Long-Term Load Forecasting Using Neural Network Technique for Distribution Substation System Expansion Planning

(Case Study: Debre Work Town)

Alemante Ketema Melese

A Thesis Submitted to the Department of Electrical Power and Control Engineering

School of Electrical Engineering and Computing

Presented in Partial Fulfillment of the Requirement for the Degree of Master's in Electrical Power and Control Engineering

(Power System Engineering)

Office of Graduate Studies

Adama Science and Technology University

July, 2023

Adama, Ethiopia

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DECLARATION

I hereby declare that this Master Thesis entitled "Long-Term Load Forecasting Using Neural Network Technique for Distribution Substation System Expansion Planning (Case Study: Debre Work Town)" is my original work. That is, it has not been submitted for the award of any academic degree, diploma or certificate in any other university. All sources of materials that are used for this thesis have been duly acknowledged through citation.

<u>Alemante Ketema Melese</u> ____________________ _________________

Name of student Signature Date

RECOMMENDATION

I, the advisor of this thesis, hereby certify that I have read the revised version of the thesis entitled "Long-Term Load Forecasting Using Neural Network Technique for Distribution Substation System Expansion Planning (Case Study: Debre Work Town)" prepared under my guidance by Alemante Ketema Melese submitted in partial fulfillment of the requirements for the degree of Master's of Science in Power System Engineering. Therefore, I recommend the submission of revised version of the thesis to the department following the applicable procedures.

___________________________	____________________	________________
Major Advisor	Signature	Date

APPROVAL SHEET

I, the advisor of the thesis entitled "Long-Term Load Forecasting Using Neural Network Technique for Distribution Substation System Expansion Planning (Case Study: Debre Work Town)" and developed by Alemante Ketema Melese, hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

Dr. C S Reddy		12-07-2023
Advisor	Signature	Date

We, the undersigned, members of the Board of Examiners of the thesis by Alemante Ketema Melese have read and evaluated the thesis entitled "Long-Term Load Forecasting Using Neural Network Technique for Distribution Substation System Expansion Planning (Case Study: Debre Work Town)" and examined the candidate during open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master of Science in Power System Engineering.

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Final approval and acceptance of the thesis is contingent upon submission of its final copy to the Office of Postgraduate Studies (OPGS) through the Department Graduate Council (DGC) and School Graduate Committee (SGC).

Department Head	Signature	Date
School Dean	Signature	Date
Office of Postgraduate Studies, Dean	Signature	Date

ACKNOWLEDGEMENT

First of all, I want to praise God and Mary, without whom it would have been impossible to finish my thesis. The second thing I want to do is to convey my sincere gratitude to my adviser, Dr. C.S. Reddy (associate professor), for his professional advice, helpful criticism, ideas, and support. Throughout my study years, he has served as a continual source of motivation. Thirdly, I would like to express my sincere gratitude to Dr. Milkias, the Department of Electrical Power and Control Engineering at Adama Science and Technology University in Adama for his insightful advice, vast knowledge, and unwavering support throughout my Masters study. He also inspired and helped me to implement additional ideas for the first stage of my thesis particularly to go through researching areas. Next, I want to express my sincere gratitude to Mr. Mesfin, Head of the Electrical Power and Control Engineering Department at Adama Science and Technology University in Adama, for his excellent direction, encouragement, and ongoing assistance during this work. His advice enabled me to reframe the scope of my investigation. Finally, I would like to express my gratitude to the Adama Science and Technology University staff members who work in the electrical power and control engineering department for their generous assistance. I want to express my gratitude to everyone who has provided me with suggestions and inspiration that have enabled me to successfully complete this thesis.

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LIST OF ACRONYMS

ABPA	Adaptive Back-propagation Algorithm
AI	Artificial Intelligent
ANN	Artificial Neural Network
CFBNN	Cascade Forward Back-propagation Neural Network
CNN	Convolution Neural Network
EEA	Ethiopian Energy Authority
EEP	Ethiopian Electric Power
EEU	Ethiopian Electric Utility
ENDGC	Ethiopia National Distribution Gride Code
ENTGC	Ethiopia National Transmission Gride Code
EP	Electrified People
ETAP	Electrical Transient and Analysis Program
FFBNN	Feed Forward Back-propagation Neural Network
FS	Fuzzy Set
GDP	Gross Domestic Product
GDP/CAP	Gross Domestic Product per Capita
GRNN	Generalized Regression Neural Network
GRU	Gated Recurrent Unit
HV	High Voltage side
IEC	International Electrotechnical Commission
IEEE	Institute of Electrical and Electronics Engineers
ISO	International Organization for Standardization
LILO	Loop In Loop Out
LV	Low Voltage side
LTLF	Long Term Load Forecasting
LSTM	Long-Short Term Memory
MAD	Mean Absolute Deviation
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MS	Micro soft
MATLAB	Matrix Laboratory
MTLF	Medium Term Load Forecasting

NASA	National Aeronautics and Space Administration
NP	Neural Prophet
ONAF	Oil Natural Air Forced
ONAN	Oil Natural Air Natural
POP	Population
PSSE	Power System Simulator for Engineers
SSE	Sum of Square Error
SS	Substation
STLF	Short Term Load Forecasting
R^2	Regression coefficient square
RMSE	Root Mean Square Error
RUL	Regular Unleaded (gasoline)
RNN	Recurrent Neural Network

ABSTRACT

Load forecasting is the prediction of demand for the next period and is an essential requirement for new planning and expansion planning of power systems. Knowing the future demand in concise way has been still a big problem in Ethiopia to meet the power demand for different load types like industrial, commercial, city municipal services or public services, agricultural and domestic services. In this thesis, load forecast for Debre Work town and its surrounding has been obtained for the period of 2023 to 2037 and distribution substation system expansion planning model has been planned with technical feasibility study, which has covered load flow analysis, contingency analysis and short circuit analysis to meet the forecasted load . The following independent variables have considered, namely - GDP, number of populations, GDP/CAP, weather conditions like temperature and electricity consumption by the people (EP) as the factors that affecting the future load growth in Debre Work town. MATLAB software has been used for training and testing for the general neural network techniques such as LSTM-RNN and GRU-RNN. LSTM-RNN result was better than GRU-RNN in good fitting from assessment measurement parameters results. From training time view point, GRU-RNN was better than LSTM-RNN. However, LSTM-RNN has selected for this thesis because the training time difference was not that much big. PSSE (power system simulator for engineers) software has been used for distribution substation system expansion planning model to simulate and test the network feasibility. After forecasting the future load demand of Debre Work town, new distribution substation system expansion planning model has been applied to meet the forecasted power demand and testing of network technical feasibility and these analyses has meet the requirements of technical feasibility analysis limit of EEA/2022 standards. The thesis has also studied the cost of the substation and transmission line from LILO point to Debre Work substation which was 528,653,214 Ethiopian Birr currently. Generally, load forecasting for Debre Work area has been done and comparison of forecasting techniques such as LSTM and GRU has been conducted and even their result has shown almost similar, LSTM result was good, modeling of distribution substation has been done and finally substation cost estimation was done.

***Keywords**: Cost Estimation, Expansion of Power System, GDP, Load Forecasting, Neural Network, Technical Feasibility Study*

CHAPTER ONE

1. INTRODUCTION

1.1 Background

Over many years, the electric power sector has developed from a low power generator serving a small area to highly interconnected networks serving numerous nations, or even entire continents. A modern electric power system is one of the most complex systems ever created by humans, with a vast number of parts, ranging from little electric appliances to enormous turbo-generators with very high powers (Hussein s. and Mohammad S.S., 2011) . Electricity is now essential to human progress and survival. To raise the standard of living of the populace, effective load forecasting and expansion planning of the energy generating and power substation are essential. Electric energy supply directly affects economic development globally, especially as the majority of industries rely nearly totally on its use. The availability of a consistent, affordable, and dependable energy source is crucial from an economic perspective. An important method for ensuring that the energy supplied by utilities meets the load plus the energy lost in the system is electrical load forecasting (S.A. Soliman, 2010).

Power system planning starts with a forecast of anticipated future load requirements. Estimates of both demand capacity and energy requirements are crucial to effective system planning. There is a time lag between awareness of a future need and serving that need. In order to serve the need, adequate generation, transmission and distribution system have to be put in place. But delivery of requested power and energy always requires some time for the construction of the generation and transmission facilities which takes a definite lead time. Thus, the time lag is the main reason for forecasting and planning of electrical power system. Objectives of load forecasting are; it determines the future trend of electricity consumption of each demand sectors starting from the base year for the whole projection period, it determines the total annual consumption as well as its decisions in to local and interconnection power pool loads, it depends mainly on the historical and current data of the base year, national GDP growth, which is the total financial or market worth of all the finished goods and services produced inside a nation's borders over a certain period of time. population growth, customers' income growth, government plan on rural electrification, government policies and view on climate issues etc., it includes the historical data analysis and modeling annual forecast of energy demand and peak capacity demand of a power system network within the projection period.

Based on the time series, the demand forecast can be categorized into three types such as long-term demand forecast, medium term demand forecast and short-term demand forecast for expansion planning.1). Long term forecast: long-term forecasts time period varies from above 10 years for studying the energy problems. It takes four to six years for the construction, installation and maintenance of the equipment in power-stations. Long term forecast indicates the sales and purchase of the equipment. Long term forecast indicates the energy policies.2) Medium term forecast: medium-term forecasts time period varies from 3 to 10 years of planning and size of the power station. Medium term forecast indicates the transmission and distribution losses. Medium term forecast indicates the sales and purchase of the energy. Medium term forecast indicates the Energy conservation.3) Short term forecast: Short-term forecasts of 3 years are mainly of value in deciding operating procedures and preparing budget estimation (Brinckerhoff, 2022). Short term forecast indicates the sales and purchase of the power. Short term forecast indicates the development of distribution networks. However, for operational planning purpose, the time horizon is different that is for short-term forecasts which are usually from one hour to one week, for medium forecasts which are usually from a week to one or two years, and for long-term forecasts which are longer than one or two years. In this thesis, I have dealt with long term load forecasting which covers 15-year load demand history to train and forecast the load.

The key parameters during load forecast are population, gross domestic product (GDP), temporal behavior patterns, and various weather parameters. Population, although energy consumption varies from household to household, overall residential load is highly correlated with population. It stands to reason that more households create more demand. GDP the wealth of households is also highly correlated with demand. Wealthier households have central air conditioning, larger living space, larger refrigerators, and more appliances. They are less sensitive to utility bills and accordingly less likely to economize their discretionary consumption, for example, turning up the thermostat on central air conditioning. In economic upturns residential demand per household increases. Weather Parameters has the largest impact on load. Weather follows seasonal and daily patterns, which coupled with temporal behavior impact residential load. Below we indicate the more significant weather parameters and discuss their impact on load and others like holidays and national days etc. In thesis, factors such as GDP, GDP/CAP which is computed by dividing a country's GDP by its population to get the economic production per person in that nation, population number, weather patterns and cost per unit of energy in kilo watt hour are addressed to for forecasting long term load demand in the selected case study which is Debre Work.

1.2 Statement of the Problem

Because maintaining a reliable supply in an environment with an increase in demand necessitates proper expansion of power system, one of power system expansion planning is distribution substation expansion planning to solve the reliability problem of the society. Using a power or energy efficiently and effectively has not been still good and it has needed to use the energy in wise way as the world energy resource is scarce. To use energy wisely, the power generation expansion system planning, the power distribution or substation expansion system planning had to plan in a good way to match the power demand of the society and to know the load demand of the future, there should be a very good load forecasting techniques. As per Ethiopian Energy Authority's (EEA)/2022 standard, SAIFI should not exceed 25 interruption per customer per year. However, from table 3.3, interruption frequency per customer per year is 455 that exceeds by 430 interruption frequency and As per Ethiopian Energy Authority's (EEA)/2022 standard, the SAIDI value should not exceed 17 hours per customer per year, but in Debre Work 15kv outgoing feeder which is from Bitchena 66kv substation, it was 477 hours per customer per year which is greater than by 460 hours. Both conditions are violating the standards greatly. This is the existing reliability problem for the present connected load which is 3.11MW. So as to solve both the present problem which reliability problem and the coming problem that is future demand of the society, the long term load forecasting has used to know the future power demand forecasting of the society which was used as an input for new substation expansion, and modeling of the new distribution substation has addressed for that area to increase reliability of network.

1.3 Objective of the Thesis

1.3.1 General Objective

To do long term load forecasting using neural network techniques and to address substation system expansion planning model in Debre Work town.

1.3.2 Specific Objectives

The following specific objectives has considered in this thesis to solve the identified problem;

- To determines the future trend of electricity consumption of Debre Work town starting from the year 2023 to 2037.

- ❖ To simulate LSTM-RNN and GRU-RNN and compare by using performance assessment measurement parameters or criteria.
- ❖ To address distribution substation system expansion planning model and to test its technical feasibility for the forecasted power demand to solve the reliability problem of power supply for the selected area or society.

1.4 Significance of the Thesis

This thesis has an importance to know the load or power demand for future fifteen years of Debre Work town and its surrounding. It provides distribution substation load expansion planning model to meet the forecasted load of Debre Work town. It has also provided that the loss and energy supply gap will be reduced by giving a key direction what will be the energy demand of Debre Work for Debre Work administration and Ethiopian electric power, EEP and Ethiopian electric utility (EEU). This thesis has another significance to non-governmental and public services to plan and invest by knowing the exact power demand and energy supply relationship for the next fifteen years.

1.5 Scope of the Thesis

This thesis involves long term load forecasting using neural network technique and doing on distribution substation system expansion planning model in Debre Work town. First, definition and importance of load forecasting was explained. Second, techniques that are used in load forecasting explained, especially neural network families were more focused. Then, load forecasting factors or parameters collected from Bitchena substation, EEU, EEP offices, from NASA and Ethiopian central statistics service. Training and testing of load forecasting neural network techniques was carried out in MATLAB software. And then, performance assessment parameters have been addressed. Finally, cost estimation and distribution substation expansion planning model were performed to meet the forecasted demand of Debre Work town and its surrounding. All in all, the thesis has covered to the simulation of both long-term load forecasting and distribution substation model.

CHAPTER TWO

2. LITERATURE REVIEW

2.1 Theoretical Background

Power system engineering cannot function without the systematic planning of power systems. Power system engineering must take into account both well-known aspects of technical and economic feasibility as well as those that can be challenging to quantify, such as load forecasts for the power system under consideration for a period of several years, long-term energy forecasts, equipment standardization, availability, exchangeability, and compatibility, equipment standardized rated parameters, restrictions on system operation, and feasibility with regard to technical, financial and time aspects, political acceptance, and ecological and environmental compatibility (Schlabbach, 2014). Therefore, developing facilities, streamlining daily operations, and managing the limited resources effectively all depend on a precise demand estimate.

2.1.1 Load Forecasting and Its Importance

The first crucial step for any planning study is to predict the consumption for the study period, as all subsequent studies will be based on that (Hussein s. and Mohammad S.S., 2011). Power system planning starts with a forecast of anticipated future load requirements. The main and pivot part of electric companies is the load forecasting. Decision makers and think tank of power sectors should forecast the future need of electricity with large accuracy and small error to give uninterrupted and free of load shedding power to consumers (Naqash Ahmad, Yazeed et al, 2022).

2.1.2 Types of Load Forecasting

Load forecasting can classify into three categories based on time horizon such as short term, medium term and long-term load forecasting. Load forecasting is generally categorized in three types: short term (few hours to few weeks), mid-term (week to year) and long term (more than a year) (T. Bashir, Chen et al, 2021). However, according to Ethiopian electric power master plan, long-term forecasts time period varies from above 10 years for studying the energy problems. It takes four to six years for the construction, installation and maintenance of the equipment in power-stations. Long term forecast indicates the sales and purchase of the equipment. Long term forecast indicates the energy policies. Medium-term forecasts time period varies from 3 to 10 years of planning and size of the power station.

Medium term forecast indicates the transmission and distribution losses, the sales and purchase of the energy, the Energy conservation. Short term forecast: Short-term forecasts of 3 years are mainly of value in deciding operating procedures and preparing budget estimation.

2.1.2.1 Short Term Load Forecasting

Short term load forecasting that monitors weekly, daily, hourly and even sub-hourly operations is gaining a lot of attention which saves time and cost while satisfying consumers' needs without interruption (T. Bashir, Chen et al, 2021). Short-term load forecast (STLF) is important to daily operations of a power utility. Short term load forecasts (STLF; lead times of 1 minute to 2 weeks) are primarily carried out for energy purchasing, effective demand-side management, peak load shifting, generation capacity planning and power purchasing (Aneeque A., 2021). The short-term load forecasting deals with the forecasting of several minutes up to one week into the future (Mithun M., Albino, et al, 2022). From these literature reviews, it is concluded that the exact time horizon is not defined, so Short-term forecasting involves horizons from a few minutes up to few days ahead and is of particular importance in day-to-day market operations and in load forecasting, very-short term forecasting deals with times in minutes and is often considered separately.

2.1.2.2 Medium Term Load Forecasting

Medium-term load forecasts (MTLF; lead times of 2 weeks to 3 years) are carried out for unit commitment and power system planning and operations (Aneeque A., 2021). Medium term load forecast is being used for the efficient operation and maintenance of the power system (M. QamarRaza and A. Khasravi, 2015).

2.1.2.3 Long Term Load Forecasting

Long term load forecasts (LTLF), with lead times ranging between three years to decades ahead, and their business needs in energy trading, energy policy, system planning and system maintenance (Aneeque A., 2021). Long term load forecast is used for the long-term power system planning according to the future energy demand and energy policy of the state (M. QamarRaza and A. Khasravi, 2015). It refers to predicting electricity load demand in a particular area for durations pertaining longer than a year (Agrawal, 2018). In this research, the focusing load forecasting type is long term load forecasting by using neural network techniques with case study of Debre Work town in Amhara region.

2.1.3 Performance Measurement Parameters of Load forecasting

The forecasted load is compared with the source data load for each regression model. By calculating four different statistical evaluations, the Root Mean Square Error (RMSE), the Mean Absolute Error (MAE), the Mean Absolute Percentage Error (MAPE), and R-squared, the load forecasting capacity of each method and model accuracy can be assessed. If the value of RMSE > MAE, it means that there is a variation in errors (Mithun M., Albino, et al, 2022). The goal is to get MAE, MAPE and RMSE zero and R^2 one. The following criteria are used to evaluate load forecasting performance using the error indices:

1) **Mean Absolute Error (MAE)**: The MAE measures the mean values of the errors, that can be evaluated by

$$\mathrm{MAE} = \frac{\sum_{t=1}^{n} |\mathrm{Yt} - \mathrm{Yp}|}{n} \tag{2.1}$$

Where Yp is the prediction, Yt is the true value from source data, and n is the number of measurement years.

2) **Mean Absolute Percentage Error (MAPE)**: This error percentage is a measure of the prediction accuracy of a forecasting method in statistics, it produces a measure of the relative overall fit, which can be calculated by

$$\mathrm{MAPE} = \frac{\sum_{t=1}^{n} \frac{|\mathrm{Yt} - \mathrm{Yp}|}{\mathrm{Yt}}}{n} \mathrm{X}100 \tag{2.2}$$

Where Yp is the prediction, Yt is the true value from source data, and n is the number of measurement years.

3) **Root Mean Square Error (RMSE)**: The RMSE is the standard deviation of the residuals. Residuals are a measure of how far from the regression line data points are, so RMSE is a measure of how spread out these residuals are. It can be calculated by

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{t=1}^{n} (|\mathrm{Yt} - \mathrm{Yp}|)^2}{n}} \tag{2.3}$$

Where Yp is the prediction, Yt is the true value from source data, and n is the number of measurement years.

