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# A Hybrid Formulation between Differential Evolution and Simulated Annealing Algorithms for Optimal Reactive Power Dispatch

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***Abstract***

*The aim of this paper is to solve the optimal reactive power dispatch (ORPD) problem. Metaheuristic algorithms have been extensively used to solve optimization problems in a reasonable time without requiring in-depth knowledge of the treated problem. The performance of a metaheuristic requires a compromise between exploitation and exploration of the search space. However, it is rarely to have the two characteristics in the same search method, where the current emergence of hybrid methods. This paper presents a hybrid formulation between two different metaheuristics: differential evolution (based on a population of solution) and simulated annealing (based on a unique solution) to solve ORPD. The first one is characterized with the high capacity of exploration, while the second has a good exploitation of the search space. For the control variables, a mixed representation (continuous/discrete), is proposed. The robustness of the method is tested on the IEEE 30 bus test system.*

***Keywords***: *Hybrid differential evolution, Simulated annealing, Reactive power dispatch, Voltage profile improvement*



### *Notation*

| | |
|---|---|
| $V_i$ | Voltage profile at bus *i*; |
| $\theta_{ij}$ | Phase angle of voltage between buses *i* and *j*; |
| $g_{ij}$ | Conductance of the branch existing between the buses i and *j*; |
| $N_B$ | Set of branch numbers; |
| $G_{ij}$ | Transfer conductance between buses *i* and *j*; |
| $B_{ij}$ | Transfer susceptance between buses *i* and *j*; |
| $N_{PQ}$ | Set of PQ bus numbers; |
| $N_{PV}$ | Set of PV bus numbers containing swing bus; |
| $N$ | Set of the total number of buses; |
| $N_0$ | Set of the bus numbers except the swing bus; |
| $N_i$ | Set of the bus numbers adjacent to bus *i* including bus *i*; |
| $T_i$ | Tap-setting of the transformer *i*; |
| $N_T$ | Set containing the numbers of tap-setting transformer branches; |
| $N_{cap}$ | Set of bus numbers containing shunt compensator banks; |
| $P_{di}$ | Active power load at bus *i*; |
| $Q_{di}$ | Reactive power load at bus *i*; |
| $P_{gi}$ | Generated active power at bus *i*; |
| $Q_{gi}$ | Generated reactive power at bus *i*; |
| $P_{kLoss}$ | Active power loss of branch *k*; |

## 1. Introduction

Reactive power dispatch (RPD) has shown an increasing attention these last years. Under voltages and over voltages in the lines cause the power system instability, the energy quality decrease and the equipment isolation degradation. Any change in the system configuration or system demand may result in higher or lower voltage profiles. The objectives of an optimal reactive power dispatch (ORPD) can mainly be summarized in the minimization of transmission losses and the improvement of the voltage profile in a power system by using a number of control tools. The optimal setting of switching VAr sources, changing transformer

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settings and adjusting generator voltages, would minimize transmission losses. (ORPD) is considered as a multi-constraints nonlinear multivariable optimization problem.

Several conventional techniques were described to solve this kind of problems after using some simplifications and special treatments [1-3]: Gradient's method, Quadratic programming, Linear programming, Newton's method and the Interior point's technique. However, all these techniques have a lot of problems such as:

a. converging in local solution,
b. large iteration number,
c. sensitivity to an initial search point,
d. limited modeling capabilities (in handling nonlinear, discontinuous functions and constraints,…).

These problems can be overcome by the introduction of intelligent techniques such as Neural networks [4], Fuzzy logic [5] and Evolutionary algorithms [6-11]. With the advancement of soft computing during the last years, many new stochastic search methods were developed for global optimization problems. Metaheuristics are stochastic algorithms for solving a wide range of problems for which there is no known effective conventional methods. These techniques are often inspired from biology (Evolutionary algorithms [6-11], Differential evolution [12-15]), physics (Simulated annealing [16-18], Gravitational search algorithm [19]) and ethnology [20-24].

In order to improve the performance of optimization algorithms, some authors have proposed hybrid algorithms [3, 11, 16-18, 25-27. Hybridization is a technique that combines the characteristics of two (or more) different methods to derive the benefits of both methods and compensate any disadvantages that were suffered by both algorithms. An ideal hybridization produces a hybrid method that combines the good properties of its constituents while inhibiting their weaknesses.

