

# Enhanced Particle Swarm Optimization Based Local Search for Reactive Power Compensation Problem

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## ABSTRACT

This paper presents an enhanced Particle Swarm Optimization (PSO) algorithm applied to the reactive power compensation (RPC) problem. It is based on the combination of Genetic Algorithm (GA) and PSO. Our approach integrates the merits of both genetic algorithms (GAs) and particle swarm optimization (PSO) and it has two characteristic features. Firstly, the algorithm is initialized by a set of a random particle which traveling through the search space, during this travel an evolution of these particles is performed by a hybrid PSO with GA to get approximate no dominated solution. Secondly, to improve the solution quality, dynamic version of pattern search technique is implemented as neighborhood search engine where it intends to explore the less-crowded area in the current archive to possibly obtain more nondominated solutions. The proposed approach is carried out on the standard IEEE 30-bus 6-generator test system. The results demonstrate the capabilities of the proposed approach to generate true and well-distributed Pareto optimal nondominated solutions of the multiobjective RPC.

**Keywords:** Multiobjective Optimization; Particle Swarm Optimization; Local Search

## 1. Introduction

Reactive Power Compensation (RPC) in power systems is a very important issue in the expansion planning and operation of power systems because it leads to increased transmission capability, reduced losses and improved power factor using shunt capacitors that have been very commonly installed in transmission and distribution networks [1,2]. By applying capacitors adjacent to loads, several advantages are obtained some of them are [3-5]:

- 1) *Improved power factor,*
- 2) *Reduced transmission losses,*
- 3) *Increased transmission capability,*
- 4) *Improved voltage control,*
- 5) *Improved power quality.*

Achievement of these items depends mainly on an adequate allocation of shunt capacitor banks. Thus, this problem can be stated as the determination of the locations and the capacities of new sources of reactive power, searching simultaneously to accomplish the following goals:

- 1) *A good bus tension profile:* The quality of service is directly related to the difference between the effective and the nominal bus voltage;
- 2) *Minimization of transmission losses:* Active power transmission losses can be directly translated into monetary losses since they are the main component in

the difference between the generated power and the consumed power;

- 3) *Minimization of the amount of reactive compensation installed:* Although shunt capacitor compensation generally provides the most economical reactive power source for voltage control, heavy use of these devices could lead to the reduction of stability margins and poor voltage regulation [6,7].

Traditionally, this problem is addressed as a Single Objective Optimization Problem (SOP) [8-14]. A Single-Objective Optimization Algorithms (SOA) usually provides a unique optimal solution. Typically, the objective function is formulated as a linear combination of several factors such as investment or transmission losses, that are subject to operational constrains such as reliability and voltage profile. These factors that are considered as the optimization objectives usually are contradictory, making very difficult to find the right linear combination. Practically most problems have more than one objective to be optimized, e.g. RPC problem requires the optimization of investment, power losses, and voltage profile. The objectives are usually contradictory. Accordingly a single objective optimization algorithm will not be preferable to solve the RPC problem. Considering this situation, Multiobjective Optimization Algorithms (MOA) were proposed to optimize independent and simultaneously sev-

eral objectives [15-17]. Therefore, a MOA usually provides a whole set of optimal tradeoff solutions known as Pareto set. The Pareto set gives the engineer the opportunity to consider more options before making a final decision.

Local search techniques have long been used to attack many optimization problems [18,19]. The basic idea is to start from an initial solution and to search for successive improvements by examining neighboring solutions. The local search used in this paper is based on a dynamic version of pattern search technique. Pattern search technique is a popular paradigm in Direct Search (DS) methods [20]. DS methods are evolutionary algorithms used to solve constrained optimization problems. DS methods, as opposed to more standard optimization methods, are often called derivative-free as they do not require any information about the gradient or higher derivatives of the objective function to search for an optimal solution. Therefore direct search methods may very well be used to solve non-continuous, no differentiable and multimodal (*i.e.* multiple local optima) optimization problems.

To solve the RPC problem, this paper presents a new approach local search based on hybrid particle swarm optimization PSO. It combines two heuristic optimization techniques GA and PSO. Our approach integrates the merits of the two optimization techniques. In order to improve the solution quality, we implement modified local search algorithm. Finally, the standard IEEE 30-bus 6-generator test system then used to verify the validity of the proposed approach.

This paper is organized as follows. In section 2, MOO is described. Section 3, provides a Multi-objective Formulation of RPC Problem. In section 5, the proposed algorithm is presented. Implementation of the proposed approach is presented in section 6. Results are given in section 6. Finally, section 7 gives a brief conclusion about this study.

