A differential evolution particle swarm optimizer for various types of multi-area economic dispatch problems

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Abstract- This paper proposes a new, efficient and powerful heuristic-hybrid algorithm using hybrid differential evolution (DE) and particle swarm optimization (PSO) techniques (DEPSO) designed to solve eight optimization problems with benchmark functions and the multi-area economic dispatch (MAED), reserve constrained MAED (RCMAED) and reserve constrained multi-area environmental/economic dispatch (RCMAEED) problems with reserve sharing in power systems operations. The proposed hybridizing sum-local search optimizer, entitled HSLSO, is a relatively simple but powerful technique. The HSLSO algorithm is used in this study for solving different MAED problems with non-smooth cost function. The effectiveness and efficiency of the HSLSO algorithm is first tested on a number of benchmark test functions. Experimental results shows the HSLSO has a better quality solution with the ability to converge for most of the tested functions.

***Keywords**:* Multi-area economic dispatch (MAED), reserve constrained multi-area economic dispatch (RCMAED), reserve constrained environmental/economic dispatch (RCMAEED), differential evolution particle swarm optimization (DEPSO).

1. Introduction

Economic load dispatch (ELD), optimal power flow (OPF) and optimal reactive power dispatch (ORPD) nonlinear problems are some of the most important optimization problems in power system operation and planning for allocating generation to the committed units [1-2]. They have been resolved using many proposed optimization mathematical methods and modern heuristic algorithms such as Hopfield neural network [1, 3], a modified harmony search algorithm (MHSA) [4], genetic algorithm (GA) [5], real-coded GA (RCGA) [6], particle swarm optimization (PSO) [7], a proposed efficient scheme in [8] for clearing of energy and reserves in multi-area markets, an immune algorithm (IA) with power redistribution [9], a new modified differential evolution (MDE) [10], cuckoo search algorithm (CSA) [11], iteration PSO with time varying acceleration coefficients [12], a hybrid DE algorithm based on PSO algorithm (DEPSO) [13], PSO for dynamic ELD problem [14], information gap decision theory (IGDT) to help the distribution network operators (DNOs) [15], risk-constrained self-scheduling of GenCos generation companies (GenCos) optimizers [16], a new continuous method of quick group search optimizer (QGSO) [17], imperialist competitive algorithms (ICA) for multi-objective OPF problems [18], tribe-modified DE (Tribe-MDE) for solving multi-objective environmental/economic dispatch (EED) [19], real coded chemical reaction algorithm (RCCRA) [20], stochastic programming [21], firefly algorithm (FFA) for multi-objective EED considering wind power penetration [22], hybrid ICA algorithm with sequential quadratic programming (HIC-SQP) [23], a new hybrid method for OPF problem with non-smooth cost functions [24], combination of chaotic DE and QP (quadratic) [25], bacterial foraging algorithm (BFA) [26], quantum PSO method [27], multi-objective CSA [28], a novel stochastic approach [29], DE based dynamic decomposed strategy [30], a new hybrid algorithm for practical optimal dynamic load dispatch (DLD) [31], self-adaptive learning charged system search algorithm (SALCSSA) [32], solving stochastic OPF incorporating electric vehicles and offshore wind farm [33], colonial competitive differential evolution (CCDE) technologies [34], and etc. The main objective of ELD and OPF problems is the effective management of electrical energy generation by minimizing the total fuel cost of power generation units of a single area, while satisfying various system and operating constraints [35- 37]. The multi-area economic dispatch (MAED), reserve constrained multi-area economic dispatch (RCMAED) and reserve constrained environmental/economic dispatch (RCMAEED) problems [38-41] are an extension of ELD problems in practical power systems, whose main objective is to determine the generation levels and the power interchange between areas to minimize the operation cost (fuel cost function) of thermal generating units in all areas of power systems while satisfying generating units power limits, system power balance, and power transmission capacity constraints of network lines [42-43].

The DE [44-45] and PSO [46] techniques are population-based optimization evolutionary algorithms. Enhanced versions of DE, PSO and hybrid DEPSO techniques have been successfully applied to different engineering optimization problems with the PSO techniques combining the positive features of Constrained Particle Swarm, Generating Set Search, and Complex (PGS-COM) for black-box optimization problems [47], a global review of PSO techniques for power systems [48], and DEPSO techniques for different engineering optimization problems [49].

Different optimization algorithms have been proposed for solving the MAED problem of electrical energy generations in the literature. Basu solved the MAED problem in different practical power systems using artificial bee colony optimization (ABCO) [38] and teaching-learning-based optimization (TLBO) [39] with prohibited operating zones, valve-point loading, multiple fuels and tie line constraints considering transmission losses. Manoharan et al. [40] solved MAED problems using evolutionary programming methods such as the DE, PSO, real-coded genetic algorithm (RGA) and covariance matrix adapted evolution strategy (CMAES) for 4-, 10- and 120-unit power systems. Sudhakar et al. [41] applied Secant method to solve the MAED problem. In [42], the evolutionary programming with Levenberg-Marquardt optimization (EP-LMO) method is proposed to solve the MAED problem of a 10-unit power generation system with multi-fuel options. In [43], a PSO-based method with the traditional solver GAMS is proposed to solve the MAED problem of a large 120-unit power system. Sharma et al. solved MAED and reserve constrained MAED (RCMAED) problems using various DE methods enhanced with time-varying mutation [50] and the improved PSO method with a parameter automation strategy having time varying acceleration coefficients (PSO_TVAC) [51]. Many other heuristic search techniques have been proposed for solving economic dispatch problem, such as a pattern search (PS) algorithm [52], an improved multi-objective PSO (MOPSO) for solving multi-area environmental/economic dispatch (MAEED) problem [53], the direct search method (DSM) [54], a new recurrent DE (RDE) method [55], PSO algorithm [56], a penalty function-hybrid direct search method (PF-HDSM) for solving multi-area wind-thermal coordination dispatch (MWCD) problem [57], enhanced direct search method (EDSM) [58], a novel approach based on harmony search (HS) algorithm [59], the optimality condition decomposition (OCD) for solving multi-area dynamic economic dispatch (MA-DED) problem [60], and different novel search approaches for solving multi-area generation scheduling such as neural networks approach [61], traditional economic dispatch method [62], modification of MAED [63], a new DE algorithm [64], an embedded multi-area optimal power flow (MA-OPF) [65], a new proposed technique [66], a decomposition methodology [67, 68], a practical approach [69], a generalized unified power flow controller [70], and evolutionary programming [71].

2. Multi-area economic dispatch problems

The main purpose of the MAED optimization problem in power systems is to minimize the total electrical energy generation cost for supplying loads of all areas with or without minimizing the total pollutant emissions (such as NO_x and SO_2 emissions) while satisfying electrical power balance constraints, electrical power generating limit constraints and transmission (tie-line) capacity constraints. The objective functions of minimizing system operation (energy generation) cost and pollutant emissions [38, 60] with valve point loading (VPL) effects and multiple fuel options [38, 39] can be written in the following form:

- **Minimizing system operation cost**

$$\text{Min} \sum_{i=1}^{N} (F_i(P_i)) \tag{1}$$

where:

1: $$F_i(P_i) = \begin{cases} a_{i1}P_i^2 + b_{i1}P_i + c_{i1} + \left| e_{i1} \times \sin\left(f_{i1} \times \left(P_{i,\min} - P_i \right) \right) \right|, & \text{fuel}\,1,\ P_{i,\min} \le P_i \le P_{i1} \\ a_{i2}P_i^2 + b_{i2}P_i + c_{i2} + \left| e_{i2} \times \sin\left(f_{i2} \times \left(P_{i,\min} - P_i \right) \right) \right|, & \text{fuel}\,2,\ P_{i1} \le P_i \le P_{i2} \\ \ldots & \\ a_{ik}P_i^2 + b_{ik}P_i + c_{ik} + \left| e_{ik} \times \sin\left(f_{ik} \times \left(P_{i,\min} - P_i \right) \right) \right|, & \text{fuel}\,k,\ P_{ik-1} \le P_i \le P_{i,\max} \end{cases}$$

2: N is the number of generation units.

3: k is the fuel type.

4: P_i is the active power generation of the i-th unit, $P_{i,\min}$ and $P_{i,\max}$ are the minimum power generation and maximum power generation limits of the i-th unit.

5: $a_{ik}P_i^2 + b_{ik}P_i + c_{ik}$ is the quadratic fuel cost function for fuel type k of the i-th unit.

6: a_{ik}, b_{ik} and c_{ik} are the fuel cost-coefficients for fuel type k of the i-th unit.

7: k for fuel type sinusoidal fuel cost function of VPL effectsthe is $\left| e_{ik} \times \sin\left(f_{ik} \times \left(P_{i,\min} - P_i \right) \right) \right|$ of the i-th unit.

8: e_{ik} and f_{ik} are the fuel cost-coefficients to model VPL effects for fuel type k of the ith unit.

Tie-line power transfer among all areas of the network plays a very important role in deciding the operating cost in multi-area networks. Taking into consideration the cost of active power transmission through each tie-line of the power system, the final objective function of the MAED optimization problem becomes [40, 50]:

$$\text{Min}\, F_T = \text{Min}\,(\sum_{i=1}^{N}(F_i\,(P_i\,)) + \sum_{j=1}^{M}(f_j\,(T_j\,))) \tag{2}$$

where, M is the number of tie-lines among the network areas. T_j is the power flow through the j-th tie-line, and f_j is the cost coefficient function associated with the j-th tie-line among the network areas.

- **Minimizing the total pollutant emissions**

$$\text{Min} \sum_{i=1}^{N}(E_i\,(P_i\,)) \tag{3}$$

where:

$$1:\; E_i(P_i) = \begin{cases} \alpha_{i1}P_i^2 + \beta_{i1}P_i + \gamma_{i1}, & \text{fuel}\,1,\; P_{i,\min} \le P_i \le P_{i1} \\ \alpha_{i2}P_i^2 + \beta_{i2}P_i + \gamma_{i2}, & \text{fuel}\,2,\; P_{i1} \le P_i \le P_{i2} \\ \ldots & \\ \alpha_{ik}P_i^2 + \beta_{ik}P_i + \gamma_{ik}, & \text{fuel}\,k,\; P_{ik-1} \le P_i \le P_{i,\max} \end{cases}$$

2: $\alpha_{ik}P_i^{\,2} + \beta_{ik}P_i + \gamma_{ik}$ is the quadratic pollutant emissions function for fuel type k of the i-th unit.

3: α_{ik} , β_{ik} and γ_{ik} are the pollutant emissions coefficients for fuel type k of the i-th unit.

