and the voltage magnitude at load buses in both normal and contingency cases are determined as follows:

$$X^{\lim} = \begin{cases} X_{\min} & \text{if } X < X_{\min} \\ X & \text{if } X_{\min} \le X \le X_{\max} \\ X_{\max} & \text{if } X > X_{\max} \end{cases} \quad (32)$$

where X represents the real power output of the generation at the slack bus P_{g1}, reactive power output of generation buses Q_{gi}, and voltage at load buses V_{li}.

Set the initialized population to the best position of each individual $Pbest_d$ with the corresponding best value of the fitness function FT_d^{best} and the best position among individuals of the population is set to the best individual *Gbest*.

Set the iterative counter $n = 1$.

Step 4: Generation of a new population
In this step, the new population is generated using the mechanism of PGPSO. The new velocity of each individual is calculated by using (22). If the new obtained individual's velocity violates its limits, a repairing action is performed as follows:

$$V_{id}^{(n)} = \begin{cases} V_{id}^{\max} & \text{if } V_{id}^{(n)} > V_{id}^{\max} \\ V_{id}^{(n)} & \text{if } V_{id}^{\min} \le V_{id}^{(n)} \le V_{id}^{\max} \\ V_{id}^{\min} & \text{if } V_{id}^{(n)} < V_{id}^{\min} \end{cases} \quad (33)$$

The new generation of the population is updated by using equation (24). If the position of any individuals violates its limits, a repairing is carried out:

$$X_{id}^{(n)} = \begin{cases} X_{id}^{\max} & \text{if } X_{id}^{(n)} > X_{id}^{\max} \\ X_{id}^{(n)} & \text{if } X_{id}^{\min} \le X_{id}^{(n)} \le X_{id}^{\max} \\ X_{id}^{\min} & \text{if } X_{id}^{(n)} < X_{id}^{\min} \end{cases} \quad (34)$$

Step 5: Evaluation of the first generated population
Solve the power flow problem again for the first newly generated population $X_{id}^{(n)}$ and the result obtained from the solved power flow problem is applied to calculate the fitness function $FT_d^{(n)}$ in equation (31).

Step 6: Mutation stage
The second new population $X_{id}^{'(n)}$ in this step is determined based on the generated population $X_{id}^{(n)}$ which was created from the PGPSO mechanism by using the mutation stage of DE in equation (25).

If the new calculated position $X_{id}^{'(n)}$ violated its limits, a preparation procedure is conducted by using (34).

Step 7: Crossover stage
The crossover stage in the DE method creates a secondly new generation by using equation (26).

Step 8: Evaluation of the secondly new population
Solve the power flow problem for the newly obtained population and the solution obtained from this problem is used to evaluate the population via calculating the value of the fitness function $FT''^{(n)}_d$ in equation (31).

Step 9: Selection stage
The selection stage is to choose the new individuals based on the previously generated populations is described by:

$$X_{id}^{new(n)} = \begin{cases} X_{id}^{"(n)} & \text{if } FT_d^{"(n)} \le FT_d^{(n)} \\ X_{id}^{(n)} & \text{if } FT_d^{"(n)} > FT_d^{(n)} \end{cases} \quad (35)$$

Update the new fitness function value $FT_d^{new(d)}$ corresponding to $X_{id}^{new(n)}$.

Step 10: Selection of the best population
The best position of each particle is updated using the new population and the best stored values given by:

$$Pbest_d = \begin{cases} X_{id}^{new(n)} & \text{if } FT_d^{new(n)} \le FT_d^{best} \\ Pbest_d & \text{if } FT_d^{new(n)} > FT_d^{best} \end{cases} \quad (36)$$

Update the corresponding best fitness function FT_d^{best}. The best position among the best individuals $Pbest_d$ is set to *Gbest*.

Step 11: Stopping criteria
If the current number of iterations is less than the maximum number of iterations $n < N_{max}$, increase the iterative counter $n = n + 1$ and return to Step 4 above. Otherwise, stop the algorithm.

