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Optimal Determination for Cost of Electric Power Generation and Plant Capacity of Utilities

Desmond Eseoghene IGHRAVWE[1] and Sunday Ayoola OKE[2,3,*]

[1]*Department of Mechanical Engineering, Faculty of Engineering and Technology, Ladoke Akintola University of Technology, Ogbomoso, Nigeria*
[2]*Department of Mechanical Engineering, Faculty of Engineering, University of Lagos, Akoka-Yaba, Lagos, Nigeria*
[3]*Department of Mechanical Engineering, Covenant University, Ota, Nigeria*

([*]Corresponding author's e-mail: sa_oke@yahoo.com)

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Abstract

Optimisation of power generation and plant capacity are of primary significance for the improvement of power supplies, cost decisions and economics. This paper develops a robust predictive model for electric power generation and capacity utilisation and integrates the output from predictive models into a multi-objective model. The optimal solution was determined after comparing the performance of a Real Coding Genetic Algorithm (RCGA), Particle Swarm Optimisation (PSO) and Big-Bang Big-Crunch Algorithm (BB-BC). Testing of the proposed model was carried out using data from a Nigerian electric power generation plant with a capacity of about 5 million Megawatt Hours (MWH) to test the presented methodology. Our findings indicate that the Auto-Regressive Integrated Moving average (ARIMA) model adequately predicts the power generation variables and compares favorably with literature results. The RCGA performed better than the BB-BC and PSO algorithms in terms of the quality of solutions for the proposed model. The outcome of this study suggests that computational complexity can be reduced in the evaluation of variables, yet producing a practical, simple and robust model.

Keywords: ARIMA, robust regression, electricity, meta-heuristics, fuzzy logic

Introduction

There are critical global challenges associated with traditional grid systems, including poor operational performance in power generation and distribution, customers' low access to electricity services, low system efficiencies, problems relating to affordability by consumers, plant reliability and quality-of-service related problems. These problems, which can be captured under technical and economic conceptualisations [1], coupled with the global governments' concerns for increased access to power services by consumers and the need to stimulate economic growth make further intensive investigations on the traditional grid system a necessity and relevant. However, given these myriads of competing factors that should be considered, an investigation concerning power generation, plant capacity and cost decisions in an innovative, integrated manner must be carried out as a real contribution towards solving some of the aforementioned problems. Interestingly, the problem addressed in this article has been a concern of scholars worldwide but an integrated and innovative treatment as presented in the current work has not previously been reported in the literature. The research and development articles on power generation, reliability issues and plant capacity topics in the energy field fully appreciate these key challenges but the pool of existing knowledge are somehow disintegrated. Novel investigations have been documented on power generation on one hand, while on the other hand, noteworthy studies have been concerned with plant reliability issues as related to plant capacity but the literature has ignored the possibility of these integrations with cost decisions. The integration of such important factors in a model is not sufficient as suboptimal results could lead to poor decisions based on such models. Therefore, a further advancement pursued in this study is to develop optimal conditions with the variables indicating optimal quantities to adopt.

Optimal power generation, plant capacity and reliability issues as well as cost decisions are one of the most important and widely advocated concerns in the electric power economic literature. However, these were based on separate factor considerations. Nigeria, being the most populated country in Africa consumes a great deal of power supplies. In fact, the electric power system had to be privatized as a result of the challenges of inefficiency of electricity generation and supplies. With a huge investment recently channeled to the power industry in Nigeria through the deployment of highly technical resources and equipment of high magnitude of costs, the issue of optimisation of power generation and plant capacity in an integrated manner such that cost is optimised should be second to none in the priorities of researchers towards providing tools to and efficiency of power generation in Nigeria.

Optimisation continues to be important in the maintenance of an efficiently and effectively maintained power generation plant. As such, optimisation of all the necessary variables that control power generation should be done [2-5]. Optimisation guarantees the proper functioning of the generation industry with the least pressure on the utilisation of resources of the power generation system. In spite of the increasing knowledge that optimisation of power plants could help in decision making, empirical models that address the power generation problem and plant reliability issues are scare. Furthermore, the rapidly changing landscape in optimisation has brought about excellent optimisation tools nowadays, which are not being fully tested in empirical studies.

The use of soft computing tools like fuzzy models and Artificial Neural Network (ANN) models has been widely acknowledged as models that minimise the discrepancies between the actual and predicted values of variables in scientific literature and so may be useful for power generation issues. However, their applications in electric power plants have been sparsely reported in literature especially in developing countries. Similarly, other models like Auto-Regressive Integrated Moving Average (ARIMA) and robust regression models are statistical models that have also gained wide acceptance especially among researchers and industrial practitioners in the social sciences disciplines. But such knowledge could be extended to engineering with success. The benefit of applying these predictive models in electric power generating plants motivates the need for the current paper. Thus, an objective of this work is to apply a predictive model that has a high predictive capacity for electric power generation and capacity utilisation. This paper considers the ARIMA model and a robust regression model in carrying out its comparative analysis using Mean Absolute Percentage Error (MAPE) for comparative basis. The modification entails incorporating a fuzzy system as well as a meta-heuristics platform in the model for analysis.

To develop the various predictive models in this paper, electric power generation and capacity utilisation models are developed using 3 inputs variables (plant reliability index, breakdown maintenance index and generation unit cost). In order to improve the management of an electric power plant, the developed predictive model for the electric power plant is used and formulated as an optimisation model which is subjected to the input as variable bounds. We consider the objective of minimising unit cost of electric power generation while maximising the plant availability index. Also, the future worth of the power plant was maximised. An attainment of optimal value input variables will provide decision makers with information that can be used during the allocation of business resources. The proposed optimisation model is solved using meta-heuristics by formulating a weighted fuzzy goal programming model as a means of handling electric power generating and capacity utilisation objectives.

The remaining sections of this paper are organised as follows: In section 2, a literature survey is presented while the description of the various prediction models considered in this paper is contained in Section 3. The application of the various predictive models is in Section 4 and Section 5 presents the discussion of the results. The conclusions of this paper are in Section 6.

Literature review

This literature survey presents information on research and development status of power generation and plant capacity as they relate to cost. A thorough literature survey of papers in the energy research area is presented, showing the latest findings and key challenges as they relate to power generation and plant capacity issues in a cost orientation.

The models of power systems have grown substantially over time due to the contribution of several researchers across the globe. A great deal of study has been carried out globally with specific local variables considered in models in the various countries; Europe and UK [6], India [7], Belgium, France, Germany and the Netherlands [8], Poland [9], Turkey [10], Malaysia [11], Australia [12], Ireland [13], Libya [14] are country-specific studies that are at the frontier of knowledge on power generation. A prominent theme of some of these studies is the need for optimisation of electric power generation [4,15]. Some authors have also linked optimisation to reliability of the plants [16]. As such, the last years have seen a growing concession in the energy field that electrical power generation and plant reliability cum capacity issues must be pursued. On one hand, substantial literature has promoted plant reliability matters. These have placed compelling pressure on the management of power generating firms [2,4,5,15]. Since priorities have been given to optimisation and plant reliability issues in the energy research arena [5,16-18], a close look at the maintenance function as well as on unit cost of power generation would drive us towards achieving our optimality goals.

