TÜBİTAK
Turkish Journal of Electrical Engineering & Computer Sciences
http://journals.tubitak.gov.tr/elektrik/
Research Article
Turk J Elec Eng & Comp Sci
(2015) 23: 2304 – 2318

doi:10.3906/elk-1307-204

Modified particle swarm optimization for economic-emission load dispatch of power system operation

Mohd Noor ABDULLAH[1,2,3,*], **Abd Halim ABU BAKAR**[1], **Nasrudin ABD RAHIM**[2], **Hazlie MOKHLIS**[2,3]

[1]Department of Electrical Power Engineering, Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia, Batu Pahat, Johor, Malaysia
[2]UM Power Energy Dedicated Advanced Centre, Wisma R&D UM, University of Malaya, Jalan Pantai Baharu, Kuala Lumpur, Malaysia
[3]Department of Electrical Engineering, Faculty of Engineering, University of Malaya, Kuala Lumpur, Malaysia

Received: 25.07.2013 • **Accepted/Published Online:** 30.09.2013 • **Printed:** 31.12.2015

Abstract: This paper proposes a modified particle swarm optimization considering time-varying acceleration coefficients for the economic-emission load dispatch (EELD) problem. The new adaptive parameter is introduced to update the particle movements through the modification of the velocity equation of the classical particle swarm optimization (PSO) algorithm. The idea is to enhance the performance and robustness of classical PSO. The price penalty factor method is used to transform the multiobjective EELD problem into a single-objective problem. Then the weighted sum method is applied for finding the Pareto front solution. The best compromise solution for this problem is determined based on the fuzzy ranking approach. The IEEE 30-bus system has been used to validate the effectiveness of the proposed algorithm. It was found that the proposed algorithm can provide better results in terms of best fuel cost, best emissions, convergence characteristics, and robustness compared to the reported results using other optimization algorithms.

Key words: Economic-emission load dispatch, fuzzy satisfying method, particle swarm optimization, Pareto front solution, weighted sum method

1. Introduction

Nowadays the awareness of environmental pollution is increasing around the world. Many campaigns and promotions have been launched to reduce the environmental pollution as well as greenhouse gases. Among the major contributors of environmental pollution is the burning of fossil fuel in power generation [1]. Hence, it is crucial to minimize the amount of emission releases from power generation.

Traditionally, power generation is determined solely based on minimizing fuel cost (called economic load dispatch) [2]. However, regarding the awareness of environmental issues, the emission amount releases (i.e. SO_X, NO_X) by thermal power generation should be considered in power dispatch. In [3,4], the economic load dispatch problem was solved considering the emission level as a constraint, but it cannot provide the tradeoff information between fuel cost and emission amount. By considering the emission level of the power generation, the electric power dispatch problem becomes a multiobjective optimization problem that requires optimization of fuel cost and emission amount simultaneously [5].

*Correspondence: mnoor@uthm.edu.my

There are two different ways to solve economic-emission load dispatch (EELD) problems. The first approach is called the multiobjective optimization method, directly applied to multiobjective optimization problems. Algorithms such as modified adaptive θ-particle swarm optimization (MA θ-PSO) [6], θ-multiobjective teaching learning based optimization (θ-MTLBO) [7], hybrid multiobjective optimization (MO-DE/PSO) [8], and strength Pareto evolutionary algorithm (SPEA) [9] have been applied for EELD problem. The second approach is transforming the multiobjective problems into single-objective problems by using the price penalty factor (PPF) approach. In this approach, the weighted sum method (WSM) is commonly applied to obtain a Pareto optimal solution [10]. The modified bacterial foraging algorithm (MBFA) [11], charged system search algorithm (CSS) [12], genetic algorithm (GA) [13], and gravitational search algorithm (GSA) [14] have been used to solve EELD problems based on this approach. In addition, the conic scalarization method (CSW) was first implemented in [15] for EELD problems and can be an alternative approach to the WSM.

In multiobjective problems, no single solution can be found, and thus a set of possible solutions called nondominated solutions (or Pareto front solutions) should be obtained in order to satisfy the desired objective function (i.e. total fuel cost and emission amount). In [14,16,17], the best compromise solution (in the set Pareto front solution) was obtained by implementing fuzzy set theory. It can help the system operator choose the best compromise solution among multiple solutions obtained by the multiobjective optimization method.

In the literature, the PSO algorithm is widely applied in power system optimization problems [18–20]. This is due to the advantages of PSO such as less complexity, fast convergence, and free-derivative algorithm. However, the classical PSO algorithm may converge at local minima, especially for complex problems with multiple local minima. Many PSO variants were proposed in [21–25] in order to enhance the searching capability of classical PSO.

In this paper, a new variant of PSO named modified particle swarm optimization considering time-varying acceleration coefficients (MPSO-TVAC) is proposed for the EELD problem. A new adaptive parameter is introduced for updating the particle movement in order to prevent the particle being trapped at a local solution (premature convergence). The PPF approach is adopted to transformed the multiobjective EELD problem into a single-objective problem. Then the weighted sum method is applied in order to capture a set of Pareto front solutions. The best compromise solution is obtained by using fuzzy set theory. The results found by the MPSO-TVAC algorithm are compared with the results obtained by other algorithms in the literature.

This paper is arranged as follows. Section 2 describes the mathematical formulation of the EELD problem. Section 3 reviews some PSO algorithms and explains the proposed MPSO-TVAC. Section 4 describes how to apply MPSO-TVAC for solving the EELD problem. The performance analysis and the comparison study with the results of existing algorithms are provided in Section 5. Section 6 draws the conclusions.