4. Numerical Results

The proposed PGPSO-DE has been tested on the benchmark IEEE 30 bus system for the two cases where the fuel cost with a quadratic function and a function with valve point loading effects are considered for the normal and contingency cases. In the contingency case, two subcases are considered with 5 and 9 outage lines. The test system has 30 buses, four transformers, two switchable capacitor banks, and 41 transmission lines. For the outage cases, the 5-outage lines include 1, 2, 3, 5, and 7 and the 9-outage lines consist of 1, 2, 4, 5, 7, 33, 35, 37, and 38.

The data of the test system with the fuel cost coefficients for the quadratic function is from [4]. The fuel cost coefficients for the case with valve point loading effects and the transmission line limit are given in the Appendix. The lower voltage limit of all buses in the system is set to 0.95 while the upper limit for the slack, generation, and load buses is set to 1.05, 1.10, and 1.05, respectively. The lower and upper limits for tap changer of transformers are set to 0.90 and 1.10, respectively. The lower limit of switchable capacitor banks is set to zero while their upper limit is set to the fixed value in the original data. The lower and upper limits of reactive power output at generator buses are selected as in [31]. The power problem in this research is solved by Matpower [31] program using the Newton-Raphson method.

For implementing the proposed method, the control parameters of the proposed PGPSO-DE for the test system are selected based on the obtained experiments. The population size is set to 10, all penalty factors for all cases set to 10^6, all the cognitive factors of PGPSO set to 2.05, the scale factor for the velocity of individuals set to 0.15, the mutation factor set to 0.7, and the crossover rate set to 0.5. For the number of iterations, the different number of iterations is used for different test cases. The number is set to 150 for the normal case with a quadratic fuel cost function, 200 for the normal case for the objective with valve point loading effects, 250 for the cases with 5 and 9 outage lines with a quadratic fuel cost function, and 300 for the cases with 5 and 9 outage lines with valve loading effects. The proposed PGPSO-DE method is coded in Matlab and each case is performed 50 independent runs to obtain the best solution. Moreover, the PSO and DE methods have been also implemented to solve the same cases with PGPSO-DE for result comparison. The control parameters of the conventional PSO and DE methods are selected similarly to those selected for the PGPSO-DE method.

A. Normal case

For the normal, the proposed PGPSO-DE is applied for solving the normal OPF problem for the two cases with the objective of a quadratic function and a function with valve point loading effects.

1. Objective with quadratic function

In this case, the only PGPSO-DE method is applied to solve the normal OPF problem with a quadratic fuel cost function. The obtained results by the proposed method including best cost, average cost, worst cost, standard deviation, and computational time are given in Table 1. As observed from the table, the average cost closes to the best cost and the standard deviation is rather small. Therefore, the solution quality obtained by the proposed method, in this case, is high.

The obtained result from the proposed PGPSO-DE has been compared to that from other methods such as tabu search (TS) [13], evolutionary programming (EP) [32], parallel EP [33], parallel self-adaptive differential evolution with augmented Lagrange multiplier (pSADE_ALM) [34], and PSO methods [19], [35]. The total cost obtained by the proposed method is better than that from many other methods except for PSO-TVIW and SOHPSO-TVAC in [6]. Besides, the total cost from the proposed PGPSO-DE is also slightly higher than that from PSO-TVIW and SOHPSO-TVAC due to the voltage limit on the slack bus. The upper voltage limit at the slack bus has an impact on the objective function. For example, the total cost obtained by PGPSO-DE, in this case, is $ 802.2484 with the upper voltage limit at the slack bus set to 1.05 pu while the total cost from the methods from [19] is obtained at the upper voltage limit of the slack of 1.06 pu. The higher upper voltage limit at the slack bus is used, the lower total of thermal units is obtained. In general, the proposed PGPSO-DE is effective to find the optimal solution for the OPF problem in the normal case. The optimal solution provided by the PGPSO-DE method for this case is given in the Appendix.

