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# POWER DEMAND FORECASTING AND GENERATION ADEQUACY IN NIGERIA UP TO 2040

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## Abstract

*The availability and reliability of power supply in Nigeria are critical issues, undermining economic and technological development. Despite policy reforms and capital investments, inadequate generation capacity and poor power system planning continue to limit progress. This study introduces a comprehensive approach to long-term power system planning in Nigeria, combining intelligent load forecasting with generation adequacy assessment up to 2040. An Adaptive Neuro-Fuzzy Inference System (ANFIS) model was developed to forecast future electricity demand, projecting a load requirement of approximately 87,304.08 MW by 2040. A metaheuristic approach utilizing the Disparity Evolution Genetic Algorithm (DEGA) was implemented to assess system adequacy. Results revealed that the current generation capacity of 4,500MW is significantly inadequate, necessitating an additional 101,564.5 MW, or 5,071.11MW annually, to maintain acceptable reliability standards. Furthermore, using a Levelized Cost of Electricity (LCOE) model under fossil-fuel-based generation assumptions, an annual investment of $3,887,005,815.52 was determined to support the expansion. These findings underscore the critical need for accurate demand forecasting, robust adequacy assessment, and strategic investment planning to ensure long-term energy security and sustainable development in Nigeria.*

## 1.0 INTRODUCTION

In today's world, no nation can achieve sustainable poverty reduction without a significant increase in energy utilization. Higher energy consumption is often associated with increased income levels and improved human development indexes [1]. Modern development trends have driven a substantial increase in electricity consumption across multiple sectors, including communication, agriculture, transportation, and industry, owing to its versatility and ease of transmission and distribution. As such, electricity has become the backbone of economic development, particularly in Nigeria, where it plays a critical role in supporting national income generation and developmental programs through foreign exchange earnings [2]. Nigeria's electricity demand has skyrocketed due to population expansion, accelerating industrialization, increased agricultural activity, and improved living standards [1]. This growth has resulted in a significant imbalance between its supply and national demand, where demand exceeds the available supply [3]. In light of this, the focus of energy policy has shifted toward ensuring the long-term availability, reliability, and sustainability of power supply to support economic growth.

Reliable power system planning is essential to meet future energy needs, requiring load forecasting and generation adequacy assessment. Load forecasting helps predict future energy requirements, while adequacy assessment evaluates the system's capacity to meet that demand under steady-state conditions. Reliability, in this context, encompasses not only the generation of sufficient power but also the infrastructure for its delivery to end users [4], [5]. While system security deals with the response to dynamic disturbances, adequacy centers on the availability of facilities to meet forecasted loads [6]. Long-term planning that holistically integrates these dimensions is essential for establishing a resilient and economically sustainable power system in Nigeria.

Different approaches to load forecasting have been investigated in the literature. Notable among these approaches are time series regression, Autoregressive Moving Average (ARMA) with exogenous variables (ARMAX), Autoregressive Integrated Moving Average (ARIMA) with exogenous inputs (ARIMAX), and exponential smoothing. The time series approach assumes that load is modeled as a function of past observed values. Similar to the ARMA [7] and spectral expansion techniques [8], the regression model detects and explores the correlation between load patterns and weather variations [9]. These models have gained diverse applications. For instance, [10] carried out load prediction of electricity demand for a power system employing the ARIMA modeling technique. Studies [11-14] utilized various methods for load demand forecasting, including ARMAX [11], ARIMA [12], ARIMAX [13], and regression analysis [14]. While these methods offer computational simplicity and flexibility, they primarily rely on linear analysis, limiting their ability to model complex nonlinear relationships inherent in load demand influenced by exogenous variables. Moreover, manual computation techniques used in these methods require an exact system model, reducing their adaptability to dynamic and evolving power systems.

Recently, the application of Artificial Intelligence (AI) methods for predicting issues in power systems has been actively investigated. Among the available AI-based techniques, Neural Networks (NN) models have received serious attention due to their potential to capture complex and nonlinear relationships among the input variables via the training processes with existing data [15]. Through this learning ability, NNs enable the modeling of any system, even for complex and nonlinear functions of the exogenous variables. However, challenges such as slow convergence have hindered their efficiency in real-time applications. The integration of NNs with faster processing systems has been proposed to address these limitations, yet their effectiveness in long-term forecasting for large-scale power systems, such as Nigeria's, remains insufficiently explored. This gap necessitates the development of an optimized AI-driven hybrid forecasting model, such as the adaptive neuro-fuzzy inference system, to enhance prediction accuracy and computational efficiency for long-term power demand forecasting in Nigeria.

