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An Optimal Solution for Smooth and Non-Smooth Cost Functions-Based Economic Dispatch Problem

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Abstract: A modified particle swarm optimization and incorporated chaotic search to solve economic dispatch problems for smooth and non-smooth cost functions, considering prohibited operating zones and valve-point effects is proposed in this paper. An inertia weight modification of particle swarm optimization is introduced to enhance algorithm performance and generate optimal solutions with stable solution accuracy and offers faster convergence characteristic. Moreover, an incorporation of chaotic search, called logistic map, is used to increase the global searching capability. To demonstrate the effectiveness and feasibility of the proposed algorithm compared to the several existing methods in the literature, five systems with different criteria are verified. The results show the excellent performance of the proposed method to solve economic dispatch problems.

Keywords: particle swarm optimization; inertia weight; chaotic search; economic dispatch

1. Introduction

In electric power systems, an economic dispatch (ED) problem is a basic optimization problem, with the main aim to reduce the total cost of the power generation operation. Basically, all solutions to solving ED problems in [1–6] can be split into: (1) traditional optimization methods and (2) evolutionary computation-based optimization techniques. ED problems can be solved by several mathematical programming methods, such as lambda iteration, base point, and participation factor method [1], interior point method [2], and with evolutionary computation-based optimization techniques, such as artificial neural networks [3]. The ED problems, with smooth and non-smooth functions, were performed in previous years by taking into consideration generation constraints, such as valve-point effects (VPE), multiple fuel options, ramp rates, and prohibited operating zones (POZ), and transmission network losses. Traditionally, the thermal generator cost function is known as a quadratic function. In reality, there has been multi-fuel options on the large steam generators, and some of the ripples appear on the cost function while the steam is recognized through the valve, which is called the VPE [4]. Problems that have non-smooth, non-continuous, or non-linear solution spaces are not capable of being efficiently solved by most of the traditional techniques [5,6]. However, evolutionary computation has developed rapidly, until now, and many modern meta-heuristic algorithms using different modifications were successfully used to solve such problems [7–15]. Generally, it can be divided into three types based on their characteristics. The first is evolutionary algorithms [10,11], the second is simulated ecosystem algorithms [12,13], and the third is swarm intelligence algorithms [14,15]. To effectively address this issue, many varieties of computational intelligence approach are employed, such as genetic algorithms (GA) [16–18], improved evolutionary programming (IEP) [19], classical evolutionary programming (CEP) [20], differential evolution (DE) [21,22], fast convergence evolutionary programming (FCEP), and particle swarm optimization [23–25], respectively.

Particularly for the particle swarm optimization (PSO), numerous researchers applied it in power systems to solve ED problems [26–33]. PSO has become a popular optimization algorithm; it is widely used in practical problem solving because it has a simple concept and is effective. Recently, researchers have been studying theoretical studies and modifying the PSO algorithm [34–39] to get better performance improvement. The performance improvements of PSO have been published, including parameter studies, a combination with auxiliary operations, and topological structures. Several studies show that even though some methods can get optimal results, some of that does not satisfy the constraints. Meanwhile, a proper selection of inertia weight gives a balance both of the global and local exploration to obtain a sufficiently optimal solution with less iterations [40–42]. To overcome this deficiency, a new, modified inertia weight of particle swarm optimization algorithm (MIW-PSO) is proposed in this paper. In the MIW-PSO, the constriction factor and inertia weight approaches are used together where a new modification of inertia weight is introduced with a combination of chaotic behavior strategy. In addition, cognitive and social learning factors are incorporated. The cognitive learning factor reflects characteristics of a particle performance toward the individual performance and the social learning factor reflects the performance of a particle affected by the environment toward best position of the warm. Therefore, the adjustment in the cognitive and social learning factors is used to turn the system strain. The feasibility of the proposed method is applied on five case studies, and some methods from previous literature are used to compare the results.

The significant contributions of this study are:

1. this study demonstrates a modification of the PSO algorithm with incorporated chaotic search to get optimal scheduling of the operation of generators with an economical advantage, such as optimal total cost;
2. this study shows extraordinary performance among other method approaches, which can generate optimal solutions with stable solution accuracy, offer faster convergence characteristics, and satisfy the constraints.

The remainder of this paper is structured as follows. Section 2 shows the ED problem formulation. Section 3 presents the proposed method. Section 4 verified the results of the simulation from case studies. Section 5 presents the advantages of the study. Finally, Section 6 concludes the study.

2. Economic Dispatch Problem Formulation

The ED problem is essentially an optimization problem to obtain an optimal fuel cost by scheduling an appropriate combination of the power output from each generating unit and satisfy the constraints [38]. To minimize the total cost, the formulation is stated in the following formula [9]:

$$Minimize\ TC = \sum_{i=1}^{N_G} C_{Gi}(P_{Gi}) \tag{1}$$

where $C_{Gi}(P_{Gi})$ represents the cost function of unit generator ith ($/hr), P_{Gi} represents the output power of the unit generator ith (MW) . and N_G represents the total of the generators. The unit generator cost function is stated as follows [10]:

$$C_{Gi}(P_{Gi}) = \alpha_i + \beta_i\, P_{Gi} + \gamma_i\, P_{Gi}^2 \tag{2}$$

where α_i, β_i, and γ_i represents the unit generator cost coefficients.