2. Problem formulation

2.1. Objective functions

2.1.1. Economic load dispatch problem

The main objective of this problem is to distribute the power demand to the scheduled generator at a minimum total fuel cost (FC). With N_g scheduled generators to operate, the total FC can be formulated as

$$FC = \sum_{i=1}^{Ng} FC_i(P_i) = \sum_{i=1}^{Ng} (a_i P_i^2 + b_i P_i + c_i), \tag{1}$$

where P_i = real power output of ith generator (MW); a_i, b_i, and c_i = fuel cost coefficients of the ith generator; and FC_i = fuel cost for the ith generator.

The fuel cost characteristics of the thermal generator are shown in Figure 1 (solid line).

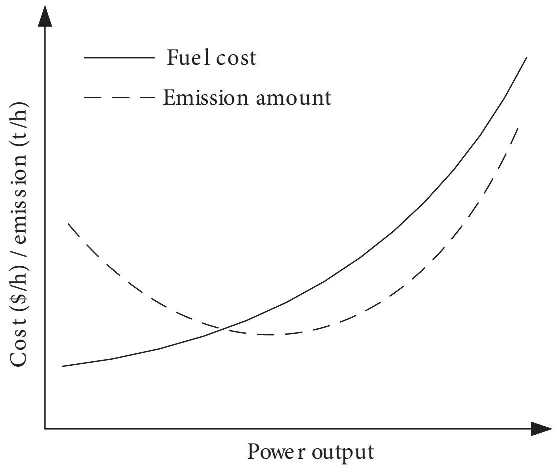

Figure 1. Fuel cost and emission function of the thermal generator.

2.1.2. Emission dispatch problem

The main objective of this problem is to distribute the power demand to the scheduled generator at minimum total emission amount (EM) caused by the thermal generator (i.e. SO_X, NO_X). The total emission amount can be modeled as a combined quadratic and exponential function as shown in Figure 1 (dashed line) and formulated as [26]:

$$EM = \sum_{i=1}^{Ng} EM_i(P_i) = \sum_{i=1}^{Ng} 10^{-2}(\alpha_i P_i^2 + \beta_i P_i + \gamma_i) + \xi_i \exp(\lambda_i P_i)t/h, \quad (2)$$

where α_i, β_i, γ_i, ξ_i, and λ_i = pollution coefficients of the ith generator, and EM_i = emission amount for the ith generator.

2.2. System and operational constraints

The minimization of both problems is subjected to the following constraints:

Power balance constraints: The total generated power must be equal to the total power demand (P_D) and transmission loss (P_L) as given in Eq. (3).

$$\sum_{i=1}^{Ng} P_i = P_D + P_L \quad (3)$$

There are two methods that can be used to calculate the transmission loss: the power flow method [27] and the B-coefficients method (Kron's formula) [23]. In this paper, the B-coefficients method is adopted in line with the previous research done in [12,16,26] based on following formula:

$$P_L = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} P_i B_{ij} P_j + \sum_{i=1}^{Ng} B_{i0} P_i + B_{00}, \quad (4)$$

where B_{ij}, B_{i0}, and B_{00} = the loss coefficient matrix.

Generation limit constraints: The power output of the scheduled generator is limited by the minimum limit (P_i^{min}) and maximum limit (P_i^{max}) for stable operation as follows:

$$P_i^{\min} \leq P_i \leq P_i^{\max}. \tag{5}$$

2.3. Economic-emission load dispatch problem

The total fuel cost and emission amount in Eqs. (1) and (2) should be minimized simultaneously in order to satisfy both objectives mentioned in Section 2.1. Figure 1 shows the behavior of the fuel cost and emission characteristics of the thermal generator. These two conflicting objectives give a set of possible optimal solutions instead of one optimal solution. Therefore, this problem can be solved by transforming the multiobjective optimization problem into a single-objective function by using the appropriate PPF [14]. The PPF is used to blend the emission level into cost level as described in [28]. The new objective function (OF) for the EELD problem can be formulated as:

$$MinOF = k \times FC + (1-k) \times ppf \times EM \tag{6}$$

where k = weight factor for total fuel cost (FC) and total emission (EM).

A set of Pareto front solutions can be produced by assigning the weight factor k between 0 to 1 [12,14,29]. If k is set to 1, OF represents the minimizing fuel cost only, whereas if k is set to 0, OF is to minimize emission only.

The minimization of Eq. (6) is subjected to the constraints in Eqs. (2) to (4). The k value is increased from 0 to 1 by an increment step of 0.1 in order to achieve the set of Pareto front solutions. This set of solutions called Pareto front solutions can provide multiple solutions to the decision-makers in order choose a desired solution based on their preferences. In addition, the best compromise solution can be selected based on fuzzy set theory as explained in the next section.

2.4. Best compromise solution based on fuzzy theory

To help the system operator make a balanced decision between two objectives in the multiobjective EELD problem, the best compromise solution can be determined by using the fuzzy satisfying method. In this approach, each objective function (F_i) will be transformed into a fuzzy set (membership function) to represent the degree of membership in fuzzy sets based on a value within 0 to 1 [30]. It can be calculated by using the following equation:

$$\mu(F_i) = \begin{cases} 1 & F_i \leq F_i^{\min} \\ \frac{F_i^{\max} - F_i}{F_i^{\max} - F_i^{\min}} & F_i^{\min} < F_i < F_i^{\max} \\ 0 & F_i \geq F_i^{\max} \end{cases}, \tag{7}$$

where F_i^{min} and $F_i^{\max}$ = the lower and higher value of each F_i, respectively; $\mu(F_i) = 1$ and means the membership function is completely satisfied with the sets; and $\mu(F_i) = 0$ and means the membership function is unsatisfied with the sets.

