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# ELECTRIFICATION STRATEGY FOR SUSTAINABLE RURAL AGRICULTURE: A LEAST COST ANALYSIS APPROACH

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## Abstract
*Electric energy is one of the most widely used form of energy around the globe and as such has the most dynamic means of impacting positively on economic development of any nation in the world. Therefore, to further grow the economy through increased agricultural productivity and rural development, there is an urgent need to address the issue of poor and ineffective rural electrification strategy for sustainable farm operations. Consequently, this paper presents a framework that uses intelligent load forecast, geospatial and cost-effective metric for the analysis of the economic optimality of grid extension, diesel and hybrid photovoltaic (PV)/diesel renewable power generation systems for rural farm operations. The historic national load demand data for 20 years obtained from the national bureau of statistics and central bank was used for the training and validation of the forecast model. The historic electric load data for the case study farm cluster (Adani Enugu Nigeria) was taken to be the electric energy equivalent of the contribution of Adani Enugu to the gross domestic product (GDP) of Enugu state. Input parameters to the neuro-genetic forecast model are the contribution of rice production to the national GDP, contribution of Adani Enugu farm cluster to the national GDP, electric energy consumption (EEC) per ton of rice produced at Adani Enugu and the annual population growth rate. From the simulations carried out, the economic viabilities of the generation options were assessed in terms of capital expenditure (CAPEX) and operational expenditure (OPEX). However, with a 93.84% decrease in CAPEX per kWh if massive investment and expansion of rice processing capacity were made over the forecast horizon, grid extension was found to have the lowest CAPEX. The OPEX for this generation option remained relatively steady for the mentioned condition. However, the approach presented in this paper can be integrated as core components in any generation analysis tool for driving support in optimal generation planning.*

## 1.0 INTRODUCTION
Poor and ineffective rural electrification strategy for sustainable farm operations has impacted on the socio-economic advancement of developing countries like Nigeria. This has inhibited the economic capacities and impacted negatively on food security of countries in sub-Saharan Africa. On the other hand, carrying out analysis in order to determine the least cost power generation options is a key component for the formulation of effective electrification strategies for sustainable farm operations. Thus, any measure that demonstrates the capacity to reduce costs of energy usage for agro-industries and also have socio-economic impacts as it relates to job creation and

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maintainable local community development should constitute a vital area of research [1].

Data driven analysis is a key requirement for determining the optimal electrification option for any use case scenario. With respect to data in this paper's case study, data on the location of the farm settlement is important, information regarding the geographical proximity of the farm community to the existing power grid infrastructure, electrical machineries used in the location etc. are very essential. A key component of the required data is to have information not only on the current load demand but also on the evolution of that demand over time [2]. That is where intelligent load demand forecast comes in since the basis of the generation capacity plan rests on the projected load demand to be provided. Hence to achieve accurate load demand forecast that considers the evolution of load over time, this paper proposes an intelligent meta heuristic load demand forecast model. This paper should be understood from the context of providing the analytic framework for adopting a least cost electrification strategy for a remote agricultural community.

As has been said, the accuracy of the analysis of various power generation technologies is impacted by the electric load demand forecasting model and its output evolution within a time horizon.The level of the accuracy of the load demand model is affected by the availability and reliability of data and information on example distribution and concentration of population, habitation, electricity load demand, GDP, farming operations etc. Also impeding the accurate economic analysis of generation technologies is the problem of infrastructure data gaps. Low quality (erroneous or inadequate) data set of grid networks (distance of functional infrastructure:transmission and distribution networks, power stations etc.) and other infrastructure like roads.

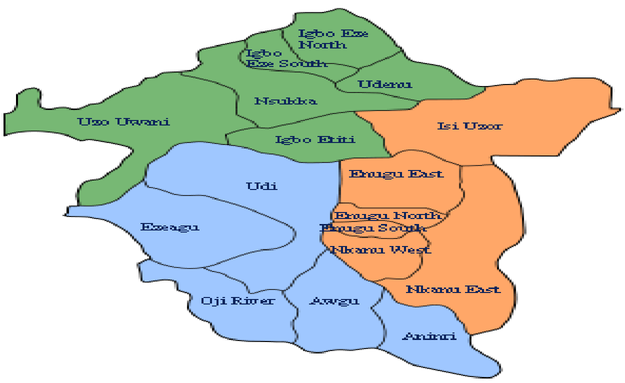


**Figure 1:** Map of Enugu State showing Adani-Uzouwani Local Government Area

Ultimately, with critical emphasis on our case study location which is a farm cluster in Adani, Uzo-uwani local government area of Enugu State, located at the eastern part of Nigeria, this paper addresses also the problems that impede the effective carrying out of accurate cost-benefit analysis for choosing the optimal power generation systems in the formulation of effective electrification strategy for sustainable agricultural operations. Figure 1 shows the map of Enugu State-Nigeria, case study location.

