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Genetic Algorithm-based Cost Optimization Model for Power Economic Dispatch Problem

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Authors' contributions

This work was carried out in collaboration between all authors. Authors SAO, Olatubosun Olabode and O. Olusi designed the study and conducted experimental studies. Authors GBI and AEA wrote the first draft of the manuscript and managed literature searches. Authors SAO, GBI and Olatubosun Olabode managed the analyses of the experimental results. All authors read and approved the final manuscript.

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ABSTRACT

In any power generation and distribution system, a continuous balance must be maintained between electrical generation and varying load demand, while the system frequency, voltage levels, and security must all be kept constant and the cost of generation maintained at minimal level. Numerous classical techniques such as Lagrange, linear programming, non-linear programming and quadratic programming-based methods have been proposed for attaining these objectives. The attendant weaknesses to these methods include economic dispatch problem-induced non-optimal power flow and cost increment. Classical approach-based solution to the economic dispatch problem suffered some limitations, which include restriction to the local minima while the cost functions show non-convex or piecewise discontinuity in the functional space. Furthermore, treatments of operational constraints are very difficult using the classical approach. This paper reports on the formulation of a Genetic Algorithm (GA)-based model as a solution to the problems of economic power dispatch. The model considered GA as numerical optimization algorithms based on the principle inspired from the genetic and evolution mechanisms observed in natural systems and population of living being. The implementation of the model produced an

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application whose performance evaluation on power demand and transmission loss of three power generating systems and three Nigerian Thermal Power Plants showed superior performances of the new model over some existing ones.

Keywords: Economic dispatch problem; power generation and distribution; cost optimization; genetic algorithm.

1. INTRODUCTION

For a growing and sustainable economy and reliable power system, the power service companies must consider Economic Dispatch (ED) as one of the options. Based on ED, the generation unit is scheduled to provide necessary support for servicing the load demand at the minimum operating cost while meeting all plant and system constraints [1]. Some very cogent factors influencing the economic operation of the power system include operational efficiency of generating units, fuel and operating cost and transmission losses [2]. In an electrical power system, a continuous balance between electrical generation and varying load demand is required along constant system frequency, voltage levels and security. The cost of generation must be minimal while great emphasis is laid on the division of load in the generating plant as well as all economic issues to be solved at every load change [3]. With the opening of the power industry to competition, the power system structure is changing, necessitating the modification of the power system operation, planning and control. In the past, utilities had to produce power to satisfy their customers with the objective of minimizing the costs and meeting all demands [4]. However, under a new structure, generation companies schedule their generators with the objectives of profit maximization, increase system social benefit and greater influence from the power and reserve prices [5]. The core objective of the introduction of competitiveness into electricity supply industry through privatization is to increase efficiency in the production and distribution of electricity for better choice to market participants and constant and reliable supply [1].

Optimal Load Flow (OPF) problems have been solved through researches on optimization techniques based on linear or nonlinear programming algorithms which are generally limited to convex regular, multi-modal, discontinuous and not differentiable functions. These functions are being optimized based on stochastic sampling methods [6]. The stochastic methods determine the next sampled point based on stochastic sampling or decision rules rather than on a set of deterministic rules or the characteristics of the problem (for example, gradient, Hessians, linearity and continuity) being used in the traditional resolution techniques. Economic Load Dispatch (ELD) is a subset of the Optimal Power Flow (OPF) and uses equal incremental cost and penalty factors criteria for building and relating loss-less systems. Existing techniques for providing solution to ELD problems include lambda-iterative, gradient, Newton, linear and quadratic programming methods which are all based on assumption of continuity and differentiability of cost functions. These methods are unable to provide global optimal solution, get stuck at local optima and imperfect for handling integer or discrete variables [1,7].

