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Solving Economic Load Dispatch for Power Generation Using Genetic Algorithm Techniques

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ABSTRACT

The economic load dispatch is the planning of generators production levels such that the system load is sufficient at the lowest total cost of the fuel subject to the constraints of production and operation. It is also becoming multi-objective for combinatorial optimization, solving by both traditional and artificial intelligence techniques. With more integrated power grids, power utilities are trying to strike a sensitive equilibrium between credible power supply to customers and minimum operating costs. Therefore, due to its flexibility, adaptability, reduced implementation time and fast convergence, the Artificial Intelligent (AI) technique is preferred. In addition, this project solved the economic load dispatch using an efficient optimization technique based on genetic algorithm procedure. The simulation is conducted on a 315 MW, 330 MW, and 342 MW IEEE-30 bus system with 6 generators considering losses. In this paper, the results were then observed and compared between the operating costs. The fuel cost for the bus system at load demand 450 MW considering losses are compared. Both operating cost and power loss are important in the system framework in order to make the system more dependable and higher invalidity.

Key words: Economic load dispatch, genetic algorithm optimization, operating cost, power loss.

1. INTRODUCTION

The world has become more advanced and increases rapidly day by day with the human's technology that has led to the increment in load demand for power supply. In power system area, the economic load dispatch (ELD) is the main issues in the operation of the power system as to generate and transmit the power to meet the system load demand at minimum fuel cost. Hence, with the development of an integrated power system, it becomes necessary to operate the plant units economically [1]. In this case, ELD is defined as to minimize the overall cost of generating real power (production cost) with the generating limit impose (upper and lower limit) at various stations while satisfying the loads and the losses in the transmission links [2], [3]

Although in a power system, total operating cost includes fuel cost, labour cost, supplies and maintenance, but for simplicity only fuel costs is considered for power production. This is due to the assumption that these cost make the major portion of the total operating (variable) cost and are directly related to the value of power output [2], [4]. In [5], for the process of transmitting the generated power, an estimated 4% of the total energy produced is lost as the electric power systems are large, geographically distributed, yet highly interconnected. An approach to achieving this optimum is to include the transmission losses as one of the objectives in the economic dispatch (ED) problem. Thus, the economic dispatch problem becomes a multi-objective optimization in which the fuel cost and the transmission losses are minimized.

In order to solve the emission – economic dispatch problem, a grey wolf optimization (GWO) has been proposed by [14]. In this paper, GWO is used to find an optimal solution for the combined economic and emission dispatch problem which aims to minimize the generation cost and keeping emission reduction. In this case, six mutation operators are applied to the GWO to enhance its performance and this is simulated in a test system that consists of 10 units. GWO is meta-heuristics natural inspired method belongs to swarm intelligence algorithms.it mimics the grey wolves' manner in hunting prey. From the result, it shows that the convergence of solutions and indicates the effectiveness of the GWO in obtaining the best total cost with the least emission. This GWO then is compared with other optimization methods, and it shows that GWO is demonstrated as a good optimization method for all cases.

A differential evolution ant colony optimization has been proposed by [16]. In this paper, the combination of DE and ACO is studied to perform better in optimizing the ELD on a reliable test system. This optimization method is implemented in the IEEE reliability test system. DE algorithm is confirmed to have a good performance and simple process, compared to the other evolutionary algorithm. However, DE does not guarantee to discover an optimal solution since it does not use the gradient of the optimization problem, while ACO quickly gains a good reputation. However, the algorithm would converge to an optimal solution slowly and has the potential to experience stagnation that might limit the wide application to various fields. The comparison between three methods, traditional, ACO and DEACO indicates that DEACO not only successfully reduced the total generating cost, but it also helps to reduce the power loss. Although slower than the conventional method, DEACO is proven to have faster computational time compared to ACO algorithm and slightly higher than the traditional approach.

Another research made by [17], has proposed the effect of any parameter on DEACO in economic load dispatch. In recent years, ACO has gained huge popularity and turned out to be a candidate approach to many optimization problems. However, this algorithm suffers several drawbacks, including stagnation and slow convergence toward an optimal solution. Thus, a new algorithm termed as DEACO has been modelled to compensate the drawbacks. In this paper, DEACO algorithm was employed on IEEE 57 bus system. The comparative studies between conventional ACO and DEACO were conducted by considering the behaviour of both algorithms by manipulating a number of ants and nodes the number of ants is varied between 5 to 15 ants, while the number of nodes is varied between 5 to 25 nodes. From the result, it shows that the number of nodes affects the computation time of both algorithms. As the nodes increase, the computation time also increases. Meanwhile, the number of ants displays consistent solutions. This study indicates that DEACO has effectively minimized the power loss to the system.

