ISSN 2176-5480

22nd International Congress of Mechanical Engineering (COBEM 2013)
November 3-7, 2013, Ribeirão Preto, SP, Brazil

ECONOMIC DISPATCH OPTIMIZATION OF THERMAL UNITS BASED ON A MODIFIED FIREFLY ALGORITHM

Gabriel Maidl
Mechatronics Engineering Undergraduate program, Pontifical Catholic University of Parana (PUCPR)
Imaculada Conceição, 1155, Curitiba, PR, Brazil
gabriel_maidl@hotmail.com
Diogo Schwerz de Lucena
Federal University of Parana (UFPR), Graduate Program in Electrical Engineering,
Rua Cel. Francisco Heraclito dos Santos, 100, Curitiba, PR, Brazil
diogo.lucena90@gmail.com
Leandro dos Santos Coelho
Industrial and Systems Engineering Graduate Program (PPGEPS), Pontifical Catholic University of Parana (PUCPR)
Imaculada Conceição, 1155, Curitiba, PR, Brazil and Department of Electrical Engineering (DEE/PPGEE)
Federal University of Parana (UFPR), Rua Cel. Francisco Heraclito dos Santos, 100, Curitiba, PR, Brazil
leandro.coelho@pucpr.br

Abstract. *The objective of the economic dispatch problem (EDP) of electric power generation, whose characteristics are complex and highly nonlinear, is to schedule the committed generating unit outputs so as to meet the required load demand at minimum operating cost while satisfying all unit and system equality and inequality constraints. Recently, as an alternative to the conventional mathematical approaches, modern heuristic optimization techniques have been given much attention by many researchers due to their ability to find an almost global optimal solution in EDPs. This paper proposed a modified firefly algorithm (MFA) based on situational knowledge applied to EDPs. The FA is a stochastic metaheuristic approach based on the idealized behavior of the flashing characteristics of fireflies. In FA, the flashing light can be formulated in such a way that it is associated with the objective function to be optimized, which makes it possible to formulate the firefly algorithm. A classical FA and the MFA are validated for a test system consisting of a 13 thermal units whose incremental fuel cost function takes into account the valve-point loading effects. Furthermore, the obtained results are compared with results presented in the literature.*

Keywords: thermal units, economic dispatch, optimization, metaheuristics, firefly algorithm.

1. INTRODUCTION

Power utilities are expected to generate electrical power at minimum cost within the generator and system limits. Economic dispatch (ED) plays a major role in this aspect (Wood and Wollenberg, 1996). The basic objective of ED problem is to schedule the committed generating units to meet the system load demand at minimum operating cost while satisfying the various system equality and inequality constraints (Sivasubramani and Swarup, 2011).

Bio-inspired metaheuristics such as genetic algorithm (Walters and Sheblé, 1993), evolutionary programming (Sinha et al., 2003), differential evolution (Noman and Iba, 2008), cultural differential evolution (Coelho et al., 2008), ant colony (Pothiya et al., 2010), bacterial foraging (Saber, 2012), honey bee mating (Niknam et al., 2011), and particle swarm optimization (Panigrahi et al., 2008) have been used to solve ED optimization problem.

Recently, a new metaheuristic algorithm called firefly algorithm (FA) was proposed. FA is a new population-based metaheuristic approach developed by Xin-She Yang (Yang, 2008; Yang, 2009), which is nature-inspired by the behavior of the flashing characteristics of fireflies. In this context, the flashing light can be formulated in such a way that it is associated with the objective function to be optimized, which makes it possible to formulate the firefly algorithm.

In this paper, we present a modified FA (MFA) based on the situational knowledge source (memories of successful solutions). This kind of knowledge is usual in cultural algorithms (Reynolds, 1994). An economic dispatch problem is employed to demonstrate the performance of the FA and IFA approaches. In this context, a 13-unit test system (Sinha et al., 2003) with incremental fuel cost function taking into account the valve-point loading effects is used to illustrate the effectiveness of the FA and the proposed IFA. Simulation results obtained with the FA and IFA approaches were analyzed and compared with other optimization results reported in the literature.