The main objective of this paper is to present a new hybrid formulation between differential evolution and simulated annealing algorithms for solving the optimal reactive power dispatch problem. The proposed methodology can be viewed as a two-stage algorithm. In the first level, a modified DE algorithm (based on the SA selection) is used to increase the diversity of solutions and resist premature convergence. When this modified DE algorithm is completed, the solution found can be improved by using the SA algorithm as a local search algorithm. To illustrate the suitability of this algorithm, the proposed hybridization is tested on the IEEE 30 bus test system.

The organization of this paper is as following: Problem formulation of the ORPD is presented in section 2. Sections 3 and 4 provide a brief overview of differential evolution technique and the simulated annealing algorithms, respectively. The proposed hybridization is presented in section 5. Detailed simulation results and also performance analysis are given and explained in section 6. Finally, conclusions and perspectives are given in section 7.

## 2. Problem Formulation

In general, minimization problem with constraints can be written in the following form:

$$\begin{aligned} &\text{Minimize} : f(x) , \\ &\text{Subject to: } h_i(x) = 0 , i = 0, , . . . . , m, \\ &g_j(x) \leq 0 , j = 0, , . . . . , n, \end{aligned} \qquad (1)$$

Where:

$m$ : Number of equality constraints;
$n$ : Number of inequality constraints;
$f(x)$ : Objective function;
$h_i(x)$ : Equality constraint;
$g_j(x)$ : Inequality constraint;

The number of variables is equal to the dimension of the vector $x$.

The purpose of an optimal reactive power dispatch (ORPD) can be summarized mainly in the minimization of transmission losses and the improvement of the voltage profile in a power system. The total loss can be described so, as the objective function:

$$f(x) = p = \sum_{k \in N_B} P_{kLoss} = \sum_{k \in N_B} g_{ij}(V_i^2 + V_j^2 - 2V_iV_j \cos \theta_{ij}) \tag{2}$$

where *k* is the branch between buses *i* and *j*. The function *f(x)* is subjected to a number of equality constraints (real and reactive power balance at each node) related to the load flow:

$$\Delta P_i = P_{gi} - P_{di} - V_i \sum_{j \in N_i} V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) = 0, \; i \in N_0 \tag{3}$$

$$\Delta Q_i = Q_{gi} - Q_{di} - V_i \sum_{j \in N_i} V_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}) = 0, \; i \in N_{PQ} \tag{4}$$

Inequality constraints of control variables are given as:

$$T_{i\min} \le T_i \le T_{i\max}, \; i \in N_T \tag{5}$$

$$Q_{g_{i\min}} \le Q_{g_i} \le Q_{g_{i\max}}, \; i \in N_{cap} \tag{6}$$

$$V_{i\min} \le V_i \le V_{i\max}, \; i \in N_{PV} \tag{7}$$

Inequality constraints of state variables are written as:

$$V_{i\min} \le V_i \le V_{i\max}, \; i \in N_{PQ} \tag{8}$$

$$Q_{g_{i\min}} \le Q_{g_i} \le Q_{g_{i\max}}, \; i \in N_{PV} \tag{9}$$

The control variables such as generator bus voltage, transformer tap-setting, and switchable shunt capacitor banks are self restricted. While the load bus voltages and reactive power generations are state variables, which are restricted by adding them to the objective function as the quadratic penalty terms to form a penalty function:

$$Min \;\; F(x) = p + \sum_{i \in N_{PQ}} \lambda_{Vi} (V_i - V_i^{\lim})^2 + \sum_{i \in N_{PV}} \lambda_{Qgi} (Q_{gi} - Q_{gi}^{\lim})^2, \tag{10}$$

This new formulation of the objective function is subject to equality constraints (3)-(4) and inequality constraints of control variables (5)-(7). The coefficients $\lambda_{Vi}$ and $\lambda_{Qgi}$ are considered as penalty factors.

$$V_i^{\lim} = \begin{cases} V_{i\min} & if \quad V_i < V_{i\min} \\ V_{i\max} & if \quad V_i > V_{i\max} \\ V_i & if \quad V_{i\min} \le V_i \le V_{i\max} \end{cases} \tag{11}$$

$$Q_{gi}^{\lim} = \begin{cases} Q_{gimin} & if \quad Q_{gi} < Q_{gimin} \\ Q_{gimax} & if \quad Q_{gi} > Q_{gimax} \\ Q_{gi} & if \quad Q_{gimin} \le Q_{gi} \le Q_{gimax} \end{cases} \tag{12}$$

### 3. Differential Evolution Algorithm

Differential evolution (DE) is a stochastic optimization technique proposed by Storn and Price in 1997 [12]. It was originally designed to solve problems with continuous variables. Based on a population of solutions, it belongs, like genetic algorithms (GA), to the family of evolutionary algorithms (EA). It uses the same genetic algorithms operators: crossover, mutation and selection, but it is distinguished by the way of creating new individuals. Genetic algorithms are based on the crossing, while DE algorithm is based on the mutation operation that is based on the difference between pairs of solutions randomly chosen from population.

