



An Intelligent Approach Based on Meta-Heuristic Algorithm for Non-Convex Economic Dispatch

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ABSTRACT

One of the significant strategies of the power systems is Economic Dispatch (ED) problem, which is defined as the optimal generation of power units to produce energy at the lowest cost by fulfilling the demand within several limits. The undeniable impacts of ramp rate limits, valve loading, prohibited operating zone, spinning reserve and multi-fuel option on the economic dispatch of practical power systems are scrutinized in this paper. Thus, the proposed nonlinear non-convex formulation is solved by a new modified version of bio-inspired bat algorithm. Due to the complexities associated with the large-scale optimization problem of economic dispatch, adaptive modifications are added to the original bat algorithm. The modification methods are applied at two separate stages and pledge augmentation in convergence rate of the algorithm as well as extricating the algorithm from local optima. Veracity of the proposed methodology are corroborated by performing simulations on three IEEE test systems.

KEYWORDS: Non-convex economic dispatch, Modification mechanism, Meta-heuristic algorithm, Nonlinear constrained optimization.

1. INTRODUCTION

Scarcity of energy resources, increasing generation cost of the power systems, and ever-growing load demand for electric energy necessitate optimal Economic Dispatch (ED) in the current electric power systems. As power demand increases and considering that the fuel cost of the power generation is exorbitant, reducing the operation costs of power systems has turned to a significant topic [1]. Economic dispatch is an essential and significant optimization problems task for the operation of power systems. The main objective of ED in power systems is to economically distribute the total required generation between the generation units, while satisfying the load demand and system equality and inequality constraints [2].

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Improvements in the scheduling of the unit power outputs can contribute to significant cost savings. Furthermore, it offers information in forming market-clearing prices.

Previously, different algorithms to find rate of optimum product for each power generation unit are proposed in the literature. Conventional algorithms such as gradient method, Lambda Iteration Method (LIM), Linear Programming (LP), Quadratic Programming (QP), Lagrangian multiplier method, and classical technique based on coordination equations can solve the ED problems.

There are complex and nonlinear characteristics with equality and inequality constraints associated with the practical ED, which may be imposed to the problem to ensure the system operator of system reliability during disturbances and a secure operation. Many generating units are supplied with multiple fuel sources and should be scheduled by the most economic fuel to burn [3]. Taking everything

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into account, the system operator must consider ramp rate limits, Prohibited Operating Zones (POZs), system spinning reserve, valve loading effects, and multiple fuel source options to solve a realistic ED problem, which makes hard the finding of the optimum solution difficult [4].

Recently, as an alternative for conventional mathematical approaches, the modern stochastic optimization algorithms based on operational research and artificial intelligence concepts, such as Genetic Algorithms (GA), Tabu search, simulated annealing (SA), differential evolution and Particle Swarm Optimization (PSO) are considered as realistic and powerful solution schemes for obtaining the global optimums in power system optimization problems and due to their ability to find an almost global optimal solution for ED problems with operating constraints. While each of the above studies has considered different parts of the practical ED problem, none of them have considered all the practical constraints simultaneously [5]. In addition, the utilized algorithms are not robust at all and have found different results for different runs. In response to these deficiencies, a practical formulation was devised for ED and then a new method is proposed as its solution in this paper. Thus, a modified version of bat algorithm (BA) as an evolutionary metaheuristic algorithm was employed to solve the proposed realistic ED problem. BA tries to formulate and simulate the journey of bats in search of nutritious resources or chasing preys. The algorithm is simple in concept; thus, it is easy to implement, since many adjusting parameters are not included in the formulation. However, the original algorithm suffers low convergence rate and it is destined to get trapped in local optima due to the lack of diversity in the population. Thus, two modification stages are emplaced in the original algorithm to help increase the convergence rate of the algorithm and diversify the population. Interspersing the population to the entire search space improved the odds of finding the global optima. The robustness and capability of the proposed methodology is demonstrated by applying the procedure to two various IEEE standard test systems. In sum, the main contributions of this study can be summarized as follows:

- Proposing a comprehensive model for ED problem to consider practical constraints in real systems.
- Modifying the original BA to enable it of seeking the search space faster and more precisely.

2. PRACTICAL ED MATHEMATICAL DISCRIPTION

The ED problem is a nonlinear optimization problem, the objective of which is to determine the optimal combination of power generations, which minimizes the cost function while satisfying an equality constraint and an inequality constraint. The mathematical representation of the classical ED problem and the proposed practical ED are described in this section.

