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DYNAMIC ECONOMIC DISPATCH USING MODIFIED BACTERIAL FORAGING ALGORITHM ORIENTED WITH WEIGHTED PARTICLE SWARM OPTIMIZATION

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ABSTRACT

The goal of dynamic economic dispatch (DED) is to minimize the total operating cost of all committed generating units considering all physical and operational constraints. The DED problem is very complicated nonlinear optimization problem due to transmission losses, ramp-rate limits and valve-point effects constraints. Both bacterial foraging algorithm (BFA) and particle swarm optimization (PSO) methods have poor convergence characteristics. So, weighted PSO (WPSO) is employed to avoid the drawbacks of original PSO by employing the adaptive inertia weight factor. In this paper, modified BFA (MBFA) oriented with WPSO method is proposed by integrating MBFA and WPSO. By combining these two algorithms, the advantages of both of them can be extracted. This leads to get better solution of DED problem. Also, the diversity strategy is used in the proposed algorithm to solve the problem of early convergence. To prove the efficiency of the proposed method in solving the DED problem, different systems are employed. The obtained results prove the efficiency of the proposed method when comparing with other state of the art methods.

الهدف الاساسى لحل مشكلة التوزيع الاقتصادى للقدرة الفعالة ذات القيود الديناميكية هو الحصول على اقل تكلفة تشغيل مع الاخذ فى الاعتبار كل القيود المختلفة. ان مشكلة التوزيع الاقتصادى للقدرة الفعالة ذات القيود الديناميكية من المشكلات الغير خطية والمعقدة وذلك بسبب العديد من القيود مثل قيود معدل المنحدر و القدرة المفقودة وكذلك نقاط الصمام. لذلك فإن اقتراح طرق فعالة لحل هذه المشكلة من الامور ذات الاهتمام الكبير. طريقة أفراد السرب و الخوارزمية البكتيرية الأصلية يعانيان من مشكلة التقارب البطيء. لحل مشاكل طريقة أفراد السرب التقليدية تم استخدام طريقة أفراد السرب الموزونه. فى هذا البحث تم اقتراح طريقة الخوارزمية البكتيرية المعدلة والموجهة باستخدام طريقة أفراد السرب الموزونه. باستخدام كلا من هاتان الطريقتان فانه يمكن الحصول على المميزات الموجودة فى كلا منهم وبالتالى الحصول على حلول مثلى افضل لمشكلة التوزيع الاقتصادى للقدرة الفعالة ذات القيود الديناميكية. كما تم استخدام استراتيجية التنوع فى الطريقة المقترحة لحل مشكلة التقارب المبكر. تم تطبيق الطريقة المقترحة على عدة انظمة لبيان مدى فاعلية الطريقة المقترحة. وكذلك تمت مقارنة النتائج مع نتائج بعض الطرق المنشورة وقد أثبتت النتائج مدى فاعلية الطريقة المستخدمة ومدى تفوقها على بقية الطرق المستخدمة في المقارنة.

Keywords: Modified bacterial foraging algorithm, weighted particle swarm optimization, diversity strategy, dynamic economic dispatch, ramp-rate constraint.

NOMENCLATURE

F	Total generation cost over the entire operating horizon.
$F_{i,t}$	Fuel cost of generator i at time t.
$P_{Gi,t}$	Output power of generator i at time t.
i	Unit index.
t	Time index , $t=1,\dots,T$ (hour)
j	Unit index ($j=1,\dots,n$).
n	Number of generation units.
T	Number of hours in the operating horizon.
a_i, b_i, c_i	Fuel cost's coefficients for generator i.
α_i, δ_i	Valve-point's coefficients for generator i.
$P_{Gi,min}$	Minimum output power of generator i (MW).
$P_{D,t}$	The load demand at time t.
$P_{Loss,t}$	Total real power loss at time t.
$B_{ij,t}$	Loss coefficient relating the productions of units i and j at time t (MW^{-1}).
$B_{i0,t}$	Loss coefficient associated with the production of unit i at time t.
$B_{00,t}$	Loss coefficient parameter at time t (MW).
UR_i	Limit of ramp-up of generator i (MW/h).
DR_i	Limit of ramp-down of generator i (MW/h).
$P_{Gi,max}$	Maximum power output of generator i (MW).
p_i^k	Position of particle i at iteration k.
u_i^k	Velocity of particle i at iteration k.

