SHORT-TERM ELECTRICITY LOAD FORECASTING IN UASIN GISHU COUNTY USING A HYBRID ANFIS MODEL

BY

ARUSEI ABRAHAM KIRWA

A Thesis Submitted to the School of Engineering, Department of Mechanical, Production and Energy Engineering in Partial Fulfillment for the Requirements of the Award of the Degree of Master of Science in Energy Studies
(*Renewable Energy Resources*)

MOI UNIVERSITY

2022

DECLARATION

Declaration by Candidate

I hereby declare that this thesis is my original work and it has not been submitted for the award of any other attachment evaluation.

Sign: ______________________________ Date: _______________________

Abraham Arusei

ENG/MES/18/19

Declaration by the Supervisor

This thesis has been submitted for examination with my approval as the university supervisor.

Sign: ______________________________ Date: _______________________

Prof.(Eng.) S. Sitati

Department of Electrical and Communication Engineering

School of Engineering

Moi University

Sign: ______________________________ Date: _______________________

Prof.(Eng.) Augustine B. Makokha

Department of Mechanical, Production and Energy Engineering

School of Engineering

Moi University

DEDICATION

I dedicate this project to my family who have been great sources of strength and inspiration in my life. They have supported me through the highs and lows of life, for which I am grateful. Indeed, their love has been unconditional.

ACKNOWLEDGEMENT

The success of this report was made possible by the grace of God in providing good health and protection during the entire period.

My sincere appreciation and gratitude goes to ACE PTRE for the opportunity offered, my Supervisors, Prof.(Eng.) S. Sitati and Prof.(Eng.) Augustine B. Makokha for their valuable guidance and assessment of my progress during the research period.

ABSTRACT

Accurate forecasting is becoming increasingly important due to the energy consumption's rapid rise. To manage and plan the use of energy resources efficiently, it is crucial to predict the demand for electricity, whose high increase in Uasin Gishu City has had a negative impact on the reliability of the electrical supply. The utility company KPLC) presently forecasts medium-term electricity demand through feeder load checks to support decision-making on operations, maintenance or infrastructure development planning, but this has not been sufficient to address the impact on power stability. Therefore, the main objective of this study was to model and simulate a hybrid model to forecast short-term electricity demand in Uasin Gishu County. The specific objectives were to determine the short-term electricity demand profile as affected by weather variables, time effects, economic factors and Load parameters, apply an Hybrid model based on Adaptive Neuro-fuzzy inference System (ANFIS) to estimate load demands from an hour to a week ahead, and assess the system's performance. Using temperature, wind speed, humidity, and historical load data as the primary parameters, this study describes the development and application of an ANFIS-based STLF model for the power networks in the Uasin Gishu County. Past load data from Kenya's electricity networks and meteorological data from the cloud data base www.timeanddate.com were used to test and validate the model. An adaptable neuro-fuzzy inference system (ANFIS) was used for machine learning-based electricity predictions. The forecasting model was constructed using a total of 49,860 dataset points, with training accounting for 75% of the work and checking and validation accounting for 15%. The novelty of this research lies in the large quantity of availed data, input parameters, validation of the ANFIS model for the training, testing, and validation data using four different membership functions: triangular, trapezoidal, generalized bell shaped, and Gaussian curve shaped, which produced the mean absolute percentage error (MAPE) values of 0.588, 0.359, 0.671, and 0.567, respectively. The effectiveness of the suggested approach is demonstrated by the evaluation of trained FIS results and a separate set of data based on Uasin Gishu county's electricity demand estimates. The suggested model's efficacy is clearly demonstrated by its average mean absolute percentage error of 0.0997%. The acquired results and forecasting performance demonstrate the viability of the suggested strategy and demonstrate the significant influence of meteorological variables on the short-term load demand profile.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER ONE: INTRODUCTION

1.1 Background and Motivation for the Study

Electrical energy ranks among the most important energies in human life. People want a high-quality life as the economy grows, therefore demand for electrical energy in industries, commerce, and for personal use is increasing. As a result, the electric sector must produce electricity and construct power substations in order to meet the energy needs of users. Because electric energy cannot be stored economically and has the characteristic of production and consumption occurring at the same time, it is critical to accurately forecast the electric load and achieve supply and demand equilibrium in order to avoid producing too much electric energy or causing outage accidents due to insufficient electric energy. More production of electric energy than demand is inefficient; nevertheless, insufficient production of electric energy will result in consumer complaints and dissatisfaction. According to Bunn et al, a 1% increase in forecasting error increases annual operational costs by £10 million. Accurate forecasting of electric load can improve the electric industry's management performance as well as reduce the frequency of outages, increasing customer happiness and the electric industry's image. This study examined how the passage of time,Load parameters and meteorological variables has had on short term load profile and electricity demand forecasting in Uasin Gishu County.

A specific forecasting process can be characterized as follows, depending on the period of interest:

- Long-term load forecasting (LTLF): is for a period ranging from one year to twenty years. This form of projection is crucial for strategic planning, new generating building, and the development of the power supply and delivery system (generation units, transmission system, and distribution system).

- Medium-term load forecasting (MTLF): is used for maintenance scheduling and planning fuel purchases, as well as energy trading and revenue assessment for utilities, and is normally for a month to a year.
- Short-term load forecasting (STLF): is for time intervals of one hour to one week.

1.2 Electricity Load forecasting

Load forecasting is done using historical load data as well as other influencing factors. Therefore, the following parameters must be considered in the analysis for accurate electricity demand forecasting.

- Data on electricity: Electricity consumption over time.
- Time effects: season, hour, holidays, etc.
- Weather data: Temperature, humidity, rainfall, wind speed, and other weather data.
- Economic Data from the utility company: Electricity prices, promotions, and marketing initiatives.
- Social – political data, Cultural and behavioral aspects data and political elements that a country is currently experimenting with.

1.2.1 Classification of Demand Forecasting Techniques

The current and future electricity demand, as well as load pattern changes, must be accurately estimated when planning and operating an electric power system. Accurate forecasting leads to significant operating and maintenance cost savings, improved power supply and delivery system reliability, and informed development decisions. Engineers used charts and tables to manually estimate future demand in the past. Because of the non-stationarity of the load forecast process, as well as the complicated relationship between meteorological variables and electric load, these traditional methods were rendered obsolete, as they assumed a simple linear relationship during the prediction process. Smoothing techniques, regression procedures, and statistical analysis were all used in traditional Short term electric load forecasting (STELF) processes. Peak load models and load shape models are among the statistical models utilized in STELF. These methodologies and models are reliable, but they are unable to adjust to odd weather circumstances and a variety of seasonal activities, which have a non-linear relationship with the daily load. As a result, their load projections are not as precise as they would want to be in the presence of such situations. The following is a timeline of how predicting methodologies have changed over time.

- **Traditional Forecasting Approaches:** In the beginning, traditional/conventional mathematical techniques were used to forecast future load demands. Multiple Regression, Exponential Smoothing, and Iterative Reweighted Least-Squares are examples of regression methods.
- **Modified Traditional forecasting approaches:** In order to enable them to automatically adjust the forecasting model's parameters in response to changing environmental conditions. Stochastic Time Series Techniques, Support Vector Machines, and Adaptive Demand Forecasting are a few of the methods used.
- **Soft Computing Techniques:** Soft computing techniques have grown in popularity during the past few decades. A novel technique called soft computing imitates the human mind's exceptional capacity to reason and learn in ambiguous and imprecise situations. It's becoming more and more used as a means of assisting computer-based intelligent systems in mimicking the human mind's aptitude for approximation rather than precise reasoning methods. examples include fuzziness and neural networks.

A load forecasting method should have all the following characteristics: causation, reproducibility, functionality, sensitivity, and simplicity. The three main groups into which the models are typically separated are those used for statistical analysis, those used for artificial intelligence, and those used for Grey prediction. Statistical methods are built on a mathematical model of the load curve. Just a few statistical methods that have been used regularly include regression processes, time series methods, and exponential smoothing. The time series approaches, for instance, presuppose that the only factor influencing future load demand is past demand. When the variables that influence load demand suddenly change, statistical models' accuracy deteriorates. The fundamental drawback of statistical modeling is that it relies on the availability of enough data samples, a variety of complex variables, and a number of statistical data assumptions to predict outcomes accurately.

Artificial intelligence (AI)-based forecasting models have shown improved non-linearity and other issue handling capabilities. They don't require intricate mathematical formulas or a quantitative relationship between inputs and outputs, which is their fundamental advantage. These techniques include genetic algorithms, fuzzy logic, expert systems, artificial neural networks, and particle swarm optimization. One disadvantage of artificial intelligence (AI) systems is that the volume of training sample data limits how accurate they can be. The Grey model focuses on model uncertainty and lack of enough information in analysing and understanding systems through research on conditional analysis, prediction and decision-making. This model is suitable for application to system analysis, data processing, modelling, prediction, decision-making, and control. The model was developed to overcome the challenges associated with statistical analysis and AI forecasting models. The chaotic evolutionary algorithm, which mixes fuzzy logic and regression techniques, is one example of a hybrid load forecasting method that successfully blends statistical and AI methods.

1.3 Requirements of the STLF Process

A module for anticipating short-term load is present in almost all energy management systems used in contemporary control centers. A strong STLF system should be accurate, quick to respond, quick to identify poor data, friendly to use, quick to retrieve data, and quick to generate forecasting results.

i. **Accuracy**

The accuracy of STLF's prediction is its most crucial criteria. The foundation of efficient dispatch, system dependability, and electricity markets requires good accuracy. Making the forecasting outcome as accurate as feasible is the primary objective of most STLF literatures, as well as of this thesis.

ii. **Speed**

Utilizing the most recent historical data and weather forecast data aids in improving accuracy. The forecasting program must, therefore, meet the fundamental criteria of forecasting speed. Programs that need excessively extended training periods should be discontinued and replaced with innovative methods that reduce training requirements. Typically, fewer than 20 minutes should satisfy the basic need of a day forecasting..

iii. **Friendly Interface**

The load forecasting interface should be simple, practical, and intuitive to use. Whether using images or tables, users may readily specify what they wish to forecast. The result should also be presented in both graphical and numerical form so that users may quickly access it.

iv. **Automatic Data Access**

The database contains historical load, weather, and other load-related information. The STLF system ought to be able to automatically access it and obtain the required information. Additionally, it should be able to automatically access the weather forecast online via the Internet or through a specific communication line. This lessens the workload for the dispatchers.

v. **Automatic Forecasting Result Generation** Multiple models are frequently used in a single STLF system to lower the possibility of individual forecasts being inaccurate. Such a system has historically required the operators' meddling. To put it another way, the operators must select a weight for each model in order to produce the combinatorial result. For convenience, the system should produce the final forecasting result in accordance with the historical days' forecasting behavior.

vi. **Portability**

The characteristics of load profiles vary amongst power systems. A typical STLF software application is therefore only appropriate for the domain for which it was designed. A generic STLF software application that is transferable from one grid to another could potentially greatly minimize the amount of time needed to develop separate software for multiple sites. This is a very complex requirement for the load forecasting that has not yet been fully realized

1.4 Limitation of Forecasting

There are several benefits to forecasting, including the following:

i. **Idea Generation** - For operations to produce accurate forecasts, gaining knowledge is essential. By using forecasting, you can develop the habit of predicting future demand by analyzing both historical and current data. By doing this, you will improve your ability to predict changes in demand. It will also give you information about the health of your company's supply chain and give you the chance to make any necessary modifications or adjustments based on fresh data obtained from real-time data.

ii. **Recognizing Past Errors** - Forecasting also gives you the ability to base judgments on past mistakes and may offer suggestions for how to avoid repeating them in the future. After each forecast, you don't start over. Even if your prediction couldn't have been further from the truth, it still offers a place to start. Reviewing the instances and causes of events that didn't turn out as you had anticipated is typical, and you should see an improvement in your forecasts. Additionally, you'll develop the practice of thinking back on your prior performance as a whole.

iii. **Cost reduction** - Given that forecasting can lower the amount of errors caused by adhering to a timetable based on the past, cost reduction is another important consideration in manufacturing operations. Your ability to anticipate demand will help you improve the efficiency of every step of the supply chain. You will eventually be able to lower surplus inventory levels and boost overall profitability because you can anticipate what customers will want and when they'll want it.

The following are some forecasting-related drawbacks:

i. **The accuracy of forecasts is never 100%.** - Future predictions can never be made with absolute certainty, and forecasts are never 100% accurate. Your projections will never be completely accurate, even if you have a superb procedure in place and hiring forecasting specialists. Particularly during times of crisis, some markets and products will experience high levels of volatility. Understanding what elements affect your demand can perhaps help with making forecasts during this period because the coronavirus has undoubtedly amplified and increased this volatility within the industry. Nevertheless, the primary flaw in projections is that they are usually never accurate, which causes either an excess or a shortfall of inventories.

ii. **It could require a lot of effort and time.** Data collection, organization, and coordination are all components of forecasting. Businesses will hire demand planners, and it will be their team's responsibility to make the projection. To perform this job well, demand planners will need a lot of assistance from the sales and marketing teams. Processes are frequently labor- and labor-intensive, which adds to the overall time required. If you have the correct technology in the right area, the problem is significantly reduced

iii. **Might be Expensive -** In particular, accurate forecasting can be very expensive. Spending the money, time, and resources necessary will result in a forecast that is adequate and nearly correct. It costs more to use high-quality tools when a team of demand planners is hired, which is a considerable expenditure. Despite being expensive, you should quickly see a return on this investment over time, and your forecast should be considerably more accurate, saving you money and paying for itself in the long run.

1.5 Adaptive Neuro –fuzzy inference System (ANFIS) model

ANFIS technique was first developed in 1993.It is a combination of neural networks and fuzzy-logic to leverage on their strengths and address their short falls, this makes it excellent for complicated and uncertain data. It is a data learning technique that use fuzzy logic to turn provided inputs into desired outputs using highly interconnected

Neural network processing elements and information connections that are weighted to translate numerical inputs into outputs. The properties of a fuzzy inference technique are updated by ANFIs using the neural network learning method. The proposed ANFIS may construct a feedback mapping based on human understanding (in the form of a fuzzy if then rule) and particular input data pairs by using a hybrid learning approach. The ANFIS architecture is used in the simulation in order to visualize nonlinearities, detect nonlinear elements on a control line, and anticipate chaotic time series.

1.5.1 ANFIS Architecture

The ANFIS architecture is shown in Figure 1.1 and consists of five levels and nodes (Jaya et al, 2011). ANFIS employs five network layers to carry out the subsequent fuzzy inference procedures: (1) Fuzzification of the input, (2) application of the fuzzy operator, (3) normalization, (4) defuzzification, and (5) output summation

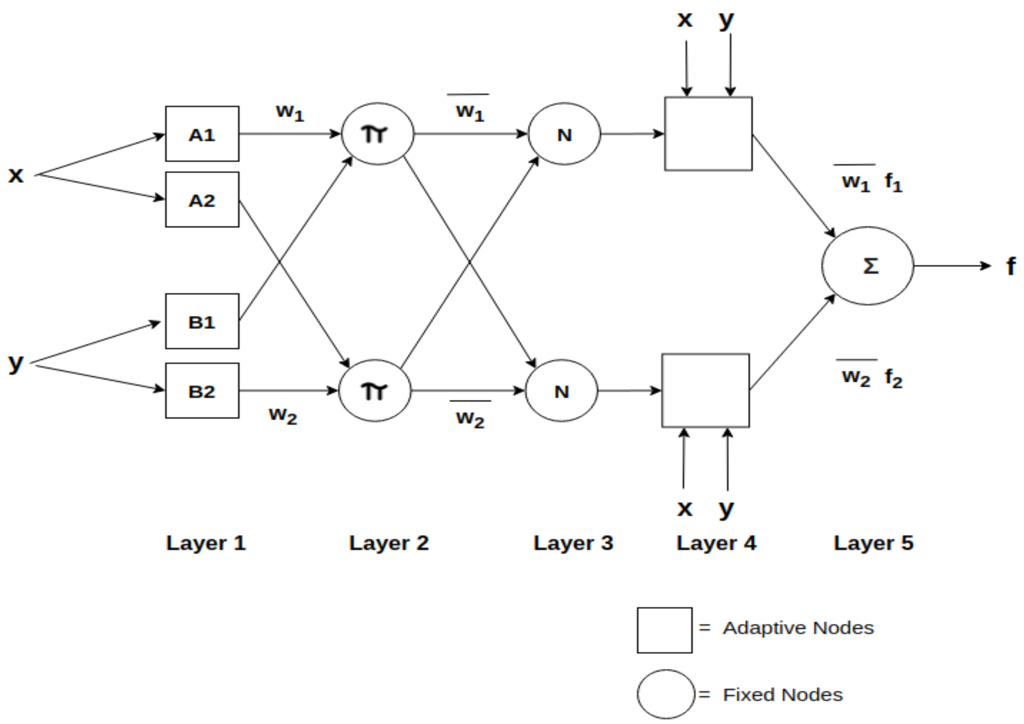


Fig 1.1: ANFIS architecture (Jaya et al., 2011)

i. **Fuzzification, the first layer:**

- The neuron here represents fuzzy sets, which are utilized as an antecedent to fuzzy rules.
- The neuron gets the crisp input and determines which fuzzy set it belongs to.

The role of the node is given by;

$$\mu_A(x) = \frac{1}{1+\left|\frac{x-C_i}{a_i}\right|^{2b}} \quad (2)$$

Where x, y are the neuron's inputs Linguistic labels (Ai, Bi)

Where ai, bi, and ci are the premise parameter set.

The bell-shaped function in the Sugeno model changes as the values of these parameters change.

ii. **Fuzzy Rule, 2nd layer**

- Each fixed node performs has an output equal to the total of all incoming signals from layer 1, rendering it a layer of fixed nodes.
- The firing strength refers to the output of each layer 2 node.

For layer 2, the node function is:

$$O_{2,i} = w_i = \mu_{A_i(x)\mu B_i(y), i=1,2} \quad (3)$$

iii. **Normalization, the third layer.**

- Each stable node in this tier is identified by the letter "N."
- The ith node calculates the activation level of the ith rule in relation to the combined firing strength of all rules. $o_{3,i} = \overline{w}_i = \frac{w_i}{w_1+w_2} i = 1,2$ (4)

iv. **Defuzzification is the fourth layer**.

- This layer has only one node, which is a fixed node. The overall output is calculated as the sum of all incoming signals. As a result, the entire result is;

$$O_{5,i} = \sum_i \overline{w}_i f_i = \frac{\Sigma_i w_i f_i}{\Sigma_i w_i} \tag{5}$$

v. **The output node the fifth Layer**, its single, calculates the overall output via summing all incoming signals.

1.5.2 ANFIS Learning Algorithm

Neural-fuzzy systems combine artificial neural networks and fuzzy set theory, making them incredibly powerful. The fuzzy system is a neural network structure with knowledge distributed across connection strengths, and neural networks are well-known for their ability to learn and adapt to new or changing environments in order to improve performance. They also have the benefit of simplifying the transition of the final system into a series of if-then rules. The values of a collection of adjustable parameters through which the nodes are connected determine an adaptive network's overall input-output behavior (Jang, 1995.) The adaptive system applies a hybrid learning technique to identify parameters for Sugeno-type fuzzy inference systems. It combines a combination of the least-squares methodology and the back-propagation gradient descent method for training FIS parameters for the membership function to model a particular collection of training data (Rezaei, Hosseini, & Mazinani, 2014). The network's learning process is broken into two stages. In the forward phase of the learning method, consequential parameters determine the least squares estimate. The error signals, which are the derivatives of the squared error with respect to each node output during the backward phase, travel from the output layer to the input layer. The gradient descent method is used in this backward step to modify the parameters for the premise. A neural network's learning or training phase is the process of determining parameter values that are appropriate for the training dataIn order to reduce training error, other strategies might be applied during ANFIS training. A mix of the least squares algorithm and the gradient descent technique is used to find the best settings. The main benefit of a hybrid technique is that it converges much faster because neural networks' backpropagation process has smaller search space dimensions (Hamdan & Garibaldi, 2010). ANFIS is a fuzzy Sugeno model incorporated in an adaptive system that helps with model building and validation, making training and adaptation easier.

