Self-Organizing Hierarchical Particle Swarm Optimization for Nonconvex Economic Dispatch

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***Abstract*—The economic dispatch has the objective of generation allocation to the power generators in such a manner that the total fuel cost is minimized while all operating constraints are satisfied. Conventional optimization methods assume generator cost curves to be continuous and monotonically increasing, but modern generators have a variety of nonlinearities in their cost curves making this assumption inaccurate, and the resulting approximate dispatches cause a lot of revenue loss. Evolutionary methods like particle swarm optimization perform better for such problems as no convexity assumptions are imposed, but these methods converge to sub-optimum solutions prematurely, particularly for multimodal problems.**

To handle the problem of premature convergence, this paper proposes to apply a novel self-organizing hierarchical particle swarm optimization (SOH_PSO) for the nonconvex economic dispatch (NCED). The performance further improves when time-varying acceleration coefficients are included. The results show that the proposed approach outperforms previous methods for NCED.

***Index Terms*—Nonconvex economic dispatch (NCED), premature convergence, prohibited operating zones (POZ), ramp rate limits, self-organizing hierarchical particle swarm optimization (SOH_PSO), time-varying acceleration coefficients (TVAC), valve point loading effect.**

I. Introduction

ECONOMIC dispatch is one of the major optimization issues in power system. Its objective is to allocate the power demand among committed generators in the most economical manner, while all physical and operational constraints are satisfied. The cost of power generation, particularly in fossil fuel plants, is very high and economic dispatch helps in saving a significant amount of revenue. Conventional methods like lamda iteration, quadratically constrained programming, gradient methods etc. rely heavily on the convexity assumption of generator cost curves and usually approximate these curves using quadratic or piecewise quadratic monotonically increasing cost functions [1]. This assumption is not valid because the cost functions of modern generators have discontinuities and higher order nonlinearities due to valve point loading [2], [3], prohibited operating zones [4] and ramp rate limits of generators [5]. The practical ED with above nonlinearities translates into a complicated optimization problem having complex and nonconvex characteristics, with multiple minima, making the challenge of obtaining the global minima, very difficult. Conventional gradient based optimization methods fail to model these discontinuities and usually result in inaccurate dispatches causing loss of revenue. Dynamic programming [6] has no restriction on cost curve, but this method is computationally extensive, and suffers from the problem of dimensionality.

Methods like dynamic programming [6], genetic algorithm [2], [4], [7], [8], evolutionary programming [3], [9]–[11], artificial intelligence [12], and particle swarm optimization [13]–[23] solve nonconvex optimization problems efficiently and often achieve a fast and near global optimal solution. The PSO, first introduced by Kennedy and Eberhart [13] is a flexible, robust, population based algorithm with inherent parallelism. This method is increasingly gaining acceptance for solving economic dispatch [14]–[18] and a variety of power system problems [19]–[22], due to its simplicity, superior convergence characteristics and high solution quality. Recent research however has observed that classical PSO approach suffers from premature convergence, particularly for complex functions having multiple minima [16], [23].

A hybrid PSO is proposed [27] for OPF with emission constraint where inequality constraints are handled by a novel hybrid mechanism. Recently fuzzy adaptive PSO [28] has been applied for optimization in power spot price market [29]. Different techniques have been proposed to handle premature convergence in nonconvex ED solution with stochastic search based evolutionary methods. In [8] an improved GA is proposed with multiplier updating to increase search efficiency and to handle constraints. The NCED problem was solved by integrating evolutionary programming, tabu search and quadratic programming [12]. ED with adynamic space reduction technique is proposed in [15] to accelerate convergence. The concept of generating crazy agents was effectively applied in [16] to combat premature convergence in dynamic dispatch with valve point loading. [18] combined a local search operator with PSO to enhance local exploration once the solution region is identified.

A novel parameter automation strategy called self-organizing hierarchical PSO (SOH_PSO) is applied in this paper for the NCED to address the problem of premature convergence. In this approach, the particle velocities are reinitialized whenever the population stagnates at local optima during the search. A relatively high value of the cognitive component results in excessive wandering of particles while a higher value of the social

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component causes premature convergence of particles [13]. Hence, time-varying acceleration coefficients (TVAC) [23] are employed to strike a proper balance between the cognitive and social component during the search. Integration of the TVAC with SOH_PSO for solving the practical economic dispatch problem has been found to avoid premature convergence during the early stages of the search and promote convergence towards the global optimum solution. The proposed approach was first tested on some less complex systems and then the effectiveness of the SOH_PSO was demonstrated on three medium and large sized power systems with 6, 15 and 40 generating units respectively. The results have been compared to recently published results [12], [14], [18] and found to be superior.

II. Nonconvex Economic Dispatch

The practical NCED problem with generator nonlinearities such as valve point loading effects, prohibited operating zones and ramp rate limits, are modeled in this paper.

A. Valve Point Loading Effects

The valve-point effects introduce ripples in the heat-rate curves and make the objective function discontinuous, nonconvex and with multiple minima. For accurate modeling of valve point loading effects, a rectified sinusoidal function [2] is added in the cost function in this paper. The fuel input-power output cost function of the ith unit is given as

$$F_i\left(P_i\right) = a_i P_i^2 + b_i P_i + c_i + \left|e_i \times \sin\left(f_i \times \left(P_{i\min} - P_i\right)\right)\right| \tag{1}$$

where a_i, b_i and c_i are the fuel-cost coefficients of the ith unit, and e_i and f_i are the fuel cost-coefficients of the ith unit with valve-point effects. The NCED problem is to determine the generated powers P_i of units for a total load of $\mathrm{P_D}$ 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 $\mathrm{Min} F_T = \sum_{i=1}^{N} F_i(P_i)$, subject to the constraints given by

$$\sum_{i=1}^{N} P_i - \left(P_{\mathrm{D}} + P_L\right) = 0 \tag{2}$$

$$P_i^{\min} \leq P_i \leq P_i^{\max} \qquad i = 1, 2, \ldots, N. \tag{3}$$

For a given total real load P_{D} the system loss P_L is a function of active power generation at each generating unit. To calculate system losses, methods based on penalty factors and constant loss formula coefficients or B-coefficients [1] are in use. The latter is adopted in this paper as per which transmission losses are expressed as

$$P_L = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{oi} P_i + B_{oo}. \tag{4}$$

B. Generator Ramp Rate Limits

When the generator ramp rate limits are considered, the operating limits given in (3) are modified as follows:

$$\mathrm{Max}(P_i^{\min}, P_i^o - DR_i) \leq P_i \leq \mathrm{Min}(P_i^{\max}, P_i^o + UR_i). \tag{5}$$

The previous operating point of the ith generator is P_i^o and DR_i and UR_i are the down and up ramp rate limits, respectively.