$p_{best,i}^{k}$	The best previous position of particle i at iteration k.
$g_{best,i}^{k}$	The best position among all particles in the population.
w	Inertia weight parameter.
r_1, r_2	Random numbers ϵ [0,1].
c_1, c_2	PSO's acceleration coefficients.
$\overline{w}$	Adaptive inertia weight factor.
w_{min}, w_{max}	Minimum and maximum value of w.
O	Particle's current objective value.
O_{avg}	Average objective value of all particles in the population.
O_{min}	Minimum objective value of all particles in the population.
d	Search space's dimension.
Nb	Number of bacteria.
N_l	Length of a swim.
N_{cs}	Number of chemotactic steps.
N_{rs}	Number of reproduction steps.
N_{es}	Number of elimination dispersal events.
P_{es}	Elimination dispersal's probability.
$C(i)$	Size of the step taken by each bacterium i in the random direction.
$\varphi(j)$	Random direction of movement after a tumble
$\theta^i(j,k,l)$	Position vector of the bacterium i in j^{th} chemotactic, k^{th} reproduction and l^{th} elimination dispersal step.
$F(i,j,k,l)$	Objective value of bacterium i in j^{th} chemotactic, k^{th} reproduction and l^{th} elimination dispersal step.
ξ	Constriction coefficient.
b_{Lbest}	Best position of each bacterium.
b_{Gbest}	Global best bacteria.
$I(j,k,l)$	Position of each bacterium of the population.
$d_{attract}$, $w_{attract}$, $h_{repellant}$, $w_{repellant}$	Coefficients which characterize the features of the attractant and repellant signals.
θ_m^i	The m^{th} element of i^{th} bacterium location θ_i

1. INTRODUCTION

The economic dispatch (ED) represents one of the fundamental operation functions of the electrical power systems, particularly with the growth in cost of available fuel types [1]. The main goal of ED is to schedule the output power of all generation units. In addition, it aims to meet the load demand at a specific time with least operating cost taking into account all constraints. This makes the ED problem as a significant non-linear optimization problem [1].

There are two different types of ED. The first one called static economic dispatch (SED), while the second one is called dynamic economic dispatch (DED). In general, SED optimizes the total generation cost in a definite time without considering the connection of different operating times. On the other hand, the DED considers these connections by taking into consideration the ramp-rate limits [2].

In DED, all physical and operational constraints such as ramp-rate limits are taken into account which makes it a very complicated optimization problem [3]. Therefore getting the global optimum for this non-convex problem is a great challenge.

In literature, different algorithms are employed to get the accurate solution of the DED problem. The conventional optimization approaches such as Lagrangian relaxation (LR) [4] and dynamic programming (DP) [5] have some drawbacks. They suffer from curse of the dimensionality problem particularly in solving the problems with large scale systems. In addition, they fail to achieve the accurate solutions due to the nonlinear characteristics of the DED problem.

On the other hand and however, the artificial intelligence (AI) based methods such as differential evolution (DE) [6] and particle swarm optimization (PSO) [7] give better performance than conventional methods, they may be trapped in local optima. For this reason, researchers used hybrid methods to solve the DED problem [2, 8]. The hybrid methods have many merits. They decrease the search space. Moreover, they give an acceptable computation time in solving the DED problem. Lastly, they can deal with more constraints [2].

In recent years, swarming methods such as bacterial foraging algorithm (BFA) and PSO have been employed to get an accurate solution of the economic dispatch problem [7, 9]. To overcome the disadvantages of the conventional PSO method, weighted PSO (WPSO) is proposed and employed by merging the PSO and adaptive inertia weight factor which described in [10-12]. In the BFA, there are three essential steps. They are chemotaxis, reproduction and elimination-dispersal steps [13]. Like other AI methods, the conventional BFA may be trapped in local optima and gives poor convergence characteristics especially for non-convex DED problem. So, these disadvantages should be overcome before using the original BFA to solve the DED problem [9].

In this paper, a hybrid WPSO and modified BFA (MBFA) is proposed to solve the problem of DED by merging the WPSO and MBFA. The WPSO method is resulting by using adaptive inertia weight factor with conventional PSO to regulate the global search, whereas, the MBFA can be derived by merging adaptive stopping criterion with original BFA. So, the proposed method has the merits of both WPSO and MBFA. In the same time it excludes the drawbacks of both methods. In addition, diversity strategy is employed in this paper to avoid the early convergence problem.

To prove the efficiency of the proposed method over other state of the art methods in solving the DED problem, different standard systems are serving as test systems. The contributions of this research work are: to propose a hybrid optimization method by merging MBFA with WPSO and using diversity strategy, to employ the proposed method to get the optimal solution of the DED problem and to achieve lower operating cost in comparison with other methods.

The paper is organized as follows: Section 2 shows the problem formulation of the DED problem. Section 3 describes the implementation of the proposed method. The simulation results and comparisons are shown in Section 4. Lastly, Section 5 concludes the work.