The growing interest for the application of Artificial Intelligence (AI) techniques to power engineering has introduced the potentials of using the state-of-the art methods in many problems in power systems. AI methods are very promising, still evolving and are being applied in various fields of human endeavor [8]. The four methods that are currently perceived as affiliated in some measure with the AI field and have gained prominence as frameworks for solving different problems are Neural Networks (NN), Simulated Annealing (SA), Tabu Search (TS) and Micro-Genetic Algorithm (M-GA) [2,9-11]. M-GA, NN and TS are inspired by principles derived from biological processes while SA is derived from material sciences. These methods need not be viewed competitively, and they comprise the emergence of promise for conquering the combinatorial explosion in a variety of decision-making arenas. NN have claimed intriguing successes in pattern-recognition applications, but have generally performed below expectation in optimization settings. SA, TS and M-GA have the attractive feature of assured convergence under appropriate assumptions [12].

Genetic Algorithm (GA) are essentially derived from a simple model of population genetics and are associated with three prime operators; namely reproduction, crossover, and mutation.

They have been used to solve difficult problems with objective functions that do not exhibit continuity, differentiability and other related characteristics [13]. They also maintain and manipulate a set of solutions as well as implementing survival of the fittest strategies in their search for better solution. They are resolution algorithms based on the mechanics of natural selection and genetics, combine survival of the fittest among string structures with un-randomized information exchange to form a resolution algorithm. In every formation, a new set of artificial creatures (strings) is created from bits and pieces from the fittest of the old while occasional new part is used for good measure. While randomized, genetic algorithms are non-simple random walk, they efficiently exploit historical information to speculate on new research points with expected improvement on the performance [6].

2. RELATED WORKS

The authors in [14] developed a Simple Genetic Algorithm (SGA) with two different encoding schemes for solving the ELD problem and valve point effect. The SGA tested for ELD problem with and without losses for smooth and non-smooth cost curves using three machine test systems for five different cases by comparing the results obtained from dynamic programming technique. Useful observations were made and conclusion was drawn that GA has the ability to handle any type of unit characteristics. In [15], the authors presented a genetic algorithm based approach for large-scale economic dispatch subject to the network losses, ramp rate limits and prohibited zone avoidance. The encoding scheme was selected such that chromosome contains only an encoding of the normalized system incremental cost thus making chromosome size independent of number of units. Though the comparison of obtained results with those of lambda –iteration method establishes the fast and robust nature of the approach, it however experiences computational complexities. The authors in [16] presented a genetic algorithm-based solution to economic dispatch problem. Test results with systems of about 72 generating units with non-convex cost functions show the superiority of genetic algorithms over the dynamic programming solution. The solution time is however dependent and increases linearly with the size of the system. In [17], the authors developed a standard and deterministic genetic algorithm-based solution for non-convex economic dispatch problem based on the prohibited operating zones of the generators. Practicality test conducted on 15 generators system (with 4 of the units up to three prohibited operating zones system) presented the system as strong for cost optimization but highly dependent on parameter selection. Fuzzy-Logic Controlled Genetic Algorithm (FCGA) was applied to environmental/economic dispatch by the authors in [18]. Two fuzzy controllers were designed to adaptively adjust the crossover probability and mutation rate during the optimization process based on some heuristics. Adequacy tests also showed promising results but heavily dependent on the right levels of input.

While the authors in [19] developed a genetic algorithms based method for solving the problems of economic dispatch and distribution system expansion planning, the authors in [20-21] proposed real coded genetic algorithm that relies on elitism, arithmetic crossover and mutation to proffer solution to economic dispatch problem. Both solutions underperformed with large population. The authors in [22] proposed an algorithm based on parallel micro genetic algorithm for the solution of ramp rate constrained economic dispatch neglecting the transmission loss for generating units with non-monotonic and monotonic incremental cost functions. The algorithm is constrained by its complex nature and poor loss minimization. In [23], the authors presented a GA-based solution for the operational planning of hydro-thermal power systems to get around the deficiencies in nonlinear programming-based approaches. The solution adapted the technique with an actual application on the optimization of the operation planning for a cascaded system composed of interconnected hydroelectric plants. A real coded GA for the solution of network constrained power economic dispatch for minimizing the dispatch cost subject to branch power flow limits is proposed in [24]. The algorithm retained the advantages of the GAs over the traditional ELD methods and eliminated the main disadvantage of the binary coded GAs (long execution time). While the authors in [25] presented an economic dispatch solution that is based on valve point loading effect, SGA, generation-apart elitism and atavism, the authors in [26] presented a genetic algorithm-based solution to EDP taking into account the valve point effect and multiplier update. Both solutions rely on effective loading and parameter specifications for optimum performance on non-explosive population.