In fact, the ED problem have non-differentiable points due to the valve-point loadings and multiple fuels in the objective function. Hence, the objective function should consist of some of the non-smooth cost functions [11]. In case a cost function considers the VPE problem, the objective function is usually explained as a superposition of sinusoidal and quadratic functions. In other words, the generator with multi-valve steam turbines has a contrast input-output characteristic compared to the smooth cost function. The VPE should be included in the cost model to consider the precise cost curve of each generating unit. The ED problem, considering VPE, is mathematically stated as follows [16]:

$$C_{Gi}(P_{Gi}) = \alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2 + \left|g_i \, Sin(h_i(P_{Gi\,min} - P_{Gi}))\right| \tag{3}$$

where g_i and h_i are the generator cost coefficients reflecting the VPE.

In this paper, the ED problem is described as an optimization process with taking into account the following constraints. First, in terms of power balance constraint, the total power of all generators should be balanced to total demand of the system, as shown in the following formula:

$$\sum_{i=1}^{N_G} P_i = P_D \tag{4}$$

where P_D is the total demand (MW) and P_i is power output of generator ith (MW).

Second, in terms of power output constraint, as shown in the following:

$$P_{i\,min} \leq P_i \leq P_{i\,max} \tag{5}$$

where $P_{i\,min}$ and $P_{i\,max}$ are the minimum and maximum power output (MW).

Third, in terms of POZ, a generator has discontinuous fuel-cost characteristics. Therefore, POZ is described as a thermal unit, which has a steam valve, while operation, or in another case a vibration in a shaft bearing, which may result in interference and suspend the performance of the input–output curve. Constraints of the POZ are written as (6):

$$P_{Gi} \begin{cases} P_i^{min} \leq P_i \leq P_{i,j}^{lower} \\ P_{i,\,j-1}^{upper} \leq P_i \leq P_{i,j}^{lower} \\ P_{i,PZ_i}^{Upper} \leq P_i \leq P_i^{max} \end{cases} , \; j = 2, 3, \ldots, PZ_i \tag{6}$$

where $P_{i,j}^{lower}$ and P_{i,PZ_i}^{Upper} are the lower boundaries and the upper boundaries of POZ of generator ith in (MW), respectively. PZ_i is the number of POZ of generator ith.

3. Proposed Method

Basically, the velocity and each particle position of PSO are updated as (7) and (8), respectively [43]:

$$V_i^{t+1} = V_i^t + C_1 \, rand_1\left(Pbest_i^t - X_i^t\right) + C_2 rand_2\left(Gbest^t - X_i^t\right) \tag{7}$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \tag{8}$$

where V_i^{t+1} is the individual ith velocity modification at iteration tth, V_i^t is the individual ith velocity at iteration tth, C_1 and C_2 are the cognitive and social learning factors, $Pbest_i^t$ is the individual particle ith best position at iteration tth, $Gbest^t$ is the best position of the global particle ith at iteration tth, X_i^t is the position of individual ith at iteration tth, and X_i^{t+1} is the modified position of individual.

In 1999, Maurice Clerc introduced that the use of a constriction factor, K, may be significant to ensure PSO convergence. The constriction factor approach (CFA) is written as (9):

$$V_i^{t+1} = K\left(V_i^t + C_1 \, rand_1\left(Pbest_i^t - X_i^t\right) + C_2 rand_2\left(Gbest^t - X_i^t\right)\right) \tag{9}$$

and K is defined as (10):

$$K = \frac{2}{\left|2 - \varnothing - \sqrt{\varnothing^2 - 4\varnothing}\right|} \tag{10}$$

where $\varnothing$ is a function of C_1 and C_2, $\varnothing = C_1 + C_2$, and $\varnothing > 4.0$.

The system convergence can be controlled by ∅ [44]. To guarantee stability, the ∅ value must be greater than 4.0. The K will be decreased if the value of ∅ increases and gives a slower response. Therefore, it has been observed that the ∅ value is 4.1. This value makes the algorithm stability guaranteed (and fast response). Research shows that set the ∅ to 4.1≤ ∅ ≤4.2 gives a better result. In [45], it introduces the turbulence factor, which explained that the perturbation for each particle *i*th is equivalent to the range itself and randomly selected particle *i*th. The CFA assists the algorithm for optimal convergence compared to the turbulence factor because of: (1) in the beginning stages of the process, both the turbulence factor and distance between particles should be large to avoid premature convergence, and (2) at the end of the stages of the process, the turbulence factor should be smaller due to the distance between particles becoming smaller, so the swarm enables to converge in the global optimum.

Furthermore, inertia weight, w, is known as importance parameters on the PSO algorithm. The w was proposed to control exploration and exploitation balancing of PSO. Typically, particles will incline to trapped in the local optima if the value of the w is small. However, the particles will incline to do the global search if the w is within the range, which is 0.8 to 1.2 [46]. A proper value of the w makes the exploration of global and local balance to get an optimal solution with less iterations [47]. PSO with inertia weight approach is stated as:

$$V_i^{t+1} = w\, V_i^t + C_1\, rand_1\left(Pbest_i^t - X_i^t\right) + C_2 rand_2\left(Gbest^t - X_i^t\right) \tag{11}$$

w is defined as shown in (12):

$$w = w_{max} - \frac{w_{max} - w_{min}}{Iter_{max}} Iter \tag{12}$$

Time-varying and adaptive parameter control strategies are two parameter control categories for w in [30] and [47]. A large number of studies with time-varying control strategies conclude that the form of the fitness landscape needs to know to make the algorithms perform better. However, it is impracticable in many of the applications. Therefore, as shown in many of the strategies, even though the assumptions can be wrong in some applications, it assumed that algorithm maximum iterations are known by default. Moreover, most of the researchers adjust the w, use the fitness and its derivatives when the adaptive parameter control strategy (APCS) applied for w. Therefore, the APCS is used for completion on this paper. Different to the standard w on initial PSO, and the modification of w in [48], in this paper, the modification of w is formulated as follows:

$$w_m = w_{min} + \frac{(w_{max} - w_{min})(Iter_{max} - Iter)}{Iter_{max}} \tag{13}$$

where w_m is the proposed modified inertia weight, w_{max} is the maximum inertia weight, w_{min} is the minimum inertia weight, $Iter_{max}$, and $Iter$ is the maximum iteration and current iteration, respectively.