Similarly, power system adequacy evaluation has been approached through analytical and numerical simulation techniques. The numerical simulation approaches were mainly used in present-day studies [16], [17] due to their computational accuracy and flexibility. Among the numerical simulation-based methods, intelligent-based algorithms have extensively been used [18], [19]. Despite their advantages, these methods often suffer from slow convergence, premature optimization, and high execution time [16], [20], limiting their efficiency in large-scale power system studies. Given Nigeria's growing energy demand and the need for a robust expansion strategy, an advanced adequacy assessment technique that overcomes these challenges is essential. Thus, this study fills a critical gap by developing a power demand forecasting model using ANFIS and evaluating Nigeria's generation adequacy using the disparity evolution genetic algorithm. It aims to provide a comprehensive and computationally efficient framework for long-term power planning, ensuring optimal generation expansion to meet Nigeria's electricity demand by 2040. This target year is selected due to projections indicating a 30% increase in global energy consumption by that time [21], driven by population growth, industrialization, and rising living standards.

This paper contributes to the body knowledge in the following ways:


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- It determined power demand in Nigeria up to 2040 using an intelligent forecast algorithm based on an adaptive neuro-fuzzy inference system.
- It assessed the adequacy of the country's existing power generation capacity employing a novel disparity evolution genetic algorithm.
- A strategic generation expansion plan is developed to ensure sufficient capacity to meet the power demand for the stated period.
- It determined the level of investment required for the projected power demand.

## 2.0 METHODOLOGY

The methodology used for the power demand projection model and the generation system adequacy evaluation is based on ANFIS architecture and DEGA respectively. The study first projected the load demand up to 2040 and subsequently carried out an adequacy assessment of the generating system. Following this, a generation expansion plan was developed to satisfy the projected load demand and maintain acceptable reliability standards. LCOE was subsequently determined to evaluate the economic viability of the expansion plan.

### 2.1 Data Collection

The following data were utilized in this research paper for load projection: yearly electricity consumption, population ~~(*Pop*)~~, gross domestic product, stock index, average ambient temperature, percentage relative humidity, and average precipitation. In addition, historical yearly data on generating plant unit capacity, hours of operation, forced outages, and peak electric power demand were employed for the adequacy assessment of the generating system. Furthermore, input parameters needed for the investment costing including annualized capital cost, operation and maintenance costs, fuel cost per unit, quantity of fuel per unit electricity, heat rate, capacity factor, discount rate, and lifetime of the generating plant were also used.

These data were obtained directly from the Central Bank of Nigeria Statistical Bulletin, National Bureau of Statistics (NBS), World Climate and Food Safety Chart International Energy Agency (IEA), and Nigerian Electricity Regulatory Commission (NERC). The collected data covered twenty years (1999 – 2018).

### 2.2 Design of the Network Model for the Power Demand Projection

The important socio-economic and environmental parameters that greatly influence long-term electricity consumption were selected as inputs to the network. These parameters include: the Yearly Electricity Consumption ($EleC_i$), Gross Domestic Product (*GDP*), Population (*Pop*), Stock Index (*Si*), average ambient Temperature ($T_{avg}$), percentage Relative Humidity (*Hum*), and Precipitation (*Prep*). The choice of these parameters was informed by the data available at the time of this research. Using these variables, a five-layer, feedforward neuro-fuzzy architecture shown in Figure 1 was designed for the load projection. The input variables were fuzzified using the fuzzy set consisting of two linguistic terms: {LOW, HIGH}, and the model then dynamically generated the associated fuzzy inference rules. The associated fuzzy inference rules were dynamically generated by the model. The final yearly electricity load demand for the given period was obtained at the output end of the network.