In [20], firefly algorithm (FA) is implemented in solving the economic load dispatch problem by minimizing the fuel cost and considering the generator limits and transmission losses. FA is a meta-heuristic algorithm which is inspired by the flashing behaviour of fireflies. In this paper, the 26-bus system is utilized to show the effectiveness of the FA in solving the problem. The result is compared with the continuous genetic algorithm and the conventional method. The proposed method has been tested on 26 bus system which consists of six generators located at buses 1, 2, 3, 4, 5 and 26. From the simulations, it can be seen that FA gave the best result of total cost minimization compared to lambda iteration method and CGA. The comparison with CGA has been conducted to see the robustness and consistency of FA compared CGA in solving the optimal ED problem.

A modified FA (MFA) in solving economic dispatch problems with practical constraints is also proposed by Sulaiman and Daniyal [21]. This paper implemented the algorithm techniques on 6-unit system consists of 26 buses and 46 transmission lines. The load demand is 1263 MW. in addition, this paper also considers the prohibited operating zones which embedded in the 4 units of units 2,5,6 and 12 in the 15 units system. From the result, MFA gives better solution quality in terms of total cost generated compared to the others. Chiang [22], has proposed a cuckoo search algorithm to solve power economic/ environmental dispatch problem. In his research, a standard IEEE 30 bus system with six generators for solving EEDP is employed to demonstrate performances of the suggested CSA-MUT. Simulation outcome has shown that the suggested method is better than former studies in answer character for resolving the EEPD. Contributions of this paper are the MUT efficaciously controls constraints of EEDP system in emission management, the CSA precisely finds the optimal answers for EEDP in the economic dispatch procedure of power systems.

Singh, Tyagi and Goel [1] have proposed a genetic algorithm for solving the economic load dispatch. This paper deals with GA and lambda iteration method which have been used individually for solving two cases first is three generator test system and second is ten generator test system. The LIM is the most popular method for the solution of the economic load dispatch problem. It gives a decentralized solution to the ELD problem by equating the marginal cost of generation of each thermal unit to the price of electricity, or, equivalently, the marginal revenue of each unit under perfect competition conditions, known as system lambda. The GA is a stochastic global search method that mimics the metaphor of natural biological evolution such as selection, crossover, and mutation. For the three-generator system, the power demand is 300 MW, while for ten generator system, the power demand is 1440 MW. From both results, it shows that GA proves itself as a fast algorithm and yields true optimum generations of both operating costs and transmission line losses of the power system.

In addition, Saha [24] has proposed particle swarm optimization to solve the economic load dispatch. This technique has been implemented for the IEEE 30 bus system. The outcome is then compared with other optimization technique such as lambda iteration method and genetic algorithm technique. From the results, the total cost of generation for lambda iteration, genetic algorithm and particle swarm optimization are 802.63$/h, 801.8551 $/h and 799.9895 $/h respectively. Based on the result, we can clearly observe that PSO showed a high-quality solution and stable convergence.

2. METHODOLOGY

2.1 Generator Operating Cost

In the generator working framework, the general expense of the framework to work incorporates the expense of fuel, cost of work, supplies and [2]–[7]. Typically, expenses of work, supplies and upkeep are fixed rates of approaching fuel costs. The power yield of fossil plants is expanded consecutively by opening a lot of valves to its steam turbine at the delta. The throttling misfortunes are huge when a valve is simply opened and little when it is completely [2].