In [49] and [50], effect of chaotic sequence is observed. An iterator, namely logistic map, is a part of the dynamic system that shows chaotic behavior. The equation is written as follows:

$$f_t = \mu\, f_{t-1}\, (1 - f_{t-1}) \tag{14}$$

where f_t is the chaotic parameter and μ is the control parameter with value 0 to 4.

In many fields of science, chaos phenomenon is often to occur. Combining the chaotic sequences with the mutation factor in differential evolution can improve the solution quality. The solution shows a rich variety of behaviors despite the simplicity of the equation. Variation of μ gives a significant impact to (14) as representative of the behavior of the system. In this paper, the μ value is 4 [50]. In order to improve the global searching capability, and to increase the probability of escaping from a local minimum, a new, modified inertia weight with chaotic is offer, stated as (15). Through the employment of chaotic sequences with inertia weight in PSO makes the global searching capability improve by preventing premature convergence through increased diversity of the population.

$$w_p = w_m\, f_t \tag{15}$$

where w_p is the proposed inertia weight modification and w_m is the modified inertia weight.

The adjustment of cognitive learning factor, C_1, and social learning factor, C_2 are incorporated with aims to change the system tension. In these terms, if the adjustment value is lower, it makes the particles enable to drift away from the target zone before being pulled back. On the other hand, the abrupt movement toward the target region will happen if the adjustment value is higher. In this paper, the adjustment parameters of cognitive learning and social learning factors are determined as Cp_1 and Cp_2, respectively. Different values can be found for the cognitive and social learning factors in published references, such as 2.0 [24,40,50] or 2.05 [14,36]. In this study, the chosen values of Cp_1 and Cp_2 are 2.05 because they lead to good solution. Finally, the MIW-PSO is formulated in (16) [51].

$$V_i^{t+1} = K\left(w_p\, V_i^t + Cp_1\, rand_1\left(Pbest_i^t - X_i^t\right) + Cp_2 rand_2\left(Gbest^t - X_i^t\right)\right) \tag{16}$$

4. Case Study

The proposed MIW-PSO is applied to five case studies and addressed to deal with an optimal total cost in generator scheduling. Overall, the comparison methods through published journal papers, with different years, are used to shows the performance of the MIW-PSO. The comparison methods used are numerical lambda-iteration method (NM), modified Hopfield neural network (MHNN), IEP, modified PSO (MPSO), GA, evolutionary programming (EP), PSO, PSO with local random search (PSO-LRS), new PSO with local random search (NPSO-LRS), differential evolution (DE), improved bird swarm algorithm (IBSA), crossover operation with PSO (COPSO), combination of DE-PSO-DE (DPD), improved fast evolutionary programming (IFEP), FCEP, improved differential evolution (IDE), modified symbiotic organisms search (MSOS), and new PSO (NPSO). All numerical simulations in this paper are coded in MATLAB (R2017a, MathWorks, Natick, MA, US) and executed in the Intel i5-6500, 3.20-GHz, 32-GB RAM processor. w_{max} = 0.9, w_{min} = 0.4 and also Cp_1 and Cp_2 are used as parameters for the implementation of the proposed method. The values of Cp_1 and Cp_2 have the same value, which implies the same weights are given between *Pbest* and *Gbest* in the evolution processes. All the parameters are tuned in the initialization process and also in process of velocity and position update of the particle.

4.1. First Case Study

MIW-PSO is used to solve ED problems, considering the smooth cost function in this case study. The obtained results are compared with NM [40,52], MHNN [40], IEP [40], and modified PSO (MPSO) [40]. In this case study, the MIW-PSO is tested to the test power system on [52], which consists of three generators, with total demand of 850 MW. The generating unit capacity and coefficients used in this case study are shown in Table 1 [52]. Comparison of generator power output on the first case study with different methods is shown in Table 2. The calculation of economic operations in this case study is done by finding the optimal scheduling combination of each generating unit. The input–output characteristics of each generator are used as a priority measure of the selection of the optimal combination of power outputs to obtain the optimal fuel costs. Moreover, Table 3 shows that all methods satisfy the power balance except MHNN. Therefore, even though the total cost obtained by MHNM is lower, it does not make it the best result. Obviously, the total cost obtained from each method does not differ much. Nevertheless, the MIW-PSO shows the superiority among other methods because MIW-PSO is able to obtain an optimal total cost and, in the meantime, also satisfies the constraints given. The MIW-PSO obtains 8194.35513 $/h for the total cost, as seen in Table 3.

Table 1. Generator unit capacity and coefficients on the first case study.

Unit	α_i($)	β_i($/MW)	γ_i($/MW)	P_{imin}(MW)	P_{imax} (MW)
1	561	7.92	0.001562	150	600
2	310	7.85	0.00194	100	400
3	78	7.97	0.00482	50	200

Table 2. Comparison of generator power output on the first case study.