The remainder of this paper is organized as follows: Section 2 describes the formulation of the ED optimization problem, while Section 3 explains the fundamentals of FA and IFA. After, Section 4 presents the simulation results for a test system with 13 thermal units. Finally, the conclusion and further research are discussed in Section 5.

ISSN 2176-5480

2. FUNDAMENTALS OF ECONOMIC DISPATCH OPTIMIZATION PROBLEM

The primary concern of an economic dispatch problem is to minimize the total fuel cost at thermal power plants subjected to the operating constraints of a power system. Therefore, it can be formulated mathematically with an objective function and two constraints. The equality and inequality constraints are represented by equations (1) and (2) given by (Vianna Neto et al., 2009):

$$\sum_{i=1}^{n} P_i - P_L - P_D = 0 \tag{1}$$

$$P_i^{min} \le P_i \le P_i^{max} \tag{2}$$

In the power balance criterion, an equality constraint must be satisfied, as shown in equation (1). The generated power should be the same as the total load demand plus total line losses. The generating power of each generator should lie between maximum and minimum limits represented by equation (2), where P_i is the power of generator *i* (in MW); *n* is the number of generators in the system; P_D is the system's total demand (in MW); P_L represents the total line losses (in MW) and P_i^{min} and P_i^{max} are, respectively, the output of the minimum and maximum operation of the generating unit *i* (in MW) (Vianna Neto et al., 2009). The objective of minimization of the total fuel cost function is formulated as follows:

$$min\ f = \sum_{i=1}^{n} F_i(P_i) \tag{3}$$

where F_i is the total fuel cost for the generator unit *i* (in \$/h), which is defined by equation:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i \tag{4}$$

where a_i, b_i and c_i are cost coefficients of generator *i*.

The sequential valve-opening process for multi-valve steam turbines produces ripple like effect in the heat rate curve of the generator. This effect is included in economic dispatch problem by superimposing the basic quadratic fuel-cost characteristics with a rectified sinusoidal component. In this context, the equation (4) can be modified as (Vianna Neto et al., 2009):

$$\tilde{F}_i(P_i) = F(P_i) + \left| e_i sin\left(f_i \left(P_i^{\min} - P_i \right)\right)\right| \quad \text{or} \tag{5}$$

$$\tilde{F}_i(P_i) = a_i P_i^2 + b_i P_i + c_i + \left| e_i sin\left(f_i \left(P_i^{\min} - P_i \right)\right)\right| \tag{6}$$

where e_i and f_i are valve-point loading coefficients of generator *i*. Hence, the total fuel cost that must be minimized, according to equation (3), is modified to:

$$min\ f = \sum_{i=1}^{n} \tilde{F}_i(P_i) \tag{7}$$

where $\tilde{F}_i$ is the cost function of generator *i* (in \$/h) defined by equation (6). In the case study presented here, we disregarded the transmission losses, P_L (mentioned in equation (1)), i.e., in this work $P_L = 0$.

3. FIREFLY ALGORITHM

This section describes the proposed FA. First, a brief overview of the FA is provided, and finally the modification procedures of the proposed MFA are presented.

ISSN 2176-5480

3.1 Classical firefly algorithm

The FA is a metaheuristic algorithm, inspired by the flashing behavior of fireflies. As a firefly's attractiveness is proportional to the light intensity seen by adjacent fireflies, we can now define the attractiveness β of a firefly in terms of Cartesian distance between firefly *i* and firefly *j*. In this case, the movement of a firefly *i* is attracted to another more attractive (brighter) firefly *j* is determined by (Yang, 2008)

$$x_i = x_i + \beta_0 e^{-\gamma \cdot r_{ij}^2}(x_j - x_i) + \alpha\left(rand - \frac{1}{2}\right) \tag{8}$$

where the second term is due to the attraction, where γ is the absorption coefficient, and β_0 is the attractiveness at $r = 0$. The third term is related to randomization factor with α being the randomization parameter. The value of *rand* is a random number generator uniformly distributed in [0, 1]. The procedure for implementing the FA can be summarized as the pseudocode (adapted of Yang (2008) and Yang (2009)) shown in Fig. 1.

```
Objective function of optimization problem f(x), x = (x1, ..., xd)^T
Generate initial population of n fireflies xi (i = 1, 2, ..., n) using generation of numbers with uniform distribution
Light intensity Ii at xi is determined by f(xi)
Define light absorption coefficient γ
Initial generation, k = 0

while (k < Maximum_Generations)
  Update the generation number, k = k + 1
  for i = 1 to n (all n fireflies)
     for j = 1 to i (all n fireflies)
        if (Ij < Ii) in case of a minimization problem
           Move firefly i towards j in d-dimension;
        end if
        Attractiveness varies with distance r via equation (8)
        Evaluate new solutions and update light intensity
      end for j
  end for i
  Rank the fireflies and find the current best
end while
Postprocess results and visualization
```

Figure 1. Pseudocode of the FA.

