Approach of economic-emission load dispatch using Ant Lion Optimizer

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Abstract—To solve the problem of the economic emission load dispatch (EELD) is necessary minimize the total cost of fuel consumption and carbon emission. In this study is applied the ant lion optimizer (ALO) to this problem. The cost function and emission function with their respective restrictions are being used. To present the results this proposal is applied in IEEE 30 bus system that consists of six thermal units. The results for this case study with the application of ant lion with all generators on with demand being met, the total fuel cost is 48915.36652 ($/h). The results this method can be compared with another metaheuristic algorithms and helps the plant operators in the decision making of preventive maintenance.

Keywords—Ant lion Optimizer, EELD, Power Plants.

I. INTRODUCTION

The Thermal Power Plant (TPP) operation is dependent upon incineration of fossil fuel which generates sulfur dioxide (SO₂), carbon dioxide (CO₂) and nitrogen oxides (NOₓ) which create atmospheric pollution. Reduce the emission level and total cost of generation and at the same time accomplishing the demand for electricity from the power plant is is the goal of economic emission load dispatch (EELD). To solve the EELD problem is necessary minimize the total cost of fuel consumption and carbon emissions (De, Das, Mandal, & Mandal, 2018; Moraes, Bezerra, Moya Rodríguez, Nascimento, & Leite, 2018). The problem is formulated as a multiobjective economic emission load dispatch (EELD) problem in which both the objectives (emission and economy) have to be minimized (Chopra, Kumar, & Mehta, 2016). This is a complex problem to solve because of its large size, a nonlinear objective function and a wide number of restrictions (Bhattacharya & Chattopadhyay, 2010). Various evolutionary, heuristic and meta-heuristics optimization algorithms have been developed such as: Grey Wolf Optimization (GWO) (Chopra et al., 2016; Hong, MH, & Mohd Ruslim, 2014), non-dominated sorting genetic algorithm (NSGA-II) (Basu, 2008; Moraes et al., 2018), hybrid genetic algorithm (Thenmozhi & Mary, 2004), Tabu Search Algorithm (Li, Yang, Tseng, Wang, & Lim, 2018), Simulated annealing (Júnior, Nunes, Nascimento, Rodríguez, & Leite, 2017; Ziane, Benhamida, & Graa, 2017), Neural Networks (Deng, He, & Zeng, 2017), Harmony Search Algorithm (El Ela, El-Sehiemy, Shaheen, & Shalaby, 2017), particle swarm optimization (De et al., 2018), Differential Evolution (Jebaraj, Venkatesan, Soubache, & Rajan, 2017), Ant Colony Optimization (Zhou et al., 2017), Biogeography-Based Optimization (Ma, Yang, You, & Fei, 2017), genetic algorithm controlled by fuzzy logic (Song, Wang, Wang, & Johns, 1997). This research use the emission function and economic function in the multiobjective optimization ALO, with restrictions.

II. MATERIAL AND METHODS

To solve a problem of EELD, two important objectives in an electrical power system must be considered; they are: environmental, and economy impacts (Basu, 2014).

2.1 Economic Load Dispatch
The fuel cost is considered as an essential criterion for economics analysis in ELD. The most simplified cost function of each generator can be assumed to be approximated by a quadratic function of generator power output $P_i$ (Ghosh, Chakraborty, Bhownik, & Bhattacharya, 2017; Jebaraj et al., 2017):

$$F1(P_i) = \sum_{i=1}^{N} (a_i + b_i P_i + c_i P_i^2) \ $$/h \quad (1)

where $a_i$, $b_i$, and $c_i$ are the fuel cost coefficients of the $i$th unit generating, $N$ the number of generators and $P_i$ the active power of each generator. Fig. 1 illustrates the fuel cost curve without valve-point effects and emissions.

\[\text{Fig.1: Fuel cost and emission function of the thermal generator.}\]
\[\text{Source: (Gitizadeh & Ghavidel, 2014)}\]

2.2 Economic Emission Dispatch

Emissions can be represented by a function, that links emissions with power generated by each unit. The emission function in kg/h, which normally represents the emission of SO2 and NOx, is a function of the power output of the generator, and it can be expressed as follows (Swain, Sarkar, Meher, & Chanda, 2017):

$$F2(P_i) = \sum_{i=1}^{N} (d_i + e_i P_i + f_i P_i^2) \ \text{kg/h} \quad (2)$$

Where $d_i$, $e_i$, and $f_i$ are the emission coefficients of the $i$th unit generating, $N$ the number of generators and $P_i$ the active power of each generator, from the TPP.

