DEVELOPMENT OF A STATE ESTIMATION BASED IMPROVED DETECTION AND LOCALIZATION OF NON-TECHNICAL LOSSES USING SMART METER MEASUREMENTS

By

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A DISSERTATION SUBMITTED TO THE SCHOOL OF POSTGRADUATE STUDIES, AHMADU BELLO UNIVERSITY, ZARIA
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DEPARTMENT OF ELECTRICAL ENGINEERING,
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DECLARATION

I declare that the work in this Dissertation titled“Development of State Estimation based Improved Detection and Localization of Non-Technical Losses Using Smart Meter Measurements”has been carried out by me in the Department of Electrical Engineering. The information derived from the literature has been duly acknowledged in the text and a list of references provided. No part of this dissertation was previously presented for another degree or diploma at this or any other Institution.

Abdulkareem ZAKARIYYAH ______________________ ______________________
Signature Date

CERTIFICATION

This dissertation entitled "**DEVELOPMENT OF STATE ESTIMATION BASED IMPROVED DETECTION AND LOCALIZATION OF NON TECHNICAL LOSSES USING SMART METER MEASUREMENTS**" by Abdulkareem ZAKARIYYAH meets the regulations governing the award of the degree ofMaster of Science in Power System Engineering of the Ahmadu Bello University, and it is approved for its contribution to knowledge and literary presentation.

Prof. B. Jimoh
(Chairman, Supervisory Committee) Signature Date

Dr. Y. Jibril
(Member, Supervisory Committee) Signature Date

Dr. Y. Jibril
(Head of Department) Signature Date

Prof. S. Z. Abubakar
(Dean, School of Postgraduate Studies) Signature Date

DEDICATION

This research work is dedicated to Almighty God.

ACKNOWLEDGEMENT

All the praises and thanks be to Allah (S.W.T) for completing this research work to obtain my Master degree from Ahmadu Bello University.

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April 2019.

ABSTRACT

This research work presents the development of branch current based state estimation for Non-Technical Losses (NTLs) Detection and Localization. The use of weighted least square (WLS) state estimation for the evaluation of branch current of a network during theft is considered. In order to confirm the presence of theft in a network, current measurement value obtained from Distribution Transformer Controller (DTC) installed at substation was compared with that of all customers' smart meters readings, a difference above an estimated threshold signifies the presence of theft. For the case of locating the point of theft, the concept of weighted least square state estimation was used for the evaluation of the actual branch current of each branch of the network despite theft, the estimated branch current is compared with the calculated branch current based on meter reading, and the difference is exploited in order to locate the point of location. The developed method was implemented on a 415V Low Voltage network used in this literature. The results obtained were validated by comparing it with the work of Marques et al., 2016. All modelling and analysis were carried out using OPENDSS and MATLAB R2015a. From the results obtained, when the total theft in the network is 30%, 40% or 50% the maximum variation of the estimated branch current are 0.62%, 0.83%, 1.02% respectively, these are taken to be the threshold for decision of theft in the network. It was also observed that the True Positive Rate (TPR) and The False Positive Rate (FPR) irrespective of the percentage of theft in the networkshow an improvement of 27.5% and 11.11% respectively. The method was further compared with other works where the used of machine learning was exploited. This method shows 7.5% improvement in terms of TPR than the use of Artificial Intelligent method.

TABLE OF CONTENT

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

LIST OF ABBREVIATIONS

ACRONYMS MEANING

AIArtificial Intelligent
AMIAdvanced Metering Infrastructure
ANNArtificial Neural Network
ANOVA Analysis of Variance
BCBVBranch Current to Bus Voltage
BCM Branch Connection Matrix
BIBCBus Injected to Branch Current
CC
CCB Calculation of Current in Branch
CPU Central Processing Unit
DER Distributed Energy Resources
DGs Distributed Generators
DLFDistribution Load Flow
DN Distribution Network
DSDistribution System
DTCDistribution Transformer Controller
ETDLSEnergy Theft Detection and Localization System
ECB Estimated Current in Branches
EPRI Electric Power Research Institute
IEEEInstitute of Electrical and Electronics Engineering
KCLKirchhoff's Current Law
KWKilo Watt
KVArKilo Voltage Ampere Reactive
LAV Least Absolute Value
LVLow Voltage
MDMsMeter Data Management System
MATLABMatrix Laboratory
NEV Neutral to Earth Voltage
P Power
p.u.Per Unit
PPEPer Phase Error
PENDSSOpen Distribution System Simulator
QReactive power
RAM Random Access Memory
SE State Estimation
SMsSmart Meters
SGSmart Grid
SHGM Schweppes Hubber Generalized M

SVMSupport Vector Machine
U.SUnited State
RResistance
WLSWeighted Least Square
XReactance
Z Impedance

CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

Non-Technical Losses (electrical energy theft) has been a major concern in traditional power systems worldwide. In the United States (U.S.) alone energy theft was reported to cost utility companies around $6Billion/year (McDaniel & McLaughlin, 2009)this Figure appears relatively low when compared to the losses faced by utilities in developing countries such as Nigeria, Bangladesh, India and Pakistan (Eskom Annual Report 2009).Implementation of Advanced Metering Infrastructure (AMI) as one of the key technologies in smart grids promises to mitigate the risk of energy theft through its monitoring capabilities and the fine grained usage measurements. However, application of digital smart meters and addition of a cyber-layer to the metering system introduce numerous new vectors for energy theft.While traditional mechanical meters can only be compromised through physical tampering, in AMI the metering data can be tampered with, both locally and remotely before being sent to the smart meters or inside the smart meters or over the communication links. Penetration tests have already revealed several vulnerabilities in smart meters (Wright, 2009). In 2009, an organized energy theft attempt against AMI was reported by U.S. Federal Bureau of Investigation, which potentially could cost a utility company up to $400Million annually (Krebs B. 2012).Therefore, an Energy Theft Detection and Localization System (ETDLS) that can effectively and efficiently detect and localize energy theft attacks against AMI is urgently required.

Technical losses are inherent losses in power system network due to the inefficiency of power systems devices or iron core losses which occur during the transmission and distribution of electric power. While nontechnical losses on the other hand, are caused by actions external to the power system. These may include electricity theft, partial or non-payment of energy used by the customers.

In 1970s, Schweppe first proposed the idea of state estimation in power systems. Power system state estimation constitutes the core of the on-line system monitoring, analysis and control functions. State estimation acts like a filter between the raw measurements received from the system and all the application functions that require the most reliable data base for the current system operation state, and it typically includes bad data processing, state estimation solutions, parameter and topology error processing. Energy theft comprises of meter by pass, data attacks among other. In this work, the ideaof weighted least square state estimation will be explored to detect theft in power network.

Percentage of Non-Technical Losses (NTLs) and their monetary equivalent in some of the European countries is shown in Table 1.1

Table 1.1: Non-Technical Losses in European Countries (Marques *et al.*, 2016)

Country	NTLs (M€/year)	Total Losses (%)
Germany	504	4.7
Italy	408	6.3
Spain	426	7.8

1.2 Motivation

The power sector economic fatality caused by NTL cannot be over emphasized, the benefits of researches done on the reduction of technical losses will only be completely harnessed if the menace caused by NTL is completely or reasonably reduced. In Nigeria, According to a World Bank report seventy five percent (75%) of the total cost of energy injected in the various distribution feeder to serve customers are loss due to the combine effects of both technical and nontechnical loss of which only less than twenty percent are as a result of technical loss (Antmann, 2009). This implies that large portion of the energy loss are attributed to NTL which are mostly due to deliberate energy theft by customers, improper billing of customers, high level of indiscipline and unawareness of the customers to pay bills of electricity consumed and high level display of unprofessionalism on the side of the Electricity marketers. Despite the advent ofSmart Meters(SMs) which are introduced purposely to reduce and eliminate the menace of estimated billing and reduce energy theft, unfortunately rate of energy theft is increasing.

1.3 Significance of Research

The significance of this research is the development of branch current of LV Power network under theft. The accurate estimation of branch current makes it more easier to locate the point of theft which increases the true positive rate. To the best of my knowledge previous researchers have not considered the use of this method for improving the Localization of energy theft as at this time of compilling this thesis.

1.4 Statement of Problem

When there is an energy theft on a network supplying consumers' load, there tend to be imbalance between the energy sold by utility companies and the energy purchase by customers which lead to economic fatality of utility companies and high energy charge to the customers. Therefore to create a profitable market for the utility company, it is quite important to locate the points of theft in order to finethe consumers and recover the monetory value of the energy loss.

So many attempts have been made using the Artificial Intelligent method but accurate prediction of customers' consumptions have always been very difficult which affect the accuracy of the result obtained(Marques *et al.*, 2016). In this work the localization of theft is done considering the network operating condition through the data obtained from smart meters. Thus, this research present Detection and Localization of energy theft using branch current based weighted least square state estimation.

1.5Aim and Objectives

The aim of this research is developmentof a state estimation based improved detection and localization of Non-Technical Losses (NTLs) Using Smart Meter (SM) Measurements

The objectives of the research are as follows:

i. To replicate thedetection of NTLs algorithm from the work of(Marques *et al.*, 2016)

ii. To Develop a Weighted Least Square State Estimator for the estimation of state variables andmodification of the localization of NTLs algorithms

iii. Performance comparison of the result obtained in ii above with the work of (Marques *et al.*, 2016)in terms of True Positive Rate (TPR) and False Positive Rate (FPR).

1.6 Methodology

The following steps described the methodology used to carry out this research work:

1. Replication of the Detection of NTLs algorithm from the work of marques et al., (2016)

(a) Data acquisition (SMs' current, DTC currents and power factors)

(b) Acquisition of Network Topology

(c) Calculation of the Per Phase Error (PPE)

(d) Comparison of the SMs reading and DTC Reading.

2. Development of Weighted Least Square State estimator for the estimation of the network's states

    (a) Development of the network model equations

    (b) Collection of measurement and initial states.

3. Development of Localization algorithm

    (a) Acquisition of network model and topology (type of network configuration)

    (b) Acquisition of network parameters

    (c) Branch current Calculation and Estimation

    (d) Searching for the suspicious branches starting from the last level of the network.

4. Validation of the developed model using the work of marques *et al.,* (2016).

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This section presents the review of the fundamental concepts and that of similar works which are relevant to this research.Under fundamental concepts, discussion covered Advanced Metering Infrastructure (AMI), Smart Grid, SMs, DTC and Weighted Least Square (WLS) state estimation principle and model equations. On the other hand, the review of similar researches established the extent of research in the subject area which led to a different approach used to achieve the desired significant contributions.

2.2 Review of Fundamental Concept

In this section, concepts that are fundamental to Electric power system, Distribution System, Distribution System Losses etc. are presented:

2.2.1 Electric power system

Electric Power system comprises of three main system namely Generation system, Transmission system and Distribution system. The Transmission and Distribution are classified based on Voltage levels. In Nigeria, the transmission network is characterized by 330kV and 132kV and the distribution network is characterized by a lower voltage of 33KV, 11KV and 0.415KV as the case may be(Adesina & Fakolujo, 2015).

Distributionnetwork represent the last part of the classification which is also sub divided into primary distribution voltages (33kV and 11 kV in Nigeria) and secondary distribution voltages (415V and 240V). Electricity consumers are connected to the grid at the distribution voltage levels this makes it the most critical part of the network.

2.2.2Technical characteristic of low voltage distribution network

Low Voltage (LV)networkstypicallyhavearadial configuration, i.e., anarborescent configuration,meaningthateachconsumeronlyhasoneelectricalpathtobesupplied.Example of a radial network is presented in Figure 2.1.

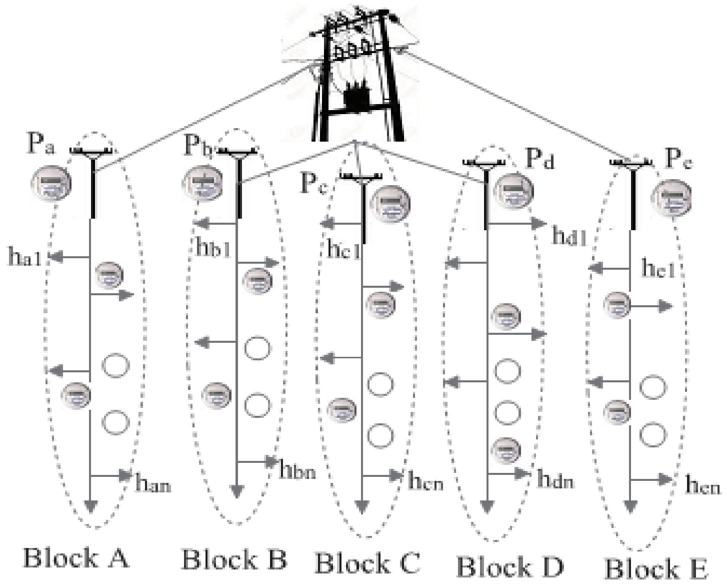

Figure 2.1: Schematic diagram of an LV radial network (Jindal*et al.*, 2016)

TheapplicationofKirchhoffCurrentsLaw(KCL), which demonstrates that the algebraicsumofallcurrentsenteringandexitinganodemustequalzero(Schilders& Ter Maten, 2005)allowsthe directcalculation of the currents in branches.Therefore, this meansthatthe currents in the upstream branches will be the sum of all currents consumed in the downstream bus bars.

TheapplicationoftheKCLtothesimplifiednetworkschematicrepresentedinFigure2.2 is given as follows:

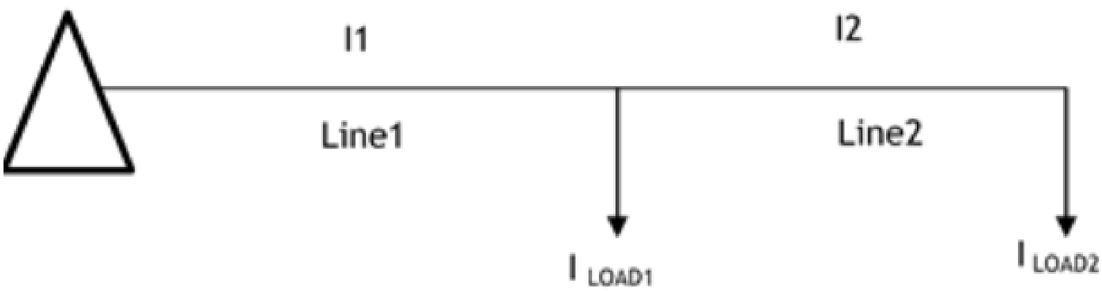

Figure 2.2: Two bus load distribution on LV network (Marques *et al*., 2016)

$I_1 = I_{LOAD1} + I_2$ (2.1)

$I_2 = I_{LOAD2}$ (2.2)

Application of KCL is used for the calculation of branch currents based on the measurement obtained from the smart meters throughout this work.

2.2.3Power flow in low voltage networks

Application ofpowerflowstudiesisrequiredinordertosimulatetherealnetworks' behavior, sincetheinformationprovidedbysmart metersmaybeusedtoevaluatetheoperation conditionsofthenetworks.Therefore, depending on the type of networks, namely the neutral configuration, the adopted power flow method may have different characteristics. Mostofthetraditionalpowerflowapproachesmergetheneutralwireintothephases using the Kron's reduction(Alam *et al.*, 2012) such approximation may not be desirable when neutral wire and grounding effects need to be assessed(Alam *et al.*, 2012; Ciric *et al.*, 2003).Thus,whentheknowledgeofNeutral to Earth Voltage (NEV)in nodesisrequiredacompletemodelofthenetworkshouldbeused.Otherwise, the power flows studies may be performed by the Kron's reduction.

The power flows simulations using a complete model of the network require a full knowledge of the locations where the neutral is grounded and both impedances of phases and neutral wires. Figure 2.3shows the line model when the neutral is considered explicitly modelled and considering the earth as a perfect conductor.