Table 1. Obtained result obtained by PGPSO-DE in the normal case with the objective of quadratic fuel cost function

Best total cost ($)	**Average total cost ($)**	**Worst total cost ($)**	**Standard deviation**	**Average computational time (s)**
802.2484	805.8013	840.1040	8.7117	8.719

2. Objective with valve point loading effects

In this case, the objective function with valve loading effects is considered in the objective of the problem. However, the DE method can be able to find a feasible solution with the selected parameters as the PGPSO-DE. Therefore, to obtain a feasible solution for the problem, in this case, the population for DE is set to 70. The obtained solutions including the best cost, average cost, the worst cost, standard deviation, and computational time from PSO, DE, and the proposed method are given in Table 3. Among the three methods, the proposed PGPSO-DE can provide the best total cost and the DE provides the worst total cost. For computing time, the PSO method is the fastest among the applied methods while the DE method takes a longer time than the others due to using a large population. The convergence characteristics of PGPSO-DE, PSO, and DE methods for this case are shown in Figure 1. As shown in the figure, the PSO method can converge in about 30 iterations while DE method can converge in about 100 iterations but the obtained solution is not good enough compared to PGPSO-DE method. The proposed method can reach a better solution than both PSO and DE after 200 iterations.The optimal solutions yielded by the PGPSO-DE, PSO and DE methods are given in the Appendix.

Table 2. Result comparison for the normal case with the objective of quadratic fuel cost function

Methods	**Best total fuel cost ($)**	**Computational time (s)**
TS [13]	802.29	NA
EP [32]	802.62	NA
Parallel EP$^{\alpha}$ [33]	802.51	5.02
SADE_ALM [34]	802.404	15.934
pSADE_ALM [34]	802.405	17.295
Conventional PSO [35]	802.586	28.208
PSO-TVAC [35]	802.67	11.255
PG-PSO [35]	802.252	11.416
BPSO [19]	803.13	35.15
PSO-TVIW [19]	802.11	33.756
PSO-TVAC [19]	803.56	35.82
SOHPSO-TVAC [19]	802.03	29.43
PGPSO-DE	802.248	9.298

Table 3. Obtained result for the normal case with the objective considering valve point loading effects

Method	Best total cost ($)	Average total cost ($)	Worst total cost ($)	Standard deviation	Average computational time (s)
PSO	930.3223	974.6577	1042.9890	29.1070	7.750
DE	970.7400	999.3013	1038.7125	14.4135	39.779
PGPSO-DE	917.7518	958.5162	1099.4167	23.1749	11.517

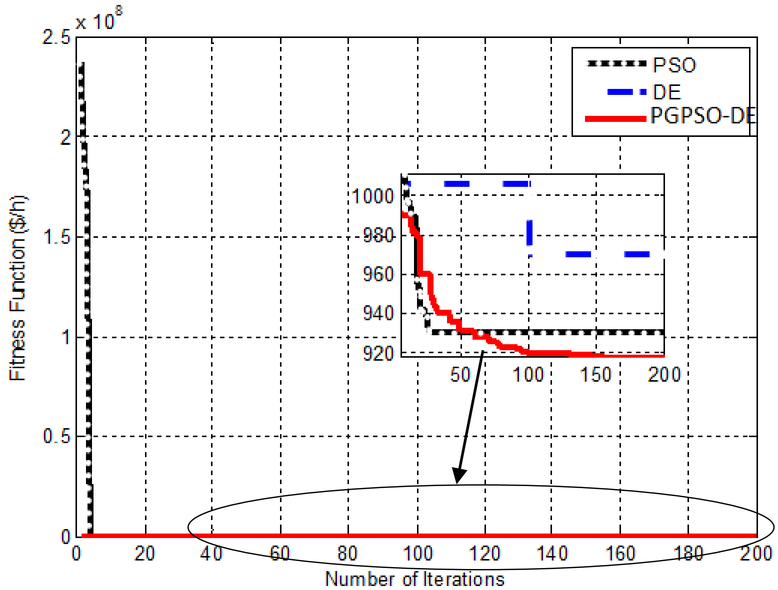

Figure 1. Convergence characteristics of PSO, DE and PGPSO-DE for the normal case with valve point loading effects.

