INTELLIGENT ALGORITHM SOLUTIONS TO ECONOMIC DISPATCH WITH MULTIPLE FUELS AND NON-SMOOTH COST FUNCTION

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Key words: Economic power dispatch (EPD), Monkey algorithm (MA), Genetic algorithm (GA), Multiple fuels, Valve-point effects, Hybrid method.

This paper presents a new and efficient method for solving economic power dispatch (EPD) problem. To solve this problem we have combined two meta-heuristic methods, the monkey algorithm (MA) and the genetic algorithm (GA). The acceleration of the convergence speed, the improved solution quality and the balance between exploration and exploitation are achieved with GA-MA approach. The strength of the proposed approach is tested and validated on a system with 10 generators. The obtained results are compared with those in literature. The results show that the proposed approach provides accurate solutions for the EPD problem in power systems.

1. INTRODUCTION

The economic power dispatch (EPD) problem has been one of the most widely studied subjects in the power system community since Carpentier who published the first concept in 1962 [1]. The EPD problem is large-scale nonlinear non-convex optimization problem, very constrained [2]. To solve it, a number of conventional optimization techniques such as nonlinear programming (NLP) [3, 4], quadratic programming (QP) [5], linear programming (LP) [6], and interior point methods [7], Newton-based method [8], mixed integer programming [9], dynamic programming [10], branch and bound [11] have been applied. All of these mathematical methods are fundamentally based on the convexity of objective function to find the global minimum. However, the EPD problem has the characteristics of high non-linearity and non-convexity.

Recently, many attempts to overcome the limitations of the mathematical programming approaches have been investigated such as meta-heuristic optimization methods. Examples of these attempts include tabu search (TS) [12], simulated annealing (SA) [13], genetic algorithms [14], evolutionary programming (EP) [15], artificial neural networks (ANN) [16], particle swarm [17–19], ant colony optimization (ACO) [20], harmony search algorithm [21].

Their applications to global optimization problems become attractive because they have better global search abilities over conventional optimization algorithms. The meta-heuristic techniques seem to be promising and evolving, and have come to be the most widely used tools for solving EPD problem. For minimization / max-imization problems the meta-heuristic methods allow to find solutions closer to the optimum but with high cost in time.

To solve this problem, we have combined two meta-heuristic methods, the MA and the GA. The acceleration of convergence speed, the improved solution quality and the balance between exploration and exploitation is achieved with approach GA-MA.

2. PROBLEM FORMULATION

2.1. CONVENTIONAL EPD PROBLEMS

The EPD problem is to find the optimal combination of power generations which minimize the total fuel cost while satisfying the power balance equality constraint and several inequality constraints on the system. The EPD problem is a non-linear, non-convex optimization problem which determines the optimal control variables for minimizing some objectives subject to the several equality and inequality constraints [22].

2.2. OBJECTIVE FUNCTIONS

2.2.1. Minimization of fuel cost

The total fuel cost function is formulated as follows:

\[ f(P_G) = \sum_{i=1}^{N_g} f_i(P_{Gi}) . \] (1)

The cost function \( f(P_{Gi}) \) can be represented in two forms:

2.2.1.1. Smooth cost function

It is given as follows [23]:

\[ f_i(P_{Gi}) = a_i P_{Gi}^2 + b_i P_{Gi} + c_i . \] (2)

where \( f(P_G) \) is the total production cost, in $/hr, \( f(P_{Gi}) \) is the fuel cost function of unit \( i \), in $/hr, \( a_i \), \( b_i \) and \( c_i \) are the fuel cost coefficients of unit \( i \), \( P_{Gi} \) is the real power output of unit \( i \) in MW.

The cost function is modeled thus for reasons of simplification, but in reality this function is non-smooth.

2.2.1.2. Non-smooth cost function

To control the power output of the unit, power generators have multiple steam admission valves that are used. When valve point effects are considered, the ED problem becomes extremely difficult to solve via conventional gradient based techniques [24], due to the abrupt changes and discontinuities present in the corresponding incremental cost functions. Valve-points are those output levels at which a new admission valve is opened; when a steam admission valve starts to open, a sudden increase in losses occurs, which results in ripples in the unit's cost function (Fig. 1).