Considerably, critical data/methodological gaps that impact on accurate analysis of grid, diesel and hybrid renewable power generation systems for rural farm operations have been identified and also tackled in this paper:

(i) Hybrid meta heuristic electric load demand forecast model that combines econometric (top down) end-use (bottom up) variables and can work with incomplete, noisy and uncertain data is used in this paper to address the problem of scarce and unreliable electric load demand data.
(ii) The integration of geospatial analysis in the modeling of grid extension is used to address the problem of infrastructure data gaps.

Conclusively, we will be carrying out in this paper a Cost-Benefit Analysis over a planning horizon to compare the economic implications for implementing the grid extensions with those of diesel and solar hybrid power generation systems.

[3] carried out performance analysis of different power generation system scenarios. Analysis scenarios include all possible standalone diesel generators, hybrid PV/diesel/battery, and 100% PV/battery. Identified gap with this study is that the effect of the evolution of load (via forecast) was not accounted for in the modeling and analysis. [4] carried out studies on the dynamic modeling and economic analysis of alternative power generation technologies for farm irrigation purposes. The economic comparison calculated by hybrid optimization model for electric renewable (HOMER) based on total net present cost and levelized cost of energy was done among four options: battery-less, battery-based system, pairing of both systems, and diesel engine system based on total cost. However, a gap identified in this study shows the load forecast was not carried out to support the validity of the economic feasibility result obtained, for the projected 25 years operational plan, since simulation result was reportedly based on daily load data. [5], [6], [7] and[8] conducted studies on the economic rating of electrical systems for rural electrification. The main purpose of this study in rural




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communities was to investigate the workability and economic viability of adopting a hybrid electric system. Results indicate that the renewable energy-based system, PV/Battery, has the least cost of energy and net present cost as relates to the PV/DG/B (photovoltaic/distributed generation/Battery) and standalone DG systems. Though the diesel generator DG/ hybrid electric system HES has lower net present cost(NPC) and cost of energy (COE) values compared to PV/DG/B, the DG system was found to have the highest substantial pollution discharge. More so, the result showed that the PV/B system has the least capital and total costs compared to the hybrid renewable energy. Also, PV/B system for rural community electrification demands was found to have the highest return on investment (ROI), making the system the most economically feasible and considered to be a better alternative.

On the other hand, the study observed certain gaps, such as: (i) not incorporating the long-term performance envelope of the generation solutions based on load forecast. (ii) the effects of load evolution on the techno-economic performance of the studied generation solutions. (iii) associated infrastructure development planning and energy access cannot without respect to the spatial nature and dynamics of human habitation and economic production be addressed [9],[10],[11] and [12]. Geo-spatial information system (GIS) tools supported with availability of increasing open data are extensively becoming the method of choice [13]. [14] developed in rural areas a GIS-based decision backup tool for renewable energy planning. The tool permits planning of a significant inclusion of renewable energy options and management of the systems already installed. This study somewhat weighs majorly on the implementation of solar and wind power technologies, neglecting the penetration capabilities of other technologies (for example grid expansion or mini hydro power)to provide electricity to unserved areas.[15,16] presents a model that merges mobile phone data evaluation, socio-economic and geospatial data and magnificent energy infrastructure engineering techniques in order to appraise the workability of a number of different electrification options for rural areas, such medium voltage grid extensions, diesel engine based micro grids and standalone solar PV systems.

To summarize, despite the existence of many mathematical frameworks, the application is very limited in rural contexts. [15, 16] pointed out that most of the studies in the rural energy planning literature do not contemplate any development in the energy demand along their planning horizon. The forecast models have the limitations that they rely on externally originating assumptions on demand growth (e.g. population growth).