2. MATHEMATICAL DESCRIBTION OF DYNAMIC ECONOMIC DISPATCH

2.1 DED Problem's Objective Function

To achieve the objective of DED, the following quadratic objective function can be used [2]:

minimize

$$F = \sum_{t=1}^{T}\sum_{i=1}^{n} F_{i,t}(P_{Gi,t}) = \sum_{t=1}^{T}\sum_{i=1}^{n}(a_i + b_i P_{Gi,t} + c_i P_{Gi,t}^2) \tag{1}$$

When the valve-point effect is taken into account, the total fuel cost of each generation unit can be rewritten by adding the sinusoidal function as follows [3]:

$$F_{i,t}(P_{Gi,t}) = a_i + b_i P_{Gi,t} + c_i P_{Gi,t}^2 + \left|\alpha_i \times \sin(\delta_i (P_{Gi,\min} - P_{Gi,t}))\right| \tag{2}$$

2.2 Constraints

To solve the above objective function of DED problem, the following equal and unequal constraints are considered [2, 3].

1) System power balance:

$$\sum_{i=1}^{n} P_{Gi,t} = P_{D,t} + P_{Loss,t} \tag{3}$$

The B-coefficients formula is employed to get the transmission network losses as follows:

$$P_{Loss,t} = \sum_{i=1}^{n}\sum_{j=1}^{n} P_{Gi,t} B_{ij,t} P_{Gj,t} + \sum_{i=1}^{n} B_{i0,t} P_{Gi,t} + B_{00,t} \tag{4}$$

2) Generation limits:

$$P_{Gi,\min} \le P_{Gi,t} \le P_{Gi,\max} \tag{5}$$

3) Up/down ramp rate limits:

$$UR_i \ge P_{Gi,t} - P_{Gi,t-1} \tag{6}$$

$$DR_i \ge P_{Gi,t-1} - P_{Gi,t} \tag{7}$$

Taking into account the ramp rat limits, the generation limits can be rewritten as follows:

$$P_{Gi,t} \ge \max\left(P_{Gi,\min}, P_{Gi,t-1} - DR_i\right) \tag{8}$$

$$\min\left(P_{Gi,\max}, P_{Gi,t-1} + UR_i\right) \ge P_{Gi,t} \tag{9}$$

3. PROPOSED METHOD

3.1 Particle Swarm Optimization

The original PSO begins with initial population of random solution. Each of them called particle which moves around in the search space to find the best solution. In PSO, the swarm direction of each particle depends on its own experience and the experience of closest particles [10].

In *d*-dimensional search space, the updated velocity and position of each particle of PSO can be determined as follows [14]:

$$u_i^{k+1} = w.u_i^k + c_1.r_1.(p_{best,i}^k - p_i^k) + c_2.r_2.(g_{best,i}^k - p_i^k) \tag{10}$$

$$p_i^{k+1} = p_i^k + u_i^{k+1} \tag{11}$$

More details about conventional PSO can be found in [10, 14].

3.2 Bacterial Foraging Algorithm

The original BF algorithm has been extensively used as a global optimization method to solve many optimization problems. The foraging performance of the bacterium can be demonstrated as an optimization process where each bacterium can search for its food and avoiding noxious substances. In addition, there is a communication among bacteria [13].

As other optimization methods, the BF algorithm begins with randomly generated initial population where the number of bacteria is equal to the number of individuals in the initial population. These bacteria attempt iteratively to achieve a global optimum via four stages. They are chemotaxis, swarming, reproduction and elimination dispersal stages [9].

Firstly, each bacterium is swimming and tumbling via flagella. By altering between these two kinds of motion, the bacterium spends its lifetime. Then, the bacteria assemble into sets. They move as concentric forms with high bacterial density. After that, only fitter bacteria remain and split into two bacteria. Finally, some bacteria may be disappeared with a very small probability. More details about conventional BFA can be found in [9, 13, 15].

3.3 Modified BFA Oriented with Weighted PSO

In the original PSO, choosing the parameters affects its performance. One of these parameters is the inertia weight (w). This parameter controls the effect of the preceding velocity of the particle on its present one. The incorrect choice of the value of this parameter will affect the convergence speed of the algorithm. So, Liu, et al [11] combined the adaptive inertia weight factor with the PSO to regulate the global search.

By using the adaptive inertia weight factor, the parameter w of the PSO will vary adaptively according to the particles' objective values as follows [11]:

$$\overline{w} = \begin{cases} w_{\min} - \dfrac{(w_{\max} - w_{\min})(O - O_{\min})}{O_{avg} - O_{\min}}, & O \le O_{avg} \\ w_{\max}, & O > O_{avg} \end{cases} \quad (12)$$

In original BFA, the multiplication of the number of chemotactic, reproduction and elimination/dispersal steps determines the stopping criterion. This increases the execution time of the BFA.

Consequently, Farahat, et al. [16] proposed an adaptive stopping criterion to treat this problem. By employing this criterion, the number of iterations is determined according to the improvement of the objective function where the chemotaxis process stops either when the solution achieves a specific condition or when chemotactic steps equal to its maximum value [16].

