Addis Ababa University

Addis Ababa Institute of Technology

School of Electrical and Computer Engineering

Neural Network-based Smart Meter Demand Response Analysis: A case study of Addis Ababa power system

By
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A Thesis Submitted to the School of Graduate Studies of Addis Ababa University, Addis Ababa Institute of Technology in Partial Fulfillment of the Requirements for the Degree of Master of Science in Electrical and Computer Engineering (Industrial Control Engineering)

Advisor
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This is to certify that the thesis prepared by Betelhem Abera Teklemariam, entitled "**Neural Network-based Smart Meter Demand Response Analysis: The case of Addis Ababa power system** ", submitted in partial fulfillment of the requirements for the degree of Master of Sciences in Electrical Engineering (Industrial Control Engineering).

Approved by Board of Examiners

Thesis Advisor	Signature	Date
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DECLARATION

I certify that my research work titled 'Neural Network-based Smart Meter Demand Response Analysis: A case study of Addis Ababa power system' is my work. The work has not been presented elsewhere for assessment. For materials used from other sources, it has been it has been properly referred.

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Date of submission: ______________

The MSC thesis has been submitted for examination with my approval as a university advisor.

Advisor Name Signature

Dr. Dereje Shiferaw ______________

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Completing this project also required the support, appraisal, and criticism of my advisor, committee members, my family, and my peers.

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Betelhem Abera Teklemariam

ABSTRACT

Most African countries including Ethiopia used the old way of going door to door to record usages of electricity. This results lots of guesswork, which has direct impact on consumers, especially in billing.

In case of Ethiopian Electric Utility (EEU) getting real-time information about power interruption, maximum power consumption in the grid is difficult to maintain and implement especially when going down towards the end consumers. The concepts of Smart Meters are introduced to address problems associated in electricity transmission throughout the usual traditional grid, which allows a bidirectional communication between the household smart meters and the supplier.

This study aims to explore demand response analysis of smart meters using available recorded information by training Neural Network method to identify maximum demand response, type of power interruption and identify theft, by means of Artificial Neural Networks (ANNs) with Feedforward backpropagation algorithm for the selected cases in Addis Ababa as a case study. Four districts in the EEU Addis Ababa City were used for collecting quantitative data.

The result for theft identification purpose consists of 169,296 samples, 25 neurons, two outputs. The best validation performance is 0.003124, and the overall correctly predicted percentage becomes 99.7%. In power fluctuation classifications, the model data sets consist of 3,596 sample sizes with 30 hidden neurons. The best validation performance is 0.03197. Moreover, the overall percentage of correctly predicted values is 97.2%. Finally, for the maximum power demand the percentage of correctly predicted values is 100%. The data analysis highly affected the performance of the NN system. Lastly the study recommends, further improvements can be achieved by process real-time data from millions of smart metering, more efficient modeling can lead to higher prediction accuracy.

Key words: ***Smart Grid, Demand Response, Smart Meter, Data, Neural Network, Fault detection Theft detection, MATLAB***

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LIST OF ABBREVIATIONS & SYMBOLS

ABBREVIATIONS

SM	Smart Meter
SG	Smart Grid
ANN	Artificial Neural Network
DL	Deep Learning
NNM	Neural Network Model
DR	Demand Response
DEM	Dynamic Energy Management
EEPCO	Ethiopia Electric Power Corporation
AAEU	Addis Ababa Electric Utility
WAAD	West Addis Ababa District
EAAD	East Addis Ababa District
NAAD	North Addis Ababa District
SAAD	South Addis Ababa District
MATLAB	Matrix Laboratory
nprtool	Neural Net Pattern Recognition tool
ROC	Receiver Operating Characteristic Curve
R	R Phase
S	S Phase
T	T Phase
N	Neutral
NTL	Non- Technical Losses
TL	Technical Losses
AMI	Advanced Metering Infrastructure

SYMBOLS

KWH	Kilowatt Hour
A	Load Current
MW	Energy in Mega Watt
MSE	Mean Square Error
Tanhsig	Tanh Sigmoid Function
Xn	Input Matrix
Y	Output Matrix
Wnm^1	Input Weight Matrix
Wnm^2	Output Weight Matrix
$g(n_m^1)$	Activation function
α	Learning rate

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CHAPTER ONE

1. Introduction

Electricity is becoming the most indispensable components of modern human life. It is among the driving forces of modern life in the world. However, electricity is something most of us may take for granted. On one hand, there are almost 1.3 billion people still not unable to benefit from electricity and instead, the electricity demand is expected to increase significantly over the coming years [1].

The role of electricity in human society is vital. Thus, conservation and appropriate utilization strategies for better use of the grids are a must.

Currently, the demand for a smarter approach becomes crucial so as to overcome the increasing prices and shortages of electrical energy. Accordingly, systems for a smarter energy management calls for the development of appropriate technologies such as smart grids and demand-side management [1].

With the advance of the smart grid, there are four major drivers for the development and also the smart grids implementation within the existing grid networks. These major drivers, according to a report by VINNOVA (2011), are growth, sustainability, market, and vulnerability. Growth refers at the rate of exponential growth regarding the demand for electric power. With the new technological advances and increase in the coverage of the electrical network, the net demand keeps increasing exponentially. Market refers to the competition and the market rules concerning energy management and distribution to the end-use customers. Vulnerability is an important factor in the market, as it deals with the grid vulnerability and the probability of outages, or events like grid failure, overloading, or irregularities in supplied voltage [1].

A network that allows different devices to communicate customer and utilities, and allowing to manage demands, protect network distribution, energy saving, and cost reduction are smart grids [2].

It is reliable, economical, and environmentally friendly can be applied in sensing technologies and control infrastructures. Compared with the conventional power grids, the new smart grid is advantageous in terms of structural flexibility, great system performance that can improve social development.

Smart electricity meters track (i.e., "meter") household or business energy consumption and communicate that data, usually a few minutes' intervals, back to the utility. This task is called "energy metering" and it takes place inside the meter itself [3].

One smart meter in isolation has limited uses. However, if most meters in an area are now "smart", the utility can reap large benefits. With the added information provided by large numbers of smart meters, a utility can adjust their services as needed to improve the efficiency, reliability, costs, and sustainability of their service. Smart meters have made possible the collection and proper storage of real-time electricity data. These data are used by DR programs to shift consumption from peak demand to off-peak hours so they can benefit from better energy costs [4].

Smart grid transmission lines are the most exposed elements in the electrical system due to their extensive dimensions and continuous exposure to atmospheric phenomena and accidents provoked by human activity. Automatic methods of faults detection and classification solve several significant problems involved in the operation of power systems [5]. One of these problems is the inspection and maintenance of transmission lines. Because of the great length of the lines and the environment, they traverse it is rather a difficult task. Automatic methods that can determine the exact location of particular fault allow quick re-establishing of the power supply.

Therefore, a system to the electricity billing is implemented for the consumers based on their consumption of power. Consuming power illegally without paying the bill for the utility company is considered a crime. Stealing electricity is an offense and punishable by law and it comes under non-technical loss of electricity. Power theft is a big issue in developing countries. Power theft affects GDP hard. Overloading power distribution systems, power disruption, poor quality of supply, high electricity prices, etc.., are among the serious problems caused by power theft. So, it is very important need to prevent power theft for the undisturbed supply of good quality power everywhere [6].

Therefore, for the customer and the government to truly benefit from the smart grid investment, it is critical that the massive amount of data available from smart grid technology can be transformed to helpful information in an organized, and prioritized manner that benefits grid operators make timely decisions to control the grid safely, economically, and reliably.

This thesis focuses on processing smart meter data, with the aid of MATLAB, customer billing, customer energy consumption data aiming to achieve accurate maximum power demand forecasting, power interruption and power theft forecasting in the smart meter.

1.1 Background

World bank's latest report (2017) on electricity access indicates (% of the population), Ethiopian coverage about 44.3%, a rapid growth relative to the previous. If we continue to grow close to 100% current methods for collecting and analyzing data may be very difficult to scale [7].

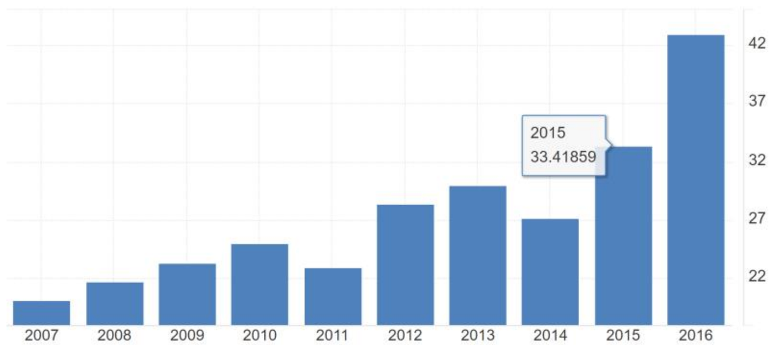

Figure 1-1 Ethiopian Access to electricity (percentage of population) [7]

The Electromechanical energy meter is the most traditional and widely used energy meter over a century. It is capable of measuring only the active energy which is typically displayed on a mechanical counter in kWh. However, they have many susceptible errors due to environmental variations and regular operations. Besides Electromechanical meters require manual readings it induces tampering of meter readings, human errors in readings, Regularities in billing time, and controversial billing are also possible with manual reading. Besides power theft is caused by electromechanical meters [8].

To overcome the problems of the traditional measurements, are capable of measuring electricity usage with digital technology. At the same time, they can measure the other electrical parameters such as phase voltages, phase currents, frequency, power factor, active power, reactive power, apparent power and maximum demand. Smart meters are the latest type of electricity meters, they allow two-way communication between the meter and the base station. Load profiling, pre-payment, remote disconnection and reconnection, power outage notification, tamper detection, and multi-tariffing are also possible with smart meters [8].

Advanced, secure, and reliable grid is required to manage the increasing demands and also rising costs of electricity. Establishment of reducing grid vulnerabilities can be done through information technology integration systems in the existing electrical grids. In addition to this, establishment of data feedback system helps to reduce grid vulnerabilities. Demand Side Management (DSM) is among the advanced form of grid management which deals with the monitoring and manipulating of peak demands and attending of the load profile over the day [1].

Demand response is a key factor of DSM. Demand response (DR) is Changes in electric usage by end-use customers from their day-to-day normal consumption patterns in response to variation in the price of electricity over time [24]. Hence studying the demand response analysis using smart meters applying neural network-based technique is objective of this thesis [1].

1.2 Problem statement

As the number of consumers of electricity increases, it’s getting very difficult to manually record meters by going door to door. And this method can’t scale with the future demand even after recoding the data encoding and accessing it for bills and analysis is by itself another headache.

These problems are resulting in lots of guesswork and other sampling methods that decrease accuracy of data gathered, this has a major impact on consumers, especially in billing. Information to consumers about their power usage is very limited, this makes difficult decisions about how to use energy and subsequently reduce costs.

Apart from those current infrastructures that enable power supplier (EEP) to get real-time information about power interruption, maximum power consumption in the grid and problems (like equipment malfunction) are difficult to maintain and implement (in new areas) especially when going down towards the end consumers (households, business, and industries).

Reliable power delivery is a key factor in profitability and customer satisfaction. The current power supplier seems to rely heavily on consumer manual reports and handling these (usually phone calls). Ethiopian electric utility (EEU) has tried to improve the delivery mechanism and quality of supply. But electricity distribution system has remained inadequate to meet customer demand.

1.3 Significance of the study

This study helps the customer to able to know the maximum power demand and help the supplier to get real-time information that aims for a balanced way of power distribution and for identifying the problems like power cuts and power theft.

1.4 Objectives

1.4.1 General Objective

This thesis explores demand response analysis of smart meters using available recorded information by training Neural Network for maximum power demand, power interruption and theft identification.

1.4.2 Specific Objectives

- To analyze bulk data from the various smart meter in the grid for input to train Neural Network
- To train Neural Network to classify and identify power interruption, power theft and maximum demand
- Simulate result with MATLAB

1.5 Scope of Study

The study of this thesis is on collected energy meter data locate in the four districts in Addis Ababa. The performance analysis in this thesis done on MATLAB.

1.6 Methodology

With the aim of achieving the major objective of this study starting from the problem identification, various procedural tasks were followed by the author. Besides the following formal methodologies were followed subjected to changes, if need be, in the due course of the work

- Literature Review: The work of this thesis is necessarily based on previous work done by other scholars related to this selected topic. To look into the works of these scholars and get necessary and important information related to the topic; different kinds of literatures will be referred from different available sources such as books, papers, journals, the internet, etc. Therefore, the literature review includes reading books, articles, papers, journals, simulation tools, and searching the internet related to demand response, Smart meter, and Artificial Neural network.

- Data Collection: Since the success of this research is determined by the required data, various data will be collected from the Addis Ababa power system. This helps to train the Neural network.
- The model will be shown and simulated using MATLAB.
- Then after analyzing the simulated system, the whole work of the thesis will be concluded by suggesting implied recommendations on the area.

1.7 Organization of Thesis

This thesis consists of six chapters which are summarized as shown below. In the first Chapter introduction of a wireless electric meter (smart meter) has been discussed and describes the General and Specific objective, statement of the problem, significance, scope, and methodology of the thesis.

Chapter 2: Present definition and description on theoretical and conceptual background and previous study survey required to understand the concepts of the wireless electric meter and its integration with customer demand response.

Chapter 3: Discusses the basic theory of the neural network, type of power interruption, and fault.

Chapter 4: Analyses smart meter data and neural network training processes are described in detail.

Chapter 5: Explain the simulation result

Chapter 6: Conclusion and recommendation of the thesis will be presented.

CHAPTER TWO

2. Theoretical background and literature review

2.1 Theoretical Framework

Operation Principles of an Electromechanical Energy Meter

The Electromechanical meter is the most traditional and widely used energy meter over a century. It is capable of measuring only the active energy which is typically displayed on a mechanical counter in kWh. Figure 2.1shows a typical single-phase electromechanical meter [8].

It is basically designed with four major systems which are the driving system, moving system, braking system, and registering system. The driving system have two electromagnets while the moving system consists of an aluminum disc. The permanent magnet acts as the braking system while the gear train and counteract as the registering system. The electromagnetic force is produced by the arrangement of voltage and current coils. The voltage coil produces a magnetic flux in proportion to the voltage and the current coil produces a magnetic flux proportional to the current. The aluminum disc is mounted on a rigid axis. A mechanical force applies on the disc by the Eddy currents produced. The register mechanism integrates the speed of the disk over time by counting the number of revolutions. Figure 2.2 shows the basic arrangement of a single-phase electromechanical energy meter [8].

The current coil of the series coils produces alternating flux which is proportional and in phase with the load current. The flux produced by the voltage coil is not in phase with the supply voltage. This flux is 90-degree lagging with the supply voltage. This is implemented by having properly adjusted copper rings in the flux path as shown in Fig. 2.2. However, some electromechanical meters use winding with the series-connected lag adjusting resistor to perform this task [8].

Figure 2-1A single phase electromechanical meter [8]

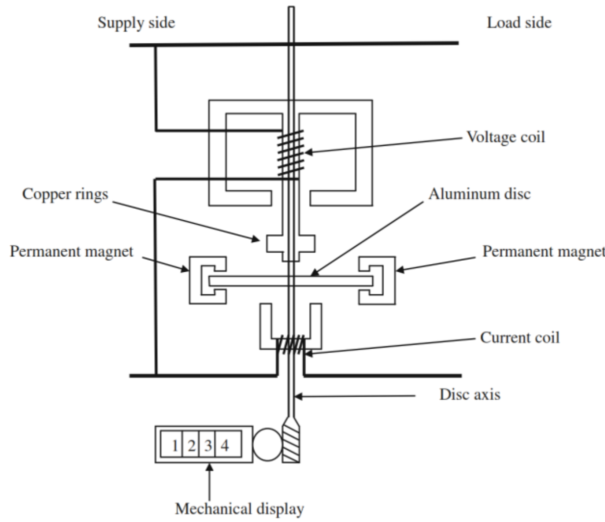

Figure 2-2Components of a single-phase electromechanical energy meter [8]

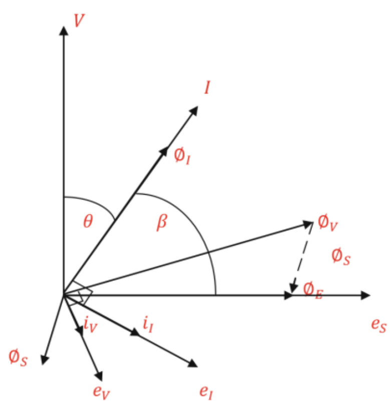

Figure 2-3Phasor diagram of a single-phase electromechanical energy meter [8]

Where:

ϕ_l is the flux due to current coil
ϕ_s is the flux due to quadrature band
ϕ_v is the flux of voltage coil
ϕ_E is the effective flux $(\phi_s + \phi_v)$
e_s is induced e.m.f due to ϕ_E
el is induced e.m.f due to ϕ_l
iv is the current rotor due to ev
i_l is the current rotor due to el
I is the current through the series coil
V is supply voltage
θ is phase angle between the current and voltage

The energy calculation inside an ellectromechanical meter is described as follows

The average driving torque acting upon the disc can be written as

$$T_{d(av)} = k_d[\phi_E I_I \cos(\theta) - \phi_l i_V \cos(180-\theta)] \qquad (2.1)$$

Where:

$T_{d(av)}$ is referred to average driving torque

kd is a constant for meter

Since $\phi_E \alpha \frac{V}{\omega} \rightarrow \phi_E = \frac{V}{\omega}$ (2.2)

Drawbacks of Electromechanical Meters

Electromechanical meters react to the changes more slowly than digital meters. They have many susceptible errors due to environmental variations and regular operations. The moving parts inside these meters are subjected to wear through time, varying temperature, and conditions. Whereas, mechanical gears wear due to the effects of dirt, dust, and humidity. The gear ratios also change over time due to the lack of lubricants. Nevertheless, vibration and shock affect the meter accuracy in the long run. Therefore, periodic calibrations are required at regular intervals. Furthermore, due to the lack of linearity of the iron core and the inertia of the spinning disk, errors can be caused at low and high loading [8].

Electromechanical meters require manual readings. In other words, meter readers must go and take the reading manually to issue the bill. Because of the manpower requirement, there is always an additional cost to the bill apart from the energy consumed. Moreover, the tampering of meter readings, human errors in readings, Regularities in billing time, and controversial billing are also possible with manual reading [8].

Power theft is a critical problem caused by electromechanical meters. Illegal power line reconnection, energy meter bypassing, and weak conditional access enforcement cannot be detected directly with these meters [8].

They have a Limited measurement, since the disk meters have only one dial it can only measure active or reactive power at a time. Furthermore, they cannot measure MDIs, instantaneous power, voltage, current, or other important factors.

Electronic Meters

Electronic meters are capable of measuring electricity usage with digital technology. Simultaneously, they can measure the other electrical parameters such as phase voltages, phase currents, frequency, maximum demand, power factor, active power, apparent power, reactive power, and power quality. Hence, electric meters perform all tasks done by the other types of meters. They have also the capability of sending the data through a different communication method. The readings are digital in electronic meters in contrast to the electromechanical meters [8].

Figure 2-4Electronic meter [8]

Smart Meters

Smart meters are the newest version of electricity meters. The new addition to electric meter types are smart meters. They resemble an electronic meter and much better as compared to the electronic and electromechanical meters. Thus, no need for personnel from the electric utility office to come to take meter readings. Since the readings are sent automatically through the internet. Therefore, such meters by far save money for costs incurred in taking the reading, also avoid mistakes during reading, overall, the reading is done on time so as to measure the monthly total units consumed [12].

Smart meters are different from electronic meters because of their additional functionalities and features. Apart from electricity measurements and automatic meter reading (AMR), they allow two-way communication between meter and base station. Load profiling, pre-payment, remote disconnection and reconnection, power outage notification, tamper detection, and multi-tariffing are also possible with smart meters [8].

2.2 Smart Grid

The latest type of electrical grids are Smart grids, that employ information, communication, and control techniques to improve the reliability and efficiency of electrical grids [2]. With the current exponential growth for smart metering systems in grids, high volumes of data and information are being available from the grid structure, Since massive data that generated from smart metering systems cannot be processed locally and using normally available methods, big data technologies are employed, which are designed to extract logical outcomes from very large data volumes. There are several big data sources in smart grids, with the major sources being power consumption data measured in kWh, energy pricing data collected by the automated revenue metering system (ARM), and operational data for grid operation and control [13].

It is interesting to note that smart grids can hold all types of storage and generation-related data, thus increasing the scope for user participation, asset optimization, and enabling services that are essential for markets [1].

2.2.1 Traditional Vs Smart Electricity Metering Systems

Show difference between the conventional meter and smart meters as [11].

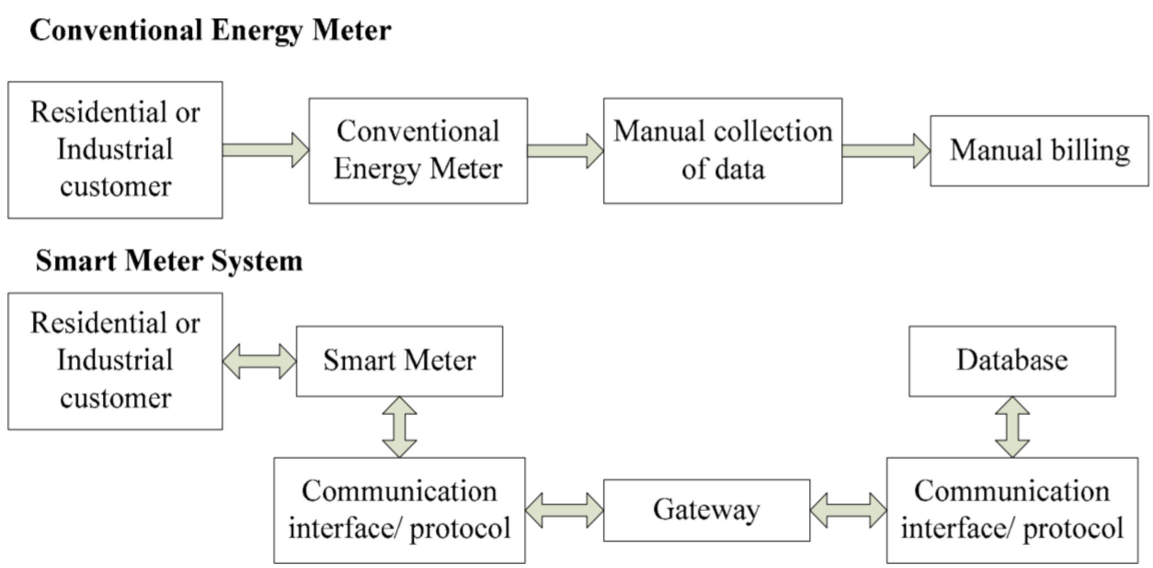

Figure 2-5 Metering architectures of traditional and smart energy meter [11]

The issues and challenges to consider in making these meters and smart grid Identified as

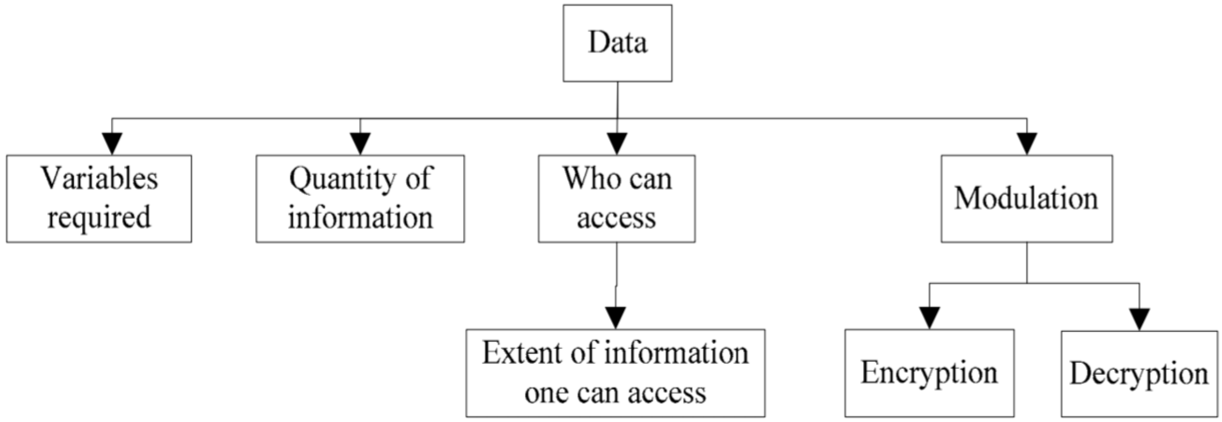

Figure 2-6 Challenges with data transfer for a smart meter system [11]

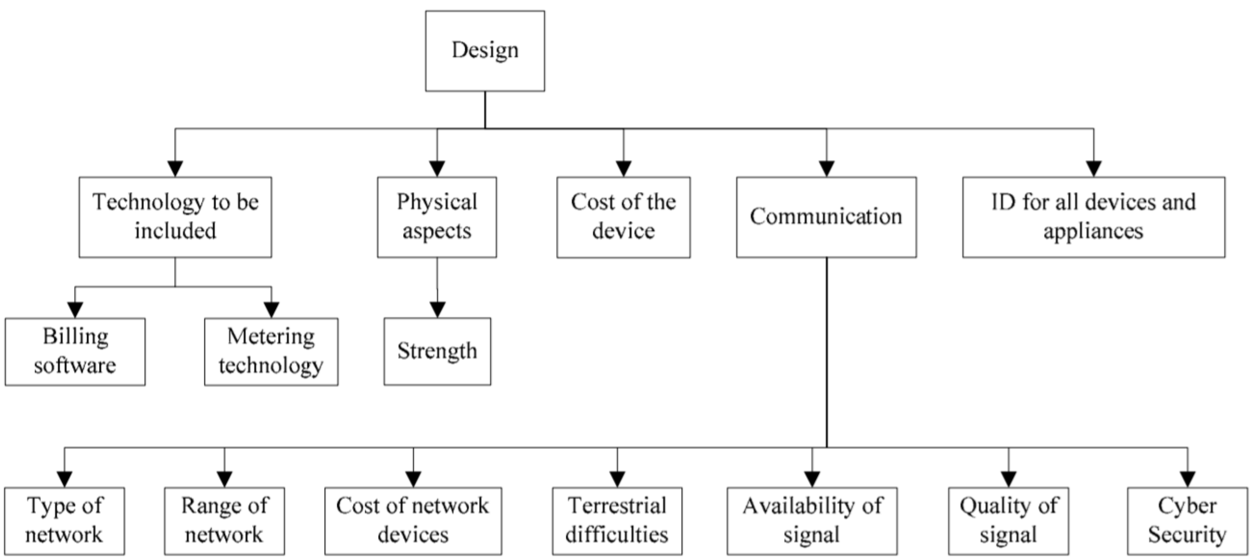

Figure 2-7 Design issues for a smart meter system [11]

Customers receive electricity produced by generating units through the electrical grid (a system of generation, transmission, distribution, and other services). Electricity meters are installed at customer premises for effective billing purposes as well as their function is measuring electricity consumption.

electricity meters working principles is, Using Ohm's law: P=V x I

Where P is the instantaneous power passing through the entire electric load of a house at any given moment; V is the voltage (or potential difference) across that element, and I is the current passing through that element. Therefore, the sum of each instantaneous power value over a period of time is the power used by the customer. It is expressed in Watt-hour. From the above equation, the electricity bill becomes

Electricity bill= electricity used (KW)* TIME (hours)*cost of 1 kwh.

Countries and also organizations are currently modernizing their existing utility grids with digital electricity meters, which measure, and record electricity use every hour. The basic difference between traditional electricity meters and smart electricity meters are briefly shown in table 2-1.

Table 2-1 Comparison between Traditional meter & Smart meter [22]

Traditional electricity meters	Smart electricity meters
No data storage	Data storage, stores electricity consumed every half of an hour
A meter reader needs to go door to door to customer's home or business to collect the information and send it to utility	Data transferred to utility automatically
If the meter reader cannot be able to take the reading this results in estimated bills,	
Electricity energy conception information collected by waiting for customer's monthly or quarterly bill	Digital data of energy consumption and TOU provided in real-time
No outage detection, as distribution companies cannot react quickly to interruptions in the supply	Automated outage detection enables companies to restore power fatly than conventional electricity metering
Connections and disconnections must be done manually	Connections of power and disconnections are quickly because they managed remotely

Smart Meter have two parts Analog Part and Digital Part. The Analog Part has a Power supply, Anti-Aliasing Filter, Battery Charger, Real-Time Clock (RTC), Voltage and Current Measurement, Anti-Tampering Circuit, Sigma Delta ADC, and Harmonics Analysis. The Digital Part consists of a microcontroller unit (with register and RAM) [15].

Smart meters are fit for recording energy consumption information including frequency, voltage, current, and power factor [15].

