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Using PSO and Genetic Algorithms to Optimize ANFIS Model for Forecasting Uganda's Net Electricity Consumption

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ABSTRACT

Uganda seeks to transform its society from a peasant to a modern and largely urban society by the year 2040. To achieve this, electricity as a form of modern and clean energy has been identified as a driving force for all the sectors of the economy. For this reason, electricity consumption forecasts that are realistic and accurate are key inputs to policy making and investment decisions for developing Uganda's electricity sector. In this study, we present an ANFIS long-term electricity forecasting model that is easy to interpret. We use the model to forecast Uganda's electricity consumption. The ANFIS model takes population, gross domestic product, number of subscribers and average electricity price as input variables and electricity consumption as the output. We use particle swarm optimization (PSO) algorithm and genetic algorithm (GA) to optimize the parameters of the model. A forecast accuracy of 94.34% is achieved for GA-ANFIS, while 90.88% accuracy is achieved for PSO-ANFIS as compared to 87.79% for multivariate linear regression (MLR) model. Comparison with official forecasts made by Ministry of Energy and Mineral Development (MEMD) revealed low forecast errors.

Keywords: *Electricity consumption forecasting, Adaptive Neuro-Fuzzy Inference System, Genetic algorithm, Particle swarm optimization algorithm, Uganda.*

1. INTRODUCTION

The national vision statement, "A Transformed Ugandan Society from a Peasant to a Modern and Prosperous Country within 30 years" was approved by the cabinet of Uganda in the year 2007. Through consultations with stakeholders, the National

Planning Authority (NPA) developed the Uganda Vision2040³ to operationalize this Vision statement and it was launched on 18th April 2013. To achieve the required transformation, electricity as a form of modern energy is identified as a driving

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³ <http://npa.ug/wp-content/themes/npatheme/documents/vision2040.pdf> accessed on 3rd-Sept-2016

force, not only for industrial and commercial sectors but also for domestic and transport sectors among others. Presently the mostly used source of energy in Uganda is traditional biomass (wood and charcoal) and this comprises 88.8% of the total energy use. It is used in both rural and urban areas for heating and cooking. Electricity is mainly hydro and contributes only 1.7% of the total energy use. Only 20% of Uganda's population have access to electricity (MEMD⁴, annual report 2015). Despite the low energy access rates, electricity supply is still of poor quality. It is characterized by blackouts, deficiencies in supply leading to load shedding. It is estimated that a total of 41,738 MW of electricity will be required by the year 2040 for 80% of the total population to have access to electricity at 3,668kWh electricity per capita consumption. In light of the above, the Power Sector Investment

Plan (2009-2030) was reviewed and the results of the review were presented in the Demand Forecast Report 2015. The Demand forecast report forecasted electricity consumption from 2015 up to 2040. The objective of both studies was to "provide adequate and reliable power based on the demand to spur Uganda's economic development". The findings of the two studies are now used as basis for decision making regarding planning and investment in Uganda's electricity sector. The situation has not changed much though and the forecasted consumption in the Demand Forecast Report has not been realized. We note that there is a very big difference between the forecasted values for all forecast scenarios in the Demand forecast report and the observed consumption for the years 2015-2017 as shown in Table 1 below.

Table 1.

Percentage relative errors between actual consumption and MEMD forecasts for the different forecast scenarios.

| Year | Actual Consumption (GWh) | Forecasts (GWh) | | | | % Relative errors | | | |
|------|-----------------------------|-----------------|-----------|-----------|-------------|-------------------|-----------|-----------|-------------|
| | | Low case | Base case | High case | Vision 2040 | Low case | Base case | High case | Vision 2040 |
| 2015 | 3,219 | 4,407 | 4,645 | 5,082 | 25,506 | 36.9 | 44.3 | 57.9 | 692.4 |
| 2016 | 3,489 | 5,451 | 6,665 | 8,193 | 31,090 | 56.2 | 91.0 | 134.8 | 791.1 |
| 2017 | 3,715 | 5,853 | 7,114 | 8,815 | 37,035 | 57.6 | 91.5 | 137.3 | 898.9 |

Source: Uganda Bureau of Statistics, Demand Forecast Report 2015.

In Table 1, "Actual Consumption" is the recorded electricity consumption for the corresponding year in GWh, "Low case", "Base case", "High case" and "Vision 2040" are MEMD electricity forecast scenarios developed for different annual growth rates of Uganda's economy. Since the forecasts were intended for planning purposes in the power sector, the big difference between the forecasted and observed consumption are misleading. These big differences can lead to inadequate planning and place more burden on the electricity generation and production costs. The result is inappropriate investment decisions for the country's energy systems and electricity sector in particular. For this reason, there is need for alternative forecasts with

much lower deviations from the actual consumption in order to make appropriate investment decisions. Various techniques and methods have been used to forecast electricity consumption. Among the most popular techniques is regression analysis which is based on formulation of mathematical relationships between independent and dependent variables. However, in cases where the mathematical relationships are not known or hard to formulate it becomes a challenge and in such cases appropriate and effective models are hard to build. To avoid the above limitations of regression analysis, we propose an Adaptive Neuro-Fuzzy Inference System (ANFIS) model to forecast electricity consumption as an alternative