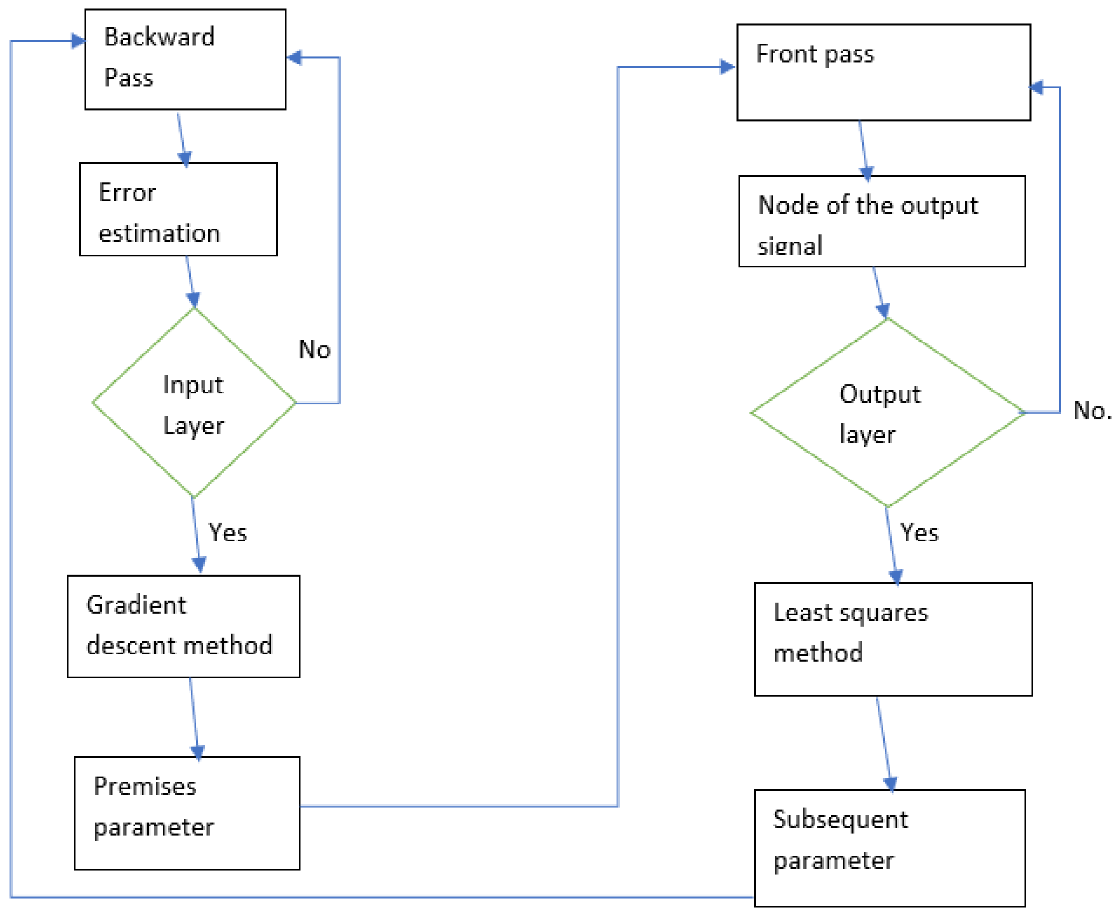


Fig 1.2: ANFIS Learning algorithm.

1.5.3 ANFIS Training Process

The ANFIS training technique is as outlined, obtaining training data sets, checking data sets (input/output data pairings), and testing data sets are the first steps. An assortment of input and output vectors are used as part of the training and testing data to program the ANFIS system. The membership functionality criterion value is determined by comparing the actual and desired outputs, and training and verification data sets are used to do this.

i. Start
ii. Data preprocessing; prepare data sets (training data, checking data, testing data) by arranging the data in matrix form
iii. Generation of FIS models either by grid portioning or sub clustering.
iv. Define the Input parameters of the fuzzy system and FIS method (sugeno or Mamdani)
v. Select the MF type and number per input parameters, number of epochs and optimization method,
vi. Load training and checking data from workspace to ANFIS.
vii. Train the ANFIS model.
viii. Load test data into ANFIS and test by plotting the generated FIS against the test data.
ix. Examine the structure of ANFIS, as well as the generated rules and the output surface.
x. Determine the system's performance by Evaluate the validation data against the trained FIS and Compute MAPE by plotting actual values against predicted values.

Prepare the training, checking, and testing data sets and import them into a MATLAB workspace in matrix form, with the target output in the last column and the system's input parameters in the other columns. All of the data that is currently available is represented by the rows. The type of membership functions, the technique for generating FIS, and how many epochs are used are all decided by the system designer.

After loading the Training and Checking data into the ANFIS system, the training begins, with a total number of 200 epochs on a hybrid optimization approach with 0% error tolerance The incorporation of both training and checking data in ANFIS system training enhances the system's accuracy and efficacy by increasing the chances of it being understood. After the training is over, the ANFIS offers an evalfis function which can be used to gauge how well the system is working. The knowledge derived from the training result (fuzzy inference system) is created. The loading of a testing data set into ANFIS, is the first step in the research and assessment of system performance. The result of the evalfis function represents the system's response or the ANFIS system's final output. The proposed hybrid system's functionality and reliability are also determined by the correlation between the desired values (actual data) and the predicted values as the system output.

1.6 Uasin Gishu County and Its Demographic nature

Located in the formerly Rift Valley Province lies Uasin Gishu County. It shares borders with Elgeyo Marakwet County to the east, Trans Nzoia County to the north, and Nandi County to the south. With a population of 894,179 and 3,345 square kilometers of land (KNBS, 2015). According to kenya power records, UasingGishu county has an annual electricity uptake of approximately 232Gwhrs against ahuge electricity demand according to (Mutai, Sneider, & Kiprop, 2019). It is therefore crucial to create a model that could precisely forecast the electricity demand on a short-term basis and enable decision-making regarding day-to-day safe operation of the power system, especially actions that go toward alleviating breakdown, like optimal and dispatch power flow and load management. This is necessary because the current grid is already under stress from the rising household and industrial energy demands.

1.7 Statement of the Problem

Due to the absence of an accurate instrument for predicting energy consumption, the effects of increased residential and commercial energy needs on the growth and management of the power system are not well understood. The significant rise in load demand and related effects on the reliability of the power supply in Uasin Gishu County make planning crucial and necessary. A noted rise in the frequency of power outages, low voltage, and load shedding for customers is a result of the unchecked rising demand for electricity. The recently commissioned Turkana wind power output has not been adequate to solve the spike in interruptions because of its intermittent nature. As a result, this study describes the creation and use of an ANFIS-based STLF model for Uasin Gishu networks that accounts for time, temperature, humidity, and wind speed as the main climatic variables affecting the load and allows rapid decision-making. Although the utility company currently inspects all feeder networks and equipment annually, allowing for decisions on infrastructure growth and system capacity upgrade, this has not been enough to stop the outages. In light of this, timely planning and decision-making from an hour to a week ahead depend on accurate short-term forecasting of electricity consumption.

1.8 Justification

The management and planning of power resources depend on the ability to forecast electricity consumption. The effectiveness of operations (STLF) is significantly impacted by short-term load forecasting (Bazmi, Daroody, & Gholamreza, 2012). Being extremely exact about the projected electric demand is crucial for energy producers, merchants, and system operators' business activities. The benefits of soft computing-based load forecasting and the increasing number of power outages, low voltage supply, and load shedding for customers as a result of the unchecked rising demand for electricity that the traditional medium-term load checks conducted by Local Power Utility company (KPLC) have not adequately addressed served as the driving forces behind this project, respectively. For specific load centers, such as Uasin Gishu county, the utility company can prepare for peak electrical load reduction using a range of procedures, including electric load shedding, analytical operations like optimum power flow, and dispatch power flow on distribution line (feeders). Consequently, it is possible to decide quickly what corrective actions, such as load shedding, power purchases, and the activation of peaking units, should be prepared.

1.8.1 Significance of the study

Knowing the expected electric demand with high accuracy is a crucial aspect of any company for system operators, energy producers, and merchants. Better demand side management practices and more accurate forecasts from single end users, up to system scale, are required by the new energy market and the smart grid paradigm. The analytical load forecasting methods perform admirably under typical everyday conditions however, they are not continuously updated since they cannot provide satisfactory results when dealing with meteorological, social, or economic changes. The benefit of using soft computing techniques instead of mathematical models has been a driving force behind the existing research. The current research focuses short term electricity demand prediction through building a hybrid ANFIS model and training it with a large quantity of data. The motivation for this project came from the benefits of soft computing-based load forecasting and the observed rise in the number of power outages, low voltage supply, and load shedding for customers as a result of the unchecked rising demand for electricity that the medium-term load checks traditionally performed by Local Power Utility Company (KPLC) have not adequately addressed.

1.9 Main objective

Develop a hybrid model based on Adaptive Neuro-Fuzzy Inference System for forecasting short-term electricity demand in Uasin Gishu County and evaluate its accuracy.

1.9.1 Specific objective

1. To determine the Short-term electricity demand profile as affected by Weather variables, time effects, economic factors and Load parameters.
2. Develop and apply a hybrid model based on Adaptive Neuro-Fuzzy Inference System that can predict electricity demand from an hour ahead to a week ahead.
3. Assess the performance (accuracy) and dependability of the model.

1.10 Overview of the Thesis

Chapter 2: Highlights the more often used methods for predicting electrical load. The focus is on ANFIS techniques that will be used to develop an STLF for the county of Uasin Gishu after reviewing the material already in existence and various techniques.

Chapter 3: Explains the analysis methods utilized to put an STLF into place for Uasin Gishu county. We cover the procedures and Matlab® tools used to build an ANFIS and a commands to load training data.

Chapter 4: shows the STLF simulation's results using several Membership functions and contrasts the predicted outcomes with the real 24-load from Kenya Power's Rivatex distribution substation. The short-term load profile's influence on real load and meteorological variables is shown in a time series correlation plot.

Chapter 5: Concludes the study's findings and research done. Future electrical STLF work for Uasin Gishu county is also recommended.

CHAPTER TWO: LITERATURE REVIEW

2.1 Overview of Electricity Demand Forecasting

Forecasting electric load is critical in the transmission and distribution of power, as well as in the control and adjustment of electricity, feeder dispatch, and the treatment of emerging situations. Because of the significance of country's electric load, a variety of electric load forecasting models have been developed namely: Multiple regressions, Exponential smoothing, Iterative reweighted least squares, Adaptive load forecasting, Stochastic time series, ARMAX model based on genetic algorithm, Fuzzy logic, Neural network, Knowledge based expert systems. Several methods for forecasting electricity load demand have been developed and implemented. Some studies concentrate on model construction, while others employ iteration and regression techniques. The basic goal is to create a system or model that can forecast the load within the smallest possible error and within the time limit specified.

2.2 Previous Studies on Short term Load Forecasting Using ANFIS

The creation of a short-term load forecasting model that predicts the electric load is shown in (Seema & Dr. Sharma, 2015). This model is based on the Adaptive Neuro Fuzzy Inference System (ANFIS). According to previous load data, time, temperature, and other factors, this report predicts the amount of electricity needed. The mean absolute percentage error (MAPE) for a specific Tuesday was found to be 5.705% based on the study performed on the ANFIS-based model. The acquired results and predicting performance demonstrate the value of the suggested methodology and demonstrate that a high accuracy model may be constructed with fewer historical data points. The work by (Amevi, Ternor, Asabre, Adjei, & Iddrisu, 2020) focuses on the accurate forecasting of electricity needs utilizing Ghana's historical data on electric load and the Adaptive Neuro-Fuzzy Inference System (ANFIS). The effectiveness of the ANFIS algorithm was evaluated by contrasting its forecasts with those of the Support Vector Regression (SVR), Least Square Support Vector Machine (LS-SVM), and Auto-Regressive Integrated Moving Average forecast models (ARIMA). The results showed that the ANFIS algorithm can make predictions with high accuracy, that it converges more quickly with more training data, and that raising the membership function caused data overfitting, which had a negative impact on the RMSE values. The potential for the ANFIS algorithm to improve forecast accuracy while depending on high-quality training data and trustworthy parameter setup was demonstrated by comparison of the ANFIS findings to other previously utilized techniques of estimating power demands, including SVR, LS SVM, and ARIMA.

Adaptive Neural-Fuzzy Inference System (ANFIS) was investigated in the (Zohreh, Hadi, Mahdi, & Mohammad-R, 2010) pape to analyze the design of Short-Term Load Forecasting (STLF) systems for the east of Iran. Using multiple ANFIS, this study forecasts consumption load. Entries into the multi-ANFIS system for the presented model include the day's date, the day's maximum and minimum temperature, the climate condition, the previous day's consumed load, and The findings indicate that temperature and features from 2, 7, and 14 days ago have a significant impact in load forecasting; they came to the conclusion that separating working days from holidays by adding a temperature time series improves load consumption predictions. In order to estimate the short-term electric load on the Power System of the Greek Island of Crete, (Kodogiannis & Petrounias, 2014) outlines the development of a novel hybrid intelligence model and verifies its predictions. A two-stage clustering method was utilized in the proposed system to determine the rules, the number of fuzzy sets, and the initial values of the parameters (centers and widths) of the fuzzy membership functions. The results for the lowest and highest load time series demonstrate that, in comparison to conventional neural network models, the proposed load forecasting model provides forecasts that are significantly more accurate.

Aqeel, Meysam, and Gholamreza, (2012) describes a paper in which an ANFIS network (adaptive neuro fuzzy inference system) was designed to map six parameters as input data for the State of Johor, Malaysia, including four demographic and economic parameters (e.g., employment, GDP, industry efficiency, and population) and two meteorological parameters related to annual weather temperature (e.g., minimum and maximum average annual temperature) to electricity demand as output variable. The network's MSE of 0.0016 demonstrated remarkable forecasting capability. To predict the load on an actual South African distribution network, an adaptive neuro-fuzzy inference system (ANFIS) was deployed (Sibonelo, Ali, & Rian, 2015). This research was done to look at the use of a potent of ANFIS approach in actual South African distribution networks load forecasting. Investigations also looked at the effects of temperature and real-world difficulties. It was found that the cleaned-up loading data and characteristics linked to loading time of day produced the best ANFIS forecast results. Without temperature as an input variable, the lowest attainable errors were a Symmetric Mean Absolute Percentage Error (sMAPE) of 0.207322, Mean Absolute Error (MAE) of 0.059294, and Root Mean Square Error (RMSE) of 0.081476. Additionally, it was shown that, in contrast to expectations, adding temperature to forecasts did not improve the accuracy. With properly processed data, the majority of artificial intelligence systems produce mean absolute percentage errors (MAPE) of under 2%. For a one-day hourly forecast, a MAPE of less than 5% is considered acceptable at the corporate level (Guo & Niu, 2008).

The application of neuro fuzzy logic for forecasting electricity demand based on a huge quantity of combined data of past electric loads, temperature, humidity, and wind speed conditions has not been investigated despite the fact that many studies have been conducted on short and long term electricity demand/load forecasting. Therefore, the short-term load forecasting model developed in this study applies an Adaptive Neuro Fuzzy Inference System (ANFIS) that forecasts the electric load by taking into account time, temperature, humidity, wind speed, and previous load data. Historical load information is sourced from the Kenya Power-Rivatex distribution substation, while weather information is sourced from www.timeanddate.com.

2.3 Factors Affecting Electricity Demand Forecasting

Consumer load demand, as well as overall transmission line losses are influenced by a number of factors (Muhamma & Naeem, 2014). These variables factors, as well as their impact on electric power consumption are examined through Load analysis. Figure 2.1 shows a sample load curve for a county in Kenya base average hourly usage.

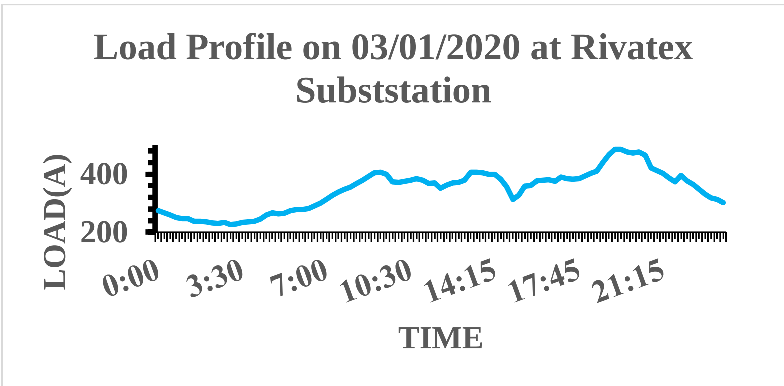


Fig 2.1: Load profile at Distribution Substation-Rivatex

According to figure, electricity usage varies all through the day. Early mornings, when people are sleeping, have the lowest consumption levels. When people get ready for work, consumption gradually climbs between 4:30 and 9:00 a.m., between 10:00am and 10:30 a.m., a morning peak is seen, which can be explained by domestic tasks. The after-work, dinner, and bedtime activities are highlighted by the afternoon and evening peaks. As a result, consumption patterns are influenced by consumer behavior and activities.

The geographical location has an impact on energy use. It has been discovered that residences in rural locations use less energy than those in urban areas (Heinonen, 2014). Consumers in rural regions mostly use firewood and gas for heating and cooking, with RES accounting for a significant portion of the total. In addition, customers in urban areas utilize more electric HVAC (Heating, Ventilation, and Air Conditioning) systems and appliances. The weather is another component that is influenced by the geographical location. Consumers in hot-climate countries are more likely to utilize air conditioning (Qamber, 2012), resulting in a noon peak that lasts until the temperature drops. Load curves in cold-climate countries reach a peak anytime the temperature falls below a certain level due to heating systems. As a result, load curves follow the temperature patterns throughout the day. Tropical settings, such as Singapore (Chuan, 2015), have a generally steady temperature, hence temperature has a small impact. Residences, offices, and colleges all have different consumption patterns (Sial, 2014). (Gul & Patidar, 2015). Between 30 and 45 percent of worldwide energy demand is accounted for by offices and institutions. The academic and administrative areas of universities experience a peak during the day till late afternoon. A second surge can be seen in the residential area until late at night, when students return to their dorms (Sial, 2014). However, in office buildings, there is a peak between 10:00 and 16:00, after which consumption is rather low and stable (Gul & Patidar, 2015).

Other variables that impacts on changes in load patterns Economic consideration, Client-related factors and Random Spikes. The state's economy has an impact on power demand. Economic factors are more important in long-term forecasting (Taylor & TX, 2010), although they can also affect the load curve in short-term load forecasting (Taylor & TX, 2010). Thus, in order to anticipate load, we must consider the country's economic status (GDP) as well as the country's industrial development for long-term load forecasting (Taylor & TX, 2010). The hourly load curves of affluent countries, for instance, differ from those of developing countries in their patterns. Due to the high level of industrial activity, the peak of the load profile curve for industrialized countries occurs between 11:00 and 4:00 pm. whereas the peak for developing countries occurs after 6:00 p.m. The cost of electricity and people's purchasing power have an impact on its consumption; as a result, the more expensive electricity is, the less it is utilized by home users. As a result, the daily load curve is influenced by the price of electricity (Taylor & TX, 2010). Peak load duration and incidence can be influenced by time of use pricing. Electricity is cheaper at night in several nations than during the day. As a result, time of use pricing can encourage domestic and industrial customers to alter their load, reducing peak shaving and filling the night valley. As a result, economic factors like as energy pricing, load management, and the degree of industrialization have a significant impact on average load and maximum demand in the system. In light of the foregoing, this element is not included as an input parameter to the model because it will have no effect on short-term forecasting in Kenya- Uasin Gishu County

2.3.1 Weather Variables

In load forecasting, the weather is an independent variable. Although the load profiles of industrial users can also be impacted by the weather, it has the greatest impact on home and agricultural consumers. Weather is frequently cited as a tipping point that can lead to system unreliability by lowering power supply efficiency. External factors such as unexpected sea breezes, after-moon thunderstorms, and back door fronts are just a few examples of what can lower the temperature, resulting in an inflated load forecast (Rahman, 2002). The following weather factors are included in the weather factor (Franco & Sanstad, 2007) (Belzer, Scott, & Sands, 1996): Temperature, Humidity, Wind speed.

a) **Temperature:** "The measurement of a body's degree of hotness or coolness," according to its definition. During the summer, temperature and load have a strong positive relationship, but during the winter, they have a strong negative relationship (Paravan, Debs, Hansen, Hirsch, & Golob.). This shows that larger loads are associated with greater temperature variations during dry (hot) seasons, but lower temperatures result in lower daily average loads and peak demand. In the summer, customers will use electricity for cooling (more air conditioners, refrigerators, and fans), but in the winter, electricity will be used for heating. As a result, during the winter, the connection between temperature and load consumption is negative or inverse.

b) **Humidity:** It is used to describe the amount of moisture in the air and measured in percentages. Humidity can make a room feel warmer while having little effect on the actual temperature. Because evaporative cooling is used to control body temperature, humans are sensitive to humidity. In a humid atmosphere, the rate of evaporation via the skin (perspiration) is slower than normal. We sense the rate of heat transfer rather than the temperature in high humidified environments, thus we feel warmer. People's comfort levels drive the need for electricity. Humans may feel more at ease when the temperature is high and the relative humidity is low, or when the temperature is low and the relative humidity is high. It is appropriate to include both relative humidity and temperature in load forecasts because they have a combined impact on human comfort levels. In late spring, summer, and early autumn, Saifur Rahman (1990) studied the effect of relative humidity. This was used to replace temperature in his model when the expected day's temperature was between 76°F and 91°F. Hor et al. (2005) discovered that including relative humidity in the model enhances monthly load forecast accuracy in the UK during the summer months.

c) **Speed of Wind:** It is the measurement of air flow relative to the earth's surface over a given distance in a given time period." Wind speed is today measured with an anemometer, however it was previously measured using the Beaufort scale, which was based on people's observations of well-defined wind impacts. In cold weather, the wind speeds up heat loss, making people feel even colder (Bluestein, 2015). The NOAA NWS WCI measures the human-perceived equivalent temperature in cold weather, taking both temperature and wind speed into account. When there is low humidity, the wind speed decreases the apparent temperature and speeds up the evaporation of perspiration from the human body, resulting in a cooling effect. As a result, on a windy summer day (hot weather), power consumption is lower because fewer cooling appliances are used. As a result, a distribution load forecasting model must take wind speed into account as an influencing parameter that can both decrease and increase load consumption (during warmer seasons). The increase in load consumption is described by the wind chill index. The temperature that is perceived on exposed skin owing to the wind is known as the wind chill factor. It has the effect of bringing the temperature of the warmer bodies closer to that of the surrounding environment. People frequently utilize heating equipment to stay warm during wind chills. In direct proportion to wind speed is the rate of heat loss. The greater the wind speed, the more heat is lost, this phenomenon is referred to as wind chill.