2.1. Constraints

2.1.1. Area real power balance

The real power balance constraints of the system for area q without consideration of network losses can be given as [50, 53]:

$$\sum_{i=1}^{N_q}(P_i) = \left(P_{Loadq} + \sum_{j=1}^{M_q}(T_{qj}) \right) \quad (4)$$

where N_q is the number of real power generating units for the q-th area (q=1, 2, …, M), and P_{Loadq} is the active load demand in the q-th area and M_q is the number of tie-lines connected to the q-th area.

2.1.2. Unit power generating limit

The active power output of units is restricted to their lower and upper limits as:

$$P_{i,\min} \le P_i \le P_{i,\max}, \quad i = 1,\ldots,N \quad (5)$$

2.1.3. Thermal generation unit's ramp-rate limits

The ramp-rate limit constraints can be formulated as follows:

$$\max(P_{i,\min}, P_i^0 - DR_i) \le P_i \le \min(P_{i,\max}, P_i^0 + UR_i) \quad (6)$$

where P_i^0 is the previous output real power of the i-th generation unit, and the DR_i and UR_i are the down and up ramp rate-limits of the i-th thermal generation unit, respectively.

2.1.4. Prohibited operating zones

A performance curve, i.e. input-output power generation curve, of a thermal generating unit with prohibited operating zones (POZ) has discontinuities due to physical operational limitations of the generator such as faults in the machines themselves or in the associated auxiliaries [38-39]. The discontinuous input–output power range of a generator can be formulated as follows [50]:

$$P_i \in \begin{cases} P_{i,\min} \le P_i \le P_{i1}^{l} \\ \dots \\ P_{ik-1}^{u} \le P_i \le P_{ik}^{l} \\ \dots \\ P_{iz_i}^{u} \le P_i \le P_i^{\max} \end{cases} \tag{7}$$

where z_i is the number of prohibited zones in the input-output power curve of i-th generator, k is the index of prohibited zone of i-th generator, P_{ik}^{l} and P_{ik}^{u} are the lower and upper limits of k-th prohibited operating zone of the i-th generation unit, respectively.

2.1.5. Tie-line power transfer limits

The tie-line real power flow (economic flow) from the q-th area to the j-th area (T_{qj}) should be between the limits of tie-line power transfer capacity [50].

$$T_{qj,\min} \le T_{qj} \le T_{qj,\max}, \quad j = 1, 2, \dots, M_q \tag{8}$$

2.1.6. Area spinning reserve constraints

In the q-th area of a power system, a spinning reserve is set aside in each region for the contingency prerequisite of that region (required spinning reserve) and reserve contribution, the necessary spinning reserve is fulfilled through multi area reserve sharing [53]:

$$\sum_{i=1}^{N_q} S_{iq} \ge S_{q,req} + \sum_{k.k \ne q} RC_{qk}, k = 1, 2, \dots, M_q \tag{9}$$

where $\sum_{i=1}^{N_q} S_{iq}$ is the reserve prevailing on all the generation units of q-th area, and can be considered as, $\sum_{i=1}^{N_q} (P_i^{\max} - P_i)$, $S_{q,req}$ is the prerequisite spinning reserve in the q-th area, and RC_{qk} is the reserve contributed from k-th area to q-th area.

2.1.7. *Tie-line power transfer restrictions with contributed reserve*

The tie-line power transfer restrictions with allowing for contributed reserve RC_{qk} is as follows [53]:

$$T_{qj,\min} \le T_{qj} + RC_{qj} \le T_{qj,\max}, \quad j = 1, 2, ..., M_q \tag{10}$$

It is worth declaring that the control variables are self-constrained. The hard constraints of real power balance can be combined with the objective function as quadratic penalty expressions. For that reason, the objective function of different MAED optimization problems can be presented as follows:

$$\mathrm{Min}\, F_T = \mathrm{Min}\left(\sum_{i=1}^{N} (F_i(P_i)) + \sum_{j=1}^{M} (f_j(T_j)) + \phi \times \sum_{i=1}^{N} (E_i(P_i)) + \lambda \times (\sum_{i=1}^{N} (P_i) - P_{Load}) \right) \tag{11}$$

where ϕ is an appropriate value which will be nominated by the user for the RCMAEED problem, λ is the penalty factor and P_{Load} is the total active load demand in the whole area.

3. Hybrid DEPSO techniques

3.1. Original differential evolution

The DE algorithm is one of the population-based optimization algorithms, which was first proposed by Storn and Price [44-45] and has been widely applied to optimization problems in the power systems and engineering [49].

The steps for implementing original DE algorithm are as follows [72-73]:

***Step 1*: *Initial population*:** A population of N_P initial solutions randomly distributed in the D dimensional search space of the optimization problem, are initiated.Each individual is generated as follows:

$$X_{j,i}^{Iter=0} = X_{j,\min} + \text{rand}(0,1) \times (X_{j,\max} - X_{j,\min}); \quad j = 1, 2, ..., D, \; i = 1, 2, ..., N_P \tag{12}$$

where rand (0,1) is a random number between 0 and 1.

***Step 2*: *Mutation operator*:** In mutation step, for each individual X_i (target vector) of the new population, three different individuals X_{r1}, X_{r2}, and X_{r3} ($r1 \neq r2 \neq r3 \neq i$) are pseudo-randomly extracted from the population to generate a new vector as:

$$Z_i = X_{r1} + F \times (X_{r2} - X_{r3}) \tag{13}$$

where $F \in [0, 2]$ is a uniformly distributed random number which controls the length of the population exploration vector $(X_{r2} - X_{r3})$.

***Step 3*: *Crossover operator*:** After mutation step, the crossover operator, according to the following equation, is applied on the mutation vector Z_i and the vector X_i to generate the trial vector U_i, for increasing the population diversity of the mutation vector.

$$U_{j,i} = \begin{cases} Z_{j,i}, & \text{if } \mathrm{rand}_{i,j}(0,1) \le CR \\ X_{j,i}, & \text{otherwise} \end{cases} \quad (14)$$
$$j = 1, 2, ..., D,\ i = 1, 2, ..., N_P.$$

where $CR \in [0, 1]$ is known as the crossover rate which is a constant.

***Step 4*: *Selection operator*:** The selection process is repeated for each pair of target/trial vectors using the evaluation function $F(U_i)$ to compare with the evaluation function value $F(X_i)$, and the better one will be selected to be a member of the DE population generation for the next iteration (X_i^{Iter+1}).

3.2. Original particle swarm optimization (classical PSO with the Gbest model)

The PSO algorithm is one of the population-based metaheuristic algorithms, a powerful tool in search and optimization [48], which is based on the swarm intelligence theory and was first proposed by Kennedy and Eberhart [46]. In this stochastic optimization algorithm, each individual in the swarm population, called particle, represents one solution of the optimization problem. The *i*-th particle, X_i^{Iter} is moved by a velocity ($V_{j,i}^{Iter+1} = \{V_{1,i}^{Iter+1}, V_{2,i}^{Iter+1}, ..., V_{D,i}^{Iter+1}\}$) which is calculated by three components: social component ($Gbest_{j,i}^{Iter} - X_{j,i}^{Iter}$), cognitive component ($Pbest_{j,i}^{Iter} - X_{j,i}^{Iter}$), and inertia component (ω). The mathematical model of PSO algorithm can be stated as follows [46-47]:

$$V_{j,i}^{Iter+1} = \omega \times V_{j,i}^{Iter} + c1 \times \mathrm{rand1}(0,1) \times (Pbest_{j,i}^{Iter} - X_{j,i}^{Iter}) + c2 \times \mathrm{rand2}(0,1) \times (Gbest_{j,i}^{Iter} - X_{j,i}^{Iter}) \quad (15)$$

$$X_{j,i}^{Iter+1} = X_{j,i}^{Iter} + V_{j,i}^{Iter+1} \quad (16)$$

where $Pbest_i^{Iter} = \{Pbest_{1,i}^{Iter}, Pbest_{2,i}^{Iter}, ..., Pbest_{D,i}^{Iter}\}$ denotes the best position that is found so far by the *i*-th particle, $Gbest_i^{Iter} = \{Gbest_{1,i}^{Iter}, Gbest_{2,i}^{Iter}, ..., Gbest_{D,i}^{Iter}\}$ is the global best position that is found by all of the particles in the swarm. The constants $c1$ and $c2$ are the so-called acceleration factors usually chosen to be 2, and the constant ω is the inertia weight.

3.3. DEPSO1

Hybrid DEPSO1 [74] algorithm using hybridization of DE/best/2/bin [72] and the classical PSO with *Gbest* model algorithms is proposed by Zhang and Xie. In the hybrid algorithm, DE algorithm follows PSO algorithm at each generation, with consensus on the population diversity along with the evolution and further improving the *Pbest* of PSO algorithm. The hybrid DEPSO1 algorithm is applied to a set of the generalized Griewank function, the Rosenbrock function and the generalized Rastrigrin function, and the results show the better performance of the DEPSO1 algorithm in comparison with DE and PSO algorithms. The DE operators are given by [74]:

$$Z_i = Xbest\,(Gbest) + F \times (Pbest_{r1} - Pbest_{r2} + Pbest_{r3} - Pbest_{r4}) \tag{17}$$

$$U_{j,i} = \begin{cases} Z_{j,i}, & \text{if } \mathrm{rand}_{i,j}(0,1) \le CR \\ Pbest_{j,i}, & \text{otherwise.} \end{cases} \tag{18}$$

3.4. DEPSO2

A new hybrid algorithm using DE/mid-to-better/1/bin and PSO-cf algorithm was proposed by Hao *et al*. [75], which can maintain the diversity of swarm and enhance the ability of global (*Gbest*) and local (*Pbest*) search using improved particle positions. The experimental results of testing the DEPSO2 algorithm for benchmark test functions showed the effectiveness of the hybrid algorithm. The DE and PSO operators of DEPSO2 are selected as follows [75]:

$$
\left.\begin{array}{l}
V_{j,i}^{Iter+1} = \omega \times V_{j,i}^{Iter} + c1 \times \mathrm{rand1}(0,1) \times (Pbest_{j,i}^{Iter} - X_{j,i}^{Iter}) \\
+ c2 \times \mathrm{rand2}(0,1) \times (Gbest_{j,i}^{Iter} - X_{j,i}^{Iter}) \\
Z_{j,i}^{Iter+1}(\mathrm{PSO}) = X_{j,i}^{Iter} + V_{j,i}^{Iter+1}
\end{array}\right\} \rightarrow \mathrm{PSO}
$$

$$
\left.\begin{array}{l}
Z_{j,i}^{Iter+1}(\mathrm{DE}) = \left(\dfrac{X_{j,r1}^{Iter} + X_{j,i}^{Iter}}{2} \right) \\
+ F \times (X_{j,r1}^{Iter} - X_{j,i}^{Iter} + X_{j,r2}^{Iter} - X_{j,r3}^{Iter})
\end{array}\right\} \rightarrow \mathrm{DE} \tag{19}
$$

$$
U_{j,i} = \begin{cases} Z_{j,i}^{Iter+1}(\mathrm{DE}), & \text{if } \mathrm{rand}_{i,j}(0,1) \le CR \\ Z_{j,i}^{Iter+1}(\mathrm{PSO}), & \text{otherwise.} \end{cases} \tag{20}
$$