In adaptive BFA (ABFA) proposed in [16], the bacteria still move randomly. This may cause delay in achieving the best solution of the optimization problem. So, random movement of bacteria can be improved in the proposed method by combining the MBFA and WPSO where the suitable direction of each bacterium will determined by its best position.

In addition, a diversity strategy based on constriction coefficient is used in this paper to avoid the premature convergence [17].

The steps of the proposed method can be summarized as follows:

Step 1: Initialize all parameters (Nb, N_l, N_{cs}, N_{rs}, N_{es}, P_{es}, $C(i)$, $\varphi(j)$, $\theta(j,k,l)$, c_1, c_2, r_1, r_2, w_{min}, w_{max}) and create a random vector $\varphi(j)$ from [-1, 1].

Step 2: Begin the elimination dispersal loop: $l = l+1$.

Step 3: Begin the reproduction loop: $k = k+1$.

Step 4: Begin the chemotaxis loop: $j = j+1$.

- Take a chemotactic step for each bacterium (i).
- Calculate the objective function $F(i, j, k, l)$. Let $F_{last} = F(i, j, k, l)$ therefore, the best value can be found.
- For $i=1,\dots,Nb$, both tumbling and swimming' decision can be taken as follows:

Tumble: the best position of each bacterium and the global best position will decide the direction as follows:

$$\phi(j+1) = \xi(\overline{w}.\phi(j) + c_1.r_1.(b_{Lbest} - b_c) + c_2.r_2.(b_{Gbest} - b_c))) \quad (13)$$

where

$$\xi = \frac{2}{\left|2 - c_1 - c_2 - \sqrt{(c_1+c_2)^2 - 4(c_1+c_2)}\right|}, \quad (14)$$

and $c_1+c_2 > 4$.

Move: Let:

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\phi(j)' \quad (15)$$

- Compute: $F(i, j+1, k, l)$, then let:

$$\begin{aligned} F(i,j+1,k,l) &= F(i,j+1,k,l) + \\ &+ F_{cc}(\theta^i(j+1,k,l), I(j+1,k,l)) \\ &= F(i,j+1,k,l) + \\ &+ \sum_{i=1}^{S}\left[-d_{attract}\exp\left(-w_{attract}\sum_{m=1}^{d}(\theta_m - \theta_m^i)^2\right)\right] \\ &+ \sum_{i=1}^{S}\left[-h_{repellant}\exp\left(-w_{repellant}\sum_{m=1}^{d}(\theta_m - \theta_m^i)^2\right)\right]' \end{aligned} \quad (16)$$

- Loop of swimming: Let $q = 0$ (q is swim length's counter).

  While q < N_l

  Let q =$q + 1$
- If $F(i, j + 1, k, l) < F_{last}$, then let:

  $F_{last} = F(i, j + 1, k, l)$.
- Let

  $$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\phi(j)'$$
- At that moment, compute the new objective function $F(i, j + 1, k, l)$ using (16).
- Else, let $q = N_l$ (finishing the while statement).

- If $i \neq Nb$, proceed to the following bacterium.
- After that the best objective value gotten ($F_{best}(j)$) can be calculated.
- The difference (f) in the objective value obtained in the current chemotactic step can be computed as follows [16]:
- $f(j) = F_{best}(j) - F_{best}(j-1)$.
- If $j > N_{cs}/2$.
- If $|f(j) - f(j-b)| < \varepsilon; \quad b = 1,2,\ldots,b_m$ and $b_m < N_{cs}/2$.
- $j = Nc$ (stop chemotactic steps).

Step 5: If $j < N_{cs}$, return to step 4.

Step 6: Reproduction: each bacterium's health can be computed as:

$$F^i_{health} = \sum_{j=1}^{N_c+1} F(i,j,k,l) \qquad (17)$$

Arrange the bacteria in an ascending order where bacteria with highest health will die while the residual bacteria reproduce.

Step 7: If $k < N_{rs}$, return to step 3, otherwise, go to step 8.

Step 8: Elimination-Dispersal: a few bacteria are removed with small probability (P_{es}). So, the number of bacteria in the population is kept constant.

Step 9: If $l < Nes$, then return to step 2; otherwise end.

4. SIMULATION RESULTS

The proposed method is evaluated by applying it on three commonly used test systems. These systems are 5 thermal generation units system, 10 thermal generation units system and 30 thermal generation units system. The required data of each system (Fuel cost's coefficients for each thermal generator unit, valve-point's coefficients for each thermal generator unit, minimum and maximum output power of each thermal generator unit, limit of ramp-up and ramp-down of each thermal generator unit, B - matrix coefficients and load profile) is collected from Ref. [18]. To sake the fair comparison with other methods, valve-point effect is considered for the three test systems, while the transmission losses are considered only for the first two systems. Table 1 shows the details of these three commonly used test systems.