⁴ Ministry of Energy and Mineral Development

solution. ANFIS can be used to build models whose mathematical relationships are hard to formulate or not known. For such cases, ANFIS modelling's only requirement is to provide independent variables (inputs) and dependent variables (targets) data, specify ANFIS parameters such as membership functions, a learning algorithm and through a training process ANFIS learns the relationships between the suggested inputs and targets. In this study we present an easy to interpret as well as accurate ANFIS model to forecast Uganda's electricity consumption with low forecast errors between the actual and forecasted consumption. We use population, gross domestic product, number of subscribers and average electricity price as inputs (independent variables) and electricity consumption as the target (dependent variable). Traditionally ANFIS parameters have been optimized using back propagation and a hybrid algorithm of least squares and back propagation algorithms. These algorithms are gradient based and are often trapped in local minima. Genetic algorithm (GA) and particle swarm optimization (PSO) algorithm are population based algorithms and have been widely used when it is difficult to obtain derivatives [1]. Thus in a bid to avoid the scenario of being trapped in local minimum we use GA and PSO to tune the parameters of ANFIS forecasting model. We compare results with official MEMD forecasts and a multivariate linear regression (MLR) model that uses the same variables as independent and dependent variables. The novelty of the study is to provide forecasts that are realistic with less forecast errors between the actual and forecasted consumption. These forecasts will help in formulation of appropriate investment decisions and policies in regard to electricity generation, transmission and distribution planning and expansion. These decisions and policies will help Ugandan society transform from a peasant to a largely urban and industrialized society as outlined in the Uganda Vision 2040.

The rest of the paper is organized as follows; in

section 2 we present related and methods and materials in section 3. In section 4 we discuss the results and we give a conclusion in section 5.

2. RELATED WORK

ANFIS has been used in many fields such as control systems, image processing, time series forecasting, and load forecasting. For example [2] developed ANFIS by hybridizing subtractive clustering technique with GA and applied it to forecast electricity consumption for the Iranian industrial sector. The GA was used to find the optimum value of cluster radius which guaranteed the minimum number of rules and error. For both accuracy and the number of rules, the hybrid approach performed better than the conventional ANFIS based on grid partitioning, fuzzy c-means, and subtractive clustering. A hybrid PSO-ANFIS approach for short term wind power prediction in Portugal is used in [3]. The parameters of membership functions were tuned using PSO algorithm to lower the error between the observed and predicted wind power. A hybridized ANFIS, computer simulation and time series algorithm was used with monthly electricity consumption in Iran from 1995 to 2005 to predict electricity consumption [4]. A novel genetic-based adaptive neuro-fuzzy inference system (GBANFIS) for short-term load forecasting expert systems and controllers is presented in [5]. GA is first used to find the most suitable feature of inputs to construct the model and at a later stage GA is used to optimize weights among rules. GBANFIS is used to forecast Iranian monthly energy demand and shows better results when compared to regression, GA, simulated-based GA, Artificial Neural Network (ANN), simulated-based ANN, fuzzy decision tree, and simulated-based ANFIS approaches. In [6] fuzzy sets were used to investigate the effect of weather, time, historical data, and random disturbances on load forecasting during the generation process. After the

investigation, they predicted Jordanian short term loads for generation scheduling and unit commitment decisions. A scaled conjugate gradient algorithm (CGA) and back propagation (BP) algorithm was used to train ANN and evolving fuzzy neural network (EFuNN) to predict electricity demand in the State of Victoria, Australia [7]. They conclude that the performance of neuro-fuzzy system was better than that of neural networks and Autoregressive Integrated Moving Average (ARIMA) models. The number of customers connected to the electricity distribution network, the temperature and the precipitation of rain are used in [8] as exogenous variables for Seasonal autoregressive integrated moving average with exogenous variables (SARIMAX) and ANFIS models to forecast electric load time series. The ANFIS model gave lower forecast error values than the SARIMAX model. Hence concluded that ANFIS model performed better than SARIMAX model for electric load time series forecast. [9] combined Back Propagation (BP) neural network, Adaptive Network-based Fuzzy Inference System (ANFIS) and Difference Seasonal Autoregressive Integrated Moving Average (diff-SARIMA) to forecast short-term electricity consumption. BP and ANFIS were able to deal with the nonlinearity of the data, and diff-SARIMA dealt with linearity and seasonality in the data. Though the forecasting results of the combined method had reduced errors and better accuracy than the individual methods, ANFIS model showed better forecast results among the individual methods. An ANFIS based model for solving the medium term electric load-forecasting using time series monthly data is presented by [10]. Comparison with Autoregressive (AR) and an Autoregressive Moving Average (ARMA) models showed that the ANFIS model's results were better than those of AR and ARMA models. Using weather data, [11] developed and compared linear regression, artificial neural networks and ANFIS