3. PROPOSED MODEL

The proposed model uses ELD problem and the Lagrangian and genetic algorithm methods with some special fitness functions. The main objective of ELD is to promote cost minimization and satisfaction of the equality and inequality constraints by allocating the generation among the committed units. The ELD objective function is mathematically formulated as follows [2]:

$$MinF_T = \sum_{n=1}^{N} F_n\{P_n\} \tag{1}$$

Subject to the following constraints:

$$\sum_{n=1}^{N} P_n = P_D \tag{2}$$

$$P_n^{min} \leq P_n \leq P_n^{max} \tag{3}$$

F_T represents the total cost of power generation, $F_n\{P_n\}$ represents the cost of producing P units of power by unit n while P_D is the power demand. P_n^{min} and P_n^{max} are the minimum and maximum power, respectively which can be generated by unit n. P_n is the power output of unit n and N is the total number of unit n. The major component of the operating cost for thermal and nuclear units is the power production cost, which is the cost of fuel input per hour, of the committed units and is expressed as a quadratic function of the unit output power as follows [5]:

$$F_n(P_n) = a_n + b_n P_n + c_n P_n^2 \tag{4}$$

a_n, b_n and c_n represent the cost coefficients of the n^{th} generator.

The economic load dispatch problem focuses on the minimization of the cost of generating the power at any load demand with or without the transmission line losses [17]. Based on Lagrangian multiplier λ, the auxiliary function is obtained from:

$$F = F_T + \lambda\left(P_D - \sum_{n=1}^{N} P_n\right) \tag{5}$$

The equation of the differentiation of F with respect to the P_n gives the condition for optimal operation of the system as follows:

$$\frac{\partial F}{\partial P_n} = \frac{\partial F_T}{\partial P_n} + \lambda(0-1) = 0 \tag{6}$$

$$\frac{\partial F_T}{\partial P_n} - \lambda = 0 \tag{7}$$

Given that $F_T = F_1 + F_2 \ldots + F_n$, then:

$$\frac{\partial F_T}{\partial P_n} = \frac{\partial F_n(P_n)}{\partial P_n} = \lambda \tag{8}$$

The condition for optimum operation is:

$$\frac{\partial F_1(P_1)}{\partial P_1} = \frac{\partial F_2(P_2)}{\partial P_2} = \cdots = \frac{\partial F_n(P_n)}{\partial P_n} = \lambda \tag{9}$$

$\frac{\partial F_n(P_n)}{\partial P_n}$ is the incremental production cost of generator *n* per MWhr.

However,

$$F_n(P_n) = a_n + b_n P_n + c_n P_n^2 \tag{10}$$

$$\frac{\partial F_n(P_n)}{\partial P_n} = b_n + 2c_n P_n = \lambda \tag{11}$$

$$P_n = \frac{\lambda - b_n}{2c_n} \tag{12}$$

Equation (12) implies that the machine can be loaded such that there are equal incremental costs of production for all machines. In addition, consideration is given to active power generation constraints while solving these equations. If these constraints are violated for any generator, it is tied to the corresponding limit and the rest of the load is distributed to the remaining generator units according to the equal incremental cost of production.