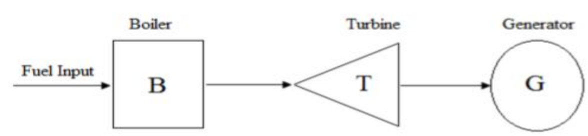

Figure 1: Simple model of a fossil plant

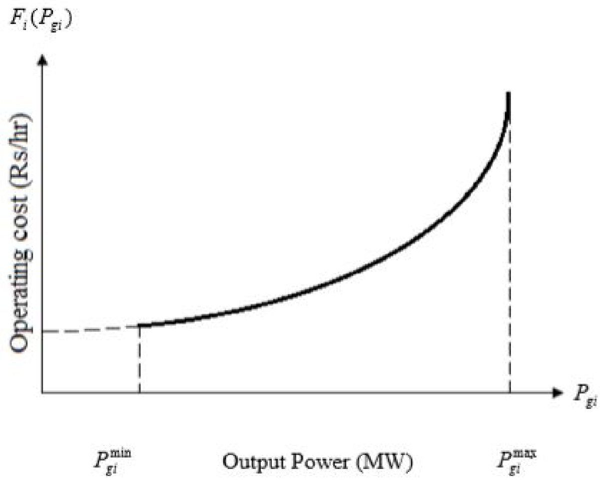

Figure 2: Operating costs of the fossil-fired generator

Figure 1 shows the simple model of fossil plant dispatching purposes. The cost is usually approximated by one or more quadratic segments. The operating cost of the plant has the form shown in Figure 2. For dispatching purposes, this cost is usually approximated by one or more quadratic segments. Hence, the fuel cost curve in the active power generation is given in quadratic form as below:

$$F_i(P_{gi}) = a_i P_{gi}^{\ 2} + b_i P_{gi} + c_i \$/\mathrm{hr} \tag{1}$$

Where

$F(P_{gi})$ = the total cost of generation.

P_{gi} = the generation of i^{th} plant.

a_i, b_i, ci = cost coefficients for i^{th} unit.

2.2 Economic Load Dispatch with Losses

Most of the case, the transmission losses may be neglected when the transmission losses are very small with a large interconnected network where the power is transmitted over long distances. However, the transmission losses are the major factor and affect the optimum dispatch of power generation. For this case, the ELD with the present of transmission power losses, P_L for the objective function is formulated as:

Minimize:

$$F_i(P_{gi}) = \sum_{i=1}^{NG} F_i(P_{gi}) \tag{2}$$

$$F_i(P_{gi}) = a_i P_{gi}^{\ 2} + b_i P_{gi} + c_i \$/\mathrm{hr} \tag{3}$$

Subject to:

The energy balance equation

$$\sum_{i=1}^{NG} P_{gi} = P_D + P_L \tag{4}$$

The inequality constraints

$$P_{gi}^{min} \le P_{gi} \le P_{gi}^{max} \ (i = 1,2, \ldots..NG) \tag{5}$$

The general form of the loss formula is given as:

$$P_{gi} = \sum_{i=1}^{NG} \sum_{j=1}^{NG} P_{gi} P_{gj} B_{ij} \ \text{MW} \tag{6}$$

Where

P_{gi} and $P_{g.}$ = the real power generations at i^{th} and j^{th} buses

B_{ij} = the loss coefficients

2.3 Economic Load Dispatch without Losses

In a power system, the simplest economic load dispatch problem is the case where the transmission losses are neglected. Therefore, the total demand P_D will be the sum of all generations and cost functions F_i (P_{gi}) is assumed to be unknown for each plant. The optimization problem is stated as equation (7) – (10).

Minimize:

$$F_i(P_{gi}) = \sum_{i=1}^{NG} F_i(P_{gi}) \tag{7}$$

Subject to:

The energy balance equation

$$\sum_{i=1}^{NG} P_{gi} = P_D \tag{8}$$

The inequality constraints

$$P_{gi}^{min} \le P_{gi} \le P_{gi}^{max} \ (i = 1,2, \ldots..NG) \tag{9}$$

The general form of the loss formula is given as:

$$P_{gi} = \sum_{i=1}^{NG} \sum_{j=1}^{NG} P_{gi} P_{gj} B_{ij} \ \text{MW} \tag{10}$$

2.4 Genetic Algorithm Structure

This calculation or improvement has been broadly utilized in taking care of identified with ELD issue for power framework and furthermore in any application because of its adaptability and productivity. John Holland (1975) was the person who found this technique and GA has been ordered as worldwide pursuit heuristic [2]–[10].

