J. Inst. Eng. India Ser. B (April 2017) 98(2):221–229
DOI 10.1007/s40031-016-0248-2

ORIGINAL CONTRIBUTION

Large Scale Multi-area Static/Dynamic Economic Dispatch using Nature Inspired Optimization

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Received: 11 December 2013 / Accepted: 4 July 2016 / Published online: 21 July 2016

Abstract Economic dispatch (ED) ensures that the generation allocation to the power units is carried out such that the total fuel cost is minimized and all the operating equality/inequality constraints are satisfied. Classical ED does not take transmission constraints into consideration, but in the present restructured power systems the tie-line limits play a very important role in deciding operational policies. ED is a dynamic problem which is performed on-line in the central load dispatch centre with changing load scenarios. The dynamic multi-area ED (MAED) problem is more complex due to the additional tie-line, ramp-rate and area-wise power balance constraints. Nature inspired (NI) heuristic optimization methods are gaining popularity over the traditional methods for complex problems. This work presents the modified particle swarm optimization (PSO) based techniques where parameter automation is effectively used for improving the search efficiency by avoiding stagnation to a sub-optimal result. This work validates the performance of the PSO variants with traditional solver GAMS for single as well as multi-area economic dispatch (MAED) on three test cases of a large 140-unit standard test system having complex constraints.

Keywords Nature inspired techniques · Constrained non-linear optimization · Modified PSO · Premature convergence · Static/dynamic economic dispatch · Ramp-rate limits · Transmission constraints

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Introduction

Power utilities have acquired a highly competitive status, particularly in generation and in the marketing of electricity. The ED aims to dispatch the committed generating units, such that, the operating cost if minimized while all the operating constraints are satisfied. In multi-area power systems the fuel cost of a pool can be decreased by importing power from areas having cheaper generating units. In such cases, the cost will depend on area-exchange agreements, characteristics of a pool, the policies adopted by utilities, types of interconnections, tie-line limits and load demands in individual areas. Transmission limits have a very significant role in deciding the cost of operation and in maintaining reliability. The traditional economic dispatch problem is normally solved without including the tie-line limits. The added tie-line constraints and area power balance requirements make the MAED problem more difficult to solve as compared to the conventional ED problem. This paper aims to formulate the ED problem with tie-line constraints and to analyze the effect of area loads and tie-line limits on the optimal operating cost for large multi-area power systems.

A complete formulation of multi-area generation was presented [1]. Desell, et al. [2] proposed an application of LP and Farmer, et al. [3] presented a probabilistic method. Hopfield neural network based approach was also proposed to solve the MAED problem [4]. MAED problem by using spatial dynamic programming with linear losses has been solved [5]. Linear programming [6] and decomposition approach by Shahidehpour [7] also addressed this problem.

These days nature inspired (NI) optimization methods are becoming very popular due to their ability to solve discontinuous and non-convex optimization problems in a very simple manner. The other advantages of NI techniques as compared to the traditional solvers are (i) non-dependence on nature of objective function, (ii) effective constraint handling, and (iii) population based powerful parallel search capability. Over the last few years many new NI methods like PSO [8, 9], differential evolution (DE) [10], bacterial foraging (BF) [11, 12], biogeography based optimization (BBO) [13], and artificial bee colony optimization (ABC) [14] have been proposed for solving complex economic load dispatch problems.

Recently and group search optimizer [15] and hybrid methods [16, 17] which combine evolutionary and swarm intelligence based techniques are also proposed. A series hybrid of PSO and DE can be found [17]. DE based on Lévy-flights has been proposed to improve convergence [18]. Multiobjective evolutionary approaches for optimizing cost and emission simultaneously are also available [19–22].

Many improved techniques based on parameter automation [8–10, 12] and hybridization of two methods [11, 16–18] are seen to enhance the performance. Iterative tuning of parameters and randomization of velocity vector [8] and introduction of additional operators [9] are used in PSO to prevent stagnation. In [10] a comparison of DE strategies for the MAED problem is carried out and some time-varying DE variants are proposed. Hybridization of BF with Nelder-Mead method [11] and an improved BF algorithm [12] with crossover and chaotic variation of step size is proposed to improve performance.

