



A NOVEL PARTICLE SWARM OPTIMIZATION ALGORITHM SOLUTION OF ECONOMIC DISPATCH WITH VALVE POINT LOADING

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Key words: non-convex economic dispatch, valve-point effect, particle swarm optimization, inertia weight mechanism, direct search method.

ABSTRACT

It is widely recognized that a proper schedule of available generating units may save utilities millions of dollars per year in production costs. A novel particle swarm optimization (PSO) combined with the direct search method (DSM) is developed in this paper for the solution of economic dispatch (ED) problem with valve-point effect. A new inertia weight mechanism is incorporated into PSO to enhance its search capacity that leads to a higher probability of obtaining the global optimal solution. The main attractive feature of the proposed inertia weight mechanism is to monitor the weights of particles, which were linearly decreased in general applications, and to further provide a well-balanced mechanism between the global and local exploration abilities. The DSM algorithm is used as a fine tuning to determine the eventual global optimal solution with a reduced computing time. The validity, robustness, and effectiveness of the proposed approach is verified through numerical experiments for extended economic dispatch application.

I. INTRODUCTION

With increasing of the fuel prices and restructuring of the power industry, the non-convex economic dispatch (NED) problem may become a more important problem due to the inclusion of non-smooth cost function. The objective of economic dispatch (ED) is to schedule the outputs of the online generating units so that the fuel cost of generation can be minimized, while simultaneously satisfying all unit and system equality and inequality constraints. Improvements in sched-

uling the unit outputs may save utilities millions of dollars per year in production costs. Several classical optimization techniques, such as the lambda dispatch approach, the gradient method, the linear programming and the Newton's method, were used to solve the ED problem [18]. The lambda-iteration approach has been widely used in practice and requires the associated incremental costs of the units that are assumed to be monotonically increasing. However, the generating units exhibit a greater variation in the fuel cost functions due to the physical operation limitations of power plant components, such as valve points or combined cycle units. The inclusion of non-smooth cost function increases the non-linearity as well as the number of local optima in the solution space. Inaccurate dispatch results could be induced by the classical calculus-based techniques. The importance of the NED problem is thus likely to increase and more advanced algorithms for NED problem are worth developing to obtain accurate dispatch results.

Dynamic programming (DP) solution is one of the approaches to solving the ED problem with non-convex unit cost functions. Unlike the lambda-iteration approach, the DP method has no restrictions on generator cost function and performs a direct search of solution space. However, the DP method may cause the problems of curse of dimensionality [18] or local optimality [7] in the solution procedure. In this respect, several optimization algorithms based on stochastic searching techniques, including simulated annealing (SA) [16], genetic algorithm (GA) [6, 10, 15], tabu search algorithm (TSA) [5, 8], evolutionary programming (EP) [12, 13, 19], particle swarm optimization (PSO) [3] and hybrid stochastic search [1, 9, 14, 17], were developed to solve the highly non-linear ED problem without restrictions on the shape of fuel cost functions. Although these heuristic approaches do not always guarantee a global optimal solution, they generally provide a reasonable solution. Simulated annealing mimics the physical operation of the annealing process. It is easy to implement, yet the complicated annealing schedule is closely related to performance optimization. However, a poor tuning of the annealing schedule may inadvertently affect the performance of simulated annealing. Genetic algorithms were inspired by the principles of natural evolution and are very popular in solving optimization problems in power systems. The drawbacks of this approach are attributed to the long

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computing time, degradation in efficiency with highly correlated objection functions, premature convergence leading to local minima and the complicated process in coding and decoding the problem. Evolutionary programming with a Gaussian operator was originally proposed for machine intelligence but has been successfully applied to many optimization problems. It is more efficient than GA in computation time, and can generate a high quality solution with a shorter calculation compared to other stochastic algorithms. The disadvantage of this method is its slow convergence to a good near optimal solution.