C. Prohibited Operating Zones

Practical generating units have prohibited operating zones due to some faults in the machines or their accessories such as pumps or boilers, etc. [4]. A unit with prohibited operating zones has discontinuous input-output characteristics. This feature can be included in the NCED formulation as follows:

$$P_i \in \begin{cases} P_i^{\min} & \leq & P_i & \leq & P_{i1}^L \\ P_{ik-1}^U & \leq & P_i & \leq & P_{ik}^L \\ P_{izi}^U & \leq & P_i & \leq & P_i^{\max} \end{cases}. \tag{6}$$

Here z_i are the number of prohibited zones in the ith generator curve, k is the index of prohibited zone of the ith generator, P_{ik}^L is the lower limit of the kth prohibited zone, and P_{ik}^U is the lower limit of the kth prohibited zone of the ith generator.

III. Overview of Some PSO Strategies

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 significant developments is presented which will serve as a performance measure for the SOH_PSO technique applied in this paper.

A. Classical PSO

The PSO [13] is a population based modern heuristic search 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*, i.e., solutions into the problem space. These particles, called *swarms* collect information from each other through an array constructed by their respective positions. The particles update their positions using the *velocity* of particles. Position and velocity are both updated in a heuristic manner using guidance from particles' own experience and the experience of its neighbors.

The position and velocity vectors of the ith particle of a d-dimensional search space can be represented as $X_i = (x_{i1}, x_{i2}, \ldots\ldots\ldots \ldots x_{id})$ and $V_i = (v_{i1}, v_{i2}, \ldots\ldots\ldots v_{id})$, respectively. On the basis of the value of the evaluation function, the best previous position of a particle is recorded and represented as $pbest_i = (p_{i1}, p_{i2} \ldots\ldots\ldots p_{id})$. If the gth particle is the best among all particles in the group so far, it is represented as $pbest_g = gbest = (p_{g1}, p_{g2}, \ldots\ldots\ldots\ldots p_{gd})$. The particle tries to modify its position using the current velocity and the distance from $pbest$ and $gbest$. The modified velocity and position of each particle for fitness evaluation in the next, i.e., (k + 1)th iteration, are calculated using the following equations:

$$\begin{aligned} v_{id}^{k+1} = & C[w \times v_{id}^k + c_1 \times rand_1 \times (pbest_{id} - x_{id}) \\ & + c_2 \times rand_2 \times (gbest_{gd} - x_{id})\} \end{aligned} \tag{7}$$

$$x_{id}^{k+1} = x_{id} + v_{id}^{k+1}. \tag{8}$$

Here w is the inertia weight parameter which controls the global and local exploration capabilities of the particle. Constant C is constriction factor, c_1, c_2 are cognitive and social coefficients, respectively, and $rand_1$, $rand_2$ are random numbers between 0 and 1. A larger inertia weight factor is used during initial exploration its value is gradually reduced as the search proceeds. The concept of time-varying inertial weight (TVIW) was introduced in [24] as per which w is given by

$$w = (w_{\max} - w_{\min}) \times \frac{(iter_{\max} - iter)}{iter_{\max}} + w_{\min} \tag{9}$$

where $iter_{\max}$ 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. Usually these parameters are selected in the range of 0 to 4. To improve the convergence of PSO algorithm, the constriction factor is also in use [22], [25]

$$C = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|}, \text{ where } 4.1 \le \varphi \le 4.2. \tag{10}$$

As ϕ increases, the factor C decreases and convergence becomes slower because population diversity is reduced.

B. Passive Congregation-Based PSO (PC_PSO)

Passive congregation is swarming by social forces which attract a particle towards other swarm members. In this approach [22], [26] in addition to local and global best particles guiding the swarm to achieve global best position, a random particle $prand$ is also employed as a guide

$$v_{id}^{k+1} = C[w \times v_{id}^k + c_1 \times rand_1 \times \left(pbest_{id}^k - x_{id}^k\right) + c_2 \times rand_2 \left(x_{id}^k - prand_{id}^k\right) + c_3 \times rand_3 \times (gbest_{id}^k - x_{id}^k)]. \tag{11}$$

C. Concept of Time-Varying Acceleration Coefficients (TVAC)

The time-varying inertia weight (TVIW) can locate good solution at a significantly faster rate but its ability to fine tune the optimum solution is weak, due to the lack of diversity at the end of the search. It has been observed by most researchers that in PSO, problem-based tuning of parameters is a key factor to find the optimum solution accurately and efficiently [14], [15], [17], [26]. Kennedy and Eberhart [13] stated that a relatively higher value of the cognitive component, compared with the social component, results in roaming of individuals through a wide search space. On the other hand, a relatively high value of the social component leads particles to a local optimum prematurely. Normally studies keep each of the acceleration coefficients at 2, in order to make the mean of both stochastic factors in (7) equal to one, so that particles would over fly only half the time of search.

