Multi-area Economic Dispatch Using Dynamically Controlled Particle Swarm Optimization

Vineet Kumar, Ram Naresh Sharma and Shiv Kumar Sikarwar

Abstract The goal of multi-area economic dispatch (MAED) is lower term resolution of optimal power generations of no. of electricity facilities to cater system demand at lowest feasible cost which can satisfy power balance, generating limit and transmission constraints. The generators watt and var power are controlled within the constraint of the generators' power limit to attain the minimum cost, satisfying the system burden. It is imperative to find an alternative route between two areas to supply spare power if the two areas are such that one of them is having surplus power as compared to other, or tie-line constraint joining the two areas is at transmission line. The power distribution of every unit is done in such that after supplying the total load, some specified reserve is left behind. In this paper, the comparison of classical PSO strategies and their variations for MAED has been accomplished. The ability to handle constraint of these meta-heuristic techniques allows them to produce high-quality solutions. The performance is subjected on a single area 3 generation units, a two area system with 4 generating units and a 4-area, 40-unit system with six tie lines.

Keywords Particle swarm optimization (PSO) · Particle swarm optimization time-varying acceleration coefficients (PSO-TVAC) · Dynamically controlled particle swarm optimization (DCPSO)

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1 Introduction

Economic dispatch problem is of considerable importance in the area of power generation. Economic dispatch is the determination of electrical power outputs from all the thermal generators supplying power to the system at minimum total cost in a single area subject to the condition that total meets the load demand including losses while power capacity limit constraints of generators are satisfied. Multi-area economic dispatch (MAED) is formulated by extending ED model. The goal of MAED is to find out electric power outputs of committed generators in all the interconnected areas at minimum cost while satisfying load balance constraints, electric power capacity limits of generators and transmission line capacity constraints. An electrical power system consists of generation, transmission and distribution utilities to enhance electrical power to the consumers. ED problem for single area power system is addressed by most of the research papers, whereas only few papers address ED for multi-area power system but the optimization problem still solved in a sequential way. The objective is to find the solution MAED problem using a developed Lagrange's decomposed method. Large networked systems are break down into areas or zones. MAED problem is a methodology in power network operation that allows measure of generation to committed units within the areas. Earlier ED problem is solved by lambda iteration method, gradient method, reduced gradient method, Newton method and other methods like participation factor method, binary weighted method. All these classical techniques have several disadvantages like: problem complexity, time computation factor, characteristics should be non-convex in nature. All these factors are removed by other classical methods like priority method, dynamic programming and Lagrange relaxation method. These methods have several advantages that these techniques are applied to complex characteristics problems of generator but there is problem in these techniques that they have take several stages to solve the problem and time taken is too large [1]. These things are overcome by meta-heuristics methodologies. Many methodologies are implemented on economic dispatch like GA, ABCO and PSO [2–6]. But proposed DPSO when varying all variants of PSO has not implemented yet.

2 Nomenclatures

a_{ij}, b_{ij}, c_{ij}	The cost coefficients of the jth generator in area i (Rs/h), (Rs/h MW^{-1}), (Rs/h MW^{-2})
C_1, C_2	Acceleration coefficients for best and social experience of PSO
C_{1b}, C_{1p}	Acceleration coefficients for best and preceding experience
e_{ij} and f_{ij}	The valve-point effect coefficients of the jth generator in area i (Rs/h, MW^{-1})
$g\text{best}^t$	Best particle during tth iteration
$g\text{rms}^t$	Root mean square experience of the swarm during tth iteration

itr	Current iteration count
itr_{max}	Maximum iteration count
itr_{min}	Minimum iteration count
k	Ratio of dynamic cognitive and social acceleration coefficients
k_w	Ratio of maximum and minimum bound of the inertia weight
M	Number of areas
N_{Gi}	Number of generating units in the system in area i
N_{Gi}	Number of generating units in the ith area
$P\text{best}_n$	Best position of nth particle achieved based on its own experience
PD	Total real power demand of the system (MW)
P_{Di}	Total real power demand of area i (MW)
P_{Gi}	Total real power generation in area i (MW)
P_{Gij}	Real power output of the jth generator in area i (MW)
$P_{Gij}^{min}/P_{Gij}^{max}$	Minimum/maximum generation limits of jth generator in area i (MW)
$P_{Tim}^{min}/P_{Tim}^{max}$	Minimum/maximum tie-line power limit from area i to area m (MW)
$p\text{preceding}_n$	Preceding position of nth particle achieved based on its just previous experience
P_{Tim}	Tie-line real power flow from area i to area m (MW) rand1 () and rand2 () random numbers in [0,1]
V_n^t	Velocity of nth particle at tth iteration
W	Inertia weight
W_{min}/W_{max}	Minimum/maximum value of inertia weight
Δt	Time step (s)
ζ_1 and ζ_2	Exponential constriction functions
η	Ratio of current and maximum iteration count
η_t	The value of g at which cognitive and social behaviour equalizes
μ	Constant
μ_1, μ_2	Coefficients of exponent terms

