Review

Multi-objective based on parallel vector evaluated particle swarm optimization for optimal steady-state performance of power systems

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A R T I C L E   I N F O

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A B S T R A C T

In this paper the state-of-the-art extended particle swarm optimization (PSO) methods for solving multi-objective optimization problems are represented. We emphasize in those, the co-evolution technique of the parallel vector evaluated PSO (VEPSO), analysed and applied in a multi-objective problem of steady-state of power systems. Specifically, reactive power control is formulated as a multi-objective optimization problem and solved using the parallel VEPSO algorithm. The results on the IEEE 30-bus test system are compared with those given by another multi-objective evolutionary technique demonstrating the advantage of parallel VEPSO. The parallel VEPSO is also tested on a larger power system this with 136 busses.

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1. Introduction

Recently, modern meta-heuristic algorithms are considered as effective tools for nonlinear optimization problems with applications to power systems scheduling (Aik et al., 2008). The algorithms do not require that the objective functions and the constraints have to be differentiable and continuous. A particle swarm optimization (PSO) introduced by Kennedy and Eberhart (1995) is such an algorithm that can be applied to nonlinear optimization problems. The PSO has been developed from the simulation of simplified social systems such as bird flocking and fish schooling. Unlike other heuristics techniques such as genetic algorithm (GA), PSO has a flexible and well-balanced mechanism to enhance and adapt to the global and local exploration and exploitation abilities within a short calculation time. Although PSO seems to be sensitive to the tuning of its parameters, many researches are still in progress in regulating these (Chaturvedi, Pandit, & Srivastava, 2008; Parsopoulos & Vrahatis, 2002; Storn, 1999; Storn & Price, 1997; Vlachogiannis, 2006; Vlachogiannis & Lee, 2006).

The PSO has been very successfully developed in solving single optimization problems in power systems such as power loss minimization (Esmín, Lambert-Torres, & De Souza, 2005), reactive power and voltage control (Vlachogiannis, 2006), economic dispatch considering nonlinear characteristics of power systems (Chaturvedi et al., 2008), practical distribution state estimation (Liu & Gu, 2007), generation expansion planning (Kanan, Slochanal, Subbaraj, & Padhy, 2004), optimal capacitor placement with harmonic distortion consideration (Yu, Xiong, & Wu, 2004), practical distribution state estimation (Naka, Genji, Yura, & Fukuyama, 2003) and short-term load forecasting (Huang, Huang, & Wang, 2005). Consequently, PSO has been found to be quite successful in a wide variety of optimization tasks in power systems but it has not handled satisfactorily multi-objective optimization problems, in these areas yet; except two works: Abido (2008), and Vlachogiannis and Lee (2005) where they used the PSO for the multi-objective operation of power system. However, its high convergence speed and relative simplicity make PSO a highly viable candidate for solving problems with several objectives (called: “multi-objective optimization problems”).

There have been several fundamental approaches proposed using PSO to handle multiple objectives, some of which are presented below:

- The swarm metaphor of Ray and Liew (2002): This algorithm uses Pareto dominance and combines the concepts of evolutionary-ary techniques with the particle swarm. The approach uses crowding to maintain diversity and a multilevel sieve to handle constraints.
- Dynamic neighbourhood PSO proposed by Hu and Eberhart (2002): In this algorithm, only one objective is optimized at a time using a scheme similar to lexicographic ordering. A revised version of this approach that uses a secondary population is presented by Hui, Eberhart, and Shi (2003).
- The Multi-Objective PSO (MOPSO) by Coello and Salazar Lechuga (2002): This proposal is based on the idea of having a global repository in which every particle will deposit its flight
experiences after each flight cycle. Additionally, the updates to
the repository are performed considering a geographically-
based system defined in terms of the values of objective function
of each individual; this repository is used by the particles to
identify a leader that will guide the search.