models for load prediction and found that ANFIS model gave more accurate results. For Canada's Ontario province, [12] used ANFIS to model electricity demand using data from the year 1976-2005. The inputs to the model were population, gross domestic product, number of employment, dwelling count, hottest and coldest temperatures of the day. Their results showed that employment affected electricity demand most. ANFIS was used for next week electric load forecasting [13]. The input variables consisted of half hour weekly load time series data. Similarly [14] used ANFIS to model and predict electricity demand using population, Gross Domestic Product (GDP), Gross National Income (GNI), imports and exports data for India. short-term load forecasting models using fuzzy logic and ANFIS were developed in [15]. They used historical load, temperature and season as input variables. Forecasting ability of ANFIS model is demonstrated in [16] and is applied to regional electricity loads in Taiwan. A neurofuzzy methodology using historical energy data for load prediction to estimate the energy consumption for several future years is presented in [17]. Jordanian industrial sector electricity consumption was modeled and predicted using MLR and neuro-fuzzy models [18]. The variables used in these models were electricity tariffs, fuel prices, production outputs, capacity utilizations, number of establishments, number of employees, and structural effects. A comparison of the models using the root mean squared error showed that the neuro-fuzzy model performed better than the MLR model. [19] presented a deep neural network algorithm for short-term load forecasting. The algorithm describes two main processes i.e. feature extraction and load forecasting. Feature extraction is performed by convolution layers and pooling layers. The forecasting process is performed when Pooling3 layer is flattened into one dimension to construct a fully connected structure to the output

layer. The experiment results show that the proposed algorithm displays very high forecasting accuracy in comparison with Support Vector Machines, Random Forests, Decision Trees, Multi-Layer Perceptron and Long Short Term Memory that are commonly used in load forecasting. Youshan and Qi [20] proposed and utilized a Regressive Convolution Neural Network (RCNN) model to extract features from data. The extracted features are used to train a Regressive Support Vector Machine (SVR) to predict the electricity consumption. Results show that the forecasting accuracy of the proposed approach is high compared to BP neural network and SVM. Youshan et al [21] using historical data proposed a modified particle swarm optimization-back propagation neural network model to forecast electricity consumption for a mineral company of Anshan in China. Comparison of the proposed algorithm's convergence and forecast accuracy with Back Propagation, PSO and fuzzy neural network showed better results.

3. METHODS AND MATERIALS

Our goal is to model Uganda's net electricity consumption using ANFIS. The model structure should be easy to interpret at the same time exhibit a significant level of forecasting accuracy. We train the model (optimize the parameters of input and output membership functions) and use the optimized/trained ANFIS model to forecast Uganda's long-term net electricity consumption. We take socio-economic variables as inputs to the model and electricity consumption as the output. In general, forecasting approaches and methodologies aim to minimize the error term between the observed/actual and the forecasted values. Therefore all forecasting methods use some form of

error function (loss function) as the objective function. Commonly used error functions include sum of squared errors (SSE), mean square error (MSE), root mean square error (RMSE) and mean absolute percentage error (MAPE). In this study we use MSE, Eq. (1) as the objective function for the training algorithm.

$$\min f = \frac{1}{n} \sum (Y_i^{actual} - Y_i^{predicted})^2 \quad (1)$$

where Y_i^{actual} is the observed consumption (target) and $Y_i^{predicted}$ is the computed consumption using ANFIS model (output) for the observed period.

3.1. Dataset

Electricity consumption is affected by many factors such as weather, socio-economic and demographic factors. Weather factors normally affect short term electricity consumption while socio-economic and demographic factors affect long term electricity consumption. In this study the dataset comprised of historical data for electricity consumption as the dependent variable, and socio-economic factors i.e. population, gross domestic product (GDP), total exports, total imports, total number of electricity subscribers/customers (residential, commercial and industrial consumers), and average electricity price as independent variables from 1990 to 2016. Population and GDP data was obtained from the world bank population⁵ and GDP⁶ data APIs, electricity consumption, number of subscribers and electricity prices data was obtained from the 1997 statistical abstract of the Ministry of planning and economic development, Uganda Bureau of Statistics statistical abstracts⁷ from 2002 to 2016 and Electricity Regulatory Authority⁸ of Uganda.

⁵ api.worldbank.org/v2/en/indicator/SP.POP.TOTL?downloadformat=excel retrieved on 12-Sept-2017

⁶ api.worldbank.org/v2/en/indicator/NY.GDP.MKTP.CD?downloadformat=excel

retrieved on 12-Sept-2017

⁷ www.ubos.org/publications/statistical-abstract last accessed 10th-Sept-2017

⁸ www.era.or.ug/index.php/statistics-tariffs/tariffs, last accessed 10th-Sept-2017