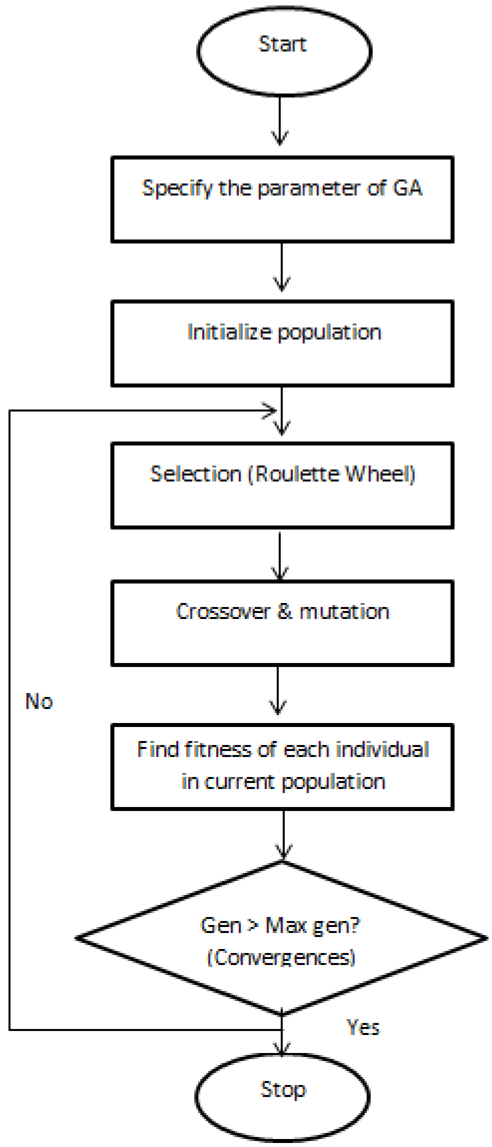

Figure 3: GA flowchart for optimum total fuel cost

In the hereditary task stage, we create another population from the past population utilizing hereditary administrators. They are multiplication, hybrid and change. Multiplication is the administrator used to duplicate the old chromosome into tangling pool as per its fittest esteem. Higher the wellness of the chromosome more is some of the duplicates in the cutting edge chromosome. The different techniques for choosing chromosomes for guardians to hybrid are roulette-wheel selection, Boltzmann selection, competition selection, position selection, enduring state selection and so on. The usually utilized proliferation administrator is the roulette wheel choice technique where a string is chosen from the mating pool with a likelihood corresponding to the wellness [4], [11]. There are numerous favourable circumstances of GA's which are easy to comprehend and to actualize, and early give a decent close arrangement. Next, it takes care of issues with numerous arrangements. Since the hereditary calculation execution procedure isn't relying upon the mistake surface, we can fathom multidimensional, non-differential, non-consistent, and even non-parametrical issues. GA additionally is appropriate for parallel PCs and streamlines factors with incredibly complex cost surfaces (they can bounce out of a nearby least).

A simple GA is an iterative method, which keeps up a steady size population P of a competitor arrangement. Amid every emphasis step (age) three hereditary administrators (selection, Crossover and mutation) are performing to create new populaces (offspring's), and the chromosomes of the new populace are assessed by means of the qualities to the wellness which is identified with the cost capacity. In view of these hereditary administrators and the assessment, the better new population of hopeful arrangements is framed[1]

Step 1. Initialization
Initialize population size, maximum generation, stall time limit and read the cost coefficients.

Population size= 20

Step 2. Formation of population
The initial power search for each generator can be obtained by:

```
x1(:1) = Pmin (1,1) +rand*Pmax (1,1)
```

Where,

i = number of generator   j = number of generations

Step 3. Apply genetic operators
Determine the best fitness and mean fitness values for the current population.

Step 4. Evaluate the fitness function.
Parent individuals are selected using 'Roulette Wheel' selection procedure and single point crossover is used and finally, the mutation operator is used for regaining the lost characteristics during the process.

Step 5. Repeat
Repeat step 3 and step 4 until the process has been converged or it satisfies the stopping criteria.