2.1. Classic ED

ED in its classical formulation aims to minimize the summing costs of thermal generating units which are generally considered as the second order polynomial function of the generation [2], as follows:

$$f(X) = Cost(X) = \sum_{i=1}^{n} F_i(P_i) = \sum_{i=1}^{n} (a_i + b_i P_i + c_i P_i^2)$$
(1)

in which P_i denotes output power of the i^{th} unit and n stands for the number of generators in the network. The polynomial coefficients of cost for the i^{th} unit are represented by a_i , b_i , and c_i as well. The conventional ED optimization problem is subjected to the following constraints forcing generators to produce power within specific limits so that their total generation equals to total power demand in the network (D).

$$\sum_{i=1}^{n} P_i = D \tag{2}$$

$$P_i^{\min} \le P_i \le P_i^{\max} \tag{3}$$

In the above formulation, the lower and upper bounds of power generation for the i^{th} unit are denoted by P_i^{min} and P_i^{max} , respectively.

2.2. Proposed practical ED formulation

Effects of valve-point loadings

However, it is more practical to consider the effect of valve point loading for thermal power plants [6]. These effects, which occur as each steam admission valve in a turbine, create a rippling influence on the unit's cost curve. Typically, as each steam valve starts to open, the valve point results in the ripples like in Fig. 1. Considering the valve-point effects, the fuel cost function of the i^{th} thermal generating unit is expressed as the sum of a quadratic and a sinusoidal function in the following form:

$$F_{i}(P_{i}) = a_{i} + b_{i}P_{i} + c_{i}P_{i}^{2} + |e_{i}\sin(f_{i}(P_{i}^{\min} - P_{i}))|$$
(4)

Costs of valve loading effect are represented by coefficients e_i and f_i in the sinusoidal term.



Multiple fuels

Since the dispatching units are practically provided with multi-fuel sources, each unit should be really represented by several piecewise quadratic functions reflecting the effects of fuel type changes and a generator must identify the economic fuel to burn. Thus, since different fuels possess various costs, the final generation cost of the units will depend on their choice of fuel, leading to divided cost function for generators as follows:

$$F_{i}(P_{i}) = \begin{cases} a_{i1} + b_{i1}P_{i} + c_{i1}P_{i}^{2} & ; \text{ Fuel 1: } P_{i}^{min} \leq P_{i} \leq P_{i1}^{max} \\ a_{i2} + b_{i2}P_{i} + c_{i2}P_{i}^{2} & ; \text{ Fuel 2: } P_{i2}^{min} \leq P_{i} \leq P_{i2}^{max} \\ \dots \\ a_{ij} + b_{ij}P_{i} + c_{ij}P_{i}^{2} & ; \text{ Fuel j: } P_{ii}^{min} \leq P_{i} \leq P_{i}^{max} \end{cases}$$
(5)

By adding the term related to valve-loading effect, the above formulation is turns to the following form:

$$F_{i}(P_{i}) = a_{ij} + b_{ij}P_{i} + c_{ij}P_{i}^{2} + |e_{ij}\sin(f_{ij}(P_{ij}^{\min} - P_{i}))| ;$$

Fuel j: $P_{ij}^{\min} \le P_{i} \le P_{i}^{\max}$
 $j = 1, 2, ..., n_{f}$ (6)

The number of different fuel types that are provided is denoted by n_{f} .

Apart from the two previously mentioned conventional constraints, the secure operation of network mandates respecting the following constraints:

Ramp rate limits

$$\begin{cases} P_i - P_{0i} \le UR_i; & \text{If generation increases} \\ P_{0i} - P_i \le DR_i; & \text{If generation decreases} \end{cases}$$
(7)

Ramp-up and ramp-down rate limits of the i^{th} unit are denoted by UR_i and DR_i , respectively. Also, P_{0i} is the active power output of the i^{th} unit in the previous hour. It is an significant matter that, due to the consideration of ramp rates, the output power of each unit is now bounded by a new limit as follows:

$$\max(P_{i}^{\min}, P_{0i} - DR_{i}) \le P_{i} \le \min(P_{i}^{\max}, P_{0i} + UR_{i})$$

$$i = 1, 2, ..., n$$
(8)

Prohibited Operating Zones (POZs)