2.3.2 Time effects – Holiday, Weekends etc.

It's a variable that affects electric load at different times of the day, including weekdays and weekends. The time-dependent electric load variance can represent people's lives, such as work schedules, leisure time, and sleeping patterns. The load curves generated by Rivatex illustrate that the load curve has a time of day feature (Feinberg & Genethliou).

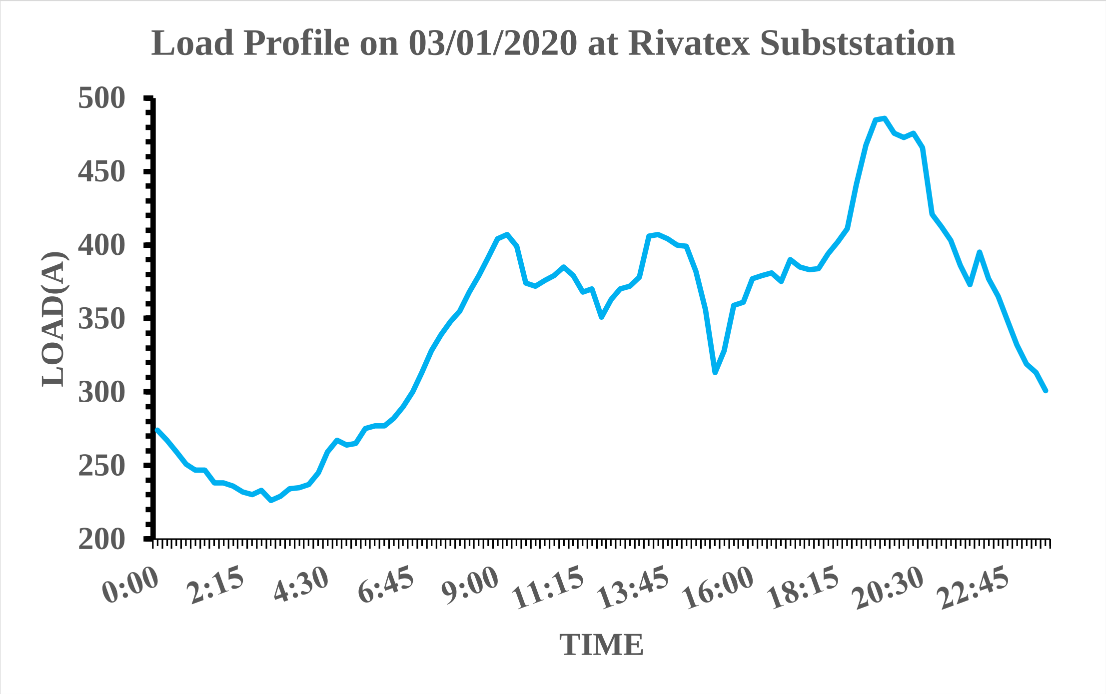


Fig 2.2: Load profile of 3/1/2020 at Rivatex substation

As shown by the hourly load curves, the load is modest and steady from 0.00 am to 06.00 am. They rise from 07.00 a.m. to around 09.00 a.m., then are lowered or flattened till 13.00 a.m. to around 14.30 a.m., and then fall until 17.00 a.m., when they begin to rise again at 19.00 a.m. The maximum load demand is observed between 19.00 and 21.00 hours, while the lowest load demand is observed after midnight. So, if we take a hard look at this load curve, we can observe that load demand mirrors the consumer's lifestyle The demand is lowered because no one is awake in the middle of the night. At eight o'clock, when everyone is inside watching television and huddling up to the heat, the load is at its peak. The load curves are by definition periodic.

2.3.3 Economic Factors

Power demand is influenced by the state's economy. Economic considerations are more essential in long-term forecasting although they can also alter the load curve in short-term load forecasting (Taylor & TX, 2010). For long-term load forecasting, we must take into account both the country's economic condition (GDP) and its industrial development for example, there are differences between the typical load curves of developed and developing nations. The hourly load curve for developed countries peaks from 11:00 a.m. till 4:00 p.m. due to heavy industrial activity, whereas the peak for developing countries occurs after 6:00 p.m. Load Consumption is affected by energy costs and people's purchasing power; as a result, the more expensive electricity is, the less it is consumed by household users. The daily load curve is affected by power costs (Taylor & TX, 2010). Peak load duration and occurrence can be affected by time of use pricing. Electricity is cheaper at night in many nations than it is during the day. As a result, time of use pricing may encourage residential and commercial customers to alter their load patterns, lowering peak shaving and filling the night valley. The average load and maximum demand of the system are heavily influenced by economic factors such as energy prices, load management, and the degree of industrialization.

2.3.4 Social - Political

The electricity system is made up of various types of customers, including residential, agricultural, and industrial. Domestic consumer loads are generally predictable and obey strong statistical rules, whereas industrial and agricultural loads are extremely inductive, creating big spikes in the load curve when they start up and shut down. These spikes are characterized as random disturbances because the startup and shut-down of these large loads are unpredictable in nature and there is no way to foresee when they will occur. Special occasions such as religious, political, or cultural festivals can also produce random disturbances. Special occasions include Eid al-Fitr and Christmas. Similarly, new year celebrations fall under this category of exceptional days that generate massive spike in the load curve due to increased television viewing.

2.4 Forecasting Models

2.4.1 End-use models

The end-use approach predicts energy consumption directly utilizing a wealth of data on end use and end users, including appliances, customer usage, age, housing sizes, and so on. The projection is based on statistical information about customers as well as changing dynamics. The diverse applications of electricity in the residential, commercial, and industrial sectors are the subject of end-use models. These models work on the assumption that power consumption is derived from customer need for light, cooling, heating, and refrigeration, among other things. On the contrary hand, end-use models, describe energy demand as a result of the quantity of appliances on the market (Rice, Mustafa, & Engle, 1992). This method is, in theory, quite precise. However, the number and quality of end-use data are important considerations. The distribution of equipment age, for example, is crucial in this strategy for specific types of appliances. End-use forecasting necessitates a greater amount of knowledge about customers and their equipment rather than previous data.

2.4.2 Econometric models

The econometric method integrates economic theory with statistical tools to forecast electricity demand. The method calculates the links between energy consumption (dependent variables) and factors that influence consumption (independent variables). The least-squares approach or time series methods are used to calculate the relationships. One of the options in this framework is to aggregate the econometric approach, which involves calculating consumption in different sectors (residential, commercial coal, industrial, and so on) as a result of weather, economic, and other variables, and then putting together estimates using recent historical data. When the econometric technique is combined with the end-use approach, behavioral factors are introduced into the equations.

2.4.3 Statistical based learning Models

End-use and econometric methodologies both necessitate a considerable amount of data about appliances, consumers, economics, and other factors. Their use is difficult and necessitates the involvement of humans. Furthermore, such information is frequently unavailable for specific consumers, thus, a utility maintains and supports a profile of a "average" customer or customers for various customer types. It becomes challenging for the utility to make estimates for sub-areas, also referred to as load pockets, for the following year. to avoid depending on unavailable information, to improve the accuracy of medium-term estimates, and to make them easier to understand. The investigation's primary subject was the summertime data. The multiplicative model below was found to be the most accurate after a number of load models were investigated (Willis, 1996.)

$$L(t) = F(d(t), h(t)) \cdot f(w(t)) + R(t) \quad (1)$$

Where $L(t)$ is the actual load at time t,

$d(t)$ is the day of the week,

$h(t)$ is the hour of the day,

$F(d, h)$ is the daily and hourly component,

$w(t)$ is the weather data that include the temperature and humidity,

$f(w)$ is the weather factor, and $R(t)$ is a random error

In fact, w (t) is a vector made up of present and lagged weather variables. This represents the fact that electric load is influenced by weather not only in the present, but also in prior hours and days. The use of air conditioners increases when the hot weather lasts for several days, which is a well-known effect of so-called heat waves. Both medium- and long-term forecasting can benefit from the strategies provided. However, economic and demographic dynamic estimates should be included as input parameters for long-term forecasts (Willis, 1996.) Load forecasting can be done in a number of ways (Kyriakides and Polycarpou, 2007; Feinberg and Genethliou, 2005; Taylor and McSharry, in press; Hippert et al., 2001; Tzafestas and Tzafestas, 2001). Regression-based techniques, time-series approaches, artificial neural networks, and expert systems are just a few examples. A brief summary of some of the concepts and methodologies may be seen in the Fig.2.3.

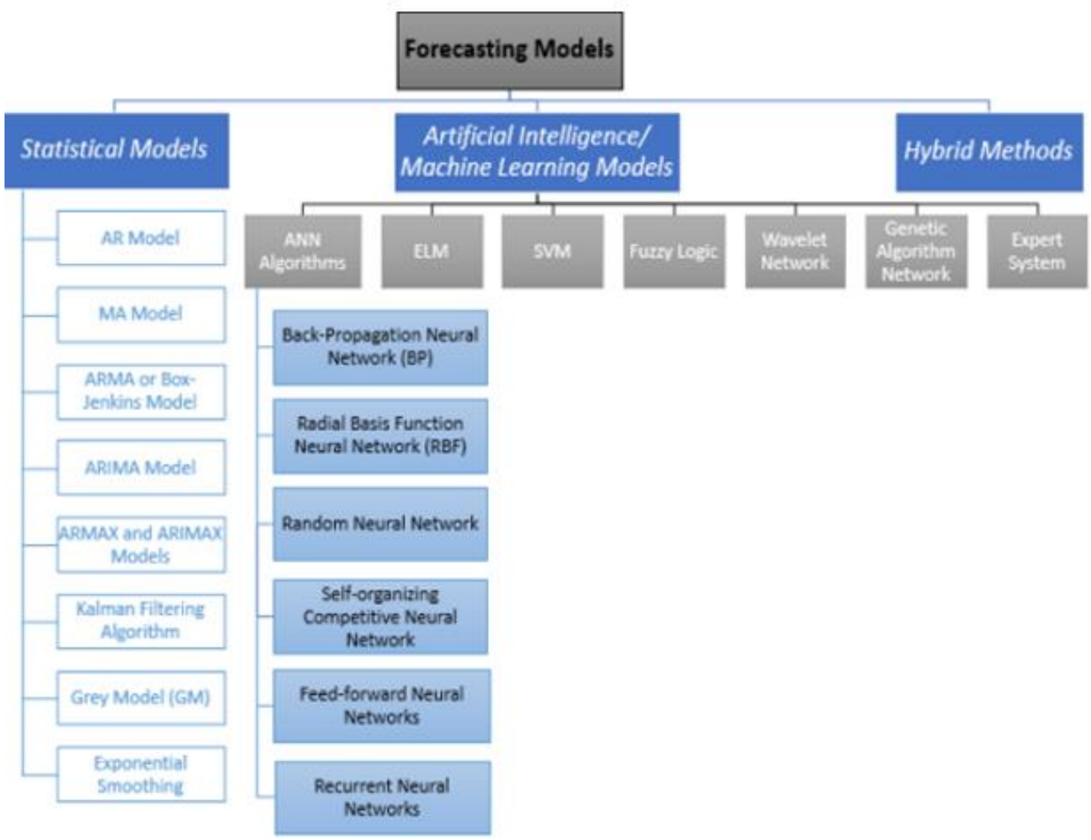


Fig. 2.3: Forecasting models (Kyriakides and Polycarpou, 2007).

Statistical techniques necessitate the use of a mathematical model that expresses the relationship between load and a number of input variables. For load forecasting, regression-based approaches, time series methods, state space models, and Kalman-filtering are used.

2.4.4 Artificial intelligence Models

Fuzzy systems, artificial neural networks (ANN), evolutionary computation, and swarm intelligence are all topics that are usually referred to as computational intelligence. Neural networks and fuzzy logics are the subtypes of these domains that are most commonly used in load forecasting.

a) Neural networks

Neural networks are a type of computer network. The essential functioning principle of neural networks is based on that of human brains. They are made up of a lot of neurons. As illustrated in figure 2.4, a neuron collects the information it gets from its input nodes. It then determines its activity and propagates its response to other neurons through the output node. For a survey, neural networks are commonly used for load forecasting (Hippert et al. 2001) (Suhas & ALI, 2015).

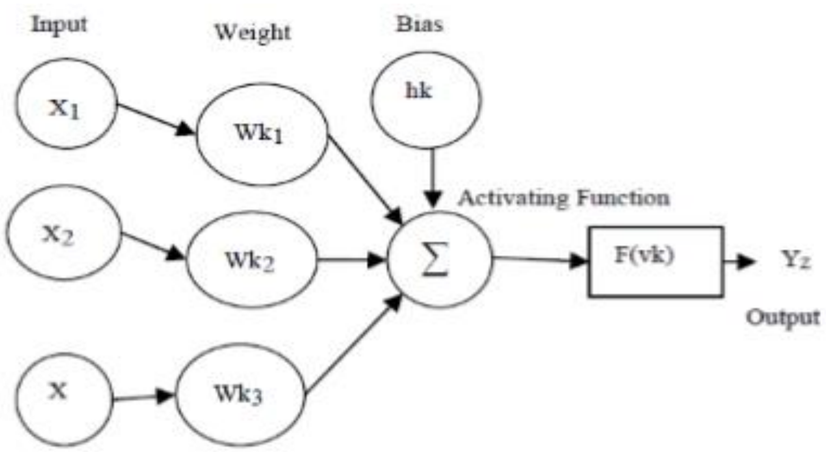


Fig. 2.4: Neural model (Suhas & ALI, 2015)

The neuron model is made up of three essential elements:

1. A set of weights, each with its own strength. The weight wkj is multiplied by the signal xj connected to neuron k. An artificial neuron's weight can range from negative to positive.
2. An adder for summing the input signals, which is weighted by the neuron's weights.
3. A function for restricting the amplitude of a neuron's output. Due to the fact that it limits the output signal's amplitude range to a specific value, it is often referred to as a squashing function.

b) Support vector machines (SVM)

Support vector regression (SVR) has recently been used to the subject of load forecasting by (Chen et al. 2004), (Niu et al. (2007), (Hsu et al. 2006), Wang et al. (2007), Afshin and Sadeghian (2007), and Li et al. (2007), to mention a few. Support vector machines are extensively used for data classification and regression. They are non-linear approaches based on kernels.

c) Fuzzy Logic:

Fuzzy logic is a generalization of Boolean logic, which is commonly utilized in the design of digital circuits. A truth value of "0" or "1" is assigned to an input by Boolean logic. An input in fuzzy logic has a specified qualitative range associated with it (Suhas & ALI, 2015). Fuzzy logic is a type of many-valued logic that deals with approximate reasoning rather than precise reasoning.

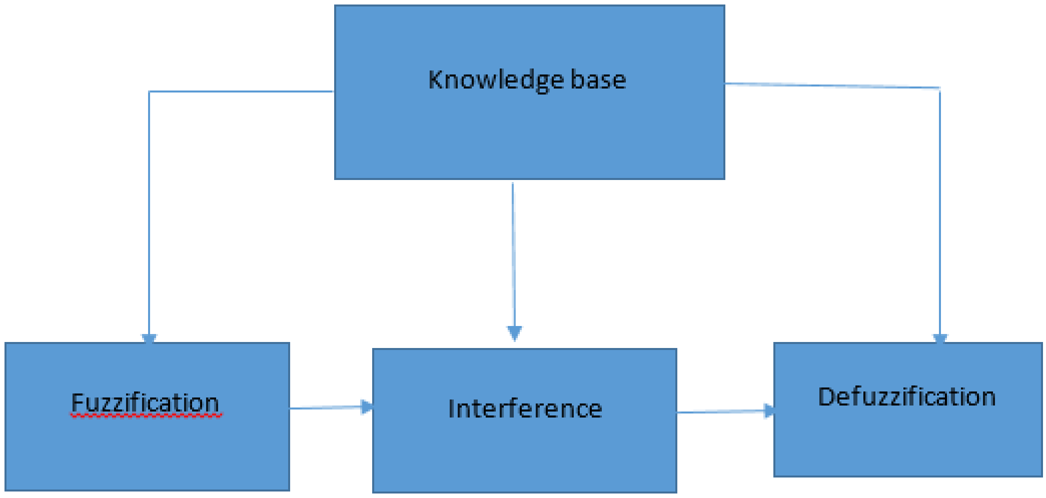


Fig. 2.5: Block diagram of a fuzzy system

2.5 Approaches to Load Forecasting

Forecasts are created for a variety of reasons: day-to-day power system management (Kyriakides & Polycarpou, 2007) necessitates the prediction of load for the next day, whilst deciding whether or not to make large structural expenditures necessitates a far longer prediction horizon. The time-horizon, or lead time, can thus be used to distinguish forecasts: The goal of short-term load predictions (STLF) is to predict with a lead time of one hour to seven days. The study's main focus is on STLF because it provides necessary information for system management of day-to-day operations and unit commitment energy transactions, security analysis, economic dispatch, fuel scheduling, and system maintenance (Jain, Nigam, & Tiwar, 2012) (Shayeghi, Shayanfar, & Azimi, 2007) (Guo & Niu, 2008). STLF can also assist in the estimation of load flows and the making of decisions that will prevent overloading (Feinberg & Genethliou, 2006). Methods for anticipating short-term load demand include:

2.5.1 Similar Day Look up Approach

The similar day technique is based on looking up past data for days that were one, two, or three years ago and had characteristics comparable to the predicted day. Similar weather conditions, as well as a similar day of the week or date, are among the characteristics. (2010, Qingqing, Yonggang, Xiaoqiang, Liangyi, and Xian)

2.5.2 Regression based Approach

Linear regression is a technique that looks at the dependent variable in relation to a set of independent variables. The dependent variables are considered initially because they are the ones that change the most. Demand for electricity is frequently the dependent variable in energy forecasting because it is reliant on production, which is dependent on independent variables (Jing-Min & Li-Ping, 2008). (Ruzic, Vuckovic, & Nikolic, 2000).

2.5.3 Time Series Forecasting

Time series forecasting is based on the idea that by modeling patterns in a time series plot and extrapolating those patterns into the future, reliable predictions can be made. Time series analysis fits a model based on seasonality and trend using historical data as an input. In some cases, time series models can be accurate, but they are particularly difficult to use and require a lot of historical data.

2.5.4 Soft Computing based approach

The amazing capacity of the human mind to reason and learn in an environment of ambiguity and uncertainty is paralleled by these strategies. They include techniques such as artificial neural networks, fuzzy logic, expert’s system and Machine learning, although soft computing theory and techniques were first introduced in 1980s, it has now become a major research and study area in.

2.5.5 Hybrid approach

This technology employs two single model forecast approaches, resulting in a hybrid system capable of performing its own tasks. Because it performs various activities in the system, combining and complementing them to attain a comparable goal, this sort of merging is beneficial in both control and pattern recognition.

Many models, including traditional, Artificial Intelligence (AI), and hybrid models, have been developed to study short-term load forecasting. These models, however, have a variety of issues, such as sluggish convergence (conventional), high complexity (AI), and more. Given this, this work recommends a hybrid strategy that makes use of the Adaptive Neuro Fuzzy Inference System (ANFIS). ANFIS is an artificial intelligence method that is frequently and extensively used in literature. This method combines the advantages of fuzzy logic and artificial neural networks into a single tactic. The ANFIS topology combines a strong inference system with learning capability. ANFIS structure for Sugeno type can be broken down into five steps. First Stage: This layer is known as the fuzzification layer. During this step, the used parameters are referred to as premise parameters, and they are rearranged based on output error during each loop.

Stage 2: It is possible to calculate the output of a fixed node whose input is the sum of all incoming signals. Every output from stage two affects the level at which the rule triggers in stage three. In a fuzzy system, the AND operator is known as the trigger level, and the firing strength is known as the norm operator.

The third stage is the normalizing layer. For this layer, every firing power is once more arranged while taking into consideration each particular weight.

Stage 4: Defuzzication, which is a first estimation of the output for the real world. This layer is expressed as functions and features adaptive nodes.

The final stage is the summation neuron, which is a fixed node that computes the final output as the sum of all incoming signals.

Adopting non-mathematical models as the research's major computing tools has several benefits, however, the primary difference is that the ANFIS method corresponds more fast with more training data and is capable of producing precise predictions. This benefit of soft computing-based load forecasting serves as the impetus for the current research. The following are the advantages of ANFIS.

i. It refines fuzzy IF THEN rules to represent complicated system behavior.
ii. It does not necessitate the use of human skill.
iii. Simple to put into practice
iv. It allows for quick and accurate learning.
v. It provides required data sets, such as a wider range of membership functions to choose from, strong generalization capabilities, and superior explanation capabilities using fuzzy rules
vi. It's simple to combine language and numerical skills while solving problems.