2.1 Problem Formulation

Cost function of generator is generally quadratic when valve-point loading is not considered. Large turbine generator usually has no. of fuel admissions valve that are operated such that to meet the increased generation. Objective function of MAED is stated as:

$$\text{Minimize } F\left(P_{Gij}\right) = \sum_{i=1}^{M} \sum_{j=1}^{N_{Gi}} \left(a_{ij} + b_{ij} P_{Gij} + c_{ij} P_{Gij}^2\right) + \left|e_{ij} \sin\left(f_{ij}\left(P_{Gij}^{min} - P_{Gij}\right)\right)\right| \quad (1)$$

Subject to following constraints,
Area power balance constraints:
Total power generation of all generators is equal to the demand P_{Di}.

$$\sum_{j=1}^{N_{Gi}} P_{Gij} = P_{Di} + \sum_{m, i \neq m} P_{Tim} \quad i \in \{1, 2, \dots M\} \tag{2}$$

Generator constraints:

$$P_{Gij}^{\min} \leq P_{Gij} \leq P_{Gij}^{\max} \tag{3}$$

Tie-line constraints:

$$-P_{Tim}^{\min} \leq P_{Tim} \leq P_{Tim}^{\max} \tag{4}$$

3 Solutions Technique

3.1 Proposed DPSO

PSO mainly depends on three components, i.e. inertial weight, cognitive and social influence factors.

Each particle velocity and position is updated by the equations that are

$$\begin{aligned}
v_n^{t+1} = {} & W \times v_n^t + e_1 \times c_{1b} \times r_1() \times (p\text{best}_n - x_n^t) + (1 - e_1) \\
& \times c_{1p} \times r_2() \times (x_n^t - p\text{preceding}_n) + e_2 \times c_2 \times r_3() \\
& \times (g\text{best}^t - x_n^t) + e_2 \times c_2 \times r_4() \times (g\text{rms}^t - x_n^t)
\end{aligned}$$

$$S_n^{t+1} = S_n^t + V_n^{t+1} \times \Delta t \tag{5}$$

where Δt is time generally taken as 1 s.

Inertia weight equation is:

$$W = W_{\min} + \frac{(W_{\max} - W_{\min}) \times (\text{itr}_{\max} - \text{itr})}{\text{itr}_{\max}} \tag{6}$$

In proposed DPSO, the inertial weight W is changed by proposing an exponentially decomposed function to check trade-off between overall explorations and ceil exploitation of swarm. The preceding expertise of particle $p\text{preceding}_n$ is taken to enrich the cognitive part by studying just older experience, whereas total experience of group of swarms is embedded in $g\text{rms}^t$ to enrich the social part of particles. Further, dynamic acceleration coefficients have been introduced using constriction functions e_1 and e_2 dynamically to regulate the cognitive and social nature of birds. These modifications are explained below:

- Updating inertia weight: The trend of linear module of inertial weight is succeeded to solve ED problems using PSO by many researchers. In the suggested method,

inertial weight is permitted to vary an exponential decomposed function and module suggested to modernize the inertial weight which is controlled by the following relation:

$$W = e^{(-\eta \ln k_w)}$$
$$k_w = \frac{w_{\min}}{w_{\max}}$$

where $\eta = \text{itr}/\text{itr}_{\max}$ and k_w is selected within minimum and maximum bounds of inertial weight. In this study, value of k_w is proportion of max and min condition of inertial weight.

Updating preceding experience: The cognitive behaviour was split in by considering also the bad experience in addition to good idea of particle and provides certain more diverseness, but it results in poor local exploitation unless supported by a local random search. Therefore in existing method, the plan of preceding experience is evoked where existing fitness of every particle is compared with its fitness value in that preceding iteration, and if it is found less, it will be treated as the preceding experience. The past experience of the random particle produces less variety in comparison with the worst experience resulting in better exploration and exploitation of entire quest space without the aid of any additional local random search or else.