Electric power generation and its effective distribution to consumers is one of the most challenging tasks in the power generation industry [15,19]. A related article by Pettinau *et al*. [20] aimed at bringing down the capital and operating costs for commercial power generation plants. A shortcoming of the work is the absence of optimisation analysis in it. The implication is the possible weakness in decisions made based on sub-optimal values of decision variables.

There are several indices utilised in evaluating the capacity utilisation of industrial plants. However, most of these indices have been solely utilised for manufacturing systems while sparse information is available on their applications for electric power generation plants. A second problem is the disjointed treatment of electric power generation concept [5,19] as well as the concept relevant to capacity utilisation [15] index. It makes sense to have a holistic treatment of electric power generation and capacity utilisation problems and such information would provide a sound basis for management decisions. Electric power generation problems are a common issue across the globe [10,11,13,21]. This is evident in large amounts of research work available in the literature.

When studying electricity-related problems, different aspects in which improvements are achievable have been pursued in the literature. One of such aspects is the use of renewable forms energy as an alternative and supplement to existing sources of generating electric power. For instance, Liu *et al*. [22] investigated the possibility of incorporating wind energy into China's energy system while Hossain and Badr [23] examined the potential of using renewable energy as a complement to existing electric power generation methods in Bangladesh. Also, a similar inquiry was conducted in Libya by Mohammed *et al*. [14]. Their study focused on wind and solar energy as forms of renewable energies. Furthermore, a study was carried out in Brazil which considered the use of fuel cells development and hydrogen production as supplements to non-renewable energy [24].

Electric power generation problems have resulted in regional investigations in seeking ways forward to solving common problems in electricity generations and distributions [6,8], although, researchers are more interested in addressing country-wide problems [9,15,21,25]. Tasdoven *et al*. [21] studied electricity efficiency in Turkey.

Apart from the aforementioned electric power generation and management problems, other problems have been studied and solved using different methodologies. Bazmi and Zahedi [5] examined the applications of optimisation modeling approach in electric power generation and system. A hybrid electric power system was proposed by Paska *et al*. [26] for managing primary energy sources. Wurg *et al*. [19] proposed the use of simulation models for dealing with the household demands for electric power while Papatopoulos and Karaqiannidis [3] described how decentralised energy systems can be optimised using a multi-criteria method (Electre III). Wurg *et al*. [4] proposed the use of small-scale embedded generators in addressing electric power shortage in developing countries. The prospect of using large scale solar power generation system in addressing electric power shortage was investigated by Rao *et al*. [27].

Furthermore, the use of a thermoelectric cogeneration system for electric power generation was proposed by Zheng *et al*. [28] while Cormos *et al*. [29] studied fossil fuel power generation plants in order to evaluate quantities of water and construction materials consumptions. Saver *et al*. [25] estimated the energy efficiency and power quality from an uninterrupted power system. Akdaq and Guler [30] considered the cost of electric power generation when using wind energy. Augutis *et al*. [17] addressed electrical power transient stability assessment problem using a Bayesian technique. Analysis of electric power marginal outage costs was conducted by Ghajar and Billinton [16] using the reliability technique.

From the studies that were reviewed, we observe trends of case-specific approaches to the electric power generation problem. The 2-domain trends are electric power generation sources and country-wide approaches in studying power generation problems. The current paper draws its case study from Nigeria. Although few studies [15,18] were identified that were conducted in Nigeria in the papers reviewed, none of these studies considered electric power generation and capacity utilisation indices in problem prediction.

Research methodology

In this section, the structure of the research scheme adopted is shown in **Figure 1**, this summaries the main steps of the technical analysis carried out in order to obtain near-optimal results for the electric power system studied.

ARIMA model

The ARIMA model is a predictive model that integrates auto-regressive and moving averages in mapping sets of independent variables to desired values of a dependent variable. The nomenclature of ARIMA is given as (p,d,q), where p represents the degree of autoregressive, d is the degree of integrated difference and q stands for the degree of moving averages. Mathematical expressions for autoregressive, integrated differences and moving average in ARIMA [31,32] are expressed using Eqs. (1) to (3), respectively.

$$y_t = \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + \cdots + \alpha_p x_{t-p} + \varepsilon_t \tag{1}$$

$$y_t = \mu + \varepsilon_t + \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-2} + \cdots + +\beta_q \varepsilon_{t-q} \tag{2}$$

$$x_t = (1 + B)^d \, y_t \tag{3}$$

where, y_t is the value of the dependent variable at time t, α_i and β_i are the coefficients to be estimated, ε_t is known as the error term at time t and μ is a constant mean of a process. B is known as the backshift and (1-B) is called the differencing operator.

A model that contains only p and q is called ARMA. Such a model does not have differencing. An application of ARIMA during prediction is often considered when there exists non-stationarity in datasets that are used for forecasting. For datasets whose average is stable over time (i.e., stationary), ARIMA is applied instead of ARMA. Correlogram is used in the evaluation of the global and partial autocorrelations that will be utilised in determining the values of p and q for particular datasets.

Robust regression model

Robust regression models are statistical models that are used in addressing the problem on non normal regression errors that cannot be captured with linear least-squares estimation [33]. A common example of a robust regression model is M-estimation. This approach selects a β that will be minimised. The equation to be minimised [34] is expressed as follows;

