Medium Term Load Forecasting and Transmission Line Expansion Planning
(Case Study: Gefersa to Fiche Transmission Line)

Alemach Kahsay Gebre-Mikael

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

September, 2023
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DECLARATION

I declare that this thesis entitled **"Medium Term Load Forecasting and Transmission Line Expansion Planning (Case Study: Gefersa to Fiche Transmission Line)"** is my work and has not been submitted to any university for a similar purpose. The references used in this proposal are duly recognized by proper citations.

______________________	________________	________________
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 "**Medium Term Load Forecasting and Transmission Line Expansion Planning (Case Study: Gefersa to Fiche Transmission Line)"** prepared under my/our guidance by **Alemach Kahsay Gebre-Mikael** 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.

______________________	______________________	_______________
Advisor Name	Signature	Date

APPROVAL PAGE

I the advisors of the thesis entitled "**Medium Term Load Forecasting and Transmission Line Expansion Planning (Case Study: Gefersa to Fiche Transmission Line)**" and developed by **Alemach Kahsay Gebre-Mikael** hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

__________________	________________	___________
Advisor Name	Signature	Date

We, the undersigned, members of the Board of Examiners of the thesis by **Alemach Kahsay Gebre-Mikael** have read and evaluated the thesis entitled "**Medium Term Load Forecasting and Transmission Line Expansion Planning (Case Study: Gefersa to Fiche Transmission Line)"** 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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ABSTRACT

A sustainable supply of electric power is a prerequisite to foster all sorts of development in any country. Development of electricity infrastructure is undoubtedly a capital-intensive project that needs a careful planning, especially when future expansion of Generation and Transmission Line is taken into consideration. In this thesis load forecasting of Gefersa-Fiche 66kv transmission line from 2023-2027 was carried out using ANN and the forecasted load was 31.90MW.Then, we have used PSS/E software for network modeling and load flow analysis. There are many cost optimization methods, but, Particle Swarm Optimization, or PSO for short, has been used because it has fewer parameters to adjust, it is easy to implement and program, also it gets the best solution via particle's interaction. PSO is based on the analogy of bird and fish swarms that school together to achieve efficient search through memory and feedback systems. The existing Gefersa-Fiche 66kv transmission line supply carries a maximum active power of 21.6MW but, the existing required power in Fiche was 28.09MW. Therefore this transmission line supply didn't satisfy the demand in that area. Then supplying 230kv transmission line from Gerbe-Guracha substation to Fiche substation has been chosen considering the existing demand, future demands and cost optimization out of the three options (Gefersa *to Fiche 132kv, Gerbe-Guracha to Fiche 230kv and Chancho to Fiche 132kv) transmission lines to balance demand and supply in Fiche and surrounding areas.*

Key words; *Load flow analysis, Medium Term load forecasting, Power System Simulation for Engineers (PSS/E), Transmission expansion planning*

LIST OF ACRONYMS

AI	Artificial Intelligence
ANC	American National Standards Institute
ANN	Artificial Neural Network
EEP	Ethiopian Electric Power
EEU	Ethiopian Electric Utility
EPG	Ethiopian Power Grid
FL	Fuzzy Logic
GA	Genetic Algorithm
GDP	Gross Domestic Product
EEPCO	Ethiopian Electric Power Corporation
SVR	Support vector regression
ARMA	Auto Regression Moving
AR	Auto Regression
IEEE	Institute of Electrical and Electronics Engineers
MATLAB	Matrix Laboratory
PSS/E	Power System Simulation for Engineers
PSO	Particle Swarm Optimization
EEP	Ethiopian Electric Power
EAPP	East African Power Pool
MSE	Mean Square Error
PB	Parsons Brinkerhoff
FBIO	Forensic Based Investigation Optimization
WAKA	Waikato Environment for Knowledge Analysis
TEP	Transmission Expansion Planning
GDP	Gross Domestic Product
GWh	Giga watt hour
MW	Mega watt
ETB	Ethiopian Birr

CHAPTER ONE

1. INTRODUCTION

1.1 Background

Ethiopian power market was controlled and managed by sole company called Ethiopian Electric Power Corporation (EEPCO). In the last few years the company has been divided into two. They are Ethiopian Electric Power (EEP) and Ethiopian Electric Utility (EEU). EEP is responsible in generating & transmitting to deliver power for EEU which is responsible for distributing and selling power to the end customer.

In Ethiopian Power Grid (EPG) there are 500kV, 400kV, 230kV, 132kV, and 66kV and 45kV transmission/sub-transmission system voltage levels; 33kV and 15kV distribution system voltage levels. The 15kV is the voltage level where almost all customers are connected through distribution transformers. Power system expansion is a concern to be considered carefully in the electricity sector.

Consumers need reliable service from the sector to be delivered when they need not when the service provider need. The electric service provider has a key indication parameter when and where the consumers need electricity through forecasting depending on the GDP growth rate, extrapolated number of consumers, and random load demand request.

Fiche is the capital town for North Shewa zone (Oromia Region) which is located about 120km from Addis Ababa. Its latitude and altitude is 9°48’N 38°44E and its elevation is between 2,738meters and 2782 meters above sea level.

Due to population growth and industry expansion at Fiche town, the energy demand is radically growing. Meanwhile the electric energy supply capability of Gefersa-Fiche 66kV transmission line does not satisfy demand growth in the area. Due to this, the customers in the city are complaining for frequent power interruption.

Fig. 1.1: Overview of Fiche Substation

1.1.1 Existing Electric Power Supply of Fiche Town

Fiche 66kV Substation has 2 (Two) 66/33/15KV, 12/12/8MVA transformers with a 66kV supply line from Gefersa 230/132/66kV substation. One of the 66/33/15KV, 12/12/8MVA power transformers is supplying power only to 15KV loads and the second 66/33/15KV, 12/12/8MVA power transformer which is currently sitting idle used to supply power to 33KV loads. Due to Gefersa 132/66/15kV transformer capacity limitation, the maximum electric power which can be provided at Fiche substation currently is 12MVA. In addition, the 66kV line is a wooden pole with a conductor of type ACSR Merlo which has a thermal rating of 24MVA.

The existing Fiche Substation with its two transformers is shown below figure 1.2.

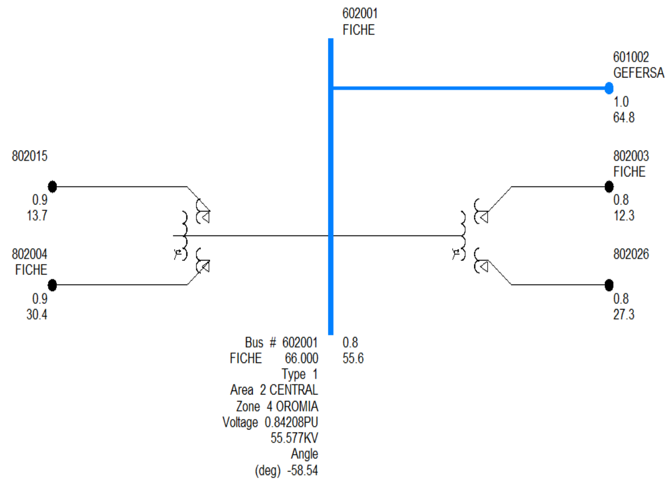


Fig. 1. 2: Fiche Existing 66KV Substation Topology

1.2 Statement of the Problem

Power consumption and power demand is always growing in every power sector. In power systems load forecasting is necessary to perform expansion planning. Because of lack of proper planning, a lot of power is lost in generation, transmission and distribution system. So that, there is a need of forecasting the load demand and make ready the necessary generation, transmission, and distribution infrastructures.

Fiche town is located 120 km from Addis Ababa. There are so many customers in Fiche town but, there is a large gap between the customer's power demand and the power supply. The thermal rating of Gefersa-Fiche 66kv transmission line is 24MVA, then the maximum active power carrying capacity of this transmission line is 21.6MW but, due to aging of the transmission line it carries below 21.6MW and the existing power demand of this area is 28.09MW. As a result, unbalance between the customer's power demand and power supply occurs. Therefore, an expansion planning of Gefersa to Fiche Transmission Line is required.

1.3 Objectives:

1.3.1 General Objective

The general objective of this thesis is to carry out load forecasting for Fiche town and to model transmission line expansion planning of the existing Transmission line.

1.3.2 Specific Objectives

The specific objectives of this thesis include the following:

- ✓ To study the existing system as a whole.

- ✓ To develop load forecasting using Artificial Neural Network (ANN) and MATLAB software.
- ✓ To develop Load flow analysis using PSS/E software.
- ✓ To model transmission line expansion planning of Gefersa to Fiche Transmission Line.
- ✓ To develop cost optimization using PSO algorithm.

1.4 Scope of the Study

Scope of the study includes forecasting load demand of Fiche using five years historical load data, and number of consumers and expansion planning of Gefersa-Fiche transmission line. Fiche transmission line voltage level included in this study is 66kV.

1.5 Significance of the Study

Power demand from Fiche has grown to an extent where it is not possible to secure additional power to consumers. To meet current and future power demand from this transmission line, assessment has to be done considering demand growth of the city, to see how the system will respond if all loads are going to be peak, to determine outstanding transmission expansion, need and make decisions to coordinate further project works and finally to suggest further studies on the gaps or problems faced when this thesis is conducted.

1.6 Motivation of the Study

Transmission line expansion planning analyzes the issue of how to expand or reinforce an existing power transmission line to adequately service system loads over a given time horizon. This problem is challenging for several reasons.

1, Transmission investments are capital intensive and have long useful lives (up to 40 years), which makes transmission investment decisions to have a long-standing impact on the power system as a whole.

2, Energy production and use is interconnected with many other aspects of modern life, such as water consumption, use of goods and services, transportation, economic growth, land use and population growth. Thus, changes in any of these variables might influence load demands, and thereby affect transmission line expansion planning.

CHAPTER TWO

2. LITERATURE REVIEW

2.1 Theoretical Background

Accurate load forecasting will aid both the electricity generation, transmission and the distribution companies to make unit commitment decisions with regards to power, load switching, voltage control, network reconfiguration, and infrastructure development (E. C Ashigwuike, 2020). It also reduces the generation cost and increases reliability of power systems. Because of how important load demand forecasting has become overtime, research has been intensified in this field, with different models being developed and employed by different researchers for short-term, medium-term and long-term load forecasting over the last decade.

Load demand forecasting is an essential process in electric power system operation and planning. It involves the accurate prediction of both magnitudes and geographical locations of electric load over the different periods of the planning horizon. Many economic implications of power utility such as economic scheduling of generating capacity, scheduling of fuel purchases, security analysis, planning of power development, maintenance scheduling and dispatching of generation units are mainly operated based on accurate load forecasting(Prommee, 2016). In the past years, improvements in electricity access have been made. The proportion of the population with access to electricity increased from 43% in 2010 to 51% in 2020 (Pappis, 2019).However, during the same period, the total number of people without access to clean cooking fuel remained stable. Lack of access to clean cooking facilities means that, in many countries' women need to spend average of an hour per day to collect fuel wood and several hours to cook with inefficient stoves. Indoor air pollution has health implications and increases the number of premature deaths. Meeting the energy demand required for Africa's transformation is difficult. Accurate medium-term electric load forecasting plays an essential role for electric power system planning (Naji Ammar, 2018). It corresponds to load forecasting with lead times long enough to plan for medium-term maintenance, construction scheduling for developing new-generation facilities, purchasing of generating units, and developing of transmission and distribution systems.

The aim of load forecasting is to estimate the load pattern. There are several factors that should be taken into consideration for load forecasting, which can be classified as economic factor, weather condition and customer factor (Pappis, 2019).

Artificial Neural Network (ANN) developed by Warren McCulloch and Walter Pitts in 1943 is one of the widely used supervised learning approaches which was inspired by the structural complexity of the human brain(Arthur, C. K., Temeng, V. A. and Ziggah, Y. Y., 2020).The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in uniting to solve specific problems. ANNs, like people, learn by example. Neural networks are essentially nonlinear circuits that have the demonstrated capability to do non-linear curve fitting (Baglaeva, 2011). ANN is always referring to a category of modules inspired by the biological nervous system.

A neural network layer can be categorized as input layer, hidden layer, and output layer. A hidden layer is simply a layer between the input layer and output layer. ANN with one or more hidden layers is known as multilayer perceptron (MLP) and ANN without hidden layer is known as single layer neural network (SLNN)(Arjuna Baliyan, Kumar Gaurav, and Sudhansu Kumar Mishra, 2015) .

The general interest in neural networks arises from their fascinating features that enable them to overcome some of the limitation of conventional information processing system like a need of detailed programming. They have some inherent distinct capabilities unavailable in other methods (Chaudhari, 2017). Medium-term load forecasting is done in (Ramachandran, 2011) by using end use approach. Ideally end-use approach is very accurate but is very sensitive to the quality and end user's data. The big problem with this approach is that, most end use model assumes a constant relationship between electricity and electricity per appliance (M D. H., 2008). It gives a mathematical demand forecast without considering of customers" behavior, demographic, socioeconomic and cultural factors. Methods, based on artificial neural networks, can solve various power system problems, such as design, planning, control, protection, security analysis, fault diagnosis and load forecasting. Artificial neural networks are very popular in load forecasting because of their ability in mapping complex non-linear relationships. Load forecasting and generation expansion planning was done using Waikato Environment Acknowledgment (WEKA) in (Jemal, 2017) and authors suggest that applying Artificial Neural Network (ANN) to forecast the Medium-term demand is advantageous than WEKA for better accuracy. A short-term (next-day) EED forecasting model based on the historical meteorological parameter to forecast the future load on the Greek Electric Network Grid using Support Vector Machine (SVM), ensemble XGBoost, Random Forest (RF), k-Nearest Neighbors(KNN), Neural Networks (NN) and Decision Trees (DT) was proposed by (P-N, 2017).

Al-Saba and El –Amain(Motepe S, 2019) used artificial neural network for medium-term electricity load forecasting using Saudi Arabian Utility data. The utility provides service to large industry, commercial and residential load. They compared the result of ANN with Auto Regression (AR) and the obtained result showed that ANNs provides relatively accurate result over Auto Regression (AR). This is due to ANNs methods are able to automatically map the relationship between input and output by learning this relationship and store this learning.

The other category to be reviewed is transmission expansion planning. Transmission expansion planning used (OVA, 2022)an analytical algorithm which has been implemented for specific load condition with variations in generation and the power system operation condition will not be disturbed or compromised (George A. Orfanos, 2013).For that purpose, an economical factor has been measured that considers economic aspects of the line to be added for expansion. The prescribed analytical approach is also implemented for its feasibility check on a practical case study system(OVA, 2022).

TEP is classified as static and dynamic according to planning time (S. L. Gbadamosi and N. I. Nwulu,, 2020). Static TEP is concerned with where and how many a new transmission line will be added to the system for only one time slot during the planning period, with minimum cost (OVA, 2022).Unlike static TEP, in dynamic TEP, the planning period is divided into multiple time intervals and the planning study is carried out for each time interval (E. G. Morquecho, S. P. Torres, N. E. Matute, F., 2020).

2.2 Load Forecast Technique and Time Horizons

2.2.1 Load Forecast Time Horizons

Forecasting is simply a systematic procedure for quantitatively defining future loads. Depending on the time period of interest, a specific forecasting procedure it is classified as short-term load forecasting, medium -term load forecasting and long-term load forecasting. According to (R.L.Sullivan) for planning of generation, transmission and distribution facilities must begin 4-10 year in advance of the actual in-service date.

2.2.1.1 Long Term load forecasting

Long-term forecast time period varies from 15 to 20 years of 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 and also it indicates the energy policies.

2.2.1.2 Medium Term load forecasting

Medium-term forecasts time period vary from 5 to 6 years of planning and size of the power station. It indicates the transmission and distribution losses. Also, Medium term forecast indicates the Energy conservation. According to EEP master plan, For least-cost power development planning, a forecast of sent-out energy (MWh or GWh) and sent-out maximum demand (MW) is required in the medium-term load forecasting.

2.2.1.3 Short Term Load Forecasting

Short-term forecasts of 1 to 2 years are mainly of value in deciding operating procedures and preparing budget estimation. Short term forecast indicates the sales and purchase of the power and development of distribution networks.

2.2.2 Load Forecast Technique

The only thing about load forecasting that is certain is, the results won't be what you want to be. To address this variation of unmatched results, it is crucial to develop a proper demand forecasting method. For forecasting loads, there is no such thing as an inappropriate technique. Parametric and artificial intelligence-based methodologies make up the two categories of load forecasting techniques. In order to build a statistical model of load, parametric approaches examine the qualitative connections between load and its influencing elements. These techniques include moving averages, auto-regression, multiple linear regression, and needed assumed parametric estimates from historical data. They frequently cannot handle interactions that are random or nonlinear between the load and the elements that impact the load. Fuzzy logic, artificial neural networks (ANN), dynamic theory (DT), and particle swarm optimization (PSO) are examples of artificial intelligence techniques. In addition, a number of hybrid methods (Girma, 2019) integrate the strengths of separate approaches to enhance the accuracy of medium-term load forecasting (MTLF).

2.3 Artificial Neural Network

This thesis provides a thorough theoretical explanation of an artificial neural network, its parts, and the knowledge of how they act to operate a machine.

2.3.1 What Is an Artificial Neural Network?

An artificial neural network is a linked collection of basic processing units, often known as nodes, whose operation is somewhat modeled after that of an animal neuron. The inter unit connection strengths, or weights, acquired through a process of adaptation to, or learning from, a set of training patterns, are where the network's processing power is stored (Simon). To further develop this, let's first quickly review some fundamental neuroscience. The estimated 100 billion nerve cells or neurons that make up the human brain are depicted in Figure 2.1 in a highly stylized manner. Electrical signals, which are brief impulses or "spikes" in the voltage of the cell wall or membrane, are used by neurons to communicate.

Electrochemical junctions called synapses, which are found on cell branches known as dendrites, mediate the inter neuron connections. Each neuron typically has thousands of connections to other neurons, which results in a continual influx of messages that finally reach the cell body. Here, they are combined or integrated in some manner, and the neuron will "fire" or produce a voltage impulse in response if the resulting signal is greater than a predetermined threshold. The axon, a branching fiber, is subsequently used to relay this to additional neurons (Simon).