4) **R-Squared:** is a statistical measure of how close the fitted regression line is to the results. R-squared lies between 0 and 1. Generally, a higher R-squared value implies that the model matches the data better.

$$\mathrm{R}^2 = 1 - \left(\frac{\mathrm{sum}((\mathrm{Yp} - \mathrm{Yt})^2)}{\mathrm{sum}(((\mathrm{Yt} - \mathrm{mean}(\mathrm{Yt}))^2)}\right) \tag{2.4}$$

Where Yp is the prediction, Yt is the true value from source data, and n is the number of measurement years.

2.1.4 Methods of Load forecasting

Methods or techniques of load forecasting are classified into the following categories such as statistical methods, expert methods, fuzzy systems and neural networks (Artificial Intelligence) based on their prediction style and used ways. (B. Abrham and J. Ledolter , 2005) Among many other forecast criteria, the choice of the forecast model or technique depends on (1) what degree of accuracy is required, (2) what the forecast horizon is, (3) how high a cost for producing the forecasts can be tolerated, (4) what degree of complexity is required, and (5) what data are available.

2.1.4.1 Statistical Methods

Statistical techniques usually need a mathematical model that represents load as function of different variables such as time, weather, and customer class. The important categories of such models are additive and multiplicative models (Mithun M., Albino, et al, 2022). Types of statistical methods are; linear regression, stochastic time series, general exponential smoothing, and state space method. In (Haleema, 2020), Auto-regressive (AR), Moving Average (MA), Auto-regressive Moving Average (ARMA), Auto-regressive Integrated Moving Average (ARIMA), and Seasonal Auto-regressive Integrated Moving Average (SARIMA) are some of the numerous types of statistical methods. In the ARMA model, the load forecasting problem is not particularly straightforward, although in some circumstances, these challenges may be avoided if Kalman filtering techniques are applied. It (Isaac Kof Nti, T. Teimeh, et al, 2020) was suggested to predict Kuwait's EED using (10-year) long-term predicting techniques such as NN and ARIMA. The results of the study showed that NN beat ARIMA.

2.1.4.2 Expert Methods

Expert systems incorporate rules and procedures used by human experts in the field of interest into software that is then able to automatically make predicts without human assistance. This means this program can reason, explain and have its knowledge base expanded as new information becomes available to it. The load-forecast model can be built using the knowledge about the load forecast domain from an expert in the field (Olajuyin, 2018). According to (Kandil, 2002), knowledge based expert method has a better performance than statistical methods such as time series methods. The expert systems store (M. S. S. Rao, S. A. Soman,et al, 2006) the expert knowledge in the computer as rules or data. You can use these guidelines and facts to help you solve issues as they arise. The components of this rule-based algorithm are as follows: Weather and load shapes are logically and syntactically related, Relationships between the load and the imposed and natural variables that fluctuate, and rule base consists of all rules taking the IF-THEN form and mathematical expressions.

2.1.4.3 Fuzzy Set Theory

Fuzzy set theory is used to design a type of uncertainty related with imprecision, vagueness and lack of information (S.Buns, 2001). Unlike precise reasoning, Fuzzy logic is a multi-variant logic that handles reasoning approximately. In this time, many methods have been used in demand forecasting, however, artificial intelligence methods (fuzzy logic and ANN) provide better efficiency compared to traditional techniques (e.g., regression and time series) (Ali*, Yohanna, et al, 2016). The comparison of Fuzzy set (FS) and ANN based on the criteria of MAPE which was 0.268% and 1. 0335% for ANN and FS respectively (Jahan, 2020). From this, we can conclude that ANN is better than FS for load forecasting. ANN does not need mathematical formulas to train the model but in Fuzzy logic system, it needs mathematical formula. In (Badri, 2012) the error between the actual power demand and the forecasted power demand is 0.5% and 4.91% for ANN and FS respectively. From these two evidences, ANN is more accurate than FS and ANN is more accurate than FS for more complex and non-linear system.

2.1.4.4 Neural Networks

Artificial intelligent (AI) is a by-product of information technology (IT) revolution, and is an attempt to substitute human intelligence with machine intelligence (S.Buns, 2001). Neural networks are highly interconnected simple processing units designed in a way to model how the human brain performs a particular task. Each of those units, also called neurons, forms a weighted sum of its inputs, to which a constant term called bias is added. This sum is then passed through a transfer function: linear, sigmoid or hyperbolic tangent (Pandey, 2016). Families or technological upgrades of neural networks are; artificial neural network (ANN), recurrent neural network (RNN), convolution neural network (CNN), long-short term memory (LSTM) and gated recurrent unit (GRU). In this thesis, long term load forecasting in Debre Work has investigated using LSTM and GRU both of them are an advancement of RNN.

A. **Artificial Neural Network (ANN)**

Conventional models such as regression are limited and can sometime lead to unsatisfactory solutions and the reasons include the too high number of computational possibilities leading to large solution times and the complexity of certain nonlinear data patterns, so on this type of challenges, artificial neural networks and intelligent machine learning technique, provide a promising and attractive alternative (C. Kuster, Y.Rezgui, et al, 2017). ANN is the first machine system which tries to replace human thinking activities in a machine system. It is basics of all of neural network families. The basic model of a single artificial neuron consists of a weighted summer and an activation (or transfer) function as shown in Figure 2.1. Figure 2.1 shows a neuron in the j^{th} layer.

Where, X_l... x_i, are inputs, W_{jl}. . . W_{ji} are weights, b_j is a bias, f_j is the activation function and y_j is the output. The weighted sum s_j is therefore given by

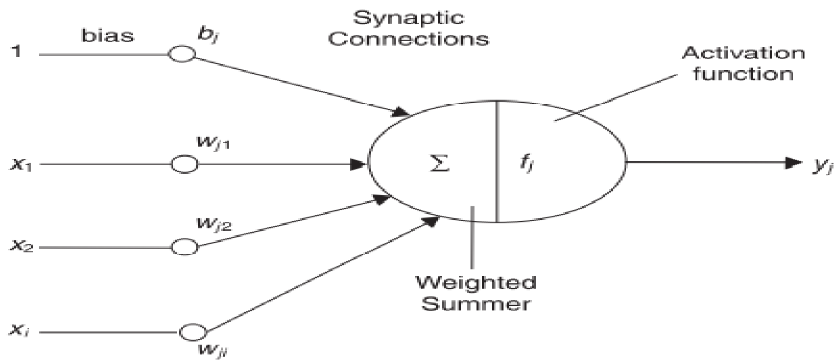


FIGURE 2.1: Basic model of a single ANN (S.Buns, 2001).

$$S_j(t) = \sum_{i=1}^{N} W_{ji}\, x_i(t) + b_j \quad (2.5)$$

B. **Recurrent Neural Network (RNN)**

Feedback (recurrent) networks are based on the work of Hop-field and contain feedback paths. Figure 2.2 shows a single-layer fully-connected recurrent network with a delay (Z^{-1}) in the feedback path. The RNN may be used as a network memory, different from the feed forward neural network. Consequently, the current state is associated with the previous state and the current input. That helps the RNN handle time series problems by storing, preserving, and evaluating the previous complex signals over a given time (Ardeshiri and Chengbin , 2021).

$$y(k+1)T = W_1 y(KT) + W_2 x(KT) \quad (2.6)$$

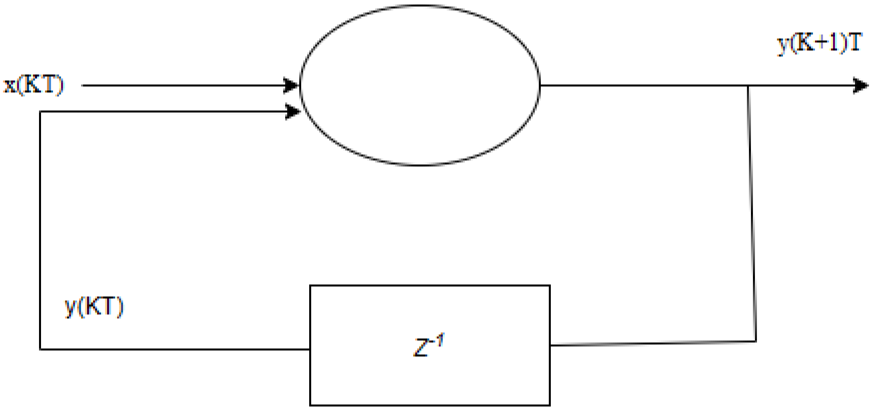


FIGURE 2.2: Basics Structure of RNN

An artificial neural network (ANN) has multiple major restrictions such as stateless structure, messy scaling, fixed-sized inputs and outputs, and ignorance of time-related structure are some of these limitations. To solve these types of problems, recurrent neural network (RNN) is formed. RNN is a feed-forward multi-neural network with additional feedback cycles from previous time steps used to store temporal information as internal states as we have seen in figure 2.2 above. As the RNN weights are changed, which quickly leads to either too little (vanishing gradient) or too big changes in the weights (exploding). As a result, the RNN finds it incredibly challenging to learn and understand the dependencies between observations made at earlier and later time steps (Zhalla and Ismael, 2022).

C. **Long-Short Term Memory (LSTM)**

LSTM has the ability to remove or add information to a cell's state through a well-designed structure called a "gate" (Ke Li*, Yunxin Sun, et al, 2019). LSTM is one kind of recurrent neural network (RNN) model, which can solve the short-term dependency problem by learning the long-term dependencies of the parameters. The basic structure for the LSTM model consists of four layers, which are represented in Figure 2.3. The four critical layers of LSTM are; forget gate layer, input gate layer, memory cell layer, and output gate layer.

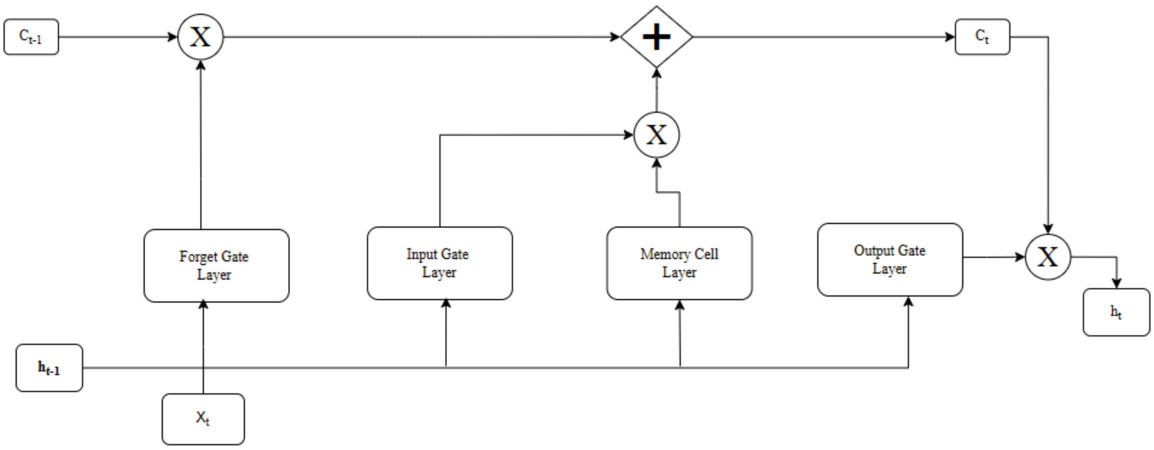


FIGURE 2.3: The Basic Structure of LSTM model

D. **Gated Recurrent Unit (GRU)**

Across all the enhanced RNNs, the GRU-RNN not only has a simple structure but also able to capture long-term sequential dependencies. Furthermore, the gradients are more resistant to vanishing-compared to other RNNs, and fewer memory resources are needed. Therefore, GRU-RNN is ideal for dealing with highly correlated issues with time series, such as RUL prediction of the battery system (Ardeshiri and Chengbin , 2021).The structure of the GRU cell is shown in Figures 2.4.

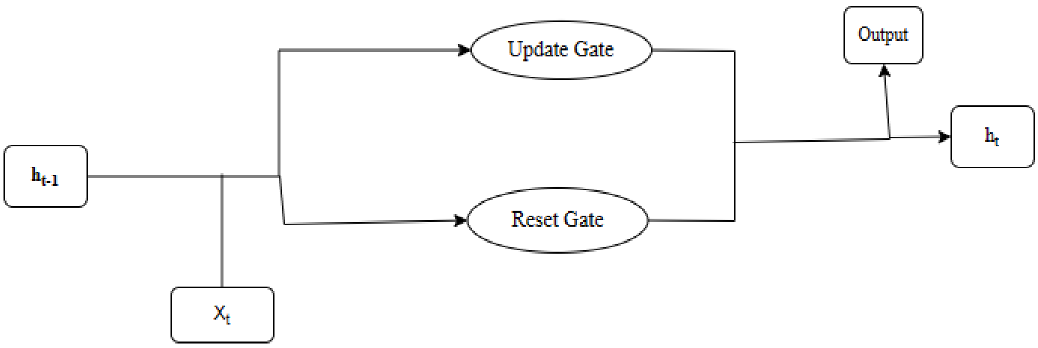


FIGURE 2.4: The structure of GRU

The key difference between GRU and LSTM is that GRU's bag has two gates that are reset and update while LSTM has three gates that are input, output, forget. GRU is less complex than LSTM because it has less number of gates. GRU exposes the complete memory and hidden layers but LSTM doesn't. From working of both layers i.e., LSTM and GRU, GRU uses less training parameter and therefore uses less memory and executes faster than LSTM whereas LSTM is more accurate on a larger datasets. Therefore, both LSTM-RNN and GRU have investigated in this thesis to compare the performance assessment parameters for long-term load forecasting.

All in all, neural networks are more advantageous than other forecasting techniques from the above discussions. The advantages of neural network are: it is better for large and for complex system, it handles easily non linear system, it does not need any mathematical formulation or equation simply it takes inputs and outputs and process and forecast and works with insufficient knowledge or incomplete data.

2.1.5 Power System Expansion Planning

Next to load forecasting, expansion planning is must so as to meet the load demand of the society. Power expansion planning can be categorized as generation expansion planning, transmission expansion planning and distribution expansion planning based on the network configuration of power system. This thesis has focused on distribution expansion planning for Debre Work town and its surrounding administration after forecasting what will be the future power demand of Debre Work town and its surrounding. Making decisions on expansions of the power system as a result of the growth on power demand in the society is essential to maintain an uninterrupted network (K. Yurtseven and E. Karatepe, 2021). Due to the fact that substations form the intermediate system which links the power supplies and the areas, it is evident that substation expansion planning (SEP) is an essential subject in power system planning studies (Behal, 2019).

Nowadays (Zihao Li, 2020), the reliability of a distribution system has been technically characterized by the following indices: customer interruption frequency (CIF), customer interruption duration (CID), the loss of load probability (LOLP), system average interruption frequency index (SAIFI), system average interruption duration index (SAIDI) and the expected energy not supplied (EENS), which are generally taken into account in planning models . With transmission system elements are needed to overcome electric power consumption growth, desired new the possible lack of adequacy problems so that with least costs, various operational constraints are meet.

2.1.5.1 Power System Planning Criteria

Planning criterion has adopted from international standards like IEEE, IEC and national standards such as EEA and EEP. The criterion adopted for use in the power system analysis and transmission and distribution system planning includes line and bus voltage or system voltage limit, thermal rate loading capacity, transmission line parameters, load power factor, fault level, system contingencies, and system reliability. The criteria take into account the normal operating practices and generally follow well established international practice.

2.2 Review of Related Fields

It used generalized regression neural network for long term electricity load forecasting. In this study, the idea of generalized regression neural network (GRNN) was used to predict long-term electricity load. The pro of the GRNN technique that can estimate the absolute function between input and output datasets directly from training data was studied. The research compared the results of Feed Forward Back-propagation Neural Network (FFBNN), Cascade Forward Back-propagation Neural Network (CFBNN) and Generalized Regression Neural Network (GRNN) based on the Mean Absolute Deviation (MAD) and Mean Absolute Percentage Error (MAPE) indices (Widi Aribowo, 2020). The limitation was not including the limitation of RNN such as vanishing and exploding problems which could be solved by LSTM and GRU.

This study has developed an improved ANN with an Adaptive Back-propagation Algorithm (ABPA) for greatest trend in the forecasting of long term demand of electricity. The ABPA has included proposing new forecasting formulations that adapt forecast values, so it has taken into consideration the deviation between trained and future input datasets different behaviors. The developed ANN model, including its proposed ABPA, has then compared with classical and popular forecasting techniques such as regression and other advanced machine learning approaches, including RNNs, to justify its superiority among them. The results reveal that the most accurate long-term forecasts with the minimum Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE) values of (1.195) and (0.045), respectively, have successfully overcomed by applying the proposed ABPA and It has concluded that the proposed ABPA, including the adjustment factor, enables traditional ANN methods to be efficiently applied for long term forecasting of electricity load demand (Mohammed NA, 2021). The shortcoming of this is not including parameters like GDP, POP, energy consumption by the people, weather data and also it didn’t include GRU technique effect.

In this paper, a novel and hybrid forecasting method was proposed, combining a long short-term memory network (LSTM) and neural prophet (NP) through an artificial neural network. The paper aimed to predict electric load for different time horizons with improved accuracy as well as consistency. The proposed model used historical load data, weather data, and statistical features that were obtained from the historical data. Multiple case studies were conducted with two different real-time data sets on three different types of load forecasting that were hour ahead, day ahead and year ahead load forecasting. The hybrid model was later compared with a few established methods of load forecasting found in the literature with different performance metrics: MAPE, RMSE, and R. Moreover, a guideline with different attributes was provided for different types of load forecasting considering the applications of the proposed model. The results and comparisons from their test cases have showed that the proposed hybrid model improved the forecasting accuracy for three different types of load forecasting over other forecasting techniques (Shohan, 2022).

This thesis focused on the long-term forecasting of electricity demand using hourly resolution. A methodology was developed to design a model that able to fit accurately historical data and to forecast future demand in these particular territories. Historical data were first analyzed through a clustering analysis to identify trends and patterns, by using a k-means clustering algorithm. Specific calendar inputs were then modeled to consider these first observations. External inputs, such as weather data, demographic and economic factors were also included. Forecasting algorithms were selected based on the literature and they were than tested and compared on different input datasets. Generalized additive model, a relatively new model in the power forecasting field, gives promising results as its performances were close to the one of ANN and represent an interesting model for future research (Caron, 2021). The limitation of this study, it did not see other neural network forecasting techniques like LSTM-RNN, GRU.

In this thesis, load forecast for Addis Ababa Region Transmission System was done for the period of 2018 to 2022 and transmission system expansion planning was carried out to meet the forecasted load. Load forecasting was carried out using MS Excel software and following the general stochastic regression techniques. Two independent variables, like GDP and number of customers were considered as the main factors affecting the future load growth. Network modeling using ETAP software was done for expansion planning and simulation studies (Workie, 2019). The shortcoming of the research is not using the intelligent based forecasting algorithms like ANN and other deep learning algorithms and as it was suggested by the researcher, this research was limited on the factors of GDP and number of electricity customers only.