A traditional method General Algebraic Modeling System (GAMS) has been effectively used for large scale ED problems without considering practical multi-area operation [23]. For large dimensional problems the nature inspired optimization techniques may sometimes converge to near-global solutions due to saturation and premature convergence. The present paper proposes some modified PSO variants where a tuning of cognitive and social coefficient is carried out to improve global search. Static/dynamic MAED is solved for three test systems having different complexity levels. The performance is validated using NLP solver in GAMS and some recently published results from literature.

Multi-area Static/Dynamic Economic Dispatch

The objective of the economic dispatch problem is to determine the generated powers P_i of units for a total load of P_D so that the total fuel cost, F_T for the N number of generating units is minimized subject to the power balance constraint and unit upper and lower operating limits. The objective is to minimize $\sum_q^M \sum_i^{Nq} F_{iq}(P_{iq})$ subject to the following equality and in equality constraints given below. Here F_{iq} is the total fuel cost for the ith generator in qth area defined by [8–10],

$$F_{iq}\left(P_{iq}\right) = a_{iq}P_{iq}^2 + b_{iq}P_{iq} + c_{iq} + \left|e_{iq} \times \sin\left(f_{iq} \times \left(P_{iq}^{\min} - P_{iq}\right)\right)\right| \tag{1}$$

where a_{iq}, b_{iq}, c_{iq}, e_{iq} and f_{iq} are the fuel-cost coefficients.

Equality Constraints

Area-Wise Power Balance Constraint

In MAED problem the power balance constraints need to be satisfied for each area. The power balance constraints for area q can be given as [10]

$$\sum_{i=1}^{N_q} P_{iq} - \left(P_{Dq} + \sum_{j}^{M_q} T_{jq} - P_{qL}\right) = 0, \quad \text{such that } j \neq q \tag{2}$$

For the qth area, P_{Dq} is the load; P_{qL}, the power loss; T_{jq}, the tie-line flows from other areas; N_q, the number of generating units; and M_q is the count of tie-lines connected to the qth area.

Transmission Losses

The transmission losses using the B-loss coefficients is expressed as [24]

$$P_{qL} = \sum_{i=1}^{N}\sum_{j=1}^{N} P_{iq}B_{ij}P_{jq} + \sum_{i=1}^{N} B_{oi}P_{iq} + B_{oo} \tag{3}$$

Inequality Constraints

Unit Operating Limits Constraint

The output of the ith generating unit should lie within the minimum and maximum operating limits as given by

$$P_{iq}^{\min} \le P_{iq} \le P_{iq}^{\max}; \quad i = 1, 2, \ldots, N_q; \quad \text{for all } q \tag{4}$$

Unit Ramp-Rate Limit Constraints

When the generator ramp rate limits are considered, the operating limits are modified as follows:

$$\max\left(P_{iq}^{\min}, P_{iq}^{o} - DR_{iq}\right) \le P_{iq} \le \min\left(P_{iq}^{\max}, P_{iq}^{o} + UR_{iq}\right) \tag{5}$$

The previous operating point of ith generator in qth area is P_{iq}^{o} and DR_{iq} and UR_{iq} are the down and up ramp-rate limits, respectively.

Dynamic Economic Dispatch

Dynamic economic dispatch deals with sharing the system load including system losses among the available generators in such a way that all equality and inequality constraints are met and the cost of operation is minimized for each time interval 't' in a time period T such that $\sum t = T$. In order to solve dynamic load dispatch problem, ramp-rate limit must be considered. The dynamic economic dispatch (DED) model can be described as follows:

$$\begin{cases} \min F = \sum_{t}^{T} \sum_{q}^{M} \sum_{i=1}^{N_q} F_{iq}\left(P_{iq}(t)\right) \\ \sum_{i=1}^{N_q} P_{iq}(t) = P_{Dq}(t) + P_{Lq}(t) \\ P_{iq\min} \le P_{iq}(t) \le P_{iq\max} \\ -DR_{iq} \le P_{iq}(t) - P_{iq}(t-1) \le UR_{iq} \end{cases} \tag{6}$$

PSO Variants

A number of different PSO strategies are being applied by researchers for solving the ED and other power system problems. Here, a short review of the PSO variants is presented.

