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Time-varying acceleration coefficients IPSO for solving dynamic economic dispatch with non-smooth cost function

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ABSTRACT

The objective of the dynamic economic dispatch (DED) problem is to schedule power generation for the online units for a given time horizon economically, satisfying various operational constraints. Due to the effect of valve-point effects and prohibited operating zones (POZs) in the generating units cost functions, DED problem is a highly non-linear and non-convex optimization problem. The DED problem even may be more complicated if transmission losses and ramp-rate constraints are taken into account. This paper presents a novel and heuristic algorithm to solve DED problem of generating units, by employing time varying acceleration coefficients iteration particle swarm optimization (TVAC-IPSO) method. The effectiveness of the proposed method is examined and validated by carrying out extensive tests on different test systems, i.e. 5-unit and 10-unit test systems. Valve-point effects, POZs and ramp-rate constraints along with transmission losses are considered. To examine the efficiency of the proposed TVAC-IPSO algorithm, comprehensive studies are carried out, which compare convergence properties of the proposed TVAC-IPSO approach with conventional PSO algorithm, in addition to the other recently reported approaches. Numerical results show that the TVAC-IPSO method has good convergence properties and the generation costs resulted from the proposed method are lower than other algorithms reported in recent literature.

1. Introduction

DED is an extension of the static economic dispatch (SED) problem. SED problem determines the economical combination of generators' production to satisfy a predicted single load demand at a specified hour. Due to large load variation in power system, SED may fail to satisfy generator operation constraints like as ramp-rates. Furthermore, when considering a time horizon instant of a time instance, the results of SED will not be optimal due to look-ahead incapability [1]. The main objective of the DED is to minimize the total generation cost while satisfying equality constraints, inequality constraints and dynamic constraints. Load demand balance is an equality constraint, prohibited operating zone (POZ) constraints and generation capacity limits are inequality constraints and ramp rate limit is a dynamic constraint. Considering dynamic constraints make the solution of DED problem more complicated. To overcome the complication of dynamic constraint handling, DED problem has been considered as a sequential SED problem [2] and ramp rate limits are enforced between the sequential hours. However, This method results in a local optimal solution [1]. Considering the effect of valve-points (due to the existence of multiple steam admitting valves) in generator cost function make the DED problem non-convex and more nonlinear optimization problem [3].

A lot of optimization methods including classical and metaheuristic algorithms have been applied to solve DED problem and obtain higher economic benefit, over the recent years. Due to non-convexity of the DED problem, application of classical methods like as Lagrangian relaxation approach [4] and dynamic programming [5] are restricted [6]. Maclaurin series (MLS) approximation has been applied to model the valve-point effects [7,8] and it has been observed that this method leads to non-optimal solution with great economic loss. Lower solution time is the main advantage of MLS in comparison with stochastic search methods.

In order to overcome the drawback of mathematical methods in solution of DED problem, many iterative stochastic search methods have been employed to solve DED problem with practical modeling of operation constraints. These methods did not enforce any restriction on the shape of the generator cost functions. Genetic algorithm is one of the pioneering stochastic search methods that has been applied to solve DED problem [9]. An improved pattern search algorithm used in [10] for solving DED problem and dynamic emission economic dispatch. Improved chaotic particle swarm optimization (ICPSO) algorithm is proposed in [11] to solve

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DED with value-point effects. Artificial bee colony algorithm [6], artificial immune system method [12], hybrid artificial immune systems and sequential quadratic programming (AIS-SQP) [13], particle swarm optimization (PSO) and its variants [14–16], covariance matrix adapted evolution strategy algorithm [17], differential evolution (DE) algorithm and its variants [18–24], multiple tabu search algorithm [25], simulated annealing algorithm [26], hybrid evolutionary programming (EP) and SQP method [27,28], hybrid swarm intelligence based harmony search algorithm [3], hybrid approach of Hopfield neural network (HNN) and quadratic programming (QP) [29,30] and hybrid PSO and SQP [31] have been employed to solve DED problem in recent years.

In this paper a novel time varying acceleration coefficients iteration PSO method (TVAC-IPSO) is proposed to solve non-convex DED problem with considering operation constraints. Local and global search ability in PSO algorithm are controlled using two stochastic acceleration components known as cognitive component and social component, respectively. Assuming constant values (usually 2) for these components may lead to premature convergence [32]. Tuning relative values of cognitive and social components plays important role in solution quality of the PSO. Many researches have been carried out to find the best combination of these components [33,34]. The TVAC structure leads to a proper balance between the cognitive and social components in the initial phase and latter of the iterations [35]. Using iteration PSO (IPSO) enriches the solution quality and avoids being trapped into local optimum [36]. More details of the proposed algorithm will be provided in Section 3.

The remainder of the paper is organized as follows. Section 2 gives the mathematical formulation of the DED problem considering POZs, ramp-rate limits, valve-point effects and transmission losses. Section 3 describes the proposed TVAC-IPSO algorithm. Section 4 presents two application cases and gives the corresponding comparison with the results of most recent applied methods. Conclusions are finally given in Section 5.