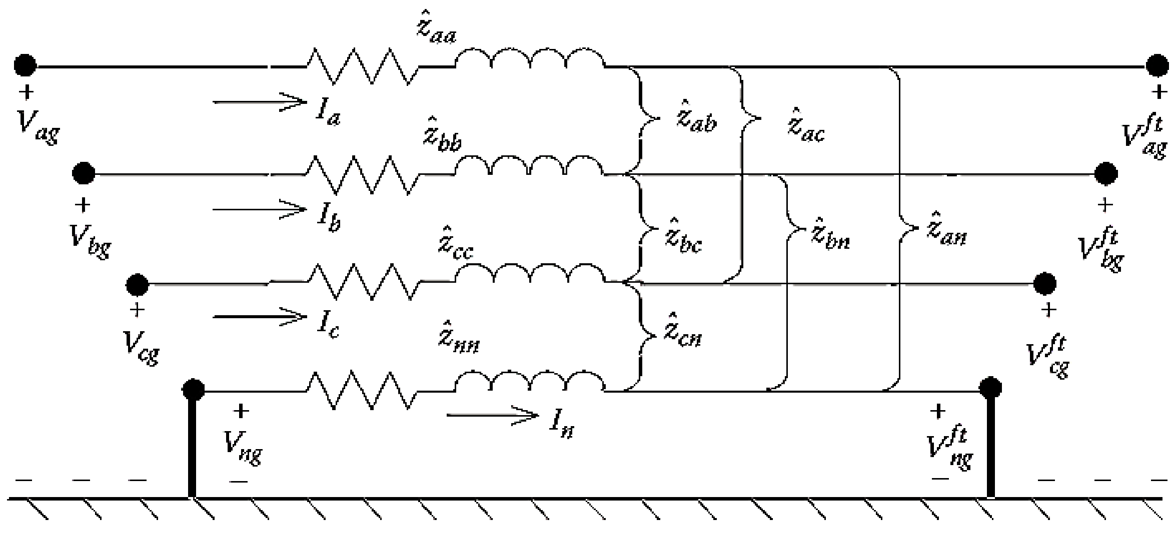

Figure 2.3 Complete LV line model(Kersting, 2012)

The matrix approach to calculate the electrical variables of the model presented in the Figure 2.3 is as follows: (Marques *et al.*, as cited in Kersting, 2012)

$$\begin{bmatrix} V_{ag} \\ V_{bg} \\ V_{cg} \\ V_{ng} \end{bmatrix} = \begin{bmatrix} V_{ag}^{'} \\ V_{bg}^{'} \\ V_{cg}^{'} \\ V_{ng}^{'} \end{bmatrix} + \begin{bmatrix} Z_{aa} & Z_{ab} & Z_{ac} & Z_{an} \\ Z_{ba} & Z_{bb} & Z_{bc} & Z_{bn} \\ Z_{ca} & Z_{cb} & Z_{cc} & Z_{cn} \\ Z_{na} & Z_{nb} & Z_{nc} & Z_{nn} \end{bmatrix} \begin{bmatrix} I_a \\ I_b \\ I_c \\ I_n \end{bmatrix} \qquad (2.3)$$

In ordertosimplifythenotationused,theequation(2.3)mayberewrittenbygrouping the similar matrix as shown in the equation (2.4).(Marques *et al.*, as cited in Kersting, 2012)

$$\begin{bmatrix} [V_{abc}] \\ [V_{ng}] \end{bmatrix} = \begin{bmatrix} [V'_{abc}] \\ [V'_{ng}] \end{bmatrix} + \begin{bmatrix} \left[Z_{ij}\right] & \left[Z_{in}\right] \\ \left[Z_{nj}\right] & \left[Z_{nn}\right] \end{bmatrix} \cdot \begin{bmatrix} [I_{abc}] \\ [I_n] \end{bmatrix} (2.4)$$

where:

$\left[V_{abc}\right]$ is the phase voltages' vector in the emission busbar referred to the ground;

$\left[V'_{abc}\right]$ is the phase voltages' vector in the emission busbar referred to the ground;

$\left[V_{ng}\right]$ is the neutral voltages' vector in the emission busbar referred to the ground;

$\left[V'_{ng}\right]$ is the neutral voltages' vector in the emission busbar referred to the ground;

$\left[I_{abc}\right]$ is the phase currents' vector referred to the ground;

$\left[I_n\right]$ is the neutral current;

$\left[Z_{ij}\right]$ is the matrix impedance between the conductors i and j;

$\left[Z_{in}\right]$ is the matrix impedance between the conductors i and n;

$\left[Z_{nj}\right]$ is the matrix impedance between the conductors j and n;

$\left[Z_{nn}\right]$ is the self-matrix impedance the conductors n;

At the opposite side, the kron reduction by considering a multi-grounded system and the Neutral to Earth Voltage (NEV) at the ground's potential, merges the neutral effects to the phase wires.Thisis achievedbyconsideringthatatbothnodesoftheline,theneutralisgrounded, and thereforetheNEVatbothnodesiszero.Applying theKirchhoff’sVoltageLaw(KVL)tothe circuitandtakingintoaccountthattheneutralisgrounded,thus,thevoltagesvector [Vng] and [V’ng] are equal to zero. (Marques *et al.*, as cited in Kersting, 2012):

$$\left[V_{abc}\right]=\left[V_{abc}^{'}\right]+\left[z_{ij}\right].\left[I_{abc}\right]+\left[z_{in}\right].\left[I_{n}\right] \text{(2.5)}$$

$$\left[0\right]=\left[0\right]+\left[z_{ij}\right].\left[I_{abc}\right]+\left[z_{nn}\right].\left[I_{n}\right] \text{(2.6)}$$

Solving the Equation (2.5)in relation to $\left[I_{n}\right]$, the result is expressed in Equation (2.7):

$$\left[I_{n}\right]=-\left[z_{nn}\right]^{-1}.\left[z_{nj}\right].\left[I_{abc}\right] \text{(2.7)}$$

Replacing Equation (2.7) into Equation (2.5):

$$\left[V_{abc}\right]=\left[V_{abc}^{'}\right]+\left(\left[z_{ij}\right]-\left[z_{in}\right].\left[z_{nn}\right]^{-1}.\left[z_{nj}\right]\right).\left[I_{abc}\right]$$

$$\left[V_{abc}\right]=\left[V_{abc}^{'}\right]+\left[z_{abc}\right].\left[I_{abc}\right] \text{(2.8)}$$

Where

$$\left[z_{abc}\right]=\left[z_{ij}\right]-\left[z_{in}\right].\left[z_{nn}\right]^{-1}.\left[z_{nj}\right] \text{(2.9)}$$

The resultant matrix impedance is expressed in equation (2.10). As can be observed, the initialmatrixwithdimensions4x4hasbeenreducedintoa3x3matrix.Thisissimilarto solvingapowerflowignoringtheneutralwire,withthedifferencethatlines’impedances have been modified to represent the neutral effects. (Marques *et al.*, as cited in Kersting, 2012)

$$z_{abc}=\begin{pmatrix} z_{aa} & z_{ab} & z_{ac} \\ z_{ba} & z_{bb} & z_{bc} \\ z_{ca} & z_{cb} & z_{cc} \end{pmatrix} \text{(2.10)}$$

With the kron’s reduction the final model of the line is shown in Figure 2.4

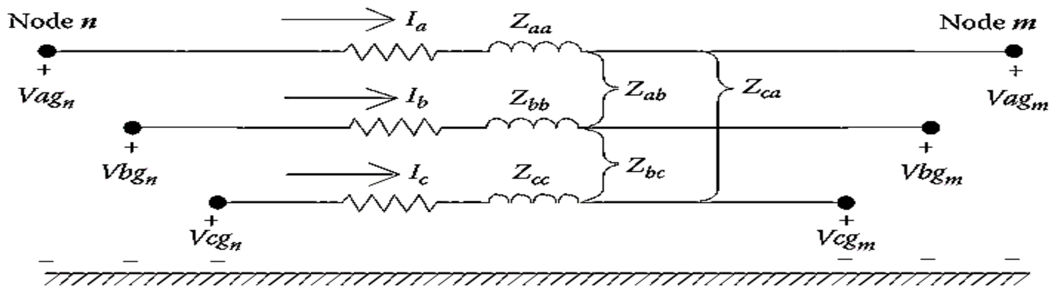

Figure 2.4:Line Model after Kron's Reduction(Kersting, 2012)

2.2.4Distribution power system losses

Generally,powerlossesrefertotheamountsofelectricity injectedintothetransmissionanddistributiongridsthatare notpaidforbyusers. (Navani *et al.*, 2012),(Adesina & Fakolujo, 2015). Total power losses have two components: Technical and non-Technical power losses.

2.2.4.1Technical losses

Technical power lossesare naturallyoccurringand consistmainly of power dissipated in the system components suchastransmissionanddistributionlines,transformers, power control equipment and measurement systems. Technical losses are possible to compute and control, provided the power system network in question consists of known quantities of loads(Navani *et al.*, 2012). Technicalpowerslossesoccurduringtransmissionand distributionprocessesandalsoinvolvestationtransformers and line related losses. These losses include resistive losses of the primary feeders,distribution transformer losses (resistive losses in windings and the core losses),resistive losses in the secondarynetwork(inNigeria,typically33kV&11kV networks), resistive losses in service drops to customers and lossesinkWhMeter(mostespeciallyattheinductiveload customers).Technicalpowerlossesareclassifiedascopper losses(I^2R),Dielectriclossesandinduction&radiation losses.However, the occurringtechnical power losses known inpowersystemshavedifferentcausesandtheseincludeharmonicdistortion,improper earthingofelectrical equipmentatvariousinjectionsubstations,unbalancedloadingofdistributiontransformerandsubstandard equipment such as Aluminum conductor, cable etc (Navani *et al.*, 2012),(Adesina & Fakolujo, 2015) and(Kim *et al.*, 2013).

2.2.4.2Non-Technical losses

Non-technical losses are losses caused by actions external to the power system. These may includeelectricity theft, partial or non-payment of energy used by thecustomers, use of substandard current transformer for industrial metering and industrial usage of electricity on low power factor amounting to undercharging and hence underbilling by the utility company.Accurate reading of meters, accuratecustomers billing, collection ofbilledamountsand properaccountabilityarefunctionsthatrequirespecific managementtactics.Non-technical losses are more difficult to measure because these losses are often unaccounted for bythe system operators and thus have no record information. (Navani *et al.*, 2012),(Adesina & Fakolujo, 2015).

2.2.5Analysis of non-technical losses

Non-Technical Losses by contrast, relate mainly to power theft in one form or another. They are related to the customer management process and can include a number of means of consciously defrauding the utility concerned. By default, the electrical energy generated should be equal to the energy registered as consumed. However,inreality,thesituationisdifferentbecauselossesoccurasan integral result of energy transmission and distribution.Figure 2.5is an illustration of the load distribution among customers in an LV network under ideal condition, Power injected from the generator bus is equal to Power consumed by loads plus Technical losses.

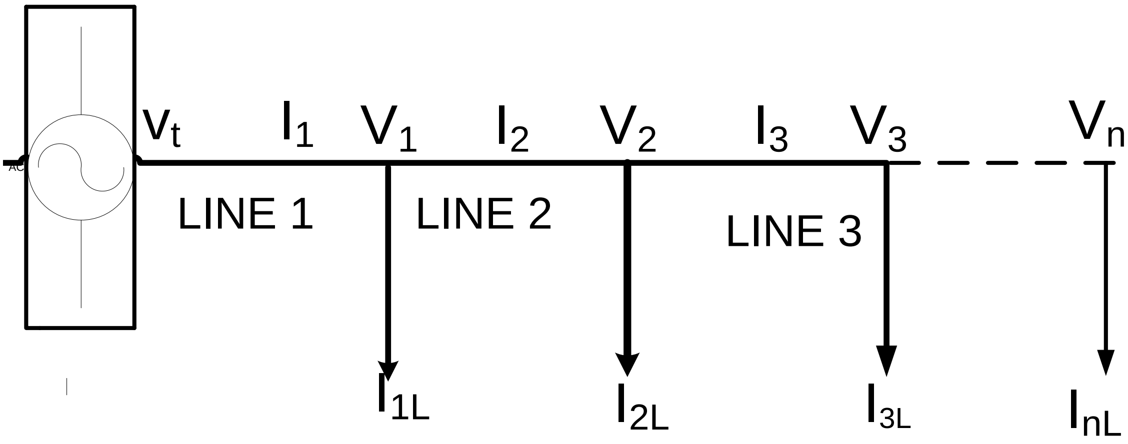

Figure 2.5: Example of load distribution on LV Network.

From Figure 2.5

$P_{inj} = V_t I_1$ (2.11)

$P_{consumed} = V_1 I_{1L} + V_2 I_{2L} + V_3 I_{3L} + \ldots V_n I_{nL}$ (2.12)

In a compact form,

$$V_t = \sum_{k=1}^{n} V_K \text{ ,(2.13)}$$

$I_1 = \sum_{i=1}^{n} I_{iL}$ (2.14)

Therefore,

$$P_{inj} = V_t \sum_{i=1}^{n} I_{iL} \text{ (2.15)}$$

$$P_{consumed} = \sum_{k=1}^{n} V_K \sum_{i=1}^{n} I_{iL} \text{ (2.16)}$$

Expressing equation 2.15 and 2.16 in terms of energy, we get

$$E_{inj} = P_{inj} t \text{ (2.17)}$$

$$E_{consumed} = P_{consumed} t \text{ (2.18)}$$

Also, the value of branch current along any branch of the network can be found by knowing the magnitude of the voltages at both terminals of the branch for example in Figure 2.5 the branch current I_1 is expressed in terms of nodes voltages as:

$$I_1 = \frac{V_t - V_1}{Z_{t1}} \quad (2.19)$$

This concept will be used in the estimation of branch current through this work.

Where

V_t, V_1, V_2, V_3, V_n are the node voltages at the Generator bus, bus 1, bus 2, bus 3 respectively;

I_1 I_2 $I_3$are the line current for Line 1, Line 2, Line 3, respectively;

I_{1L}, I_{2L}, I_{3L}, are the load current of load 1, load 2, load 3, respectively;

p_{inj} and $p_{consumed}$ are power injected and power consumed respectively;

E_{inj} is the energy supplied at the generator bus;

$E_{consumed}$ is the energy consumed at the load buses;and

t is the total time of power consumption and is expressed as;

$$t = \sum_{m=1}^{z} t_m \quad (2.20)$$

Where

t_m is the time of power consumption of a device.

Consider another scenario illustrated in Figure 2.6 where there is tap on the line at node 1 and 3 (I_{T1} and I_{T3} respectively) these extra-consumptions at these nodes are not recorded by the utility meters and are termed as non-technical losses.

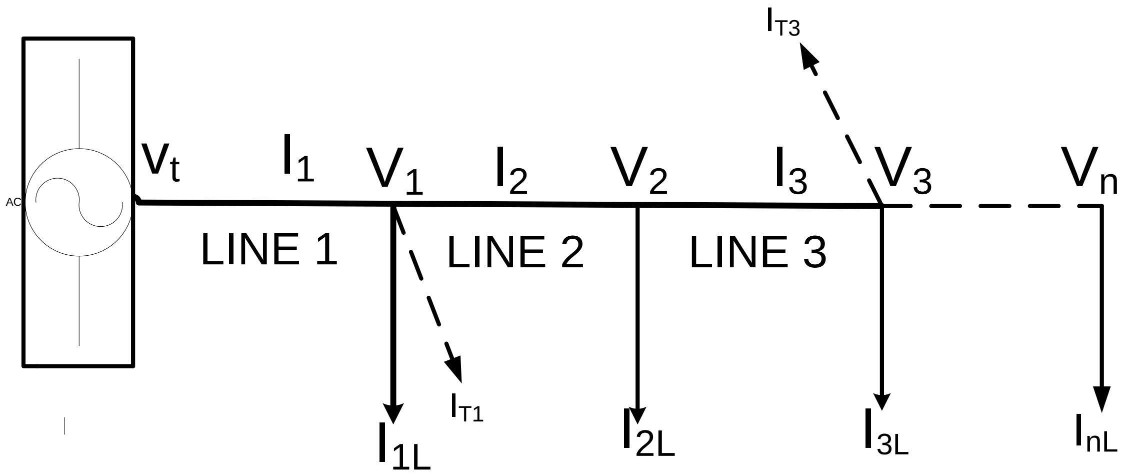

Figure 2.6: Example of Load Distribution with Theft on LV Network

In this case, $P_{inj} > P_{consumed}$ (recorded) + T.Losses

Where $P_{consumed}$ is the power consumed as recorded by SMs.

Therefore,

$$P_{inj} = P_{consumed} + P_{NTL} + P_{TL} \quad (2.21)$$

Making P_{NTL} the subject of equation (2.21)

$$P_{NTL} = P_{inj} - P_{consumed} - P_{TL} \quad (2.22)$$

In terms of Energy,

$$E_{NTL} = E_{inj} - E_{onsumed} - E_{TL} \quad (2.23)$$

2.2.6Description of methods for detection and location of NTLs

Several methods have been exploited for the detection and the location of NTLs, these methods can be divided in two categories:Artificial Intelligence Methods (AIM), which have been the most widelyinvestigated method thatarebasedoncustomers'loadprofilesanalysisandpatternrecognition usingdataminingtechniques;thesecondapproach,SMsBasedMethod,takes advantage of theexistingSMsinLVnetworks to perform the detectionand location of NTLs

The different methods may be evaluated and compared considering several characteristics:

i. The quantitate and the type of costumers' data required;

ii. The computational effort;

iii. Thetypeofnetworksinwhichtheyareusedandthemodellingofthenetwork required;

iv. The impact on consumers;

v. The type of NTLs identified;

2.2.6.1 The Artificial Intelligent Methods (AIM)

Artificial Intelligent methods extract relevant features from the data of the consumers such as the load profile and the ratio between the average load and the maximum load of the consumer (Ramos *et al.*, 2009). Based on these features, these methods implement a training algorithm that provides the ability to classify consumers' behavior.

Forexample,inMonedero *et* *al.*, (2006)ispresentedaschemebasedonArtificialNeuralNetworks(ANNs), whichisusedwhentheexactrelationshipbetweentheinputsandtheoutputsisunknown. Specifically, this scheme uses Kohonen networks that allows the design of an objective way of clustering data as presented in Figure 2.7.

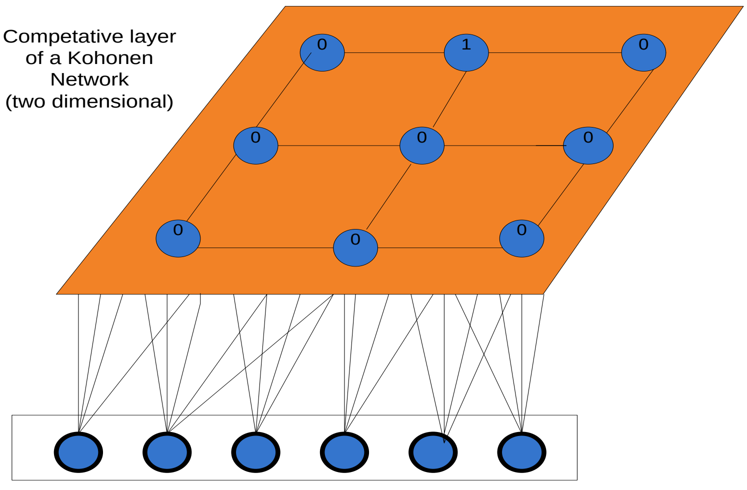

Figure 2.7: A particular type of neural network- kohonen network (Marques *et al.*2016)

The selection of fraudulent consumers is performed by searching the similarities between theconsumptionpatternoftherecordsandtheconsumptionpatternsofthecustomers' database.

2.2.6.2 The Smart Metering Based Methods

The smart metering based method is the second category of methods that has been investigated for the detection and location of NTLs under the presence of an AMI in LV network. A work presented by Huang *et al*., (2013)proposesaStateEstimation (SE)of the Medium Voltage (MV) network to detect the presence of NTLs or inconsistent data measurementsatthesecondarysideofthedistributiontransformers.TheSEisperformed usingelectricalmeasuresprovidedbySMspresentineachLVnetwork,suchasvoltagesand the power consumption, and the voltage (magnitude and angle) at the MV substation. Thedatarequiredbythismethodologyandthecommunicationsinfrastructure used are shown in Figure 2.8.