## 2. Multiobjective Optimization

A Multi-objective Optimization Problem (MOP) can be defined as determining a vector of design variables within a feasible region to minimize a vector of objective functions that usually conflict with each other. Such a problem takes the form:

$$\begin{aligned} &\text{Minimize} && \{f_1(X), f_2(X), \dots, f_m(X)\} \\ &\text{subject to} && g(X) \leq 0, \end{aligned}$$

where  $X$  is vector of decision variables;  $f_i(X)$  is the  $i$ th objective function; and  $g(X)$  is constraint vector. A decision vector  $X$  is said to dominate a decision vector  $Y$  (also written as  $X \succ Y$ ) if:  $f_i(X) \leq f_i(Y)$  for all

$i \in \{1, 2, \dots, m\}$  and  $f_i(X) \leq f_i(Y)$  for at least one  $i \in \{1, 2, \dots, m\}$ . All decision vectors that are not dominated by any other decision vector are called no dominated or Pareto-optimal. These are solutions for which no objective can be improved without detracting from at least one other objective.

## 3. Multiobjective Formulation of RPC

The following assumptions are considered in the formulation of the problem:

- 1) A shunt-capacitor bank cost per MVar is the same for all busbars of the power system;
- 2) Power system is considered only at peak load.

Based on these considerations [20,21], three objective functions  $f_1(\cdot)$ ,  $f_2(\cdot)$ ,  $f_3(\cdot)$  (to be minimized) have been identified for the present work:  $f_1(\cdot)$  and  $f_2(\cdot)$  are related to investment and transmission losses, while  $f_3(\cdot)$  are related to quality of service.

The objective functions to be considered are:

### 3.1. $F_1$ : Investment in Reactive Compensation Devices

$$F_1 = \sum_{i=1}^n \alpha_i B_i \quad \text{s.t.} \begin{cases} 0 \leq F_1 \leq F_{1\max} \\ 0 \leq B_i \leq B_{i\max} \end{cases}$$

where for simplicity the cost per MVar is taken as unity ( $\alpha = 1$ ),  $n$  is the number of buses in the power system;  $F_1$  is the total required compensation;  $F_{1\max}$  is the maximum amount available for investment;  $B_i$  is the compensation at busbar  $i$  measured in MVar and  $B_{i\max}$  is the maximum compensation allowed at a particular bus of the system.

### 3.2. $F_2$ : Active Power Losses

$$F_2 = P_g - P_l \geq 0 \quad \text{s.t.} \quad P_{g\min} \leq P_g \leq P_{g\max}$$

where:  $F_2$  is the total transmission active losses of the power system in MW;  $P_g$  is the total active power generated in MW and  $P_l$  is the total load of the system in MW.

### 3.3. $F_3$ : Average Voltage Deviation

$$F_3 = \frac{\sum_{i=1}^n |V_i - V_i^*|}{n} \quad \text{s.t.} \quad V_{i\min} \leq V_i \leq V_{i\max}$$

where:  $F_3$  is the per unit (pu) average voltage difference;  $V$  is the actual voltage at busbar  $i$  (pu) and  $V_i^*$  is the desired voltage at busbar  $i$  (pu).

In summary, the optimization problem to be solved is the following:

$$\text{Minimize } F = [F_1 \quad F_2 \quad F_3]$$

where

$$F = \left[ \sum_{i=1}^n B_i \quad P_g - P_l \quad \frac{\sum_{i=1}^n |V_i - V_i^*|}{n} \right]$$

subject to

$$0 \leq F_1 \leq F_{1\max}, 0 \leq B_i \leq B_{i\max}, \\ P_{g\min} \leq P_g \leq P_{g\max}, V_{i\min} \leq V_i \leq V_{i\max}$$

and the load flow equations [22]:

$$\Delta P_p = P_{Gp} - P_{cp} = \sum_{q=1}^{N_B} V_p V_q Y_{pq} \cos(\delta_p - \delta_q - \theta_{pq})$$

$$\Delta Q_p = Q_{Gp} - Q_{cp} = \sum_{q=1}^{N_B} V_p V_q Y_{pq} \sin(\delta_p - \delta_q - \theta_{pq})$$

where,  $P_{Gp}$ ,  $Q_{Gp}$  are the real and reactive power generations at bus  $P$ ;  $P_{cp}$ ,  $Q_{cp}$  the real and reactive power demands at bus  $P$ ;  $V_p$ , the voltage magnitude at bus  $P$ ;  $V_q$ , the voltage magnitude at bus  $q$ ;  $\delta_p$ , the voltage angle at bus  $p$ ;  $\delta_q$ , the voltage angle at bus  $q$ ;  $Y_{pq}$ , the admittance magnitude;  $\theta_{pq}$ , the admittance angle;  $N_B$ , the total number of buses;  $P = 1, 2, \dots, N_B$  and  $q = 1, 2, \dots, N_B$ .