The initial population of DE algorithm is randomly generated within the control variable bounds. The population contains *N* individuals. Each individual $x_{i,G}$ is a vector of dimension $D$, where $G$ is the generation:

$$x_{i,G} = (x_{1i,G}, x_{2i,G}, \dots, x_{Di,G}) \text{ , } i = 1,2,\dots,N \tag{13}$$

In every generation, the algorithm successively applies the three operations (mutation, crossover and selection) on each vector to produce a trial vector:

$$u_{i,G+1} = (u_{1i,G+1}, u_{2i,G+1}, \dots, u_{Di,G+1}),\ i = 1,2,\dots,N \tag{14}$$

A selection operation selects individuals to be saved for the new generation $(G + 1)$. DE has a specialized nomenclature that takes the form of $DE/x/y$, where $x$ signifies the solution to be perturbed (random or best). The $y$ represents the number of difference vectors used in the perturbation of $x$. The difference vector is the difference between two randomly selected distinct members of the population.

#### 3.1. Mutation

For each current vector $x_{i,G}$ is generated a mutant vector $v_{i,G+1}$ which can be created using one of the following most used mutation strategies:
*DE/Rand/1 :*

$$v_{i,G+1} = x_{r_1,G} + F(x_{r_2,G} - x_{r_3,G}) \tag{15}$$

*DE/Best/1 :*

$$v_{i,G+1} = x_{best,G} + F.(x_{r_1,G} - x_{r_2,G}) \tag{16}$$

*DE/Current to best/1 :*

$$v_{i,G+1} = x_{i,G} + F.(x_{r_1,G} - x_{r_2,G}) + F.(x_{best,G} - x_{i,G}) \tag{17}$$

*DE/Best/2 :*

$$v_{i,G+1} = x_{best,G} + F.(x_{r_1,G} - x_{r_2,G}) + F.(x_{r_3,G} - x_{r_4,G}) \tag{18}$$

*DE/Rand/2 :*

$$v_{i,G+1} = x_{r_1,G} + F.(x_{r_2,G} - x_{r_3,G}) + F.(x_{r_4,G} - x_{r_5,G}) \tag{19}$$

Where $r_1$, $r_2$, $r_3$, $r_4$ and $r_5 \in \{1,2, \dots, N\}$, with $r_1 \neq r_2 \neq r_3 \neq r_4 \neq i$ are mutually different integers randomly selected from the set $\{1,2, \dots, N\}$. $x_{best,G}$ is the best individual in the generation $G$. The constant value $F \in [0,2]$ (called differential weight or mutation constant), controls the amplification of the difference between two individuals so as to avoid search stagnation. If $v_i$ is found outside variable limit, it will be fixed to the accepted upper or lower limit.

### 3.2. Crossover

The crossover operation is introduced to increase the diversity of the perturbed parameter vectors. The new vector is given by the following formula:

$$u_{ji,G+1} = \begin{cases} v_{ji,G+1} & if\ (randb(j) \leq CR) \\ x_{ji,G} & if\ (randb(j) > CR) \end{cases} \quad (20)$$

This Equation is applied for every vector component $i \in \{1,2,\ldots,N\}$, $j \in \{1,2,\ldots,D\}$. Where $randb\,(j)$ is a random number that belongs to the interval [0,1]. $CR \in [0,1]$ is the coefficient of crossover.

### 3.3. Selection

To decide if the vector $u_{i,G+1}$ should be a member of the population of the next generation or not, it is compared to the vector $x_{i,G}$ .

$$x_{i,G+1} = \begin{cases} u_{i,G+1} & if\ f(u_{i,G+1}) < f(x_{i,G}) \\ x_{i,G} & otherwise \end{cases} \quad (21)$$

### 3.4. Stopping Criteria

The optimization process is stopped when a predefined maximum iteration is achieved or other predetermined convergence criterion is satisfied. DE algorithm is represented in the algorithm of Figure 1.