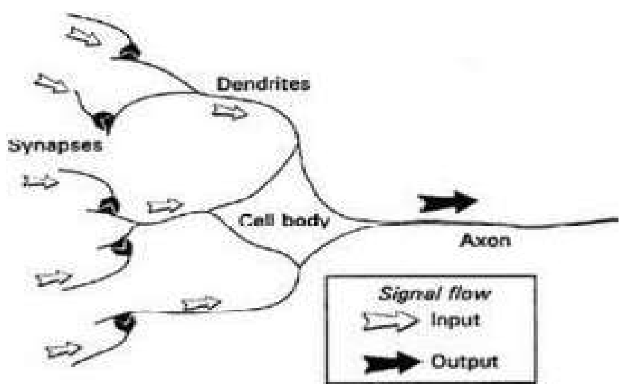


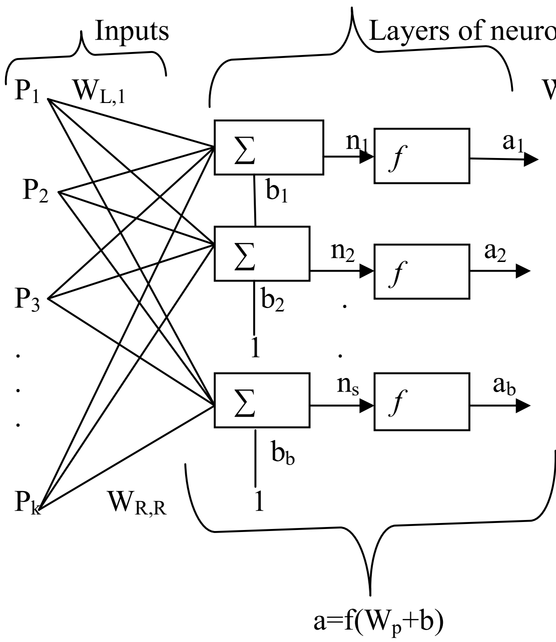
Fig. 2.1: ANN Components

Some incoming signals have an inhibitory effect and tend to prevent firing, while others have an excitatory effect and tend to encourage the generation of impulses. According to (Simon and Haykin), the kind (excitatory or inhibitory) and strength of each neuron's synaptic connections with other neurons determines how each neuron processes information differently. Because of the emphasis on the significance of inter-neuron connections, this form of system is occasionally referred to as being connectionist, and the study of this general approach as connectionism. It is this design and style of processing that we seek to incorporate in neural networks. When discussing models of human cognitive function that are psychologically inspired, this language is frequently used to refer to neural networks. Nevertheless, we will use it quite broadly to refer to neural networks without mentioning any specific application areas.

2.3.2 Neural Network Architectures

2.3.2.1. One Layer of Neurons

A one-layer network with *R* input elements and *S* neurons follow.



Where,

R= number of elements in input vector

S=number of neurons in layer

Fig. 2.2: One Layer of Neurons

Each input neuron in this network is linked to an element of the input vector p via the weight matrix W. A summer in the i^{th} neuron collects its weighted inputs and bias to create its own scalar output, n(i). An S-element net input vector n is formed when all of the n(i) are combined. The neuron layer outputs culminate in a column vector called a. The following figure displays the expression for a.

Where,

$$W=\begin{bmatrix} W1,1 & \cdots & W1,R \\ \vdots & \ddots & \vdots \\ Ws,1 & \cdots & Ws,R \end{bmatrix} \tag{2.1}$$

Be aware that R is not always equal to S and that the number of inputs to a layer frequently differs from the number of neurons. The number of inputs to a layer does not have to match the number of neurons in the layer**.**

2.3.2.2. Multiple Layers of Neurons

Multiple levels are possible in a network. A weight matrix W, a bias vector b, and an output vector are present in every layer. The layer number is added as a superscript to the variable of interest in the figures to help distinguish between the weight matrices, output vectors, etc. for each of these layers.

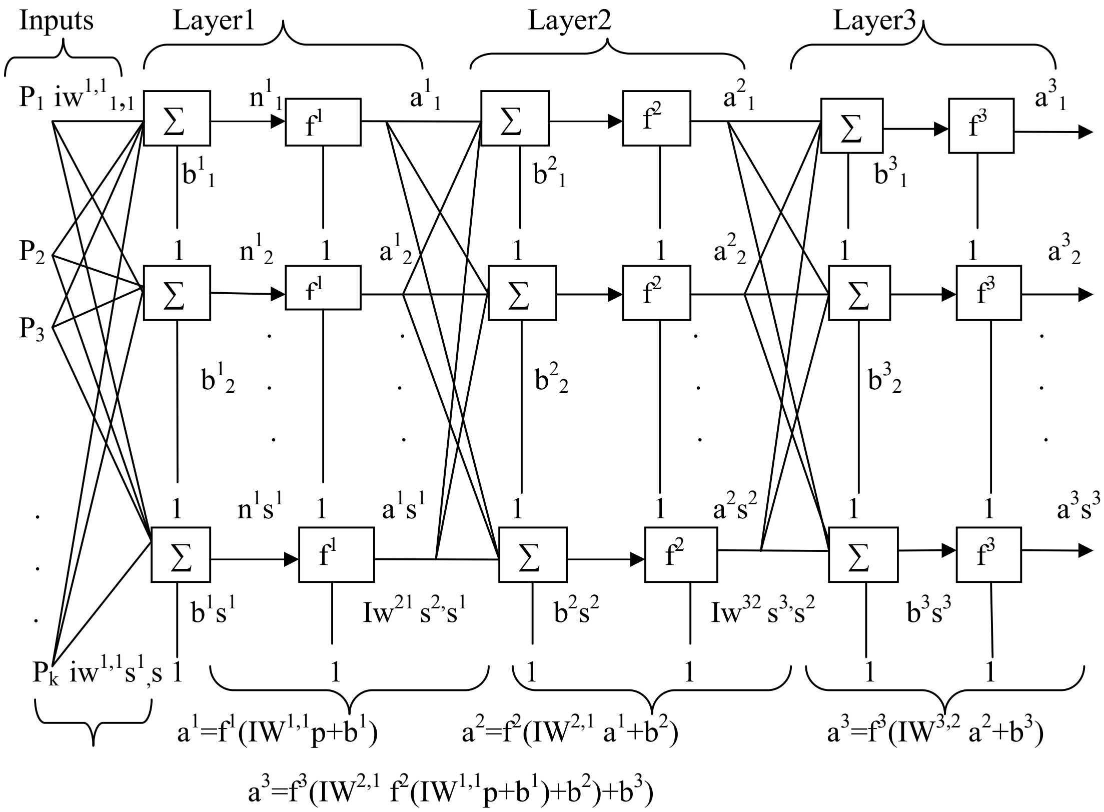


Fig.2.3: Multiple Layers of Neurons (Simon and Haykin)

R_1 inputs, S_1 neurons in the first layer, S_2 neurons in the second layer, etc. are all features of the network in the figure above. Different layers frequently include varying numbers of neurons. Each neuron's bias is supplied by a fixed input 1, which is constant. Keep in mind that each intermediate layer's output serves as the next layer's input. Since layer 2 has S_1 inputs, S_2 neurons, and S_2S_1weight matrixW_2, layer 2 can be examined as a single-layer network. a_1 is the input, and a_2 is the output of layer 2. Since layer 2's vectors and matrices have all been recognized, layer 2 may now be thought of as a standalone single-layer network. This approach can be taken with any layer of the network. Different responsibilities are played by the layers of a multilayer network. An output layer is a layer that creates the network output. The term "hidden layers" refers to all other layers. One output layer (layer 3) and two hidden layers (layers 1 and 2) make up the three-layer network that was previously illustrated. The inputs are referred to as a fourth layer by certain authors. That description is not applicable to this toolkit. The notation R S_1S_2 ... SM, where the number of input vector elements and the number of neurons in each layer are provided, can be used to describe the architecture of a multilayer network with a single input vector.

2.3.3 Feed-Forward Neural Network

2.3.3.1 Single Layer Feed-Forward Networks

The neurons in a layered neural network are arranged in layers. In the most basic configuration of a layered network, source nodes in the input layer project directly onto neurons in the output layer (computation nodes), but not the other way around. To put it another way, this network is wholly of the feed-forward variety. Figure 2.4 illustrates the scenario when there are four nodes in the input and output layers. The output layer of computing nodes (neurons) in such a network is referred to as the "single-layer" layer, hence the name. The input layer of source nodes is not included in our calculation because no processing takes place there.

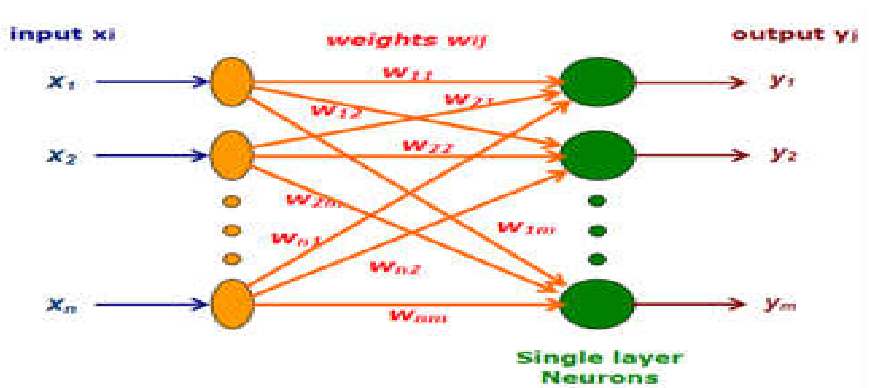


Fig. 2.4: Single Layer Feed-Forward Networks

2.3.3.2 Multilayer Feed-Forward Networks

The presence of one or more hidden layers, whose computation nodes are referred to as hidden neurons or hidden units, distinguishes the second class of feed-forward neural networks. The term "hidden" refers to the fact that this portion of the neural network is not directly visible from either the input or output of the network. The purpose of hidden neurons is to act as a beneficial intermediary between the network output and external input. The network is given the ability to extract higher-order statistics from its input by adding one or more hidden layers. Due to the additional set of synaptic connections and the additional dimension of neural interactions, the network, in a somewhat loose sense, gains a global perspective despite its local connectedness. The input layer of the network's source nodes provides the corresponding components of the activation pattern (input vector), which make up the input signals applied to the neurons (computation nodes) in the second layer (i.e., the first hidden layer). The second layer's output signals are used as the third layer's inputs, and so on throughout the rest of the network. Neurons in each layer of the network typically only receive the output signals from the layer before them as inputs. The network's overall reaction to the activation pattern provided by the source nodes in the input (first layer) layer is represented by the collection of output signals produced by the neurons in the output (final) layer of the network.

Feed-forward networks are made up of several layers. The network input is connected to the top layer. There is a connection from the previous layer to each succeeding layer. The output of the network is produced by the top layer. Any input-to-output mapping can be done using feed-forward networks. Any finite input-output mapping problem can be solved using a feed-forward network with one hidden layer and enough neurons in the hidden layers.

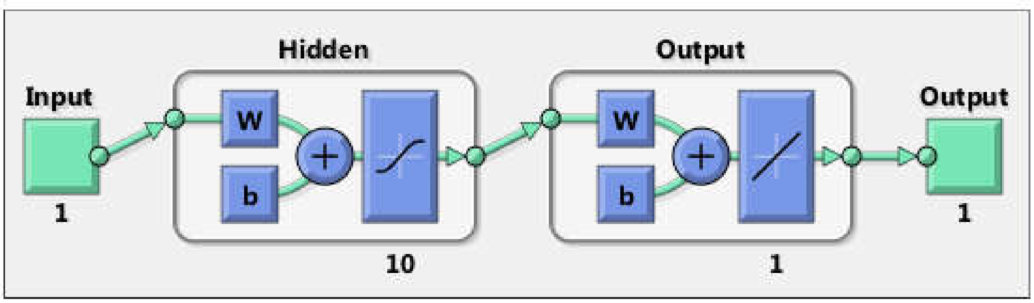


Fig. 2.5: Multi-Layer Feed-Forward Neural Network

2.4 Learning Processes of an ANN

As there are various ways that we, as individuals, learn from our own circumstances, so too are neural networks. We may broadly group the learning mechanisms that neural networks use into the following categories: Learning that is supervised and un-supervised.

2.4.1 Supervised Learning Process

A teacher must provide the neural network with a target response for supervised learning to take place. The network parameters change under the combined influence of the training vector and error signal using the training vector and error signal. To get the neural network to mimic the teacher, error correction learning (a gradual modification procedure) is performed. The training set for supervised learning comprises input patterns and their accurate outcomes, which are represented by the precise activation of all output neurons. As a result, the output, for example, can be immediately compared with the right answer, and the network weights can be adjusted in accordance with the difference for each training set that is fed into the network. The goal is to adjust the weights so that the network can reliably predict unknown, comparable input patterns in addition to independently associating input and output patterns during training.

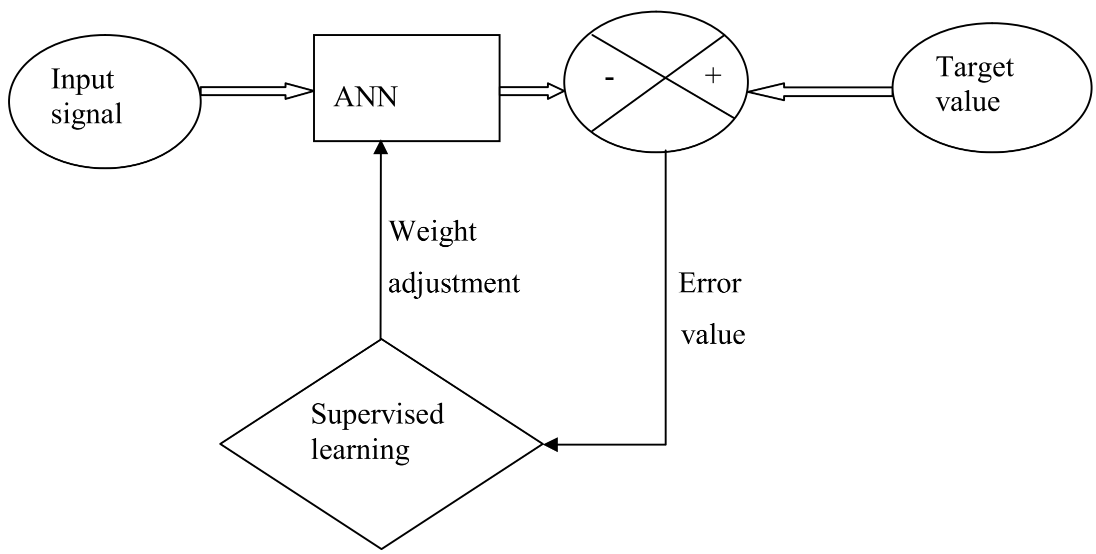


Fig. 2.6: Supervised Learning Process

2.4.2 Unsupervised Learning Process

Without the aid of a teacher, the learning process is unsupervised or self-organized. In other words, the network does not need to learn any particular examples of the function. The network can automatically generate internal representations for encoding aspects of the input data once it has a grasp of the statistical regularities of the input data. Although unsupervised learning is the approach that makes the most biological sense, it is not appropriate for all issues. The network attempts to find comparable patterns and classify them into related groups using only the input patterns (Girma, Long Term Load Forecasting and Transmission System Expansion Planning, 2019).

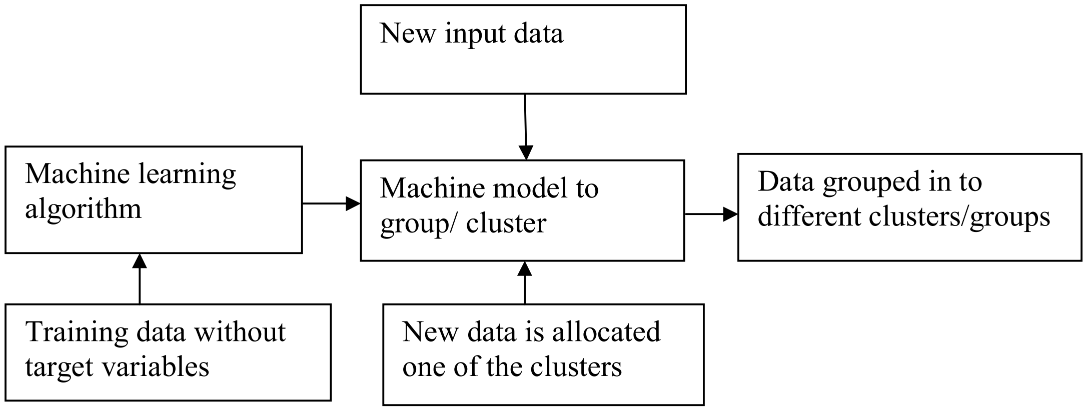


Fig.2.7: Unsupervised Learning Process

2.5 Transmission Line Optimization Techniques

The key objective of transmission planning problem is to ensure sufficient transmission capacity for the current and future load of a power system at a minimum investment cost as well as minimum loss of load cost. Investment cost is the total capital spent on installing new transmission lines along with reinforcement of the existing network.

Transmission line optimization techniques can be classified in to mathematical optimization, heuristic optimization and Meta heuristic optimization methods.

2.5.1 Mathematical Optimization Methods

Mathematical optimization methods search for an optimal expansion plan by using a calculation procedure that solves a mathematical formulation of the planning problem. In the problem formulation, the transmission expansion planning is converted into an optimization problem with an objective function subject to a set of constraints (Mohit Poonia, 2Ram Avtar Jaswal, 2014). Mathematical optimization methods are known to be effective to solve simple and linear optimization problems with a relatively small search space, guaranteeing convergence toward the best solution. However, in combinatorial explosion problems with large search space, these methods tend to demand higher and sometimes unaffordable computational efforts. Furthermore, mathematical optimization techniques cannot guarantee the global optimum of a problem if nonconvexities are content within the search space (Meisam Mahdavi , Carlos Sabillon Antunez , Majid Ajalli , and Rub´en Romero, 2018).

2.5.2Heuristic Optimization Methods

These methods analyze possible options and logically select good quality solutions using simple step-by-step search processes. Although heuristic methods can find feasible solutions with low computational effort, they can guarantee neither good quality nor optimality of solutions.(Meisam Mahdavi , Carlos Sabillon Antunez , Majid Ajalli , and Rub´en Romero, 2018). Also, its application is complicated on networks with a large number of expansion candidates (new transmission lines which can be installed in the network).

2.5.3 Meta heuristic Optimization Methods

Meta-heuristics involve applying heuristic techniques iteratively in order to find good quality solutions, using smart-criteria in the optimization process. Although they represent a higher computational burden, they can lead to better solutions when compared to heuristics. On the other hand, meta-heuristics tend to find high quality solutions with less computational burden in comparison with mathematical optimization methods. Meta-heuristic algorithms are designed to reliably obtain optimal solutions from different types of problems (Ahmet Ova, et al, 2022).