The proposed method is executed in personal computer with Pentium 4 processor, 2.8 GHz clock frequency and 4 GB of RAM using MATLAB R2012a. In each system, 100 independent runs were carried out with random initial values for each run and results (minimum, average, maximum) were obtained.

In order to execute the proposed method, some parameters should be adjusted first. These parameters affect not only the speed of convergence but also solution's quality. In this work, these parameters are chosen using empirical tests by solving the DED problem with different values of the parameters. Table 2 shows the best values of the parameters used in each system.

4.1 Test System 1: 5-Unit system

The best solution obtained for this system is shown in Table 3. The performance of the proposed method is compared with adaptive particle swarm optimization (APSO) algorithm [20], simulated annealing (SA) algorithm [19], artificial immune system (AIS) [21], Maclaurin series-based Lagrangian (MSL) method [22], GA [23], PSO [23], artificial bee colony (ABC) algorithm [23], time varying acceleration coefficients improved particle swarm optimization (TVAC-IPSO) [24], hybrid immune-genetic algorithm (HIGA) [2] and hybrid genetic algorithm and bacterial foraging (HGABF) [25]. This comparison is shown in Table 4. The results of Table 4 prove that the proposed method yields better results than other methods.

To test the superiority of the solution, the standard deviation (SD) from 100 independent runs by the proposed method is obtained. The value of this SD is equal to \$13.63. This shows a small range of variation the total cost achieved by the proposed method. This is evidence of the robustness of the proposed method.

4.2 Test System 2: 10-Unit system

The performance of the proposed method is compared with evolutionary programming (EP) [26], hybrid evolutionary programming and sequential quadratic programming (EP-SQP) [26], modified EP-SQP (MHEP-SQP) [26], GA [23], PSO [23], ABC [23], improved PSO (IPSO) [27], Enhanced cross-entropy (ECE) [28], AIS [21], enhanced bee swarm optimization (EBSO) [8], HIGA [2], enhanced adaptive particle swarm optimization (EAPSO) [29] and HGABF [25]. This comparison is shown in Table 5. These results demonstrate that the proposed method is more efficient than other methods.

The obtained SD from among 100 independent runs in this system is \$199.87 which emphasizes again the robustness of the proposed method.

4.3 Test System 3: 30-Unit system

Many state of the art methods are used in comparison in this test system. These methods are EP [30], EP-SQP [30], MHEP-SQP [27], IPSO [28], improved chaotic (ICPSO) [31], harmony search algorithm

Table (1), The Details of the Three Test Systems.

	System 1	System 2	System 3
Number of generation units	5	10	30
valve-point effects	Yes	Yes	Yes
Constraints used to sake the fair comparison with other methods	• Transmission losses. • Generation limits. • Ramp-rate limits	• Transmission losses. • Generation limits. • Ramp-rate limits	• Generation limits. • Ramp-rate limits
Dispatch horizon	One day with periods of 1h.	One day with periods of 1h.	One day with periods of 1h.
Data of the system (coefficients of each generator, minimum and maximum output power of each generator and limit of ramp-up and down of each generator)	Data of this system is collected from Ref. [18]	Data of this system is collected from Ref. [18]	Data are gained by tripling the data of system 2.
B - matrix coefficients	These coefficients are given in Ref. [18]	These coefficients are given in Ref. [18]	Transmission losses are neglected to sake the fair comparison with other methods.
Load profile	Hourly load values are extracted from Ref. [2].	Hourly load values are extracted from Ref. [2].	Hourly load values are extracted from Ref. [2].

Table (2), Parameters of the Proposed Method for Each Test System.

	System 1	System 2	System 3
Parameters of MBFA	Nb = 100, N_{cs} = 25, N_l = 4, N_{rs} = 4, N_{es} = 2, P_{es} = 0.25 and $C(i)$ = 0.1	Nb = 120, N_{cs} = 30, N_l = 4, N_{rs} = 4, N_{es} = 2, P_{es} = 0.25 and $C(i)$ = 0.1	Nb = 120, N_{cs} = 50, N_l = 4, N_{rs} = 4, N_{es} = 2, P_{es} = 0.25 and $C(i)$ = 0.1
Parameters of WPSO	c_1=c_2=2.1, w_{min}=0.2 and w_{max}=0.9	c_1=c_2=2.1, w_{min}=0.4 and w_{max}=1.2	c_1=c_2=2.1, w_{min}=0.4 and w_{max}=1.2

Table (3), The Best Solution Obtained for System 1 (5 Unit System).