***Initialisation***
Lets G = 0
***Repeat***
Mutation step
Crossover step
Selection step
G = G+1 (increment the generation counter)
***Until a stopping criterion is satisfied***

Figure 1. Differential Evolution Algorithm

## 4. Simulated Annealing (SA)

Simulated annealing (SA) is a stochastic optimization approach proposed by Kirkpatrick in 1983. It is inspired from the natural process of annealing related to thermodynamics. The annealing process is used in metallurgy to improve the quality of a solid. A metal is heated to a very high temperature $T_{max}$ and slowly cooled to a low temperature $T_{min}$ that can crystallize. The heating procedure lets the atoms travel arbitrarily, if the cooling is done slowly enough, so the atoms have enough time to regulate themselves so as to reach a minimum energy state. This similarity can be applied in optimization problems where the state of metal is corresponding to the $T_{max}$ possible solution and the minimum energy state represent the final best solution.

The principle of SA algorithm is to browse iteratively the solution space. We start with initial solution $S_0$ randomly generated which corresponds to an initial energy $E_0$, and initial temperature $T_{max}$ generally high. At each iteration of the algorithm, a basic change is made to the solution. This modification varies the energy $\Delta\mathrm{E}$ of the system. If this variation is negative (the new solution $s'$ improves the objective function $f(s')$, and reduces the energy of the system $\Delta E = f(s') - f(s) < 0$), it is accepted. If the solution found $s'$ is worse than the previous one $s$ $(\Delta E = f(s') - f(s) > 0)$, so it may be accepted with a probability distribution $p$ calculated according to the following Boltzmann distribution:

$$p(E,T) = exp^{-\frac{\Delta E}{T}} \quad (22)$$

A random number $r \in [0,1]$ is compared to the probability $p = exp^{-\frac{\Delta E}{T}}$. If $p \geq r$, the new solution is accepted. Otherwise, the new solution is rejected, we try with another solution. Temperature $T$ is gradually decreased in each iteration. In this paper the decrement of temperature at iteration $(t+1)$ is implemented using:

$$T(t+1) = \alpha . T(t) \tag{23}$$

The coefficient $\alpha$, is a constant close to 1. This procedure is repeated until the stopping criteria is satisfied, which is in our algorithm $T \leq T_{min}$. SA algorithm can be summarized in Figure 2, where *Trymax* is the max tries happened at each temperature value.

***Initialization***
Choose $T_{max}, T_{min}, \alpha, Trymax$ and initialize temperature at $T = T_{max}$.
Generate an initial solution $s$ randomly and compute its objective function $f(s)$.
***while*** $T \geq T_{min}$
  ***while*** the number of tries $\leq Trymax$
   Generate an adjacent solution $s'$ randomly and compute its objectif function $f(s')$.
   ***if*** $f(s') \leq f(s)$
    accept the new solution and replace the previous solution with the new.
   ***else if*** $f(s') > f(s)$
    Then, let $\Delta E = f(s') - f(s)$, generate a random number $r \in [0,1]$, accept the new solution if $exp^{-\frac{\Delta E}{T}} \geq r$ and replace the previous solution with the new.
   ***end of if***
  ***end of while***
  Decrease the temperature $T(t) = \alpha . T(t-1)$
***end of while***

Figure 2. Simulated Annealing Algorithm

## 5. Proposed Hybridization for ORPD

In this paper, a hybrid formulation between differential evolution and simulated annealing algorithms (HDESA) is proposed to solve the optimal reactive power dispatch problem. DE is a powerful global optimization technique that is simple and easy to use. It is characterized by its suitability for parallelization. The difference between DE and other EA's appears in the mutation and recombination phases. In the EA techniques such as GA, the perturbation occurs in accordance with a random quantity, while DE uses weighted differences between solution vectors to perturb the population. When the population lost completely its diversity, it will contain identical elements, and it remains unchanged by DE perturbation. To avoid premature convergence, it is necessary to keep a reasonable level of diversity in the population.

In the other side, SA method is characterized by the ability to escape from local minima because of its probability function incorporated to accept or reject new solutions. It does not need large computer memory. In this paper a hybrid formulation, shortened HDESA, is proposed. The proposed hybridization benefits from the global search ability of DE and the local search ability of SA, and offset the weaknesses of each other. The combination of DE and SA will provide so a good balance between exploration and exploitation. In this study, we start the hybrid algorithm with the DE algorithm described in section 3, but at the time of selection of the individual, we replace the stage:

$$x_{i,G+1} = \begin{cases} u_{i,G+1} & if\ f(u_{i,G+1}) < f(x_{i,G}) \\ x_{i,G} & otherwise \end{cases} \tag{24}$$

with this expression inspired from SA selection:

$$x_{i,G+1} = \begin{cases} u_{i,G+1} & if\ f(u_{i,G+1}) < f(x_{i,G}) \\ otherwise & \begin{cases} u_{i,G+1} & if\ r \le exp^{-\frac{\Delta E}{T}}, r \in [0,1] \\ x_{i,G} & otherwise \end{cases} \end{cases} \quad (25)$$

The decrease in temperature is calculated here in each generation. This method of selection can enable the exploration of areas not improving objective function value by accepting less good solutions, so it can avoid local point, resist premature convergence, and increase the diversity of DE solutions. When this modified DE algorithm is completed, we improve the solution found from it by using the SA algorithm as a local search algorithm to refine the best solution found so far.