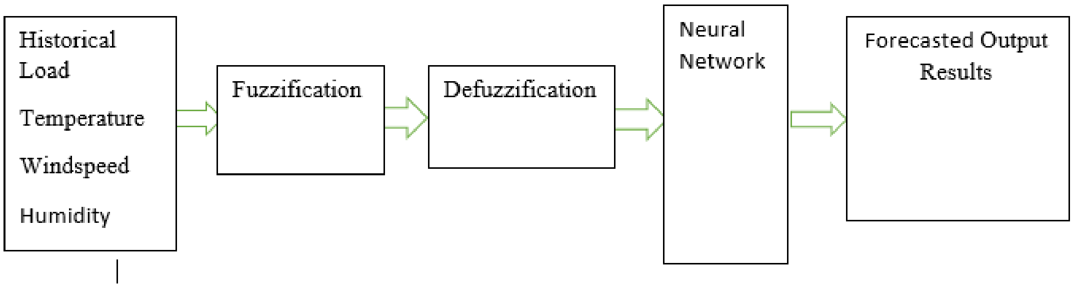


Fig 2.6: Block diagram of Hybrid model.

The model work is divided into three stages:

1. Fuzzy set-based classification: classification of training data into fuzzy sets;
2. Neural network training: Neural network training for each hour of each day for which the load is to be projected using the training data for the class to which that hour belongs.
3. Short-term load forecasting: Using a trained neural network, forecasting hourly load.

2.6 Other Studies on Hybrid load demand models

Hybrid methods integrate two or more procedures to solve some of the shortcomings of traditional methods. Many computational intelligence techniques, as well as hybrids of CI and traditional procedures, are widely used. As previously stated, particle swarm optimization (PSO) was used to determine the order and coefficients of an ARMAX-model (Huang et al., 2005). In addition to fuzzy neural networks (Liao, 2007), neural networks (Bashir and El-Hawary, 2007), and support vector machines (Niu et al., 2007a), particle swarm optimization has been applied with support vector machines (Wang et al., 2007). Genetic or other evolutionary algorithms are frequently used in conjunction with artificial neural networks (de Aquino et al., 2007). (El Desouky and colleagues, 2001). (2006) (Liao and Tsao). Genetic programming (Eiben and Smith, 2003) was used directly in load forecasting (Huo et al. 2007). In essence, evolutionary algorithms work as demographically focused search or optimization heuristics that, just like in the natural world, use recombination, mutation, and selection to find workable solutions. Because they are both population-based and randomized algorithms, they should be more resistant to local optima convergence and noise (Kyriakides and Polycarpou, 2007). Additionally, unlike some older approaches, they do not make the same confining assumptions. Genetic programming is an evolutionary algorithm that directly evolves "programs" or functions. Aside from genetic programming, evolutionary algorithms and PSO appear to be the most popular methods for selecting the best control parameter settings for the main approach. A pattern-base is constructed in (Guo & Niu, 2008) that employs classification and regression tree (CART) to identify distinct data patterns before using ANN to anticipate the load for each forecasting day. A wavelet fuzzy neural network (WFNN) with fuzzified wavelet inputs and a fuzzy neural network Choquet-integral (FNCI) as the output is described in (Hanmandlu & Chauhan, 2011). WFNN performs better than its competitors. In the study (Honghui & Yongqiang, 2012), the model was used to compare load forecasting to the conventional ANN, and the results showed that the improved ANFIS has a greater accuracy and takes less training time than the ANN. In order to get over discontinuities and non-periodicity in load behavior and accuracy, a novel approach was described in (Mourad, Bouzid, & Mohamed, 2012). This strategy uses wavelet technology. With some data overlap, separate ANFIS (multi ANFIS) are were employed for each season of the year in (Souzanchi, Fanaee-T, Yaghoubi, & Akbarzadeh-T, 2010). Switching is a technique for preventing unwanted data from entering the system.Temperature and the load pattern from the previous day improve the method's accuracy and performance. A fuzzy regression was presented by (Hong & Wang, 2013). (Li, Cui, & Guo, 2014) employed a single spectrum analyser to decompose and reconstruct power load series (SSA). To predict hourly load, the load series is reconstructed and used in an Autoregressive (AR) model. An Artificial Neural Network (ANN) is used to handle the nonlinear and difficult problem of load forecasting (Bala, Yadav, Hooda, & Registrar, 2014). The output of the constructed model is compared to utility data, and after numerous ANN architecture and training, a MAPE of 1.24 percent is achieved. 'tansig' was the hidden layer in the presented multilayer ANN, and 'purelin' was the output layer. A self-organizing map Neural Network is utilized to forecast a short-term load in (Valero, Aparicio, Senabre, & Sancho, 2010). The method entailed energy pattern identification for the hourly load, which allowed for the determination of consumption behavior. A model is developed for predicting short-term electricity load (Bahrami, Hooshmand, amp; Parastegari, 2014). It was improved via particle swamp optimization and a Grey-model and wavelet-transform combination. The results reveal that the association between meteorological variables and load consumption varies depending on the season. To forecast short-term electrical load demand, a hybrid method is used in (Sudheer & Amp; Suseelatha, 2015). The first model employs triple exponential smoothing, whereas the second employs weighted closest neighbor. Both models are applied to the deconstructed data using deterministic and fluctuation series. The level of competency determines the approach used to project electric load requirements. The bulk of Artificial intelligence algorithms achieve a mean absolute percentage error (MAPE) of less than 2% with well-processed data. According to (Guo & Niu, 2008), at the corporate level, a MAPE of less than 5% for one-day hourly forecast is acceptable.).

2.7 Membership Functions

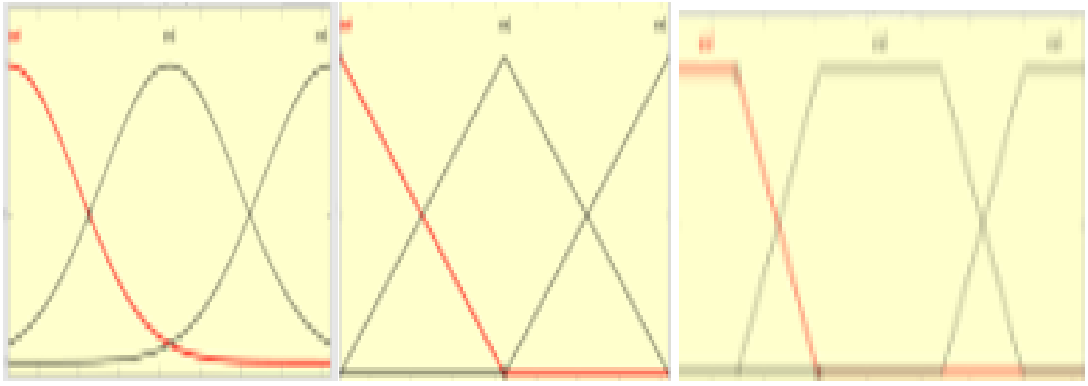
A membership function specifies the level of membership that a given input has in a set. In the fuzzification and defuzzification stages of a FIS, they are employed to translate fuzzy linguistic concepts from non-fuzzy input values and vice versa. The degree of the input function of a set is determined by an MF. Additionally, it is a curve that specifies how each input point is translated to a membership degree between 0 and 1. Zadeh et al., 2007 established the notion of MF for the first time. One must take into account representation, construction, optimization, adaptivity, innovation, analytical structure, continuity, monotonicity, stability, resilience, computational cost, and control performance when choosing which MFs to use. The focus of representation is on how to effectively and accurately describe an MF. A MF shape with simpler representations is often desirable, especially if the MF's parameters need to be tuned, because a simpler representation usually equals faster convergence. It is known as optimization to use a method to adjust the MFs' parameters. In general, MF shapes with higher efficiency of optimization are used. Expert knowledge and data-centric generation are two methods for creating MFs.

2.7.1 Expert knowledge-based MF

This Membership function is based on a group of experts deciding on specific intervals of a set to divide and hence generate a function (Casillas & Moreno, 2011). Expert knowledge-based MFs, on the contrary, it has a number of flaws, including a loss of accuracy due to bias (Guillaume, 2001) and a large rise in fuzzy rules for higher-dimension situations.

2.7.2 Data-centric techniques.

This are another way to calculate membership function. Grid partitioning and fuzzy clustering are two examples of data-centric MF generation methods. The input space of the function is spread uniformly between curves (clusters) in grid partitioning, Figure 2.7 illustrates this, showing that all curves for all three types of MFs are equally dispersed throughout the input space (triangular, Gaussian, and trapezoidal).



(a) (b) (c)

Fig 2.7 (a) Triangular, (b) Gaussian and (c) Trapezoid membership function

The clustering strategy, which is an unsupervised learning method in which data points are closely packed together in clusters according to metrics supplied, is an alternative to the grid partitioning method. The most common MFs are triangular and trapezoidal, as well as Gaussian, and none of them can be classified as the best form for all FIS solutions. The goal, type of data, and experimental results are typically taken into consideration while selecting the ideal forms for MFs. A triangular MF is characterized by a lower and upper limit, l and u, and a middle value, m, where l m u. (Vargas & M, 2018), subsequently, The trapezoidal MF shown in Fig.2.9 is defined by a lower limit l, an upper limit u, a lower support limit m, and an upper support limit n, where $l < m < n < u$ (Kreinovich, Kosheleva, & Shahbazova, 2020), As shown in Figure 2.8, a triangular MF is defined by the three parameters l, c, and u, whereas a trapezoidal MF is defined by the four parameters l, a, b, and u, as shown in Figure 2.9.

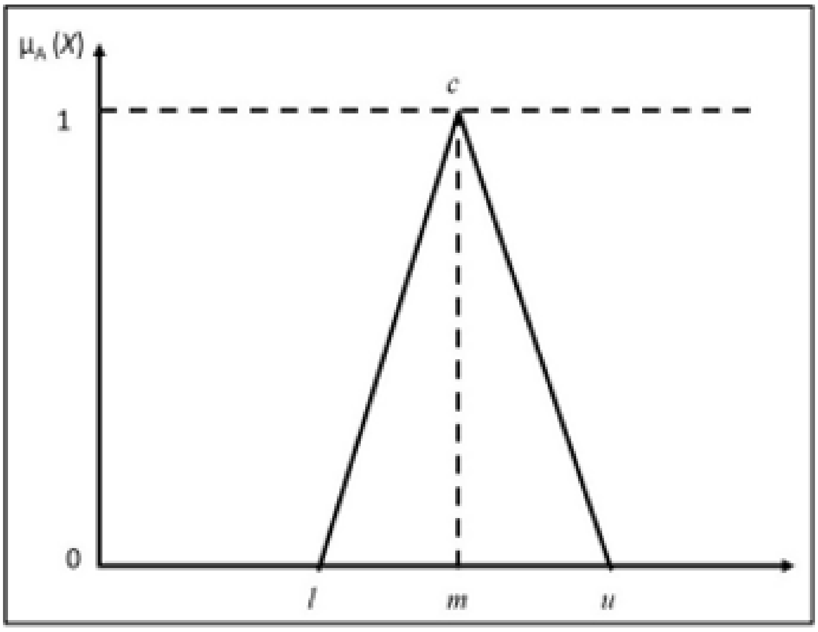


Fig 2.8: Triangular Membership function

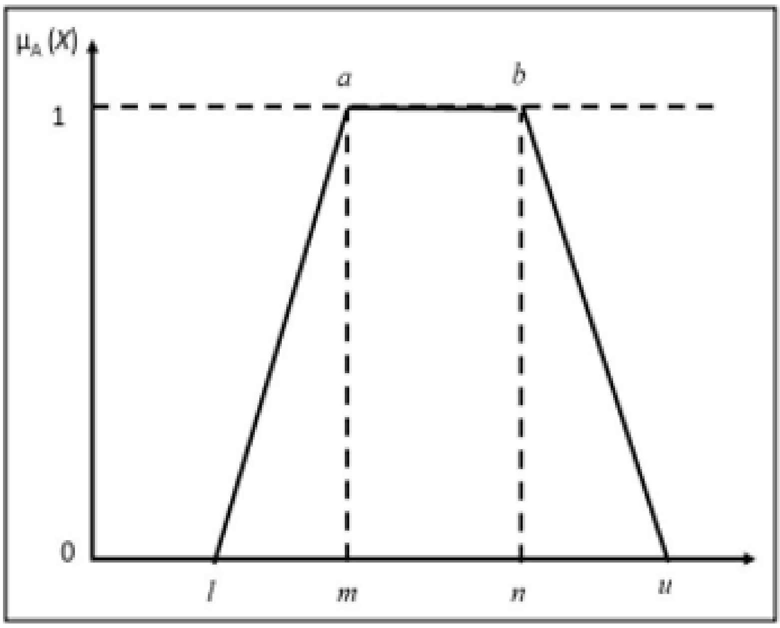


Fig 2.9: Trapezoidal Membership Function

2.7.2.1 Formalization and the Results

In many practical applications, however, it turns out that using simple triangular or trapezoid membership functions is enough to produce a decent quality outcome – for example, a good quality control. A triangular membership function has the following form, for some parameters xe and $\Delta > 0$: (Kreinovich, Kosheleva, & Shabazova, 2018)

• $\mu(x) = 0$ for $x \leq xe-\Delta$;

• $\mu(x) = x-(xe-\Delta)\ \Delta$ for $xe-\Delta \leq x \leq xe$; (6)

• $\mu(x) = (xe+\Delta) -x\ \Delta$ for $xe\leq x \leq xe+\Delta$, and

• $\mu(x) = 0$ for $x \geq xe+\Delta$.

Similar to this, the following is the form of a trapezoid membership function for certain parameters xe, δ, and Δ, for which $0 < \delta < \Delta$:

• $\mu(x) = 0$ for $x \leq xe-\Delta$;

• $\mu(x) = x-(xe-\Delta)\ \Delta -\delta$ for $xe-\Delta \leq x \leq xe-\delta$; (7)

• $\mu(x) = 1$ when $xe-\delta \leq x \leq xe+\delta$;

• $\mu(x) = (xe+\Delta) -x\ \Delta -\delta$ for $xe+\delta \leq x \leq xe+\Delta$, and

• $\mu(x) = 0$ for $x \geq xe+\Delta$

From a purely mathematical perspective, many different types of membership functions can be created. In the majority of real-world scenarios, straightforward "trapezoid" membership functions—for which we use normal approximation to obtain both endpoints of the interval—perform effectively. The necessity to ensure that if the values x and x ′ are close, then the associated membership degrees (x) and (x′) should also be close was one of the fundamental reasons for fuzzy techniques. What is the best way to formalize this concept? When x and x ′ are near, i.e., when x ′ = x+x for some small x, the difference (x ′) (x) = (x+x) (x) between the respective values of the membership function can be written as ′(x)x+o(x) at least for smooth membership functions. As a result, needing a small difference is identical to requiring relatively low absolute value of the derivative | ′ (x)|.

There are two approaches to formalize this requirement:

• we can demand that the derivative's worst-case value be small, or

• we can require that the derivative's average – e.g., mean squared – value be small.

The membership function that results is more in line with the original fuzzy idea as the related feature gets smaller. As a result, choosing a membership function with relatively low absolute value of the associated feature is sensible for both formalizations. This principle, which leads to triangular and trapezoid membership functions, is demonstrated in the following workout.

The Outcomes of Formalization

Definition 1. Consider two real numbers, x and x. Let us define the worst-case non-fuzziness degree Dw() for any continuous nearly everywhere differentiable function (x) defined on the interval [x, x) as (Kreinovich, Kosheleva, & Shabazova, 2018)

$$D_W(\mu') = Max|\mu'(x)| \tag{8}$$

Proposition 1. All continuous virtually everywhere differentiable functions (x) defined on the interval [x, x] for (x) = 0 and (x) = 1 have the following linear function as their worst-case non-fuzziness function, and it has the highest worst-case non-fuzziness degree.

$$\mu(x) = \frac{x-\underline{x}}{\overline{x}-\underline{x}\cdot} \tag{9}$$

Proposition 2. All continuous virtually everywhere differentiable functions (x) defined on the interval [x, x] for (x) = 1 and (x) = 0 have the same worst-case non-fuzziness degree, but the following linear function has the lowest value.

$$\mu(x) = \frac{\overline{x}-x}{\overline{x}-\underline{x}\cdot} \tag{10}$$

Assuming that (x) = 0 for every x [xe, xe+] and (xe) = 1, the most fuzzy membership function – i.e., Due to Propositions 1 and 2, the function with the lowest worst-case non-fuzziness degree will be the matching triangle function. Similarly, if we suppose that (x) = 0 for all x [xe, xe+] and (x) = 1 for all x [xe, xe+], then the most fuzzy membership function – i.e. The related trapezoid function will be the function with the fewest possible worst-case non-fuzziness degree. As a result, we have a relatively easy explanation for the widespread use of triangular and trapezoid membership functions. (2018, Kreinovich, Kosheleva, and Shabazova) As a result, this conclusion provides a theoretical explanation for the practical success of trapezoidal membership functions, which explains why I included it in the hybrid forecasting system modeling.

The number of membership functions for each input was taken to be 3 3 3 3 in this study. The model was trained using four distinct membership functions in order to select the best system with the lowest RMSE error or computed MAPE (Triangular, Trapezoidal, generalized bell, Gaussian curve). *Trimf* was chosen as a starting point for this inquiry (Triangular membership function).

2.8 Fuzzy Inference system

Sugeno and Mamdani systems are two types of fuzzy inference systems supported by the Fuzzy Logic Toolbox. Sugeno FIS was chosen over Mamdani FIS for this model because Mamdani excels at human input while Sugeno excels at mathematical analysis. Output membership functions used in Sugeno fuzzy inference are either fixed or singletons. Sugeno defuzzification uses a weighted average or weighted sum of a small number of data points rather than determining the centroid of a two-dimensional area, making it more computationally efficient than Mamdani defuzzification (Honghui & Yongqiang, 2012). Each rule in the Sugeno system acts in the manner depicted in Figure 2.10. The diagram depicts how the Sugeno model's rules work. Because the study system has four (4) input parameters, each one is given the values w, x, y, and z.

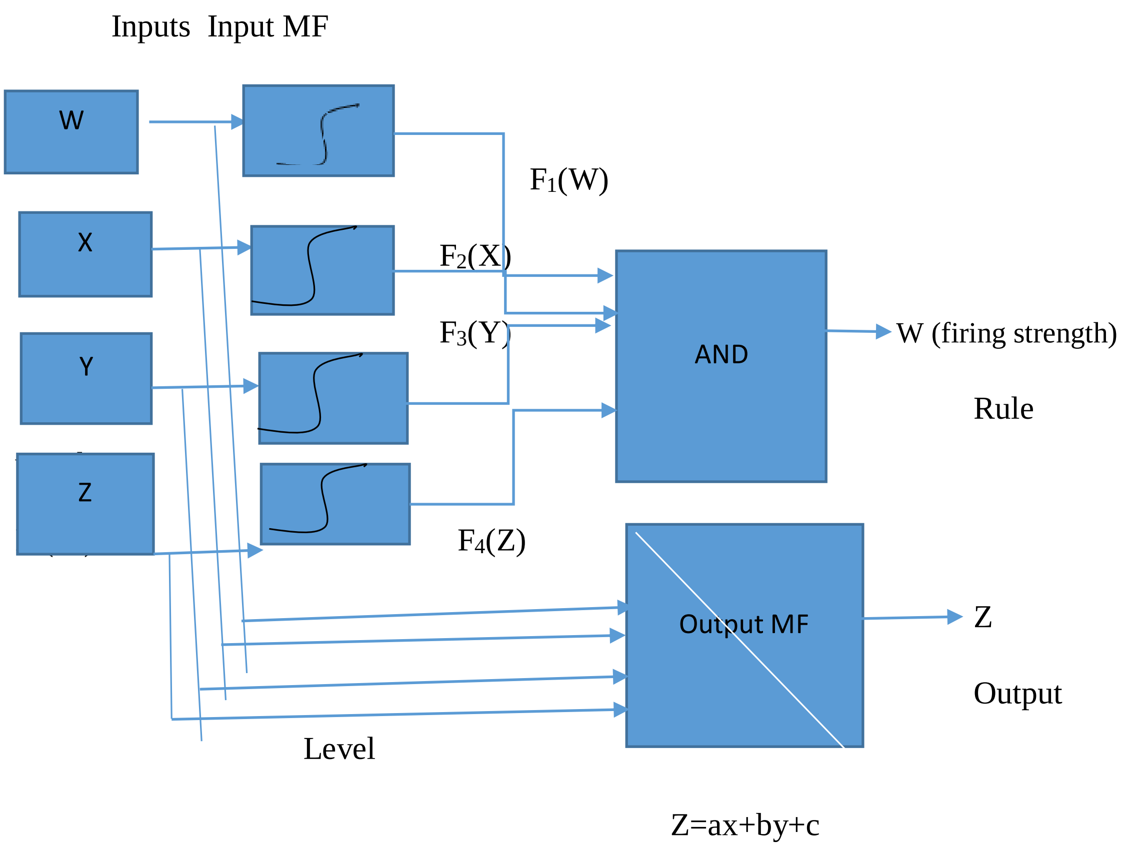


Fig 2.10: Representing how rules in sugeno system operates

Two values are generated by each rule.

a) z_i — Rule output level,

$$z_i = a_i w + b_i x + c y_i + d_i z + e_i \quad (11)$$

Here, w, *x*, y and *z* are the values of input 1, 2, 3 and 4, respectively, and a_i, b_i, c_i, d_i, and e_i are constant coefficients. For a zero-order Sugeno system, z_i is a constant ($a = b =$ c $= d = e = 0$).

b) w_i — Rule antecedent yielding a rule with a stronger firing force

$$w_i = \textit{And Method}\ (F_1(w),\ F_2(x)\ F_3(y)\ F_4(z)) \quad (12)$$

Here, $F_1(\ldots)$, $F_2(\ldots)$, $F_3(\ldots)$, and $F_4(\ldots)$ are the membership functions for inputs 2, 3, and 4, respectively.