B. Contingency case

For the outage case, two scenarios are considered including 5 and 9 outage lines in the system for both cases with the objective with a quadratic function and a function of valve point loading effects.

1. Objective with quadratic function

• *The case with 5-outage lines*

The obtained results including the best cost, average cost, the worst cost, standard deviation, and computational time from the PGPSO-DE, PSO, and DE methods, in this case, are given in Table 4. As observed from the table, the PGPSO-DE can obtain better cost than the other methods in terms of the best total cost, average total cost, the worst total cost, and standard deviation while the PSO method is faster than the others. The convergence characteristic of these methods for this case is given in Figure 2. As observed, the proposed PGPSO-DE and PSO methods can reach an approximate solution while the DE method needs more iterations but the obtained solution is not good enough compared to PGPSO-DE and PSO methods. The optimal solutions provided by these methods for this case are also given in the Appendix.

Table 4. Obtained result for the case of 5-outage lines with the objective of quadratic fuel cost function

Method	**Best total cost ($)**	**Average total cost ($)**	**Worst total cost ($)**	**Standard deviation**	**Average computational time (s)**
PSO	826.1400	840.5281	904.3178	19.5032	70.675
DE	833.6628	877.0613	936.0727	24.1500	469.641
PGPSO-DE	825.3571	834.9393	870.7170	14.5300	99.638

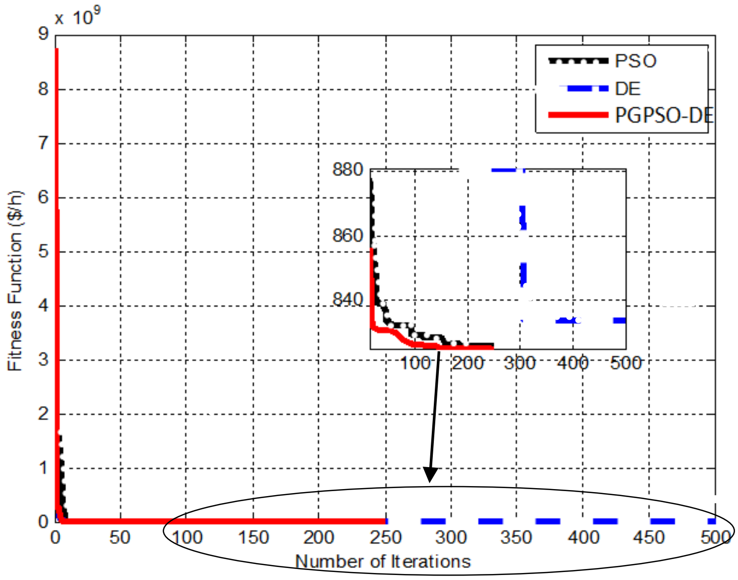

Figure 2. Convergence characteristics of PSO, DE and PGPSO-DE for the case of 5-outage lines with the objective of quadratic fuel cost function

Table 5. Comparison of best result for the case of 5-outage lines with the objective of quadratic fuel cost function

Methods	**Best total fuel cost ($)**	**Computational time (s)**
SADE_ALM [34]	826.979	46.896
pSADE_ALM [34]	826.242	119.812
Conventional PSO [35]	827.186	175.245
PSO-TVAC [35]	828.012	130.59
PSO	826.1400	70.675
DE	833.6628	469.641
PGPSO-DE	825.3571	99.638

The best cost from the PGPSO-DE, PSO, and DE methods have been compared to those obtained from other PSO and DE based methods from the literature as in Table 5. As seen from this table, the proposed method can yield a better total cost than other methods do. The result comparison has verified that the proposed PGPSO-DE is effective for dealing with the problem in this case with 5-outage lines.