The optimal load dispatch problem including transmission losses is defined in Equation (1), and in the current case, it is subject to:

$$\sum_{n=1}^{N} P_n = P_D + P_L \tag{13}$$

P_L is the total system transmission loss, which is assumed to be a function of generation. Based on the Lagrangian multiplier λ, the auxiliary function is obtained from:

$$F = F_T + \lambda\left(P_D + P_L - \sum_{n=1}^{N} P_n\right) \tag{14}$$

The partial differentiation equation of this expression gives the condition for optimal load dispatch as follows:

$$\frac{\partial F}{\partial P_n} = \frac{\partial F_T}{\partial P_n} + \lambda\left(\frac{\partial P_L}{\partial P_n} - 1\right) = 0 \tag{15}$$

$$\frac{\partial F_T}{\partial P_n} + \lambda\,\frac{\partial P_L}{\partial P_n} = \lambda \tag{16}$$

$\frac{\partial P_L}{\partial P_n}$ is the incremental transmission loss at plant *n and* λ is known as the incremental cost of received power per MWhr. The loss formula equation (also known as George's loss formula) [2] is expressed in terms of the generations as follows:

$$P_L = \sum_{m=0}^{M}\sum_{n=1}^{N} P_m B_{mn} P_n \tag{17}$$

P_m and P_n are the source loadings and B_{mn} is the transmission loss coefficient. The formula is based on the assumption that the equivalent load current at any bus, the generator bus voltage magnitudes and angles as well as the power factor of each source are all constants. The solution of the coordination equation is obtained from:

$$\frac{\partial P_L}{\partial P_n} = \sum_{m=0}^{M} 2P_m B_{mn} \tag{18}$$

Furthermore,

$$\frac{\partial F_T(P_n)}{\partial P_n} = b_n + 2c_n P_n \tag{19}$$

The coordination equation can be written as:

$$b_n + 2c_n P_n + \lambda \sum_n 2P_m B_{mn} = \lambda \tag{20}$$

The solution to P_n is obtained from:

$$P_n = \frac{1 - \frac{b_n}{\lambda} - \sum_{m\neq n} 2B_{mn}P_m}{\frac{c_n}{\lambda} + 2B_{mn}} \tag{21}$$

3.1 Economic Load Dispatch Problem Based on Genetic Algorithm

The algorithm is in four phases; namely initialization, coding, evaluation and genetic operations as shown in Fig. 1. Genetic algorithm (flowchart shown in Fig. 2) operates on a set of strings known as population and it involves the process of evolution to produce new set of individual strings [13]. The initial population is made up of chromosomes (between 20 and 100) obtained from randomly or heuristically selected strings and contains a wide variety of structures. At the coding phase, each generation unit loading is represented by a binary number of N units, such that each unit is loaded within its upper and lower limits (P_n^{max}, P_n^{min}) and the length (number of bits), l_n which represents the value of P_n is calculated from:

$$l_n \geq log_2\left(\frac{P_n^{max} - P_n^{min}}{\Delta P} + 1\right) \tag{22}$$

ΔP is the chosen error tolerance.