Particle swarm optimization (PSO) was originally presented by Kennedy and Eberhart in 1995 [4]. It was inspired by observation of the behaviors in bird flocks and fish schools. PSO is one of the latest versions of nature inspired algorithms, which characteristics of high performance and easy implementation. With a parallel searching mechanism, the PSO algorithm has high probability to determine the global or near-global optimal solution for the NED problem [3]. However, there are many problems in the solution process by the conventional PSO. One of the main drawbacks of the conventional PSO is its premature convergence, especially while handling problems with more local optima and heavier constraints. A hybrid particle swarm optimization-sequential quadratic programming (PSO-SQP) method is presented to increase the possibility of exploring the search space where the global optimal solution exists [14]. In this paper, an alternative approach is proposed to the ED problem considering valve-point effects using an improved PSO, which focuses on the adjustment of inertia weight factor ω [11]. A novel inertia weight mechanism is incorporated into PSO to further provide a well-balanced mechanism between the global and local exploration abilities. Instead of maximum iteration count $iter_{max}$, another parameter Z is designed to improve the searching abilities. A local optimization technique, which utilizes the direct search method (DSM) [2], is also used as a fine tuning to determine the eventual global optimal solution with light computational expenses. Test results are provided to illustrate the merits of the proposed hybrid PSO-DSM algorithm. The same multiple minimum problem has been solved by the HSS in [14], the TSA in [5], the EP-SQP in [14] and the PSO-SQP in [14].

II. PROBLEM FORMULATION

The main objective of solving the ED problem is to minimize the total generation cost of a power system while satisfying various constraints. The objective function can be formulated as follows:

$$\text{Minimize } F_T = \sum_{i=1}^N F_i(P_i) \quad (1)$$

where F_T is the total fuel cost. N is the number of units in the system. $F_i(P_i)$ is the fuel cost function of unit i , and P_i is the

power output of unit i . Generally, fuel cost of generation unit will be in second-order polynomial function [18].

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 \quad (2)$$

where a_i , b_i and c_i are the cost coefficients of unit i . However, the fuel cost functions of units may be much more complicated due to the physical operation limitations, which actually exist in a practical optimization problem. Reference [15] has shown the input-output performance curve for a typical thermal unit with many valve points. The fuel cost functions taking into account the valve-point effects were expressed as

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 + \left| e_i \sin(f_i (P_i^{min} - P_i)) \right| \quad (3)$$

where e_i and f_i are the constants from the valve-point loading effect of generators.

Subject to following constraints:

- Power balance constraint

$$\sum_{i=1}^N P_i = P_D + P_{Loss} \quad (4)$$

- Unit capacity constraints

$$P_i^{min} \leq P_i \leq P_i^{max} \quad (5)$$

where P_D is the total load demand; P_{Loss} is the transmission loss; P_i^{min} and P_i^{max} are minimum and maximum generation limits of unit i respectively. The transmission losses are traditionally represented by

$$P_{Loss} = \sum_{i=1}^N \sum_{j=1}^N P_i B_{ij} P_j + \sum_{i=1}^N B_{0i} P_i + B_{00} \quad (6)$$

where B_{ij} is the coefficient of transmission losses.

III. PARTICLE SWARM OPTIMIZATION WITH INERTIA WEIGHT (PSO-IW)

PSO is a population based optimization approach. It was inspired by observation of the behaviors in bird flocks and fish schools. In a physical N -dimensional search space, the position and velocity of particle q are represented as the vectors $X_q = \{x_{q1}, x_{q2}, \dots, x_{qN}\}$ and $V_q = \{v_{q1}, v_{q2}, \dots, v_{qN}\}$ in the PSO algorithm. Let $Pbest_q = \{x_{q1}^{Pbest}, x_{q2}^{Pbest}, \dots, x_{qN}^{Pbest}\}$ and $Gbest = \{x_{1,Gbest}, x_{2,Gbest}, \dots, x_{N,Gbest}\}$ be the best position of particle q and the best position that has been achieved so far by any particles, respectively. By tracking two best values, i.e. $Pbest_q$ and $Gbest$, the global optimal might be reached by this optimization technique. Similar to other evolutionary algorithms,

the PSO has a number of parameters that must be selected. The acceleration constants $c1$ and $c2$ should be determined in advance that control the maximum step size. The inertia weight ω controls the impact of the previous velocity of the particle on its current one. Selection of the inertia weight ω and weighting factors $c1$ and $c2$ considerably affects the performance of the PSO. The appropriate selection of these parameters justifies the preliminary efforts required for their experimental determination. The modified velocity and position of each particle can be calculated using the current velocity and the distance from $Pbest_q$ to $Gbest$ as shown in the following formulas:

$$V_q^{k+1} = \omega \times V_q^k + c1 \times rand \times (Pbest_q^k - X_q^k) + c2 \times rand \times (Gbest^k - X_q^k) \quad (7)$$