Each generator has its generation capacity limitation, which cannot be exceeded. The prohibited operating zones in the input-output performance curve, due to steam valve operating in shaft bearing, were considered in this paper in order to determine the optimum ED problem. In practice, when adjusting the generation output of a unit, operation in the prohibited zones must be avoided. Thus, the shape of the input-output curve in the neighborhood of the prohibited zones is difficult to be determined and the best economical approach is achieved by avoiding the operation in these areas, as shown in Fig. 2. The POZ restrictions might be represented for the i^{th} unit as follows:

$$\begin{cases} P_{i}^{\min} \leq P_{i} \leq P_{i,1}^{LB} \\ P_{i,j-1}^{UB} \leq P_{i} \leq P_{i,j}^{LB}; j = 2, 3, ..., NP_{i} \\ P_{i,j}^{UB} \leq P_{i} \leq P_{i}^{\max} \end{cases}$$
For $i = 1, 2, ..., N_{GP}$

$$(9)$$

 N_{GP} is the number of generators incorporating POZ and NP_i is the number of POZs of the i^{th} unit. Besides, $P_{ij}^{\ LB}$ and $P_{ij}^{\ UB}$ refer to the lower and upper

boundaries of the j^{th} POZ of the i^{th} generator respectively.



Fig. 2. The prohobited operating zones and generation limits for a generator

Spinning reserve

Due to the inclusion of POZ in the formulation of ED problem, spinning reserve of the system should be written in the following form:

$$S_{i} = \begin{cases} \min\{(P_{i}^{\max} - P_{i}), S_{i}^{\max}\} & \forall i \in (\Omega - \Theta) \\ 0 & \forall i \in \Theta \end{cases}$$
(10)
$$S_{r} = \sum_{i=1}^{n} S_{i}$$
(11)
$$S_{r} \geq S_{R}$$
(12)

in which, S_i and S_i^{max} refer to the spinning reserve of the *i*th unit and its maximum value, respectively. The set of operating units is denoted by Ω and the set of operating units with POZ is represented by Θ . S_R refers to the total spinning reserve required by the system.

3. OPTIMIZATION TECHNIQUE 3.1. Original bat algorithm

Bats locate the position of food or prey by echolocation. Echolocation is the process of figuring out the position of objects from their response to some sort of subsonic signals. Bats spreads a signal in the perimeter and waits to receive the reverberated signal from food or prey. This idea has been simulated to form a meta-heuristic evolutionary optimization algorithm called the (BA) [7]. The ruling ideas behind the BA are listed as bellow: 1) Reverberated signals from various objects are different and thus bats are capable of distinguishing between food and prey;

2) The generated signal by a bat stationed in position X_i or flying at the velocity of V_i is specified by f_i and A_i as signal frequency and amplitude, respectively;

3) Amplitude of the signal denoted by A_i is reduced gradually;

4) Frequency of the signal denoted by f_i and its rate denoted by r_i are changed automatically.

The algorithm is initiated by generating a preliminary population of bats which are randomly interspersed in the search space. The process of evolution is followed by updating the position of bats based on two separate steps. The first adjustment in the bat position is according to:

$$\mathbf{V}_{i}^{new} = \mathbf{V}_{i}^{old} + f_{i}(X_{G} - X_{i}); i = 1, ..., N_{Bat}
X_{i}^{new} = X_{i}^{old} + \mathbf{V}_{i}^{new} ; i = 1, ..., N_{Bat}
f_{i} = f_{i}^{\min} + \varphi_{1}(f_{i}^{\max} - f_{i}^{\min}) ; i = 1, ..., N_{Bat}$$
(13)

Where, X_G indicates the best global solution. The upper and lower frequency limits of the *i*th bat are represented by f_i^{max} and f_i^{min} , respectively. The population size is equal to the total number of bats denoted by N_{Bat} and φ_I is a randomly generated number between 0 and 1.

The second movement in the bat position is simulated as follows:

$$X_i^{new} = X_i^{old} + \varepsilon A_{mean}^{old}; i = 1, \dots, N_{Bat}$$
(14)

where, ε is a random number in the range of [-1,1] and A_{mean}^{old} is the mean value of amplitude of all the bats. Once the position of bats is improved by the above adjustments, a new random individual X_i^{new} is generated in case the rate of its signal r_i is greater than a random value β . This new solution will be inserted to the population in case the following constraint is respected:

$$[\beta < A_i] \& [f(X_i) < f(Gbest)]$$
⁽¹⁵⁾

As mentioned formerly, the value of signal amplitudes generated by bats has a gradual decrease formulated by:

$$A_i^{new} = \alpha A_i^{old}$$

$$r_i^{lter+1} = r_i^0 [1 - exp(-\gamma \times t)]$$
(16)

Where *t* represents iteration number and α and γ are constant parameters.