Classical PSO

The PSO [25] is a population based NI method inspired by the movement of a flock of birds searching for food. It is a simple and powerful optimization tool which scatters random particles into the problem space. The particles represent the various random solutions of the optimization problem. The position and velocity vectors of the ith particle of a d-dimensional search space can be represented as

$$X_i = (x_{i1}, x_{i2}, \ldots, x_{id}); \quad V_i = (v_{i1}, v_{i2}, \ldots, v_{id}) \tag{7}$$

The best prior location of a particle is stored as $p\text{best}_i = (p_{i1}, p_{i2}, \ldots, p_{id})$. If the gth particle is the best among all particles in the group so far, it is represented as $p\text{best}_g = g\text{best} = (p_{g1}, p_{g2}, \ldots, p_{gd})$. The updated velocity and location of each particle for fitness evaluation in the next, that is, $(k+1)$th iteration are calculated using the following equations [25]:

$$\begin{aligned} v_{id}^{k+1} = {} & [w \times v_{id}^{k} + c_1 \times \text{rand}_1 \times (p\text{best}_{id} - x_{id}) + c_2 \\ & \times \text{rand}_2 \times (g\text{best}_{gd} - x_{id})] \end{aligned} \tag{8}$$

$$x_{id}^{k+1} = x_{id} + v_{id}^{k+1} \tag{9}$$

The global and local search capabilities of the particle are controlled by w, the inertia weight parameter, constriction factor is C, the cognitive and social coefficients are c_1, c_2, respectively, and $\text{rand}_1, \text{rand}_2$ are random numbers between 0 and 1. The inertia weight w is modified with time as given by

$$w = (w_{\max} - w_{\min}) \times \frac{(\text{iter}_{\max} - \text{iter})}{\text{iter}_{\max}} + w_{\min} \tag{10}$$

where $\text{iter}_{\max}$ is the maximum number of iterations. Constant c_1 pulls the particles towards local best position whereas c_2 pulls it towards the global best position.

PSO with Chaotic Inertia Weight (PSO_CIW)

The weight w (11) is changed iteratively in chaotic fashion by making use of the logistic map as given by

$$w(t) = \mu \times w(t-1) \times [1 - w(t-1)] \tag{11}$$

Here μ is a control parameter between 0–4. A very small difference in $w(0)$ causes significant difference in its variation pattern. The system at Eq. (11) displays chaotic behavior when $\mu = 4$ and $w(0) \notin \{0, 0.25, 0.5, 0.75, 1.0\}$.

PSO with Chaotic Acceleration Coefficients (PSO_CAC)

In the proposed PSO_CAC approach the cognitive coefficient c_1 is reduced from an initial value c_{1i} to a final value c_{1f} while the social coefficient c_2 is increased chaotically from an initial value c_{2i} to c_{2f} using the following dynamics:

$$cx_1(t) = \mu \times cx_1(t-1) \times [1 - cx_1(t-1)] \tag{12}$$

$$c_1(t) = \left[(c_{1f} - c_{1i}) \frac{\text{iter}}{\text{iter}_{\max}} + c_{1i} \right] cx_1(t) \tag{13}$$

$$cx_2(t) = \mu \times cx_2(t-1) \times [1 - cx_2(t-1)] \tag{14}$$

$$c_2(t) = \left[(c_{2f} - c_{2i}) \frac{\text{iter}}{\text{iter}_{\max}} + c_{2i} \right] cx_2(t) \tag{15}$$

Time Varying PSO (PSO_TVAC)

In population-based optimization methods, the policy is to encourage exploration during initial search and exploitation as the solution approaches convergence. In PSO_TVAC the cognitive component is decreased and the social component is increased as shown in Fig. 1. The acceleration coefficients are expressed as [8, 26]:

$$c_1 = (c_{1f} - c_{1i}) \frac{\text{iter}}{\text{iter}_{\max}} + c_{1i} \tag{16}$$

$$c_2 = (c_{2f} - c_{2i}) \frac{\text{iter}}{\text{iter}_{\max}} + c_{2i} \tag{17}$$

where c_{1i}, c_{1f}, c_{2i} and c_{2f} are initial and final values of cognitive and social acceleration factors, respectively.