3.5. DEPSO3 [76]

In [76], Xu et al. also proposed a DE mixed with particle swarm intelligence, called DE-SI method (which is called DEPSO3 in this paper). The experimental results indicate that, for most benchmark problems, the DE-SI hybrid algorithm keeps the most rapid convergence rate and obtains the global optima compared with DE and PSO algorithms. As proposed by Xu et al. [76], the mutation and crossover operators of DE algorithm are as follows:

$$
X_{j,i}^{Iter+1} = \begin{cases} X_{j,i}^{Iter} + c2 \times \mathrm{rand1}(0,1) \times (Gbest_{j}^{Iter} - X_{j,i}^{Iter}) \text{ if } \mathrm{rand2}(0,1) \le CR \\ X_{j,i}^{Iter}, \text{ otherwise.} \end{cases} \tag{21}
$$

3.6. DEPSO4

In reference [77], Liu et al. proposed a new hybrid-optimized cultural algorithm based on DE/rand/1/bin and PSO algorithms (namely DEPSO4). The simulation results of [77] showed that the proposed algorithm had the best solution and performed better for most test functions. The algorithm formula is given by [77]:

$$X_{j,i}^{Iter+1} = \begin{cases} X_{j,r1}^{Iter} + F \times (X_{j,r2}^{Iter} - X_{j,r3}^{Iter}) + V_{j,i}^{Iter+1} \text{ if } \mathrm{rand}(0,1) \le CR \\ X_{j,i}^{Iter} + V_{j,i}^{Iter+1}, \text{ otherwise.} \end{cases} \tag{22}$$

3.7. The improved hybrid DEPSO algorithms

3.7.1. IDEPSO1

According to the simulation results of DEPSO1 algorithm, it can be said that the DEPSO1 algorithm for the benchmark functions with large dimensions, converges to a local optimal solution and thus the static result is not satisfactory and is away from the global optimum solution.

In this paper, we proposed a simple change in the DEPSO1 algorithm (as shown in (20)) so it can achieve a satisfactory performance for large dimensions.

In the improved DEPSO1 (IDEPSO1) the roles of $Xbest(Gbest)$ and $Pbest$ in (17) and (18) were exchanged according to (23), and the simulation results in Tables 2 and 3 show the effectiveness of this simple change to the problems with large dimensions.

$$U_{j,i} = \begin{cases} Pbest_{j,i} + F \times (Pbest_{j,r1} - Pbest_{j,r2} + Pbest_{j,r3} - Pbest_{j,r4}), \quad \text{if } \mathrm{rand}_{i,j}(0,1) \le CR \\ \Updownarrow\Updownarrow\Updownarrow \\ Xbest_j(Gbest), \text{ otherwise.} \end{cases} \tag{23}$$

3.7.2. IDEPSO3

According the obtained experimental results from the DEPSO3 [76] algorithm for benchmark functions which are summarized in Tables 1-3, it is seen that the DEPSO3 algorithm is weak for specific problems such as third benchmark function. In the improved version of DEPSO3, called IDEPSO3, in (21), the role of $Gbest$ was replaced with $Pbest$ and for $\mathrm{rand}(0,1) > CR$, the global best ($Gbest$) was used instead of X_i value. The population move model of IDEPSO3 is shown as follows:

$$X_{j,i}^{Iter+1} = \begin{cases} X_{j,i}^{Iter} + F \times (Pbest_{j,i}^{Iter} - X_{j,i}^{Iter}) \text{ if } \mathrm{rand}(0,1) \le CR \\ Gbest_{j}^{Iter}, \text{ otherwise.} \end{cases} \tag{24}$$

3.7.3. IDEPSO4

With a simple change and no extra cost in population move equation (22) of DEPSO4 algorithm, a more powerful improved hybrid algorithm can be achieved, called IDEPSO4. The population move equation of IDEPSO4 is described as follows:

$$X_{j,i}^{Iter+1} = \begin{cases} Pbest_{j,r1} + F \times (Pbest_{j,r2} - Pbest_{j,r3}) + V_{j,i}^{Iter+1}, \quad \text{if } \mathrm{rand}(0,1) \le CR \\ Pbest_{j,i} + \mathrm{rand}(0,1) \times V_{j,i}^{Iter+1}, \text{ otherwise.} \end{cases} \tag{25}$$

3.8. The proposed hybridizing sum-local search optimizer (HSLSO)

In this hybrid sum-local search optimizer (HSLSO), the sum differential evolution with particle swarm optimizer (SDEPSO) based DEPSO2 [75] is used along with the local (*Pbest*) optimal value in DE crossover operator. We can use the (19) and (20) of DEPSO2 for HSLSO algorithm:

$$U_{j,i} = \begin{cases} \dfrac{Z_{j,i}^{Iter+1}(\mathrm{DE}) + Z_{j,i}^{Iter+1}(\mathrm{PSO})}{2}, \quad \text{if } \mathrm{rand}_{i,j}(0,1) \le CR \\ Pbest_{j,i}, \ \text{otherwise.} \end{cases} \tag{26}$$

Fig. 1 shows the flowchart of the proposed HSLSO algorithm.

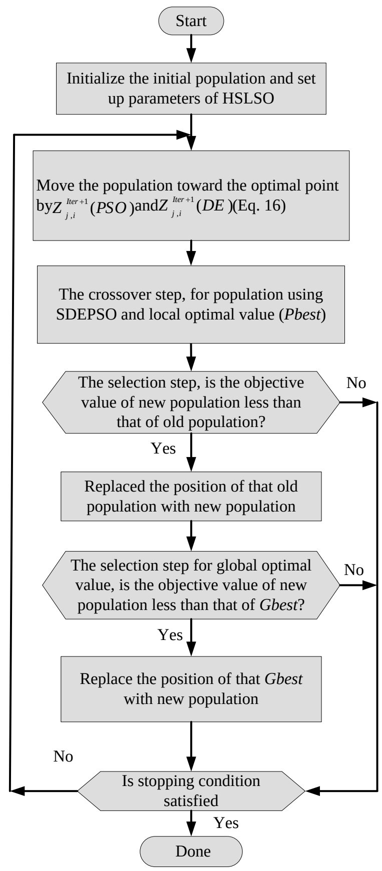

Fig. 1. Flowchart of HSLSO algorithm.

4. Performance test of HSLSO on benchmark functions

In the experiments, several multi-modal and uni-modal benchmark test functions were chosen for testing the HSLSO and comparing it with other hybrid DEPSO algorithms. All of the benchmark functions are listed as follows:

1) Sphere function, $f_1 = \sum_{j=1}^{D} x_j^2$ with $x_j \in$ [-100, 100] and $f(x)$ =0.

2) Quadric function, $f_2 = \sum_{j=1}^{D} \left(\sum_{i=1}^{j} x_i \right)^2$ with $x_j \in$ [-100, 100] and $f(x)$ =0.

3) Rosenbrock's function, $f_3 = \sum_{j=1}^{D-1} (100(x_j^2 - x_{j+1})^2 + (x_j - 1)^2)$ with $x_j \in$ [-2.048, 2.048] and $f(x)$ =0.

4) Rastrigin's function, $f_4 = \sum_{j=1}^{D} x_j^2 (x_j^2 - 10\cos(2\pi x_j) + 10)$ with $x_j \in$ [-5.12, 5.12] and $f(x)$ =0.

5) Noncontinuous Rastrigin's function,

$$f_5 = \sum_{j=1}^{D} y_j^2 (y_j^2 - 10\cos(2\pi y_j) + 10)$$

$$y_j = \begin{cases} x_j, & |y_j| < \frac{1}{2} \\ \frac{round(2x_j)}{2}, & |y_j| \geq \frac{1}{2} \end{cases} \quad , \; for \; j = 1, 2, \ldots, D$$

with $x_j \in$ [-5.12, 5.12] and $f(x)$ =0.

6) Ackley's function,

) =0.x(f32.768, 32.768] and -[$\epsilon_j x$with

$$f_6 = -20\exp(-0.2\sqrt{\frac{1}{D}\sum_{j=1}^{D} x_j^2}) - \exp(\frac{1}{D}\sum_{j=1}^{D}\cos(2\pi x_j)) + 20 + e$$

7) Weierstrass function,

$$f_7 = \sum_{j=1}^{D}\left(\sum_{k=0}^{k\max}\left[a^k \cos(2\pi b^k (x_j + 0.5))\right]\right) - D\sum_{k=0}^{k\max}\left[a^k \cos(\pi b^k)\right], a = 0.5 \;\; b = 3 \;\; k\max = 20.$$

with $x_j \in$ [-0.5, 0.5] and $f(x)$ =0.

8) Exponential function, $f_8 = -\exp(-0.5\sum_{j=1}^{D} x_j^2)$ with $x_j \in$ [-1.0, 1.0] and $f(x)$ =-1.

The Mean, Best and standard deviation (Std) index values for the hybrid DEPSO algorithms of each benchmark test function over 30 runs with optimization variable dimension equal to 10, 50 and 100 (10-*D*, 50-*D*, and 100-*D*) are presented in Tables 1, 2, and 3, respectively, which shows that the HSLSO algorithm is statistically superior to most of the other hybrid DEPSO and IDEPSO algorithms. The used parameter values for all hybrid DEPSO algorithms in the experiments are selected as: the initial population size $N_P = 2.5\times D$, number of iterations $Iter$ = 20,000, F=2×*r*and (0, 1) for the hybrid algorithms proposed in other references [74-77] and F= 2×(0.5-rand (0, 1)) for the hybrid algorithms proposed in this paper, and crossover rate CR=0.5. The results indicate that HSLSO algorithm is suitable for solving the employed test function optimizations with better performance than most of other algorithms for most of the test functions; particularly for larger dimensions, the hybrid algorithm responds very well. For five of the benchmark test functions including Sphere, Rastrigin's, Noncontinuous Rastrigin's , Weierstrass, and Exponential test functions, HSLSO algorithm obtained the global optimum solution with Mean =0.0, and Std =0.0. And also, a simple comparison of HSLSO algorithm with two standard PSO algorithms in the recent literature is given in Appendix.

Table 1. Comparison of the simulation results for *D*=10.