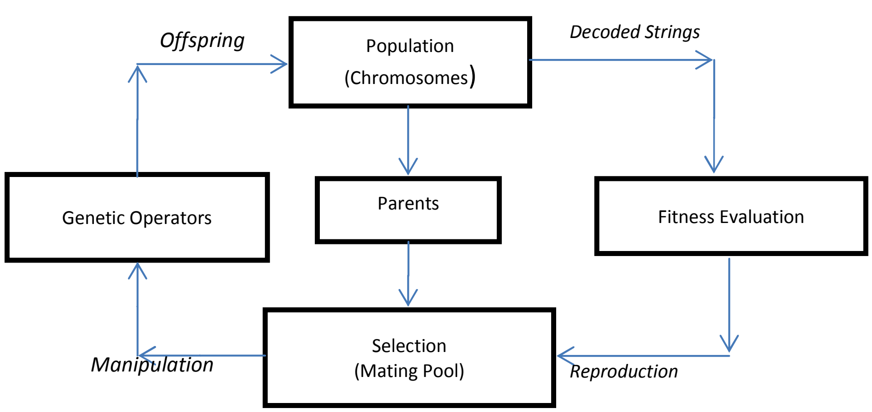

Fig. 1. The generic algorithm model

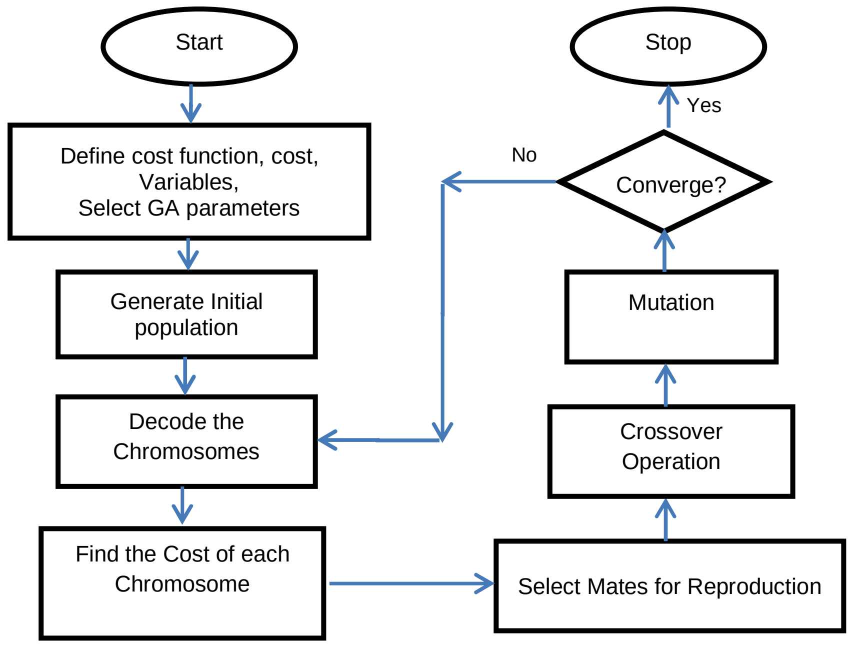

Fig. 2. Flowchart of genetic algorithm

In the evaluation phase, the suitability of the solutions from the initial set of the solution is determined based on a fitness function which is determined from the objective function, F_T. Since the ELD Problem is a minimization problem, the fitness function (f_x) is related to the power demand as follows:

$$f_x = (1 + \frac{error}{Power\ Demand})^{-1} \tag{23}$$

4. IMPLEMENTATION

The implementation of the Genetic Algorithm-based method was carried out using Microsoft Visual Studio C++ as frontend on Microsoft Window 8 platform. The performance is evaluated without considering losses using two case studies (each with two power demands), three generator test systems and three Nigerian thermal plants. For GA without considering losses, the length and size of the population were 48 and 50 respectively with three substrings (each of 16 bits) of a single string and the mutation and crossover probabilities were 0.015 and 0.8 respectively.

4.1 Case Study 1

This study involved two power demands of 340MW and 850MW with three generating units and different characteristics (a, b and c) and operating ranges (inequality constraints) as presented in Table 1. The parameters and the results for the optimum solution are presented in Table 2.

Table 1. Three generators system characteristics

Unit	a (₦/MWhr)	b (₦/MWhr)	c (₦/MWhr)	P_n^{min}	P_n^{max}
Gen 1	561	7.92	0.001562	150	600
Gen 2	310	7.85	0.00194	100	400
Gen 3	78	7.97	0.00482	50	200

Based on the results presented in Table 2, GA returned better results than the Lagrangian method, despite the convex nature of the cost functions and this is derived principally from the specifications of the convergence criteria and the degree of convexity near the global optimum in the functional space. It is also observed from the results obtained for GA that the unit real power allocations are, to all intents and purposes, very close to those obtained through the classical methods. Based on the calculated error values, there is greater accuracy for power allocation based on GA compared to the Lagrangian method. However, the total production costs obtained through GA and µGA are slightly lower when compared with the Lagrangian method. It is observed for Lagragian method, that the minimum cost curve converges within the range of 1500 - 2000 iterations while in GA technique, the cost curve converge within the range of 100-200 iterations. So the computational time of the proposed algorithm is much less than the Lambda iteration method. However, μGA required less computational time (58% and 63% time reduction for loading conditions 1 and 2, respectively) as compared with GA. Fig. 3 (obtained based on Grapher 5.5.6) shows that the population size of 100 returned the best minimum cost and therefore, it plays very important role in the optimization process. The plot of total cost against power demand presented in Fig. 4 shows direct proportionality.