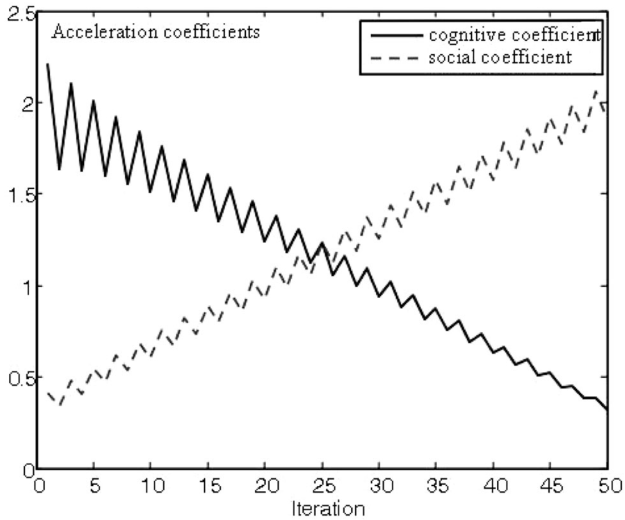

Fig. 1 Cognitive and social coefficients in PSO_CAC for $\mu = 3$, c_1, c_2 $(t = 0) = 0.48$

Improved Search through Parameter Automation

The above PSO variants are designed to improve search by better control of the swarm as compared to classical PSO which has fixed value of w, c_1 and c_2. In PSO_CIW the inertia weight which reflects the previous position of the swarm is varied chaotically to increase population diversity. In PSO_CAC and PSO_TVAC, during the initial search, exploration of the swarm is encouraged; as solution trajectory nears convergence, exploitation is strengthened.

Static/Dynamic MAED Solution using Modified PSO Variants

The flow chart of the proposed PSO variants for solving static/dynamic MAED problem is given in Fig. 2.

Generation of the Initial Population

A population of feasible solutions is randomly generated between the lower/upper bounds.

Evaluation of Swarm Population

A fitness function is used to judge the merit of each population. This function converts the constrained problem into unconstrained problem by using penalty function method. This approach minimizes cost and achieves constraint satisfaction as shown.