## 6. Simulation

### 6.1. Data of the Studied Network

In this section, we describe an evaluation of the hybrid differential evolution simulated annealing-based algorithm for solving the ORPD problem. This evaluation is carried out through an application on the standard IEEE 30-bus test system. The network consists of 30 bus, 41 branches, 6 generators, 4 tap-setting transformers and 9 VAR switching sources. Bus 1 is the swing bus. Buses 2, 5, 8, 11 and 13 are selected as PV buses. The possible reactive power installation buses are 10, 12, 15, 17, 20, 21, 23, 24 and 29. The branches with tap-setting transformer are branches (6-9), (6-10), (4-12) and (28-27). It should be mentioned that the system data is taken from [8, 15, 24, 28]. The constraints of control and state variables are shown respectively in Tables 1 and 2. The used base of power is SB = 100 [MVA].

To demonstrate the effectiveness of the proposed algorithm, the currant section proposes also to compare the achieved results by HDESA with those achieved by an application of a number of benchmark algorithms : SA, DE, PSO [29] and GA Based FGP [30].

### 6.2. Load Flow Calculation

The execution of Newton-Raphson method for the load flow gave the results presented in Table 3 where the total transmission loss is 5.8223 [MW]. The voltages outside the limits are $V_{19}$, $V_{20}$, $V_{21}$ $V_{22}$, $V_{23}$, $V_{24}$, $V_{25}$, $V_{26}$, $V_{27}$, $V_{29}$ *and* $V_{30}$. In fact, it is of primary importance to adjust the control variables at the end of ensuring a minimization of transmission losses and an improvement of the voltage profile in the studied network.

Table 1. Control Variable Constraints

| | Transformation ratio | Generator bus voltage [pu] | Reactive power installation [pu] |
|---|---|---|---|
| Lower limit | 0.9 | 0.95 | 0.0 |
| Upper limit | 1.1 | 1.1 | 0.05 |

Table 2. State Variable Constraints

| | Voltage of PQ buses [pu] | Reactive power of PV buses (generators) [pu] | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | Bus | 1 | 2 | 5 | 8 | 11 | 13 |
| Lower limit | 0.95 | | -0.2 | -0.2 | -0.15 | -0.15 | -0.1 | -0.15 |
| Upper limit | 1.05 | | 0.25 | 1 | 0.8 | 0.6 | 0.5 | 0.6 |