$$\sum_{i=1}^{N} \rho\left(y_i - x_i^T \beta\right) \tag{4}$$

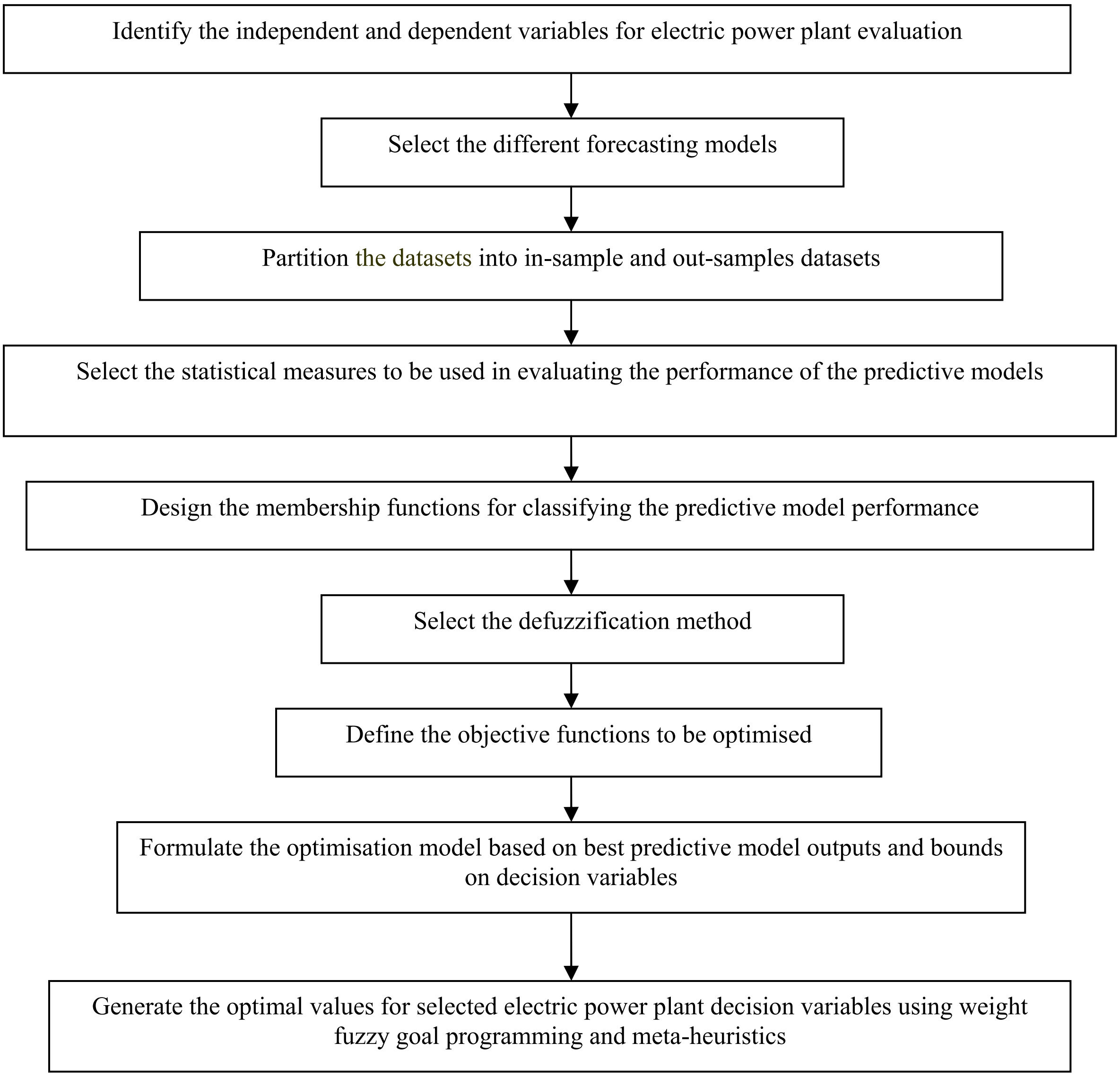


Figure 1 Research scheme.

By introducing weights into a least-square estimate, the normal least-square equation becomes Eq. (5).

$$\sum_{i=1}^{N} w_i x_{ij} (y_i - \sum_{j=1}^{P} x_{ij} \beta_j = 0 \tag{5}$$

By differentiating the *M*-estimate criterion with respect to β_j, Eq. (5) becomes Eq. (6).

$$\sum_{i=1}^{N} \rho' \left(\frac{y_i - \sum_{j=1}^{P} x_{ij}\beta_j}{\sigma} \right) x_{ij} = 0 \tag{6}$$

Fuzzy classification of prediction model overall performance

In this paper, the MAPE that is Eq. (7), is used in evaluating the performance of each of the predictive models considered in this work. The decision on which of the predictive models considered in this paper is the most preferable is based on the concept of fuzzy modelling. Partitioning of the overall performance of the predictive model is based on the conversion of Lewis's classification of MAPE, as reported by Ofori *et al*. [35].

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \frac{|actual_i \text{ - } predict_i|}{actual_i} \times 100\% \tag{7}$$

An integration of the MAPE from the electric power generation index and the plant capacity utilisation index is achieved using the weighted average fuzzy method [36], as shown in Eq. (8). The input value for a membership function in Eq. (8) is obtained using **Figure 2**. The expressions for the various membership functions in **Figure 2** are given as Eqs. (9) - (12).

$$\mu(overall) = \frac{\sum_{i=1}^{2} \mu(MAPE_i) MAPE_i}{\sum_{i=1}^{2} \mu(MAPE_i)} \tag{8}$$

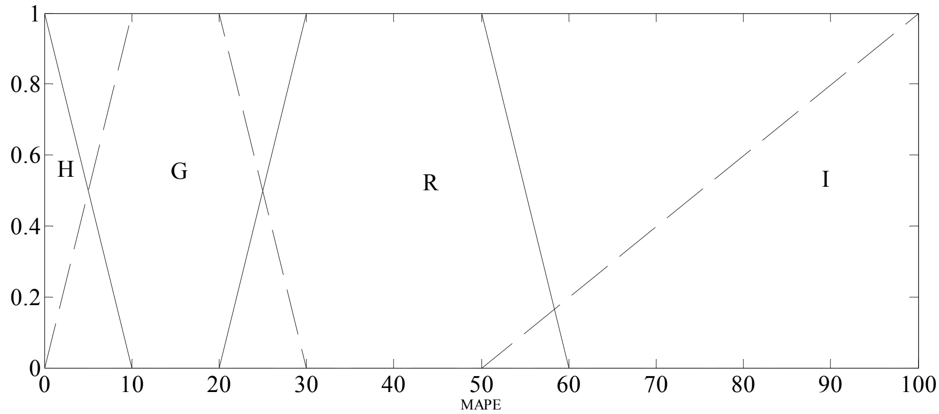


Figure 2 Memberships function for MAPE.

$$\mu_{overall}(H)=\begin{cases}1-\dfrac{x}{10} & 0\le x\le 10\\ 0 & 10\le x\le 100\end{cases} \tag{9}$$

$$\mu_{overall}(G)=\begin{cases}0 & 0\le \text{x}\le 10\\ 1 & 10\le \text{x}\le 20\\ 3-\dfrac{\text{x}}{10} & 20\le \text{x}\le 30\\ 0 & 30\le \text{x}\le 100\end{cases} \tag{10}$$

$$\mu_{overall}(R)=\begin{cases}0 & 0\le \text{x}\le 10\\ \dfrac{\text{x}}{10}-2 & 20\le \text{x}\le 30\\ 1 & 30\le \text{x}\le 50\\ 6-\dfrac{\text{x}}{10} & 50\le \text{x}\le 60\\ 0 & 60\le \text{x}\le 100\end{cases} \tag{11}$$

$$\mu_{overall}(I)=\begin{cases}0 & 0\le \text{x}\le 50\\ \dfrac{\text{x}}{50}-1 & 50\le \text{x}\le 100\end{cases} \tag{12}$$

where $\mu(H)$ represents the high accuracy membership function, $\mu(G)$ is the membership function for good prediction, $\mu(R)$ stands for membership function for reasonable prediction, and $\mu(I)$ represents the membership function for inaccurate predictions.

Optimisation model

Some of the notations used in presenting the proposed optimisation model are as follows;

b_k	Aspiration level for *k*-th goal
x_3	breakdown maintenance index
F	future worth
i	interest rate
x_{Li}	lower limit of decision variable *i*
$\overline{p}$	percentage difference between unit cost and sales price of electric current
x_1	plant reliability index
P	present worth
Q_{1t}	quantity of electric current produced in period $\bar{t}$

Q_{2t} quantity of electric current sold in period $\bar{t}$
Δ_{kR} quantity of tolerance for fuzzy goal k
n total number of years
C_t total cost of electric power at period $\bar{t}$
C total installed capital cost
S_t total sales of electric power at period $\bar{t}$
x_2 unit cost price of electric current
x_{Ui} upper limit of decision variable i
$\bar{x}_2$ unit sales price of electric current
$\bar{t}$ Year

Development of predictive models has helped in avoiding complex mathematical expressions for interrelationships among variables in a system while trying to generate realistic value for the variables of interest. Given that in an electric power plant, electric power generation index (Z_1) is to be maximised while the plant capacity utilisation (Z_2) is being maximised, the developed mathematical equations for electric power generation and plant capacity utilisation indices prediction can be used in obtaining the optimal values for the plant reliability index and unit cost of generation of electric power. Since large values of electric power generation and plant capacity utilisation indices are desirable, the electric power generation index constraint is given by Eq. (13) and the plant capacity utilisation constraint index is expressed as Eq. (14).

$$Z_1 = \alpha_0 + \alpha_{11}x_1 + \alpha_{21}x_2 + \alpha_{31}x_3 \tag{13}$$

$$Z_2 = \bar{\alpha}_0 + \alpha_{12}x_1 + \alpha_{22}x_2 + \alpha_{32}x_3 \tag{14}$$

The coefficients ($\alpha_0, \bar{\alpha}_0, \alpha_{11}, \alpha_{21}, \alpha_{31}, \alpha_{12}, \alpha_{22}, \alpha_{32}$) in Eqs. (13) and (14) can be obtained using a suitable predictive model. Furthermore, Eqs. (13) and (14) can be substituted with non-linear interrelationships in models that accept these as inputs (e.g., artificial neural network and support vector machines).