Hour	**P_1**	**P_2**	**P_3**	**P_4**	**P_5**	**Loss**	**Hour**	**P_1**	**P_2**	**P_3**	**P_4**	**P_5**	**Loss**
1	10.00	20.00	30.03	123.08	229.80	2.91	**13**	62.60	99.14	111.30	211.43	230.08	10.55
2	10.00	20.00	54.44	124.58	229.21	3.23	**14**	48.52	98.95	111.30	211.22	230.08	10.07
3	10.00	28.55	87.10	124.23	230.02	4.90	**15**	36.66	98.12	111.30	186.97	230.08	9.13
4	11.38	56.51	111.99	125.22	231.32	6.42	**16**	10.00	98.55	111.30	137.20	230.11	7.16
5	10.12	86.51	110.32	126.21	231.30	6.46	**17**	10.00	86.65	111.41	126.41	230.15	6.62
6	10.12	97.33	110.32	167.00	231.12	7.89	**18**	10.21	101.1	107.27	167.25	230.08	7.91
7	10.12	100.15	83.46	210.09	231.02	8.84	**19**	11.30	99.56	110.55	211.44	230.08	8.93
8	13.27	100.99	107.26	211.43	230.08	9.03	**20**	41.73	98.68	131.80	211.44	230.38	10.03
9	42.26	104.84	111.54	211.43	230.08	10.15	**21**	38.06	100.5	109.92	211.44	230.02	9.89
10	62.31	99.11	111.54	211.43	230.11	10.50	**22**	10.00	98.88	109.92	162.91	231.17	7.88
11	75.00	103.14	111.30	211.43	230.08	10.95	**23**	10.00	98.30	109.92	126.00	188.70	5.92
12	73.99	98.78	137.03	211.43	230.08	11.31	**24**	10.00	97.83	92.45	126.00	141.22	4.50
Total cost = 40160.54 $													

Table (4), Fuel Cost Comparison for System 1 (5-unit system).

Method	Minimum Cost ($)	Average Cost ($)	Maximum Cost ($)
MSL [20]	49216.81	NA*	NA
SA [19]	47356.00	NA	NA
GA [23]	44862.42	44921.76	45893.95
APSO [20]	44678.00	NA	NA
AIS [21]	44385.43	44758.84	45553.77
PSO [23]	44253.24	45657.06	46402.52
ABC [23]	44045.83	44064.73	44218.64
TVAC-IPSO [24]	43136.56	43185.66	43302.23
HIGA [2]	43125.37	43162.24	43259.35
HGABF [25]	41574.80	41599.68	41652.56
Proposed method	40160.54	40182.21	40220.30

Table (5), Fuel Cost Comparison for System 2 (10-unit system).

Method	Minimum Cost ($)	Average Cost ($)	Maximum Cost ($)
EP [26]	1054685	1057323	NA
EP-SQP [26]	1052668	1053771	NA
GA [23]	1052251	1058041	1062511
MHEP-SQP [26]	1050054	1052349	NA
PSO [23]	1048410	1052092	1057170
IPSO [27]	1046275	1048145	NA
AIS [21]	1045715	1047050	1048431
ECE [28]	1043989.154	1044470.0849	NA
ABC [23]	1043381	1044963	1046805
HIGA [2]	1041087.802	1042980.147	1044926.653
EBSO [8]	1038915	1039188	1039272
EAPSO [29]	1037898	1038109	1038238
HGABF [25]	1036507	1037068	1038092
Proposed method	1035573	1036076	1036762

Table (6), Fuel Cost Comparison for System 3 (30-unit system).

Method	Minimum Cost ($)	Average Cost ($)	Maximum Cost ($)
EP [30]	3164531	3200171	NA
EP-SQP [30]	3159204	3169093	NA
MHEP-SQP [26]	3151445	3157438	NA
DGPSO [33]	3148992	3154438	NA
HS [32]	3143253.84	NA	NA
IPSO [27]	3090570	3090570	NA
CE [28]	3086109.595	3088869.8572	NA
ECE [28]	3084649.032	3087847.1893	NA
ICPSO [31]	3064497	3071588	NA
HHS [32]	3057313.39	NA	NA
HIGA [2]	3055435.068	3058126.233	3066754.92
EAPSO [29]	3054961	3055257	3055641
EBSO [8]	3054001	3054697	3055944
HGABF [25]	3050235	3051291	3053567
Proposed method	3047150	3048277	3050349

*** NA: means that this data is not available in the reference.**

(HS) [32], hybrid swarm intelligence-based harmony search (HHS) [32], deterministically guided PSO (DGPSO) [33], cross entropy (CE) [29], enhanced cross entropy (ECE) [29], HIGA [2], EAPSO [30], EBSO [8] and HGABF) [26]. This comparison is shown in Table 6. In this test system, the gained SD among 100 independent runs is \$502.08. This proves the robustness of the proposed method despite the number of generation units.

From the results in tables 4 - 6 which depicted in figures 1-3, one can notice that the proposed method is compared with different stat of the art methods based on minimum, average and maximum fuel costs. The stat-of-the-art methods' results are obtained from their references.