• The approach of Fieldsend and Singh (2002): This approach
incorporates an unconstrained elite archive (in which a special
data structure called dominated tree is adopted) to store the
non-dominated individuals found along the search process.
The archive interacts with the primary population in order to
define local guides. This approach also uses a turbulence opera-
tor, which is basically a mutation operator that acts on the
velocity value used by PSO.

• The algorithm of Mostaghim and Teich (2003): This approach
uses a sigma method in which the best local guides for each par-
ticle are adopted to improve the convergence and diversity of a
PSO algorithm used for multi-objective optimization. They also
use a turbulence operator, but applied on decision variable
space. The use of the sigma values increases the selection pres-
sure of PSO (which was already high). This may cause premature
convergence in some cases.

• The non-dominated sorting PSO by Li (2003): This approach
incorporates the main mechanisms of the NSGA (Deb, Pratap,
Agarwal, & Meyarivan, 2002) into a PSO algorithm. The proposed
approach has shown a very competitive performance with
respect to the NSGA (even outperforming it in some cases).

• Another Multi-Objective Particle Swarm Optimization (AMO-
PSO) by Pulido and Coello (2004): This approach is based on
the use of Pareto ranking and a subdivision of decision variable
space into several sub-swarms (this is done using clustering
techniques). Since independent PSOs are run into each swarm,
AMOPSO can be seen as a meta-MOPSO algorithm (Coello & Sal-
azar Lechuga, 2002). After a certain (pre-defined) number of
iterations, the leaders of each swarm are migrated to a different
swarm in order to vary the selection pressure.

• The algorithm of Parsopoulos, Tasoulis, and Vrahatis (2004):
Parallel vector evaluated particle swarm optimization (VEPSO)
is a multi-swarm variant of PSO, which is inspired by the vector
evaluated genetic algorithm (VEGA) (Schaffer, 1984). In VEPSO,
each swarm is evaluated using only one of the objective func-
tions of the problem under consideration and the information
it possesses for this objective function is communicated to other
swarms through the exchange of their best experience.

Among them the last (parallel V EPSO) is especially suited to
solve multi-objectives because it searches for multiple optimal
solutions in a single run using co-evolutionary technique. Co-evo-
lation refers to a reciprocal evolutionary change between swarms
that interact with each other. The relationships between the popu-
lations of two different swarms can be described considering all
their possible types of interactions. Such interaction can be posi-
tive or negative depending on the consequences that such interac-
tion produces on the population. Evolutionary computation
researchers have developed several co-evolutionary approaches
in which normally two or more swarms related to each other using
any of the possible relationships, mainly competitive (Schaffer,
1984) or cooperative (Paredis, 1998) relationships. The key issue
in these co-evolutionary algorithms is that the fitness of an indi-
vidual in a population depends on the individuals of a different
population. They are more capable of exploring and exploiting
space than others and detect convex, concave or partially convex
and/or concave and/or discontinuous Pareto front (Potter & Jong,
1994).

In this paper, we analyse the parallel V EPSO algorithm and
apply it on a multi-objective optimization problem of power systems
in a steady-state. Specifically, we evaluate reactive power control
formulating it as a multi-objective optimization problem and solve
using the above co-evolutionary algorithm. The main reasons in or-
der to do this are, firstly, classical methods (such as nonlinear pro-
gramming, NLP) have drawbacks in that they don’t satisfactorily
handle nonconvexities and nonsmoothness such as operating con-
straints of the transmission lines such as thermal limits and
switchable VAR source constraints (fixed capacitor banks), and sec-
ondly, the parallel V EPSO algorithm handles satisfactorily previ-
ously mentioned operating problems and does not require that
the objective functions and the constraints have to be differentia-
ble and continuous. The results obtained by parallel V EPSO on
the IEEE 30-bus test system are compared with those given by an-
other state-of-the-art multi-objective EA (Abido & Bakhashwain,
2005) demonstrating the advantage of the first. Moreover the par-
allel V EPSO is tested on a large power system with 136 busses.