A novel method for long term load forecasting with hourly resolution was proposed. The model was fundamentally centered on Recurrent Neural Network consisting of Long-Short-Term-Memory (LSTM-RNN) cells. The long-term relations in a time series data of electricity power demand were taken into account using LSTM-RNN and hence resulted in more accurate forecasts. The proposed model was found to be highly accurate with a Mean

Absolute Percentage Error (MAPE) of 6.54 (Agrawal, 2018). However, this study did not see GRU forecasting technique effect.

In this thesis, long-term demand forecasting has been attained by using neural network techniques. The summarized related works have given in the following table 2.1 below. From the gaps which have identified as in table 2.1 below, most of these related works have missed Gate Recurrent Unit in their work which most recent, simple and fast in training of regressional forecasting technique and most of them were less multi-variant. In this thesis, GRU has applied for training of long term load forecasting in the selected area in addition to LSTM.

Table 2.1: Summarized Related Works

No	Reference	Title	Method	Gaps
1	(Workie, 2019)	Study on Transmission Expansion Planning	Use General Stochastic Regression Technique	No AI technique and economic feasibility study
2	(Mohammed NA, 2021)	An adaptive back-propagation algorithm for long-term electricity load forecasting	Comparison of ABPA with ANN & RNN to show its superiority	Not include GRU in the comparison
3	(Shohan , et al, 2022)	LSTM with NP through ANN	LSTM with NP through ANN	No GRU,
4	(Widi Aribowo, 2020)	generalized regression neural network for long-term electricity load forecasting	GRNN Compared with FFBNN & CFBNN which eliminates back-propagation algorithm	no saw limitation of RNN

CHAPTER THREE

3. MATERIALS AND METHODS

3.1 Procedures

In order to attain the objectives of the thesis, the following methods and techniques have been followed.

A. Review literature's related to load forecasting problems and power system expansion planning

B. Identify the existing problem in the Debre Work distribution system by collecting the necessary historical factors or data from EEU, EEP, Ethiopian central statistical services and from NASA which are weather factors.

C. Propose, identify and apply the adequate load forecasting technique for the long-term load forecasting.

D. Test the load forecasting techniques using performance measurement parameters such as MAE, MAPE, RMSE and R^2.

E. Analyze the performance of the applied long term load forecasting techniques using (D)

F. Finally, apply distribution substation system expansion planning model for the forecasted load of Debre Work town and cost estimation of the substation.

3.2 Data Collection and Analysis

The very challenging task in load forecasting and power system expansion planning was data collection. Data collection in demand prediction is pillar issue to train and test our demand of power. In this thesis, historical factors or data which are independent variables used as input variables and historical power demand output data or dependent variables in Debre Work town and its surrounding have been collected and analyzed. Independent variables that have been considered in this thesis were demographic factors such as number of populations, electrified people, economic factors like GDP, GDP/CAP, and weather factors such as temperature, humidity and precipitation of Debre Work town and its surrounding collected as shown in table 3.1 which is fifteen years back data. Dependent variables which have been included in this research have categorized into sectorial data like average domestic demand, LV industrial demand, commercial demand and straight light demand, total average demand and peak demand of Debre Work town and it surrounding were collected as shown in table 3.2. Based on IEC 60038 /2009 standard of voltage, low voltage is ranging from 100 voltage to 1000 voltage which is AC rms voltage. According to EEA/2022 distribution network standard, low voltage is 230V for single phase and 400V for three phase networks.

3.2.1 Assumption in Data Collection and Analysis

The following assumption have been taken to during data analysis and data collection generally;

I. To do number of electrified people, annual peak demand in the feeder line in MW and peak demand per customer which is 7KW with coincident factor 0.4 have been taken.

II. Lumped transmission line impedance has been taken to simplified the calculation.

Table 3.1: Input Factors of Load Forecasting of Debre Work Town

Year	POP (Enarj Enawga)	POP (Urban)	EP	GDP ($M)	Per capita ($)	temp(deg. centigrade)	Humidity (%)	Preciptatio n (mm/year)
2008	171038	14113	190	54.9	321	17.73	61.81	106.79
2009	174433	15263	216	65.3	374	17.79	58.69	97.56
2010	177973	15095	245	59.7	335	17.2	59.69	100.19
2011	181569	17023	279	63.2	348	17.48	66.44	133.15
2012	185236	17931	315	85.0	459	18.02	60.75	62.84
2013	188734	19027	358	92.7	491	17.15	57.06	88.77
2014	192095	20148	408	107.2	558	18.19	63.75	126.12
2015	195301	21308	465	123.0	630	18.10	67.62	139.30
2016	198376	22500	526	140.0	706	17.05	60.44	78.22
2017	201391	23724	593	152.3	756	17.98	64.06	119.97
2018	204228	25045	679	154.5	758	18.48	60.94	102.39
2019	207063	26353	772	173.4	840	19.33	63.31	81.29
2020	209777	27764	880	192.8	919	19.35	65.25	112.50
2021	212481	29155	1001	196.6	925	19.31	65.62	141.50
2022	215081	30656	1164	203.5	945	18.37	64.44	165.05

From table 3.1, number of populations were collected from Ethiopian statistic service which is the projection based on 2007 Ethiopian national census, GDP and per capita were collected from world bank and macro-trends, and weather factors such as temperature, humidity and precipitation were collected from NASA.

Table 3.2: Training and Testing Dependent Variables for Load Forecasting

Peak load from smart energy meter (MW)	Peak load in MW from real demand record
0.54	3.17
0.61	4.20
0.69	6.25
0.78	7.05
0.88	8.85
1.01	10.12
1.15	12.23
1.31	14.08
1.48	16.25
1.67	18.95
1.92	21.75
2.17	25.00
2.47	28.21
2.81	31.75
3.11	36.26

Historical load datasets were collected from both EEP and EEU as shown above in table 3.2. Peak load from smart energy meter (MW) has used as training data and Peak load in MW from real demand record has used as testing data or used as target data the load forecasting. The detail information the energy consumption has given in Appendix D.

An interruption data is collected from November-2022 to October-2023 from Bichena substation. From this data collection, Debre Work town 15KV outgoing feeder line violates the standard of Ethiopian Energy Authority (EEA)/2022 which should not exceed 25 interruption frequency per customer per year that is SAIFI value. However, from table 3.3, interruption frequency per customer per year is 455 that exceeds by 430 interruption frequency and as per Ethiopian Energy Authority (EEA)/2022 standard which is shown in Appendix B, the SAIDI value should not exceed 17 hours per customer per year but in Debre Work town. it is 477 hours per customer per year which is greater than by 460 hours.

Table 3.3: Interruption Data of Debre Work Town Outgoing feeder line

Time	Frequency	Duration in hours	Causes
November	33	48.40	

December	53	56.96	Earth fault, short circuit and operation are common causes of interruption for Bitchena substation outgoing feeder lines
January	45	45.40	
February	26	24.01	
March	30	32.23	
April	45	50.13	
May	38	39.82	
June	40	42.15	
July	50	54.00	
August	43	44.92	
September	25	16.83	
October	27	21.15	

3.2.2 Existing Bitchena Substation Load Distribution

By taking a peak load which happened in 2022 from Bitchena substation, The capability of Bitchena substation has tested as follows:

Table 3.4: Peak Loads of Bitchena Substation in 2022

Feeder line name	Feeder voltage level in KV	Peak power in MW
Degen	15	1.56
Medroke	15	2.86
Bitchena	15	2.60
Debre Work	15	3.11
Kuye	15	1.82
Telemez	33	0.64
Tike	33	0.28
Total		12.88

The modeling parameter of Bitchena substation has given in table 3.5 below that has contained line parameters from Debre Markos to Bitchena substation and load parameters.

Table 3.5: The Line from D.Markos to Bitchena and Load Parameters of Bitchena SS

Line parameters from Debre Markos to Bitchena substation					
R(Ohms)	X(Ohms)	B(μF)	Rate(MVA)	Length(KM)	Voltage(KV)
40.53	27.43	0.569	24	65.7	66

Lod parameters	
Real Power(MW)	Reactive Power(MVAr)
12.88	4.24

Having this power, the capacity has tested of Bitchena substation. The result has given in the following figure 3.1 and table 3.6.

FIGURE 3.1: One Level Grow Load Flow Analysis Diagram Bitchena Substation

Table 3.6: The Result of Load Flow Analysis of Bitchena substation

Substation Name	Voltage		Angle
	Pu	KV	(deg.)
D.markos 66kv	1.0190	67.3	-59.85
Bitchena 66kv	0.8578	56.6	-62.62
Fnoteselam 66kv	0.9043	59.7	-61.58

From table 3.6 above, Bitchena 66kv substation and Fnoteselam 66kv substation violates EEA/2022 distribution steady state network load flow standard which should be from 0.95 to 1.05 per unit. Specially, Bitchena 66kv substation violates greatly that is differenced by 0.0922 per unit which is big difference in load flow analysis. It also violates N-1 contingency analysis means it is not reliable. Therefore, there should be new substation expansion to overcome this problem that is why the new substation expansion model is needed for Debre Work town and its surrounding area.

3.3 Techniques Used in Long-Term Load Forecasting

In this thesis, the branch of artificial intelligence technique that is neural network based load forecasting technique has been used and the detail has been given as follows. From neural network techniques, LSTM-RNN and GRU-RNN training or learning algorithms have discussed more in detail and used to train and test the proposed load forecasting. The best training algorithm has been selected based on the performance assessment parameters like RMSE, MAPE, MAE and R^2.

3.3.1 Neural Network Techniques

Neural Network is the most famous machine learning techniques and also outperforms other techniques in both accuracy and speed. It consists of different layers connected to each other, working on the structure and function of a human brain and trains from large volumes of datasets and uses complex techniques to train a neural network. There are different types of neural networks. For example, feed-forward neural network: Used for simple regression and classification problems, convolutional neural network: Used for object detection and image classification, deep belief network: Used in healthcare sectors for cancer detection and RNN: Used for speech recognition, voice recognition, time series prediction, and natural language processing. In this thesis, RNN has been discussed in detail as follows

3.3.1.1 Recurrent Neural Network (RNN)

The techniques most commonly used for time series forecasting among deep learning methods are the RNN, LSTM, and GRU (Son, 2020). The RNN has many advantages in relating with the processing of sequence data but has more disadvantages in the problems of long-term dependency, gradient disappearance, and gradient explosion. However, these problems are solved by using long-short term memory (LSTM). RNN which is also known as feedback neural network works on the principle of saving the output of a particular layer and feeding this back to the input in order to predict the output of the layer. The structure of RNN is given in figure 3.2 below.

$$y(K+1)T = \left(W_{1y}(kT) + W_2x(KT)\right) \tag{3.1}$$

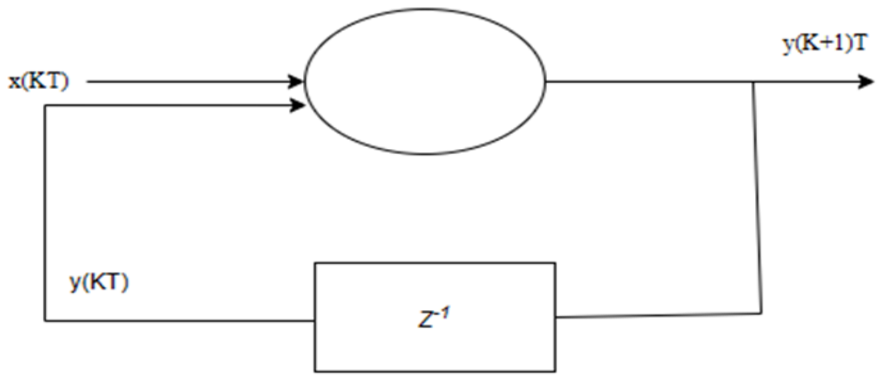


FIGURE 3.2: Basics Structure of RNN

The need of RNN was increased, because there were issues in the feed-forward neural network such as cannot handle sequential data, considers only the current input and cannot memorize previous inputs. The solution to these limitations is the RNN. An RNN can handle sequential data, accepting the current input data, and previously received inputs. RNNs can memorize previous inputs due to their internal memory.

How does RNN function? Information circulates around a loop in recurrent neural networks before reaching the intermediate hidden layer. The neural network's input is received by the input layer "x," which processes it before sending it to the middle layer. Several hidden layers with unique activation functions, weights, and biases may make up the middle layer "h". Vanishing gradients are a difficulty for RNNs. When the gradient decreases too much, the parameter changes lose their significance because the gradients convey information that the RNN uses. Long data sequences are difficult to learn as a result. An exploding gradient occurs when the slope of a neural network during training tends to increase exponentially rather than decrease. Large error gradients that build up during training lead to very large modifications to the neural network model weights, which causes this issue. The main problems with gradient problems are excessive training time, subpar performance, and subpar accuracy. Let's now talk about the most well-liked and effective technique for overcoming gradient issues: Long Short-Term Memory Networks (LSTMs) and Gate Reset Units (GRU).

3.3.1.2 Long Short-Term Memory Networks (LSTMs)

The default behavior of LSTMs, a particular type of RNN, is to recall input for extended durations in order to learn long-term dependencies. Figure 3.3 shows the structure of LSTM, which consists of four gates: forget, input, update, and output gates.

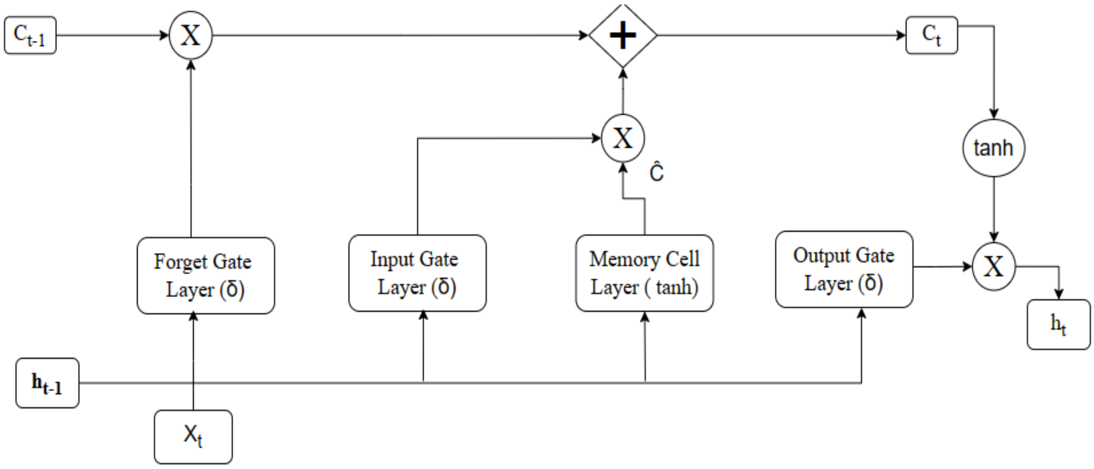


FIGURE 3.3. Structure of the Long Short-Term Memory

The forget gate determines which information to delete, the input gate determines whether new information is stored in the cell state, the update gate updates the cell state, and the output gate determines which output value to output.

$$f_t = {}^{\delta}(h_{t-1}W_f + x_tU_f + b_f) \tag{3.2}$$

$$i_t = {}^{\delta}(h_{t-1}W_i + x_tU_i + b_i) \tag{3.3}$$

$$\hat{C}_t = \tanh\left(h_{t-1}W_g + x_tU_g + b_c\right) \tag{3.4}$$

$$C_t = {}^{\delta}\left(f_t * C_{t-1} + i_t * \hat{C}_t\right) \tag{3.5}$$

$$o_t = {}^{\delta}(h_{t-1}W_o + x_tU_o + b_o) \tag{3.6}$$

$$h_t = o_t * \tanh(C_t) \tag{3.7}$$

Where, x is input gate, f is forget gate, h is hidden layer, $\hat{C}$ is candidate hidden state, C_t is the unit's internal memory, O_t is the output gate, U is the weight matrix that connects the input layer to the hidden layer, W is the connection between the current and previous hidden layer and b is the bias of each layer.

LSTMs operate in three step: Choosing which data should be excluded from the cell at that specific time step is the first stage in the LSTM. This is decided using the sigmoid function. It computes the function while taking into account the current input x_t and the previous state (h_{t-1}).

$$f_t = {}^{\delta}(h_{t-1}W_f + x_tU_f + b_f) \tag{3.8}$$

F_t which is forget gate that decides which information to delete that is not important from previous time step.

In the second layer, there are two parts. One is the sigmoid function, and the other is the tanh function. In the sigmoid function, it decides which values to let through (0 or

1). tanh function gives weight to the values which are passed, deciding their level of importance (-1 to 1).

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \quad (3.9)$$

$$\hat{C}_t = \tanh\left(h_{t-1}W_g + x_tU_g + b_c\right) \quad (3.10)$$

Where, i_t is input gate that determines which information to let through based on its significance in the current time step.

Making a decision regarding the output is the third phase. To determine which components of the cell state are output, let first run a sigmoid layer. Finally, we multiply the cell state by the output of the sigmoid gate after pushing the values through tanh to be between -1 and 1.

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \quad (3.11)$$

$$h_t = O_{t*}\tanh(C_t) \quad (3.12)$$

Where, O_t is an output gate that allows the passed in information to impact the output in the current time step.

3.3.1.3 Gate Recurrent Unit(GRU)

A sort of improved LSTM and RNN known as a "gated recurrent unit" (GRU) may efficiently retain the relationships and data that are crucial to the input sequences while discarding the information that isn't as crucial, which helps to save memory and speed up processing. Because of its distinctiveness, GRU is frequently employed in sequential data prediction and speeds up processing. To lessen latency and delay in neural network processing, GRU is innovated from LSTM with two gates but no distinct memory cell, the GRU's structure is a simplification of the LSTM. In GRU, the input gate and forget gate were replaced by a single update gate, which is utilized to quickly analyze the output's current state. In the GRU, the reset gate is purged unnecessary data of the previous hidden state.

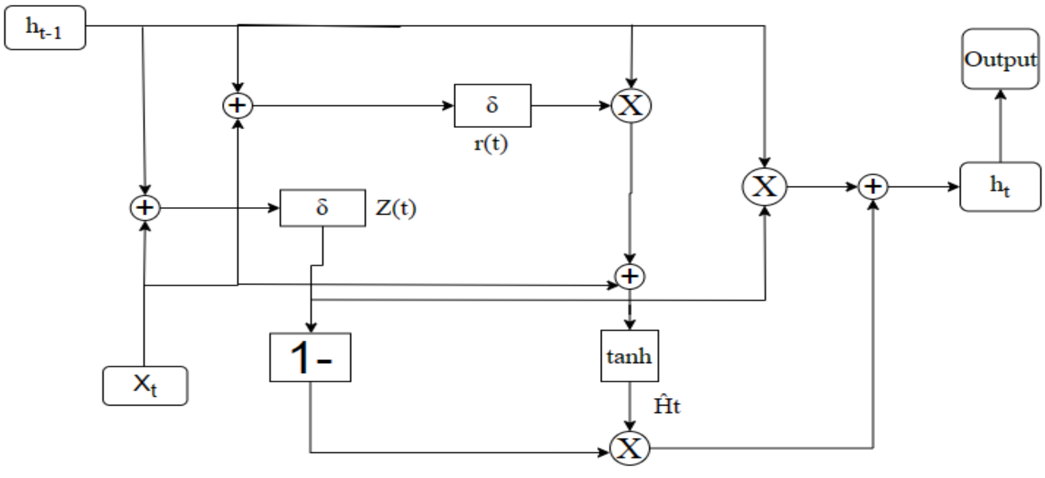


FIGURE 3.4: The Structure of GRU Memory Cell

The equations that describe the GRU are as follows;

$$H_t = \hat{H}_{(t)}(1 - Z(t)) + Z(t).H_{t-1} \tag{3.13}$$

$$Y_t = W_{yt}H_t + b_y \tag{3.14}$$

$$Z_{(t)} = \delta(W_Z\,.\,[H_{t-1}, X_t] + b_Z) \tag{3.15}$$

$$r_{(t)} = \delta(W_r\,.\,[H_{t-1}, X_t] + b_r) \tag{3.16}$$

$$\hat{H}_{(t)} = \tanh\,(W_{\hat{h}}\,.\,[r(t).H_{t-1}, X_t] + b_{\hat{h}}) \tag{3.17}$$

Were, H_t is hidden state or current hidden memory at time, t, Y_t is output, z(t) is an update gate, r(t) is reset gate, Ĥ(t) is candidate hidden layer, b is bias, W_{hx}, W_{hh}, and W_{yh} imply the weights of each step.