In population-based optimization methods, the policy is to encourage the individuals to roam through the entire search space, during the initial part of the search, without clustering around local optima. During the latter stages, however convergence towards the global optima should be encouraged, to find the optimum solution efficiently. In TVAC, this is achieved by changing the acceleration coefficients c_1 and c_2 with time in such a manner that the cognitive component is reduced while the social component is increased as the search proceeds. A large cognitive component and small social component at the beginning, allows particles to move around the search space, instead of moving towards the population best prematurely. During the latter stage in optimization, a small cognitive component and a large social component allow the particles to converge to the global optima. The acceleration coefficients are expressed as [23]

$$c_1 = (c_{1f} - c_{1i}) \frac{iter}{iter_{\max}} + c_{1i} \tag{12}$$

$$c_2 = (c_{2f} - c_{2i}) \frac{iter}{iter_{\max}} + c_{2i} \tag{13}$$

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

D. Self-Organizing Hierarchical PSO With TVAC (SOH_PSO)

In this novel PSO strategy the previous velocity term in (7) is made zero. With this modification the particles rapidly rush towards a local optimum solution and then stagnate because of the absence of momentum. To make this strategy effective, the velocity vector of a particle is reinitialized with a random velocity whenever it stagnates in the search space. When a particle stagnates, its associated $pbest$ remains unchanged for a number of iterations. When more particles stagnate, the $gbest$ also undergoes the same fate and the PSO algorithm converges prematurely to a local optima and v_{id} becomes zero. A necessary push to the PSO algorithm is imparted by reinitializing v_{id} by a random velocity term. The method works as follows [23]:

$$\begin{aligned} v_{id}^{k+1} = &\left((c_{if} - c_{1i}) \frac{iter}{iter_{\max}} + c_{1i}\right) \times rand_1 \times (pbest_{id} - x_{id}) \\ &+ \left((c_{2f} - c_{2i}) \frac{iter}{iter_{\max}} + c_{2i}\right) \times rand_2 \times (gbest_{gd} - x_{id}) \end{aligned} \tag{14}$$

$$\begin{aligned} &\text{If } v_{id} = 0 \text{ and } rand_3 < 0.5 \text{ then} \\ &\quad v_{id} = rand_4 \times V_{d\max} \text{ else } v_{id} = -rand_5 \times V_{d\max}. \end{aligned} \tag{15}$$

Thus a series of particle swarm optimizers are generated inside the main PSO until the convergence criteria is reached. The variables $rand_3$, $rand_4$ and $rand_5$ are randomly generated numbers between 0 and 1.

IV. Solution of NCED Problem Using SOH_PSO With TVAC

The paper presents solution of NCED problem with valve point loading, prohibited operating zones and ramp rate limits employing SOH_PSO with TVAC for practical power system operation. This novel PSO method is found to perform very efficiently for the discontinuous and non-smooth cost functions as premature convergence is avoided. The idea is 1) to exercise proper control over the global and local exploration of the swarm during the optimization process by using TVAC; 2) to reinitialize the velocity vector whenever it stagnates causing saturation. This dual strategy is found to perform very efficiently for the discontinuous and nonsmooth cost functions of practical generators. The flowchart for this algorithm is given in Fig. 1. The implementation steps are as follows:

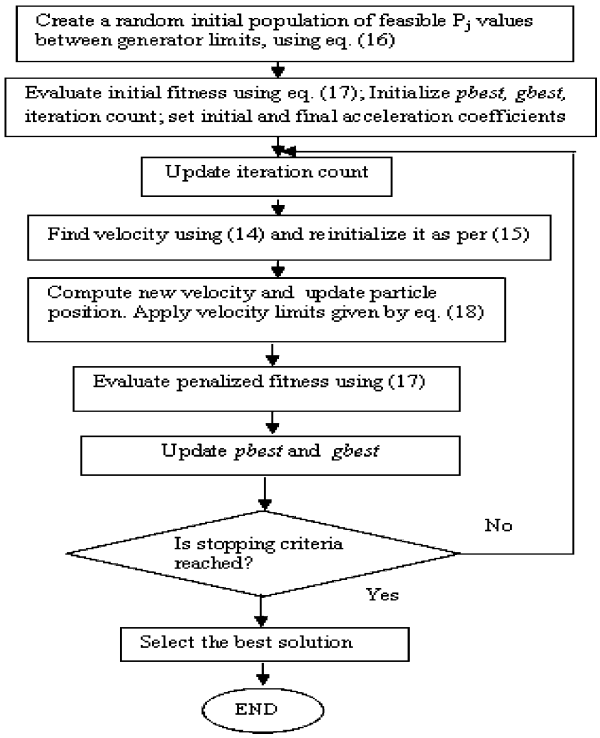

Fig. 1. Flowchart of NCED solution using SOH_PSO with TVAC.

Step 1) *Initialization of the swarm*: For a population size P, the particles are randomly generated in the range 0–1 and located between the maximum and the minimum operating limits of the generators. If there are N generating units, the ith particle is represented as $P_i = (P_{i1}, P_{i2}, P_{i3} \ldots\ldots\ldots \ldots\ldots\ldots \ldots P_{iN})$. The jth dimension if the ith particle is allocated a value of P_{ij} as given below to satisfy the constraint given by (3). Here, $r \in [0, 1]$

$$P_{ij} = P_{j\,\min} + r(P_{j\,\max} - P_{j\,\min}). \tag{16}$$

For generators with ramp rate limits the initialization is based on (5) and for prohibited zones (6) is employed.

Step 2) *Defining the evaluation function*: The merit of each individual particle in the swarm, is found using a fitness function called evaluation function. The popular penalty function method employs functions to reduce the fitness of the particle in proportion to the magnitude of the constraint violation. The penalty parameters are chosen carefully to distinguish between feasible and infeasible solution.

The evaluation function $f(P_i)$ is defined to minimize the nonsmooth cost function given by (1) for a given load demand $\mathrm{P_D}$ while satisfying the constraints given by (2) and (3) as

$$f(P_i) = \sum_{i=1}^{N} F_i(P_i) + \alpha \left[\sum_{i=1}^{N} P_i - (P_{\mathrm{D}} + P_L) \right]^2 + \beta \left[\sum_{k=1}^{n_i} P_i(violation)_k \right]^2 \tag{17}$$

where α is the penalty parameter for not satisfying load demand and β represents the penalty for a unit loading falling within a prohibited operating zone.

Step 3) *Initialization of pbest and gbest*: The fitness values obtained above for the initial particles of the swarm are set as the initial $pbest$ values of the particles. The best value among all the $pbest$ values is identified as $gbest$.