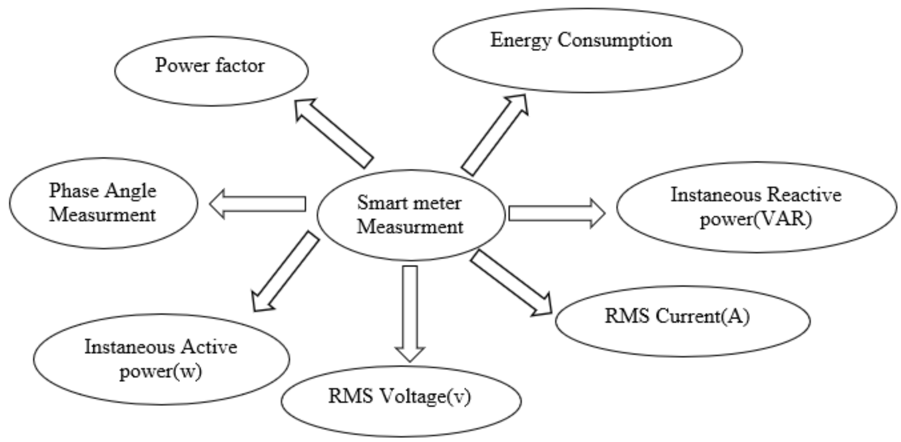

Figure 2-8 Measurements are taken by Smart Meter [15]

2.2.2 Benefits and Impact of smart meter

1. User Convince and accessibility

Nowadays, for the use of remote electricity metering system, different smart metering apparatus and systems were developed that can apply to Automatic Meter Reading (AMR), micro grid, and smart grid. As relevant markets are expanded, they are widely utilized by end-users. However, neither their energy efficiency nor user their convenience considered. In their paper, there is presentation of a smart metering device, which provides energy-efficient functions and easy accessibility for user convenience [16].

2. Energy efficiency- a climate change solution

Smart grids improve energy efficiency, provide a solution to climate change, and serve as an economic growth engine. To improve energy efficiency, smart grid technology optimizes electric power demand and supply management, minimizes electricity loss between power plants and consumers, and saves electricity. Due to reduced peak demand, related costs of building the more power plants can be avoided as well. As a solution to climate change, smart grids generate lower greenhouse gas amount through improved efficiency and the use of clean renewable energies. Smart grid technologies will improve the integration of this renewable energy capacity into existing and new grid infrastructure while creating new jobs for the industry as well [2].

3. Smart Place (Smart Consumer)

This domain will use the Advanced Metering Ifrastructure (AMI) system to reduce needless energy usage and increase its overall efficiency. In doing so, the smart place domain will create and continue to provide a two-way communication energy management system between consumers and suppliers [2].

4. Consumer Behavior Tailored Billing system

the concept of an intelligent smart energy meter that has some control features also has been put forth and the SCADA interface is implemented. The proposed meter can able to identifies the rate of consumption at various environments, can calculates tariff rates on that the consumers to view publication status and avail them necessary correctable measures.

It could be considered that the rate of increase of tariff rate is very less on offload or light load condition. The rate is gradually increasing in a factional range up to medium range. It has an exponential variation as the load varies to peak load. Thus, these make the user aware of regulating the load consumption. For this purpose, these data are made available to the customer frequently.

Faults, irregularities, power theft, and blackout could be easily identified so that it’s a much convenient method to provide a quality output economically and provides a quality improved efficient power system [17].

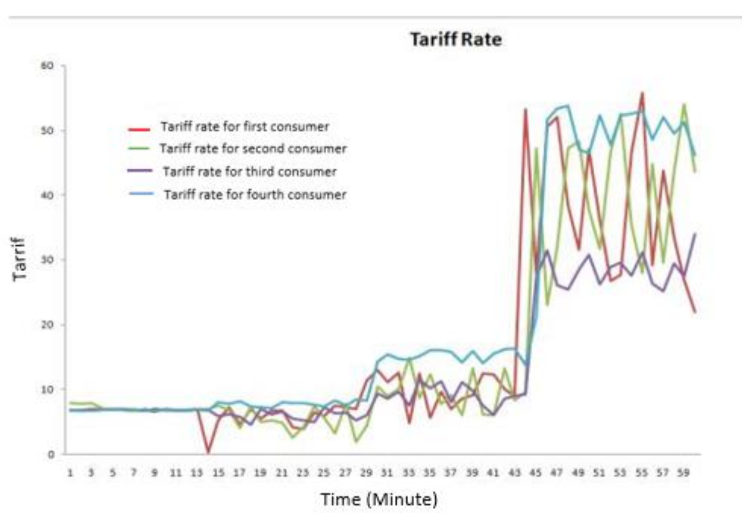

Figure 2-9 Consumer Behavior Tailored Billing system [17]

5. Smart metering to Electric utilities

SM helps by eliminating manual monthly meter readings, reduce capital expenses for establishment of new power plants, regulate income with available resources, and dynamic pricing that increase or decrease the cost of electricity based on demand and power resources utilization more efficiently [14].

6. Smart metering to electricity consumers

SM allow consumer to regulate their needs and minimize electricity bills, decrease the frequency of blackouts and system-wide electricity failures, obtain greater and more detailed feedback on electricity usage [14].

7. Smart metering to the environment

SM helps the environment by Reduce the need for new power plants, which produce greenhouse gases (GHG) that substantially creates pollution resulting in health risks, curb existing GHG emissions from existing power plants [14].

2.2.3 Study on Smart Meter technology

The old analog power meters that were used to measure commercial and residential power usage are being replaced with more intelligent electronic meters (Smart Meter). This SM communicates either through wired or wireless communication to the power company. Wired communication includes USB, Ethernet Cu, PLC, Hybrid RF+PLC, and Wireless communication includes WMBUS, Bluetooth, Wi-Fi, Infrared. The SM consists of functional units. these are measurement, communication, power supply, regulator, host processing subsystem or Display [18].

Battery/Super capacitor

The Smart Grid needs reliability as well as rapid recovery from any grid outages. Smart electricity meters with AMI networks need to continue operating for some time when the main power from the utility is not available to notify the operators that an outage has. This allows the operator to find out the root cause, deploy resources and personnel to repair the issue, and restore service to consumers as rapidly as possible [19].

The meter must have enough local energy storage to energize the AMI network for a period long enough that all meter endpoints can report their status to the utility’s central office; this can take several minutes depending on the geographical and network topology involved [19].

When considering AMI network that implements a RF mesh topology, each meter node act as link to the central office for other node, the requirement is clear. So as to ensure that any node which has lost power can report the outage, every other node must stand ready to act as a bridge and ‘hop’ the outage notification to the data concentrator head-end system or the next node in the mesh. Therefore, all meter nodes must be fully operational after an outage [19].

Smart meter creators must balance the required amount of energy available to the system during an outage versus the system cost of the super capacitor and its required charging and output regulation circuitry. The key to this balance is increase the usable energy extracted from each super capacitor [19].

Such backup power supplies need to protect hardware like, telecommunication equipment, solid-state drives (SSDs), storage systems, electrical equipment, where an unexpected power disruption can cause breakdown or data loss [19].

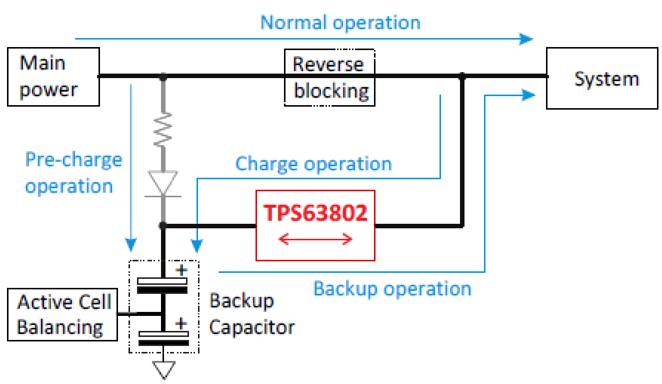

Figure 2-10 block diagram for backup power supply [20]

In this application, TPS63802 which is IC to charge backup capacitor during main power supply is available. When the main power fails, the IC supplies stored energy to the system from the backup capacitor.

Metering Applications

It has current and voltage sensors, ADCs. The current sensors connected to the current channels, and a simple voltage divider is used to measure the corresponding voltages [21].

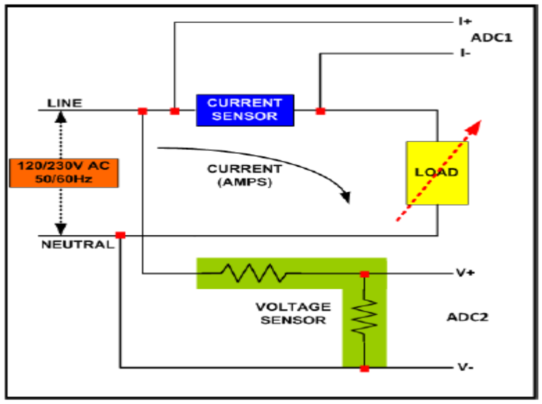

Figure 2-11 Typical Connections Inside Electronic Meters [21]

Figure 2.11 shows typical connections of smart meter in real life usage. The supported alternative current voltages with its corresponding currents are 230 V or 120 V at 50 Hz or 60 Hz. The labels LINE and NEUTRAL indicate low-voltage ac coming from the utilities.

The key parameters calculated during energy measurements are:

• Active, reactive, apparent power and energy

• RMS line current, RMS neutral current, and RMS voltage

• Power factor

• Line frequency

Formulas

the formulas used for the voltage, current, and energy calculations.

Voltage and Current

Samples of voltage and current are obtained from three independent ΣΔ converters at a sampling rate of 4096 Hz. Track of sample numbers that are present in 1 second is kept and used to obtain the RMS values for voltage and current for each phase [21].

$$V_{RMS} = K_V * \sqrt{\frac{\sum_{n=1}^{sample\ count} V^2(n)}{sample\ count}} \quad (2.3)$$

$$I_{RMS} = K_i = * \sqrt{\frac{\sum_{n=1}^{sample\ count} i^2(n)}{sample\ count}} \quad (2.4)$$

Where, v(n)= Voltage sample at a sample instant ‘n’, I(n)= Current sample at a sample instant ‘n’

Sample count= Number of samples in 1 second, Kv = Scaling factor for voltage & KI = Scaling factor for current

Power and Energy

Power and energy are calculated for a frame's worth of active and reactive energy samples. These samples are phase-corrected and passed to the foreground process that uses the number of samples (sample count) and use the formulae shown below, total active and reactive powers.

$$P_{ACT} = K_P = \sqrt{\frac{\sum_{n=1}^{sample\ count} V(n) * i(n)}{sample\ count}} \tag{2.5}$$

$$P_{\mathrm{Re}\,ACT} = K_P = \sqrt{\frac{\sum_{n=1}^{sample\ count} V_{90}(n) * i(n)}{sample\ count}} \tag{2.6}$$

V90 (n) = Voltage sample at a sample instant 'n' shifted by 90°

Kp = Scaling factor for power

The consumed energy is then calculated based on the active power value for each frame similarly as the energy pulses are generated in the background process except that:

$$E_{ACT} = P_{ACT}\ x\ sample\ count \tag{2.7}$$

For reactive energy, the 90° phase shift approach is used for two reasons:

• This allows us to measure the reactive power accurately down to very small currents.

• This conforms to the international accepted specified method of measurement.

Tampering attack

Each year, billions of dollars are lost by utilities due to non-technical losses. Electricity meter tampering, the non-technical loss for electricity providers, which is the individuals hack meters to stop the accumulation of energy usage data's, by stealing electricity. The most common tamper method is to put on a magnet on it to paralyze the transformers in power supplies as well as current transformer current sensors, thereby enabling electricity theft. Since magnets can affect current transformers (CT), shunts are often used as a current sensor for one-phase meters. The output voltage produced by shunts at low currents is small, especially when compared to the output voltage produced by current transformers over the same low input current range. As a result, for shunt-based high-accuracy meters, an accurate ADC is needed to sense the low output voltages from shunts to accurately bill utility customers [22].

The utility company is responsible to guarantee for providing quality service besides ensuring accurate customer billing for the customers. However, current harmonics from a utility customer load can induce voltage harmonics, which may affect multiple utility customers.

The high sample rate, in turn, also requires more processing, a standalone ADC can be used with a host microcontroller (MCU) to simultaneously overcome the processing and accuracy limitations of electricity meter SoCs [22]. Using an accurate standalone ADC typically has the following advantages:

• It enables meeting the most stringent of accuracy requirements
• It enables meeting minimum sample rate requirements (without compromising on accuracy) that may not be obtainable with applications-specific products or metrology SoCs
• It enables flexibility in selecting the host MCU

In addition, magnetic tampering could affect a transformer in power supply. To deal with magnetic tamper attacks that affecting the power supply of the meter, one method is to use cap-drop supplies, that does not use a magnetically susceptible transformer. but disadvantage of cap-drop supplies is their maximum output current is small. To increase this maximum output current from a cap-drop supply without increasing the capacitor size of the power supply, a buck converter could be used [22].

Removing neutral wire from the meter makes the voltage 0V in which the active power becomes 0 watt is used as a method for tempering electricity. If the neutral is missed AC/DC is not working backup system should used to power the metering system.

For this tamper technique, even though the active power reading is 0 W, the current is flowing through the line [22].

2.3 Demand Response

The increasing demands and rising electricity costs needs a more advanced, reliable and secure grid. With the integration of information technology systems in the current electrical grids, a data feedback system can be established to reduce grid vulnerabilities [1].

An advanced types of grid management includes DSM that deals with the monitoring and manipulating of peak demands and attending of the load profile over the day.

Dynamic Energy Management (DEM) is an innovative approach to managing load at the demand-side of the grid. The main parts of DEM are DSM and DR. DEM attains long-term energy savings through DSM by reducing the peak load occurrences in a utility [1].

DSM also define as planning, implementation, and monitoring of the utility activities that influence the customer's consumption of electricity in such a way that changes the utility load shape, i.e., changes in the time pattern and magnitude of a utility load. One type of demand-side management is demand response, which focuses on price signals to handle peak demand. Peak demand can be handled by either using a price-based system, where the electricity price fluctuates according to the load or by using an incentive-based system, where incentives are given to customers to reduce load at peak times [1].

Demand response is a key factor of DSM. Demand response (DR) is the technique to manipulate a customer's load during peak demand to the other time, when the demand is less. This helps in reducing the peak demand of the grid, and also in the reduction of prices on the customer side. DR can be applied to both residential and industrial loads and includes three different concepts: energy consumption reduction, shifting consumption to periods of low (or high) demand, and efficient utilization of energy storage systems Thus, a crucial issue in Smart Grids (SGs) is to manage DR to reduce peak electricity load, utilizing the existing infrastructure more efficiently and in a better-planned manner [1].

2.3.1 Demand Response in Smart Grid

The increased demand for electricity at particular hours of the day leads to several problems like short circuits, failure of transformers. To address these issues in transmission of electricity through the current traditional grids, there is a necessity to predict the consumption patterns of the customers to effectively deliver the electricity. In this context, the concept of smart grids (SG) has been introduced. The SG can able to predict and transmit the demands of electricity. This intelligent sensing and predicting ability could address different problems in conventional grids in forecasting demands, reducing power consumption, short circuit risk minimization, and saving live loses and properties [23].

(DR) encourages the customers to off load non-essential consumption of electricity during the peak hours of the day. Also, DR can effectively manage the supply of electricity in a balanced way during peak hours. By integrating the recent technologies such as ML, IoT, and big data analytics with SG, the electricity demand of the customers can be predicted, and the DR can be automated.

As of generated data from SG network is very large, deep Learning-based models can be used to learn the patterns from the data and predict the demand for electricity and peak hours [23].

CHAPTER THREE

3. ARTIFICIAL NEURAL NETWORK AND SMART METER

3.1 Artificial neural network

3.1.1 Introduction

Artificial neural networks are structures that process information in order to provide a connection between input data and output data by simulating the physiological structure artificially and functioning of human brain structure.

A natural neural network (biological neuron) is made up of a cell body, axon, and dendrite. Dendrite receives electro-mechanical signal from another neuron into the cell body. The cell body, also known as soma contains the nucleus and chemical configuration necessary to support the cell. The axon transfer by carrying signal from the neuron to other neurons. The synapse is the connection between dendrites of two neurons, or neuron to muscle.

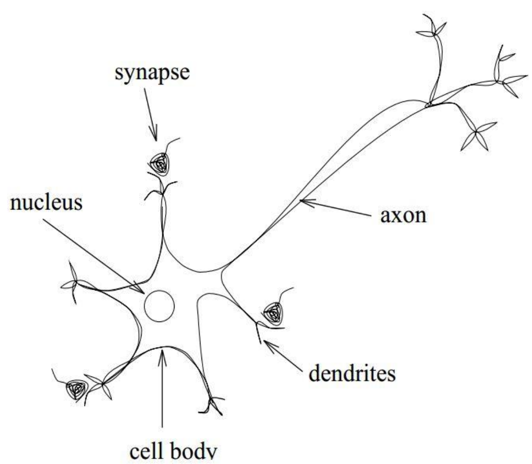

Figure 3-1 Biological neuron

The neuron gets signals from other neurons with dendrites. When the signal strength exceeds a certain threshold, this neuron triggers its signal to be passed on to the next neuron via the axon using synapses. The signal sent to other neurons through synapses triggers them, and this process continues. A huge number of such neurons work simultaneously. The brain has the capacity to store a large amount of data at a time.

An artificial neural network (ANN) is the simulation of the human brain. Significant features of the natural neural network, which artificial neural models intend to simulate, are:

- Parallel processing, due to the fact that neurons process simultaneously the information.
- The two-fold function of the neuron acts simultaneously as memory and signal processor.
- The distributed nature of the data representation, i.e., knowledge is distributed throughout the network, not circumscribed, or predetermined.
- The network's ability to learn from experience. This last but fundamental capacity enables neural networks to self-organize, adapt to new incoming information, and extract the input-output connections from known examples that are the basis of their organization. An artificial neural network captures this attitude in an appropriate "learning" stage.

This Chapter is intended to provide a general introduction to neural networks, power interruption, and electric faults. The special interest from ANN is Feedforward Neural Network with a backpropagation learning algorithm. Application of ANN for estimation of power interruption, power fluctuation, and theft based on customer energy consumption, cost, and load are presented for customer demand response analysis.

3.1.2 Learning methods

Artificial neural networks work through the optimized weight values. The method of optimizing weight values called ***learning.*** In this method the learning processes the network learned how to produce the output the input is available. After the completion of the learning process, the trained neural network, able to produce the output within the desired accuracy according to the input pattern.

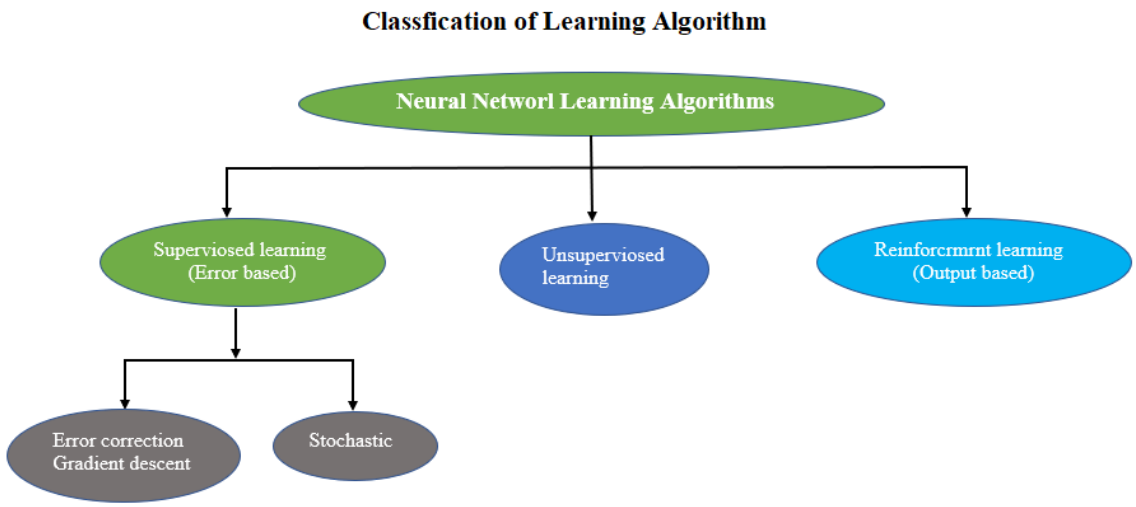

Figure 3-2 Classification of learning algorithm

Supervised learning

Supervised learning means guided learning by "teacher"; requires a training set which consists of Input vectors and a target vector are associated with each input vector.

Unsupervised learning

The purpose of this type of learning is to realize features in the input data without any aid from the trainer, fundamentally performing clustering of input space. The system learns about the pattern from the data itself without prior knowledge about the given input data.

Reinforced learning

This type of learning deals with how intelligent agents ought to take actions in a given environment so as to maximize the concept of collective reward. Reinforcement learning different from other supervised learning is because it does not need labeled input/output pairs to be presented, and in not needing sub-optimal actions to be clearly adjusted. Instead, the focus is on finding a balance between exploration and exploitation.

3.1.3 ANN Topologies

An ANN consists of interconnected nodes, often called "neurons" to form the network and perform advanced intelligent activities. Some of those nodes are input nodes - they receive information from the outside world. Some of them are output nodes - they provide the results of the calculation. Finally, there are hidden nodes, which are just intermediate steps of computation.

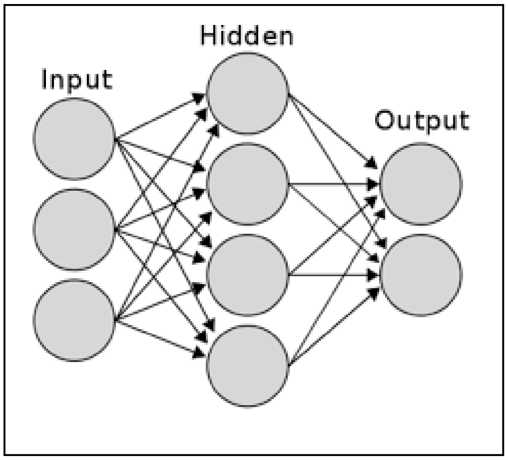

Figure 3-3 ANN with one hidden layer

Nodes of the artificial neural network are usually ordered into layers.

- **Input layer:** The neurons **n**umber of the input layer same to the number of inputs to the neuronal network. This layer has **passive nodes**, that do not participate in the actual signal modification but only transmit the data to the next layer.
- **Hidden layer:** This hidden layer has random number of layers with random number of neurons. The nodes of this layer are **active**.
- **Output layer:** The number of neurons consists in this layer are same to the number of the output values of the neural network. The nodes in this layer are **active** ones.

ANN architectures

Neural Networks are called universal function approximations. Nonlinear functions can be approximated by using different architectures depending on the type of connections between the neurons. There are two main categories of network architectures, “feed-forward neural networks” and “recurrent neural networks”. If there is no “feedback” from the outputs of the neurons towards the inputs throughout the network, then the network is referred to as a “feed-forward neural network”.

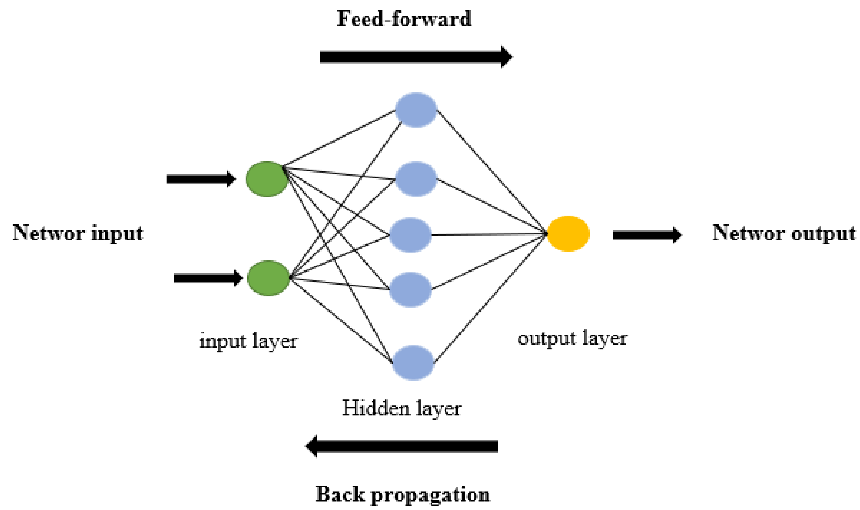

Figure 3-4 Feed forward back propagation

From different learning algorithms, the "back-propagation algorithm" is the common and widely used for training of feed-forward neural networks. It is, a means of updating the network's synaptic weights through back-propagating a gradient vector which each of the element is defined as the error measure derivative concerning a parameter. the difference between the actual network outputs and the desired outputs are called error signals. Therefore, a set of desired outputs must be available for training. For that reason, back-propagation is a supervised learning rule

3.1.4 Artificial Neuron Model

While artificial neurons are inspired by the biological counterparts, they are just cartoonish simplifications of actual neurons. Typical artificial neuron just multiplies its inputs with respective weights sums the results and applies an activation function.

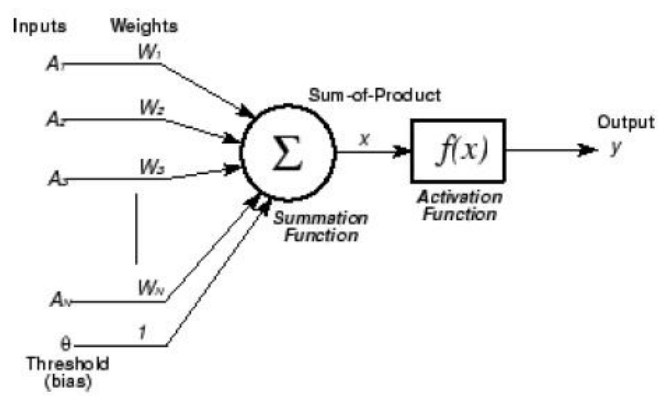

Figure 3-5 Artificial neuro model

$$X = \sum_{j=0}^{N} W_j A_j \tag{3.1}$$

where elements wj, are called synapse weights, can be modified during the learning process. Neuron output unit is defined as follows:

$$y = F(x) \tag{3.2}$$

Note, that wo - is adjustable bias and F – is activation function (also called transfer function). Thus, the output, y, is obtained by adding the weighted inputs and passing the results through a nonlinear (or linear) activation function F.

Activation Functions

The purpose of activation functions is to add non-linearity into the calculations. Common activation functions are sigmoid (squashes) any real value ranging from 0 to 1. The sigmoid F function is a continuous, bounded, monotonic, non-decreasing function that provides a graded, nonlinear response within a prespecified range.

$$F(x) = \frac{1}{1+exp(-\beta x)} \tag{3.3}$$

where β>0(usually β=1), which provides an output value from 0 to 1.

The alternative activation function is tanh (squashes any real value to between -1 and 1)

$$F(x) = tanh(\beta x) = \frac{exp(\beta x)-exp(-\beta x)}{exp(\beta x)+exp(-\beta x)} \tag{3.4}$$

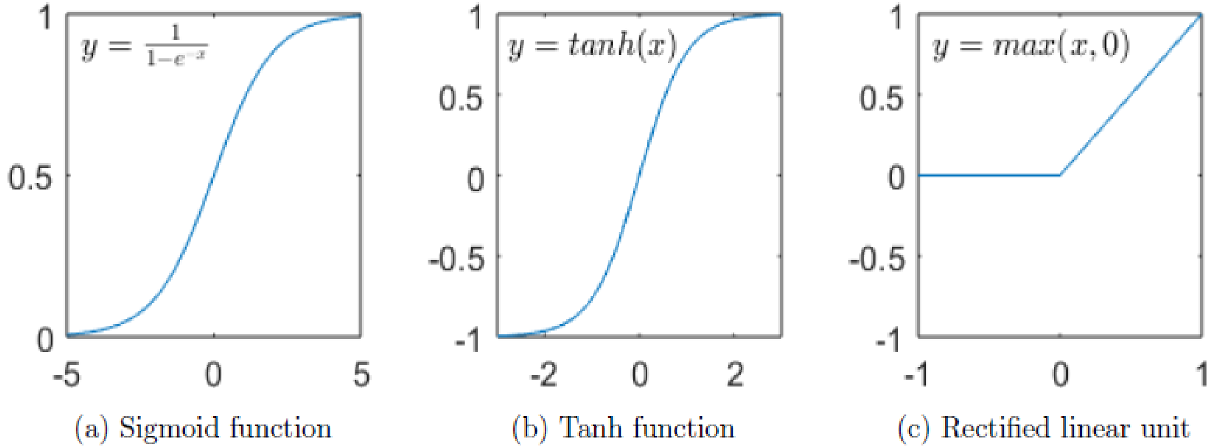

Figure 3-6 Common activation functions

Both the sigmoid and tanh functions provide smooth, non-zero derivatives with respect to input signals. Sometimes these two activation functions are known as squashing functions since the inputs to these functions are squashed to the range [0,1] or [-1,1]. They are also called sigmoidal functions because their S-shaped curves exhibit smoothness and asymptotic properties. Both of these activations are used often on regression and classification problems.

For neural networks to approximate a continuous-valued function not limited to the interval [0,1] or [-1,1], usually the output layer node function is a weighted sum with no squashing functions. This same situation as a situation in which the activations function is an identity, and output nodes of this type are often called linear nodes.

3.1.5 Neural network training process

1) First define the architecture of the neural model: input layer, hidden layer, and output layer and set the activation function, each node has its activation function.