Consequently, following an in-depth review in this section, these assumptions of load demand evolution or use of discretionary constant growth coefficients to project future electric load would create inaccuracies in the estimation of load demand forecast for accurate rural electrification planning, design and implementation. This will not be robust enough for rural electrification for agricultural operations, since dispersed settlements associated with rural areas make such assumptions that are prone to errors. Hence hybrid intelligent meta heuristic technique, as considered in this present study, works with no assumptions rather learns with little data input, is used for rural agricultural electric load forecast, and extensive simulations for generation configuration optimization and sensitivity analysis employed to bridge these gaps.

## 2.0 METHODOLOGY

In order to choose electrification strategy for rural farming on the basis of least cost approach, the technical and economic costs of each of the generation technologies: grid extension, hybrid PV and diesel generation will be considered. The methodology used in this paper consists of (1) electric load demand forecast for the case study farm settlement cluster to meet its GDP contribution covering a planning horizon of 20 years is obtained using neuro-genetic algorithm for the analysis of the various generation technologies considered in this paper. (2) modeling and carrying out simulations for (a) extending the existing power grid infrastructure to the case study settlement (b) the diesel generation technology and (c) the solar hybrid standalone mini-grid extension technologies. (3) estimating (a) the cost of meeting the forecasted load demand using solar hybrid standalone mini-grid generation technologies. (4) comparing the economic (based on levelized cost of energy LCOE) and technical performance of the three electrification options over the considered forecast horizon. The key to effective planning on the basis of the above information is the accuracy of the load demand forecast. Unlike the existing forecast models that do not intelligently take the evolution of the demand over the time period under review, this paper uses a forecast model that combines neural network and genetic algorithm.

However, rice production is used for the case study farm operations. The case study location is Adani rice cluster settlement in Uzo-uwani local government area of Enugu State, Nigeria. This methodology is based on electric energy equivalence of the subsector's GDP contribution. The obtained historic electric energy consumption required for Adani rice settlement cluster to meet its GDP contribution was used to obtain the forecast required for the analysis of the various generation technologies considered in this paper.

### 2.1 Extracting Parameters and Data for Modeling the Neuro-Genetic Algorithm

The consumption requirement data set for the case study is estimated on the basis of the standardized usage of electric power for all tooling processes required in a modern rice mill. The core base of obtaining the data set is to use known national information to obtain the local case study data to be used as input to the neuro-genetic algorithm for generating the energy usage forecast. Figure 2 shows the procedure for obtaining the contribution of Adani rice cluster settlement to national GDP.

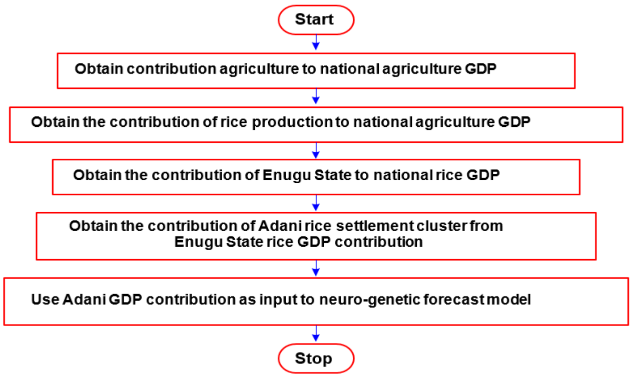


**Figure 2:** Procedure for obtaining the contribution of Adani rice cluster settlement to national GDP

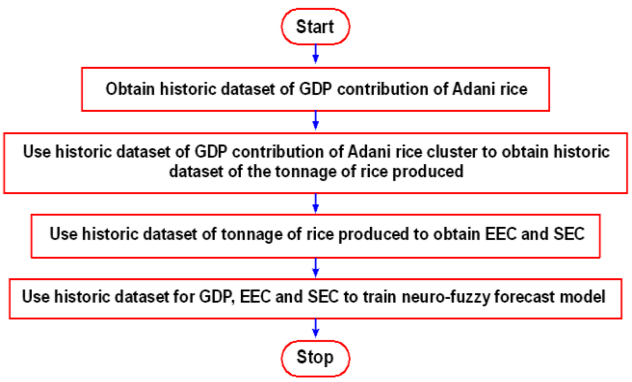


**Figure 3:** Procedure for obtaining historic data set for training the neuro-genetic forecast model

The EEC in kilowatt hour kWh/year and the Specific Energy consumption(SEC) in kWh/ton used for rice production associated with the case study is very vital for obtaining the data set for training of the neuro-genetic forecast model. Figure 3 shows the processes for obtaining the data set for training the neuro-genetic algorithm forecast model.