Due to the versatility of these methods, it is possible to solve complex TEP models over large-size test systems.

Tabu Search (TS), Simulated Annealing (ST), Particle Swarm Optimization (PSO) and Grey Wolf Optimizer (GWO)etc are some examples of Meta-heuristic optimization methods.

A. Tabu Search (TS)

Tabu search (TS) is an iterative improvement procedure that starts from some initial feasible solution. The implementation of tabu search was proposed to cope with long-term transmission network expansion planning problem. The disadvantages of tabu search include that it can make the tabu list less reliable and predictable, which can inject some unpredictability and uncertainty into the search process. Particularly if the aspiration criteria are too weak or too frequent, this may have an impact on the convergence and stability of tabu search.

B. Simulated Annealing (SA)

Simulated annealing is a metaheuristic that can be used to approximate global optimization in a large search space. This optimization method is able to locate the global optima for numerous local optima and it is frequently employed when the search space is discrete. It normally begins in one valley and descends to that valley's lowest point.

C. Particle Swarm Optimization (PSO)

Particle Swarm Optimization, or PSO for short, is based on the analogy of bird and fish swarms that school together to achieve efficient search through memory and feedback systems. PSO has strong performance for optimization issues by mimicking the behaviors of biomes. Swarms begin at several locations throughout the mountain range and simultaneously hunt through numerous valleys for the lowest spot. PSO's key benefit is having fewer parameters to adjust, easy to implement and program, also it gets the best solution via particle's interaction.

D. Grey Wolf Optimizer (GWO)

A population-based meta-heuristics algorithm called Grey Wolf Optimizer (GWO) imitates the hierarchy of authority and hunting techniques of grey wolves in the wild. The drawbacks of GWO include its slow convergence rate, poor solution precision, and propensity to easily enter the local optimum.

2.6 Transmission Network Model

In general, for transmission planning studies, the power system can be modeled with one of the following models:

1- Alternating Current (AC) model

2- Direct Current (DC) model

2.6.1 AC Model

There is no simplification in the AC model. Consequently, a power system's variables have a nonlinear relationship. Equations (2.1) and (2.2), respectively, give the reactive power (Q_k) and active power (P_k) flowing in a transmission line k between buses i and j.

$$P_k = V_i V_j \left(G_{ij}Cos(\theta_i - \theta_j) + B_{ij}Sin(\theta_i - \theta_j)\right) - G_{ij} \tag{2.2}$$

$$Q_k = V_{ij} \left(Sin(\theta_i - \theta_j) - B_{ij}Cos(\theta_i - \theta_j)\right) - B_{ij}{V_i}^2 \tag{2.3}$$

2.6.2 DC Model

In order to solve this planning challenge for long-term TEP research, several assumptions are made and introduced. For instance, reactive power allocation is not taken into account at the beginning of the planning process. Finding the primary power corridors that will likely be included in the expanded system is the main focus at this point(Mohit Poonia, 2Ram Avtar Jaswal, 2014).

2.7 Transmission Line Constraints

Optimum power flow (OPF) constraints can be categorized into two types: 1) equality and 2) inequality constraints.

2.7.1 Equality Constraints

The equality constraints of the optimum power flow show the physical condition of a power network.

$$P_{Gi} - P_{Di} = V_i \sum_{i=1}^{N} V_j\left(G_{ij}\cos\delta_{ij}\right) + \left(B_{ij}\sin\delta_{ij}\right) \tag{2.4}$$

$$Q_{Gi} - Q_{Di} = V_i \sum_{i=1}^{N} V_j\left(G_{ij}\sin\delta_{ij}\right) + \left(B_{ij}\cos\delta_{ij}\right) \tag{2.5}$$

WhereP_{Gi} andQ_{Gi} represent the real and imaginary parts of a power network, P_{Di}andQ_{Di} are the real and imaginary parts of the network demands on thei^{th} bus. Moreover,B_{ij} andG_{ij} reflect the susceptance and conductance between the node i and j. $\delta_{ij} = \delta_i - \delta_j$denotes a change in voltage angle. N represents the number of buses.

2.7.2 Inequality Constraints

The inequality constraints, confines the physical devices to certain limits, to assure the security of the power network. Active power outputs, reactive power outputs, the voltage of all the generator units as well as slack should be limited by their upper and lower limits as formulated.

$$P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max}, \text{ i= 1,2,3 ...}, N_G - 1 \tag{2.6}$$

$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max}, \text{i= 1,2,3 ...}, N_G \tag{2.7}$$

$$V_{Gi}^{min} \le V_{Gi} \le V_{Gi}^{max}, \text{ i= 1,2,3 ...}, N_G \tag{2.8}$$

Security constraints, such as the voltage values of P_Q buses and voltage of transmission line should be limited within the boundaries of its capacity. Which can be formulated as follows:

$$V_{line\ i}^{min} \le V_{line\ i} \le V_{line\ i}^{max}, \text{ i= 1,1,3 ...,NL} \tag{2.9}$$

$$S_{line\ i} \le S_{line\ i}^{max}, \text{ i= 1,2,3 ...,NL} \tag{2.10}$$

Where, NL is number of lines.

2.8 Related Works

(Motepe S, 2019) proposed an adaptive neuro-fuzzy inference system (ANFIS) model for forecasting South African electricity demand using previous year transformer loading data and temperature as an input. But, humidity, GDP data were not considered and adding temperature as an input parameter to the proposed model did not enhance forecast accuracy, as typically expected.

Demand forecasting is done by EEP from 2018 to 2030 using linear regression method. In the forecasting, using linear regression, only previous year demand data is considered and factors such as GDP growth, population growth and humidity and others that affect demand forecasting could not be included. Due to this fact, linear regression-based load forecasting method led to inaccurate future demand estimation and thus the future load is underestimated.

Also another attempt was made to forecast the electricity consumption of Ghana by 2030 using ARMA-based model. The study outcome projected that Ghana's electricity consumption would grow from 8.5210 billion kWh in 2012 to 9.5597 billion kWh in2030 (M. A. Momani, 2016). However, in 2017, a report by the energy commission revealed that electricity consumption was 14,247 GWh (J. X. Zhao, 2021).

Transmission line expansion was done by (Ahmet Ova, et al, 2022) using FBIO algorithm in a DC model, but, it is the linearized and simplified version of the AC model and does not deal with power flow parameters such as line losses, reactive power flow, voltage variation.

Transmission Expansion Planning in Low-Carbon Energy System Models has been done in (Fabian Neumann and Tom Brown , 2019) using heuristic optimization with big-M method, but, big-M method adds new parameter and also too small value doesn't guarantee the convergence to the same optimum of the original problem while too big value generates loss of precision and numerical instabilities.

Medium-term load forecasting is done in (M G. L., 2008) by using end use approach. Ideally end-use approach is very accurate but is very sensitive to the quality and end user's data. The big problem with this approach is that, most end use model assumes a constant relationship between electricity and electricity per appliance (Yang L, 2018). It gives a mathematical demand forecast without considering of customers" behavior, demographic, socioeconomic and cultural factors.

In (Navid Shirzadi , Ameer Nizami, Mohammadali Khazen and Mazdak Nik-Bakht , 2021) Medium-Term Regional Electricity Load Forecasting through Machine Learning and Deep Learning has been done considering wind speed, previous year load data and humidity. But, they didn't consider other factors that affect load forecasting like temperature and GDP data.

Table 2.1: Summary of Related Work

Author(s), year	Title	Methodology used	Contributions	Gap
(Motepe S, 2019)	Power Distribution Networks Load Forecasting Using Deep Belief Networks: The South African Case	Adaptive Neuro-Fuzzy Inference System (ANFIS) Model	Studying South African load forecasting, with a focus on distribution networks, using a sophisticated deep learning artificial intelligence technique	Only previous year transformer loading data and temperature as an input were considered
(Ahmet Ova, et al, 2022)	Transmission Expansion Planning Using A Noval Meta-Heauristic Method	Forensic Based Investigation Optimization (FBIO)	FBIO algorithm in a DC model has been applied on various scenarios with different objective functions	Considers DC model but, DC model is a linearized and simplified version of the AC model and does not deal with power flow parameters such as line losses, reactive power flow, voltage variation.
(Fabian Neumann and Tom Brown ,	Transmission Expansion Planning in	Heuristic Optimization with Big-M	Optimization is done heuristic method	Big-M method adds new parameter and

2019)	Low-Carbon Energy System Models	Method	combination with Big-M method to solve complex problems	also too small value doesn't guarantee the convergence to the same optimum of the original problem while too big value generates loss of precision and numerical instabilities.
(Navid Shirzadi , Ameer Nizami, Mohammadali Khazen and Mazdak Nik-Bakht , 2021)	Medium-Term Regional Electricity Load Forecasting through Machine Learning and Deep Learning	Machine Learning and Deep Learning Algorithm	Systematic selection of a proper model based on the data behavior and setting the related parameters to achieve the maximum possible accuracy in load forecasting has been done	Only wind speed, previous year load data and humidity were considered

CHAPTER THREE

3. METHODOLOGY

3.1 Overall Methodology

The successful completion of duties has been achieved by following step-by-step processes. Data gathering, load forecasting, simulation and analysis, as well as transmission expansion are all parts of the method that was used. The first step in tackling a public problem is to identify it. Ethiopian Electric Power (EEP), Ethiopia Electricity Utility (EEU), NASA and the Ethiopian Central Statistical Agency (ECSA) are the sources of the information required for this study.

Medium-term load forecasting for the years 2023–2027 of Fiche is done using an artificial neural network algorithm based on the data collected. Using a Computer Program Software "PSS/E" the forecasted load found from Artificial Neural Network (ANN) was analyzed to manage Gefersa to Fiche Transmission Line expansion plan for the electrical transmission line. Again, based on the gathered network data and predicted data, all relevant simulations, such as load flow analysis, short circuit analysis, and N-1 contingency analysis, were performed on the modeled system using PSS/E software. Results from the PSS/E simulation were obtained for additional analysis and expansion planning. The results of the load forecast for the years 2023–2027 were inputted into the simulation software. Following the receipt of the analysis results, further analysis was conducted on the data, and transmission expansion planning was completed.

3.2. Data Collection

As mentioned above, different types of data were collected from different institutions and web sites. Some of them are listed below.

3.2.1 Connected Active Peak Load and Real Peak Load of Fiche

Connected Active Peak load: Is the connected industrial, commercial, domestic and straight light active loads.

Real Peak load: Is the real load in which the summation of connected active load and suppressed demand of industrial, commercial, domestic and straight light customers' for each year.

Table 3. 1: Yearly peak Demand

Year (GC)	Connected Active Peak load(MW)	Real Peak load (MW)
2018	9.51	15.74
2019	9.00	16.23
2020	10.00	16.83
2021	10.31	18.07
2022	11.07	28.09

(Source: Ethiopian Electric Utility)

Table 3.2: Population data

Year	Population (in thousands)	Percentage growth (%)
2018	46,756	
2019	49,203	5.23
2020	51,741	5.16
2021	54,362	5.066
2022	57,067	4.98

(Source: Ethiopian Central Statics Agency)

The population data of Fiche was collected from Ethiopian Central Statics Agency but, this data was the forecasted data not a real data, because census has not been conducted from 2007 until now. Population all over the world is continually increasing, which demands for more electricity to satisfy the individual needs. Also, with the advent of new technologies and improved life-style, average use of electrical equipment is also increasing gradually.

Table 3.3: Annual average temperature

Year	Annual average-Temperature
2018	20.85
2019	20.90
2020	20.59
2021	20.20
2022	20.59

(Source: NASA)

Table 3.4: Annual humidity at 2meters(%)

Year	Annual humidity (%)
2018	57.56
2019	59.81
2020	60.88
2021	58.44
2022	59.31

(Source: NASA)

Table 3.5: Annual average precipitation (mm/year)

Year	Annual average-precipitation(mm/year)
2018	854.10
2019	1091.35
2020	1335.90
2021	1255.60
2022	1097.35

(Source: NASA)

3.2.2 GDP data: Gross domestic product (GDP) is the standard measure of the value of final goods and services produced by a country during a period. It is the single most important indicator to capture these economic activities; it is not a good measure of societies' well-being and only a limited measure of people's material living standards. The sections and indicators that follow better address this and other related issues and it is one of the primary purposes of this publication. We have collected GDP data of Fiche from World Bank GDP data of Ethiopia by dividing GDP data of Ethiopia to the total number of Ethiopia's population and multiply the GDP per capita by the number of populations in Fiche for each year.

$$\text{GDP of Fiche} = \frac{\text{GDP of Ethiopia}}{\text{Total number of Ethiopian population}} * \text{number of Fiche populatio}n \qquad (3.1)$$

Table 3.6: GDP Data

Year	GDP data(dollars)
2018	35,455,308.580
2019	41,351,529.681
2020	47,533,007.952
2021	50,288,546.616
2022	54,060,596.306

Source: World Bank.

3.3. Load Forecasting Techniques

In order to build a statistical model of load, parametric approaches examine the qualitative connections between load and its influencing elements. These techniques include moving averages, auto-regression, multiple linear regression, and needed assumed parametric estimates from historical data. They frequently cannot handle interactions that are random or nonlinear between the load and the elements that impact the load. Fuzzy logic, artificial neural networks (ANN), dynamic theory (DT), and particle swarm optimization (PSO) are examples of artificial intelligence techniques.

3.3.1. Load Forecasting Using Artificial Neural Network

3.3.1.1. Feed Forward Neural Networks

One of the artificial neural networks that only follow one path and one direction is the feed forward neural network, which ensures that the output always follows the input. Loops are absent in such a network, and the output layer behaves differently from the other levels. Even though their primary application is pattern recognition, they are also used in load forecasting with better performance. In this research we have used feed forward neural network due to its simplicity and accuracy, but Feedback neural network the network is complex due to its backup secondary feedback system used to produce the results.

3.3.1.2. Feedback Neural Network

One of the varieties of artificial neural networks that don't carry signals along a single path is feedback neural networks. Signals can move in both directions in these networks, from input to output as well as from output to input. Feedback neural networks constantly modify themselves as well as compare signals and units in order to maintain an equilibrium state. Up to a change in input, the equilibrium state is held. The network attempts to reach a new point of equilibrium whenever the input changes.

3.4 Transmission Line Optimization Using Particle Swarm Optimization Algorithm (PSO)

PSO works by the behavior of bird flocking, insect swarming, and fish schooling. It consists of several individuals (particles) refining their position in a given search space. Each particle is characterized by its position and represents a candidate solution to the problem at hand. The particles change their positions in a multi-dimensional search space to explore higher fitness positions. It starts with an initial random population of particles where each particle is a candidate solution. The particles' velocity and position are initialized at random. Each particle memorizes its own best position encountered so far during the optimization process, which is called the local best. On the other hand, the population memorizes the best position among all individual best positions obtained so far, the global best. Inertia weight is introduced to balance the particle's global and local exploration capabilities. The inertia weight is linearly decreased through optimization to emphasize the search globally at initial iterations and locally at final iterations. PSO has several advantages over other optimization techniques, including simple concepts, easy implementation, and computationally efficient.

The PSO algorithm can be described in the following steps:

1. Initialization: Initialize n position vectors of size m with Vk (0), k = 1, 2... n, at random (depending on the task to be addressed). The components of Vk are evenly dispersed over an appropriate range. Then, uniformly distribute the elements of the randomly initialized velocity vectors Vk (0), k = 1, 2,...,n between a minimum and a maximum value. Each particle's fitness is assessed using an objective function. Set the global best to the best fitness among the best locals, and the local best of each particle to its initial position. The range of the inertia weights w (0) should then be initialized.

2. Update Velocity: Each element j of the velocity vector of the k^{th} particle can be updated as follows:

$$vk,j(t) = w(t)vk,j(t-1) + c_1 r_1 \ (xk,jL\ (t-1) - xk,j(t-1)) + c_2\, r_2\ (xk,jG\ (t-1) - xk,j(t-1)) \tag{3.2}$$

The cognitive parameter, or c_1, governs the step toward the particle's local optimal position and is a positive constant where t is the iteration number. The social parameter, orc_2, is a positive constant that regulates the magnitude of the step taken in the direction of the overall optimum position the swarm has found. In order to add randomness to the velocity updates r_1 and r_2 are uniformly distributed random numbers in the range [0, 1]. Xk,j(t) represents the particle's current position, whereas Xk,j L (t) and Xk,j G (t) represent its best and global positions, respectively. W(t) is an inertia weight that regulates the acceleration of the particle in its initial direction. Lower values of w speed up the convergence to the optima and higher values of w encourage exploration of the entire search space. The first term of the velocity update ($w(t)vk,j(t-1)$) is the inertia component to keep the particle moving in the same direction as in the previous iteration. The second term c_1r_1 (xk,jL $(t-1) - xk,j(t-1)$) is called the cognitive component and acts as a memory of the particle, causing it to return to its local best that it has encountered so far. The third term c_2r_2(xk,jG $(t-1) - xk,j(t-1)$) is called the social component, as it causes the particle to move towards the global best.

3. Update Position: After updating the velocity of each particle, the particle position is updated using the latest updated velocity as:

$$xk,j(t) = vk,j(t) + xk,j(t-1) \tag{3.3}$$

4. Update Bests: The fitness of each particle is evaluated according to the newly updated position. If the updated position leads to a better objective function value, the local best and the global best are updated.

5. Stopping Criteria: The process is repeated until the number of iterations since the last change of the best solution is greater than a pre-specified number, or the number of iterations reaches a maximum allowable number or the desired value of the objective function is reached.