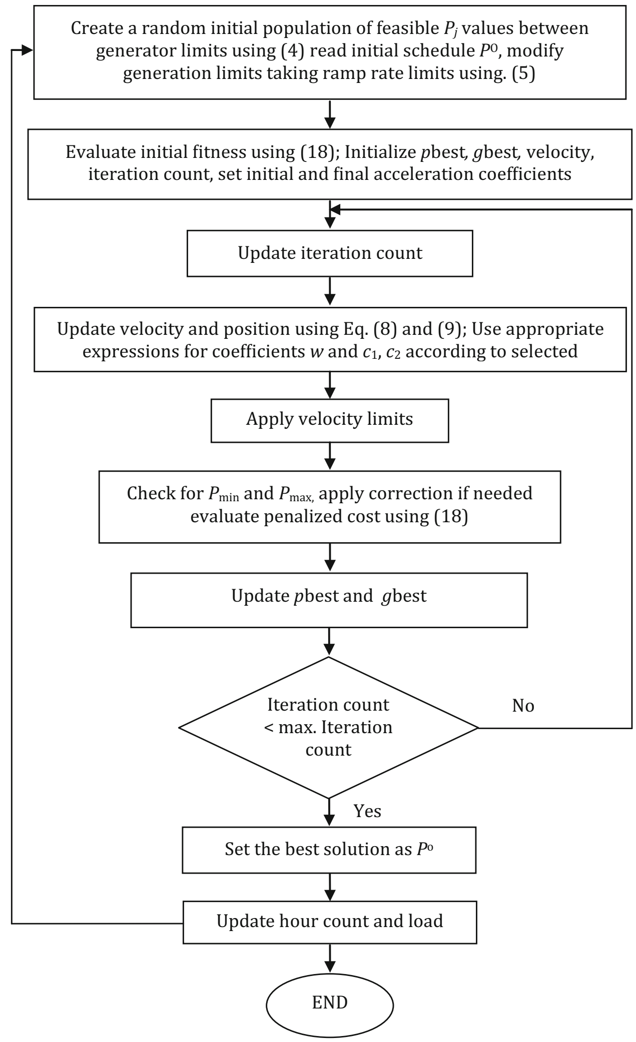

Fig. 2 Flow chart of proposed PSO variants for static/dynamic MAED solution

$$\min \sum_{t}^{T} \sum_{q}^{M} \sum_{i=1}^{N_q} F_{iq}\left(P_{iq}(t)\right) + \sum_{q=1}^{M} \alpha_q \left[\sum_{i=1}^{N_q} P_{iq}(t) - \left(P_{Dq}(t) + \sum_{j}^{M_q} T_{jq}(t) \right) \right]^2 \quad (18)$$

For the static dispatch consists of solution of any one time period, that is, for fixed t.

Results and Discussion

Simulations were carried out using MATLAB 7.0.1 on a Pentium IV processor, 2.8 GHz. with 1 GB RAM.

Details of the Test Cases

The large dimensional test cases are described below. For the sake of comparison with available results, transmission losses and cost of tie-line power flow are neglected.

(i) Test Case I: This is a large 140-unit system taken from [9] with ramp rate limits supplying a load of 49342 MW. The best cost reported is $1655685/h. The PSO variants have obtained slightly lower cost which is reported in Table 1. The results are compared

Table 1 Performance comparison of PSO variants for Test Case I

Variant	Classical PSO	PSO_CIW	PSO_CAC	PSO_TVAC	GAMS	IPSO [9]	HEE [17]
Best Cost, $/h	1666442.1002	1655679.9621	1655679.80621	**1655677.8509**	**1655677.8509**	1655685.00	1655679.4116

Bold values indicate the best results

Table 2 Best result of PSO_TVAC method (Test Case I)

Unit	Output, MW	Unit	Output, MW	Unit	Output, MW	Unit	Output, MW
P1	119.000	P36	500.000	P71	141.585	P106	880.900
P2	164.000	P37	241.000	P72	365.908	P107	873.700
P3	190.000	P38	241.000	P73	195.000	P108	877.400
P4	190.000	P39	774.000	P74	217.549	P109	871.700
P5	190.000	P40	769.000	P75	217.549	P110	864.800
P6	190.000	P41	003.000	P76	258.663	P111	882.000
P7	490.000	P42	003.000	P77	403.245	P112	094.000
P8	490.000	P43	250.000	P78	330.000	P113	094.000
P9	496.000	P44	250.000	P79	531.000	P114	094.000
P10	496.000	P45	250.000	P80	531.000	P115	244.000
P11	496.000	P46	250.000	P81	542.000	P116	244.000
P12	496.000	P47	250.000	P82	056.000	P117	244.000
P13	506.000	P48	250.000	P83	115.000	P118	095.000
P14	509.000	P49	250.000	P84	115.000	P119	095.000
P15	506.000	P50	250.000	P85	115.000	P120	116.000
P16	505.000	P51	165.000	P86	207.000	P121	175.000
P17	506.000	P52	165.000	P87	207.000	P122	002.000
p18	506.000	P53	165.000	P88	175.000	P123	004.000
P19	505.000	P54	165.000	P89	175.000	P124	015.000
P20	505.000	P55	180.000	P90	180.424	P125	009.000
P21	505.000	P56	180.000	P91	175.000	P126	012.000
P22	505.000	P57	103.000	P92	575.400	P127	010.000
P23	505.000	P58	198.000	P93	547.500	P128	112.000
P24	505.000	P59	312.000	P94	836.800	P129	004.000
P25	537.000	P60	308.589	P95	837.500	P130	005.000
P26	537.000	P61	163.000	P96	682.000	P131	005.000
P27	549.000	P62	095.000	P97	720.000	P132	050.000
P28	549.000	P63	511.000	P98	718.000	P133	005.000
P29	501.000	P64	511.000	P99	720.000	P134	042.000
P30	499.000	P65	490.000	P100	964.000	P135	042.000
P31	506.000	P66	256.826	P101	958.000	P136	041.000
P32	506.000	P67	490.000	P102	947.900	P137	017.000
P33	506.000	P68	490.000	P103	934.000	P138	007.000
p34	506.000	P69	130.000	P104	935.000	P139	007.000
P35	500.000	P70	294.562	P105	876.500	P140	026.000
				Power balance violation			**0.0000**
Cost, $/h		**1655677.8509**					