### 2.2 Design of the Neuro-Genetic Algorithm for Electric Load Demand Forecast

For the design of the neuro-genetic algorithm, genetic algorithm (GA) evolutionary process is used in the construction(evolution) of artificial neural network (ANN) for the forecast of electricity load demand. That is using evolutionary processes for evolving feed forward artificial neural network to output a forecast vector spanning a planning period. Specifically the proposed neuro-genetic model is the optimization of the neural network construction using genetic algorithm techniques.

The genetic algorithm operators of mutation (weight and topology mutation), crossover and selection are applied cyclically and iteratively to a population of ANN in order for evolution to help select the fittest individual. As in the reference [15, 16], this paper exploited the idea of optimizing the weights and topology of the ANN. Specifically the evolutionary processes applied in this paper for the construction of the ANN are mutation (insertion of hidden layer in the ANN; deletion of one hidden layer in the ANN and insertion of one neuron in the ANN) of the ANN topology, mutation of the weights in the ANN, weight control and neural elimination.

**Encoding of individuals in the GA process:**
As per the GA evolutionary process the individual being encoded, in this case, is an ANN.

**Initialization of the population in the GA process:**
For the initialization of the ANN population in the GA process a new population is created. The population is initialed with different hidden layers sizes and different number of neurons for each individuals, in order to maintain diversity between all the individuals in the new population. Exponential distributions are used to determine the number of hidden layers and the number of neurons for each layer in each individual, while a normal distribution is used to initialize all the weights and biases values for the new ANN. A population of this individual will be subjected to GA evolutionary processes (selection, mutation, crossover) and then the fittest individual selected as the optimal ANN for use in outputting the load demand forecast.

#### 2.2.1 Modeling the individual in the GA evolutionary process

Inputs to the ANN that computes and outputs the load demand forecast:
$Rice_{GDP}$: Contribution of rice production to national GDP
$Adani_{GDP}$: contribution of Adani rice settlement cluster to national GDP
$EEC_{per\_ton}$: EEC per ton of rice produced at Adani
$Rice_{tonage}$: total annual tonnage of rice produced at Adani
$P_{g\_rate}$: annual population growth rate

Output of the artificial neural network (ANN) that computes the electricity load demand forecast for rice production operations. Hence, Figure 4 shows that,the output of the ANN is the electric load demand forecast: $LoadDemand_{forecast}$

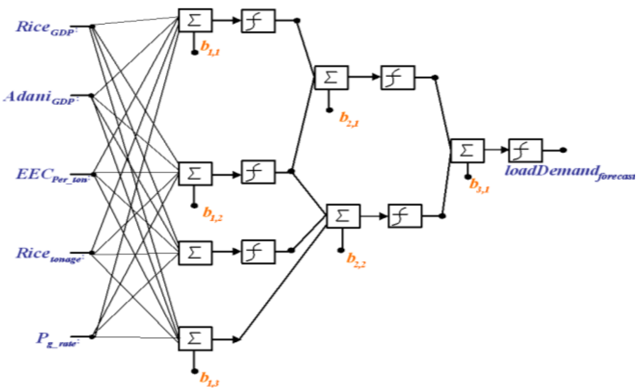


**Figure 4:** ANN model (individual) subjected to evolutionary process for the computation of electric load demand forecast

Neat-Python was used for modeling and training the neuro-genetic algorithm. Neat-Python is a Python implementation of NEAT (Neuro Evolution of Augmenting Topologies) algorithm, a method for evolving ANN. It evolves both the weight and topology of the ANN. It generates initial population (ANN population), carries out mutation (modifies AN weight and topology), crossover and selection (fittest individual is selected).

### 2.3 The Geospatial Grid Extension Model

This model enables one to capture the layout and technical traits of the existing grid, and cost implication of extending the medium voltage MV and low voltage LV power networks. Therefore, the grid extension algorithm is hinged on geometric attributes, population clusters. The following are the steps of the algorithm:

**Step 1: Sizing transmission lines (HV or MV)**
At this first stage, the algorithm determines the type of extension line high voltage HV or MV to be used to connect a settlement, and the decision is based on two parameters [17], [18], [19] and [20].

**Step 2: Sizing transformers and connection to sub-station**
At this stage, the algorithm estimates the number of service transformers required to provide full coverage of the population cluster [17], [18], [19] and [20].