Total Power Output (MW)	Method				
	NM [40,52]	MHNN [40]	IEP [40]	MPSO [40]	MIW-PSO
Generator 1	393.17	393.80	393.18	393.17	393.03
Generator 2	334.60	333.10	334.59	334.60	334.71
Generator 3	122.23	122.30	122.23	122.23	122.26

NM: numerical lambda-iteration method; **MHNN**: modified Hopfield neural network; **IEP:** improved evolutionary programming; **MPSO**: modified particle swarm optimization; **MIW-PSO:** modified inertia weight of PSO.

Table 3. Simulation result comparison on the first case study.

Method	NM [40,52]	MHNN [40]	IEP [40]	MPSO [40]	MIW-PSO
Total power output (MW)	850.00	849.20	850.00	850.00	850.00
Total cost ($/hr)	8194.35612	8187.00000	8194.35614	8194.35612	8194.35513

4.2. Second Case Study

In the second case study, the MIW-PSO is applied, considering non-smooth cost function due to the VPE. The obtained results are compared to GA [16,40,42], evolutionary programming (EP) [40,42], IEP [19,40], and MPSO [40]. The system applied in this study contains three thermal units with total demand of 850 MW, and the generating unit capacity and coefficients are shown in Table 4 [16]. Comparison of generator power output on the second case study using different methods is shown in Table 5. Total power output of all methods satisfy the power balance constraints, which is 850 MW. The MIW-PSO obtained optimal total cost, which is 8234.06 $/h. Table 6 shows the simulation results comparison for the second case study.

Table 4. Generator unit capacity and coefficients on the second case study.

Unit	α_i($)	β_i($/MW)	γ_i($/MW)	g_i	h_i	P_{imin}(MW)	P_{imax} (MW)
1	561	7.92	0.001562	300	0.0315	100	600
2	310	7.85	0.00194	200	0.042	100	400
3	78	7.97	0.00482	150	0.063	50	200

Table 5. Comparison of generator power output on the second case study.

Total Power Output (MW)	Method				
	GA [16,40,42]	IEP [19,40]	EP [40,42]	MPSO [40]	MIW-PSO
Generator 1	300.00	300.23	300.26	300.27	300.43
Generator 2	400.00	400.00	400.00	400.00	400.00
Generator 3	150.00	149.77	149.74	149.73	149.57

GA: genetic algorithm; **IEP**: improved evolutionary programming; **EP**: evolutionary programming; **MPSO**: modified particle swarm optimization; **MIW-PSO:** modified inertia weight of particle swarm optimization.

Table 6. Simulation result comparison on the second case study.

Method	GA [16,40,42]	IEP [19,40]	EP [40,42]	MPSO [40]	MIW-PSO
Total power output (MW)	850.00	850.00	850.00	850.00	850.00
Total cost ($/hr)	8237.60	8234.09	8234.07	8234.07	8234.06

4.3. Third Case Study

The third case study is applied, considering the POZ constraint, and the results are compared with GA, PSO [22,24,41], DE [22], PSO-LRS [41], NPSO-LRS [22], and IBSA [53]. In this case study, the input data for the system with six generators are given in Table 7, with total demand of 1263 MW [38]. Comparison of generator power output on the third case study, using different methods, is shown in Table 8. Besides GA, DE, IBSA, and MIW-PSO, there are three methods that obtain the same total cost, which are PSO, PSO-LRS, and NPSO-LRS. However, the MIW-PSO obtains an optimal total cost among the other methods, which is 15,448.97 $/hr. The MIW-PSO proves its superiority among the other methods to obtain optimal generation cost. Comparison of simulation results for the third case study is shown in Table 9. Total generation cost comparison is shown in Table 10.

Table 7. Generator unit capacity and coefficients on the third case study.

Unit	α_i($)	β_i($/MW)	γ_i($/MW)	P_{imin}(MW)	P_{imax} (MW)	Prohibited Zones (MW)
1	240	7.0	0.0070	100	500	[210, 240] [350, 380]
2	200	10.0	0.0095	50	200	[90, 110] [140, 160]
3	220	8.5	0.0090	80	300	[150, 170] [210, 240]
4	200	11.0	0.0090	50	150	[80, 90] [110, 120]
5	220	10.5	0.0080	50	200	[90, 110] [140, 150]
6	190	12.0	0.0075	50	120	[75, 85] [100, 105]

Table 8. Comparison of generator power output on the third case study.

Total Power Output (MW)	Method						
	GA [22,24,41]	PSO [22,24,41]	PSO-LRS [41]	NPSO-LRS [22]	DE [22]	IBSA [53]	MIW-PSO
Generator 1	474.81	447.50	447.44	446.96	448.27	447.48	448.56
Generator 2	178.64	173.32	173.34	173.39	172.96	173.30	172.34
Generator 3	262.21	263.47	263.36	262.34	263.44	263.44	265.31
Generator 4	134.28	139.06	139.13	139.51	139.30	139.05	130.54
Generator 5	151.90	165.48	165.51	164.71	165.28	165.46	173.13
Generator 6	74.18	87.13	87.17	89.02	86.68	87.12	86.15

GA: genetic algorithm; **PSO**: particle swarm optimization, **PSO-LRS**: PSO with local random search; **NPSO-LRS**: new PSO with local random search; **DE**: differential evolution; **IBSA**: improved bird swarm algorithm; **MIW-PSO:** modified inertia weight of PSO.