Step 4) *Evaluation of velocity:* The update velocity is computed using (14). To control excessive roaming of particles, velocity is made to lie between $-V_j^{\max}$ and $V_j^{\max}$ The maximum velocity limit for the jth generating unit is computed as follows:

$$V_j^{\max} = \frac{P_{j.\max} - P_{j\,\min}}{R} \tag{18}$$

where R is the chosen number of intervals in the jth dimension. For all the examples tested using the PSO approach, $V_j^{\max}$ was set between 10%–15% of the dynamic range of the variable on each dimension.

Step 5) *Reinitialization of velocity:* In the SOH_PSO, the particles are provided with a momentum by reinitializing the modulus of the velocity vector with a random velocity, as per (15) which helps the particles in locating global optimum solution.

Step 6)*Update the swarm:* The particle position vector is updated using (8) and then $pbest$, and $gbest$ values are updated.

Step 8) *Stopping criteria:* For comparison with other strategies, maximum number of iterations is adopted as the stopping criterion in this paper.

V. Numerical Results and Analysis

A. Testing Strategies

The NCED problem was solved using the SOH_PSO with TVAC and its performance is compared with classical PSO and PC_PSO [22], [26]. In classical simple PSO (SPSO) and PC_PSO the constriction factor was decreased from 0.73 to 0.64 during the search, TVIW is applied using (9) and w is varied from 0.9 to 0.4. In the PC_PSO $c_1 = c_2 = c_3 = 2$ is used in (11) for all the systems as these values were found to produce the best results. Similarly, in the classical PSO $c_1 = c_2 = 2$ is employed. The performance of each system has been judged out of 50 trials, using MATLAB 7.0.1 on a Pentium IV processor, 2.8 GHz with 512 MB RAM.

B. Effectiveness of SOH_PSO on Different Benchmarks

The convergence behavior of the SOH_PSO was tested for different cases having different dimensions and varying levels of complexity to study the effectiveness of the approach in handling premature convergence. The first test system has six-generating units [14], a total load of 1263 MW; all the units have prohibited zones and ramp rate limit constraints and power losses have been calculated using B-matrix from [14]. The best reported cost is \$15 450/h [18]. The second test system consists of 15-generating units, a total load of 2630 MW and all the units have prohibited zones and ramp rate limit constraints [14] along with power losses. The best cost reported is \$32 858/h [14].The third system consists of 40 units with valve point loading effects and a total load of 10 500 MW [3]. The system has many local minima and the global minimum is not reported

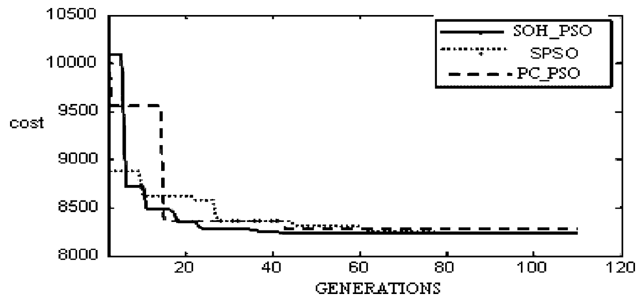

Fig. 2. Convergence characteristics of PSO strategies (three-unit system).

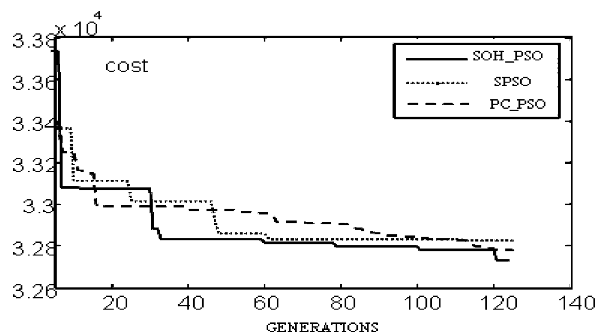

Fig. 3. Convergence characteristics of PSO strategies (15-unit system).

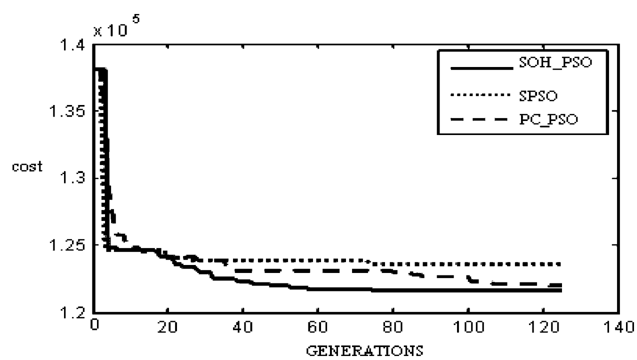

Fig. 4. Convergence characteristics of PSO strategies (40-unit system).

yet. The best cost reported so far is $121 664.43/h [18]. Power losses have not been considered for this system for comparison with previous results [18]. The cost found in this paper using SOH_PSO is lower than reported for all three systems under test.

For comparison, first a few less complex systems were tested. 1) the three-unit system [2], [15] without losses with valve point effects for a demand of 850 MW; 2) the six-unit system for demand of 1263 MW [14] without complexity, i.e., losses, POZ and ramp limits; and 3) 15-unit system with POZ for a demand of 2650 MW [4], [12]. The convergence characteristic of the three-unit system is plotted in Fig. 2 for all three methods. The global best cost of $8234.07/h reported in [15] was achieved by all three methods. The SOH_PSO with TVAC was found to achieve global best cost with all combinations of TVAC for this system. However the superiority of this method is more pronounced for larger systems with higher complexity discontinuity and nonconvexity as is evident from Fig. 3 for 15-unit system [14] and Fig. 4 for 40-unit system [3].