- Updating RMS experience: In PSO, only local and global best positions are transparent to other particles. This poor communication among particles may lead to lack of diversity and thus results in poor performance, especially while dealing with large dimensional problems. One way to improve communication of particles is to add RMS component of all particles' velocities in the measured equation. These results in overall sharing of data and particles gained from the discoveries and older experience of each escort during their search.

- Dynamic regulation of acceleration coefficients: Governance via aid of static acceleration coefficients of social and cognitive nature of particles is done in conventional PSO. It is suggested by many researchers that in order to regulate particle velocity dynamic control must be experienced. In the recent work, with the introduction of two exponential constrictions function e_1 and e_2 acceleration coefficients are made dynamic. The cognitive and social conduct of swarm is regulated by the aid of constriction functions while this regulation is taking place. Velocities of particles are limited during their flight and are as follows:

$$e_1 = e^{(-\mu_1 \eta)}$$
$$e_2 = k \cdot e^{(\mu_2 \eta)}$$
$$k = \frac{e_1 \cdot c_{1b}}{e_2 \cdot c_2}$$

where k is proportion of conducted dynamic cognitive and social acceleration coefficients. For same values of these coefficients at $\eta = \eta_t$.

These variations control the conventional PSO that regulates particles velocity, within predefined limits without any extra formulation is bang in various enhanced performance of PSO, yet preserving variety because of stochastic nature of cognitive and social behaviours of swarm.

The coefficients of the exponents μ_1 and μ_2 are selected as 5 and 3.9, as beyond that the term $e^{-\mu_1\eta}$ is not perceptible in ending of search. Further, the most applicable value of η_t is obtained as 2/3 after experimentations.

Thereafter, performing 1000 independent trials of DPSO we get average fuel cost, and on the basis of this average cost, we obtain optimal solution.

3.2   Methodology of DPSO

The solution of an MAED problem is the set of most optimal generations for the desired objective bounded by certain operational constraints. In the proposed PSO, the particles are encoded in real numbers as the set of current generations in MW, as shown in Figs. 1 and 2.

(a) Particle encoding and initialization: The initial population is randomly created with predefined number of particles to maintain diversity. Each of these particles satisfies the problem constraints already defined. Infeasible particle, whenever appeared, is corrected by employing a constrained handling algorithm as described later in the section. The fitness of each particle is evaluated using Eq. (1), and then *p*best, *p*preceding, *g*best and *g*rms are initialized. The initial velocity of particles is assumed to be zero.

(b) Constrained handling: The velocity and position update may create infeasible solutions. In profound research, constrained handling algorithm is used to correct the infeasible individuals by the help of feasible ones. Using this process, power is adjusted within its limits and tie-line variables as given in Eqs. (2) and (3), respectively. If the generated power is within its min or max generation level, then set it as its lower or higher bound limits as in Eq. (4). Similarly, if the transfer of real tie-line powers from area *i* to area *k* exceeds its limit then the tie-line power is fixed at tie-line limits as mentioned in Eq. (4) for security consideration. The power balance error is calculated by Eq. (2). The error is equally divided among all generators, and the procedure is iterated till it disrates to a predefined mismatch value *e*. In this work, *e* is taken as 0.001.

(c) Solution preservation and termination criterion: In stochastic-based algorithms like PSO, the solution with the good fitness in the present iteration may be lost in the next iteration. Particle with best fitness is *k* hold preserved for upcoming iteration. The algorithm stops when we reached to maximum iteration or all particles converges to a single position.