The sum of the membership function for all objective functions is computed in order to evaluate each solution in satisfying N number of objectives. Each membership function can be normalized with respect to

M number of nondominated solutions and represented as a fuzzy cardinal priority ranking (μ^k) as follows:

$$\mu^k = \frac{\sum_{i=1}^{N} \mu_{F_i}^k}{\sum_{k=1}^{M} \sum_{i=1}^{N} \mu_{F_i}^k}, \tag{8}$$

where i = number of objective functions (i= 1,2,... N) and k = number of nondominated solutions (k= 1,2,..., M).

Therefore, the best compromise solution among the nondominated solutions is selected according to the highest value of (Max μ^k ; (k= 1,2,..., M)).

3. Proposed MPSO-TVAC algorithm

3.1. The PSO algorithm

PSO is one of the metaheuristic methods that is widely implemented in optimization problems. This population-based approach was first introduced by Kennedy and Eberhart in 1995 [31]. The principle operation of PSO is inspired by the behavior of fishes schooling and birds flocking.

In PSO, a population consists of a number of particles that represent the possible solution. Every particle will move around dth dimensional solution space for finding an optimal solution. The movement of a particle is guided by it best personal experience (*pbest*) and best group experience (*gbest*). In the jth iteration, the ith particle in a population has memorized its own position and velocity, presented as vector $x_i^j = [x_{i1}^j, x_{i2}^j, \ldots, x_{id}^j]$ and $v_i^j = [v_{i1}^j, v_{i2}^j, \ldots, v_{id}^j]$, respectively. Thus, the particle will be updated according to the previous experience based on the following equations:

$$v_{id}^{j+1} = w^j v_{id}^j + c_1 r_1 (pbest_{id}^j - x_{id}^j) + c_2 r_2 (gbest_d^j - x_{id}^j), \tag{9}$$

$$x_{id}^{j+1} = x_{id}^j + v_{id}^{j+1}, \tag{10}$$

where r_1 and r_2 are independent random numbers between 0 and 1. c_1 and c_2 are the cognitive acceleration coefficient and the social acceleration coefficient, respectively. *pbest* is the individual best position represented as $pbest_i^j = [pbest_{i1}^j, pbest_{i2}^j, \ldots, pbest_{id}^j]$. *gbest* is the group best position or the global best position represented as $gbest_d^j = [gbest_1^j, gbest_2^j, \ldots, gbest_d^j]$. w is the inertia weight factor and can be calculated using Eq. (11) [32]:

$$w^j = w_{\max} - \left(\frac{w_{\max} - w_{\min}}{j_{\max}}\right) \times j j = 1,2,\ldots iter_{\max}, \tag{11}$$

Where w_{min} and w_{max} = the initial and final inertia weights, respectively, and j_{max} = maximum iteration number.

The inertia weight should vary linearly from 0.9 to 0.4 during the iterative process as suggested in [32,33] for better exploration and exploitation of the global search.

3.2. Review of PSO-TVAC algorithm

Since the parameter selection of c_1 and c_2 affects the performance of the PSO algorithm, PSO with time-varying acceleration coefficients (PSO-TVAC) was proposed in [34] where the value of the c_1 coefficient decreases while the value of c_2 decreases linearly according to the iteration number. The varying of these coefficients is calculated as follows:

$$c_1(j) = c_{1i} + (c_{1f} - c_{1i}) \times \frac{j}{j_{\max}}, \tag{12}$$

$$c_2(j) = c_{2i} + (c_{2f} - c_{2i}) \times \frac{j}{j_{\max}}, \tag{13}$$

where c_{1i} and c_{1f} = the initial and final values of the cognitive coefficient and c_{2i} and c_{2f} = the initial and final values of social coefficient.

3.3. Proposed MPSO-TVAC

To improve and enhance the performance and robustness of the aforementioned PSO, MPSO-TVAC is proposed. An adaptive parameter is introduced into Eq. (9) for updating the particle movement and is defined as a best neighbor particle (*rbest*). The idea is to enhance the exploration and exploitation of the algorithm by providing extra information to each particle.

In this approach, each particle has its own $rbest_i^j = [rbest_{i1}^j,\ rbest_{i2}^j, \ldots,\ rbest_{id}^j]$, which is randomly selected from the best position (*pbest*) of other particles. The pseudocode for determining an adaptive $rbest_i$ value for the ith particle is shown in Figure 2.

```
for i=1:N_pop                          * N_pop is the population size
   k=fix(rand(0,1)×N_pop +1)  * random fixed number between 1 and  N_pop
   for  k=i
      k= fix(rand(0,1)×N_pop +1)* to avoid the selection of its own pbest value
   end
   rbest_i=pbest_k     * Defined rbest value for ith particle
end
```

Figure 2. Pseudocode for determining *rbest* value.

Presenting an adaptive parameter in Eq. (9), the new updated velocity can be formulated as follows:

$$v_{id}^{j+1} = w^j v_{id}^j + c_1 r_1 (pbest_{id}^j - x_{id}^j) + c_2 r_2 (gbest_d^j - x_{id}^j) + c_3 r_3 (rbest_{id}^j - x_{id}^j), \tag{14}$$

where c_3 = the acceleration coefficient that pulls the particle towards *rbest*.

As mentioned in [31], a high value of c_1 and small value of c_2 in early iterations will push the particle to move the entire solution space and high values of c_2 and small values of c_1 in later iterations will pull the particle to a local solution (premature convergence).