2. DED problem formulation

The objective function of DED problem is to minimize the total production cost over the operation period, which can be written as:

$$\min \ TC = \sum_{t=1}^{T}\sum_{i=1}^{N} C_{it}(P_{it}) \tag{1}$$

where, C_{it} is the unit i production cost at time t,N is the number of dispatchable power generation units and P_{it} is the power output of ith unit at time t. T is the total number of hours in the operation period. The production cost of generation unit considering valve-point effects is defined as:

$$C_{it}(P_{it}) = a_iP_{it}^2 + b_iP_{it} + c_i + \left|e_i \sin\left(f_i\left(P_i^{min} - P_{it}\right)\right)\right| \tag{2}$$

where, a_i, b_i and c_i are the fuel cost coefficients of the ith unit, e_i and f_i are the valve-point coefficients of the ith unit. P_i^{min} is the minimum capacity limit of unit i. It should be noted that the added sinusoidal term in the production cost function reflects the effect of valve-points. The DED problem will be non-convex and non-differentiable considering valve-point effects [37].

The objective function of the DED problem (1) should be minimized subject to following equality and inequality constraints:

1. Real power balance
Hourly power balance considering network transmission losses is written as:

$$\sum_{i=1}^{N} P_{it} = P_D(t) + P_{loss}(t) \quad t = 1,2,\ldots,T \tag{3}$$

where, $P_{loss}(t)$ and $P_D(t)$ are total transmission loss and total load demand of the system at time t, respectively. System loss is a function of units power production and can be calculated using the results of load flow problem [31] or Kron's loss formula known as B-matrix coefficients [29]. In this work B-matrix coefficients method is used to calculate system loss as follows.

$$P_{loss}(t) = \sum_{i=1}^{N}\sum_{j=1}^{N} P_{it}B_{ij}P_{jt} + \sum_{i=1}^{N} B_{i0}P_{it} + B_{00} \quad t = 1,2,\ldots,T \tag{4}$$

where, B_{ij}, B_{i0}, and B_{00} are loss coefficients. It should be noted that power system operator may use several seasonal or peak/off-peak B-matrices. In practice, proper B-matrix should be used based on the season and system condition.

2. Generation limits of units

$$P_i^{min} \leqslant P_{it} \leqslant P_i^{max} \quad i = 1,\ldots,N, \quad t = 1,2,\ldots,T \tag{5}$$

where, P_i^{max} is the maximum power outputs of ith unit.

3. Ramp up and ramp down constraints
The output power change rate of the thermal unit must be in an acceptable range to avoid undue stresses on the boiler and combustion equipments [38]. The ramp rate limits of generation units can be mathematically stated as follows.

$$P_{it} - P_{it-1} \leqslant UR_i \quad i = 1,\ldots,N, \quad t = 1,2,\ldots,T \tag{6}$$
$$P_{it-1} - P_{it} \leqslant DR_i \quad i = 1,\ldots,N, \quad t = 1,2,\ldots,T \tag{7}$$

where, UR_i is the ramp up limit of the ith generator (MW/hr) and DR_i is the ramp down limit of the ith generator (MW/hr). Considering ramp rate limits of unit, generator capacity limit (5) can be rewritten as follows:

$$\max\left(P_i^{min}, P_{it-1} - DR_i\right) \leqslant P_{it} \leqslant \min\left(P_i^{max}, P_{it-1} + UR_i\right)$$
$$i = 1,\ldots,N, \quad t = 1,2,\ldots,T \tag{8}$$

4. POZ constraint Generating units may have certain restricted operation zone due to limitations of machine components or instability concerns. The allowable operation zones of generation unit can be defined as [39]:

$$P_{it} \in \begin{cases} P_i^{min} \leqslant P_{it} \leqslant P_{i,1}^{l} \\ P_{i,j-1}^{u} \leqslant P_{it} \leqslant P_{i,j}^{l}, \quad j = 2,3,\ldots,M_i, \quad i = 1,\ldots,N, \quad t = 1,2,\ldots,T \\ P_{i,M_i}^{u} \leqslant P_{it} \leqslant P_i^{max} \end{cases} \tag{9}$$

where, $P_{i,j}^{l}$ and $P_{i,j}^{u}$ are the lower and upper limits of the jth prohibited zone of unit i, respectively. M_i is the number of prohibited operation zones of unit i.

3. Time varying acceleration coefficients iteration particle swarm optimization

3.1. Classic particle swarm optimization

PSO is one of the algorithms based on social performance of the swarm of fishes, birds, bees and other animals. Then PSO is a biology based algorithm like as ant colony optimization and genetic algorithm. This intelligent stochastic search algorithm has been developed by Kennedy and Eberhart in 1995 for first time [40]. PSO method has the flexibility to enhance and adapt to both global and local exploration abilities [33]. It is observed that original PSO suffers from premature convergence, especially for problems with multiple local optimums [35,32]. PSO applied to solve many real-world problems after inception in 1995 and many researches have been carried out to improve its performance in recent years. R. Poli has studied and classified the application of PSO algorithm in [41]. PSO starts with a fixed number of randomly initialized particles (potential solutions) in an N-dimensional solution space. A particle i at iteration $iter$ has a position vector $X_i^{iter} = (x_{i1}^{iter}, x_{i2}^{iter}, \ldots, x_{iN}^{iter})$ and a velocity vector $V_i^{iter} = (v_{i1}^{iter}, v_{i2}^{iter}, \ldots, v_{iN}^{iter})$. The best solution achieved by ith particle until the current iteration ($iter$) is defined as $P_{best_i}^{iter} = \left(p_{best_{i1}}^{iter}, p_{best_{i2}}^{iter}, \ldots, p_{best_{iN}}^{iter}\right)$. The best $P_{best_i}^{iter}$ among the entire particles is denoted as global best (g_{best}^{iter}). A particle approaches to better position (better solution) with randomly weighted acceleration using its present velocity, previous experience, and the experience of other particles. Then, the velocity and position of every particle will be updated using following equations.