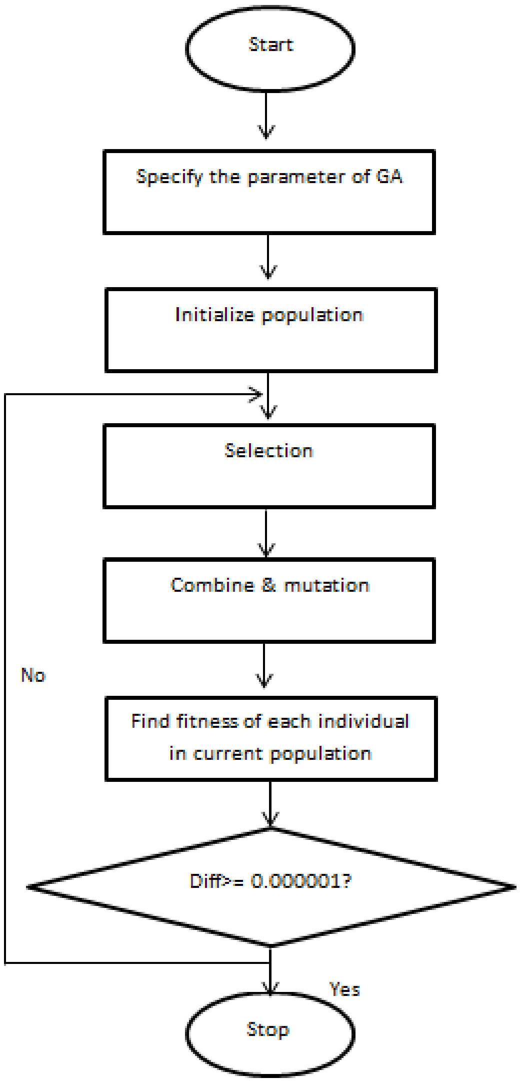

Figure 4: GA flowchart for total power loss

1. Read data, cost coefficient, (ai, bi and ci), no of iteration, population size and Pmin and Pmax.
2. Create an initial population randomly
3. Calculate the power in MW generated within the specified Pmin and Pmax and find fitness.
4. Select the parents for the combination using roulette wheel selection.
5. Perform mutation and find a population with maximum fitness and average fitness of the parents.
6. If the number of iterations is maximum generates a minimum total power loss.

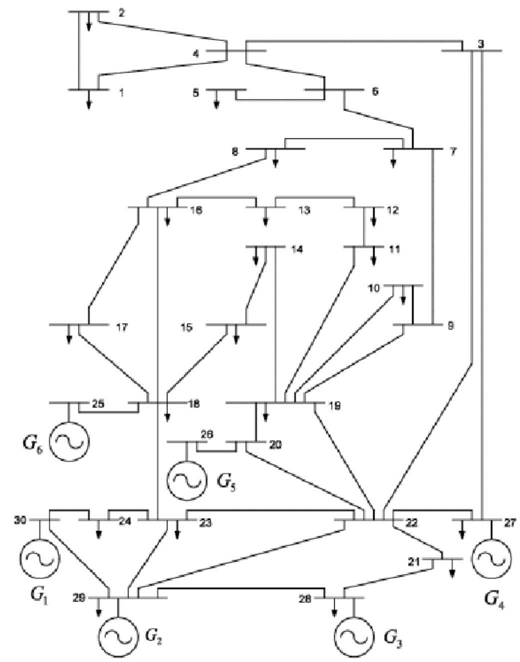

Figure 5: The IEEE 30 bus system with 6 generators

Table 1: Specifications of fuel cost coefficient [8]

Unit no.	a_i	b_i	c_i	Pmin	Pmax
P2	0.010	2.0	100	10	50
P5	0.020	2.0	300	10	80
P8	0.003	1.95	80	10	70
P11	0.015	1.45	100	50	150
P13	0.100	0.95	120	5	150

4. RESULTS AND ANALYSIS

In IEEE 30 bus system, there is 6 generator test system which is 1 slack bus and 5 generator bus. In this case, we only consider the generator bus since the slack bus is used to balance the active power and reactive power in the power system. Furthermore, it prevents power loss by emitting and absorbing active and reactive power to and from the system.

A. Case 1: Operating cost as an objective function

Table 2: Optimum Operating Cost and Power Loss for Case 1

Unit no.	Load demand (MW)		
	315	330	345
P2	15.3115	16.5950	13.2823
P5	34.7973	76.0246	11.4703
P8	40.7176	40.3798	62.2459
P11	112.8722	113.6207	131.6430
P13	111.1325	83.0406	123.6160
Fuel cost ($/hr)	1546.6	1617.6	1619.8
Power loss (MW)	6.1621	6.1701	6.1706

Table 2 shows the result for the optimum operating cost and power losses in economic load dispatch by taking the operating cost as the objective function. From the table, the fuel cost are 1546.6 $/hr, 1617.6 $/ hr and 1619.8 $/hr at power demand of 315 MW, 330 MW and 345 MW respectively. Next, the power losses in this buses system are 6.1621 MW, 6.1701 MW, and 6.1706 MW at the respect fuel cost. This simulation also gives the optimum power capacity limit for each generator needed to supply in the system framework to satisfy every power demand. This power capacity will not be less or exceed from the minimum and maximum generation limit. From the observation, as the power demand increase, the fuel cost also increases as well as the power loss.