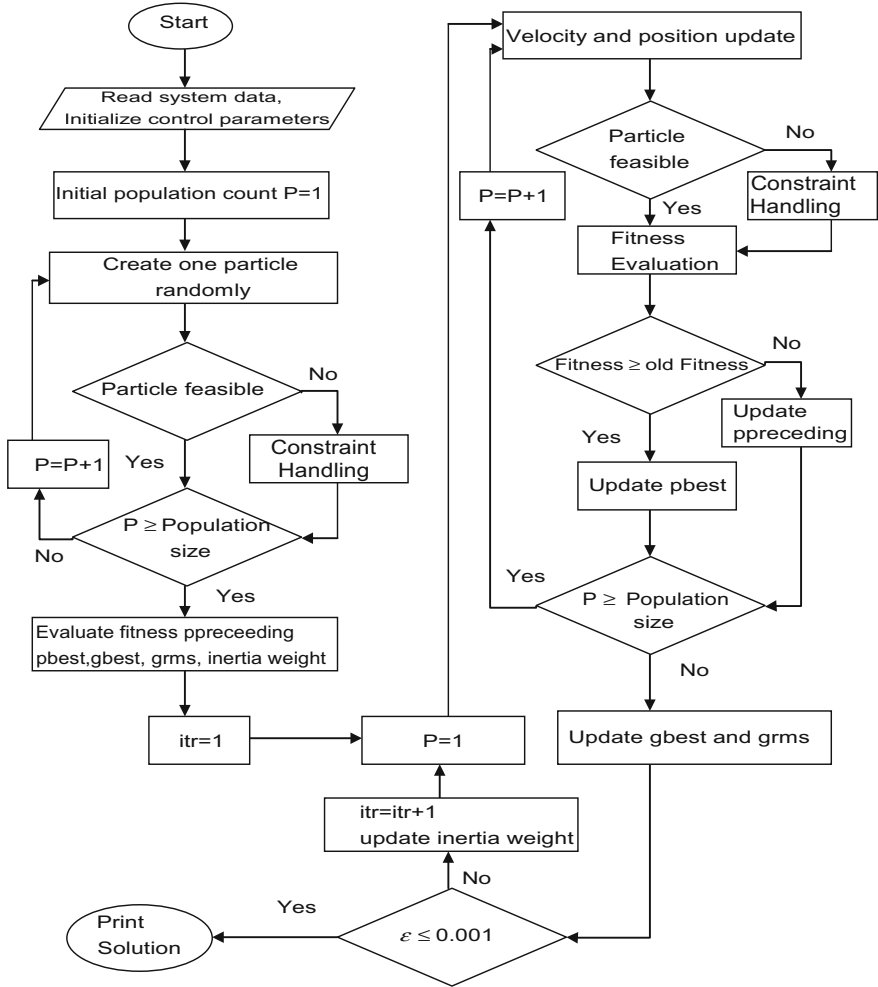| PG11	PG12	…	PG1j	…	PG1N
PG21	PG22	…	PG2j	…	PG2N
…	…	…	….	…	…
PGi1	PGi2	…	PGij	…	PGiN

Particle encoding

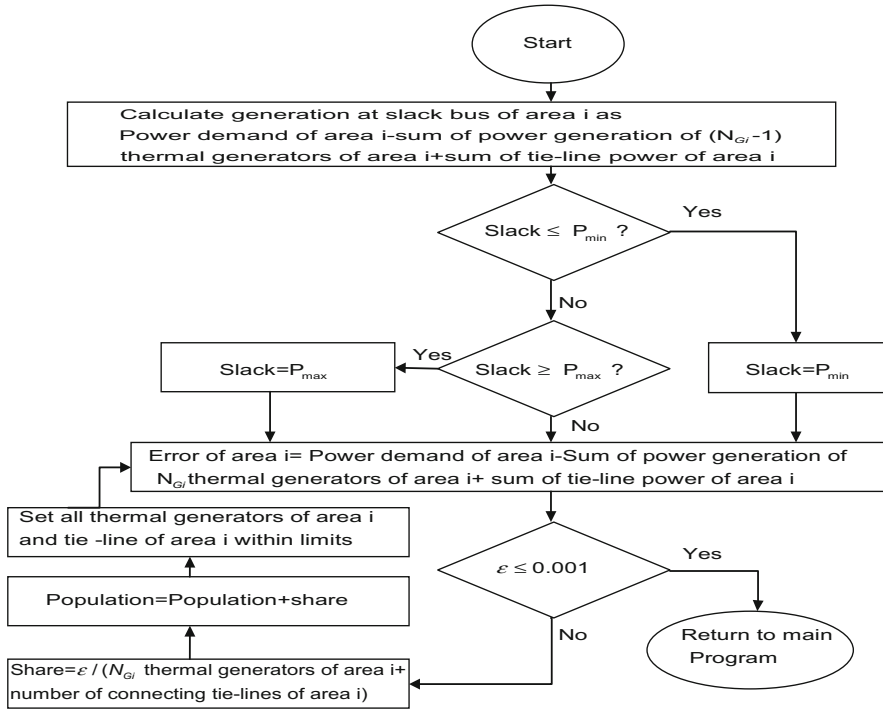**Fig. 1** Flowchart of MAED using DPSO

Fig. 2 Constraint handling algorithm of DPSO

3.3 *Particle Encoding and Initialization Methodology Algorithm*

Step 1: Initialize the control parameters and enter the system data.

Step 2: Initialize new particle randomly.