3.2. Modified BA

The original BA suffers some drawbacks such as the possibility of getting trapped in local optima and low rate of convergence to the optimal solution. Two modifications are devised and added to the algorithm in order to improve its convergence rate and diversity as follows:

Modification method 1

In the first modification step, it is attempted to diversify the bat population using Lévy flight, defined as a random walk with regular and dispersed step lengths according to heavy-tailed probability distribution [8]. The mathematical representation of the Lévy flight is formulated as:

$$Le'vy(\omega) \sim \tau = t^{-\omega} \quad ; \quad (1 < \omega \le 3) \tag{17}$$

This idea is borrowed to generate a new individual in each iteration as follows:

$$X_{i}^{new} = X_{i}^{old} + \varphi_{1} \oplus Le'vy(\omega)$$
⁽¹⁸⁾

This new solution might replace the i^{th} bat in the population in case it excels the objective function.

Modification method 2

The second modification step is devised to intersperse randomly generate solutions in the population based on conventional GA operators of crossover and mutation. To do so, three bats X_{b1} , X_{b2} and X_{b3} are chosen randomly such that $b_1 \neq b_2 \neq b_3 \neq i$ are related for i^{th} bat in the population and two test solutions are generated as follows:

$$X_{Test,1} = X_{b_1} + \varphi_1 \times (X_{b_2} - X_{b_3})$$
(19)

$$X_{Test,2} = \varphi_2 \times X_G + \varphi_3 \times (X_G - X_i)$$
⁽²⁰⁾

The above individuals are compared to the i^{th} bat and the one which enhances the objective function replaces X_{i} .

4. SOLUTION PROCEDURE

In order to apply MBA to solve the ED problem, the following steps should be implemented:

Step 1: Defining the input data. Here, all data including the network data, algorithm data (such as number of bats, initial positions, constant

coefficients, etc.), objective function parameters, constraints parameters, and etc. are defined completely.

Step 2: Formation of the fitness function. It is noted that the fitness function includes the objective function and the penalty values related to the problem constraints.

Step 3: Generation of the initial population based on the information given in the previous section.

Step 4: Evaluation of the objective functions for each bat separately and finding the best solution.

Step 5: Movement of the bat population to the new improved positions.

Step 6: Application of the proposed modification methods according to Eqs. (17)-(20).

Step 7: Updating the value of the best individual.

Step 8: Checking the termination criterion. If the termination criterion is satisfied, then the algorithm is finished and the results are printed; else, step 5 and the rest of the steps of repeated.

5. SIMULATION RESULTS

Effectiveness of the proposed approach in solving the proposed realistic ED problem is illustrated by applying the method to two test systems. It is worth noting that the adjusting parameters of MBA are all determined experimentally by several running of the algorithm. But, the significant point is that the algorithm is not much dependent on the values of the setting parameters and the output results is robust. The first example included ten generating units considering fuels valve loading effects of multiple fuels simultaneously [13]. The optimization problem is solved 100 times to generate the results according to Table 1. For comparison, the obtained results from several recently published ED solution methods (with similar trial runs) are also represented in this Table. It should be noticed that the results of the other reported methods are directly quoted from their respective references. According to the results, the best, average, and worst solutions of the proposed MBA are better than the best, average, and worst results of all other methods in the first ED test systems (IEEE 10-unit system), respectively. In addition, the optimal operating points of the units are given in Table 2.

The impact of the modifications on the convergence rate of the BA is illustrated in Fig. 3.