• *The case with 9-outage lines*

In this case, the PGPSO-DE and PSO methods can obtain the optimal solution while the DE method cannot find a feasible solution due to violating constraints. The obtained solutions including the best total cost, average total cost, the worst total cost, standard deviation, and the computational time from the PGPSO-DE and PSO are given in Table 6. The results obtained from the proposed PGPSO-DE are all better than those from the PSO method except the computational time, especially the best cost from the proposed method is much better than that from the PSO method. The convergence characteristic of these methods is shown in Figure 3. In this figure, the PGPSO-DE method reaches stable after 250 iterations while the PSO can be further improved and DE cannot reach the feasible solution. The optimal solutions by the PGPSO-DE, PSO, and DE methods are given in the Appendix.

The best cost from the PGPSO-DE and PSO methods has been compared to that from other methods including DE and PSO based methods as given in Table 7. As shown in the table, the total cost from the proposed method is better than the other methods. The result comparison has shown that the proposed method is effective for dealing with the problem for the most severe case.

Table 6. Obtained result for the case of 9-outage lines with the objective of quadratic fuel cost function

Method	**Best total cost ($)**	**Average total cost ($)**	**Worst total cost ($)**	**Standard deviation**	**Average computational time (s)**
PSO	834.3601	873.4729	937.0004	24.9403	97.566
PGPSO-DE	825.4352	849.5369	920.6872	26.2689	144.327

Table 7. Result comparison for the case of 9-outage lines with the objective of quadratic fuel cost function

Methods	**Best total fuel cost**	**Computational time (s)**
SADE_ALM [34]	834.547	82.932
pSADE_ALM [34]	826.978	157.401
Conventional PSO [35]	833.504	637.528
PSO-TVAC [35]	837.728	417.145
PG-PSO [35]	825.993	179.574
PSO	834.3601	97.566
PGPSO-DE	825.4352	144.327

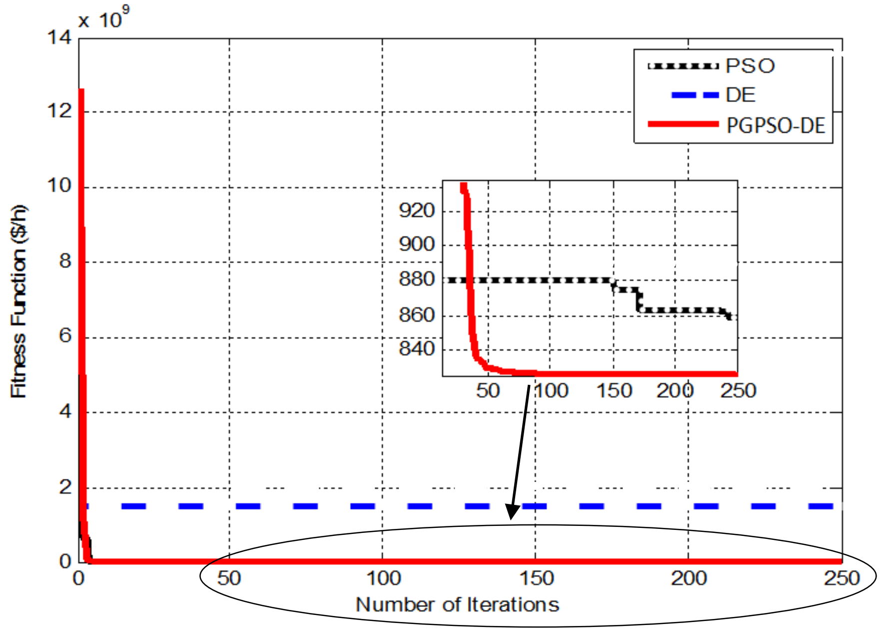

Figure 3. Convergence characteristics of PSO, DE and PGPSO-DE for the case of 9-outage lines with the objective of quadratic fuel cost function

2. Objective with valve point loading effects

For the case that the objective with valve pint loading effects, the two scenarios with 5 and 9-outage lines are also considered.