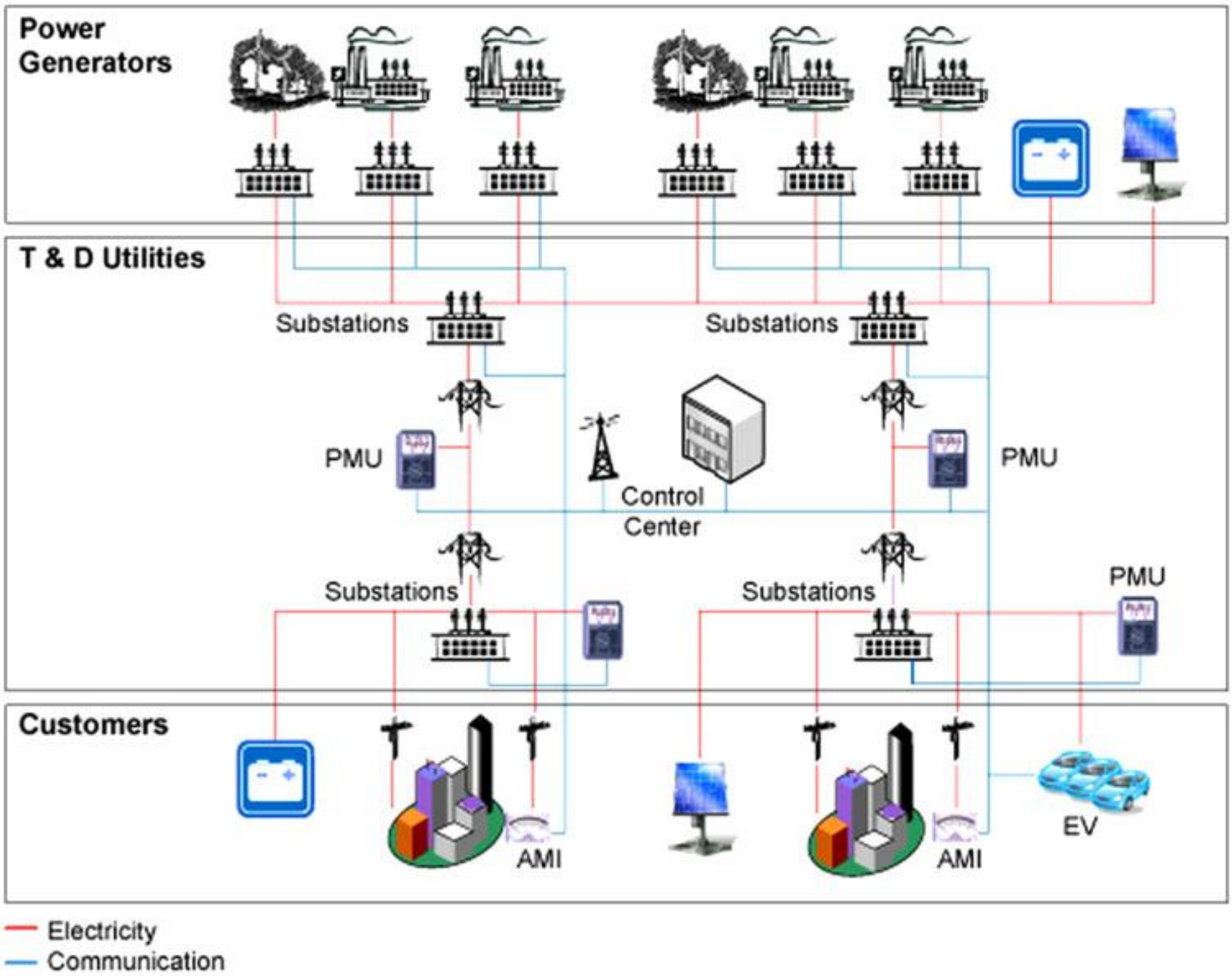

Figure 2.8: Communication Infrastructure and Meter Data Source (Papa *et al.,* 2009)

The detection oftheNTLs in an LV Network is known through the calculations of thedifferencebetweentheaggregatedconsumptionprovidedbytheSE ateach secondarysubstationwiththesumoftheSMs'measuredconsumptions.Bycontrast,inRengaraju *et al.*, (2014), Depuru *et al.*, (2011)and Van Der Bergh *et al.*, (2011)the advanced methodologies compare the total consumption registered by the clients' meters with the energy supplied through the secondary substation. With the difference of the technical losses, the total consumption must be equivalent to the energy supplied. In a situation where the balance does not occur, it is considered the presence of NTLs in the network. These approaches require a full modelofthenetworkstocalculatetheTLsinthenetwork.Incasethetechnical characteristics of the network, such as the topology and the branches' physical are unknown, thecalculationoftheTLsisafactorofuncertaintyasTLscanonlybeestimated.The computational effort required may be high in the first approach. The SE is performed through aniterativeprocessthatrequirestheavailabilityofelectricalmeasuresfromdifferentlocations of the network and a full knowledge of the network. In this proposed work a method is improved for the calculation of the network's branch current, the value obtained is compared with the summation of all the currents recorded by all the smart meters connected to the branch and any significant discrepancy indicate leakage or theft.

2.3Smart Grid

Smartgridisacyber-physicalsystemwhichincludes communicationsystemwiththepowerflowstructure,togain intelligenceandautomatedcontrol (National Energy Technology Laboratory).As a result, it dealswith not only the power flow but also information flow.The communication support schemes and real-time measurementtechniques of smart grid enhance resiliency and forecasting aswell asoffer protection against internal and external threats(Momoh, 2012).Smart grid is a synergistic combinationoftheexisting technologiesandtheemergingtechnologies.Smart grid uses Advanced Metering Infrastructure (AMI) for collecting and processing information from smart meters.In

AMI technology, a database known as Meter Data Management system (MDMS) is required to store and manage the data(Barai *et al.*, 2015).Traditionally, AMI uses centralized MDMS architecture. Communication architecture of smart grid is also very complex. Smart grid has automated control through bidirectional connection of power flow as well as data flow.Addition of communication technology is a major part of the idea of smart meter.However, for a stable and well integrated communication architecture, proper infrastructure is a must.(Barai *et al.*, 2015).

2.3.1Advanced Metering Infrastructure (AMI)

Advanced Metering Infrastructurecan be seen as thesystemthat enable the integration ofthecommunicationlinktothe smartgridnetwork.AMI enables bidirectional data flow between end users and utilities. It alsoprovidesintelligent management,bettermaintenance,easierandproperadditions andreplacement ofutilityassetswhich resultsinbetterpower quality.AMIconsistsofthreebasiccomponents:Smart metering devices at the user end, twoway Communication path betweenenduserandutility,andautomatedsoftwareand operation center for data processing (Barai *et al.*, 2015). Advanced Metering Infrastructure is as shown in Figure 2.9

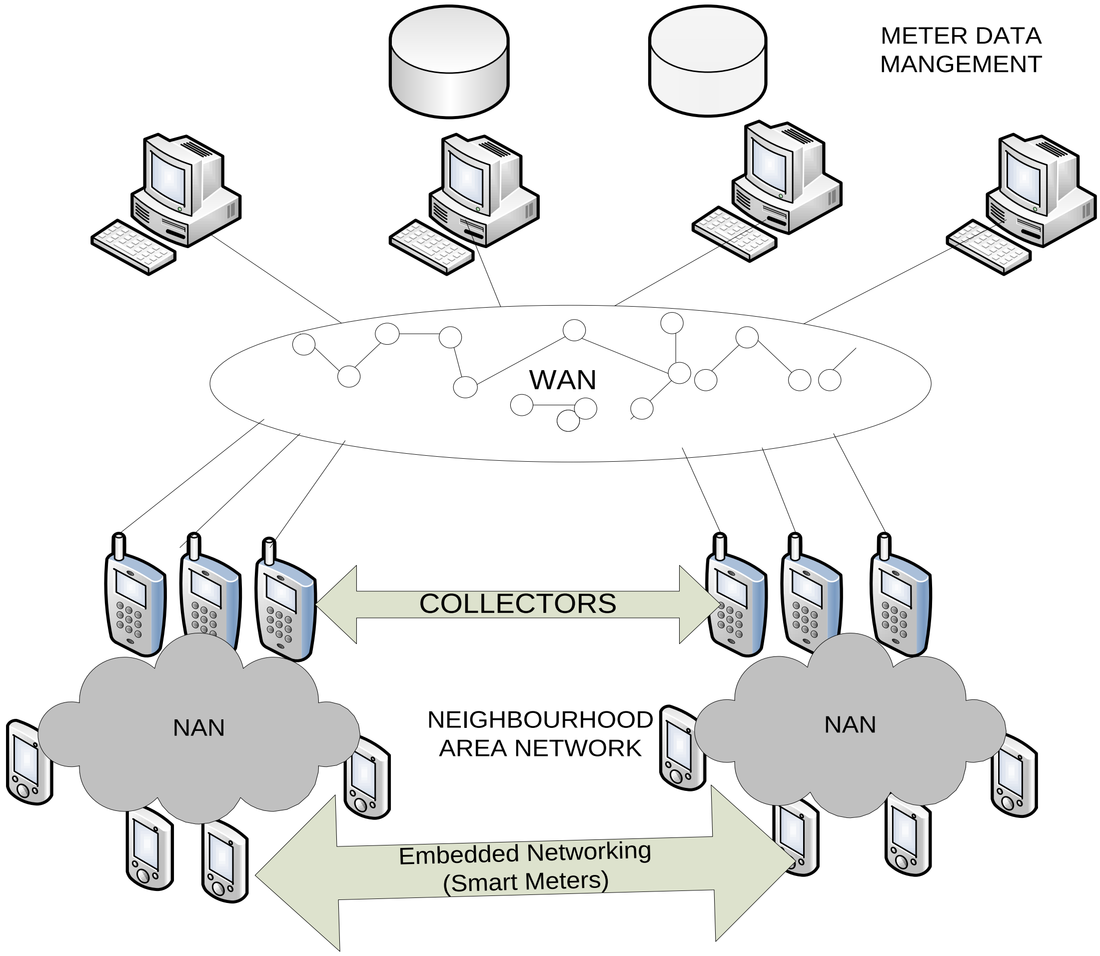

Figure2.9: Advanced Metering Infrastructure(Foreman & Gurugubelli, 2016)

2.3.2 Smart Meters (SMs)

Smartmetersarepowerfultoolswhichfundamentally changetheoperationofpowergrids(Arif *et al.*, 2013; Yeung & Jung, 2012).Inadditionto performingthefunctionsofatraditionalmeter,smartmeters canbeusedassensorsacrosstheentiredistributiongrid (Ekanayake *et al.*, 2012)When an Advanced Metering Infrastructure (AMI) is in place, smart meter can measure and record real power, reactive power usage, voltage, current and power factor during a day at certain time interval.These collected data are sent to a central data management system over a secure network via wireless communication.In addition, these sensors can be used bytheutilitiestodetectfaultandsendoutageorrestoration notifications(Smart grid report III 2012)

&(Tram H., 2008). Use of this information allows the utilities to provide more reliable power supply, better planning, operation, and faster outage response of the grid. It also guides towards the detection and location of nontechnical losses in power system network.These meters also allow increased resolution of data on various measurement parameters across the grid and these data can be used by utilities for the following applications(Yeung & Jung, 2012).

i. Faster outage detection, response, and restoration by providing data to the field operations timely.

ii. Keeping customers better informed about the status of power grid. Utilities can communicate relevant information, e.g., cause of outage, field-estimated restoration time, and public safety notice.

iii. Improving resilience against disruptions, reducingpotential outages, reducing frequency and duration of outages by enhancing accuracy of the grid asset planning and management.

Figure 2.10 shows the functional block diagram of a smart meter

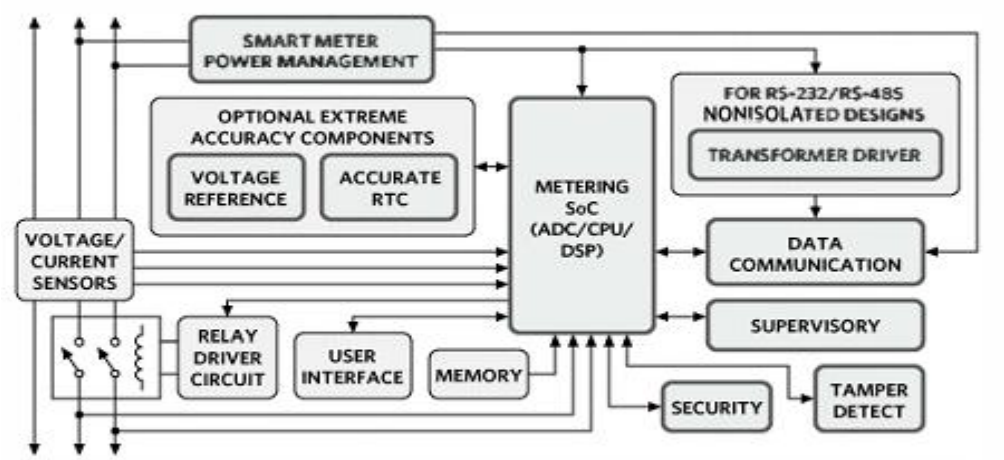

Figure 2.10: Functional Block Diagram of a Smart Meter (Barai*et al.*2015,)

There are four basic categories of Smart Meter System technologies as defined by their Local Area Network (LAN). They are:

a. Wireless

b. Radio Frequency (RF)

c. Power Line Carrier (PLC)

d. GSM/GPRS based

2.3.3Distribution Transformer Controller (DTC)

This is an electrical device installed at the secondary substation of a power network it interact with the Smart Meters providing meter data management as well as electrical measures of each phase. The DTC serves as the gateway between the smart meters and the central system such as Low Voltage (LV) Supervisory Control AndData Acquisition (SCADA) systems present in high level of the AMI hierarchy. Figure 2.10 shows a DTC equipment and Figure 2.11 is the functional block of a DTC.

Plate 2.11: Pictorial Diagram of a DTC Equipment (Marques *et al*., 2016)

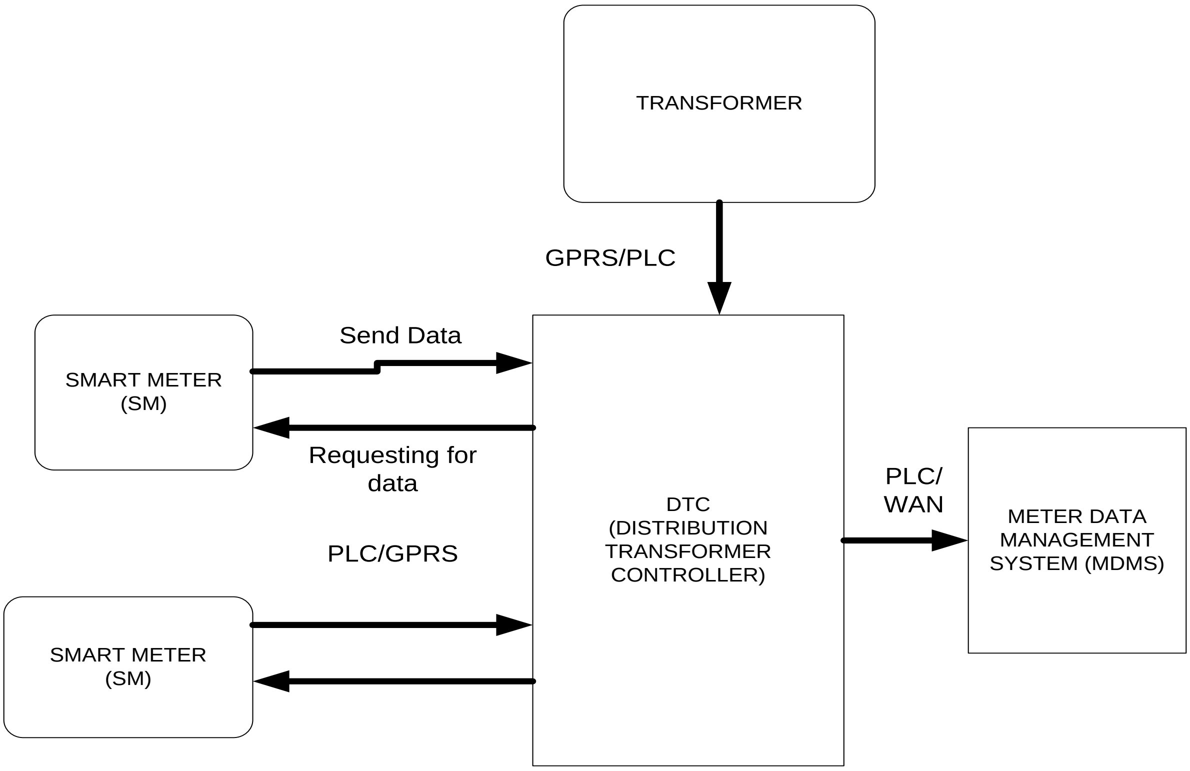

Figure 2.12: Functional Block Diagram of a DTC as understood from the Literatures.

From the block diagram of Figure 2.12, a DTC is a multi-function device. It sends signal to smart meters requesting for captured data, and also captures the reading of electrical parameters from the transformer. This data are simultaneously sent to the MDMS with the aid of Wide Area Network (WAN) or Power Line Communication Infrastructure.

The DTC may also provide several electrical measures such as:

i. Meteringof three-phaseactiveandreactiveenergyfortheLVsideoftheDistribution Transformer
ii. Voltage
iii. Current
iv. Power (3-phase active and reactive)
v. Power Factor

2.3.4Data Concentrator

Data concentrator is an important node in the AMI which is connected with several smart meters and central utility servers known as Meter Data Management System (MDMS).It enables communication of the data between smart meters and MDMS. Data concentrators securely aggregate data from a number of meters and send to MDMS.Figure2.13is theblock diagram of a data concentrator. Smart meter data is collected through Neighborhood Area Network (NAN) and passed to MDMS through Wide Area Network (WAN) (Prakash, 2013).

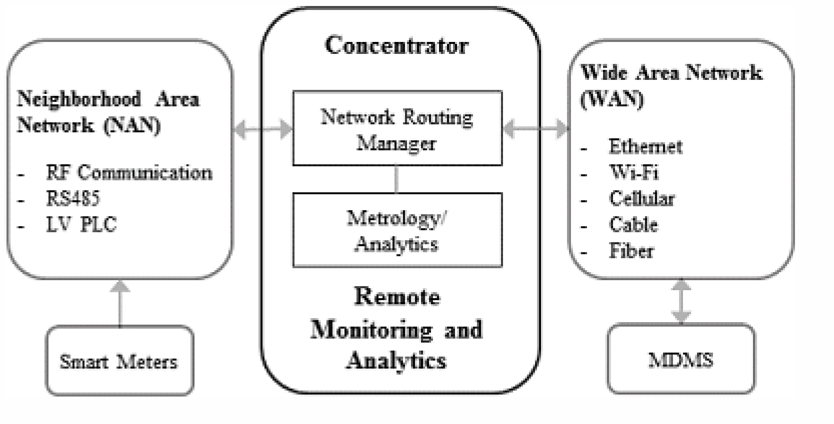

Figure 2.13:Block diagram of data concentrator. (Barai*et al.*, 2015)

2.4 State Estimation (SE)

Stateestimationfor electric transmission grids was first formulated as a weighted least-squares problem by FredSchweppeandhisresearch group in 1969. (Abur & Exposito, 2004).A state estimator is a central part of every control center.The basic motivation for state estimation is for the purpose of performing computeranalysisofthe networkundertheconditionscharacterizedby the current set of measurements. Specifically, it is mostly aimed at knowing the values of the bus voltage phasor magnitudes and angles $|V_k|$, &$\theta_k$forall k=1 or the line current magnitude and angles I_{ij},&α_{ij} .