The result of each rule is the weighted output level, which is calculated by multiplying wi by zi.

The system's final output, which is calculated as the weighted average of all rule outputs, is given by;

$$\text{Final Output} = \frac{\sum_{i=l}^{n} WiZi}{\sum_{i=l}^{n} wi} \tag{13}$$

where *n* is the number of rules.

2.8.1 Advantages of Sugeno Fuzzy inference method

Compared to Mamdani, Sugeno has a number of advantages.

1. Its calculation is quick.
2. Compatible with adaptive and optimization approaches
3. It ensures that the output surface is consistent.

Sugeno is the optimal model in this case since each rule is linearly dependent on the four input variables. The Sugeno method is appropriate for interpolating a large number of linear controllers that will be used in a dynamic nonlinear system under various operating conditions. Historical loads, for example, have been found to alter drastically with changes in meteorological variables such as humidity, wind speed, and temperature. As a natural and effective gain scheduler, Sugeno fuzzy inference systems are well adapted to the task of smoothly interpolating linear gains throughout input space. In a similar vein, a Sugeno system, which interpolates between numerous linear models, is particularly well suited for modeling nonlinear systems (Azadeh A. , Saberi, Gitiforouz, & Saberi, 2009). As mentioned earlier, there are 4 input variables and 1 output variable, accordingly. This is because the four inputs were historical load, temperature, wind speed, and humidity, which are all characteristics that influence short-term load predictions. The output parameter was set to 1 since just one output was required: the expected load.

2.9 Measure and Testing of Forecasting Performance

It is vital to choose the suitable criteria for a particular application because there are no global performance criteria (Seo, Kwan, & Chai, 2018) .Accordingly, several statistical criteria were used to evaluate the validity of the models that were categorized into absolute, relative, and dimensionless errors. There are three main indicators to take into account, however there are virtually infinite numbers of metrics that can be used to measure forecast accuracy and error: There are three main indicators to take into account, however there are virtually infinite numbers of metrics that can be used to measure forecast accuracy and error:

1. Forecast Bias

The difference between predicted and actual demand is known as forecast bias.
Forecast Bias = S (Forecast - Actual Demand)

The graph is used to see if your forecasts tend to over-forecast (i.e., the forecast is higher than the actual) or under-forecast (i.e., the forecast is lower than the actual) (i.e., the forecast is less). You can use the formula to change this metric to a percentage.

Forecast Bias Percentage = SForecast / (S Actual Demand)

Forecast bias is distinct in that it identifies whether your projections are routinely over- or under-forecasting, allowing for necessary adjustments.

2. Mean Average Deviation (MAD)

The MAD indicator shows the average distance between your forecasts and the actual demand. As the MAD metric measures deviation, or error, in units, it is suitable for comparing the results of two or more forecast models applied to the same variable (e.g., product, product category, labor). In contrast, it is inappropriate to compare various data sets using average deviations because they are arbitrary. Mean Absolute Percent Error – and MAD – Mean Absolute Deviation – are two of the most commonly used forecast accuracy / error assessments.

3. Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) are two terms for the same. MAPE is extremely similar to MAD, with the exception that it expresses forecast inaccuracy as a percentage (rather than units) of actual demand. MAPE is a simple and easy-to-understand means of quantifying forecast error because it estimates the average percentage points your projections are wrong by.

MAPE = 1/n S|(Forecast - Actual Demand)/(Actual Demand)| 100

$$\text{MAPE} = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{A_{t-F_t}}{A_t}\right| \tag{14}$$

Where "n" is the absolute number of predictions and "Ft, At" are the expected and actual values. The residual errors are measured by MAPE and RMSE, which provide a broad picture of the difference between expected and actual values. Except for MAPE, all methods have output that is scaled. Because the input data for model estimation, preprocessed data, and raw data have various scales (Azadeh A., Saberi, Gitiforouz, & Saberi, 2009) (Akdemir & Cetinkaya, 2012), The disadvantage of MAPE is that it does not reveal if the forecast is over- or under-forecasting. MAPE approach is utilized in

CHAPTER THREE: METHODOLOGY

3.1 Introduction

The quantitative research methodologies were utilized to construct and compile a model that were used to anticipate short-term electricity demand projections in Uasin Gishu County. According to Stake, 2010 a quantitative methodology is appropriate in a study that attempts to explain a specific occurrence by analyzing and interpreting data. Because the primary goal of this research is to develop a forecasting model using previous data on loads and meteorological variables, quantitative data collecting was the best option.

3.2 Experimental analysis on weather variables impact on short-term Load Profile

Load demand is influenced by a number of factors. These variables factors identified as well as their impact on electric power consumption were examined (Muhamma & Naeem, 2014)

1) **Effects of time**; The load variation follows specific principles depending on the. “time point" of the day.
2) **Meteorological factors**; weather data; temperature, humidity, wind speed and rainfall
3) **Economic factors** –state of development of a country, people’s buying power, time of use pricing, energy cost
4) **Social factors/political** –customer effects/source of random disturbance
5) **Geographical location** – Load demand varies based on geographical location of consumer.

The most well-known techniques for assessing the relation between household energy use and factors affecting it are correlation analysis and regression modeling. The estimation of these components via regression modeling, however, is fraught with uncertainty. The Correlation time series plot of past load of electricity consumption and weather data of temperature, humidity and wind speed revealed a trend that positively relates with the published literature that load demand alter drastically with changes in meteorological variables and with significant impact on short term load profile. The analysis was carried out with a different batch of historical data of Load, temperature, wind speed, humidity and time gave a consistent trend as illustrated.

3.2.1 Effects of Time Factor

Load consumption fluctuates not just between seasons but also all throughthe the day. Early mornings, when people are sleeping, have the lowest consumption levels. When people get ready for work, consumption gradually climbs between 7:30 and 10:00 a.m., between 10:30 and 11:30 a.m., a morning peak is seen, which can be explained by domestic tasks. The after-work, dinner, and bedtime activities are highlighted by the afternoon and evening peaks. As a result, consumption patterns are influenced by consumer behavior and activities.

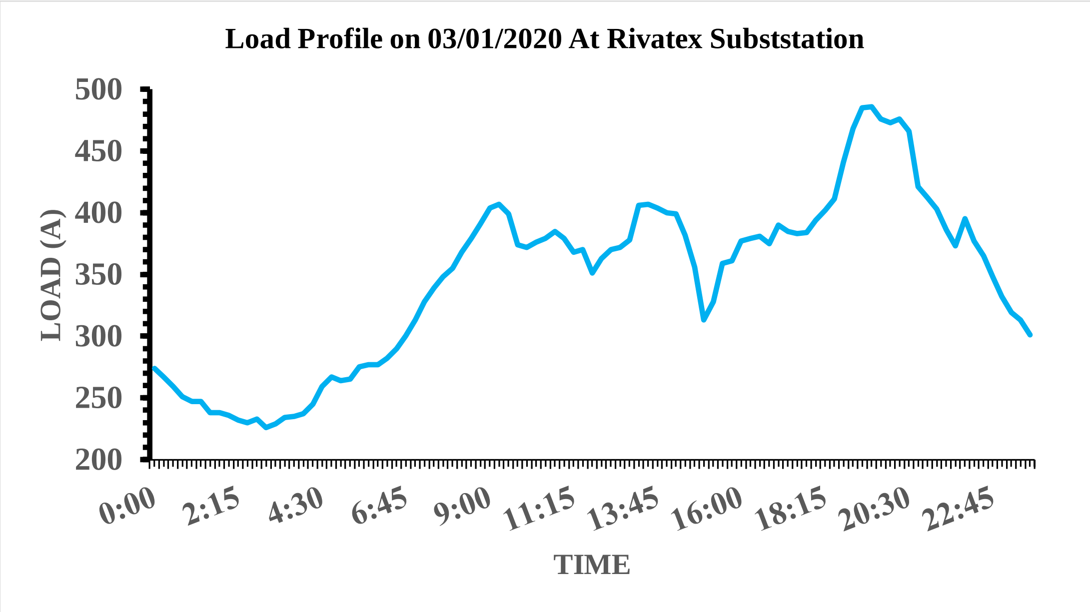


Fig 3.1: Load Profile 03/01/2020 at Rivatex distribution substation

The load variation follows specific principles depending on the "time point" of the day. The load is low from 0.00 am to 06.00 am, then begins to rise from 07.00 a.m. to approximately 09.00 a.m., flattens till 13.00 a.m. to around 14.30 a.m., and then again falls until 17.00 a.m. when they begin to rise at 19.00 a.m. It can be observed that the highest load demand occurs between 19.00 and 21.00 hours, while the lowest load demand occurs after midnight. This load curve reflects the consumer’s lifestyle as far as load demand is concern. The load curves are inherently periodic, as represented on figure 3.1

3.2.2 Combine effects of weather variables (Temperature, humidity, wind speed)

Relative humidity and temperature have a combined impact on human comfort levels. Humidity raises the perception of temperature severity, causing individuals to use more cooling equipment. As a result, the hourly load pattern will display a high value during humid days. Figure 3.2, shows that temperature and load have An increase in temperature led to an increase in the demand for electricity, showing a strong positive association as depicted in the figure indicating that when temperatures are high, consumers use electricity more for cooling purposes, such as using the refrigerator, air conditioner, and fan, and when temperatures are low, there is a negative or inverse relationship between temperature and load consumption.

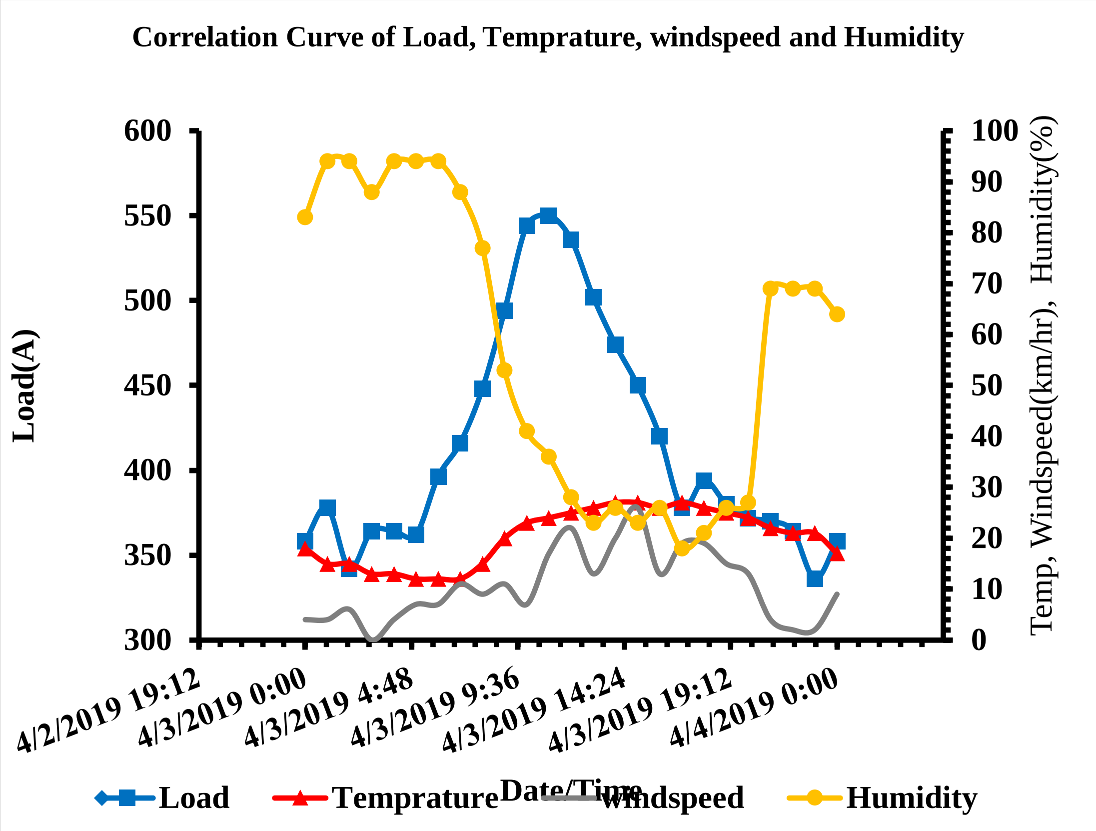


Fig. 3.2: A 24-hour Correlation curves at Rivatex Substation in Uasin Gishu.

Apparent temperature is greatly dependent too on wind speed and humidity. The speed of the wind lowers the apparent temperature and increases the rate of perspiration resulting in a cooling effect when there is low humidity (Muhamma & Naeem, 2014). As it is seen in figure 3.2, 3.3 on a windy day in hot weather, electricity usage is reduced because fewer cooling appliances are utilized. Therefore, Load demand is low on a humid windy day in Uasin Gishu County.

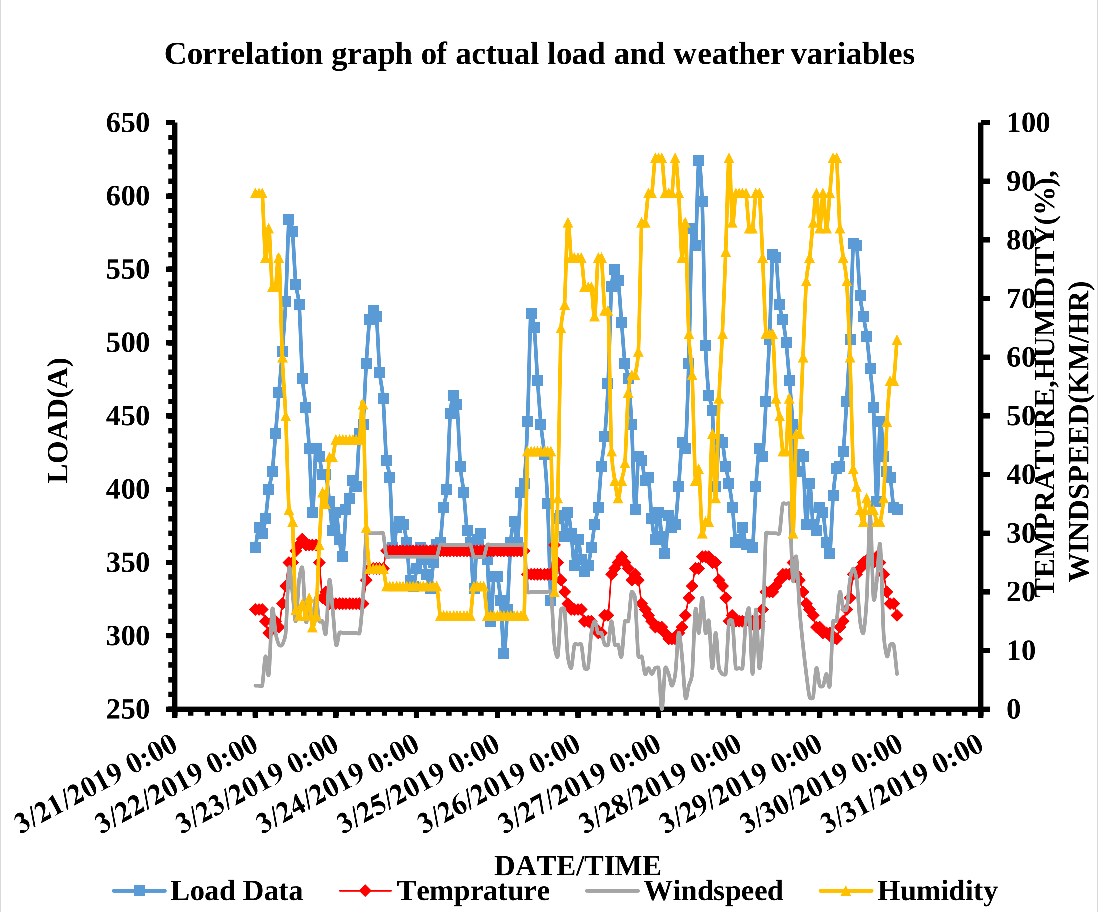


Fig. 3.3: Correlation Graph of Actual Load and Weather Variables

The real load curve over time is positively correlated and in line with existing literature when compared to the plotted variables of temperature, humidity, and wind speed (Muhamma & Naeem, 2014). In light of this, it can be argued that meteorological elements such as temperature, humidity, and wind speed have a substantial impact on short-term load forecasting.

3.2.3 Pearson Correlation test

The Pearson correlation measures the degree to which two variables are linearly related. Its values can range from -1 to 1, with -1 being a wholly negative linear correlation, 0 signifying no relationship, and 1 signifying a wholly positive correlation. One utilizes Pearson's r to determine whether there is a relationship between or among variables.

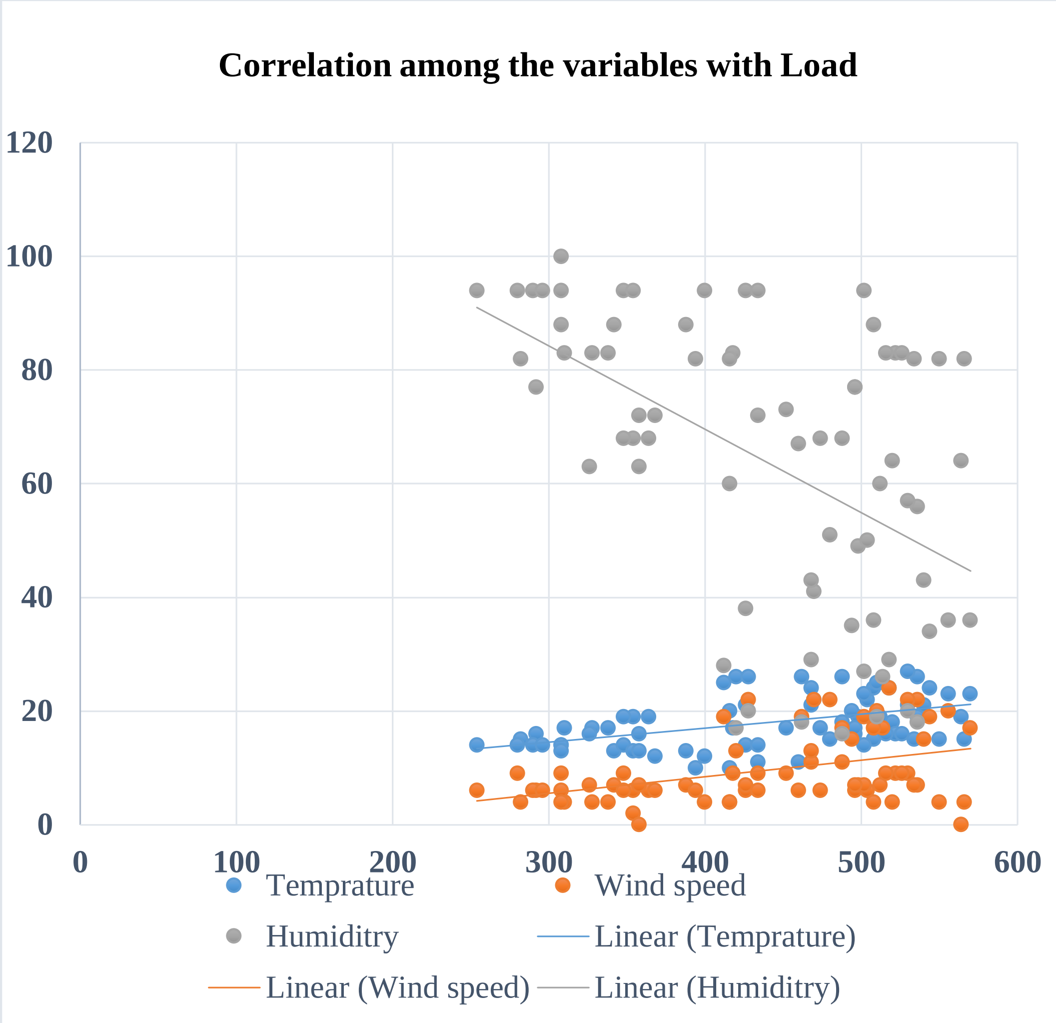


Figure 3.4: Correlation among the variables with Load

A moderate positive correlation is shown in the preceding graph. A positive linear line can be seen because of the positive slope between variables of temperature and wind speed, which indicates that if one variable rises, the other one will as well. This indicates a straight proportionality between the changes in the Load when the two variable change with coefficient values of +0.47 and +0.42 respectively. In contrast, the scatter plots for humidity in the graph are not as near the straight line.