The third objective (Z_3) considered is the maximisation of the future worth of the power plant (Eq. (15)). By considering Eqs. (16) and (17), the need to determine the operation hours and capacity of the plant is eliminated. This is because the quantity of electric power generated is a function of a plant's capacity and operation time. Thus, our interest is in the optimal unit cost of electric power generation. **Figure 3** shows the cash-flow diagram of sales and cost of electric power at different periods. The worth of the plant at any period t is expected to be less than its worth at period t-1, give that inflation does not occur at period t. One reason for the reduction of the future worth of the plant at period t is depreciation of installed equipment, which may be due to wear and tear of machine (turbines) parts. Depreciation cost is usually included during the analysis of the cost of electric power generation. For this study, depression cost is considered to be part of the unit cost of electric power generation. Furthermore, it is assumed that cost interest and repayment is part of the unit of producing electricity.

$$Z_3 = C(F/P,i,n) + \sum_{t=1}^{n}(S_{\bar{t}} - C_{\bar{t}}) * (F/P,i,n) \tag{15}$$

$$\bar{x}_2 = (1 + \bar{p}\%)x_2 \tag{16}$$

$$C_t = Q_{1\bar{t}} x_2 \tag{17}$$

$$S_t = Q_{2\bar{t}} \bar{x}_2 \tag{18}$$

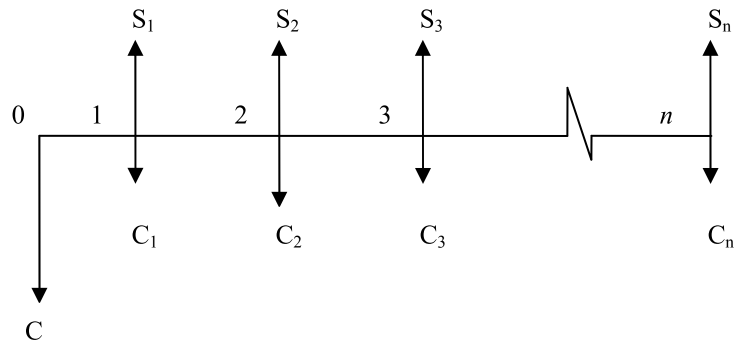


Figure 3 Cash-flow diagram.

To further constrain the values of the decision variables, a benefit-cost ratio of cash inflow and outflow is considered (Eq. (19)). This is necessary in order to ensure that the proposed model generates values for the plant that are viable at each period.

$$\frac{Q_{1t}\bar{x}_2(P/F, i, n)}{Q_{2t}x_2(P/F, i, n)} \geq 1 \tag{19}$$

Other sets of constraints considered are the bounds on x_1, x_2 and x_3 and are defined as follows;

$$x_{Li} \leq x_i \leq x_{Ui} \qquad \forall i \tag{20}$$

Meta-heuristics

Meta-heuristics are solutions methods for solving mathematical (linear and non-linear) models; these models can either be constrained or unconstrained models. Two commonly used meta-heuristics groups in the artificial intelligence domain are evolutionary algorithms (genetic algorithm, differential evolution) and swarm algorithms (particle swarm algorithm, bat algorithm). Other meta-heuristics which are gaining recognition are the big-bang big-crunch algorithm [37], firefly algorithm [38], simulated annealing [39], harmony search algorithm [38] and ant colony optimisation algorithm [40]. The stochastic search attribute of meta-heuristics have given them edge over conventional optimisers like Newton-Raphson, big-M and branch and bound methods.

A. Real Coding Genetic algorithm

RCGA is a meta-heuristic modelled after the concept of evolution, and it hinges on the concept of survival of the fittest $\left(f(x_i^t)\right)$ among individuals in a population [41]. The basis procedure of RCGA involves mutation, reproduction (crossover) and selection operations. During the early introduction of RCGA, its coding is done using binary strings. Recent studies have showed that the coding of Genetic Algorithm (GA) using a real-coding method has the benefits of generating improved solutions over binary coding method [42]. The first operation deals with the generation of mutant vector (Eq. (21)). The decision on whether to allow a selected parent (x_i^t) to undergo mutation is determined using the concept of flipping an unbiased coin, and this depends on the relationship between a random number (0,1) and mutation rate. The value of x_i^t is increased when a head occurs and decreased when a tail occurs [42].

$$x_i^t = \begin{cases} x_i^{t-1} + \bar{\delta}\left(x_{\max} - x_i^{t-1}\right) \\ x_i^{t-1} - \bar{\delta}\left(x_i^{t-1} - x_{\min}\right) \end{cases} \tag{21}$$

where $\bar{\delta}$ is a constant parameter that lies between (0,1).

Trial vectors are generated during the reproduction operation. To achieve this, 2 parents (x_i^{t-1}) are randomly selected from the selection pool $\left(P_i\right)$ and then used in reproducing 3 off-springs (x_i^t), as expressed in Eq. (22). Among the 3 offspring, the best 2 are selected and allowed to compete with the existing individuals in the population for survival to the next generation.

$$P_1, P_2 = \begin{cases} O_1 = 0.5P_1 + 0.5P_2 \\ O_2 = 1.5P_1 - 0.5P_2 \\ O_3 = -0.5P_1 + 1.5P_2 \end{cases} \tag{22}$$

In the third operation, determinations of individuals which will survive to the next generation are evaluated. The selection process is usually between x_i^{t-1} in the selection pool and x_i^t . For a minimisation problem, a simple selection criterion is expressed as Eq. (23).

$$x_i^t = \begin{cases} x_i^t & \text{If} \quad f(x_i^t) \le f(x_i^{t-1}) \\ \\ x_i^{t-1} & \text{Otherwise} \end{cases} \tag{23}$$

The value of $\bar{\delta}_t$ decreases with an increase in the iteration step and it is estimated at each iteration step using Eq. (24).

$$\bar{\delta}_t = \bar{\delta}_{t-1}(1 - r^{(1-t/T)^{\bar{B}}}) \tag{24}$$

where $\bar{B}$ is a constant parameter that the lies between (1,5), t is the current iteration step value, T is the maximum iteration step attainable, and r is a random number that lies between 0 and 1 [42].