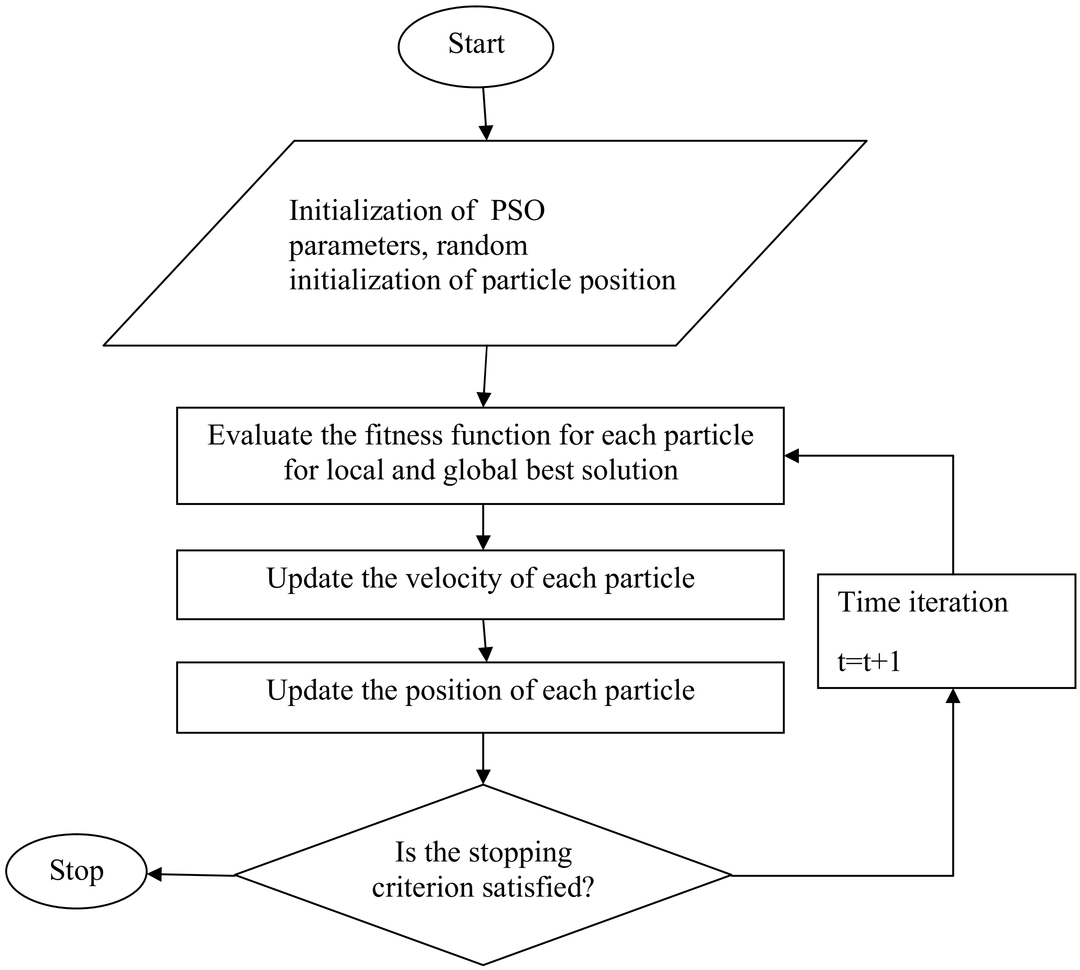


Fig. 3.1: PSO Flowchart

3.4.1 Problem Formulation

In a power system represented by the AC load flow model, the mathematical formulation for the static TEP model is given by:

$$\mathrm{Min}\left\{\sum_{(i,j)} c_{i,j}\, n_{i,j} + p_f \sum_{k} r_k\right\}$$

Where $c_{i,j}$ represents cost of a line added to the i-j right of way, $n_{i,j}$ represents number of new lines added to the i-j right of way, r_k is vector of load curtailment, p_f is load penalty factor which is given by $p_f = \frac{1}{1-{P_l}/{P_g}}$ and this is always greater than unity.

In the above, TEP formulation, the objective is to find an optimal transmission structure to meet the peak load demand with minimum investment and loss of load cost, while satisfying operational limitations.

Table 3.7: Parameters and Fixed Cost of Each Options

Options	Fixed cost	Generated active power (P_g)	Peak load (P_l)	load penalty factor (p_f)
Option-1	15,518,760.84	32.8	31.9	36.44
Option-2	11,470,129.40	32	31.9	320
Option-3	8,891,619.53	33	31.9	30

3.5 Transmission Line Modeling

During both normal and single contingency conditions, transmission lines should be operated within their normal thermal ratings. The normal thermal rating is the level of loading that may be sustained indefinitely.

3.5.1 Voltage Selection

The system voltage in high voltage system very much affects the capital cost of transmission line. The weight of conductor material, the efficiency of the line, the voltage drop in the line and system stability depends upon system voltage. The choice of voltage therefore, a major factor in the line designs. While selecting the transmission voltage the present and future expectable voltage of other lines in vicinity of the line under design are considered. The high voltage systems are not only the power transporting system but fulfill the need of interconnecting the different high voltage systems so as to improve the reliability as well as efficiency of the system. The voltage level of a transmission line depends on the transmitted power, the transmission distance and the system configuration around there. Since Gerbe-Guracha 230kV and Chancho 132kV Substations are the nearest one compared to Gefersa substation, supplying by 230kV and 132kV lines has been considered beside to the 66kV in this study.

3.5.2 Number of Circuits

The number of circuits has been pre-determined to sufficiently deliver the requested power, but as clearly depicted in the detailed load flow in the technical analysis single or double circuit 230kV or 132KV transmission line.

3.5.3. Conductor Selection

Many types of conductors are available for carrying power through overhead lines. The factors governing the selection of the conductor materials are low resistivity, high tensile strength, weather condition, low cost, ease of availability and the existing situation.

3.6. Load flow Analysis

The flow of active and reactive power is known as load flow or power flow. Load flow analysis is an important tool used by power engineers for planning and determining the steady state operation of a power system. Power flow studies provide a systematic mathematical approach to determine the various bus voltages, phase angles, active and reactive power flows through different branches, generators, transformer settings and load under steady state conditions. Load flow studies are the most common of all power system analysis calculations. They are used in planning studies to determine if and when specific elements will become overloaded. Major investment decisions begin with reinforcement strategies based on load flow analysis. The main information obtained from the load flow analysis comprises (Elgerd, O.L., 2012), magnitudes and phase angles of load bus; voltages, reactive powers and voltage phase angles at generator buses, real and reactive power flows on transmission lines together with power at the reference bus; losses on transmission lines and distribution cables. The Gauss-Siedel method, the Newton-Raphson method, and the fast-decoupled method are the three main load flow techniques.

3.6.1. Newton-Raphson Method

For the solution of non-linear algebraic equations, the Newton-Raphson Method for Load Flow Analysis is a potent technique. In comparison to the GS approach, it is more efficient and will converge in the majority of circumstances. It is, in fact, a practical approach to solving the load flow problem in large power networks. It's one flaw is that a huge amount of computer memory is needed; however, this has been fixed with a compact storage system. By completing the first iteration using the GS approach and using the values so obtained for beginning the NR iterations, convergence can be significantly sped up. Due to this advantage we have used this technique load flow analysis in this research.

3.6.2 Gauss-Siedel Method

An iterative procedure called the Gauss-Seidel method is used to resolve a number of nonlinear load flow equations. One iteration refers to the process of computing all bus voltages. Once the bus voltage converges within the required precision, the iterative process is repeated. Programming the Gauss-Seidel technique is simple. Each repetition happens rather quickly (the number of branches and buses in the system determines the sequence of calculations). Less memory is required than with the NR technique. The Gauss-Seidel load flow method's erratic convergence is one of its key drawbacks. Particularly for large power systems with significant levels of nonlinearity, the technique may not always converge on a solution. The Gauss-Seidel load flow method's slowness is another drawback.

3.6.3 Fast Decoupled Method

The Newton-Raphson method is extended by the fast-decoupled load flow approach, which produces a quick algorithm for solving load flow problems when written in polar coordinates with some approximations. The Newton-Raphson approach needs less iteration than the fast-decoupled method. The primary benefit of the so-called Fast Decoupled Load Flow (FDLF) approach over the traditional Newton-Raphson method is its ability to compute huge power systems in a short amount of time because of a smaller Jacobian matrix. However, the fast-decoupled load flow's accuracy is primarily influenced by three variables: the system's size and structure, the convergence tolerances, and the level of system loading.

CHAPTER FOUR

4. RESULT AND DISCUSSION

4.1. Load forecasting Model

4.1.1 Development of the ANN Model

The historical five-year data has been fed into the neural network fitting function in the Neural Network Toolbox of the MATLAB software by saving the data in an Excel spreadsheet. As seen in figure 4.1, the neural network has a two-layer feed-forward network with sigmoid hidden neurons and linear output neurons. It was trained using a Scaled Conjugate Gradient technique.

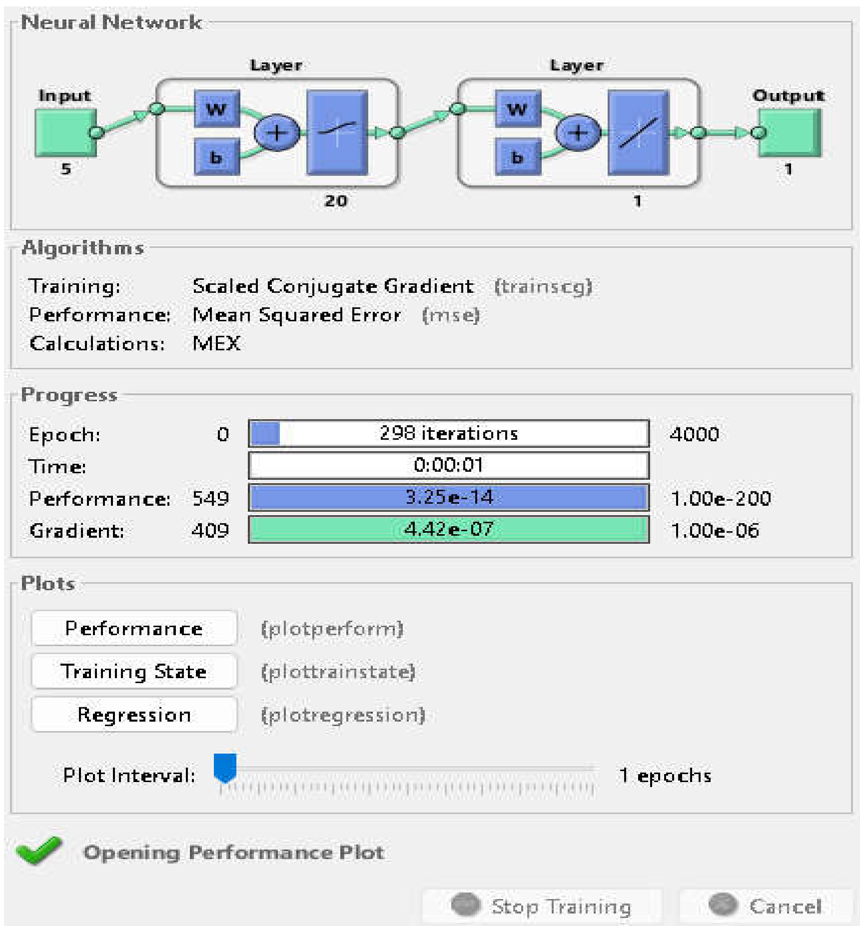


Fig. 4.1: ANN Train Result

The training was carried out in a supervised way, which means that the desired outputs were specified for each input vector and weights were adjusted to minimize an error function that gauges the difference between the desired output and the output calculated by the network. The training tool in the neural network toolbox processed 298 iterations given the input historical data and the number of neurons in the hidden layers for this particular network.

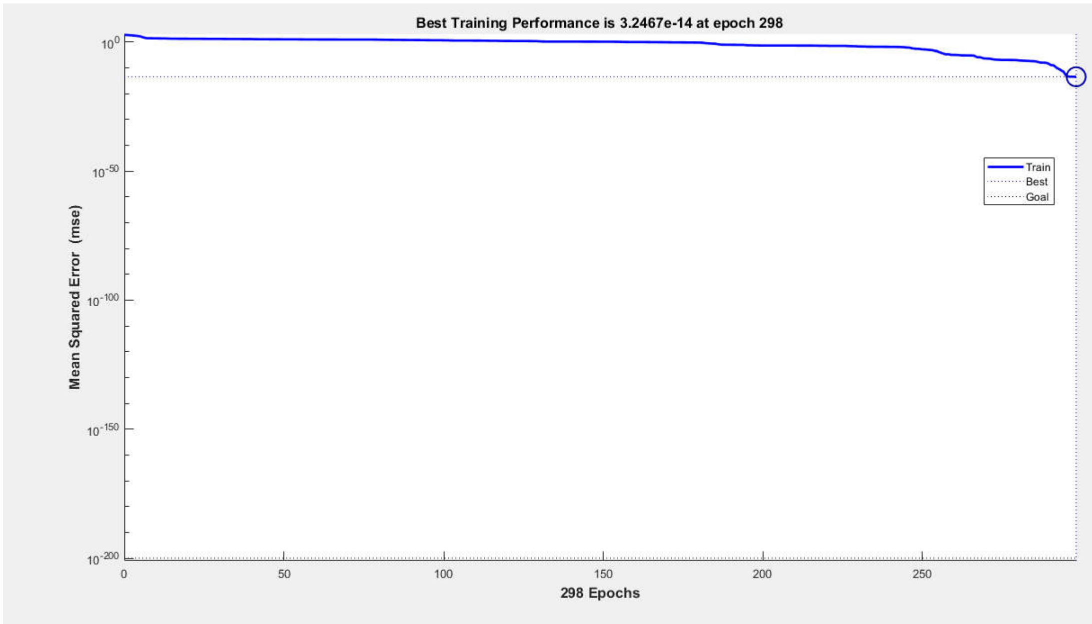


Fig. 4.2: ANN Training Performance

After the training phase has completed processing all epochs (a complete data set is only passed through ANN once forward and backward), its performance is evaluated in terms of the MSE calculated globally. After processing every epoch of the training phase, the network was prepared for prediction and generalization.

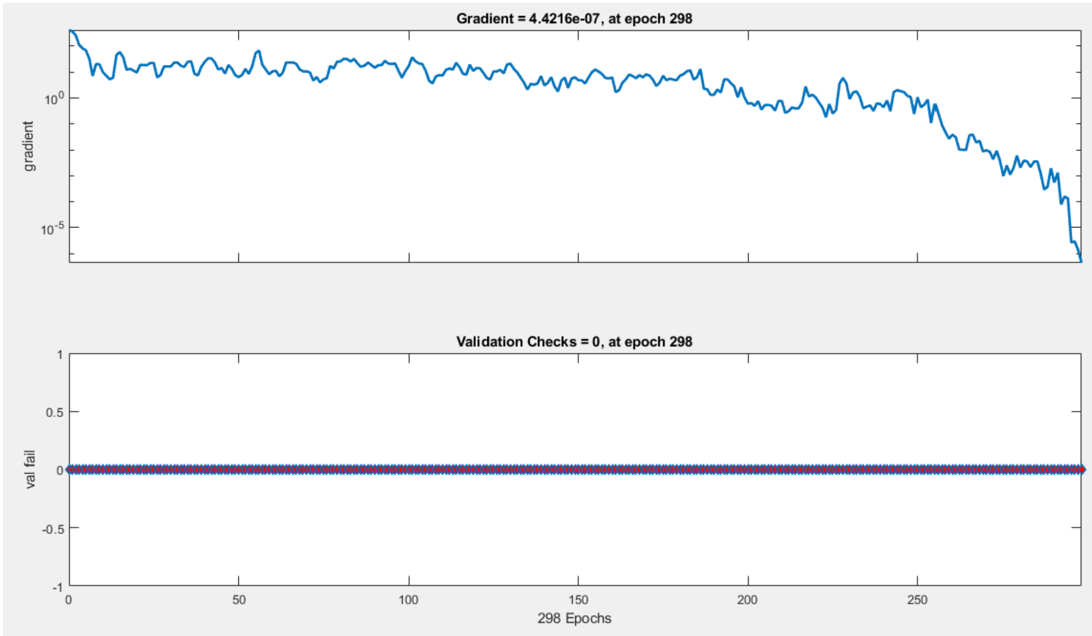


Fig. 4.3: Gradient and Validation Check of ANN Result

Gradient in ANN measures the change in all weights with regard to the change in error. The higher the gradient the steeper the slop and the faster the model can learn, but, if the slop is zero, the ANN stops learning.

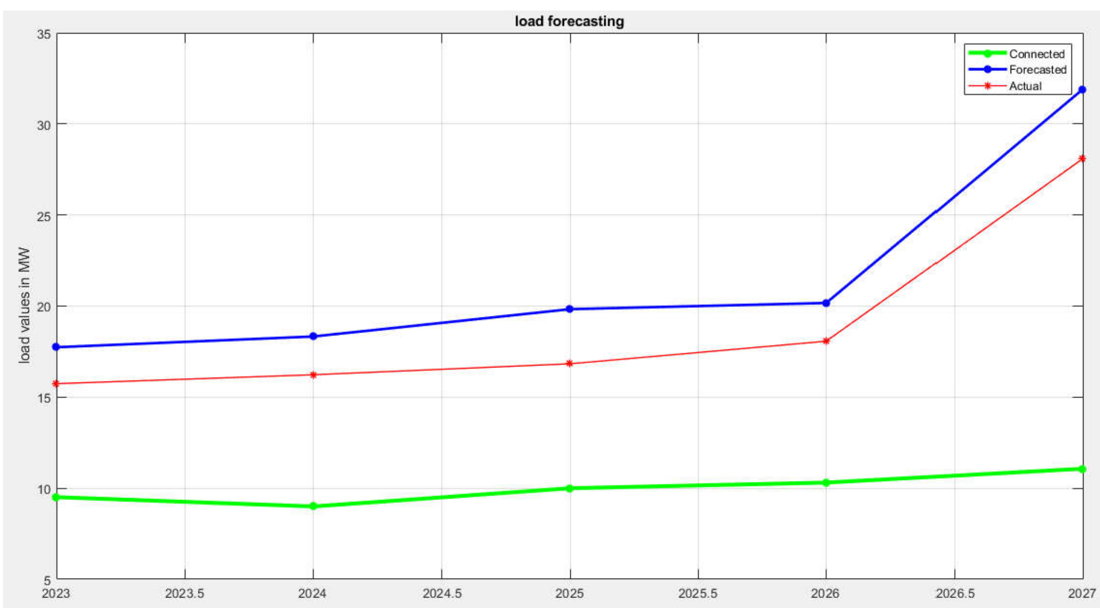


Fig. 4.4: Simulation Result of Forecasted Load

Table 4.1: Forecasted Load of the Existing Fiche Substation

Year	Forecasted load
2023	17.74
2024	18.33
2025	19.83
2026	20.17
2027	31.90

4.2. Transmission Line Expansion Planning and Simulation Results

4.2.1 Transmission line Optimization using PSO algorithm

The given planning problem was solved using the PSO algorithm. For this purpose, the investment cost was estimated for each particle in a randomly generated starting population of the PSO algorithm. The best particle has been selected, and each particle's velocity has been updated in accordance with the PSO criteria. Finally, the PSO algorithm's stop condition has been verified.