Table 3. Load Flow Results

| | Voltage | | Load | | Generation | |
|---|---|---|---|---|---|---|
| Bus | V [pu] | Θ [degree] | $P_d$ [pu] | $Q_d$ [pu] | $P_g$ [pu] | $Q_g$ [pu] |
| 1 | 1.0500 | 0 | 0 | 0 | 0.9922 | -0.01535 |
| 2 | 1.0400 | -1.7623 | 0.217 | 0.127 | 0.8000 | 0.15644 |
| 3 | 1.0279 | -3.9323 | 0.024 | 0.012 | 0 | 0 |
| 4 | 1.0222 | -4.6963 | 0.076 | 0.016 | 0 | 0 |
| 5 | 1.0100 | -6.4824 | 0.942 | 0.190 | 0.5000 | 0.16406 |
| 6 | 1.0166 | -5.4355 | 0 | 0 | 0 | 0 |
| 7 | 1.0059 | -6.3969 | 0.228 | 0.109 | 0 | 0 |
| 8 | 1.0100 | -5.6272 | 0.300 | 0.300 | 0.2000 | 0.13537 |
| 9 | 0.9755 | -7.0162 | 0 | 0 | 0 | 0 |
| 10 | 0.9547 | -9.1959 | 0.058 | 0.020 | 0 | 0 |
| 11 | 1.0500 | -4.6886 | 0 | 0 | 0.2000 | 0.38002 |
| 12 | 0.9976 | -8.7884 | 0.112 | 0.075 | 0 | 0 |
| 13 | 1.0500 | -7.2567 | 0 | 0 | 0.2000 | 0.39545 |
| 14 | 0.9773 | -9.7952 | 0.062 | 0.016 | 0 | 0 |
| 15 | 0.9680 | -9.7932 | 0.082 | 0.025 | 0 | 0 |
| 16 | 0.9718 | -9.2538 | 0.035 | 0.018 | 0 | 0 |
| 17 | 0.9540 | -9.4522 | 0.090 | 0.058 | 0 | 0 |
| 18 | 0.9501 | -10.3964 | 0.032 | 0.009 | 0 | 0 |
| 19 | 0.9429 | -10.5331 | 0.095 | 0.034 | 0 | 0 |
| 20 | 0.9450 | -10.2636 | 0.022 | 0.007 | 0 | 0 |
| 21 | 0.9408 | -9.7516 | 0.175 | 0.112 | 0 | 0 |
| 22 | 0.9413 | -9.7419 | 0 | 0 | 0 | 0 |
| 23 | 0.9467 | -10.1714 | 0.032 | 0.016 | 0 | 0 |
| 24 | 0.9274 | -10.2804 | 0.087 | 0.067 | 0 | 0 |
| 25 | 0.9204 | -10.3073 | 0 | 0 | 0 | 0 |
| 26 | 0.9008 | -10.8220 | 0.035 | 0.023 | 0 | 0 |
| 27 | 0.9257 | -10.0102 | 0 | 0 | 0 | 0 |
| 28 | 1.0116 | -5.8711 | 0 | 0 | 0 | 0 |
| 29 | 0.9035 | -11.5199 | 0.024 | 0.009 | 0 | 0 |
| 30 | 0.8907 | -12.6115 | 0.106 | 0.019 | 0 | 0 |
| Total real losses : 5.8223 [MW] | | | | | | |

### 6.3. Treatment of Control Variables, Initiation and Evaluation Steps

Each possible solution is represented as a vector containing the values of control parameters (generator voltages, transformer taps and injected reactive power of switchable shunt capacitor). It is represented as:

$$X = \left[ V_{N-N_{PV}+1} \;\; \ldots \;\; V_N \middle| T_1 \;\; \ldots \;\; T_{N_T} \middle| Q_{gc_1} \;\; \ldots \;\; Q_{gc_{N_{cap}}} \right] \quad (26)$$

Generator voltages are considered as continuous values. However, reactive power installation and the transformer taps are regarded as discrete ones. At the initiation step of each approach (DE, SA or Hybridization), the initial solutions are created using uniform random variables:

$$X_i = X_{i\min} + rnd \times \left( X_{i\max} - X_{i\min} \right) \quad (27)$$

where *rnd* is a random value $0 < rnd < 1$. To deal with discrete variables, we must adjust the variable value to have a formulation as:

$$X_i = X_{i\min} + NX_i \times \Delta X_i \quad (28)$$

$NX_i$ : Integer number represents the variation number of the variable $X_i$
$\Delta X_i$ : Step size of the variable $X_i$

In this paper, each one of the transformers contains 32 steps. Each one of the nine shunt compensator banks has 100 possible variations. To evaluate any solution, the corresponding fitness function value is obtained by running load-flow with Newton-Raphson method.

### 6.4. Application of Simulated Annealing (SA)

The basic SA optimization procedure has 4 principal parameters: $T_{max}$, $T_{min}$, $\alpha$ and $Trymax$. In order to help the SA algorithm to find optimal solution, we must use a large initial temperature, a small final temperature, a large max try times with a slow decrement on the temperature. The parameters used here for the SA are:

a. Initial temperature $T_{max}$ : 1000

b. Final temperature $T_{min}$ : 0.1

c. Constant of temperature decrement $\alpha$ : 0.99

d. Max tries at each temperature $Trymax$ : 50

The SA results are presented in Table 4. One can clearly perceive an important improvement of 10.59% in total real losses, ranging also from 5.8223 [MW] in the case of load flow calculation to 5.2055 [MW] in our current case. The voltage profile has been improved and all the constraints have been respected. The convergence characteristic of the algorithm is shown in Figure 3.