The load flow equations reflect the physics of the power system as well as the desired voltage set points throughout the system. The physics of the power system are enforced through the power flow equations which require that the net injection of real and reactive power at each bus sum to zero.

To represent the amount of reactive compensation to be allocated at each busbar  $i$ , a decision vector  $B$  [23], is used to indicate the size of each reactive bank in the power system, *i.e.*:

$$B = [B_1, B_2, \dots, B_n], B_i \in R, |B_i| \leq B_{i\max}$$

Thus RPC is a complex combinatorial optimization problem involving multiple nonlinear functions having multiple local minima, which may be ill-defined and nonlinear with discontinuous constraint, which lead to non-convex Pareto-optimal front [23,24].

### 3.4. Formulation of MORPC

The multiobjective reactive power compensation optimization problem is therefore formulated as:

$$\text{minimize} \begin{cases} F_1 = \sum_{i=1}^n B_i \\ F_2 = P_g - P_l \geq 0 \\ F_3 = \sum_{i=1}^n |V_i - V_i^*|/n \end{cases}$$

S.t.

$$\begin{cases} 0 \leq F_1 \leq F_{1\max} \\ 0 \leq B_i \leq B_{i\max} \quad \forall i = 1, \dots, N_B \\ P_{g\min} \leq P_g \leq P_{g\max} \quad \forall i = 1, \dots, N_B \\ V_{i\min} \leq V_i \leq V_{i\max} \quad \forall i = 1, \dots, N_B \\ \Delta P_p = P_{Gp} - P_{cp} \\ \quad = \sum_{q=1}^{N_B} V_p V_q Y_{pq} \cos(\delta_p - \delta_q - \theta_{pq}) \quad \forall P = 1, 2, \dots, N_B \\ \Delta Q_p = Q_{Gp} - Q_{cp} \\ \quad = \sum_{q=1}^{N_B} V_p V_q Y_{pq} \sin(\delta_p - \delta_q - \theta_{pq}) \quad \forall P = 1, 2, \dots, N_B \end{cases}$$

## 4. The Proposed Approach

In this section we present a novel optimization algorithm to solve the RPC problem formulated in the previous section. The proposed methodology introduces a hybrid approach combining GAs and PSO to improve the performance of each algorithm. Also, to improve the solution quality we implement LS technique as neighborhood search engine where it intends to explore the less-crowded area in the current archive to possibly obtain more nondominated solutions nearby (*i.e.* that we search near every solution by LS technique to obtain a new solution best than current one or nondominated with it and therefore the less-crowded area will be discovered automatically). The description diagram of the proposed algorithm is shown in **Figure 1**, and it is described as follows:

### 4.1. PSO Stage

In this stage, we implement PSO as follows:

**Step 1:** Initialize parameters for PSO, initialize randomly  $N$  particles with position  $X_i^{t=0}$  with velocities  $V_i^{t=0}$  where  $t$  is the time counter and  $i = 1, \dots, N$ .

**Step 2:** Identify the local set ( $L_i^{t=0}$ ) for each particle as  $L_i^{t=0} \triangleq \{X_i^{t=0} | i = 1, \dots, N\}$ . Also, identify the local preferred element ( $LP_i^{t=0} \subset L_i^{t=0}$ ) of the  $i$ -th particle as  $\forall \text{particle } i \exists LP_i^{t=0} \triangleq (X_i^{t=0})$ .

**Step 3:** Collect all local sets ( $L_i^{t=0}$ )  $\forall i = 1, \dots, N$  in a pool  $C$  such that

$$C = \bigcup_{i=0}^N L_i^{t=0}.$$

**Step 4:** Define a global set  $G_i^{t=0} \triangleq ND(C)$ , where we assume that the function  $ND(\cdot)$  can get all nondominated solutions.

**Step 5:** In the objective space, The distance between  $X_i^{t=0} \forall i = 1, \dots, N$  and the members in  $G^{t=0}$  are measured using the Euclidean distance, where the distance between any two d-dimensional points  $x_i$  and  $x_j$  is given by

