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# 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]. 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 meta-heuristic 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:

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

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:

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^{\,2} + |\, e_i \sin(f_i (P_i^{\min} - P_i)) \,| \tag{4}$$

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

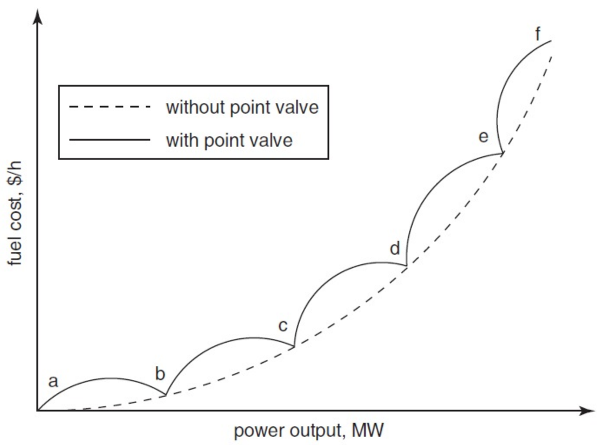


**Fig. 1.** Input–output curve under valve point loading

- **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:

$$F_i(P_i) = \begin{cases} a_{i1} + b_{i1} P_i + c_{i1} P_i^{\,2} & ;\ \text{Fuel 1: } P_i^{min} \le P_i \le P_{i1}^{max} \\ a_{i2} + b_{i2} P_i + c_{i2} P_i^{\,2} & ;\ \text{Fuel 2: } P_{i2}^{min} \le P_i \le P_{i2}^{max} \\ \ldots & \\ a_{ij} + b_{ij} P_i + c_{ij} P_i^{\,2} & ;\ \text{Fuel j: } P_{ij}^{min} \le P_i \le P_i^{max} \end{cases} \tag{5}$$

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

$$\begin{aligned} & F_i(P_i) = a_{ij} + b_{ij} P_i + c_{ij} P_i^{\,2} + |\, e_{ij} \sin(f_{ij} (P_{ij}^{\min} - P_i)) \,| \quad ; \\ & \text{Fuel j: } P_{ij}^{min} \le P_i \le P_i^{max} \\ & j = 1, 2, .., n_f \end{aligned} \tag{6}$$

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**

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

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:

$$\begin{aligned} & \max(P_i^{\min}, P_{0i} - DR_i) \le P_i \le \min(P_i^{\max}, P_{0i} + UR_i) \\ & i = 1, 2, .., n \end{aligned} \tag{8}$$

- **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:

$$\begin{aligned} & \begin{cases} P_i^{\min} \le P_i \le P_{i,1}^{LB} \\ P_{i,j-1}^{UB} \le P_i \le P_{i,j}^{LB} ; \ j = 2, 3, .., NP_i \\ P_{i,j}^{UB} \le P_i \le P_i^{\max} \end{cases} \\ & For \quad i = 1, 2, .., N_{GP} \end{aligned} \tag{9}$$

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

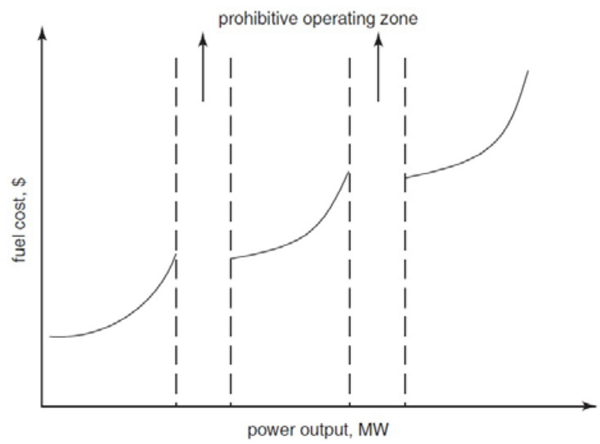


**Fig. 2.** The prohobited operating zones and generation limits for a generator

- **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:

$$S_i = \begin{cases} \min\{(P_i^{\max} - P_i), S_i^{\max}\} & \forall i \in (\Omega - \Theta) \\ 0 & \forall i \in \Theta \end{cases} \qquad (10)$$

$$S_r = \sum_{i=1}^{n} S_i \qquad (11)$$

$$S_r \geq S_R \qquad (12)$$

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 $\Omega$ and the set of operating units with POZ is represented by $\Theta$. $S_R$ 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:

$$\begin{aligned} &\mathbf{V}_i^{new} = \mathbf{V}_i^{old} + f_i(X_G - X_i); i = 1,\ldots,N_{Bat} \\ &X_i^{new} = X_i^{old} + \mathbf{V}_i^{new} \qquad ; i = 1,\ldots,N_{Bat} \\ &f_i = f_i^{\min} + \varphi_1(f_i^{\max} - f_i^{\min}) \qquad ; i = 1,\ldots,N_{Bat} \end{aligned} \qquad (13)$$