 Table 1. Cost function optimization using the proposed method on the IEEE 10-unit test system

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Best	Average	Worst			
624.7193	627.6093	633.8652			
624.5178	625.8692	630.8705			
624.5146	624.5246	624.5458			
624.5081	624.5079	624.5088			
624.5074	624.5074	624.5074			
624.2297	624.7887	628.3214			
624.1624	625.2180	627.4237			
624.1273	625.9985	626.9981			
624.1763	625.8636	626.8660			
623.8963	623.9883	623.9964			
	Best 624.7193 624.5178 624.5146 624.5081 624.5074 624.2297 624.1624 624.1273 624.1763 623.8963	Best Average 624.7193 627.6093 624.5178 625.8692 624.5176 624.5246 624.5081 624.5079 624.5074 624.5074 624.2297 624.7887 624.1624 625.2180 624.1273 625.9985 624.1763 625.8636 623.8963 623.9883			

 Table 2. Optimal operating point for the generators on the IEEE

 10 unit test system

10-unit test system					
Unit	Optimal Generation				
1	216.0512				
2	211.9071				
3	280.6641				
4	240.7613				
5	279.6584				
6	239.7952				
7	292.2220				
8	240.4925				
9	424.2443				
10	274.2036				

It is obvious that the proposed MBA was effectively successful in approaching the global optimal solution in less than 100 iterations.



Fig. 3. Convergence speed of the proposed MBA on the IEEE 10-unit test system

For the sake of better demonstrating the robustness of the proposed methodology, the procedure is applied to the 40-unit IEEE power system and the second test case was fully introduced in [15]. Similar to the first case, 100 trials are done to the IEEE-40 unit system and the optimization results and the unit allotted outputs are illustrated in Table 3 and Table 4, respectively. Investigation of the results revealed the dominance of the proposed MBA in terms of finding the optimal solution compared to other methods.

 Table 3. Cost function optimization using the proposed method on the IEEE 40-unit test system

Method	Best	Average	Worst					
SPSO[16]	124,350.40	126,074.40	NA					
PSO[17]	123,930.45	124,154.49	NA					
CEP[17]	123,488.29	124,793.48	126,902.89					
HGAPSO [16]	122,780.00	124,575.70	NA					
FEP[16]	122,679.71	124,119.37	127,245.59					
IFEP[16]	122,624.3500	123,382.0000	125,740.6300					
MPSO[18]	122,252.2650	NA	NA					
ESO[19]	122,122.1600	122,558.4565	123,143.0700					
PSO-LRS [18]	122,035.7946	122,558.4565	123,461.794					
Improved GA [20]	121,915.9300	122,811.4100	123,334.0000					
HPSOWM[21]	121,915.3000	122,844.4	NA					
IGAMU[22]	121,819.2521	NA	NA					
NPSO [18]	121,704.7391	122,221.3697	122,995.0976					
HDE[23]	121,698.5100	122,304.3000	NA					
NPSO-LRS [18]	121,664.4308	122,209.3185	122,981.5913					
KH [24]	121,694.5938	121,721.0043	121,756.9473					
BA	121,678.7742	122,218.8773	122,867.8832					
Proposed MBA	121,578.4832	121,583.3029	121,601.0001					

The improvements were obvious in all average and the worst and best solutions. The convergence behavior of the proposed MBA is depicted in Fig. 4 and it can be seen that the modifications enhanced convergence rate of the algorithm.

 Table 4. Optimal operating point of the generators on the IEEE

 40 unit test system

40-unit test system						
Unit	Optimal Generation	Unit	Optimal Generation			
1	112.2460	21	523.2798			
2	112.3141	22	523.2793			
3	97.8202	23	523.2804			
4	179.7331	24	523.2796			
5	91.7458	25	523.2796			
6	140.0000	26	523.2798			
7	259.6055	27	10.0000			
8	284.6495	28	10.0001			
9	284.6061	29	10.0002			
10	130.0000	30	92.3796			
11	243.5996	31	190.0000			
12	168.7997	32	190.0000			
13	125.0000	33	190.0000			
14	304.5195	34	200.0000			
15	394.2796	35	192.1066			
16	304.5196	36	200.0000			
17	489.2798	37	109.9999			
18	489.2794	38	109.9996			
19	511.2794	39	109.9999			
20	511.2792	40	511.2794			