**Step 3: Sizing distribution lines**
The area of each service transformer is divided into a number of smaller circles each one representing an electric load demand node (in this case load demand within the planning horizon), is assumed to be equally spaced within the larger circle. The distance between two demand nodes is defined as twice the radius of one of the smaller circles. The calculations do not consider the routing of LV lines from the transformer.

**Step 4: Estimating the total investment cost for grid extension per cluster**
In this last step, the total cost of grid extension per cluster is calculated by taking into account all partial cost as described in the following equations (1,2,3) [17], [18], [19] and [20]:

### 2.4 Calculating the Levelized Cost of the Power Generation Technologies

LCOE is obtained with the following equation 1:

$$LCOE = \frac{\sum_{t=1}^{n} \frac{l_t + O\&M_t + F_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1+r)^t}} \quad (1)$$

Where, $n$ is the lifetime of the generation technology option (in years); $l_t$ is the investment cost for a specific generation system (grid or diesel and solar hybrid system) option in year$t$ (in USD); $O\&M_t$ are the operation and maintenance costs (in USD/kWh) in year$t$; $F_t$ is the fuel expenditures (in USD/kWh) in year$t$; $E_t$ is the electricity generated (in kWh) in year $t$; $r$ is the discount rate (in %).

Another economic indicator that will be computed in the simulation carried out in this work is the accumulated Net Present Value of all costs (NPV) [21]:

$$Accumulated\ NPV\ of\ cost = l_0 + O\&M\left[\frac{(1+r)^n - 1}{r(1+r)^n}\right] \quad (2)$$

However, in order to account for topological factor while considering an additional investment cost depending on the topological characteristic (e.g. road network and land cover type) of the case study location, the spatial LCOE is considered. The spatial LCOE is obtained with equation 3:

$$spatial\ LCOE = \frac{\sum_{t=1}^{n} \frac{l_t \times (1 + topology\ factor) + O\&M_t + F_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1+r)^t}} \quad (3)$$

Therefore, from the comparative analysis carried out in this work, results for the LCOE were obtained for each of the generation systems under investigation.

## 3.0 RESULTS AND DISCUSSION

In this paper, the load demand forecast constitutes the key input for the analysis of the various generation technologies. The load forecast [projected] for 10 years represents the energy demand profile used in the generation analysis. This provides information for the grid extension design software to generate the design of the grid extension. The energy demand profile also provides information for the program used in the processing analysis to compute the cost of the various technologies.

### 3.1 Load Forecast Data Collection

Historic load demand data was used to carry out simulations for the training and validations of the neuro-genetic forecast model. Historic load demand that has spanned a period of 20 years (from 2001 - 20021) was used. Historic load data for Adani agricultural cluster could not be obtained from the national bureau of statistics and the central Bank of Nigeria. However, the national and electric consumption data for 20 years was obtained. Hence the historic data for the case study was taken to be the electric energy equivalent to the contribution of Adani agricultural cluster to GDP of Enugu state.

The work takes a capacity planning perspective, hence the analysis of the economic optimality of the three considered power generation solutions in meeting forecasted load demand. Hence the accuracy of load forecast algorithm is a key consideration in the simulation carried out. To ensure that this validated, the accuracy of the neuro-genetic algorithm was compared with that of the popular conventional forecast model ARIMA(Auto Regressive Integrated Moving Average).

### 3.2 Training the Neuro-Fuzzy Network and Executing Load Demand Forecast

In term of data set preparation, the data obtained is divided into two data sets. Half of the data set was used for training of the neuro-genetic algorithm. The other half was use for validating the neuro-genetic forecast algorithm. First half of the dataset covers the period 2001-2011 and the second half covers the period 2012-2021.The fitness function for the neuro-genetic model was defined in Neat-Python. Neat-Python was configured for population size, mutation rates, and ANN structure. The neuro-genetic model was trained by running NEAT algorithm for multiple generations. The final neuro-genetic model was tested to validate its ability. Figure 5 is the result of the validation(which visualizes the plot of the actual against the predicted load demand). The ARIMA forecast was executed using the Python library *statsmodel*. The library has the flexibility and comprehensive support for time series analysis required for ARIMA forecast computation. The output of the validation load forecast (i.e. forecast for the period 2012-2021) is shown in Figure 5. It can be observed from the graph that the trajectory representing the neuro-genetic forecast lies closer to the actual load consumption data than that of the ARIMA forecast.