3.2. Overview of Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is a combination of neural networks and fuzzy systems. The fuzzy system component defines the membership functions while the neural network component is used to automatically extract fuzzy rules from numerical data and adaptively tunes the parameters of the membership function through a learning process. ANFIS was introduced in 1993 as a basis for constructing “IF-THEN” rules to map the input to output space through appropriate membership functions [22]. Jang’s work is an extension Takagi and Sugeno’s 1985 work on fuzzy identification and modelling of systems [23]. Fuzzy “IF-THEN” rules also define the relationship between ANFIS’s premise and consequent parameters [1]. Each rule describes a local behavior of the mapping. In the Sugeno fuzzy model, a basic fuzzy rule is represented as;

IF X_1 is a_1 and X_2 is a_2 and X_3 is a_3 and X_4 is a_4 THEN $Y = f(X_1, X_2, X_3, X_4)$,

where X_1, X_2, X_3 and X_4 are fuzzy sets in the antecedent inputs (influential variables) and Y is a crisp function representing the output (electricity

consumption). Inputs and outputs in ANFIS are represented by membership functions. The type and number of membership functions, number of inputs and outputs and the number of rules determines the number of parameters to be tuned/optimized through a learning process. Fuzzy rules are generated from the input space through a partitioning process. Commonly used partitioning processes are grid partition, subtractive clustering and fuzzy c-means clustering. Each of these partitioning processes have advantages and disadvantages; such as complexity of the rules and computation time among others. In this study we use fuzzy c-means clustering as a partitioning process to reduce the complexity and number of rules and parameters to be optimized. The fuzzy c-means clustering allows data points to belong to multiple clusters and it is identified by a membership value in each cluster. The membership value of each data point in cluster is specified by a membership function on the basis of its distance between the cluster’s center and the data point. ANFIS structure with four inputs and one output used in this study is shown in Figure 1 below.

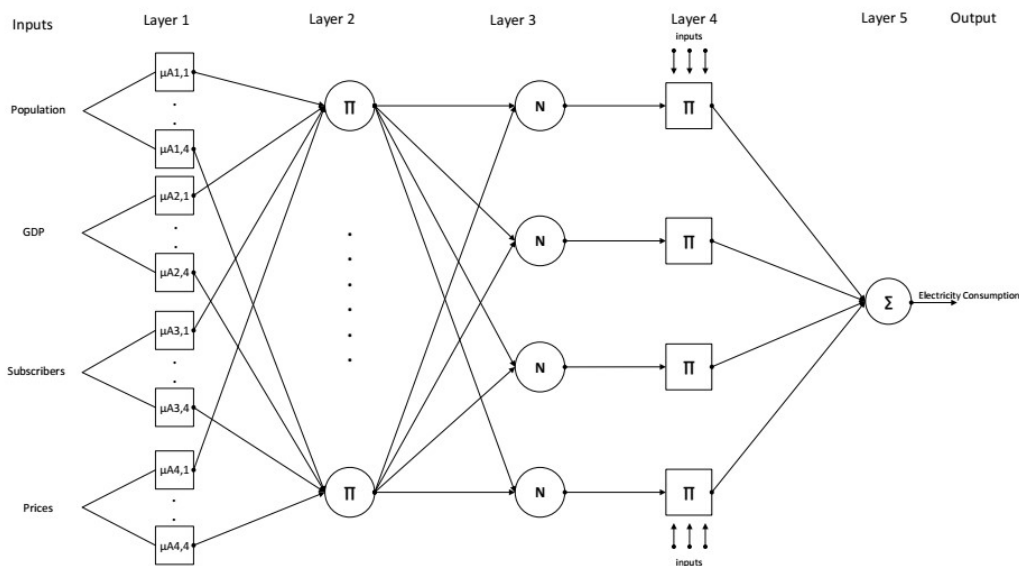


Figure 1 ANFIS structure with four inputs and one output

In layer 1, we have inputs and their membership functions $\mu A(x)$. Nodes in this layer are adaptive,

i.e. the parameters are changed during the training process. The outputs of each node is of the form

$O_{1,i} = \mu A_i(x)$, a result of computing membership functions.

Commonly used membership functions include generalized bell, Gaussian, triangular, and trapezoidal functions. We use the Gaussian function for the input membership functions as shown in Eq. (2) below.

$$\mu A(x_i) = \exp\left\{\frac{-(x_i - c_i)^2}{2\sigma_i^2}\right\} \quad (2)$$

where c_i and σ_i are called premise parameters. These parameters are adjusted through a learning process to get an optimal state of ANFIS. In layer 2 the rules are formed. The output of layer 2 is the firing strength w_i of each rule. The firing strength is a product of membership functions in layer one, mathematically the output of each node in layer 2 can be expressed as Eq. (3) below.

$$O_{2,i} = w_i = \mu A_i(X_1)\mu B_i(X_2)\mu C_i(X_3)\mu D_i(X_4), i = 1,2,3,4. \quad (3)$$

where X_1, X_2, X_3 and X_4 are the inputs. In layer 3, the firing strength of each rule is normalized using Eq. (4) below.

$$O_{3,i} = \bar{w}_i = \frac{w_i}{\sum_{i=1}^4 w_i} \quad (4)$$

The next layer defines the output membership functions, for this study we Sugeno fuzzy model that uses linear functions shown in Eq. (5) as membership functions.