$$X_q^{k+1} = X_q^k + V_q^{k+1}, \quad q = 1, 2, \dots, Q \quad (8)$$

where V_q^k is the velocity of particle q in iteration k , X_q^k is the position of particle q in iteration k , $Pbest_q^k$ is the best value of fitness function that has been achieved by particle q before iteration k , $Gbest^k$ is the best value of fitness function that has been achieved so far by any particle, $c1$ and $c2$ represent the weighting of the stochastic acceleration terms that pull each particle toward $Pbest_q$ and $Gbest$ positions, $rand$ means a random variable between 0.0 to 1.0, and ω is the inertia weight factor. It is obvious that the inertia weight ω is an important factor to avoid being entrapped in a local minimum. As originally developed, ω is usually linear decreasing during iterations and is calculated using the following expression [11].

$$\omega = \omega_{\max} - (\omega_{\max} - \omega_{\min}) \times \frac{iter}{iter_{\max}} \quad (9)$$

where ω_{\max} and ω_{\min} are the initial and final weight respectively, $iter_{\max}$ is the maximum iteration count, and $iter$ is the current number of iterations. The process of implementing the PSO is as follows:

- Step 1:** Create an initial population of particles with random positions and velocity within the solution space.
- Step 2:** For each particle, calculate the value of the fitness function.
- Step 3:** Compare the fitness of each particle with each $Pbest$. If the current solution is better than its $Pbest$, then replace its $Pbest$ by the current solution.
- Step 4:** Compare the fitness of all the particles with $Gbest$. If the fitness of any particles is better than $Gbest$, then replace $Gbest$.
- Step 5:** Update the velocity and position of all particles according to Eqs. (7) and (8).
- Step 6:** Repeat steps 2-5 until a criterion is met.

IV. PARTICLE SWARM OPTIMIZATION WITH IMPROVED INERTIA WEIGHT (PSO-IIW)

In applying the conventional PSO to solve the generation scheduling problem, it is quite likely that the final solution may lead to sub-optimal solution owing to the inclusion of non-smooth cost function in the NED problem. In general, the initial candidate solutions are usually far from the global optimum and hence the larger inertia weight ω may be proved to be beneficial. Large inertia weight enables the PSO to explore globally and small inertia weight enables the PSO to explore locally. This inertia weight ω plays the role of balancing the global and local exploration abilities. The value of ω for all particles will decrease at the same time as the iteration number increases. However, it is not reasonable for all particles to employ the linearly decreasing inertia weights of formula (9). The standard PSO has oscillatory problem and easy to be trapped in local optima if a promising area where the global optimum is residing is not identified at the end of the optimization process. The conventional PSO still need further research and development to improve its performance and to obtain the robustness.

To increase the possibility of exploring the search space where the global optimal solution exists, we follow a slightly different approach to further provide a well-balanced mechanism between the global and local exploration abilities. The proposed weighting function is defined as follows:

$$\begin{cases} \omega_{qi}^k = \omega_{\max} - (\omega_{\max} - \omega_{\min}) \times \frac{Z_{iter,qi}^k}{Z}, & \text{if } v_{qi}^k \times (x_{i,Gbest}^k - x_{qi}^k) > 0 \\ \omega_{qi}^k = \omega_{qi}^{k-1}, & \text{if } v_{qi}^k \times (x_{i,Gbest}^k - x_{qi}^k) < 0 \end{cases} \quad q = 1, 2, \dots, Q; \quad i = 1, 2, \dots, N \quad (10)$$

where ω_{qi}^k is the element inertia weight i of particle q in iteration k .

From (10), if the v_{qi}^k and $(x_{i,Gbest}^k - x_{qi}^k)$ move at the same direction, the value of ω_{qi}^k employed will be the linearly decreasing to prevent the particles from flying past the target position during the flight. Otherwise, the value of ω_{qi}^k will be kept without decreasing to facilitate a free movement of particles in the search space. Instead of maximum iteration count $iter_{\max}$, another parameter Z is designed to further provide a well-balanced mechanism between the global and local exploration abilities. It is obvious that the value of Z is an important factor to control the linearly decreasing dynamic parameter framework descending from ω_{\max} to ω_{\min} . Suitable selection of Z provides a balance between global and local explorations, thus requiring less iteration on average to find a sufficiently optimal solution. The main attractive feature of inertia weight mechanism described above is to monitor the weights of a particle, which were linearly decreased in general applications, to avoid storing too many similar particles at the

end of the optimization process. The significance of control of inertia weight ω in the PSO algorithm is also retained to increase the possibility of occurrence of escaping from local optimal solutions.