2. Parallel vector evaluated particle swarm optimization
(VEPSO)

The Parallel VEPSO (Parsopoulos et al., 2004) can solve multi-
objective problems inspired by the concept and main ideas of the
VEGA (Schaffer, 1984) algorithm. The main features of parallel
VEPSO are explained below.

The VEPSO assumes that M swarms, S1, S2, …, SM of size N, aim to
optimize simultaneously M functions. Each swarm is evaluated
according to one of the objective functions. Let \( y_i, y_1, \) and \( p_j \)
be the current position, velocity, and the best previous position
of the ith particle, respectively, and \( p^g_j(t) \) the global best in the jth
swarm, at a given time \( t \).

The VEPSO assumes that the search behaviour of a swarm is affec-
ted by a neighbouring swarm. Specifically, it proposes that the
global best position \( p^g_j \) and the best previous position of its parti-
cle \( p_j \) in the jth swarm should be taken into consideration for
the evaluation of the velocities of the jth swarm, assuming a “ring”
migration topology (Fig. 1) (Parsopoulos et al., 2004; Parsopoulos
& Vrahatis, 2002) defined as:

\[
s = \begin{cases}  M & \text{if } j = 1, \\ j - 1 & \text{if } j = 2, 3, \ldots, M \end{cases}
\]  

(1)

Fig. 1. Ring-migration scheme.
Then the VEPSO's swarms are manipulated according to the equations:

\[
V_i^{j}(t+1) = k_i \cdot |w_i| \cdot V_i^{j}(t) + c_1 \cdot \text{rand}_1 \cdot (P^j_i - S_i^{j}(t)) \\
+ c_2 \cdot \text{rand}_2 \cdot (P^j_{gb} - S_i^{j}(t)) \tag{2}
\]

\[
S_i^{j}(t+1) = S_i^{j}(t) + V_i^{j}(t+1) \tag{3}
\]

where \(j\) is the number of swarm; \(c_1\) and \(c_2\) are the cognitive and social parameters, respectively; \(\text{rand}_1\) and \(\text{rand}_2\) are random numbers uniformly distributed within \([0, 1]\); and the superscript \([s]\) represents the ring migration defined in \(1\). The inertia weighting function for the velocity of particle-\(i\) is defined by the inertial weight approach:

\[
w_i = w_{\max} - \frac{w_{\max} - w_{\min}}{\text{iter}_{\max}} \cdot \text{iter} \tag{4}
\]

where \(\text{iter}_{\max}\) is the maximum number of iterations and \(\text{iter}\) is the current number of iterations.

The role of the inertia weighting function is considered critical for the PSO’s convergence behaviour. It is employed to control the influence of the previous history of the velocities on the current one. Accordingly, the inertia weighting function regulates the trade-off between the global and local exploration abilities of the swarms (Parsopoulos et al., 2004).

In this paper, in order to guarantee the convergence of the PSO algorithm, the constriction factor \(k\) is adopted (Naka et al., 2003):

\[
k = \frac{2}{2 - \sqrt{4\phi^2 - 4\phi}} , \quad \phi = c_1 + c_2, \quad \phi > 4 \tag{5}
\]

When the system behaviour is controlled by constriction factor and parameter \(\phi\) it has the following features.

The system does not diverge in a real value search space and finally can converge, and can search different and discrete regions of search space efficiently by avoiding premature convergence.