$$f_i = p_i x_1 + q_i x_2 + r_i x_3 + s_i x_4 + t_i, i = 1,2,3,4. \quad (5)$$

where p_i, q_i, r_i, s_i, t_i are called consequent parameters and x_i are the inputs. Like the premise parameters in layer 1, consequent parameters are also adjusted through a learning process to get an optimal ANFIS model. The normalized firing strength of each rule is applied on the corresponding output membership function to get

the output of each rule as shown in Eq. (6)

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i(p_i x_1 + q_i x_2 + r_i x_3 + s_i x_4 + t_i), i = 1,2,3,4. \quad (6)$$

The final output of layer 5 is a summation of all incoming signals of the firing strengths and output membership functions as shown in Eq. (7).

$$O_{5,i} = \sum \bar{w}_i f_i = \sum_{i=1}^4 \bar{w}_i(p_i x_1 + q_i x_2 + r_i x_3 + s_i x_4 + t_i) \quad (7)$$

3.3. Overview of Particle Swarm Optimization (PSO) algorithm

Developed in 1995 by Eberhart and Kennedy, PSO algorithm is a computational intelligence technique that gets inspiration from the social behavior of a flock of birds or a school of fish. PSO algorithm originates from artificial life, social psychology, computer and engineering science. The swarm intelligence concept as used in PSO algorithm applies the collective behavior of agents that locally interact with their environment to create global functional patterns that are coherent [24]. A population of random solutions is used to initialize PSO algorithm and search for optimal solution is done by updating the positions of the particles at each successive iteration using Eq. (8).

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (8)$$

In Eq. (7) x_i^{k+1} is the new position, x_i^k is the previous position and v_i^{k+1} is the updated velocity. Velocity is updated using Eq. (9).

$$v_i^{k+1} = v_i^k + c_1 rand_1(pbest_i^k - x_i^k) + c_2 rand_2(gbest^k - x_i^k) \quad (9)$$

In Eq. (8), c_1 and c_2 are social and cognitive coefficients, $rand_1$ and $rand_2$ are random numbers uniformly distributed in the [0, 1] interval. A user defined fitness function is used to derive particle and global best positions. Every particle's

movement at each iteration evolves to an optimal or near-optimal solution. The process is repeated until improved positions that satisfy a set criteria are discovered.

3.4. Overview of Genetic Algorithm (GA)

GA is a stochastic optimization technique based on evolution of biological processes. GA starts with a random initialization of solutions in the search space, this initial set of solutions is called a population. Using genetic operators, the population is improved over multiple iterations until a specified stopping criteria is reached. The basic operators of GA are selection, crossover and mutation. Selection is used to choose individuals for reproduction. The selection procedure is based on the probability of fitness of individuals with in the population. The higher the fitness of an individual, the higher the probability of being selected. Selection probability is calculated based on the Eq. (10) below.

$$P_i = \frac{F_i}{\sum_{k=1}^n F_k} \quad (10)$$

F_i in Eq. (9) is the fitness value of solution i , and n is the population size. Common selection procedures are roulette wheel selection, fitness ranking and tournament selection. After the selection procedure, crossover operator is applied to the selected individuals. Using a crossover rate genetic material of two or more solutions is combined to form a better solution. The mutation operator is used to create diversity in the new population to enable a wider search space.

3.5. ANFIS model for long term electricity consumption forecasting

ANFIS model for long term electricity forecasting is modeled based on the Sugeno fuzzy inference system. It takes four inputs i.e. population, gross domestic product, number of subscribers and

electricity price and the output is electricity consumption. The model was implemented using MATLAB 2017 on a dual core processor with 4GB of RAM. The structure of ANFIS model is shown in Figure 2.

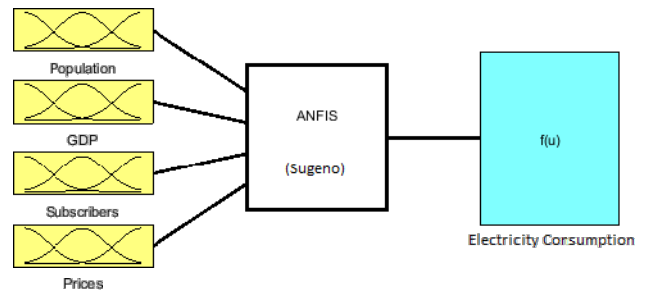


Figure 2 ANFIS model for electricity consumption forecasting

The Gaussian function has only two parameters to tune as opposed to three for the triangular, and four for the trapezoidal function. Because of the limited data available, we choose the Gaussian function for the membership functions of inputs in order not to have many premise parameters to optimize. Because the more the parameters to optimize become the more data is needed. More so [25] examined the four mostly used membership functions on the performance of ANFIS while solving various classification problems and concluded that the Gaussian membership function demonstrated higher degree of accuracy with lesser computational complexity as compared to its counterparts. The linear function is used for output membership function. Interpretability of ANFIS relates to its structure. Thus to easily interpret an ANFIS model we look at the number and structure of “IF-THEN” rules, and the number of input variables i.e. the smaller the number of rules and the less number of input variables, the easier it is to interpret the ANFIS model. Accuracy on the other hand relates to how precisely an ANFIS model can correctly estimate the modeled system. Accuracy is usually measured as a percentage [26]. The higher the percentage the more accurate an ANFIS model is. In order to achieve interpretability, we used

fuzzy c-means clustering to divide our dataset into four clusters, each cluster containing inputs and their corresponding outputs. One rule is generated

for each cluster, giving a total of four rules as shown Figure 3 below.