2.4.1 Challenges of state estimation in distribution systems

State estimation in transmission networks has been state-of the-art since 1970 (shweppe&wilde, 1970), and it is now considered as a routine task. However, these methodologies cannot be directly applied to distribution systems because of the following reasons (Abdel-Majeed & Braun, 2012):

i. There are very few real-time measurements available in medium and low voltage levels (several thousand nodes usually have a few measurements at the head of the feeder).

ii. The modeling of complex multi-phase asymmetric distribution represents a challenge for developing efficient and robust estimation algorithms which are suitable for different types of measurements.

These two reasons have arisen from the following fundamental differences between transmission and distribution grids:

a. Transmission grids are meshed and must be analyzed as a whole, while distribution networks are usually radially constructed and can be analyzed separately as sub networks.
b. In transmission systems, the impedance ratio R/X << 1 and can be ignored, but in distribution systems the R/X > 1 or R = X in some cases, and can no longer be neglected.
c. There are fairly balanced loads in a transmission system, in contrast to distribution grids, particularly low voltage grids, and an obvious asymmetry exists between the phase loadings, therefore, a much more complex calculation is needed.
d. The transmission grid is usually observed by an adequate number of measurement points on the network. At low and medium voltage networks, the network operator usually has no or very few measuring points compared with approximately 1,000-10,000 nodes. Distribution network operators are, thus, generally “blind”; this can change in the future with the use of a smart meter infrastructure.
e. The number of nodes in the distribution may even be higher than the transmission system. However, the specific cost for measurement, information and communication infrastructure per unit of transmitted energy is much higher.

However, the advent ofsmart meters is now contributing new types of measurements in the low voltage level,such as real power, reactive power, and voltage measurements, current measurements power factor at each customer connection almost in real-time.

The availability of this information is a necessary basis for state estimation in low voltage networks. With a more accurate real-time model of the network through the distribution state estimation, other operational functions, such as real and reactive power optimization, network restoration, load balancing, and optimal network configuration, can be more reliably performed and controlled.

2.4.2 State estimation in low voltage network

There are different methods for state estimation in distribution networks in the literatures. The state variables can be estimated using different estimator techniques (Kamireddy *et al.*, 2008; Singh *et al.*, 2009):

i. Weighted Least Squares (WLS) estimator.
ii. Least Absolute Value (LAV) estimator.
iii. Weighted Least Absolute Value (WLAV) estimator.
iv. SchweppesHubber Generalized M (SHGM) estimator.

Singh *et al*. (2009) evaluated the performance of WLS, WLAV and SHGM algorithms. They concluded that the WLAV and SHGM algorithms cannot be applied directly to distribution systems and require significant modifications in order to obtain consistent and good quality estimation. Singh and colleagues found that WLS gives consistent and better quality performance in distribution systems. The WLS estimator will be used in this paper as it gives a consistent performance under Gaussian assumptions for known noise characteristics.(Singh *et al.*, 2009)

2.4.3 WLS Estimator

In WLS estimation, the goal is to minimize the weighted differences between measured network variables

andtheirestimatedvalues.Themostlikelystateofthenetworkcanbecalculatedbysolvingequation (2.23). (Abur & Exposito, 2004)

$$\min_x J(\mathrm{x}) = \min_x \frac{1}{2}\sum_{k}^{n}\frac{[z_i - h_i(\mathrm{x})]^2}{\sigma_i^2} \quad (2.23)$$

WhereJ(x) is the cost function to be minimized.

x isa state vector that contains all state variables

z_i is value of measurement i.

$h_i(\mathrm{x})$ is measured variable i as a function of state variables

σ_i Is the standard deviation of measurement

I is number of measurements

If measurements and measurement functions are presented in vector form and measurement variances are presented in a matrix form, the equation (2.23) can be expressed in a simpler form as is in the following(Abur & Exposito, 2004).

$$\min_x J(\mathrm{x}) = [\mathrm{z} - \mathrm{h}(\mathrm{x})]^T R^{-1}[z - h(\mathrm{x})] \quad (2.24)$$

Where $z = \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_n \end{bmatrix}$ is the measurement vector(2.25)

$h(\mathrm{x}) = \begin{bmatrix} h_1(\mathrm{x}) \\ h_2(\mathrm{x}) \\ \vdots \\ h_n(\mathrm{x}) \end{bmatrix}$ is the measurement function vector(2.26)

$R = \begin{bmatrix} \sigma_1^2 & 0 & \cdots & 0 \\ 0 & \sigma_2^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_n^2 \end{bmatrix}$ is the measurement covariance matrix(2.27)

The minimum of cost function $J(x)$ can be found by differentiating it with respect to state variables and searching for the zero point. The cost function derivative in respect to state vector

$\boldsymbol{x}$is equal to its gradient. Therefore, the state vector minimizing the cost function, forces the gradient to zero. The gradient of $J(x)$is given in equation (2.28)(Abur & Exposito, 2004)

$$\nabla_x J(\mathrm{x}) = \mathrm{H}^T R^{-1} z_i - H^T R^{-1} h_i(x) \quad (2.28)$$

Where $H = \frac{\partial h(x)}{\partial x}$

When the gradient of the cost function is zero$\boldsymbol{x}$ can be solved from equation (2.29)

$$x = (H^T R^{-1} H)^{-1} H^T R^{-1} z \quad (2.29)$$

Equation(2.29) is non-linear,therefore solving the state vector$\boldsymbol{x}$requires the use of iterative methods, such as theNewton-Raphsonmethod.Oneveryiterationround,alinearizedapproximationofthestatevector change$\Delta\boldsymbol{x}$, shown in equation 2.30, is added to the initial state vector value. The iteration is continued until $\Delta\boldsymbol{x}$ is small enough (Abur & Exposito, 2004).

$$\Delta x = (\mathrm{H}^T R^{-1} H)^{-1} H^T R^{-1} \left[Z - h(\mathrm{x}) \right] (2.30)$$

2.4.3.1 WLS State Estimation Algorithm

WLS State Estimation involves the iterative solutionof theNormal equations given by equation (2.30).An initial guess has to bemade for the statevector x^o.As in the case of the powerflowsolution,this guess typically corresponds to theflatvoltageprofile,where all bus voltages are assumed to be1. 0 per unit and in phasewith eachother.

Theiterative solution algorithm for WLS state estimationproblem can be outlined as follows (Abur&Exposito 2004):

i. Start iterations, set theiterationindex k =0
ii. Initialize the statevector x^k,typically asa flatstart.
iii. Calculate the gain matrix $G(x^k)$

iv. Calculate the partial derivatives of the objective function with respect to the state variables (as in equation 2.28)

v. Decompose $G\left(x^k\right)$ and solve for Δx^k

vi. Test for convergence, max $\left|\Delta x^k\right| \le \varepsilon$?

vii. If no, update $x^{k+1} = x^k + \Delta x^k$, $k = k+1$ and go to step 3. else stop

The above algorithm essentially involves the following computations in each iteration, k:

1. Calculation of the right hand side of equation (2.30).

a. Calculating the measurement function, $h\left(x^k\right)$.

b. Building the measurement Jacobian, $H\left(x^k\right)$.

2. Calculation of $G\left(x^k\right)$ and solution of Equation (2.12).

a. Building the gain matrix, $G\left(x^k\right)$

b. Decomposing $G\left(x^k\right)$ into its Choleskyfactors.

c. Performing the forward/back substitutions to solve for Δx^{k+1}

2.5 Monte Carlo Simulation

Monte Carlo Simulation is used to estimate the expected value of random variable when it is infeasible or impossible to compute an exact result with a deterministic algorithm. Monte Carlo methods are a class of computational algorithms that rely on repeated sampling to compute the result.

2.5.1 Characteristics of Monte Carlo

i. Monte Carlo Simulation allow several inputs to be used at the same time to create the probability distribution of one or more outputs.

ii. Different types of probability distributions can be assigned to the input of the model. When the distribution is unknown, the one that represent the best fit could be chosen.

iii. The use of random numbers characterized Monte Carlo Simulation as a stochastic method.

iv. The random numbers have to be independent, no correlation should exist between them.

v. Monte Carlo Simulation generate the output as a range instead of a fixed value and shows how likely the output value is to occur in the range.

2.5.2 Steps Involve in the Monte Carlo Simulation.

Step I- Construct a simulated universe of some randomizing mechanism whose behavior we wish to describe and investigate.

Step II- Specify the procedure that produces a pseudo sample which simulates the real-life sample in which we are interested.

Step III- If several simple events must be combined into a composite event, the composite event must be describe.

Step IV- Calculate the Probability of interest from the tabulation of outcomes of the resampling trials.

2.5.3 Monte Carlo simulation procedure in Branch Current State Estimation (BCSE) Method.

Step 1– BCSE method tries to find a system state, represented by $[I_{KM}, \delta_{KM}]$, by minimizing the weighted sum of the squares of the measurements errors.

Step 2– First the actual measurements are obtained by running a power flow for the given loads. Then measurement error obtained from random generator based on Normal distribution was added to the actual measurements. The forecasted load data is created by perturbing the actual load data by adding error of 30%, 40% and 50% as the case may be. The power measurement errors are selected from Normaldistribution with a standard deviationσ corresponding to the degree of uncertainty in the measured value.

Step 3– The sample size is defined in order to achieve acceptable results.In this thesis, 200 Monte Carlo simulationshave been chosen.

Step 4– To calculate the probability of interest, the estimated states ($\left[I_{KM}, \delta_{KM} \right]$) of branch currents are obtained.

2.6Description of the Reference Algorithm and the Proposed Algorithm.

The reference algorithm is the work of Marquez *et al*., (2016). The algorithm in this work follows the steps of Marques *et al*., (2016) but employs the application of weighted least square state estimator instead of full dependence on meter reading. In the work of Marques *et al*., (2016) two algorithms were developed one is used for the detection of nontechnical losses while the other was used for the localisation of the NTLs. In the former the aggregated per phase current consumed by loads is measured and recorded by the DTC and it is compared with the summation of individual current measured byeach smart meter of that phase. If the value measured by the DTC is quite higher than that of the smart meters, then NTLs is detected. The algorithm is as shown inFigure 2.14. Furthermore, in the localisation Algorithm, the branch currents of each branch on the feeder is first calculated based on the ampere reading of the meters on the branch then it is also estimated based on the voltage measurement at each node of the branch. This form the core for the localisation of NTLs. In this work, the method of detection of NTLs used by Marques *et al*., (2016) was adopted and also the steps for its localisation was maintained However, in the estimation of branch current a weighted least square state estimator was used to estimate the value of voltages at nodes. This actually improves the robustness of the algorithms against the use of noisy measurement from meters as well as making it possible to accurately estimate the branch current in a case where there is loss of data due to meter outage or fault.

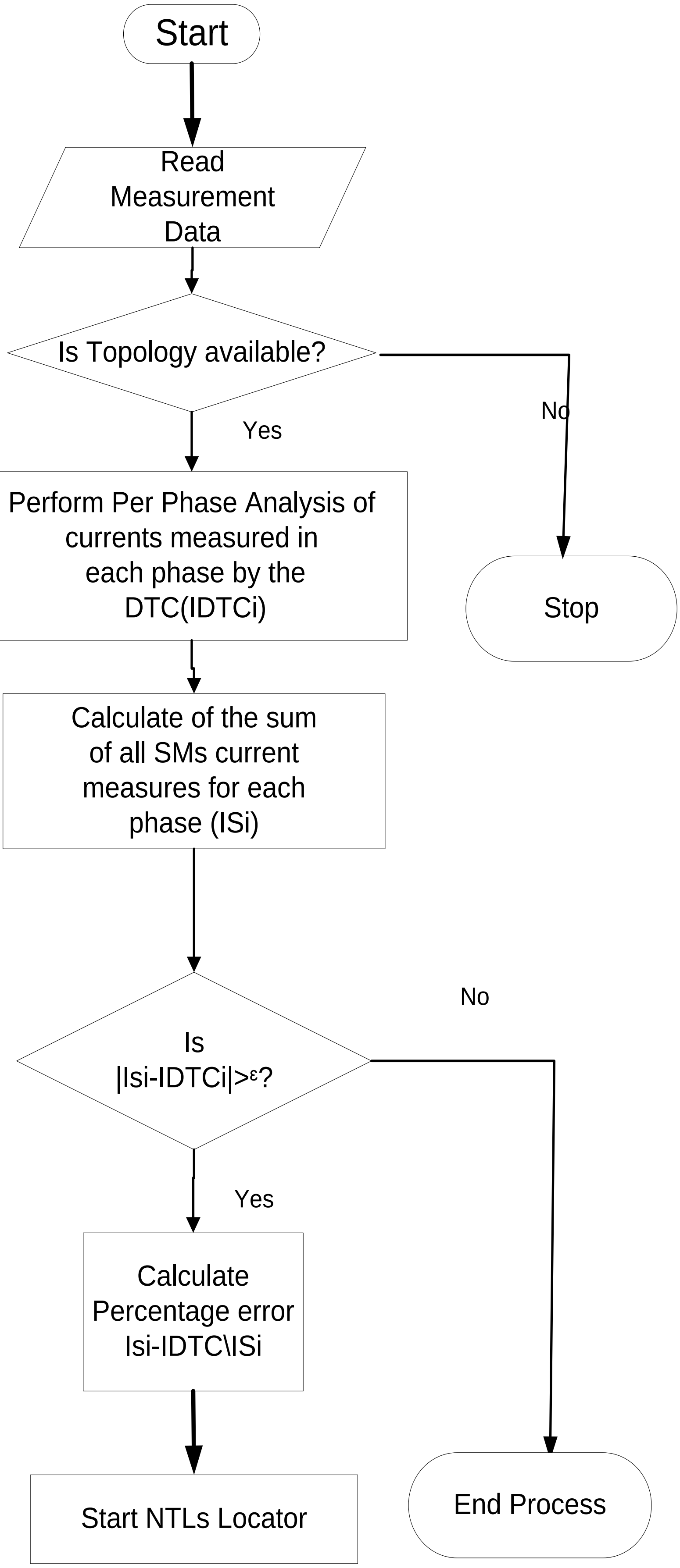

Figure 2.14: Flowchart of the Algorithm for Detection of NTLs (Marques *et al*., 2016)

Figure 2.14 could be further explain as follows:

I. The first algorithmic stage, detection of NTLs, starts with the acquisition of the historical records.TherecordsrequiredcomprisetheSMs'currents,therespectivepowerfactorsandtheperphasecurrentsmeasuredby the DTC at the secondary substation.
II. After reading the measured data from the database, the measurement are categorized based on the phase it was captured using the availability of the topology.
III. In step III the DTC reading is also categorized phase wise.
IV. In step IV the customer's loads on each phase are summed
V. In step V the values acquired in step III and IV are compared to confirm the presence of theft.
VI. The last step is to calculate the percentage of losses based on the total load on the network.
VII. If the losses are beyond the acceptable margin, NTLs is Locator is called to process if not the detection location is stopped.

2.7Case Study

The modified Algorithm will be validated on a typical Portuguese low voltage (LV) overhead distribution network. This network will be used because the use of other networks which differ in characteristics from the one used by the Marques*et al.* (2016) may not clearly indicate the improvement in the results obtained by Marques*et al.* (2016).

2.7.1 Description of Case Study

The single line diagram of the LV distribution network in Figure 2.15 represent the test feeder that will be used to assess the modified algorithm developed. The network also includes Distributed Energy Resources (DER) as micro generation made from photovoltaic panels for some client. The network has a total of 33 bus-bars and a total of 48 consumers. Their contracted power varies in ranges between 3.45kVA and 10.35kVA single phase loads. The location of the installed micro-generators and the respective installed power is shown in Table 2.1. It has been considered that the loads power factor varies randomly between 0.8 and 1 and the power factor of the micro-generation is equal to 1.