Bold values indicate the best results

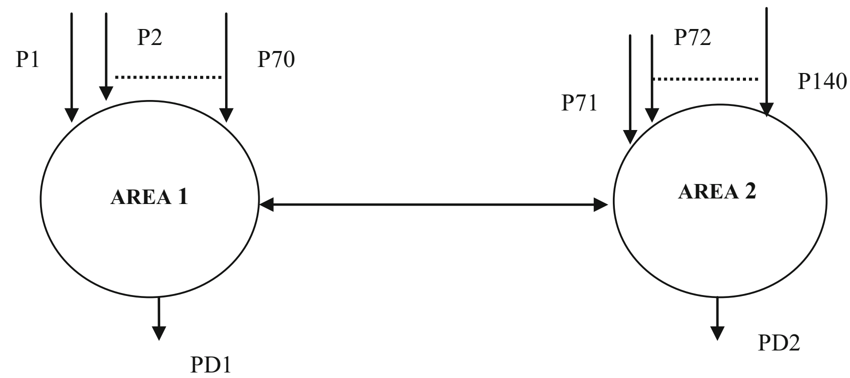

Fig. 3 Block diagram of large two-area 140 unit system

with [9, 17]. For the non-convex case the PSO_TVAC obtained \$1657962.7130 whereas [18] the reported cost is \$1657962.7166 which are very close.

The optimal dispatch results for all 140-units are given in Table 2.

(ii) Test Case II: For multi-area operation the above 140-unit system is divided into two areas having 70 generators in each area. The block diagram of this system is given in Fig. 3. Optimal cost is computed for (i) different area load demands and (ii) different tie-line limits using the proposed PSO variants.
(iii) Test Case III: Dynamic economic dispatch is carried out for 24-h load schedule for the 140-unit single-area system, that is, Test Case I.

Parameter Setup for PSO Variants

For all PSO variants the population size was taken as 100 and number of iterations was set at 1000 for all test cases. For classical PSO both c_1 and c_2 were fixed at 2, for variants the initial and final acceleration coefficients were taken as 2.5 and 0.5, respectively. The best results are taken out of 50 trials, each with different initial populations. This is because PSO family comes under random search methods which converge to near global solutions in every run.

Figure 4 shows the final convergence for Test Case I. All there PSO variants can be seen to converge fast but the performance of PSO_TVAC was found to be the best as it produces a better solution closely followed by PSO_CAC. The performance of PSO_CIW is inferior to these two variants because the acceleration coefficients c_1 and c_2 play a more significant role in locating the new position of the swarm as compared to the inertia weigh w. Therefore effective control of these parameters gives an improved solution.

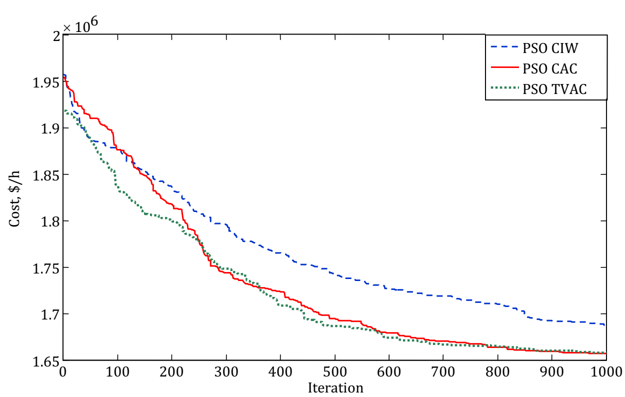

Fig. 4 Comparison of convergence characteristics of PSO variants for Case I

Effect of Tie-Line Limits and Load Variation on Optimal Cost in MAED

The performance of best performing variant PSO_TVAC is given in Tables 3 to 5. Traditional GAMS method also produced the same costs for the different cases. For the Test Case II, that is, two-area, 140-unit large system (total load PD = 49342 MW) three different load variation cases are taken.