Table 9. Simulation result comparison on the third case study.

Method	GA [22,24,41]	PSO [22,24,41]	PSO-LRS [41]	NPSO-LRS [22,41]	DE [22]	IBSA [53]	MIW-PSO
Total power output (MW)	1,276.03	1,276.01	1,275.94	1,275.94	1,275.93	1,275.88	1,276.03
Total loss (MW)	13.0217	12.9584	12.9571	12.9361	12.95	12.95	13.02
Total cost ($/hr)	15,459.00	15,450.00	15,450.00	15,450.00	15,449.58	15,448.98	15,448.97

Table 10. Total generation cost comparison on the third case study.

Method	GA [22,41]	PSO [22,41]	PSO-LRS [41]	NPSO-LRS [22,41]	DE [22]	IBSA [53]	MIW-PSO
Minimum	15,459.00	15,450.00	15,450.00	15,450.00	15,449.58	15,448.98	15,448.97
Maximum ($/h)	15,524.00	15,492.00	15,455.00	15,455.00	15,449.65	15,449.00	15,449.47
Average	15,469.00	15,454.00	15,454.00	15,454.00	15,449.61	15,448.98	15,448.99

4.4. Fourth Case Study

The fourth case study is applied to the 40-unit system and considers the VPE. The comparison result with other methods, such as COPSO [50], DPD [54], IDE [55], MSOS [56], NPSO-LRS, IFEP, and FCEP [23]. In this case study, the input data have been adopted from [23], as shown in Table 11, with total demand 10,500 MW. The MIW-PSO proves its superiority among the other methods to obtain optimal generation cost. MIW-PSO obtains the lowest total cost among all stated methods, which is 121,218 $/h, and the acquired results satisfy all the considered constraints. Comparison of the simulation result for the fourth case study is shown in Table 12.

Table 11. Generator unit capacity and coefficients on fourth case study.

Unit	α_i($)	β_i($/MW)	γ_i($/MW)	g_i	h_i	P_{imin}(MW)	P_{imax} (MW)
1	94.705	6.73	0.00690	100	0.084	36	114
2	94.705	6.73	0.00690	100	0.084	36	114
3	309.540	7.07	0.02028	100	0.084	60	120
4	369.030	8.18	0.00942	150	0.063	80	190
5	148.890	5.35	0.01140	120	0.077	47	97
6	222.330	8.05	0.01142	100	0.084	68	140
7	287.710	8.03	0.00357	200	0.042	110	300
8	391.98	6.99	0.00492	200	0.042	135	300
9	455.76	6.60	0.00573	200	0.042	135	300
10	722.82	12.9	0.00605	200	0.042	130	300
11	635.20	12.9	0.00515	200	0.042	94	375
12	654.69	12.8	0.00569	200	0.042	94	375
13	913.40	12.5	0.00421	300	0.035	125	500
14	1760.40	8.84	0.00752	300	0.035	125	500
15	1760.40	8.84	0.00752	300	0.035	125	500
16	1760.40	8.84	0.00752	300	0.035	125	500
17	647.85	7.97	0.00313	300	0.035	220	500
18	649.69	7.95	0.00313	300	0.035	220	500
19	647.83	7.97	0.00313	300	0.035	242	550
20	647.81	7.97	0.00313	300	0.035	242	550
21	785.96	6.63	0.00298	300	0.035	254	550
22	785.96	6.63	0.00298	300	0.035	254	550
23	794.53	6.66	0.00284	300	0.035	254	550
24	794.53	6.66	0.00284	300	0.035	254	550
25	801.32	7.10	0.00277	300	0.035	254	550
26	801.32	7.10	0.00277	300	0.035	254	550
27	1055.10	3.33	0.52124	120	0.077	10	150
28	1055.10	3.33	0.52124	120	0.077	10	150
29	1055.10	3.33	0.52124	120	0.077	10	150
30	148.89	5.35	0.01140	120	0.077	47	97
31	222.92	6.43	0.00160	150	0.063	60	190
32	222.92	6.43	0.00160	150	0.063	60	190
33	222.92	6.43	0.00160	150	0.063	60	190
34	107.87	8.95	0.00010	200	0.042	90	200

Table 11. *Cont.*

Unit	α_i($)	β_i($/MW)	γ_i($/MW)	g_i	h_i	P_{imin}(MW)	P_{imax} (MW)
35	116.58	8.62	0.00010	200	0.042	90	200
36	116.58	8.62	0.00010	200	0.042	90	200
37	307.45	5.88	0.01610	80	0.098	25	110
38	307.45	5.88	0.01610	80	0.098	25	110
39	307.45	5.88	0.01610	80	0.098	25	110
40	647.83	7.97	0.00313	300	0.035	242	550

Table 12. Total generation cost comparison on the fourth case study.

Method	Minimum	Average	Maximum
	Cost ($/ht)		
COPSO [50]	121,411	121,499	121,751
NPSO-LRS [23]	121,664	122,209	122,981
DPD [54]	121,410	121,412	121,441
IFEP [23]	121,442	121,448	121,457
FCEP [23]	121,393	121,394	121,395
IDE [55]	121,411	121,429	121468
MSOS [56]	121,412	121,412	121,412
MIW-PSO	121,218	121,218.3	121,223

COPSO: crossover operation with PSO; NPSO-LRS: new PSO with local random search; DPD: combination of DE-PSO-DE; IFEP: improved fast evolutionary programming; FCEP: fast convergence evolutionary programming; IDE: improved differential evolution; MSOS: modified symbiotic organisms search; MIW-PSO: modified inertia weight of PSO.