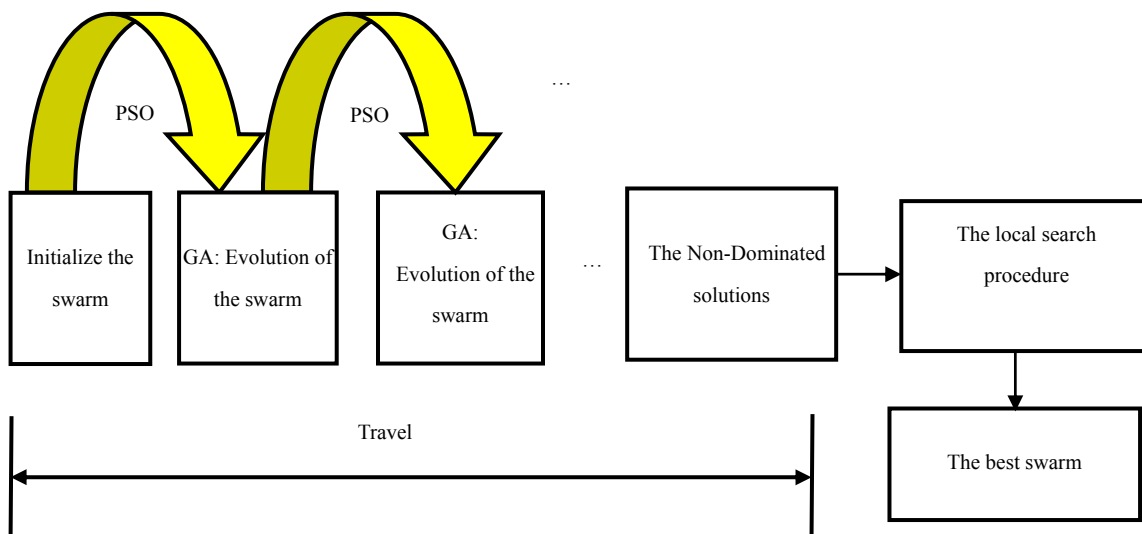


Figure 1. The description diagram of the proposed algorithm.

$$d(x_i, x_j) = \|x_i - x_j\|_2 = \sqrt{\sum_{p=1}^d (x_{i,p} - x_{j,p})^2}$$

The nearest member in  $G^t$  to the  $i$ -th particle set as the global preferred element  $GP_i^t$ .

**Step 6:** Set the external set  $E^{t=0}$  equal to  $G^{t=0}$ .

In an example, let we have 6 particles initially located as shown in **Figure 2**.

- Define the local set

$$\text{set } \forall \text{particle } i \exists L_i^{t=0} \triangleq \{X_i^{t=0} | i = 1, \dots, N\}$$

$$L_1^{t=0} = \{x_1\}, L_2^{t=0} = \{x_2\}, L_3^{t=0} = \{x_3\},$$

$$L_4^{t=0} = \{x_4\}, L_5^{t=0} = \{x_5\}, L_6^{t=0} = \{x_6\}$$

- Define the local preferred element

$$\forall \text{particle } i \exists LP_i^{t=0} \triangleq \{X_i^{t=0}\}$$

$$LP_1^{t=0} = \{x_1\}, LP_2^{t=0} = \{x_2\}, LP_3^{t=0} = \{x_3\},$$

$$LP_4^{t=0} = \{x_4\}, LP_5^{t=0} = \{x_5\}, LP_6^{t=0} = \{x_6\}$$

- Construct a pool C such that

$$C = \bigcup_{i=1}^N L_i^{t=0}$$

$$C = \bigcup_{i=1}^6 L_i^{t=0} = \{x_1, x_2, x_3, x_4, x_5, x_6\}$$

- Define a global set  $G^{t=0} \triangleq ND(C)$ ,

$$G^{t=0} \triangleq ND(C) = \{x_1, x_2, x_3\}$$

- Identify the global preferred element

$$GP_i^t \forall \text{particle } i$$

$$GP_1^{t=0} = \{x_1\}, GP_2^{t=0} = \{x_2\}, GP_3^{t=0} = \{x_3\},$$

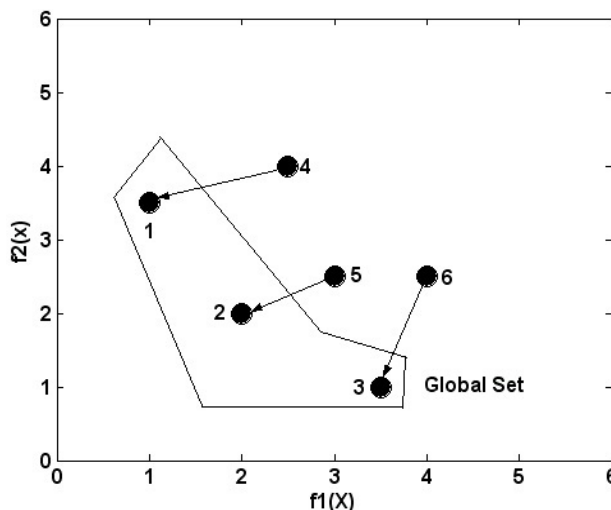


Figure 2. Location of initially 6 particles.