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 $\varphi_1$ is a randomly generated number between 0 and 1.

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

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

where, $\varepsilon$ 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 $\beta$. This new solution will be inserted to the population in case the following constraint is respected:

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

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

$$\begin{aligned} &A_i^{new} = \alpha A_i^{old} \\ &r_i^{Iter+1} = r_i^0[1 - exp(-\gamma \times t)] \end{aligned} \qquad (16)$$

Where $t$ represents iteration number and $\alpha$ and $\gamma$ 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:

$$X_i^{new} = X_i^{old} + \varphi_1 \oplus Le'vy(\omega) \tag{18}$$

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:

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

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

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

| Method | Best | Average | Worst |
|---|---|---|---|
| CGA-MU [13] | 624.7193 | 627.6093 | 633.8652 |
| IGA-MU [13] | 624.5178 | 625.8692 | 630.8705 |
| DE [14] | 624.5146 | 624.5246 | 624.5458 |
| RGA [14] | 624.5081 | 624.5079 | 624.5088 |
| PSO [14] | 624.5074 | 624.5074 | 624.5074 |
| PSO-LRS [15] | 624.2297 | 624.7887 | 628.3214 |
| NPSO[15] | 624.1624 | 625.2180 | 627.4237 |
| NPSO-LRS [15] | 624.1273 | 625.9985 | 626.9981 |
| BA | 624.1763 | 625.8636 | 626.8660 |
| Proposed MBA | 623.8963 | 623. 9883 | 623.9964 |

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

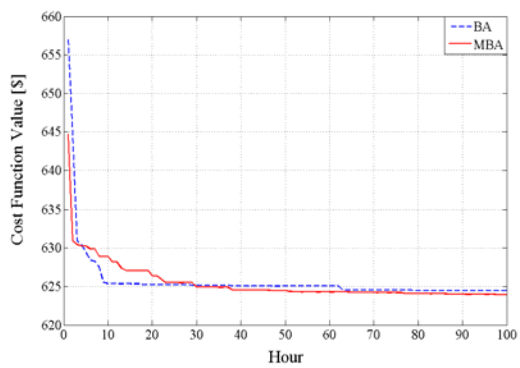


**Fig. 3.** Convergence speed of the proposed MBA on the IEEE 10-unit test system

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

| 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 |

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

| Unit | Load | P1(MW) | P2(MW) | P3(MW) | P4(MW) | P5(MW) | P6(MW) | P7(MW) | P8(MW) | P9(MW) | P10(MW) | $P_{loss}$(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 |

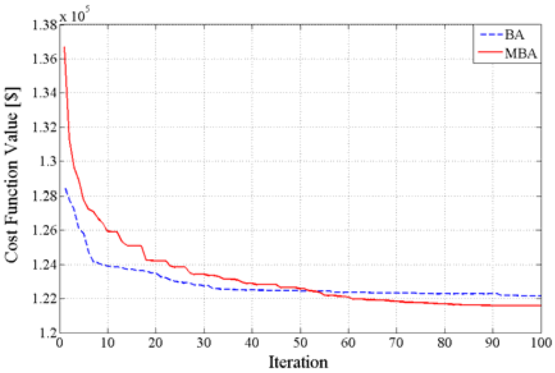


**Fig. 4.** Convergence speed of the proposed MBA on the IEEE 40-unit test system

**Table 5.** Optimal operating point of the generators on the IEEE 10-unit test system optimizing both cost and emission functions

| Unit | Optimal Generation | Best | Average | Worst |
|---|---|---|---|---|
| Cost Function | 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 |
| | AIS [29] | 1 045 715 | 1 047 050 | 1 048 431 |
| | 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 Function | BA | 289 309 | 289 367 | 289 413 |
| | 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 non-convex 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.

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