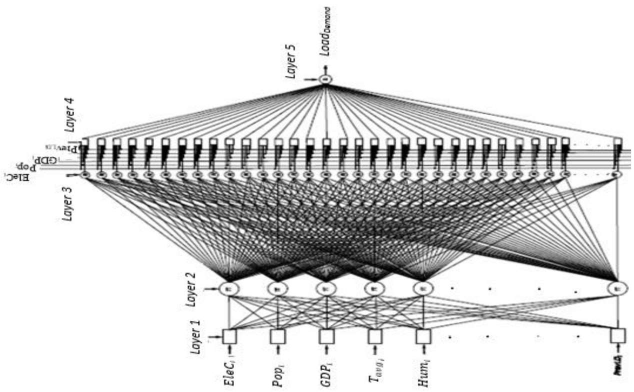


**Figure 1:** ANFIS architecture for the load projection

### 2.3 The Power Demand Processing Flow

The Levenberg-Marquardt algorithm was used for the network training. The inter-unit connections (i.e., the weighted links) across the different layers were iteratively optimized to minimize prediction error. This process continued until the forecast horizon was reached or no significant difference between successive iterations was observed. These weight adjustments helped the ANFIS model to effectively learn the complex relationship between the input and output variables. After training, the network was fed with new input vector samples, and the output was compared with the corresponding target values Validation was carried out to ensure that the network could accurately generalize the output vector for any given input vector. Following training and validation, the network was employed to predict electricity load demand. The power demand processing flow of the network model is illustrated in Figure 2. A detailed description of the ANFIS processing flow is provided in [22].


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### 2.4 Adequacy Assessment for Power Generation System

Adequacy evaluation of the generating system was carried out to investigate the aptitude of the system to satisfy the projected load request. The reliability index used for this purpose was Loss of Load Probability (LOLP). This index quantifies the probability that the system's load demand will exceed the available generation capacity at any given time. The evaluation process was implemented using DEGA, with the flow chart illustrated in Figure 3. At the beginning, the set of chromosomes referred to as the generation was initialized by choosing random binary numbers for their bits. A fitness evaluation test was carried out to determine the ability of the chromosomes to carry the forecasted load. A new generation with a higher fitness value was selected from the old generation. Through crossover and mutation operations, a final new generation was selected and stored in the state array. Only states whose permutations were not previously added were stored in the state array. The process was repeated using different generations until no significant improvement in fitness values was observed between successive generations or the total generation capacity was reached. A detailed step-by-step implementation of DEGA can be found in [23]. Once the final generation was determined, the LOLP index was calculated using the developed state arrays and the discrete convolution of hourly load values over one year.