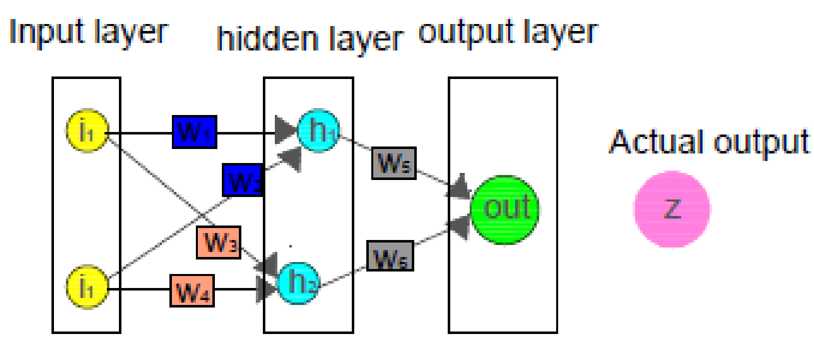

Figure 3-7 Neural network model

2) **Weights**

Neural network training is about finding weights that minimize prediction error. It is usually start The training with a set of randomly generated weights. Then, backpropagation is used to update the weights in an attempt to correctly map arbitrary inputs to outputs.

3) **Dataset**

Find out the data set, from figure one the dataset has two inputs (i1 and i2) and one output(Z)

4) **Forward Pass**

use given weights and inputs to predict the output. Inputs are multiplied by weights; the results are then passed forward to the next layer.

$$\begin{bmatrix} i_1 & i_2 \end{bmatrix} \begin{bmatrix} W_1 & W_2 \\ W_3 & W_4 \end{bmatrix} \quad (3.5)$$

5) Calculating Error

Now, find out how our network performed by calculating the difference between the actual output and the predicted one. Then check the network output, or **prediction** is close to **actual output**. If note, calculate the difference or the error as following.

$$\text{Error} = \frac{1}{2}\left(\text{Prediction-Actual}\right)^2 \quad (3.6)$$

6) Reducing Error

The main goal of the training is to reduce the error or the difference between prediction and actual output. Since the actual output is constant, "not changing", the only way to reduce the error is to change prediction value. The question now is, how to change prediction value

By decomposing prediction into its basic elements, we can find that weights are the variable elements affecting prediction value. In other words, to change the prediction value, first change the values of the weights. to change\update the value of the weights uses Backpropagation.

7) Backpropagation

Backpropagation, short for "backward propagation of errors", is a mechanism used to update the **weights** using **gradient descent**. It calculates the gradient of the error function with respect to the neural network's weights. The calculation proceeds backward through the network.

Gradient descent is an iterative optimization algorithm for finding the minimum of the error functions. The error function local minimum value using gradient descent, one takes steps proportional to the negative of the gradient of the function at the current point.

$$^{*}W_x = W_x - a\left(\frac{\partial Error}{\partial W_x}\right) \quad (3.7)$$

and subtract the partial differential of **error** function with respect to old weight. Optionally, we multiply the differential of the **error** function by a selected number to make sure that the new updated **weight** is minimizing the error function; this number is called **learning rate**.

Learning rate: is a hyperparameter which means that we need to manually guess its value.

The derivation of the error function is calculated with the chain rule as following

$$\frac{\partial Error}{\partial W_x} = \frac{\partial Error}{\partial prediction} * \frac{\partial prediction}{\partial W_x} \tag{3.8}$$

8) Backward Pass

Using the new weights, we will repeat the forward pass. We can notice that the new prediction is either get closer to actual output than the previously predicted one. We can repeat the same process of the backward and forward pass until the error is close or equal to zero.

The ANN applications

- ✓ Classification, to predict the class of an input vector
- ✓ For Pattern matching, the goal is to create a pattern best matched with a given input vector
- ✓ For Pattern completion, its goal is to complete a given input vector missing parts
- ✓ For Optimization, to find the optimized value parameters
- ✓ Control, to give suggestion based on given an input vector
- ✓ Function approximation/times series modeling, to learn the functional relationships between corresponding input and required output vectors
- ✓ Data mining, to discover knowledge

3.2 power interruption in smart grid

Since electricity has become an integral part of everyday life. A loss of electricity also known as a power outage, can negatively affect everything in human life. Therefore, granting electricity supply should be the primary and essential task of electric utility suppliers and governments.

Any interruption of power generation and delivering the power to a specific load causes a power outage. The outage can be affected by different factors like; inclement weather conditions, human error, equipment failure, animal interference, scheduled maintenance [24].

Most of the time power outages last seconds or minutes after beginning. However, sometimes outages can last such as for several weeks. Some power outages caused by different critical natural like lightning or violent windstorms the power lines become damaged seriously and hence this leads to long delays when restoring power. Extended outages impact entire communities and can even affect the economy when power is unavailable to large areas of the population [24].

3.2.1 Power outage types

There are four main types of power outages, that are listed below,

i. **Blackout**

The most sever outage type of power loss when the power completely outage in an area called a blackout. structural damage from violent windstorms or lightning strikes and other basic big problems causes this type of power outage in an area and this leads a problem on the society at that specific area. This type of outage would be difficult to fix quickly — this is why these types of outages can last for several weeks in the worst-case scenarios.

ii. **Brownout**

Brownouts occur when there is electrical voltage drop in the mail electrical power supply. While it does not cause a total loss of power, it results degraded apparatus performance and some home used devices cannot function with the lowered voltage during one of these outages.

iii. **Permanent Fault**

This type of power outage is caused by caused by a power line fault and results is a sudden loss of electricity. The power will be automatically restored when the problem is once solved.

iv. Rolling Blackouts

It is unique from the other blackouts as they are programed power outages. These implemented in unstable grids areas or with power infrastructure that cannot the population it serves. This type of outage can also be caused if there’s not enough source of electricity to operate power at full capacity, whether for the short time or long time.

3.2.2 Electrical Faults

Introduction

The trends of electric power systems are becoming rising and sophisticated in terms of generation, distribution and transmission and loading system. Any fault in electric power system results in sever economic loss and decreasing the consistency of power system directly. An electrical fault is an irregular condition, caused by equipment failures such as transformers and motors, manmade errors, and natural phenomena. The faults in the power system cause over current, under voltage, unbalance of the phases, reversed power, and high voltage surges. This causes the interruption of the normal operation of the network, failure of equipment, electrical fires, etc. Due to this the power interrupts, and also equipment damages. Usually, power system networks are protected with switchgear protection equipment such as circuit breakers and relays in order to limit the loss of service due to electrical failures.

The faults in the electrical system causes fire breakout in tern leads to life loss, property damage, power system breakdown of the electric network system. The fault may also lead to cut off the power beyond the fault point in the distribution and transmission network leading to electric blackout; this affects the industrial and domestic users heavily.

3.2.3 Types of faults

There are two types of faults which present in any power transmission line namely; balanced (also known as symmetrical) faults and unbalanced (also known as asymmetrical) faults.

1. **Asymmetrical Faults**

Asymmetrical faults are most commonly occurred type of fault power transmission networks.

The most common faults that occur in the power system network are unsymmetrical faults. These faults are also known as unbalanced faults as it causes unbalanced currents in the power system.

unsymmetrical faults comprise of open circuit (single- and two-phase open condition) and short circuit faults (excluding L-L-L-G and L-L-L).

a) Earth fault or line to ground fault (LG)

If there is a connection creates between one of the transmission lines and the ground by a means of ice, wind, falling tree or another incident causes falling in one conductor to the ground or contact the neutral line results this type of fault. This type could be represented as in Figure 3.8.

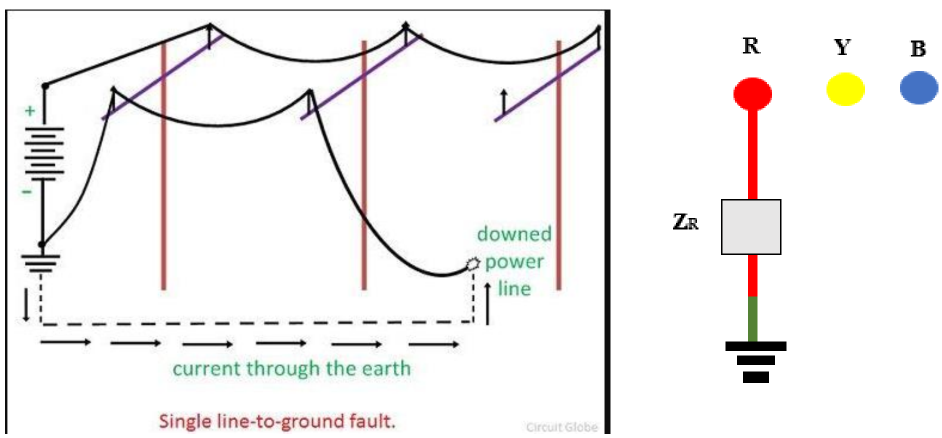

Figure 3-8 Single -phase-to-earth

Short Circuit Faults or Line to line fault (LL)

A line-to-line fault occurs when a live conductor gets in contact with another live conductor. The major cause of this type of fault is massive wind during which swinging of overhead conductors may touch together.

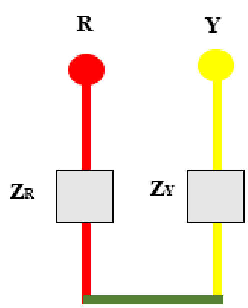

Figure 3-9 phase-to-phase

Double fault or Double line to ground fault (DLG)

This type of fault is caused by the falling tree where two phases become in contact with the ground could lead to this type of fault. In addition, two phases will be involved instead of one at the line-to-ground faults conditions. The Double Line-to-Ground fault (DLG) is shown in Figure 3.10. This can be a result of a tree falling on two of the power lines or other causes.

In double line to ground faults, two lines come into the contact with each other as well as with the ground. These are severe faults, and the occurrence of these faults is about 10% when compared with total system faults.

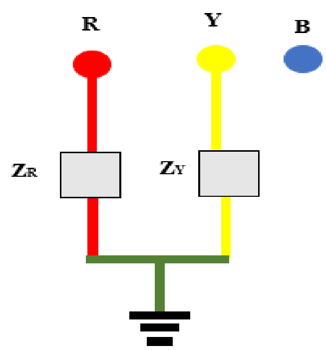

Figure 3-10 Two-phase-to-earth

2. **Symmetrical Faults**

A symmetrical fault also known as balanced fault, occurs when all three phases are simultaneously short-circuited. These faults occurred rarely in real life as compared with asymmetrical faults examples of this types of include line to line to line (L-L-L) and line to line to line to ground (L-L-L-G) as shown in the figure 3-11 to figure 3-12.

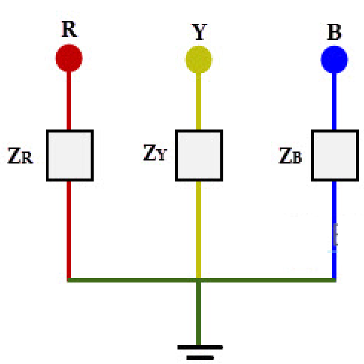

Figure 3-12Three-phase-to-earth (L-L-L-G)

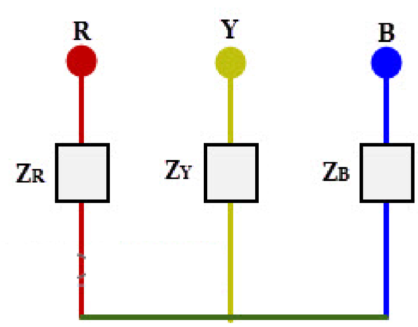

Figure 3-11 Three-phase-fault(L-L-L)

Analyzing this type of fault based on a per-phase basis using bus impedance matrix or Thevenin's theorem in the power system is necessary in order to selecting the rupturing capacity of the circuit breakers, choosing set-phase relays and other protective switchgear.

Cause of electric fault

Weather conditions: this includes environmental conditions that interrupts power supply including lightning strikes, massive rains, speedy winds, salt deposition on overhead lines and conductors, accumulation of snow and ice on distribution lines, etc.

Equipment failures: failures in different electrical apparatus used in the power system due to high current to flow through the devices fault due to mal functioning, aging insulation failure of cables and winding on generators, transformers, switching devices, reactors and the like causes a short circuit which further damages the equipment and the system.

Human errors: human error that cause electrical faults such as improper rating electrical apparatuses, forgetting metallic or electrical conducting parts servicing or maintenance, switching problem of the circuit under servicing, etc.

Smoke of fires: a flashover that causes insulators to lose their insulating capacity due to high voltages may arise from ionization of air, smoke particles, surrounding the overhead lines results in spark between the lines or between conductors to an insulator.

Effects of electrical faults

Over Current Flow: Causes tripping of relays, cause shocks to individuals, damaging insulation and components of the equipment because of very low impedance path for the current flow occurred in tern it results high current drawn from the supply. The severity of the shock depends on the current and voltage at the fault location and even may lead to death.

Loss of Equipment: The electrical components would be burn or probably completely burn out due to short circuit as a result of heavy current flow.

Disturbs Interconnected Active Circuits: Faults not only affect the location at which they occur but also disturb the active interconnected circuits to the faulted line.

Electrical Fires: Flashover and sparks resulted as a result of short circuit due to ionization of air between two conducting lines results in fires on buildings and the like.

Protection Devices against Faults

When the fault occurs in any part of the system, it must be cleared in a very short period in order to avoid greater damage to equipment and personnel and also to avoid interruption of power to the customers. The fault clearing system uses different security gadgets such as relays and circuit breakers to distinguish and clear the fault. A few of these faults clearing or issues restricting gadgets are given underneath

Fuse: It opens the circuit at whatever point a fault exists within the framework. It comprises a lean copper wire encased in a glass or a casing with two metallic contacts. The high fault current rises the temperature of the wire and subsequently, it melts. A fuse requires the manual substitution of wire each time when it blows.

Circuit Breaker: It is the foremost common assurance the gadget that can make or break the circuit either physically or through inaccessible control beneath ordinary working conditions. There are a few sorts of circuit breakers accessible depending on the working voltage, counting discuss brake, oil, and vacuum.

Protective Relays: These are the blame-recognizing devices. These gadgets distinguish the blame and start the operation of the circuit breaker so as to confine the defective circuit. A hand-off comprises an attractive coil and contacts (NC and NO). The blame current energizes the coil and this causes to the creation of the field, in this manner the contacts get worked.

Lighting Arrestor: Surges within the control system arrange are caused when lightning strikes on transmission lines and equipment. This comes about in tall voltage and tall streams within the framework.

3.3 Energy theft in Smart meter

Presently days, electric power loss ended up one of the foremost obvious issues influencing both conventional power networks and smart grids. The difference between the energy produced in one system and the metered energy delivered to the users is known as power loss. To determine the amount of electricity loss, smart meters in smart grids play a prominent role. Advanced energy meters obtain information from the consumers' load devices and measure the consumption of energy in some intervals of an hour. The energy meter provides additional information to the supplier company and the system operator for better monitoring and billing and provides two-way communications between the utility companies and consumers.

Electricity loss is mainly classified into two categories, namely technical loss (TL) and non-technical loss (NTL). TL happens since of the joules impact on power lines and transformer misfortune amid the transportation of electricity. TD losses represent the difference between the electricity generated and the electricity consumed. TL are those losses which are internal to the system such as energy dissipation by the electrical equipment used in distribution lines, transformers, transmission lines, and iron losses in transformers. On the other hand, NTL constitutes misfortunes emerging due to inadequate meters, errors in billing, blemishes in supply, unmetered connections, and noxious exercises by the consumer such as tampering of a meter. Table 3.1 provides an overview of different types of electricity losses caused by different components of the power sector. The easiest way to determine the amount of non-technical losses (NTL) is by merely calculating the technical losses (TL) in the system and subtracting them from total losses (TD).

We can evaluate it as follows:

NTL = Total Energy Losses *(*TD*)* – Technical loss (TL)

Total Energy Losses = Energy Supplied − Bills paid

Table 3-1Classification of method of electricity

Element	Method of theft
Meter	Bypassing the meter Deliberately damaging the meter seal or removing of the meter
Wires/Cables	Illegal tapping to bare wires or underground wire
Transformer	Illegal tapping of transformer terminal and junction boxes of overhead lines
Billing Irregularities	An error made by meter readers
Unpaid bills	Unpaid bills by individuals or institutions

3.3.1 Meter Tampering Methodologies

There are various mechanisms through which an adversary can tamper with Smart Meters.

Methods of meter tampering can be divided into four classes:

- Current related tampering methods.
- Voltage related tampering methods.
- Mechanical tampering methods.

•Tampering by hacking and altering the memory.

A summary of mechanisms that are generally used to tamper smart meters is listed below

1) Swapping of Phase and Neutral Lines

In this kind of tampering the customer interchanges the two phases that are phase and neutral lines. This swapping of phase and neutral lines cause reverses of the energy flow thereby effecting the billing calculation (Figs. 3.13 and 3.14).

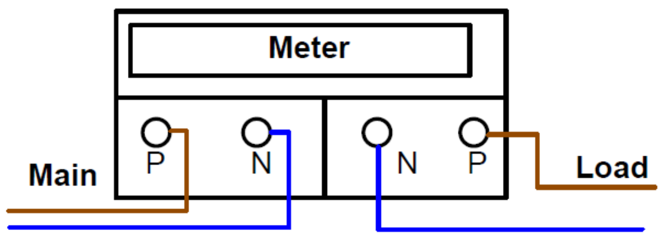

Figure 3-13Actual connection

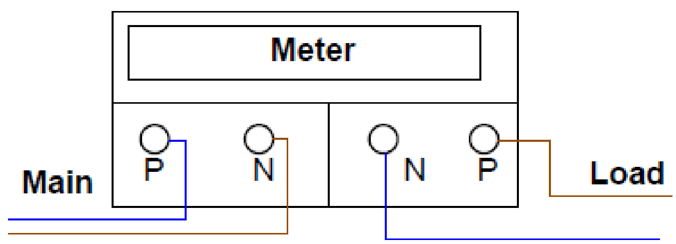

Figure 3-14 Swapping of phase and neutral line

2) Double Feeding

Double feeding as the name suggests is a meter bypassing technique where an additional feeder connected with meter in a manner of the meter bypassed and the energy consumption of meter is not accounted for. In such a scenario, the consumption for the load affixed to the supplementary feeder won't be recorded by the meter even if the connection is legitimate. This kind of tampering is done to connect heavy electric devices so that its consumption remains unnoticed (Fig. 3.15).

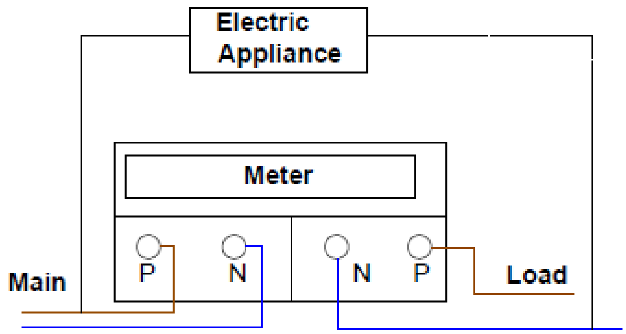

Figure 3-15 Double feeding

3) Neutral Missing

In neutral missing method of meter tampering, the neutral line is cut off from the meter so that this resulting in zero input voltage. Hence the power computed by the meter is zero (Since P = V * I and for given condition V = 0, therefore P = 0) This tampering method is also referred to as single wire operation (Figs.3.16 and 3.17).

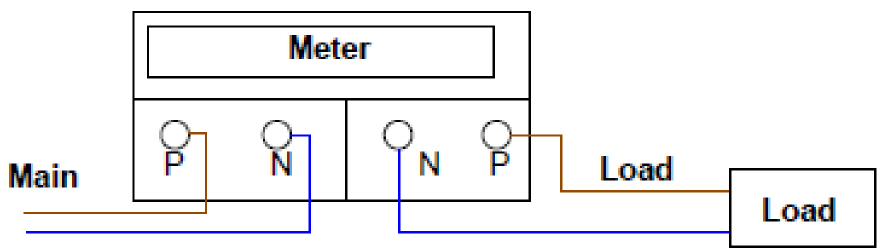

Figure 3-16 Actual condition

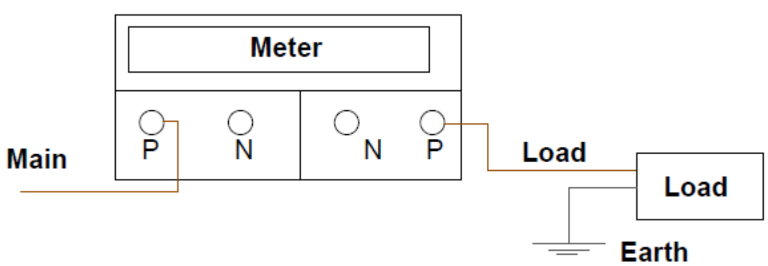

Figure 3-17 Neutral missing

4) Neutral Disturbance

In neutral disturbance tampering High-Frequency voltage signals added to the neutral line of the meter by connecting it through diode or variable capacitor resistance. The neutral of the meter gets deviated from its original point and becomes unbalanced leading to less voltage recording by the meter and therefore less energy consumption is recorded by the meter (Fig. 3.18).

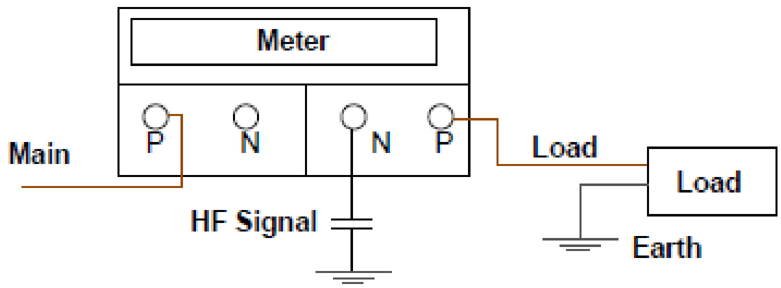

Figure 3-18 Neutral disturbance

5) Current Reversal by Connecting Input and Output in Reverse

In this tampering event, the adversary connects the phase and neutral wires to the wrong inputs. This causes the current to change direction from its original path in which it was intended to flow. This type of tampering intends to dupe the billing computation by reversing the route of current flow (Fig. 3.19).

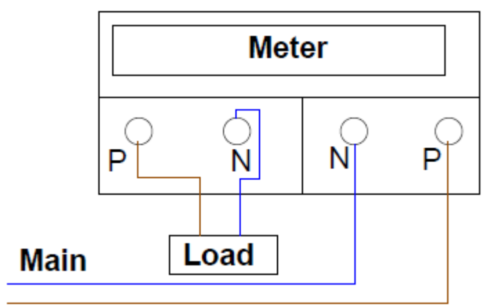

Figure 3-19 Current reversal

6) Partial Earth Fault Condition

It is a tampering method in which the load is connected to the earth due to which the return current going back to the meter is reduced. This generates a difference in the current stream flowing through the neutral wire and phase wire leading to current in neutral wire become less than the current in the phase wire. Under normal conditions, the current in the phase wire and the neutral wire is equal (Fig. 3.20).

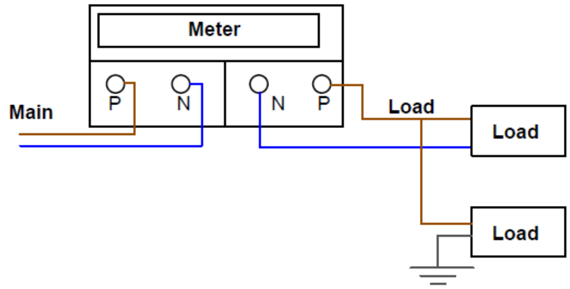

Figure 3-20 Partial fault connection

3.3.2 Types of energy theft and fraud

Generally, energy theft and fraud are grouped as follows:

- Direct theft - the thief can simply take energy from the distribution system operator without the DSO having the opportunity to meter the consumption. This is achieved through connecting spurs to the main supply and drawing energy directly, and consequently, this is often visible from the street.
- Meter tampering - the meter is compromised in such a way that it delivers false readings. Again, often this is visible on the meter, but with most meters in cabinets or buildings, this is less visible from the street. With the new smarter meters, the opportunity for cyber-attacker in order to tamperthe meter, or the data it consists, and this can be very difficult to spot.
- Unpaid bills - customers simply do not pay their bills and make it hard for the DSO to cut off the power supply.

With conventional "non-smart" metering frameworks within the network, it was difficult to distinguish events of burglary and extortion without conducting audits - either within the roads and buy homes, in back-end charging/ bookkeeping records, or in preparing execution records. Cutting edge AMI (Progressed Metering Foundation) arrangements offer components to distinguish endeavored and genuine extortion and burglary through expanded insights. At the same time, this increased intelligence offers increased vulnerability to cyber-attack, often for fraud or theft, and requires new forms of protection to be put in place.

Advanced Metering Infrastructure brings significant improvements:

- Meter tampering and supply alarms - the latest generation of smart meters provide a rich set of events and alarms to indicate both the preparation for and the actual execution of fraud and theft at the meter. In the most sophisticated smart meters, this can include events that indicate attempts to hack the meter or the communications network.
- Complete automation of meter-to-cash - the human can be largely removed from the process. Often, the reduction of theft and fraud is a major business driver for initiating a smart meter project.
- Remote control and cut-off –smart meters allow the distribution system operator to control access to energy and cut off the supply for thr customer who didn’t pay their bills. Not only is the remote control convenient and reduces costs, the energy cut-off is faster, reducing the revenue leakage, and it avoids the need for physicalconfrontations with the thief.
- Low-voltage grid topology analysis- a pre-requisite for analysis is to know the topology of the low- voltage grid. This is a challenge for many DSOs as records may be out of date or simply not exist. Thelatest AMI solutions allow the topology to be inferred from communications statistics

In summary, the mechanisms are now in place to combat theft and fraud close to its source with the new generation of SM.

CHAPTER FOUR

4. Methodology

4.1 Introduction

This research paper is going to collect quantitative data from Ethiopian Electric Utility Office by formal request. The data consists of the Kilowatt Hour (KWH) reading and the corresponding amount charged for four regions in Addis Ababa, West Addis Ababa District (WAAD), East Addis Ababa District (EAAD), North Addis Ababa District (NAAD), and South Addis Ababa District (SAAD). The data were analyzed, interpreted and train in the Neural Network model for further processing and prediction which includes whether the reading in the energy meter is normal or energy fraud. This is accomplished by training, validating, and testing the neural network model via the existed data recorded by the Ethiopian Electrical Utility Company.

To analyze the power fluctuation in 24 hours and some extended hours even years, some data which are the line currents and energy in the six lines are collected. This data is further analyzed, interpreted, and trained the Neural Network Model to learn from the existing data and classify the type of interruptions the occurred based on the data feed. This enables the neural model to predict or classify the type of interruptions that happened. The power interruption includes Ground Fault, Short Circuit, Double Fault, Normal Interruption (interruption by request), and Normal operation. So, the trained Artificial Intelligent system can identify the different modes of power system operation interruption based on the previously existed data.

Short circuit cures when the same current carrying wires forming the closed circuit which results in the damage of the current carrying conductor wires since the current may be high. In the ground failure problem, in the normal operations, there is current passes through the protective wire. In a double fault, both the short circuit and ground failure happen.

4.2 Data Collection Method

This research project is a data-intensive work since Artificial Intelligence Systems are required to be learned from past experiences either in quantitative or qualitative data even in some cases both types of data. So, for this Neural Network model, quantitative data is preferred to train, validate and test the neural network model.

It has been known that digital energy meter (smart meter) is not in use in our country as well as most countries in the world. Hence, previous energy billing data and some inspection data recorded by the supplier are being used to constitute the smart Energy Meter Reading Data by further processing the existed data.

4.2.1 Data Sources

As the study focus on the analysis of power interruptions (Short Circuit, Ground Failure, Double Fault (both Short Circuit and Ground problem), requested interrupt), predictions the power theft and the maximum power demand response from the existed data, the primary data source in Addis Ababa Electric Utility since the case studies resides on this city which includes the four districts namely East, West, North, and South Addis Ababa Districts.

The data for theft detection and power interruption classifications are different, so they are collected, processed, and analyzed independently. In addition to these, the maximum power demand is investigated by extracting the power data distributions for 3596 hours extracted from the six lines.

4.3 Data Filtering and Analysis

Getting an organized data from the relevant institutions or companies in Ethiopia is difficult since recording data in the modern data center is not common. Instead of recording and organizing the data in digital form, they have been recording manually and unusual way which results in the missing of some useful information because the measurement is taken during the fault analysis only. Even, the data have not been taken in regular time intervals, so there is some missed data for some months.

For the filtering purpose, excel is used. Most of the time, the recorded data consists of free space, the wrong entry i.e., for numeric value field, there is string data. Moreover, for the missing field, it was fitted with randomly generated entry between the maximum and minim value recorded ever.

Hence, it is required to shape the scattered data in an organized form and filtering the relevant entries Microsoft Excel is used.

4.3.1 Data Analysis for Theft Detections

The original data collected for theft identifications are so tedious to filter and analysis. It includes the information of Region, District office, portion, meter reading unit, tariff, bill month, no of days, business partner, contract account, contract, customer name, bill document number, invoice number, meter number, previous reading, present reading, multiplication factor, kwh sold, service charge, power factor charge, invoice amount and other entries.