$$GP_4^{t=0} = \{x_1\}, GP_5^{t=0} = \{x_2\}, GP_6^{t=0} = \{x_3\}$$

- Define External set  $E^{t=0} = G^{t=0}$

$$E^{t=0} = G^{t=0} = \{x_1, x_2, x_3\}$$

**Step 7: Update particles:** Update the velocity  $v_i^t$  and position  $x_i^t$  of each particle to get new velocity  $v_i^{t+1}$  and position  $x_i^{t+1}$  according to the following equations:

$$v_i^{t+1} = wv_i^t + c_1r_1(LP_i^t - x_i^t) + c_2r_2(GP_i^t - x_i^t)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1}$$

where  $i = 1, 2, \dots, N$ , and  $N$  is the size of the population;  $w$  is the inertia weight;  $c_1$  and  $c_2$  are two positive constants, called the cognitive and social parameter respectively;  $r_1$  and  $r_2$  are random numbers uniformly distributed within the range  $[0,1]$ .

**Step 8: Evolution of particles:** To restrict velocity and control it, We present a modified constriction factor (*i.e.*, dynamic constriction factor) to keep the feasibility of the particles. e.g., **Figure 3** shows the movement of the particle  $i$  through the search space with and without modified constriction factor. Where the particle  $i$  start at position  $x_i^t$  with velocity  $v_i^t$  in the feasible space, the new position  $x_i^{t+1}$  depends on velocity  $v_i^{t+1}$ . Then,  $v_i^{t+1}$  makes the particle to lose its feasibility, so we introduce a modified factor  $x$  such that:

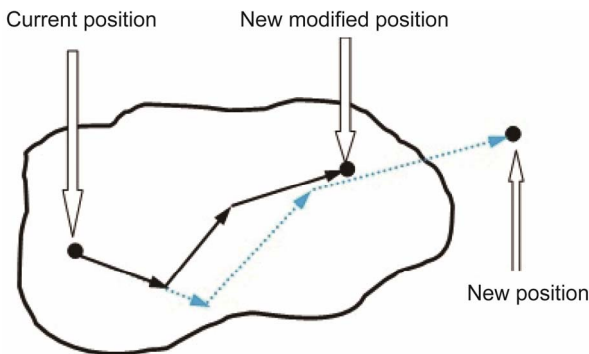
$$x = \frac{2}{|-2 - \tau - \sqrt{\tau^2 + \tau}|}$$

where,  $\tau$  is the age of the infeasible particle (*i.e.*, How long it's still unfeasible) and it is increased with the number of failed trial to keep the feasibility of the particle. The new modified position of the particle is computed as:

$$\bar{x}_i^{t+1} = x_i^t + \chi v_i^{t+1}$$

For each particle we check its feasibility, if it is infeasible, we implement  $x$  parameter to control its position and velocity according to **Algorithm 1**.

**Step 9:** Update local set  $L_i^t$  to get  $L_i^{t+1} \forall i = 1, \dots, N$ : The new position of *each* particle  $X_i^{t+1}$  is added to  $L_i^t$  to form  $L_i^{t+1}$  which is updated according to **Algorithm 2**.



**Figure 3.** The movement of the particle  $i$  through search space.

**Algorithm 1. Evolution of particles.**

```

input( $x_i^t, v_i^{t+1}, x_i^{t+1}$ )
while
     $x_i^{t+1}$  is infeasible | number of trial not satisfied
        generate  $\bar{x}_i^{t+1} = x_i^t + \chi v_i^{t+1}$ 
         $x_i^{t+1} = \bar{x}_i^{t+1}$ 
end
output( $v_i^{t+1}, x_i^{t+1}$ )
    
```

**Step 10:** Update global set  $G$ :

$$G^{t+1} = ND \left( \bigcup_{i=1}^N L_i^{t+1} \right)$$

which contain all nondominated solution of  $\bigcup_{i=1}^N L_i^{t+1}$ .

**Step 11: Update external set  $E^t$ :** Copy the members of  $G^{t+1}$  to  $E^t$  and apply dominance criteria to remove all dominated solution from  $E^t$  (*i.e.*, each member of  $G^{t+1}$  has three probabilities as in **Algorithm 3**).

**Step 12: Update local preferred element  $LP_i^{t+1}$  and global preferred element  $GP_i^{t+1}$  for each particle:** In the objective space, The distance between  $X_i^{t+1} \forall i = 1, \dots, N$  and members in  $LP_i^{t+1}$  are measured using Euclidean distance. The nearest member in  $LP_i^{t+1}$  to the  $i$ -th particle set as  $LP_i^{t+1}$ . Also, The distance between  $X_i^{t+1} \forall i = 1, \dots, N$  and the members in  $G^{t+1}$  are measured using Euclidean distance. The nearest member in  $G^{t+1}$  to the  $i$ -th particle set as the global preferred  $GP_i^{t+1}$ .