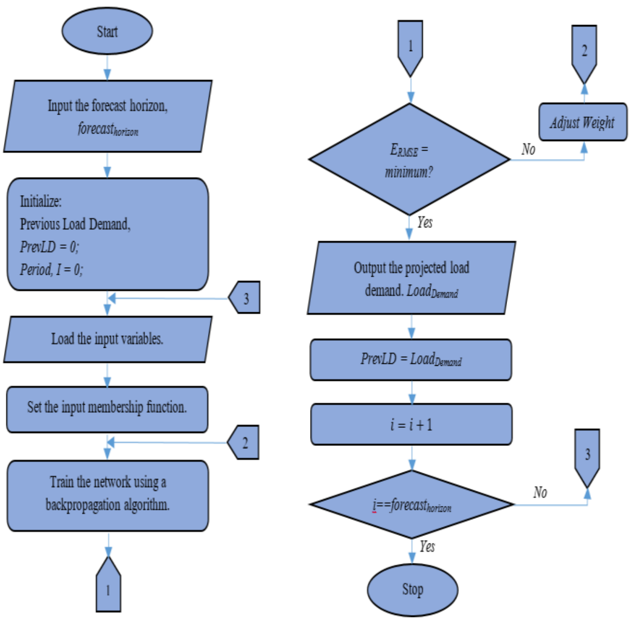


**Figure 2:** Power demand processing flow of the ANFIS model

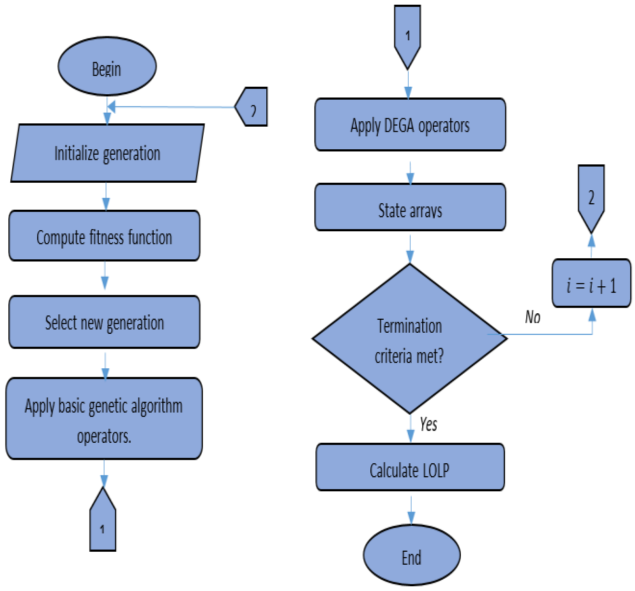


**Figure 3:** Flowchart for the adequacy evaluation

Representing the load value at hour "$i$" with "$LH_i$", the corresponding LOLP is calculated using Equation (1).

$$LOLP(LH_i) = \sum_{j=1}^{sa} S_j \,.\, P_j . Copy_j \quad (1)$$

where "$sa$" represents the total number of state arrays, while $S_j$ denotes the status of the system in state $j$, assigned a value of 0 if generation meets or exceeds load (success state), and 1 if it does not (failure state). $P_j$ is the probability of the system being in state $j$, and $Copy_j$ is the copy factor indicating the frequency of that state in the population.

It is important to note that, for the purpose of this study, it was assumed that the transmission network is adequately reinforced and capable of delivering the generated power reliably to all demand centers. This assumption allowed the analysis to focus exclusively on generation adequacy, with the understanding that transmission planning involves a separate consideration.

### 2.5 Investment Costing Model

The average per unit cost of electricity produced by any power plant is known as the levelized cost of electricity. It is a key indicator that was utilized in the evaluation of the costs with respect to the quantity of power generated during the fiscal life span of a plant and spinning through the whole energy generation process. In addition, early construction capital, as well as operations and maintenance costs were also involved. The LCOE was calculated using Equation (2).

$$LCOE = \frac{P + O\,\&\,M_f}{8760 * C_f} + (F_c * Q) + O\&M_v \quad (2)$$


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where LCOE was the levelized cost of electricity, $P$ depicted the early investment cost in putting up the generation plant station, $O \& M_f$ were the static operation and maintenance cost, 8760 was the total hours in a year, $C_f$ was the percentage capacity factor, or the ratio of the real energy output of the plant to the energy output if it were always running at full capacity, $F_c$ was the fuel cost, $Q$ depicted the plant heat rate and $O \& M_v$ gave the variable cost of operations and maintenance.

This model was implemented using data on investment cost, operation and maintenance costs, fuel cost, heat rate, capacity factor, and economic life of the generating plant, with the aid of MATLAB Toolbox.

The LCOE is determined solely based on economic cost components. It excludes all financial transfers such as subsidies, taxes, grants, and concessional loans from governments or development partners. Additionally, it does not account for environmental externalities associated with fossil fuel technologies, nor does it consider interest accrued during the construction period or the source and cost of financing (example, debt or equity).

## 3.0 RESULTS AND DISCUSSION

The performance of the ANFIS model after training was compared with that of the Auto-Regressive Integrated Moving Average (ARIMA) model on the same dataset. Figure 4 shows the validation results of the two models. The load demands (both actual and modeled values) were plotted against years from 2009-2018. Observations from Figure 4 show that the ANFIS model closely follows the variations in the actual load demand, unlike the ARIMA model for the given period.