Table 4-1 The original collected data from customers' bills

REGION	District Office	CSC Office	Portion	Meter Reading Unit	Tariff	Bill Month	No of Days	Business Partner	Contract Account	Contract
ADDIS ABABA REGION ELECTRIC UTILITY	EAAD (BOLE & YEKA SUB CITY)	EAST AA CSC NO.4	PAAG1001	AA03A036	ICS-DOM	HIDAR-2013	42	2000024322	100000005302	7000007
ADDIS ABABA REGION ELECTRIC UTILITY	EAAD (BOLE & YEKA SUB CITY)	EAST AA CSC NO.4	PAAG1001	AA03A023	ICS-DOM	HIDAR-2013	31	2000024582	100000005436	7000008
ADDIS ABABA REGION ELECTRIC UTILITY	EAAD (BOLE & YEKA SUB CITY)	EAST AA CSC NO.4	PAAG1001	AA03A023	ICS-DOM	HIDAR-2013	31	2000024590	100000005441	7000008
ADDIS ABABA REGION ELECTRIC UTILITY	EAAD (BOLE & YEKA SUB CITY)	EAST AA CSC NO.4	PAAG1001	AA03A024	ICS-DOM	HIDAR-2013	31	2000024596	100000005443	7000008
ADDIS ABABA REGION ELECTRIC UTILITY	EAAD (BOLE & YEKA SUB CITY)	EAST AA CSC NO.4	PAAG1001	AA03A005	ICS-DOM	HIDAR-2013	31	2000024677	100000005482	7000008
ADDIS ABABA REGION ELECTRIC UTILITY	EAAD (BOLE & YEKA SUB CITY)	EAST AA CSC NO.4	PAAG1001	AA03A023	ICS-DOM	HIDAR-2013	31	2000024685	100000005485	7000008
ADDIS ABABA REGION ELECTRIC UTILITY	EAAD (BOLE & YEKA SUB CITY)	EAST AA CSC NO.4	PAAG1001	AA03A025	ICS-LV_IND	HIDAR-2013	31	2000024692	100000005488	7000008
ADDIS ABABA REGION ELECTRIC UTILITY	EAAD (BOLE & YEKA SUB CITY)	EAST AA CSC NO.4	PAAG1001	AA03A023	ICS-DOM	HIDAR-2013	31	2000024700	100000005490	7000008
ADDIS ABABA REGION ELECTRIC UTILITY	EAAD (BOLE & YEKA SUB CITY)	EAST AA CSC NO.4	PAAG1001	AA03A030	ICS-DOM	HIDAR-2013	31	2000024994	100000005624	7000008
ADDIS ABABA REGION ELECTRIC UTILITY	EAAD (BOLE & YEKA SUB CITY)	EAST AA CSC NO.4	PAAG1001	AA03A009	ICS-DOM	HIDAR-2013	31	2000025147	100000005693	7000008
ADDIS ABABA REGION ELECTRIC UTILITY	EAAD (BOLE & YEKA SUB CITY)	EAST AA CSC NO.4	PAAG1001	AA03A007	ICS-DOM	HIDAR-2013	31	2000025264	100000005753	7000008
ADDIS ABABA REGION ELECTRIC UTILITY	EAAD (BOLE & YEKA SUB CITY)	EAST AA CSC NO.4	PAAG1001	AA03A007	ICS-DOM	HIDAR-2013	31	2000025404	100000005819	7000008
ADDIS ABABA REGION ELECTRIC UTILITY	EAAD (BOLE & YEKA SUB CITY)	EAST AA CSC NO.4	PAAG1001	AA03A010	ICS-DOM	HIDAR-2013	31	2000025424	100000005834	7000008
ADDIS ABABA REGION ELECTRIC UTILITY	EAAD (BOLE & YEKA SUB CITY)	EAST AA CSC NO.4	PAAG1001	AA03A008	ICS-DOM	HIDAR-2013	31	2000025431	100000005838	7000008
ADDIS ABABA REGION ELECTRIC UTILITY	EAAD (BOLE & YEKA SUB CITY)	EAST AA CSC NO.4	PAAG1001	AA03A036	ICS-DOM	HIDAR-2013	31	2000025439	100000005842	7000008
ADDIS ABABA REGION ELECTRIC UTILITY	EAAD (BOLE & YEKA SUB CITY)	EAST AA CSC NO.4	PAAG1001	AA03A007	ICS-DOM	HIDAR-2013	31	2000025446	100000005847	7000008
ADDIS ABABA REGION ELECTRIC UTILITY	EAAD (BOLE & YEKA SUB CITY)	EAST AA CSC NO.4	PAAG1001	AA03A010	ICS-DOM	HIDAR-2013	31	2000025461	100000005855	7000008
ADDIS ABABA REGION ELECTRIC UTILITY	EAAD (BOLE & YEKA SUB CITY)	EAST AA CSC NO.4	PAAG1001	AA03A010	ICS-DOM	TIKIMIT-2013	30	2000025461	100000005855	7000008
ADDIS ABABA REGION ELECTRIC UTILITY	EAAD (BOLE & YEKA SUB CITY)	EAST AA CSC NO.4	PAAG1001	AA03A006	ICS-DOM	HIDAR-2013	31	2000025464	100000005859	7000008
ADDIS ABABA REGION ELECTRIC UTILITY	EAAD (BOLE & YEKA SUB CITY)	EAST AA CSC NO.4	PAAG1001	AA03A001	ICS-DOM	HIDAR-2013	31	2000025596	100000005921	7000008
ADDIS ABABA REGION ELECTRIC UTILITY	EAAD (BOLE & YEKA SUB CITY)	EAST AA CSC NO.4	PAAG1001	AA03A012	ICS-DOM	HIDAR-2013	31	2000025673	100000005953	7000009
ADDIS ABABA REGION ELECTRIC UTILITY	EAAD (BOLE & YEKA SUB CITY)	EAST AA CSC NO.4	PAAG1001	AA03A013	ICS-DOM	HIDAR-2013	31	2000025685	100000005962	7000009
ADDIS ABABA REGION ELECTRIC UTILITY	EAAD (BOLE & YEKA SUB CITY)	EAST AA CSC NO.4	PAAG1001	AA03A018	ICS-DOM	HIDAR-2013	31	2000025733	100000005992	7000009

Table 4-2 The sample data from the customers' bills

Business Partner	Contract Account	Contract	Customer Name	Bill Doc No	Invoice No	Meter No	Previous Reading	Present Reading
2000024322	100000005302	7000007734	HAMERE MULUGETA	041802826679	013002764663	779406	88380.00	88783.11
2000024582	100000005436	7000008000	ZHELEKE TFEREA	042202607543	013002764718	788380	65314.00	65997.00
2000024590	100000005441	7000008007	DEMEREKU DEMSE	042002732528	013002764720	820684	64522.00	64894.00
2000024596	100000005443	7000008015	WORKENESH TESEMA	042602662975	013002764722	2352041	83480.00	83480.00
2000024677	100000005482	7000008092	DEMISSE KASAHUN	042002734253	013002764745	738740	47933.00	48455.00
2000024685	100000005485	7000008099	NEAMA HOUSENE	042002734254	013002764748	762168	43882.00	44006.00
2000024692	100000005488	7000008105	MUDSER HASEN	042602662979	013002764750	643021	250690.00	251574.00
2000024700	100000005490	7000008113	MULATU BESUFEKAD	042202607545	013002764753	805780	68621.00	68980.00
2000024994	100000005624	7000008383	PUBLIC HOUSING & REN .	042002734255	013002764820	1289270	38927.00	39488.00
2000025147	100000005693	7000008531	GEDEWON KEBEDE	041802826687	013002764865	2372072	103478.00	103478.00
2000025264	100000005753	7000008643	SENAYIT DEMISE	042202612964	013002764903	752138	44156.00	45149.00
2000025404	100000005819	7000008774	NEGASHE ABEGAZE	042602662989	013002764948	639228D-1	64210.00	64983.00
2000025424	100000005834	7000008793	OLANA JEBESSA	042202610581	013002764952	842465	28532.00	28871.00
2000025431	100000005838	7000008800	MAMO ABYE	042202612970	013002764955	791369	83339.00	88123.00
2000025439	100000005842	7000008807	GETACHEW ZELEKE	042602662990	013002764957	797032	72845.00	73854.00
2000025446	100000005847	7000008814	WEGENE TADESS	042202607556	013002764959	682771	54570.00	54570.00
2000025461	100000005855	7000008827	ADANE MEKURIYA	010003830465	200008120104	216940	41463.00	41914.00
2000025461	100000005855	7000008827	ADANE MEKURIYA	010003830462	200008120103	216940	41012.00	41463.00
2000025464	100000005859	7000008834	ABERA DEMISE	042602665244	013002764966	813034	51183.00	52013.00
2000025596	100000005921	7000008960	GEZAHEGNE MAMMO.	042002732534	013002765006	966753	11378.00	11797.00
2000025673	100000005953	7000009040	GETACHEW TESSEMA	042002734258	013002765029	2351115	62708.00	63159.00
2000025685	100000005962	7000009054	MOLA HIALE	042202604302	013002765032	799714	54332.00	54740.00
2000025733	100000005992	7000009106	MESELECHE TESFAYE	042202604304	200008077368	702412	70452.00	70985.00
2000025739	100000005996	7000009114	BIRKNESH SAYE	042602667037	013002765048	959076	28949.00	29248.00

For the theft identification purpose, it is required to extract the history, which is one year energy consumption of each customer for the four regions and the cost charged for the corresponding energy usage. This is done for the same tariffs, so it only consists of the home usage which has the same tariffs.

After collecting the data, it was required to remove the irrelevant entries and filling the missing cells using different techniques. In such case, the generation of random values between the maximum and minimum of the recorded historical data.

After filtering and fitting the missing data, the kwh reading, and the cost charged for all regions are put in a separate sheet for further processing. The samples for the kwh usage and its cost is shown in the table 4.3 and table 4.4 respectively:

Table 4-3The KWH reading for all regions in 12 months

	Tah 2013	Hid 2013	Tik 2013	Mes 2013	Neh 2012	Ham 2012	Sen 2012	Gin 2012	Miy 2012	Meg 2012	Yek 2012	Tir 2012
1	913	913	913	913	913	913	913	913	913	913	913	913
2	243	221	222	229.338	240.579	234.976	222.936	226.877	239.662	241.141	237.38	222.831
3	196	180	194	195.425	195.46	181.089	195.33	192.427	182.042	183.755	180.42	185.255
4	96	67	80	78.672	72.767	79.952	71.804	92.68	74.131	87.235	93.514	79.071
5	48.26	363.74	253	243.689	138.403	85.705	279.488	160.107	65.863	261.774	95.693	267.273
6	0	198	449	320.819	285.109	80.747	228.246	190.416	165.9	286.362	85.79	82.934
7	1280	1363	2229	1434.412	1320.924	1645.033	2023.954	1835.211	1481.48	1605.569	1321.361	1734.309
8	643.79	508.86	291.77	443.322	535.472	331.303	432.088	292.288	544.507	364.09	514.96	392.051
9	2085.56	4161	3851	2536.858	3694.8	2928.326	3746.877	3934.306	2665.98	3623.698	2951.457	2419.087
10	834	971.36	436.64	946.666	909.698	927.209	862.326	572.692	470.454	678.621	738.585	918.807
11	777	823	1040	979.212	940.907	820.311	957.434	956.858	1031.191	966.762	835.37	855.974
12	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0
14	20859	39	0.36	14662.06	7774.922	425.568	16945.94	11559.44	17043	10257.63	3952.112	20656.94
15	0	366.21	0	61.247	100.074	234.407	56.996	273.099	217.578	126.472	237.315	131.279
16	1212	1908	3347	3158.271	2825.415	2564.542	2928.45	2777.138	3090.86	1850.692	1870.922	2341.172
17	928	1070	894	946.813	1067.906	929.731	903.941	1061.356	1025.527	910.333	1065.658	921.797
18	0	0	0	0	0	0	0	0	0	0	0	0
19	336	0	1033	1022.181	116.732	550.567	589.59	871.81	423.898	179.47	794.452	406.789

Table 4-4 The cost for the corresponding energy usage in 12 months

	Tah 2013	Hid 2013	Tik 2013	Mes 2013	Neh 2012	Ham 2012	Sen 2012	Gin 2012	Miy 2012	Meg 2012	Yek 2012	Tir 2012
1	1532.34	2678.31	1224.84	1532.718	2521.898	2474.114	2354.121	2676.412	2118.376	1281.51	2430.215	1423.542
2	1062.32	648.83	325.05	477.028	1040.536	1001.05	608.286	1037.44	459.688	372.085	490.168	780.523
3	252.03	13.63	248.07	213.195	192.907	159.207	86.236	250.152	24.885	94.341	111.65	195.975
4	102.83	79.63	86.94	89.628	89.824	93.716	88.718	85.9	100.928	96.867	82.293	89.979
5	73.78	894.14	364.58	729.638	263.182	857.073	534.432	831.89	512.097	796.75	169.805	485.408
6	0	57333.55	57081.23	19773.47	39288.79	22589.89	45596.46	24965.59	20790.84	51748.32	47468.24	46691.2
7	46121.53	43990.11	41784.07	42712.17	44828.12	42046.43	43936.43	43642.55	44708.45	45614.94	44864.31	43898.35
8	45275.85	44171.73	43321.81	43878.81	43553.59	43475.4	43344.41	45008.26	43857.62	44399.53	44276.05	45251.49
9	39346.65	36015.81	29367.39	32715.82	37331.76	37562.55	39327.83	34696.94	31247.9	32465.68	34570.75	29690.78
10	36934.18	35419.05	33811.02	34363.35	36788.8	36770.09	36829.26	35595.2	35520.88	35757.12	33836.13	36240.8
11	35934.25	34623.9	33275.22	35196.9	35120.86	35725.63	33636.43	34922.66	33331.61	33783.56	35869.32	33962.07
12	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0
14	33470.36	62.53	41.88	13012.98	25724.39	28450.02	28489.16	8469.054	21961.72	5671.439	14691.43	33094.4
15	0	33426.54	0	22838.64	27128.23	24567.82	24995.33	7958.364	27622.22	24282.77	2847.512	4037.623
16	32921.77	30861.76	27790.43	29211.11	29961.61	31044.07	28592.17	30268.48	31674.7	32686.63	30568.16	30409.73
17	30661.37	29132.17	27401.13	28034.05	28800.73	28066.8	28620.58	28127.26	29252.7	28334.03	29857.17	30410.84
18	0	0	0	0	0	0	0	0	0	0	0	0
19	28676.12	0	28147.77	26433	5689.203	2997.669	4141.842	4397.199	9711.046	1799.57	8033.622	14651.24

The big challenge for this data is to identify which energy meter reading is abnormal i.e. the theft occurs. By looking at the above data, we cannot determine the presence of the theft action. Hence, it was required to further process these data. This is done through the ratio between the energy consumed and the amount charged.

Table 4-5 The ratio between the KWH usage and the corresponding cost

	Tah 2013	Hid 2013	Tik 2013	Mes 2013	Neh 2012	Ham 2012	Sen 2012	Gin 2012	Miy 2012	Meg 2012	Yek 2012	Tir 2012
1	0.595821	0.340887	0.745403	0.595674	0.362029	0.369021	0.387831	0.341128	0.430991	0.712441	0.375687	0.641358
2	0.228745	0.340613	0.682972	0.480764	0.231207	0.23473	0.366499	0.218689	0.521358	0.64808	0.484283	0.285489
3	0.777685	13.20616	0.782037	0.916649	1.013234	1.137444	2.265063	0.76924	7.315331	1.947775	1.615943	0.945299
4	0.93358	0.841391	0.920175	0.877761	0.810106	0.853131	0.809351	1.078929	0.734494	0.900565	1.136354	0.878772
5	0.654107	0.406804	0.693949	0.333986	0.525883	0.099997	0.522963	0.192462	0.128614	0.328552	0.563546	0.550615
6	0.014219	0.01152	0.006735	0.010103	0.012295	0.00762	0.009969	0.006494	0.012415	0.0082	0.011631	0.008664
7	0.053005	0.115533	0.131132	0.077542	0.098972	0.077959	0.095273	0.113391	0.085317	0.111616	0.085374	0.081476
8	0.022581	0.027425	0.012914	0.027549	0.024728	0.025216	0.023414	0.016089	0.013244	0.018979	0.021828	0.025353
9	0.021623	0.02377	0.031254	0.027821	0.026791	0.022961	0.028464	0.027399	0.030937	0.028616	0.023289	0.025204
10	0.036815	0.061824	0.120437	0.108119	0.094301	0.08261	0.102421	0.09175	0.097581	0.056619	0.061205	0.076988
11	0.030266	0.036729	0.032626	0.033774	0.037079	0.033126	0.031584	0.037734	0.035058	0.032129	0.035692	0.030311
12	0.037028	0.033934	0.049671	0.037912	0.041816	0.047334	0.041782	0.046562	0.035301	0.045991	0.047555	0.04282
13	0.020355	0.051416	0.088745	0.046373	0.07265	0.040567	0.046426	0.036783	0.055718	0.059956	0.050892	0.074657
14	0.021797	0.021829	0.010114	0.017946	0.019048	0.016351	0.010357	0.02141	0.014978	0.02059	0.019833	0.016029
15	0.028877	0.027134	0.030939	0.030829	0.028428	0.027983	0.028332	0.029227	0.030935	0.029888	0.02804	0.029147
16	0.126346	0.131089	0.234693	0.178363	0.168184	0.166057	0.205338	0.224516	0.140851	0.218556	0.177447	0.171522
17	0.046679	0.042261	0.04351	0.039436	0.050282	0.051142	0.046911	0.046255	0.050678	0.040275	0.047159	0.04636
18	0.03067	0.030363	0.036571	0.032455	0.032421	0.032429	0.033504	0.034696	0.031813	0.032694	0.031776	0.035212
19	0.025541	0.017612	0.65417	0.791853	0.15006	0.34268	0.425255	0.689321	0.478542	0.45572	0.073725	0.523877

However, the ratio may have not been used for theft detection. The variance between early pervious and current data were used to distinguish how the current data deviates from the previously recorded data. Large change in ratio show there is abnormal consumption. Hence, the consecutive change in the ratio is used for classifying the reading as normal and abnormal data.

Table 4-6 The consecutive deference of the ratio data

	Tah 2013	Hid 2013	Tik 2013	Mes 2013	Neh 2012	Ham 2012	Sen 2012	Gin 2012	Miy 2012	Meg 2012	Yek 2012	Tir 2012
1	0.254934	-0.40452	0.14973	0.233645	-0.00699	-0.01881	0.046702	-0.08986	-0.28145	0.336754	-0.26567	0.045537
2	-0.11187	-0.34236	0.202208	0.249557	-0.00352	-0.13177	0.147809	-0.30267	-0.12672	0.163797	0.198794	0.056745
3	-12.4285	12.42413	-0.13461	-0.09659	-0.12421	-1.12762	1.495823	-6.54609	5.367556	0.331832	0.670644	0.167614
4	0.092188	-0.07878	0.042413	0.067655	-0.04302	0.04378	-0.26958	0.344435	-0.16607	-0.23579	0.257583	-0.05481
5	0.247303	-0.28714	0.359963	-0.1919	0.425886	-0.42297	0.330501	0.063847	-0.19994	-0.23499	0.012931	-0.10349
6	0.002699	0.004785	-0.00337	-0.00219	0.004674	-0.00235	0.003475	-0.00592	0.004215	-0.00343	0.002967	-0.00556
7	-0.06253	-0.0156	0.05359	-0.02143	0.021013	-0.01731	-0.01812	0.028073	-0.0263	0.026242	0.003898	0.028471
8	-0.00484	0.014511	-0.01463	0.002821	-0.00049	0.001802	0.007325	0.002845	-0.00573	-0.00285	-0.00352	0.002772
9	-0.00215	-0.00748	0.003434	0.00103	0.003829	-0.0055	0.001065	-0.00354	0.002321	0.005327	-0.00191	0.003581
10	-0.02501	-0.05861	0.012318	0.013818	0.011691	-0.01981	0.010671	-0.00583	0.040962	-0.00459	-0.01578	0.040173
11	-0.00646	0.004103	-0.00115	-0.00331	0.003953	0.001542	-0.00615	0.002677	0.002929	-0.00356	0.00538	4.54E-05
12	0.003093	-0.01574	0.011759	-0.0039	-0.00552	0.005552	-0.00478	0.011261	-0.01069	-0.00156	0.004735	0.005792
13	-0.03106	-0.03733	0.042372	-0.02628	0.032083	-0.00586	0.009643	-0.01894	-0.00424	0.009064	-0.02376	0.054302
14	-3.20E-05	0.011714	-0.00783	-0.0011	0.002698	0.005993	-0.01105	0.006431	-0.00561	0.000757	0.003805	-0.00577
15	0.001743	-0.0038	0.00011	0.002401	0.000445	-0.00035	-0.00089	-0.00171	0.001047	0.001848	-0.00111	0.000269
16	-0.00474	-0.1036	0.05633	0.010179	0.002126	-0.03928	-0.01918	0.083665	-0.0777	0.041109	0.005925	0.045176
17	0.004418	-0.00125	0.004074	-0.01085	-0.00086	0.004231	0.000656	-0.00442	0.010403	-0.00688	0.0008	-0.00032
18	0.000307	-0.00621	0.004117	3.34E-05	-8.16E-06	-0.00107	-0.00119	0.002884	-0.00088	0.000919	-0.00344	0.004542
19	0.007929	-0.63656	-0.13768	0.641794	-0.19262	-0.08258	-0.26407	0.210779	0.022822	0.381995	-0.45015	0.498337

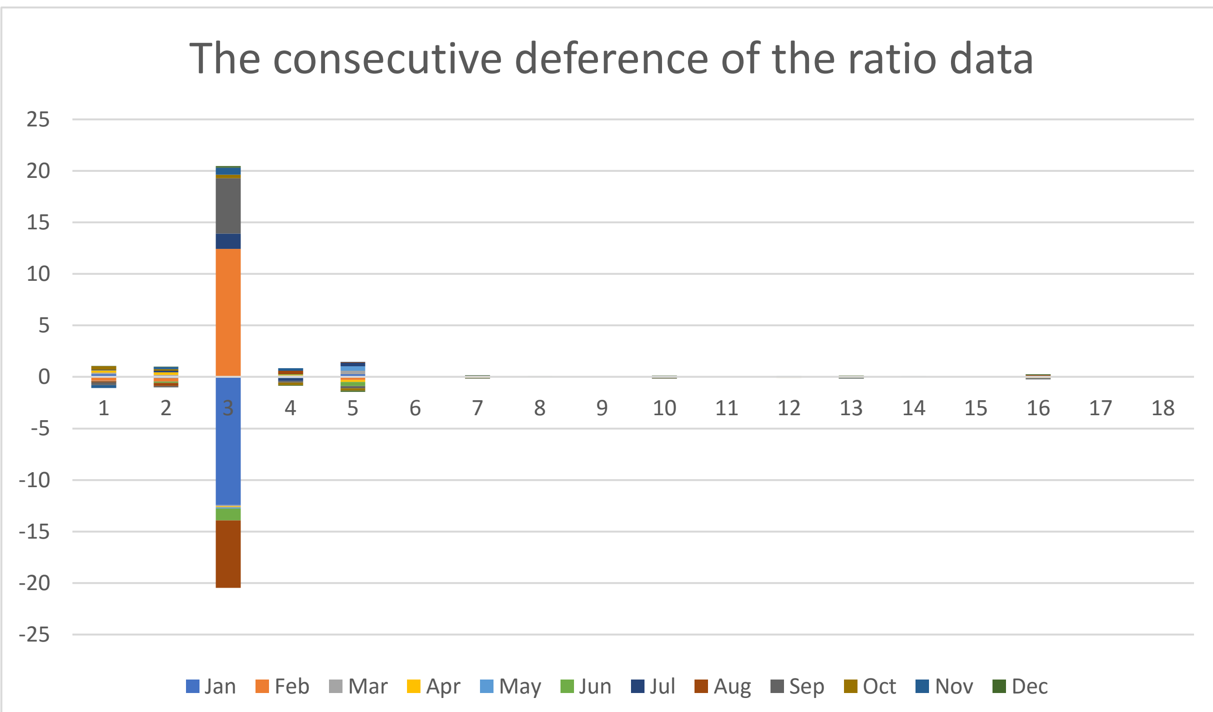

Figure 4-1 The consecutive deference of the ratio data in graph

After processing the input data, the targeted data should be generating. Using 0.5 as a threshold we can generate the output 0 and 1, so we can make 0 below the threshold and 1 above it. The generated target data is shown in table 4.7:

Table 4-7 The generated target data (output in binary form)

1	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0
3	**1**	**1**	0	0	0	**1**	**1**	**1**	**1**	0	**1**	0
4	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0

4.3.2: Data Filtering and Analysis for Load Fluctuation Classifications

The original data collected from the utility company were in hardcopy. By collecting each data recorded in manual, it has been stored in the computer through intensively working on this data for further data filtering, analysis, and processing. After converting the manual data into a computer, it looks as shown in table 4.8 which includes the load current and given line energy consumption for approximately one month. The data is collected every hour for each day. In table 4.8 Yellow shows interruption by request, red show's short fault, green shows Ground (Earth) fault and Blue shows Double fault.

Putting the manual data into a digital one is not enough for fluctuation classifications. These digital data must be further enhanced for the neural model. The input data and the target data need to organize based on the original data set. The input data consists of the load current, the power, and the currents of R, S, T, and N. The target data includes the normal operation, request interruption, earthling failure, short and double fault. For all these interruptions the readings for all inputs have been unique values.

1		5/24/2013		5/26/2013		5/27/2013		5/28/2013		5/29/2013		5/30/2013		6/1/2013	
2	Time(hr.)	A	MW	A	MW	A	MW	A	MW	A	MW	A	MW	A	MW
3	1	80	2	100	2.5	101	2.5	89	2.2	98	2.4	88	2.2		
4	2	81	2	95	2.3	94	2.3	83	2.1	98	2.4	73	1.8		
5	3	85	2.1	80	2	89	2.2	83	2.1	115	2.8	74	1.8		
6	4	94	2.3	98	2.4	96	2.4	97	2.4	120	3	92	2.3		
7	5	134	3.3	140	3.5	160	4	143	3.6	130	3.2	100	2.5		
8	6	200	5	200	5	183	4.5	212	5.3	190	4.7	123	3		
9	7	247	6.1	246	6.1	264	6.6	143	6.1	256	6.4	180	4.5		
10	8	234	5.8	239	5.9	237	5.9	241	6	272	6.8	265	6.6		
11	9	243	6	251	6.2	251	6.3	267	6.6	295	7.3	325	8.1		
12	10	240	6	264	6.6	252	6.3	261	6.2	290	7.2	328	8.2		
13	11	**10:31:00 -11:08** 0	0	272	6.8	254	6.5	278	6.9	278	6.9	311	7.7	271	6.7
14	12	270	6.7	280	7	263	6.6	291	7.1	284	7.1	300	7.5	304	7.6
15	13	256	6.4	254	6.3	249	6.2	266	6.6	279	6.9	286	7.1	300	7.5
16	14	250	6.2	226	5.6	216	5.4	227 **14:15-16:58** 5053,271.2 5214,10.4	5.6	251	6.2	255	6.4	267	6.6
17	15	216	5.8	212	5.3	200	5			229	5.7	238	5.9	264	6.6

Table 4-8 The data collected from the manual for load fluctuations and interruptions

1		6/9/2013		6/10/2013		6/11/2013		6/12/2013		6/13/20
2	Time(hr.)	A	MW	A	MW	A	MW	A	MW	A
3	1	120	3	140	3.5	147	3.6	100	2.5	
4	2	95	2.3	138	3.4	142	3.5	92	2.2	
5	3	78	2.2	148	3.7	138	3.4	95	2.3	
6	4	140	3.7	170	4.2	149	3.7	120	3	
7	5	165	4.2	185	4.6	152	3.8	140	3.7	
8	6	200	5	212	5.3	196	4.9	164	4.2	
9	7	240	6.5	309	7.7	300 **07:10-07:13** 6760,6450 363.2,22.4	7.5	306	7.5	
10	8	340	8.5	312	7.8	300	6.5	323	8	
11	9	364	9.2	368	9.2	300	6.5	326 **09:09-09:46** 515,383 376,152	8.1	321
										428

Table 4-9Final Data for Load Fluctuations Classifications

Load Current	R	S	T	N	Energy	Double	Short	Earth	Normal Intrrupt	Normal
80	80	80	80	0	2	0	0	0	0	1
81	81	81	81	0	2	0	0	0	0	1
85	85	85	85	0	2.1	0	0	0	0	1
134	134	134	134	0	3.3	0	0	0	0	1
227	5053	271.2	5214	10.4	5.6	0	0	1	0	0
0	0	0	0	0	0	0	0	0	1	0
256	256	256	256	0	6.4	0	0	0	0	1
325	325	325	325	0	8.1	0	0	0	0	1
402	402	402	402	0	10	0	0	0	0	1
300	6780	6450	363.2	22.4	7.5	1	0	0	0	0
364	364	364	364	0	9.1	0	0	0	0	1
294	294	294	294	0	7.3	0	0	0	0	1
196	196	196	196	0	4.9	0	0	0	0	1
124	124	124	124	0	3.1	0	0	0	0	1
100	100	100	100	0	2.5	0	0	0	0	1
98	98	98	98	0	2.4	0	0	0	0	1
98	98	98	98	0	2.4	0	0	0	0	1
115	115	115	115	0	2.8	0	0	0	0	1

4.3.3. Data Analysis for Maximum Power Demand Response

The excel data which determines the maximum power demand response is extracted from the load fluctuation data taking only the energy delivered by each line.