V. SOLUTION METHOD AND IMPLEMENTATION OF PSO-IIW

The main computational processes of the algorithm presented in this paper to solve ED with valve-point effects problem of power systems are discussed in the following subsections. This algorithm is an implementation of PSO-IIW.

Step 1: Initialize the PSO-IIW parameters.

Set up the set of parameters of PSO, such as, number of particles Q , weighting factors $c1$, $c2$, parameter Z , and maximum number of iterations $iter_{max}$.

Step 2: Create an initial population of particles randomly.

Each particle contains the real power generation of the generators. Eq. (11) shows a particle q ,

$$X_q^k = [P_1^k, P_2^k, \dots, P_i^k, \dots, P_N^k], \quad q = 1, 2, \dots, Q \quad (11)$$

Let $rand$ be a uniform random value in the range $[0,1]$. The initial power outputs of $N - 1$ thermal generating units, without violating (5), are generated randomly by

$$P_i = P_i^{\min} + rand \times (P_i^{\max} - P_i^{\min}) \quad (12)$$

To satisfy the power balance equation, a dependent generating unit is arbitrarily selected among the committed N units and the output of the dependent generating unit P_d is determined by

$$P_d = P_D + P_{Loss} - \sum_{\substack{i=1 \\ i \neq d}}^N P_i \quad (13)$$

Whereas P_d can be calculated directly from the quadratic equation as shown in below [16].

$$AP_d^2 + (B - 1)P_d + \left[C + P_D - \sum_{\substack{i=1 \\ i \neq d}}^N P_i \right] = 0 \quad (14)$$

where,

$$A = B_{dd}$$

$$B = \sum_{\substack{j=1 \\ j \neq d}}^N B_{dj} P_j + \sum_{\substack{i=1 \\ i \neq d}}^N P_i B_{id} + B_{d0}$$

$$C = \sum_{\substack{i=1 \\ i \neq d}}^N \sum_{\substack{j=1 \\ j \neq d}}^N P_i B_{ij} P_j + \sum_{\substack{i=1 \\ i \neq d}}^N B_{i0} P_i + B_{00}$$

If P_d violates (5), a repairing strategy is applied to pick one unit at random to increase (or decrease) its output by the random or predefined step (e.g., 10 MW), one by one, until it can satisfy all the constraints.

Step 3: Evaluate the fitness of the particles.

For each particle, calculate the value of the fitness function. The fitness function is an index to evaluate the fitness of the particles. Eq. (1) shows the fitness function of the ED problem.

Step 4: Record and update the best values.

The two best values are recorded in the searching process. Each particle keeps track of its coordinate in the solution space that is associated with the best solution it has reached so far. This value is recorded as $Pbest$. Another best value to be recorded is $Gbest$, which is the overall best value obtained so far by any particle.

Step 5: Update the velocity and position of the particles.

Eq. (15) is applied to update the velocity of the particles. The velocity of a particle represents a movement of the generation of the generators. Eq. (16) is applied to update the position of the particles. The new positions of the particles are forced to satisfy the unit's generation limit constraint given by (5) and other constraints if they exist. The position of a particle is the generation of the generators.

$$V_{qi}^{k+1} = \omega_{qi} \times V_{qi}^k + c1 \times rand \times (Pbest_{qi}^k - X_{qi}^k) + c2 \times rand \times (Gbest_i^k - X_{qi}^k) \quad (15)$$

$$X_{qi}^{k+1} = X_{qi}^k + V_{qi}^{k+1} \quad q = 1, 2, \dots, Q; i = 1, 2, \dots, N \quad (16)$$

Step 6: End conditions.

Check the end condition. If it is reached, the algorithm stops, otherwise, repeat steps 3-5 until the end conditions are satisfied. In this study, the "end conditions" of PSO are

- (1) The total operating cost between two consecutive iterations is unchanged or the variation of operating cost is within a permitted range.
- (2) The variation of $Gbest$ is within a permitted range.
- (3) The maximum number of iterations is reached.