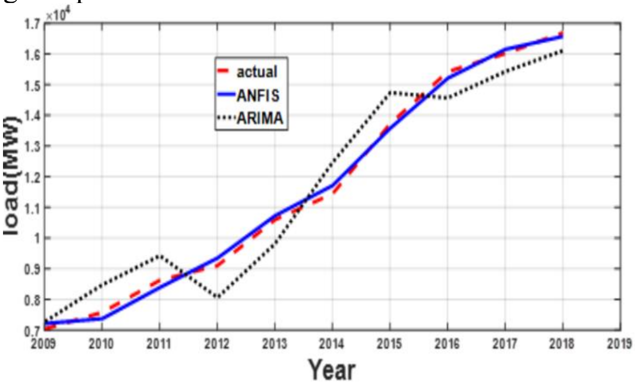


**Figure 4:** Validation results of ANFIS and ARIMA models

To determine how far the models were able to accurately forecast the load; error measures of the accuracy were employed. The models were evaluated using the Root Mean Squared Error (RMSE). The validation results showed that the ANFIS and the ARIMA models respectively have RMSE values of 193.84 and 816.76. The values were high; however, this is attributed to the small sample data size used for the study. A comparison of the two values showed that the proposed model has lesser accuracy error.

While RMSE dwells more on the forecast error, such information as the degree of the actual relationship of the modeled values with the actual value was not provided by this analysis tool. Therefore, the regression coefficient of the models was examined. The regression coefficients for the two models (ANFIS and ARIMA) were 0.9984 and 0.9718 respectively. Although both values are relatively high, suggesting good correlations, the ANFIS model demonstrated a slightly stronger relationship between the predicted and actual values. While the difference may appear marginal, it is reasonable to anticipate that with a larger dataset, the disparity in performance could become more pronounced. Given these observations, the ANFIS model was considered to offer better predictive accuracy and was therefore selected for load forecasting. Figure 5 shows the projected load demand in Nigeria up to 2040 using the ANFIS model.

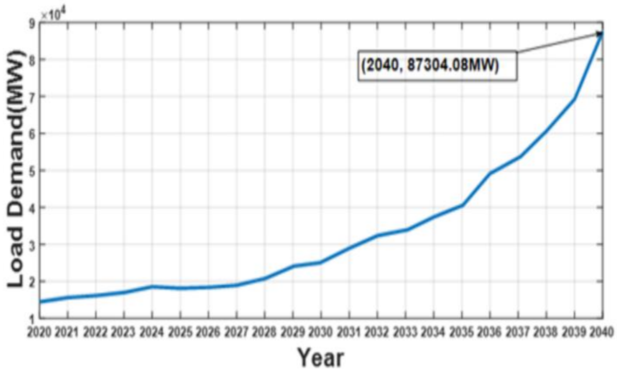


**Figure 5:** Projected energy demand in Nigeria up to 2040

### 3.1 Evaluation of the Base System LOLP

The LOLP simulation was based on the current available Nigerian generation capacity of 4,500MW [24]. The input parameters were loaded as matrices into the program. The program iteratively increments the generation, while computing the LOLP until the total generation capacity is reached. Figure 6 shows the variation of the LOLP with the generation capacity as seen in the output of the DEGA program. The LOLP was seen to reduce with the increased generation, meaning that an increase in the generation capacity increased the system's reliability. An average reliability threshold of 5% was adopted in this study for the adequacy assessment. The 5%, taken from expert analysis was considered the upper boundary for LOLP value when consideration is only technically based. Therefore, looking at Figure 6, it is observed that the LOLP reduced from 100% to 18% at the point where the generation capacity equals the available capacity. This is more than the 5% benchmark, thus, reducing the value further from 18% to 5% requires an additional generation capacity. In other words, this showed that the available generation capacity cannot match the present load demand.