Function	Index	Algorithms							
		DEPSO1	DEPSO2	DEPSO3	DEPSO4	IDEPSO1	IDEPSO3	IDEPSO4	HSLSO
f_1	Best	**0.0**	**0.0**	5.2895e-033	2.9029e+03	0.0011	0.0483	1.8520e-241	**0.0**
	Mean	**0.0**	**0.0**	0.0114	5.6213e+03	58.8331	0.2448	1.5709e-237	**0.0**
	Std	**0.0**	**0.0**	0.0362	1.8152e+03	74.5253	0.1917	0.0	**0.0**
f_2	Best	2.3878e-130	8.0888e-205	36.9353	5.3041e+03	0.0082	2.7136	9.4565e-049	**0.0**
	Mean	3.2576e-123	1.9956e-191	642.2169	6.8059e+03	757.8297	8.0906	2.5901e-044	**0.0**
	Std	8.2012e-123	0.0	773.0697	1.5283e+03	1.3265e+03	4.4774	4.9682e-044	**0.0**
f_3	Best	**0.0**	8.1964e-010	3.3318	210.4062	5.4669	2.3497	1.2787e-013	7.6395e-020
	Mean	0.79732	0.7973	17.1286	275.2018	17.8329	6.2164	2.9729e-010	**2.2191e-016**
	Std	1.6809	1.6809	22.7084	49.4059	19.3227	1.8242	8.6022e-010	**4.0830e-016**
f_4	Best	**0.0**	**0.0**	1.9599	78.3083	2.6083e-06	1.8623e-06	**0.0**	**0.0**
	Mean	3.1358	0.392	42.5274	203.0712	8.9173	5.0388e-05	**0.0**	**0.0**
	Std	4.8183	0.6852	76.9012	68.8529	8.7947	8.0750e-05	**0.0**	**0.0**
f_5	Best	**0.0**	**0.0**	9.0625	74.7382	8.2893e-07	6.9180e-07	**0.0**	**0.0**
	Mean	**0.0**	0.5	69.9063	175.2241	6.5444	2.1334e-05	**0.0**	**0.0**
	Std	**0.0**	0.7071	68.3498	60.0366	15.8	1.9761e-05	**0.0**	**0.0**
f_6	Best	**8.8818e-016**	**8.8818e-016**	3.2224	17.0196	1.4257	0.1054	8.8818e-016	**8.8818e-016**
	Mean	0.1155	3.3751e-015	6.6094	17.6188	2.1285	0.3371	4.0856e-015	**8.8818e-016**
	Std	0.3653	1.7161e-015	3.591	0.5103	0.923	0.1783	1.1235e-015	**0.0**
f_7	Best	**0.0**	**0.0**	2.6419	9.8117	0.4261	0.3546	**0.0**	**0.0**

	Mean	2.1e-04	6.4277e-06	5.7135	10.9352	1.7869	0.4605	**0.0**	**0.0**
	Std	6.6408e-04	2.0326e-05	1.4247	0.687	1.1844	0.0676	**0.0**	**0.0**
f_8	Best	**-1.0**	**-1.0**	**-1.0**	-0.8345	**-1.0**	**-1.0**	**-1.0**	**-1.0**
	Mean	**-1.0**	**-1.0**	**-1.0**	-0.7446	**-1.0**	**-1.0**	**-1.0**	**-1.0**
	Std	**0.0**	**0.0**	**0.0**	0.0493	**0.0**	**0.0**	**0.0**	**0.0**

Table 2. Comparison of the simulation results for D=50.

Function	Index	Algorithms							
		DEPSO1	DEPSO2	DEPSO3	DEPSO4	IDEPSO1	IDEPSO3	IDEPSO4	HSLSO
f_1	Best	2.1012e-162	8.633e-209	0.0017	1.12098e+04	5.0899e-213	1.9745e+03	3.0644e-026	**0.0**
	Mean	1.6187e-159	3.9535e-204	78.7089	9.65e+05	2.8712e-200	2.2458e+03	7.5424e-026	**0.0**
	Std	4.0673e-159	0.0	222.4663	7.8985e+03	0.0	239.1772	5.4667e-026	**0.0**
f_2	Best	3.0127e-04	1.2893e-16	5.5785e+03	1.43690e+03	3.8078e-016	8.2963e+03	72697	**1.9786e-152**
	Mean	0.0011	5.2835e-15	2.0325e+04	1.63187e+05	1.3418e-014	1.2071e+04	7.8334e+04	**4.6483e-149**
	Std	9.1008e-04	9.4065e-15	9.7133e+003	1.5035e+004	2.9665e-014	2.8873e+03	4.5637e+03	**7.6904e-149**
f_3	Best	0.2144	2.1158	43.3163	1.1755e+04	**2.5534e-09**	143.7027	30.9549	9.7480
	Mean	9.1054	3.8951	89.8648	1.3898e+04	**2.3739**	163.5496	31.6758	12.6106
	Std	5.2880	1.3811	40.2577	1.1260e+03	1.7545	15.2909	**0.4605**	2.2078
f_4	Best	31.3575	0.9799	148.2584	5.6576e+03	30.3776	52.4316	**0.0**	**0.0**
	Mean	82.0187	13.0657	365.8380	6.6263e+03	69.5741	76.3394	**0.0**	**0.0**
	Std	35.2097	8.9945	187.0932	657.9707	28.2801	14.4461	**0.0**	**0.0**
f_5	Best	2.0	1.0	219.1250	5.0107e+03	**0.0**	38.8786	5.5968e-026	**0.0**
	Mean	25.4	9.90	395.2688	6.2760e+03	0.5	58.4317	8.0905e-017	**0.0**
	Std	26.9946	6.8710	163.9032	712.3232	0.8498	12.7038	2.5576e-016	**0.0**
f_6	Best	1.1551	1.8652e-14	10.2675	20.6509	2.5797	8.6144	3.2863e-014	**8.8818e-016**
	Mean	1.7390	1.0570	12.6168	20.7883	3.0793	9.0531	6.3771e-014	**8.8818e-016**
	Std	0.3800	0.8375	1.2762	0.080	0.3875	0.2856	2.1839e-014	**0.0**
f_7	Best	2.6344	0.0875	28.1509	78.9128	1.2644	25.8683	8.5265e-014	**0.0**
	Mean	7.4560	1.0364	36.2182	84.6735	4.5173	27.8957	2.6716e-013	**0.0**
	Std	2.9257	0.9412	4.7922	2.8798	1.6148	1.3868	1.4333e-013	**0.0**
f_8	Best	**-1.0**	**-1.0**	**-1.0**	-0.0071	**-1.0**	-0.9303	**-1.0**	**-1.0**
	Mean	**-1.0**	**-1.0**	-0.9981	-0.0036	**-1.0**	-0.8966	**-1.0**	**-1.0**
	Std	**0.0**	**0.0**	0.0032	0.0015	**0.0**	0.0149	**0.0**	**0.0**

Table 3. Comparison of the simulation results for D=100.

Function	Index	Algorithms							
		DEPSO1	DEPSO2	DEPSO3	DEPSO4	IDEPSO1	IDEPSO3	IDEPSO4	HSLSO
f_1	Best	2.4684e-88	2.5175e-126	9.0717	2.3704e+05	1.3782e-107	1.1494e+04	1.4660e-07	**0.0**
	Mean	1.5679e-86	3.7729e-125	984.6936	2.5606e+05	2.5730e-103	1.2170e+04	2.2939e-07	**0.0**
	Std	3.4748e-86	3.4236e-125	985.7990	1.1912e+04	6.8237e-103	556.6970	5.8201e-08	**0.0**
f_2	Best	2.2655e+03	7.9922e-04	3.1744e+04	5.0484e+05	0.2763	4.0530e+04	2.9939e+05	**1.0171e-119**
	Mean	8.5776e+03	0.0029	3.8764e+04	5.79187e+05	2.7102e+03	5.6475e+04	3.43609e+05	**1.7258e-116**
	Std	4.6410e+03	0.0019	5.6591e+03	5.4717e+04	2.9463e+03	8.1895e+03	2.7408e+04	**1.8868e-116**
f_3	Best	47.8718	44.4778	156.5041	2.7715e+04	36.0573	598.7444	90.4093	**7.1697**
	Mean	74.8912	47.5198	241.6502	3.1559e+04	62.8081	674.7838	91.1971	**55.1356**
	Std	25.8379	2.2638	62.7884	2.5600e+03	29.1964	61.2077	1.2698	**13.2934**
f_4	Best	183.2444	23.5184	469.4335	1.4557e+04	445.8552	314.6328	2.1573e-09	**0.0**
	Mean	425.8638	41.6469	721.4407	1.5546e+04	1.0651e+003	382.6508	7.1986e-09	**0.0**
	Std	166.8864	14.4110	185.1772	663.5110	514.1258	61.4573	3.5334e-09	**0.0**
f_5	Best	71.0	29.0	526.1250	1.2888e+04	**0.0**	268.2701	40.2331	**0.0**
	Mean	208.90	41.10	1.0855e+03	1.4624e+04	150.60	342.4116	49.9680	**0.0**
	Std	157.1669	10.7543	404.0017	885.6257	264.3689	47.9663	7.8527	**0.0**
f_6	Best	3.5237	2.1404	12.9831	20.7819	4.8729	11.3171	8.2351e-05	**8.8818e-016**

	Mean	5.1746	2.4650	14.9261	20.9181	8.7829	11.8329	9.1188e-05	**8.8818e-016**
	Std	1.4038	0.3748	0.9275	0.0645	3.5860	0.3432	5.5450e-06	**0.0**
f_7	Best	28.6819	6.5584	68.6311	170.0688	17.5815	71.8828	0.1321	**0.0**
	Mean	35.4578	9.1751	82.8843	177.4577	21.9614	75.8958	0.1410	**0.0**
	Std	4.4921	2.3480	8.9549	3.6109	3.7215	2.1531	0.0086	**0.0**
f_8	Best	**-1.0**	**-1.0**	-0.9980	-1.3336e-05	**-1.0**	-0.5856	**-1.0**	**-1.0**
	Mean	**-1.0**	**-1.0**	-0.9140	-4.6770e-06	**-1.0**	-0.5458	**-1.0**	**-1.0**
	Std	**0.0**	**0.0**	0.0817	3.7485e-06	**0.0**	0.0298	**0.0**	**0.0**

5. Implementation of the proposed algorithm for MAED optimization

In this section, the method of implementing the novel HSLSO algorithm for solving the MAED optimization in different power systems will be described. The process of the HSLSO can be summarized as follows:

Step 1: Set the parameters F, CR, N_P, $Iter_{max}$, $c1$ and $c2$, and call out the needed information for testing the system units, such as a_{ik}, b_{ik}, c_{ik}, e_{ik}, f_{ik}, $P_{i,\min}$, $P_{i,\max}$, DR_i, UR_i, (i=1: N_P) with the total active load demand P_{Dq}.