B. Case 2: Power loss as the objective function

Table 3: Optimum Operating Cost and Power Loss for Case 2

Unit no.	Load demand (MW)		
	315	330	345
P2	14.5781	12.4486	18.8232
P5	35.3667	78.6651	22.4744
P8	40.5862	12.7656	67.7868
P11	113.6056	146.0832	101.2955
P13	110.5631	80.9652	134.6201
Power loss (MW)	5.1008	5.3749	5.390.2
Fuel cost ($/hr)	1622.1	1744.2	1783.5

Table 3 shows the result for the optimum operating cost and power losses in economic load dispatch by taking the power loss as the objective function. The power losses for Case 2 are 5.1008 MW, 5.3749 MW and 5.390.2 MW correspond to the load demand. Meanwhile, the fuel cost are 1622.1 $/hr, 1744.2 $/hr and 1783.5 $/hr at specified power loss. As we can see, the power losses are slightly increasing depends on the power demand in the bus system as well as the operating cost. For Case 2, the power capacity is at optimum for each generator bus and within the generation limit.

C. The comparison between Case 1 and Case 2

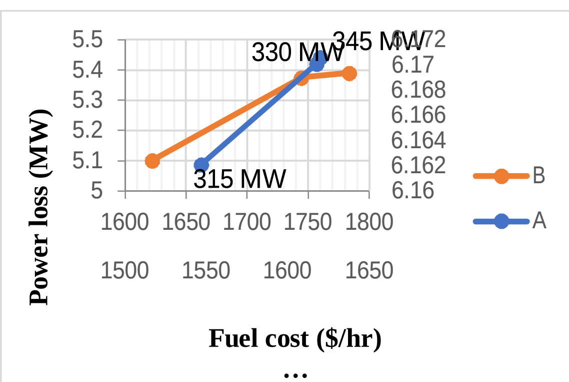

Figure 6: The Comparison between Case 1 and Case 2

The relationship between Case 1 and Case 2 is shown in Figure 4.1 above. Based on the graph, both Case 1 and Case 2 increase linearly as the fuel cost high, the power loss in the system also rise to correspond to the power demand 315 MW, 330 MW, and 345 MW. From the result of Case 1, the power losses are slightly higher compared to the power loss in Case 2 whereas the fuel cost is lower than the fuel cost for Case 2. This is because, in Case 1, the fuel cost becomes the objective function. Hence, the optimization of the fuel cost will be prioritizing in this case. On the other hand, for Case 2, the power loss act as the objective function and this lead the program to optimize power loss first compared to the fuel cost. Both cases are important in the power system network and need to be at the optimum value. Therefore, in order to reduce and minimize the fuel cost, the power loss also needs to be lowered to make the system more stable and efficient.

D. The comparison of fuel costs considering losses and without losses at 450MW

Table 4: The Comparison of Fuel Costs Considering Losses and Without Losses

Unit no.	With losses	Without losses
P2	78.9584	29.9516
P5	18.3627	11.0102
P8	87.8732	161.0286
P11	127.1635	95.4038
P13	137.6422	87.4080
Power demand (MW)	450	450
Fuel cost ($/hr)	1622.1	1744.2

Table 4 shows the comparison of fuel cost for the bus system considering losses and without losses at power demand 450 MW. The results for the fuel cost considering losses are taken by setting the power demand at 450 MW and the value of fuel cost is compared with the fuel cost from the previous study that has been conducted without considering losses in the transmission line. From the table, the fuel cost considering losses are 1997.6 $/hr which higher than the fuel cost without losses which are 1971.1 $/hr. The results also show the optimum power for each generator to generate in order to satisfy the load demand of 450 MW. In addition, the presence of transmission loss in a system can increase the operating cost compared to the one without losses.

5. CONCLUSION

A solution method for the optimal economic load dispatch issue is formulated and implemented using the genetic algorithm method in this study. economic load dispatch problem is referred as to minimize the total operating cost in a power system within the generation limit satisfying to the load demand and reducing the power loss in the transmission links while generators supplying the energy. From the result, the operating cost and the lost power is successfully optimized for both Case 1 and Case 2. It shows that, as the cost of the fuel is subjected as the objective function in Case 1, the fuel cost will be lower compared to fuel cost in Case 2 since the power loss is the objective function in the simulation. With more integrated power grids, power utilities try to strike a delicate balance between the reliable customer power supply and minimal operating costs. Therefore, the result shows that both cases can be done or considered by the utility company since the result was approximate and slightly different in value between the operating cost and the power loss. In order to make the system network more reliable and operate effectively, both operating cost and loss power need to be considered especially for a long distance transmission line.

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