4.2.1.1 PSO Simulation Result for Option-1

In this paper, we have used a particle swarm optimization method to optimize investment cost and cost of load loss. The simulation was initialized with 50 swarms (particles), and it was converged at 1000 iterations. From the PSO algorithm result the total investment cost and load loss cost of Gefersa-Fiche 132kv transmission line expansion was 15,520,400 USD (847,662,166.4 ET birr).

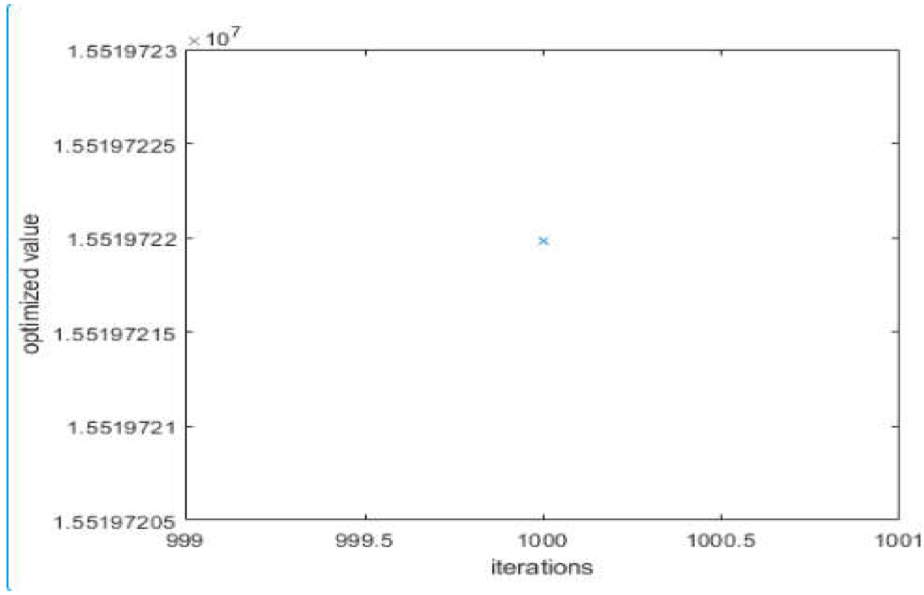


Fig. 4.5: Optimized Cost of Option-1

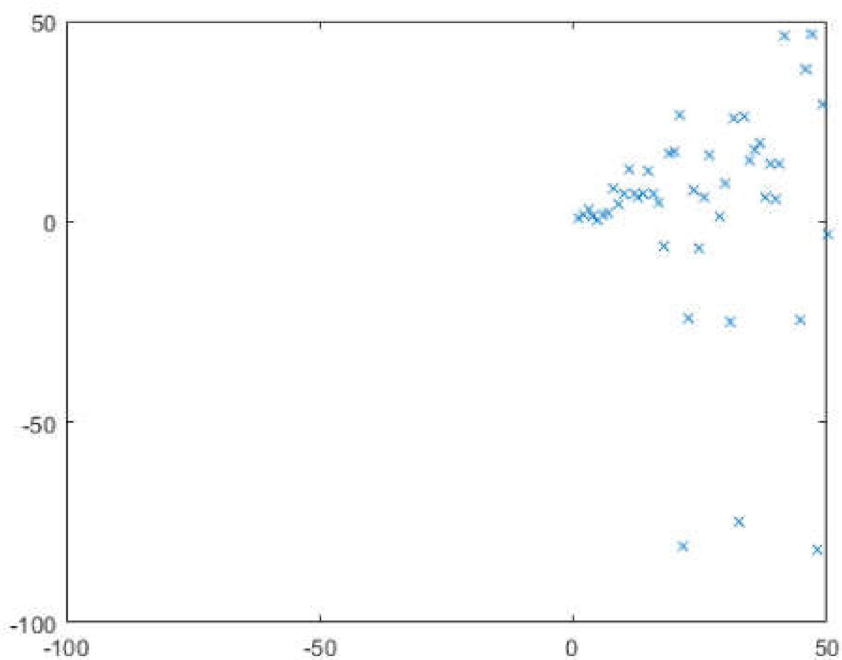


Fig. 4.6: Swarm position of option-1

4.2.1.2 PSO Simulation Result for Option-2

The simulation was initialized with 50 swarms (particles), and it was converged at 1000 iterations. From the PSO algorithm result the total investment cost and load loss cost of Gerbe-Guracha to Fiche 230kv transmission line expansion was 11,473,300 USD (626,625,752.8 ET birr).

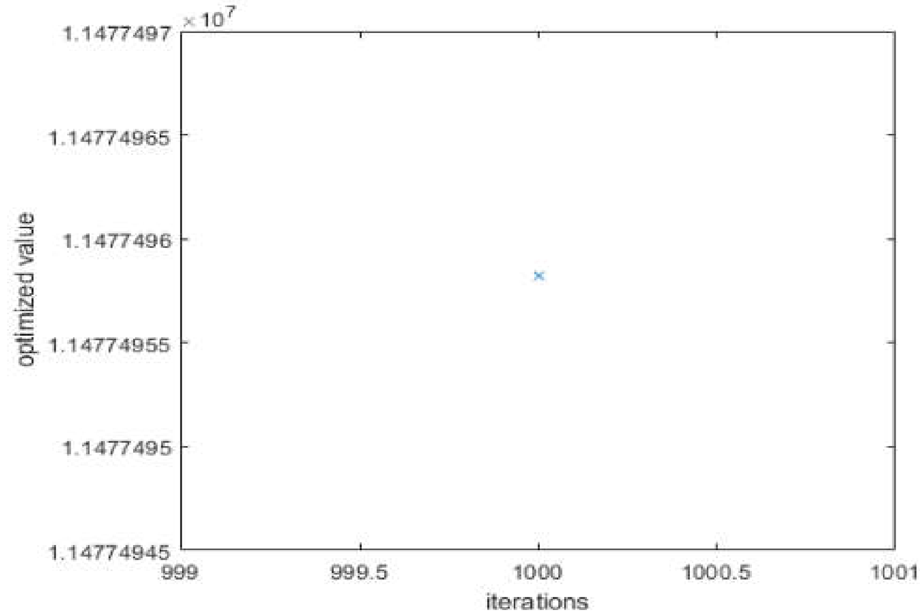


Fig. 4.7: Optimized Cost of Option-2

As shown below the swarms (particles) were distributed throughout the square to search the optimized cost. At the first iteration the particle's position was distributed randomly, but, after some iterations their position were adjusted to find the optimized cost.

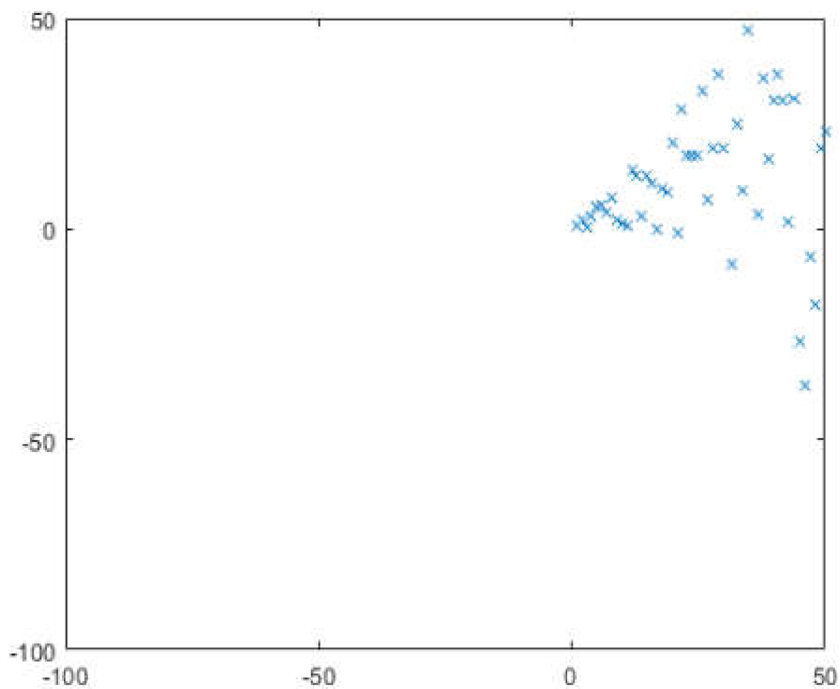


Fig. 4.8: Swarm Position of Option-2

4.2.1.2 PSO Simulation Result for Option-3

The simulation was initialized with 50 swarms (particles), and it was converged at 1000 iterations. From the PSO algorithm result the total investment cost and load loss cost of Chancho-Fiche 132kv transmission line expansion was 8,892,120 USD (485,652,025.92 ET birr).

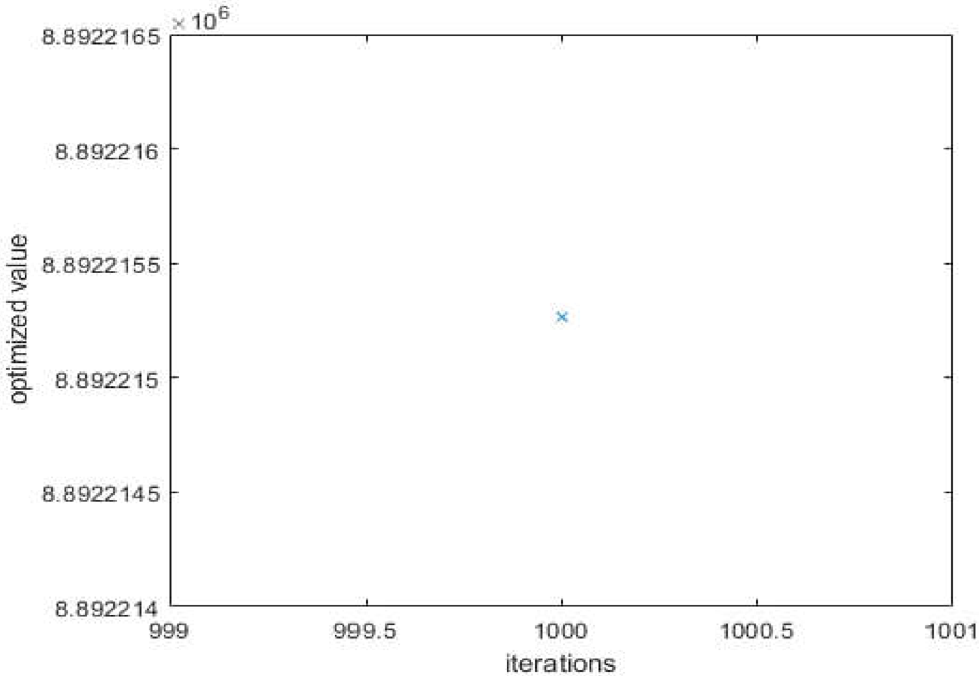


Fig.4.9: Optimized Cost of Option-3

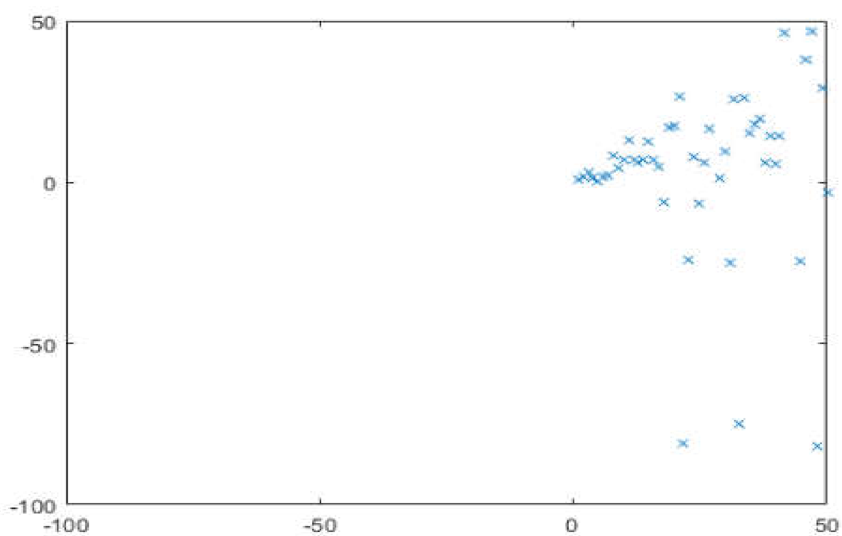


Fig. 4.10: Swarm Position of Option-3

Table 4.2: Optimized Cost of Each Options

Options	Fixed cost	Generated active power (P_g)	Peak load (P_l)	load penalty factor (p_f)	Optimized cost
Option-1	15,518,760.84	32.8	31.9	36.44	15,520,400
Option-2	11,470,129.40	32.0	31.9	320.00	11,473,300
Option-3	8,891,619.53	33.0	31.9	30.00	8,892,120

Fixed cost: Is the cost of total transmission line cost, engineering and administration cost , expected environmental and social cost , total project cost, physical contingency cost, price contingency cost, grand total project cost and also it includes line bay and bus bar cost for options one and two and capacitor bank cost for option three.

Generated active power (P_g) : In this thesis we have assumed that the active power supplied from the source substation through the new transmission line to Fiche substation as a generated active power.

Peak load (P_l) : Is the forecasted peak load power and it is similar in each option.

Optimized cost: Is the optimized cost obtained from PSO algorithm including fixed cost and load loss cost.

4.2.1 Transmission Line Expansion Planning

Today, one of the biggest issues facing power engineers is the design of transmission expansion for an existing power system under various restrictions. There are a number of causes, one of which is the quick increase in load and the insufficient addition of capacity. Therefore, it is crucial and significant to build a transmission expansion method that functions well and has good feasibility under certain assumptions and available limitations. Transmission expansion planning made use of an analytical algorithm that was implemented for a specific load condition with variations in generation so that the power system operation condition would not be disturbed or compromised (Khuntia, Swasti; Rueda, José L.; van der Meijden, Mart, 2016).

An economic element that considers the financial aspects of the line that will be introduced for expansion has been measured for that reason. The viability of a real case study system is also tested using the recommended analytical technique ((Khuntia, Swasti; Rueda, José L.; van der Meijden, Mart, 2016)).

4.2.1.1 Planning Criteria

This section contains a list of the criteria that were chosen for use in the study and planning of the power system. The criteria generally adhere to well-established worldwide practice and consider standard operating procedures. All the planning criteria considered in this thesis were according to EEP and EAPP grid codes.

i. System Voltage

The voltage at each bus must fall between 95% and 105% of the bus nominal or base voltage under typical operating circumstances. Bus voltages shall not fall below 0.9 units (pu) and should not rise beyond 1.10 units (pu) during emergency conditions (N-1).

ii. Equipment Thermal Loading Limits

Each transformer's maximum rating must be less than the load placed on it, and each line's thermal rating must be less than the load placed on it under normal operating conditions. A transformer and a transmission line should not be loaded above 120% of their capacity when there is an emergency.

iii. Load Power Factor

The power factor of the loads was fixed at 90%, considering the load of Ethiopian consumers and a recent master plan analysis on the reactive power consumption of the system conducted by PB.

iv. System Contingencies

After any line within the mesh portion of the network goes down, the transmission line must be able to serve all loads within the emergency limitations for bus voltages and equipment loadings.

v. Transmission Line Expansion Options

Fiche's need for energy is rising substantially as a result of population growth and industry expansion. Fiche 66 kV transmission line is unable to supply enough electricity to meet the region's expanding demand. The bus voltage lowers to 0.1 PU, below the EEP grid code standard's minimum permitted bus voltage in an emergency circumstance of 0.9 PU, as shown below when we add 28.09 MW of demand to the existing transmission line, overloading it.

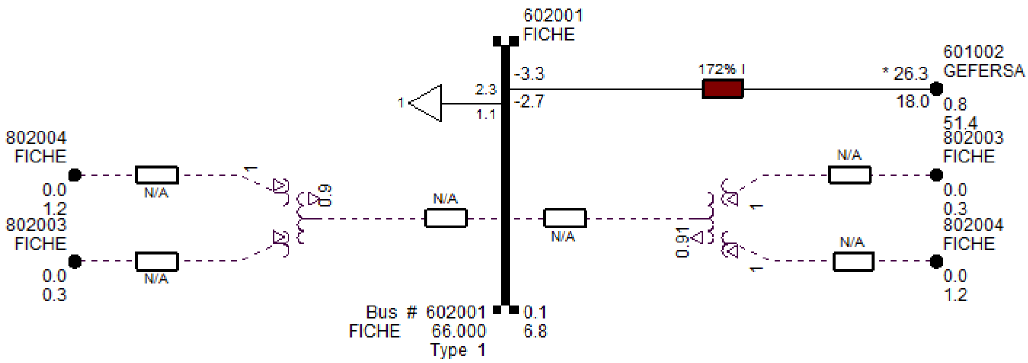


Fig. 4.11: The Existing Fiche 66kv Transmission Line

Electric power outages occur frequently and last a long time in the city as a result of an imbalance between client demand and supply. As a result, Gefersa-Fiche Transmission Line expansion planning was necessary.

4.3.1 Option-1

Supplying 132kv double transmission line from Gefersa substation and upgrading Fiche substation.