For maximum power demand response identification, it is required to classify the data into two classifications. These are the maximum power and the normal power consumption.

It is going to organize the data into three categories since the maximum power demand for each line is different. These are lines one and three are combined while lines 4, 5, and 6 are combined. In the third category, line two has different maximum power distributions, so it is analyzed independently. The targeted values are a binary of 1 and 0. The zero indicates the normal power demand and the 1 indicates the maximum demand.

Table 4-10The sample data for line 1,3 in combined, Line two and Line 4,5,6 in combined respectively

	Energy	Target value
1	2	0
2	2	0
3	2.1	0
4	2.3	0
5	3.3	0
6	5	0
7	6.1	0
8	6	0
9	6	0
10	6	0
11	0	0
12	6.7	0
13	6.4	0
14	6.2	0
15	5.8	0
16	5.2	0
17	6.3	0
18	7.2	0
19	8.9	0
20	8.8	0
21	7.2	0

	Energy	Target value
149	5	0
150	5	0
151	5	0
152	14.7	1
153	12.2	1
154	11.5	0
155	10.2	0
156	9.9	0
157	9.9	0
158	9.7	0
159	9.8	0
160	11.5	0
161	11.8	0
162	8	0
163	4.3	0
164	5	0
165	4.1	0
166	3.3	0
167	2.5	0
168	2.3	0
169	2.2	0
170	3	0
171	4	0

	Energy	Target value
263	1.6	0
264	2	0
265	2.3	0
266	3	0
267	3.7	0
268	4.2	0
269	5.8	0
270	5.8	0
271	5.7	0
272	8.3	1
273	8.3	1
274	5.6	0
275	5	0
276	4.5	0
277	4.6	0
278	4.8	0
279	5	0
280	6.2	0
281	6.3	0
282	5.6	0
283	4	0

The peak power demand is the maximum energy delivered to the individual customers in 24 hours of a given day. In every hour, the power demand in any line is different since the customers are energizing their home appliances dependent on time. Most of the time, maximum energy is consumed in the evening and morning. because, most people prepare their dinner, breakfast and lunch at these times.

The maximum power demand is analyzed first in the three categories according to the similarity of the data distribution plotted in figure 4-2 to figure 4-5. Then, by mixing all the lines' data, it is going to train, validate and test the neural network model.

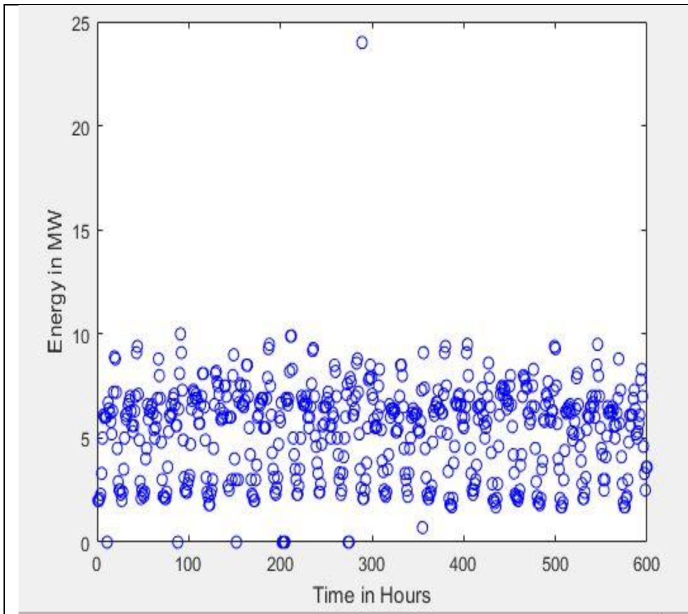

Figure 4-2 Energy Demand Distribution for Line One

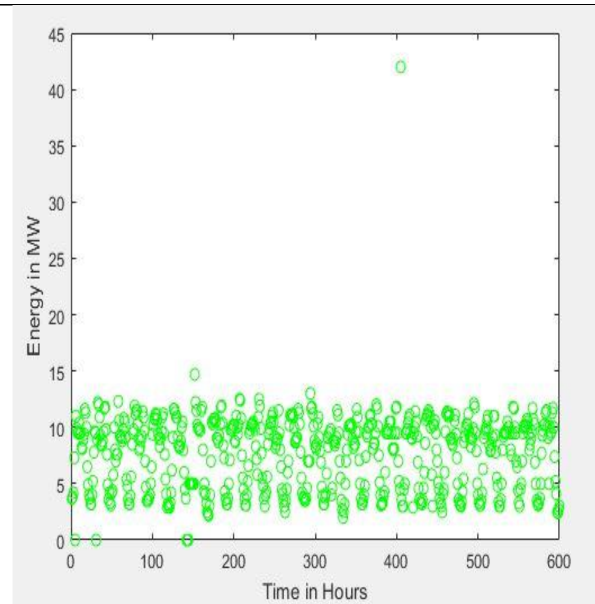

Figure 4-3 Energy Demand Distribution for Line Two

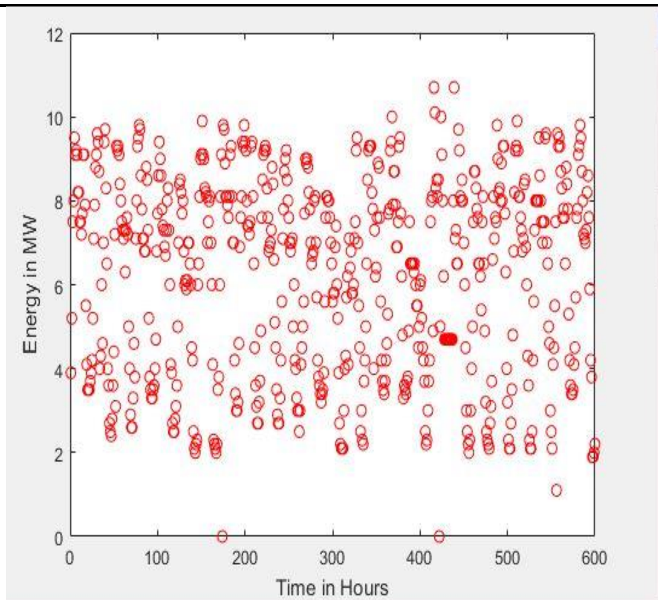

Figure 4-4 Energy Demand Distribution for Line Three

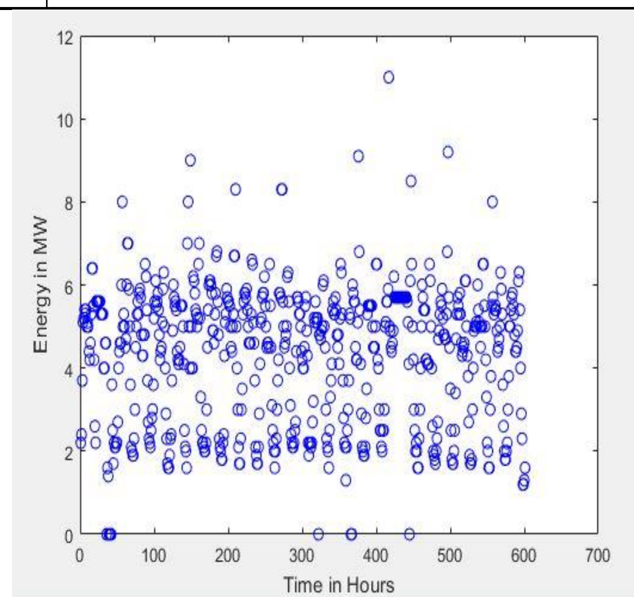

Figure 4-5 Energy Demand Distribution for Line Four

The power demand distributions of the six power lines in 600 hours are plotted as shown from figure 4.2 to figure 4.7 which are invaluable for maximum power demand identifications.

The vertical axis represents the energy consumed by the customers in megawatt and the horizontal axis becomes the time in hours

Based on the power demand to scatter plot, the maximum power demand for lines one and three are approximately the same which is above 9MWwhile lines four, five and six have approximately the same maximum power distributions which are above 7MW. However, line two is different from the others. It has a maximum power above 12 MW. Hence, it requires analyzing the data in three different models as the target output data may be different for the same input data. This is because, in each line, there is a different number of customers and loads. The maximum power demand response for each line is different.

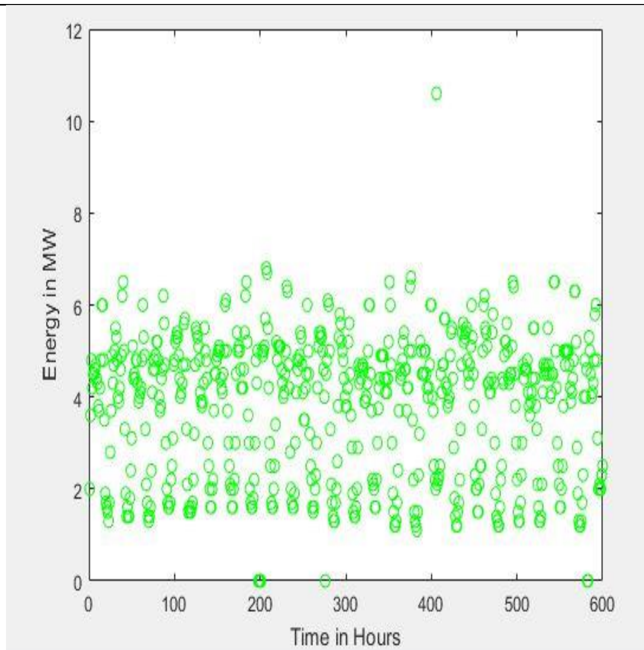

Figure 4-6 Energy Demand Distribution for Line Five

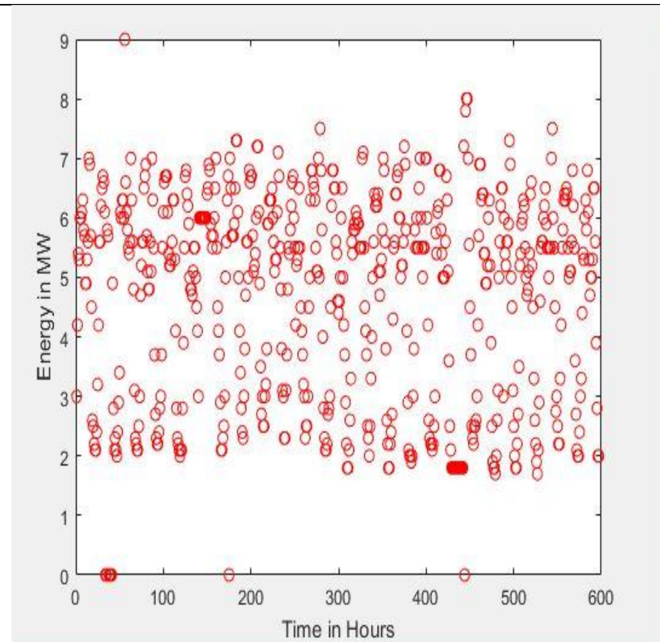

Figure 4-7 Energy Demand Distribution for Line Six

4.4. Neural Network Model

The power interruption classifications, maximum power demand are analyzing using its own neural network independently of the detection of power theft. This is due to fact the that for three cases, their data types, number inputs, the size of the samples, and the size of outputs are different. So, it is required to design three independent models for training, validating, and testing the system. However, these three models, three-layer shallow neural networks with a different number of inputs, outputs, neurons, and the size of samples. The layer includes the input layer, hidden layer, and output layer. It is known that the performance of the Artificial Intelligence system depends on the quality and size of data, the size of hidden layers, the features of inputs, and the size of neurons. By changing the size of the hidden layer neurons, we can retrain the model to get the improved performance.

4.4.1. Neural Model for Theft Detection

One feature input with finally extracted 14,108 different energy meters reading for 12 months are used and the single hidden layer with 30 neurons, two outputs namely normal reading and abnormal reading are configured as shown in figure 4-8. If the data samples are converted in one dimension, it consists of 169,296 samples. This is the last data after filtering and processing the data.

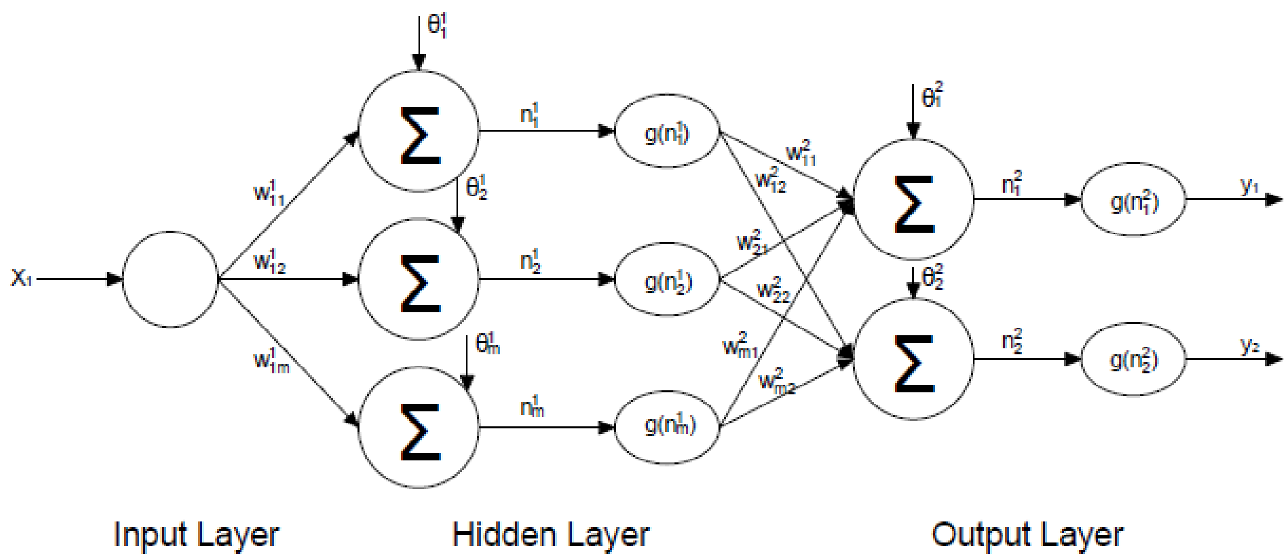

Figure 4-8 Neural Architecture for Theft Identification

From figure 4.8, we can develop the following mathematical relationships:

$$n_1^1 = x_1 {w_{1_1}}^1 + \theta_1^1 \quad (4.1)$$

$$n_2^1 = x_1 {w_{1_2}}^1 + \theta_2^1 \quad (4.2)$$

$$n_m^1 = x_1 w_{1m}^1 + \theta_m^1 \quad (4.3)$$

After generating the first attenuation functions, we use it as independent variable for the output activation functions.

$$n_1^2 = g(n_1^1){w_{11}}^2 + g(n_2^1){w_{21}}^2 + ... + g(n_m^1){w_{m1}}^2 + \theta_1^2 \quad (4.4)$$

$$n_2^2 = g(n_1^1){w_{12}}^2 + g(n_2^1){w_{22}}^2 + ... + g(n_m^1){w_{m2}}^2 + \theta_2^2 \quad (4.5)$$

At the end of the network, it is required to find the expression of the output after passing it through output activation function. The mostly used for output activation function is sigmoid.

$$y_1 = g(n_1^2) \text{ and } y_2 = g(n_2^2) \quad (4.6)$$

4.4.2: Neural Model for Power Interruption Classification

For power interruption classifications, the number of feature inputs is six which are load current, current readings in the four-wire system of the transformer’s R, S, T, and N, the load energy for 25 days in which every day are divided into 24 hours. These data are taken for six lines in Addis Ababa Region. Since all measurements have been taken in all 25 days, for the six lines, it has been 3,596 samples which are recorded in different hours on different days.

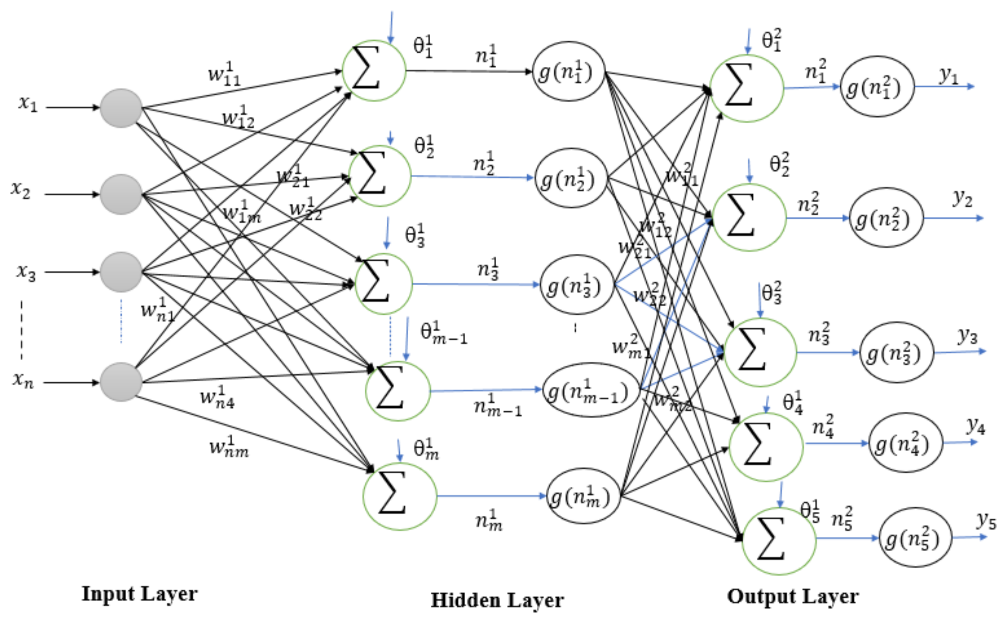

Figure 4-9Neural Network Architecture for Power Interruption Classifications

From the architecture of the neural model as shown in figure 4.9, the mathematical expressions of the output of the first layer are given by:

$$n_1^1 = x_1 w_{11}{}^1 + x_2 w_{21}{}^1 + x_3 w_{31}{}^1 + \ldots + x_n w_{n1}{}^1 + \theta_1^1 \quad (4.7)$$

$$n_1^1 = x_1 w_{12}{}^1 + x_2 w_{22}{}^1 + x_3 w_{32}{}^1 + \ldots + x_n w_{n2}{}^1 + \theta_2^1 \quad (4.8)$$

$$n_m^1 = x_1 w_{1m}{}^1 + x_2 w_{2m}{}^1 + x_3 w_{3m}{}^1 + \ldots + x_n w_{nm}{}^1 + \theta_m^1 \quad (4.9)$$

After moving from the input layer to the hidden layer using the first weighting matrices and biases, it is required to use this value as input and calculate the next activation values as follows:

$$n_1^2 = g(n_1^1) w_{11}{}^2 + g(n_2^1) w_{21}{}^2 + \ldots + g(n_m^1) w_{m1}{}^2 + \theta_1^2 \quad (4.10)$$

$$n_2^2 = g(n_1^1) w_{12}{}^2 + g(n_2^1) w_{22}{}^2 + \ldots + g(n_m^1) w_{m2}{}^2 + \theta_2^2 \quad (4.11)$$

$$n_3^2 = g(n_1^1) w_{13}{}^2 + g(n_2^1) w_{23}{}^2 + \ldots + g(n_m^1) w_{m3}{}^2 + \theta_3^2 \quad (4.12)$$

$$n_4^2 = g(n_1^1) w_{14}{}^2 + g(n_2^1) w_{24}{}^2 + \ldots + g(n_m^1) w_{m4}{}^2 + \theta_4^2 \quad (4.13)$$

$$n_5^2 = g(n_1^1) w_{15}{}^2 + g(n_2^1) w_{25}{}^2 + \ldots + g(n_m^1) w_{m5}{}^2 + \theta_5^2 \quad (4.14)$$

After driving the actuation values at layer 2 through the output activation function is given by:

$$y_1 = g(n_1^2) \quad (4.15)$$

$$y_2 = g(n_2^2) \quad (4.16)$$

$$y_3 = g(n_3^2) \quad (4.17)$$

$$y_4 = g(n_4^2) \quad (4.18)$$

$$y_5 = g(n_5^2) \quad (4.19)$$

From equation 4.15 – 4.19 represents the five classes of outputs which represent the types of power or load fluctuations. Based on these mathematical expressions, the model is expected to predict the type of load interruptions or fluctuations based on the input data feed.

4.5 Training Algorithms

As proposed in the proposal, the neural model is trained by feed-forward followed by backpropagation which is used to minimize the cost function by adjusting the weighting matrices in different iteration or epochs. The cost function is the mean square error which is the mean square of the difference between the hypothesis data and the targeted data.

The general algorithms for training the five neural network modes are as described below:

a. First, the architecture of the neural model is defined. In the network, set the activation functions which are the critical component in Artificial Intelligence Neural Network System (Sigmoid, rectifier linear function, Tanh). The network parameters, biases and weighting matrices are initialized.
b. Based on the parameter with the training algorithm including the cost function value (mean square error) and the maximum number of training iterations or epochs are defined.
c. Divide the total input and target data into Training set data, validation, and testing data in the percentage of 70%, 15%, and 15% respectively.
d. Call the training algorithm. accordingly, the feed-forward followed by backpropagation is called.
e. After training the neural network model, validate it using 15% of the total data.
f. Testing the model to finalize the performance of the classification algorithm.

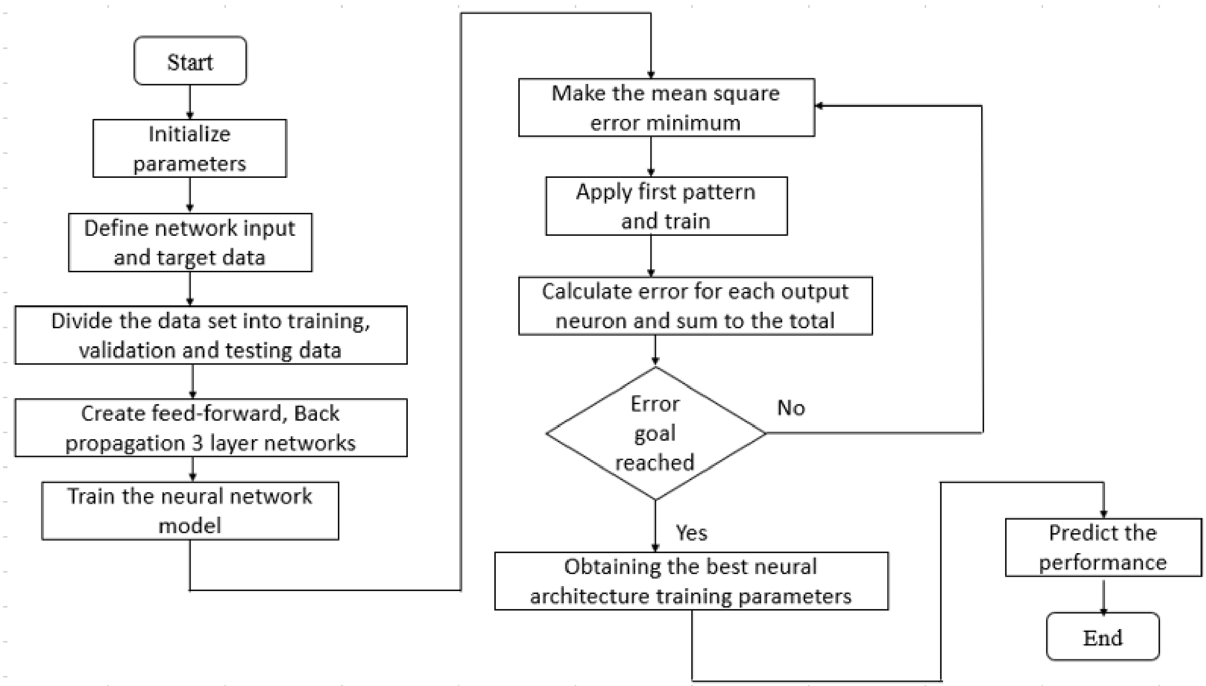

Figure 4-10 Gradient descent training Algorithm Flow-chart

Activation functions are the critical part of the design of artificial neural network models. Sometimes, the activation function is called the transfer function which controllers the behaviors of the output. For these systems, the Tanh sigmoid activation is used for the hidden layer and output layer as the toolbox this features.

CHAPTER FIVE

5. Results

5.1 Introduction

This research thesis is going to describe the data analysis output, the power, and load fluctuations in 24 hours for different power lines and even 600 hours, the theft detection neural network architecture, the power interruption classification neural model, and the maximum power demand response. Since the raw data collected from the AAEU office is so disordered and much information is missed, it is required to extensively filter and analyze for which the neural model can handle it easily for training, validation, and testing.

The power delivered to customers is being fluctuated from different factors. Most of the time one of the causes of power interruptions is a short circuit. This is because the power lines are exposed to different physical contacts and vulnerable to short-circuit. During the short circuit, there is excessive current reading in R, S, T lines.

Ground failure is also one of the causes of power fluctuations. Under these interruptions, some currents draw into the neutral lines. In double fault interruptions, many currents beyond the rating current draw into the four lines, R, S, T, and N. this is the fatal problem that endangers the power transmission lines. The other interruption is based on the request for the power line improvement or maintenance service, during this, there is no energy delivered to the lines. Furthermore, there the load current becomes zero.

By processing the relevant data, train the neural network model for different power interruptions classifications. Furthermore, based on the customers' Bills data, the pattern of each customer's kwh and cost charge are described, then this pattern classified either normal payment or abnormal to generate the target data. Finally, using the power reading, the cost charge, and the target data, the neural network model is feed with such data.

Finally, the maximum power demand curve is described by distributed the energy delivery to the six lines and extracting the peak power registered independently. Then, combine the lines data which have approximately the same peak power demand. Using this peak power, the neural network model is feed to predict the maximum power demand response. After combining all lines of data, it is also analyzed by feeding it to a neural model.

5.2 Load and Power Fluctuations

The power delivered to the customers in Ethiopia has been fluctuating in a redundancy manner within 24 hours. This is since the lines are exposed to different vulnerabilities. The power fluctuation may be caused by a short circuit, ground failure, and interruption by a formal request for maintenance or other services, and double fault. During these interruptions, the power lines are down for some extended minutes, hours even days until the system returns.

In the load fluctuation curve, the current delivered to the customer line versus the hours are plotted as shown in figure 5.1. The zero load currents mean there is no current delivered to the customer due to the interruption in the power lines. So, the customers have no access to electricity for this case. During sudden power loss, there may result in damage to connected electronic devices, home appliances, and any exposed electrical equipment. Because, during on-off, the current through the load may increase or decrease beyond the rating load. Most of the time, the current is exceeding the rating current during the start, so having fluctuate current may result in excessive current through the electronic devices. This causes the damage of the winding in electrical machines, electrical components in the electronic devices and appliances.

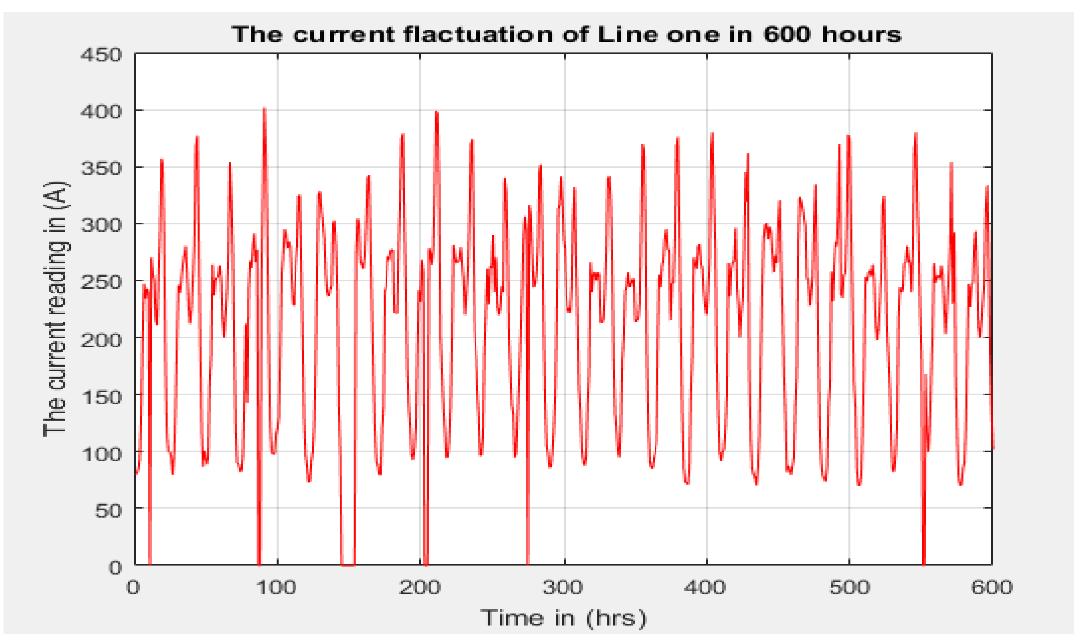

Figure 5-1Load fluctuation of Line one

On the other extreme side, the peak value in the load fluctuation curve indicates that the maximum power used in the 600 hours. Most of the time, the maximum energy is consumed in the evening from 4:00 PM to 9:00 PM and morning from 5:00 AM to 8:00 AM. because so many electric appliances are energized at this time in Addis Ababa, Ethiopia.