Update gate: is used to tell the model about how much of the previous information needs to be passed along to the next.

Reset gate: is used to tell model to decide how much of the previous information to delete. The main difference between GRU and LSTM is that GRU's bag has two gates that are reset and update while LSTM has three gates that are input, output, forget. GRU is less complex than LSTM because it has less number of gates. GRU exposes the complete memory and hidden layers but LSTM doesn't. From working of both layers i.e., LSTM and GRU, GRU uses less training parameter and therefore uses less memory and executes faster than LSTM whereas LSTM is more accurate on a larger datasets. Therefore, I have investigated both LSTM-RNN and GRU-RNN in this thesis to compare the performance assessment parameters like root mean square error (RMSE), MAE, MAPE and R^2 for long-term load forecasting by taking the case study Debre Work town. The overall block diagram has given in the following figure 3.5 which contains data preparation stage, design and training of both LSTM and GRU architecture and testing of the techniques.

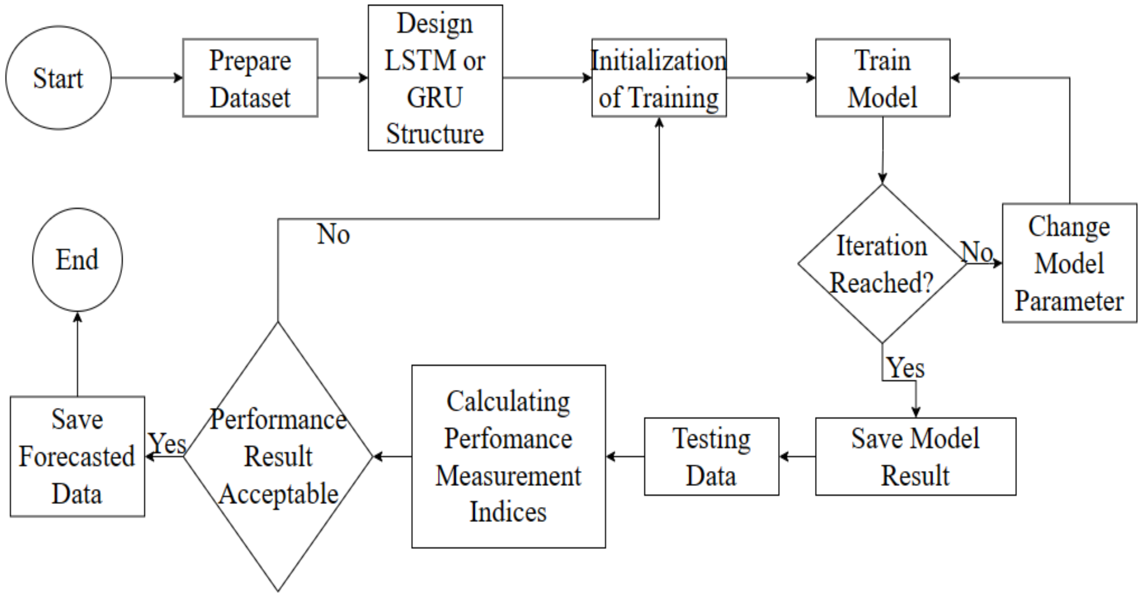


FIGURE 3.5: Overall Block Diagram of the Load Forecasting Techniques

3.4 Power System Expansion Planning

After knowing power demand by forecasting the load in specific area, power system planning is must so as to meet the demand in that area that means, power demand forecasting is followed by Power system planning. This planning may be either generation system expansion planning, transmission system expansion planning or distribution system expansion planning. In this thesis, I have focused on distribution substation power system expansion planning taking as the case study in the area of Debre Work town in Enarj Enawga woreda after forecasting the power demand in this area. Distribution substation system power expansion planning can be classified as short-term, medium-term and long-term planning based on time horizon. This thesis has focused on long term distribution substation power system expansion planning in Debre Work. According to EEA planning criteria, long-term planning takes a minimum ten years.

Planning criteria, planning parameters and distribution substation power system expansion feasibility analysis have been covered in this research which is fifteen year long term planning.

3.4.1 Power System Planning Criteria

The criterion adopted for using in the power system analysis and transmission and distribution system planning includes line and bus voltage or system voltage limit, thermal rate, load power factor, fault level, system contingencies, and system reliability. The criteria take into account the normal operating practices and generally follow well established international practice. According to Ethiopia National Distribution Gride Code (ENDGC) and Ethiopia National Transmission Gride Code (ENTGC), the detail planning criteria have been discussed as follows.

A. System Voltage

Under normal operating conditions, the voltage at each bus shall fall in the range of 0.95 per unit to 1.05 per unit of the bus nominal or base voltage. Under emergency conditions (N-1), bus voltages shouldn't be less 0.9 per unit and shouldn't exceed 1.1per unit.

B. Equipment Thermal Loading Limits

Under normal operating conditions, the loading of each transformer shall be less than the maximum rating of the transformer, and the loading of each line shall be less than the thermal rating of the line. Under emergency conditions, the loading of a transformer and the loading of a line should not exceed 120% of its capacity.

C. Load Power Factor

Considering consumers load in Ethiopia and recent master plan study done by planning body on the reactive power consumption of the system, the power factor of the loads was set to 95% and above it for users consuming 25KW and above as per EEE/2022 in page 71 in distribution networks.

D. System Contingencies

Following the failure of any line, transformer, or generator inside the mesh portion of the network, the transmission system must be able to provide all loads within the emergency limits for bus voltages and equipment loading. Bus voltages should not be less than 0.9 per unit or greater than 1.1 per unit in emergency situations (N-1), and a transformer's and a line's loads should not be greater than 120% of their capacity.

E. Fault level

The circuit breaker fault interrupting rating should be respected at all network nodes when calculating short circuit levels using generator sub transient reactance. When the network grows and becomes more intricately coupled with more generation capacity added, short circuit levels will rise above current levels, and the system's short circuit level should be verified when new installations are made. For these computations, each generator and each of its corresponding transformers must be operating.

F. Network Stability

The system shall maintain synchronism between plants for a three-phase fault occurring anywhere on the meshed parts of the system followed by opening of the most heavily loaded line at the point of fault within the meshed part of the network. The fault duration shall be 4 cycles for 400KV and 500KV, 5 cycles for 230KV faults and 6 cycles for 132KV faults. The system should maintain synchronism between plants for a fault followed by opening and successful re-closure of the most heavily loaded line at the point of fault within the radial part of the network. The fault duration should be 5 cycles for 230 KV faults and 6 cycles for 132 KV faults, while the reclose delay should be 15 cycles.

3.4.2 Parameters in Distribution Substation System Planning Model

Parameters are determinant of a system. Parameters in this analysis includes transmission line, transformer, bus bar and load parameters. Line parameter include voltage level, conductor type, conductor configuration, number of conductor, positive sequence impedance, zero sequence impedance and thermal rating as shown in an appendix E. However, in this thesis the voltage level is 230KV which is from Debre Markos to Mota using LILO construction method. The line parameters selected for this thesis are shown below in table 3.7. The line parameters are assumed to be lumped for simplifying the calculation and these parameters are taken from EEP.

Table 3.7 Voltage Level, Conductor Type and Transmission Line Parameters

KV	Conductor type	Tower Config.	No cond.	Positive Sequence			Zero Sequence			Thermal rating
				R (Ω/km)	X (Ω/km)	B (μF/km)	R_0 (Ω/km)	X_0 (Ω/km)	B_0 (μF/km)	MVA
230	Yew	double	1	0.0815	0.4234	0.009	0.322	1.14	0.06	280
230	Yew	single	1	0.0815	0.4234	0.009	0.322	1.14	0.06	280

Even though there are other conductor types for 230KV, here I have selected Yew conductor type which is common conductor type used in EEP for 230KV. So, for this thesis, Yew conductor double tower configuration type from the LILO point to Debre Work substation which is 10 kilo meter length has been selected because the existed conductor type between

Debre Markos and Mota substations is Yew conductor single tower configuration. So as to match the line parameters Yew conductor type and double tower configuration has been selected. The transmission line parameters from Debre Markos to Debre Work and from Debre Work to Mota substations are given below in table 3.8. Distance from Debre Markos to Debre Work is 65 kilo meter and from Debre to Motta is 57 kilo meter.

Table 3.8: Line Parameters for D.Markos to D.Work and D.Work to Mota Substation

Line Parameter for Debre Markos to Debre Work										
KV	cond. type	tower config.	No of Cond.	Positive sequence			Zero sequence			Thermal Rating
				R (Ω)	X (Ω)	B (μF)	R_0 (Ω)	X_0 (Ω)	B_0 (μF)	MVA
230	Yew	Single	1	5.31	26.96	0.59	20.93	73.78	0.39	280
230	Yew	Single	1	4.62	24.03	0.51	18.35	64.70	0.34	280

The bus bar and transformer configuration scheme in Debre Work substation has the following parameters which are shown in table 3.9. The bus bar is double bus bar with 230kv and has two transformers with 230/15kv, 50MVA and having ten number of outgoing feeders.

The following components of Debre Work substation; 230 KV double bus bar system, two 230/15KV, 50MVA transformers, two transformer bays, two 230KV line bays and one bus coupler bays, number of outgoing feeders; ten 15KV feeder with control and protection panels.

Table 3.9: Bus Bar, Transformer and Load Parameters

Bus Bar	Transformer	Load

Base KV	230	KV	230/15kv	P_{load} (peak)	36.8MW
Nominal V_{max}(pu)	1.05	Nominal V_{max}(pu)	1.05	Q_{load} (peak)	12.09MVAr
Nominal V_{min}(pu)	0.95	Nominal V_{min}(pu)	0.95		
Emergency V_{max}(pu)	1.1	Rate MVA	50		
Emergency V_{min}(pu)	0.90	Windng MVA	50		
Bus bar scheme	Double	R_{max} (MVA)	1.1		
Types of bus bar	230KV	R_{min} (MVA)	0.90		

From table 3.9, R_{max} and R_{min} can be calculated as follows;

$$R_{max} = \frac{\text{KV at tap position 1}}{\text{Rated KV or KV at tap position 11}} \tag{3.18}$$

$$R_{min} = \frac{\text{KV at tap position 21}}{\text{Rated KV or KV at tap position 11}} \tag{3.19}$$

Rated KV of the transformer is 230kv, KV at a tap position 1 is 253kv and KV at a tap position 21 is 207kv. Therefore, by using equation 3.18 and 3.19, R_{max} and R_{min} are calculated.

$R_{max} = \frac{253KV}{230KV} = 1.1$ and $R_{min} = \frac{207KV}{230KV} = 0.9$ which are given in table 3.9 as shown above.

The peak real load is given by forecasting of power demand in Debre Work area which is shown in table 4.1. I have used the last year power demand to test feasibility of the network that is 36.79MW. According to EEP network performance, the power factor of the network is reached 0.95. Using this power factor and equation 3.20, peak reactive power is given as 12.09MVAr.

$$Q_{load} = P_{load}\tan(\phi) \tag{3.20}$$

$$\phi = \cos^{-1}(\text{power factor}) \tag{3.21}$$

Power factor is 0.95. Therefore, Q_{load} and $\boldsymbol{\phi}$ are calculated as follow;

$\boldsymbol{\phi} = \cos^{-1}(0.95) = 18.19487$degree. Having this, Q_{load} is calculated using equation 3.20 as follows;

$Q_{load} = 36.80\text{MW} * \tan(18.19487) = 12.095$MVAr.

Therefore, having real load which is 36.79MW and reactive load that is 12.095MVAr, the technical feasibility study has been conducted to test whether the proposed substation model is feasible or not feasible.

The number of outgoing feeder has been calculated as each 15KV outgoing feeder can utilize 5MVA according to EEA/2022 distribution network standard, therefore, 50MVA transformer divide by 5MVA gives ten number of outgoing feeders. These feeder line has been shown in figure 3.6.

Table 3.10: Assumed Transformer Data of Debre Work Substation

Transformer type	50MVA, 230/15KV	No load loss(KW)	23.353
Number of phases	3	Load loss (KW)	155.8
Vector group	YNd11	No load current (%)	0.096
Frequency	50Hz	impedance(%)	13.10

3.4.3 Feasibility Study

Distribution substation power system expansion planning technical feasibility analysis must when we deal about either new substation expansion or existing substation expansion planning to see the effect of new substation on the existing Gride or network. The feasibility analysis of this thesis has covered load flow analysis, contingency analysis and short circuit analysis for new substation expansion planning in Debre Work.

In figure 3.6, F1, F2, …, L1 indicates that 15kv out going feeder lines of Debre Work Substation.

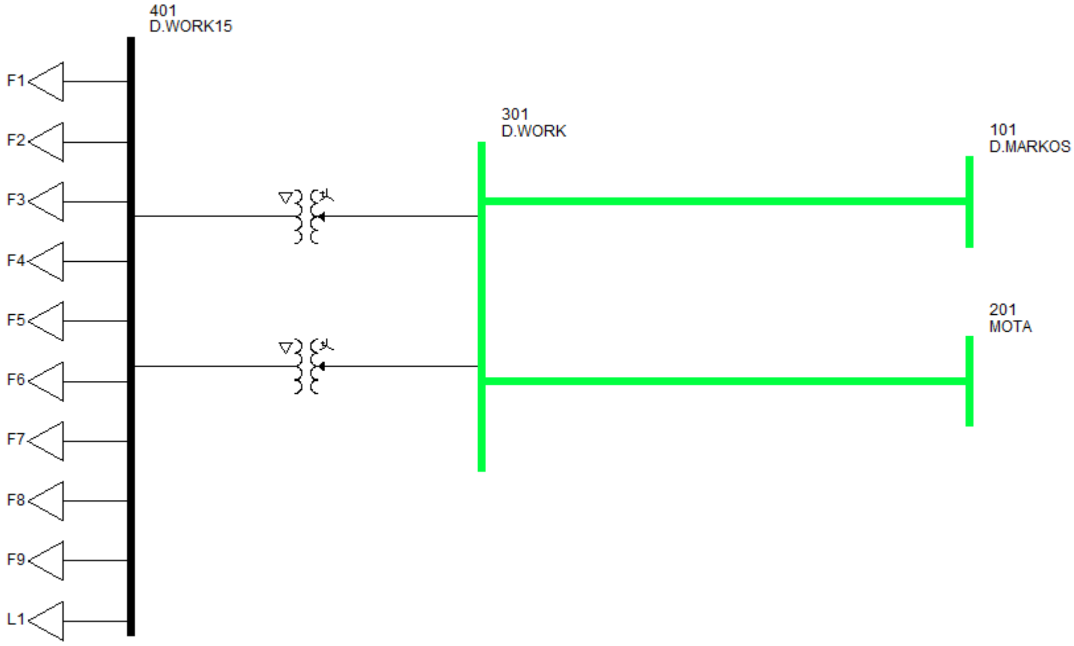


FIGURE 3.6: The Model of Debre Work Distribution Substation

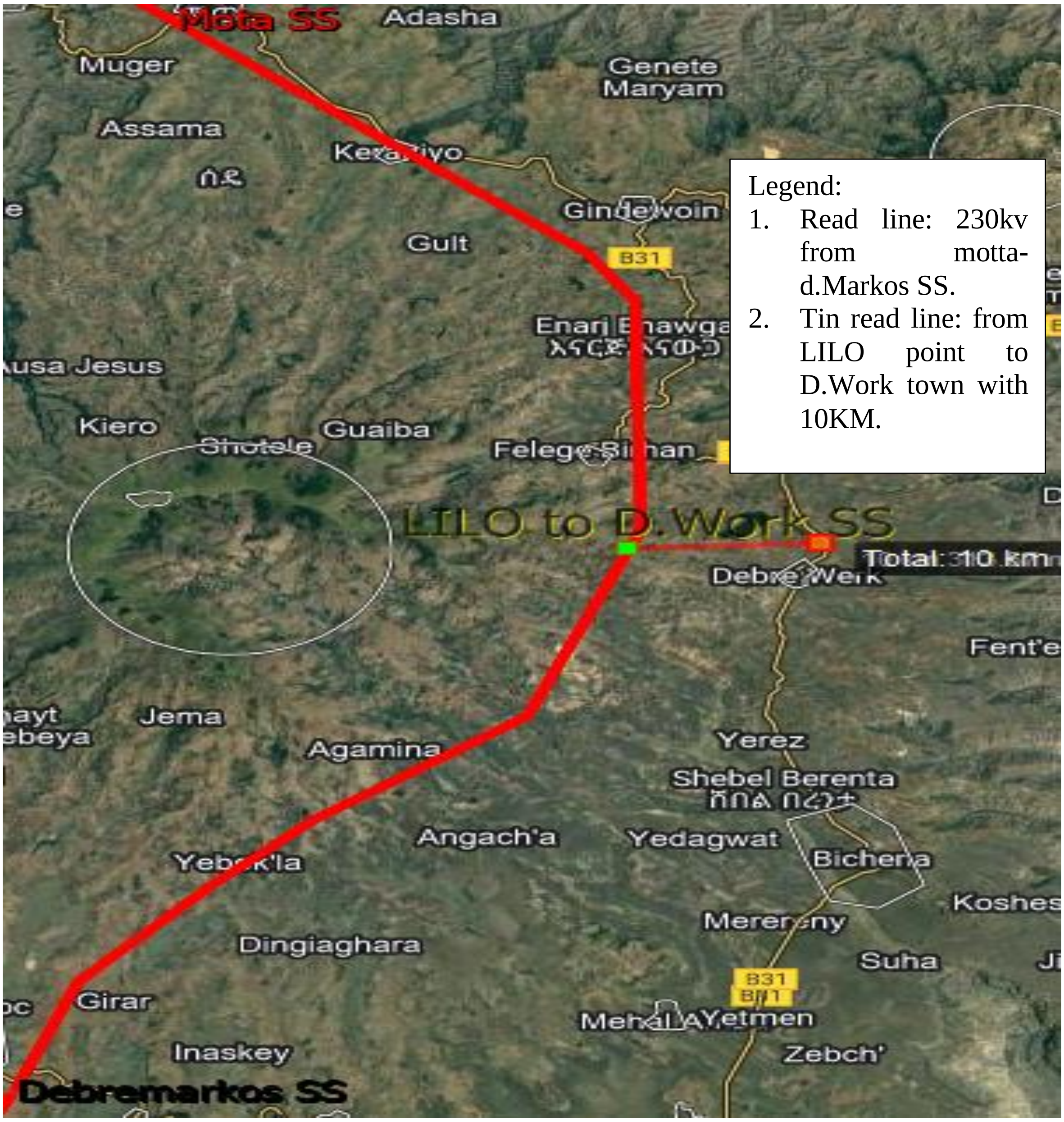


FIGURE 3.7: The Geographical Location of the Proposed Debre Work Substation

The proposed model contains the following elements; transmission line from Debre Markos to Debre Work and from Mota to Debre Work, bus bar, transformer and the load as shown in figure 3.7 above.