Table 2.1 Micro-Generators and their respective installed power (Marques *et al.*2016)

S/NoPhase Bus-bar Power(kVA)
12 103.68
21 13 3.68
31 22 3.68
43 24 3.68
52 313.68

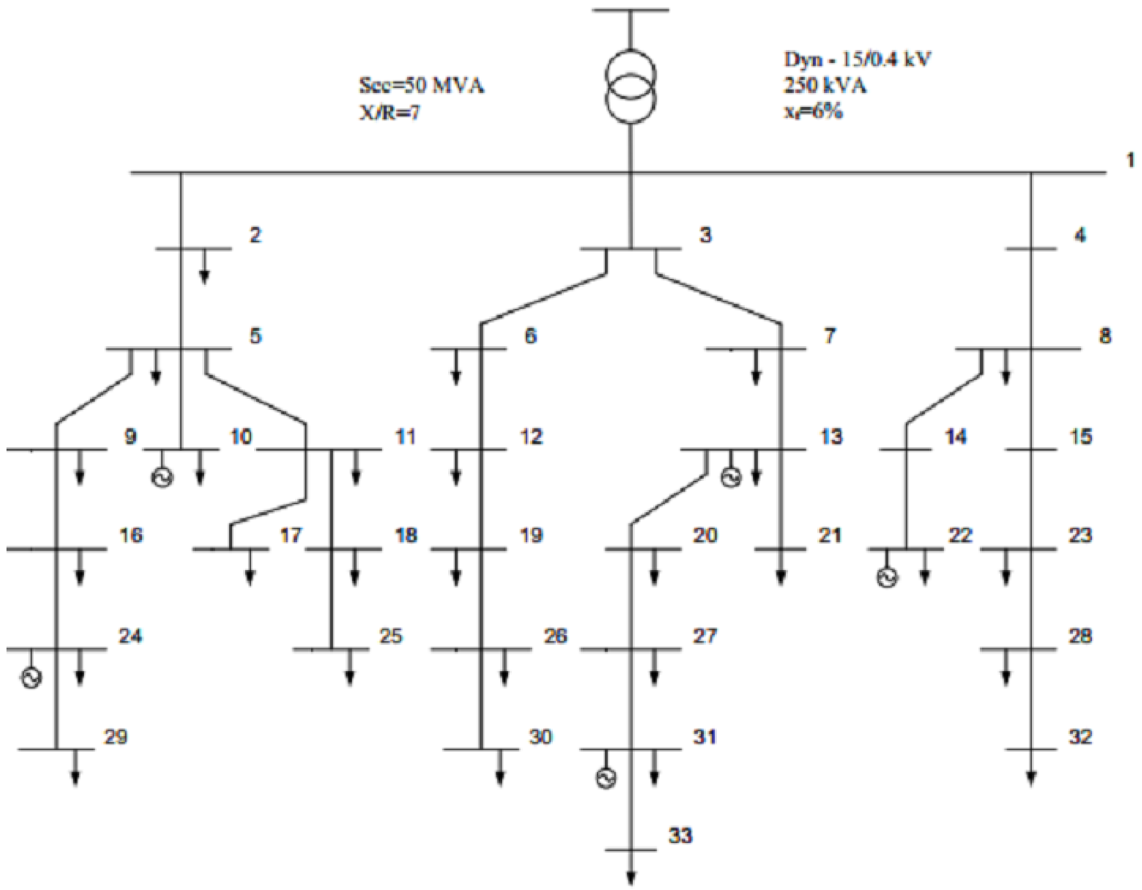

Figure 2.15: Test Feeder (Marques*etal*.2016)

2.8Review of Similar Works

So many researchersworked and still working on detection of nontechnical losses in power line network in order to reduce theft, increase efficiency, enhance proper planning of power network through appropriate forecasting,andelimination of financial starvation of power utility companies that may occur as a result of high level of nontechnical losses. Amongst the work done are:

Nizar *et al.* (2006)Presented a work on the use of load profiling method in the detection of nontechnical losses in power system network. Historical load consumption data of customers characterized by different loading conditions like type of customers, (industrial residential or commercial), location, voltage level, climate and day was considered. The data collected based on prior knowledge of consumer's consumption behavior are classified into typical and atypical load profile. Future customer's consumption that matches with the typical load profile are stored as normal while those that does not correspond are termed nontechnical losses. Also customers whose meter recorded no consumption for a particular period of time are classified under the NTL case. However historical consumption data needed to ascertain a consumer consumption pattern are much and the classification of zero consumption meter reading data may give a lot of false positive result.

Nagi *et al.* (2010)Worked on detection of nontechnical loss for metered customers in power utility using support vector machine. In their work, variety of sources of NTLs such as fraudulent activities such as like meter tempering and bypassing as well as consumption abnormalities have been considered. ASupport Vector Machine (SVM) pattern classification technique was applied in order to detect and identify load consumption pattern of fraudulent customers using historical customer's consumption data. However this required a large amount of training data with data collected from smart meters in addition to encoding and data mining technique this resulted to large computational effort and time.

Huang*et al.*,(2012) worked on detection of NTL using state estimation and analysis of variance. A novel meter data validation and estimation framework to enhance the Data Validation Editing and Estimation (VEE) practice in Meter Data Management system (MDMs) was presented. Their work helped in exposing the defect in using customers' historical data as a reference for the detection of nontechnical loss also it showed that Analysis of Variance (ANOVA) is useful in detecting individual meter data anomaly. However the authors did not consider other cases of NTL which is not as a result of meter defect but as a result of direct tapping from overhead Low Voltage network. This will affect the real estimate of the NTLs in the network.

Monedero*et al.*,(2012) presented a method for the detection of fraud and nontechnical losses in a power utility using Pearson coefficient, Bayesian network and decision tree. In the work, characteristics of previously detected NTLs customer was used to detect other customers of similar features of NTLs through Bayesian network. Furthermore, in order to characterize the pattern of consumption of each customer, a set of indicators such as maximum and minimum value of the monthly or bimonthly consumptions, number of readings, reactive/active energy coefficient, number of hours of maximum power consumption, number of streaks of the customer, estimator from the streaks of customer, etc. were generated these helps in tracing the deviation in normal consumption of customers. However deviation in consumption behavior may not be the absolute result of nontechnical losses in a power grid because a customer might deviate from his regular consumption pattern due to climate condition, lack of fund among others.

Martino*et al.*, (2012)proposed a solution to the problem of class imbalance for energy theft detection in traditional power systems. Considering that the number of people who committedfraudaremuch less than the number of honest customers, standard classifiers are overwhelmed by benign samples and tend to ignore the minority class. To achieve a higher performance, different classification techniques, including one-class SVM, optimumpath forest and C4.5 decision tree, were combined. The combined classifier showed 2%–10% improvements overindividual classifiers. The shortcoming of this method is thatwhile it imposes a high-computational load, the performanceimprovement is not substantial.

Mashima and Cárdenas (2012)Suggested modeling the probability distributions of the normal and malicious consumption patterns, and application of the generalized likelihood ratio (GLR) test to detect energy theft attacks. They used autoregressive moving averageto model customers' normal and malicious consumption distributions. They assumedthat an attacker would choose a probability distribution that decreases the mean value of the real consumption. This,however, is not necessarily true with AMI. Considering the dynamic pricing in smart grids, by only changing the order ofmeter readings without altering the average, electricity theft is possible. Another major issue with ARMA–GLR detector isthat it is only effective if the normal electricity theft behavior rand attack patterns can accurately be modeled by an ARMAprocess.

Costa *et al.,* (2013) proposed an ANN-based scheme to discoverknowledge in databases for classifying the consumers as malicious. Various consumer's patterns of consumption are analyzed and based on the total connected load of the consumer, range of discovered pattern are classified as malicious or benign. Unfortunately, this model was found to be ineffectiveduring uneven distribution of records. Moreover, the schemewitnessed low precision which eventually leads to large falsepositives.

Sonica Agrawal (2013) presented a work on the determination of nontechnical losses usingmatlab environment. In the work, a case of two bus system was considered, one is taken as the slack bus and the other is the load bus. It was assumed that 3% of each customer's load is the additional load that is not billed, and this was used to estimate the increment in technical loss of the whole system, the increment is taken as the NTL in the system. However location of the nontechnical loss was considered in this work.

Depuru*et al*., (2013)proposedan improved encoding technique where both SVM and a rule engine-based algorithm were applied on encoded data to improve the classification accuracy. Portions of the algorithms were parallelized to reduce the detection time. Still the algorithm suffered from the common shortcomings of classification-based methods. The database used for performance evaluation is not publicly available and the authors did not explain howthey obtained theft samples for all customers or what percentages of the training and testing data were theft patterns.

Rengaraju *et al.* (2014)usestheapproachbasedonpowerline communication principle which is use for detecting theft in electricity.Ahighfrequencysignalisintroducedinthe distributionnetworkwhich changes its amplitude and frequencyastheloadinthelinesincreasesordecreases. The changes were detected through the gain detectors if any illegal connection is made between the poles then there willbemodificationinthevaluesofgainandthrough whichtheillegalconnectionintheelectricitywillbe discoveredandproperactionwillbetakenbythe authorities to neutralize such connection but this approach is not tried for the theft detection for the customers illegal use and it is infrastructure based.

Jokar*et al.*, (2016)also improved an effort towards the detection of electricity theft in an advanced metering infrastructure using an algorithm called Consumption Pattern Based Energy Theft Detector (CPBETD). CPBETD relies on the predictability of customer's normal and malicious usage pattern. Along with application of SVM anomaly detector,the algorithm uses silhouette plots to identify the different distributions in the dataset, and relies on distribution transformer meters to detect NTL at the transformer level. However the major drawback of this scheme was manual data collection from the customers which was an infeasible approach.

Jindal *et al*., (2016) proposed a scheme which comprised the use of Decision Tree (DT) and SVM-Based Data Analytics for energy theft detection in smart grid. A number of features was used as input to the DT to predict the electricity consumption of a customer, the predicted consumption as well as the feature are further imputed in to the SVM to compare the customer's actual consumption and the predicted consumption and make a decision for theft detection. This technique helps to eliminate the need for previous consumption data of customers. However perfect prediction of customer's electricity consumption is unrealistic due to the complexity that surrounds human decision.

From the reviewed literatures, it is evident that a lot of method has been proposed and utilized for the detection and localization of NTLs. Howeverto the best of our knowledge, majority of researchers exploited much the artificial intelligence methods and only few work have been done using the smart metering method which is more accurate and reliable. In this work a methodology is proposed to improve the accuracy of the Smart metering method and decrease the false positive rate.

CHAPTER THREE

MATERIALS AND METHODS

3.1 Introduction

In this chapter, the detailed procedures (materials and methods) used in achieving the research work, and are discussed below.

3.2 Materials

The materials employed for the actualization of this research are as follows:

3.2.1 Personal computer

All simulations analysis are carried out using HP-14r002ne Personal Computer with the following specification:

I. Processor: Intel(R) Core(TM) i5-4210u CPU @ 1.7GHz 2.40GHz

II. Installed Memory (RAM): 8.00GB

III. System type: 64-bit Operating system, x64-based processor

IV. Operating System: Windows 8.1 single language.

3.2.2Softwares

The major softwares used for the course of this work are Matlab 2015a and OPENDSS, these softwares are described as follows:

3.2.2.1 Matlab 2015a software

The branch current state estimation code, analysis and evaluation are carried out in MATLAB 2015a environment and details of the program developed are provided in appendix C.

3.2.2.2 OPENDSS software

OpenDSS is an open distribution system simulation tool developed by the Electric Power Research Institute (EPRI). A user can simulate any distribution system using OpenDSS while utilizing COM interfacing (see OpenDSS manual for details). Here, OpenDSS is utilized for a distribution system load flow using Matlab COM Interfacing. The power flow solution of the test feeder was simulated using the opendss software.

3.2.3 The test case feeder.

The Test Case Feeder which was discussed in subsection 2.6.1 and itssingle line diagram were shown in Figure 2.15 For the purpose of this work, the network was modified by removing all the DGs present in the network. The line data and the bus data are given in appendix A. Table A1 and Table A2 show the detail of the consumer's contracted power and the line impedances of the test case feeder which was discussed in subsection 2.6.1.

3.3 Methodology

The methodology used in carrying out the research work are listed in chapter one sub-section 1.5 and are further discussed below: In this work, two main algorithms are used the Detection algorithm and the localization algorithm.

3.3.1 Detection Algorithm

The Detection algorithm was adopted from the work of Marques *et.al.*, (2016) this algorithm was employed in order to affirm the existence of NTLs before searching the affected branch. The steps followed in this algorithm could be summarized as follows

A Distribution Transformer controller is installed at the Low voltage side that feeds the customers connected to the distribution transformer. The function of the DTC as described earlier in chapter two is to monitor and record per phase total load consumption of the customers.These readings are sent to the Meter Data Management System (MDMS) at a specified time interval.

Also all the customers on the network are assumed to be having a smart meter that captures their consumption on the network. The reading of all smart meters together with the DTC are sent simultaneously to MDMS with a time interval (reflecting the time it was captured) and address that describes the Meter and its location depending on the type of communication system used stamped on each data.

All loads are assumed to be single phase and all customers are shared according to the phase they get their supply from. This facilitate the per phase analysis of the network.

TheprocessofNTLsdetectionisbasedontheassumptionthat the voltages' angles in nodes is nearly the same in the entire network. As a consequence, the detection of NTLs has anassociatederrorthatneedstobeestimated.Thiserrorisused as a benchmark to decide about the presence of NTLs inthe network. When the consumers of each phase are known, a PerPhaseError(PPE)isused.ThePPE is calculateda priori by performing power flowstudies,withoutthepresenceofNTLs.Therationalebehindtheestimationof these errorswithoutthepresenceofNTLsistoassessthemarginoferror that should be used to ensurethatthemethodologyhasalowvalueoffalsepositiverate (detection of NTLs when they are not present). In case of being known the topology and the branches' impedances of thenetwork,onlythePPEisestimatedusingtherealloadsprofiles as input to the power flowstudy. This margin of error is estimated applying the methodology of detection to the results provided by the power flow. Thus, the PPE_i for each phase i is calculated using the Equation (3.1)

$$PPE_i = \frac{ISS_i - ITL_i}{ISS_i} \times 100\% \quad (3.1)$$

Where;

ISSiisthecurrentofeachphaseiinthesecondary substation

ITLiis the sum of the load currents of the phase i

3.3.2 Development of power flow algorithm based on thevenin's and norton's equivalent circuit approach in distribution network.

The whole solution technique is summarized as follows:

The normal circuit solution technique in the EPRI OPENDSS program may be concisely written as a simple fixed-point iterative method:

$V_{n+1} = \left[Y_{system}\right]^{-1} I_{PC}(V_n)$ n= 0, 1, 2, … until converged (3.2)

Where V_n is the voltage magnitude at bus n

Y_{system} is the admittance matrix of the network

I_{PC} is the compensation current of the power delivery element.

In words, after building the Y-system, the process starts with a guess at the system voltage vector, V_0, and computes the compensation currents from each power conversion (PC) element to populate the I_{PC} vector. Using a sparse matrix solver, the new estimate of $V_{n+1}$is computed as shown in equation (3.2). This process is repeated until a convergence criterion is met. For distribution systems, convergence is typically achieved in four (4) to ten (10) iterations for the initial power flow solution and two (2) to three (3) iterations for Subsequent solutions in a time series. The Y-system matrix is not refactored until there is a major change in the system configuration. Thus, this method is very fast for a Quasi-Static Time-Series (QSTS) simulation.

3.4 Development of State Estimation Algorithm

Thissubsection describes how the state estimation algorithm was used for the location of NTLs in this work. Weighted Least Square estimator which uses branch currents as state variables is selected for this task.

3.4.1 Formulation for branch current based state estimation

The formulation of the measurement equations used in the estimation of the defined state variables are described in the following subsections.

3.4.1.1 Basic WLS Formulas

In WLS estimation, the goal is to minimize the weighted differences between measured network variables and their estimated values. The most likely state of the network can be calculated by solving equation 2.23 stated in chapter 2. Unlike the conventional power system state estimation where voltage magnitude and angle are taken as the state variables, for the purpose of this work, the branch current magnitude and angle are taken as state variables in order to directly detect which branch of the network is actually affected by theft.

3.4.1.2 Measurement equations and jacobian matrices

In order to run the developed state estimator, measurements of various types are taken from various point in the network this measurements which can beActive power flow, reactive power flow, current flow, node voltage, current injection, active power injection and reactive power injection measurements can all be used in the developed branch current based state estimator. But in this work, nodes voltages and active and reactive power flow are taken as the available measurement, equivalent branch current flows of the active and reactive power flows are assumed to be the initial values of the state variables. Measurements, their symbols and measurement equations used are as stated below. (Dansk Energi, Universidad Carlos III de Madrid& Tampere University of Technology, 2014)

i. **Active power flow between nodes K and M**

The Active power equation as a function of branch current used in the state estimation is described in equation 3.3

$$P_{KM} = V_K I_{KM} \sin(\delta_k - \delta_{KM}) \quad (3.3)$$

Where P_{KM} is the power flow between nodes K and M

V_K Is the voltage magnitude at node K

I_{KM} Is the current flow between node K and M

ii. **Reactive power flow between nodes K and M**

The Reactive power equation as a function of branch current used in the state estimation is described in equation 3.4

$$Q_{KM} = V_K I_{KM} \sin(\delta_K - \delta_{KM}) \quad (3.4)$$

Where V_K is the voltage magnitude at bus K

I_{KM} is the current flow between node K and M

δ_K is the voltage angle at bus K

δ_{KM} is the angle of the

iii. Voltage at node K

If the substation voltage as well as line current and impedance are known, the value of node voltages at any point in the network could be calculated using equation 3.5

$$V_K = \left| V_1 - \sum_{KM \in E} I_{KM} Z_{KM} \right| (3.5)$$

Where; Z_{KM} is the branch impedance of line KM

E belong to the group of lines located between nodes 1 and k

iv. Current flow between nodes K and M

$$I_{KM} = \left| I_{KM} \right| (3.6)$$

v. Current Injection at node K

The current Injected at any node K in the network can be calculated using equation 3.7

$$I_k = \left| \sum_{i \in B} I_{iK} - \sum_{j \in C} I_{KJ} \right| (3.7)$$

Where b is the group of upper-stream nodes connected to node K and C is the group of lower-stream nodes connected to nodes K.

vi. Active Power Injection at node K

$$P_k = \sum_{i \in B} V_k I_{iK} \cos(\delta_k - \delta_{ik}) - \sum_{j \in C} V_k I_{Kj} \cos(\delta_k - \delta_{Kj}) \quad (3.8)$$

vii. Reactive Power Injection at node K

$$P_k = \sum_{i \in B} V_k I_{iK} \sin(\delta_k - \delta_{ik}) - \sum_{j \in C} V_k I_{Kj} \sin(\delta_k - \delta_{Kj}) \; (3.9)$$

3.4.1.3. The Jacobian Matrix. (H(x))

The elements of the Jacobian matrix are the derivatives of available measurement with respect to the state variables. In our own case the power flow and node voltages measurement equations are differentiated with respect to branch current magnitude and angle. The derivatives of each measurement with respect to the state variables are as follows:

i. **Derivative of active power flow with branch current and angle**: When branch power flow measurements are in the same line segments as the state variable, the partial derivatives are:

$$\frac{\partial P_{km}}{\partial I_{km}} = V_K \cos(\delta_K - \delta_{KM}) \quad (3.10)$$

$$\frac{\partial P_{KM}}{\partial \delta_{KM}} = V_K I_{KM} \sin(\delta_K - \delta_{KM}) \quad (3.11)$$

Otherwise, whenthemeasurementandthestatevariablearenotinthe same line segment, all the partial derivatives are zeros.

ii. **Derivative of reactive power flow with branch current and angle**:When branch power flow measurements are in the same line segments as the state variable, the partial derivatives are:

$$\frac{\partial Q_{km}}{\partial I_{km}} = V_K \sin(\delta_K - \delta_{KM}) \quad (3.12)$$

$$\frac{\partial Q_{KM}}{\partial \delta_{KM}} = -V_K I_{KM} \cos(\delta_K - \delta_{KM}) \quad (3.13)$$

Otherwise,whenthemeasurementandthestatevariablearenotinthesamelinesegment,allthe partial derivatives are zeros.

iii. **Voltage magnitude measurements:**Whenthesourcenodevoltageand line currents are known, voltage at any point of the network can be calculated by subtracting the voltage drops that occur between source node (node 1) and the studied node k from the source node voltage. In a radial feeder, thevoltageatnodekcan be calculated with equation 3.13 assuming the feeder nodes have been numbered as in Figure 3.1

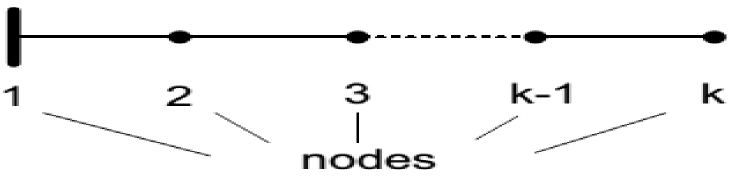

Figure 3.1: Node numbering on radial feeder

The Jacobian matrixelementsrelatedtovoltagemagnitudemeasurements can be divided into two groups. The first group contains elements that are between node 1 and measured node k. Then the partial derivatives are:

$$\frac{\partial V_K}{\partial I_{i-1,i}} = -\cos\delta_k . Z_{i-1,i}\cos(\alpha_{i-1,i}+\delta_{i-1,i}) - \sin\delta_k . Z_{i-1,i}\sin(\alpha_{i-1,i}+\delta_{i-1,i}) \quad (3.14)$$

$$\frac{\partial V_K}{\partial \delta_{i-1,i}} = -\cos\delta_k . I_{i-1,i} . Z_{i-1,i}\sin(\alpha_{i-1,i}+\delta_{i-1,i}) - \sin\delta_k . I_{i-1,i} . Z_{i-1,i}\cos(\alpha_{i-1,i}+\delta_{i-1,i}) \quad (3.15)$$

Where;

$I_{i-1,i}$ is the current magnitude on line that goes from node $i-1$ to node i ,

i belongs to a group of nodes that are between nodes 1 and k (node k belongs to this group, node 1 is excluded from this group)

$\delta_{i-1,i}$ is the current angle on the line that goes from node i−1 to node

$Z_{i-1,i}$ is the impedance on the line that goes from node i−1 to node i

$\alpha_{i-1,i}$ is the impedance angle on the line that goes from node i−1 to node i

δ_K is the voltage angle at node k.