$$v_{in}^{iter+1} = \omega \times v_{in}^{iter} + C_1 \times r_1^n \times \left(p_{best_{in}}^{iter} - x_{in}^{iter}\right) + C_2 \times r_2^n \times \left(g_{best}^{iter} - x_{in}^{iter}\right) \tag{10}$$

$$x_{in}^{iter+1} = x_{in}^{iter} + C \times v_{in}^{iter+1} \tag{11}$$

where, ω is inertia weight, r_1^n and r_2^n are two independently generated random numbers between 0 and 1. C_1 and C_2 are cognitive and social component acceleration coefficients, respectively. C is the constriction factor and can be calculated using (12) [42]. The inertia weight (ω) is linearly decreasing as the iterations proceed and can be calculated using (13) [43].

$$C = \frac{2}{2 - \phi - \sqrt{\phi^2 - 4\phi}} \tag{12}$$

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{iter_{max}} \times iter \tag{13}$$

where, $\phi = (C_1 + C_2) \geqslant 4$. ω_{max} and ω_{min} are initial and final weights. $iter_{max}$ is the maximum iteration number.

3.2. TVAC-IPSO

In order to improve the performance of PSO, a new index named as iteration best is added to Eq. (10). This method is known as iteration PSO (IPSO) [36,44,45]. The velocity updating formula considering iteration best will be as follows.

$$v_{in}^{iter+1} = \omega \times v_{in}^{iter} + C_1 \times r_1^n \times \left(p_{best_{in}}^{iter} - x_{in}^{iter}\right) + C_2 \times r_2^n \times \left(g_{best}^{iter} - x_{in}^{iter}\right) + C_3 \times r_3^n \times \left(I_{best}^{iter} - x_{in}^{iter}\right) \tag{14}$$

where I_{best}^{iter} is the best solution that has been obtained by any particle in iteration $iter$ and C_3 is the weighting factor of the stochastic acceleration. r_3^n is a random number in the range of $[0, 1]$. The performance of PSO and other stochastic search algorithms is dependent to the tuned parameters. Hence, parameter selection should be done very carefully to achieve better solutions. In the classic PSO algorithm the acceleration coefficients are set to a fixed value (conventionally fixed to 2.0). The relative values of two acceleration coefficients control the local and global search ability of the algorithm. If the value of social component C_2 is selected to be higher than the cognitive component C_1 then algorithm will be guided to a local optimum prematurely. In the other hand selection of the higher value for cognitive component (comparing to social component) will wander the particles around the search space [40,34]. In TVAC-IPSO, in initial iterations, the cognitive component value is higher which force the particles to wander around the search space. With proceeding the iterations the value of social component is increased, which force the particles to reach optimal solution. Adaptive update of acceleration coefficients improves the solution quality. The acceleration coefficients are updated using the following equations.

$$C_1 = C_{1i} + \frac{C_{1f} - C_{1i}}{iter_{max}} \times iter \tag{15}$$

$$C_2 = C_{2i} + \frac{C_{2f} - C_{2i}}{iter_{max}} \times iter \tag{16}$$

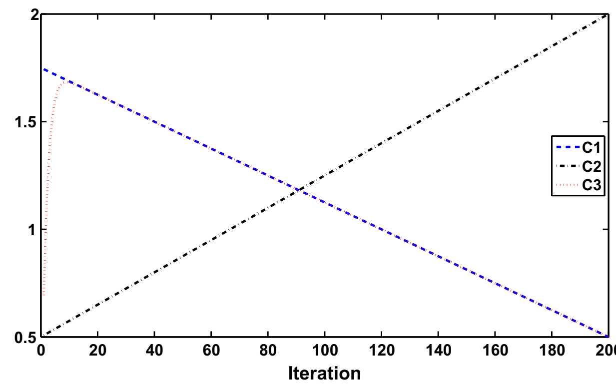

Fig. 1. Variation of C_1, C_2 and C_3 according to iteration number ($iter$).

At initial iterations, the particles are far away from the optimum point, and hence adding a new term (i.e. iteration best) to the velocity formula, will help the algorithm to converge to a better solutions, due to this fact that I_{best}^{iter} is the best solution obtained in the current iteration. Hence, in this paper, C_3 is updated as follows:

$$C_3 = C_1 \times (1 - \exp(-C_2 \times iter)) \tag{17}$$

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

To explain (17), one may consider a numerical example as follows. By assuming $C_{1i} = 1.75$, $C_{1f} = 0.5$, $C_{2i} = 0.5$ and $C_{2f} = 2$, and $iter_{max} = 200$ the coefficients C_1, C_2 and C_3 are depicted in Fig. 1.