• *The case with 5-outage lines*

For dealing with the case of 5-outage lines, the DE needs 500 iterations to find the optimal solution. The results including the best total cost, average total cost, the worst total cost, standard deviation, and computational time obtained by the PGPSO-DE, PSO, and DE methods are given in Table 8. As seen from this table, the PGPSO-DE method can obtain better results than other methods for all the best total cost, average total cost, the worst total cost, and standard deviation. For the computing time, the PSO method is also the fastest method among the applied methods. The obtained results have indicated that the proposed PGPSO-DE can be a very effective method for dealing with the complex problem in this case. The convergence characteristics of PGPSO-DE, PSO, and DE are given in Figure 4 and the optimal solution obtained by these methods is given in the Appendix.

Table 8. Best result of SCOPF in case of 5-outage lines considering objective with valve point loading effects

Method	**Best total cost ($)**	**Average total cost ($)**	**Worst total cost ($)**	**Standard deviation**	**Average computational time (s)**
PSO	1036.3883	1051.0038	1145.2705	22.6513	64.796
DE	1047.5443	1090.9916	1185.9028	31.1450	565.113
PGPSO-DE	1035.9443	1040.5190	1081.6711	7.3536	117.571

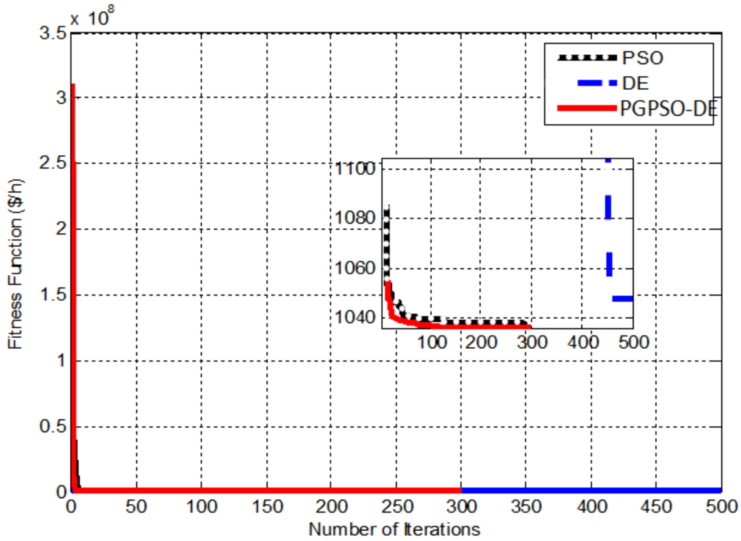

Figure 4. Convergence characteristics of PSO, DE, and PGPSO-DE for the case of 5-outage lines with the objective of valve point loading effects

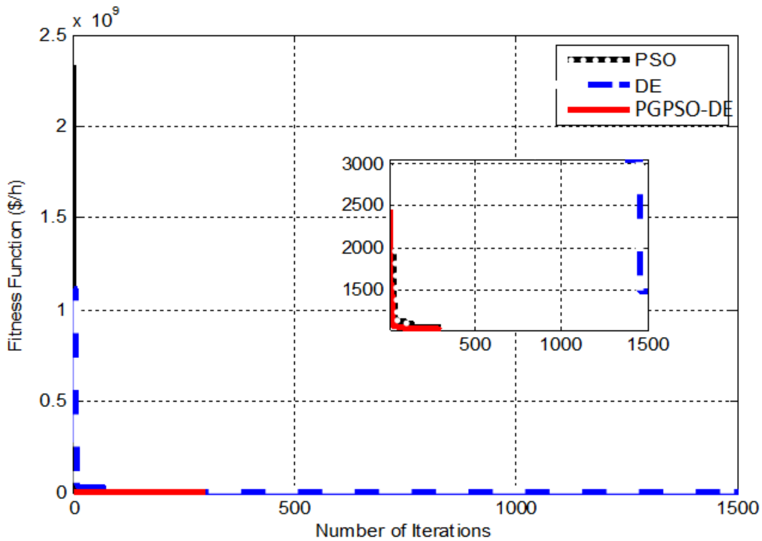

Figure 5. Convergence characteristics of PSO, DE, and PGPSO-DE for the case of 9-outage lines with the objective of valve point loading effects.