TABLE I
RESULTS OF SIX-UNIT SYSTEM WITHOUT COMPLEXITY

Unit power output	SPSO	PC_PSO	SOH_PSO
P1(MW)	442.86	445.00	446.68
P2(MW)	175.58	173.21	171.24
P3(MW)	263.04	262.86	264.13
P4(MW)	128.35	123.78	125.18
P5(MW)	172.37	172.64	172.15
P6(MW)	80.80	85.51	83.62
Total Cost($/h)	15,276.38	15,276.05	**15,275.93**
Total Power output(MW)	1263.00	1263.00	1263.00

TABLE II
COMPARISON OF RESULTS FOR 15-UNIT SYSTEM [4], [12] WITH POZ

Unit power output	SPSO	PC_PSO	DCGA	ETQ	SOH_PSO
P1(MW)	415.07	454.98	406.10	450.00	455.00
P2(MW)	455.00	455.00	453.80	450.00	455.00
P3(MW)	130.00	130.00	130.00	130.00	130.00
P4(MW)	129.89	130.00	130.00	130.00	130.00
P5(MW)	335.02	335.05	355.00	335.00	259.98
P6(MW)	460.00	424.25	456.80	455.00	460.00
P7(MW)	465.00	464.98	459.80	465.00	465.00
P8(MW)	60.00	60.00	60.00	60.00	60.00
P9(MW)	25.00	25.00	26.60	25.00	25.00
P10(MW)	20.00	20.00	21.60	20.00	20.00
P11(MW)	20.00	20.69	36.20	20.00	59.97
P12(MW)	79.99	75.00	59.00	55.00	75.01
P13(MW)	25.00	25.00	25.00	25.00	25.00
P14(MW)	15.00	15.00	15.00	15.00	15.00
P15(MW)	15.00	15.00	15.00	15.00	15.00
Total Cost($/h)	32,515.87	32,512.35	32,515.00	32,507.50	32,505.88
Total Power output(MW)	2649.97	2649.95	2649.90	2650.00	2649.96

The best results of case 2) for the three methods are tabulated out of 50 trials in Table I for six-unit system. The proposed SOH_PSO obtained the global minimum cost of $ 15 275.93/h with 87% consistency while classical PSO and PC_PSO converged to near global costs. The 15-unit system with POZ [4], [12] of case 3) was also tested and the results of the three methods are compared in Table II with DCGA [4] and ETQ [12]. The SOH_PSO obtained the best results with ETQ [12] close behind. The results clearly show the effectiveness of SOH_PSO; this method particularly dominates other methods for complex multimodal functions. For simple problems classical PSO and its variants work equally well, but the consistency of SOH_PSO in locating good solutions remains more.

C. Selection of Parameters for SOH_PSO With TVAC

The performance of PSO algorithm is quite sensitive to the various parameter settings. Tuning of parameters is essential in all PSO based methods [14], [15], [17], [18], [27]. Based on empirical studies on a number of mathematical benchmarks [23] has reported the best range of variation as 2.5–0.5 for c_1 and 0.5–2.5 for c_2. The idea is to use a high initial value of the cognitive coefficient c_1 to make use of full range of the search space and to avoid premature convergence with a low social coefficient c_2. As the search progresses c_1 is reduced to reduce search space and c_2 is increased to accelerate the solution towards global convergence. The authors experimented on a number of ED problems by changing the range of variation for the coefficients (c_{1i} and c_{2f} between 2.5–1.6 and c_{1f} and c_{2i} from 0.5–0.1). The results for two systems out of 50 different trials are presented in Tables III and IV. It can be observed that in general SOH-PSO

TABLE III
EFFECT OF ACCELERATION COEFFICIENTS ON SOH_PSO (SIX-UNIT SYSTEM)

S.No.	c_{1i}	c_{1f}	c_{2i}	c_{2f}	Minimum Cost ($/h)	Maximum cost($/h)	***Average cost($/h)***
1	2.5	0.2	0.2	2.5	15,456.73	15,664.30	15,497.43
2	**2.5**	**0.2**	**0.2**	**2.2**	**15,446.02**	**15,609.64**	**15,497.35**
3	2.5	0.2	0.2	1.9	15,454.79	15,625.85	15,502.48
4	2.5	0.2	0.2	1.6	15,452.13	15,613.24	15,510.35
5	2.2	0.2	0.2	2.5	15,450.54	15,680.67	15,501.45
6	2.2	0.2	0.2	2.2	15,456.03	15,622.64	15,508.24
7	2.2	0.2	0.2	1.9	15,457.88	15,616.40	15,499.64
8	2.2	0.2	0.2	1.6	15,456.74	15,620.77	15,503.22
9	1.9	0.2	0.2	2.5	15,453.36	15,635.67	15,508.30
10	1.9	0.2	0.2	2.2	15,452.27	15,642.44	15,550.43
11	1.9	0.2	0.2	1.9	15,458.44	15,622.35	15,506.99
12	1.9	0.2	0.2	1.6	15,451.75	15,616.54	15,504.35

TABLE IV
EFFECT OF ACCELERATION COEFFICIENTS ON RESULTS OF 40-UNIT SYSTEM

S.No.	c_{1i}	c_{1f}	c_{2i}	c_{2f}	Minimum Cost($/h)	Max cost($/h)	Average cost($/h)	***Fr****
1	2.5	0.2	0.2	2.5	121,603.00	122,996.71	122,096.12	33
2	**2.5**	**0.2**	**0.2**	**2.2**	**121,501.14**	**122,446.30**	**121,853. 69**	**36**
3	2.5	0.2	0.2	1.9	121,590.22	122,800.41	122,005.15	18
4	2.5	0.2	0.2	1.6	121,605.71	123,356.29	122,217.33	26
5	2.2	0.2	0.2	2.5	121,646.07	123,611.42	122,119.23	32
6	2.2	0.2	0.2	2.2	121,631.33	123,006.19	122,084.12	24
7	2.2	0.2	0.2	1.9	121,610.71	123,400.85	121,997.68	28
8	2.2	0.2	0.2	1.6	121,600.71	123,509.16	122,115.12	24
9	1.9	0.2	0.2	2.5	121,656.52	123,226.31	122,036.06	28
10	1.9	0.2	0.2	2.2	121,605.07	123,007.30	122,101.32	24
11	1.9	0.2	0.2	1.9	121,603.56	123,600.03	122,221.34	28
12	1.9	0.2	0.2	1.6	121,606.84	123,488.10	122,197.89	28
13	1.6	0.2	0.2	2.5	121,654.52	123,694.32	122,185.43	28
14	1.6	0.2	0.2	2.2	121,610.71	123,478.91	122,061.48	30
15	1.6	0.2	0.2	1.9	121,651.80	123,511.07	122,144.88	26
16	1.6	0.2	0.2	1.6	121,603.00	122,998.24	122,007.60	32