**4.2. GA Stage**

In this subsection, we describe the procedure of GA.

**Step 1:** Initialize parameters for GA.

**Step 2: Evaluation & Ranking:** A way to transform the values of objective functions to the fitness function of

**Algorithm 2. Update local set  $L_i^t$ .**

```

Input( $L_i^t, X_i^{t+1}$ )
If  $\exists X \in L_i^t \mid X > X_i^{t+1}$  then?
     $L_i^{t+1} = L_i^t$ 
Else if  $\exists X \in L_i^t \wedge X_i^{t+1} > X$  then
     $L_i^{t+1} = L_i^t \cup \{X_i^{t+1}\} / \{X\}$ 
Else if  $\nexists X \in L_i^t \mid X > X_i^{t+1}$  then
     $L_i^{t+1} = L_i^t \cup \{X_i^{t+1}\}$ 
End
Output( $L_i^{t+1}$ )
    
```

**Algorithm 3. Update external set  $E^t$ .**

```

Input( $E^t, X \in G^{t+1}$ )
If  $\exists Y \in E^t \mid Y > X$  then?
     $E^t = E^t$ 
Else if  $\exists Y \in E^t \wedge X > Y$  then
     $E^t = E^t \cup \{X\} / \{Y\}$ 
Else if  $\nexists Y \in E^t \mid Y > X$  then
     $E^t = E^t \cup \{X\}$ 
End
Output( $E^t$ )
    
```

each string in the genotype world is to combine the  $m$  objective functions into a scalar function as follows:

$$f(x) = w_1 f_1(x) + w_2 f_2(x) + \dots + w_m f_m(x)$$

where  $f(x)$  is the fitness function of  $x$  and  $w_1, \dots, w_m$  are non-negative weights which determined as follows:

$$w_i = \text{random}_i / \sum_{j=1}^m \text{random}_j, \forall i = 1, \dots, m$$

where  $\text{random}_1, \text{random}_2, \dots, \text{random}_m$ , are non-negative random integers.

Then rank them on the basis of the fitness values.

**Step 3: Selection:** Selection is an operator to select two parent strings for generating new strings (*i.e.*, offspring). In the selection, a selection probability  $P_s(x_i)$  of each string  $x$  based on the linear scaling is defined by the roulette wheel selection as follows:

$$P_s(x_i) = \frac{f(x_i) - f_{\min}(x_\psi)}{\sum_{j=1}^N \{f(x_j) - f_{\min}(x_\psi)\}}, \forall i = 1, 2, \dots, N$$

where  $f_{\min}(x_\psi)$  is the minimum fitness value (*i.e.*, the worst fitness value) in the current population  $\psi$ . According to this selection probability, a pair of parent strings are selected from the current population  $\psi$ .

**Step 4: Crossover:** Crossover is an operator to generate new strings (*i.e.*, offspring) from parent strings according to the crossover probability ( $Pc$ ). Various crossover operators have been proposed for GAs [25,26]. In the proposed approach we implement single point crossover.

**Step 5: Mutation:** Mutation is an operator to change elements in a string which is generated by a crossover operator. Such a mutation operator can be viewed as a transition from a current solution to its neighborhood solution in local search algorithms [27] according to the mutation probability ( $Pm$ ). In the proposed approach, we mutate each variable in a string  $x_i \in [a_i, b_i]$  with  $Pm$  by addition of small random values according to the equations below:

$$x'_i = \begin{cases} x_i + \Delta(t, b_i - x_i) & \text{if } \delta = 0 \\ x_i - \Delta(t, x_i - a_i) & \text{if } \delta = 1 \end{cases}$$

$$\Delta(t, y) = y \left[ 1 - r^{(1-t/t_{\max})^\beta} \right]$$

where  $r$  is a random number  $r \in [0, 1]$ ,  $t_{\max}$  is the maximum number of generations, and  $\beta$  is a positive constant chosen arbitrarily.

**Step 6: Elitist strategy (Replacing):** Randomly remove a string from the current population and add the best string in the previous population to the current one.

**Step 7: Repairing:** Repair the infeasible individuals of the population to be feasible. The idea of this technique

is to separate any feasible individuals in a population from those that are infeasible by repairing infeasible individuals. This approach co-evolves the population of infeasible individuals until they become feasible, the reader is referred to [28].