Therefore, in MPSO-TVAC, the values of c_1 and c_2 vary according to the iteration number, similar as PSO-TVAC, by using Eqs. (12) and (13), while the value of c_3 varies according to the following equation:

$$c_3(j) = c_1 \times (1 - \exp(-c_2 \times j)). \tag{15}$$

Presenting the best neighbor particle (*rbest*) and TVAC approach for all acceleration coefficients in Eq. (14) will encourage every particle to converge at the global/near-to-global solution. The extra information provided by the *rbest* parameter enhances the searching behavior and avoids convergence at local solutions. Therefore, the proposed algorithm can improve the solution quality and produce consistent results after different trials.

4. MPSO-TVAC algorithm for solving EELD problems

The implementation step of the MPSO-TVAC algorithm for EELD is discussed in this section. The following steps should be performed in order to determine the optimal generator output considering the minimization of fuel cost and emission amount simultaneously.

Step 1: Input data required for EELD problem.

Step 2: Initialize the MPSO-TVAC parameters such as acceleration coefficients (c_{1i}, c_{1f}, c_{2i}, c_{2f}, and c_3), inertia weight (w_{max} and w_{min}), population size (N_{pop}), and maximum iteration (j_{max}).

Step 3: Define the problem variables. In EELD, the real power output (P_{id}) is a problem variable in the dth dimension. The ith particle for each generator is randomly generated according to Eq. (5) as $P_{id} = P_{id}^{min} + rand\times\ (P_{id}^{max} - P_{id}^{min})$.

Step 4: Evaluate the fitness function. Each possible solution is evaluated based on the given fitness function. The fitness function is to integrate the *OF* in Eq. (6) with the penalty function in order to meet the real power demand constraint in Eq. (3). It is required to be minimized and formulated as follows:

$$\text{Fitness } f(P_i) = \sum_{i=1}^{Ng} OF_i + \alpha \times abs\left(\sum_{i=1}^{Ng} P_i - (P_D + P_L)\right), \tag{16}$$

where α = the penalty factor for satisfying the real power demand constraints.

Step 5: Based on the calculated fitness function the *pbest*, *gbest*, and *rbest* values are determined as explained Section 3.

Step 6: The particle movement (for the next iteration) is updated by utilizing Eqs. (14) and (15).

Step 7: Constraint handling. If the updated position (P_{id}^{j+1}) is violating the generation limit in Eq. (4) it will replace its limit value as follows:

$$P_{id}^{j+1} = \begin{cases} P_{id}^{j} + v_{id}^{j+1} & \text{if} \quad P_d^{\min} \le P_{id}^{j+1} \le P_d^{\max} \\ P_d^{\min} & \text{if} \quad P_{id}^{j+1} \le P_d^{\min} \\ P_d^{\max} & \text{if} \quad P_{id}^{j+1} \ge P_d^{\max} \end{cases}. \tag{17}$$

Step 8: Repeat Steps 4–7 until maximum iteration is reached. Then the best optimum solution is selected.

Step 9: In EELD, Steps 1–8 should be repeated for each value of k by changing the value of $k$in steps of 0.1 ($0 \le k \le 1$). The best results obtained are recorded in an array according to the value of k, which known as a set of Pareto optimal solutions.

Step 10: The best compromise solution is determined based on fuzzy set theory as discussed in Section 2.4.

5. Simulation results and discussion

To validate the performance of the proposed MPSO-TVAC, 50 different trials are carried out for each case study. The results obtained are compared with PSO-TVAC and other algorithms in the literature. The algorithms are performed using MATLAB 7.6 on a Core 2 Quad processor, 2.66 GHz and 4 GB RAM.

5.1. Power system benchmark

The IEEE 30-bus six-generator system [8,9] is used as a test system to validate the effectiveness of the MPSO-TVAC algorithm. The total load demand of the system is 2.834 p.u. There are two case studies considered as follows:

Case 1: For simplicity, the test system without transmission losses is considered in order to compare with reported results in the literature. All data are presented in Table 1 [8].

Table 1. Fuel cost and emission data for IEEE 30 bus six system.

Gen.	Cost coefficients			Emission coefficients					Gen. limit	
	a	b	c	α	β	γ	ζ	λ	P_{min}	P_{max}
1	100	200	10	4.091	–5.554	6.49	2.0E-4	2.86	0.05	0.50
2	120	150	10	2.543	–6.047	5.638	5.0E-4	3.33	0.05	0.60
3	40	180	20	4.258	–5.094	4.586	1.0E-6	8.00	0.05	1.00
4	60	100	10	5.326	–3.55	3.38	2.0E-3	2.00	0.05	1.20
5	40	180	20	4.258	–5.094	4.586	1.0E-6	8.00	0.05	1.00
6	100	150	10	6.131	–5.555	5.151	1.0E-5	6.667	0.05	0.60

Case 2: In this case, the same test system with transmission losses is considered. The transmission losses are calculated according to Eq. (4). Table 2 shows the B-loss coefficient matrix for this case study [8].

Table 2. B-loss coefficients for IEEE 30 bus system.

B_{ij}	0.1382	–0.0299	0.0044	–0.0022	–0.0010	–0.0008
	–0.0299	0.0487	–0.0025	0.0004	0.0016	0.0041
	0.0044	–0.0025	0.0182	–0.0070	–0.0066	–0.0066
	–0.0022	0.0004	–0.0070	0.0137	0.0050	0.0033
	–0.0010	0.0016	–0.0066	0.0050	0.0109	0.0005
	–0.0008	0.0041	–0.0066	0.0033	0.0005	0.0244
B_0	–0.0107	0.0060	–0.0017	0.0009	0.0002	0.0030
B_{00}	0.00098573					

5.2. Parameter setting

The best parameter settings for the PSO-TVAC and MPSO-TVAC algorithms used in this paper are presented in Table 3. These values were obtained by several experiments in order to produce the best results for solving the IEEE 30-bus six-generator system.