The second group contains elements that are not between node 1 and measured node. All partial derivatives in this group are zeros.

3.4.1.4 Developed State Estimation Algorithm

The weighted least square state estimation algorithm was described in subsection 2.4.3, it was used in this work to estimate the branch current of a network under theft. The flow chart showing the process of weighted least square state estimation is shown in Figure 3.2

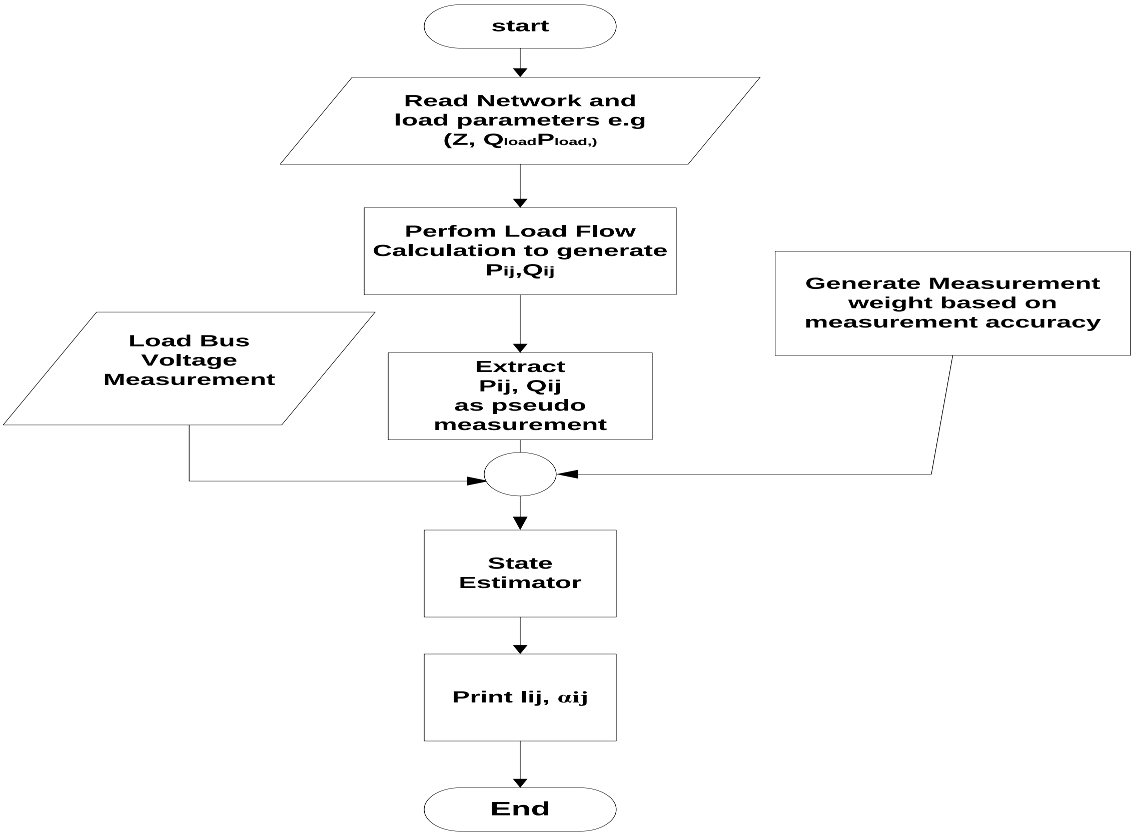

Figure. 3.2 Developed Flow Chart for State Estimation Algorithm.

The following steps described the input parameters as well as the procedure for estimating the state variables.

I. Get the network parameters (line impedance) and the load measurements (active and reactive power) captured by each smart meters and stored in the meter data management system

II. Input the data in step (I) in load flow calculator and run the power flow to get the branch power flows

III. Add the percentage of loss to all the branch flows

IV. Input the values in step (II), Captured Voltage magnitude, and the measurement weight to the State Estimator

V. Run the state estimator to the get the state variables

VI. Print out the state variables.

3.4.1.5 State Estimator Accuracy

In order to reduce high false positive rate, a threshold value is estimated above which the branch current magnitude of a segment is treated as NTLs. This is achieved by calculating the relative error between the estimated value of the state variables and the real values of the state variables of the state estimator when there is no NTLs on the Network through a Monte Carlo approach. Equation 3. 16describesthe state estimator relative error.

$$RE(\%) = \frac{sv_e - sv_{true}}{sv_{true}} \quad (3.16)$$

Where RE is the relative error of the estimator,

sv_e is the value of the estimated state variable

sv_{true} is the value of the true state variable.

3.4.2 Calculation of Branch Current

In order to know the extent of theft,Calculationof the Currents in Branches (CCB)usingtheconsumption'smeasurementsprovidedbySMs (currents) is performed.

Defining the Branches' Connections Matrix (BCM), which represent the network's topology given in snippet (3.17):

$$\begin{cases} BCM_{ij} = 1, if\ i = j\ or\ (i \neq j\ and\ j\ is\ a\ downstream\ busbar\ of\ busbar\ i \\ BCM_{ij} = 0, in\ other\ cases \end{cases} \quad (3.17)$$

Branch Connection Matrix has a dimension of n x n where n is the total number of busbars. Defining the vector of per phase current consumption (CC) in each busbar$i$ as expressed in snippet (3.18), the CCB is calculated using equation (3.19)

$$\begin{cases} CC_i = SMs\ Current, if\ SMs_z \in busbar\ i \\ CC_i = 0\ in\ other\ cases \end{cases} \quad (3.18)$$

$[CCB] = [BCM].[CC]$(3.19)

Where

[CCB]= Current in Branches

[BCM]=Branches Connection Matrix

[CC]= Current Consumption

3.5 Developed Method for the NTLs Location

The developed method involved the use of branch current state estimation to estimate the current at each branch of the network. Theirvalues is compared with the actual value which is supposed to flow assuming energy theft has not occurred. Figure 3.3 shows the Localization flowchart.

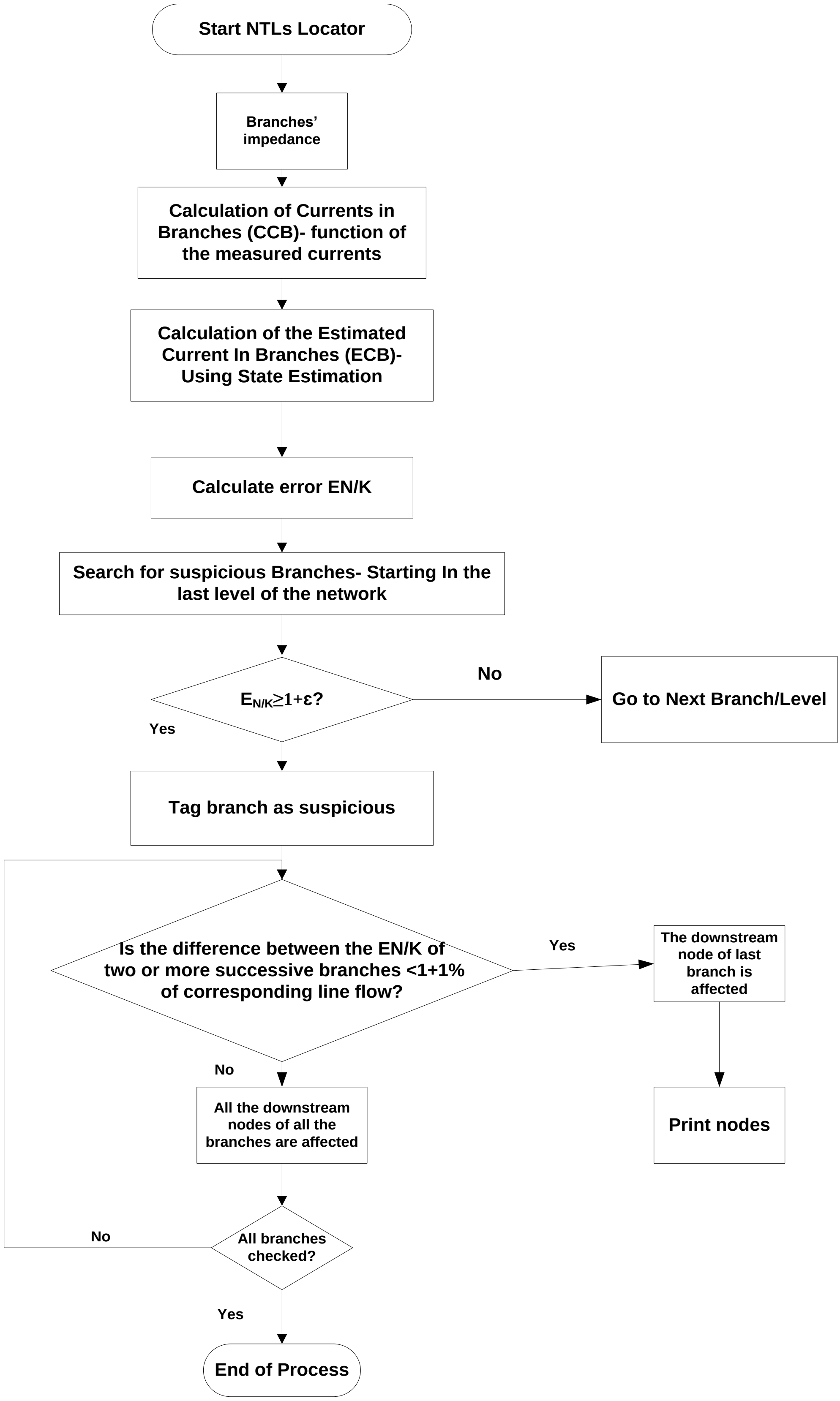

Figure 3.3: Developed Flowchart for Localization of NTLs

Figure 3.3 could be further explained as follows:

I. Input the Network parameters (Line resistances and reactance) together with the captured load at each bus of the network as recorded in the Meter Data Management System.
II. Calculate the branch current of each branch using the smart meter measurement
III. Estimate the branch current using state estimator, the calculated branch current in II serves as the initial values of current injected in the state estimator.
IV. Calculate the relative error (difference between the calculated current and the estimated branch currents)
V. Use the value obtain in IV to search for suspicious branch starting from the last busbar of the Network
VI. If the difference in IV is greater the threshold (1+1%) set for localization, tag the branch as suspicious move if not go to next branch.
VII. Refresh the currents injected into the nodes and send an alarm to the DSO
VIII. Do VI for all branch
IX. End Process.

3.6 Scenario Considered

Three cases are examined to test the effectiveness of this methodology.

Case 1

When the NTLs is 30% of the Total Load and randomly located at five different buses.

Case 2

When the NTLs is 40% of the total Contracted Load and the randomly spread across ten buses of studied network.

Case 3

When the NTLs is 50% of the Total Load and randomly spread across fifteen buses of the studied test case feeder.

3.7 Modification of the Test case Feeder.

The test case feeder was modified in order to test the improvement of this methodology as follows:

- All the DG of the test feeder was removed.
- Single phase equivalent of the original three phase network was calculated and used.

3.8 Performance Evaluation.

At the end of this work, the performance of this methodology was evaluated base on three factors:

1. **True Positive Rate:** This describes the actual performance of the improved algorithm. It gives the percentage of NTLs Locations correctly detected among the total number of NTLs Location Present. This is calculated mathematically using Equation

   $$TPR = \frac{NLD}{NP} \times 100\% \quad (3.17)$$

   Where

   TPR is the percentage of success obtained.

   NP is the number of NTLs Location present

   NLD is the numbers of NTLs Location Detected

2. **False Positive Rate:** This describes the limitation of the performance of this algorithm. It gives the percentage of NTLs Location Detected but not actually present. It is calculated using equation

   $$FPR = \frac{NWD}{NP} \times 100\% \quad (3.18)$$

   Where NWD is the number locations detected wrongly.

3. **No Detection Rate:** This gives the percentage of undetected locations of NTLs present in the network it is calculated using equation

$ND = 1OO - TPR$ (3.19)

Where

TPR is the percentage of success obtained.

These factors serve as the performance matrix used to measure the success and the robustness of the developed methodology.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents the results obtained and the discussion of the results. The implementation of the work was done on the test case feeder used by Marques *et al*., (2016) with a little modification. The comparison of the results obtained between the developed method and the work of Marques *et al.*, (2016) are also presented in this chapter.

4.2 Assumption Made

In the course of this work the following assumptions have been made in order to assess the workability and the robustness of the developed methodology.

i. All the customers on the network uses smart meters, and customer's data are communicated through Power Line Communication (PLC) Technology.

ii. The Location of the theft was randomly generated.

iii. The value of each NTLs varies between 80% and 200% of the contracted power of the respective customer.

4.3 Calculation of the errors for the Detection and Localization of NTLs

In order to obtain a relatively more accurate detection and localization of NTLs, a margin of acceptable error is considered. These errors which might be due to incomplete modelling of the characteristics of the network and the measurement data, was carefully considered to reduce the percentage of false positive rate. In this section, the calculation of the Per Phase Error (PPE) is demonstrated.

4.3.1 Calculation of the Per Phase Error (PPE).

Following the description of the methodology of detection explain in subsection 3.12 the PPE of the network used as test case is shown in Figure 4.1

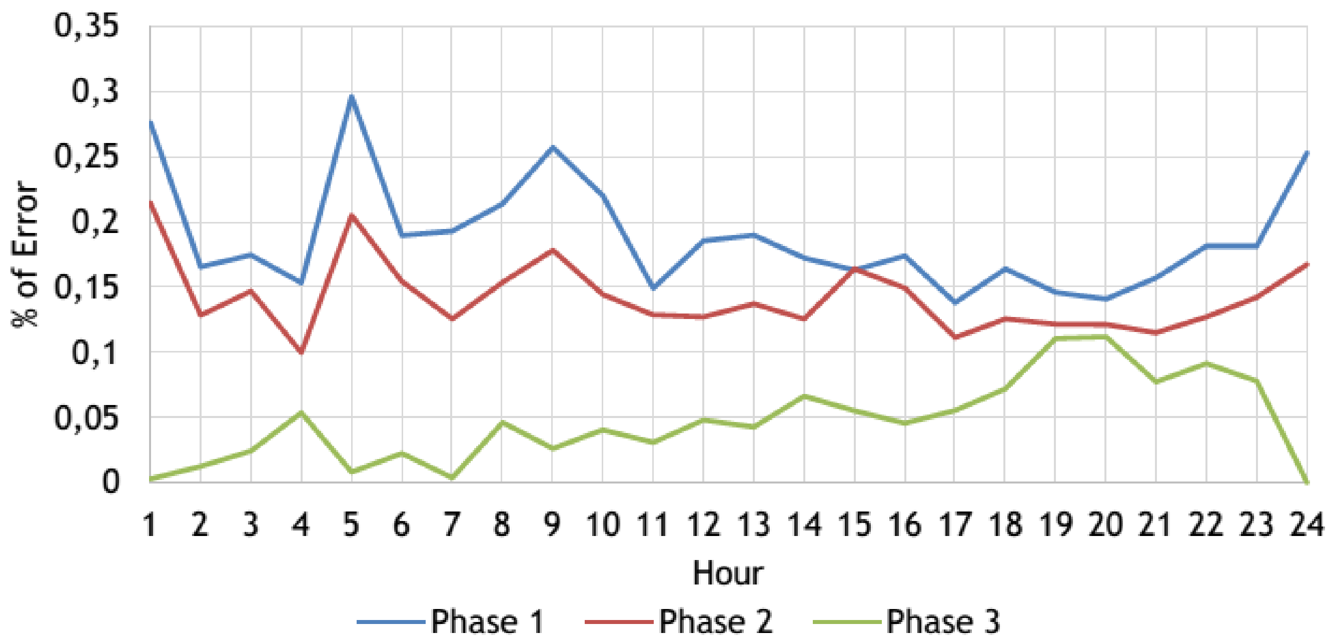

Figure 4.1 Per Phase Error evolution during the day

As it can be seen in Figure 4.1, the PPE is higher in phase 1 than in the other phases with a maximum value of 0.3% .Considering that the load may present variations and influencing the PPE, this value is increased in 30% and is considered the same error for the three phases.

Thus the PPE considered is given by equation 4.1

PPE=0.3 *1.3=0.39% (4.1)

The interpretation of the value obtained in equation 4.1 is that the maximum difference between the DTC reading and smart meter reading that should be allowed before concluding on the presence of NTLs should not exceed 0.39% of the DTC reading.