2.3 Economical Load Dispatch constraints

2.3.1 Equality power balance constraint

The real power of each generator is limited by the lower and upper limits. The following equation is the equality restriction of power balance (Rizk-Allah, El-Sehiemy, & Wang, 2018).

$$\sum_{i=1}^{n} P_i - P^D - P^L = 0 \quad (2)$$

where $P_i$ is the output power of each $i$ generator, $P^D$ is the load demand and $P^L$ are transmission losses, in other words, the total power generation has to meet the total demand $P^D$ and the actual power losses in transmission lines $P^L$ (Dewangan, Jain, & Huddar, 2015).

$$\sum_{i=1}^{n} P_i = P^D - P^L \quad (3)$$

The calculation of power losses $P^L$ involves the solution of the load flow problem, which has equality constraints in the active and reactive power on each bar as follows (Nwula & Xia, 2015):

$$P^L = \sum_{i=1}^{n} B_i P_i^2 \quad (4)$$

A simplification is applied to model the transmission losses, setting them as a function of the generator output through Kron’s loss coefficient derivatives of the Kron formula for losses (Huang et al., 2018).

$$P^L = \sum_{i=1}^{n} \sum_{j=1}^{n} B_{ij} P_i P_j + \sum_{i=1}^{n} B_{i0} P_i + B_{00} \quad (5)$$

where $B_{ij}$, $B_{i0}$ and $B_{00}$ are the energy loss coefficients in the transmission network and $n$ is the number of generators. A reasonable accuracy can be obtained when the actual operating conditions are close to the base case, where the $B$ coefficients were obtained (Gitizadeh & Ghavidel, 2014).

2.3.2 Production Capacity Constraint

The power capacity total generated from each generator is restricted by the lower limit and by the upper limit, so the constraint is (De et al., 2018):

$$P_{\text{min,}i} \leq P_i \leq P_{\text{max,}i} \quad (6)$$

where $P_i$ is the output power of the $i$ generator, $P_{\text{min,}i}$ is the minimal power of the $i$ generator and $P_{\text{max,}i}$, the maximal power of the $i$ generator.

2.3.3 Fuel Delivery Constraint

At each time interval, the amount of fuel supplied to all units must be less than or equal to the fuel supplied by the seller, i.e. the fuel delivered to each unit in each interval should be within its lower limit $F_{\text{min,}i}$ and its upper limit $F_{\text{max,}i}$ so that (Qu et al., 2018):

$$F_{\text{min,}i} \leq F_{i,m} \leq F_{\text{max,}i} \quad (7)$$

where $F_{i,m}$ is the fuel supplied to the engine $i$ at the interval $m$, $F_{\text{min}}$ is the minimum amount of fuel supplied to $i$ generator and $F_{\text{max}}$ is the maximum amount of fuel supplied to $i$ generator.

2.3.4 Optimization problem

The multi-objective optimization problem is defined as follow:

$$\text{Minimize } P = [F1(P), F2(P)] \quad (8)$$

where $F1(P)$, $F2(P)$ are the objective functions to be minimized over the set of permissible decision vector $P$.

2.3.5 Incremental fuel cost method
The incremental fuel cost can be obtained from the following equation (Tiwari, Dave, & Dwivedi, 2017):

\[ IC_i = (2. a_i P_g i + b_i) \text{ } \text{S/MWh} \]  

(9)

where \( IC_i \) is the incremental fuel cost at \( t \), \( a_i \) are the values of the different points of the actual curve of the incremental cost and \( b_i \) are the values of the points on the approximated curve (linear) of incremental cost. \( P_g i \) is the total power generation. The curve of incremental fuel cost is shown in the following Figure. 2:

![Image](https://www.ijaers.com)

**Fig.2: Incremental Cost Curve of Power Generator.**  
Source: (Nascimento, Nunes, Rodriguez, Leite, & Junior, 2016)

### 2.4 Ant lion optimization

The Ant Lion Optimizer (ALO) is a algorithm inspired by nature (Mirjalili, 2015). The ALO algorithm mimics interaction between ants and ant lions in the trap. To model such interactions, ants are required to move over the search space, and antlions are allowed to hunt them and become fitter using traps. Since ants move stochastically in nature when searching for food, a random walk is chosen for modelling ants’ movement as follows [28]:

\[ X(t) = \left[ 0, \text{cumsum}(2r(t_1) - 1), \text{cumsum}(2r(t_2) - 1), ..., \text{cumsum}(2r(t_n) - 1) \right] \]  

(10)

where cumsum calculates the cumulative sum, \( n \) is the maximum number of iteration, \( t \) shows the step of random walk (iteration in this study), and \( r(t) \) is a stochastic function defined as follows (Trivedi, Jangir, & Parmar, 2016):

\[ r(t) = \begin{cases} 1 & \text{if } \text{rand} > 0.5 \\ 0 & \text{otherwise} \end{cases} \]  

(11)

where \( t \) shows the step of random walk (iteration in this study) and \( \text{rand} \) is a random number generated with uniform distribution in the interval of [0, 1].