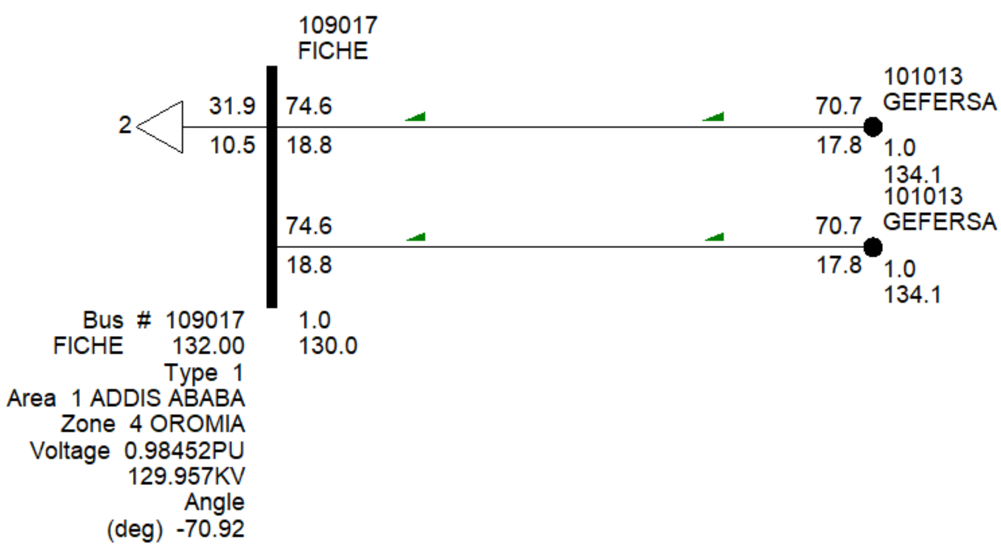


Fig. 4.12: 132kv Gefersa-Fiche Transmission Line

4.3.1.1. Voltage drop across the transmission line

The distance between Gefersa to Fiche substation is 96 kilometers, and the formula for the voltage drop along the transmission line is,

$$.V_d = I * Z \tag{4.1}$$

Where I, is the entire current flowing through the transmission line, Z is the total impedance of the transmission line, and V_d is the voltage drop across the transmission line respectively. Assume the transmission line is lamped for analysis simplicity, then according to the EEP grid code standard transmission line resistance and reactance are given by, R= (0.2132 Ω /km), X=(0.4265 Ω /km), are the values for a 132 kV Ash conductor double tower design, and from PSS/E simulation I=74.6A. The overall resistance and reactance of the transmission line are 20.467 Ω and 40.944 Ω correspondingly due to the 96 km transmission line length. The total impedance is then determined by:

$$Z = \sqrt{(R^2 + X^2)} \tag{4.2}$$

$$= \sqrt{(20.467^2 + 40.944^2)}$$

$$= 45.775\Omega$$

$$\text{Then } V_d = I * Z \tag{4.3}$$

$$= 74.6A * 45.775\Omega$$

$$= 3{,}414.8V$$

$$= 3.4148kV$$

As was mentioned above, the voltage level achieved at the Fiche substation is 128.5852kV as a result of the significant voltage drop through the transmission line.

4.3.1.2 Cost of the Transmission Line for option-1

Table 4.3: Summary of Cost Estimate for Option-1

Item	Total Price (USD)	Total price (Birr)
Total Transmission Line, line bay and bus bar Cost	13,062,930	713,444,984.90
Engineering and Administration 5%	653,146.5	35,672,249.24
Expected Environmental and Social cost 3%	391,887.9	21,403,349.55
Total Project Cost	14,107,964.4	770,520,583.70
Physical Contingency (5%)	705,398.22	38,526,029.18
Price Contingency (5%)	705,398.22	38,526,029.18
Grand Total Project Cost	15,518,760.84	847,572,642.00

Rate: 1USD=54.616ETB

As we have seen from the above table, the total cost of supplying 132kv transmission line from Gefersa substation to Fiche substation is 15, 518,760.84USD (847,572,642.00 Ethiopian birr).

4.3.2 option-2

Supplying 230kv transmission line from Gerbe-Guracha substation and upgrading Fiche substation. The second alternative consists of supplying a 36 km long, double-line 230 kV transmission line from Gerbe-Guracha 400/230 KV substation.

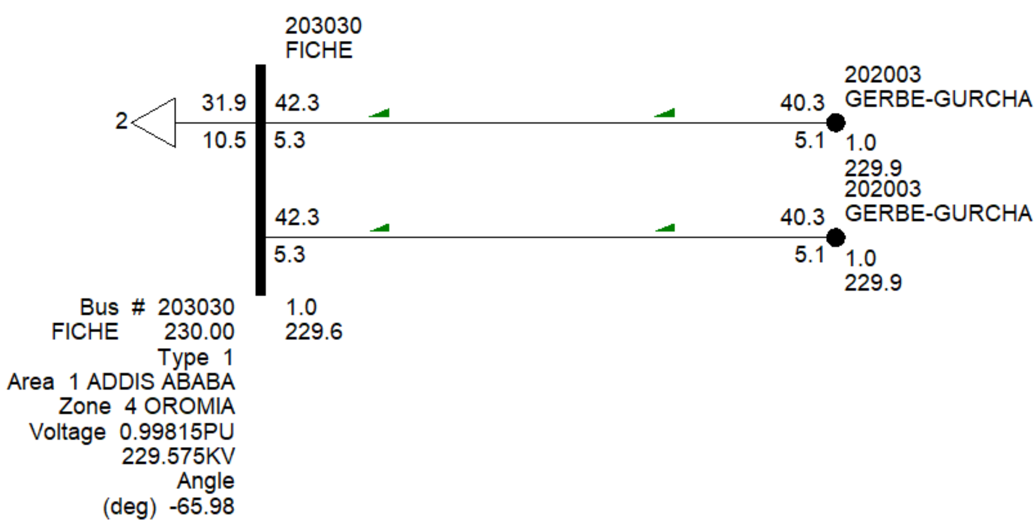


Fig. 4.13: Simulation of 230kv Transmission Line Supply From Gerbe-Guracha Substation

4.3.2.1 Voltage drop across the transmission line

$$V_d = I * Z \tag{4.4}$$

Where V_d, is the voltage drop across the transmission line, I and Z are the total current flowing though the transmission line and the total impedance of the transmission line respectively. According to EEP grid code standard, For lamped transmission line and 230kv twin Ash conductor double tower configuration, R= (0.1069 Ω/km), X=(0.3174 Ω/km),and from PSS/E simulation I=42.3A. As the transmission line length is 36km, the total resistance and reactance of the transmission line are 3.85Ω and 11.43Ω respectively. Then the total impedance is given by:

$$Z = \sqrt{(R^2 + X^2)} \tag{4.5}$$

$$= \sqrt{(3.85^2 + 11.43^2)}$$

Z=12.06Ω

$$\text{Then,} V_d = I * Z \tag{4.6}$$

= 42.3A*12.06Ω

=510.138V

=0.510kv

As we have seen above, if we supply 230kv transmission line from Gerbe-Guracha substation, the voltage drop through the transmission line is 0.510kv and the voltage level reached at Fiche substation is 229.49kV.

4.3.2.2 Cost of the Transmission Line for option-2

Table 4.4: Summary of Cost Estimate for Option-2

Item	Total Price (USD)	Total price (Birr)
Total Transmission Line, bus bar and line bay Cost	9,654,991.08	527,316,992.80
Engineering and Administration 5%	482,749.554	26,365,849.64
Expected Environmental and Social cost 3%	289,649.732	15,819,509.76
Total Project Cost	10,427,390.366	569,502,352.20
Physical Contingency (5%)	521,369.518	28,475,117.60
Price Contingency (5%)	521,369.518	28,475,117.60
Grand Total Project Cost	11,470,129.402	626,452,587.40

Rate: 1USD=54.616ETB

The total cost estimate for this option is about 626,452,587.4 Ethiopian birr as shown in table 4.2 above.

4.3.3 Option-3

Supplying 132kv transmission line from Chancho substation to Fiche substation and upgrading Fiche Substation. The third option is supplying 132kv line from Chancho substation by stretching around 55km.

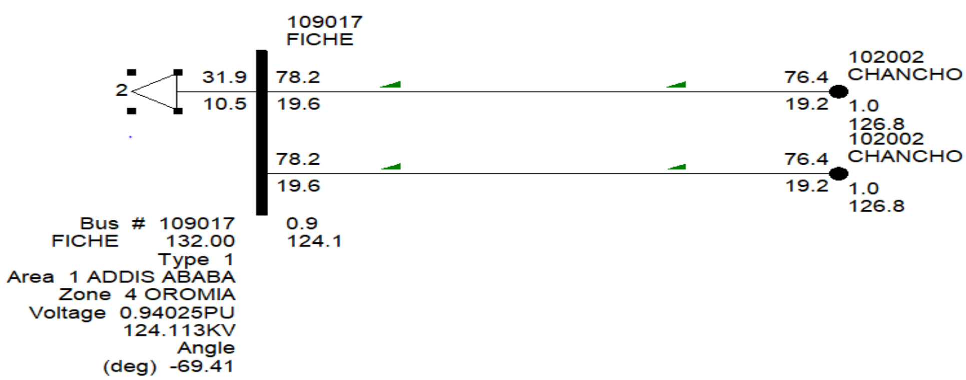


Fig. 4.14: 132kv Transmission Line of Chancho-Fiche

4.3.3.1 Voltage Drop across the Transmission Line

$$V_d = I * Z \qquad (4.7)$$

Where, V_d, is the voltage drop across the transmission line, I and Z are the total current flowing though the transmission line and the total impedance of the transmission line respectively. According to EEP grid code standard, For lamped transmission line and 132kv Ash conductor double tower configuration the transmission line parameters are given by: R= (0.2132 Ω/km), X=(0.4265 Ω/km), and from PSS/E simulation I=78.3A. As the transmission line length from Chancho to Fiche is 55km, the total resistance and reactance are 11.726Ω and 23.458Ω respectively. Then the total impedance is given by:

$$Z = \sqrt{(R^2 + X^2)} \tag{4.8}$$

$$= \sqrt{(11.726^2 + 23.458^2)} = 26.223\Omega$$

$$\text{Then } V_d = I * Z \tag{4.9}$$

=78.3A*26.223Ω

=2053.26V

=2.053kV

As we have seen above, the voltage drop through the transmission line is 2.053kv and the expected voltage level reached at Fiche substation is 129.947kv, but, as the voltage level in source substation Chancho is 126.8kv, actual voltage reached through the new transmission line to Fiche substation is 124.1kv.

4.3.3.2 Cost of the Transmission Line for option-3

Table 4.5: Summary of Cost Estimate for Option-3

Item	Total Price (USD)	Total price (Birr)
Total Transmission Line and capacitor bank Cost	7,484,528.220	408,774,993.00
Engineering and Administration 5%	374,226.411	20,438,749.70
Expected Environmental and Social cost 3%	224,535.847	12,263,249.80
Total Project Cost	8,083,290.478	441,476,993.00
Physical Contingency (5%)	404,164.524	22,073,849.60
Price Contingency (5%)	404,164.524	22,073,849.60
Grand Total Project Cost	8,891,619.526	485,624,692.00

Rate: 1USD=54.616ETB

As we have seen from the above table the total cost of supplying 132kv double transmission line from Chancho substation to Fiche substation is 8,891,619.526 USD (485,624,692.00 ET birr).

When we summarized the cost of the three options supplying 132kv double circuit transmission line from Gefersa substation to Fiche substation requires 847,572,642.00 birr, supplying 230kvdouble circuit transmission line from Gerbe-Guracha substation to Fiche substation needs 626,452,587.40 birr and supplying 132kv double circuit transmission line from Chancho substation to Fiche substation is 485,624,692.00 birr.

4.4. Load Flow Analysis of Each Option

4.4.1. Load Flow Analysis of Option-1

In this load flow analysis, the active has been taken from the forecasted load. Then the voltage magnitude and phase angle were obtained from the load flow analysis. As shown below fig. 4.15, the voltage level is 0.985pu, which is within the EEP allowable limit under normal operation: (0.950 $\leq$ 0.987 $\leq$ 1.050)pu.

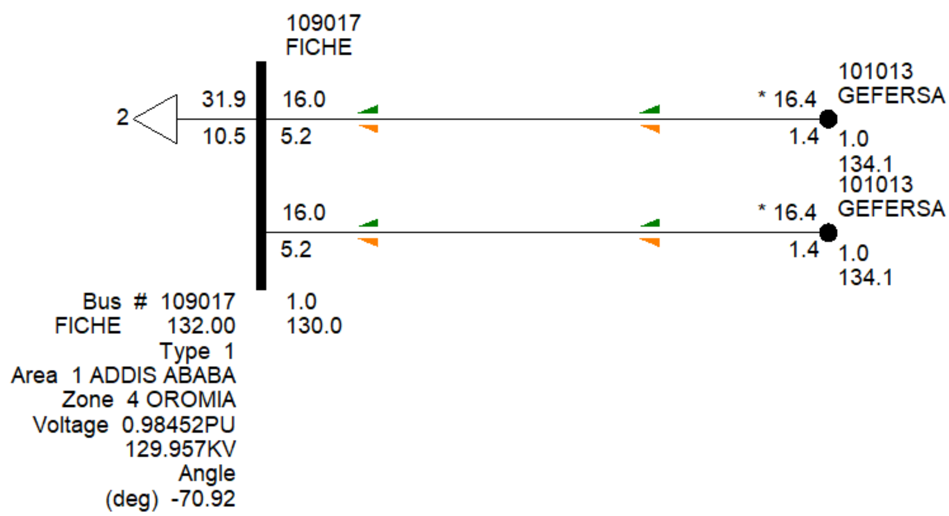


Fig. 4.15: Load Flow Analysis of Option-1

4.4.2 Load Flow Analysis of Option-2

In this load flow analysis, the active power was taken from the forecasted load. Then the voltage magnitude and phase angle have been obtained from the load flow analysis. As shown below fig. 4.16, the voltage level is 0.999pu, which is within the EEP grid code allowable limit under normal operation :(0.95 $\leq$0.998$\leq$1.05) pu.

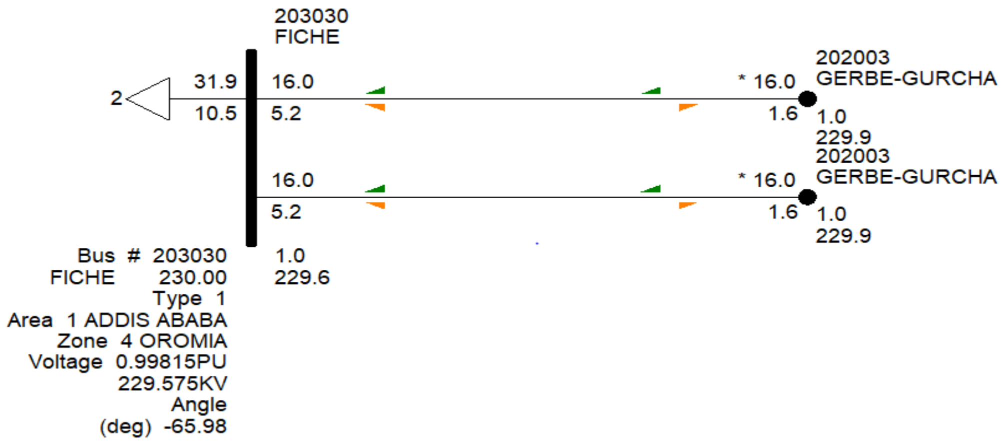


Fig. 4.16: Load Flow Analysis of Option-2

4.4.3 Load Flow Analysis of Option-3

In this option, the active power has been taken from the forecasted load. Then the voltage magnitude and phase angle were obtained from the load flow analysis. As shown below fig. 4.17, the voltage level is 0.940 pu, this is less than the EEP grid code allowable minimum limit under normal operation, which is 0.95pu.

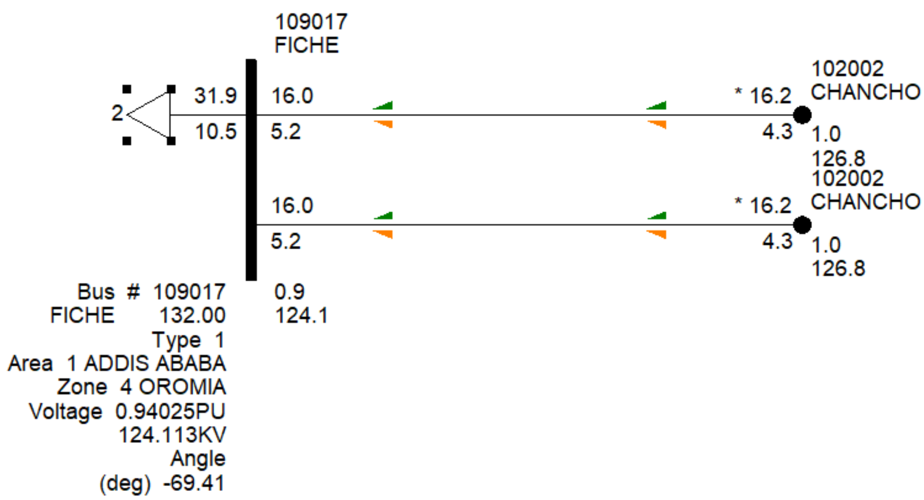


Fig. 4.17: Load Flow Analysis of Option-3

The provision of 132 kV transmission line from Chancho substation, as shown above figure 4.17, it did not fulfill the load flow limits, necessitating the use of compensating devices. Reactive power comes in two varieties: inductive and capacitive. To maintain a balance between inductive reactive power and capacitive reactive power, reactive power compensation is required. Otherwise, the transmission network will be used to carry the reactive power. Additionally, reactive power lowers the ability to transfer active power. So-called compensation techniques are methods for achieving a balance between inductive and capacitive reactive power. These methods supply or absorb the reactive power that is inductive and capacitive. So, it increases the transmission network's effectiveness and power quality. Shunt capacitor banks are mostly used to raise the network's power factor. They also decrease network losses and increase voltage stability. A higher power transmission capacity and better control of the power flow are further benefits of increasing the power factor. 45Mvar shunt capacitor has been added to improve the voltage.

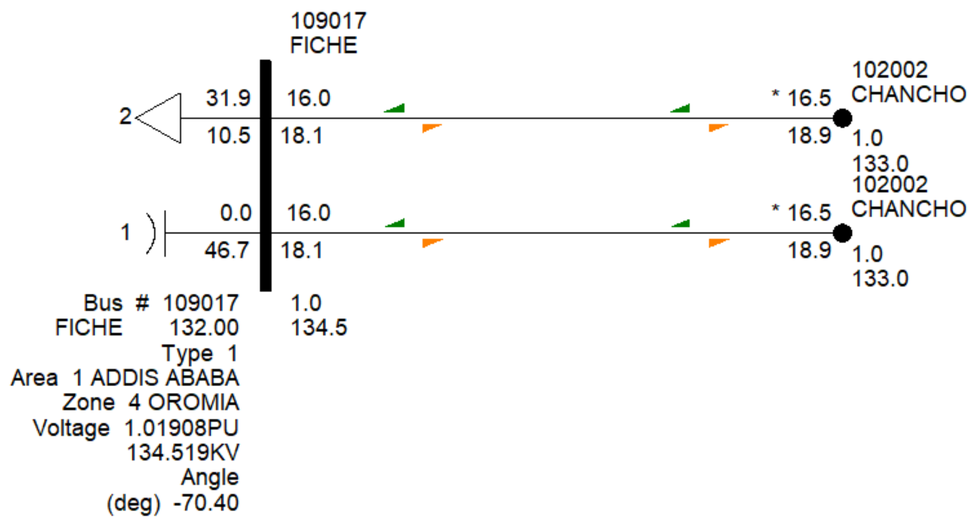


Fig.4.18: Load Flow Analysis of Option-3 with Shunt Capacitor

In this load flow analysis, when 45Mvar shunt capacitor has been added, the voltage increases to 1.02pu as shown above figure 4.18. This satisfies EEP grid code allowable limit under normal operation, which is (0.95 ≤0.1.02 ≤1.05) pu.