- *The case with 9-outage lines*

For dealing with this case, the number of individuals and the maximum number of iterations for the DE method is set to 70 and 1500, respectively. However, DE cannot obtain any feasible solution. Therefore, the DE method cannot properly deal with a very complex problem in this case. The results obtained by PGPSO-DE and PSO, in this case, are given in Table 9. In this case, the best cost and average cost from the proposed PGPSO-DE are better than those from the PSO method while the worst cost and standard deviation from the PSO method are better than those from the proposed method. The PSO method is faster than the PGPSO-DE in this case.

The convergence characteristic of PSO, DE, and PGPSO-DE are given in Figure 5 and the optimal solutions by PGPSO-DE and PSO methods are given in the Appendix.

Table 9. Obtained result for the case of 9-outage lines considering objective with valve point loading effects

Method	Best total cost ($)	Average total cost ($)	Worst total cost ($)	Standard deviation	Average computational time (s)
PSO	1041.9920	1072.2306	1172.6504	23.6435	117.247
PGPSO-DE	1036.8080	1061.3965	1173.9480	34.8727	175.688

5. Conclusion

In the paper, the proposed PGPSO-DE method has been successfully applied for dealing with the complicated SCOPF problem in power systems. The SCOPF problem is a real challenge optimization problem due to its complexity and large-scale dimension. The proposed PGPSO-DE has effectively exploited the advantages of both PGPSO and DE methods for dealing with the SCOPF for different scenarios. The effectiveness of the proposed PGPSO-DE method has been tested on the benchmark IEEE 30 bus system for quadratic and valve point effects objectives considering 5-outage and 9-outage lines. The obtained results by the proposed method for these cases have been validated by comparing to those from both conventional PSO and DE methods as well as other methods as reported in the literature. The result comparisons have shown that the PGPSO-DE method can be an effective method for dealing with this problem for different cases. Therefore, the proposed PGPSO-DE method could be an alternative method for solving the large-scale and complex SCOPF problem in power systems.

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Appendix

Table A.1. Fuel cost of the IEEE 30-bus system with valve point loading effects

Unit	a_i (\$/h)	b_i (\$/MWh)	c_i (\$/MW^{2}h)	e_i (\$/h)	f_i (1/MW)
1	150	2.00	0.00160	50	0.063
2	25	2.50	0.01000	40	0.098
3	0	1.00	0.06250	0	0
4	0	3.25	0.00834	0	0
5	0	3.00	0.02500	0	0
8	0	3.00	0.02500	0	0

Table A.2. Transmission limits of the IEEE 30-bus system

Line number	1	2	3	4	5	6	7	8	9
S_{lmax} (MVA)	130	130	65	130	130	65	90	130	130
Line number	10	11	12	13	14	15	16	17	18
S_{lmax} (MVA)	32	65	32	65	65	65	65	32	32
Line number	19	20	21	22	23	24	25	26	27
S_{lmax} (MVA)	32	16	16	16	16	32	32	32	32
Line number	29	30	31	32	33	34	35	36	37
S_{lmax} (MVA)	32	32	16	16	16	16	16	16	65
Line number	38	39	40	41	42				
S_{lmax} (MVA)	16	16	16	32	32				

Table A.3. Optimal solutions by PSO, DE and PGPSO-DE for the objective with quadratic fuel cost function