VI. LOCAL OPTIMIZATION USING THE DIRECT SEARCH METHOD

Usually, the stochastic search technique can identify a near global region but slows in a finely tuning local search. In contrast, the local searching technique can climb hills rapidly

but is easily trapped in local minima. In this paper, the PSO-IIW algorithm was responsible for “global exploitation” and the DSM algorithm was used to “local optimization” with the current solutions of the PSO-IIW as the starting points. Like many local search techniques, the DSM is more sensitive to the initial starting points. To further weaken the dependence of finding the global optimal solution on the initial starting solutions, the selection of calculation step S in the direct search procedure is vital to the success of DSM to find the global optimal solution. In this study, the DSM with large initial calculation step S_1 and small reduced factor K is usually commended to enhance its search capacity that leads to a higher probability of obtaining the global optimal solution. It is obvious that the reduced factor K is an important factor to avoid being entrapped in a local minimum. Although a small selection of the reduced factor K in the direct search procedure often leads to slow convergence, it increases the possibility to create and explore the new solution in the search space. In general, as the number of convergence level increases, more potential candidates yielding economic schedules are retained, so that the system production cost can be decreased. Therefore, a larger convergence level is desired to provide a better chance to reach the global optimal solution when the problem has a number of local optimal points. Although an arbitrary choice of larger S_1 may be misleading the search, it can be improved by the multi-level convergence technique for preventing premature convergence. The main attractive feature of multi-level convergence is to reduce the step size gradually to increase the possibility of occurrence of escaping from local optimal solution. Unfortunately, the appropriate selection of these parameters justifies the preliminary efforts required for their experimental determination. From our experience, a proper initial calculation step S_1 is chosen to be 10~20% of the largest generation unit in the power system. The recommended value of reduced factor K is 1.1~3.0 depending on the number of local minimum points in the cost functions. The details for solving the extended economic dispatch problem are the same as that in [2]. The outline of the proposed algorithm is shown in the flowchart in Fig. 1.

VII. NUMERICAL EXPERIMENTS

To verify the feasibility and effectiveness of the proposed PSO algorithm, two test systems were simulated. All the computation was performed on a PC Genuine Intel @CPU T2300@1.66GHz computer with 1.0GRAM size, and several computer programs were developed in FORTRAN:

PSO: Basic particle swarm optimization

PSO-IW: Particle swarm optimization with inertia weight

PSO-IIW: Particle swarm optimization with improved inertia weight

PSO-IIW*: PSO-IIW with local optimization

After testing and evaluating different parameter combina-

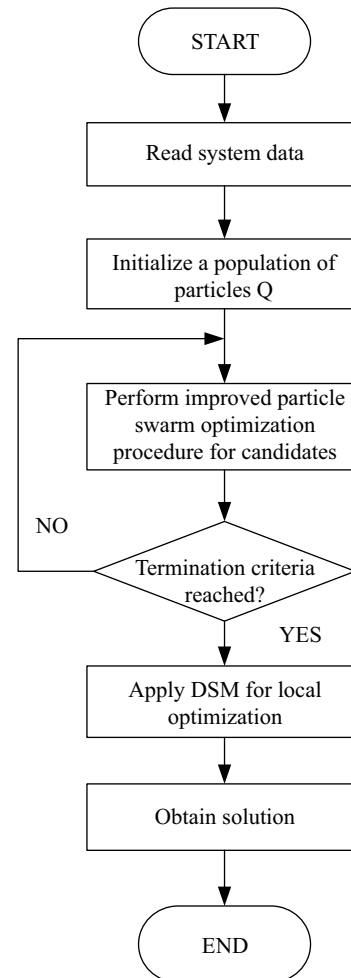


Fig. 1. Flow chart for the proposed PSO-IIW* algorithm.

tions, parameters of the PSO, PSO-IW and PSO-IIW algorithms used in the two examples are listed in Table 1 for clarity. The studied cases are stated in detail as follows:

1. Example 1: Test for a 3-unit System

In the first example, a system with three generating units considering the valve-point effects is studied to test the solution quality and performance of the proposed PSO-IIW algorithm. The system unit data is shown in Table 2 [12] and the total load demand is 850 MW. The traditional approaches, such as lambda-iteration dispatch method cannot be used to solve the above problem due to its non-smooth fuel cost function. Owing to the randomness of the heuristic algorithms, their performance cannot be judged by a single run result. Many trials with different initial conditions should be made to acquire a useful conclusion about the performance. To investigate effects of different parameters chosen on the final results, three cases were simulated for the three PSO strategies. Table 3 shows the worst cost, average cost, and best cost achieved for 100 trial runs. From the results, the superiority of the PSO-IW and PSO-IIW algorithms over basic PSO can be

Table 1. Best parameter setting of the three PSO strategies.