4.5. Fifth Case Study

The fifth case study is applied in the East Java 150 kV power system, which is located in East Java, Indonesia, as shown in Figure 1. The East Java 150 kV power system consists of ten generator units. Units 1–4 are located in the Gresik 1 electric steam power plant which in Indonesia is called pembangkit listrik tenaga uap Gresik 1 (PLTU Gresik 1), units 5 and 6 are located in the Perak electric steam power plant which in Indonesia is called pembangkit listrik tenaga uap Perak (PLTU Perak), and units 7–10 are located in Gresik 2 integrated gasification combined cycle plants which in Indonesia is called pembangkit listrik tenaga gas dan uap Gresik 2 (PLTGU Gresik 2). Single line diagram of the East Java 150 kV is shown in Figure 2.

Figure 1. Location of the East Java 150 kV power system.

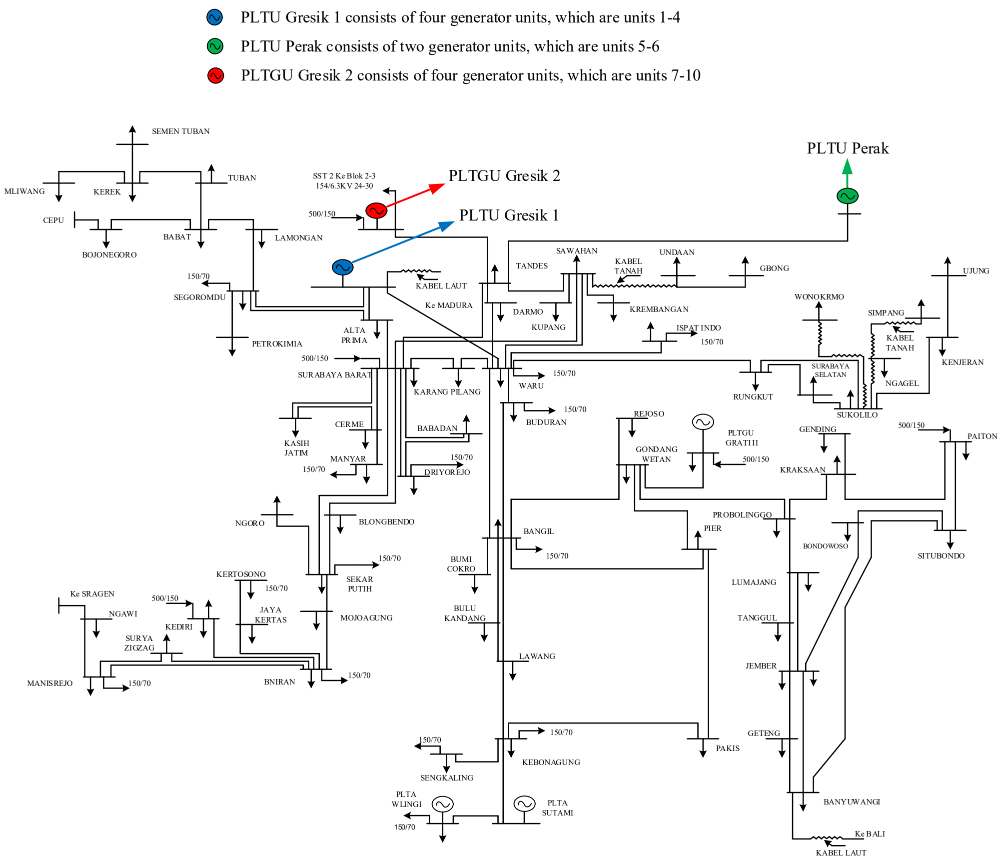

Figure 2. Single line diagram of the East Java 150 kV power system.

The input data used in the fifth case study are shown in Table 13. Moreover, MIW-PSO is applied with total demand 616 MW. In this case study, the MIW-PSO is used to solve ED problems with smooth cost function. Using PSO obtain total cost 95,840.57 \$/h. However, MIW-PSO gets 95,835.53 \$/h for total cost, as written in Table 14.

Table 13. Generator unit capacity and coefficients on fifth case study.

Unit	α_i(\$)	β_i(\$/MW)	γ_i (\$/MW)	P_{imin}(MW)	P_{imax} (MW)
1	4088.5375	42.5118	0.2162	23.00	92
2	4547.8075	20.5021	0.4108	23.00	92
3	4601.9649	32.9483	0.0562	47.25	189
4	4316.1074	22.2655	0.1266	47.25	189
5	3707.7500	50.6244	0.6210	10.25	41
6	3459.6950	69.7050	0.1255	10.25	41
7	9045.7750	370.6642	3.6454	23.00	95
8	1124.9075	31.9013	0.3981	23.00	95
9	8549.5500	484.7006	2.3185	23.00	95
10	4486.6174	31.8112	0.1142	41.25	165

Table 14. Simulation result comparison on the fifth case study.

Unit Generator (MW)	PSO	MIW-PSO
1	38.63	36.34
2	38.94	46.58
3	178.00	189.00
4	142.20	139.16
5	13.43	11.06
6	13.42	10.25
7	29.00	23.00
8	26.84	29.90
9	29.00	23.00
10	106.54	107.71
Total power (MW)	616.00	616.00
Total cost ($/hr)	95,840.57	95,835.53

PSO: particle swarm optimization; MIW-PSO: modified inertia weight of PSO.