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Unit	Load	P1(MW)	P2(MW)	P3(MW)	P4(MW)	P5(MW)	P6(MW)	P7(MW)	P8(MW)	P9(MW)	P10(MW)	Ploss(MW)
1	1036	150.0000	135.0000	206.2299	60.0000	122.8666	122.4500	129.5905	47.0000	20.0000	55	12.1370
2	1110	150.0000	135.0000	282.7915	60.0000	122.8666	122.4503	129.5904	47.0000	20.0000	55	14.6988
3	1258	226.6238	135.0000	307.4811	60.0000	172.7504	122.4596	129.5905	47.0000	20.0000	55	17.9054
4	1406	303.2465	215.0000	304.3687	60.0000	172.7337	122.4605	129.5906	47.0000	20.0000	55	23.4000
5	1480	379.8698	222.2664	297.3988	60.0000	172.7329	122.4495	129.5902	47.0000	20.0000	55	26.3076
6	1628	456.5075	226.3025	308.4565	72.4387	222.6419	122.8118	129.5904	47.0000	20.0000	55	32.7493
7	1702	456.5444	306.3025	307.1318	121.3848	172.7468	122.3960	129.5905	47.0000	20.0358	55	36.1326
8	1776	456.4974	309.5562	298.4469	171.3705	172.7428	122.4498	129.5906	77.0000	20.0000	55	36.6542
9	1924	456.4967	389.5562	296.8421	192.1576	222.6014	122.4640	129.5907	85.2939	20.0000	55	46.0026
10	2072	456.5033	396.7990	323.0990	242.1576	222.6067	160.0000	129.5905	115.2939	20.0000	55	49.0500
11	2146	457.1994	396.7997	340.0000	292.1576	225.9023	160.0000	129.5907	120.0000	20.2852	55	50.9349
12	2220	456.4968	460.0000	324.8436	300.0000	222.5994	160.0000	129.5909	120.0000	50.2501	55	58.7808
13	2072	456.4970	396.7995	306.6229	291.2521	222.6005	122.4516	129.5904	120.0000	20.2504	55	49.0644
14	1924	456.4976	316.8009	310.8607	241.2521	222.6085	122.4469	129.5904	90.0000	20.0000	55	41.0571
15	1776	379.8727	309.2594	296.1432	191.2536	222.5823	122.4639	129.5905	85.3111	20.0000	55	35.4767
16	1554	303.2464	229.2594	281.1420	179.7180	172.7089	122.4453	129.5902	85.3106	20.0000	55	24.4208
17	1480	226.6385	309.2594	305.1282	129.7337	122.8699	122.5016	129.5951	85.3116	20.0000	55	26.0380
18	1628	303.2405	309.5331	296.9850	163.0457	172.7322	122.4489	129.5903	85.3094	20.0000	55	29.8851
19	1776	379.8730	316.0412	299.8847	181.0377	222.6179	122.4680	129.5906	85.3138	20.0000	55	35.8269
20	2072	456.4940	396.0411	336.7905	231.0377	222.5993	160.0000	129.5945	85.3105	50.0000	55	50.8676
21	1924	456.4971	389.5926	307.6317	181.0377	222.6025	122.5375	129.5914	85.3119	20.0000	55	45.8024
22	1628	379.8759	309.5926	284.8721	131.0377	172.7304	122.4478	129.5904	55.3122	20.0000	55	32.4591
23	1332	303.2483	229.5926	204.8721	118.6365	122.8462	122.4423	129.5900	47.0000	20.0000	55	21.2280
24	1184	226.6173	222.2665	184.6396	120.3965	73.0000	122.4494	129.5903	47.0000	20.0000	55	16.9596

Table 6. Optimal operating point of the generators on the IEEE 10-unit with 24 periods and considering power losses



Fig. 4. Convergence speed of the proposed MBA on the IEEE 40-unit test system

10-unit test system optimizing both cost and emission functions	mal operating point of the generators on the IEEE
	stem optimizing both cost and emission functions

Unit	Optimal Generation	Best	Average	Worst
	EP [27]	1 054 685	1 057 323	NA
	EP-SQP [27]	1 052 668	1 053 771	NA
	IPSO [28]	1 046 275	1 048 154	NA
Cost	AIS [29]	1 045 715	1 047 050	1 048 431
Function	TVAC-IPSO [30]	1 041 066	1 042 118	1 043 625
	EBSO [31]	1 038 915	1 039 188	1 039 272
	BA	1 040 203	1 041 091	1 043 467
	Proposed MBA	1037571	1037862	1038031
Emission	BA	289 309	289 367	289 413
Function	Proposed MBA	289208	289229	289246

According to the following results, the proposed MBA could achieve better results from both cost and emission targets.

Finally, Table 6 shows the optimal generation values of the power units associated with the best result found by MBA. It is worth noting that these results belonged to the cost function optimization and the emission results were not shown to avoid repetition.