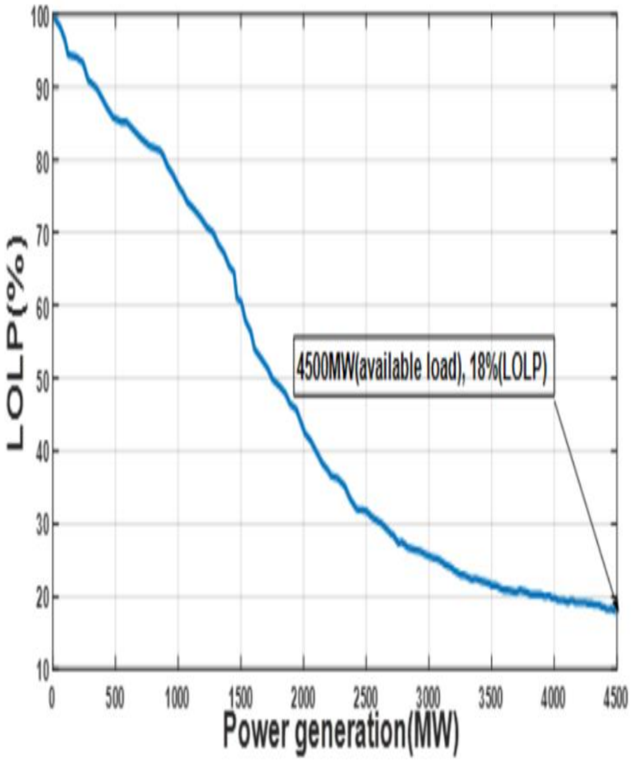


**Figure 6:** Variation of the LOLP with generation capacity

### 3.2 Analysis of the Impacts of the Load Forecast on the Base System Reliability

Using the 2040 projected load (87, 304.008MW) in Figure 4, the program iteratively increments the generation per annum until the forecasted load is reached. Figure 7 shows the effect of the forecasted load on the LOLP of the base power generation system. The result showed that the LOLP increased with the load series. It could be observed that with the projected load, LOLP increased from 18% to 97.73%, thus, indicating an inadequate system. To cushion the effects of this increase on the base system LOLP, additional generation capacity would be needed.

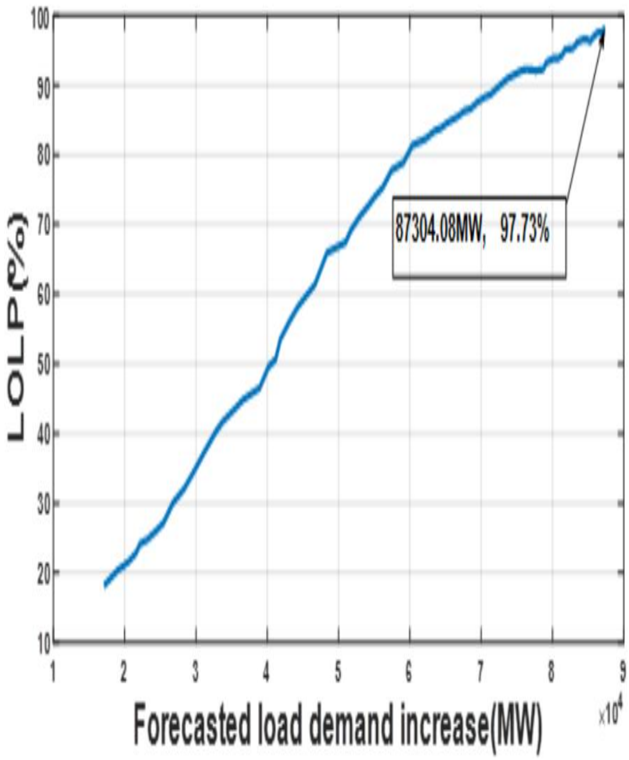


**Figure 7:** Effect of the forecasted load on the base system LOLP

### 3.3 Analysis of the Generation Expansion Plan

The study performed simulation using MATLAB Software to determine the additional generation capacity that would reduce the LOLP from 97.73% to 5% up to 2040. However, the yearly increment in the generation should be such that will keep the LOLP below 5% over the forecast horizon. Figure 8 shows the reduction in the LOLP with additional generation capacity. At point (101564.5MW, 5%), a plan that will provide an additional 101564.5MW by 2040 with 2020 as the base year is required. From the result, the reduction in LOLP from 97.73% to 5% due to the impact of the forecasted load is about 92.73%. With 2020 as the base year, the forecast horizon spans 20 years. 2020 was chosen as the base year due to its strategic significance in Nigeria's Vision 2020, which aimed to position the country among the world's top 20 economies through sustained economic growth of 11%–13%. As a key milestone year, it provides a meaningful reference point for assessing energy infrastructure needs and projecting future electricity demand toward 2040.