Step 3: If the current particle is not feasible, run constraint handling algorithm for it.

Step 4: Else go to Step 5.

Step 5: Increase population count by 1. If population count is less than its maximum, go to Step 2.

Step 6: Else go to Step 7.

Step 7: Evaluate fitness by (Eq. 1), pbest, ppreceding,$g$rms, inertia weight, constriction function by Eqs. (5) and (6).

Step 8: Initialize iteration count.

Step 9: Repeat Step 2 and Step 3. Update ppreceding for the current particle. Then repeat Step 5.

Step 10: Update gbest and*g*rms.
Step 11: Increase iteration count by 1. If iteration count is less than its maximum repeat Step 9.
Step 12: Print final results.

4 Test Systems and Results

4.1 Test System 1: Single Area Problem

Test system 1 simply has one area having no tie line. Table 1 shows coefficients of three generators with maximum and minimum limits of power, whereas Table 2 shows cost when demand is varying of test system 1, and its results are compared with classical methods, i.e. lambda iteration method (Fig. 3).

Test system 2 simply has one area having a tie line. Table 3 shows coefficients of four generators with maximum and minimum limits of power, whereas Table 4 shows cost when demand is varying of test system 2, and its results are compared with base paper (Fig. 4; Tables 5, 6, 7 and 8).

Table 1 Cost coefficients of three generators [1]

a	b	c	$P_{\min}$	$P_{\max}$
561	7.92	0.001562	150	600
310	7.85	0.00194	100	400
78	7.97	0.00482	50	200

Table 2 Cost of three generator units according to demand

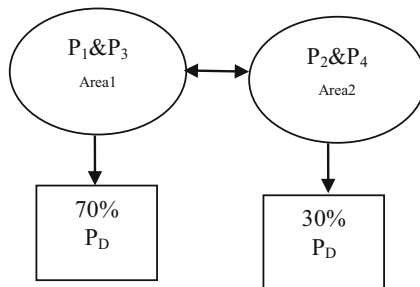| P_D (power demand) (MW)	PSO (Rs/h)	Classical method (Rs/h)
850	8194.4	8194.4
1000	9583.2	9583.1

Fig. 3 Test system 2: two areas, four generator units and a tie line

Table 3 Cost coefficients of four generators

a	b	c	P_{min}	P_{max}
561	7.92	0.001562	150	600
310	7.85	0.00194	100	400
78	7.97	0.00482	50	200
250	7.5	0.00181	70	340

Table 4 Cost of four generator units and its tie-line value

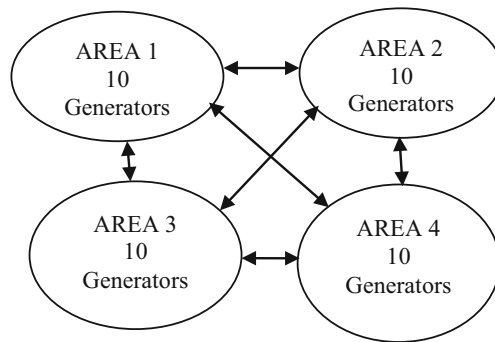| P_D (power demand) (MW)	Tie-line limit (MW)	PSO-TVAC (Rs/h)
1000	200	9520.4
1120	200	10,605

Fig. 4 Test system 3: 4 areas, 40 generation units, 6 tie-lines limit. Each area consists of ten generators with valve-point loading and is connected with three tie lines [7]

Table 5 Results of four generator units and two areas

Power (MW)	$P_D = 1000$ (MW) (PSO-TVAC)	$P_D = 1120$ (MW) (PSO-TVAC)
P_1	381.73	444.95
P_2	195.58	215.93
P_3	118.3	139.05
P_4	304.39	320.07
Tie-line power flow (MW)	199.97	200
CPU time In seconds	0.37159	0.27059

Test system 3 simply has four areas having six tie lines. Table 9 shows power of each generator, whereas Table 11 shows tie-line limit of each area of test system 3, and its results are compared with base paper (Table 10).