Table 3. Parameter setting for the selected algorithm.

Algorithm	c_1	c_2	c_3	w_{min}	w_{max}	N_{pop}	j_{max}
MPSO-TVAC	c_{1i}= 1.0 c_{1f} = 0.2	c_{2i}= 0.2 c_{2f} = 1.0	$c_3 = c_1*$ (1-exp$(-c_2 * j)$)	0.4	0.9	50	500
PSO-TVAC	c_{1i}= 1.0 c_{1f} = 0.2	c_{2i}= 0.2 c_{2f} = 1.0	-	0.4	0.9	50	500

Table 4 shows the effect of population size (N_{pop}) of the proposed algorithm for minimization of fuel cost and emission amount. Increasing the N_{pop} size produced the same results. However, the simulation time is increased according to N_{pop} size.

Table 4. Effect of the population size using proposed MPSO-TVAC (case 2).

N_{pop}	Best fuel cost			Best emission		
	Cost ($/h)	Emission (t/h)	Time (s)	Emission (t/h)	Cost ($/h)	Time (s)
10	606.0009	0.220934	0.90	0.194179	646.2279	0.88
20	605.9984	0.220730	1.75	0.194179	646.2072	1.75
30	605.9984	0.220729	2.69	0.194179	646.2070	2.68
40	605.9984	0.220729	3.55	0.194179	646.2070	3.53
50	605.9984	0.220729	4.47	0.194179	646.2070	4.47

5.3. Simulation results

The proposed MPSO-TVAC algorithm has been tested according to the following objectives:

i. Minimize fuel cost function only.

ii. Minimize emission function only.

iii. Minimize fuel cost and emission function simultaneously.

Table 5 presents the optimal power output for the best fuel cost and the best emission obtained by the MPSO-TVAC algorithm. It shows that the generator output produced satisfies all the constraints in Eqs. (3) and (5).

Table 5. The best individual fuel cost and emission obtained by MPSO-TVAC algorithm.

Power output (p.u.)	Case 1		Case 2	
	Best fuel cost	Best emission	Best fuel cost	Best emission
P_1	0.109721	0.406074	0.120969	0.410925
P_2	0.299769	0.459069	0.286312	0.463668
P_3	0.524297	0.537939	0.583557	0.544419
P_4	1.016198	0.382953	0.992854	0.390374
P_5	0.524298	0.537939	0.523971	0.544459
P_6	0.359717	0.510027	0.351899	0.515485
P_{total}	2.834000	2.834000	2.859562	2.869330
P_{Loss}	-	-	0.025562	0.035330
Cost ($/h)	600.1114	638.2734	605.9984	646.2070
Emission (t/h)	0.222145	0.194203	0.220729	0.194179

The comparison of convergence characteristics of MPSO-TVAC and PSO-TVAC for minimizing fuel cost are shown in Figure 3 for a single run. It demonstrated that MPSO-TVAC can converge near the best solution as compared to PSO-TVAC.

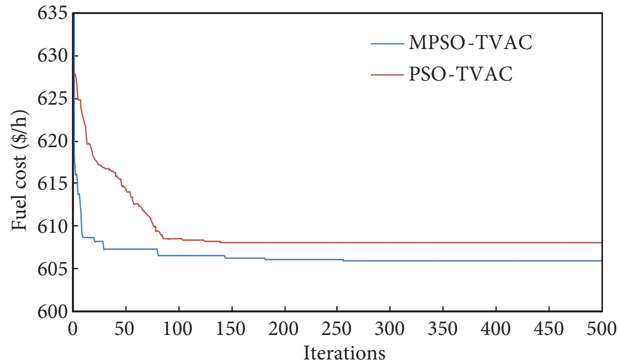

Figure 3. Convergence characteristics of MPSO-TVAC and PSO-TVAC (case 2).

In order to minimize the combined fuel cost and emission function, the value of k in Eq. (6) is varying from 0.0 to 1.0 with steps of 0.1 for each simulation. The results obtained by the proposed MPSO-TVAC are presented in Table 6. Figure 4 shows the comparison of the Pareto optimal solution achieved by the MPSO-TVAC and PSO-TVAC algorithms according to different k values. This set of solutions can be used by system operators to choose the best solution based on their preferred objective according to the k value.

Table 6. Optimal fuel cost and emission solution using proposed MPSO-TVAC.

k	Case 1		Case 2	
	Cost ($/h)	Emission (t/h)	Cost ($/h)	Emission (t/h)
1.0	600.1114	0.2221	605.9984	0.2207
0.9	604.1316	0.2066	609.6877	0.2067
0.8	610.1645	0.2005	615.5829	0.2008
0.7	615.7707	0.1976	621.3173	0.1979
0.6	620.6219	0.1961	626.4452	0.1962
0.5	624.7609	0.1952	630.9302	0.1953
0.4	628.2956	0.1947	634.8355	0.1948
0.3	631.3330	0.1944	638.2432	0.1944
0.2	633.9626	0.1943	641.2329	0.1943
0.1	636.2568	0.1942	643.8688	0.1942
0.0	638.2734	0.1942	646.2070	0.1942

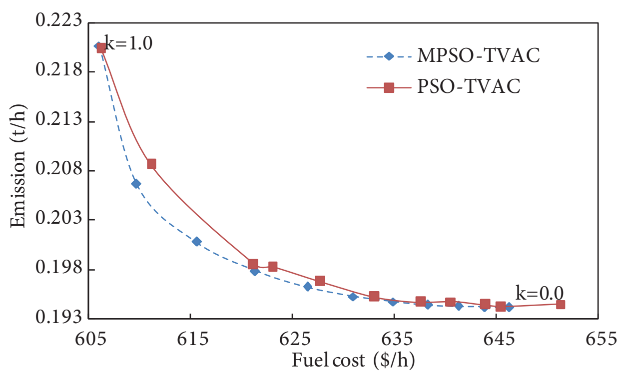

Figure 4. The optimal solution according to weight factor (case 2).