As it is evidently observed from Fig. 1, when iterations proceed, C_1/C_2 decreases/increases monotonically. But, C_3 is increased swiftly at the initial iterations, and then, decreases slowly. This feature helps us to use benefits of I_{best} at the initial iterations, where the algorithm aims to find proper direction for search. But, when the iterations proceed, due to the high value of the social component (C_2) in comparison with cognitive component (C_1) will lead particles to the optimum solution.

4. Case studies and numerical results

In this section, the proposed TVAC-IPSO algorithm is applied on two benchmark DED test systems with different number of generating units, i.e. 5 and 10 units. All simulations are executed by a Pentium IV, 2.33-GHz, and 3.25 GB of RAM personal computer.

4.1. TVAC-IPSO parameter selection

The selection of proper values for algorithm plays a significant role in both solution's quality and speed of the algorithm's convergence. In order to obtain the best population size for different test cases, minimum cost was calculated for different set of population sizes. the optimal value for the population size is achieved to be 200 for both test cases. Besides, to select a proper maximum iterations number, numerous studies is carried out based on the optimal aforementioned population size for different test systems. The optimal value for maximum iterations number is reported in corresponding test cases. The effect of the initial and final values of cognitive and social components acceleration factors on solution performance are studied by varying their values for the above optimal values of population size and maximum iterations number. The resultant optimal parameters for the proposed algorithm based on the above analysis, are as follows: $\omega_{max} = 0.9$, $\omega_{min} = 0.4$, $C_{1i} = 1.75$, $C_{1f} = C_{2i} = 0.5$, $C_{2f} = 2$, $R = 5$.

Table 1
Optimal solution of 5-unit using proposed algorithm without considering POZs.

Hour	P_1	P_2	P_3	P_4	P_5	Cost ($)	Loss (MW)
1	10	20	30	124.489	229.5	1226.588	3.989
2	19.078	20	30	140.846	229.52	1418.345	4.444
3	10	20	30	190.846	229.52	1493.568	5.366
4	10	20	67.023	209.816	229.52	1662.801	6.359
5	10	20	95.516	209.813	229.513	1667.465	6.842
6	13.948	50	112.675	209.817	229.519	1826.622	7.959
7	10	72.451	112.673	209.816	229.52	1840.605	8.460
8	12.709	98.54	112.674	209.816	229.52	1797.226	9.259
9	42.709	105.479	112.674	209.816	229.523	2012.366	10.201
10	64.012	98.54	112.674	209.815	229.52	1996.599	10.561
11	75	104.003	112.706	209.816	229.52	2037.947	11.045
12	75	124.711	112.673	209.816	229.52	2180.024	11.720
13	64.019	98.531	112.673	209.816	229.52	1996.63	10.559
14	49.62	98.54	112.673	209.816	229.52	1977.662	10.169
15	47.442	98.54	112.674	174.909	229.519	2061.836	9.084
16	21.558	98.541	112.674	124.909	229.52	1654.431	7.202
17	10	87.585	112.672	124.908	229.517	1615.304	6.682
18	10	98.54	112.674	165.218	229.52	1853.473	7.952
19	12.703	98.54	112.679	209.816	229.52	1797.234	9.258
20	42.703	119.944	112.674	209.816	229.521	2115.529	10.658
21	39.353	98.54	112.674	209.816	229.52	1944.599	9.903
22	10	98.54	110.181	164.643	229.519	1861.02	7.883
23	10.003	98.556	70.181	124.908	229.525	1643.209	6.173
24	10	73.392	30.181	124.906	229.518	1455.477	4.997
Total						43136.56	196.725

Table 2
Comparison of optimization results for 5-unit test system,without considering POZs.

Method	Minimum cost ($)	Average cost ($)	Maximum cost ($)	Simulation time (min)
SA [26]	47356	NA	NA	5.86
APSO [14]	44678	NA	NA	NA
AIS [12]	44385.43	44758.8363	45553.7707	4
GA [6]	44862.42	44921.76	45893.95	3.3242
PSO [6]	44253.24	45657.06	46402.52	3.5506
ABC [6]	44045.83	44064.73	44218.64	3.2901
MLS [7]	49216.81	NA	NA	0.024
IPS [10]	46530	NA	NA	4.53
Proposed	**43136.561**	**43185.664**	**43302.233**	**1.1**

NA denotes that the value was not available in the literature.

4.2. Test System I

The first test system is a 5-unit test system. The cost coefficients, generation limits, load demand in each interval, and ramp-rate limits are taken from [26], as given in Appendix. Two different cases are studied using this test system. In the first case, valve-point effects, transmission losses, ramp-rate constraints and generation limits are considered. The POZs are not considered in this case for the sake of comparison with the results that reported in literature. In the second case, POZs are also taken into account for evaluating the capability of proposed algorithm. The proposed POZs for 5-unit test system are given in appendix. In this case POZ constraints, transmission losses, ramp-rate constraints and generation limits are considered. Quadratic cost function is used for second case. The maximum iteration number is selected to be 500.