Out of the three options, option-1 and option-2 have been satisfied the EEP Grid code maximum and minimum allowable voltage limits whereas option-3 need compensation devices to improve the pu voltage, after 45MVar has been added, the pu voltage increases to 1.02

4.5. Contingency analysis

Power system planning and operation include a significant activity known as contingency analysis. Typically, a failure of one transmission line or transformer can result in overloading in other branches and/or a sudden surge or fall in system voltage. Calculating violations involves using contingency analysis.

4.5.1. Contingency Analysis of Option-1

When one line has been out of service, the voltage was 0.943pu and the second transmission line can carry the load as shown in figure 4.19 below. According to EEP grid code, the allowable minimum and maximum limit under emergency conditions are 0.9pu and 1.10pu respectively. So, option-1 was satisfied contingency analysis condition of EEP Grid code.

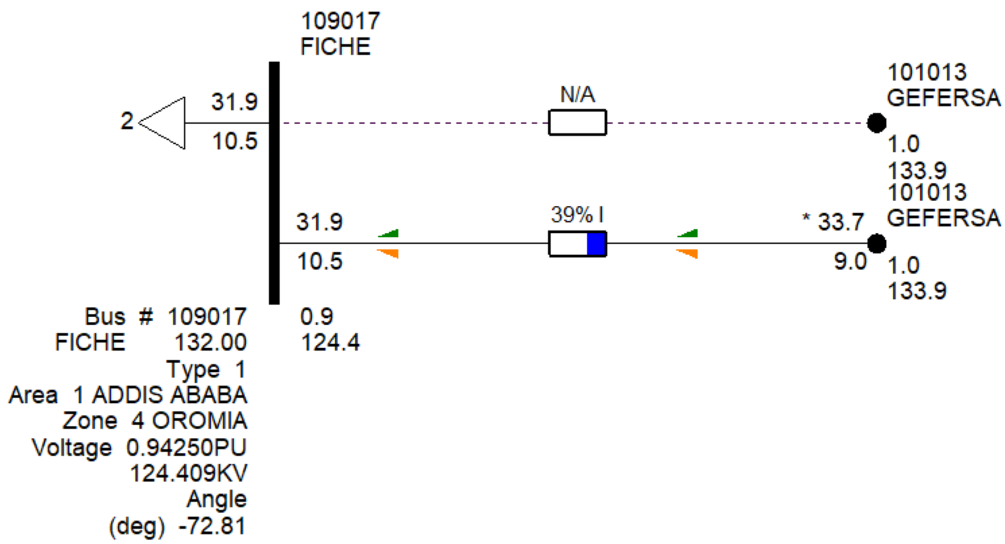


Fig. 4.19: Contingency Analysis of Option-1

4.5.2. Contingency Analysis of Option-2

When one line has been out of service, the voltage was 0.988pu and the second transmission line can carry the load as shown in figure 4.20 below. According to EEP grid code, the allowable minimum and maximum limit under emergency conditions are 0.9pu and 1.10pu respectively. Then option-2 was satisfied contingency analysis.

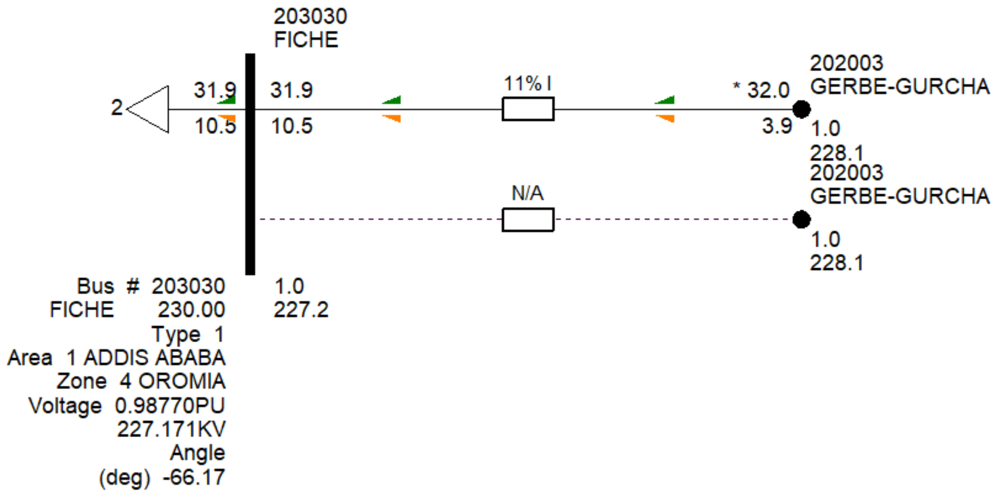


Fig.4.20: Contingency Analysis of Option-2

4.5.3. Contingency Analysis of Option-3 with Shunt Capacitor at Fiche Bus Bar

When one line has been out of service, the voltage was 1.026pu and the second transmission line can carry the load. According to EEP grid code, the allowable minimum and maximum limit under emergency conditions are 0.9pu and 1.10pu respectively. Then option-3 has been satisfied contingency analysis.

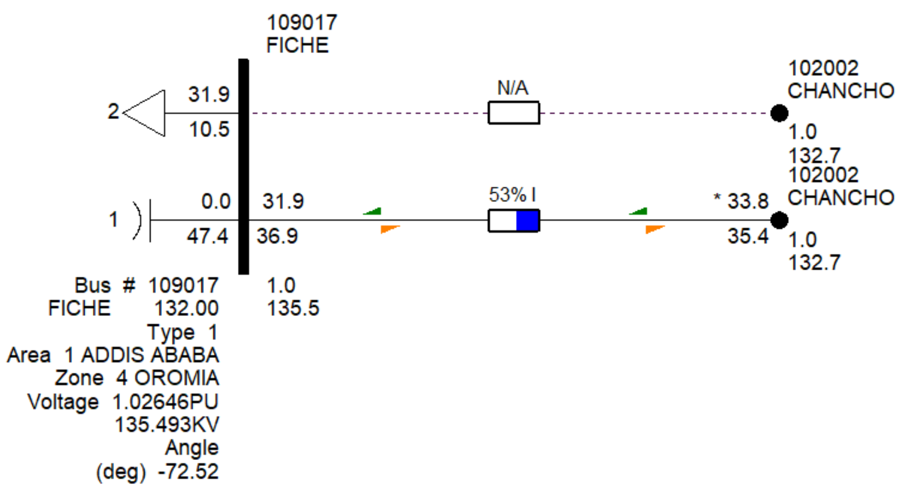


Fig. 4.21: Contingency Analysis of Option-3 with Shunt Capacitor

4.6 Contingency Analysis of Each Option If the Load in Fiche Increases

4.6.1 What If the Sum of Forecasted Load Increases By 25% for 5 years After the Forecasted Time (2028-2033)?

If the load increases by 25%, the actual load will be:

$$P_{load} = (31.9 + 31.9 * 0.25)\text{MW}$$

=39.875MW

Then let's see contingency analysis of the three options.

4.6.1.1 Option-1

Gefersa to Fiche 132kvdouble circuit transmission line. As shown figure 4.22 below, the pu value of voltage when one line has been out of service was 0.919 which was between the allowable minimum EEP grid code pu voltage ($0.90 \leq 0,919 \leq 1.10$). Therefore, Gefersa to Fiche transmission line has been satisfied the N-1 contingency analysis 5 years after the forecasted time (after 10 years from now).

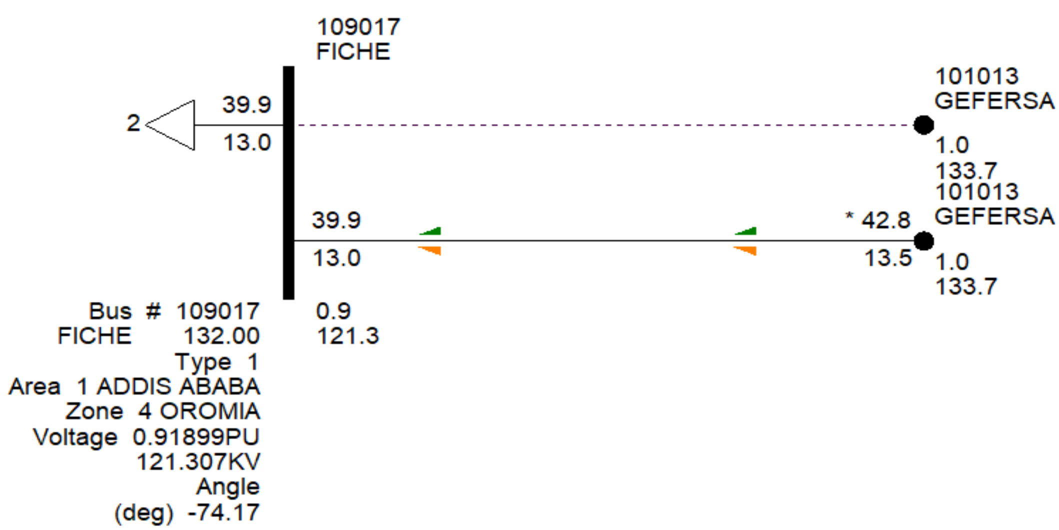


Fig. 4.22: Contingency Analysis of Gefersa to Fiche when Load Increases 25%

4.6.1.2 Option-2

Gerbe-Guracha to Fiche 230kv transmission line.

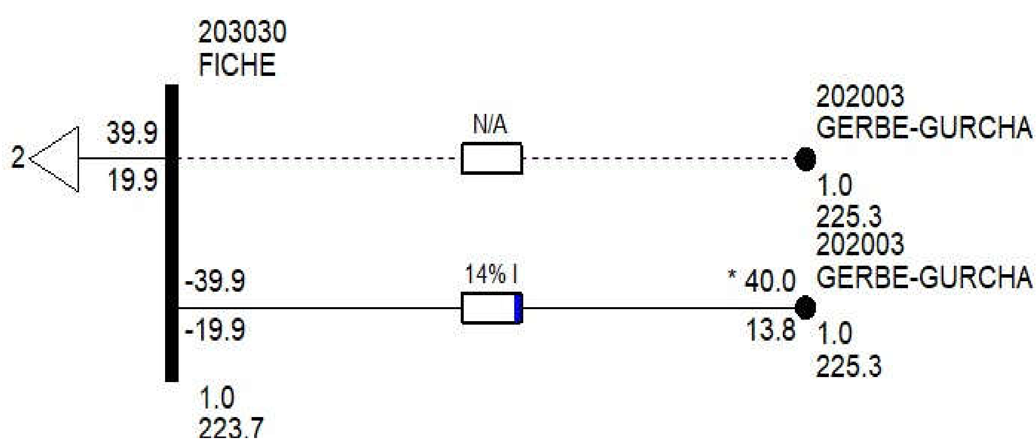


Fig. 4.23: Contingency Analysis of Gerbe-Guracha to Fiche When Load Increases 25%

As shown above figure 4.23, the pu value of voltage when one line has been out of service is 1 which is between the allowable minimum EEP grid code pu voltage (0.9). Therefore, Gerbe-Guracha to Fiche transmission has been satisfied the N-1 contingency analysis 5 years after the forecasted time.

4.6.1.3 Option-3

As shown figure 4.24 below, the pu value of voltage when one line has been out of service was 1.01 which is between the allowable minimum EEP grid code pu voltage ($0.90 \leq 1.01 \leq 1.10$).Therefore, Chancho to Fiche transmission line has been satisfied the N-1 contingency analysis 5 years after the forecasted time.

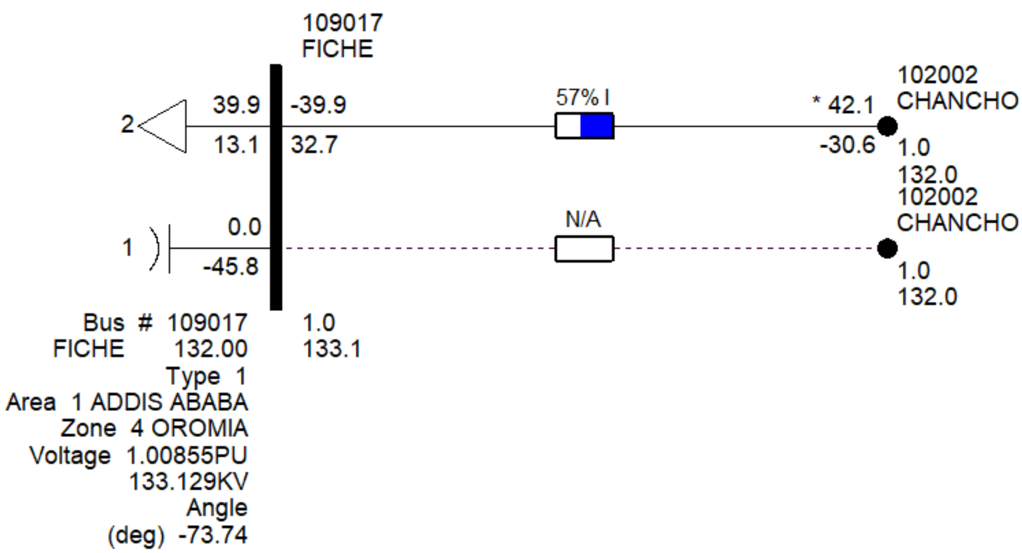


Fig. 4.24: Contingency Analysis of Chancho to Fiche When Load Increases 25%

4.6.2 What If the Sum of Forecasted Load Increases By 50% for 10 years After the Forecasted Time (2033-2038)?

If the load increases by 50%, the actual load will be:

$$P_{load} = (31.9 + 31.9 * 0.50)\text{MW}$$
$$=47.85\text{MW}$$

4.6.2.1 Option-1

As shown figure 4.25 below, the pu value of voltage when one line has been out of service was 0.9 which is between the allowable minimum EEP grid code pu voltage ($0.90 \leq 0.9 \leq 1.10$). Therefore, Gefersa- Fiche transmission line has been satisfied the N-1 contingency analysis 10 years after the forecasted time.

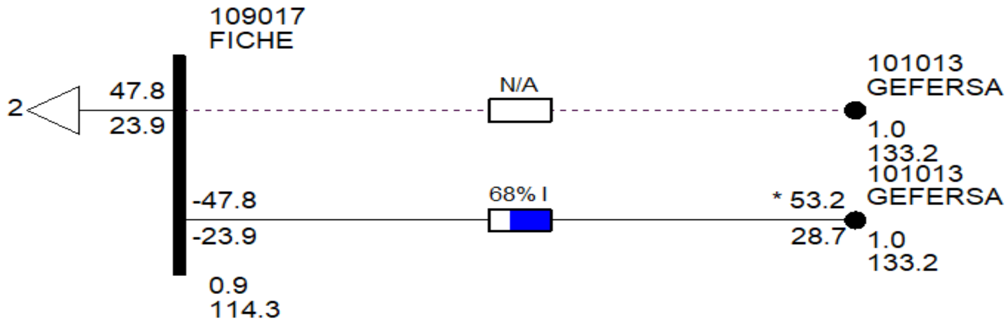


Fig. 4.25: Contingency Analysis of Gefersa- Fiche Transmission Line When Load Increases 50%

4.6.2.2 Option-2

As shown figure 4.26 below, the pu value of voltage when one line has been out of service was 1, which is between the allowable minimum EEP grid code pu voltage (0.90 ≤ 1.00 ≤ 1.10).. Therefore, Gefersa- Fiche transmission line has been satisfied the N-1 contingency analysis 10 years after the forecasted time.

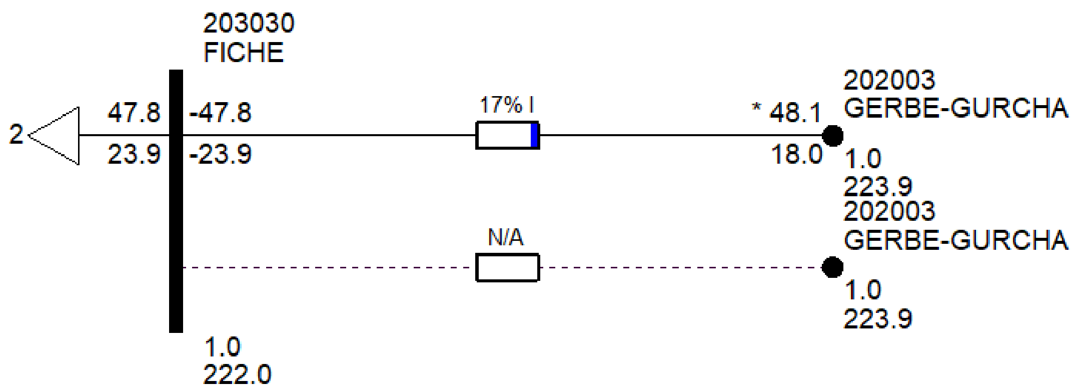


Fig. 4.26: Contingency Analysis of Gerbe-Guracha to Fiche Transmission Line When Load Increases 50%

4.6.2.3 Option-3

As shown figure 4.27 below, the pu value of voltage when one line has been out of service was 1, which is between the allowable minimum EEP grid code pu voltage (0.90 ≤ 1.00 ≤ 1.10). Therefore, Gefersa- Fiche transmission line has been satisfied the N-1 contingency analysis 10 years after the forecasted time.

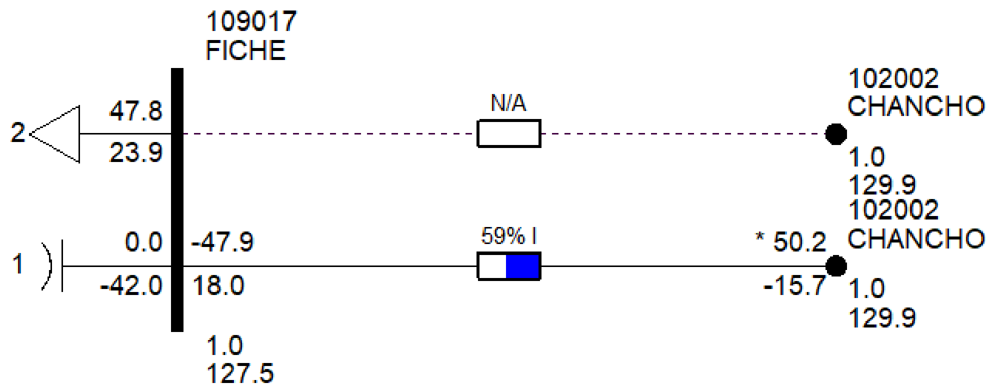


Fig. 4.27: Contingency Analysis of Chancho-Fiche Transmission Line When Load Increases 50%

4.6.3 What If the Sum of Forecasted Load Increases By 75% for 15 years After the Forecasted Time (2038-2043)?

If the load increases by 50%, the actual load will be:

$$P_{load} = (31.9 + 31.9 * 0.75)\text{MW}$$
$$=55.825\text{MW}$$

4.6.3.1 Option-1

As shown figure 4.28 below, the pu value of voltage when one line has been out of service was 0.8 which is below the allowable minimum EEP grid code pu voltage 0.9. Therefore, Gefersa- Fiche transmission line didn't satisfy the N-1 contingency analysis 15 years after the forecasted time.