Table 7 presents the comparison of the best compromise solution achieved by MPSO-TVAC and PSO-TVAC. It was found that the proposed MPSO-TVAC algorithm can provide lower fuel cost and emission amount as compared to PSO-TVAC. Moreover, the total objective function (OF) in Eq. (6) obtained by the proposed algorithm is smaller than that obtained by PSO-TVAC.

Table 7. The best compromise solution according to fuzzy set theory.

Output	Case 1		Case 2	
	MPSO-TVAC	PSO-TVAC	MPSO-TVAC	PSO-TVAC
P_1	0.261014	0.239199	0.252759	0.336156
P_2	0.375496	0.417883	0.371616	0.376469
P_3	0.539481	0.636733	0.565826	0.573600
P_4	0.686269	0.678224	0.689033	0.645759
P_5	0.539481	0.452467	0.549576	0.501686
P_6	0.432258	0.409495	0.431222	0.429128
P_{total}	2.834000	2.834000	2.860033	2.862798
P_{Loss}	-	-	0.026033	0.028798
Cost ($/h)	610.1645	611.2755	615.5829	621.1694
Emission (t/h)	0.200527	0.201460	0.200841	0.198514
PPF	5928.71345	5928.71345	5928.71345	5928.71345
OF	725.9048	727.90069	730.6115	732.3225

5.4. Comparison of the best results

To verify the performances of the MPSO-TVAC algorithm, the best results obtained are compared with some reported results in the literature. In case 1, the best fuel cost and emission amount obtained by the proposed solution are compared with the results of BB-MPSO [16], Tribe-MDE [26], MA θ-PSO [6], NSGA [9], NPGA [9], SPEA [9], MBFA [11], and DE [35] as given in Table 8.

Table 8. The best results obtained by various algorithms (case 1).

Algorithm	The best fuel cost			The best emission amount		
	Cost ($/h)	Emission (t/h)	Time (s)	Emission (t/h)	Cost ($/h)	Time (s)
MPSO-TVAC	600.1114	0.22214	1.71	0.194203	638.2734	1.71
BB-MPSO [16]	600.1120	0.22220	-	0.194203	638.262	-
Tribe-MDE [26]	600.1114	0.22214	2.3	0.194203	638.2734	2.5
MA θ-PSO [6]	600.1114	0.2221	1.73	0.194203	638.2734	1.73
NSGA [9]	600.34	0.2241	-	0.1946	633.83	-
NPGA [9]	600.31	0.2238	-	0.1943	636.04	-
SPEA [9]	600.22	0.2206	-	0.1942	640.42	-
MBFA [11]	600.17	0.2200	1.32	0.1942	636.73	1.32
DE [35]	600.11	0.2231	-	0.1952	638.27	-

'-': not mentioned in the reference.

In terms of fuel cost, the best results achieved by the proposed algorithm are better than with other algorithms and equal to the latest results obtained Tribe-MDE [26] and MA θ-PSO [6]. For the best emission amount, the result obtained is essentially the same as the results of BB-MPSO [16], Tribe-MDE [26], and MA θ-PSO [6].

In case 2, the comparison of best fuel cost and emission amount produced by the proposed algorithm are presented in Table 9. It was compared with the results of BB-MOPSO [16], Tribe-MDE [26], MA θ-PSO [6], MO-DE/PSO [8], CMOPSO [8], SMOPSO [8], and TV-MOPSO [8]. The best simulation time of the proposed

Table 9. The best results obtained by various algorithms (case 2).

Algorithm	The best fuel cost					The best emission amount				
	P_{total}	P_{Loss}	ΔP*	Cost ($/h)	Emission (t/h)	P_{total}	P_{Loss}	ΔP*	Emission (t/h)	Cost ($/h)
MPSO-TVAC	2.859562	0.025562	0.0000	605.9984	0.220729	2.86933	0.03533	0.00000	0.194179	646.2070
BB-MOPSO[16]	2.8595	0.02562	–0.0001	605.9817	0.220190	2.8694	0.03537	0.00003	0.194179	646.4847
Tribe-MDE [26]	2.859561	0.025562	0.0000	605.9984	0.220729	2.86933	0.03533	0.00000	0.194179	646.207
MA θ-PSO [6]	2.859561	0.025562	0.0000	605.9984	0.220629	2.86933	0.03533	0.00000	0.194179	649.207
MO-DE/PSO[8]	2.8597	0.02555	0.0001	606.0073	0.22089	2.8693	0.03535	–0.00005	0.194179	646.0243
CMOPSO [8]	2.8597	0.0256	0.0001	606.0472	0.220468	2.8691	0.03517	–0.00007	0.194182	645.9985
SMOPSO [8]	2.8598	0.02597	–0.0002	605.9909	0.220692	2.869	0.03495	0.00005	0.19425	648.5035
TV-MOPSO [8]	2.8601	0.02604	0.0001	606.4028	0.21977	2.8679	0.33922	–0.3053	0.194267	642.7938

*$\Delta P = P_D - -\sum(P_i) - -P_{Loss}$.

algorithm to achieve the best fuel cost and emission amount is 1.75 s. However, the simulation time obtained by published results is not reported in order to make a comparison.