3.4.3.1 Load Flow Analysis

The load flow analysis is a very important and fundamental tool in power system analysis (Venkatesh, 2012). Any system's operational phases, including the stages of expansion and design, control, and economic planning, heavily rely on its results. Any load flow analysis's main goal is to determine the accurate steady-state voltages and voltage angles of all network buses as well as the actual and reactive power flows into each line and transformer while assuming that the generation and load are known. When the system's transient behavior is being investigated, the load flow solution also provides the system's initial conditions. It will be necessary to implement a number of power flow solutions under various circumstances in practice.

The following node equation can be used to represent the relationship between node current and voltage in the linear network (Venkatesh, 2012).

$$I_i = \sum_{j=1}^{n} Y_{ij} V_j \ , \ i=1,2,\ldots,n \tag{3.22}$$

where I_i and V_j stand for the respective injected current at bus i and voltage at bus j. In polar coordinates, the voltage at a typical system bus i is given by

$$V_i = |V_i|(\cos\delta_i + j\sin\delta_i) \tag{3.23}$$

Y_{ij} a components of the admittance matrix, is given by

$$Y_{ij} = |Y_{ij}|(\cos\theta_{ij} + j\sin\theta_{ij}) = G_{ij} + jB_{ij} \tag{3.24}$$

where *n* is the number of nodes in the system.

The complex power injected by the source into the *i*^th^ bus of a power system is given as follows

$$S_i = P_i + jQ_i = VI^* \tag{3.25}$$

Substitute I_i value from equation (3.17), then equation (3.24) becomes after complex conjugate

$$S_i = P_i\text{-}jQ_i = V^* \sum_{j=1}^{n} Y_{ij} V_j \tag{3.26}$$

Therefore, the load flow equation can be written as follows in polar forms.

Real power,

$$P_i = |V_i| \sum |V_j||Y_{ij}| \cos(\theta_{ij} + \delta_j\text{-}\delta_i) \tag{3.27}$$

$$Q_i = \text{-}|V_i| \sum |V_j||Y_{ij}| \sin(\theta_{ij} + \delta_j\text{-}\delta_i) \tag{3.28}$$

Equation (3.27) and (3.28) are usually expressed in the following forms as mathematical model of the static power flow problem.

$$\Delta P_i = P_i,\text{sch-}P_i,\text{calc} = (\text{Pgi-Pdi})\text{-Pi},\text{calc} \tag{3.29}$$

$$\Delta Q_i = Q_i,\text{sch-}Q_i,\text{calc} = (\text{Qgi-Qdi})\text{-Qi},\text{calc} \tag{3.30}$$

Where, in accordance with the two simultaneous equations above, P_i,sch, and Q_i,sch are the designated active and reactive powers at node i. Finding the voltage vector $|V_i|$ and δ_i such that the magnitudes of power errors P_i and Q_i are less than the permissible tolerance is a rough summary of the load flow problem.

Due to the intricacy of these static load flow equations, an accurate analytical solution cannot be found. The power flow calculations therefore frequently use iterative methods. These iterative methods are Gauss–Seidel method, Newton–Raphson method and Fast decoupled method.

Table 3.11: Comparison of Load Flow Solution Methods

Methods	Advantage	Disadvantage
Gauss-seidel	Computation time per iteration is less. Less memory required. Tolerant of data error and poor starting voltage. Indicates area of network with problems.	Requires a large number of iterations to reach convergence. It has linear convergence characteristics. The number of iterations depend on the size of the system. Sensitive to acceleration factors.
Newton–Raphson(fully coupled)	Requires a less number of iterations. It has quadratic convergence characteristics. Independent of the size of the system.	time per iteration is more. More memory required. Intolerant of data errors No indication for cause of convergence failure. Difficulty converging when reactive limits are restrictive.
Fast decoupled Newton-Raphson	Time per iteration is less. It does not depend on the size of the system. Less memory required than NR Faster than full NR.	Requires a more number of iterations than Newton–Raphson method.

From the above iterative methods, Fast decoupled method has been selected because it is faster than NR method and not depend on size of the system as compared with Gauss-Seidel method.

3.4.3.2 Contingency Analysis

The contingency analysis is used to see the effect of outage of one or more elements from the power system on the connected substations. It is also called reliability analysis or emergency case analysis. Debre Work substation transformers and the transmission lines which are used to connect the substation with the system are selected to satisfy N-1 contingency criteria. This means when one element is out of service, the remaining element must carry the load demand.

3.4.3.3 Short Circuit Analysis

For proper choice of circuit breakers and protective relaying, the magnitude of currents that would flow under short-circuit conditions shall be determined by fault analysis. In this thesis, symmetrical and asymmetrical fault analysis have done. Asymmetrical fault calculation or analysis has covered single line to ground, line to line and both line to ground fault. The data required for short circuit analysis of Debre Work substation is given in table 3.10 below. The forecasted load demand, transmission line zero and positive sequence impedance and transformer short circuit tested result zero sequence impedance are required. The transformer tested zero sequence impedance has taken from 230/15kv, 50MVA transformer test result in 2017 from one of EEP substation, which was 134.7ohms per phase which is equal to 404.1ohms. This has been converted in to per unit value in the following way.

$$Z_{\text{base}} = \frac{\sqrt{3}\ (\text{KV})^2}{\text{MVA}_{\text{base}}} \tag{3.31}$$

$$X_0(\text{pu}) = \frac{\text{X0}}{\text{Zbase}} \tag{3.32}$$

Where, MVA_{base} was taken as 100MVA and X_0 was taken from transformer test result which is 404.1ohms having this, X_0(pu) is 0.44103.

Table 3.12: Short Circuit Analysis Input Parameters

Transmission line parameters from D.markos-D.work					
Positive sequence impedance			Zero sequence impedance(pu)		
R (ohms)	X (ohms)	B (μF)	R_0	X_0	B_0
5.310	26.96	0.585	0.0383	0.1434	0.000737
Transmission line parameters from Mota-D.work					
4.623	24.03	0.513	0.0345	0.1218	0.000646
Transformer zero sequence impedance test result(pu)				0.44103	

A. Symmetrical Short Circuit Analysis

A symmetrical fault on the power system is one that results in symmetrical fault currents, or equal fault currents in the lines with a 120° displacement (Mehta). To enable quick short circuit calculations, the reactance of generators, transformers, reactors, etc. is typically given as a percentage.

$$\%X = \frac{IX}{V}100 = \frac{(KVA)X}{10(KV)^2} \tag{3.33}$$

Where, I = full-load current, *V* = phase voltage, *X* = reactance in ohms per phase.

The multiple of nominal system voltage and short-circuit current at the location of fault expressed in MVA is known as short-circuit MVA.

$$I_{SC} = I(\frac{100}{\%X}) \tag{3.34}$$

$$MVA_{SC} = \frac{3VI_{SC}}{10^6} = MVA_{base}\frac{100}{\%X} \tag{3.35}$$

Where, I_{SC} is three phase short circuit current and MVA_{SC} is three phase short circuit MVA.

B. Single Phase to Ground Fault

The single line-to-ground fault, the most common type, is caused by lightning or by conductors making contact with grounded structures (J.Grainger and D.Stevnson , 1994). The phase current, sequence current, phase voltage and sequence voltage of single phase to ground fault are given in the following equations.

$$I_b = I_c = 0 \tag{3.36}$$

$$V_f = Z_f I_f = Z_f I_a \tag{3.37}$$

$$\begin{bmatrix} I_0 \\ I_+ \\ I_- \end{bmatrix} = \frac{1}{3}\begin{bmatrix} 1 & 1 & 1 \\ 1 & a & a^2 \\ 1 & a^2 & a \end{bmatrix}\begin{bmatrix} I_a \\ 0 \\ 0 \end{bmatrix} = \frac{1}{3}I_a = \frac{V_f}{Z_+ + Z_- + Z_0 + 3Z_f} \tag{3.38}$$

$$V_0 = V_- = 0 \tag{3.39}$$

$$V_+ = E_g \tag{3.40}$$

$$\begin{bmatrix} V_0 \\ V_+ \\ V_- \end{bmatrix} = \begin{bmatrix} 0 \\ E_g \\ 0 \end{bmatrix} - \begin{bmatrix} I_0 Z_0 \\ I_+ Z_+ \\ I_- Z_- \end{bmatrix} \tag{3.41}$$

$$\begin{bmatrix} V_a \\ V_b \\ V_c \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & a^2 & a \\ 1 & a & a^2 \end{bmatrix}\begin{bmatrix} V_0 \\ V_+ \\ V_- \end{bmatrix} \tag{3.42}$$

Where, a is an operator which when multiplied to a vector rotates the vector through 120° in the anticlockwise direction by referencing phase a to convert asymmetrical component to symmetrical component.

C. Line to Line Fault

A line-to-line (LL) fault happens when two conductors are short circuited. The fault impedance is assumed to be Z_f. Let the LL fault is placed between lines b and c in order that the fault be symmetrical with respect to the reference phase a which is unfaulted. The sequence currents and voltages and also the phase currents and voltages are given in the following equation.

$$I_a = 0 \tag{3.43}$$

$$I_b = I_f = -I_c \tag{3.44}$$

$$V_b - V_c = Z_f I_b \tag{3.45}$$

Where, equation (3.38), (3.39) and (3.40) are called boundary conditions.

$$\begin{bmatrix} I_0 \\ I_+ \\ I_- \end{bmatrix} = \frac{1}{3}\begin{bmatrix} 1 & 1 & 1 \\ 1 & a & a^2 \\ 1 & a^2 & a \end{bmatrix}\begin{bmatrix} I_a \\ I_b \\ I_c \end{bmatrix} \tag{3.46}$$

$$\begin{bmatrix} V_0 \\ V_+ \\ V_- \end{bmatrix} = \begin{bmatrix} 0 \\ E_g \\ 0 \end{bmatrix} - \begin{bmatrix} Z_0 & 0 & 0 \\ 0 & Z_+ & 0 \\ 0 & 0 & Z_- \end{bmatrix}\begin{bmatrix} I_0 \\ I_+ \\ I_- \end{bmatrix} \tag{3.47}$$

D. Double Line to Ground Fault

When two line with ground short circuit, the fault is known as Double Line to Ground Fault. Double Line to Ground Fault has shown in figure 3.6 below.

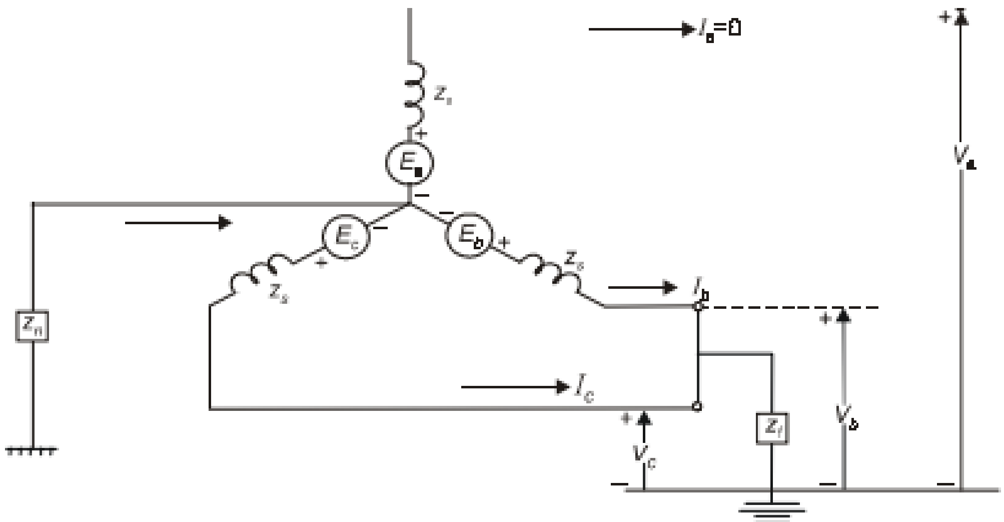


FIGURE 3.8: Double Line to Ground Fault (D.Das, 2006)

Assume the fault happens between phase b and c to ground as shown in figure 3.9 above. The boundary condition is given below

$$I_a = 0 \tag{3.48}$$

$$I_0 + I_+ + I_- = 0 \tag{3.49}$$

$$V_b = V_c = (I_b + I_c)Z_f = I_f Z_f = 3Z_f I_0 \tag{3.50}$$

The relation between symmetrical components voltage and the phase voltages are given by

$$\begin{bmatrix} V_0 \\ V_+ \\ V_- \end{bmatrix} = \frac{1}{3}\begin{bmatrix} 1 & 1 & 1 \\ 1 & a & a^2 \\ 1 & a^2 & a \end{bmatrix}\begin{bmatrix} V_a \\ V_b \\ V_c \end{bmatrix} \tag{3.51}$$

$$\begin{bmatrix} I_0 \\ I_+ \\ I_- \end{bmatrix} = \frac{1}{3}\begin{bmatrix} 1 & 1 & 1 \\ 1 & a & a^2 \\ 1 & a^2 & a \end{bmatrix}\begin{bmatrix} I_a \\ I_b \\ I_c \end{bmatrix} \tag{3.52}$$

3.5 **Materials**

The materials that have used in thesis were software materials such as MATLAB for training and testing of the long-term load forecasting, PSSE software, which is used for simulating of distribution substation expansion planning model and Google Earth Pro software for distance calculation and point location.

3.6 Cost Estimation of the New Substation

After technical feasibility study, the cost estimation of the substation is followed. Here the cost of Debre Work new substation and the double transmission line from LILO point to Debre work substation which is 10KM has been estimated based on the current currencies of substation and transmission line equipment. The detail cost analysis is given in appendix F. The cost estimation contains 230 KV bus bar system(double bus bar system), 2x230KV line bay (from Debre Markos-Mota line LILO point to Debre Work SS), 2 x 230KV side, 230/15KV, power transformer bay, outdoor terminal cabinets, control & protection panels, 15kv GIS metal clad switch-gear (indoor), 15kv outdoor switch-gear, digital control & monitoring system, low voltage, ac supply system, low voltage, 125V dc and dc supply system, steel structures, RTU, SCADA interface/cross-connection panel, fiber optic communication, miscellaneous, two 230/15kv,50MVA power transformers, shield wire system, diesel generator and civil works except land compensate cost.

The method used here for cost estimation was bottom up technique which starts by listing each equipment with respect to their present cost value and adding up to get total cost of the transmission line from LILO point to the substation and substation cost.

CHAPTER FOUR

4. RESULT AND DISCUSSION

4.1 Introduction

In this thesis, two main parts have been discussed that are long term load forecasting and distribution substation power system expansion planning model with substation and transmission line cost estimation. Neural network techniques such as LSTM-RNN and GRU-RNN have used for training and testing of long-term load forecasting. Based on assessment measurement parameters such as RMSE, MAE, MAPE and R^2 these forecasting algorithms or techniques have been identified. The forecasting result has included the peak load forecasting using both LSTM-RNN and GRU-RNN and their comparative result is given in table 4.1.

The distribution power system expansion planning model of this thesis has included the following analysis results: load flow analysis, power contingency analysis and short circuit analysis.

4.2 Long-Term Load Forecasting Results

In table 4.1, the peak power demand long term forecasting result of both GRU-RNN and LSTM-RNN has given. The detail discussion has given in each portion the result of LSTM and GRU.

Table 4.1: Comparative Result of Peak Demand for LSTM and GRU

Year	Peak demand Prediction using LSTM	Peak demand Prediction using GRU
2023	4.19	4.21
2024	5.23	5.24
2025	6.40	6.40
2026	7.70	7.70
2027	9.17	9.16
2028	10.77	10.79
2029	12.59	12.62
2030	14.63	14.66
2031	16.89	16.91
2032	19.40	19.45
2033	22.21	22.28
2034	25.31	25.34
2035	26.76	28.78
2036	32.58	32.60
2037	36.79	36.80
Time	00:20:29	00:14:48
Iteration	2000	2000
MAE	0.0447	0.0625
MAPE	0.0132	0.0195
RMSE	0.2992	0.3535
R^2	1.0000	1.0000

The goal is to get MAE, MAPE, RMSE value zero and R^2 value one. Then, From table 4.1, LSTM-RNN result is better than GRU-RNN from assessment measurement parameters result such as MAE which is 0.0447, MAPE that is 0.0132 and RMSE is 0.2992 and R^2 is 1, but for GRU-RNN MAE is 0.0625, MAPE is 0.0195 , RMSE is 0.3535 and R^2 is 1 in an iteration of 2000. When saw the difference between LSTM-RNN and GRU-RNN by taking the results of peak power demand difference of each assessment measurements that is MAE value of LSTM-RNN result minus MAE value of GRU-RNN result which is equal to 0.0178, MAPE value of LSTM-RNN result minus MAPE value of GRU-RNN result which is equal to 0.0065 and RMSE value of LSTM-RNN result minus RMSE value of GRU-RNN result is equal to 0.0543. From training time view point, GRU-RNN is better than LSTM-RNN as shown in table 4.1 above. However, LSTM-RNN has selected for this thesis because the training time difference is not that much issue. But both LSTM and GRU will be applied for long term load forecasting as we saw their results have shown good fitting.

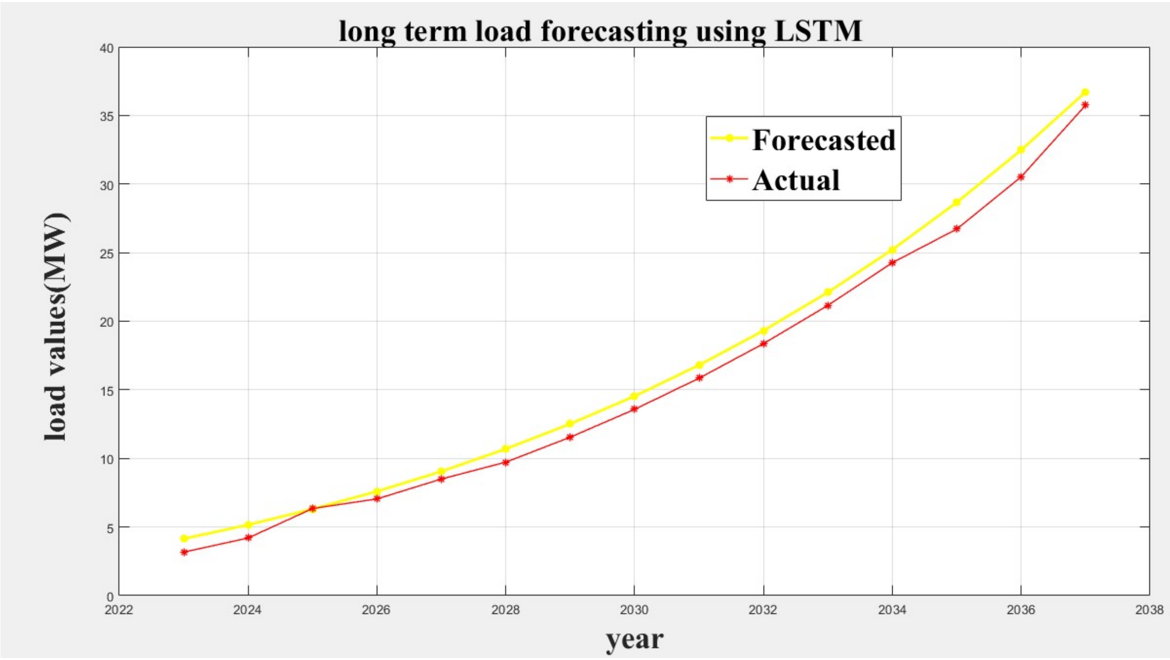


FIGURE 4.1 Peak Load Curve Result of LSTM-RNN in 2000 iteration

LSTM-RNN result is good fitting from assessment measurement parameters result such as MAE which is 0.0447, MAPE that is 0.0132 and RMSE is 0.2992 and R2 is 1 as shown in the above figure 4.1 or in the following chart, the actual peak demand and the predicted peak demand have almost the same value. Where, actual and original have the same meaning and means that the real power demand record from the field.