B. Particle Swarm Optimisation (PSO) algorithm

PSO algorithms are population-based stochastic algorithms which have the capacity in generating near-optimal solutions for linear and non-linear models. It was originated based on the characteristics of swarms (fish, bird) in relating with one another [41]. To achieve the task of generating near-optimal solutions for a problem of interest, the positions and velocities of the particles in a swarm are updated at each iteration step. In the standard PSO algorithm [43], the velocity of a particle is updated using the particle cognitive (personal best solution) knowledge (x_i^p), social (global solution) knowledge (x_i^g) of the swarm, its previous velocity (v_i^{t-1}) and position (x_i^{t-1}), inertia weight (w_t) and other constant parameters. The combination of these parameters is expressed as Eq. (25).

$$v_i^t = w_t v_i^{t-1} + c_1 r_1 \left(x_i^{p,t-1} - x_i^{t-1}\right) + c_2 r_2 \left(x_i^{g,t-1} - x_i^{t-1}\right) \tag{25}$$

$$w_t = w_{\max} - \frac{w_{\max} - w_{\min}}{t_{\max}} t \tag{26}$$

where c_1 and c_2 are constant parameters, r_1 and r_2 are random parameters whose value lies between (0,1), t_{max} is the total number of iterations, w_{max} is maximum value of inertia weight and w_{min} is minimum value of inertia weight.

In order to control the exploitative and explorative capacity of PSO algorithms, the velocity of particles are usually capped, this allows each particle velocity in a swarm to oscillate between a minimum ($v_i^{\min}$) and a maximum ($v_i^{\max}$) velocities. The values of $v_i^{\min}$ and $v_i^{\max}$ are problem dependent (Rini *et al*. 2011), and may be estimated using Eqs. (27) and (28).

$$v_i^{\max} = \delta\left(x_i^{\max} - x_i^{\min}\right) \tag{27}$$

$$v_i^{\min} = \delta\left(x_i^{\min} - x_i^{\max}\right) \tag{28}$$

where δ is a constant parameter that lies between (0,1).

Engelbrencht [41] reported that a simple velocity capping scheme is expressed as Eq. (29).

$$v_i^t = \begin{cases} v_i^{\max} & \text{If } v_i^t \geq v_i^{\max} \\ v_i^{\min} & \text{If } v_i^t \leq v_i^{\min} \\ v_i^t & \text{If } v_i^{\min} \leq v_i^t \leq v_i^{\max} \end{cases} \tag{29}$$

The generations of new positions for the particles in a swarm are obtained by combining the values of v_i^t and x_i^{t-1} (Eq. (30)).

$$x_i^t = v_i^t + x_i^{t-1} \tag{30}$$

C. Big-Bang Big-Crunch (BB-BC) algorithm

The BB-BC algorithm mimics the evolution of the universe using the concept of attraction of particles (big-crunch) and the disintegration of particles (big-bang). The application of BB-BC algorithm involves the determination of the center of mass in generating new particles. In the BB-BC literature, the center of mass [44,45] is computed after the end of each generation using Eq. (31). However, some researchers take the center of mass (x_{ig+1}^c) as the value of the global solution in a particular generation. The value of the new decision variables are determined using a random number (R) that lies between (-1,1), the range of the decision variables, the constant parameter ($\hat{\delta}$), step-size (g) and the center of mass of decision variables [45], as shown in Eq. (31).

$$x_{ig+1}^{c} = \frac{\sum_{i=1}^{m} x_{ij}^{g} / f\left(x_{ij}^{g}\right)}{\sum_{i=1}^{m} 1 / f\left(x_{ij}^{g}\right)} \tag{31}$$

$$x_{ij}^{g} = x_{ig+1}^{c} + R\hat{\delta}\,\frac{(x_i^{\max} - x_i^{\min})}{g} \tag{32}$$

The novelty of the proposed integrated power generation and capacity model can be studied as follows: (1) the model has the ability to monitor uncertain attributes of the variables of concern (such uncertainties including fluctuations in the machine breakdown, generation unit cost); (2) a simple, practical and novel approach that compares the performance of 2 predictive methods, ARIMA and a robust regression model has been explored for the first time; (3) the integration of cost decisions variables with plant reliability measures and power generation variables in new and not previously studied way from an in-sample and out-sample perspective.

Case study

The case study used in this paper is drawn from an electric power generation plant located in the western part of Nigeria. At the time in which the datasets used in this paper were collected from the plant, the annual electricity generated stood at approximately 5.4 million Megawatt Hours (MWH) while the achieved amounts of electricity sent out from the plant was approximately 5 million MWH. The differences in the amounts of electricity generated and the energy sent out constitute the amounts of electric energy utilised within the plant. Datasets for 3 consecutive years were collected from the plant and this accounted for a total of 36 datasets used in this paper. These datasets consist of information on monthly unit electric power generation cost, plant reliability index, breakdown maintenance index, electric power generation index and the plant capacity utilisation index.

To improve the quality of results from the predictive models used in this study, 26 randomly selected datasets (in-sample) were used in developing 2 prediction equations. The remaining datasets, which serve as the out-sample datasets, were used in validating the performance of the developed predictive models.

Using expert modeller in the SPSS software on the in-sample datasets, the ARIMA model for electric power generation index (y_{11}) was (0 0 0) and the predictive equation obtained for this ARIMA model is represented in Eq. (33). The robust regression model is implemented using the STATA software and Eq. (34) was obtained as the predictive equation for the electric power generation index (y_{12}).

$$y_{11} = 145.647 - 0.233x_1 - 17.395x_2 - 0.478x_3 \tag{33}$$

$$y_{12} = -1.869 + 0.431x_1 + 6.406x_2 + 0.202x_3 \tag{34}$$

when Eqs. (32) and (33) were applied to the in-sample and out-sample datasets, **Figures 4** and **5** were obtained.

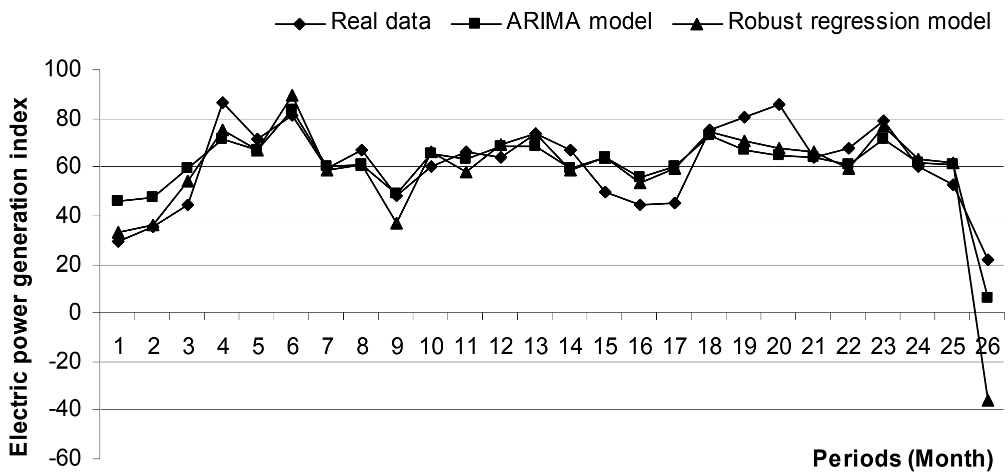


Figure 4 Comparison of prediction values for the electric power generation index using the in-sample datasets.