4.2 Case Study 2: The Three Nigerian Thermal Power Plants

The Nigerian power system grid is essentially a 24-bus, 330kV network interconnecting three thermal generating stations (Sapele, Delta and Egbin) and three hydro stations to various load points. The quadratic cost functions for the various thermal units were developed as the best curve fits to their actual operating cost data for a period of one year. Table 3 presents the obtained cost coefficients for the three thermal units and their minimum and maximum loading limits. The parameters and the results for the optimum solution are presented in Table 4.

Table 2. Computational results and GA settings for case study 1

Parameters	Lagragian method		Micro-genetic algorithm (μGA)		Genetic algorithm	
	Power demand P_d(MW)		Power demand P_d(MW)		Power demand P_d(MW)	
	340	850	340	850	340	850
P1 (MW)	150.19	395.22	171.60	414.24	173.85	395.313
P2 (MW)	140.58	331.08	118.47	287.46	108.40	346.094
P3 (MW)	50.00	124.34	50.10	149.06	57.50	108.594
$\sum Pn\ (MW)$	340.77	850.64	340.17	850.76	340.017	850.001
Error	0.77	0.64	0.17	0.76	0.017	0.001
Total cost (₦/hr)	3742.90	8351.40	3742.13	8347.00	3721.05	8195.52
Crossover probability P_c			0.65	0.65	0.80	0.80
Mutation probability P_m			0.005	0.005	0.015	0.015
Maximum generation			150	400	200	200
Processing time (seconds)			3	8	8	10
Population size			5	5	100	100

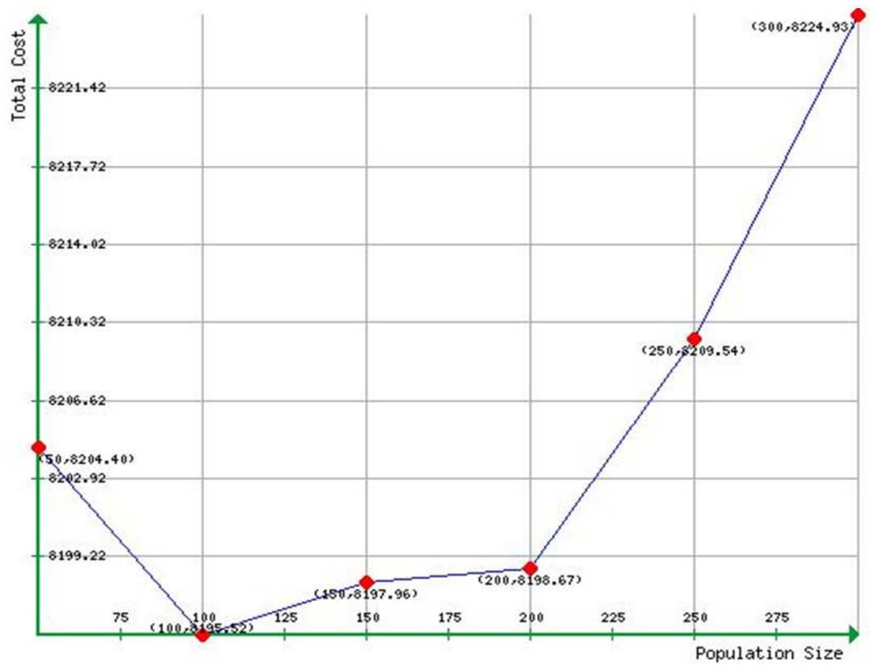

Fig. 3. A graph of population size versus total cost (Pd = 850MW)