The correlation is roughly -0.5 and is negative linear. Since the slope is negative, a change in Humidity variable will have an inverse relationship to a change in the Load.

Table 1: Correlation coefficients of the variables

	Load	Temperature	Wind speed	Humidity
Load	1			
Temperature	0.4704977	1		
Wind speed	0.4176507	0.7403399	1	
Humidity	-0.507843	-0.9057923	-0.7898062	1

However, strong positive correlation is noted in temperature and wind speed with a coefficient of 0.74 and a strong inverse correlation is confirmed between Humidity and temperature and between Humidity and Wind speed with a negative coefficient of -0.91 and -0.79 respectively

3.3 Data Collection

A record analysis was used as the main data collection method in this study. According to (Bahrami, Hooshmand, & Parastegari, 2014), this is a type of quantitative research method in which researchers examine and interpret data from records or documents in order to gain a better understanding of the phenomenon under investigation. The literature on load forecasting was assessed using high-quality, scholarly-reviewed articles from Google Scholar. Historical load data was obtained from the KPLC Rivatex substation database in Uasin Gishu County, and weather records of temperature, humidity and wind speed were obtained from the website www.timeanddate.com. The rationale for this data gathering method is that scheme triangulation may be done from a range of articles in order to obtain the best and most fantastic information, and it helps cooperation finding that is also related to quality data.

3.4 Data description and Pre-processing

Data considered in this study includes hourly loads from January 1, 2019 to June 30, 2020. The time of day, temperature, humidity, wind speed, and past load are used as input variables in the Adaptive Neuro-fuzzy based inference system (ANFIS) to estimate the load forecast for the Uasin Gishu county over the next hour to seven days a s the training, checking, and testing dat., a total of 49860 hourly data for the years 2019 and 2020 were used in a matrix structure with a percentage proportion of 75:15:15.

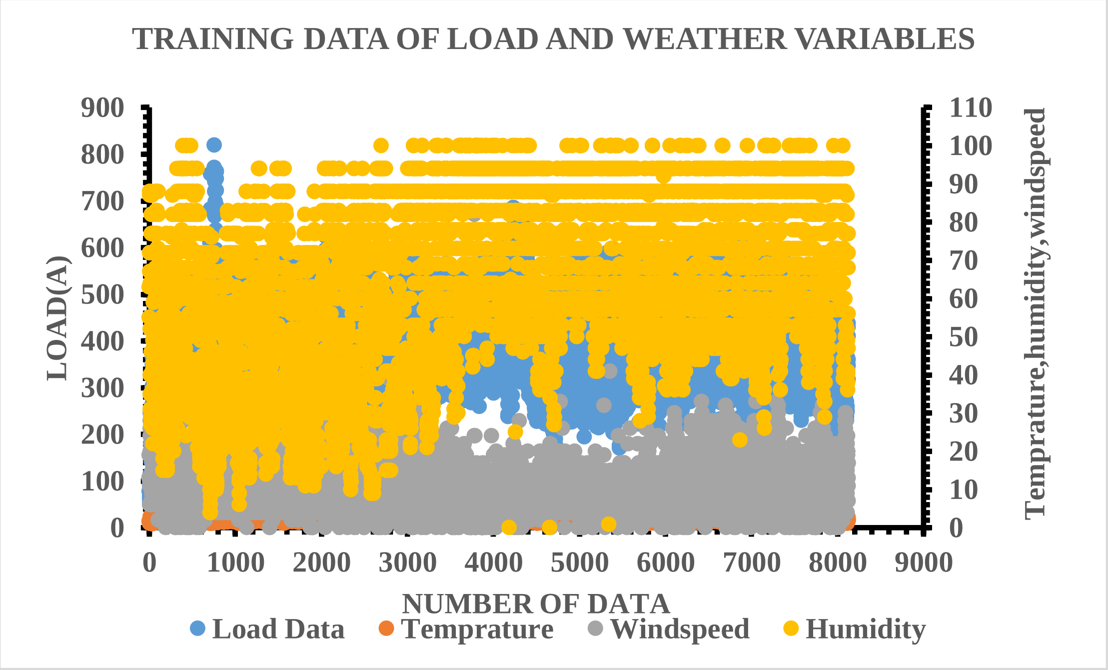


Fig 3.4: Training Data for one year

The first five (5) columns, which are te hour of the day, temperature, humidity, wind speed, and historical electric loads, respectively, constitute the inputs to the ANFIS model. The final column displays the ANFIS model's desired output. Each hour of the day has a certain allocated temperature, humidity, wind speed, and past loads set into it.

Table 2: Training data set

		INPUTS					OUTPUT
		Date & Time	Load Data	Temprature	Windspeed	Humidity	TARGET
Training Data 75%	1	1/1/2019 0:00	106	14	19	55	214
	2	1/1/2019 1:00	78	13	13	63	222
	3	1/1/2019 2:00	82	12	11	67	210
	4	1/1/2019 3:00	68	12	6	72	232
	5	1/1/2019 4:00	78	12	6	72	226
	6	1/1/2019 5:00	54	10	13	88	234
	7	1/1/2019 6:00	62	10	11	88	230
	8	1/1/2019 7:00	98	9	19	87	262
	9	1/1/2019 8:00	90	15	13	72	284
	10	1/1/2019 9:00	106	17	20	64	302
	11	1/1/2019 10:00	102	18	26	52	302

Table 3: Checking data

		INPUTS					OUTPUT
		Date & Time	Load Data	Temprature	Windspeed	Humidity	TARGET
Checking Data-15%	9116	2/11/2020 2:00	268	12	9	72	236
	9117	2/11/2020 3:00	264	12	13	77	226
	9118	2/11/2020 4:00	264	11	9	67	234
	9119	2/11/2020 5:00	264	12	17	67	254
	9120	2/11/2020 6:00	268	10	15	71	312
	9121	2/11/2020 7:00	290	11	17	72	390
	9122	2/11/2020 8:00	330	13	15	63	398
	9123	2/11/2020 9:00	378	17	9	59	470
	9124	2/11/2020 10:00	410	20	4	43	464
	9125	2/11/2020 11:00	398	24	7	27	472
	9126	2/11/2020 12:00	414	25	0	28	498
	9127	2/11/2020 13:00	416	25	13	26	510

Table 4. Testing data sets generated after every one hour.

		INPUTS					OUTPUT
		Date & Time	Load Data	Temprature	Windspeed	Humidity	TARGET
Testing 15%	10635	4/14/2020 9:00	446	20	15	73	490
	10636	4/14/2020 10:00	490	21	13	64	520
	10637	4/14/2020 11:00	516	22	9	61	522
	10638	4/14/2020 12:00	538	23	7	53	528
	10639	4/14/2020 13:00	492	24	7	54	538
	10640	4/14/2020 14:00	482	24	17	47	502
	10641	4/14/2020 15:00	498	21	19	73	518
	10642	4/14/2020 16:00	494	20	15	73	522
	10643	4/14/2020 17:00	470	19	11	78	464
	10644	4/14/2020 18:00	416	19	7	83	420
	10645	4/14/2020 19:00	474	18	6	88	468

3.5 Model Development and Analysis

3.5.1 ANFIS-Based Model Design

For the objective of short-term electricity demand forecasting, MATLAB R2018a was used to model the ANFIS (Adaptive neuro fuzzy inference system).

Type of MFs	No. of input MFs	No. of Rules	No. of Epocs
Trapezoidal, Generalized bell, triangular, gauss	3:3:3:3	81	200

Each of the four input parameters contain three membership functions, resulting in Eighty-one (81) fuzzy rules. Historical load data (A), temperature (degrees Celsius), humidity (percent), and wind speed (km/hr.) are the input parameters. The aforementioned specified parameters were used for the ANFIS model's design.

- Membership function type

- Membership count function

-Optimization method

- Data volume.

- Number of input variables

The actions taken by ANFIS include:

-Receiving the training data;

-Mapping the input traits to the membership functions;

-Receiving the training data defining outputs in accordance with the rules;

-Applying particular rules to the input data from the previous phase;

-Mapping output features to output membership functions; and

-Estimating the network's overall output as a single valued output.

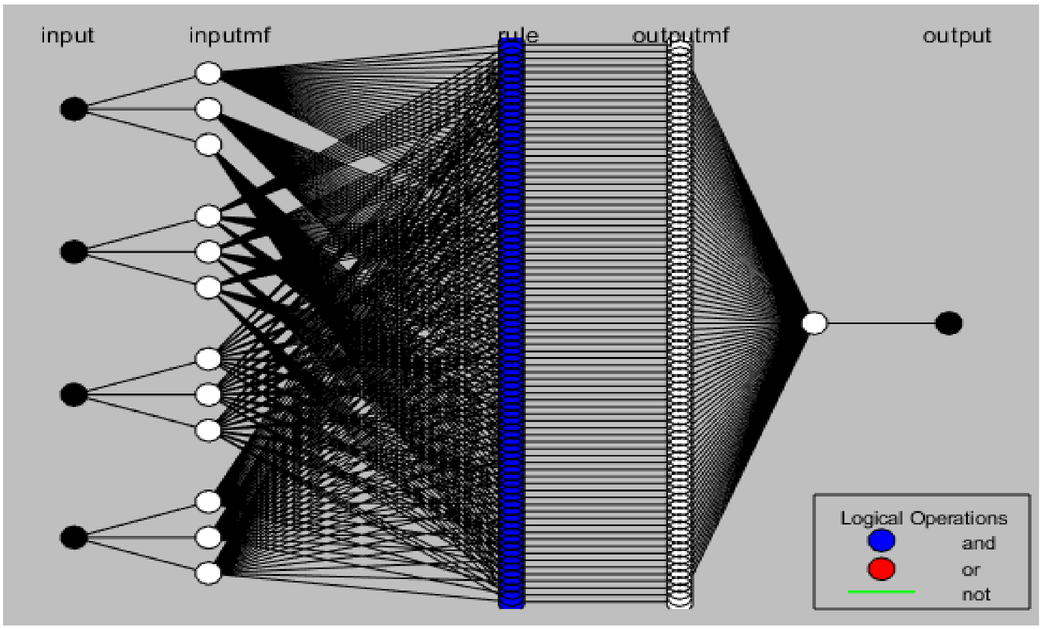


Fig. 3.5: ANFIS structure.

3.6 Data Presentation and ANFIS training

The desired input/output relationship is learned during training by changing the membership function parameters in the desired way. The network is repeatedly shown the training data set (epochs) until convergence is reached (usually when root mean square error between output and target is minimized). The finished matrix is then saved in a computer location and transformed from a.mat to a.dat format that is usable by ANFIS using the MATLAB code "dlmwrite ('filename.dat', [variables])".

The testing data set is used for model validation, which is the procedure by which the input vectors from input/output data sets on which the FIS was not trained are presented to the trained FIS model to see how well the FIS model predicts the matching data set output values. You can assess the fuzzy inference system's ability to generalize using the testing data set.

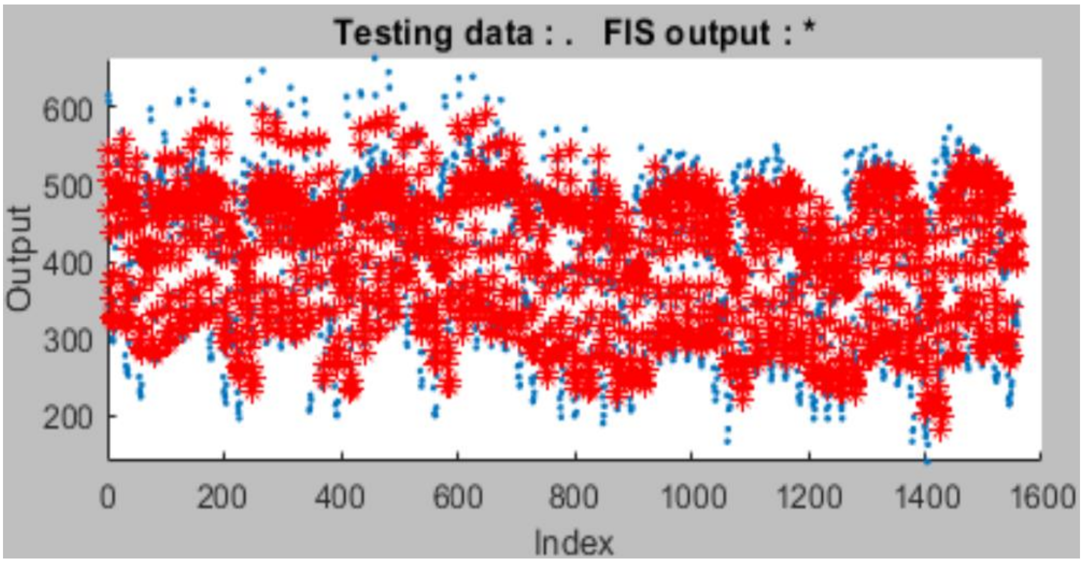


Fig. 3.6: Layout plot of Trained FIS against the Testing data

The following Ten steps were followed to developed, train and test the ANFIS model in this study as illustrated below.

Step 1. Pre-processing data (prepare the data sets in matrix form)

Step 2: Define the fuzzy system's input & output parameters and choose FIS method

Step 3. Loading training data (39,460) and checking data (6,080)

Step 4: Define the ANFIS training parameters: Mode of FIS generation, Number of Epochs, optimization method, Type and number of MF per input

Step 5: Training the ANFIS Model.

Step 6: Load testing data from workspace (6,080) and Plot it against the trained FIS.

Step 7: Export trained FIS to MATLAB workspace

Step 8: Load Forecasting: and Load Validation data 1,248 and it against the Trained FIS

Step 9: Validate model accuracy by Computing Mean absolute percentage error.

Step 10: Plot forecasted values against the actual system load

The flow chart in Figure 3.7 gives a summary of the proposed forecasting model.

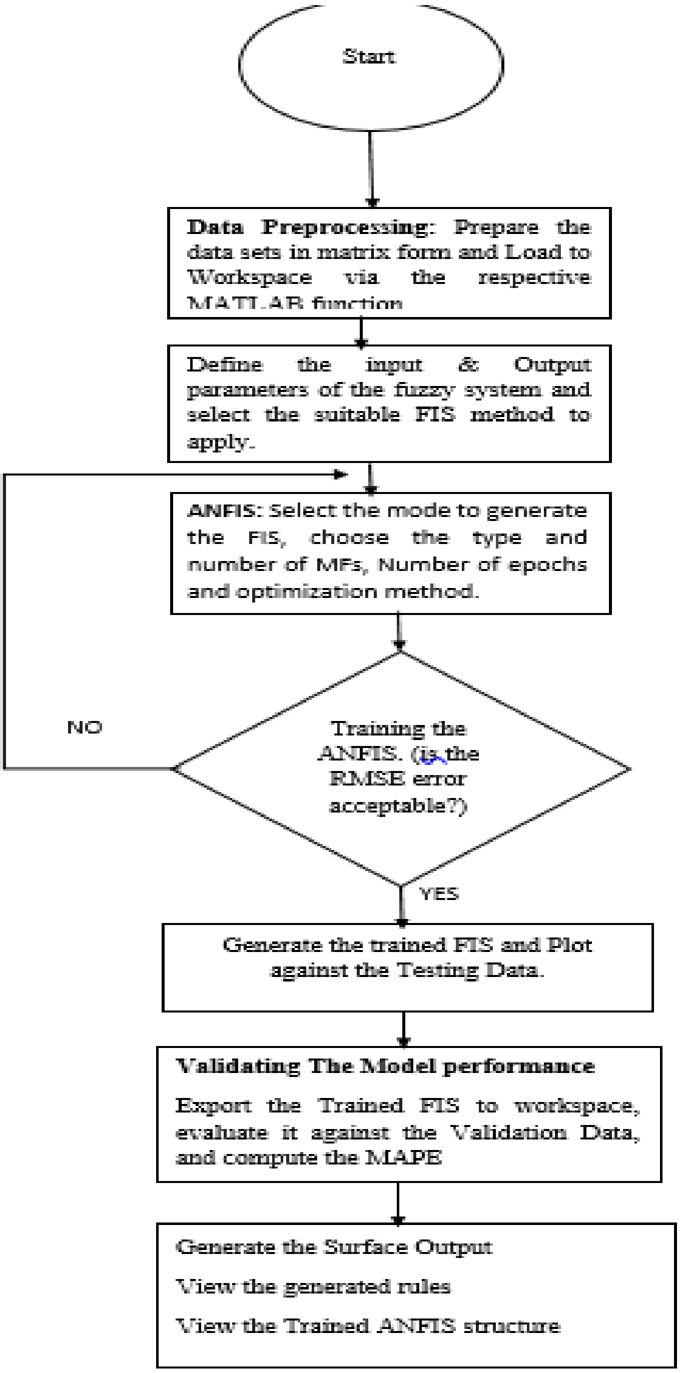


Fig. 3.7: A Flow Chart of the proposed model development

The membership function was successfully tuned using the ANFIS modeling criterion to reduce output error and increase performance index. The grid partition approach is used to construct the rules after the training data has been loaded successfully. A method for initializing the structure in a fuzzy inference system is called grid partitioning. By listing all potential combinations of the membership functions of all inputs, this approach generates rules. Based on input patterns, the training process automatically modifies the membership functions.

3.6.1 Fuzzy rule generation and membership function selection

The following commands were used to load the respective data sets into the MATLAB RX2018a workspace in matrix form:

Trainingdata=[];

Checkingdata=[];

Testingdata=[];

The creation of the rules is one of the key features of a fuzzy model. The construction of rules that connect the fuzzy input and the desired output are discussed in this section. Figure 3.8 shows the whole structure of fuzzy logic system included input, reasoning rules and also the proposed output. The inference rules relate the input to the output and every rule represents a fuzzy relation.

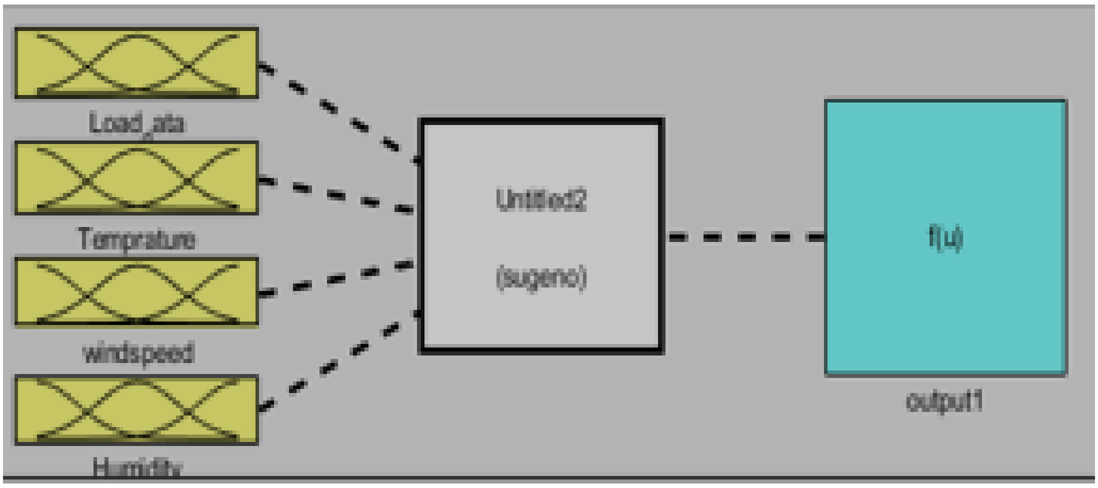


Fig 3.8: Structure of ANFIS

This fuzzy logic designer tool allows creation and test of the fuzzy inference systems for simulating complicated system behavior. Fuzzy inference systems (FIS) are systems that map inputs to outputs using fuzzy set theory. The program can add, remove, specify input and output variables, as well as the kind of membership functions, in addition to adding and removing them. There are a variety of strategies available to create the fuzzy inference system, but the study in this case uses Grid partitioning instead of subtractive clustering because of the following benefits: Grid partitioning divides input variable ranges uniformly and establishes input membership functions to produce a single-output Sugeno fuzzy system. The fuzzy rule base has a rule for each combination of an input membership function. The number of membership functions for each input was taken to be 3 3 3 3 and the model trained using four distinct membership functions in order to choose the best system with the lowest RMSE error and computed MAPE (Triangular, Trapezoidal, generalized bell, Gaussian curve). By inserting the relevant data function, the data was loaded into the ANFIS system from the MATLAB workspace ready for training

The training data is then trained against the checking data using a hybrid optimization strategy. As previously indicated, this stage uses a neural adaptive learning strategy such as the hybrid method, which combines back propagation and the least squares method to automatically update parameters. In this design, the number of epochs in the model was set at 200. The grid partition approach is used to construct the rules after the training data has been loaded successfully. The rule set has($81 = 3^4$) rules because there are four inputs and three membership functions. A method for initializing the structure in a fuzzy inference system is called grid partitioning. By listing all potential combinations of the membership functions of all inputs, this approach generates rules.