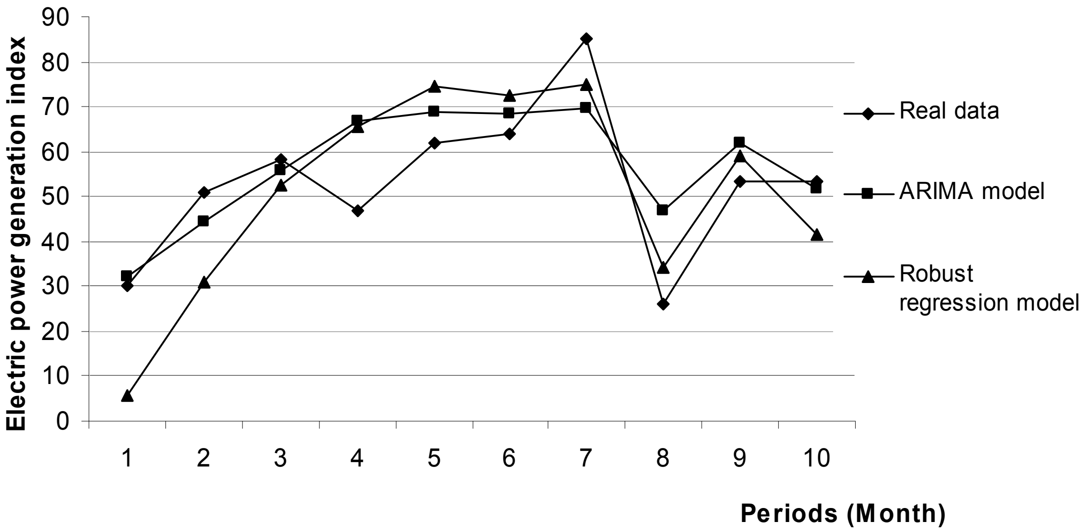


Figure 5 Comparison of prediction values for the electric power generation index using the out-sample datasets.

For the electric power plant capacity index, ARIMA (0 0 0) was obtained from the expert modeller in the SPSS software. The prediction equation obtained using this ARIMA model was observed to be approximately the same as that of the robust regression model. **Figures 6** and **7** were obtained when the generated equations from the developed ARIMA and robust regression models were utilised in computing the prediction values for the in-sample and out-samples electric power plant capacity index datasets.

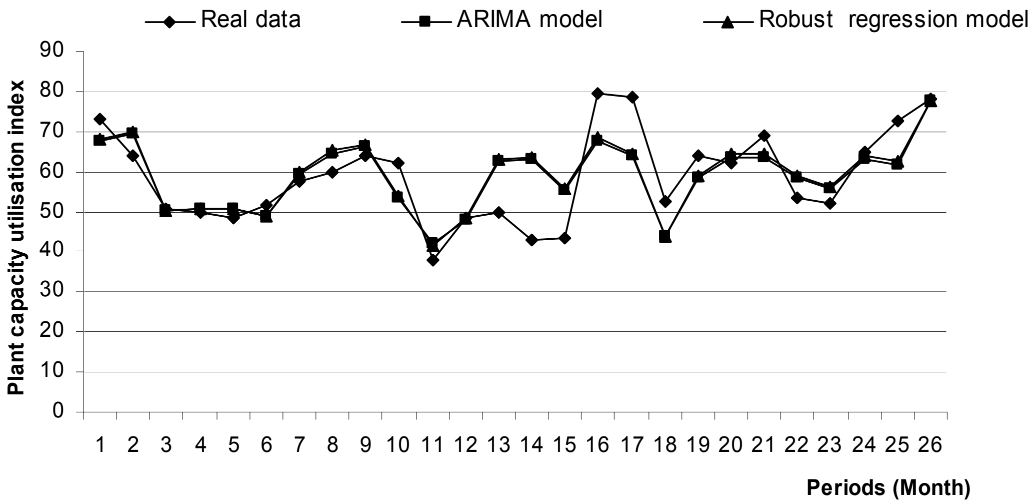


Figure 6 Comparison of prediction values for the plant capacity utilisation index using the in-sample datasets.

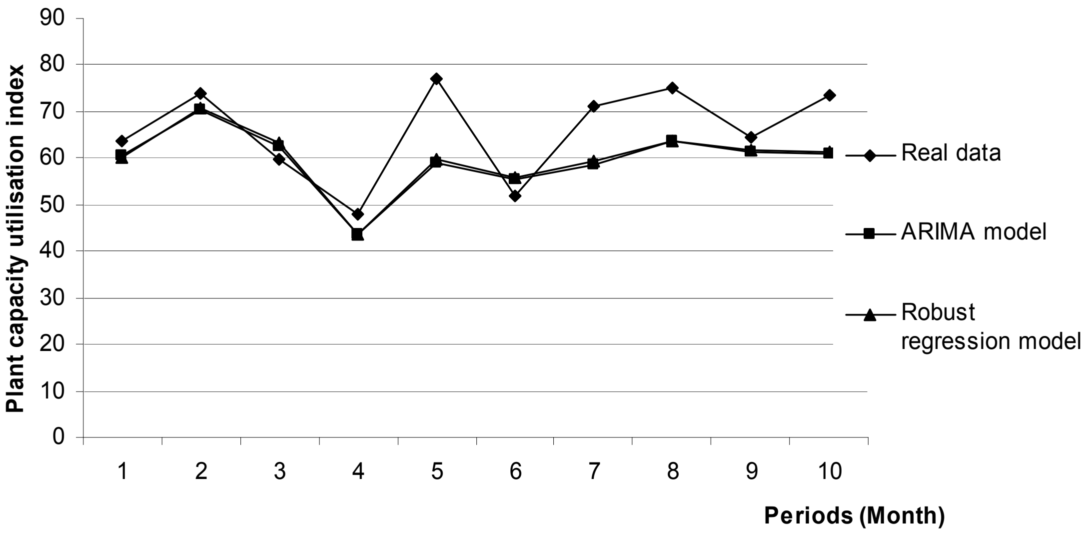


Figure 7 Comparison of prediction values for the plant capacity utilisation index using the out-sample datasets.

We utilized the MAPE in evaluating accuracy of the developed ARIMA and robust regression models in this paper, as presented in **Table 1**. The application of Eqs. (9) - (12) generates the linguistic values in **Table 1**.

Table 1 Mean absolute percentage errors for predictive models.

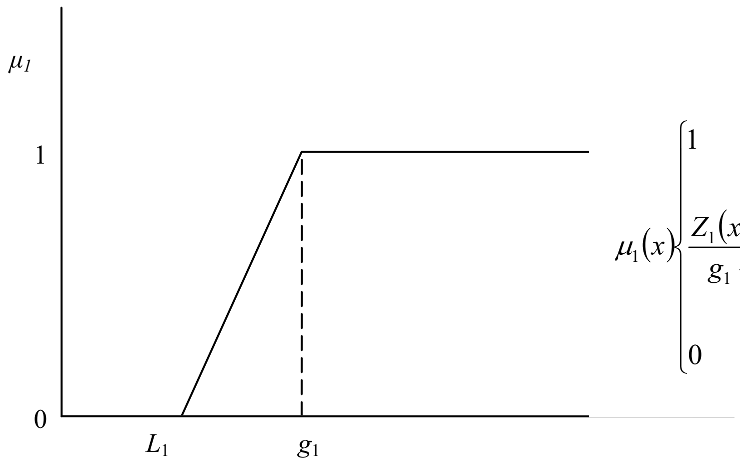
		Electric power generation Index		Plant capacity utilization index	
		ARIMA model	**Robust regression model**	**ARIMA model**	**Robust regression model**
In-sample datasets	Crisp value	17.06	21.66	0.02	0.03
	Linguistic value	Good forecasting	Reasonable forecasting	Highly accurate forecasting	Highly accurate forecasting
Out-sample datasets	Crisp value	20.13	28.01	10.75	10.71
	Linguistic	Reasonable forecasting	Reasonable forecasting	Good forecasting	Good forecasting

In order to determine the overall performance of the developed predictive models, the weighted average defuzzification method was used in combining the MAPE for electric power generation and plant capacity utilisation indices. The crisp values obtained for the 2 prediction models are depicted in **Table 2**. The interpretation of these values in linguistic terms is presented in **Table 2**, achieved using **Figure 2**.