6. CONCLUSION

This paper addressed the impacts and constrains imposed to the ED formulation of practical power systems in order to optimally solve it. In a practical system the existence of limitations such as multiple fuel option, valve loading effects, power generation limits, spinning reserve, ramp rate limits, and POZs made solving the ED problem complicated. The system operator faced a complicated nonlinear nonconvex optimization problem mandating the use of power full optimization techniques.

As a result, the MBA was proposed to add diversity to the algorithm and ensure fast convergence to the global optimal solution. Contributions of the proposed methodology were corroborated through the numerical analysis of two various test systems. In order to see the effect of power units on the emission function, this target was also considered in the paper. Simulation results showed high capability of the algorithm for solving this target as well.

REFERENCES

- K. Afshar and A. Shokri Gazafroudi, "Application of stochastic programming to determine operating reserve with considering wind and load uncertainties," *Journal of Operation and Automation in Power Engineering*, vol. 1, no. 2, pp. 96-109, 2013.
- [2] M.A. Ortega-Vazquez and D.S. Kirschen, "Estimating the spinning reserve requirements in systems with significant wind power generation penetration," *IEEE Transactions on Power Systems*, vol. 24, no.1, pp. 114-124, 2009.
- [3] H. Khorramdel, B. Khorramdel, M. Tayebi Khorrami and H. Rastegar, "A multi-objective economic load dispatch considering accessibility of wind power with here-and-now approach," *Journal* of Operation and Automation in Power Engineering, vol. 2, no. 1, pp. 49-59, 2014.
- [4] A. Hatefi and R. Kazemzadeh, "Intelligent tuned harmony search for solving economic dispatch problem with valve-point effects and prohibited operating zones," *Journal of Operation and Automation in Power Engineering*, vol. 1, no. 2, pp: 84-95, 2013.
- [5] J. B. Park, K.S. Lee, J.R. Shin and K.Y. Lee, "A particle swarm optimization for economic dispatch with non-smooth cost functions," *IEEE Transactions on Power Systems*, vol. 20, no. 1, pp. 34-42, 2005.
- [6] T. Niknam, R. Azizipanah-Abarghooee, R. Sedaghati and A. Kavousi-Fard, "An Enhanced hybrid particle swarm optimization and simulated annealing for practical economic dispatch," *Energy Education Science and Technology Part A: Energy Science and Research*, vol. 30, no. 1, pp. 553-564, 2012.
- [7] G. Komarasamy, A. Wahi, "An Optimized k-means clustering technique using bat algorithm," *European Journal of Scientific Research*, vol. 84, no. 2, pp. 263-273, 2012.
- [8] C. Brown, L.S. Liebovitch and R. Glendon, "Lévy flights in Dobe Juhoansi foraging patterns," *Human Ecology*, vol. 35, no. 1, pp. 129-138, 2007.
- [9] A. Kavousi-Fard, T. Niknam, H. Taherpoor, A. Abbasi, "Multi-objective probabilistic reconfiguretion considering uncertainty and multi-level load model," *IET Science, Measurment and Technology*, vol. 10, no. 1, pp. 1-8, 2014.