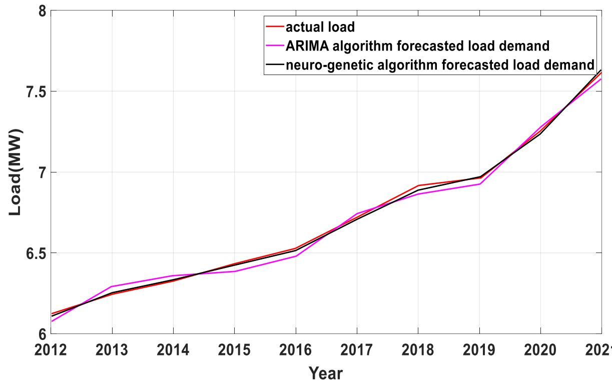


**Figure 5:** Combined plots of the neuro-genetic and the ARIMA validation load forecast

However, the result does not tell us about the degree of correlation of the ARIMA output forecast with the actual load data. To obtain information on the correlation i.e. by how much the forecast corresponds with the actual load data of the forecast, the Pearson Correlation Coefficient for both models were obtained. Hence, to obtain this correlation coefficient, the values as plotted in Figure 5 using the simulation software are extracted into Tables 1 and 2. These extracted values are used for obtaining the correlation coefficients for the neuro-genetic validation load forecast and the ARIMA forecast respectively.

**Table 1:** Values for obtaining the correlation coefficient for the neuro-genetic validation forecast

| $y$ | $x$ | $y^2$ | $x^2$ |
|---|---|---|---|
| 6.1243 | 6.0766 | 37.5071 | 36.9251 |
| 6.2451 | 6.2915 | 39.0013 | 39.5830 |
| 6.3257 | 6.3587 | 40.0145 | 40.4331 |
| 6.4332 | 6.3855 | 41.3861 | 40.7746 |
| 6.5272 | 6.4796 | 42.6043 | 41.9852 |
| 6.7220 | 6.7428 | 45.1853 | 45.4654 |
| 6.9168 | 6.8637 | 47.8421 | 47.1104 |
| 6.9638 | 6.9255 | 48.4945 | 47.9626 |
| 7.2526 | 7.2801 | 52.6002 | 52.9999 |
| 7.6153 | 7.5757 | 57.9928 | 57.3912 |

The Pearson correlation coefficient is given by

$$r = \frac{n\sum xy - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} \quad (4)$$

Where, $x =$ forecasted value; $y =$ actual value; $n =$ the number of test samples.

From the values in the Table 1, the correlation coefficient for the neuro-genetic forecast is $r = 0.9995$. this coefficient obtained indicates that the forecast has a very high level of correlation with the actual historic load data. The correlation coefficient is higher than 0.5. This level of correlation coefficient shows very high accuracy for the neuro-genetic forecast model. Table 2 shows the values for the estimation of the correlation coefficient for the ARIMA model.

**Table 2:** Extracted values for obtaining the correlation coefficient for the ARIMA test forecast

| $y$ | $x$ | $y^2$ | $x^2$ |
|---|---|---|---|
| 6.1243 | 6.1088 | 37.5071 | 37.3174 |
| 6.2451 | 6.2539 | 39.0013 | 39.1113 |
| 6.3257 | 6.3345 | 40.0145 | 40.1259 |
| 6.4332 | 6.4258 | 41.3861 | 41.2909 |
| 6.5272 | 6.5145 | 42.6043 | 42.4387 |
| 6.7220 | 6.7079 | 45.1853 | 44.9959 |
| 6.9168 | 6.8879 | 47.8421 | 47.4432 |
| 6.9638 | 6.9712 | 48.4945 | 48.5976 |
| 7.2526 | 7.2345 | 52.6002 | 52.3380 |
| 7.6153 | 7.6321 | 57.9928 | 58.2490 |

Obviously from the values in the table and using Equation (4), the correlation coefficient for the ARIMA forecast is 0.9963.