The DED problem of 5-unit system is solved using proposed algorithm. Table 1 shows the obtained results for this system. These results are compared with simulated annealing (SA) algorithm [26], adaptive PSO (APSO) algorithm [14], artificial immune system (AIS) [12], genetic algorithm (GA) [6], PSO [6], artificial bee colony (ABC) algorithm [6], Maclaurin Series (MLS) [7], and improved pattern search (IPS) algorithm [10] in Table 2. Results of the proposed method are in bold. It is observed from this table that the proposed method gives better solutions in terms of minimum, average and maximum costs, which shows its ability in finding better solution for such complicated DED problems. Also, the problem is solved using original PSO [40], in order to compare the convergence characteristics of the TVAC-IPSO with original PSO. Minimum costs obtained using our formulation for the TVAC-IPSO and original PSO are 43136.561 $/day and 44800.001 $/day, respectively, which shows prominency of the proposed approach. Besides, the convergence characteristic of the proposed algorithm is compared with the original PSO algorithm and depicted in Fig. 2. This figure implies that the proposed TVAC-IPSO outperforms the classical PSO in both convergence speed and optimality of objective function.

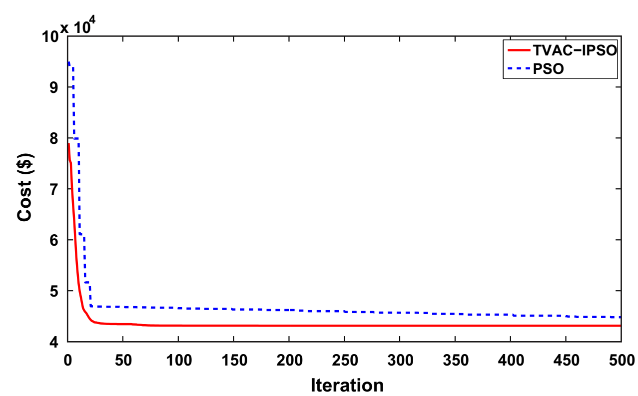

Fig. 2. Convergence characteristics of the proposed algorithm for 5-unit test system.

Table 3
Optimal solution of 5-unit using proposed algorithm with considering POZs.

Hour	P_1	P_2	P_3	P_4	P_5	Cost ($)	Loss (MW)
1	15.398	72.812	60	119.266	146.148	1202.839	3.623
2	16.325	75.214	70	126.465	151.046	1260.047	4.05
3	17.686	90	77.24	136.789	158.127	1352.965	4.843
4	21.117	80	99.832	160	175	1482.145	5.948
5	23.212	93.105	113.251	160	175	1549.084	6.568
6	23.557	93.951	116.063	182.281	200	1669.83	7.851
7	25	98.526	140	195.735	175	1714.708	8.261
8	25	99.377	140	198.454	200.202	1782.801	9.032
9	25	104.935	143.87	214.833	211.464	1872.414	10.103
10	30	106.042	146.676	218.11	213.671	1907.53	10.499
11	30	107.969	151.58	223.837	217.599	1947.888	10.986
12	30	110.38	157.715	231.001	222.515	1998.645	11.611
13	30	106.042	146.676	218.11	213.671	1907.53	10.499
14	30	104.357	142.389	213.101	210.236	1872.397	10.083
15	25	99.377	140	198.454	200.202	1782.801	9.032
16	17.223	90	100	180	200	1602.519	7.223
17	20.923	90	98.737	180	175	1549.031	6.66
18	25	97.705	125	193.126	175	1670.244	7.831
19	25	99.377	140	198.454	200.202	1782.801	9.032
20	25	106.621	148.158	219.842	214.899	1907.599	10.52
21	30	103.038	140	209.195	207.554	1847.407	9.787
22	23.383	93.503	114.934	180.956	200	1662.544	7.776
23	20.262	90	94.214	156.724	171.717	1474.941	5.917
24	18.07	90	60	139.548	160.065	1325.49	4.683
Total						40126.2	192.418

Table 4
Optimal solution of 10-unit system without considering transmission losses using the proposed algorithm.

Hour	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	Cost ($)
1	150	135	193.87	60	122.867	122.673	129.591	47	20	55	28239.26
2	226.625	135	191.441	60	122.868	122.475	129.592	47	20	55	29828.153
3	303.249	142.264	185.234	60	172.736	142.927	129.59	47	20	55	33340.448
4	379.875	222.264	196.966	60	172.733	122.571	129.591	47	20	55	36291.51
5	379.872	222.266	183.679	60	222.592	160	129.59	47	20	55	37991.359
6	456.497	302.266	262.464	60.001	172.733	122.449	129.59	47	20	55	41372.334
7	379.875	309.538	305.737	110.001	222.733	122.519	129.598	47	20	55	42845.798
8	456.497	316.797	297.958	120.417	172.734	160	129.597	47	20	55	44600.38
9	456.491	396.797	297.392	130.818	222.6	160	129.59	55.312	20	55	48037.399
10	456.499	460	302.168	180.818	222.609	160	129.595	85.312	20	55	51577.925
11	456.497	459.333	297.027	230.641	222.6	160	129.59	115.312	20	55	53705.795
12	456.498	460	325.063	241.247	222.601	160	129.591	120	50	55	55512.708
13	456.497	396.805	314.887	234.055	222.611	122.538	129.606	120	20	55	51479.047
14	456.496	396.798	296.881	184.055	172.733	122.449	129.588	90	20	55	47895.816
15	379.872	393.124	297.371	170.415	122.866	122.449	129.59	85.312	20	55	44650.187
16	303.249	313.124	331.856	120.415	73	122.45	129.593	85.312	20	55	39815.184
17	226.589	309.533	291.796	116.954	122.779	122.45	129.59	85.31	20	55	37980.322
18	303.265	315.375	303.652	120.425	172.778	122.598	129.592	85.314	20	55	41293.486
19	379.866	395.375	295.272	120.414	172.724	122.447	129.589	85.312	20	55	44375.407
20	456.508	460	312.57	170.414	222.601	160	129.596	85.312	20	55	51768.905
21	456.498	389.533	322.312	120.414	222.6	122.739	129.592	85.312	20	55	47915.685
22	379.749	309.533	283.56	70.414	172.601	122.243	129.59	85.31	20	55	41285.803
23	303.249	229.533	203.561	60	123	122.755	129.591	85.312	20	55	34951.995
24	226.629	222.267	189.701	60	73	122.498	129.592	85.312	20	55	31462.318
Total											1018217.224