Step 2: Produce the initial population matrix $\left[X_0\right]$ with the following equations:

$$P_i^L = \max\left\{P_{i,\min}, P_i^0 - DR_i\right\}, \tag{27}$$

$$P_i^U = \min\left\{P_{i,\max}, P_i^0 + UR_i\right\},$$

$$P_i^L \le P_i \le P_i^U,$$

$$\left[X_{j,i}^0\right]_{D\times N_p} = \left[P_i^L + rand_{j,i}(0,1)\times(P_i^U - P_i^L)\right]_{D\times N_p}. \tag{28}$$

Step 3: Calculate the objective function $F(P_i)$ of MAED optimization problem by imposing the real power limit constraint and real power generation-demand balance for every available solution in the initial population of the algorithm. The penalty functions [24][59] have been used most often for the constraint-handling procedure of MAED problems and are also used in HSLSO.

Step 4: Produce the new population of HSLSO using velocities of population, mutation, crossover and selection operators.

Step 5: Calculate the objective function $F(P_i)$ of MAED optimization problem.

Step 6: Repeat steps 4 and 5 till reaching the maximum number of iterations.

6. Simulation results

To evaluate the performance, effectiveness and efficiency of the hybrid DEPSO algorithms, they have been applied to MAED problems in three test power systems. These are a two-area system with four generating units, a four-area system with sixteen generating units, and a two-area system with forty generating units. All of the algorithms have been implemented in MATLAB 7.0 on a PC.

6.1. Test system 1: A two-area system with four generating units

The test system 1 is a two-area test system with four generating units (a small-scale system) whose details are available in Ref. [54, 61], and active tie-line flow limit and active load demand are set at 200 MW and 1120 MW, respectively. The total load demand in area 1 (P_1 and P_2 units) is 70% and in area 2 (P_3 and P_4 units) is 30% [40, 50]. The experimental results of DEPSO algorithms for the test system 1 with three different crossover rates CR =0.3, 0.5, and 0.7 are tabulated in Table 4 with N_P =20. The simulation results show that the DEPSO1 for CR =0.7, DEPSO2 for CR =0.3 and 0.5, IDEPSO1 for CR =0.7, and HSLSO for CR =0.5 and 0.7, find the best solutions with standard deviation of the best results obtained for 30 trials equal to zero for a small-scale system. The convergence characteristics of DEPSO algorithms for the best solution of CR =0.5 are plotted in Fig. 2. It can be seen that HSLSO algorithm converges faster than the other DEPSO algorithms for this test system.

Table 4. Comparison of the simulation results for test system 1 with different crossover rates.

CR	Index	Algorithms							
		DEPSO1	DEPSO2	DEPSO3	DEPSO4	IDEPSO1	IDEPSO3	IDEPSO4	HSLSO
0.3	Best	10605.0819	**10604.6741**	10604.6852	10607.4662	10606.1858	10605.0052	10604.6783	**10604.6741**
	Mean	10605.1859	**10604.6741**	10605.149	10612.4492	10611.6158	10605.5726	10604.7053	10604.67415
	Std	0.0897	**0.0**	0.4871	2.6937	6.1401	0.5312	0.0235	9.4868e-015
0.5	Best	10604.6772	**10604.6741**	10604.6962	10611.6001	**10604.6741**	10604.9085	10604.7322	**10604.6741**
	Mean	10604.6799	**10604.6741**	10605.196	10614.0376	10604.7516	10605.9641	10604.8006	**10604.6741**
	Std	0.0028	**0.0**	0.7776	1.5733	0.2565	0.8166	0.06	**0.0**
0.7	Best	**10604.6741**	**10604.6741**	10604.7015	10612.337	**10604.6741**	10605.3276	10604.7149	**10604.6741**
	Mean	**10604.6741**	10604.6746	10606.5715	10617.2091	**10604.6741**	10606.0265	**10604.7741**	**10604.6741**
	Std	**0.0**	3.6194e-016	2.3115	4.0643	**0.0**	0.5369	0.0503	**0.0**

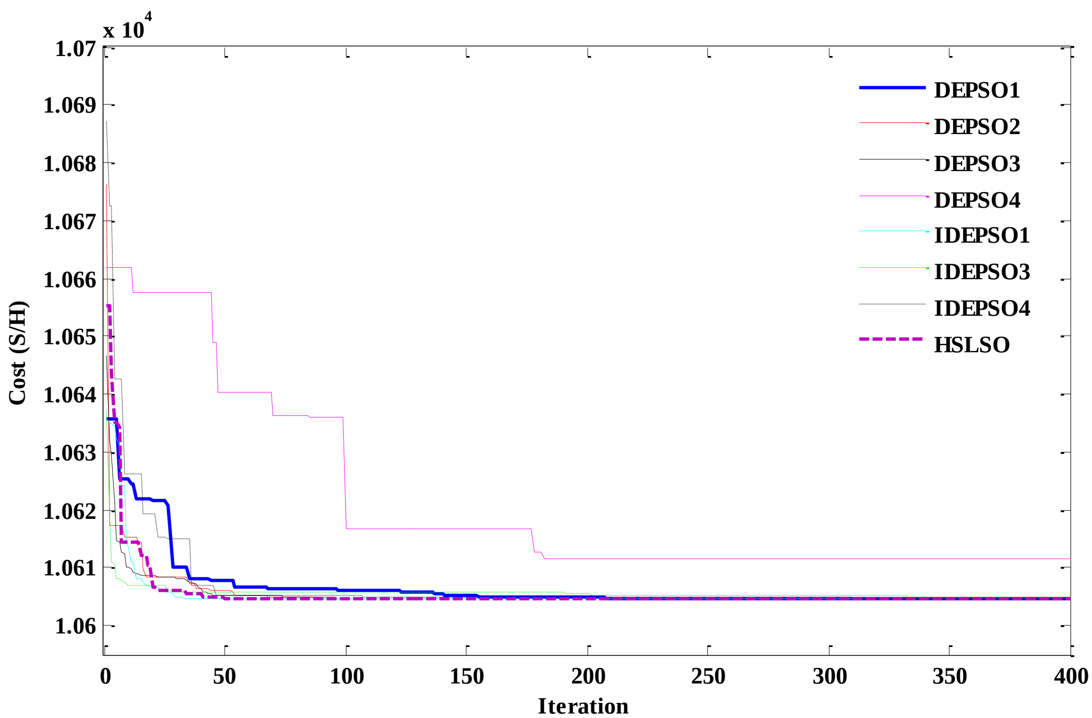

Fig. 2. Convergence characteristics of algorithms for test system 1.

The best solutions obtained from HSLSO algorithm has been compared with direct search method (DSM) [54], Hopfield neural network (HNN) approach [61], covariance matrix adapted evolution strategy (CMAES) [40], and PSO with time-varying acceleration coefficients (PSO_TVAC) [50]. Their best solutions are shown in Table 5. Ref. [40] reported a cost of 10,574.0 ($/H) for CMAES method but the reported results are infeasible as they do not satisfy the area power balance constraints [50]. The performance of HSLSO and DEPSO algorithms are very good among all algorithms for finding the optimal solution of MAED problem in the small-scale system.

Table 5. Comparison of the simulation results for test system 1.

Method	P_1 (MW)	P_2 (MW)	P_3 (MW)	P_4 (MW)	T_{12} (MW)	$\sum P_g$	Cost ($/H)
HNN [61]	-	-	-	-	-	-	10605.0
DSM [54]	-	-	-	-	-	-	10605.0
PSO_TVAC [50]	444.8047	139.1953	211.0609	324.9391	- 200.0000	1120.0	10604.6781
CMAES [40]*	560.9383	168.9300	99.9890	290.1427	- 194.39	1120.0	10574.0
HSLSO	445.1254	138.8747	211.9889	324.011	-199.9999	1120.0	10604.6741

For solving reserve constrained MAED (RCMAED) problem of test system 1, the area reserves are taken as 40% of area 1 load demand (313.6 MW) for area 1 and 30% of area 2 load demand (100.8 MW) for area 2, and the tie-line limit is assumed to be 300 MW [50]. The obtained simulation results for RCMAED problem with optimal control variables using DEPSO hybrid algorithms are given in Table 6 with the obtained best CR of Table 4 and N_P =50. The convergence characteristics of the objective function (optimal total fuel cost) of all hybrid algorithms are shown in Fig. 3, which is clear that most of the proposed DEPSO hybrid algorithms can converge to their optimal total fuel cost in less iterations.

Table 6. Comparison of the simulation results for reserve constrained MAED (RCMAED) problem of test system 1.

	Algorithms							
	DEPSO1	DEPSO2	DEPSO3	DEPSO4	IDEPSO1	IDEPSO3	IDEPSO4	HSLSO
P_1 (MW)	369.5737	369.5737	369.6679	370.6286	369.5737	369.5965	369.5737	369.5737
P_2 (MW)	114.4264	114.4264	114.5224	113.4921	114.4264	114.5100	114.4264	114.4264
P_3 (MW)	295.9999	295.9999	295.8099	295.8795	295.9999	295.8939	295.9999	295.9999
P_4 (MW)	340.0000	340.0000	340.0000	340.0000	340.0000	340.0000	340.0000	340.0000
T_{12} (MW)	-299.9999	-299.9999	-299.8097	-299.8793	-299.9999	-299.8935	-299.9999	-299.9999
Reserve area 1	315.9999	315.9999	315.8097	315.8793	315.9999	315.8935	315.9999	315.9999
Reserve area 2	104.0001	104.0001	104.1901	104.1205	104.0001	104.1061	104.0001	104.0001
Best Cost (\$/H)	10566.9946	10566.9946	10567.0107	10567.0114	10566.9946	10567.0062	10566.9946	10566.9946
Mean Cost (\$/H)	10566.9958	10566.9946	10571.0405	10567.0381	10566.9946	10567.2167	10566.9946	10566.9946
S.D.	0.0164	0.0	2.0184	0.0358	0.0	0.1841	0.0	0.0