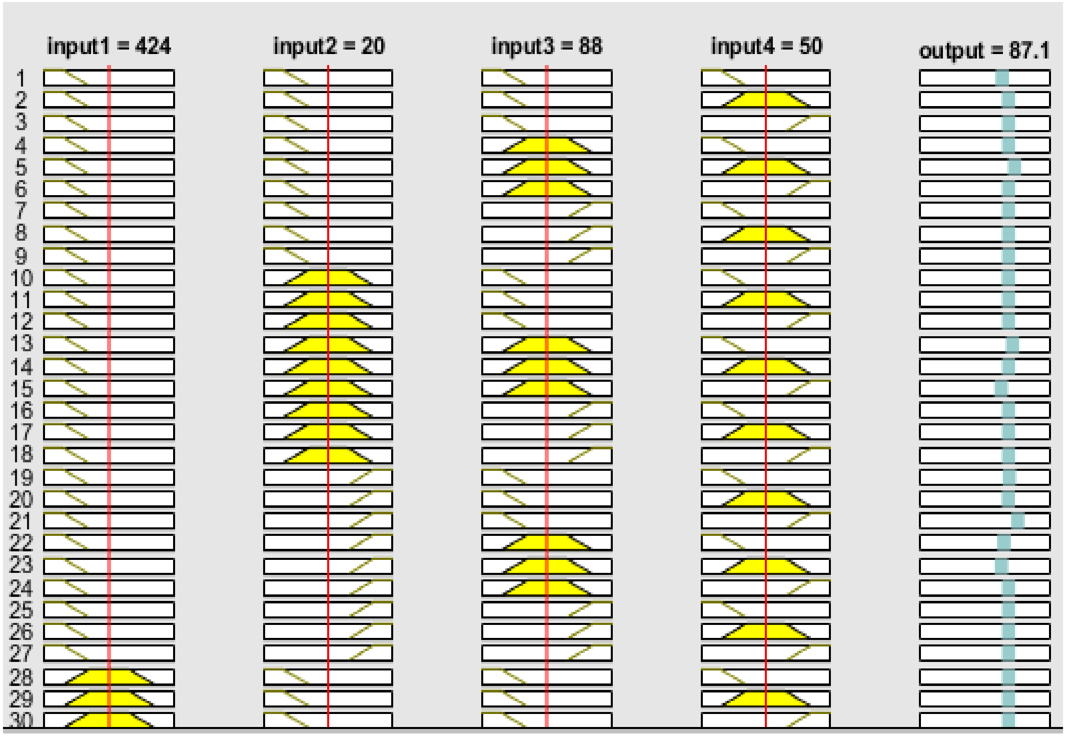


Fig. 3.9: The Generated Rules by the trained ANFIS model

3.6.2 ANFIS Electricity Demand Forecasting

The result of the system is generated using the evalfis function. The method aids the research in generating an outcome by evaluating the developed fuzzy inference system (FIS) against the input (Testing data).

Thus; *Anfis_outputmf1 = evalfis (input, FIS);*

Where:

- ANFIS output is the name of the function that represent forecasted load values.
- The input consists of the Testing data that has been loaded into the MATLAB workspace but without the output values.
- The Fuzzy Inference System (FIS) is a memory that stores both training and checking data using a membership function. For the remaining four membership functions, the process is repeated calculating the result of the testing set using a trained adaptive neuro-fuzzy inference system and contrasting it with the intended output of the testing data set. The aimed value and predicted value are

shown in figure. The Mean Absolute Percentage Error (MAPE) for each membership function is then calculated in order to find the Optimal membership function with the lowest MAPE value. The system was then modelled for the short-term demand forecast using the membership function with the least MAPE error in training and computing, as shown in the findings. Once a suitable MF has been selected, the trained FIS and Testing data (input variables) are evaluated using the evalfis function, and MAPE is computed:

Anfis_output = evalfis (input, FIS),

Hence: *Anfis_output (prediction) = evalfis (testing data, FIS)*

3.7 Evaluating the ANFIS based Model's reliability

A model's design serves as an approach to an objective, but its effectiveness is determined by the accuracy of the predicted results. The performance of the training set and the test set must be fairly similar as one of the main reliability tests for a solid system. The performance of the model when put through common procedural and statistical tests like the mean absolute percentage error serves as the primary indicator of such a model (MAPE). The anticipated outputs are assessed for the ANFIS-Based model using the MATLAB toolbox and the command line displayed below.

• Calling the Neuro-fuzzy Editor by its name, "ANFIS," with the command "anfisedit"

• Data loading command; Trainingdata=[]; Checkingdata=[]; Testingdata=[];

• Use the command: evalfis to assess the output of ANFIS.

i.e Prediction made by Anfis output = Evalfis (testing data, FIS)

The anticipated output values will be acquired from the command line above and will thus fit in with the established procedural and statistical measurements. This will be accomplished by using procedural and statistical tools like the Mean Absolute Percentage Error (MAPE) Microsoft Excel Statistical package.

In order to assess the ANFIS approach, equation 14's computation of the Mean Absolute Percentage Error (MAPE) was used. The average percentage points of the projections inside a set of validation data are estimated using the concept MAPE. One of the key factors determining the forecast method accuracy level is the MAPE error, which measures how accurate the organization's forecasting approach was. Because it calculates the average percentage points of the projections in a data collection, it is an easy to use and comprehend method of evaluating forecast error.

$$\text{MAPE} = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{A_{t-F_t}}{A_t}\right|$$

Where "n" is the absolute number of predictions and "Ft, At" are the expected and actual values.

CHAPTER FOUR: RESULTS AND DISCUSSIONS

4.1 Introduction

The results obtained in this research confirms the applicability as well as the efficiency of the hybrid system to execute short term electricity demand forecast. The model was validated with a distinct batch of data for an hour, 24 hours and a week a head prediction and the results analyzed and discussed for consistency

4.2 Model Design and training Details

The model's input variables are temperature, humidity, wind speed, and historical load information, as was mentioned in the part before. Based on these data, an ANFIS network with a Sugeno-style inference system has been constructed, which maps the input data to the output data and uses these four independent variables to produce output data (electricity demand).

The model was created with the use of MATLAB 2018a. Each input data set was subjected to the application of four different membership functions, including trapezoidal, triangular, gaussian, and generalized bell. The Model's design parameters and training results are as shown in the table.

Table 5: The Model design details and Training results

ANFIS Modelling				
	Membership Functions			
	trapmf	gbellmf	gausmf	trimf
Training RMSE	48.85	49.23	49.45	49.85
Computed MAPE	0.35949	0.67097	0.56682	0.5879
input variables	4			
optimization method	Hybrid			
FIS generation method	Grid partitioning			
Number of iterations	200 epochs			
FIS method	Sugeno			
Tolerance error	0			
Output	1			

Two (2) sets were chosen to train the network out of the four (4) data sets that were available. In order to test the trained network, one (1) set of data was used, and another set was used to validate the network. This process makes sure that the intended network performs well with any type of data. Root means square error (RMSE) for training the data was 485 after the network had been trained. As a result of the low training error, the trained network was able to provide highly accurate estimates of separate set of data meant to test reliability of the model

4.2.1 Prediction results per type of membership function.

The table 5. Shows the evaluated output data obtained for the four different membership function applied in the model, the full table of results is attached in appendix 2.

Table 6: Sample of Predicted results per applied membership function

PREDICTED VALUES PER MEMBERSHIP FUNCTION					
TIME	ACTUAL LOAD	trimf	trapmf	gbell	gauss
0:00	366	369.2020325	348.6693	364.3357	356.2205
1:00	326	349.6344019	330.5988	345.3045	336.7928
2:00	344	338.5786516	319.7566	334.1122	325.4892
3:00	312	322.1650841	326.116	327.5587	324.9823
4:00	320	312.1157867	315.2737	316.954	313.9405
5:00	344	322.1650841	326.116	327.5587	324.9823
6:00	362	323.5242477	327.8396	323.1304	324.1892
7:00	370	344.4376727	350.5974	350.3903	350.3847
8:00	442	428.0997863	427.3486	428.2072	427.4879
9:00	504	482.9131286	481.9687	482.7689	484.8494
10:00	528	506.6091951	498.507	508.0424	506.0644
11:00	526	511.3173101	503.3588	505.9635	503.9954
12:00	542	508.038064	505.1615	517.5597	517.5077
13:00	536	504.246552	511.5156	511.4669	511.2731
14:00	486	483.0998602	488.5399	485.0191	486.7128
15:00	518	478.6155758	481.1917	477.6604	479.7069
16:00	536	477.0250749	496.9887	489.1713	488.3515
17:00	492	471.1768859	489.3301	481.4525	480.9621
18:00	482	467.1795261	458.5181	459.844	463.7864
19:00	502	500.2333054	515.3005	491.5629	494.8387
20:00	604	580.5817216	418.6778	484.6551	525.9687
21:00	572	537.0441482	480.7639	500.9402	520.9013
22:00	506	503.08823	501.9223	501.5845	502.7096
23:00	434	427.4012745	425.3061	423.4494	424.6639

Using the model's four different membership functions, which are described below, the mean absolute percentage error was calculated and determined. You may assess how well the models match the data by looking at the models training RMSE index, which is automatically calculated between the desired and output values and then averaged over all the data. Furthermore, it can give information regarding the model's future consistency. ANFIS's ability to make better predictions on data for which there has been no prior training is demonstrated by the fact that the RMSE values associated with the suggested model are quite low for the trapezoidal membership function, with a value of 48.85.

Triangular (trimf) = 0.5879

Trapezoidal (trapmf)=0.35949

Gaussian (gaussmf)=0.56682

General bel shaped (gbellmf)l = 0.67097

Since the Trapezoidal membership function had the lowest MAPE value, its generated FIS was chosen to train the input/output data pattern because it minimizes the RMSE. The same generated FIS was loaded from workspace and plotted against testing data to test the model, as shown in Figure 4.1. The similarities between the curves, as can be observed, suggest that the model has an exact prediction that fits the actual data.

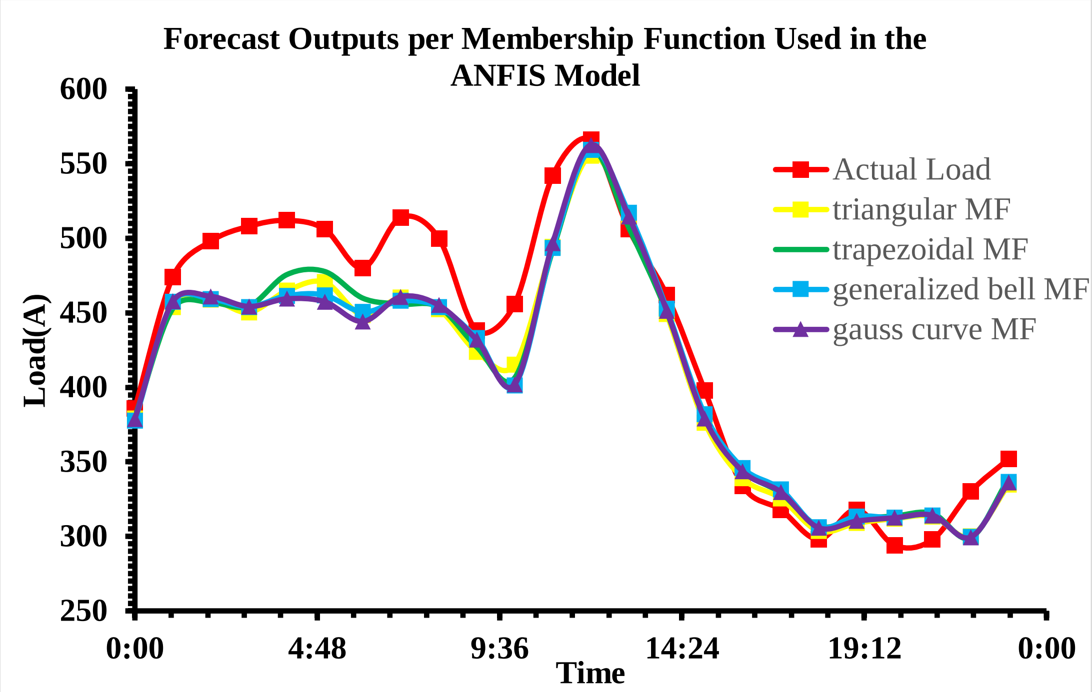


Fig 4.1: A 24-hour Prediction Output per MF used in the ANFIS model.

4.3 Models Validation

4.3.1 Hourly prediction results

To verify the model reliabilty, a separate data set of 1248 data points was employed, which was evaluated to the trained FIS using the evalfis function, resulting in Forecasted results.

After the ANFIS network training is completed, next hour load forecast for the upcoming hours can be calculated from the generated FIS. For example, if we want to forecast the load at 1400hrs of June 29th, 2020. One set of inputs is given as follows:

- Temperature = Tjune/29/2020/1400hrs
- Humidity = Hjune/29/2020/1400hrs
- Current--hour load = CL1300hrs
- wind speed = Wjune/29/2020/1400hrs
- Time of the day = TOD 1400hrs

With the help of the aforementioned notion, the predicted load for the following hour was calculated for all 1248 validation data points for 2020 as well as for a few chosen days. Using the results, the mean absolute percentage error (MAPE) was also determined.

Table 7: Models prediction results of Monday 29/06/2020

Time	Actual load	Predicted Values
0:00	302	273.1509408
1:00	274	257.600437
2:00	260	255.2973447
3:00	260	253.9637516
4:00	260	255.2973447
5:00	266	256.7923795
6:00	290	269.1527781
7:00	348	328.8149748
8:00	406	384.8333902
9:00	464	449.7864242
10:00	476	474.038521
11:00	492	479.1442256
12:00	496	484.2499302
13:00	484	477.6253169
14:00	456	453.9980676
15:00	496	478.6685273
16:00	468	469.7682382
17:00	448	450.8245226
18:00	424	429.9842984
19:00	492	476.8765476
20:00	548	529.3728987
21:00	506	504.0862314
22:00	434	437.7745278
23:00	350	364.9495632

Table 8: Hourly forecasting results of Wednesday 17.06.2020

WEDNESDAY 17/06/2020		
Time	**Actual load**	**Predicted Values**
0:00	368	362.8655668
1:00	318	326.9157523
2:00	332	342.9516874
3:00	312	314.6005598
4:00	316	321.5704406
5:00	328	342.9516874
6:00	350	357.7618253
7:00	374	368.3874248
8:00	420	434.3609778
9:00	500	481.790223
10:00	534	509.4422696
11:00	520	504.541897
12:00	516	509.1810124
13:00	520	506.5242985
14:00	496	474.6136447
15:00	538	494.4157705
16:00	548	510.9255252
17:00	514	477.8218635
18:00	456	470.6416341
19:00	492	480.7921166
20:00	618	589.8122141
21:00	576	535.3388644
22:00	500	489.8709569
23:00	408	427.5176497

Plotting the actual load versus the ANFIS load for values from tables 9 to 10 is shown in the graph of Figures 4.2 to 4.6.

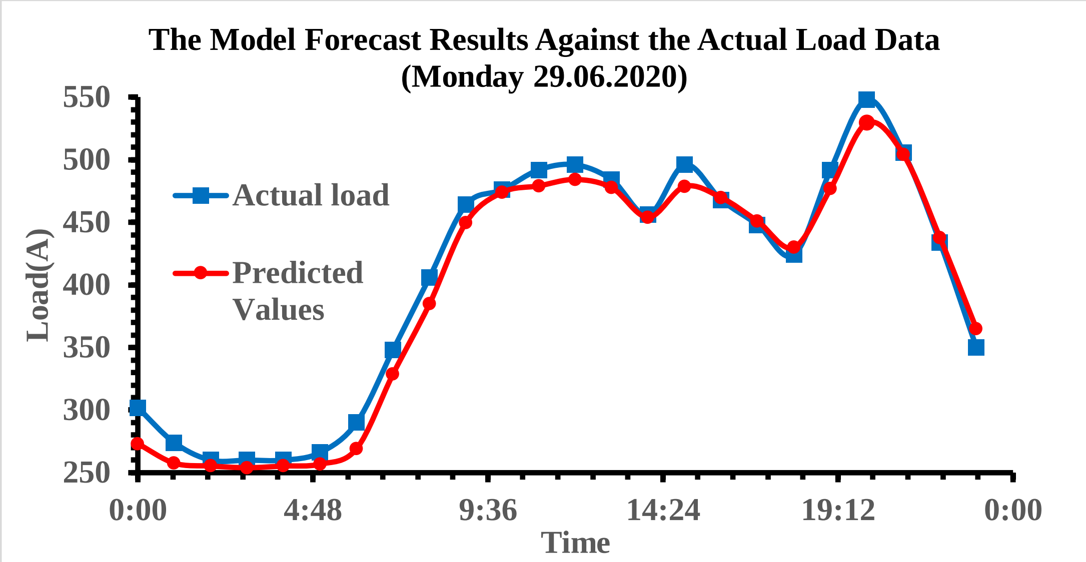


Fig. 4.2: The Model Forecast results of Monday 29.06.2020 .

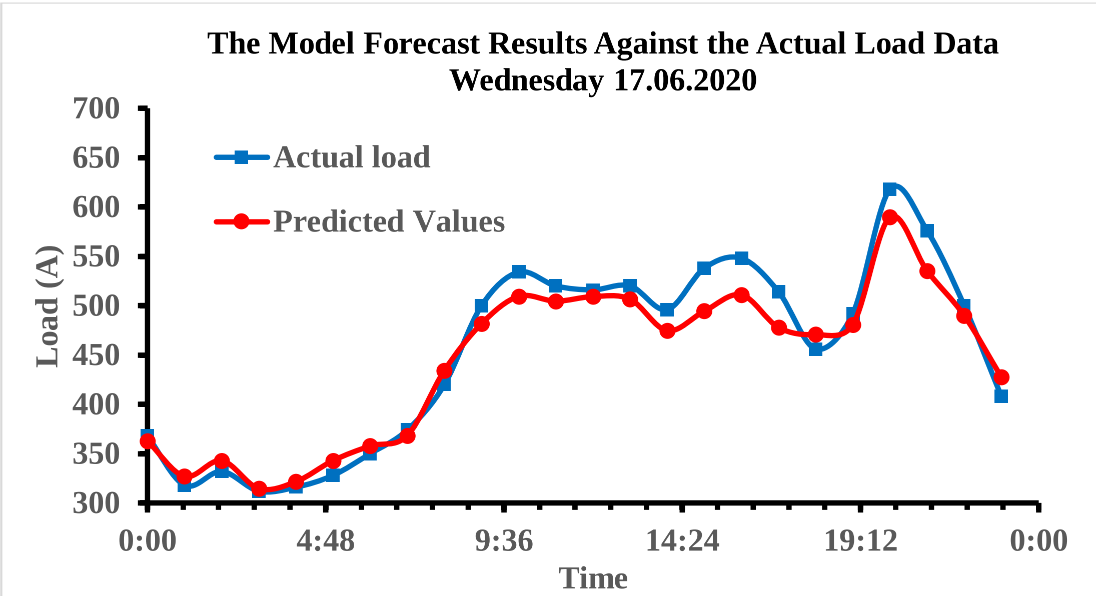


Fig. 4.3: The Model Forecast results of Monday 17.06.2020 .

Table 9: Hourly forecasting results of Thursday 18.06.2020 and 25.06.2020

Model Forecasted results						
THURSDAY 18/06/2020				**THURSDAY 25/06/2020**		
Time	**Actual load**	**Predicted Values**		**Time**	**Actual load**	**Predicted Values**
0:00	350	362.50103		0:00	366	372.1130018
1:00	330	317.9567657		1:00	338	347.1155677
2:00	310	330.4291597		2:00	290	334.6431737
3:00	288	312.611454		3:00	276	320.3890091
4:00	312	315.9391928		4:00	308	334.6431737
5:00	316	326.6298162		5:00	298	320.3890091
6:00	326	348.7497824		6:00	314	336.4249443
7:00	386	371.2921405		7:00	374	364.4954247
8:00	444	410.2993592		8:00	444	397.8854054
9:00	468	487.8414242		9:00	488	470.369241
10:00	506	510.7543636		10:00	504	496.5659038
11:00	522	500.4480189		11:00	524	501.9248968
12:00	512	497.4149103		12:00	510	520.2651331
13:00	510	500.0934233		13:00	518	506.1451313
14:00	458	487.4212568		14:00	486	498.9948216
15:00	522	512.7538232		15:00	512	512.530631
16:00	508	527.0769588		16:00	526	501.3640697
17:00	476	496.9536583		17:00	476	503.096106
18:00	470	445.2855279		18:00	462	478.7925962
19:00	520	475.0835942		19:00	502	485.0418129
20:00	580	611.1227645		20:00	538	586.5998802
21:00	528	561.8628368		21:00	500	536.304358
22:00	464	485.0525476		22:00	424	474.0757724
23:00	372	404.241177		23:00	348	409.0753221

A whole week projection, as shown in figure 4.4, shows a nearly same Load curve flow, meaning that the error rate is quite low and that the model produced a better outcome.