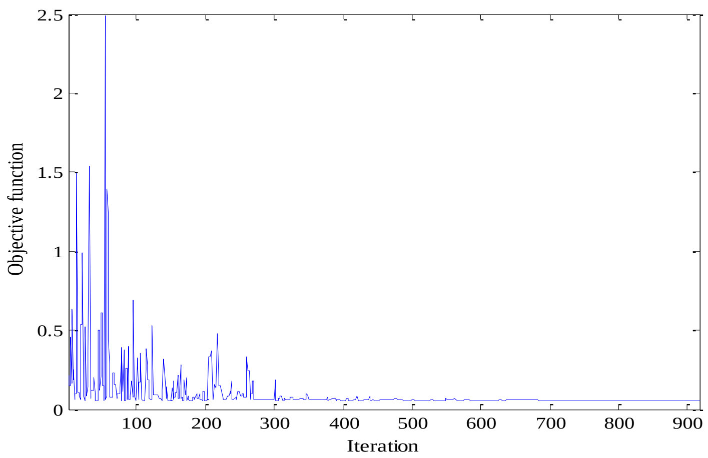


Figure 3. Convergence of the SA Algorithm

### 6.5. Differential Evolution Algorithm Application

The main parameters of the DE are differential weight *F* (step size), and crossover coefficient *CR*. The parameter *F* controls the scale of differential variation. It is usually selected to be in the range of $0 \leq F \leq 2$. If *F* is too small, the differentiation vectors will lead us to a local search around $x_{r_1,G}$. In the case, where *F* is too large, the new vectors may often violate the constraints imposed on the search space. On the other side, *CR* is usually within the range $0 < CR < 1$. Furthermore, it must be sufficiently close to 1 to enable the acceptance of new vectors and increase the diversity level in the population. In this paper, the different parameters of the DE are decided based on trial simulation run. The used parameters are:

a. Maximal number of generations : 100

b. Population size : 500

c. Differential weight *F* : 1

d. Crossover coefficient *CR* : 0.8

The convergence characteristic of the algorithm is shown in Figure 4. The DE results are given in Table 4. Hence, we can clearly perceive the superiority of DE over SA, where the losses are moved from 5.2055 [MW] to 5.1439 [MW].

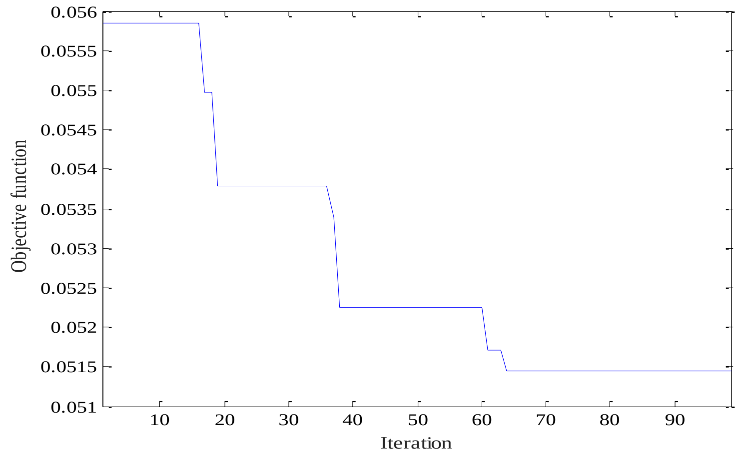


Figure 4. Convergence of the DE Algorithm

### 6.6. Proposed Hybridization between DE and SA

In this study, the hybridization starts with a DE algorithm but at the time of selection the equation (21) is replaced with the expression (25). Once the execution of modified DE algorithm is finished, the solution found is used as an initial solution for the SA algorithm. We use the SA as a local search algorithm in the final stage to refine the best solution found so far. The convergence characteristic of the algorithm is shown in Figure 5 and the simulation results are resumed in Table 4. The total loss is considerably reduced to 5.1298 [MW]. The results obtained from the proposed hybrid approach are better than those obtained from DE or SA. The results of our applied algorithm have been also compared in Table 4 with those achieved by a multiobjective RPD using classical PSO algorithm in [29] and genetic algorithm based fuzzy programming (GA based FGP) in [30]. Once again, the comparison shows the efficiency and the superiority of our hybrid algorithm.

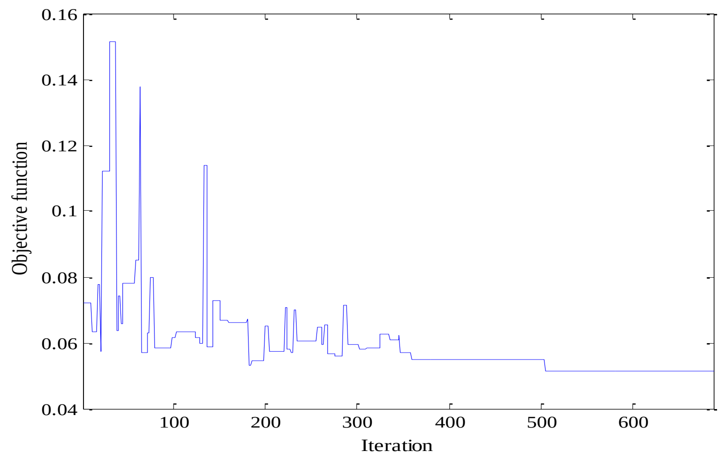


Figure 5. Convergence of the Hybridization Algorithm

Table 4. Control Variables and Losses Obtained From Execution of SA, DE, HDESA, PSO [29] and GA Based FGP [30]