To validate accuracy of the MIW-PSO getting the optimal total cost, we computed the MIW-PSO in 100 trials. Figure 3 shows the accuracy validation of the MIW-PSO. Figure 3a represent the accuracy of the MIW-PSO in the first case study. MIW-PSO yields smaller generation cost deviation to obtain the optimal total cost, which is 8194.35513 $/hr. A similar thing is shown in Figure 3b–e, which represent the second to fifth case studies. Overall, through 100 trials for all case studies, it is shown that the MIW-PSO yields smaller generation costs deviation; thus, verifying that the MIW-PSO solution accuracy is acceptable stable.

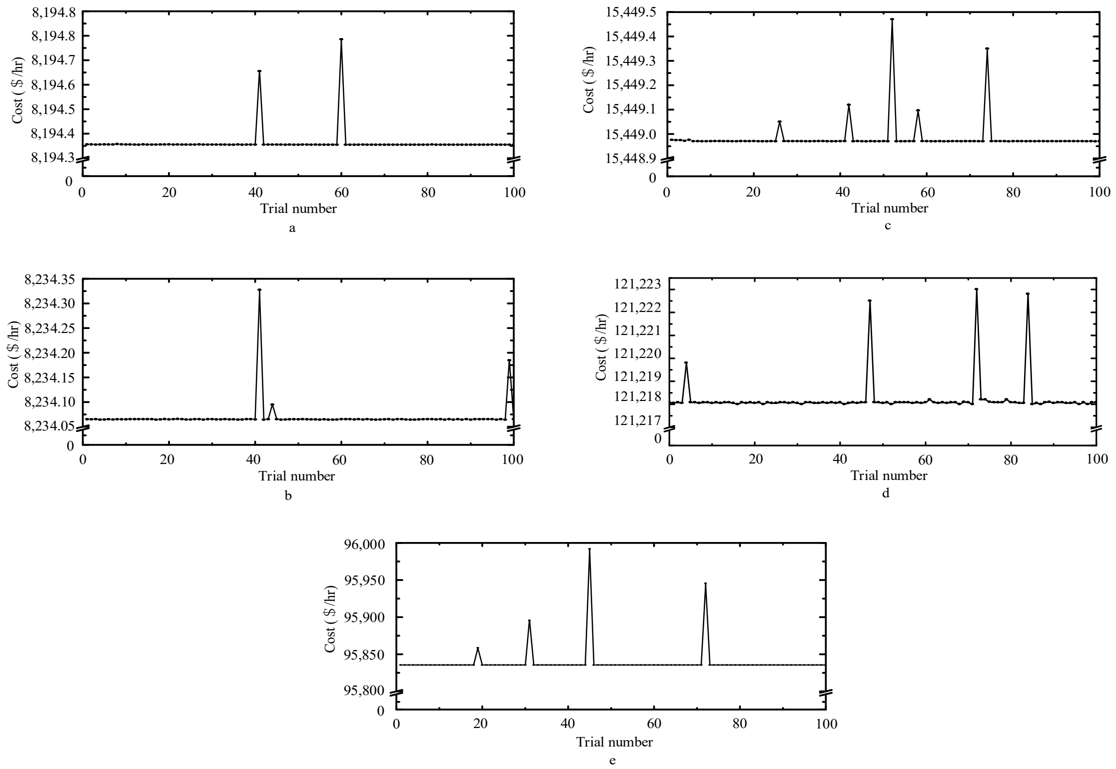

Figure 3. The accuracy of the MIW-PSO: (**a**) first case study; (**b**) second case study; (**c**) third case study; (**d**) fourth case study; (**e**) fifth case study.

Convergence test is performed to verify the quickness of the proposed approach in terms of iterations number. Figure 4 depicts the convergence test of MIW-PSO. Figure 4a–e shows that the

MIW-PSO has a good convergence ability; thus, obtaining good evaluation value of iteration and low generation cost. The MIW-PSO is consistently faster to convergence than the other algorithms, such as NM [51] for the first case study, MPSO [40] for the second case study, GA, PSO [24], NPSO, PSO-LRS, and NPSO-LRS [41] for the third case study, NPSO-LRS, IFEP, and FCEP [23] for the fourth case study, and the PSO for the fifth case study. Table 15 summarizes the comparison of the convergence test in terms of the number of iterations among different methods.