For the three test systems, the maximum fuel cost obtained using the proposed method is better than the minimum fuel cost obtained from all methods except HGABF method in system 2 and 3. This shows the superiority of the proposed method over other methods for different systems with different number of generation units. Also, the results prove the stability of the proposed method which evident from the small difference between minimum and maximum fuel cost whatever the number of generation units.

As we know, the execution time is highly affected by many factors such as, coding the algorithm and the configuration of the computer. So, in this paper, the execution time of the proposed method and HGABF method is compared using the same computer configuration. The execution times of other methods are not used in the comparison because they may have employed different computer configuration. Figure 4 shows the results of this comparison. These results demonstrate the high convergence speed for the proposed method over HGABF and original BFA methods. This is due to employing the adaptive stopping criterion in the proposed method which reduces the number of chemotaxis steps. The real life DED problem is solved offline. This makes the execution time of the proposed method (several minutes) is suitable to solve this problem.

5. CONCLUSION

In this work, an optimization method is proposed to solve the DED problem. The proposed method is resulting by merging BFA, adaptive stopping criterion, PSO, adaptive inertia weight factor and diversity strategy. This leads to avoid the drawbacks of these methods and gain the merits of them. The

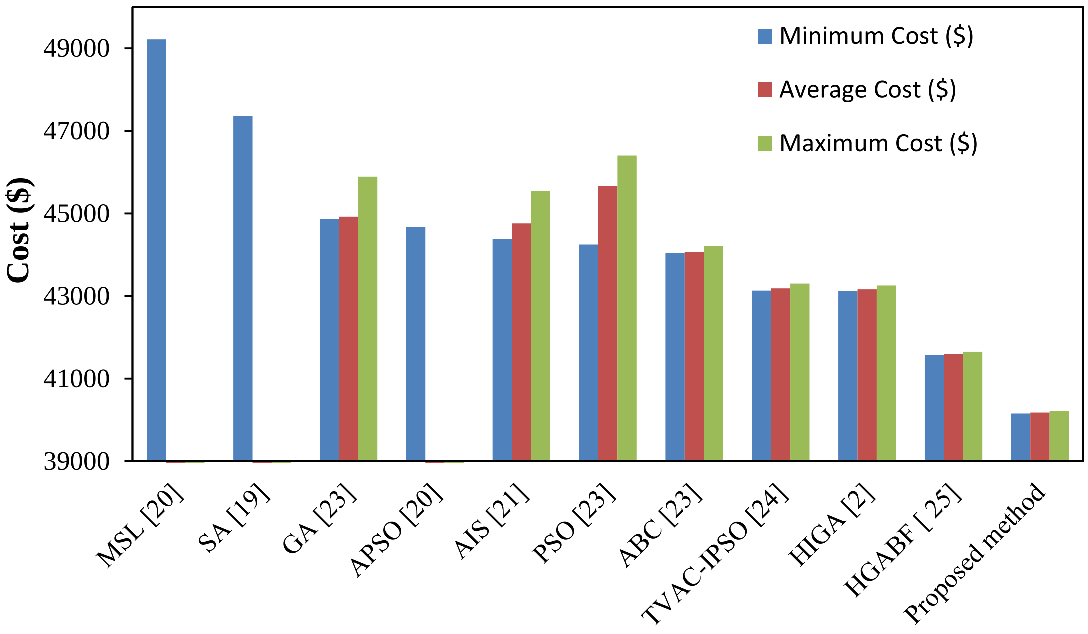

Fig. 1, Fuel Cost Comparison for System 1 (5-unit system).