Table 2 Overall performance of the predictive models.

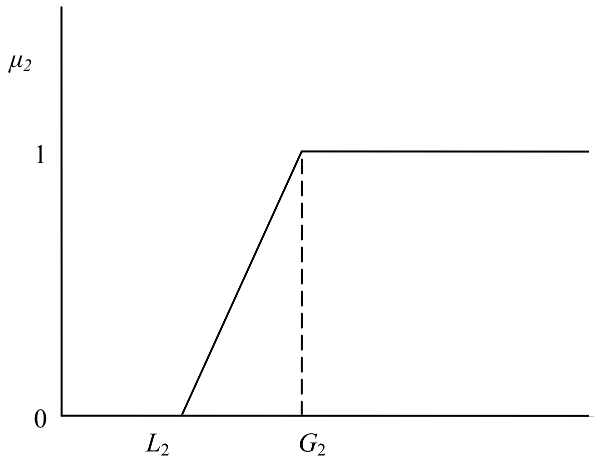
		ARIMA model	**Robust regression model**
In-sample datasets	Crisp value	8.82	10.86
	Linguistic value	Good forecasting	Reasonable forecasting
Out-sample datasets	Crisp value	10.36	19.40
	Linguistic value	Reasonable forecasting	Reasonable forecasting

From the above results presented in **Tables 1** and **2**, the ARIMA models are selected in generating the coefficient in Eqs. (13) and (14). The handling of the multi-objective is carried out using the weighted fuzzy goal programming approach. The membership functions in **Figures 8 - 10** are designed for the 3 objective functions in the proposed model [46]. In **Figures 8** and **9**, L_i and G_i are the lower and upper limit of the *i*-fuzzy goal, respectively. μ_i is the membership function for the *i*-fuzzy goal.



$$\mu_1(x)\begin{cases} 1 & \text{If } Z_1(x) \geq g_1 \\ \dfrac{Z_1(x)-L_1}{g_1-L_1} & \text{If } L_1 \leq Z_1(x) \leq g_1 \\ 0 & \text{If } Z_1(x) \leq g_1 \end{cases}$$

Figure 8 Membership function for the plant reliability index.



$$\mu_2(x)\begin{cases} 1 & \text{If } Z_2(x) \geq g_2 \\ \dfrac{Z_2(x) - L_2}{g_2 - L_2} & \text{If } L_2 \leq Z_2(x) \leq g_2 \\ 0 & \text{If } Z_2(x) \leq g_2 \end{cases}$$

Figure 9 Membership function for the plant capacity utilisation index.

Using the weighted fuzzy goal programming model, the summary of the proposed model is presented as follows;

$$\text{Min } Z = \sum_{k=1}^{3} w_k \frac{\delta_k^-}{\Delta_{kR}} \tag{35}$$

subject to:

$Z_1 + \delta_1^- \geq b_1$ (Maximising the electric power generation index)

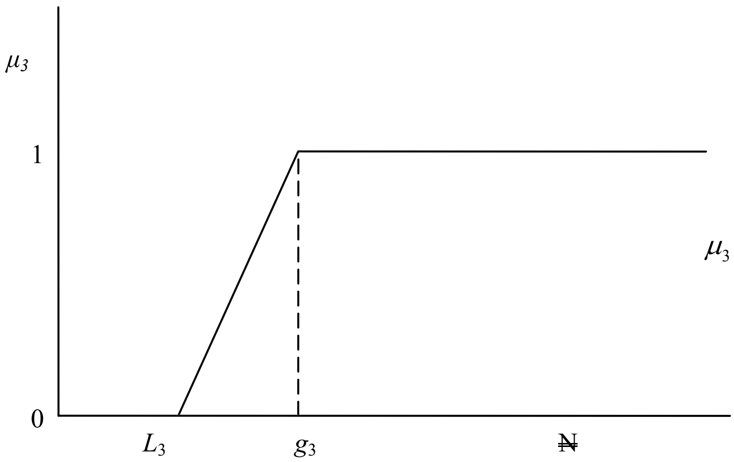
$Z_2 + \delta_2^- \geq b_2$ (Maximising the plant capacity utilisation)

$Z_3 + \delta_3^- \geq b_3$ (Maximising the future worth of the plant)

$$\frac{Q_{2t}\bar{x}_2(P/F, i, n)}{Q_{1t}x_2(P/F, i, n)} \geq 1 \ \forall n$$

$$x_{Li} \leq x_i \leq x_{Ui} \ \forall i$$

$$\mu_k + \frac{\delta_k^-}{\Delta_{kR}} \leq 1 \ \forall k$$



$$\mu_3(x)\begin{cases} 1 & \text{If } Z_3(x) \geq g_3 \\ \dfrac{Z_3(x)-L_3}{g_3-L_3} & \text{If } L_3 \leq Z_3(x) \leq g_3 \\ 0 & \text{If } Z_3(x) \leq g_3 \end{cases}$$

Figure 10 Membership function for the future worth of the plant.

During the testing of the proposed model, i is taken as 20 %, and n as 5 years. The quantities of electric power expected to be generated for 5 consecutive periods is simulated around the quantities of electric power generated between 2 historical quantities of electric power that was generated from the plant (3,383,990.3 and 5,385,475.96 MWH). The range of electric power sent-out to prospective customers is between 93 and 97 %. The plant consists of 6 gas turbines that were installed at different periods. The average capacity of the turbine is 220 MW and this gives a plant rating of 1320 MW. The approximate cost of a plant rating of this size in 2012 is about ₦ 297 billion, which is about $1.1 billion [47]. Some of the gas turbine are fired using natural gas while others are fired using low pour fuel oils (LPFO) or high pour fuel oils (HPFO).We desired that the worth of the plant at the end of period n should be at least 60 % (₦ 178.2 billion) of the total installed capital cost of the plant.

The minimum and maximum values for x_1, x_2 and x_3 datasets that are utilised in applying the proposed optimisation model are shown in **Table 3**. Similarly, the partition of membership functions for the 3 objective functions are contained in **Table 3**. The simulated values for the quantities of electricity generated and sent-out to prospective customers are depicted in **Table 4**. Currently, the size of the maintenance crew of the plant is about 194 workers and their annual expense is about ₦ 500 million. Man power utilisation of the plant is between 83.79 and 95.75 %. The major maintenance work in the plant are repair of the cold reheat pipes, tap-off steam pipes, hydraulic snubbers, boilers and valves (1/AS-V-251, 2/FW-V-252, 4/FW-V-213B2 and 4/MV-V-1). The volume utilisation efficiency of the plant per year is between 0.0110 and 0.0118. The plant has a value of between 6.16 and 7.96 % as energy utilised by the generating station.