To guide the expansion strategy, a simplified approach was employed in which the 92.73% LOLP reduction was distributed evenly across the 20-year forecast horizon. This translates to an annual LOLP reduction of 4.63%, meaning that each year, an additional generation capacity sufficient to reduce


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LOLP by 4.63% is required. The equivalent annual generation capacity needed to achieve this is determined to be 5,071.11 MW. For simplicity, this study distributes the 92.73% Loss of Load Probability (LOLP) evenly over the 20 years; however, a more sophisticated approach that takes into account uncertainties and variability in demand could be explored in future research.

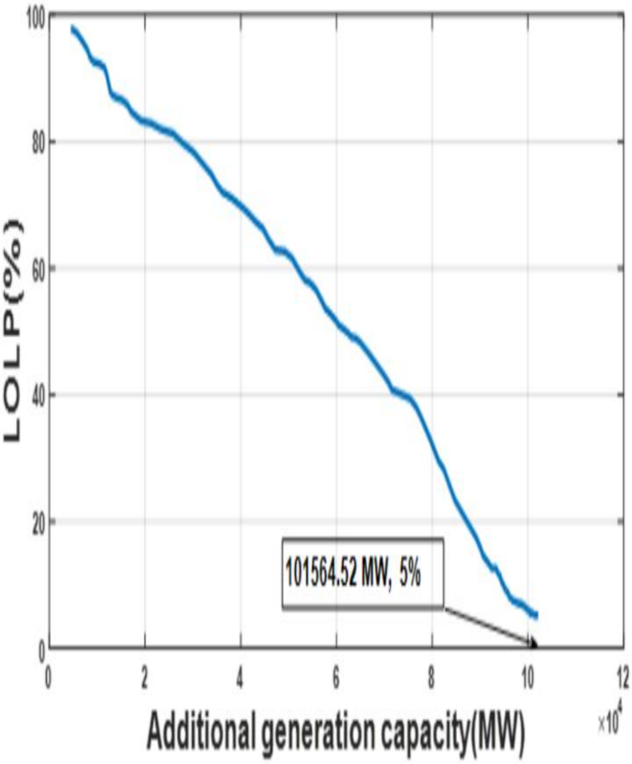


**Figure 8:** Reduction in LOLP with additional generation capacity

### 3.4 Determination of the Required Annual Investment

Based on the forecasted load, a generation capacity of 5071.11MW per annum is required to provide a LOLP of 4.63% to maintain the adequacy of the power generation. Assuming that the levelized life cycle cost of a fossil fuel power generator is about $125 per megawatt-hour (MWh) and a capacity factor of 70%, the cost per year of the expansion plan using Equation (2) is $3,887,005,815.52. The choice of Equation (2) was guided by its relevance to the economic context of the study and the availability of required data. It effectively captures key cost components, capital, operational, and fuel costs, normalized over energy output. Although alternative LCOE approaches exist, no direct comparison was made in this work, as the chosen model provides sufficient clarity and applicability for long-term electricity planning given the defined assumptions.

This investment cost did not take optimization in terms of types of generation technology, fuel type, generator unit size, and other factors into consideration.

## 4.0 CONCLUSION

This study successfully developed and implemented an intelligent forecasting framework for Nigeria's power system demand up to 2040, utilizing an adaptive neuro-fuzzy inference system. The model projected a load demand of approximately 87,304.08 MW by 2040. To evaluate generation adequacy, the disparity evolution genetic algorithm was employed. Findings revealed that the existing generation capacity is insufficient, necessitating an additional 101,564.5 MW to meet the forecasted demand.

The study further performed an economic evaluation to determine the investment requirement for this generation expansion. Utilizing a levelized cost of electricity (LCOE) model based on fossil-fuel generation assumptions, an annual investment of approximately $3,887,005,815.52 was calculated to meet the future demand.

Despite the comprehensive integration of load forecasting, adequacy assessment, and cost analysis, this study leaves room for further investigation. Future work could enhance the expansion modeling by incorporating renewable and hybrid generation technologies, as well as adopting more advanced methodologies that account for demand uncertainties and system variability. Additionally, alternative LCOE calculation methods could be explored for comparative analysis, alongside an evaluation of the impacts of financing mechanisms and policy incentives on generation planning and investment decisions.

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