-
1. *If (in1 is in1cluster1) and (in2 is in2cluster1) and (in3 is in3cluster1) and (in4 is in4cluster1) then (out1 is out1cluster1) (1)'*
 2. *If (in1 is in1cluster2) and (in2 is in2cluster2) and (in3 is in3cluster2) and (in4 is in4cluster2) then (out1 is out1cluster2) (1)'*
 3. *If (in1 is in1cluster3) and (in2 is in2cluster3) and (in3 is in3cluster3) and (in4 is in4cluster3) then (out1 is out1cluster3) (1)'*
 4. *If (in1 is in1cluster4) and (in2 is in2cluster4) and (in3 is in3cluster4) and (in4 is in4cluster4) then (out1 is out1cluster4) (1)'*
-

Figure 3 ANFIS rules

In the rules above $in1$ =population, $in2$ =gross domestic product, $in3$ =number of subscribers, $in4$ =average electricity price and $out1$ =electricity consumption. Similarly " inX is $inXclusterY$ " means input X in cluster Y, and " $out1$ is $out1clusterY$ " means output 1 in cluster Y. Each input is defined by four membership functions and each output is defined by one membership function. The number of tunable parameters for each input is eight ($2 \times 4 = 8$) and each output has five (5) parameters, giving a total of thirteen (13) tunable parameters for each cluster. For all the four clusters the total number of parameters is fifty two (52). A learning algorithm is used to tune the parameters of ANFIS through a learning process. In this study we use PSO algorithm and GA as learning algorithms to tune the parameters of ANFIS.

3.5.1. Training ANFIS with PSO algorithm and GA

The training process by a learning algorithm tunes the parameters of the membership functions to construct a mapping and learn relationships between inputs and outputs.

-
1. *Load dataset*
 2. *Create ANFIS forecasting model*
Set the parameters of ANFIS
 3. *Train ANFIS using training dataset*
Choose algorithm (PSO or GA)
 4. *Output trained ANFIS*
 5. *Test trained ANFIS using test dataset*
Calculate RMSE and MAPE
 6. *Make forecasts using forecast dataset*
-

Figure 4 Pseudo code for the main procedure for training ANFIS

In this study we use PSO algorithm and GA to tune membership functions' parameters of inputs and polynomial coefficients of output of the ANFIS model shown in Figure 2. The pseudo code for the main procedure for training the model is shown in the Figure 4 above. In PSO-ANFIS and GA-ANFIS models, ANFIS is considered as particle or individual representing a potential solution to the optimization problem. The premise and consequent parameters of ANFIS are the dimensions of the problem. The data set was divided randomly into a training and a testing data set in the ratio 0.7:0.3. The parameters of PSO algorithm and GA were set as follows, population size=100, maximum number of iterations=1000, lower and upper bound interval [-10, 10], $c_1 = c_2 = 2.1$, crossover rate=0.7 and mutation rate=0.15. The algorithm evaluates the objective function defined in Eq. (1) until a stopping criteria or maximum number of iterations is reached. The Y_i^{actual} is regarded as the target and the $Y_i^{predicted}$ is the ANFIS output at each every iteration.

3.6. Model performance assessment

To assess the forecasting ability and accuracy of PSO-ANFIS and GA-ANFIS we use the root mean square error (RMSE) and mean absolute percentage error (MAPE). The lower the values the better the forecasting ability. RMSE and MAPE are calculated using the formulas below.

Table 2

RMSE and MAPE values to assess the performance of models

| PSO-ANFIS forecast | | GA-ANFIS forecast | | MLR | |
|--------------------|----------|-------------------|----------|--------|----------|
| RMSE | MAPE (%) | RMSE | MAPE (%) | RMSE | MAPE (%) |
| 1.4707 | 9.1164 | 0.8977 | 5.6543 | 1.6490 | 12.2135 |

$$RMSE = \sqrt{\frac{1}{N} \sum (Y_i^{actual} - Y_i^{predicted})^2} \quad (11)$$

$$MAPE = \frac{1}{N} \sum \left| \frac{Y_i^{actual} - Y_i^{predicted}}{Y_i^{observed}} \right| * 100 \quad (12)$$

In Eqs. (11) and (12), N is the number of observations, Y_i^{actual} is the observed electricity consumption and $Y_i^{predicted}$ is the forecasted electricity. To use the trained ANFIS model to forecast electricity consumption, forecasted input variables obtained using multilayer perceptron network for time series forecasting were used [27].