In figure 5.2, the power fluctuation curve is shown. This data pattern is similar to the load fluctuation curve to some extent. The lower peak shows the minimum power consumed by the customers due to different factors including power interruptions and the peak value indicates the maximum power usage at different hours.

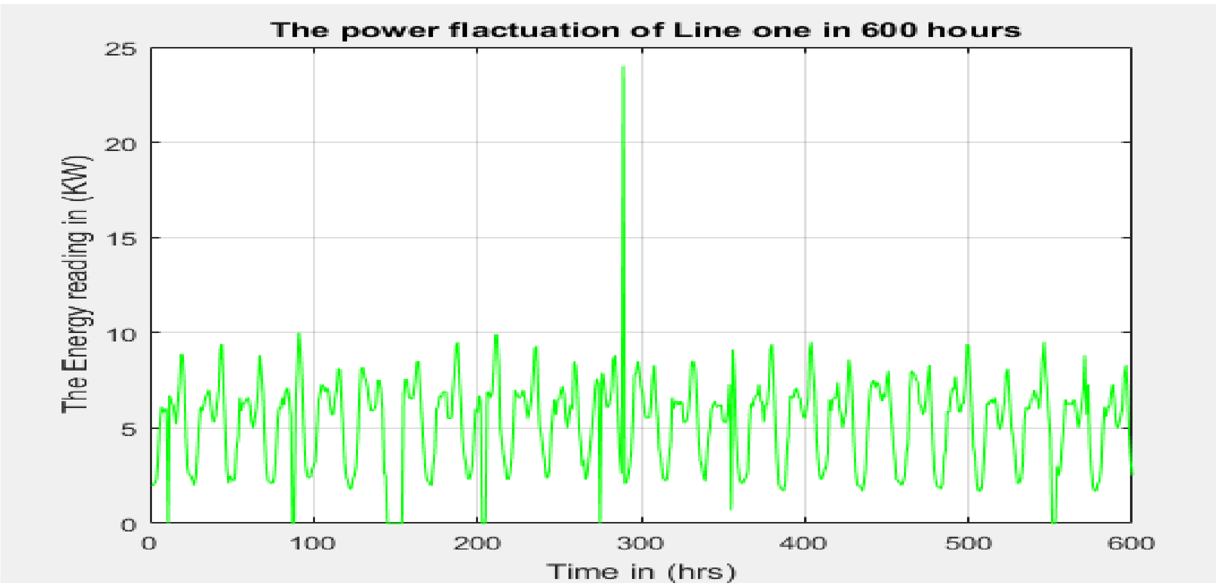

Figure 5-2 Power Fluctuation Curve for Line one

The relation between the load current and the energy consumed on line one is shown in figure 5.3. If the line is interrupted, there is no current and energy delivered to the customer. As shown in the distribution line, there are some unusual data distributions either low current and high energy consumption or high load current and low energy consumption.

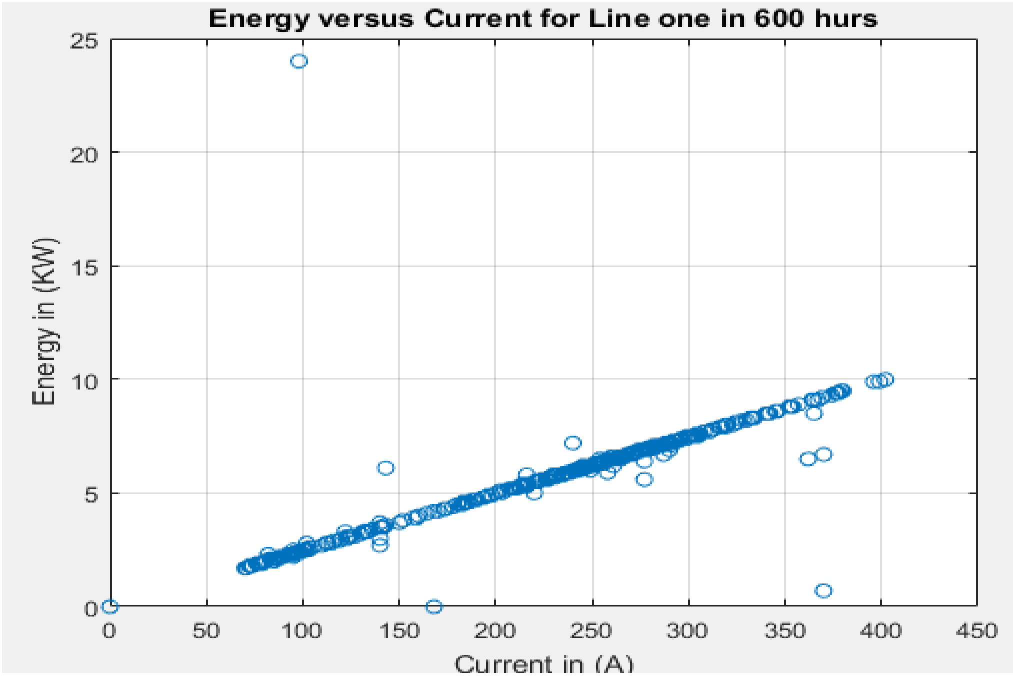

Figure 5-3 Energy vs. Load Current Distributions for Line One

5.2.1. Trained Neural Network Model for Power Fluctuation Classifications

In power fluctuation classifications, the NNM is feed with data consisting of six features including the load current, R, S, T, and N current reading, and the measured load power. The data sets consist of 3,596 sample sizes. Hence, the input size becomes 3,596 by 6. The output consists of five classes. These are the feature of short circuits, ground fault, double fault, normal operation, and request interruptions.

After extracting the proper reading from the AAEU company from the manual recording (paper), it is going to train, validate and test the classification neural model using the data proportion of 70%, 15%, and 15%, respectively.

The neural network model has three layers namely, input layer, hidden layer, and output layer. In the input layer, there are 6 feature inputs with 3,596 sets. The hidden layer consists of 30 hidden neurons. These neurons may vary until the best performance is achieved. The output layers include 5 target classes.

The model is shown in figure 5.4. This is drawn using the matlab toolbox nprtool.

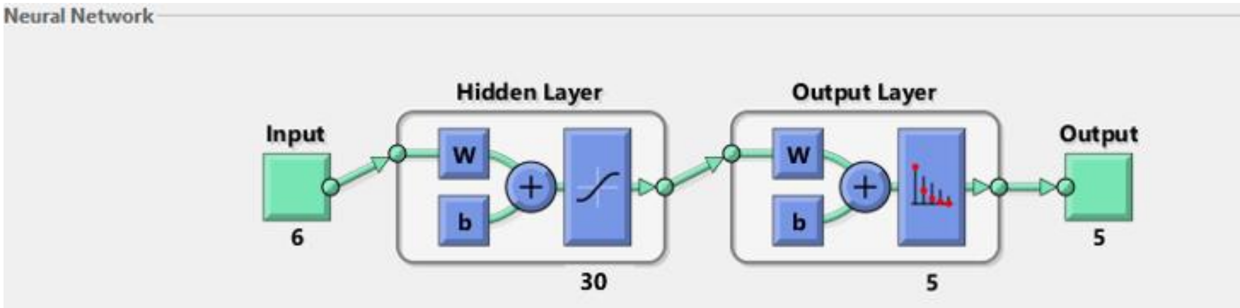

Figure 5-4 Load Fluctuation Classification Neural Network Architecture

As shown in figure 5.4 the number of input features is six, the number of hidden layer neurons is 30 and the output class is 5. The model is also a three-layer shallow neural network with input, hidden, and output layers, so it involves two weighting matrices and biases. The first weighting matrix and biases are from the input layer to the hidden layer while the second one is from the hidden layer to the output layer.

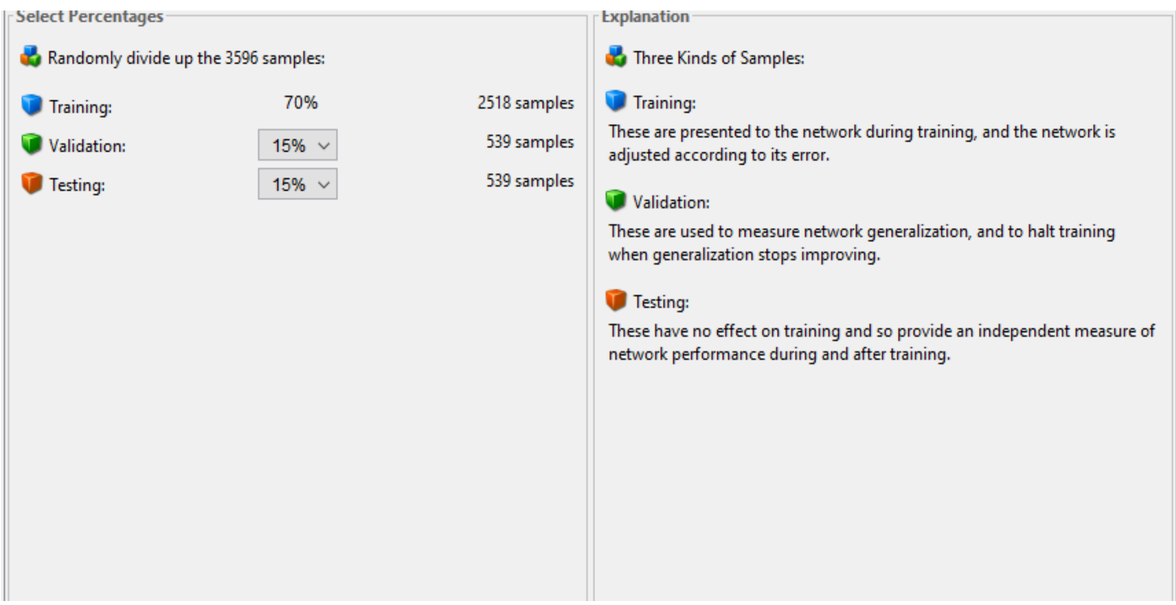

Figure 5-5 Classifying the Data into Training, Validation and Testing

Among 3,596 data samples, 2,518 are assigned for trained the model which is to teach the model experiences and adjust the network according to the error, 539 for validation or for measure the network generalization and stop the training when the generalization stops improving and 519 are for testing or to verify the correctness of the model. The result of the training model output is shown in the following figures:

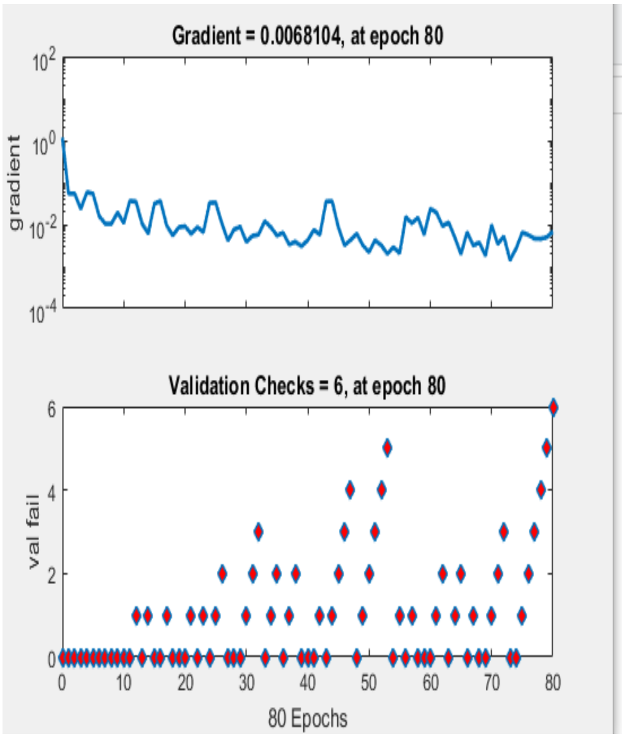

Figure 5-7 The gradient vs. iterations

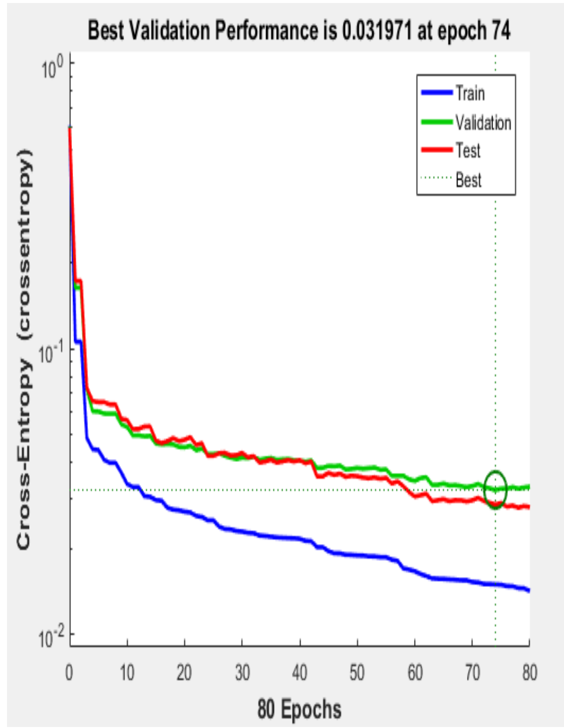

Figure 5-6 The performance Curve

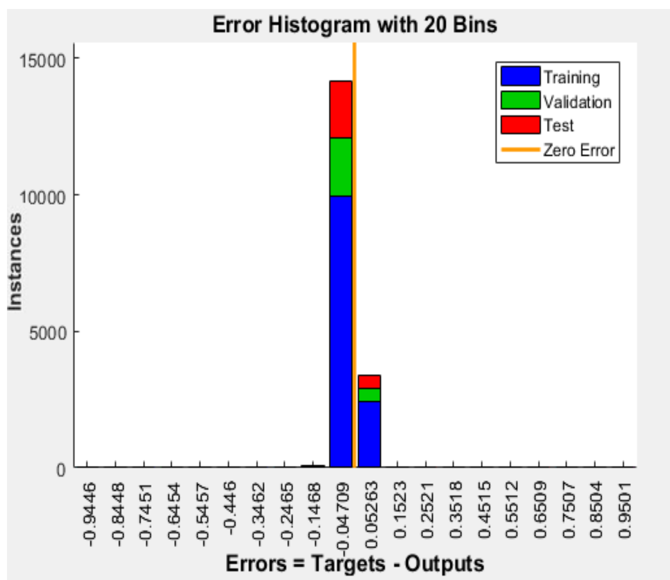

Figure 5-8 The error histogram (instances vs. errors)

From the performance curve, the train, validation and test performances are improved as the iterations of training are increased. as shown in figure 5.6. The best validation performance is 0.031971 at the iteration of 74. Furthermore, the minimum gradient which is 0.0068104 occurs after 80 iterations. In every iteration, the weighting values are updated until the performance is improved.

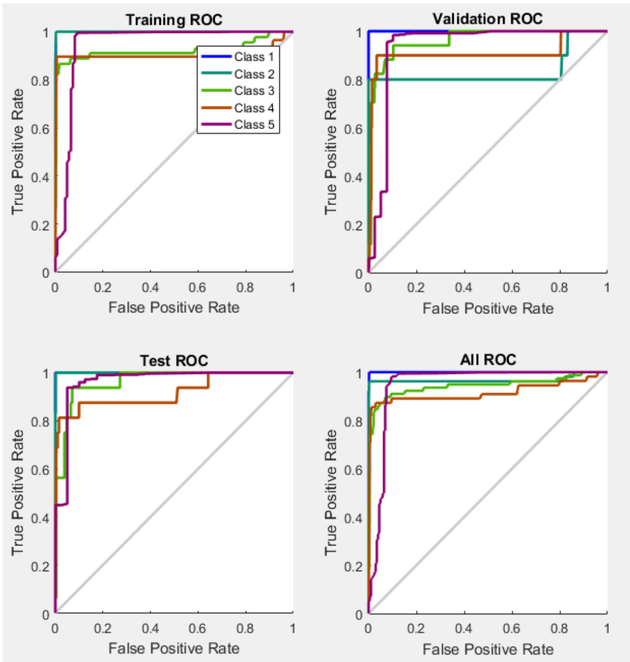

Figure 5-9 ROC curve

Figure 5-10 Confusion Matrix for Interruption Classifications

The percentage of correctly predicted sets in the training process is 98.1%, in the validation is 94.6% and testing is 96.1%. Moreover, the overall percentage of correctly predicted values is 97.2% while 2.8% of the data are predicted incorrectly as shown in figure 5.10.

On the ROC curve (True Positive vs. False Positive) plot, all classes are close to the zero vertical axes which show that the true positive values are much larger than the false positive values. As the curve is going to close to the zero vertical axes, the performance for the training, validation, and test are improved significantly.

At the mid of the error histogram plot, there is a bin corresponding to the error of -0.04709 and the height of that bin for training dataset lies below 10,000 and validation and test dataset lies between 12,000 and 14,000. It means that many samples from our different datasets have an error lies in this.

5.2.2. Maximum Power Demand Response Neural Network Model Training

First, the result for similar data that has approximately the same maximum power demand response been presented as described in chapter 4. Line one and three are merged while Line four, five, and six merges, and line two remain themselves.

The result shown in the figures from 5.11 to 5.15 is the neural network model feed with lines one and three data. The best validation performance value 0.000001 is achieved at the iterations of 60, The cross-entropy vs. iterations for train, validation, and test curve is going to decrease approximately at the same rate as shown in figure 5.11. The cross-entropy vs. iterations for train, validation, and test curve is going to decrease approximately at the same rate.

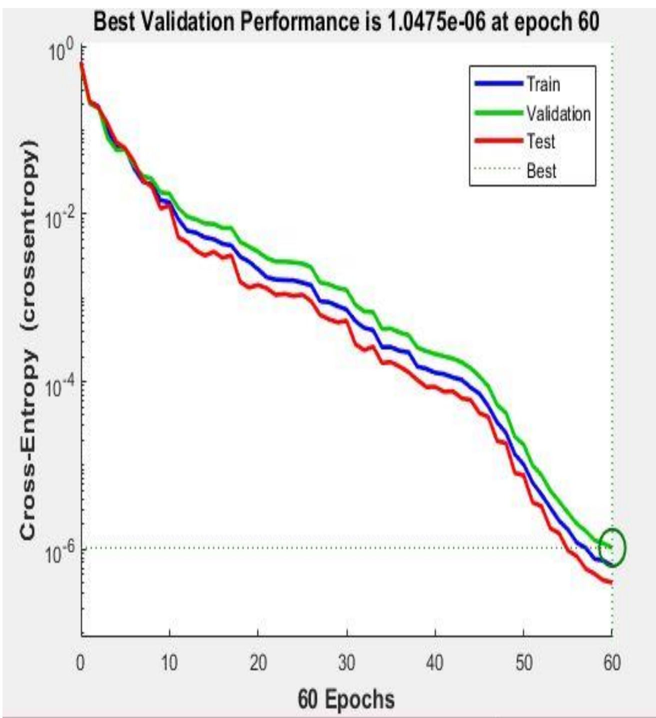

Figure 5-11 Performance curve for lines 1 & 3

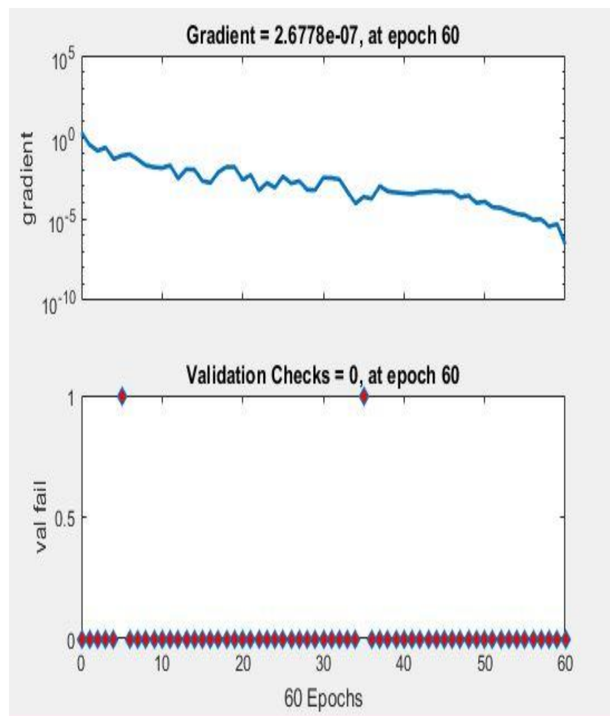

Figure 5-12 The training state

As the mean square error is approximately zero, the error histogram is nearly on the zero vertical axes which represent the zero error. No data is misclassified. Hence, the percentage of correctly predicted values are embedded on the diagonal matrixes which are in green. This is 100% if they are summed together. From the overall confusion matrix, 92.1% of the data is predicted as the normal power demand responses while the remaining 7.9% are predicted as the maximum power demand.

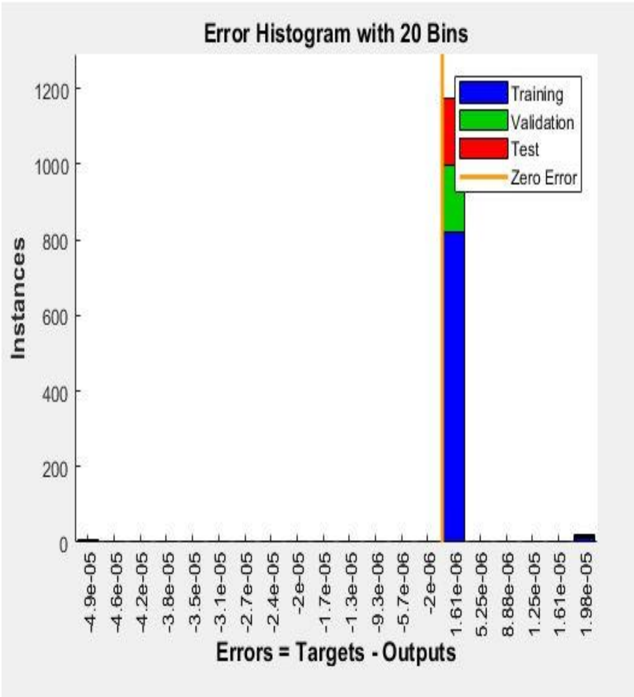

Figure 5-13 The Error Histogram

Figure 5-14 The confusion matrix

The receiver operating characteristic curve is going to show the relationship between the true positive rate and the false positive rate as shown in figure 5.15. Since there are no data sets misclassified as false positive, the curve lies on the zero vertical axes i.e., there is only the true positive rate.

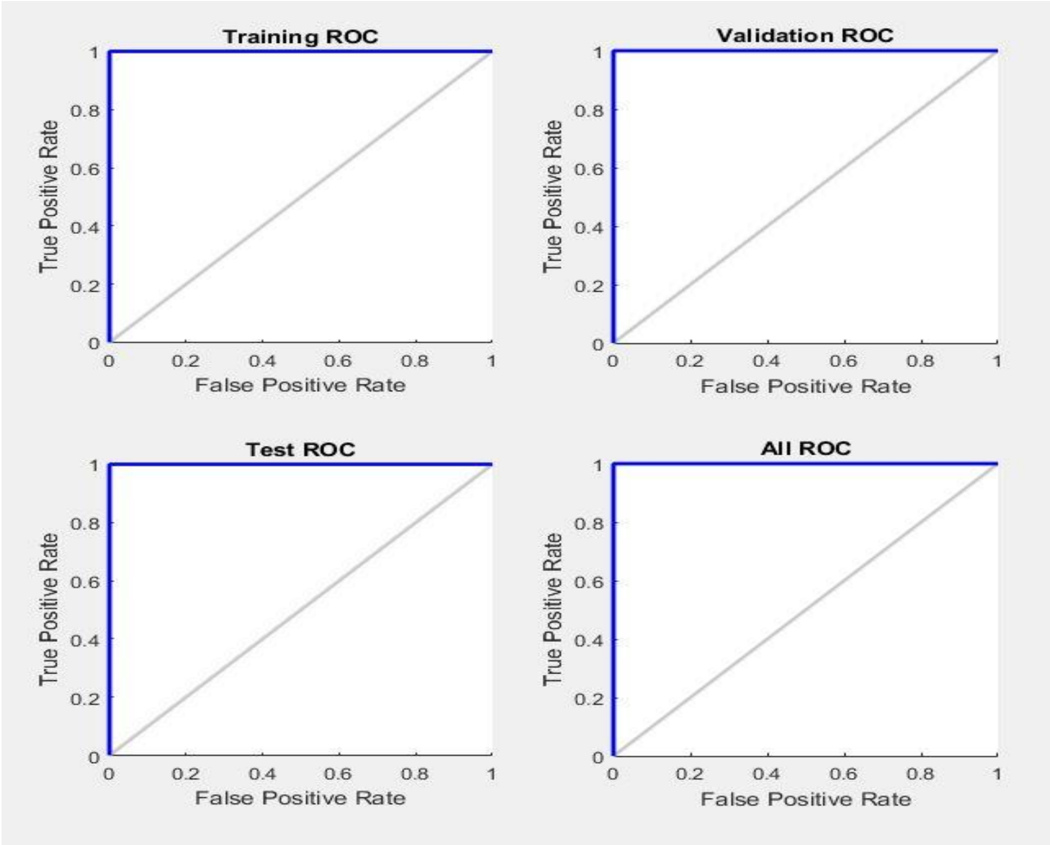

Figure 5-15 The true positive vs. the false positive curve

The results for training neural network model with the data of Lines four, five, and six are shown from figure 5.16 to figure 5.20. At the performance curve, the best validation performance which is 0.000000739 is achieved at iterations of 39. This is approximately zero and the mean square error is approximately zero.

From the overall confusion matrix, 98.5% of the data predicted as the normal power demand responses while the remaining 1.5% are predicted as the maximum power demand.