- [10] A. Kavousi-Fard and T. Niknam, "Optimal stochastic capacitor placement problem from the reliability and cost views using firefly algorithm," *IET Science, Measurment and Technology*, vol. 8, no. 5, pp. 260-269, 2014.
- [11] A. Kavousi-Fard and H. Samet, "Multi-objective performance management of the capacitor allocation Problem in distributed system based on modified HBMO evolutionary algorithm," *Electric Power and Component systems*, vol. 41, no. 13, pp. 1223-1247, 2013.
- [12] A. Kavousi-Fard, T. Niknam, "Optimal distribution feeder reconfiguration for reliability improvement considering uncertainty," *IEEE Transactions on Power Delivery*, vol. 29, no. 3, pp. 1344-1353, 2014.
- [13] C. L. Chiang, "Improved genetic algorithm for power economic dispatch of units with valve-point effects and multiple fuels," *IEEE Transactions on Power Systems*, vol. 20, no. 4, pp. 1690-1699, 2005.
- [14] P. S. Manoharan, P.S. Kannan, S. Baskar, and M.W. Iruthayarajan, "Penalty parameter-less constraint handling scheme based evolutionary algorithm solutions to economic dispatch," *IET* Proceedings *on Generation Transmission and Distribution*, vol. 2, no. 4, pp. 478-490, 2008.
- [15] A. I. Selvakumar and K. Thanushkodi, "A new particle swarm optimization solution to nonconvex economic dispatch problems," *IEEE Transactions* on *Power Systems.*, vol. 22, no. 1, pp. 42-51, 2007.
- [16] N. Sinha, R. Chakrabati and P.K. Chattopadhyay, " Evolutionary programming techniques for economic load dispatch," *IEEE Transactions on Evolutionary Computation*, vol. 7, no. 1, pp. 83-94, 2003.
- [17] T.A.A. Victoire, A.E. Jeyakumar, "Hybrid PSO-SQP for economic dispatch with valve-point effect," *Electric Power Systems Research*, vol. 71, no. 1, pp. 51-59, 2004.
- [18] J.-B. Park, K.-S. Lee, J.-R. Shin and K. Y. Lee, "A particle swarm optimization for economic dispatch with non-smooth cost functions," *IEEE Transactions* on *Power Systems*, vol. 20, no. 1, pp. 34-42, 2008.
- [19] A. Pereira-Neto, C. Unsihuay and O. R. Saavedra, "Efficient evolutionary strategy optimization procedure to solve the non-convex economic dispatch problem with generator constraints," *IEE Proceedings on Generation, Transmission and Distribution*, vol. 152, no. 5, pp. 653-660, 2005.
- [20] S.H. Ling and F.H.F. Leung, "An improved genetic algorithm with average-bound crossover and wavelet mutation operations," *Soft Computing*, vol. 11, no. 1, pp. 7-31, 2007.
- [21] S.H. Ling, H.H.C. Iu, K.Y. Chan, H.K. Lam, B.C.

W. Yeung and F.H. Leung, "Hybrid particle swarm optimization with wavelet mutation and its industrial applications," *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, vol. 38, no. 3, pp. 743-763, 2008.

- [22] C.-L. Chiang, "Genetic-based algorithm for power economic load dispatch," *IET Proceeding on Generation, Transmission and Distribution*, vol. 1, no. 2, pp. 261-269, 2007.
- [23] S.-K. Wang, J.-P. Chiou, and C.-W. Liu, "Nonsmooth/non-convex economic dispatch by a novel hybrid differential evolution algorithm," *IET Proceedings on Generation, Transmission and Distribution*, vol. 1, no. 5, pp. 793-803, 2007.
- [24] A.H. Gandomi and A. H. Alavi, Krill herd: A new bio-inspired optimization algorithm, *Communications in Nonlinear Science and Numerical Simulation*, vol. 17, no. 12, pp. 4831-4845, 2012.
- [25] C.K. Panigrahi, P.K. Chattopadhyay, R.N. Chakrabarti, and M. Basu, "Simulated annealing technique for dynamic economic dispatch," *Electric Power Components and Systems*, vol. 34, no. 5, pp. 577-586, 2006.
- [26] T.A.A. Victoire and A.E. Jeyakumar, "A modified hybrid EP-SQP approach for dynamic dispatch with

valve-point effect," *Electric Power & Energy Systems*, vol. 27, no. 8, pp. 594-601, 2005.

- [27] P. Attaviriyanupap, H. Kita, E. Tanaka, and J. Hasegawa, "A hybrid EP and SQP for dynamic economic dispatch with nonsmooth fuel cost function," *IEEE Transactions on Power Systems*, vol. 17, no. 2, pp. 411-416, 2007.
- [28] X. Yuan, A. Su, Y. Yuan, H. Nie, and L. Wang, "An improved PSO for dynamic load dispatch of generators with valve-point effects," *Energy*, vol. 34, no. 1, pp. 67-74, 2009.
- [29] S. Hemamalini and S.P. Simon, "Dynamic economic dispatch using artificial immune system for units with valve-point effect," *Electric Power Energy Systems*, vol. 33, no. 4, pp. 868-874, 2011.
- [30] B. Mohammadi-ivatloo, A. Rabiee and M. Ehsan, "Time-varying acceleration coefficients IPSO for solving dynamic economic dispatch with nonsmooth cost function," *Energy Conversion and Management*, vol. 56, pp. 175-183, 2012.
- [31] T. Niknam and F. Golestaneh, "Enhanced bee swarm optimization algorithm for dynamic economic dispatch," *IEEE Systems Journal*, vol. 23, pp. 219-228, 2012.