4. RESULTS AND DISCUSSION

The objective of this study was to propose ANFIS forecast model as an alternative approach to Uganda's electricity consumption forecasting. By taking social economic factors that influence electricity consumption as inputs to ANFIS model, we were able to train the model using PSO and GA. The proposed model is not only easy to interpret, it also gives low forecast errors. ANFIS models are generally complex black box models and not always easy to interpret because of the so many inputs and many number of rules. We managed to reduce this complexity to make our model easy to interpret by taking only four inputs. Using FCM, our inputs were divided into four clusters and four rules. Each rule takes number of customers, electricity prices, GDP and population as inputs in each cluster, passes the input to either PSO or GA training algorithm and gives electricity consumption as the output. The training process was done a number of times and each time the values of RMSE and MAPE were recorded. The

target was to get the best (lowest) values of RMSE and MAPE. The best RMSE and MAPE values for both algorithms are shown in the Table 2. From Table 2, GA-ANFIS gives lower values for both RMSE and MAPE than both PSO-ANFIS and MLR models. The forecasting accuracy of a model is a common parameter that is used to determine how good or bad a forecast model is. This parameter is usually measured as a percentage. A high forecasting accuracy indicates a good model. On the other hand a low forecast accuracy means a bad model. In this study, we use MAPE to measure the percentage error in the forecast, hence subtracting this error from one hundred gives the forecast accuracy of the model. As shown in Table 2, GA-ANFIS model gives a forecast accuracy of 94.3457% compared to that of 90.8836% for PSO-ANFIS and 87.7865% for MRL model. We can say that GA-ANFIS is a better forecasting model than PSO-ANFIS forecasting model and MRL model. The optimized ANFIS models after training are shown in Figures 5 and 6 below.

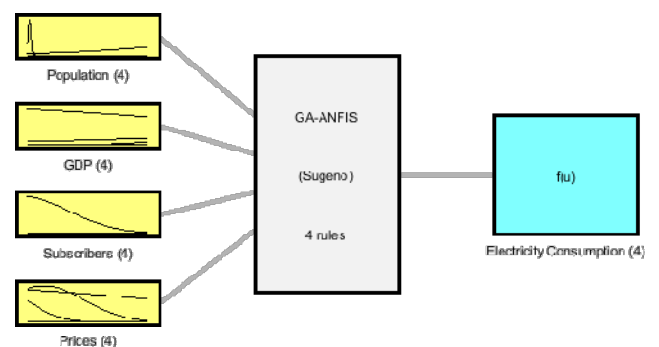


Figure 5 ANFIS model optimized using GA

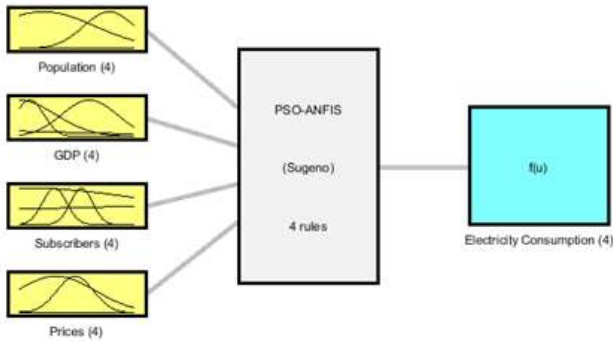


Figure 6 ANFIS model optimized using PSO algorithm

Using these optimized GA-ANFIS and PSO-ANFIS we forecast Uganda’s electricity consumption from year 2015 up to year 2040. The forecasted consumption along with the actual consumption, MEMD base case and Vision 2040 scenario forecasts and regression model forecasts are shown in Table 3. As expected each model shows a general increase in electricity consumption from 2015 up to 2040. As the consumption increases, the error between the actual and forecasted consumption also increases though not to a bigger magnitude as that of the MEMD forecasts. For planning purposes this error is manageable. The graph in Figure 7 show the forecasts. The percentage relative errors of our

Table 3 Comparison of forecast results and MEMD forecast report

| Year | Actual Consumption (GWh) | MEMD Forecast (GWh) | | MLR Model (GWh) | PSO-ANFIS (GWh) | GA-ANFIS (GWh) |
|------|--------------------------|---------------------|-------------|-----------------|-----------------|----------------|
| | | Base case | Vision 2040 | | | |
| 2015 | 3,219 | 4,645 | 25,506 | 3,854 | 3,219 | 3,269 |
| 2016 | 3,489 | 6,665 | 31,090 | 4,416 | 3,780 | 3,637 |
| 2017 | 3,715 | 7,114 | 37,035 | 5,246 | 4,444 | 4,284 |
| 2018 | | 7,591 | 43,358 | 6,325 | 5,347 | 5,099 |
| 2019 | | 8,099 | 50,077 | 7,861 | 6,614 | 6,264 |
| 2020 | | 8,638 | 57,214 | 9,318 | 7,825 | 7,358 |
| 2021 | | 9,211 | 64,790 | 10,990 | 9,182 | 8,629 |
| 2022 | | 9,819 | 72,825 | 12,784 | 10,638 | 9,997 |
| 2023 | | 10,370 | 81,344 | 14,502 | 12,049 | 11,298 |
| 2024 | | 10,992 | 90,370 | 16,227 | 13,465 | 12,602 |
| 2025 | | 11,648 | 99,927 | 17,969 | 14,914 | 13,906 |
| 2026 | | 12,338 | 110,033 | 19,714 | 16,343 | 15,228 |
| 2027 | | 13,064 | 120,723 | 21,535 | 17,866 | 16,579 |
| 2028 | | 13,828 | 132,026 | 23,395 | 19,404 | 17,966 |