For the second case, where POZs are included, the obtained results are presented in Table 3. It is evidently observed from this table that the proposed approach is well capable to handle POZ constraints, too.

4.3. Test System II

The second test system is a 10-unit system. Two different cases studied here. In the first case, generators capacity limits, ramp-rate constraint and valve-point effects are considered. Whereas in the second case, transmission losses are also considered, in addition to the aforementioned constraints. The data for this system are adopted from [26], as given in Appendix. The maximum iteration number is selected to be 700 for this test system.

Table 4 shows the obtained results for the 10-unit system without considering transmission losses. These results are compared with the results of previously developed algorithms, like as differential evolution (DE) [20], hybrid EP and SQP [27], hybrid PSO-SQP [31], deterministically guided PSO (DGPSO) [15], modified hybrid EP-SQP (MHEP-SQP) [28], improved PSO (IPSO) [16], hybrid DE (HDE) [21], improved DE (IDE) [22], artificial bee colony algorithm (ABC) [6], modified differential evolution (MDE) [23], covariance matrix adapted evolution strategy (CMAES) [17], artificial immune system (AIS) [12], hybrid swarm intelligence based harmony search algorithm (HHS) [3], hybrid artificial immune systems and sequential quadratic programming (AIS-SQP) [13], chaotic sequence based differential evolution algorithm (CS-DE) [18], chaotic differential evolution (CDE) method [24], and improved chaotic

Table 5
Comparison of optimization results for 10-unit test system without considering transmission losses.

Method	Minimum cost ($)	Average cost ($)	Maximum cost ($)	Simulation time (min)
DE [20]	1019786.000	NA	NA	11.25
EP-SQP [27]	1031746.000	1035748.000	NA	20.51
PSO-SQP [31]	1027334.000	1028546.000	1033986.000	16.37
DGPSO [15]	1028835.000	1030183.000	NA	15.39
MHEP-SQP [28]	1028924.000	1031179.000	NA	21.23
IPSO [16]	1023807.000	1026863.000	NA	0.06
HDE [21]	1031077.000	NA	NA	NA
IDE [22]	1026269.000	NA	NA	NA
ABC [6]	1021576.000	1022686.000	1024316.000	2.6029
MDE [23]	1031612.000	1033630.000	NA	12.50
CMAES [17]	1023740.000	1026307.000	1032939.000	0.63
AIS [12]	1021980.000	1023156.000	1024973.000	19.01
HHS [3]	1019091.000	NA	NA	12.233
AIS-SQP [13]	1029900.000	NA	NA	NA
CS-DE [18]	1023432.000	1026475.000	1027634.000	0.24
CDE [24]	1019123.000	1020870.000	1023115.000	0.32
ICPSO [11]	1019072	1020027	NA	0.467
Proposed	**1018217.224**	**1018965.355**	**1020417.821**	**2.8**

NA denotes that the value was not available in the literature.

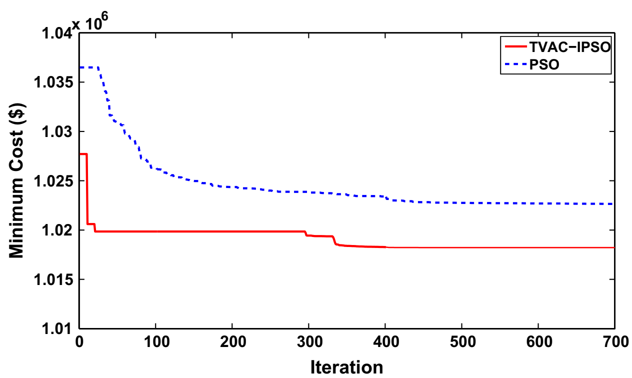

Fig. 3. Convergence characteristics of the proposed algorithm for 10-unit test system.

particle swarm optimization (ICPSO) algorithm [11] in Table 5. Results of the proposed method are in bold. The detailed comparison for quality of solutions, i.e. minimum, average and maximum costs along with the simulation time are presented in this table. It is evident from Table 5 that the proposed TVAC-IPSO algorithm yields more optimal results, i.e. less costs, in comparison with the approaches reported in literature. Although, some of previously proposed algorithms have less solution time than the TVAC-IPSO, but still its simulation time is good enough. It should be noted that the mean simulation time of cited papers are directly driven from the corresponding papers, which are executed on different machine with different parameters.