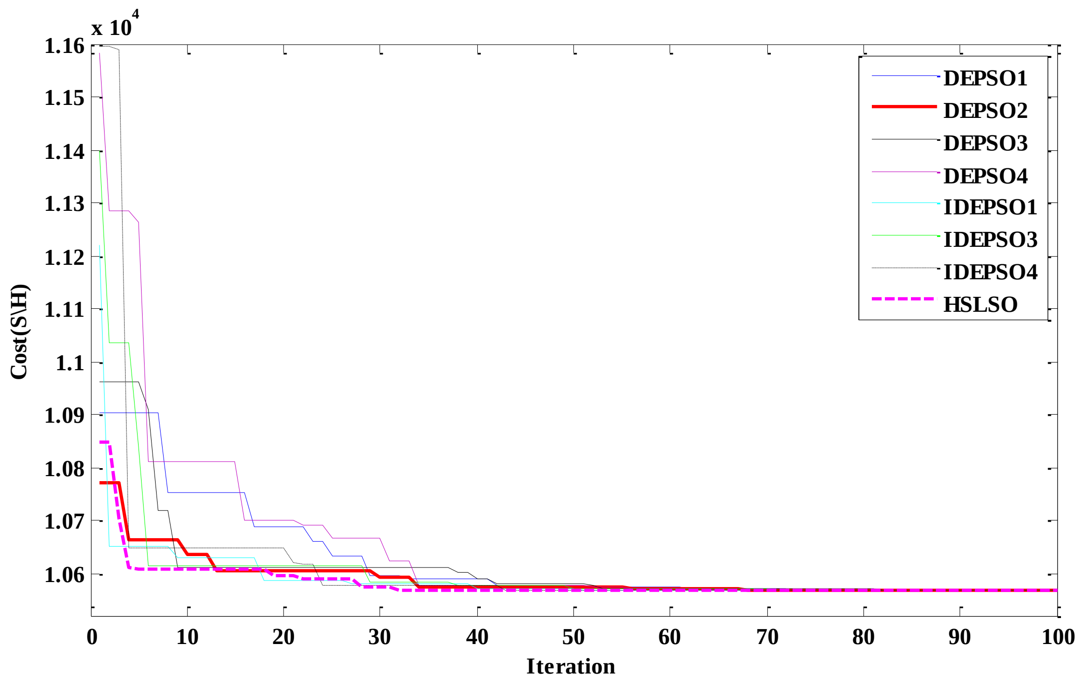

Fig. 3. Convergence characteristics of algorithms for reserve constrained MAED (RCMAED) problem of test system 1.

6.2. Test system 2: A four-area system with sixteen generating units

6.2.1. Case 1: Test system 2 for MAED problem based References [59, 62]

This test system is a medium-scale test system with sixteen generating units, whose parameters with active tie-line flow limit are available in Ref. [59, 62]. The active load demand are set to 400 MW for area 1 (P_1, P_2, P_3 and P_4 units), 200 MW for area 2 (P_5, P_6, P_7 and P_8 units), 350 MW for area 3 (P_9, P_{10}, P_{11} and P_{12} units), and 300 MW for area 4 (P_{13}, P_{14}, P_{15} and P_{16} units). The obtained results of DEPSO algorithms for the test system 2 with three different crossover rates are tabulated in Table 7. The simulation results show that the proposed HSLSO algorithm finds the best solution with minimum standard deviation for 30 trials, and the proposed improved DEPSO algorithms yield better results than DEPSO algorithms in this test system. Convergence characteristics of the various algorithms on test system 2 for the best solution of CR =0.5 are plotted in Fig. 4. It is observed that the convergence characteristics for various DEPSO algorithms are stable and steady.

Table 7. Comparison of the simulation results for test system 2 with different crossover rates.

CR	Index	Algorithms							
		DEPSO1	DEPSO2	DEPSO3	DEPSO4	IDEPSO1	IDEPSO3	IDEPSO4	HSLSO
0.3	Best	7584.5	7338.0787	7393.1215	7765.4585	7448.365	7362.5005	7338.2339	7338.1303
	Mean	7708.75	7342.6777	7430.6659	7905.9843	8269.4694	7419.1895	7339.9968	7338.4278
	Std	129.7749	8.9864	50.1082	125.8137	436.9393	58.9327	1.7621	0.4008
0.5	Best	7371.4803	7338.6095	7344.7284	7915.3542	7338.0299	7368.2032	7342.3242	7337.042
	Mean	7599.7476	7340.0318	7411.8184	8173.1453	7339.7626	7419.9534	7350.7301	7337.8804
	Std	162.6943	1.6176	67.0561	158.8003	1.3896	43.1228	7.9251	0.6599
0.7	Best	7375.1265	7338.0188	7379.8855	7916.0613	7338.0299	7507.8628	7341.1164	**7337.024**
	Mean	7514.1761	7338.3982	7443.9999	7993.9544	7339.906	7755.9244	7349.2803	7338.5734
	Std	116.3733	0.4125	40.9244	66.0229	1.3896	295.8965	11.1432	0.7518

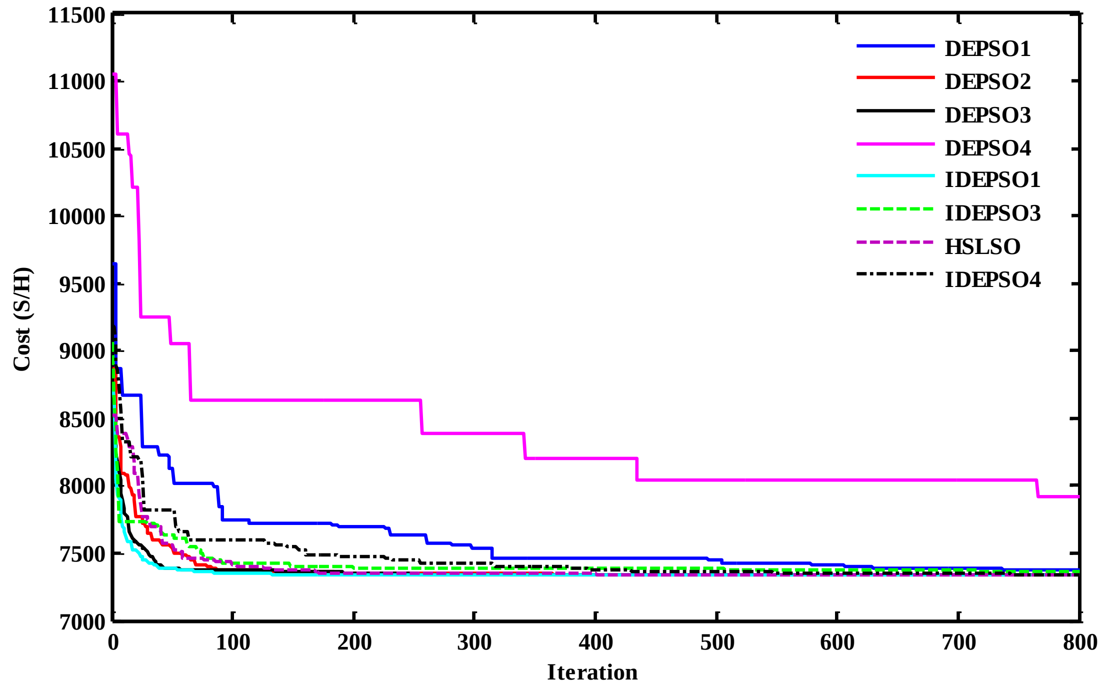

Fig. 4. Convergence characteristics of algorithms for test system 2.

The best solutions obtained by the hybrid algorithms and the solutions reported in literature are given in Table 8. The solution obtained by the HSLSO algorithm is a feasible solution ($\sum P_g$ =1250.0 MW) compared with results reported in literature by methods such as the pattern search (PS) method ($\sum P_g$ =1249.9982 MW) [52], PSO ($\sum P_g$ =1249.95 MW), classical evolutionary programming (CEP) approach ($\sum P_g$ =1247.995 MW) [56], network flow programming (NFP) ($\sum P_g$ =1249.98 MW) [62], and the hybrid harmony search (HHS) method ($\sum P_g$ =1249.29 MW) [59].

Table 8. Comparison of the simulation results for test system 2.

Area no. (*PD*)		PSO [56]	NFP [62]	CEP [56]	PS [52]	HHS [59]	HSLSO
1 (400 MW)	P_1 (MW)	150.00	150.00	150.00	150.0000	150.00	150
	P_2 (MW)	100.00	100.00	100.00	100.0000	100.00	100.0
	P_3 (MW)	67.366	66.97	68.826	66.9710	66.86	67.3848
	P_4 (MW)	100.00	100.00	99.985	100.0000	100.0	100.0
2 (200 MW)	P_5 (MW)	56.613	56.970	56.373	56.9718	57.04	57.0625
	P_6 (MW)	95.474	96.250	93.519	96.2518	96.22	96.1749
	P_7 (MW)	41.617	41.870	42.546	41.8718	41.74	41.8472
	P_8 (MW)	72.356	72.520	72.647	72.5218	72.5	72.4505
3 (350 MW)	P_9 (MW)	50.00	50.00	50.00	50.0020	50.0	50.0
	P_{10} (MW)	35.973	36.270	36.399	36.2720	36.24	36.3190
	P_{11} (MW)	38.21	38.490	38.323	38.4920	38.39	38.5911
	P_{12} (MW)	37.162	37.320	36.903	37.3220	37.2	37.3719
4 (300 MW)	P_{13} (MW)	150.000	150.000	150.0	150.0000	150.0	150.0
	P_{14} (MW)	100.000	100.000	100.0	100.0000	100.0	100.0
	P_{15} (MW)	57.830	57.050	56.648	57.0510	56.9	56.9272
	P_{16} (MW)	97.349	96.270	95.826	96.2710	96.2	95.8709
Active tie-line power	T_{12} (MW)	0.00	0.00	-0.018	0.0	0.0	0.0
	T_{13} (MW)	22.588	18.18	19.587	18.181	16.86	17.4643
	T_{14} (MW)	-5.176	-1.21	-0.758	-1.210	0.0	-0.0795
	T_{23} (MW)	66.064	69.73	68.861	69.73	7061	70.2537
	T_{24} (MW)	-0.004	-2.11	-1.789	-2.111	-3.11	-2.7186
	T_{34} (MW)	-100.000	-100.0	-99.927	-100.0	-100.0	-100
$\sum P_g$		1249.95	1249.98	1247.995	1249.9982	1249.29	**1250.0**
Cost ($/H)		7336.93	7337.00	7337.75	7336.98	7329.85	7337.0299

6.2.2. Case 2: Test system 2 for RCMAED and RCMAEED problems with reserve sharing based on Reference [53]

The different fuel and emission characteristics data of all generators, including all generators operating limits and tie-line limits, are available in Ref. [53]. The active load demand are set to 30 MW for area 1 (P_1, P_2, P_3 and P_4 units), 50 MW for area 2 (P_5, P_6, P_7 and P_8 units), 40 MW for area 3 (P_9, P_{10}, P_{11} and P_{12} units), and 60 MW for area 4 (P_{13}, P_{14}, P_{15} and P_{16} units). The spinning reserve requirement for the four areas are 30% of the area load demand in each area, i.e. 9 MW for area 1, 15 MW for area 2, 12MW for area 3 and 18MW for area 4, respectively. Tables 9 and 10 illustrate the optimal control variables characteristic for the fuel cost and emissions (Table.10) obtained using hybrid DEPSO algorithms for two RCMAED and RCMAEED problems with the obtained best CR of Table 7, respectively. The weighting factor is selected to be 120.0 for RCMAEED problem, and zero value for RCMAED problem. According to the presented results, the HSLSO algorithm has better performance than other hybrid DEPSO algorithms for RCMAED and RCMAEED problems.