The training status and convergence of LSTM-RNN technique has been given the following figure 4.2 and figure 4.3 below in 2000 iteration which has shown both training loss and RMSE status.

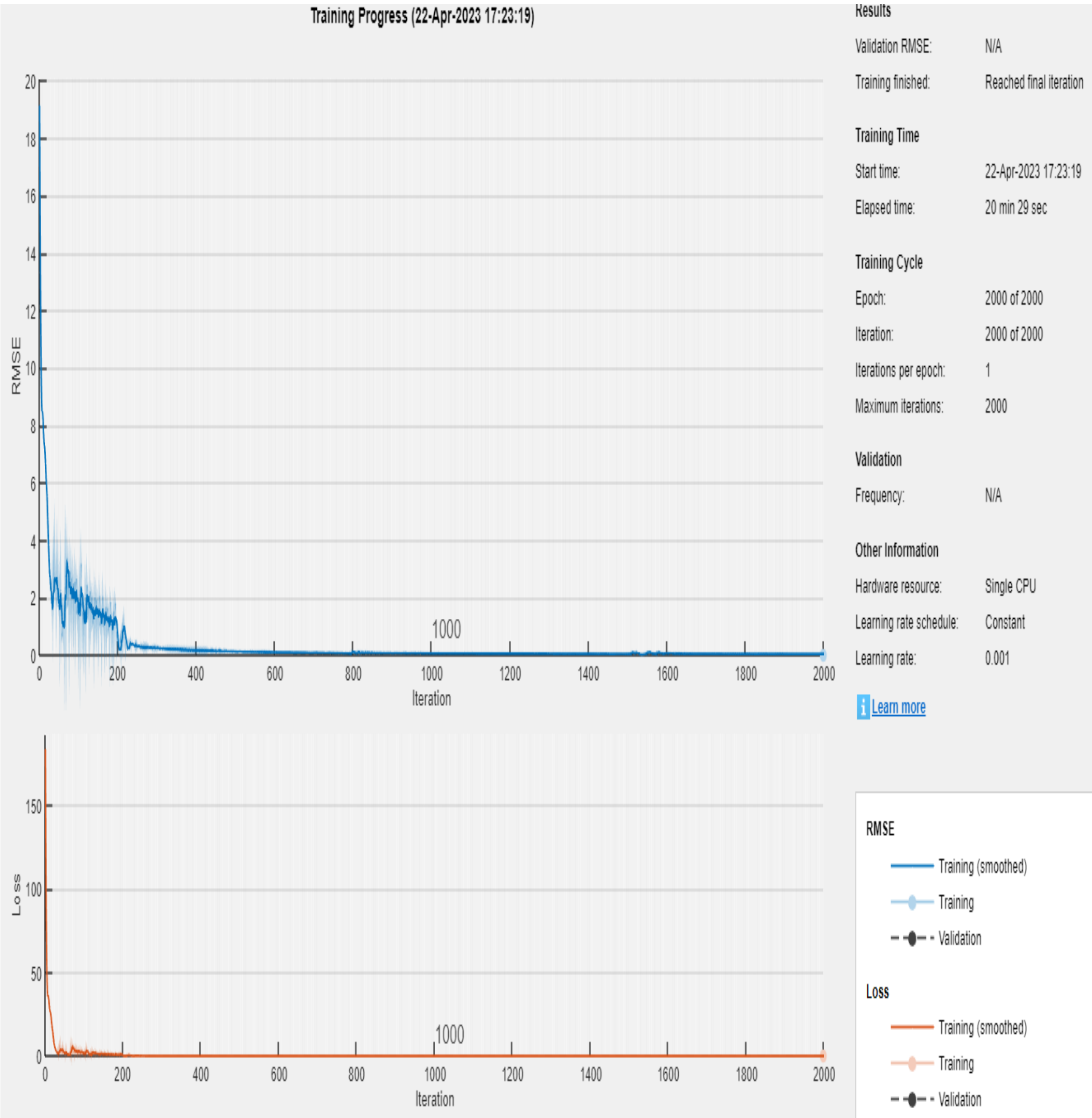


FIGURE 4.2: The Training Loss and RMSE Status of LSTM-RNN

GRU-RNN forecasting result has shown that, MAE is 0.0625, MAPE is 0.0195 , RMSE is 0.3535 and R^2 is 1 which is slightly less accurate than LSTM-RNN. The GRU-RNN has shown in the following figure 4.3.

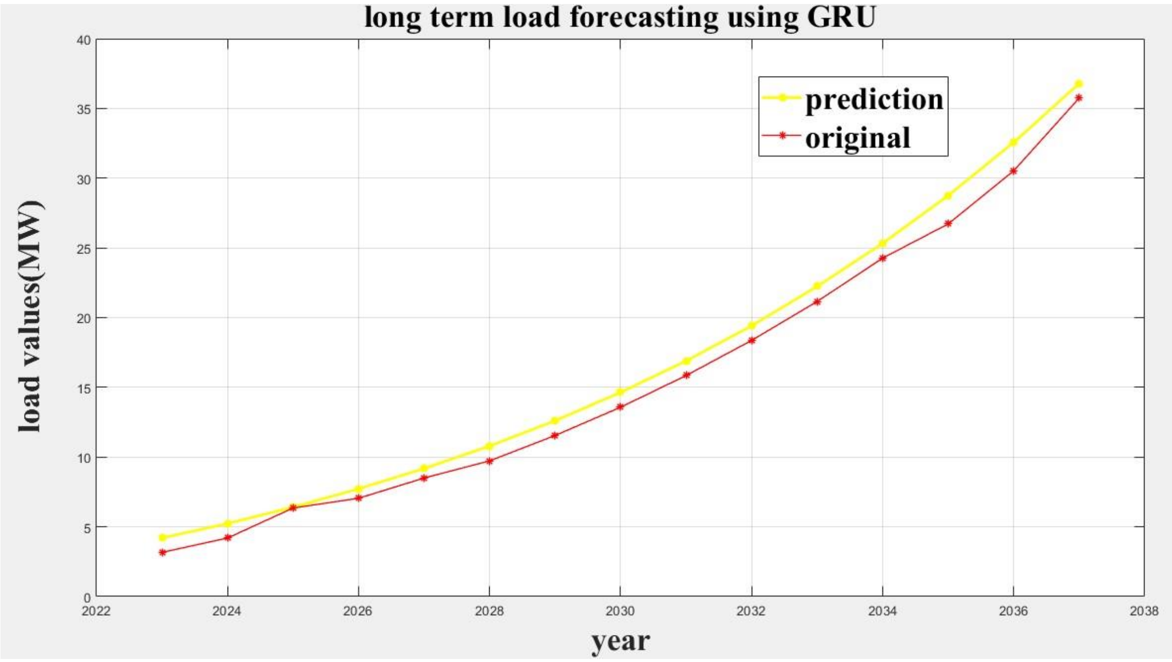
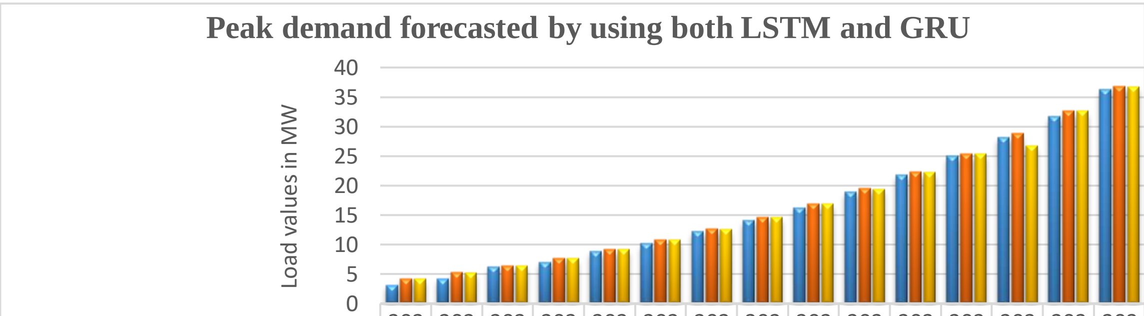


FIGURE 4.3: Peak Load Curve of GRU-RNN in 2000 iteration

As shown in figure 4.4 below, the residual or an error is more in GRU-RNN forecasting technique than LSTM-RNN forecasting technique mostly. LSTM-RNN forecasting technique has been selected for this case study even though the two forecasting techniques have almost the same results sense in load forecasting small difference makes the feasibility study infeasible. Where, actual and original have the same meaning and means that the real power demand record from the field.



	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035	2036	2037
Actual peak demand(MW)	3.17	4.2	6.25	7.05	8.85	10.12	12.23	14.08	16.25	18.95	21.75	25	28.21	31.75	36.26
Forecasted peak demand (GRU)	4.21	5.24	6.4	7.7	9.16	10.79	12.62	14.66	16.91	19.45	22.28	25.34	28.78	32.6	36.8
Forecasted peak demand(LSTM)	4.19	5.23	6.4	7.7	9.17	10.77	12.59	14.63	16.89	19.4	22.21	25.31	26.76	32.58	36.79

FIGURE 4.4: Chart that Shows Peak Demand Forecasted Using both LSTM and GRU

The training status and convergence of GRU-RNN technique has been given the following figure 4.5 below in 2000 iteration which has shown both training loss and RMSE status.

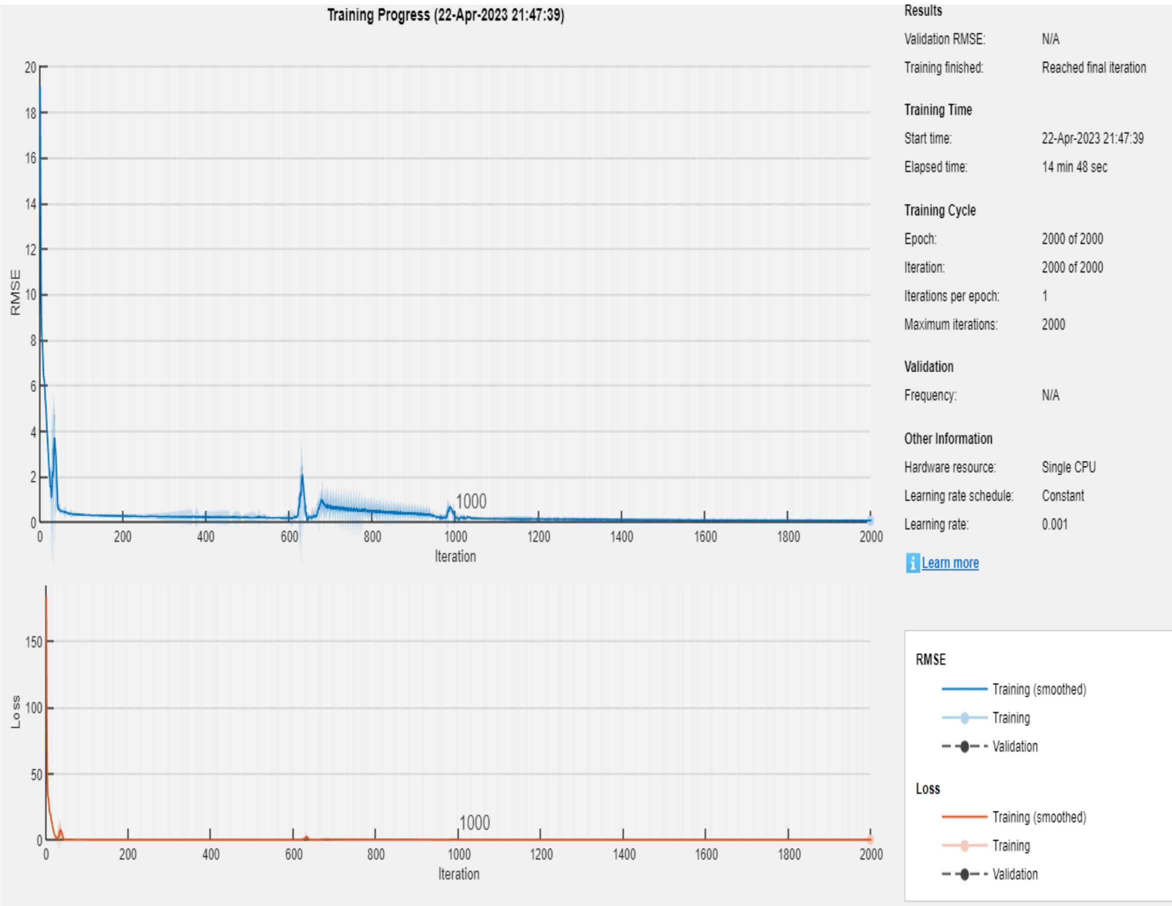


FIGURE 4.5: The Training Loss and RMSE Status of GRU-RNN

4.3 Feasibility Study (Analysis)

As discussed in chapter three, the feasibility study (analysis) has included load flow analysis, contingency analysis and short circuit analysis. The technical feasibility study is the study of a network or the Gride behavior when the new network element is added to the network or Gride system which is focused on load flow analysis, contingency analysis and short circuit analysis mostly.

4.3.1 Load Flow Analysis

Load flow analysis is dealing of the power flow in steady or static state that includes the voltage, angle, active and reactive power analysis in the bus bar and the line flow and losses analysis in the line.

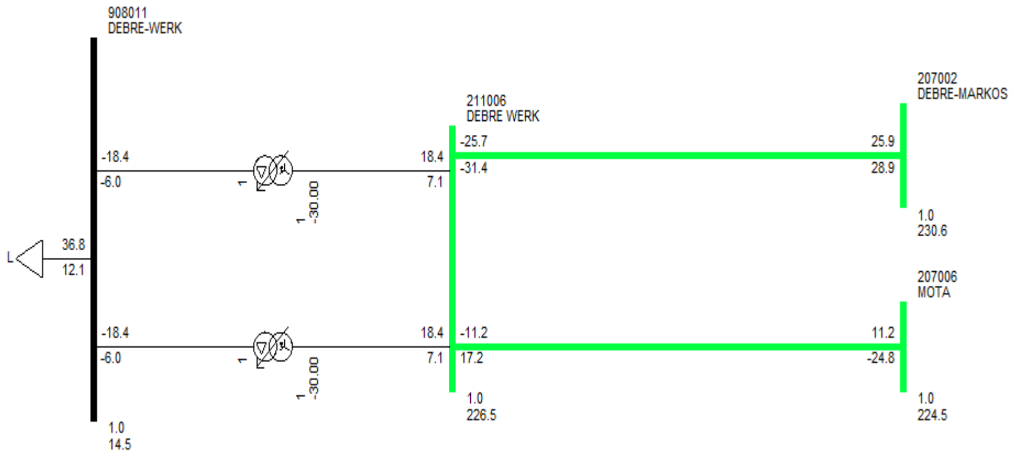


FIGURE 4.6: One Level Grow Load Flow Analysis Diagram

Table 4.2: The Result of One Level Grow Network Voltage Load Flow Analysis

Substation name	Voltage		Angle
	pu	KV	degree
D.markos 230kv	1.0027	230.6	-57.18
Mota 230kv	0.9759	224.5	-57.36
D.Work 230kv	0.9866	226.5	-57.77
D.Work 15KV	0.9658	14.5	-30.65

Table 4.3: The Result of One Level Grow Network Line Flow Load Flow Analysis

Transmission lines	Line Flow		Loss	
	P(MW)	Q(MVAr)	P(MW)	Q(MVAr)
From D.markos-D.work	25.7	31.4	0.2	-2.5
From Mota-D.work	11.2	17.2	0.0	7.6

From figure 4.6, table 4.2 and table 4.3 above, the load flow result has shown that fulfill the voltage limit and line loading in normal load flow. The voltage limit ranges from 0.95 to 1.05 in per unit. The convergence has reached in 14 iterations using fixed slope fast Decoupled Newton-Raphson method, for full Newton-Raphson method, it has reached in 9 iteration and for Fast Decouple Newton-Raphson, it has taken 1 iteration. Therefore, Fast Decoupled Newton-Raphson load flow iteration method is better in point of view of number of iteration.

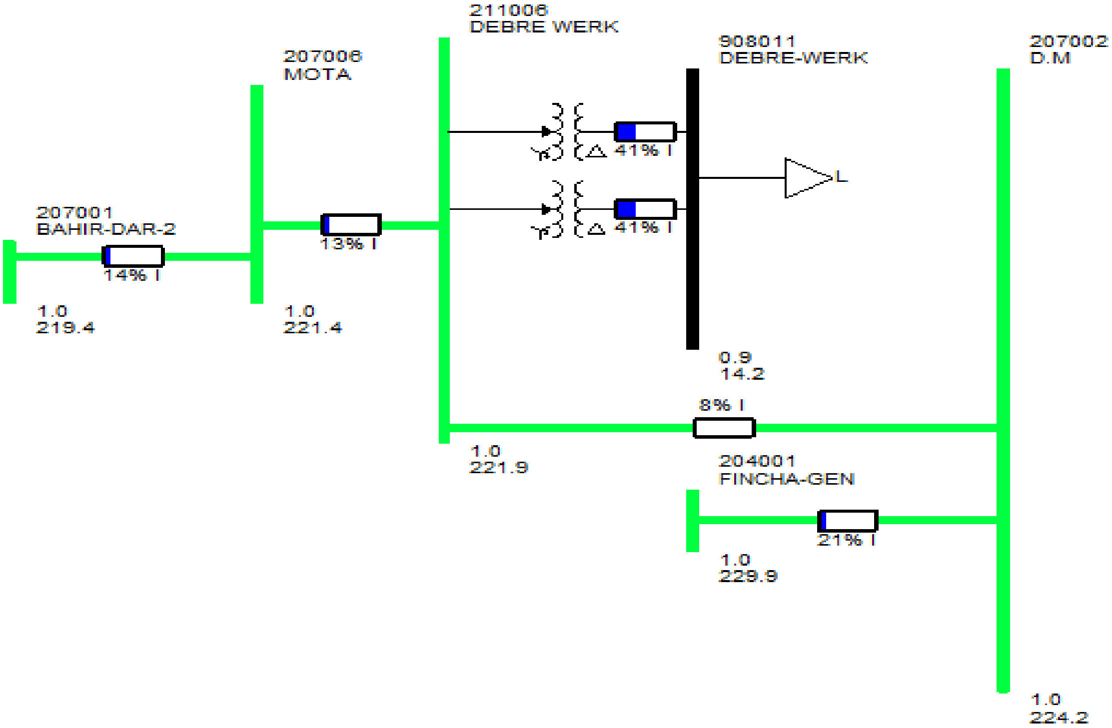


FIGURE 4.7: Two Level Network Grow of Load Flow Analysis Diagram

From figure 4.7 above and table 4.4 below, the load flow result has shown also fulfill the voltage limit and line loading in normal load flow. The convergence has reached in 1 iteration for Decouple Newton-Raphson which was good.