forecasts in comparison to the MEMD forecast for the years 2015, 2016 and 2017, are very low while those MEMD and regression model are very high, especially those for Vision 2040 forecast as Table 4.

5. CONCLUSIONS

Uganda’s development goals as stated in Uganda vision 2040, identify electricity as a key variable in the development process. Therefore, planning in the electricity sector should be emphasized more than ever before. One of the critical inputs to the planning process is realistic and achievable forecast targets. In this study we have modelled Uganda’s electricity consumption forecasting using ANFIS and tuned the parameters of the model using PSO algorithm and GA. The ANFIS model takes four socio-economic variables as inputs and electricity consumption as output. From the results of the study we can make the following conclusions;

- i. Based on the RMSE and MAPE values as shown in Table 2, the results indicate that the GA-ANFIS model a better model as compared to the PSO-ANFIS and MRL models.

| | | | | | |
|------|--------|---------|--------|--------|--------|
| 2029 | 14,632 | 143,973 | 25,285 | 20,947 | 19,400 |
| 2030 | 15,453 | 156,320 | 27,346 | 22,728 | 20,901 |
| 2031 | 16,289 | 169,042 | 29,411 | 24,395 | 22,479 |
| 2032 | 17,138 | 182,087 | 31,470 | 26,102 | 24,016 |
| 2033 | 17,994 | 195,410 | 33,538 | 27,797 | 25,578 |
| 2034 | 18,857 | 208,961 | 35,608 | 29,458 | 27,160 |
| 2035 | 19,721 | 222,688 | 37,686 | 31,201 | 28,698 |
| 2036 | 20,584 | 236,534 | 39,755 | 32,880 | 30,273 |
| 2037 | 21,441 | 250,440 | 41,829 | 34,623 | 31,816 |
| 2038 | 22,289 | 264,345 | 43,901 | 36,310 | 33,390 |
| 2039 | 23,124 | 278,183 | 45,981 | 38,056 | 34,926 |
| 2040 | 23,941 | 291,889 | 48,055 | 39,751 | 36,494 |

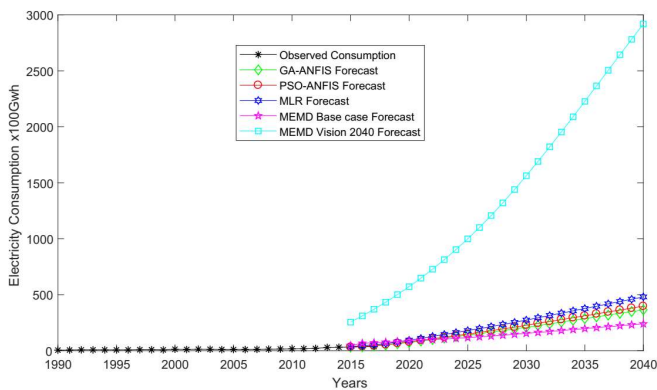


Figure 7 Comparison of forecasts

achievable targets as seen in the relative errors between the observed consumption and ANFIS forecasts in comparison to the official forecasts of the Ministry of Energy and Mineral Development.

Results arising from this study provide important reference materials for policy makers and utility companies to access Uganda’s electricity consumption needs and targets in order to align them with the national development goals outlined in Uganda Vision 2040.

- ii. In regard to easy interpretability we managed to model ANFIS with only four rules using with four inputs and one output. We were able to achieve forecast accuracy of 94.3457%, for GA-ANFIS, 90.8836% for PSO-ANFIS. Both ANFIS models exhibited better accuracy than the MLR model whose accuracy was 87.7865%.
- iii. ANFIS model for long term electricity forecasting has given more realistic and

Forecasting literature suggests that various forecasting approaches and methods when combined together give better forecast results with minimal forecast errors. There are various methods to combine forecast methods. As further research, we propose that the PSO-ANFIS and GA-ANFIS forecast models can combined into one model. Results of the combined model can be compared with results of the individual models.

Table 4

Percentage relative errors

| Year | MEMD | | MLR | ANFIS | |
|------|-----------|-------------|-------|-----------|----------|
| | Base case | Vision 2040 | | PSO-ANFIS | GA-ANFIS |
| 2015 | 44.30 | 692.36 | 19.73 | 0.00 | 1.55 |
| 2016 | 90.48 | 788.54 | 26.57 | 8.03 | 3.94 |
| 2017 | 91.49 | 896.90 | 41.21 | 19.62 | 18.06 |

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