The individual best fuel cost and emission amount achieved by the proposed algorithm is slightly better than other algorithms and the same as the best results obtained by Tribe-MDE [26] and MA θ-PSO [6]. When analyzing the results in Table 9, some results are violating the power balance constraints in Eq. (3), where the value of ΔP $(P_D - \sum(P_i) - P_{Loss})$ is not equal to zero. From these comparisons, MPSO-TVAC is capable of obtaining the best results as well as satisfying power balance constraints ($\Delta P = 0$) effectively.

5.5. Robustness analysis

In order to show the consistency results produced by the proposed algorithm, 50 different trials have been conducted for each algorithm. This analysis is important to analyze the performance of metaheuristic algorithms like PSO due to the random number involved during optimization processes. The algorithm is more robust when it is capable of producing consistent results (at global solutions) after several trials.

Figures 5 and 6 show the distribution of the optimal results obtained by the proposed MPSO-TVAC and PSO-TVAC during 50 different trials. It clearly shows that the MPSO-TVAC algorithm can produce consistent results at the lowest fuel cost and emission.

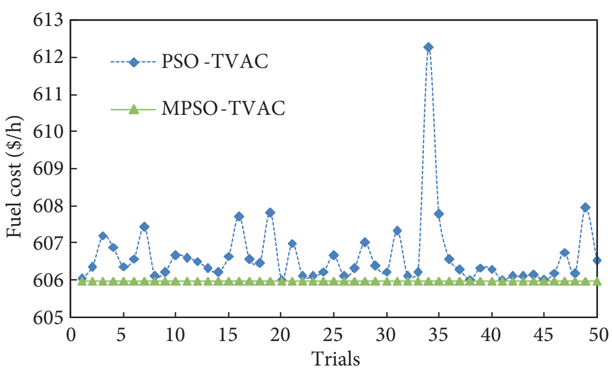

Figure 5. Best fuel cost after 50 different trials (case 2).

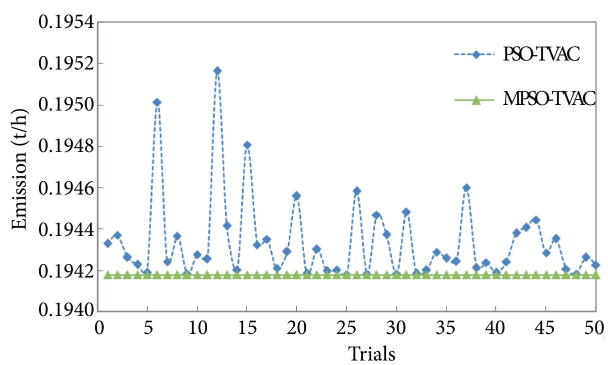

Figure 6. Best emission after 50 different trials (case 2).

Table 10 presents the best, mean, worst, and standard deviation (Std) values of the results obtained by the proposed MPSO-TVAC algorithm compared with PSO-TVAC. It shows that the MPSO-TVAC algorithm can produce lower best values as well as mean values for the total fuel cost and emission amount compared to other algorithms. Moreover, the smallest Std obtained shows the best quality of results produced by the proposed algorithm.

Table 10. Statistical results for minimizing fuel cost and emission function separately (case 2).

Algorithm	Fuel cost function				Emission function			
	Best	Mean	Worst	Std	Best	Mean	Worst	Std
MPSO-TVAC	605.9984	605.9984	605.9984	0.0000	0.194179	0.194179	0.194179	0.00000
PSO-TVAC	606.0191	606.6471	612.2694	0.9607	0.194179	0.194336	0.195164	0.000204

6. Conclusion

The MPSO-TVAC algorithm has been proposed for the EELD problem. In MPSO-TVAC, a new adaptive parameter named *rbest* is introduced into the velocity equation in order to prevent premature convergence and improve its robustness. Moreover, the value of acceleration coefficients changes according to the iteration number instead of a fixed value. The EELD problem is transformed into a single-objective problem by using the PPF and a weighted sum method is applied for finding a set of Pareto solutions. Fuzzy set theory is implemented to determine the best compromise solution. The simulation results show that the proposed algorithm has improved the convergence characteristics and is more robust compared to PSO-TVAC. By comparing with the results of the published algorithm, it shows that the best results obtained with MPSO-TVAC are better than those of many other algorithms. Therefore, it can be used as an alternative approach for solving EELD problems effectively.

Acknowledgments

The authors would like to acknowledge the Universiti Tun Hussein Onn Malaysia (UTHM) and Minister of Higher Education of Malaysia (MOHE) for supporting this research work.

References

[1] Alves LA, Uturbey W. Environmental degradation costs in electricity generation: the case of the Brazilian electrical matrix. Energ Policy 2010; 38: 6204–6214.

[2] Sayah S, Hamouda A, Zehar K. Economic dispatch using improved differential evolution approach: a case study of the Algerian electrical network. Arab J Sci Eng 2013; 38: 715–722.

[3] Ramanathan R. Emission constrained economic dispatch. IEEE T Power Syst 1994; 9: 1994–2000.

[4] Abou El Ela AA, Abido MA, Spea SR. Differential evolution algorithm for emission constrained economic power dispatch problem. Electr Pow Syst Res 2010; 80: 1286–1292.

[5] Hamedi H. Solving the combined economic load and emission dispatch problems using new heuristic algorithm. Int J Elec Power 2013; 46: 10–16.

[6] Niknam T, Doagou-Mojarrad H. Multiobjective economic/emission dispatch by multiobjective θ-particle swarm optimisation. IET Gener Transm Dis 2012; 6: 363–377.

[7] Niknam T, Golestaneh F, Sadeghi MS. θ-Multiobjective teaching-learning-based optimization for dynamic economic emission dispatch. IEEE Syst J 2012; 6: 341–352.