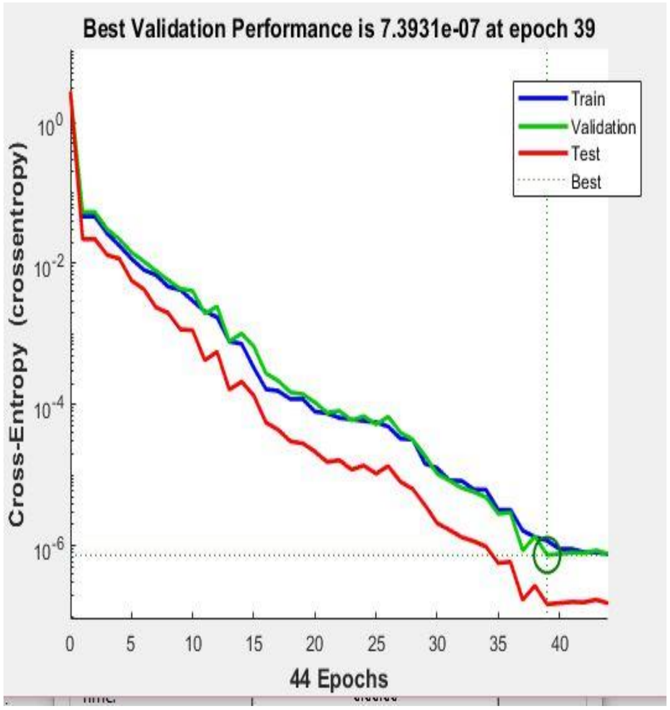

Figure 5-16 Performance curve

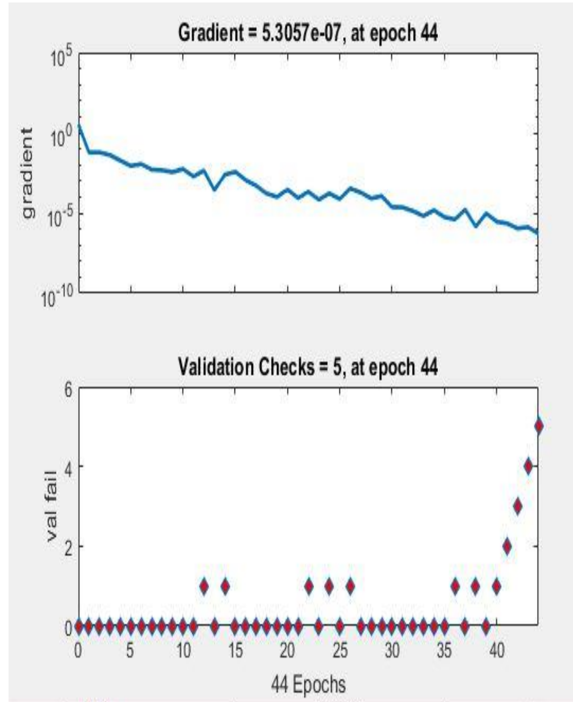

Figure 5-17 The training state

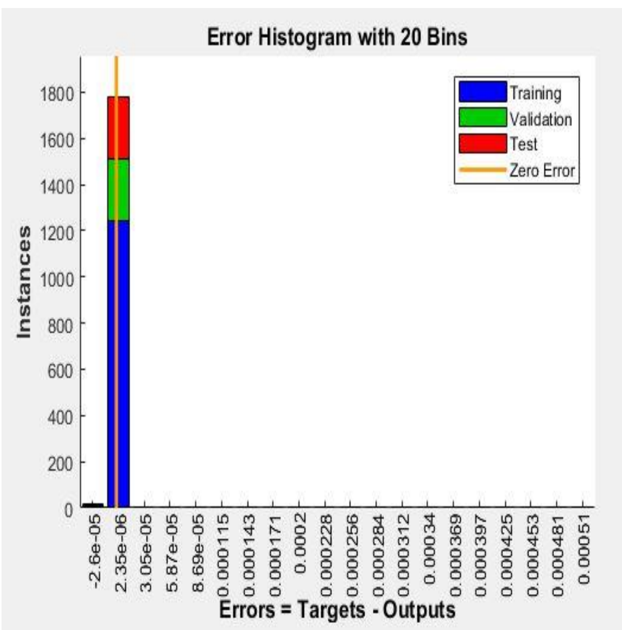

Figure 5-18 The Error Histogram

Figure 5-19 Confusion matrix

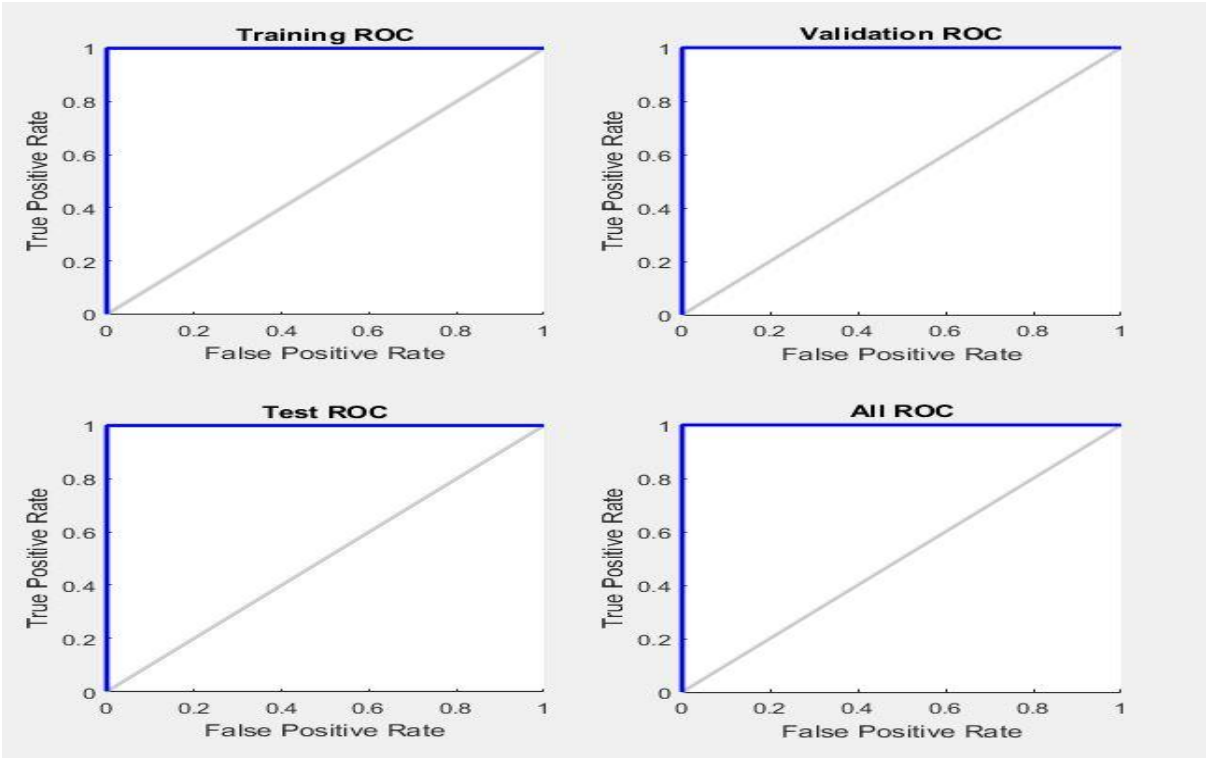

Figure 5-20 The true positive vs. the false positive curve

The results for the training neural network model with the data of Line two is shown from figure 5.21 to figure 5.25. The performance of the test, validation, and test is going to increase as the iterations of the training is increasing. However, the rate of individuals' performance increasing is different as shown in figure 5.21.

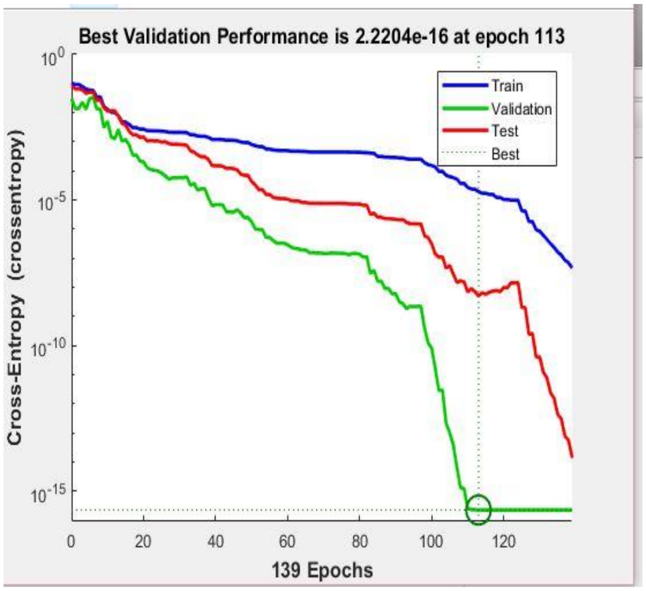

Figure 5-21 The performance curve

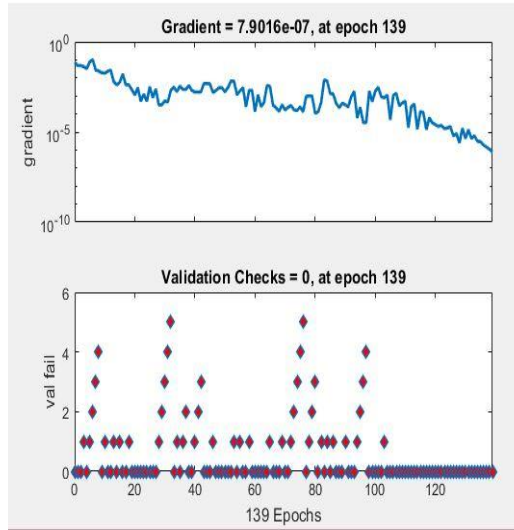

Figure 5-22 Training State

Since no data is misclassified during the training, validation, and testing of the neural network model, the error is close to the zero vertical axes. So, the difference between the target and output is approximately zero as shown in figure 5.23. From the confusion matrix shown in figure 5.24, 98.3% of the total 600 data sets are predicted as the normal power demand while 1.7% of the data are predicted as the peak power demands.

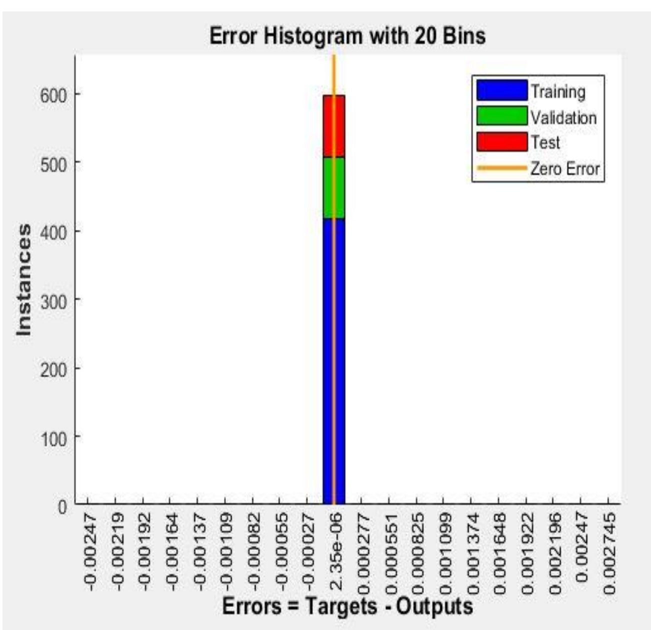

Figure 5-23 The error histogram

Figure 5-24 The confusion matrix

Another performance measurement for neural network training is the receiver operating characteristic curve. This is the true positive rate vs. false positive rate curve plotted in the x-y plot. The ROC curve for this training as shown in figure 5.25 is nearly lies on the zero vertical axes or the true positive axis. This shows that there is not any data classified as false positive values.

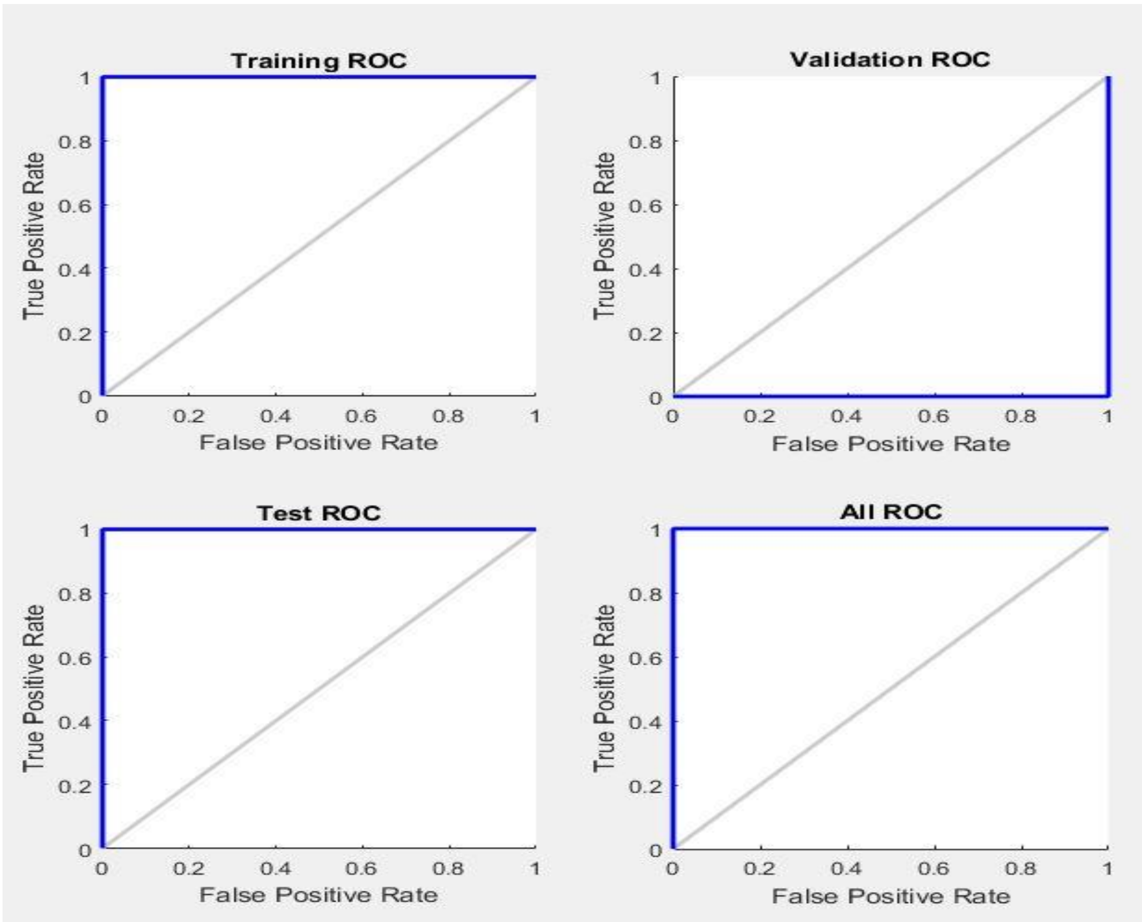

Figure 5-25 The true positive vs. false positive curve

5.3. Smart Energy Meter Reading Data Analysis

As there is no smart energy meter in current trends, the KWH and the corresponding expenses are collected from the four districts of Addis Ababa City. These are EAAD, NAAD, WAAD and SAAD. The data collected from these districts are not organized properly and there is misinformation. So, it was required to filter, analysis and organize the relevant data. Hence, it consumes too much time to accomplish this task.

By analyzing these unique data features, the data is classified into two categories. These are normal reading and abnormal reading. In the abnormal category, it includes power theft or fraud. This is because there is no output response with the energy meter reading, this study generates the output by analyzing the collecting data.

5.4. Theft Detection Neural Model Training, Validation and Testing

After filtering the required data, the neural network model is training, validating and testing with the previous experiences or data to predict the future feed data. The whole data should be divided into two-three categories. These are the Training, Validating, and Testing data with 70 %, 15 %, and 15 % of the whole respectively.

First, the model is trained with the first 70% of data to teach it the new experiences. After training, it is required to validate the model with 15% of the total data to check the validation of the system. And then, we verify the correctness of the model with testing for the remaining 15% of data.

In the first trial, the data used for the training, validation, and testing in theft detection is the ratio of kilowatt-hour reading and the corresponding cost charged. The direct power consumed, and the charged cost does not directly feed to the neural network model. This is the due fact that the model should perform the classification task efficiently using the activation function Tanhsig. The model is generating and trained it using the MATLAB neural network toolbox.

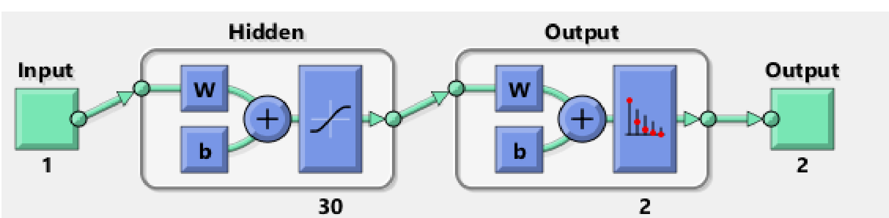

Figure 5-26 Theft detection neural network architecture with 30 hidden neurons and 2 classes

In figure 5.26, w is the weighting matrices and b is the biases. As the model is a three-layer shallow neural network, two weighting matrices and biases are required to transform the input to the output. The output has two classes namely fraudulent and normal reading.

5.4.1. Trained Neural Network Outputs with the Feed of Ratio Data

In such case, the result is due to the feed of the ratio data to the neural network model using the back-propagation algorithm. The best validation performance of 0.32847 can be achieved at 62 iterations. This value is too large which is found in the error histogram. The area under the instances vs. errors histogram plot is large. This indicates that some data is not predicted correctly.

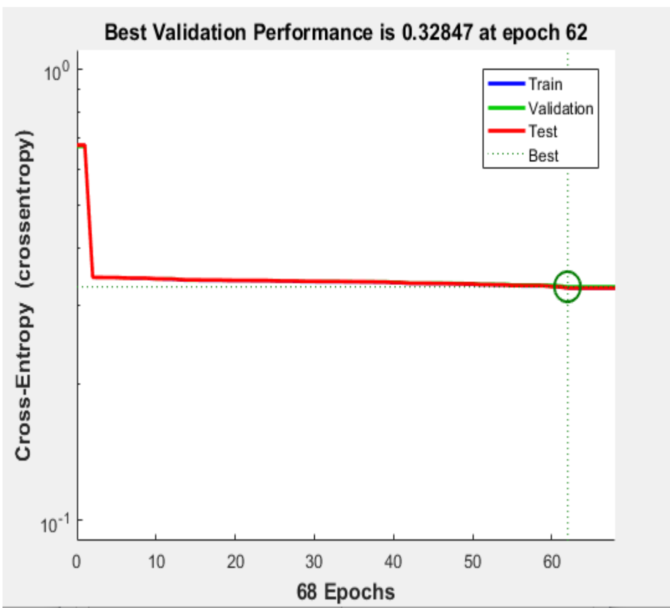

Figure 5-27Performance Curve

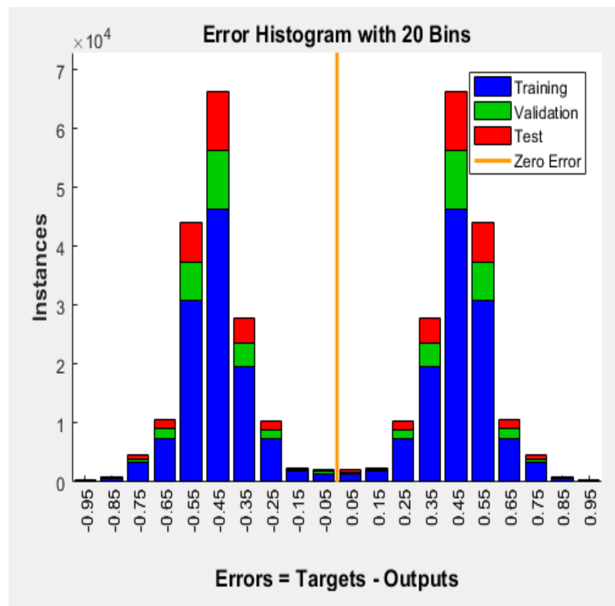

Figure 5-28 Error Histogram

As it is seen in figure 5.29, the best gradient value 0.011339 can be achieved at 68 iterations. If the iteration for training the neural model exceeds this limit, the gradient is above the minimal gradient value. Hence, the performance also decreases. Moreover, the true positive value vs. the false positive value curves for the training, validation, and test is near to the lines passes through the middle point of the vertical and horizontal axis in the first quadrant. This shows that there are so many data that are falsely predicted as positive. Hence, the performance of predicting the data correctly is reduced as shown in the confusion matrix plot.

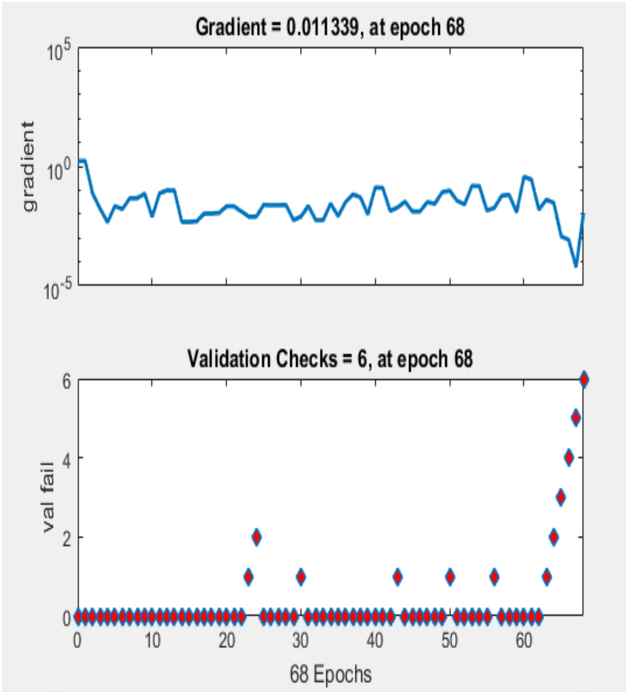

Figure 5-29 The gradient vs. the iteration or training state

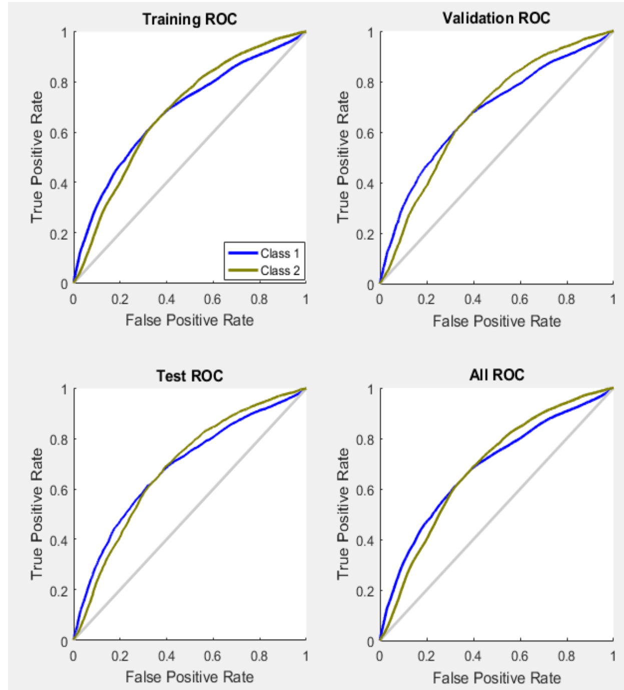

Figure 5-30 Receiver operating characteristic curve (ROC)

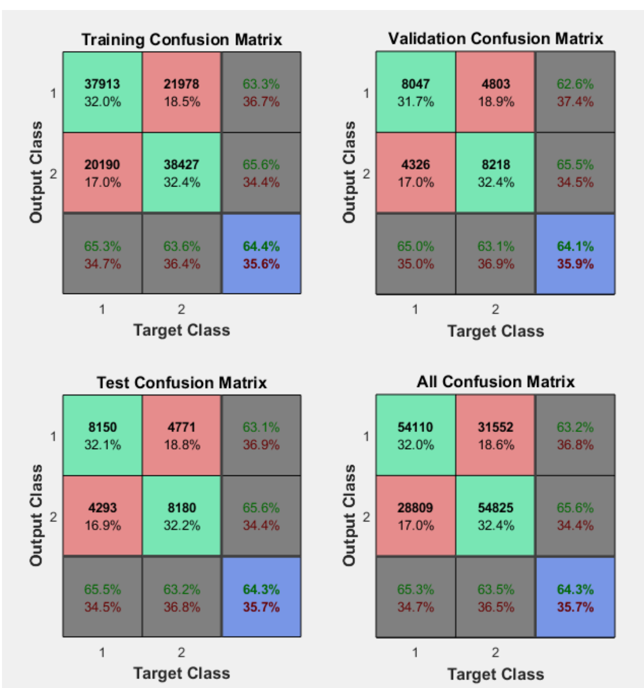

Figure 5-31Confusion Matrix for 30 Hidden Neurons.

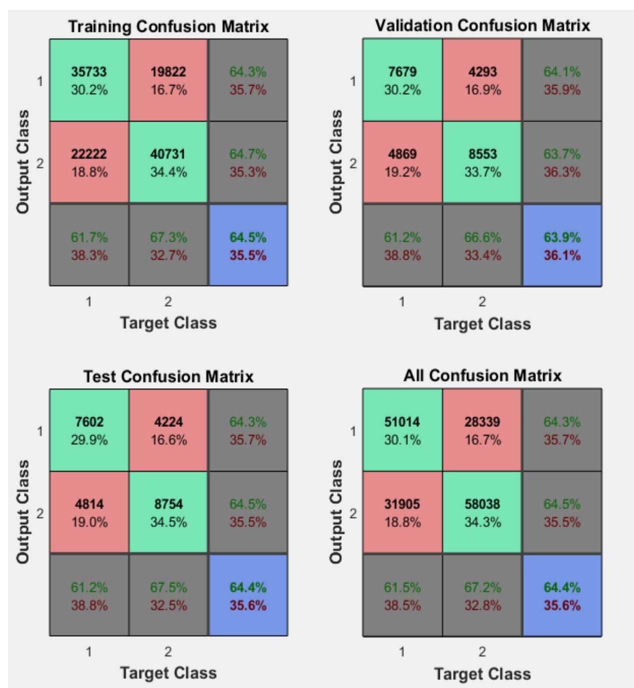

Figure 5-32Confusion Matrix for 100 Hidden Neurons.

From the confusion matrix plot, it is going to show the performance with different size of the hidden layer neurons. In figure 5.31, the hidden layer neurons are 30 and the overall correctly predicted percentage becomes 64.3%. However, as shown in figure 5.32, the hidden layers are 100. The percentage of correctly predicted values becomes 64.4%. This indicates that increasing the size of the hidden layer neurons is insignificant in improving the performance of the training. The characteristic operating curve (ROC) is a graph showing the performance of the classification model at all classification thresholds. In the plot, there is a true positive rate and a false-positive rate. Hence, the ROC curve describes the relationship between the true positive rate (TPR) and the false-positive rate (FPR).

True positive the predicted value is true and positive while true negative the prediction is negative but true. In false positive, the prediction is positive but it is false while for false negative, the prediction is negative and false.

$$TPR = \frac{TP}{TP + FN} \tag{5.1}$$

$$FPR = \frac{FP}{FP + FN} \tag{5.2}$$

Where,

TP = True Positive,

FN = False Negative

FP = False Positive

FN = False Negative

The confusion matrix is another method of describing the performance classifications. It consists of nxn matrix where n is the number of the target's classes or outputs.

5.4.2. Trained Neural Network Outputs with the Feed of change Ratio Data

The performance of the classification is 64.4%. This means that the system can predict the feed data 64.4 % correctly and misclassify the remaining 35.6 % data. This shows that the performance for this classification is poor. So, it is required to either manipulate the training data into another proper format further or change the neural network model. However, changing the neural network model is insignificant for this data. because, the performance is hardly improved.

Hence, it is preferable to analyze and manipulate the data in some form to enhance the performance of the system. For now, let's feed the consecutive difference of the ratio data. The difference between the previous ratios to the current ratio data is used as training data instead of using ratio. This data format shows how the current data has deviated from the previous and forehead recorded ratio data.

Now, the performance of the trained, validated and tested system is shown in figure 5-33 to figure 5-38 graphically. From the performance curve figure 5.33, the best validation value is 0.0031 at the iteration of 475. This shows that the mean square error is too small i.e., the performance is improved. The error (the difference between the targets and outputs) in the histogram plot is near to zero as compared to the ratio data feed to the neural network model.

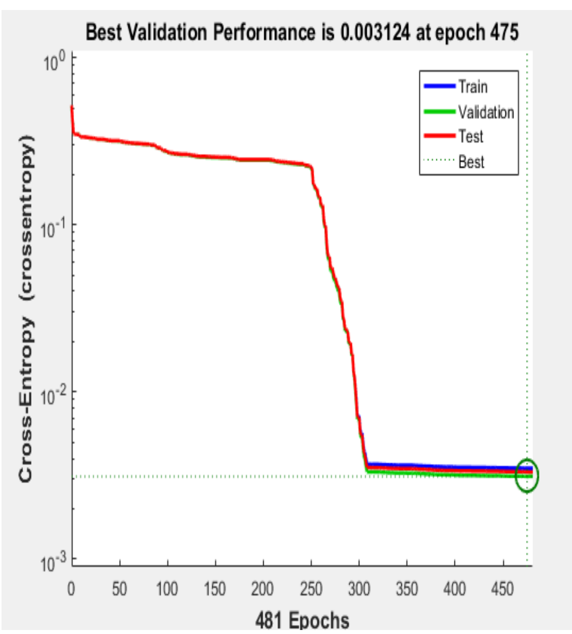

Figure 5-33Performance Curve

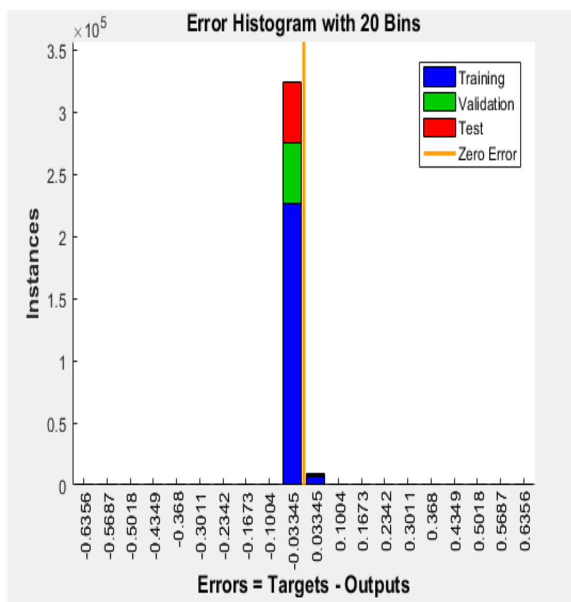

Figure 5-34Error Histogram

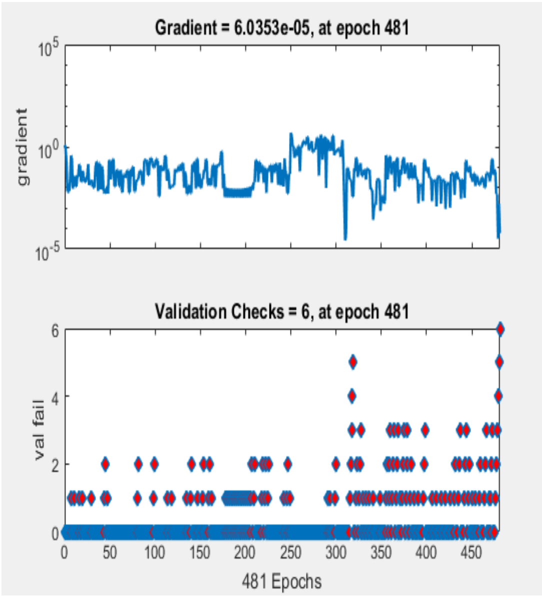

Figure 5-35The training state

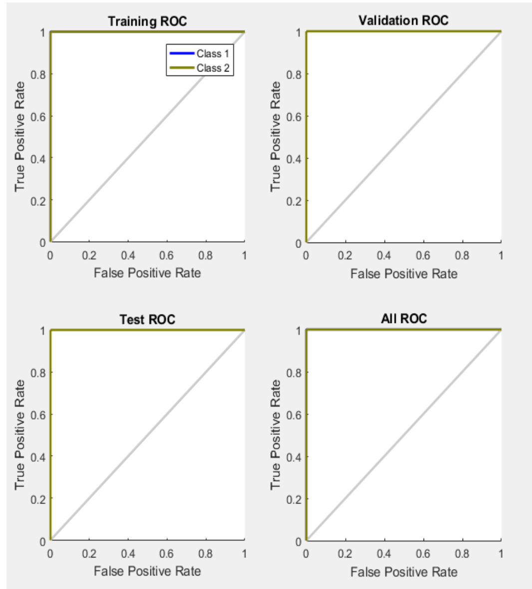

Figure 5-36 The receiver operating characteristic (ROC) Curve

Figure 5-37 Confusion Matrix

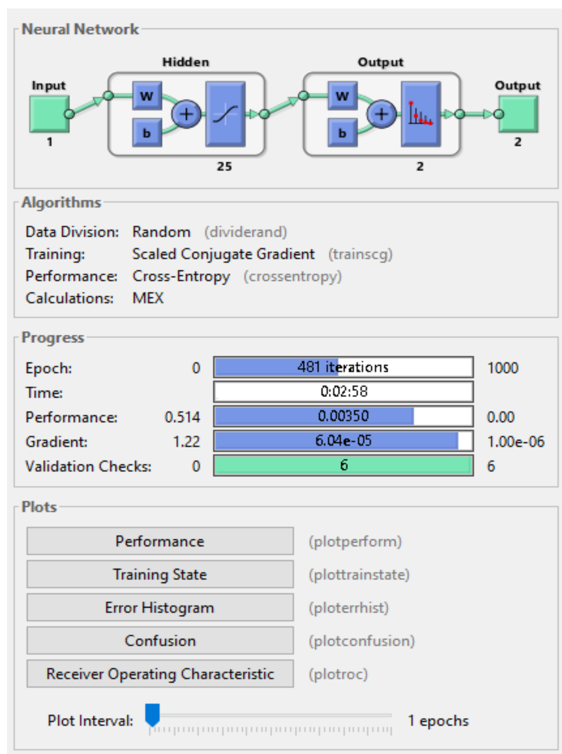

Figure 5-38 Total Number of Iterations for Training

The confusion matrix as shown on figure 5.37 indicates the percentage and number of correctly or incorrectly predicted values. The rows referring the predicted class or output class and the columns referring the true class or target class. The diagonal cells indicate the observations which are correctly classified. The off-diagonal cells referring the incorrectly classified observations. Both the number of observations and the percentage of the total observations are indicated in each cell.
The training, validation, testing and the overall confusion matrix is shown for maximum power demand response determinations. From the overall confusion matrix, 82,442 which are 48.7% of the total observations are classified as the normal reading and 86,377 which are 51.0% of the total observation is classified as the fraudulent.