3.2 Modified firefly algorithm

The MFA employs a situational knowledge source, which changes the movement equation (8). This source stores the best firefly along the iterations, that is performed by changing the situational knowledge firefly *E* to x_i, at each iteration, if x_i is feasible.

Becerra and Coello (2006) proposed a cultured differential evolution (CDE), in which MFA situational knowledge was based. The new equation (9), which replaces equation (8), is the adapted form from the CDE to the firefly algorithm, where x_j moves toward *E*, instead of x_i towards x_j. It provides a better algorithm's convergence.

$$x_i = x_j + a * \beta_0 e^{\gamma . r_{ij}^2}\left(E - x_j\right) + b\alpha\left(rand - \frac{1}{2}\right) \quad \text{where} \tag{9}$$

$$a = \frac{\mathrm{F}(x_j) - \mathrm{F}(E)}{\max(\mathrm{F}(x)) - \min(\mathrm{F}(x))} \quad \text{and} \tag{10}$$

$$b = \max(x) - \min(x) \tag{11}$$

The new equation has two new terms, *a* and *b*, each one described by equations (10) and (11), respectively. The term *a* associates firefly's light weighing to the movement, making the step proportional to the light difference. While *b* guides the random movement, updating MFA's range and this procedure can be useful to avoid performance losses. The max(x) and min(x) are the maximum and minimum values of the *x*-vector.

ISSN 2176-5480

4. DESCRIPTION OF THE TEST SYSTEM AND SIMULATION RESULTS

This case study consisted of 13 thermal units of generation with the effects of valve-point loading, as given in Table 1. The data shown in Table 1 are also available in Sinha et al. (2003). In this case, it adopted a load demand to be determined, P_D , equal to 1800 MW.

Table 1. Data for the 13 thermal units of the test system.

Thermal unit	$P_i^{\min}$	$P_i^{\max}$	*a*	*b*	*c*	*e*	*f*
1	0	680	0.00028	8.10	550	300	0.035
2	0	360	0.00056	8.10	309	200	0.042
3	0	360	0.00056	8.10	307	150	0.042
4	60	180	0.00324	7.74	240	150	0.063
5	60	180	0.00324	7.74	240	150	0.063
6	60	180	0.00324	7.74	240	150	0.063
7	60	180	0.00324	7.74	240	150	0.063
8	60	180	0.00324	7.74	240	150	0.063
9	60	180	0.00324	7.74	240	150	0.063
10	40	120	0.00284	8.60	126	100	0.084
11	40	120	0.00284	8.60	126	100	0.084
12	55	120	0.00284	8.60	126	100	0.084
13	55	120	0.00284	8.60	126	100	0.084

The optimization methods were implemented in Matlab (MathWorks). In each case study, 30 independent runs were made for each of the optimization algorithms involving 30 different initial trial solutions for each optimization method. In all optimization approaches were adopted a population of *n* fireflies equal to 20 and *Maximum_Generations* = 100. A total of 2,000 cost function evaluations in each run were performed by tested FA approaches. Furthermore, the following setups were also adopted:

- FA: $\gamma = 1$, $\beta_0 = 1$ and $\alpha = 0.8$;
- Gaussian FA (GFA): $\gamma = 1, \beta_0 = 1$ and α is obtained with absolute values from a truncated normal distribution with mean equal to zero and unit standard deviation. In the Matlab implementation, it is given by α = *abs(randn)/3.5*;
- MFA(1): $\gamma = 1$, $\beta_0 = 1$ and $\alpha = 0.8$;
- MFA(2): $\gamma = 1$, $\beta_0 = 1$ and α is a random number generator uniformly distributed in [0, 1];
- MFA(3): $\gamma = 1$, $\beta_0 = 1$ and α is given by same procedure adopted in the GFA.