[8] Gong DW, Zhang Y, Qi CL. Environmental/economic power dispatch using a hybrid multi-objective optimization algorithm. Int J Elec Power 2010; 32: 607–614.

[9] Abido MA. Multiobjective evolutionary algorithms for electric power dispatch problem. IEEE T Evolut Comput 2006; 10: 315–329.

[10] Niknam T, Narimani MR, Jabbari M, Malekpour AR. A modified shuffle frog leaping algorithm for multi-objective optimal power flow. Energy 2011; 36: 6420–6432.

[11] Hota PK, Barisal AK, Chakrabarti R. Economic emission load dispatch through fuzzy based bacterial foraging algorithm. Int J Elec Power 2010; 32: 794–803.

[12] Özyön S, Temurtaş H, Durmuş B, Kuvat G. Charged system search algorithm for emission constrained economic power dispatch problem. Energy 2012; 46: 420–430.

[13] Yaşar C, Özyön S. Solution to scalarized environmental economic power dispatch problem by using genetic algorithm. Int J Elec Power 2012; 38: 54–62.

[14] Mondal S, Bhattacharya A, Nee Dey SH. Multi-objective economic emission load dispatch solution using gravitational search algorithm and considering wind power penetration. Int J Elec Power 2013; 44: 282–292.

[15] Yaşar C. A pseudo spot price of electricity algorithm applied to environmental economic active power dispatch problem. Turk J Electr Eng Co 2012; 20: 990–1005.

[16] Zhang Y, Gong DW, Ding Z. A bare-bones multi-objective particle swarm optimization algorithm for environmental/economic dispatch. Inform Sciences 2012; 192: 213–227.

[17] Koodalsamy C, Simon SP. Fuzzified artificial bee colony algorithm for nonsmooth and nonconvex multiobjective economic dispatch problem. Turk J Electr Eng Co 2013; 21: 1995–2014.

[18] Abdelaziz AY, Mohammed FM, Mekhamer SF, Badr MAL. Distribution systems reconfiguration using a modified particle swarm optimization algorithm. Electr Pow Syst Res 2009; 79: 1521–1530.

[19] Zwe-Lee G. Particle swarm optimization to solving the economic dispatch considering the generator constraints. IEEE T Power Syst 2003; 18: 1187–1195.

[20] Mostafa HE, El-Sharkawy MA, Emary AA, Yassin K. Design and allocation of power system stabilizers using the particle swarm optimization technique for an interconnected power system. Int J Elec Power 2012; 34: 57–65.

[21] Chaturvedi KT, Pandit M, Srivastava L. Self-organizing hierarchical particle swarm optimization for nonconvex economic dispatch. IEEE T Power Syst 2008; 23: 1079–1087.

[22] Chaturvedi KT, Pandit M, Srivastava L. Particle swarm optimization with time varying acceleration coefficients for non-convex economic power dispatch. Int J Elec Power 2009; 31: 249–257.

[23] Safari A, Shayeghi H. Iteration particle swarm optimization procedure for economic load dispatch with generator constraints. Expert Syst Appl 2011; 38: 6043–6048.

[24] Cai J, Li Q, Li L, Peng H, Yang Y. A hybrid CPSO–SQP method for economic dispatch considering the valve-point effects. Energ Convers Manage 2012; 53: 175–181.

[25] Abedinia O, Amjady N, Ghasemi A, Hejrati Z. Solution of economic load dispatch problem via hybrid particle swarm optimization with time-varying acceleration coefficients and bacteria foraging algorithm techniques. Int T Electr 2013; 23: 1504–1522.

[26] Niknam T, Mojarrad HD, Firouzi BB. A new optimization algorithm for multi-objective economic/emission dispatch. Int J Elec Power 2013; 46: 283–293.

[27] Victoire TAA, Jeyakumar AE. Reserve constrained dynamic dispatch of units with valve-point effects. IEEE T Power Syst 2005; 20: 1273–1282.

[28] Bhattacharya A, Chattopadhyay PK. Application of biogeography-based optimization for solving multi-objective economic emission load dispatch problems. Electr Pow Compo Sys 2010; 38: 340–365.

[29] Slimani L, Bouktir T. Economic power dispatch of power system with pollution control using artificial bee colony optimization. Turk J Electr Eng Co 2013; 21: 1515–1527.

[30] Dhillon JS, Parti SC, Kothari DP. Stochastic economic emission load dispatch. Electr Pow Syst Res 1993; 26: 179–186.

[31] Kennedy J, Eberhart R. Particle swarm optimization. In: Proceedings of IEEE International Conference on Neural Networks; 27 November–1 December 1995; Perth, Australia. New York, NY, USA: IEEE. pp. 1942–1948.

[32] Jong-Bae P, Ki-Song L, Joong-Rin S, Lee KY. A particle swarm optimization for economic dispatch with nonsmooth cost functions. IEEE T Power Syst 2005; 20: 34–42.

[33] Jeyakumar DN, Jayabarathi T, Raghunathan T. Particle swarm optimization for various types of economic dispatch problems. Int J Elec Power 2006; 28: 36–42.

[34] Ratnaweera A, Halgamuge SK, Watson HC. Self-organizing hierarchical particle swarm optimizer with time-varying acceleration coefficients. IEEE T Evolut Comput 2004; 8: 240–255.

[35] Perez-Guerrero RE, Cedeno-Maldonado JR. Differential evolution based economic environmental power dispatch. In: Proceedings of the 37th Annual North American Power Symposium; 23–25 October 2005. New York, NY, USA: IEEE. pp. 191–197.