Valve point effects are usually modelled by adding a recurring rectified sinusoidal term to the basic quadratic cost function, as it is shown below [25, 26].

\[ f_i(P_{Gi}) = a_i P_{Gi}^2 + b_i P_{Gi} + c_i + e_i \sin \left( f_i \left( P_{Gi}^{min} - P_{Gi} \right) \right) . \] (3)

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2.2.3. Piecewise quadratic cost functions

In practical power system, many thermal generating units may be supplied with multiple fuel sources like coal, natural gas and oil. The generating cost of such fossil fired units are represented by piece-wise quadratic cost function [27, 28], as shown in Fig. 2.

\[
\begin{align*}
F(P_{Gi}) = & \begin{cases}
\frac{a_{Gi}P_{Gi}^2}{2} + b_{Gi}P_{Gi} + c_{Gi} & P_{Gi}^\text{min} \leq P_{Gi} \leq P_{Gi}^\text{max} \\
+ a_{fi} \sin(f_{ji}(P_{Gi}^\text{min} - P_{Gi})) & P_{Gi}^\text{min} \leq P_{Gi} \leq P_{Gi}^\text{max}
\end{cases} \\
= & \begin{cases}
\frac{a_{Gi}P_{Gi}^2}{2} + b_{Gi}P_{Gi} + c_{Gi} & P_{Gi}^\text{min} \leq P_{Gi} \leq P_{Gi}^\text{max} \\
+ a_{f2} \sin(f_{j2}(P_{Gi}^\text{min} - P_{Gi})) & P_{Gi}^\text{min} \leq P_{Gi} \leq P_{Gi}^\text{max} \\
+ a_{im} \sin(f_{im}(P_{Gi}^\text{min} - P_{Gi})) & P_{Gi}^\text{min} \leq P_{Gi} \leq P_{Gi}^\text{max}
\end{cases}
\end{align*}
\]

where \(a_{im}, b_{im}, c_{im}\) are the cost coefficients of the \(i^{th}\) generator for fuel type \(m\).

The incorporated fuel cost function of (4) is substituted in (3) to obtain the realistic objective function \(F\) of the practical ED problem.

3. MONKEY ALGORITHM

The monkey algorithm (MA) was invented by Mucherino and Seref in 2007. MA is a meta-heuristic approach for global optimization [29]. The concept of MA looks to strategies from other meta-heuristic methods like genetic algorithms, differential evolution, ant colony optimization and etc. [30].

Upon climbing down the tree, the monkey marks tree branches with respect to the quality of the food available in the sub tree starting at that branch. When the monkey climbs up the tree again later, using the previous marks on the branches, it tends to choose those branches that lead to the parts of the tree with better quality of food [30]. In general, the MA works as follows [31]:

**Step 1.** Define the objective function and the decision variables. Input the system parameters and the boundaries of the decision variables, the population size of monkeys \((m)\), the climb number \((n)\), for our case the optimization problem is of minimize the total fuel cost function (eq. 5).

**Step 2.** First the initial positions of monkeys \(i, i = 1; 2; \ldots; M\), respectively, are randomly generated, with \(n\) dimension:

\[
x_i = (x_{i1}, x_{i2}, \ldots, x_{in}) \quad i = 1, 2, \ldots, M .
\]

**Step 3.** Climb process. Climb process is a step by step procedure to change the monkey’s positions from the initial positions to new ones that makes an improvement in the objective function. The climb process is as follows:

3.1. A vector is generated randomly as:

\[
\Delta x_i = (\Delta x_{i1}, \Delta x_{i2}, \ldots, \Delta x_{in}) \quad i = 1, 2, \ldots, M ,
\]

where

\[
\Delta x_{ij} = \begin{cases}
+a & p(+a) = 0.5 \\
-a & p(-a) = 0.5
\end{cases}, 
\]

in which \(a\) is called the step length of the climb process.

3.2. Calculate the pseudo-gradient of the objective function \(f\) at point \(x_i\).

\[
f_{ij} = \frac{f(x_i + \Delta x_i) - f(x_i - \Delta x_i)}{2\Delta x_{ij}}, \quad j = 1, 2, \ldots, n,
\]

3.3. Define parameter \(y = (y_1, y_2, \ldots, y_n)\) which is calculated as follows:

\[
y_{i} = x_{ij} + a \sin(f'_{ij}(x_{i1})) \quad j = 1, 2, \ldots, n,
\]

if \(y = (y_1, y_2, \ldots, y_n)\) is feasible, then \(x\) is replaced by \(y\), otherwise \(x\) remains unchanged. The steps 3.1 to 3.3 are repeated until there are no considerable changes on the values of objective function or the climb number \(n\) reached.

**Step 4.** Watch-jump process: after the climb process, each monkey arrives at its own mountaintop, therefore; each monkey will look around to find a higher mountain.

**Step 5.** The climb process is repeated by considering \(y\) as initial position.

**Step 6.** Somersault process: in this step, the monkeys find out new searching domains, taking the center of all the monkeys’ positions as a pivot, each monkey will somersault to a new position forward or backward in the
direction of pointing at the pivot. Based on the new position, the monkeys will keep on climbing. The somersault process is as follows:

6.1. First a somersault interval $[c, d]$ is defined which the maximum distance that monkeys can somersault. A real number is generated randomly within the somersault interval.