Table 3 Decision variables settings.

Variables	Minimum	Maximum
X_1	31.96	98.38
X_2	0.644	4.61
X_3	63.67	97.72
$L_{1\ and}\ G_1$	40 and 70	
$L_{2\ and}\ G_2$	40 and 80	
$L_{3\ and}\ G_3$	₦ 1500 billion and ₦ 4000 billion	

Table 4 Expected quantities of electricity generated and sent-out.

Years	Expected power to be generated annually (MWH)	Proportion of power to be sent-out	Expected power to be sent-out annually (MWH)
1	4,135,185	94.50	3,907,802.40
2	4,656,856	95.54	4,449,339.50
3	3,724,124	93.68	3,488,750.90
4	3,488,924	93.21	3,252,016.30
5	5,199,283	96.63	5,023,957.30

To evaluate the performance of the BB-BC algorithm, we selected the particle swarm optimisation (PSO) algorithm and GA as 2 other solution methods for comparative purposes. The weights for objective functions are taken as 0.3, 0.3 and 0.4 for plant reliability index, generation unit cost and the future worth of the plant, respectively. The mutation rate for the RCGA was 45 %, while crossover rate was 15 %. The value for C1 in the PSO was 1.2 and C2 was 0.7. The maximum inertia weight in the PSO was 0.9, while the minimum inertia weight was 0.4. The total number of iterations for each of the algorithm was 300, while the population size was 50. The evaluation of the algorithm was based on the quality of solution and execution time. The evaluation of the different meta-heuristics performance is based on 50 different runs (**Figure 11**).

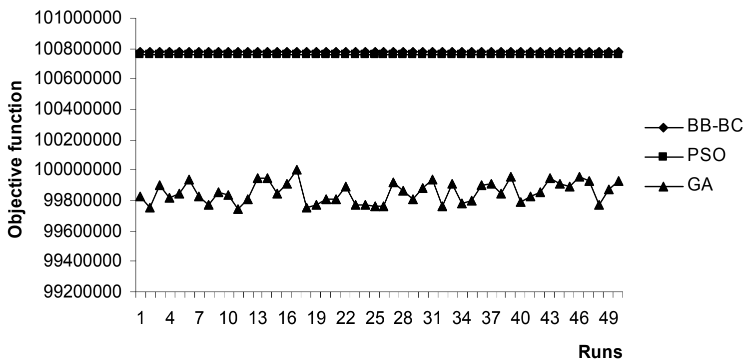


Figure 11 Values of objective function using different solution method at different runs.

The performance analysis of these solution methods are shown in **Table 5**.

Table 5 Analysis of the selected solution methods performance.

Methods	BB-BC	PSO	GA
Quality of solution	153,082,209.00	95,001,716.00	94,999,855.53.00
Execution time (s)	94.60	115.57	376.39

Discussion of results

The information presented in **Figures 3** and **4** show that the performance of the ARIMA model in predicting electric power generation index is more satisfactory than that of the robust regression model. The lower performance of the developed robust regression model may be attributed to uneven distribution of power generation index obtained from the case study. However, it could still be used as an alternative to ARIMA. It can be seen that the developed robust regression model was able to predict some of the data points closely for the in-sample datasets as shown in **Figure 4**. This implies that the developed regression model may generate satisfactory results from datasets within the limits of the in-sample datasets. **Figure 5** shows that the 2 predictive models are not able to predict the electric power generation index for the out-sample datasets. Since the MAPE presented in **Table 1** are classified as being reasonable, it can be inferred that neither of the predictive models can be used to predict out-sample electric power generation indices.

Some operational measures that could improve the performance of the plant are listed as follows:

- The introduction of a policy that will award bonuses to teams that are able to rectify the largest amounts of defects reported during a particular time interval. This will improve the breakdown maintenance indices;
- A well coordinated information management system between maintenance and planning sections. This will enhance planning decision on allocations of available resources for maintenance activities;
- Improvement in spare parts management. This will reduce shutdown of installed facilities as a result of shortage in spare parts;
- Periodic training of maintenance personnel. This will reduce the dependence on expatriates during maintenance activities especially overhaul activities;
- Establishment of improved monitoring teams. This will improve the quality of maintenance work in the plant; and
- Improvement in supply of natural gas and HPFO to the electric power plants within the study area will boost electric power generation.

The results presented in **Figures 6** and **7** show that the predictive capacity of ARIMA and modified roust regression models developed in this study are close. The improved performance of the developed robust regression model could be attributed to less fluctuation in the plant capacity utilisation index datasets obtained from the case study. The prediction error using out-samples datasets showed that the robust regression model performed better than the ARIMA model (**Table 1**). A reverse experience was observed for the in-sample datasets. However, the conversion of the crisps predictive value errors into linguistic values show that ARIMA model is a model suitable model for plant capacity utilisation index prediction. Thus, it may be inferred that the selection of predictive model for electric power generation plant performance should be based on at least 2 error values for different performance indices in an electric power generating plant. This will minimise the mistake of selecting a less accurate model as shown in **Table 2**.

From the application of the proposed model, it has been observed that the RCGA algorithm performed better than the BB-BC and the PSO algorithms in terms of the quality of the solution. In terms of execution time, the BB-BC algorithm has the lowest execution time, while the RCGA has the highest execution time (**Table 5**). Given that the quality of the solution is more important than the execution time of the algorithms, the RCGA algorithm was the best solution method for the proposed model (**Table 6**).

Table 6 Pareto solution for decision variables.

Electric power variables	Optimal values
Objective function	9.50
Plant reliability index (x_1)	72.16
Generation unit cost (x_2)	₦ 1.16
Breakdown maintenance index (x_3)	66.06
Electric power generation index (Z_1)	77.04
Plant capacity utilisation index (Z_2)	50.00
Future worth of the plant (Z_3)	₦ 1500 billion

$1 = ₦ 270

These results show that there is need for the plant to be operated at a high level of plant's reliability and breakdown indices. To improve the plant generation capacity index, certain operational measures will have to be put in place. Such measures should be able to reduce the unit cost electric power generation and increase plant reliability indices.

Conclusions

In this paper, we have successfully carried out an empirical study on 2 selected prediction models that can be used for estimating electric power generation and plant capacity utilisation. Based on the MAPE and fuzzy logic modelling approach, the ARIMA model was identified as the most suitable predictive model for the case study considered. However, the robust regression model developed yielded satisfactory results that were close to the practical datasets obtained from the case study. We also proposed a multi-objective optimisation model using the 2 developed predictive equations for electric power generation and plant capacity utilisation indices and the future worth of the power plant as objective functions to be maximised. Furthermore, RCGA was selected as a suitable optimiser for the proposed model based on a comparative study with PSO and BB-BC algorithms performance. The results from the proposed optimisation model provide insights into the optimal values of electric power generation and plant capacity utilisation indices that should be expected at near-optimal values of breakdown maintenance index, unit cost of electric power generation and plant capacity utilisation index. There is the possibility of extending the work presented using more data and other predictive models like artificial neural networks and fuzzy logic models. The effects of opportunity cost when running the plant at a partial load on the performance of the model can be investigated as a further study.

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