* Frequency of achieving cost better than mean

with TVAC performs better for all combinations of parameters as compared to PSO algorithms with fixed values of c_1 and c_2. Table III shows that for all parameter combinations the minimum cost is close to the previously reported minimum of US$15 450/h but the best cost of $ 15 446.01/h is achieved when c_1 is varied between 2.5–0.2 and c_2 between 0.2–2.2. The best cost as well as frequency of achieving the best value is highest for this range for the three test cases in this paper. The best combination may be different for other problems but it is expected to lie in the above range itself. Table IV shows that for each combination of acceleration coefficients the minimum cost achieved is less than previously reported best of $121 664.43/h [18]; the least achieved is $121 501.14/h.

D. Effect of Population Size

Eberhart and Shi [25] observed that population size does not affect the performance of a PSO algorithm significantly. However [27] has recently reported that increasing population improved the performance of their PSO algorithm. The authors too observed that the population size should be optimum for achieving global results. Too large or a very small population may not be capable of searching a minimum, particularly in complex multimodal problems. The optimum population size is found to be related to the problem dimension and complexity. Larger the dimension and/or complexity, larger is the population size required to achieve optimal results. A larger swarm size provides the necessary population diversity for complex problems and helps in finding global best solution. Tables V and VI show the performance of the three methods for different population sets. Tests were carried out for a population of 15, 20, 25 and 30 for the six-unit system and a population of 200, 300, 400 and 500 for the 15-unit and 40-unit systems, respectively.

TABLE V
COMPARISON OF DIFFERENT PSO STRATEGIES (SIX-UNIT SYSTEM)

S.no.	Population size	PSO variant	Min cost($/h)	Max cost($/h)	***Average cost($/h)***
1	15	SPSO	15,477.07	15,682.75	15,551.29
		PC_PSO	15,468.20	15,668.67	15,541.92
		SOH_PSO	15,452.05	15,640.13	15,535.12
2	20	SPSO	15,475.44	15,667.50	15,542.07
		PC_PSO	15,465.71	15,659.51	15,533.67
		SOH_PSO	15,451.31	15,625.30	15,525.30
3	25	SPSO	15,471.74	15,654.84	15,534.78
		PC_PSO	15,459.28	15,643.73	15,525.67
		SOH_PSO	15,449.34	15,613.51	15,508.30
4	30	SPSO	15,466.63	15,642.68	15,523.64
		PC_PSO	15,453.09	15,633.30	15,514.98
		SOH_PSO	15,446.02	15,609.64	15,497.35

TABLE VI
COMPARISON OF DIFFERENT PSO STRATEGIES (40-UNIT SYSTEM)

S.no.	Population	PSO variant	Minimum cost($/h)	Fr	Maximum cost($/h)	***Average cost($/h)***
1		SPSO	122,590.50	15	125,890.37	123,946.97
	200	PC_PSO	122,358.00	15	124,832.87	123,147.46
		SOH_PSO	**121,651.80**	**25**	**123,800.26**	**122,595.60**
2	300	SPSO	122,445.12	21	125,456.78	123,477.87
		PC_PSO	122,168.19	23	123,767.23	122,997.66
		SOH_PSO	**121,610.71**	**30**	**123,455.10**	**122,247.93**
3	400	SPSO	122,272.13	23	124,660.29	122,815.46
		PC_PSO	121,989.71	26	123,169.07	122,626.23
		SOH_PSO	**121,589.67**	**35**	**122,867.65**	**122,028.67**
4	500	SPSO	122,049.66	26	124,209.16	122,327.36
		PC_PSO	121,767.90	25	122,867.55	122,461.30
		SOH_PSO	**121,501.14**	**36**	**122,446.30**	**121,853.57**

With increase in population, a steady improvement in minimum and average costs was noticed. A population of 30 was found optimum for six-unit system while a population of 500 resulted in achieving global solutions more consistently for the two larger systems. Increasing the swarm size beyond these values did not produce any significant improvement. The optimum population for both the 15-unit and 40-unit systems was found to be 500 because though 15-unit system has lower dimension, the complexity level is higher due to the inclusion of POZ, ramp limits and losses while the 40-unit system has only valve loading effects. Maximum iterations used were 125 for all testing strategies.

E. Comparison of SOH_PSO With Other PSO Strategies

1) Convergence Characteristics: The Figs. 3 and 4 show the superior convergence characteristics of SOH_PSO. After some iterations the classical PSO characteristics and PC_PSO show signs of premature convergence and settle to near global results. But the characteristics of SOH_PSO are continuously drooping throughout the search because the TVAC provide optimal search capability by proper tuning of cognitive and social parameters during the search.

2) Solution Quality: Tables V and VI show that the minimum cost and average cost produced by SOH_PSO is least compared with other methods emphasizing its better solution quality. The frequency of achieving cost better than the mean is also highest. The dynamic convergence behavior of the three methods was

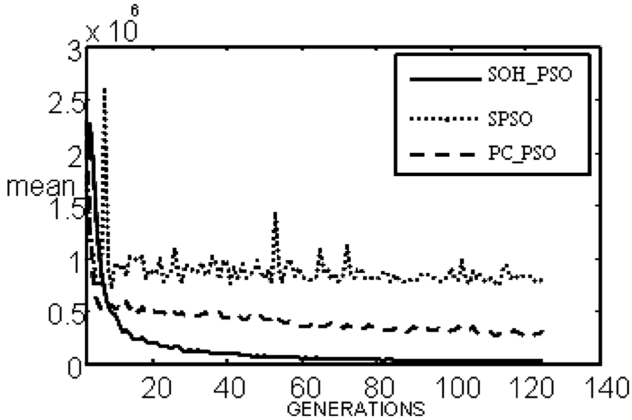

Fig. 5. Mean value of different PSO strategies (six-unit system).