A key factor in the application of optimization methods is how the algorithm handles the constraints relating to the problem. In this work, a penalty-based method proposed in Noman and Iba (2008) was used.

The results obtained for the test system are given in Table 2, which shows that the MFA succeeded in finding better solutions than the FA for the ED with load demand of 1800 MW. Furthermore, a lower standard deviation value indicated a good convergence of MFA method in the 30 runs.

Table 2. Convergence results (30 runs) for the test system with 13 thermal units with valve point.

Optimization Method	Minimum Cost ($/h)	Mean Cost ($/h)	Maximum Cost ($/h)	Standard Deviation of Cost ($/h)
FA	18685.6525	18938.5074	19094.1757	104.5127
GFA	18866.5697	18990.7972	19098.0051	68.6925
MFA(1)	18259.5242	18389.4410	18556.7491	67.7687
MFA(2)	18188.1687	18362.3008	18491.1524	81.1922
MFA(3)	17972.8177	17993.2278	18073.6082	33.3766

ISSN 2176-5480

From Table 2, the mean of cost function found by MFA(3) for the 30 runs was better than the results of FA and GFA methods. The best solution obtained for the vector P_i, i = 1,...,13 with MFA(3) with total minimum cost of 17972.8177 \$/h for P_D = 1800 MW are given in Table 3. Table 4 compares the results obtained in this paper using MFA(3) with those of other studies reported in the literature. Note that in this studied case, the best result reported, in terms of the fuel cost using MFA(3) is comparatively lower than several studies presented in the literature. Furthermore, the results presented in Chiang et al. (2005), Wang et al. (2007) and Vlachogiannis and Lee (2009) are superior than the obtained by MFA(3).

Table 3. Best result (30 runs) for the test system using MFA(3).

Power	Generation (MW)
P_1	628.3185
P_2	297.6200
P_3	224.3283
P_4	60.0000
P_5	109.8665
P_6	60.0000
P_7	109.8665
P_8	60.0000
P_9	60.0000
P_{10}	40.0000
P_{11}	40.0000
P_{12}	55.0000
P_{13}	55.0000

Table 4. Comparison of results for the test system with the fuels costs presented in the literature.

Optimization technique	Best result in terms of the fuel cost (\$/h)
Improved evolutionary programming (Sinha et al., 2003)	17994.07
Hybrid genetic algorithm (Da-kuo et al., 2008)	17992.92
Particle swarm optimization (Victoire and Jeyakumar, 2004)	18030.72
Improved genetic algorithm (Chiang et al., 2005)	17963.98
Self-tuning hybrid differential evolution (Wang et al., 2007)	17963.79
Improved particle swarm optimization (Vlachogiannis and Lee, 2009)	17960.37
Best result of this paper using MFA(3)	17972.8177

5. CONCLUSION

Practical aspect like valve-point effects makes the solution space of ED optimization problem nonconvex with many local minima. It is extremely difficult to find the optimal solution for ED with multiple minima.

In order to demonstrate the performance and applicability of the proposed MFA method, a 13-unit test system with non-smooth fuel cost function is used. It has been observed that the MFA(3) has the ability to converge to a better quality near-optimal solution and possesses better convergence characteristics and robustness than other prevailing techniques reported in the literature. Future work will include a diversity measure of the fireflies' population in the MFA(3). Furthermore, we plan to study the MFA(3) in multiobjective ED problems with units having prohibited zones and valve-point loading effects.

6. ACKNOWLEDGEMENTS

This work was supported by the National Council of Scientific and Technologic Development of Brazil - CNPq - under Grants 307150/2012-7 and 476235/2011-1. The first author, also, would like to thank the Pontifical Catholic University of Parana — PUCPR for the financial support provided through the Institutional Program for Scientific Initiation Scholarships — PIBIC.

ISSN 2176-5480

7. REFERENCES

Becerra, R.L. and Coello, C.A.C., 2006, “Cultured Differential Evolution for Constrained Optimization”, Computer Methods in Applied Mechanics and Engineering, Vol. 195, No. 33-36, pp. 4303-4322.