Parameter	PSO	PSO-IW	PSO-IIW
Example 1	Q = 400; iter _{max} = 400; c1 = 0.1; c2 = 0.1	Q = 400; iter _{max} = 400; c1 = 0.1; c2 = 0.1; $\omega_{max} = 1.1; \omega_{min} = 0.4$	Q = 400; iter _{max} = 400; c1 = 0.1; c2 = 0.1; Z = 100; $\omega_{max} = 1.1; \omega_{min} = 0.4$
Example 2	Q = 3000; iter _{max} = 3000; c1 = 0.1; c2 = 0.1	Q = 3000; iter _{max} = 3000; c1 = 0.1; c2 = 0.1; $\omega_{max} = 1.1; \omega_{min} = 0.4$	Q = 3000; iter _{max} = 3000; c1 = 0.1; c2 = 0.1; Z = 100; $\omega_{max} = 1.1; \omega_{min} = 0.4$

Table 2. Parameters for the three-unit system.

Unit No.	P_i^{max}	P_i^{min}	a_i	b_i	c_i	e_i	f_i
1	600	100	561	7.92	0.0016	300	0.0315
2	400	100	310	7.85	0.00194	200	0.042
3	200	50	78	7.97	0.00482	150	0.063

Table 3. Comparison of results with 100 trail tests for the load of 850 MW in the system Example 1.

Method	PSO			PSO-IW			PSO-IIW		
	Case A	Case B	Case C	Case A	Case B	Case C	Case A	Case B	Case C
Parameter Setting	c1 = 0.1 c2 = 0.1	c1 = 1.0 c2 = 1.0	c1 = 1.5 c2 = 1.5	c1 = 0.1 c2 = 0.1	c1 = 1.0 c2 = 1.0	c1 = 1.5 c2 = 1.5	c1 = 0.1 c2 = 0.1	c1 = 1.0 c2 = 1.0	c1 = 1.5 c2 = 1.5
Worst Cost (\$/h)	8241.399	8234.078	8234.080	8234.071	8234.071	8234.071	8234.071	8234.071	8234.071
Average Cost (\$/h)	8234.218	8234.073	8234.073	8234.071	8234.071	8234.071	8234.071	8234.071	8234.071
Best Cost (\$/h)	8234.071	8234.071	8234.071	8234.071	8234.071	8234.071	8234.071	8234.071	8234.071
NTO	25	8	10	100	100	100	100	100	100
ACT (sec.)	0.1718	0.1749	0.1759	0.1890	0.1911	0.1915	0.1903	0.1895	0.1897

NTO: number of times to reach optimal solution (\$8234.071)

ACT: average computation time for 100 trail tests

noticed. The proposed PSO-IIW algorithm has reached the optimal solution (\$8234.071) with a high probability for the solution of the small-size NED problem in these test cases.

To illustrate the convergence property of the proposed algorithm, Fig. 2 shows the PSO-IIW optimization procedure compared to PSO and PSO-IW in a typical run. In this test case, the same initial random solution (\$8274.99) was given to the three PSO strategies and search for the optimal solution along different trajectories respectively. The results show that all of the three PSO strategies can obtain the optimal solution (\$8234.071) for this small-size NED problem. However, it shows that the PSO with inertia weight provides a good convergence property to achieve the optimal solution. The total number of iterations required for the PSO-IIW is 88 and that of PSO-IW algorithm is 151 to achieve the optimal solution. The basic PSO is slow in convergence (215th iteration) in comparison with PSO-IW and PSO-IIW. The suitability of the algorithm presented in this paper to the solution of the optimal NED is, thus, confirmed.

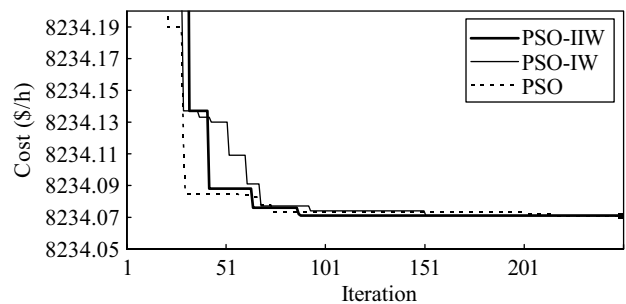


Fig. 2. Comparative convergence behavior of the three PSO strategies for the three-unit example system.