The positions of the \(i\)-th particle belonging to the \(j\)-th swarm in the \(n\)-dimensional search space are limited by the minimum and maximum positions expressed by vectors:

\[
[S_i^{j,\min}, S_i^{j,\max}] , \quad (j = 1, 2, \ldots, M), \quad (i = 1, 2, \ldots, N) \tag{6}
\]

The velocities of the \(i\)-th particle belonging to the \(j\)-th swarm in the \(n\)-dimensional search space are limited by:

\[
[-V_i^{j,\max}, V_i^{j,\max}] , \quad (j = 1, 2, \ldots, M), \quad (i = 1, 2, \ldots, N) \tag{7}
\]

where the vector of maximum velocities is comprised of terms:

\[
t^{j,\max} = S_i^{j,\max} - S_i^{j,\min}, \quad (j = 1, 2, \ldots, M), \quad (i = 1, 2, \ldots, n) \tag{8}
\]

Here, \(N_r\) is a chosen number of search intervals for the particles. It is an important parameter in the parallel VEPSO algorithm. A small \(N_r\) facilitates global exploration (searching new areas), while a large one tends to facilitate local exploration (fine tuning of the current search area). A suitable value for the \(N_r\) usually provides balance between global and local exploration abilities and consequently results in a reduction of the number of iterations required to locate the optimum solution.

In the case of \(M\)-objective functions, \(M\)-swarms are employed. Each objective function is enforced by each one of the swarms. The parallel implementation of VEPSO assumes that each one of the \(M\)-swarms is evaluated in one of \(M\)-pc, which are connected in an Ethernet network and allowing the migration of server from node to node (Fig. 2).

3. Reactive power control using parallel VEPSO

3.1. Problem formulation

The reactive power control is to optimize the steady-state performance of a power system in terms of one or more objective functions while satisfying several equality and inequality constraints. Generally the problem can be formulated as (Abido & Bakhashwain, 2005):

- The first objective is to minimize the real power losses in transmission lines that can be expressed as:

\[
J_1 = P_{\text{loss}}(x, u) = \sum_{l=1}^{N_{l}} P_l \tag{9}
\]

where: \(P_l\) is the real power losses at line-\(i\), \(N_l\) is the number of transmission lines, and \(x\) and \(u\) are state and control variables, respectively. The vector of state or dependent variables, \(x\), consists of load bus voltages \(V\), generator reactive power outputs \(Q_G\), and transmission line loadings \(S_l\). Hence, \(x\) can be expressed as:

\[
x' = [V_{1}, V_{2}, \ldots, V_{\text{load}}, Q_{G1}, Q_{G2}, \ldots, Q_{GNg}, S_{1}, S_{2}, \ldots, S_{N_{l}}] \tag{10}
\]

The vector of control variables, \(u\), consists of generator voltages \(V_G\), transformer tap settings \(T\), and shunt VAR compensations \(Q_C\). Hence, \(u\) can be expressed as:

\[
u = [V_{C1}, V_{C2}, \ldots, V_{CNg}, Q_{C1}, Q_{C2}, \ldots, Q_{CNg}, T_{1}, T_{2}, \ldots, T_{N_{T}}] \tag{11}
\]

- The second objective is to minimize the voltage magnitudes at load buses that can be expressed by:

\[
J_2 = VD(x, u) = \sum_{i=1}^{N_{d}} |V_i - V_i^p| \tag{12}
\]

where: \(V_i^p\) is the pre-specified reference value at load bus-\(i\) which is usually set at the value of 1.0 pu, and \(N_d\) is the number of load buses.

- The equality constraints represent typical load flow equations as follows:

\[
P_{L_i} - P_{D_i} - f_l(x, u) = 0 \tag{13}
\]

\[
Q_{L_i} - Q_{D_i} - f_q(x, u) = 0 \tag{14}
\]
where $P_G$ and $Q_G$ are the generator real and reactive power outputs, respectively, and $P_D$ and $Q_D$ are the load real and reactive powers, respectively.

- The inequality constraints represent the system operating constraints as follows: \[ V_{Ci}^{\text{min}} \leq V_{Ci} \leq V_{Ci}^{\text{max}} \quad i = 1,2,\ldots,NG \] \[ Q_{Gi}^{\text{min}} \leq Q_{Gi} \leq Q_{Gi}^{\text{max}} \quad i = 1,2,\ldots,NG \] where $NG$ is the number of generators.