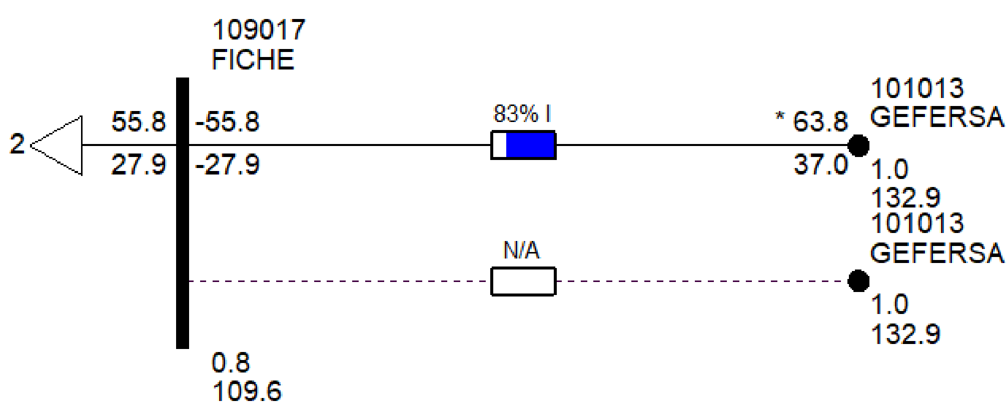


Fig. 4.28: Contingency Analysis of Gefersa- Fiche Transmission Line When Load Increases 75%

4.6.3.2 Option-2

As shown figure 4.29 below, the pu value of voltage when one line has been out of service was 1, which is between the allowable minimum and maximum EEP grid code pu voltage ($0.90 \leq 1.00 \leq 1.10$). Therefore, Gerbe-Guracha to Fiche transmission line has been satisfied the N-1 contingency analysis 15 years after the forecasted time.

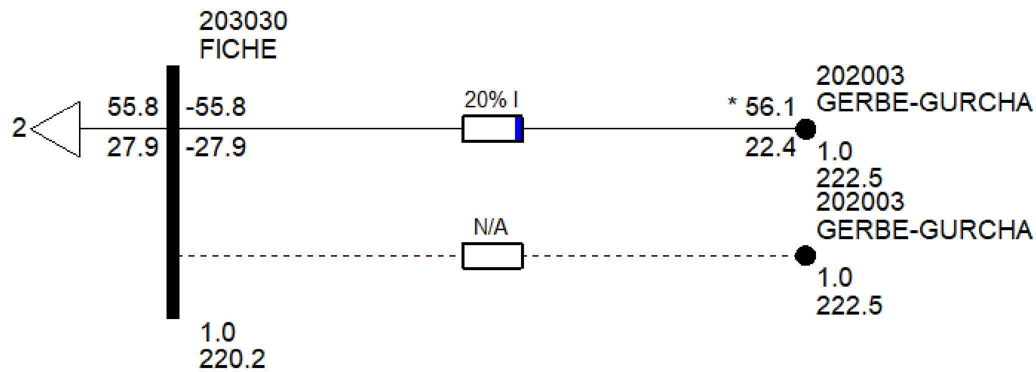


Fig. 4.29: Contingency Analysis of Gerbe-Guracha to Fiche Transmission Line When Load Increases 75%

4.6.3.3 Option-3

As shown figure 4.30 below, the pu value of voltage when one line has been out of service was 0.9, which is below the allowable minimum EEP grid code pu voltage 0.9. Therefore, Chancho-Fiche transmission didn't satisfy the N-1 contingency analysis 15 years after the forecasted time.

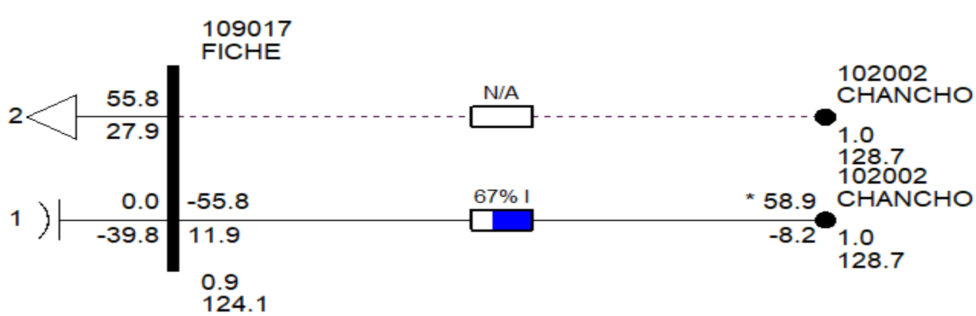


Fig. 4.30: Contingency Analysis of Chancho-Fiche Transmission Line When Load Increases 75%

From the above figures 4.28, 4.29 and 4.30 contingency analysis, when load in Fiche has been increased by 75%, 15 years after the forecasted time and if one line has been out of service, both option-1 and option-3 didn't satisfy the contingency analysis, but only option-

2 has been satisfied the contingency analysis. Constructing new transmission line requires high cost and takes long time. Therefore, we should have plan a transmission line that works for more than 15years.

4.7 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. The majority of the system faults are not three-phase faults /symmetrical faults/ but faults involving one line-to-ground or occasionally two lines-to-ground/unsymmetrical fault/. Though 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. Three-phase and single-phase-to-earth fault studies were conducted using IEC60909 method, which uses sub transient reactance of generator. 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.

4.7.1 Short Circuit Analysis of Option-1

Table 4.6: Short Circuit Analysis of Option-1

Bus No	Bus name	Voltage level(KV)	3 phase fault Current (A)	1 phase to ground (LG) Fault Current (A)	Two phase (LL) fault Current (A)
101013	Gefersa	132	1471.1	566.5	737
101013	Gefersa	132	1471.1	566.5	737

4.7.2 Short Circuit Analysis of Option-2

Table 4.7:Short circuit analysis of option-2

Bus No	Bus name	Voltage level(KV)	3 phase fault Current (A)	1 phase to ground (LG) Fault Current (A)	Two phase (LL) fault Current (A)
202003	Gerbe-Guracha	230	1085	281.8	543.8
202003	Gerbe-Guracha	230	1085	281.8	543.8

4.7.3 Short Circuit Analysis of Option-3

Table 4.8: Short Circuit Analysis of Option-3

Bus No	Bus name	Voltage level (KV)	3 phase fault Current (A)	1 phase to ground (LG) Fault Current (A)	Two phase (LL) fault Current (A)
102002	Chancho	132	1351.8	547.6	677.1
102002	Chancho	132	1351.8	547.6	677.1

4.8 Comparison of Each Option

As shown below table 4.9, comparison of each option was summarized.
Table 4.9: comparison of each option

Item	Option-1	Option-2	Option-3
Total transmission line and other cost (USD)	15,518,760.84	11,470,129.402	8,891,619.526
Availability of free bay at source substation	No	No	Yes
Availability of free space for bus bar extension	Yes	Yes	Not needed
N-1 contingency of supply line	Yes	Yes	Yes
Resettlement inside city for transmission line corridor	No	Yes	Yes
Transmission line length in km	96	36	55

From the above table 4.9 we have compared the three options in terms of investment cost, N-1 contingency of supply line, Resettlement inside city for transmission line corridor and transmission line length etc. From the three options, constructing new 132kv transmission line from Gefersa substation to Fiche substation was the longest distance, due to its high length of the transmission line, there was high voltage drop through the transmission line and also there was high cost. Supplying 132kv transmission line from Chancho substation to Fiche substation has been the cheapest and it was 55km away from Fiche substation which has a medium length of transmission line from the other options. And also supplying 230kv transmission line from Gerbe-Guracha substation to Fiche substation was intermediate in cost and it was the shortest path of transmission line expansion from the other options. Even though all the three options has been satisfied all the conditions we have considered like load flow analysis, short circuit analysis and N-1 contingency analysis, we should have to select the one which can supply secure and reliable power to customers and has least cost. But from the three options, it was not possible to get both having low cost and supplying secure and reliable power to customers. As a result tradeoff has been done and supplying 230kv double circuit transmission line from Gerbe-Guracha substation to Fiche substation has been selected.

5. Conclusions and Recommendations

5.1 Conclusion

The objective of the transmission line expansion planning problem has been to propose least cost transmission expansion strategy while fulfilling all the operation and security constraints of the system. This thesis has focused on Transmission Line Expansion Planning of Gefersa-Fiche transmission line so that the growing electrical demand will be supplied in safe, secure and reliable condition. Load forecasting of Gefersa-Fiche transmission line from 2023-2027 has been done by considering peak load, population number, GDP data, precipitation and temperature data using ANN algorithm. Also, PSS/E software has been used for network modeling and load flow analysis. The forecasted load in Fiche was 31.9 MW but, the existing 66kv transmission line supply can supply maximum of 21.6 MW and due to aging of the transmission line it carries below 21MW. Then this transmission line didn't satisfy the demand in that area. Then, three options have been taken for transmission expansion planning (Gefersa to Fiche 132kv, Gerbe-Guracha to Fiche 230kv and Chancho to Fiche 132kv) transmission lines. Even though all the three options that have been considered in this thesis satisfy load flow analysis and N-1 contingency analysis, Gerbe-Guracha to Fiche 230kv transmission line has been selected due to its intermediate cost and shortest in length, considering future expansion of Fiche and surrounding areas.

5.2 Recommendation

In this thesis, data collection from EEU was hard due to their poor data recording and handling. Then we recommend that EEU managers and staff members should take data recording and handling trainings to properly document all the data in each substation.

The existing Fiche substation transformer, circuit breaker, disconnector and other equipment's were designed to 66kv transmission line. Then these equipments should be upgraded and re-designed using the short circuit analysis done in this thesis for the new 230kv transmission line.

Now a days in Ethiopia transmission expansion planning is not common due to the shadow of substation or distribution expansion planning, but for proper planning of electric power generation, transmission and distribution should be planned separately for better performance.

5.3 Future Work

Future work in the area of transmission expansion planning: In this thesis static transmission expansion planning was done, but, in future it is better to include dynamic transmission expansion planning model.

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APPENDICES

Appendix I: Draft Cost Estimation for Option -1

No	Description	Unit	Qty	Unit cost (USD)	Total cost (USD)
1	132kv double bus bar system	lot	1	117,133.2	117,133.2
2	132kv line bay (Fiche -line)	lot	2	191,888.7	383,777.4
3	132kv double circuit Transmission line from Gefersa substation to Fiche substation	km	96	130,000	12,480,000
4	132 kV double Bus Bar System				
A	Aluminum Alloy tube for 132kV bus bar	Mts.	581	72.07	41,872.67
B	132kV Bus bar support insulators	No	42	425.85	17,885.7
C	132kV Bus bar Earthing Switch	Set	2	5,843	11,686
D	Set of steel structures for equipment support, shield wire tower, etc. including foundation anchor bolts, eyeballs and assembly nuts, bolts and washers, etc for one complete 132kV bus bar system	lot	1	4,302.2	4,302.2
E	conductors, clamps, connectors, insulator strings,	lot	1	6,272.80	6,272.80

Appendix II: Draft Cost Estimation for option-2

No	Description	Unit	Qty	Unit cost (USD)	Total cost (USD)
1	230kv double bus bar system	lot	1	194,982.3	194,982.3
2	230kv line bay (Fiche -line)	lot	2	245,432.75	490,865.5
3	230kv double circuit Transmission line from Gerbe-Guracha substation to Fiche substation	km	36	230,000	8,280,000
4	Aluminum Alloy tube for bus bar	Mts	693	117.37	81,337.4
5	Bus bar support insulators	No	42	749.79	31,491.18
6	Bus bar Earthing Switch, 3-pole	Set	2	8,161.60	16,323.2
7	Lightening Arrestors with discharge counter,	No	15	1697.67	25,465.05
8	Line Disconnector with earthling switch	Set	5	11,387.17	56,935.85
9	Current Transformers,	No	15	8,434.10	126,511.5
10	Circuit Breakers, SF6	No	15	17,372.13	260,581.95
11	Bus bar Disconnectors, pantograph type,	No	5	18,099.43	90,497.15

Appendix III Draft Cost Estimation for option-3

No	Description	Unit	Qty	Unit cost (USD)	Total cost (USD)
1	132kv double circuit Transmission line from Gefersa substation to Fiche substation	Km.	55	130,000	7,150,000
2	132kv,45Mvar, shunt capacitor complete with all accessories	No.	1	334,528.22	

Appendix IV: Transmission Line Parameter Standards

VOLTAGE(KV)	CONDUCTOR	TOWER CONFIG.	NO.OF CONDUCTORS	POSITIVE SEQUENCE				ZERO SEQUENCE				THERMAL RATING			SIL
				R	X	B		R0	X0	B0		CONDUCTOR	CIRCUIT		CIRCUIT
				Ω/KM	Ω/KM	μF/KM	μS/KM	Ω/KM	Ω/KM	μF/KM	μS/KM	A	A	MVA	MVA
45	Merlo	Single	1	0.6168	0.4122	0.008789	2.7599	0.8079	1.4684	0.0052	1.6329	214	214	17	5
45	Merlo	Double	1	0.6168	0.4194	0.008659	2.7188	0.7613	1.4742	0.004728	1.4846	214	214	17	5
45	pemice	Single	1	0.311	0.3939	0.009249	2.9041	0.5021	1.4501	0.005358	1.6823	320	320	25	5
45	53/12.3	Single	1	0.502	0.4189	0.008735	2.7428	0.6929	1.4598	0.005167	1.6224	240	240	19	5
45	Raven	Single	1	0.6	0.4209	0.008701	2.7322	0.7911	1.477	0.005169	1.6232	214	214	17	5
45	Raven	Double	1	0.6	0.4209	0.008701	2.7322	0.7911	1.477	0.005169	1.6232	214	214	17	5
66	Penguien	Single	1	0.3165	0.4043	0.009066	2.8468	0.5074	1.4452	0.005281	1.6583	316	316	36	12
66	Quail	Single	1	0.502	0.4189	0.008735	2.7428	0.6929	1.4598	0.005167	1.6224	240	240	27	11
66	Racoon	Single	1	0.4282	0.4138	0.008848	2.7782	0.6191	1.4547	0.005206	1.6348	264	264	30	11
66	70/12	Single	1	0.4882	0.4137	0.008778	2.7563	0.6791	1.4546	0.005182	1.6272	245	245	28	11
66	Merlo	Single	1	0.6169	0.4175	0.008666	2.7211	0.8078	1.4584	0.005143	1.6149	214	214	24	11
66	merlo	Double	1	0.6169	0.4175	0.008666	2.7211	0.8078	1.4584	0.005143	1.6149	214	214	24	11
132	Ash	Single	1	0.2132	0.4265	0.008604	2.7015	0.4777	1.1958	0.005291	1.6615	399	399	91	44
132	Ash	Double	1	0.2135	0.4242	0.008715	2.7366	0.4655	1.2145	0.005629	1.7676	399	399	91	44
132	Ostrich	Single	1	0.2247	0.4229	0.008594	2.6986	0.4892	1.1921	0.005288	1.6604	388	388	89	44
132	Tiger	Single	1	0.2606	0.4243	0.008535	2.6799	0.5262	1.1936	0.005266	1.6534	357	357	82	44
132	Tiger	Double	1	0.2609	0.422	0.008698	2.7311	0.5129	1.2123	0.005541	1.74	357	357	82	44
230	ACAR 228.6/241	Single	1	0.0791	0.424	0.008695	2.7302	0.3193	1.1361	0.005825	1.8292	713	713	284	134
230	Mallard	Single	1	0.0859	0.4179	0.008734	2.7424	0.3261	1.13	0.005843	1.8346	687	687	274	136
230	Mallard	Double	1	0.0861	0.4092	0.008957	2.8124	0.3136	1.159	0.00589	1.8496	687	687	274	139
230	Redwing	Single	1	0.0956	0.4213	0.00866	2.7192	0.3358	1.1334	0.00581	1.8242	646	646	257	134
230	Redwing	Double	1	0.0958	0.4126	0.008879	2.7879	0.326	1.1624	0.005854	1.8382	646	646	257	138
230	Twin Ash	Single	2	0.1067	0.3261	0.011218	3.5224	0.3469	1.0382	0.006857	2.153	399	399	318	174
230	Twin Ash	Double	2	0.1069	0.3174	0.0116	3.6425	0.3371	1.0672	0.007032	2.208	399	399	318	179
230	Yew	Single	1	0.0815	0.4234	0.008708	2.7343	0.3217	1.1355	0.005831	1.831	704	704	280	134
230	Yew	Double	1	0.0817	0.4147	0.00893	2.8039	0.3119	1.1645	0.005878	1.8456	704	704	280	138
400	Twin ASTER 8051	Single	2	0.0248	0.3292	0.01195	3.7523	0.2932	0.8293	0.008522	2.6758	1936	1936	1341	526
400	Twin ASTER 8051	Double	2	0.0244	0.3096	0.011952	3.7529	0.2634	0.9123	0.007542	2.3683	1936	1936	1342	560

Appendix V: Sales Data

Year	Domestic customer (MWh)	Commercial customer (MWh)	Industrial customer (MWh)	Street lighting (MWh)	Total sale(MWh)
2019	28,441.389	22,178.939	23,658.12	8,994.672	83,273.128
2020	60,958.695	4,633.340	9,597.007	4,022.54	79,211.580
2021	32,075.090	3,864.073	47,346.880	4,315.498	87,601.564
2022	44,243.300	6,798.408	36,984.540	8,970.240	96,996.419

Appendix VI: List of Waiting Customers

Customer Name	Demand in(MW)
Selale University	5.7
Golden mining factory	10
New domestic customers	1.8
New industrial customers	2.06
New commercial customers	0.87