Table 9. Comparison of the simulation results for RCMAED problem of test system 2.

(MW)	Algorithms							
	DEPSO1	DEPSO2	DEPSO3	DEPSO4	IDEPSO1	IDEPSO3	IDEPSO4	**HSLSO**
P_1 (MW)	5.4643	3.1018	12.6855	12.6142	13.5198	9.6169	0.4724	**11.0552**
P_2 (MW)	0.3177	7.9364	8.9795	9.9933	8.5906	3.5813	7.5553	**9.8604**
P_3 (MW)	12.9730	10.3067	7.5249	0.1144	6.6234	4.9329	10.0875	**5.4901**
P_4 (MW)	11.1998	8.6684	0.7768	7.4458	1.3766	12.0000	11.9217	**3.5849**
P_5 (MW)	11.9464	13.7007	18.3076	24.9810	23.9531	17.5893	1.1237	**2.8162**
P_6 (MW)	9.7301	1.7089	5.9683	1.4095	3.4317	11.9977	11.9819	**8.6228**
P_7 (MW)	12.0407	18.8862	17.8618	18.8194	16.5694	19.7774	19.9529	**2.0908**
P_8 (MW)	16.2852	15.7602	7.8177	4.7207	6.0516	0.6361	16.9628	**6.4706**
P_9 (MW)	0.2927	8.6018	21.5032	16.9843	12.7645	0.9991	0.4290	**2.9635**
P_{10} (MW)	13.3341	0.9835	3.1556	2.8846	9.9381	0.0777	1.0530	**0.0500**
P_{11} (MW)	0.1226	6.4470	4.1346	19.2703	3.1255	29.7699	9.2074	**8.5821**
P_{12} (MW)	26.2591	23.9569	11.2296	0.8976	14.1403	9.1460	29.3113	**8.3853**
P_{13} (MW)	0.0957	7.7491	10.3416	0.0538	1.1532	0.2214	10.6806	**6.6636**
P_{14} (MW)	19.7606	0.3072	19.3828	10.5401	8.0550	0.3289	18.8727	**3.3023**
P_{15} (MW)	29.3035	29.8405	1.3674	28.1829	26.5102	29.3861	25.0099	**2.4392**
P_{16} (MW)	10.8821	22.0311	28.9625	21.1077	24.2042	29.9163	5.3876	**7.6249**
T_{12} (MW)	-0.0197	-0.0416	0.0121	0.0434	0.0212	-0.0100	0.0235	**0.0273**
T_{13} (MW)	0.0115	0.0121	-0.0114	-0.0226	0.0276	-0.0009	-0.0139	**-0.0092**
T_{14} (MW)	-0.0419	0.0529	-0.0346	0.1426	0.0616	0.1436	0.0341	**-0.0271**
T_{23} (MW)	-0.0097	-0.0041	-0.0231	-0.0085	-0.0114	-0.0038	0.0105	**-0.0037**
T_{24} (MW)	0.0003	0.0185	-0.0099	-0.0245	0.0265	-0.0049	0.0198	**0.0145**
T_{34} (MW)	0.0007	-0.0019	-0.0131	-0.0012	-0.0075	0.0020	-0.0012	**-0.0057**
RC12	-0.0317	-0.0019	0.0492	0.0028	-0.0054	-0.0234	-0.0082	**0.0332**
RC13	0.0105	0.0177	0.0228	-0.0147	0.0122	0.0379	-0.0079	**0.0040**
RC14	0.0768	0.0071	-0.0081	-0.0005	0.0085	0.0418	-0.0413	**-0.0134**
RC23	-0.0221	-0.0134	-0.0009	0.0019	0.0164	-0.0173	-0.0042	**-0.0251**
RC24	0.0254	0.0130	0.0304	0.0026	0.0091	0.0306	0.0329	**0.0391**
RC34	0.013	0.0076	-0.0009	-0.0041	0.0046	0.0020	0.0081	**0.0049**
Reserve area 1								
Reserve area 2								
Reserve area 3								
Reserve area 4								
Cost ($\h)	2189.2012	2183.6782	2186.6061	2190.5887	2178.2986	2186.3202	2182.2914	**2159.8128**
Mean								
S.D.								

Table 10. Comparison of the simulation results for reserve constrained multi area environmental/economic dispatch (RCMAEED) problem of test system 2.

(MW)	DEPSO1	DEPSO2	DEPSO3	DEPSO4	IDEPSO1	IDEPSO3	IDEPSO4	**HSLSO**
P_1 (MW)	10.4136	12.6447	10.0196	4.9260	13.2116	12.2540	12.8502	**13.6004**
P_2 (MW)	4.9644	6.6592	5.1395	7.2540	6.6790	9.2143	7.5463	**5.3880**
P_3 (MW)	3.0067	0.1061	10.2519	10.2999	7.3117	4.0872	3.7010	**5.1218**
P_4 (MW)	11.5211	10.7641	4.5322	7.4911	2.7739	4.4428	5.9252	**5.9299**
P_5 (MW)	6.5876	16.3608	14.7624	19.5174	15.0576	24.8488	23.4908	**22.6109**
P_6 (MW)	9.7131	7.3302	11.7687	10.1479	4.7809	3.6403	0.6111	**8.3738**
P_7 (MW)	18.8575	13.6234	19.4621	4.9097	13.4996	10.4683	17.4849	**8.6524**
P_8 (MW)	14.9039	12.7100	4.0304	15.4238	16.6493	11.0494	8.4428	**10.3437**
P_9 (MW)	23.9743	12.1719	22.6546	28.6957	11.6720	13.0985	14.7230	**12.2857**
P_{10} (MW)	6.3174	6.1967	3.8454	5.5386	10.1620	15.1976	6.2322	**8.7820**
P_{11} (MW)	0.5079	10.4179	3.2815	2.0624	3.9674	2.6575	5.2089	**7.8882**
P_{12} (MW)	9.1893	11.2001	10.2180	3.7338	14.2051	9.0514	13.7952	**11.0352**
P_{13} (MW)	10.9743	7.7329	9.6932	9.9038	8.9539	10.7064	10.7395	**10.9628**
P_{14} (MW)	16.1252	9.9463	19.5799	16.1223	19.9808	15.3404	16.7964	**16.2980**

P_{15} (MW)	14.3829	15.8206	22.4566	14.6359	12.7618	11.0278	13.1715	**13.3964**
P_{16} (MW)	18.5557	26.3090	8.3138	19.4639	18.3250	22.9130	19.2884	**19.3240**
T_{12} (MW)	-0.0302	-0.0209	-0.0054	0.0394	0.0109	-0.0312	-0.0182	**0.0269**
T_{13} (MW)	-0.0005	-0.0012	-0.0023	0.0131	0.0048	-0.0141	0.0233	**-0.0041**
T_{14} (MW)	-0.0566	0.1936	-0.0535	-0.0856	-0.0320	0.0344	0.0286	**0.0060**
T_{23} (MW)	0.0005	0.0061	0.0142	-0.0029	-0.0057	0.0044	0.0085	**0.0041**
T_{24} (MW)	0.0410	-0.0074	0.0021	0.0056	0.0060	-0.0200	-0.0175	**0.0024**
T_{34} (MW)	-0.0141	0.0104	0.0125	-0.0044	-0.0009	-0.0037	-0.0131	**0.0068**
RC12	0.0045	0.0151	-0.0332	0.0177	-0.0475	0.0272	0.0122	**0.0158**
RC13	-0.0159	-0.0087	0.0125	0.0299	0.0167	-0.0003	-0.0006	**-0.0008**
RC14	0.0372	0.0040	0.0855	-0.0706	0.0247	-0.0410	0.0919	**-0.0587**
RC23	0.0233	-0.0005	0.0056	0.0079	0.0234	0.0142	0.0080	**-0.0015**
RC24	0.0117	0.0118	0.0208	-0.0072	0.0208	0.0314	0.0071	**0.0253**
RC34	0.0001	0.0026	0.0031	0.0040	0.0021	-0.0021	-0.0031	**-0.0002**
Reserve area 1								
Reserve area 2								
Reserve area 3								
Reserve area 4								
Cost ($\h)	2194.6627	2182.579	2190.9533	2202.7789	2186.0603	2185.0514	2183.0054	**2182.575**
Emission (ton/h)	4.0435	3.5833	4.465	4.3742	3.3776	3.5941	3.6018	**3.2605**

6.3. Test system 3: A two-area system with forty generating units

The test system 3 is a large-scale power system which has generating units with POZ, VPL effects, and ramp rate limits [50, 64]. The units P_1 to P_{20} are assumed to be in area one and units P_{21} to P_{40} are in area two. The total load is 10,500MW in which 7500 MW is set as the active load demand for area 1 and 3000 MW is set as the active load demand for area 2, and the maximum transmission capacity limit between two areas is 1500 MW. The results of the proposed algorithms for the test system 3 with the crossover rate CR =0.5 are tabulated in Table 11. The obtained results show that the HSLSO finds the best solution in comparison with other algorithms for the large-scale system, and the proposed improved DEPSO algorithms yield better results than DEPSO algorithms, in this test system. The convergence characteristics for the proposed DEPSO algorithms are shown in Fig. 5. It is observed that the convergence characteristic of the total fuel cost of generating units obtained by the HSLSO is slightly better than that of the other DEPSO algorithms. Table 12 compares the best solution obtained using HSLSO algorithm and DE algorithm with chaotic sequences based on logistic map (DEC2) [50, 78]. The results show that HSLSO algorithm is successfully implemented to solve the large-scale MAED problem with the generator constraints.

Table 11. Comparison of the simulation results for test system 3 with *CR* =0.5.