6.2. Defines parameter $y$ as follows:

$$ y_j = x_j + \alpha (p_j - x_j) \quad (11) $$

$$ p_j = \frac{1}{M} \sum_{i=1}^{M} x_{ij} \quad j = 1,2,...,n \quad (12) $$

where $p$ is somersault pivot.

6.3. If $y = (y_1, y_2, ..., y_n)$ is feasible then $x$ will be replaced by $y$, otherwise, repeat 6.1, 6.3 until a feasible $y$ is found.

**Step 7.** Repeat steps 3–6 until the stopping criterion (maximum number of iteration) is met.

### 4. GENETIC ALGORITHM (GA)

Chromosomes are the basic elements of genetic biology. They cross each other, pass to self-mutation and a new group of chromosomes is generated, as required only a few chromosomes survive, this is the cycle of generations in genetic biology.

This process is repeated for several generations and ultimately the best group of chromosomes according to the requirements will be retained. That is the natural process of genetic biology [32]. The mathematical algorithm equivalent to the natural process of genetic biology used as an optimization technique is called genetic algorithm artificial [33].

### 5. GENETIC ALGORITHM-MONKEY ALGORITHM (GA-MA)

The balance between exploration and exploitation is achieved with approach GA-MA. The searching process starts with the GA by initializing a group of random chromosomes, then the search is pursued by the MA, the results found by the GA are used as starting points for MA. Then, the best results (better than GA) found from MA are also communicated to the GA as an initial space search. The process is repeated until the final solution is reached. Fig. 3 shows the search mechanism of the combined global-local search without communication and considering communication. The following steps summarize description of the proposed algorithm:

**Step 1.** Run GA (with the max to iterations)

**Step 2.** The best control variables optimized based GA are communicated to MA and considered as the initial research space (with the max of iterations).

**Step 3.** Communicate the best solution found from MA to GA and considered as the initial research space.

**Step 4.** The process is repeated until the final solution is reached (the solution is repeated).

**Fig. 3 – Flowchart for economic power dispatch using GA-MA.**

### 6. SIMULATION RESULTS

The proposed GA-MA approach based on global and local search is developed in the Matlab programming language using 7.04 version. In order to validate the robustness of the proposed method, a system with 10 generators has been considered and the objective function used is that of the equation (5), the fuel cost data is given in [34]. During testing the total system demand is varied from 2400 MW to 2600 MW with 100 MW increments. The solution is compared with results of various heuristic approaches including hierarchical method (HM) [35], Hopfield neural network (HNN) [36], adaptive Hopfield neural network (AHNN) [37] and hybrid real coded genetic algorithm (HGA) [38]. The results are compared with the case whose total demand is 2600 MW, 2500 and 2400 MW respectively, since the cited papers provide only these cases of the solutions. The results of the proposed algorithms and the various heuristic approaches mentioned above are summarized in Tables 1–3. As shown, the GA-MA provides the best solution (the cheapest cost).

If we consider, for example in the case of demand of 2400 MW, and for the first type of fuel it has been improved by 0.442 $ for the second type it has been improved by 0.8742 $. In the case of demand of 2500 MW, the best cost is given by HNN [36], we have improved it more than 0.11 $, and finally for the case of demand of 2600 MW, the best cost is given by HM [35] we have improved it by 0.4972 $. So we can say that this technique has a remarkable contribution in reducing the cost of production of electrical energy.

Figures 4, 5, 6 show the curves of the last column of Tables 1, 2, 3 respectively where it is noted that the proposed method converges for different values of power requested, to a better minimum of cost than the rest of the methods mentioned in literature more it is clear that the convergence is very fast (between 60 and 80 iterations). Hence we can say that this method is very effective since led to good results in a short computing time.
Table 1
Comparison of simulation result with other methods for demand of 2 400 MW

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Cost ($/h) 481.7434 481.3014 488.5000 487.6258

*ARCGA–Adaptive real coded genetic algorithm

Table 2
Comparison of simulation result with other methods for demand of 2 500 MW

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Cost ($/h) 526.7000 526.1300 526.2300 526.2388 526.2388 526.018678

*Hybrid ICDEDP–Hybrid integer coded differential evolution dynamic programming

Table 3
Comparison of simulation result with other methods for demand of 2 600 MW

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Cost ($/h) 574.0300 574.2600 574.3700 574.3808 574.3808 573.5328

Fig. 4 – Convergence graph of GA-MA, 10 generators system, for demand of 2 400 MW.

Fig. 5 – Convergence graph of GA-MA, 10 generators system, for demand of 2 500 MW.
The paper proposes a hybrid method which has two meta-heuristics, the monkey algorithm (MA) and genetic algorithm (GA). This approach is employed to solve the economic power dispatch problem (EPD) including mixed fuel types by enhanced augmented Lagrange Hopfield neural network. The results and the speed of convergence show that this method is very effective in this kind of problem and can contribute to save thousands of dollars a year.

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