### 4.3. The Local Search

The local search phase is implemented as a dynamic version of pattern search technique. Pattern search technique is a popular paradigm in Direct Search (DS) methods. DS methods are evolutionary algorithms used to solve constrained optimization problems. DS methods, as opposed to more standard optimization methods, are often called derivative-free as they do not require any information about the gradient or higher derivatives of the objective function to search for an optimal solution. Therefore direct search methods may very well be used to solve non-continuous, nondifferentiable and multimodal (*i.e.* multiple local optima) optimization problems. This study examines the usefulness of a dynamic version of pattern search technique to improve the solution quality of MOPs. The search procedure looks for the best solution “near” another solution by repeatedly making small changes to a starting solution until no further improved solutions can be found.

The local search is started by loading the Pareto solutions for a given MOPs. At iteration  $t$ , we have an iterate  $x_t \in \text{Pareto}$ , where the changes on the values for each dimension ( $i = 1, 2, \dots, n$ ) can be implemented as

$$\Delta(t) = R(1 - r^{(1-t/T)})$$

where  $r$  is the random number in the range  $[0, 1]$ ;  $T$  is the maximum number of iterations;  $R$  is the search radius.

Let  $e_i$ , ( $i = 1, 2, \dots, n$ ), denote the standard unit basis vectors. We successively look at the points  $x_+ = x_t \pm \Delta(t)e_i$  ( $i = 1, 2, \dots, n$ ), until we find  $x_+$  for which  $f_j(x_+) \succ f_j(x_t)$  for at least one objective  $f_j, j \in Q$ . If we find no  $x_+$  such that  $f_j(x_+) \succ f_j(x_t)$ , then  $x_+ = x_t$ . Then we update the Pareto solutions by non dominated ones and the dominated ones are removed. This situation is represented in **Figure 4** for the case in  $R^2$ . Without loss of generality, the elements discussed above are synthesized to evolve the proposed approach. The flow chart of MACO and the local search phase is shown in **Figure 5**.

This local search scheme is implemented on all non-dominated solutions in  $E^t$  to get the true Pareto optimal solution and to explore the less-crowded area in the external archive.

## 5. Implementation of the Proposed Approach

The described methodology is applied to the standard IEEE 30-bus 6-generator test system to investigate the

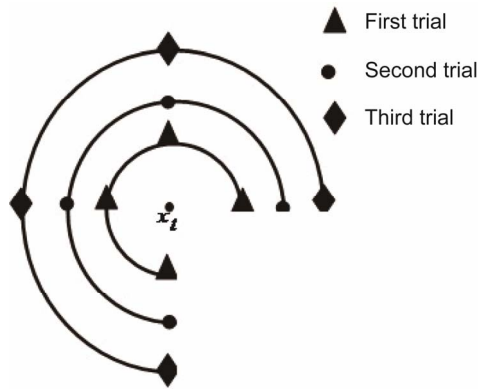


Figure 4. Mechanism of dynamic pattern search in  $R^2$ .

```

Initialize parameters for PSO and GA.
Identify local set  $L_i^{t=0} \triangleq \{X_i^{t=0}\} \forall i=1, \dots, N$  and
 $LP_i^{t=0} \triangleq \{X_i^{t=0}\} \forall i=1, \dots, N$ .
Identify global set  $G^{t=0} = ND \left( \bigcup_{i=1}^N L_i^{t=0} \right)$ 
The nearest member in  $G^{t=0}$  to the  $i$ -th particle is  $GP_i^{t=0}$ 
Set the external set  $E^{t=0} = G^{t=0}$ 
While travel not completed.
    PSO algorithm.
    While sub-travel not completed.
        Generate  $v_i^{t+1}$  and  $x_i^{t+1}$ .
        Evolve the unfeasible particles until they can
        be feasible.
        Update  $L_i^{t+1} \forall i=1, \dots, N$  and  $G^{t+1}$ 
        Identify  $LP_i^{t+1}$  and  $GP_i^{t+1}$ 
        Update  $E^t$ .
    End while.
    GA algorithm.
    While evolution not completed.
        Evaluation.
        Keep the best.
        GA operators.
        Repair.
    End while.
End travel.
Local search phase by adaptive pattern search
 $t = 0$ , load the Pareto solutions
while  $t \leq T$  do
    for  $j = 1 : n$  do
        Pareto( $i, j$ )1 = Pareto( $i, j$ ) +  $\Delta(t)$  {generate new
        search point}
        If ? Pareto( $i, :_j$ )1 > Pareto( $i, :$ ) do
            ? Pareto( $i, :$ ) = Pareto( $i, :_j$ ); break while {re-
            place old solution}
        end if
    end for,  $t = t + 1$ 
end while
Output → Pareto
End
    
```

Figure 5. The pseudo code of the proposed algorithm.

effectiveness of the proposed approach. The detailed data for this system are given in [29]. **Table 1** lists the parameter setting used in the algorithm for all runs.