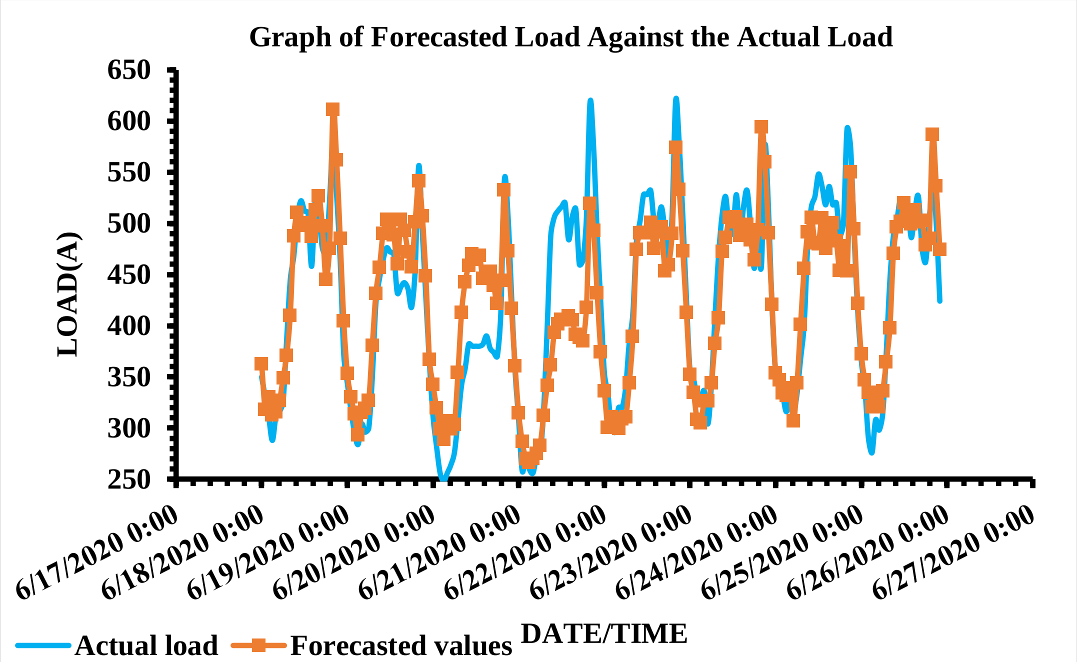


Fig. 4.4: A Week plot curve of forecasted load values against the actual load

The link between inputs and outputs achieved by the created ANFIS system is depicted in the 3-D surface plot produced by the designed ANFIS model in figure 4.5. The link between the input parameters of historical electric load, temperature, humidity, and wind speed and the output, which is the forecasted load for the next hour. As seen in this graph, there is a tendency for the load to be high at somewhat high temperatures.

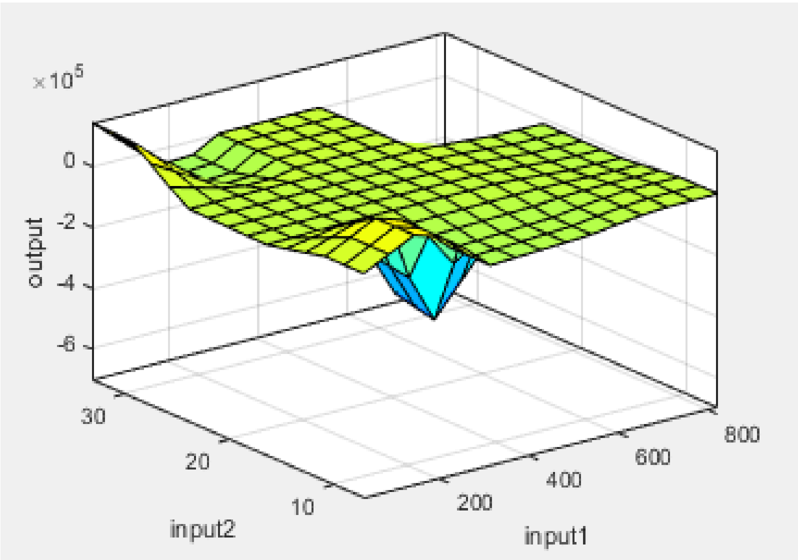


Fig. 4.5: The surface plot the ANFIS Output

4.4 Discussion

This study selection criterion of input variables based on a time series correlation plots (Pearson's correlation analysis) and the huge amount of hourly data availed for training the model enhanced the performance of the ANFIS model.

Table 10: Pearson's correlation analysis

	Load	Temperature	Wind speed	Humidity
Load	1			
Temperature	0.4704977	1		
Wind speed	0.4176507	0.7403399	1	
Humidity	-0.507843	-0.9057923	-0.7898062	1

A positive correlation with load was revealed among the variables of temperature, wind speed while an inverse correlation was noted for Humidity variable of +0. 5, +0.4 and –0.5 respectively. Accordingly, the approach of including both training and checking data in training the ANFIS system shortens the time of training due to enhanced learning (mapping of input and output vectors).

The ANFIS modeling approach utilized in this work exemplifies why choosing the membership function to use, together with the volume of input data, significantly increases the validity of the forecasting model developed. This study considers modeling ANFIS with a trapezoidal Membership function because, in comparison to ANFIS models based on triangular MF, generalized bellvMF, and gauss MF, which had MAPE values of 0.59, 0.57, and 0.67 respectively, it provided a forecast result with a minimum error of MAPE value 0.35.

The actual load deviates just slightly from the expected load, as seen in figures 4.2 to 4.4. The aforementioned Matlab command line that was presented in 4.1 was used to determine the predicted load values in tables 6 to 8. All 1248 validated data points were analyzed in order to assess the model's validity. These research employed mean absolute percentage error as the statistical metrics (MAPE).

The models' accuracy to predict short-term load demand with a lead time of 1hr - 7days is demonstrated by a Mean absolute percentage error (MAPE) result of 0.0977%, which is based on estimations of the average percentage points of the projections in a data set of 624 data points of actual and forecasted values from a validation data.

CHAPTER FIVE: CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

Modeling and forecasting electricity consumption is crucial in the power industry, especially when implementing sustainable energy policies. When demand grows at a faster rate, accurate electricity demand forecast is critical. A model that can accurately forecast the next hour's load should therefore be designed. According to input factors including the time of day, temperature, humidity, wind speed, and previous load, an ANFIS-based model was developed in this study project to forecast the next hour load to 7 days.

The large amount of hourly data available for training the model and the time series correlation plots-based selection criteria of input variables used in this study both improved the performance of the ANFIS model. Temperature and wind speed showed a positive correlation with load, but humidity showed an inverse correlation (+0. 5, +0.4, and -0.5, respectively.

Utilizing MATLAB® R2018a, the ANFIS-based model was developed. According to the results of this study, the ANFIS-based model offers an improved modeling tool for forecasts. Although there are several benefits to non-mathematical models, the fundamental advantage of the ANFIS technique is that it corresponds more quickly. In contrast to ANFIS models based on triangular MF, generalized bell MF, and gauss MF, which had MAPE values of 0.59, 0.57, and 0.67 respectively, it provided a forecast result with a minimum error of MAPE value 0.35. This study therefore considers modeling ANFIS with a trapezoidal Membership function. Based on estimation of the average percentage points of the projections in a data set of 624 data points of actual and predicted loads from a separate set of validation data, a final MAPE result of 0.0977 illustrates that the model achieved the expected accuracy to predict short-term electricity demand with a lead time of 1hr - 7day. However, hourly load data for one grid was obtained and utilized to offline train and test the model. To ensure that the model is suitable for a range of load patterns, it must be validated using data sets from other grids.

5.1.1 Limitations of the study

1. The model underwent offline testing and instruction.
2. The information on hourly load was derived from a single grid. The models developed here must be tested on data sets from other grids in order to demonstrate their suitability for use with various load patterns.
3. This thesis bases all of the aforementioned accomplishments on simulations and experiments, which are used to make its findings. No mathematical proofs were offered to justify the same.
4. The conclusions of this thesis need to be confirmed in more application fields in order to increase the robustness and generality of this approach.

5.2 Recommendation

The load variation follows specific principles depending on the "time point" of the day. For example, the daily load curve for Uasin Gishu county from Rivatex distribution substation showed that the loads begin to rise at 6 a.m. and peaked around 9 a.m., after which they remained stable at a low level until around noon to 2 p.m. when they begin to rise again, therefore, for higher accuracy of the short-term forecasting, I suggest that the day of the week component be further studied in future studies as one issue that should be considered. For instance, weekends and holidays are times of the week when loads may be high due to the fact that most people are at home or low due to the closure of the majority of energy-intensive businesses.

In order to produce a more accurate estimate of future demand, further research on this subject can incorporate additional data into the network, such as sky cover and rainfall. In summary, the proposed hybrid model based on Adaptive Neuro-Fuzzy Inference System is recommended for more accurate short-term electricity demand forecasting in both the residential and industrial sectors of Uasin Gishu County.

REFERENCES

A. Pardo, A., Meneu, V., & Valor, E. (2002). “Temperature and seasonality influences on Spanish electricity load,”. *Energy Economics, 24*, pp. 55-70.

Akdemir, B., & Cetinkaya, N. (2012). Long -term load forecasting based on adaptive neural fuzzy inference system using real energy dat,Energy Procedia. *14*, pp. 794-799.

Azadeh, A., Saberi, M., & Seraj, O. (2010, June). “An integrated fuzzy regression algorithm for energy consumption estimation with non-stationary data: A case study of Iran,. *Energy, 35*, pp. 2351-2366.

Azadeh, A., Saberi, M., Gitiforouz, A., & Saberi, A. (2009). A hybrid simulation-adaptive network based fuzzy inference system for improvement of electricity consumption" Expert systems with Applications. *36*, pp. 11108-11117.

Bahrami, S., Hooshmand, R. A., & Parastegari, M. (2014, August). “Short term electric load forecasting by wavelet transform and grey model improved by PSO (particle swarm optimization) algorithm,”. *Energy, 72*, pp. vol. 72, pp. 434–442, Aug. 2014.

Bala, A., Yadav, N. K., Hooda, N., & Registrar, D. (2014). “Implementation of Artificial Neural Network for Short Term Load Forecasting,”. *Curr. Trends Technol. Sci., no. 3*, pp. pp. 247–251.

Basheer, I. A., & Hajmeer, M. (2000). "Artificial neural networks:Fundermentals,computing,design and application". *Journal of Microbiological method, 43*(1), 331.

Bazmi, A. A., Daroody, M., & Gholamreza. (2012). Electricity demand estimation usingan Adaptrative Neuro fuzzy Network.

Belzer, D., Scott, M., & Sands, R. (1996). “Climate change impacts on U.S. commercial building energy consumption, an analysis using sample survey data,”. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 18*, p. 177.

C. Ying, e. a. (2010, 2010). Short-Term Load Forecasting: Similar Day-Based Wavelet Neural Networks. *IEEE Trans. Power System, no. 25*, pp. p. 322-330.

Cárdenas, J. J., Giacometto, F., Garcia, A., Romeral, J. L., Group, M., De Catalunya, U. P., & Nebridi, R. S. (2012). “STLF in the User-Side for an iEMS based on Evolutionary training of Adaptive Networks,” Int’l Conf. Emerg. Technol. Fact. Autom., (pp. pp. 1–8).

Casillas, J., & Moreno, D. (2011). *Analyzing strength and weaknesses of Fuzzy association rules algorithm;Universidad de Granada,Spain.* Spain.

Charytoniuk, W., Chen, M. S., & Van Olinda, P. (1998). Nonparametric regression based short term load forecasting. *IEEE Transaction on Power systems*, pp. 725-730.

Feinberg , A. E., & Genethliou, D. (n.d.). LOAD FORECASTING. *State University of New York, Stony BrookEugene.Feinberg@sunysb.edu Dora GenethliouState University of New York, Stony Brookdgenethl@ams.sunysb.edu*, Chapter 12.

Feinberg, E. A., & Genethliou, D. (2006). 'LOAD FORECASTING'. *Applied Mathematics for restructured Electric Power System, J. A. Chao, J H; Wu, F F; Momoh,*, pp. 269-285.

Franco, G., & Sanstad, A. (2007). “Climate change and electricity demand in California,”. *Climatic Change, 87*, pp. 139-151.

Ghareeb, W. T., Member, S., El Saadany,, E. F., & Member, S. (2013). “A hybrid Genetic Radial Basis Function Network with Fuzzy Corrector for Short Term Load Forecasting,” 2013 IEEE Electr. Power Energy Conf.

Giacometto, F., Cardenas , J. J., Kampouropoulos, K., Romeral, J. L., & De Catalunya , U. P. (2012). “Load Forecasting in the User Side Using Wavelet ANFIS,”. *38th Annu. Conf. IEEE Ind. Soc.*, pp. 1049–1054.

Guillaume, S. (2001). *Designing fuzzy inference systems from Data:An interpretability-Oriented review.* IEEE Trans.fuzzy syst.

Guo, Y., & Niu, D. (2008, july 12-15). “Intelligent short-term load forecasting based on pattern-base,”. *Internatinal Conf. Mach. Learn. Cybern. Kunming,*, (pp. 1282-1287).

Hamdan , H., & Garibaldi , M. (2010.). “Adaptive Neuro-Fuzzy Inference System (ANFIS) in Modelling Breast Cancer Survival,” . *WCCI 2010, IEEE World Congress on Computational Intelligence,*, pp. 18–23, .

Hanmandlu, M., & Chauhan, B. K. (2011, Feb). “Load Forecasting Using Hybrid Models,”. *IEEE Trans. Power Syst., 26*, pp. pp. 20–29.

Hong , T., & Wang, , P. (2013, september). “Fuzzy interaction regression for short term load forecasting,” ,. *Fuzzy Optim. Decis. Mak., 13*, pp. pp. 91–103.

Honghui , Z., & Yongqiang, L. (2012, March). “Application of an Adaptive Network-Based Fuzzy Inference System Using Genetic Algorithm for Short Term Load Forecasting,”. *2012 Int. Conf. Comput. Sci. Electron. Eng*, pp. 314-317.

Jain, M. B., Nigam, M. K., & Tiwar, P. C. (2012). ”Curve Fitting And Regression Line Method Based Seasonal Short Term Load Forecasting “ . *2012 World Conference on Information Technology.*

Jang , R. (1995.). “Neuro-Fuzzy Modeling,”. *proceedings of the IEEE, vol. 83, no. 3,, 83*.

Jia, Z. (2008). -Genetic Algorithm to Shortterm Forcasting in Power System,”4th Int’l Conf. Wirel. Commun. Netw. Mob. Comput., ., (pp. pp. 2–5.).

Jing-Min, W., & Li-Ping, W. (2008). Anew method for short-term electricity load forecasting Transactions of the Institute of Masurement and Control. *IEEE*, pp. 331-334.

Kandil, M. S., El-Debeiky, S. m., & Hasanien, N. E. (n.d.). Long term load forecasting for fast developing utility Using a knowledge based expert system.

Kreinovich, V., Kosheleva, O., & Shabazova, s. (2018). *Why Triangular and Trapezoid Membership Functions: A Simple Explanation.*

Kreinovich, V., Kosheleva, O., & Shahbazova, S. (2020). *Why triangular and trapezoid membership functions:A simpler Explanation.Recent Dev Fuzzy log.Fuzzy sets.*

Li, H., Cui, L., & Guo , S. (2014). “A Hybrid Short-Term Power Load Forecasting Model Based on the Singular Spectrum Analysis and Autoregressive Model,”. *Adv. Electr. Eng.*, pp. pp. 1–7.

Mori, H., & Tsuzuki, S. (1989, July). Power systems Topological Observability analysis Using a Neural Network model. *Proc. of 2nd system on Experts systems*, pp. 385-391.

Moturi , C. A., & Kioko, F. K. (2013). “Use of Artificial Neural Networks for Short-Term Electricity Load Forecasting of Kenya National Grid Power System,”. (n. 2, Ed.) *Int’l J. Comput. Appl., 63*, pp. 25–30,.

Mourad, M., Bouzid, B., & Mohamed, B. (2012, Dec.). “A hybrid wavelet transform and ANFIS model for short term electric load prediction,”. *2012 2nd Int. Conf. Adv. Comput. Tools Eng. Appl.*,(no.1), pp. 292 - 295.

Muhamma, U. F., & Naeem, A. (2014). Factors affecting Load demad Forecasting. *Clean Energy Technolgies, 4*.

Mutai, K. S., Sneider, D., & Kiprop, A. (2019, November). *Household Energy utilization & changing behavior*.

Nguyen , T., & Liao, Y. (2011). “Short-Term Load Forecasting Based on Adaptive Neuro-Fuzzy Inference System,”. (n. 11, Ed.) *J. Comput, 6*, pp. pp. 2267–2271.

Paravan, D., Debs, A., Hansen, C., Hirsch, P., & Golob., R. (n.d.). “Influence of temperature on short-term load forecasting using the EPRI-ANNSTLF.” [.

Park, D. C., El-Sharkawi, M. A., & Marks II, R. J. (1991). Transactions on Power Engineering. pp. 442-449.

Park, D. C., El-sharkawi, M. A., Mark II, R. J., Atlas, L. E., & Damborg, M. J. (1991). Electric load forecasting using an artificial neural network. *IEEE Transaction on power engineering*, pp. 442-449.

Power, I. T. (2001, August). Short term load forecasting using time series modeling with peak load estimation capability. *16*.

Puspitasari, I., Akbar, M. S., & Lee, M. H. (2012, September). “Two-level seasonal model based on hybrid ARIMA-ANFIS for forecasting shortterm electricity load in Indonesia,”. *2012 Int. Conf. Stat. Sci. Bus. Eng.*,, pp. 1–5.

Qingqing, M., Yonggang, W., Xiaoqiang, P., Liangyi, H., & Xian, L. (2010). Short term Load Forecasting Using Improved Similar Days Method.

Rahman, S. (2002). “Formulation and analysis of a rule-based short-term load forecasting algorithm,” . *IEEE*, pp. 805–816,.

Rezaei , K., Hosseini , R., & Mazinani, M. (2014.). “A Fuzzy Inference System for Assessment of the Severity of the peptic ulcers,”. *Computer Science & Information Technology,* , pp. 263-271,Haida, T., & Muto, S. (1994). Regression Based Peak Load forecasting using Transformation technique. *IEEE Transaction on power systems*, pp. 1788-1794.

Rice, J., Mustafa, C., & Engle, R. F. (1992). Modeling Peak Electricity Demand. *Journal of Forecasting*.

Ruzic, S., Vuckovic, A., & Nikolic, N. (2000). Weather Sensitive method for short term load forecasting in Electric power Utility of serbia. *IEEE Transaction on Power Systems*, pp. 1581-1586.

Seo, Y., Kwan, S., & Chai, Y. (2018). Shortbterm water demand forecasting model combinin variational model decompositon and extreme learning machine.

Shayeghi, H., Shayanfar, H. A., & Azimi, G. (2007). 'STLF Based on Optimized Neural Network using PSO'. *world Acad sci. eng technol, 3*(no. 4), pp. 874-884.

Souzanchi, Z., Fanaee-T, H., Yaghoubi, M., & Akbarzadeh-T, M. -R. (2010, Aug.). “A multi Adaptive Neuro Fuzzy Inference System for short term load forecasting by using previous day features,”. *2010 Int. Conf. Electron. Inf. Eng.,, no. 2*, pp. V2–54–V2–57.

Sudheer , G., & Suseelatha, , A. (2015, January). “Short term load forecasting using wavelet transform combined with Holt–Winters and weighted nearest neighbor models,”. *Int. J. Electr. Power Energy Syst.,*, pp. 340–346.

Suhas, B. K., & ALI, D. M. (2015, May - June). Review Paper On Load Forecasting Using Neuro Fuzzy System. *IOSR journal of Electrical and Electronic Engineers(IOSR-JEEE), 10*(3), 38-42.

Taylor, & TX . (2010). Long-Term Hourly Peak Demand and Energy Forecast, . *Electric Reliability Council of Texas, Inc*.

Valero, S., Aparicio, J., Senabre, C., & Sancho, J. (2010). “Analysis of Different Testing Parameters in Self- Organizing Maps for Short-Term Load Demand Forecasting in Spain,”. *Mod. Electr. Power Syst. 2010, Wroclaw, Pol.*

Vargas, R., & M, E. (2018). *Fuzzy analytical Hierarchy process approach for multicriteria decision-making with an application to developing an 'Urban Greenness index'.* cananda: University oftoronto.

Willis, H. L. (1996.). Spatial Electric Load Forecasting. Marcel Dekker.

Zadeh, L. A. (1965). *Fuzzy sets information control.*

APPENDICES

Appendix 1: Training data, checking data and Testing data

Training data, Checking data, Testing data.xlsx

Appendix 2: Predicted values Per Membership Function

Testing data & MAPE Results per MF.xlsx

Appendix 3: Anti Plagiarism Certificate

SR100

EDU 999 THESIS WRITING COURSE

PLAGIARISM AWARENESS CERTIFICATE

This certificate is awarded to

ARUSEI ABRAHAM KIRWA

ENG/MES/18/19

In recognition for passing the University's plagiarism

Awareness test with a similarity index of 0% and

Striving to maintain academic integrity.

Awarded by:

Prof. John Changách, CERM-ESA Project Leader

01st /07/2022