5.5 Implementation

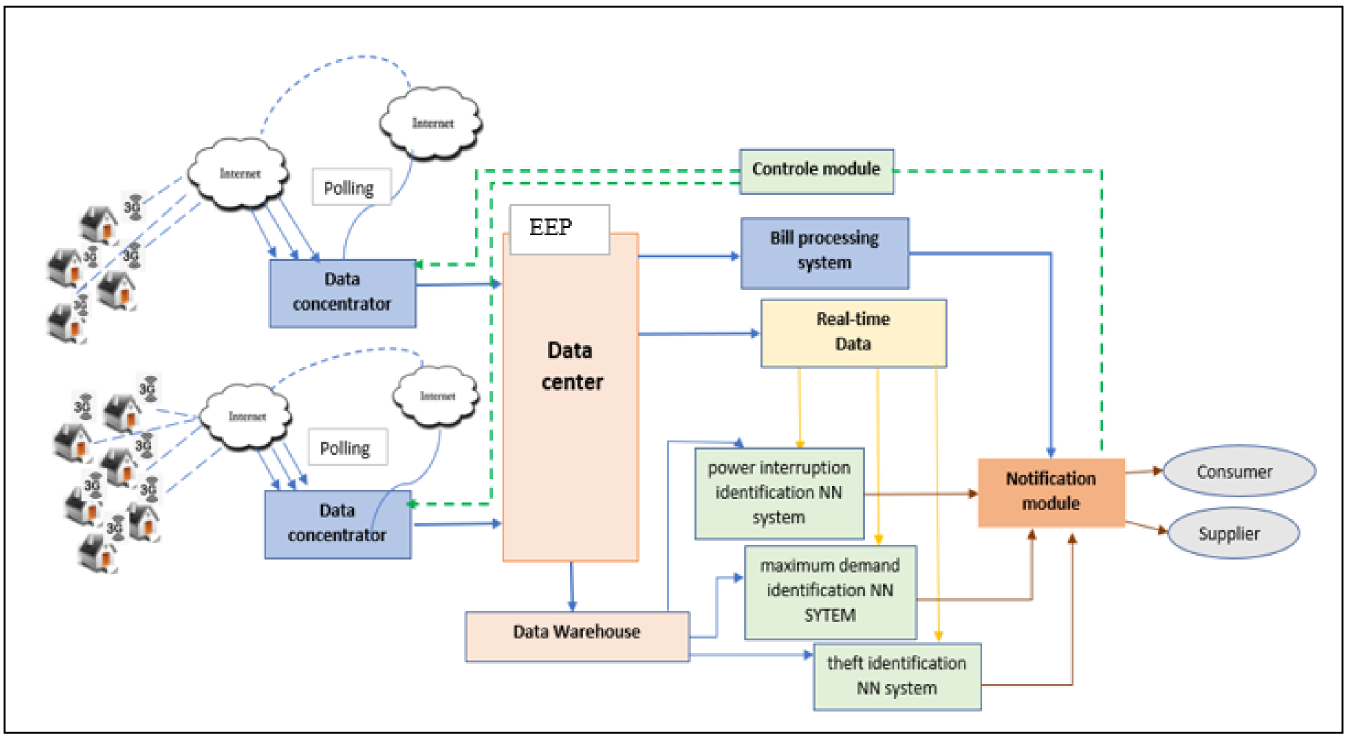

Figure 5-39 Implementation Diagram

CHAPTER SIX

6. Conclusions and recommendations

6.1 Conclusions

This study is to forecast peak power demand, theft, and types of power interruptions for the electrical grid system in Adds Ababa, it has been known that digital energy meter (smart meter) is not in use in our country Hence, previous energy billing data and some inspection data recorded by the supplier are being used to constitute the Smart Energy Meter Reading Data. So that by using smart meter data can able to detect electrical theft, peak power demand and power interruption.

This forecasting helps to reduce the power distortions, economic problems like revenue losses caused by electricity consumers who don't pay for what they consume. On the other hand, peak power demand forecasting can help the customers to shift their energy consumption pattern and reduce costs.

This research paper presents a three-layer shallow neural network model with a feed-forward backpropagation training algorithm. The whole data should be divided into two-three categories. These are the Training, Validating, and Testing data with 70 %, 15 %, and 15 % of the whole, respectively. The model is generating and trained it using the MATLAB toolbox nprtool.

The power interruption classifications, maximum power demand is analyzing using its neural network model independently of the detection of power theft. Due to their different data types, number inputs, the size of the samples, and the size of outputs are different.

For theft detection, the model consists of quantitative data that has to collect from four districts of Addis Ababa Electric Utility. The data consists of KWH reading and the corresponding amount charged for residential for September, October, November and December 2020 (or for Meskerem, Tikemet, Hidar, and Tahsas 2013 Ethiopian Calendar). The data for theft detection and power interruption classifications are different, the power fluctuation data are the line currents (load), R, S, T, and N current reading and energy in the six lines are collected every hour for 25 days from Tir24, 2013 until Yekatit 19, 2013 Ethiopian Calendar. In addition to these, the maximum power demand is investigated by extracting the power data distributions for 3,596 hours extracted from the six lines. This data is further analyzed using Microsoft Excel, by processing the input data the targeted data has generated which is 0 (normal) and 1 (abnormal).

For the theft identification purpose the input data consists of 169,296 sample sets. and a single hidden layer with 30 neurons, two outputs namely normal reading and fraudulent reading are configuring. the data used for the training, validation, and testing in theft detection is the ratio of kilowatt-hour reading and the corresponding cost charged. The best validation performance is 0.32847. This value is too large which is found in the error histogram. and the overall correctly predicted percentage becomes 64.3% and as increase the no. of nodes in the hidden layers to100. The percentage of correctly predicted values becomes 64.4%. This indicates that increasing the size of the hidden layer neurons is insignificant in improving the performance of the training. then feed the difference between the previous ratios to the current ratio data. This data shows how the current data is deviates from the previous. Now, from the performance curve, the best validation value is 0.0031. This shows that the mean square error is too small i.e., the performance is improved to 99.9 %.

In power fluctuation classifications, the Neural Network Model is feed with data of consisting of six features including the load current, R, S, T, and N current reading, and the measured load power. The data sets consist of 3,596 sample sizes. The hidden layer consists of 30 hidden neurons. The output layer consists of five target classes. These are the feature of short circuits, Ground fault, double fault, normal operation, and request interruptions. From the result the best validation performance is 0.03197, the minimum gradient is 0.0068104. the overall percentage of correctly predicted values is 97.2 %.

Finally, the maximum power demand is classified based on the power demand to scatter plot by distributed the energy delivery to the six lines and extracting the peak power registered independently. Then, combine the lines data which have approximately the same peak power demand. For line one and three data the best validation performance value is 0.000001, for lines four, five, and six data the best validation performance which is 0.000000739 and this is approximately zero. For Line two data best validation performance is approximately zero. Fortunately, all observations are correctly predicted i.e., there are no data misclassified in these neural network data classifications. The percentage of correctly predicted values is 100%.

From the above facts, we can conclude that the data analysis highly affected the performance of the NN system.

The biggest challenge of this study is limitation od data, since smart meter are not available in our country, this study presents analysis of conventional (traditional) meter data set proposition of smart meter that can affect the accuracy of theft identification.

This thesis also has explored and presented the importance of smart grid for the modern power grid including smart meter and demand response integrated with Artificial Neural Network.

6.2 Recommendations

Further improvements can be achieved by process real-time data from millions of smart metering for different categories such as commercial, industrial, service center, and others to obtain a more accurate demand forecast.

Using real time data, we can accurately forecast theft, by taking the difference between the amount of energy actually delivered through the meter and the amount registered by the meter, in consideration of loss.

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APPENDIX

Code for power and load fluctuations plot

```
clear ; close all; clc

%loading Data of line one
 L1 = csvread('L1.csv');

% separte the current and energy independentlly

 cur = L1(:,2);
en = L1(:,3);
% ploting Energy vrs Current
 figure(1)
 plot(cur,en,'o')
xlabel('Current in (A)');
ylabel('Energy in (KW)');
 grid on
 title('Energy versus Current for Line one in 600 hurs');

%Ploting the current flactuation
 figure(2)
 time = L1(:,1);
 plot(time,cur,'r')
xlabel('Time in (hrs)');
ylabel('The current reading in (A)');
 title(' The current flactuation of Line one in 600 hours')
 grid on
%Ploting the Power flactuation
 figure(3)
 plot(time,en,'g')
xlabel('Time in (hrs)');
ylabel('The Energy reading in (KW)');
 title(' The power flactuation of Line one in 600 hours')

 grid on
Code for Theft Identifications

% Solve a Pattern Recognition Problem with a Neural Network
% Script generated by Neural Pattern Recognition app
% Created 24-Jun-2021 09:33:30
%
% This script assumes these variables are defined:
%
%   onedin - input data.
%   outtwo - target data.

x = onedin';
t = outtwo';

% Choose a Training Function
% For a list of all training functions type: help nntrain
% 'trainlm' is usually fastest.
```

```
% 'trainbr' takes longer but may be better for challenging problems.
% 'trainscg' uses less memory. Suitable in low memory situations.
trainFcn = 'trainscg';  % Scaled conjugate gradient backpropagation.

% Create a Pattern Recognition Network
hiddenLayerSize = 10;
net = patternnet(hiddenLayerSize, trainFcn);

% select Input and Output or Pre/Post-Processing Functions
% For listed processing functions type: help nnprocess
net.input.processFcns = {'removeconstantrows','mapminmax'};
net.output.processFcns = {'removeconstantrows','mapminmax'};

% Setup Division of Data for Training, Validation, Testing
% For a list of all data division functions type: help nndivide
net.divideFcn = 'dividerand';  % Divide data randomly
net.divideMode = 'sample';  % Divide up every sample
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;

% Choose a Performance Function
% For a list of all performance functions type: help nnperformance
net.performFcn = 'crossentropy';  % Cross-Entropy

% Choose Plot Functions
% For a list of all plot functions type: help nnplot
net.plotFcns = {'plotperform','plottrainstate','ploterrhist', ...
'plotconfusion', 'plotroc'};

% Train the Network
[net,tr] = train(net,x,t);

% Test the Network
y = net(x);
e = gsubtract(t,y);
performance = perform(net,t,y)
tind = vec2ind(t);
yind = vec2ind(y);
percentErrors = sum(tind ~= yind)/numel(tind);

% Recalculate Training, Validation and Test Performance
trainTargets = t .* tr.trainMask{1};
valTargets = t .* tr.valMask{1};
testTargets = t .* tr.testMask{1};
trainPerformance = perform(net,trainTargets,y)
valPerformance = perform(net,valTargets,y)
testPerformance = perform(net,testTargets,y)

% View the Network
view(net)

% Plots
% Uncomment these lines to enable various plots.
%figure, plotperform(tr)
```

```
%figure, plottrainstate(tr)
%figure, ploterrhist(e)
%figure, plotconfusion(t,y)
%figure, plotroc(t,y)

% Deployment
% Change the (false) values to (true) to enable the following code blocks.
% See the help for each generation function for more information.
if (false)
% Generate MATLAB function for neural network for application
% deployment in MATLAB scripts or with MATLAB Compiler and Builder
% tools, or simply to examine the calculations your trained neural
% network performs.
genFunction(net,'myNeuralNetworkFunction');
    y = myNeuralNetworkFunction(x);
end
if (false)
% Generate a matrix-only MATLAB function for neural network code
% generation with MATLAB Coder tools.
genFunction(net,'myNeuralNetworkFunction','MatrixOnly','yes');
    y = myNeuralNetworkFunction(x);
end
if (false)
% Generate a Simulink diagram for simulation or deployment with.
% Simulink Coder tools.
gensim(net);
end\

Function

function [Y,Xf,Af] = myNeuralNetworkFunction(X,~,~)
%MYNEURALNETWORKFUNCTION neural network simulation function.
%
%  Generated  by  Neural  Network  Toolbox  function  genFunction,  24-Jun-2021
09:52:34.
%
% [Y] = myNeuralNetworkFunction(X,~,~) takes these arguments:
%
%   X = 1xTS cell, 1 inputs over TS timesteps
%   Each X{1,ts} = Qx1 matrix, input #1 at timestep ts.
%
% and returns:
%   z = 1xTr cell of 1 outputs over Tr timesteps.
%   Each Y{1,ts} = Qx2 matrix, output #1 at timestep ts.
%
% where Q is number of samples (or series) and TS is the number of timesteps.

%#ok<*RPMT0>

% ===== NEURAL NETWORK CONSTANTS =====

% Input 1
x1_step1.xoffset = -410.7203104;
x1_step1.gain = 0.00245098817134101;
x1_step1.ymin = -1;
```

```
% Layer 1
b1                                          =                                          [-
13.983981710954287;10.889319402447372;7.7782268041285798;4.6459688067670815;0.
41018300373670591;-
0.40815395983155345;4.6765929647424391;7.7863235952893284;10.888994111708749;-
13.98646686242903];
IW1_1      =      [14.015659505862034;-13.999579983172504;-13.999829880037831;-
14.001092471919414;-
89.407310900691016;89.240782796229439;13.998372287050788;13.995505002643409;13
.999916488128603;-14.013533056669047];

% Layer 2
b2 = [-2.4870374224985761;3.3274518472082346];
LW2_1   =   [2.8205067508067598   -1.8114626648392971   -1.9034559922924346   -
2.5293098729428389 -63.661969057922235 62.977901670950153 -2.3670392857813942 -
3.4694870365960138  -2.153552156643006  2.0595259115508706;-3.3974823852049005
1.7932764912437797  2.2426643527540855  3.3807530388899827  63.23546866918192  -
63.68857331386657  3.1812077072569171  2.3472158949811623  3.6002679382070388  -
2.0154259533959595];

% ===== SIMULATION ========

% Format Input Arguments
isCellX = iscell(X);
if ~isCellX, X = {X}; end;

% Dimensions
TS = size(X,2); % timesteps
if ~isempty(X)
    Q = size(X{1},1); % samples/series
else
    Q = 0;
end

% Allocate Outputs
Y = cell(1,TS);

% Time loop
forts=1:TS

% Input 1
    X{1,ts} = X{1,ts}';
    Xp1 = mapminmax_apply(X{1,ts},x1_step1);

% Layer 1
    a1 = tansig_apply(repmat(b1,1,Q) + IW1_1*Xp1);

% Layer 2
    a2 = softmax_apply(repmat(b2,1,Q) + LW2_1*a1);

% Output 1
    Y{1,ts} = a2;
    Y{1,ts} = Y{1,ts}';
end
```

```
% Final Delay States
Xf = cell(1,0);
Af = cell(2,0);

% Format Output Arguments
if ~isCellX, Y = cell2mat(Y); end
end

% ===== MODULE FUNCTIONS ========

% Map Minimum and Maximum Input Processing Function
function y = mapminmax_apply(x,settings)
y = bsxfun(@minus,x,settings.xoffset);
y = bsxfun(@times,y,settings.gain);
y = bsxfun(@plus,y,settings.ymin);
end

% Competitive Soft Transfer Function
function a = softmax_apply(n,~)
ifisa(n,'gpuArray')
    a = iSoftmaxApplyGPU(n);
else
    a = iSoftmaxApplyCPU(n);
end
end
function a = iSoftmaxApplyCPU(n)
nmax = max(n,[],1);
n = bsxfun(@minus,n,nmax);
numerator = exp(n);
denominator = sum(numerator,1);
denominator(denominator == 0) = 1;
a = bsxfun(@rdivide,numerator,denominator);
end
function a = iSoftmaxApplyGPU(n)
nmax = max(n,[],1);
numerator = arrayfun(@iSoftmaxApplyGPUHelper1,n,nmax);
denominator = sum(numerator,1);
a = arrayfun(@iSoftmaxApplyGPUHelper2,numerator,denominator);
end
function numerator = iSoftmaxApplyGPUHelper1(n,nmax)
numerator = exp(n - nmax);
end
function a = iSoftmaxApplyGPUHelper2(numerator,denominator)
if (denominator == 0)
    a = numerator;
else
    a = numerator ./ denominator;
end
end

% Sigmoid Symmetric Transfer Function
function a = tansig_apply(n,~)
a = 2 ./ (1 + exp(-2*n)) - 1;
end
```

Code for training the load fluctuation classifications

```
% Solving of Pattern identification Problem with a Neural Network
% Script generated by using Neural network Pattern Recognition app
% Created 24-Jun-2021 09:41:44
%
% The script assumes of these variables as defined:
%
%   data - input data.
%   data1 - target data.

x = data';
t = data1';

% Choosing of the Function for the Training
% For the listed functions of a training type: help nntrain
% 'trainlm' is most commonly fastest.
% 'trainbr' this function might take more time but good in challenging problems.
% 'trainscg' uses less space of memory. Convenient for situations with low
memory.
trainFcn = 'trainscg';  % Scaled conjugate gradient backpropagation.

% Create network for Pattern Recognition
hiddenLayerSize = 10;
net = patternnet(hiddenLayerSize, trainFcn);

% take Input and Output Pre/Post-Processing Functions
% For all lists of processing functions write help nnprocess
net.iinput.processFns = {'removseconstantrows','mapminnmax'};
net.outpute.processingFcns = {'removeofconstantrows','mapmminmax'};

% prepare Data for Division for Training, Validation, Testing
% For all data lists division functions write help nndivides
net. FcndivideFcn = 'dividerand'; % Divide data randomly
net. ModedivideMode = 'sample';  % Divide up every sample
net.trainRatio.divideParam.trainRatio = 70/100;
net.valRatio.divideParam.valRatio = 15/100;
net.testRatio.divideParam.testRatio = 15/100;

% Choose a Performance Function
% For all listed performance functions write help neuralnperformance
net. Fcnperform = 'crossentropy'; % Cross-Entropy

% select Plot Functions
% For lists of plot functions write: help neuralnplot
net. FcnsplotFcns = {'ploteperform','plotetrainstate','ploterrhist', ...
'plotconfusion', 'plotroc'};

% Training of the Network
[net,tr] = train(net,x,t);

% Test the Network
y = net(x);
e = gsubtract(t,y);
performance = perform(net,t,y)
tind = vec2ind(t);
```

```
yind = vec2ind(y);
percentErrors = sum(tind ~= yind)/numel(tind);

% Recalculate Training, Validation and Test Performance
traingTargets = t .* trainMask.tr {1};
validateTargets = t .* valMask. tr {1};
testofTargets = t .* testMask.tr {1};
trainngPerformance = perform(net,trainngTargets,y)
validatPerformance = perform(net,validateTargets,y)
testPerformance = perform(net,testeTargets,y)

% looke the Network
view(net)

% Plots
% comment not given to listed lines to allow different plots.
%figure, performplot or tr
%figure, trainstateplot or tr
%figure, rrhistplote or e
%figure, confusionplot or t,y
%figure, roc or plot t,y

% Deployment
% Change the (false) values to (true) to enable the following code blocks.
% See the help for each generation function for more information.
if (false)
% Generate MATLAB function for neural network for application
% deployment in MATLAB scripts or with MATLAB Compiler and Builder
% tools, or simply to examine the calculations your trained neural
% network performs.
genFunction(net,'myNeuralNetworkFunction');
    y = myNeuralNetworkFunction(x);
end
if (false)
% Generate a matrix-only MATLAB function for neural network code
% generation with MATLAB Coder tools.
genFunction(net,'myNeuralNetworkFunction','MatrixOnly','yes');
    y = myNeuralNetworkFunction(x);
end
if (false)
% Generate diagram of Simulink for simulation with .
% Coder tool for Simulink.
gensim(net);
end
```

Functions

```
function [Y,Bf,Af] = myNeuralNetworkFunction(B,~,~)
%MYNEURALNETWORKFUNCTION OR simulation function for neural network.
%
```

```
%  Generated  by  Neural  Network  Toolbox  function  genFunction,  24-Jun-2021
09:44:51.
%
% [Y] = myNeuralNetworkFunction(B,~,~) takes these arguments:
%
%   B = 1xTS cell, 1 inputs over TS timesteps
%   Each B{1,ts} = Qx6 matrix, input #1 at timestep ts.
%
% and returns:
%   Z = 1xTr cell of 1 outputs over Tr timesteps.
%   Each z{1,tr} = Qx5 matrix, output #1 at timestep tr.
%
% where FUNCTION Q is number for samples and TS is for number of timesteps.

%#ok<*RPMT0>

% ===== NEURAL NETWORK CONSTANTS =====

% Input 1
x1_step1.xoffset = [0;0;0;0;0;0];
x1_step1.gain                                                             =
[0.00274725274725275;0.000186915887850467;0.000213356091316407;0.0001834862385
3211;0.0002465483234714;0.0188679245283019];
x1_step1.ymin = -1;

% Layer 1
b1                                    =                                   [-
2.0541930963541448;2.3199595152460235;1.0950451188052059;0.80257094218701808;0
.50447760117966134;0.32433740655060161;-
1.168484566605694;2.0996224179813936;0.81041201298585219;1.7237203740825784];
IW1_1   =   [0.26749262627937892   1.0431863163558097   1.0423665212442248   -
0.36121980410158833  1.0778225897511051  0.82540525640392459;-1.078284196318352
0.64038636738921684 1.8331866103283465 1.0095773598421296 0.45582369731865285 -
0.47101882716902499;-0.80344734000897122                 -0.22593543231084978
0.16050895798324338          -1.6134502489456344          -0.62339967783743089
0.10894171811880865;-0.7172365584873408         -0.76006668460420124         -
1.1761912199129534       -0.991656481291042       -0.68563591204977747       -
0.54657082025750947;0.83047683736889222 0.93714140986353778 0.87769751370538718
0.70407522688142143                                       -1.6286970813004096
0.033438106459338438;0.13141324159044215         -1.0680590560516066         -
0.12186239006749809          0.64282713255051338          1.4969639749503196
0.59692477785903508;-0.17348424339412627         0.43059749241964163         -
1.213116697269018 4          -1.8267826809248198          0.52336818048381284
0.15810850216946148;0.019665186432251486                  -0.9097608819871843
0.81975997271295575       -0.90645541364510596       -1.1424409092750438       -
1.7819416392953129;0.9389546739440191 -1.3549282404411622 1.1234915738270694 -
1.2763564485972014  0.07427699983373888  1.75586890362204 3;1.0023802150127612  -
1.5577630503439992  0.24180586396726464  -1.207002683665267  0.64805981809345736
0.38580562514154437];

% Layer 2
b2                          =                          [-0.22778505477965683;-
0.27957949410414684;0.13046685814739384;0.6698239317839686;-
0.35097775509349932];
LW2_1   =   [-0.50272995939133347   1.5169556695307551   -0.47388899140267876
0.4990885814584976 0.24413456297661673 0.67960672067773298 -1.286858485820142 -
```

```
0.68992251185659192 0.035363848741169809 -1.6774618026104;-0.078302791178802081
1.1086666440009987 -0.42587648918571264 0.1036959443045687 0.75833975133195475
-0.52419809755867397 -1.56141754019565 -0.27888313949585919 -
0.74901354497007755 -0.14672280058268705;0.0071330379790184462
0.2824073203630319 -1.0604232411176779 0.10381023655704306 -0.71189408946633981
-0.25384826554111189 0.012340586062819514 -0.081232670014169978 -
0.68437897395395797 0.44505758126382355;-0.61561014593819374
0.17548860736568161 -0.47185408064723788 -0.90763635047590574 -
0.31543246960210469 0.012884459054892258 0.51349027002421821 -
0.73339392548697324 -0.62442932224340164 -0.45999499800881671;-
0.28902420687039576 -2.7282970203990313 0.61123751981251051 0.37635002958285424
-1.2356442346918934 -0.88996743302935755 0.82788095810140627 -
0.6571997254591635 1.6362770163580467 -0.10095702496407415];

% ===== SIMULATION ========

% Format Input Arguments
isCellB = iscell(B);
if ~isCellB, B = {B}; end;

% Dimensions
TS = size(B,2); % timeofsteps
if ~isempty(B)
    O = size(B{1},1); % samples/series
else
    O = 0;
end

% Allocate Outputs
Z = cell(1,TS);

% Time loop
forts=1:TS

% Input 1
    B{1,ts} = B{1,ts}';
    Xp1 = mapminamax_apply(B{1,ts},x1_1step);

% Layer 1
    a1 = tansig_apply(repmat(b1,1,O) + IW1_1*Xp1);

% Layer 2
    a2 = softmax_apply(repmat(b2,1,O) + LW2_1*a1);

% Output 1
    Z{1,ts} = a2;
    Z{1,ts} = Z{1,ts}';
end

% THE Final Delay States
Bf = cell(1,0);
Af = cell(2,0);

% Output Arguments Format
if ~isCellX, Y = cell2mat(Y); end
```

```
end

% ===== MODULE FUNCTIONS ========

% Map Input Processing Function  for Minimum and Maximum
function y = mapmiinmax_apply(x,settings)
z = bsbfun(@minus,B,settings.boffset);
z = bsbfun(@times,Z,settings.gain);
z = bsbfun(@plus,Z,settings.zmin);
end

% Competitive Soft Transfer Function
function a = softmax_apply(n,~)
ifisa(n,'gpuArray')
    a = iSoftmaxApplyGPU(n);
else
    a = iSoftmaxApplyCPU(n);
end
end
function a = iSoftmaxApplyCPU(n)
nmax = max(n,[],1);
n = bsxfun(@minus,n,nmax);
numerator = exp(n);
denominator = sum(numerator,1);
denominator(denominator == 0) = 1;
a = bsxfun(@rdivide,numerator,denominator);
end
function a = iSoftmaxApplyGPU(n)
nmax = max(n,[],1);
numerator = arrayfun(@iSoftmaxApplyGPUHelper1,n,nmax);
denominator = sum(numerator,1);
a = arrayfun(@iSoftmaxApplyGPUHelper2,numerator,denominator);
end
function numerator = iSoftmaxApplyGPUHelper1(n,nmax)
numerator = exp(n - nmax);
end
function a = iSoftmaxApplyGPUHelper2(numerator,denominator)
if (denominator == 0)
    a = numerator;
else
    a = numerator ./ denominator;
end
end

% Sigmoid Symmetric Transfer Function
function a = tansig_apply(n,~)
a = 2 ./ (1 + exp(-2*n)) - 1;
end
```