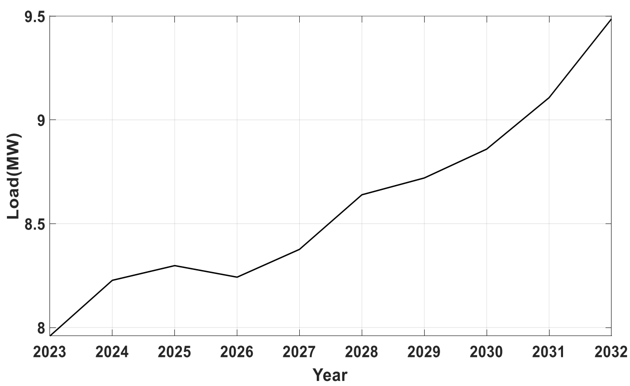


**Figure 6:** Ten year Load demand forecast for the analysis of generation technologies

The correlation coefficient tells us that both models are accurate, but that the neuro-genetic model is more accurate. Hence, the neuro-genetic model is far more accurate than the ARIMA model. The neuro-genetic model can now be relied on to generate the ten years (2023-2032) electrification planning forecast for the techno-economic analysis of grid extension, diesel generation and hybrid renewable energy power generation options for Adani agricultural cluster. The ten year (i.e. the planning period) is given in Figure 6. This is the forecast used for the analysis for the generation technologies referred to in this paper.

### 3.3 Simulation Software for Computing the Grid Extension

The reference electrification model (REF) in conjunction with a Python program are the tools used to implement the geospatial based and levelized cost of electrification methodology. The inputs to the software are complex, hence extracts of the geospatial data of Adani used as inputs were realized with the use of Python program. The load forecasts from the neuro-genetic algorithm provide data for the python program to extract the load demand model by fitting a model from the forecast obtained from the use of the neuro-genetic algorithm. This obtained extracted load demand model also serves as input to the REF software.

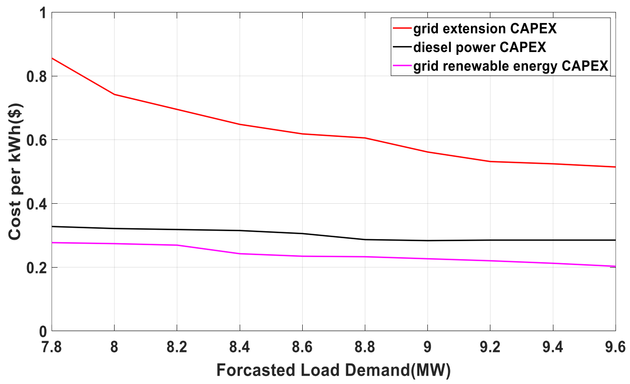


**Figure 7:** CAPEX, OPEX and non-served energy cost for grid extension

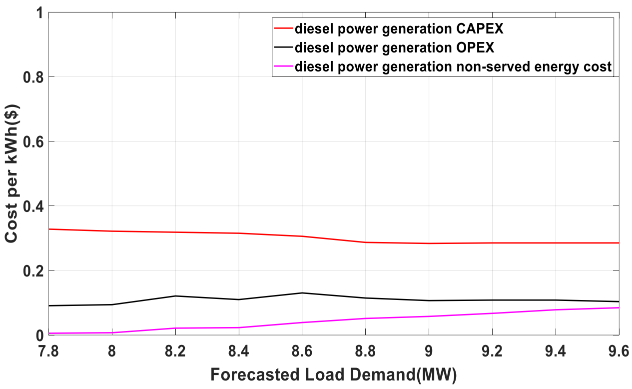


**Figure 8:** CAPEX, OPEX and non-served energy cost for the diesel generation solution

### 3.4 Simulation Software for Computing the Diesel and Hybrid Renewable Energy Generation System

The HOMER software was used for the diesel and hybrid renewable (PV/Diesel) energy design and techno-economic analysis. Results from the simulations carried out fall under cost analysis. Hence, this paper focuses on least cost analysis of the generation systems under investigation. The combined plot of CAPEX, OPEX and non-served energy cost per kWh for forecasted load demand served using grid-extension, diesel, and hybrid renewable energy generation technologies are shown in Figures 7, 8, and 9 respectively.