Index	Algorithms							
	DEPSO1	DEPSO2	DEPSO3	DEPSO4	IDEPSO1	IDEPSO3	IDEPSO4	HSLSO
Best	125299.5631	125179.5581	127386.3364	128641.7046	125594.007	127226.188	127457.4462	**125100.2621**
Mean	125474.4525	125421.1636	128757.9549	128957.7981	126238.8349	127742.0182	127744.5247	**125384.4464**
Std	173.9205	157.2532	860.0746	263.9482	478.2639	378.8191	247.7480	**104.2493**

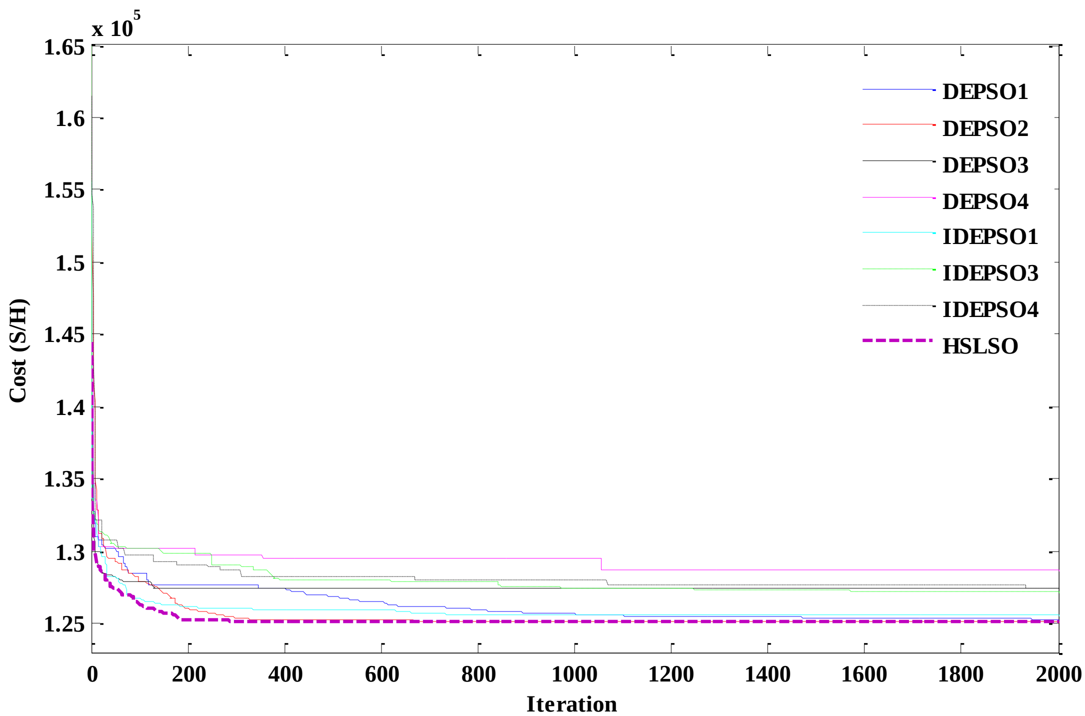

Fig. 5. Convergence characteristics of algorithms for test system 3.

Table 12. Comparison of the simulation results for test system 3.

DEC2 [50, 78]				HSLSO			
Area 1 (*PD* =7500MW)		Area 2 (*PD* =3000 MW)		Area 1 (*PD* =7500MW)		Area 2 (*PD* =3000 MW)	
P_1 (MW)	112.8292	P_{21} (MW)	343.7598	P_1 (MW)	110.8012	P_{21} (MW)	523.2792
P_2 (MW)	114.0000	P_{22} (MW)	433.5196	P_2 (MW)	113.9997	P_{22} (MW)	523.2791
P_3 (MW)	97.3999	P_{23} (MW)	523.2794	P_3 (MW)	120.0	P_{23} (MW)	523.2794
P_4 (MW)	179.7331	P_{24} (MW)	550.0000	P_4 (MW)	179.7331	P_{24} (MW)	523.2794
P_5 (MW)	97.0000	P_{25} (MW)	550.0000	P_5 (MW)	95.551	P_{25} (MW)	523.2795
P_6 (MW)	68.0001	P_{26} (MW)	254.0000	P_6 (MW)	140.0	P_{26} (MW)	254.0
P_7 (MW)	300.0	P_{27} (MW)	10.0000	P_7 (MW)	300.0	P_{27} (MW)	10.0001

P_8 (MW)	284.5997	P_{28} (MW)	10.0001	P_8 (MW)	284.5997	P_{28} (MW)	10.0
P_9 (MW)	284.5997	P_{29} (MW)	10.0000	P_9 (MW)	284.5997	P_{29} (MW)	10.0
P_{10} (MW)	130.0	P_{30} (MW)	47.0000	P_{10} (MW)	270.0	P_{30} (MW)	87.7997
P_{11} (MW)	360.0	P_{31} (MW)	159.7331	P_{11} (MW)	94.0	P_{31} (MW)	188.5959
P_{12} (MW)	94.0001	P_{32} (MW)	190.0000	P_{12} (MW)	300.0	P_{32} (MW)	159.7331
P_{13} (MW)	304.5196	P_{33} (MW)	163.7269	P_{13} (MW)	304.5195	P_{33} (MW)	159.733
P_{14} (MW)	500.0	P_{34} (MW)	164.7998	P_{14} (MW)	394.2797	P_{34} (MW)	164.8002
P_{15} (MW)	484.0392	P_{35} (MW)	200.0000	P_{15} (MW)	484.0395	P_{35} (MW)	164.7998
P_{16} (MW)	500.0	P_{36} (MW)	164.7998	P_{16} (MW)	484.0391	P_{36} (MW)	164.7998
P_{17} (MW)	489.2794	P_{37} (MW)	110.000	P_{17} (MW)	489.2794	P_{37} (MW)	89.1143
P_{18} (MW)	500.0	P_{38} (MW)	57.0571	P_{18} (MW)	489.2796	P_{38} (MW)	89.114
P_{19} (MW)	550.0000	P_{39} (MW)	25.0000	P_{19} (MW)	549.9998	P_{39} (MW)	89.1134
P_{20} (MW)	550.0000	P_{40} (MW)	511.2794	P_{20} (MW)	511.2791	P_{40} (MW)	242.0001
T_{12} *(MW)*	-1500.0000			T_{12} (MW)	-1500.0		
$\sum P_g$	10500.0			$\sum P_g$	10500.0001		
Cost ($/H)	127344.8528			Cost ($/H)	**125100.2621**		

7. Conclusions

In this paper, four IDEPSO techniques were proposed for solving optimal MAED, RCMAED, RCMAED with reserve sharing, and RCMAEED with reserve sharing problems. MAED problems are an extension of ELD problem in power systems, and multi-area systems considered in this study are a two-area system with four generating units, a four-area system with sixteen generating units, and a two-area system with forty generating units. The simulation results show that IDEPSO techniques, in particular HSLSO algorithm, have suitable performance in balancing the global search ability and convergence characteristics, and better performance in solution's quality than other algorithms proposed in the literature. So, it is believed that the proposed HSLSO algorithm in this study is capable of effectively and quickly solving optimization problems in power systems.

Appendix: Comparison of HSLSO with standard PSO algorithms

In this section, we consider two standard PSO (SPSO) algorithms in the recent literature, including SPSO2011 [79] and modified PSO (MPSO) [80-81], for comparison with HSLSO algorithm using standard benchmark test functions such as Rosenbrock (f_3), Rastrigin (f_4) and Ackley (f_6) functions under same conditions and with their original control parameters in the literature. The obtained optimal results after 25 runs are given in Table 13, and also the convergence characteristics of these algorithms for

Rastrigin function with D=60 are shown in Fig. 6. The HSLSO algorithm provides better optimal results with faster convergence compared to SPSO2011 and MPSO.

Table 13. Comparison of the HSLSO and other algorithms for benchmark test functions.

Function	D	MPSO			SPSO2011			HSLSO		
		Best	Mean	Std	Best	Mean	Std	Best	Mean	Std
Rosenbrock	30	20.7643	24.1874	13.9342	13.7951	13.8851	0.7157	12.4180	13.3847	1.0329
	60	60.1641	71.6428	38.1262	48.2355	48.8663	1.0095	43.2785	44.5325	1.1041
Rastrigin	30	48.3716	53.2907	23.9066	34.5925	34.5249	3.2363	**0.0**	**0.0**	**0.0**
	60	154.6357	282.8053	49.8403	138.0560	155.2106	11.3320	**0.0**	**0.0**	**0.0**
Ackley	30	1.479	11.5197	10.0050	4.4409e-015	7.1054e-015	1.7763e-015	**8.8818e-016**	**8.8818e-016**	**0.0**
	60	1.5915	20.7934	18.0593	7.9936e-015	0.8308	0.9788	**8.8818e-016**	**8.8818e-016**	**0.0**

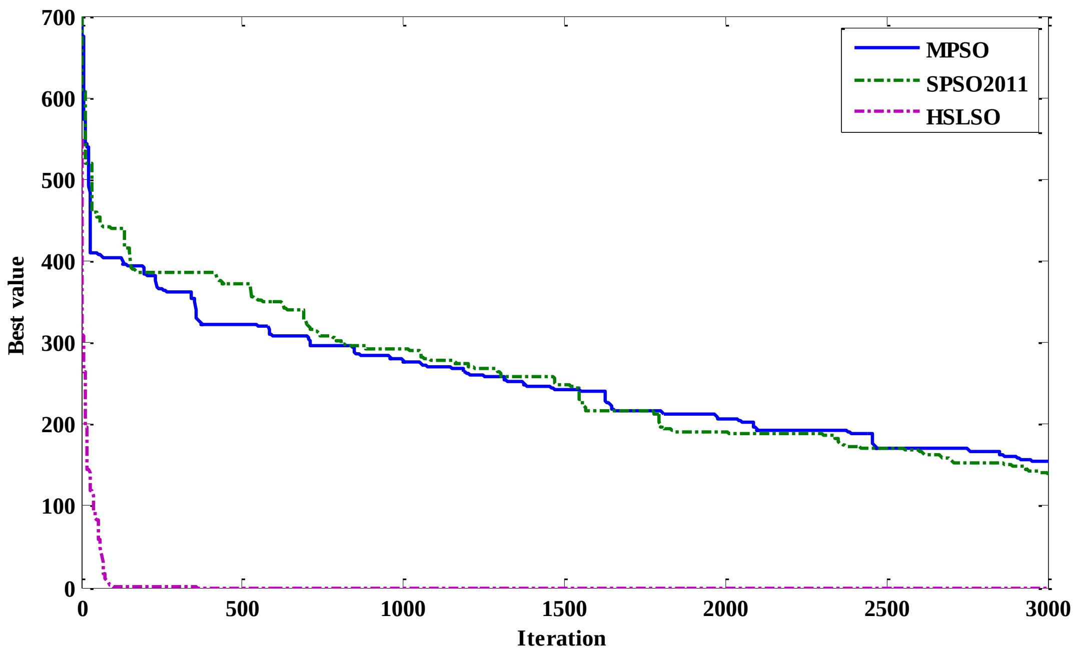

Fig. 6. Convergence characteristics of algorithms for Rastrigin function with D=60.

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