Case (i) PD1 = 32072 (65 %), PD2 = 17270 (35 %)

Table 3 Performance of PSO_TVAC with tie-limit variation for Test Case II; load Case (i)

Tie-line, MW	Tie-line flow, MW	Total cost, \$	Violation
7000	**−6397.023**	**1655677.8509**	**0.0000**
6500	−6397.023	1655677.8509	0.0000
6000	−6000.00	1655941.6841	0.0010
5500	−5500.00	1657796.9981	−0.0020
5000	−5000.00	1672916.8956	−0.0010
4000	−4000.00	1735193.2735	0.000
<4000	Infeasible solution/non convergence		

Bold values indicate the best results

Table 4 Performance of PSO_TVAC with tie-limit variation for Test Case II; load Case (ii)

Tie-line limit, MW	Tie-line flow, MW	Optimal cost, $	Violation
9000	**−8864.023**	**1655677.8509**	**0.0000**
8500	−8500	1655915.2398	−0.0020
8000	−8000	1657468.0112	−0.0010
7000	−7000	1694565.6463	−0.0010
6000	−6000	1772418.7348	0.0000
<6000	Infeasible solution/non convergence		

Bold values indicate the best results

Table 5 Performance of PSO_TVAC with tie limit variation for Test Case II; load Case (iii)

Tie-line, MW	Tie-line flow, MW	Total cost, $	Violation
14000	**−13800**	**1655677.8509**	**0.0000**
13500	−13500	1655865.1388	0.0000
13000	13000	1657046.0525	0.0010
12000	−12000	1689872.8249	−0.0020
11000	−11000	1767121.4149	−0.0010
<11000	Infeasible solution/non convergence		

Bold values indicate the best results

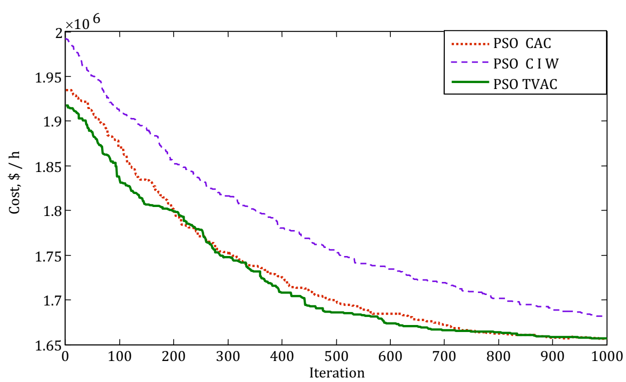

Fig. 5 Comparison of convergence characteristics of PSO variants for Case II

The results for this study are given in Table 3. For tie-line limit less than 4000 MW the system did not converge. Then, with increase in tie-line capacity the cost reduced as cheaper area 2 units transfer power to area 1 having costlier generators. The optimal tie-line flow was found to be 6397.023 MW. The convergence characteristics of the three PSO variants are compared in Fig. 5. The convergence behavior of PSO_TVAC is found to be superior but the other two variants also depict a stable convergence.

Case (ii) PD1 = 34539 (70 %), PD2 = 14803 (30 %)

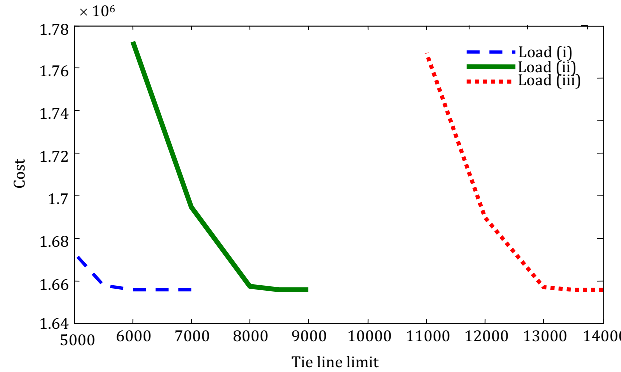

Fig. 6 Effect of load and tie-limit variation on optimal generation cost for multi-area system

Table 4 gives the results where area 1 load is increased to 70 % and tie-line limit is changed from 6000 to 9000 MW. For tie-line limit less than 6000 MW the system did not converge. For tie-line capacity 9000 MW and beyond, there is no reduction in cost as the optimal tie-line between area 1 and area 2 was found to be 8864.023 MW. The optimal cost of generation matched with the cost of operation for single area case for this tie-line limit.