2. Example 2: Test for a 13-unit System

In this example, the simulation includes test runs for the thirteen-unit system used in [17] to demonstrate the robustness and effectiveness of the proposed PSO-IIW* algorithm. There are many local optimal solutions for the dispatch prob-

Table 4. Parameters for the thirteen-unit system.

Unit No.	P_i^{\max}	P_i^{\min}	a_i	b_i	c_i	e_i	f_i
1	680	0	550	8.1	0.00028	300	0.035
2	360	0	309	8.1	0.00056	200	0.042
3	360	0	307	8.1	0.00056	200	0.042
4	180	60	240	7.74	0.00324	150	0.063
5	180	60	240	7.74	0.00324	150	0.063
6	180	60	240	7.74	0.00324	150	0.063
7	180	60	240	7.74	0.00324	150	0.063
8	180	60	240	7.74	0.00324	150	0.063
9	180	60	240	7.74	0.00324	150	0.063
10	120	40	126	8.6	0.00284	100	0.084
11	120	40	126	8.6	0.00284	100	0.084
12	120	55	126	8.6	0.00284	100	0.084
13	120	55	126	8.6	0.00284	100	0.084

Table 5. Comparison of dispatch results for the load of 2520 MW in the system Example 2.

Unit	HSS [1]	TSA [5]	EP-SQP [14]	PSO-SQP [14]	PSO-IIW
1	628.23	628.319	628.3136	628.3205	628.3185
2	299.22	299.1993	299.1715	299.0524	299.1990
3	299.17	331.8975	299.0474	298.9681	299.1990
4	159.12	159.7305	159.6399	159.4680	159.7330
5	159.95	159.7331	159.6560	159.1429	159.7330
6	158.85	159.7306	158.4831	159.2724	159.7328
7	157.26	159.7334	159.6749	159.5371	159.7328
8	159.93	159.7308	159.7265	158.8522	159.7329
9	159.86	159.7316	159.6653	159.7845	159.7329
10	110.78	40.0028	114.0334	110.9618	77.3996
11	75.00	77.3994	75.0000	75.0000	77.3996
12	60.00	92.3932	60.0000	60.0000	92.3998
13	92.62	92.3986	87.5884	91.6401	87.6868
Cost (\$/h)	24275.71	24313	24266.44	24261.05	24169.92

lem and the problem is well suitable for testing and validating the developed algorithm. The system unit data is given in Table 4 and the load demand is 2520 MW. Network losses of the system are neglected for comparison. The same multiple minimum problem has been solved by the HSS in [14], the TSA in [5], the EP-SQP in [14] and the PSO-SQP in [14]. Table 5 depicts the numerical results of various methods. From these results, although multiple local minimum solutions exist in this studied case, the proposed PSO-IIW can find a

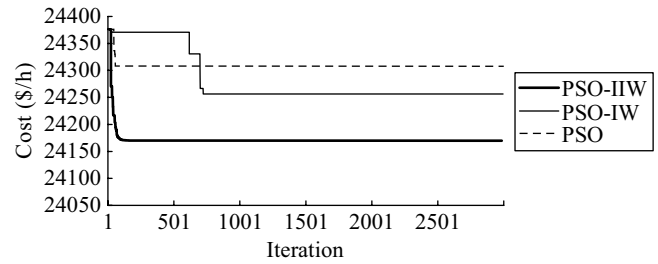


Fig. 3. Comparative convergence behavior of the three PSO strategies for the thirteen-unit example system.

better solution (\$24169.92) than many existing techniques. Details of the best solutions obtained by the proposed PSO-IIW algorithm is shown in the sixth column of Table 5. The results show that the proposed PSO-IIW provides an accurate algorithm to tackle efficiently the difficult NED problem.