Switchable VAR source constraints: Switchable VAR compensations $Q_s$ are restricted by their limits as follows:

\[ Q_{s i}^{\text{min}} \leq Q_{s i} \leq Q_{s i}^{\text{max}} \quad i = 1,2,\ldots,NC \] where $NC$ is the number of switchable VAR sources.

Transformer constraints: Transformer tap settings $T$ are bounded as follows:

\[ T_{i1}^{\text{min}} \leq T_{i1} \leq T_{i1}^{\text{max}} \quad i = 1,2,\ldots,NT \] where $NT$ is the number of transformers.

Security constraints: These include the constraints of load voltages at load buses $V_l$ and transmission line loadings $S_l$ as follows:

\[ V_{li}^{\text{min}} \leq V_{li} \leq V_{li}^{\text{max}} \quad i = 1,2,\ldots,Nd \] \[ S_{li} \leq S_{li}^{\text{max}} \quad i = 1,2,\ldots,NL \]

3.2. Parallel VEPSO algorithm applied in reactive power control

Incorporating the above modifications the proposed multi-objective parallel VEPSO algorithm for reactive power control is presented:

**Step 1 (Initialization):** Set the time counter $t = 0$ and generate two swarms, $M = 2$, with $N$-particles for each swarm. For each particle in the two swarms generate, with uniform probability distribution, initial positions $S_i(0)$ limited by (6) (limits of (6) is formulated by inequalities (15)–(20)) and initial velocities $V_i(0)$ limited by (7). To enforce the “ring” migration topology defined by (1), each particle in the initial population is evaluated using (9) if it belongs to the second-swarm and (12) if it belongs to the first-swarm. Set as best positions $P_i^{gb} = S_i(0)$ and as global positions $P_i^{gb} = \text{global best of } P_i^{gb}$ and $P_j^{gb} = \text{global best of } P_j^{gb}$. Set the cognitive and the social parameters: $c_1^{gb}, c_2^{gb}, (j = 1, 2)$.  

**Step 2 (Time update):** Update the time counter $t = t + 1$. Set random numbers $r_1$ and $r_2$ uniformly distributed within the range $[0,1]$.

**Step 3 (Velocity update):** Using the global best $P_i^{gb}$ of each swarm ($s = 1, 2$) and the best positions of each particle in the two swarms $P_i^{gb}$ ($s = 1, 2$) update the velocities of particles in the two swarms using (2). Check if the limits of (7) are enforced. If the limits are violated then they are replaced by the respective limits.

**Step 4 (Position update):** Based on the updated velocities, each particle in all swarms moves to new positions according to (3). Check if the limits of (6) are enforced. These limits are formulated by inequalities (15)–(20). If the limits are violated then they are replaced by the respective limits.

**Step 5 (Particles best position update):** Each particle in the swarm is evaluated according to its updated positions using (9) or (12), where (9) for the second and (12) for the first swarm.

**Step 6 (Global best position update):** Based on the updated best positions each swarm updates the global best position $P_j^{gb}$.

**Step 7 (Stopping criteria):** The search will terminate if the number of iterations reaches the maximum allowable number, or the criteria are all satisfied. The criteria for the objective