| Control variables | Initial | SA | DE | Hybridization (HDESA) | PSO algorithm [29] | GA based FGP [30] |
|---|---|---|---|---|---|---|
| $V_1$ [pu] | 1.05 | 1.0590 | 1.0593 | 1.0744 | 1.04189 | 1.055 |
| $V_2$ [pu] | 1.04 | 1.0545 | 1.0532 | 1.0724 | 1.03174 | 1.042 |
| $V_5$ [pu] | 1.01 | 1.0102 | 1.0279 | 1.0486 | 1.00817 | 1.035 |
| $V_8$ [pu] | 1.01 | 1.0348 | 1.0240 | 1.0498 | 1.00711 | 1.036 |
| $V_{11}$ [pu] | 1.05 | 1.0712 | 1.1000 | 1.0692 | 1.05427 | 1.085 |
| $V_{13}$ [pu] | 1.05 | 1.0717 | 1.0579 | 1.0038 | 1.00921 | 1.064 |
| $T_{6-9}$ | 1.078 | 0.9688 | 1.0312 | 1.0375 | 1.08161 | 0.9536 |
| $T_{6-10}$ | 1.069 | 0.9750 | 0.9875 | 0.9938 | 0.90668 | 0.9067 |
| $T_{4-12}$ | 1.032 | 1.0313 | 0.9812 | 0.9750 | 0.99907 | 0.9990 |
| $T_{28-27}$ | 1.068 | 0.9750 | 1.0187 | 1.0438 | 0.97220 | 0.9662 |
| $Q_{c10}$ [pu] | 0 | 0.0335 | 0.0355 | 0.0110 | 0.02752 | 0.03871 |
| $Q_{c12}$[pu] | 0 | 0.0110 | 0.0040 | 0.0330 | 0.04986 | 0.04151 |
| $Q_{c15}$ [pu] | 0 | 0.0390 | 0.0500 | 0.0465 | 0.04821 | 0.04812 |
| $Q_{c17}$ [pu] | 0 | 0.0140 | 0 | 0.0350 | 0.02367 | 0.03735 |
| $Q_{c20}$ [pu] | 0 | 0.0425 | 0.0250 | 0.0335 | 0.04998 | 0.04617 |
| $Q_{c21}$ [pu] | 0 | 0.0175 | 0.0020 | 0.0180 | 0.04999 | 0.04828 |
| $Q_{c23}$ [pu] | 0 | 0.0090 | 0.0265 | 0.0070 | 0.04954 | 0.03781 |
| $Q_{c24}$ [pu] | 0 | 0.0170 | 0.0275 | 0.0170 | 0.05000 | 0.04512 |
| $Q_{c29}$ [pu] | 0 | 0.0120 | 0.0395 | 0.0155 | 0.02591 | 0.02690 |
| Total real losses [MW] | 5.8223 | 5.2055 | 5.1439 | 5.1298 | 5.2278 | 5.169 |

## 7. Conclusions & Perspectives

Reactive power dispatch (RPD) is a nonlinear multivariable optimization problem with constrains. To solve reactive power dispatch problem, this paper has proposed DE, SA and a hybrid combination between the two. The objective of this hybridization is to benefit from the advantages of both methods and improve results. The proposed algorithm combines the global search capacity of the DE and the local search ability of the SA, and offsets the weaknesses of each other. It will provide so a good balance between exploration and exploitation. It can avoid local point, resist premature convergence, and increase the diversity of DE solutions.

In order to make the problem of RPD more practical the optimal setting of control variables are represented in a mixed (continuous/discrete) representation. Generator voltages are considered as continuous values. However, reactive power installation and the transformer taps are regarded as discrete ones.

The robustness of the proposed method is tested on the standard IEEE 30 bus test system. Compared with the use of DE or SA method alone, the hybrid method shows a potential advantage. Therefore, the hybridization techniques are a promising alternative approaches. As perspective of this work, we can hybrid SA algorithm with another technique and demonstrate the effectiveness of the proposed algorithm on different electrical test networks.

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