Chiang, C.L., 2005, “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.

Coelho, L.S., Almeida, A.D.V. and Mariani, V.C., 2008, “Cultural Differential Evolution Approach to Optimize the Economic Dispatch of Electrical Energy using Thermal Generators”, Proceedings of 13th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA), Hamburg, Germany, pp. 1378-1383.

Da-kuo, H., Fu-li, W. and Zhi-zhong, M., 2008, “Hybrid Genetic Algorithm for Economic Dispatch with Valve-point Effect”, Electric Power Systems Research, Vol. 78, No. 4, pp. 626-633.

Niknam, T., Mojarrad, H.D., Meymand, H.Z. and Firouzi, B.B., 2011, “A New Honey Bee Mating Optimization Algorithm for Non-smooth Economic Dispatch, Energy, Vol. 36, No. 2, pp. 896-908.

Noman, N. and Iba, H., 2008, “Differential Evolution for Economic Load Dispatch Problems”, Electric Power Systems Research, Vol. 78, No. 3, pp. 1322-1331.

Pothiya, S., Ngamroo, I. and Kongprawechnon, W., 2010, “Ant Colony for Economic Dispatch Problem with Non-smooth Cost Functions”, International Journal of Electrical Power & Energy Systems, Vol. 32, No. 5, pp. 478-487.

Reynolds, R.G., 1994, “An Introduction to Cultural Algorithms”, in Proceedings of the 3rd Annual Conference on Evolutionary Programming, World Scientific Publishing, pp. 131-139, 1994.

Saber, A.Y., 2012, “Economic Dispatch Using Particle Swarm Optimization with Bacterial Foraging Effect”, International Journal of Electrical Power & Energy Systems, Vol. 34, No. 1, pp. 38-46.

Sinha, N., Chakrabarti, R. and Chattopadhyay, P.K., 2003, “Evolutionary Programming Techniques for Economic Load Dispatch”, IEEE Transactions on Evolutionary Computation, Vol. 7, No. 1, pp. 83-94.

Sivasubramani, S. and Swarup, K.S., 2011, “Environmental/Economic Dispatch using Multi-objective Harmony Search Algorithm”, Electric Power Systems Research, Vol. 81, No. 9, pp. 1178-1785.

Vianna Neto, J.X., Bernert, D.L.A. and Coelho, L.S., 2009, “Improved Quantum-inspired Evolutionary Algorithm Applied to Economic Dispatch Problem of Thermal Units”, 20th International Congress of Mechanical Engineering (COBEM 2009), Gramado, RS, Brazil.

Victoire, T.A.A and Jeyakumar, A.E., 2004, “Hybrid PSO-SQP for Economic Dispatch with Valve-point Effect”, Electric Power Systems Research, Vol. 71, No. 1, pp. 51-59.

Vlachogiannis, J.G. and Lee, K.Y., 2009, “Economic Load Dispatch — A Comparative Study on Heuristic Optimization Techniques with an Improved Coordinated Aggregation-based PSO”, IEEE Transactions on Power Systems, Vol. 24, No. 2, pp. 991-1001.

Walters, D.C. and Sheblé, G.B., 1993,“Genetic Algorithm Solution of Economic Dispatch with Valve Point Loading”, IEEE Transactions on Power Systems, Vol. 8, No. 3, pp. 1325-1332.

Wang, S.K., Chiou, J.P. and Liu, C.W., 2007, “Non-smooth / Non-convex Economic Dispatch by a Novel Hybrid Differential Evolution Algorithm”, IET Generation, Transmission & Distribution, Vol. 1, No. 5, pp. 793-803.

Wood, A.J. and Wollenberg, B.F., 1996, Power Generation, Operation, and Control, 2nd ed. New York, USA: Wiley.

Yang, X.S., 2008, Nature-inspired Metaheuristic Algorithms, Luniver Press.

Yang, X.S., 2009, “Firefly Algorithms for Multimodal Optimization”, in Stochastic Algorithms: Foundations and Applications (SAGA 2009), Lecture Notes in Computer Sciences, vol. 5792, pp. 169-178.

8. RESPONSIBILITY NOTICE

The authors are the only responsible for the printed material included in this paper.