The convergence characteristic of the proposed algorithm is depicted in Fig. 3 and compared with original PSO. As it is evidently observed from this figure, the proposed approach outperforms the original PSO, both in convergence speed and optimality. The obtained minimum costs for TVAC-IPSO and original PSO using our formulation are 1018217.224 $/day and 1022650.233 $/day, respectively.

Table 6
Optimal solution of 10-unit system with considering transmission losses using the proposed algorithm.

Hour	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	Cost ($)	Loss (MW)
1	150	135	206.188	60	122.867	122.492	129.591	47	20	55	28592.053	12.138
2	226.626	135	204.568	60	122.868	122.656	129.596	47	20	55	30219.062	13.314
3	303.248	142.254	186.44	60	172.739	160	129.591	47	20	55	33727.927	18.272
4	379.873	222.254	222.386	60	172.702	122.451	129.593	47	20	55	36993.204	25.259
5	379.877	222.271	211.844	60	222.697	160	129.591	47	20	55	38789.655	28.280
6	456.519	302.271	291.844	65.913	172.733	122.45	129.594	47	20	55	41995.816	35.324
7	379.875	309.533	317.037	115.913	222.733	141.184	129.597	47	20	55	43823.14	35.872
8	456.497	310.646	297.156	165.912	172.733	160	129.59	47	20	55	45595.837	38.534
9	456.497	390.646	301.158	180.834	222.6	160	129.598	55.312	20.002	55	49222.422	47.647
10	456.499	460	317.525	191.261	222.602	160	129.595	85.312	50.002	55	53286.195	55.796
11	456.607	460	340	241.261	223.299	160	129.999	85.318	52.058	55	55021.012	57.542
12	456.497	460	340	241.246	242.044	160	129.59	115.318	80	55	57656.955	59.695
13	456.501	396.8	326.034	241.252	222.608	160	129.597	85.318	50.002	55	52779.277	51.112
14	456.516	396.799	297.424	233.392	172.733	122.456	129.59	85.315	20.002	55	48917.075	45.227
15	379.873	396.798	312.993	183.392	122.99	128.664	129.591	85.312	20	55	45535.894	38.613
16	303.243	316.798	297.363	178.568	73	122.478	129.59	85.312	20	55	40416.069	27.352
17	226.624	309.533	306.092	128.568	122.867	122.482	129.591	85.312	20	55	38649.809	26.069
18	303.248	316.757	297.399	155.824	172.733	122.45	129.59	85.312	20	55	42260.597	30.313
19	379.866	396.757	306.807	147.132	172.733	122.45	129.59	85.312	20	55	45581.697	39.647
20	456.499	460	340	197.132	222.6	160	129.998	85.312	20	55	53235.432	54.541
21	456.497	389.533	318.272	170.386	222.6	122.45	129.59	85.312	20	55	49130.833	45.640
22	379.84	309.533	264.739	120.386	172.732	122.45	129.59	85.304	20	55	42091.638	31.574
23	303.249	229.533	213.775	70.386	122.87	122.452	129.591	85.312	20	55	35606.214	20.168
24	226.626	222.269	205.493	60	73	122.538	129.861	85.317	20	55	31938.383	16.104
Total											1041066.196	854.033

Table 7
Comparison of optimization results for 10-unit test system with considering transmission losses.

Method	Minimum cost ($)	Average cost ($)	Maximum cost ($)	Simulation time (min)
EP [28]	1054685	1057323	NA	47.23
EP-SQP [28]	1052668	1053771	NA	27.53
MHEP-SQP [28]	1050054	1052349	NA	24.33
GA [6]	1052251	1058041	1062511	3.4436
PSO [6]	1048410	1052092	1057170	4.0933
IPSO [16]	1046275	1048145	NA	NA
ABC [6]	1043381	1044963	1046805	3.4083
AIS [12]	1045715	1047050	1048431	23.22
Proposed	**1041066.196**	**1042118.472**	**1043625.977**	**3.25**

NA denotes that the value was not available in the literature.

Table A.1
Generating units' characteristics in 5-unit test system.

Unit	a_i	b_i	c_i	e_i	f_i	P^{min}	P^{max}	UR	DR	POZs
1	0.008	2	25	100	0.042	10	75	30	30	[25 30], [55 60]
2	0.003	1.8	60	140	0.04	20	125	30	30	[45 50], [80 90]
3	0.0012	2.1	100	160	0.038	30	175	40	40	[60 70], [125 140]
4	0.001	2	120	180	0.037	40	250	50	50	[95 110], [160 180]]
5	0.0015	1.8	40	200	0.035	50	300	50	50	[85 100], [175 200]

DED problem also is solved for 10-unit test system including transmission losses. The corresponding generation dispatch is presented in Table 6. The obtained optimal results are compared with the results of evolutionary programming (EP) [28], hybrid EP-SQP (EP-SQP) [28], modified hybrid EP-SQP (MHEP-SQP) [28], genetic algorithm (GA) [6], PSO [6], artificial bee colony algorithm (ABC) [6], improved PSO (IPSO) [16] and artificial immune system (AIS) [12] in Table 7. Results of the proposed method are in bold. Again, it is observed that the proposed results are less than those reported in the literature, in terms of minimum, average and maximum costs, which shows the capability of the TVAC-IPSO approach in finding better solution for such complicated DED problems.