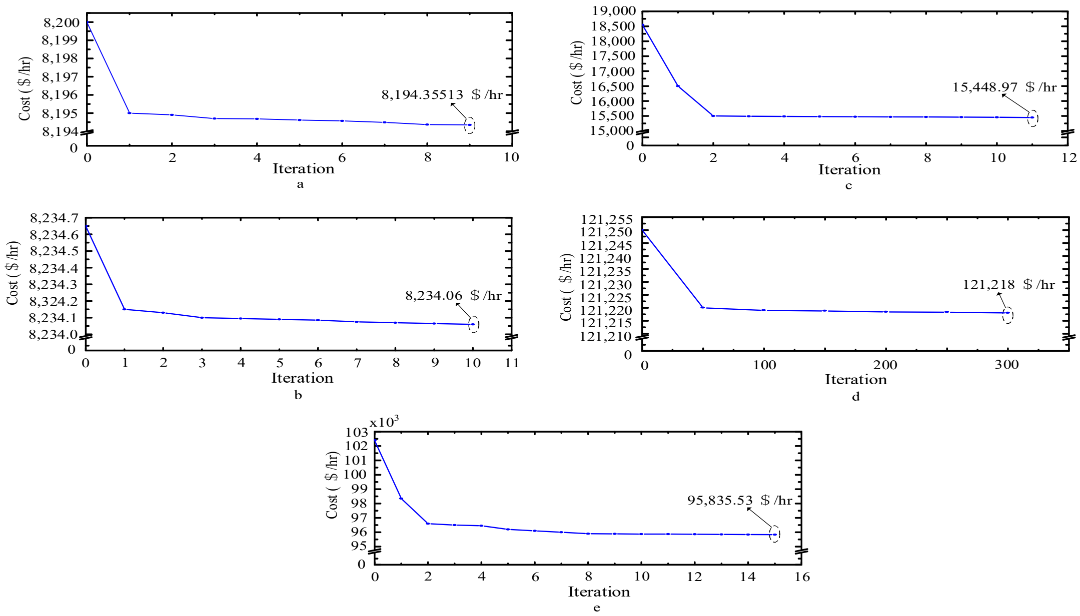

Figure 4. The convergence of the MIW-PSO: (**a**) first case study; (**b**) second case study; (**c**) third case study; (**d**) fourth case study; (**e**) fifth case study.

Table 15. Comparison of the convergence test among different methods.

Case Study	Method	Number of Iteration
1	NM [51] MIW-PSO	17 9
2	MPSO [40] MIW-PSO	12 10
3	GA [24] PSO [24] NPSO [41] PSO-LRS [41] NPSO-LRS [41] MIW-PSO	200 200 50 50 50 11
4	NPSO-LRS [42] IFEP [23] FCEP [23] MIW-PSO	1000 300 300 300
5	PSO MIW-PSO	25 15

In terms of computational efficiency, the comparison of the time computation is given in Table 16. Since some of the computation time of the other methods are not available, the comparison is just done with MHNN in the first case study, GA in the second case study, GA, PSO, and DE in the third case study, COPSO, NPSO, PSO-LRS, and NPSO LRS in the fourth case study, and PSO in the fifth case study.

Besides the encoding, the computation time comparison is greatly influenced by the specifications of the computer in use. As shown in Table 15, the MIW-PSO has better computation time.

Table 16. Comparison of computation time.

Case Study	Method	Time (s)
1	MHNN [19,40]	60
	MIW-PSO	0.26
2	GA [42]	10
	MIW-PSO	0.27
3	GA [24]	10.49
	PSO [24]	3.73
	DE [22,57]	3.63
	MIW-PSO	1,12
4	COPSO [50]	19.2
	NPSO [41]	4.71
	PSO-LRS [41]	15.86
	NPSO-LRS [41]	16.81
	MIW-PSO	4.26
5	PSO	1.52
	MIW-PSO	1.58

5. Discussion

In this study, six advantages are summarized as follow:

1. An alternative method to solve the ED problem: this study applied a modified inertia weight on the PSO (MIW-PSO) algorithm. The MIW-PSO is proposed to solve the ED problems on generator scheduling;
2. Perform well and considers the power generator characteristics: in order to solve the ED problems, the MIW-PSO performs well, and considers the power generator characteristics, such as smooth and non-smooth cost functions with prohibited operating zones and valve-point effects;
3. Obtaining an optimal solution: in this study, the MIW-PSO shows excellent performance in order to obtain optimal solution, and at the same time, satisfy the constraints. In the first case study, the MIW-PSO obtains the total cost 8194.35513 $/h. In the second case study, the MIW-PSO obtains the total cost 8234.06 $/h. In third and fourth case studies, the MIW-PSO obtains the total cost 15,448.97 $/h and 121,218 $/h, respectively. Finally, in the fifth case study, the MIW-PSO obtains total cost 95,835.53 $/hr;
4. Performing well and considers the power generator characteristics: the MIW-PSO performs well, and considers the power generator characteristics, such as smooth and non-smooth cost functions with prohibited operating zones and valve-point effects, in solving the ED problems;
5. Extraordinary among other method approaches to solve ED problems: the obtained results of MIW-PSO are compared with the other methods, such as NM, MHNN, IEP, MPSO, GA, EP, PSO, PSO-LRS, NPSO-LRS, DE, IBSA, COPSO, DPD, IFEP, FCEP, IDE, MSOS, and NPSO. The MIW-PSO has better performance to obtain optimal results;
6. Stable solution accuracy: through 100 trials, the MIW-PSO yields smaller generation cost deviation; thus, verifying that the MIW-PSO solution accuracy is acceptable stable.
7. Faster to convergent: through the results of the convergence test, the MIW-PSO demonstrates the quickness of performance in terms of the number of iterations.

6. Conclusions

This study successfully shows the performance of a new MIW-PSO with incorporated chaotic search to solve the problems of ED. In the MIW-PSO, the approach of the constriction factor and inertia weight, along with the adjustment in the cognitive and social learning factors, are used together where a modification of inertia weight is introduced with an incorporation of the chaotic search strategy. Therefore, MIW-PSO makes ED problems effectively solved, satisfying the constraints, and makes optimal solutions greatly improved. The MIW-PSO is addressed to obtain an optimal total cost in solving the ED problems in optimal generator scheduling, while considering the smooth and non-smooth cost functions. Moreover, the method can also handle ED problems, considering POZ and VPE. The MIW-PSO has been demonstrated through five different case studies, is proven to have significant features, such as an optimal solution with stable solution accuracy, and offers the quickness of performance in terms of the number of iterations. The results of the five case studies show the superiority of the MIW-PSO compared with the results of several methods that have been published in the previous paper.

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