Table 6 PSO-TVAC parameters [7]

Parameters	C_1	C_2
Initial value	1.8	0.2
Final value	0.2	1.9

Table 7 Statistical analysis for 25 runs of the system

Method	Average cost (Rs/h)	Best cost (Rs/h)	Worst cost (Rs/h)	Mean time (in sec)	Power violation	Std. dev
PSO-TVAC	10605.144	10,605	10605.34	0.264	0.00	0.077
ABCO [8]	10617.5	10608.6	10664.3	4.35	0.00	27.83

Table 8 Parameters taken into account to deal with test system 3 [8]

Parameters	Value
Total power demand (MW)	10,500
Tie-line limit (MW)	200/100
Area load demand (%)	15/40/30/15
w_{max}	0.9
w_{min}	0.1
c_{1b}	2
c_{1p}	0.5
μ_1	5
μ_2	3.9
η_t	2/3
K	4
itr_{min}/itr_{max}	1/100

4.2 Convergence Curve of Test System 3
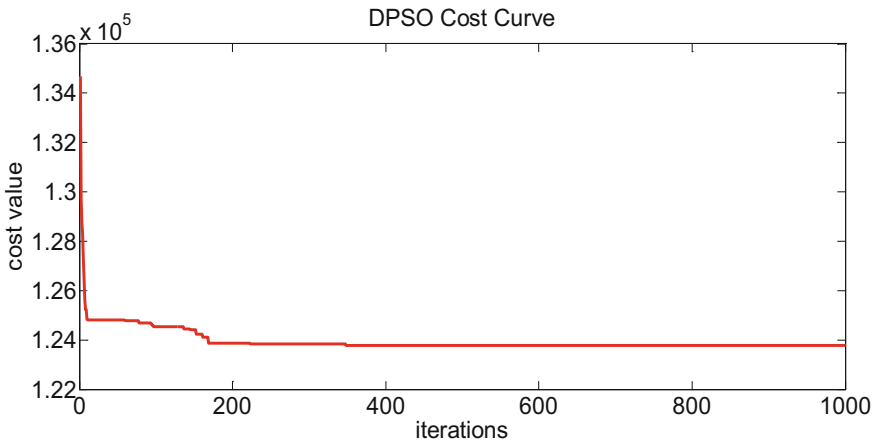
Table 9 Results of power of 40 generators by DPSO

Gen	DCPSO (MW)	Gen	DCPSO (MW)
P_1	110.5595	P_{21}	523.1689
P_2	110.5595	P_{22}	523.1689
P_3	116.5595	P_{23}	523.1689
P_4	186.5595	P_{24}	523.1689
P_5	93.5595	P_{25}	523.1689
P_6	136.5595	P_{26}	523.1689
P_7	260.2644	P_{27}	10
P_8	296.5595	P_{28}	10
P_9	296.5595	P_{29}	10
P_{10}	93.5595	P_{30}	47
P_{11}	94	P_{31}	190
P_{12}	94	P_{32}	190
P_{13}	125	P_{33}	190
P_{14}	486.610	P_{34}	168.744
P_{15}	486.610	P_{35}	168.744
P_{16}	486.610	P_{36}	168.744
P_{17}	486.610	P_{37}	110
P_{18}	486.610	P_{38}	110
P_{19}	536.610	P_{39}	110
P_{20}	536.610	P_{40}	320.744

Table 10 Statistical analysis for 25 runs of the system

Method	Average cost (Rs/h)	Best cost (Rs/h)	Worst cost (Rs/h)	Mean time (in sec)	Power violation
DCPSO	123790.9	123599.2	123,935	114.21	0.000
ABCO [8]	–	124009.4	–	126.934	0.000
DE	–	124544.1	–	134.8	0.000
EP	–	124574.5	–	144.5	0.000
RCGA	–	129911.8	–	160.5	0.000

Table 11 Tie-line results of test system 3 in both DCPSO

Tie-line limit (MW)	By DCPSO (MW)
1–2	107.5098
1–3	47.4277
1–4	7.8029
2–3	−186.610
2–4	−86.61
3–4	−73.1689

5 Conclusion

The conditions of today's market require the complex network to be considered as a set of separated, but interconnected areas and case are also very complex as it is characterized with huge number of networks, constraints, tie lines and loads. The research is successful in establishing a reliable, an efficient and fast heuristic search technique, DPSO and OPF to unravel MAED problems. The results obtained are substantially better both in the terms of cost and CPU time. MAED problem if high dimensional (as in the present case) also suffers with the case of local trappings when solved using any population-based algorithm. But as DPSO has improved the results significantly from the previous best results of powers, hence the problem is of high dimensionality and local trappings are assumed to be mitigated. The presented work can be extended to a larger problem of MAED which can further establish the validity of the present work and the DPSO technique. In future, the DPSO technique can be further modified within itself or it can be merged with another optimization technique, classical or meta-heuristic or otherwise, so that it further reduces the gap of obtained results and global best results which are not established as of now.

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