4.3.2 Result of the localization error for location of NTLs

The accuracy of Localization of NTLs is completely dependent on the accuracy of the estimation technique used. For the case of the state estimation, the variation in estimated branch current values varies with the percentage of NTLs associated with the Network.

Two hundred Monte Carlo simulations were performed with different measurement set to evaluate the average performance of the WLS state estimator. Figure 4.2, 4.3, 4.4 show the variations in estimated branch current for different percentage of measurement errors.

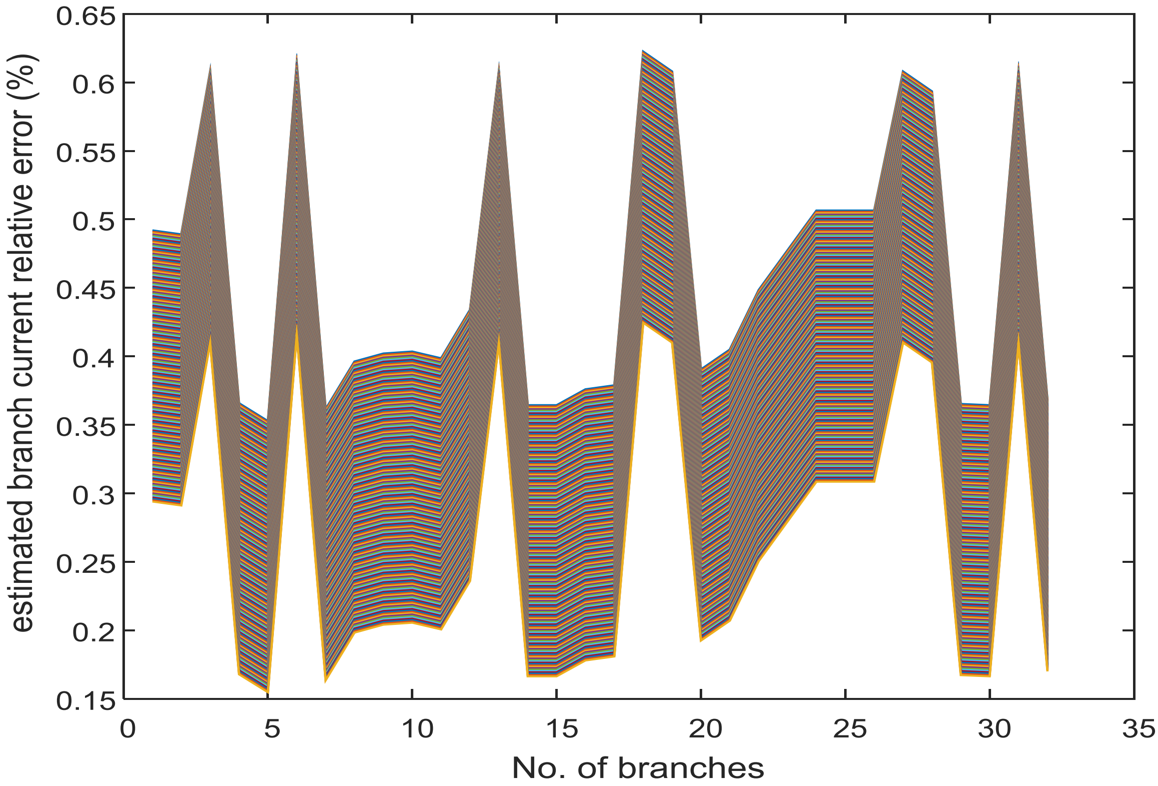

Figure 4.2: Relative error in estimated branch current (accurate voltage measurement and 30% power flow measurement)

Figure4.2, shows the percentage relative error in estimated branch current when the power theft on the network is 30% of the actual recorded consumer's consumption at that time. From the graph, it is seen that the relative error varies from node to node. For instance, at node five (5) the maximum relative error is 0.35%, at node ten (10) it is 0.38%, the maximum variation of the estimated branch current from the actual branch current is 0.61% of the actual branch current, this value is achieved after considering different measurement set of discrete variations from themean value of the actual current flow. This value will be used to determine a threshold above which a branch is tagged as affected branch when the total NTLs is the system is 30% of the total load captured.

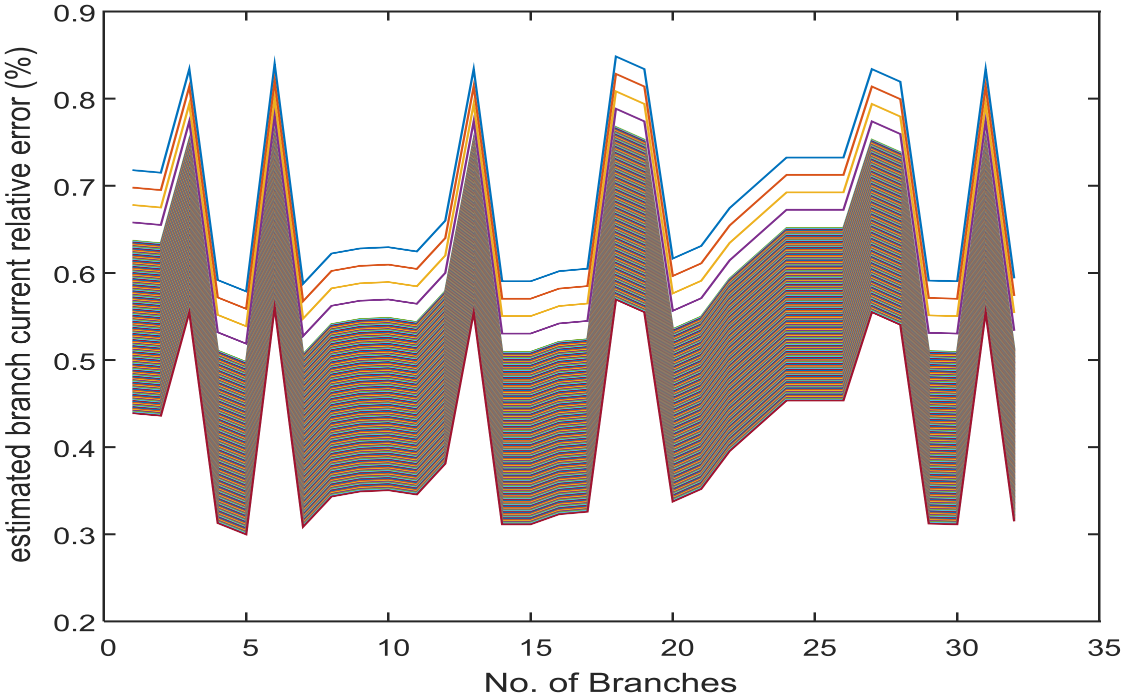

Figure 4.3: Relative error in estimated branch current (real-time voltage measurement and 40% power flow measurement)

Figure 4.3, shows the percentage relative error estimated branch current when the power theft on the network is 40% of the actual recorded consumer's consumption at that time. From the graph, it is seen that the maximum variation of the of the estimated branch current from the actual branch current flow is 0.83% of the actual branch current, this value is achieved after considering different measurement set of discrete variations from the mean value of the actual current flow.These values will be used to determine a threshold above which a branch is tagged as affected branch when the total NTLs is the system is 40% of the total load captured.

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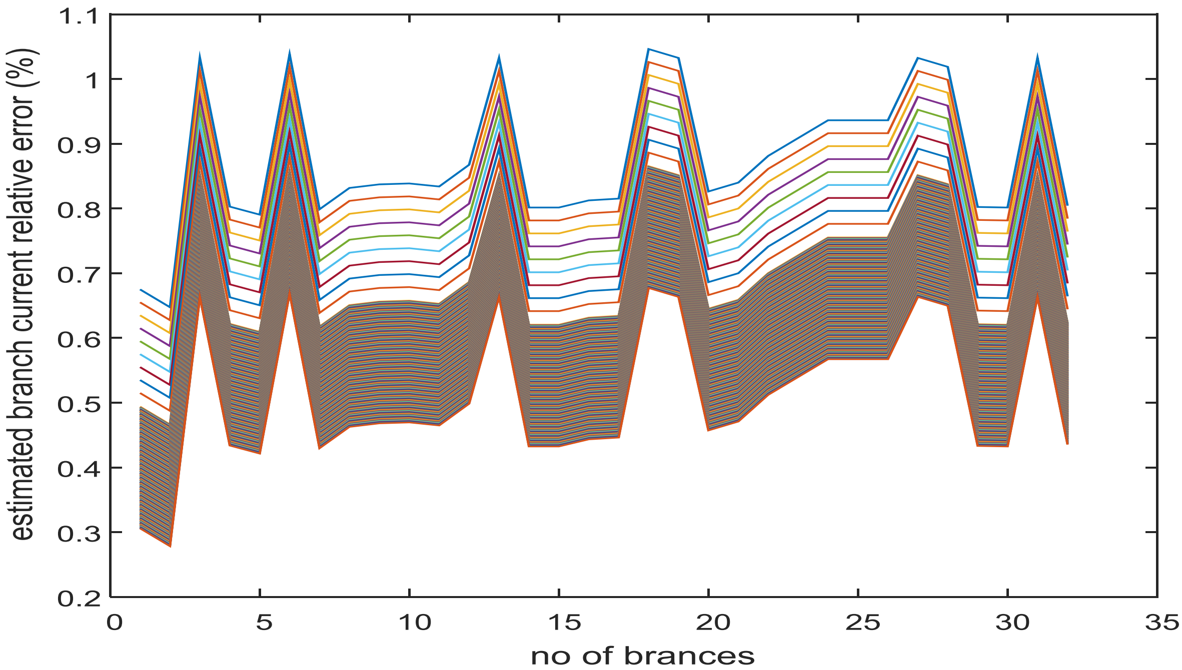

Figure 4.4: Relative error in estimated branch current (real-time voltage measurement and 50% power flow measurement)

Figure 4.3, shows the percentage relative error estimated branch current when the power theft on the network is 50% of the actual recorded consumer's consumption at that time. From the graph, it is seen that the maximum variation of the of the estimated branch current from the actual branch current flow is 1.02% of the actual branch current, this value is achieved after considering different measurement set of discrete variations from the mean value of the actual current flow. This value is subtracted from the result of the state estimator before the procedure for localization is proceeded.

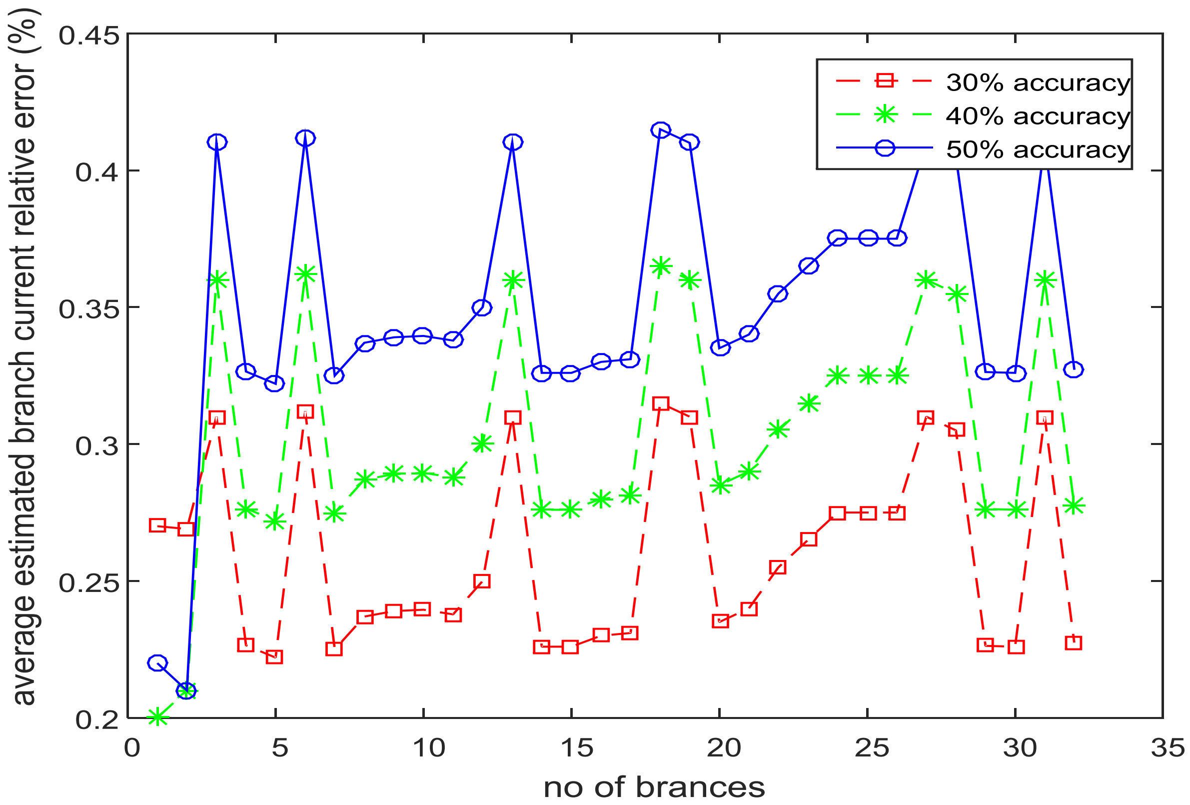

Figure 4.5: Average estimated branch current relative error

Figure 4.5 shows the average of the estimated branch current error for 30%, 40%, 50% measurement errors, these are achieved after 200 Monte Carlo simulations of measurements. From Figure 4.5 it can be observed that the maximum point of the average variation of 30%, 40%, and 50% measurement errors are 0.21%, 0.261% and 0.318% respectively.

These values will be used as safe margin for locational error depending on the percentage of theft in the network. For example, if the theft in the network is 50% of the total load in the network, the difference between the Estimated Branch Current (ECB) and Calculated Branch Current (CCB) should not exceed (1+1%) of estimated current. But if the error is between the 40% - 50%, the average estimated relative error will be used as benchmark for decision making.

4.4 Simulation and Result Analysis for Detection methodology.

Extra loads (considered as NTLs) of 30%, 40% and 50% of total load on a phase on a network was created and randomly shared among five, eight and nine randomly selected busbars of the network. The state estimation is run when the load is systematically spread among all the branches of the network. Since the customers per phase are known, a per phase analysis is performed. The result of the simulation is shown in Figure 4.6

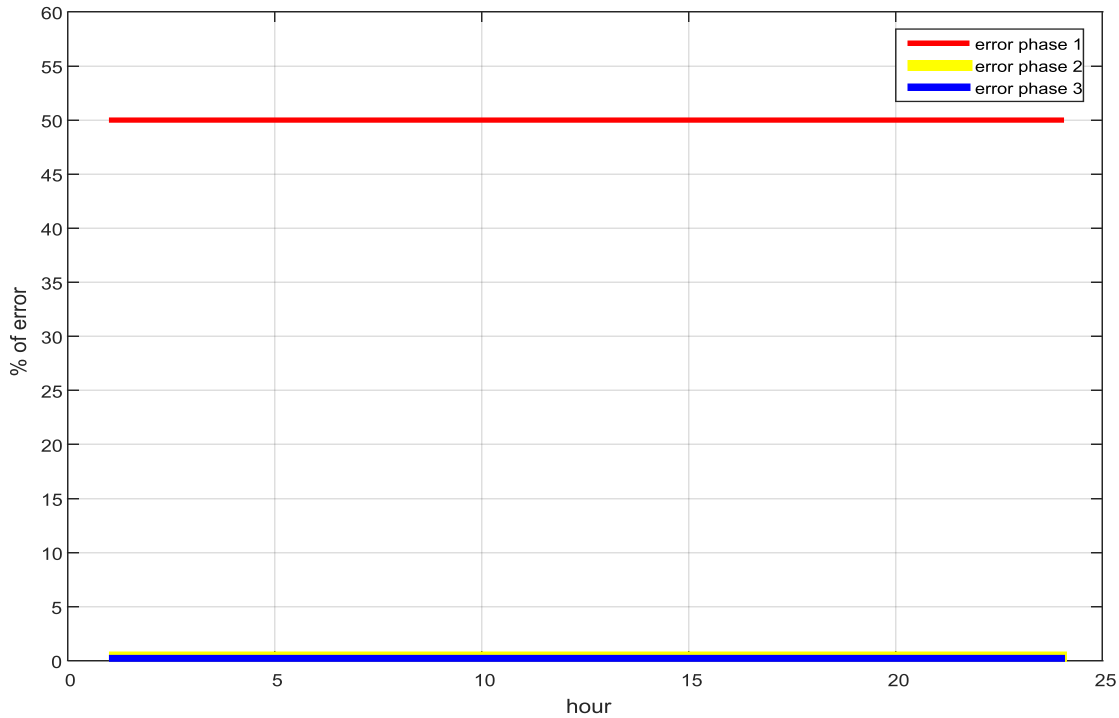

Figure 4.6: Result of detection considering 50% energy theft.

AsshowninFigure 4.6 duetothepresenceofNTLsinphase1,theerrorinthesame phaseis higher thanthe PFE value described in Figure 4.1.In the other phases the error is lower than the PFE values due to the absence of NTLs.

4.4.1 Simulation and result analysis for localization methodology.

After the NTLs is confirmed through the process of detection, the next stage which is the localization of the energy theft is proceed.

Inthissectionthe developed methodologyisassessedconsideringthedifferent scenarios detailedinSection 3.6.Theevaluationisperformedanalysingthecasescorrectly identified (true positive (TP) cases), the cases incorrectly identified (False Positives (FP) cases) and the cases Non-Detected (ND). This evaluation is performed varying the number of locations under the presence of NTLs.

Forthescenario1themainstepsoftheadvancedmethodologytolocateNTLsare also included.

In order to assess the developed methodology, a worst case scenario where the NTLs is 50% of the total network load has been picked. These thefts are shared equally among nine randomly selected bus bars. As explained in the localization flow chart, after the ECB has been calculated through state estimation, the EN/K which represent the difference between the ECB and CCB is also calculated to locate exactly the node at which theft is actually taking place. Table 4.1, 4.2, 4.3 contains the result of the estimated ECB, calculated CCB and EN/K respectively.