To keep the random walk in the boundaries of the search space and prevent the ants from overshooting, the random walks should be normalized using the following equation (Yao & Wang, 2017):

\[ X_i = \frac{(x_i^t - a_i) \times (d_i^t - c_i^t)}{(b_i - a_i)} + c_i^t \]  

(12)

where \( c_i^t \) is the minimum of \( i \)-th variable at \( t \)-th iteration, \( d_i^t \) indicates the maximum of \( i \)-th variable at \( t \)-th iteration, \( a_i \) is the minimum of random walk of \( i \)-th variable, and \( b_i \) is the maximum of random walk in \( i \)-th variable.

To simulate the trapping of ants the mathematical expression of the trapping of the ants to the ant lion’s pits is given by following equations (Trivedi et al., 2016):

\[ c_m = \text{Ant} - \text{lion}^t - c^t \]  

(13)

\[ d_m = \text{Ant} - \text{lion}^t - d^t \]  

(14)

To construction of trap, the fittest ant lion is selected using the roulette wheel method. To simulate the sliding ants towards ant lions, the boundaries of random walks should be reduced adaptively as follows (Mirjalili, 2015):

\[ c^t = \frac{c^t}{I} \]  

(15)

\[ d^t = \frac{d^t}{I} \]  

(16)

where \( I = 10^w t \) is current iteration, \( S \) is the maximum number of iterations and \( w \) is a constant whose value is given by (Raju, Salkia, & Sinha, 2016):

\[ w = \begin{cases} 2 & \text{if } t > 0.1S \\ 3 & \text{if } t > 0.5S \\ 4 & \text{if } t > 0.75S \\ 5 & \text{if } t > 0.9S \\ 6 & \text{if } t > 0.95S \end{cases} \]  

(17)

To catching the ants by ant lion and re-building the pit can be mathematically described as [28]:

\[ \text{Antlion}^j = \text{Ant}^j, \text{if } f(\text{Ant}^j) > f(\text{Antlion}^j) \]  

(18)

where \( \text{Antlion}^j \) indicates the position of selected \( j \)-th ant lion at \( t \)-th iteration and \( \text{Ant}^j \) shows the position of \( j \)-th ant at \( t \)-th iteration. \( t \) shows the current iteration.

Finally the last operator in ALO, that is elitism, calculated using roulette wheel as follows equation (Trivedi et al., 2016):

\[ \text{Ant}^j = \frac{R^j_i + R^j_i}{2} \]  

(19)

where, \( R^j_i \) is the random walk nearby the ant lion chose by means of the roulette wheel at \( t \)-th iteration, \( R^j_i \) is the random walk nearby the elite at \( i \)-th iteration, \( \text{Ant}^j \) is the location of \( j \)-th ant at \( t \)-th iteration.

### 2.5 ALO applied to ELD

Initialize random walks on ants using Eq (10) and save generation scheduling of generating units as ant position using Eq (20) described below:

\[ M_{A{n}t} = \begin{bmatrix} \text{Ant}_{1,1} & \text{Ant}_{1,2} & \text{Ant}_{1,3} & \cdots & \text{Ant}_{1,d} \\ \text{Ant}_{2,1} & \text{Ant}_{2,2} & \text{Ant}_{2,3} & \cdots & \text{Ant}_{2,d} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \text{Ant}_{n,1} & \cdots & \cdots & \cdots & \text{Ant}_{n,d} \end{bmatrix} \]  

(20)

where \( M_{A{n}t} \) is the matrix for saving the position of each ant, \( \text{Ant}_{i,j} \) shows the value of the \( j \)-th variable (dimension) of \( i \)-th ant, \( n \) is the number of ants, and \( d \) is the number of variables.
For evaluating each ant (i.e., generating units), the following objective functions described in Eq. (1) and Eq (2) are utilized during optimization and following matrix stores the fitness value of all ants:

\[
M_{OA} = \begin{bmatrix}
    f([Ant_{1,1}, Ant_{1,2}, \ldots, Ant_{1,d}]) \\
    f([Ant_{2,1}, Ant_{2,2}, \ldots, Ant_{2,d}]) \\
    \vdots \\
    f([Ant_{n,1}, Ant_{n,2}, \ldots, Ant_{n,d}])
\end{bmatrix}
\]

where \(M_{OA}\) is the matrix for saving the fitness of each ant, \(Ant_{i,j}\) shows the value of \(j\)th dimension of \(i\)th ant, \(n\) is the number of ants, and \(f\) is the objective function.