### 6. Results and Discussions

**Figure 6**, shows well distributed Pareto-optimal nondominated solutions obtained by the proposed algorithm after 200 generations.

It is clear from the figure that Pareto-optimal set is well distributed and has satisfactory diversity characteristics. This is useful in giving a reasonable freedom in choosing compensation devices from the available commercial devices.

Out of the Pareto-optimal set **Table 2** shows the values of  $f_1(\cdot)$ ,  $f_2(\cdot)$  and  $f_3(\cdot)$  in the three cases 1, 2, and 3 corresponding to minimum amount of: reactive compensation devices, active power losses and average voltage deviation respectively obtained by proposed algorithm.

Offered in this section that the proposed approach is able to obtain the approximate Pareto set. The proposed approach has been used to increase the solution quality by combing the two merits of two heuristic algorithms. However, the goal is not only to increase the solution quality, but also to generate a representative subset, which maintains the characteristics of the general set and take the solution diversity into consideration.

On the other hand, classical techniques aim to give single point at each iteration of problem solving by converting the multiobjective problem to a single objective problem by linear combination of different objectives as

Table 1. The proposed approach parameter.

Cognitive parameter	2.8
Social parameter	1.3
Inertia weight	0.6
Crossover probability	0.95
Mutation probability	0.01
Selection operator	roulette wheel selection
Crossover operator	Single point crossover
Mutation operator	Real-value mutation
PSO iteration	5
GA generation	5

Table 2. Values of  $f_1(\cdot)$ ,  $f_2(\cdot)$ , and  $f_3(\cdot)$  in three cases.

	Cases 1 (min $f_1$ )	Cases 2 (min $f_2$ )	Cases 3 (min $f_3$ )
$f_1(\cdot)$	<b>1.0928</b>	1.7667	1.1257
$f_2(\cdot)$	2.6577	<b>0.019393</b>	2.03
$f_3(\cdot)$	0.015345	0.026343	<b>0.014349</b>

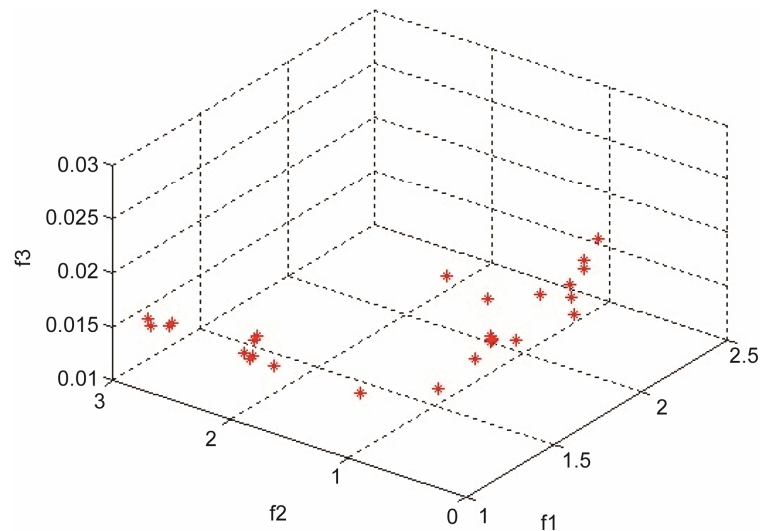


Figure 6. Pareto optimal front of the proposed approach.

a weighted sum. On the contrary, the proposed approach is a heuristics-based multiobjective optimization technique where, it uses a population of solutions in their search, multiple Pareto-optimal solutions can, in principle, be found in one single run.

Another advantage is the reality of using the proposed approach to handle complex problems of realistic dimensions has been approved due to procedure simplicity.

## 7. Conclusion

The reactive power compensation problem formulated as multiobjective optimization problem with competing amount of reactive compensation devices, active power losses and average voltage deviation is solved in this paper using a combination of GA and PSO. Our approach integrates the merits of both GA and PSO. In order to improve the solution quality, we implement LS technique as neighborhood search engine where it intends to explore the less-crowded area in the current archive to possibly obtain more nondominated solutions. The algorithm have an external archive to keep track of all the feasible solutions found during the optimization and therefore do not have any restrictions on the number of the Pareto-optimal solutions found. The proposed approach is carried out on the standard IEEE 30-bus 6-generator test system. The results demonstrate the capabilities of the proposed approach to generate true and well-distributed Pareto-optimal nondominated solutions of the multiobjective RPC. The result also confirms the proposed approach potential to solve the multiobjective RPC problem.

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