### Table 1

<table>
<thead>
<tr>
<th>Control variables/objectives</th>
<th>Parallel VEPSO</th>
<th>MEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>$V_{G1}$</td>
<td>0.9832</td>
<td>1.050</td>
</tr>
<tr>
<td>$V_{G2}$</td>
<td>1.0562</td>
<td>1.044</td>
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<td>$V_{G3}$</td>
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<td>$V_{G4}$</td>
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<td>$V_{G5}$</td>
<td>0.9500</td>
<td>1.042</td>
</tr>
<tr>
<td>$V_{G6}$</td>
<td>1.0789</td>
<td>1.043</td>
</tr>
<tr>
<td>$T_{i1-0}$</td>
<td>1.0368</td>
<td>1.090</td>
</tr>
<tr>
<td>$T_{i1-10}$</td>
<td>1.0136</td>
<td>0.905</td>
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<tr>
<td>$T_{i1-12}$</td>
<td>0.9981</td>
<td>1.020</td>
</tr>
<tr>
<td>$T_{i1-28}$</td>
<td>1.0154</td>
<td>0.964</td>
</tr>
<tr>
<td>$P_{\text{Loss}}$ (MW)</td>
<td>5.0950</td>
<td>5.1995</td>
</tr>
<tr>
<td>VD</td>
<td>0.1399</td>
<td>0.2512</td>
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Parameter sensitivity analysis on IEEE 30-bus system (50 trials).

<table>
<thead>
<tr>
<th>(w_{\text{max}})</th>
<th>(w_{\text{max}})</th>
<th>Objectives' average/minimum</th>
<th>(c_1 = c_2)</th>
<th>(c_1 = c_2)</th>
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<td>(0.4)</td>
<td>(0.9)</td>
<td>(J_1) ave = 5.1263</td>
<td>5.0978</td>
<td>0.5091</td>
</tr>
<tr>
<td>(0.4)</td>
<td>(1.0)</td>
<td>(J_2) ave = 5.1263</td>
<td>5.0978</td>
<td>0.5091</td>
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<table>
<thead>
<tr>
<th>(N_r)</th>
<th>(1)</th>
<th>(5)</th>
<th>(10)</th>
<th>(15)</th>
<th>(20)</th>
<th>(1)</th>
<th>(5)</th>
<th>(10)</th>
<th>(15)</th>
<th>(20)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(w_{\min})</td>
<td>(0.50)</td>
<td>(0.55)</td>
<td>(0.50)</td>
<td>(0.55)</td>
<td>(0.50)</td>
<td>(0.55)</td>
<td>(0.50)</td>
<td>(0.55)</td>
<td>(0.50)</td>
<td>(0.55)</td>
</tr>
</tbody>
</table>

4. Results

4.1. IEEE 30-bus test system

To verify the feasibility of the proposed parallel VEPSO algorithm in reactive power control it is applied in the IEEE 30-bus test system. The network consists of 6 generators, 41 lines and 4 transformers. In the transformer tests, tap settings were considered within the interval [0.95,1.1]. Voltages are considered within the range of [0.95,1.1].

The dimension of the chosen swarm's search space, i.e., the number of control variables, in this case study is \(n = 10\). The number of particles in each swarm is set at \(N = 15\). The stochastic parameters are set at the values \(w_{\min} = 0.1, w_{\max} = 1.0, N_r = 20\), \(c_1 = 0.55\) and \(c_2 = 0.55\), which lead the proposed parallel VEPSO algorithm faster in the global optimum and were selected after parameter sensitivity analysis (Vlachogiannis & Lee, 2005) of the proposed parallel VEPSO on the IEEE 30-bus test system. Especially for the important parameter \(N_r\), this is determined among the candidate values of \([1,5,10,15,20]\) and \(N_r = 20\) is chosen as the best.

The solutions of the proposed approach in 40 separate runs are shown in Fig. 3. This entire trade-off surface represents the Pareto-optimal front of the parallel VEPSO and it is well-distributed and has good diversity characteristics.

Figs. 4 and 5 demonstrate that two objective functions \(J_1\) (7) and \(J_2\) (10) lead to convergence after 25 and 40 iterations, respectively, achieving minimum power losses of 5.0950 MW and voltage deviation of 0.1399 pu. Convergence time for the 40 iterations is 7.6 s.

The objective functions \(J_1\) (7) and \(J_2\) (10) using a multi-objective evolutionary algorithm (Abido & Bakhashwain, 2005) (next called MEA) converge in about 70 iterations and 110 iterations, respectively, achieving minimum power losses of 5.1995 MW and voltage deviation of 0.2512 pu. Table 1 gives the optimal settings of state variables as proposed by parallel VEPSO and MEA (Abido & Bakhashwain, 2005).