5. Conclusion

This paper introduces a new approach to solve power systems dynamic economic dispatch problem, called time varying acceleration coefficients iteration particle swarm optimization (TVAC-IPSO). Valve-point effects, prohibited operation zones, ramp-rate constraints and transmission losses are modeled and the resulting non-linear and non-convex optimization problem is solved by the proposed TVAC-IPSO algorithm. The proposed method is applied on two test cases. A comprehensive comparison is made between the proposed approach and other recently reported methods, in terms of minimum, average and maximum cost values and simulation time. The analysis results demonstrate that for such multi-minimum and complicated problems, TVAC-IPSO found solutions better than so far best known results by any other method in terms of cost and power losses. Besides, by comparing the convergence properties of the proposed algorithm with the classical PSO approach, both the quickness and ability of the TVAC-IPSO approach in finding better solutions is approved. These imply the capability of the proposed method for solving such complicated DED problems.

Appendix A. Test cases' data

Generating units' characteristics of 5-unit test system are provided in Table A.1. The *B*-matrix coefficients of this test system are as follows.

Table A.2
Generating units' characteristics in 10-unit test system.

Unit	a_i	b_i	c_i	e_i	f_i	P^{min}	P^{max}	UR	DR
1	0.00043	21.6	958.2	450	0.041	150	470	80	80
2	0.00063	21.05	1313.6	600	0.036	135	460	80	80
3	0.00039	20.81	604.97	320	0.028	73	340	80	80
4	0.0007	23.9	471.6	260	0.052	60	300	50	50
5	0.00079	21.62	480.29	280	0.063	73	243	50	50
6	0.00056	17.87	601.75	310	0.048	57	160	50	50
7	0.00211	16.51	502.7	300	0.086	20	130	30	30
8	0.0048	23.23	639.4	340	0.082	47	120	30	30
9	0.10908	19.58	455.6	270	0.098	20	80	30	30
10	0.00951	22.54	692.4	380	0.094	55	55	30	30

Table A.3
Hourly load profile (in MW) for studied test systems.

Hour	5-unit system	10-unit system
1	410	1036
2	435	1110
3	475	1258
4	530	1406
5	558	1480
6	608	1628
7	626	1702
8	654	1776
9	690	1924
10	704	2072
11	720	2146
12	740	2220
13	704	2072
14	690	1924
15	654	1776
16	580	1554
17	558	1480
18	608	1628
19	654	1776
20	704	2072
21	680	1924
22	605	1628
23	527	1332
24	463	1184

$$B_{ij} = \begin{pmatrix} 0.000049 & 0.000014 & 0.000015 & 0.000015 & 0.000020 \\ 0.000014 & 0.000045 & 0.000016 & 0.000020 & 0.000018 \\ 0.000015 & 0.000016 & 0.000039 & 0.000010 & 0.000012 \\ 0.000015 & 0.000020 & 0.000010 & 0.000040 & 0.000014 \\ 0.000020 & 0.000018 & 0.000012 & 0.000014 & 0.000035 \end{pmatrix}$$

Generating units' characteristics of 10-unit test system are provided in Table A.2. The B-matrix coefficients of this test system in per-unit in 100 MW base are as follows. The hourly load demand of both test systems are provided in Table A.3.

$$B_{ij} = \begin{pmatrix} 8.7 & 0.43 & -4.61 & 0.36 & 0.32 & -0.66 & 0.96 & -1.6 & 0.8 & -0.1 \\ 0.43 & 8.3 & -0.97 & 0.22 & 0.75 & -0.28 & 5.04 & 1.7 & 0.54 & 7.2 \\ -4.61 & -0.97 & 9 & -2 & 0.63 & 3 & 1.7 & -4.3 & 3.1 & -2 \\ 0.36 & 0.22 & -2 & 5.3 & 0.47 & 2.62 & -1.96 & 2.1 & 0.67 & 1.8 \\ 0.32 & 0.75 & 0.63 & 0.47 & 8.6 & -0.8 & 0.37 & 0.72 & -0.9 & 0.69 \\ -0.66 & -0.28 & 3 & 2.62 & -0.8 & 11.8 & -4.9 & 0.3 & 3 & -3 \\ 0.96 & 5.04 & 1.7 & -1.96 & 0.37 & -4.9 & 8.24 & -0.9 & 5.9 & -0.6 \\ -1.6 & 1.7 & -4.3 & 2.1 & 0.72 & 0.3 & -0.9 & 1.2 & -0.96 & 0.56 \\ 0.8 & 0.54 & 3.1 & 0.67 & -0.9 & 3 & 5.9 & -0.96 & 0.93 & -0.3 \\ -0.1 & 7.2 & -2 & 1.8 & 0.69 & -3 & -0.6 & 0.56 & -0.3 & 0.99 \end{pmatrix}$$

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