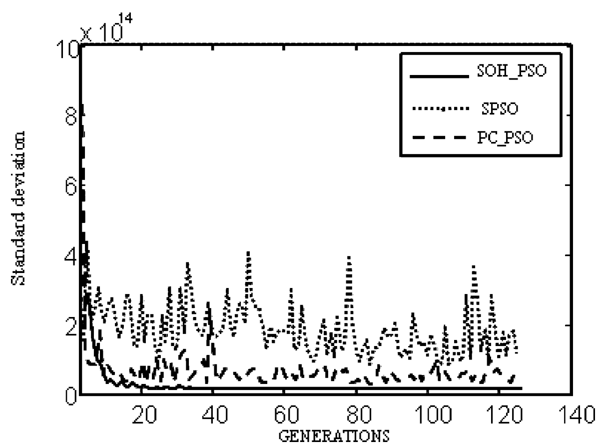

Fig. 6. Standard deviation of different PSO strategies (15-unit system).

TABLE VII
GENERATOR OUTPUT FOR LEAST COST (SIX-UNIT SYSTEM)

Unit power output	SPSO	PC_PSO	***SOH_PSO***
P1(MW)	473.66	437.79	438.21
P2(MW)	140.00	195.98	172.58
P3(MW)	240.06	256.72	257.42
P4(MW)	149.97	149.36	141.09
P5(MW)	173.78	166.20	179.37
P6(MW)	97.91	69.26	86.88
Total Power Output	1,275.38	1,275.31	1,275.55
Total loss P_L	12.38	12.32	12.55
Total generation cost($/h)	15,466.63	15,453.09	**15,446.02**
CPU time (seconds)	0.0602	0.0643	0.0633

TABLE VIII
GENERATOR OUTPUT FOR LEAST COST (15-UNIT SYSTEM)

Unit power output	SPSO	PC_PSO	***SOH_PSO***
P1(MW)	455.00	455.00	455.00
P2(MW)	380.00	380.00	380.00
P3(MW)	130.00	130.00	130.00
P4(MW)	129.28	127.15	130.00
P5(MW)	164.77	169.91	170.00
P6(MW)	460.00	460.00	459.96
P7(MW)	424.52	430.00	430.00
P8(MW)	60.00	108.38	117.53
P9(MW)	25.00	77.41	77.90
P10(MW)	160.00	97.76	119.54
P11(MW)	80.00	67.61	54.50
P12(MW)	72.62	73.26	80.00
P13(MW)	25.00	25.57	25.00
P14(MW)	44.83	19.57	17.86
P15(MW)	49.42	38.93	15.00
Total Power Output	2660.44	2660.55	2662.29
Total loss P_L(MW)	30.49	30.54	32.28
Total generation cost($/h)	32,798.69	32,775.36	32,751.39
CPU time (seconds)	0.0913	0.0967	0.0936

also studied by calculating the mean μ and standard deviation σ of the swarm at each iteration defined as

$$\mu = \frac{\sum_{i=1}^{PS} f(P_i)}{PS} \tag{19}$$

$$\sigma = \sqrt{\frac{1}{PS}\sum_{i=1}^{PS}(f(P_i) - \mu)^2}. \tag{20}$$

PS is the population size here and $f(P_i)$ is the evaluation function defined in (17). Figs. 5 and 6 plot the mean and standard deviation for the test systems obtained in one trial of 125 iterations. The SOH_PSO method shows its superiority over the other methods as both the mean and standard deviation are much lower than other methods. It is clear that SOH_PSO produces better dynamic convergence of the solution because the mean as well as the standard deviation of the members of the swarm reduces continuously. The other methods show premature convergence and hence do not achieve minima.

3) Computational Efficiency: Tables VII–IX present the best cost achieved by the different PSO algorithms for the three test cases with constraint satisfaction. The costs achieved by SOH_PSO are best and less than reported in recent literature [14], [18]. The SOH_PSO method is also computationally efficient as time requirement is quite comparable to the simple PSO (SPSO).

4) Robustness: Due to the inherent randomness involved the performance of heuristic search algorithms are judged out of a number of trials. Many trials with different initial populations were carried out to test the robustness/consistency of the different PSO algorithm. Table X shows the frequency of attaining costs within different ranges for 40-unit system out of 50-independent trials. It can be seen that SOH_PSO method is robust and most consistent in producing lower cost.

5) Comparison of Best Solutions: The best solution obtained by SOH_PSO for the six-unit system is compared with recently published results of GA [14], PSO [14], NPSO [18], and NPSO-LRS [18] in Table XI. The results show that SOH_PSO with TVAC obtains the minimum cost as compared to the other methods. Similarly the results of the SOH_PSO obtained for the 15-unit system are compared with GA [14] and PSO [14] in Table XII. Results of 40-unit system are compared with previously published results, i.e., EP [3], ESO [10], MPSO [15], NPSO [18] and NPSO-LRS [18] in Table XIII. For all the three systems the performance of SOH_PSO with TVAC is found to be superior. Using Tables XIV and XV it can be seen that the results obtained by SOH_PSO algorithm fulfils the POZ, ramp rate limits and operating min-max limits for all the units.