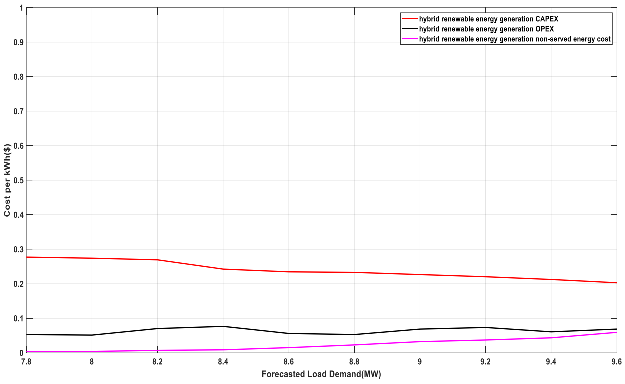


**Figure 9:** CAPEX, OPEX and non-served energy cost for hybrid renewable generation solution

Referring to Figure 6, the CAPEX for grid extension varies with increase in energy demand - using the forecast increase as a basis. Increase in energy demand, also means increase in population. In terms of the case study, this means that as the demand of energy for farming operation increases (probably due to more investment and expansion of rice processing capacity), the grid extension CAPEX per kWh decreases. Within the forecast horizon, the grid extension CAPEX decrease (although not exactly linearly) from $0.86 per kWh to $0.053 per kWh. This represents a 93.84% decrease in CAPEX over the forecast horizon. It can be noticed that the OPEX does not take the same trajectory as the CAPEX. The OPEX only varied slightly over the forecast horizon. This means that as energy demand for farming operations increases, over the period considered, the OPEX remained fairly steady. Similarly, it can be observed that the grid extension non-served energy cost per kWh increased somewhat over the forecast horizon. This means that as increased demand for energy occurs, with time, the grid extension non-served energy cost per kWh increases. It is important to note that the grid extension non-served energy cost is a function of the reliability of the power grid. This means that the reliability of the Nigerian power grid degrades with the increase of load demand with time if no upgrade or reinforcement projects are undertaken, this decrease in reliability increases the non-served energy cost of the system. It can be observed that the grid extension non-served energy cost per kWh increased from $0.1 per kWh to $0.26 per kWh over the forecast horizon. The result represents a 61.53% increase in non served energy cost for grid extension over the forecast horizon.

Referring to Figure 7, It can be observed that diesel generation CAPEX per kWh reduces with increase in load demand served. Unlike in the case of CAPEX for grid extension, the CAPEX for diesel generation decreased slightly over the range of the forecasted load demand. The diesel generation CAPEX decreased from $0.33 per kWh to $0.297 per kWh. This represents a 10% reduction in CAPEX over the forecast horizon. The percentage reduction of the diesel generation CAPEX is much lower than that for the grid extension. This means, in terms of cost, grid extension has the advantage of economies of scale over the diesel generation solution. The OPEX for diesel generation is fairly constant over the range of forecasted load demand served. However, the grid extension OPEX appears to be more constant than that of diesels generation. This means the OPEX for grid extension does not vary like that for diesel generation. The budget for operations and maintenance for grid extension is found to be more stable than that for diesel generation.

Referring to Figure 8, just like in the cases of grid extension and diesel generation, the CAPEX for hybrid renewable energy generation reduces with increase in load demand served. However, the reduction in the hybrid generation CAPEX is not as substantial as that of grid extension. From the graph the CAPEX for hybrid renewable energy generation system reduces from 0.16 per kWh to 0.11 per kWh over the rage of forecasted load demand. This variation represents a reduction of 31.25%.

## 4.0 CONCLUSION

The discussion here is made from the perspective of decision support. Results showed that grid extension has the advantage of economies of scale. There is huge advantage in this respect. The CAPEX for grid extension was found to reduce with increase in load demand served. In terms of decision support for policy making, grid extension for Adani would be the optimal choice, if the choice is not taken in isolation. This means the decision should be taken in conjunction with a strategic policy to invest more (perhaps as part of an agricultural expansion program for rice production at Adani). This means massive investment in rice production in Adani would make grid extension a more economical choice. This is so because, from the results obtained, massive investment in rice production capacity means increase




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in load demand, which in turn reduces CAPEX for grid extension than for the other two generation options. For massive government strategic investment in agriculture that is geared towards finding alternative to oil revenue in a long-term objective, the adoption of grid extension should be optimal choice. However, a key significance of this research relates to the contribution it makes towards the incorporation of technique that can account for the impact of load forecast uncertainties in the assessment of the technical and economic optimality of power generation systems. Similarly, this study has significance in the area of energy modeling. The models can be used to access future generation systems configurations and path and the analysis of the effects of energy utilizationon rural agricultural activities and the environment.

In conclusion, for further extension of the analytical framework proposed in this paper, we recommend thus the inclusion of sensitivity analysis.

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