Comparing the results of the parallel VEPSO with those given by MEA (Abido & Bakhashwain, 2005) it is concluded that the first are much better than the one given by MEA.

Table 2 shows the parameter sensitivity analysis (Vlachogiannis & Lee, 2005) of the parallel VEPSO. In the simulation the parameters \(N_r, c_1, c_2, w_{\min}\) and \(w_{\max}\) are changed. The average and function of power losses (9) and voltage deviations (12) are 5.1 MW and 0.14 pu, respectively. These are the best values obtained by other multi-objective evolutionary technique (Abido & Bakhashwain, 2005) for the same case study.
minimum of $J_1$ (7) and $J_2$ (10) with up to 100 iterations in 50 trials for each case are shown in the Table 2. The results reveal that the appropriate values for $w_{\text{min}}$ and $w_{\text{max}}$ are 0.1 and 1.0, respectively. The appropriate value for $c_1$ and $c_2$ is 0.55 and for $N_r$ is 20.

4.2. 136-bus system

The proposed parallel VEPSO algorithm is also applied to the reactive power control problem of the 136-bus system. This system consists of 136 buses (33 PV and 103 load buses), 199 transmission lines, 24 transformers and 17 reactive compensations. In this case study, the dimension of the chosen swarm’s search space is increased to $n = 25$ and the number of particles is also increased to $N = 20$ in each swarm. The stochastic parameters are set at the values $w_{\text{min}} = 0.1$, $w_{\text{max}} = 1.0$, $N_r = 20$, $c_1 = 0.5$ and $c_2 = 0.5$, and were selected also following parameter sensitivity analysis (Vlachogiannis & Lee, 2005) of the proposed parallel VEPSO on the 136 bus system. In this case study, the optimal settings of the 25 chosen control variables as proposed by parallel VEPSO are given in Table 3.

Figs. 6 and 7 demonstrate that two objective functions $J_1$ (7) and $J_2$ (10) lead to convergence after 160 and 174 iterations, respectively, achieving minimum power losses of 55.457 MW and voltage deviation of 1.0345 pu. The total convergence time for the 136 bus system is calculated at 48.2 s. The computing time can be further reduced if the two swarms are parallel distributed in a larger pc-network.

Finally, Figs. 8 and 9 show the statistical evaluation results given by parallel VEPSO in 100 trials for objective functions $J_1$ (7) and $J_2$ (10), respectively. The maximum, average and minimum values of the objective functions $J_1$ (7) and $J_2$ (10) are shown in Table 4.

In all case studies the proposed parallel VEPSO was implemented on a network of two 1.4 GHz Pentium-IV PCs so that the
two swarms to be distributed in parallel in these PCs. Therefore, the total convergence time of the proposed parallel VEPSO algorithm is the time in which the slower function converged. In the last case study, where the system is large the total convergence time can be further reduced if the proposed algorithm is distributed in faster networking pc.

5. Conclusions

In this paper, the approach of parallel VEPSO has been presented and applied to reactive power control of power systems in steady-state. The problem has been formulated as multi-objective optimization problem with two competing objectives, real power losses and bus voltage deviations. The results showed that the proposed approach is efficient for solving the multi-objective problem of reactive power control. When compared with another multi-objective evolutionary technique, it outperforms in achieving the objectives and in computing time. Since the proposed approach does not impose any limitation in the number of objectives, its extension to include more objectives is a straightforward process. As a further research, especially for large power systems parallel distribution in a larger pc-network can result in a further reduction in computing time. Moreover, a hybrid evolutionary algorithm, such as cultural-VEPSO, can be introduced to determine the optimum values of empirical parameters of the proposed parallel VEPSO algorithm.

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References