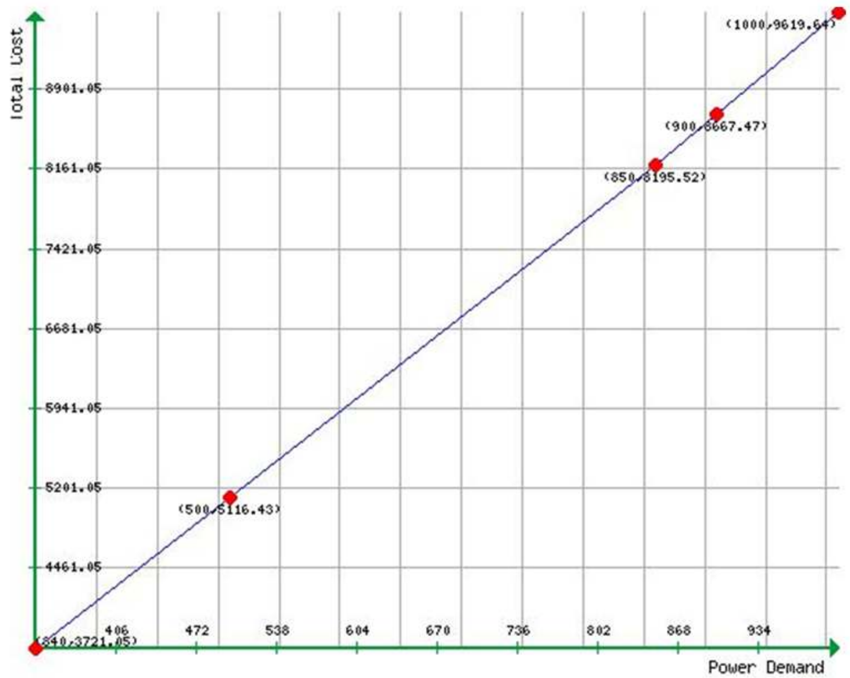

Fig. 4. A graph of power demand versus total cost

Table 3. Cost coefficients for Sapele, Delta, Egbin thermal generating stations

Unit	a (₦/MWhr)	b (₦/MWhr)	c (₦/MWhr)	P_n^{min}	P_n^{max}
Sapele	6929	7.84	0.13	137.5	550
Delta	525.74	-6.13	1.20	75.0	300.0
Egbin	12787.0	13.1	0.031	275.0	1100.0

Table 4. Computational results and GA settings for case study 2

Parameters	**Lagragian method**		**Genetic algorithm**	
	Power demand P_d(MW)		**Power demand P_d(MW)**	
	1000	**1500**	**1000**	**1500**
Sapele P1 (MW)	330.69	524.15	290.95	517.371
Delta P2 (MW)	130.62	120.08	189.075	102.225
Egbin P3 (MW)	538.72	855.92	519.922	880.054
$\sum Pn\ (MW)$	1000.03	1500.15	999.94	1499.650
Error	0.03	0.15	-0.053	-0.35
Total cost (₦/hr)	92,310.30	107,540	90,458.60	106,547
Crossover probability P_c			0.80	0.80
Mutation probability P_m			0.015	0.015
Maximum generation			1000	1000
Processing time (seconds)			8	10
Population size			50	50

The GA again offers better results when compared with the results obtained through Lagrangian method. The total production costs and the executions time obtained via GA method are also lower when compared with the values obtained using the classical approach. However, the GA started with a very low fitness and gradually reached the peak.

5. CONCLUSION

The development and implementation of a GA-based cost optimization model for economic load dispatch problem of power generation and distribution has been reported. The model partnered with the Lagrangian method with some special fitness functions to promote cost minimization and satisfaction of the equality and inequality constraints by allocating the generation among the committed units. The model also considered GA as numerical optimization algorithm that is premised on human genetic and evolution mechanisms. The implementation and performance evaluation experiments on power demand and transmission loss of three power generating systems and three Nigerian Thermal Power Plants (with very large population) showed competitive edge of the new model over some existing ones. The model attains good performance with moderate computations, appreciable loss minimization and reasonable level of parameter settings. Future research focuses on the adaptation of the model to other loading conditions and larger systems for optimum performance. Special considerations will also be given to environmental conditions and loss due to heat in the conductors.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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