LOG-NORMAL BASED MUTATION EVOLUTIONARY PROGRAMMING TECHNIQUE FOR SOLVING ECONOMIC DISPATCH PROBLEM CONSIDERING LOSS MINIMIZATION

M. H. Mansor[1], I. Musirin[2] and M. M. Othman[2*]

[1]Department of Electrical Power Engineering, College of Engineering, Universiti Tenaga Nasional, Kajang, Selangor, Malaysia

[2]Faculty of Electrical Engineering, Universiti Teknologi MARA, 40450 Shah Alam, Selangor, Malaysia

ABSTRACT

Electricity delivery to the consumer should be implemented in such a way that, cost is minimal, loss is minimal and voltage is within the acceptable limit. In general, the voltage level should be within 95% to 105% of the nominal limit in accordance to most international standard within the power engineering community. This phenomenon is addressed as secure voltage level. The dispatch of electricity is controlled by a dispatch body of the utility in a country. Economic dispatch requires a reliable optimization technique so loss is minimal. This paper presents Log-Normal Evolutionary Programming (LNEP) technique for solving Economic Dispatch (ED) problem considering loss minimization. Validations on the IEEE 6-bus and IEEE 26-bus test systems demonstrated that LNEP is feasible and convincing is addressing the issues. It was revealed that the proposed LNEP gives better solution to solve ED problem than the Classical EP and traditional load flow.

Keywords: economic dispatch; evolutionary programming, optimization.

Author Correspondence, e-mail: mhelmi@uniten.edu.my

1. INTRODUCTION

Economic Dispatch (ED) is one of the power system planning and operation problems. Solving ED problem is important to utility companies to find the lowest possible cost of dispatching power from generations to consumers. Generally, ED is solved by considering number of generating units available and demand of electricity at a time. Power is dispatched from generations to the consumers through the grid system. The main objective to solve ED is to find the best setting of generating units output that give minimal cost of dispatching electrical power with respect to system constraints and units constraints. The typical system constraints for ED problem are the real power balance between the generation and the demand, reserve generation capacity, transmission network limits and network security. Furthermore, the unit constraints are the operating limits of generators, ramp rate limits and minimum 'up time'. Many methods have been introduced to solve ED by researchers and engineers. These methods can be classified into two groups. The groups are mathematical methods and heuristic methods. For the past fifteen years, it was reported that researchers are more interested to use heuristic methods to solve ED. Some of the methods are particle swarm optimization [1] [2] [3] [4] [5] [6] [7] [8] artificial immune system [9], differential evolution algorithm [10] hybrid genetic algorithm [11] and evolutionary programming [12] [13]. This research used one of heuristic methods called Evolutionary Programming (EP) optimization technique to solve ED problem.

EP has been used by many researchers to solve ED problem. For instance, [14] used Classical EP (CEP) to solve dynamic ED problem. They used Gaussian distribution to generate offspring in the mutation process. The problem with that method is that, the strategy parameters are not evolved (or learned) in parallel with decision variables. Therefore, the decision variables do not get a larger freedom grade in adapting itself to the shape of the fitness function. This results to the small rate of optimization due to the new sprayed trials have not been tuned to follow grooves and valleys on the surface to the optimal point. This paper presents the implementation of log-normal mutation EP in solving ED problem. The loss minimization is considered while solving the ED problem. Implementation of the proposed technique on several test systems revealed that LNEP managed to achieve better solutions.

2. PROBLEM FORMULATION

The main objective of Economic Dispatch (ED) is to minimize the total operating cost while covering load demand and transmission losses. The objective function of ED can be written as follows:

$$Minimize \left(C_{total} = \sum_{i=1}^{n} C_i(P_i) \right) \qquad (1)$$

Where C_{total} is the total operating cost and $C_i(P_i)$ is the fuel cost function of generating unit i in terms of real power output, P_i. The fuel cost function for each generator can be approximately represented by a quadratic function for mathematical convenience as shown in Equation (2).

$$C_i(P_i) = \sum_{i=1}^{n} a_i P_i^2 + b_i P_i + c_i \qquad (2)$$

Where a_i, b_i and c_i are cost coefficients of generating unit i, subject to:

A. *Power balance constraint*

$$P_{demand} + P_{loss} = \sum_{i=1}^{n} P_i \qquad (3)$$

Where P_{demand} is the total system load demand and P_{loss} is the total system loss which can be calculated using *Kron's loss formula* as shown in equation (4)
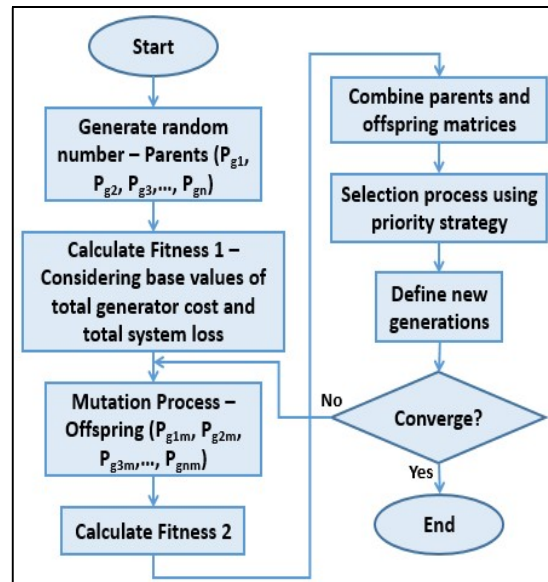
$$P_{loss} = \sum_{i=1}^{n_g} \sum_{j=1}^{n_g} P_i D_{ij} P_j + \sum_{i=1}^{n_g} D_{0i} P_i + D_{00} \qquad (4)$$

Where B_{ij}, B_{0i} and B_{00} are loss coefficients. *B* is generator operating limits. The inequality constraint for the power is given by (5).

$$P_{imin} \leq P_i \leq P_{imax} \quad ,i = 1, 2, ..., n \qquad (5)$$

Where P_{imin} and P_{imax} are the minimum and the maximum real power outputs of ith generator, respectively.

2.1 Classical Evolutionary Programming Technique

Fig.1. Flowchart of CEP for solving ED

Dr. Lawrence J. Fogel (March 2, 1928 - February 18, 2007) was a pioneer in evolutionary computation and human factors analysis. He is known as the father of evolutionary programming [15]. Evolutionary Programming technique is a stochastic optimization method under the hierarchy of evolutionary computation, which uses the mechanics of evolution to produce optimal solutions to a given problem. The first type of EP was named Standard EP (SEP). Basically, SEP was made famous by the son of Lawrence J. Fogel as a method to solve optimization problem applied mainly in the field of engineering [16]. SEP is also known as Classical EP. Generally, EP involved several processes which are initialization, fitness calculation, mutation, combination, selection and convergence test. Fig. 1 shows the flowchart of EP. The processes in EP technique are briefly explained as follows:

2.1.1 Initialization

Initialization is a process to generate random number of variables that control the objective function. The variables values are also known as parents. Variables for this case are generators real power. Real power of the generators control the objective function of the ED. In other

word, initialization is a process to produce first population. Initial population within the size of 20 is formed by a set of randomly generated individuals. Each individual is subjected to the inequality constraint equations in (5), (6) and (7).

$$C_{total} \leq C_{total(base)} \qquad (6)$$

$$Loss_{total} \leq Loss_{total(base)} \qquad (7)$$

The base values of total operating cost, C_{total} and total system loss, $Loss_{total}$ are taken from load flow result. The fitness value calculated using the generated random numbers must be smaller than the initial solution set to ensure that fitness will be improved. Only the member that satisfies the constraints are included in the initial population set.

2.1.2 Mutation

Mutation is a process to produce offspring or children. The offspring is transformed from the initial population. This process only happens for the initialization only. However, for the second iteration and above; mutation process will consider the candidates selected from the previous iteration prescribed from the tournament/selection process. Classical EP, Gaussian mutation technique is used to generate the offspring. The Gaussian mutation technique equation is shown in equation (8).

$$x_{i+m,j} = x_{i,j} + N\left(0, \beta\left(x_{jmax} - x_{jmin}\right)\left(\frac{f_i}{f_{max}}\right)\right) \qquad (8)$$

Where:

$x_{i+m,j}$ is mutated parent (offspring)

x_{ij} is parents

β is mutation scale, $0 < \beta < 1$
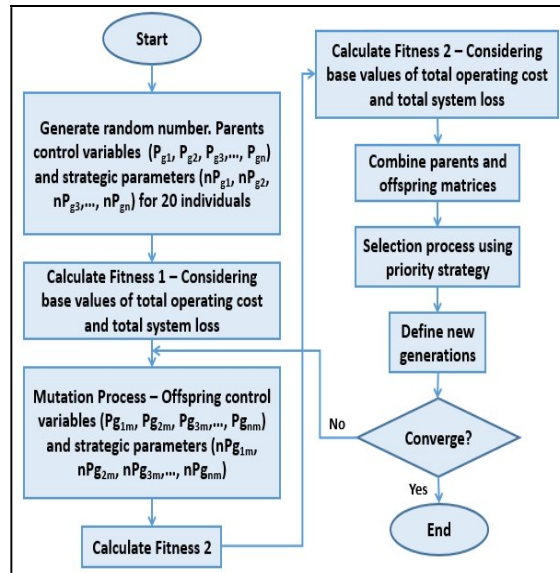
x_{jmax} is maximum random number for every variable.

Fig.2. Flowchart of proposed Log-Normal EP (LNEP) for solving ED

x_{jmin} is minimum random number for every variable

f_i is fitness for *ith* random number

f_{max} is maximum fitness

2.1.3 Selection

The parents' matrix produced on the first 20 individuals are combined with the offspring matrix formed from the mutation process to undergo a selection process in order to identify the candidates that have the chance to be transcribed into the next generation. This can be done using priority ranking techniques. The ranking process was done in accordance to the minimal total operating cost as the fitness function. In other words, the combined population is sorted in ascending order in accordance to the number of the best individual. The best vector having minimum total operating cost will be selected from parents and offspring for the new individuals for the next generation. Initialization and mutation process are repeated until there is no appreciable improvement in the fitness value.

2.1.4 Convergence Test

The stopping criterion is set so as to achieve the optimal solution, based on the difference between the maximum fitness and minimum fitness. This value should be must less than the

pre-set value. If it is not achieved, the process will be repeated until it gets converged. In this case the pre-set value is 0.00001. This can be represented mathematically as follows:

$$C_{total(max)} - C_{total(min)} \leq 0.00001 \qquad (9)$$

2.1.5 Proposed Log-Normal Evolutionary Programming to solve ED Problem

Log-Normal EP (LNEP) is proposed to improve the Classical EP (CEP) to address the ED issues. The algorithm is presented in the form of flow chart as shown in Figure 2. The mutation process has been improved by applying log-normal mutation into the original EP algorithm. The offspring are produced from each parent using

$$x'_{ij}(t) = x_{ij}(t) + \sigma_{ij}(t) N_{ij}(0,1) \qquad (10)$$

$$\sigma_{ij}(t+1) = \sigma_{ij}(t) e^{(\tau N_i(0,1) + \tau' N_{ij}(0,1))} \qquad (11)$$

Where:

σ is mutation step size

τ and τ' are operator-set parameters, and their equations are as follows:

$$\tau = \frac{1}{\sqrt{2n_x}} \qquad (12)$$

$$\tau' = \frac{1}{\sqrt{2\sqrt{n_x}}} \qquad (13)$$

Each decision variable has its own mutation step size, σ value. The mutation step size can be included in the decision variables itself as an additional variable resulting in the following form:

$$< x_1, x_2, \dots, x_j, \sigma_1, \sigma_2, \dots, \sigma_j > \qquad (14)$$

Each additional variable gets its own step size and the decision variables get a larger freedom grade in adapting itself to the shape of the cost function. These additional variables are transformed during the mutation. The e function is used to transform the σ value. The additional variables also undergo evolution as those of the decision variables. The log-normal mutation rises the population's performance over time.

3. RESULTS AND DISCUSSION

Prior to LNEP technique, the ED problem of 6-bus and 26-bus systems were solved using

Classical EP and traditional load flow (non-optimal) solution. These tests are conducted for comparative study purpose. It is important to compare the results produced by LNEP with respect to other approach to highlight its merit and feasibility.

The Classical EP and LNEP techniques were tested to solve ED for two different objective functions. The first objective function is to minimize total operating cost, while the second objective function is to minimize the total system loss.