Save the optimal cost and generation scheduling using Eqs. (22) and (23) described below:

\[
M_{OAL} = \begin{bmatrix}
    f([AL_{1,1}, AL_{1,2}, \ldots, AL_{1,d}]) \\
    f([AL_{2,1}, AL_{2,2}, \ldots, AL_{2,d}]) \\
    \vdots \\
    f([AL_{n,1}, AL_{n,2}, \ldots, AL_{n,d}])
\end{bmatrix}
\]

where \(M_{OAL}\) is the matrix for saving the fitness of each ant lion, \(AL_{i,j}\) shows the \(j\)th dimension’s value of \(i\)th ant lion, \(n\) is the number of ant lions, and \(f\) is the objective function.

This solution comprises the number of generations of the system that will be optimized, which results in minimization of cost and emissions described in Eq (8) by fulfilling all constraints described in Eq (3), Eq (6) and Eq (7).

Equation (8) are applied in the performance evaluation of the EEED until the optimum cost and emission is achieved. For inequality constraints, similar to any other techniques, when the solutions obtained for any iteration are out of boundaries, ALO chooses the boundaries values, while for equality constraint, when it is violated, the penalty factor of 1000 is implemented and embedded in the cost function as per Eq. (8). The algorithm will continue until the maximum iteration is met, and the optimum results are obtained.

III. SIMULATION TESTS AND RESULTS

The power plant selected for the case study consists of six generating units with a load demand of 900 MW where generation limits, fuel cost and emission coefficients for case study is take from Ref (Lee & Darwish, 2008; Manteaw & Odero, 2012).

The EEED problem simulated with the ALO algorithm, the systems of standard IEEE 30 bus systems have been taken into consideration (figure 3).

The data of IEEE 30 bus test system to apply in ALO optimizer is presented in table 1, table 2 and table 3.

| Gen | \(c_i\) | \(b_i\) | \(a_i\) | \(P_{min}\) | \(P_{max}\) |
|-----|--------|--------|--------|------------|------------|
|     | ($/MW^2$h) | ($/MWh$) | ($/h$) | (MW) | (MW) |
| G1  | 0.1524 | 38.539 | 756.79 | 10 | 125 |
| G2  | 0.1058 | 46.159 | 451.32 | 10 | 150 |
| G3  | 0.0280 | 40.396 | 1049.3 | 40 | 250 |
| G4  | 0.0354 | 38.305 | 1243.5 | 35 | 210 |
| G5  | 0.0211 | 36.327 | 1658.5 | 130 | 325 |
| G6  | 0.0179 | 38.270 | 1376.2 | 125 | 315 |

Source: (Manteaw & Odero, 2012)

| Unit | \(d_i\) | \(c_i\) | \(f_i\) |
|------|--------|--------|--------|
| G1   | 0.00419 | 0.32767 | 13.85932 |
| G2   | 0.00419 | 0.32767 | 13.85932 |
The results after running the simulation of the proposed ALO algorithm are displayed in Tables 4. The simulation of the proposed ALO algorithm is tested in MATLAB R2016 to meet the demand of 900MW.

Table 4: Coefficients of emission of the 6 generating unit.

| Generator | Power of each generator in Mw | Emission of each engine in Kg/h | Cost of each engine in $/h |
|-----------|-------------------------------|---------------------------------|----------------------------|
| G1        | 125                           | 8238.41182                      | 7956.60886                 |
| G2        | 92.7026704                    | 3382.26922                      | 5640.22656                 |
| G3        | 86.4365762                    | 4403.87432                      | 4750.48463                 |
| G4        | 151.819543                    | 23857.7694                      | 7876.38287                 |
| G5        | 240.571054                    | 64104.5546                      | 11619.7208                 |
| G6        | 229.179195                    | 55417.1514                      | 11071.9428                 |
| Total     | 925.709039                    | 159404.0308                     | 48915.36652                |

Source: Authors.

The graphics with pareto front of costs versus emissions and the using all generators is presented in Fig. 4.

Fig. 4: Pareto front of cost vs emission.

Fig. 5: Power generated in each generator.
Source: Authors.

Fig. 6: Emission in each generator.
Source: Authors.

Fig. 7: Cost of each generator.
Source: Authors.
IV. CONCLUSION

The ant lion optimizer is successfully applied to a 30 bus test system, to solve the EELD problem, so now it is possible to use these results to compare with other techniques that apply to this same IEEE bus test system. This application can also help workers to operate more efficiently the generators in a power plant.

ACKNOWLEDGEMENTS

To the Institute of Technology and Education “Galileo” from Amazonia (ITEGAM), The Federal University of Para (UFPA), The Research Support Foundation State of Amazonas (FAPEAM) for the financial support to this research.

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