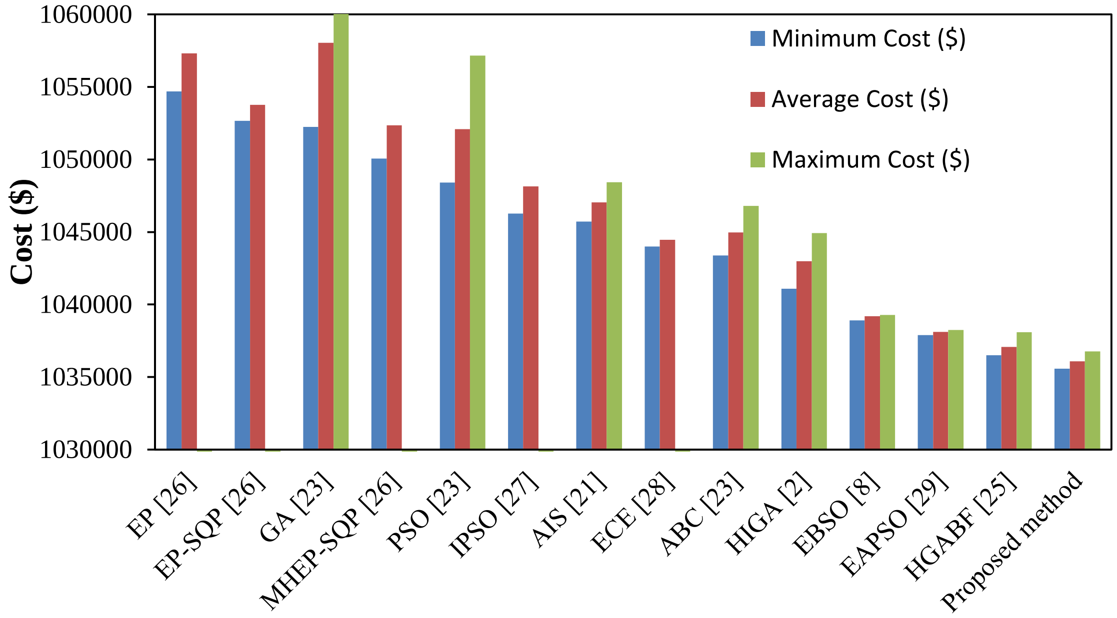

Fig. 2, Fuel Cost Comparison for System 2 (10-unit system).

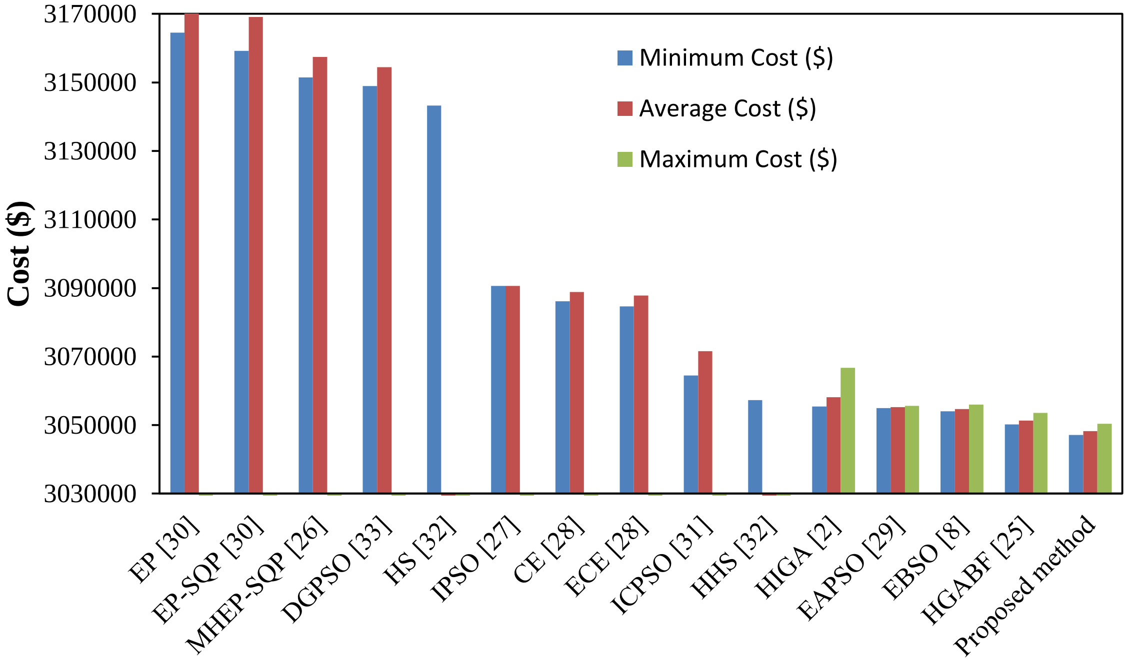

Fig. 3, Fuel Cost Comparison for System 3 (30-unit system).

feasibility and effectiveness of the proposed method have been confirmed using three test systems. The simulation results were compared with some of state of the art methods. The results show the superiority of the proposed method over these state of the art methods for solving the DED problem.

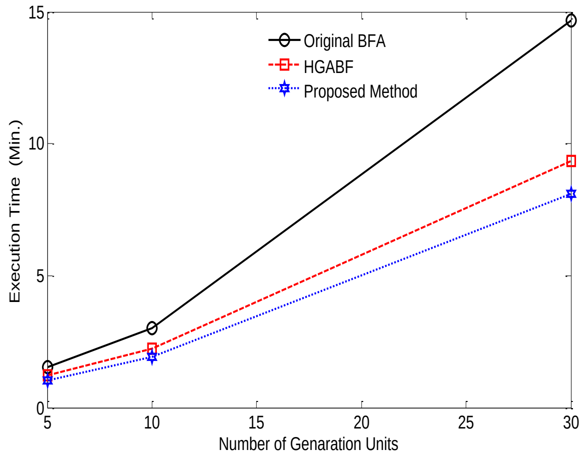

Fig. 4. Execution time for different methods

Also, they confirmed the capability of the proposed method to get the global solution of the DED problem.

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