Case (iii) PD1 = 39474 (80 %), PD2 = 9868 (20 %)

Table 5 presents the results for this case where tie-line limit is changed from 11000 to 14000 MW. The effect of variation of area load and tie-line on the optimal cost of the 140-unit multi-area system is summarized in Fig. 6.

Dynamic Economic Dispatch

In practical economic dispatch problems the generator ramp rate limits (up limits and down limits) play a very important role in finding the optimal schedule because practical generators have to follow these constraints while increasing/decreasing their power output. The results are tabulated in Table 6 for Test Case III.

Comparison of PSO Variants

For validation, the results are compared to GAMS for convex functions. The time taken by the three PSO variants is almost comparable as shown in Table 7. However, GAMS is faster, as it is a gradient based approach. But PSO is a random search method capable of optimizing non-differentiable objective functions also, whereas GAMS is unable to solve such cases [9, 17]. Due to their non dependence on nature of objective function, the nature inspired optimization methods such as PSO have an edge over traditional solvers like GAMS which are incapable for discontinuous or non-convex objective functions.

Table 6 Results of optimal dynamic dispatch for 140-unit system using PSO_TVAC (Test Case III)

Hour	Load, MW	Cost, \$/h	Hour	Load, MW	Cost, \$/h
1	49342	1655677.8509	13	60150	2418030.4307
2	49842	1661447.3510	14	58990	2300414.0502
3	50542	1662124.5121	15	57900	2201725.5755
4	50802	1664263.2533	16	56800	2107186.0608
5	51000	1674451.2603	17	54850	1951070.2148
6	52000	1744998.2215	18	52970	1814342.6930
7	53000	1816490.9740	19	51870	1735744.5826
8	55000	1962446.1948	20	50875	1672168.7649
9	57000	2123991.5313	21	50700	1652649.8375
10	58000	2210510.3624	22	50400	1531388.2063
11	59000	2301132.0366	23	49820	1590674.6277
12	60250	2434159.9030	24	49300	1554575.6590

Table 7 CPU time comparisons of PSO variants

Test Case	PSO_CIW, s	PSO_CAC, s	PSO_TVAC, s
Test Case I	13628.01	13638.06	13632.56
Test Case II	13634.02	13648.04	13642.23
Test Case III	327312.21	327325.07	327318.11

Conclusions

Generally the PSO algorithms experience the problem of untimely stagnation and early convergence which prohibits them in locating the global optimum solution. The proposed PSO variants employ powerful parameter automation strategies which prevent early convergence to local optimal results. The performance of these variants is tested on a large system under both static/dynamic conditions and validated using traditional solver GAMS. The test results clearly show that

- All three proposed variants achieve significantly better results as compared to the classical PSO for a large single as well as multi-area power system.
- The PSO variants are able to handle complex equality/inequality constraints like generation limits, area-wise power balance and ramp rate limits effectively under all static as well as dynamic test conditions.
- The variation of optimal tie line capacity with changing load demands was also computed and analyzed. By increasing the tie-line flow limit cost can be significantly reduced.
- The three PSO variants were capable of handling ramp rate constraints also for computing optimal dynamic dispatch solution.
- All three variants are shown to have a stable convergence characteristic. On comparison, PSO_TVAC is found to have better performance consistently for all cases.

Acknowledgment The authors sincerely acknowledge the financial support provided by University Grant Commission (UGC), New Delhi, India under major research project entitled Power System Optimization and Security Assessment using Soft Computing Techniques, vide F No. 34-399/2008 (SR) dated, December 24, 2008. The authors also thank Madhav Institute of Technology and Science, Gwalior for providing facilities for carrying out this work. The first author acknowledges UGC research award for post doctoral work sanctioned by UGC, New Delhi vide letter no. F-30-120(SC)/2009 (SA-II).

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