To demonstrate the good convergence property of the proposed algorithm, Fig. 3 shows the PSO-IIW optimization procedure compared to basic PSO and PSO-IW in a typical run. In the test case, the same initial random starting points were given to the basic PSO, PSO-IW and PSO-IIW algorithms. As shown in Fig. 3, the basic PSO has premature convergence problem and easy to be trapped in local optima (\$24308.12) at the 56th iteration in the test case. Similar to basic PSO algorithm in optimization, the main problem of the PSO-IW is that it also gets trapped in a local optimal solution (\$24256.32) since a promising area where the global optimal is residing is not identified at the end of the optimization process. It is seen that the satisfactory solution (\$24170.96) achieved by PSO-IIW decreases very quickly before 118 iterations and achieve the global optimal solution (\$24169.92) at the 881th iteration. The improved inertia weight mechanism is very effective and the algorithm converges much faster than the case when no inertia weight mechanism is included in the algorithm. The final results of PSO-IIW are also better than those of PSO and PSO-IW. Note that the count factor Z in Eq. (10) plays a significant role in the convergence of the PSO-IIW to the global optimal solution. To illustrate the effect, the algorithm was run 100 times for various values of the Z factors and the variation of the average minimum cost for each run is shown in Table 6. In the study case, the recommended value of the parameter Z is chosen to be 100-500 to make the search effectively. The success of the proposed inertia weight technique to ‘jump’ out of the local optimal solution is, thus, confirmed.

To investigate effects of initial trail solutions on the final results, different initial random solutions were given to the PSO, PSO-IW, PSO-IIW and PSO-IIW* approach. Table 7 shows the worst cost, average cost, and best cost achieved using the four PSO strategies for 100 trial runs. In these test cases, the proposed PSO-IIW can easily obtain the satisfactory solutions using the improved inertia weight technique. However, only the near global optimal solution can be obtained by the proposed PSO-IIW approach. The number of times

Table 6. Comparison of dispatch results with 100 trial tests under various Z in the system Example 2.

Parameter Z	Average Cost (\$/h)	Parameter Z	Average Cost (\$/h)	Parameter Z	Average Cost (\$/h)
10	24273.72	800	24236.69	2000	24239.91
20	24292.86	900	24234.45	2100	24232.81
30	24285.24	1000	24230.92	2200	24225.69
40	24255.87	1100	24236.65	2300	24237.38
50	24231.72	1200	24230.22	2400	24233.43
100	24207.71	1300	24226.21	2500	24231.26
200	24212.94	1400	24232.19	2600	24227.34
300	24213.12	1500	24239.36	2700	24224.88
400	24212.99	1600	24234.28	2800	24234.59
500	24211.87	1700	24228.76	2900	24238.14
600	24235.94	1800	24226.47	3000	24229.90
700	24235.89	1900	24238.28	---	---

Table 7. Comparison among different methods after 100 trials in the system Example 2.

Method	PSO	PSO-IW	PSO-IIW	PSO-IIW*
Worst Cost (\$/h)	24362.81	24344.24	24325.27	24169.92
Average Cost (\$/h)	24227.49	24222.34	24207.71	24169.92
Best Cost (\$/h)	24182.16	24169.92	24169.92	24169.92
NTO	0	2	23	100
ACT (sec.)	47.18	52.14	54.94	58.26

Parameter Setting in DSM: $S_1 = 80$ MW; $K = 1.2$; $\epsilon = 0.001$ MW.

NTO: number of times to reach optimal solution (\$ 24169.92).

ACT: average computation time for 100 trial tests.

reached global optimal solution (\$24169.92) for the PSO-IIW is 23 and that of PSO-IW algorithm is 2 in the test cases. The basic PSO makes no guarantee that the solutions are optimal or even close to the optimal solution. As shown in the fifth columns of Table 7, a reliable solution procedure provides the optimal solution (\$24169.92) 100 times to demonstrate its effectiveness and efficiency. This test case study converges within 58.26 sec for each run when the value of Q is chosen to be 3000. In fact, various load demands chosen were studied and the results show that the proposed PSO-IIW* method can successfully remedy the local optimal solution problem. The accurate approach makes it an attractive method for the solution of the NED problem.

VIII. CONCLUSION

This paper presents a hybrid algorithm based on a combi-

nation of improved particle swarm optimization (PSO) algorithm and direct search method (DSM) to solve the economic dispatch with valve-point effects. Using the parallel searching mechanism with improved inertia weight strategy, the proposed PSO algorithm can give a good direction to identify the near global optimal solution region. A local optimization technique, which utilizes the DSM approach, is also used as a fine tuning to determine the eventual global optimal solution with light computational expenses. Many nonlinear characteristics of units could be handled properly in the direct search procedure with a reduced computing time. It is observed that obtaining the global optimal solution is possible by using the proposed algorithm for the NED problem. Numerical experiments demonstrate that the proposed algorithm is more practical and valid than many existent techniques for the solution of the NED problem.

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