TABLE IX
GENERATOR OUTPUT FOR LEAST COST (40-UNIT SYSTEM)
(OUT OF 50 TRIALS)

Unit output	SPSO	PC_PSO	***SOH_PSO***
P1(MW)	113.97	113.98	110.80
P2(MW)	114.00	114.00	110.80
P3(MW)	109.19	97.26	97.40
P4(MW)	179.77	179.51	179.73
P5(MW)	97.00	89.38	87.80
P6(MW)	91.01	105.20	140.00
P7(MW)	259.87	259.55	259.60
P8(MW)	286.99	286.90	284.60
P9(MW)	284.09	284.71	284.60
P10(MW)	204.05	206.24	130.00
P11(MW)	168.40	166.52	94.00
P12(MW)	94.00	94.00	94.00
P13(MW)	212.30	214.56	304.52
P14(MW)	393.76	392.76	304.52
P15(MW)	303.62	306.24	394.28
P16(MW)	392.05	394.88	394.28
P17(MW)	489.49	489.26	489.28
P18(MW)	489.35	489.82	489.28
P19(MW)	512.39	510.62	511.28
P20(MW)	511.21	511.68	511.27
P21(MW)	522.61	523.52	523.28
P22(MW)	523.65	523.26	523.28
P23(MW)	523.06	523.98	523.28
P24(MW)	520.72	523.21	523.28
P25(MW)	524.86	523.54	523.28
P26(MW)	525.22	523.10	523.28
P27(MW)	10.00	10.00	10.00
P28(MW)	10.00	10.00	10.00
P29(MW)	10.00	10.00	10.00
P30(MW)	87.64	89.05	97.00
P31(MW)	190.00	190.00	190.00
P32(MW)	190.00	190.00	190.00
P33(MW)	190.00	190.00	190.00
P34(MW)	200.00	200.00	185.20
P35(MW)	167.18	164.78	164.80
P36(MW)	172.12	172.89	200.00
P37(MW)	110.00	110.00	110.00
P38(MW)	110.00	110.00	110.00
P39(MW)	95.58	94.24	110.00
P40(MW)	510.85	511.36	511.28
Total power output(MW)	10,500.00	10,500.00	10,500.00
Total cost($/h)	122,049.66	121,767.89	**121,501.14**

TABLE X
FREQUENCY OF CONVERGENCE FOR 40-UNIT SYSTEM OUT OF 50 TRIALS

Method	***Cost range (x 10^3 $/h)***					
	121.5-122.0	122.0-122.5	122.5-123.0	123.0-123.5	123.5-124.0	124.0-124.5
SPSO	0	28	15	04	02	01
PCPSO	14	11	25	0	0	0
SOH_PSO	38	12	0	0	0	0

TABLE XI
MINIMUM COST BY DIFFERENT METHODS (SIX-UNIT SYSTEM, $P_D = 1263$ MW) [14]

Method	GA	PSO	PSO_LRS	NPSO	NPSO_LRS	***SOH_PSO***
Cost($/h)	15,459	15,450	15,450	15,450	15,450	15,446

VI. CONCLUSION

The complex problem of nonconvex economic power dispatch is solved using SOH_PSO with TVAC. The problem of premature convergence is addressed by 1) reinitializing the velocity vector whenever it stagnates and 2) striking proper balance between the local and global exploration using TVAC. The performance of this method is compared with some other PSO algorithms. The test results clearly demonstrated that SOH_PSO which is capable of achieving global solutions is simple, computationally efficient and has better and stable dynamic convergence characteristics. It has been shown through different trials that this method outperforms other reported methods in terms of solution quality, computational efficiency, dynamic convergence, robustness and stability.

TABLE XII
COMPARISON OF BEST RESULTS (15-UNIT SYSTEM, $P_D = 2630$ MW) [14]

Method	Minimum cost ($/h)	Maximum cost ($/h)	***Average cost (($/h)***
PSO	32,858	33,331	33,039
GA	33,113	33,337	33,228
SOH_PSO	32,751	32,945	32,878

TABLE XIII
COMPARISON OF BEST RESULTS (40-UNIT SYSTEM, $P_D = 10500$ MW) [3]

Methods	**Total generation cost**		
	Minimum($/h)	Maximum ($/h)	Average ($/h)
IFEP	122,624.35	125,740.63	123,382.00
MPSO	122,252.26	NA	NA
ESO	122,122.16	123,143.07	122,524.07
PSO-LRS	122,035.79	123,461.68	122,558.46
NPSO	121,704.74	122,995.09	122,221.37
NPSO-LRS	121,664.43	122,981.60	122,209.32
SOHPSO	121,501.14	122,446.30	121,853.57

TABLE XIV
COST CURVES AND OPERATING LIMITS OF SIX-UNIT SYSTEM [14]

Unit	P_i^{min}	P_i^{max}	P_i^o	a_i	b_i	c_i	URi (MW/h)	DRi (MW/h)	Prohibited zone (MW)
1	100	500	440	0.0070	7	240	80	120	[210 240] [350 380]
2	50	200	170	0.0095	10	200	50	90	[90 110] [140 160]
3	80	300	200	0.0090	8.5	220	65	100	[150 170] [210 240]
4	50	150	150	0.0090	11	200	50	90	[80 90] [110 120]
5	50	200	190	0.0080	10.5	220	50	90	[90 110] [140 150]
6	50	120	110	0.0075	12	190	50	90	[75 85] [100 105]

TABLE XV
COST CURVES AND OPERATING LIMITS OF 15-UNIT SYSTEM [14]

Unit	P_{min}	P_{max}	a_i	b_i	c_i	UR_i	DR_i	P_i^o	Prohibited zone (MW)
1	150	455	0.000299	10.1	671	80	120	400	
2	150	455	0.000183	10.2	574	80	120	300	[185,225][305,335] [420 450]
3	20	130	0.001126	8.80	374	130	130	105	
4	20	130	0.001126	8.80	374	130	130	100	
5	150	470	0.000205	10.40	461	80	120	90	[180,200][305,335][390,420]
6	135	460	0.000301	10.10	630	80	120	400	[230,255][365,395][430,455]
7	135	465	0.000364	9.8	548	80	120	350	
8	60	300	0.000338	11.2	227	65	100	95	
9	25	162	0.000807	11.2	173	60	100	105	
10	25	160	0.001203	10.7	175	60	100	110	
11	20	80	0.003586	10.2	186	80	80	60	
12	20	80	0.005513	9.90	230	80	80	40	[30,40] [55,65]
13	25	85	0.000371	13.1	225	80	80	30	
14	15	55	0.001929	12.1	309	55	55	20	
15	15	55	0.004447	12.4	323	55	55	20	

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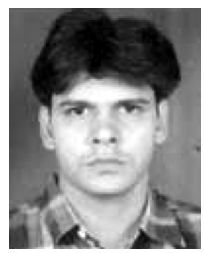

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