Table 4.4: The Result of Two-Level Grow Network Line Flow Load Flow Analysis

Transmission line	Line Flow		Loss	
	P(MW)	Q(MVAr)	P(MW)	Q(MVAr)
From D.markos-D.work	26.0	33.5	0.2	-2.5
From Mota-D.work	10.9	17.2	0.0	7.6
From Fincha-D.markos	19.5	0.5	0.1	-12.4
From Mota-Bahr dar2	13.1	23.6	0.2	3.2

Table 4.5: The Result of Two-Level Grow Network Load Flow Analysis

Substation names	Voltage		Angle
	pu	KV	(deg.)
D.markos 230kv	0.975	224.2	-57.28
Mota 230kv	0.963	221.4	-57.45
D.Work 230kv	0.965	221.9	-57.86
D.Work 15KV	0.950	14.2	-30.65
Fincha 230kv	0.999	229.9	-56.37
Bahr dar2 230kv	0.954	219.4	-56.69

4.3.2 Contingency Analysis

The contingency analysis is used to see the effect of outage of one element from the power system on the connected substations. It is also called reliability analysis or emergency case analysis. Debre Work substation transformers and the transmission lines which are used to connect the substation with the system are selected to satisfy N-1 contingency criteria. This means when one element is out of service, the remaining element must carry the load demand as discussed in chapter three.

It has used the forecasted load of 36.79MW for Debre Work substation to perform the contingency and short circuit analysis. Let's see the contingency analysis result in the following figure 4.8, figure 4.9 and figure 4.10.

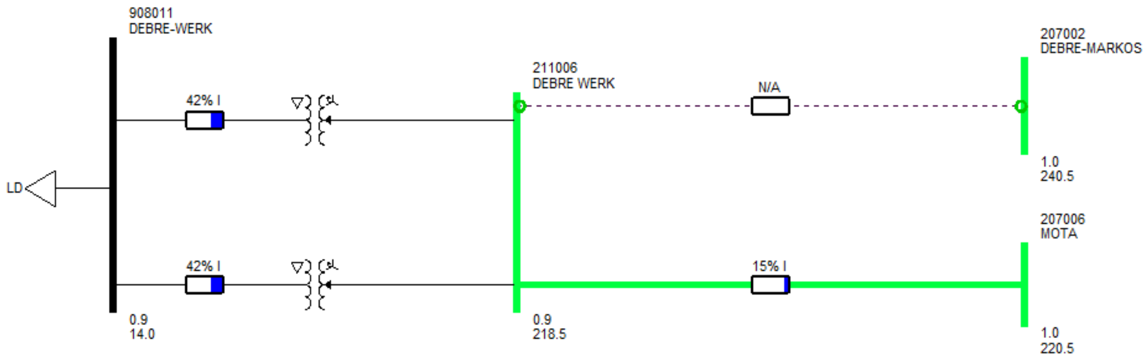


FIGURE 4.8: Contingency Analysis Debre Markos-Debre Work Line out of Service

N-1 contingency is fulfilled when we see in figure 4.10 above. The maximum line loading capacity limit is 1.2pu or 120% and bus bar voltage limit during emergency or outage of one element in the system is 1.1pu to 0.9pu. This limit has also fulfilled. The detail analysis of this result is given in table 4.6 below.

Table 4.6: Contingency Analysis When D. Markos-D. Work Line out of Service

Element	D.markos 230kv	D.work 230kv	Mota 230kv	D.work 15kv	D.markos-D.work (%)	Mota-D.work (%)	Transformer 230/15kv(%)	
							1	2
L.loading	-	-	-	-	No service	15	42	42
V (pu)	1.05	0.95	0.96	0.93	-	-	-	-

Table 4.6 has contained two things such as line loading value and bus bar voltage value. Both conditions have been fulfilled when we saw table 4.6 that means line loading limit which is 120% maximum limit and emergency voltage limit which is ranging from 0.9 to 1.1pu.

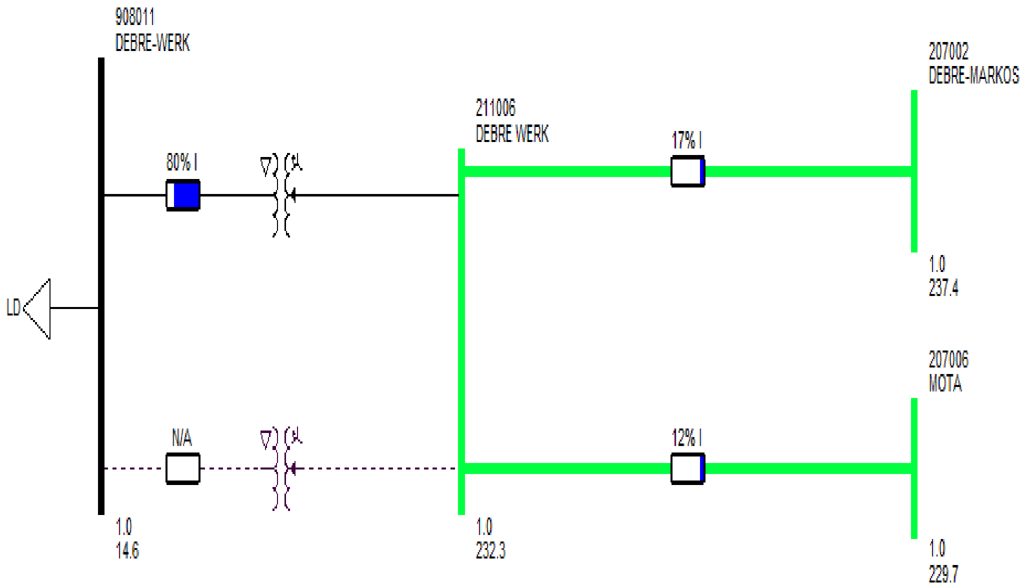


FIGURE 4.9: Contingency Analysis When One Transformer out of Service

N-1 contingency is fulfilled when we see in figure 4.11 above. The maximum transformer branch loading capacity limit is 1.2pu or 120% and bus bar voltage limit during emergency or outage of one element in the system is 1.1pu to 0.9pu. This limit has also fulfilled. The detail analysis of this result is given in table 4.7 below.

Table 4.7: Contingency Analysis when One Transformer out of Service

Element	D.markos 230kv	D.work 230kv	Mota 230kv	D.work 15kv	D.markos -D.work line(%)	Mota-D.work line(%)	Transformer 230/15kv(%)	
							1	2
Line loading	-	-	-	-	17	12	No service	80
V (pu)	1.03	1.01	0.99	0.970	-	-	-	-

Table 4.7 has contained two things such as line or transformer branch loading value and bus bar voltage value. Both conditions have been fulfilled when we saw table 4.7 that means line or branch loading limit which is 120% maximum limit and emergency voltage limit which is ranging from 0.9 to 1.1pu.

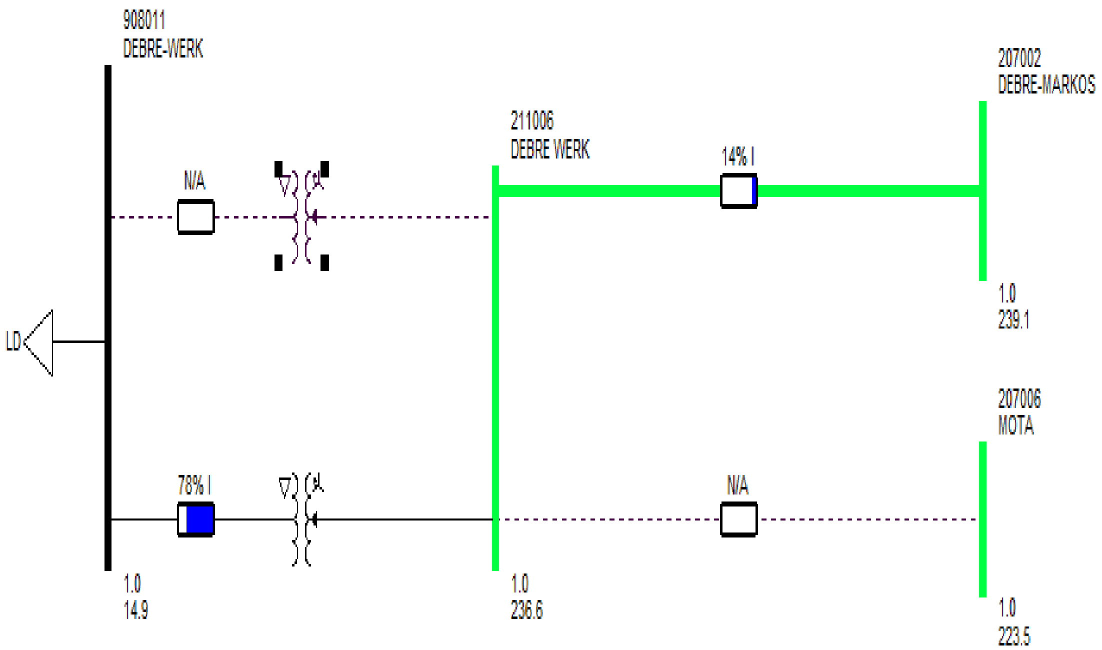


FIGURE 4.10: Contingency Study a Transformer and Mota-D.Work line out of Service

N-1 contingency is fulfilled when we see in figure 4.10 above when both one transformer and Mota-Debre Work line out of Service. The maximum transformer branch loading capacity limit is 1.2pu or 120% and bus bar voltage limit during emergency or outage of one element in the system is 1.1pu to 0.9pu. This limit has also fulfilled. The detail analysis of this result is given in table 4.8 below.

Table 4.8: Contingency Study Transformer and Mota-D. Work Line out of Service

	D.markos 230kv	D.work 230kv	Mota 230kv	D.work 15kv	D.markos-D.work line(%)	Mota-D.work line(%)	Transformer 230/15kv(%)	
							1	2
Branch loading	-	-	-	-	14	No service	78	No service
V(pu)	1.04	1.03	0.97	0.99	-	-	-	-

Table 4.8 has contained two things such as line or transformer branch loading value and bus bar voltage value. Both conditions have been fulfilled when we saw table 4.8 when both elements that are One Transformer and Mota-Debre Work line out of Service that means line or branch loading limit which is 120% maximum limit and emergency voltage limit which is ranging from 0.9 to 1.1pu. Therefore, the contingency analysis has fulfilled the given conditions.

4.3.3 Short Circuit Analysis

For proper choice of circuit breakers and protective relaying coordination, the magnitude of currents that would flow under short-circuit conditions shall be determined by fault analysis. The symmetrical faults analysis must be carried out, as this type of fault generally leads to most severe fault current flow against which the system must be protected. However, there is a situation when line-to-ground (S-L-G) fault can cause greater fault current than a three-phase fault when the fault location is close to large generating units.

The network model implemented for the load flow analysis is also used for performing the short-circuit analysis with the augmentation of negative and zero sequence of system data.

Short circuits current level output of PSSE software simulation for the bus bars near to Debre Work substation are shown in tables below.

Table 4.9: Maximum Short Circuit Level for Symmetrical Fault Analysis

Voltage in KV		I_{rms}(KA)		Angle		SCMVA	
Debre Work 230kv		4.32		-78.55		1722.22	
Voltage in KV	SS CB rating (KA)	Ia=Ib =Ic=In (A)	δ(Ia)= δ(In) (deg.)	δ (Ib) (deg.)	δ (Ic) (deg.)	Z (ohm)	δ (Z) (deg.)
Mota230	31.5	1565.5	100.79	-19.21	-139.2	68.83	100.75
D.Markos230	31.5	2702.5	99.95	-20.5	-140.05	26.59	-98.71
Bahir Dar2230	31.5	1562.6	100.65	-19.35	-139.35	37.17	-100.31
Fincha230	31.5	922.9	103.87	-16.19	-136.13	36.87	-104.58
Debre Work15	-	52.6	159.20	39.20	-80.80	11.62	-161.81

Three phase balanced fault is the most common sever fault type in the power system fault cases which is mostly happened rarely. The results of maximum current of Symmetrical Fault short circuit analysis as presented in the above table 4.9 shown that the short circuit current levels are under circuit breaker breaking capacities of the nearby substations.

Table 4.10: Minimum Short Circuit Level for Three Phase Fault Breaking Capacity

Voltage Level in KV	SS CB rating (KA)	Three Phase Fault Breaking Capacity			
		Irms (KA)	Angle (deg.)	SCMVA	I_P(KA)
Debre Work 230kv	-	4.00	-78.68	1595.14	8.82

Three phase balanced fault is the most common sever fault type in the power system fault cases which is mostly happened rarely. The results of minimum current of Symmetrical Fault short circuit analysis as presented in the above table 4.10 shown that the short circuit current levels are under circuit breaker breaking capacities of the nearby substations.

Table 4.11: Maximum Short Circuit Level Breaking Capacity for SLG Fault Analysis

Voltage in 230KV	CB rating (KA)	SC MVA	I_{rms} (KA)	I_P (KA)	Z_+ (Ohms)	Z- (Ohms)	Z_0 (Ohms)
D.Work	-	1992	4.99	11.16	6.71+j33.12	6.56+j32.76	2.89+j20.27

Table 4.12: Maximum Short Circuit Level for Single Phase Ground Phase Fault Analysis

Substation	I_a	an(Ia)	I_b	an(I_b)	I_c	an(I_c)	Z_f	an(Z_f)
D.marko230kv	2405.8	100.4	719.4	-85.0	719.0	-85.2	26.3	-99.6
Mota230kv	1563.7	102.3	259.0	-94.7	259.0	-94.0	59.2	-103.2
D.work15kv	1011.6	96.6	985.0	93.5	985.0	93.53	1.23	179.3
D.work230kv	4999.3	-79.4						
B.dar2230kv	1282.6	104.9	545.0	-92.4	544.0	-92.0	33.2	-119.7
Fincha230kv	775.3	103.3	284.0	-76.3	282.0	-78.4	34.1	-104.5

Single phase to ground fault is the most common happened fault type in the power system fault cases which is mostly 80% from unbalanced fault types. The results of maximum current of single phase to ground short circuit analysis as presented in the above table 4.11, table 4.12 shown that the short circuit current levels are under circuit breaker breaking capacities of the nearby substations.

Table 4.13: Minimum Short Circuit Single Phase Ground Fault Analysis

Voltage in 230KV	CB rating (KA)	SC MVA	I_{rms} (KA)	I_P (KA)	Z_+ (Ohms)	Z- (Ohms)	Z_0 (Ohms)
D.Work	-	1866	4.68	10.49	6.51+j32.52	6.38+j32.17	2.55+j18.94

The results of minimum breaking capacity current of single phase to ground short circuit analysis as presented in the above table 4.13, which has shown that the short circuit current level is under circuit breaker breaking capacities of the nearby substations.

Table 4.14: Maximum Short Circuit Line-Line to Ground Fault Analysis

Voltage in 230KV	CB rating (KA)	Breaking capacity for Line-Line to Ground Fault Analysis					
		SCMVA	I_{rms} (KA)	I_P (KA)	Z_+ (Ohms)	Z- (Ohms)	Z_0 (Ohms)
D.Work	-	2329.33	5.85	12.99	6.71+j33.12	6.56+j32.76	2.89+j20.27

Double line to Ground fault is the third most common happened fault type in the power system fault next to line to line fault that covers around 5% from unbalanced fault types. Results of maximum current double line to Ground short circuit analysis as presented in the above table 4.14 which shows that the breaking capacity. Which has shown the short circuit current levels are under circuit breaker breaking capacities of the nearby substations.

The results of maximum sequence current of line line to ground short circuit analysis as presented in the above table 4.14, which has shown that the short circuit current levels are under circuit breaker breaking capacities of the nearby substations.

Table 4.15: Maximum Short Circuit Line Line to Ground Fault Analysis

Voltage in kv	Phase Current, Impedance With Their Respective Angles							
	I_a	an(Ia)	I_b	an(I_b)	I_c	an(I_c)	Z_f	an(Z_f)
D.markos230	843.6	93.92	2576	-12.7	2518	-147	27.17	-94.35
Mota230	300.6	84.49	1607	-17.8	1519	-139	123.9	-85.96
D.work15	1151.2	-87.47	1126	-84.9	1208	-86.8	1.09	73.82
D.work230	0.00	0.0	4687	152.9	4830	48.65	0.0	0.0
B.dar2 230	634.3	86.72	1542	-5.89	1315	-150	39.2	-58.26
Fincha230	338.8	101.48	843.2	-6.34	856.1	-146	44.25	-104.6

Double line to Ground fault is the third most common happened fault type in the power system fault next to line to line fault that covers around 5% from unbalanced fault types. The results of maximum phase current of line line to ground short circuit analysis as presented in the above table 4.15, which has shown that the short circuit current levels are under circuit breaker breaking capacities of the nearby substations.

Table 4.16: Minimum Short Circuit Line Line to Ground Fault Analysis

Voltage in 230KV	CB rating (KA)	Breaking capacity for Line Line to Ground Fault Analysis					
		SCMVA	I_{rms} (KA)	I_P (KA)	Z_+ (Ohms)	Z- (Ohms)	Z_0 (Ohms)
D.Work	-	2217.83	5.49	12.24	6.51+j32.52	6.38+j32.17	2.55+j18.94

Results of minimum current line to line short circuit analysis as presented in the above table 4.16 which has shown that the breaking capacity current level is under circuit breaker breaking capacities of the nearby substations.

Table 4.17: Maximum Short Circuit Level for Line to Line Fault Analysis

Voltage in KV	CB rating (KA)	Breaking capacity for Line Line to Ground Fault Analysis					
		SC MVA	I_{rms} (KA)	I_P (KA)	Z_+ (Ohms)	Z- (Ohms)	Z_0 (Ohms)
D.Work 230	-	1499.81	3.76	8.28	6.71+j33.12	6.56+j32.76	0.0

Line to line fault is the second most common happened fault type in the power system fault next to single line to ground fault that covers around 15%. Results of maximum current line to line short circuit analysis as presented in the above table 4.17 which has shown that the breaking capacity current level is under circuit breaker breaking capacities of the nearby substations.

Results of minimum current line to line short circuit analysis as presented in the below table 4.18 and table 4.19 which have shown that the the phase fault current of Debre Work substation and the nearby substations with Debre Work breaking capacity current levels are under circuit breaker breaking capacities of the nearby substations.

Table 4.18: Maximum Short Circuit Line to Line Phase Fault Analysis

Voltage in kv	Phase Current, Impedance With Their Respective Angles							
	I_a	an(Ia)	I_b	an(I_b)	I_c	an(I_c)	Z_a	an(Z_a)
D.markos230kv	2.3	97.33	2352	9.86	2352	-170	338.6	-108.4
Mota230kv	2.7	-72.66	1366	10.80	1366	-169	332.9	63.36
D.work15kv	0.3	148.66	45.5	69.01	45.5	-111	0.57	88.02
D.work230kv	0.0	0.0	3765	-169	3765	11.39	0.0	0.0
B.dar2 230kv	2.7	-72.15	1363	10.66	1363	-170	363.4	64.42
Fincha230kv	7.9	91.71	796.2	13.64	797.9	-166	56.11	-104.2

All in all, the short circuit analysis of three phase or balanced fault, single phase to ground fault, double line to ground fault and line to line fault analysis have shown that both the minimum and maximum balanced fault current, phase current of asymmetrical fault are under circuit breaking capacity of the nearby substation such as Debre Markos, Fincha, Mota and Bahr dar2 substations. Therefore, the circuit breaking capacity of Debre Work substation can 31.5KA which is the breaking capacity of the nearby substations which is above the maximum short circuit analysis that is 12.99KA. However, the protection coordination should based on the minimum short circuit analysis of Debre Work substation which is 7.69KA from the short circuit analysis of minimum current of Line to Line Fault Analysis.