Optimal solution	Normal case	5-outage lines			9-outage lines		
	PGPSO-DE	PSO	DE	PGPSO-DE	PSO	DE*	PGPSO-DE
P_{g1} (MW)	176.2417	123.2310	122.0641	123.3957	116.9869	133.1681	123.3180
P_{g2} (MW)	48.8183	64.6073	48.6945	64.1584	62.0662	66.2429	63.0275
P_{g5} (MW)	21.5263	25.1179	29.6548	25.9006	22.4018	23.3168	25.0899
P_{g8} (MW)	22.1117	35.0000	35.0000	35.0000	35.0000	16.2312	35.0000
P_{g11} (MW)	12.1442	21.1329	26.4425	21.3319	23.8303	26.1852	23.3210
P_{g13} (MW)	12.0000	20.8805	27.5348	19.9969	29.3561	26.5965	19.9988
V_{g1} (pu)	1.0500	1.0500	1.0500	1.0500	1.0500	1.0214	1.0500
V_{g2} (pu)	1.0374	1.0306	1.0364	1.0348	1.0314	1.0138	1.0354
V_{g5} (pu)	1.0102	0.9966	0.9946	1.0112	1.0034	1.0197	1.0081
V_{g8} (pu)	1.0175	1.0101	1.0183	1.0210	1.0112	1.0048	1.0179
V_{g11} (pu)	1.1000	1.0981	1.0644	1.0999	1.0684	1.0726	1.1000
V_{g13} (pu)	1.0852	1.0417	1.0840	1.0741	1.0775	0.9500	1.0794
T_{11} (pu)	1.0131	1.0598	0.9696	1.0625	0.9800	0.9721	1.0324
T_{12} (pu)	0.9193	0.9022	1.0084	0.9077	0.9000	1.1000	0.9277
T_{15} (pu)	0.9988	1.0047	0.9797	0.9796	0.9859	0.9055	1.0026
T_{36} (pu)	0.9414	0.9517	0.9837	0.9653	0.9438	0.9634	0.9575

* The result is infeasible due to violating constraints.

Table A.4. Optimal solutions by PSO, DE and PGPSO-DE methods for the objective with the objective of valve point loading effects

Optimal solution	Normal case			5-outage lines			9-outage lines		
	PSO	DE	PGPSO-DE	PSO	DE	PGPSO-DE	PSO	DE*	PGPSO-DE
P_{G1} (MW)	198.8043	191.9567	199.0761	99.9253	100.0975	99.8674	98.9462	91.2403	99.9352
P_{G2} (MW)	51.4459	20.0000	49.0582	80.0000	78.6888	80.0000	80.0000	80.0000	80.0000
P_{G5} (MW)	15.0000	37.1975	15.0000	27.0034	27.4269	25.7563	29.3441	42.6574	26.8497
P_{G8} (MW)	10.0000	14.6233	10.0000	34.9769	35.0000	35.0000	35.0000	23.0529	35.0000
P_{G11} (MW)	10.0000	10.0000	10.0000	24.1627	30.0000	25.2155	21.0345	30.0000	22.3602
P_{G13} (MW)	12.0000	20.0575	12.0000	22.9804	18.9334	23.1453	24.7469	21.8148	24.9929
V_{G1} (pu)	1.0500	1.0204	1.0500	1.0500	1.0500	1.0500	1.0500	1.0500	1.0500
V_{G2} (pu)	1.0290	0.9993	1.0301	1.0391	1.0369	1.0423	1.0363	1.0361	1.0406
V_{G5} (pu)	0.9500	0.9605	1.0030	1.0183	0.9665	1.0171	0.9912	1.0244	1.0143
V_{G8} (pu)	0.9594	0.9500	1.0045	1.0256	0.9936	1.0290	1.0166	1.0017	1.0075
V_{G11} (pu)	1.0023	1.1000	1.0575	1.0999	0.9698	1.0589	1.1000	1.0825	1.1000
V_{G13} (pu)	1.0781	1.0591	1.0614	1.0561	1.0866	1.0842	1.0942	1.0340	1.0521
T_{11} (pu)	1.0557	0.9000	0.9857	1.0367	1.0833	0.9773	1.0055	0.9711	1.0160
T_{12} (pu)	0.9920	1.0770	0.9812	0.9276	0.9682	0.9574	0.9819	1.1000	0.9000
T_{15} (pu)	0.9000	0.9000	1.0589	0.9853	0.9882	1.0141	1.0149	0.9037	0.9549
T_{36} (pu)	0.9000	0.9000	0.9520	0.9538	0.9356	0.9527	0.9527	0.9345	0.9490

* The result is infeasible due to violating constraints.

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