The comparison of results produced by Load Flow, Classical EP and LNEP when total operating cost minimization as objective function are tabulated in Table 1 and Table 2. On the other hand, Table 3 and Table 4 tabulate the comparison of results obtained using the similar methods when total loss minimization is chosen as the objective function.

Table 1. Results obtained using load flow, classical EP and LNEP with total operating cost minimization as objective function for 6-bus system

Methods	Load Flow (Non-Optimal)	Classical EP	LNEP
P_{G1} (MW)	108.19	50.26	50.13
P_{G2} (MW)	50.00	38.55	37.50
P_{G3} (MW)	60.00	75.20	45.15
$\sum P_i$	218.19	164.01	133.25
Total System Loss (MW)	8.19	7.83	9.27
Total Operating Cost ($/h)	3193.40	2521.10	2155.70

Table 2. Results obtained using load flow, classical EP and LNEP with total operating cost minimization as objective function for 26-bus system

Methods	Load Flow (Non-Optimal)	Classical EP	LNEP
P_{G1}	719.53	129.64	106.68
P_{G2}	79.00	53.26	173.70

Table 2. Results obtained using load flow, classical EP and LNEP with total operating cost minimization as objective function for 26-bus system

Methods	Load Flow (Non-Optimal)	Classical EP	LNEP
P_{G3}	20.00	198.61	86.13
P_{G4}	100.00	137.97	67.16
P_{G5}	300.00	177.81	109.91
P_{G26}	60.00	105.03	50.00
$\sum P_i$	1278.53	802.32	593.59
Total System Loss (MW)	15.53	12.87	15.75
Total Operating Cost ($/h)	16760.70	10049.90	7568.00

Table 3. Results obtained using Load Flow, Classical EP and LNEP with Total System Loss Minimization as Objective Function for 6-Bus System

Methods	Load Flow (Non-Optimal)	Classical EP	LNEP
P_{G1}	108.19	58.22	59.16
P_{G2}	50.00	89.04	83.43
P_{G3}	60.00	64.80	82.44
$\sum P_i$	218.19	212.06	225.03
Total System Loss (MW)	8.19	6.80	6.72
Total Operating Cost ($/h)	3193.40	3074.20	3229.50

Table 4. Results of Load Flow, Classical EP and LNEP with Total System Loss Minimization as Objective Function for 26-Bus System

Methods	Load Flow (Non-Optimal)	Classical EP	LNEP
P_{G1}	719.53	289.16	487.96
P_{G2}	79.00	151.09	190.84

Table 4. Results of Load Flow, Classical EP and LNEP with Total System Loss Minimization as Objective Function for 26-Bus System

Methods	Load Flow (Non-Optimal)	Classical EP	LNEP
P_{G3}	20.00	263.07	220.04
P_{G4}	100.00	149.99	150.00
P_{G5}	300.00	192.42	196.38
P_{G26}	60.00	79.37	82.84
$\sum P_i$	1278.53	1125.10	1328.06
Total System Loss (MW)	15.53	12.59	12.49
Total Operating Cost ($/h)	16760.70	13634.70	16181.50

From Table 1 and Table 2, it is found that the total generation cost obtained using LNEP technique to solve ED problem for 6-bus system and 26-bus system are 2155.7 $/h and 7568.0 $/h respectively. It is found that the cost resulted using LNEP is lower than the total generation cost obtained using the Classical EP (CEP) and load flow (non-optimal) solution. This implies that implementation of LNEP is worth and better than the other two methods.

Based on the optimization results tabulated in Table 3 and Table 4, it is observed that the total operating cost computed by LNEP is slightly higher than the total operating cost computed by Classical EP. However, LNEP computed a significantly lower total system loss than Classical EP and Load Flow. This is because when total system loss minimization is set as the objective function, EP programs intent to minimize the total system loss rather than the total operating cost.

4. CONCLUSION

This paper has presented log-normal based mutation evolutionary programming (LNEP) technique for solving economic dispatch problem considering loss minimization. LNEP optimization technique has been developed to solve the ED problem. Two objective functions have been considered in sequential i.e. total operating cost minimization and system loss minimization. Results obtained from the study revealed that the proposed LNEP technique

outperformed the other two techniques to address most cases. These results imply that the proposed LNEP technique has the possibility for larger system implementation, with considerable minor amendments in the control variables setting.

5. ACKNOWLEDGEMENTS

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