Table 4.19: Minimum Short circuit level for Line to Line Fault Analysis

Voltage in 230kv	CB rating (KA)	Breaking capacity for Line Line to Ground Fault Analysis					
		SC MVA	I_{rms} (KA)	I_P (KA)	Z_+ (Ohms)	Z- (Ohms)	Z_0 (Ohms)
D.Work	-	1389.03	3.49	7.69	6.51+j32.52	6.38+j32.17	0.0

4.4 Cost Estimation of Debre Work Substation

The reference that used to do the cost estimation was Ethiopian Electric Power(EEP), Corporate Planning Executive office, Finance and Economics with Power System Network Planning Department Offices. The detail cost analysis is given in appendix F. The method used here for cost estimation was bottom up technique which starts by listing each equipment with respect to their present cost value and adding up to get total cost of the transmission line from LILO point to the substation and substation cost.

The cost estimation summery of the new substation which is Debre Work substation has been given in table 4.20 without the consideration of land compensation cost. From table 4.20 below, the cost of this substation is 528,653,214 Ethiopian Birr currently.

Table 4.20: Cost Estimation Summery of Debre Work Substation

Items	Total Price(Eth.Birr)

Total Transmission Line Cost	318,494,288
Total Substation Cost	126,500,000
Total Cost	444,994,288
Engineering And Administration(5%)	22,249,714
Environmental and Social cost (3%)	13,349,828
Total Project Cost	480,593,831
Physical Contingency (5%)	24,029,691
Price Contingency (5%)	24,029,691
Grand Total Project Cost	528,653,214

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

Long-term load forecasting, modeling of distribution substation power system expansion planning and cost estimation of the new substation expansion have addressed in this thesis for Debre Work town and its surrounding electricity demand. Long-term demand forecasting has used input factors like population number, GDP, per capita, weather conditions and number of electrified people and actual fifteen year back historical power demand. Having this, long-term demand forecasting have been trained and predicted using neural network techniques such as LSTM-RNN and GRU-RNN from the year 2023 to 2037 and the result has given in table 4.1 which has shown that the predicted peak demand in Debre Work town is 36.79MW using LSTM-RNN and 36.80MW using GRU-RNN in 2037, here the first objective has been meet. Using parameter measurement assessment methods like MAPE, LSTM-RNN has given good result which is 0.0132, but using GRU-RNN, it is 0.0195 even that is not big difference, LSTM-RNN result has been selected in this thesis, here the second objective has been meet. After demand forecasting, modelling of distribution substation power system expansion planning have addressed. The expansion planning has covered load flow analysis, contingency or reliability analysis and short circuit analysis which is also called technical feasibility analyses. The technical feasibility analysis has fulfilled all requirements or planning criteria and has passed for detail design and practical implementation, here also the third objective has been meet. The cost estimation of the new substation except land compensation has been analyzed which is 528,653,214 Ethiopian Birr currently.

5.2 Recommendations

The recommendations are; for long-term load forecasting, both LSTM and GRU can be applied and this thesis has forecasted the future demand of Debre Work town and checked the technical feasibility, therefore, there is recommendation for both EEP to take this thesis and implement this research to solve the society electricity problem.

5.3 Future Works

Someone will take this study as of reference, he/she will add more combined load forecasting techniques and deals further on the design of the substation with the dynamic analysis as future work.

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APPENDICES

Appendix A: Commercial Customers In Enarj Enawga Woreda

No	Name	Existing(number)	Planned(number)	Total
1	K. Garten	8	15	23
2	Elementary school	72	105	177
3	Junior school	7	12	19
4	Secondary school	7	10	17
5	Agro technical college	1	3	4
6	Parmacy and Clinic	20	35	55
7	Health center and Hospitals	8	19	27
8	Snacks rooms	250	400	650
9	Resturant	156	340	496
10	Bars	175	405	580
11	Hotels	25	40	65
12	Bakery	15	25	40
13	Shops	1300	1500	2800
14	Diesel Filing station	7	15	22
15	Garage	5	15	20
16	Tyre repair	10	25	35
17	Water pump-drinking	7	20	27
18	Animal clinic	30	37	67
19	Metal works	102	170	272
20	Photo studio	16	40	56
21	Government offices	1045	2050	3095
22	Church/mosque	135	150	285
23	Store house	28	40	68
24	Butchery	25	75	100
25	Tailor shop	350	500	850
26	Barber	76	100	176
27	Wood works	210	308	518
28	Total	4102	4974	9076

Appendix B: Distribution System Reliability Index Based on ENDGC Standard

Indicators	Low Standard	High Standard
SAIDI (Excludes load shedding and exceptional events): 1.Durations of unplanned or forced interruptions per customer per year 2. Durations of planned interruptions customer per year	12 hours 5 hours	8 hours 1 hour
SAIFI (Excludes load shedding and exceptional events): 1.Frequency or number of unplanned or forced interruptions per customer per year 2.Frequency or number of planned interruptions per customer per	15 times 10 times	11 times 5 times

Appendix C: Number of Low Voltage Industries in Enarj Enawga Woreda

Number	Name of Industry	Exsisting (number)	Planned (number)	Total (number)
1	Water pump(irrigation)	4	10	14
2	Flour mill	10	15	25
3	Flour mill(big)	4	8	12
4	Saw mill(big)	10	20	30
5	Oil mill	4	10	14
6	Pottery	120	150	270
7	Garmment	135	200	335
8	Hollow Bricks production	10	20	30
9	Total	297	423	730

Appendix D: Energy Sales Data for Debre Work 15kv Feeder Line

Year	Domestic Demand in KWh	Commercial Demand in KWh	LV Industry Demand in KWh	StrL in KWh	Total Demand in KWh
2008	25,825,008	113,472.39	83,824.99	4,573.38	26,026,879.5
2009	32,212,502	122,163.24	91,179.79	4,619.12	32,430,464
2010	39,404,643.32	131,519.72	99,179.91	4,665.31	39,640,008.26
2011	47,486,797.69	141,592.82	107,881.95	4,711.96	47,740,984.43
2012	56,549,694.37	152,437.41	117,347.51	4,759.08	56,824,238.38
2013	66,695,565.14	164,112.60	127,643.58	4,806.67	66,992,128.00
2014	78,033,232.34	176,681.98	138,843.03	4,854.74	78,353,612.10
2015	90,684,902.54	190,214.05	151,025.12	4,903.29	91,031,045.00
2016	104,781,611.0	204,782.55	164,276.06	4,952.32	105,155,621.9
2017	120,468,482.2	220,466.84	178,689.65	5,001.84	120,872,640.5
2018	137,902,841.3	237,352.40	194,367.88	5,051.86	138,339,613.5
2019	157,257,766.7	255,531.22	211,421.71	5,102.38	157,729,822.0
2020	178,721,775.3	275,102.35	229,971.85	5,153.40	179,232,002.9
2021	202,500,083.2	296,172.44	250,149.59	5,204.94	203,051,610.2
2022	228,818,019.8	318,856.29	272,097.71	5,256.99	229,414,230.7

Appendix E: Voltage Limits Under Different Operating Conditions (ENTGC)

Operating Conditions	Voltage limits(%)
Normal	95-105
Contingency(N-1)	90-110
Multiple contingency	85-120

Appendix F: Material List and Cost Estimation of Debre Work 230kv Substation

Debre Work 230 kV Substation			
Description	Unit	Qty	Unit Price (Eth.Birr)
230 kv Bus Bar System(double bus bar system)			
Aluminum Alloy tube for bus bar	Mts.	495	7,186
Bus bar support insulators	No	30	45,963
Capacitive Voltage Transformers, 230/√3:0.1/√3:0.1/3 kV	No	6	385,594
Bus bar Earthing Switch, 3-pole	Set	2	509,677
2x230 kv Line bay (from Debre markos-Motta Line LILO point to Debre Work town)			
Lightening Arrestors with discharge counter, 198 kv, 10 kA,	No.	6	104,625
Capacitive Voltage Transformers, 230/√3:0.1/√3:0.1/3 kv	No	6	385,594
Center break type, Line Dis-connector with earthing switch, 3-Pole 2000 A	set	2	1,190,025
Current Transformers, 400-800/1/1/1/1A, 4 core,	No	6	519,784
Circuit Breakers, SF6, single pole operation type, 3150A, 31.5kA	No	6	1,070,625
Bus bar Dis-connectors, pantograph type, 3-pole, 2000 A	No	6	1,115,448
Post insulators out door type	No	6	46,209
Conductors, Insulator strings, connectors, Clamps & hardware for equipment interconnections	lot	2	1,145,011
2 x 230 kv SIDE, 230/15 KV, power TRANSFORMER BAY			
Bus bar Dis-connectors, pantograph type, 3-pole, 2000 A	No.	6	1,065,296
Set of Circuit Breakers, SF6, three pole operation type, 3150A, 31.5kA	set	2	3,110,126
Current Transformers, 300-600/1/1/1/1A, 4 core,	No.	6	389,897
Lightening Arrestors with discharge counter , 198 kv, 10 kA,	No.	6	124,692
Post Insulators, out door type	No.	6	44,131

Conductors, Insulator strings, connectors, Clamps & hardware for equipment interconnections	lot	1	1,690,155
OUTDOOR TERMINAL CABINETS			
Outdoor Terminal Cabinets complete with auxiliary devices and terminal blocks	No.	6	365,127
CONTROL & PROTECTION PANELS			
Control and signalling panel for the 230kV lines	No.	2	1,236,247
Control and signalling panel for 230 kV Bus bar coupler bay	No.	1	674,854
Control and signalling panel for two 230/15 kV power transformers	No.	2	1,627,963
Common Control and signalling panel	No.	1	615,619
Protection panel for 230 kV line bays	No.	2	2,166,520
Protection panel for two 230/15kV power transformers circuit protection	No.	2	1,627,963
230 kV Bus bar Protection panel	No.	2	2,596,384
11KV GIS METAL CLAD SWITCHGEAR (INDOOR)			
15 kV transformer incoming cubicle with VT	No.	2	1,954,004
15 kV Outgoing line feeder cubicle	No.	6	1,591,705
15 KV AIS Bus sectionalizer feeder cubicle	no.	1	3,502,844
15 KV AIS Interconnection disconnector cubicle	No.	2	4,744,451
15 /04 kV, 250 kVA, auxiliary transformer, complete with all accessories	No.	1	814,042
15KV OUTDOOR SWITCHGEAR			
15 kV Earthing transformer, complete with all accessories	No.	2	1,286,320
15 kV disconnector with earthing switch, three pole, manual operated, 800A for 15 kV out going lines	Set	6	285,947
15 kV disconnector with earthing switch, three pole, motor operated, 2500A for 15 kV side of transformer	Set	2	345,151
15 kV lightning arrestors with discharge counters	No.	18	10,843
15 kV interconnectors, clamps, support structures, conductors, insulators, fittings, etc	Lot	2	275,720

15 kV galvanized steel structures for eight feeders line landing gantries and shield wire towers including anchor bolts, eyeballs and assembly nuts, bolts, etc	Lot	2	2,538,275
15 kV outdoor post insulators	No.	18	4,254
DIGITAL CONTROL & MONITORING SYSTEM			
Server	No.	1	658,286
Operator work stations with two monitors	No.	1	316,887
Engineering workstation with one monitor	No.	1	246,806
UPS (uninterruptible power supply)	No.	1	755,218
Set of field bus in optical fiber complete of switches, routers & other accessories	No.	1	53,311
Printer (dot matrix black and white)	No.	1	86,088
Printer (dot matrix color printer)	No.	1	240,117
Laser Jet color printer (A3 size paper printing capacity)	No.	1	240,117
LAN complete of switches routers & other accessories	No.	1	53,311
GPS time synchronizing equipment	No.	1	500,155
Clock	No.	1	2,742
Gateway for data transferring to the National Load Dispatch Center	No.	1	665,628
LOW VOLTAGE, AC SUPPLY SYSTEM			
AC auxiliary service board complete with all equipment	Set	1	2,230,242
Emergency lighting system 125 V DC lamps and emergency hand lamps system lighting	Lot	1	236,932
Battery 125 V complete with all accessories (60 cells), 350 Ah	Lot	1	1,435,055
125 V DC, Station Battery charger,	No.	1	879,758
125 V DC auxiliary service board complete with all equipment	Lot	1	748,809
Battery 48V complete with all accessories (26 cells), 250 Ah for RTU & Communication equipment	Lot	1	892,955
48 V DC, station battery charger, 50A,	No.	1	676,337
48V DC distribution panel	No.	1	356,510
STEEL STRUCTURES			

Steel fabricated structure for 230 and 15kV equipment and switch yard bus bar support, line termination gantries, etc.	Lot	1	669,828
RTU, SCADA INTERFACE/CROSS-CONNECTION PANEL			
RTU & Cross connection Panel with all cables and connectors, hardware and soft ware for auxiliary system	Set	1	4,677,961
Updating of LDC data base, interface, setting, configuration, integration to the LDC and communication system. End to end (point-to-point) test with the LDC	Lot	1	4,918,932
FIBER OPTIC COMMUNICATION			
Fiber Optical Transmitter and Receiver equipment PDH/SDH with STM-1 boards, teleprotection interface cards etc. (for 230 kV line bay)	Lot	1	11,656,570
Digital distribution frame (PCM)	Lot	1	984,127
All required telephone and data interfacing equipment	Lot	1	137,267
One set Digital electronic exchange (PABX) equipment complete with 50% spare capacity for future extension including maintenance software, modem, etc.	No.	2	4,054,043
Operator console	No.	2	35,740
Normal subscriber sets, desk type, indoor.	No.	2	18,495
Normal subscriber sets, wall type indoor.	No.	2	13,996
Normal subscriber sets, wall type outdoor, weather proof.	No.	3	13,900
All required LV power cables, and other required installation materials	Lot	1	465,100
Fiber Optic cable from gantry to control room (approach cable).	Lot	1	135,819
All required telephone cables,	Lot	1	449,665
All required suspension, dead end clamps, accessories, installation tools, mechanical fittings, joint closures, substation approach cables, cross connection cabinets for the interconnection of optical fiber ground wire & down lead cables.	Lot	1	1,386,344
MISCELLANEOUS			

Low voltage AC and DC multi-core, multi-pair and auxiliary cables and all necessary glands, installation materials, boxes, racks, conduits, trays, supports, clips, protective covers, sleeves, cleats, etc.	Lot	1	11,018,052
Switchyard lighting system for the substation area.	Lot	1	2,071,353
Supply of embedded steel, anchor bolts, channel, frame, templates, chequered plates, etc.	Lot	1	1,105,010
Boxes for padlocks and keys	Lot	1	45,105
SHIELD WIRE SYSTEM			
Conductor, clamps, hardware, etc for shield wire system.	Lot	1	442,258
POWER TRANSFORMERS			
Power transformers 2x230/15 KV,50MVA, complete with rails and accessories	No.	2	55,544,472
DIESEL GENERATOR			
Standby diesel generating set, 400V AC, 250kVA,0.8p.f. 50Hz, 1500RPM complete with all necessary parts and accessories.	No.	1	3,018,067
CIVIL WORKS			
General site preparation, excavation and top soil removal of the excavated soil (earth work)	Lot	1	650,418
Control building construction	No.	1	4,596,043
Guard house construction	No.	1	320,175
Generator house construction	No.	1	320,175
Single operator's dwelling house construction	No.	4	643,737
Single service quarter construction	No.	1	283,070
Water supply system for control room, guard house, generator house and dwelling houses; including connection with the town municipality water supply line (if it is available) or drilling of under ground water and connection with the substation.	Lot	1	372,900
Septic tank for control room, guard house and dwelling houses	Lot	1	452,640

Cable trenches, ducts & covers and other equipment foundations those are not mentioned in the above item 1 to 25.	Lot	1	4,535,840
Substation internal fence and gates	Lot	1	570,326
Dwelling houses area fence and gates	Lot	1	196,904
Dwelling house area external lighting system installation and access road construction.	Lot	1	1,131,600
Substation external access road to connect the substation with the nearest public road	Lot	1	12,870,072
Storm water and waste water drainage system	Lot	1	2,866,343
Retaining wall (if any)	Lot	1	1,364,710
Landscaping and surface finishing	Lot	1	226,320
Gravelling of the switchyard area	Lot	1	1,081,255
Final site clearing	Lot	1	67,896
Double circuit 230 kV Transmission line From Debre Markos-Motta LILO point to Debre Work	KM	10	12.65million

Appendix G: Number of Population of Enarj Enawga Woreda

Name	Urban			Rural			Year
	Total	Male	Female	total	Male	Female	
Enarj Enawuga	14,413	7,044	7,369	156,625	77,541	79,084	2008
	15,263	7,458	7,806	159,170	78,776	80,394	2009
	16,095	7,860	8,235	161,878	80,093	81,786	2010
Debire Werk	8,206	3,882	4,324				
Felege Birihan	7,888	3,977	3,911				
Enarj Enawuga	17,023	8,312	8,711	164,546	81,389	83,157	2011
Debire Werk	8,680	4,105	4,574				
Felege Birihan	8,343	4,206	4,137				
Enarj Enawuga	17,931	8,751	9,180	167,305	82,735	84,570	2012
Debire Werk	9,143	4,322	4,821				
Felege Birihan	8,788	4,429	4,360				
Enarj Enawuga	19,027	9,285	9,742	169,707	83,910	85,797	2013
Debire Werk	9,702	4,586	5,116				

Felege Birihan	9,325	4,699	4,627				
Enarj Enawuga	20,148	9,831	10,317	171,947	85,005	86,941	2014
Debire Werk	10,273	4,856	5,418				
Felege Birihan	9,875	4,975	4,900				
Enarj Enawuga	21,308	10,396	10,912	173,993	86,000	87,993	2015
Debire Werk	10,865	5,135	5,730				
Felege Birihan	10,443	5,261	5,182				
Enarj Enawuga	22,500	10,980	11,520	175,876	86,944	88,931	2016
Debire Werk	11,472	5,423	6,049				
Felege Birihan	11,027	5,556	5,471				
Enarj Enawuga	23,724	11,576	12,148	177,667	87,839	89,828	2017
Debire Werk	12,097	5,718	6,379				
Felege Birihan	11,627	5,858	5,769				
Enarj Enawuga	25,045	12,223	12,822	179,183	88,592	90,591	2018
Debire Werk	12,770	6,037	6,733				
Felege Birihan	12,275	6,185	6,089				
Enarj Enawuga	26,353	12,863	13,490	180,710	89,356	91,354	2019
Debire Werk	13,437	6,354	7,083				
Felege Birihan	12,916	6,509	6,406				
Enarj Enawuga	27,764	13,554	14,210	182,013	90,009	92,004	2020
Debire Werk	14,156	6,695	7,462				
Felege Birihan	13,607	6,859	6,748				
Enarj Enawuga	29,155	14,232	14,924	183,326	90,662	92,664	2021
Debire Werk	14,866	7,029	7,836				
Felege Birihan	14,289	7,202	7,087				
Enarj Enawuga	30,656	14,966	15,690	184,425	91,214	93,210	2022
Debire Werk	15,631	7,392	8,239				
Felege Birihan	15,025	7,574	7,451				