Table 4.1 Branches affected by theft -A

Branch	ECB(A)	CCB(A)	EN/K(A)	Affected branches
1-3				
3-7	132.88	100.21	32.69	Yes
7-13	72.957	56.032	16.925	yes
13-20	44.19	28.042	16.148	Yes
20-27	44.23	28.042	16.188	Yes
27-31	16.107	0	16.107	Yes
31-33	0.13	0	0.13	No

Table 4.1 gives the value obtained when the CCB and the ECB of the first section of feeder branch i.e from node 1 to node 33 was evaluated, as seen from the table, the difference of ECB and CCB of allthe sub branch of that section has a value much greater than the acceptable margin except branch 31-33.This allow the methodology to classify the branch 31-33 as branch not affected by theft. It is quite important to note that a branch may be affected by theft current but might not be the actual branch the act of theft is taking place.

Table 4.2 Branches affected by theft -B

Branch	ECB(A)	CCB(A)	EN/K(A)	Affected branches
1-3				
3-6	75.679	43.759	31.92	Yes
6-12	60.958	29.189	31.77	Yes
12-19	46.187	14.596	31.591	Yes
19-26	31.409	0	31.409	Yes
26-30	15.706	0	15.706	Yes

Also Table 4.2 gives the value obtained when the CCB and the ECB of the first section of feeder branch i.e from node 1 to node 30 was evaluated, as seen from the table, the difference of ECB and CCB of all the sub branch of that section has a value much greater than the acceptable margin.

So all the branches of the section are affected by theft current.

Table 4.3 Branches affected by theft -C

Branch	ECB(A)	CCB(A)	EN/K(A)	Affected branches
1-4	108.03	44.261	63.769	Yes
4-8	107.97	44.261	63.709	Yes
8-15	62.925	0	62.925	Yes
15-23	47.257	0	47.257	Yes
23-28	31.45	0	31.45	Yes
28-32	15.733	0	15.73	Yes

From Table 4.3, the value obtained when the CCB and the ECB of the first section of feeder branch i.e from node 1 to node 32 was also evaluated, as seen from the table, the difference of ECB and CCB of all the sub branch of that section has a value much greater than the acceptable margin. So all the branches of the section are affected by theft current.

Table 4.4 Branches affected by theft -D

Branch	ECB(A)	CCB(A)	EN/K(A)	Affected branches
1-2	147.74	130.78	16.96	Yes
2-5	133.02	116.21	16.81	Yes
5-10	30.395	14.288	16.107	Yes

Also Table 4.2 gives the value obtained when the CCB and the ECB of the first section of feeder branch i.e from node 1 to node 10 was evaluated, as seen from the table, the difference of ECB and CCB of all the sub branch of that section has a value much greater than the acceptable margin.

So all the branches of the section is affected by theft current.

The location of the exact busbar the theft took place was done by comparing the EN/K of successive branches.

Branch 3-7 has EN/K of 32.69 and branch 7-13 has EN/K of 16.925 since the reduction in current between the two successive branches is greater than the acceptable error then the node joining the two branches is picked as the point of theft, therefore bus-bar seven is affected. The same procedure is repeated for branch 7-13 and 13-20, the difference between the EN/K is 0.777 which is less than the margin of acceptable error therefore the next branch is proceeded.

This is done for all the branches and the final result was obtained. Table 4.5 shows the successfully identified locations.

Table 4.5 Identified Busbars

Phase	Busbar
1	7
1	31
1	26
1	30
1	15
1	23
1	28
1	32
1	10

The difference between the EN/k of branch 1-3 and branch 3-7, 3-6 has a value of 31.95, this will make the algorithm to falsely detect busbar 3 as point of theft, but in actual sense it is not, this is because branch 1-3 is a parent branch to branches 3-6 and 3-7 and the load along each of the child branch might be seen as NTLs. Figure 4.7 shows the graphical representation of the performance of this method varying the number of locations.

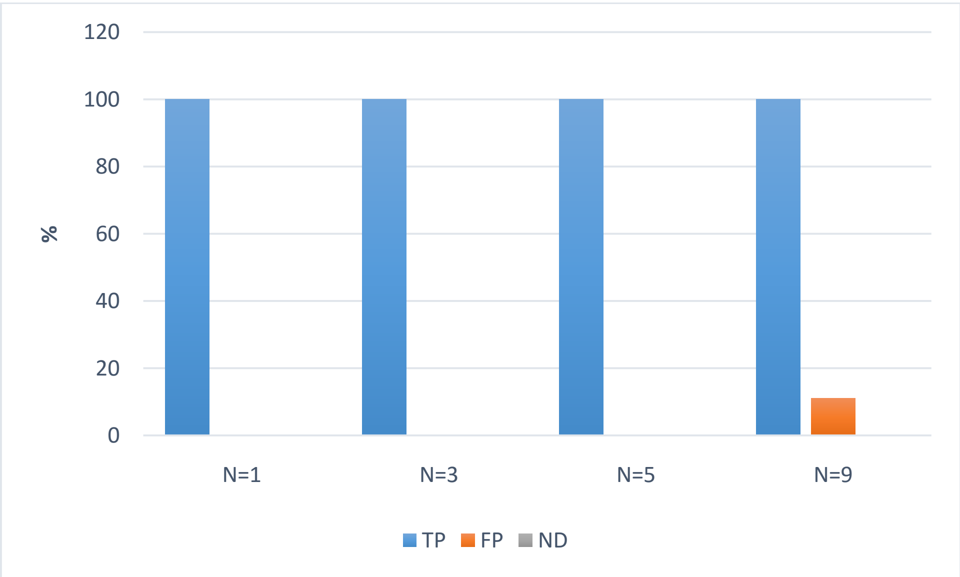

Figure 4.7: Result for location varying the number of locations, N, with NTLs.

Figure 4.7 shows that when the number of locations is between one and five the TPR was 100% and the NPR and ND was 0% but as the number of locations grow to nine the NPR became 11.11% but the ND remain at 0%.

4.5 Validation of the Improved Method

The results of the improved method are compared with the work of marques *et al,*.(2016) the performance metric used for the comparison are True Positive Rate (TPR), False Positive Rate (FPR), and No Detection Rate (NDR) and the comparison is done on the typical Portuguese Low Voltage Network.

In the developed method, the TPR (which signifies the success rate of the method) obtained is 100% but the FPR and NDR are 11.11%, 0% respectively.

For Marques *et al.*, (2016) the highest TPR, FPR, and NDR obtained was 72.5%, 20% and 3% respectively when the number of location is five which is the highest simulated. Figure 4.8 shows the improvement achieved using the developed method when compared with the work of Marques *et al., (*2016).

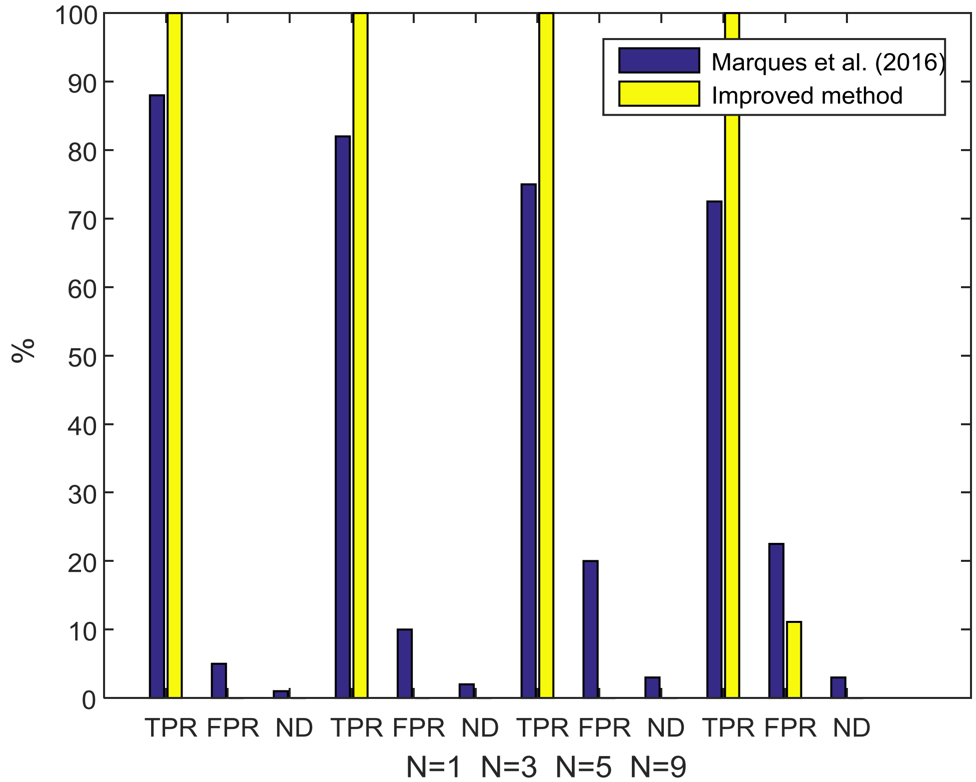

Figure 4.8.Comparison of the performance between the base method and the developed method.

As it can be seen from Figure 4.8, the blue bars represent the results of Marques *et al., (*2016) while the yellow bars represent the results of the developed method. The TPR, FPR and ND results are compared with that of Marques *et al*., (2016) when the number of location N, vary between one and nine. The result shows that the Marques et al., (2016) method has a decreasing TPR and an increasing FPR as the number of locations increases from one to nine, and the developed method has a better performance in terms of TPR ranging from 12% to 27.5 % when compared with the work of Marques *et al.*, (2016). Also there is an improvement 11.11% in terms of FPR, in conclusion, irrespective of number of locations the developed method as no case of Non Detection.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1 Summary

Development of branch current State estimation algorithm for the Localization of NTLs has been presented to reduce the False Positive Rate and increase the True Positive Rate. In the work, problem associated with distribution state estimation was stated, fundamental concept and literature on similar work were reviewed. Material and methods used in achieving the research work were presented and also results obtained were discussed. Conclusion drawn were presented, limitation and recommendation for further work were also presented.

5.2 Conclusion

This research work presents a development of branch current based state estimation for optimal Detection and Localization of NTLs in an LV Network. The state estimation is used to estimate the branches current of the Network during theft which serve as the core values for localization. The percentage of the theft with respect to total load of the network is calculated during the detection phase of the methodology. The power flow simulation and the distribution state estimation were implemented in OPENDSS 7.6.5.52 and MATLAB2015a respectively. From the analysis done, it was observed that the maximum variations in estimated branches' current when the theft in the network are 30%, 40%, and 50% of total load are 0.62%, 0.83%, 1.02% respectively. These values serve as the bases for setting margin of acceptable error which increase the performance of the Localization algorithm. Furthermore it was also observed that when the number of locations are within one to five the False Positive Rate and No Detection Rate are 0% but as the no of location increases to nine the false positive rate increases to 11.11%, it is evident that the developed method has a better performance in term of improvement in True Positive rate and reduction in False Positive Rate over the work of Marques et al., (2016).

5.3 Significant Contribution

The significant contributions of this research work are as follows:

1. Development of Branch current based state estimation for the estimation of branch current of a Network affected with theft.

2. The optimized method achieved TPR of 100% irrespective of the number of locations of energy theft as far as the total energy theft does not exceed 50% of the total load. This is a significant development when compared to the work of Marques et al. which has a maximum location of 5 at 72.5% TPR, 20% FPR, and 3% NDR.

5.4 Limitations

The aim of this research work is successfully achieved, but some of the limitations of this research work are highlighted as follows:

1. Only theft of higher current rating are considered.

2. The Per Phase analysis does not take into cognizance the effect of mutual impedance.

Recommendations

This dissertation work can be further extended to the following areas of research:

1. TheincorporationofanArtificialIntelligenceMethod(AIM)forthe locationofNTLswhenthetopologyofthenetwork is not known.
2. A further improvement in the methodology could be achieved by evaluating the margin of the acceptable error for the location of NTLs, considering the load imbalance present in the network. This may be performed using power flowstudies, without the presence of

NTLs, by analyzingthedifferencebetweenthecurrentsestimatedinbranchesandthecurrents provided by the power flow studies.

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APPENDIX A

Table A1 – Consumers' Contracted Powers

BusbarPhase A (kVA) Phase B(kVA) Phase C (kVA)
23.453.45 0
5003.45
63.4500
710.3500
80 0 6.9
9 6.93.453.45
10 3.45 10.350
113.450 6,9
12 3.45 3.450
13 6.9 3.45 3.45
1606.9 0
17 10.35 0 0
180 3.45 3.45
19 3.45 3.450
200 3,45 3.45
2106.9 0
2210.35 3.45 3.45
230 03.45
2406.910.35
250 3.45 10.35
260 10.350
276.93.453.45
2806.9 0
29 3.45 3.45 10.35
300 010.35
3106.9 0
3203.453.45
330 03.45

Table A2 – Branches' Impedances

Branch	From Busbar	To Busbar	R [Ω] (Phase and Neutral)	X [Ω] (Phase and Neutral)
1 1 2 0.05670.0085				
2 13 0.01900.0040				
3 1 40.03670.0055				
42 5 0.03100.0065				
53 6 0.07690.0180				
63 70.07000.0105				
7 480.06670.0100				
8 5 90.04670.0070				
9 5100.10400.0053				
10 5110.21870.0105				
11 6120.29170.0140				
12 7130.02330.0035				
13 8140.19890.0098				
14 8150.12420.0098				
15 9160.02330.0035				
1611 170.24960.0053				
1711180.09550.0075				
1812190.03810.0080				
1913 200.15280.0120				
2013 210.48410.0158				
2114 220.12120.0255				
2215230.26740.0210				
2316 240.04670.0035				
2418250.16140.0053				
2519260.02380.0050				
2620270.18750.0090				
2723280.09350.0210				
2824290.18440.0060				
2926 300.05330.0040				
3027 310.21420.0105				
3128 320.32270.0105				

APPENDIX B
Opendss code for dss load flow

```
Clear all;

newcircuit.mycode     bus=sourcebuspu=1.05      basekv=15     Angle=0    r1=0      x1=0.001      r0=0     x0=0.001

Redirect transformer_code.dss
Redirect linecode.dss
Redirect Linegeometry.dss
Redirect line.dss
Redirect Loadshape.dss
Redirect loadcode.dss
Redirect monitor.dss

New Energymeter.meter1    element=Line.L1   terminal=1  peakcurrent=(470 491 515)

Set Voltagebases=[15  0.4]
Calcvoltagebases

set mode=daily
Set stepsize=1h
Set Number=24
solve

//code for loads//

New Load.Ld1 phase=1 Bus=2.1.0 kv=0.24 kva=3.45 PF=0.88 model=1 daily=Semana
New Load.Ld2 phase=1 Bus=2.2.4 kv=0.24 kva=3.45 PF=0.88 model=1 daily=Semana
New Load.Ld3 phase=1 Bus=5.3.4 kv=0.24 kva=23.45 PF=0.88 model=1 daily=Semana
New Load.Ld4 phase=1 Bus=6.1.4 kv=0.24 kva=3.45 PF=0.88 model=1 daily=Semana
New Load.Ld5 phase=1 Bus=7.1.4 kv=0.24 kva=10.35 PF=0.88 model=1 daily=commercial
New Load.Ld6 phase=1 Bus=8.3.4 kv=0.24 kva=6.9 PF=0.88 model=1 daily=naija1
New Load.Ld7 phase=1 Bus=9.1.4 kv=0.24 kva=6.9 PF=0.88 model=1 daily=naija1
New Load.Ld8 phase=1 Bus=9.2.4 kv=0.24 kva=3.45 PF=0.88 model=1 daily=Semana
New Load.Ld9 phase=1 Bus=9.3.4 kv=0.24 kva=3.45 PF=0.88 model=1 daily=Semana
New Load.Ld10 phase=1 Bus=10.1.4 kv=0.24 kva=3.45 PF=0.88 model=1 daily=Semana
New Load.Ld11 phase=1 Bus=10.2.4 kv=0.24 kva=10.35 PF=0.88 model=1 daily=commercial
New Load.Ld12 phase=1 Bus=11.1.4 kv=0.24 kva=3.45 PF=0.88 model=1 daily=Semana
New Load.Ld13 phase=1 Bus=11.3.4 kv=0.24 kva=6.9 PF=0.88 model=1 daily=naija1
New Load.Ld14 phase=1 Bus=12.1.4 kv=0.24 kva=3.45 PF=0.88 model=1 daily=Semana
New Load.Ld15 phase=1 Bus=12.2.4 kv=0.24 kva=3.45 PF=0.88 model=1 daily=Semana
New Load.Ld16 phase=1 Bus=13.1.4 kv=0.24 kva=6.9 PF=0.88 model=1 daily=naija1
New Load.Ld17 phase=1 Bus=13.2.4 kv=0.24 kva=3.45 PF=0.88 model=1 daily=Semana
New Load.Ld18 phase=1 Bus=13.3.4 kv=0.24 kva=3.42 PF=0.88 model=1 daily=Semana
New Load.Ld19 phase=1 Bus=16.2.4 kv=0.24 kva=6.9 PF=0.88 model=1 daily=naija1
New Load.Ld20 phase=1 Bus=17.1.4 kv=0.24 kva=10.35 PF=0.88 model=1 daily=commercial
New Load.Ld21 phase=1 Bus=18.2.4 kv=0.24 kva=3.45 PF=0.88 model=1 daily=Semana
New Load.Ld22 phase=1 Bus=18.3.4 kv=0.24 kva=3.45 PF=0.88 model=1 daily=Semana
New Load.Ld23 phase=1 Bus=19.1.4 kv=0.24 kva=3.45 PF=0.88 model=1 daily=Semana
New Load.Ld24 phase=1 Bus=19.2.4 kv=0.24 kva=3.45 PF=0.88 model=1 daily=Semana
New Load.Ld25 phase=1 Bus=20.2.4 kv=0.24 kva=3.45  PF=0.88 model=1 daily=Semana
New Load.Ld26 phase=1 Bus=20.3.4 kv=0.24 kva=3.45 PF=0.88 model=1 daily=Semana
New Load.Ld27 phase=1 Bus=21.2.4 kv=0.24 kva=3.45 PF=0.88 model=1 daily=Semana
```

```
New Load.Ld28 phase=1 Bus=22.1.4 kv=0.24 kva=10.35 PF=0.88 model=1 daily=commercial
New Load.Ld29 phase=1 Bus=22.2.4 kv=0.24 kva=3.45 PF=0.88 model=1 daily=Semana
New Load.Ld30 phase=1 Bus=22.3.4 kv=0.24 kva=3.45 PF=0.88 model=1 daily=Semana
New Load.Ld31 phase=1 Bus=23.3.4 kv=0.24 kva=3.45 PF=0.88 model=1 daily=Semana
New Load.Ld32 phase=1 Bus=24.2.4 kv=0.24 kva=6.9 PF=0.88 model=1 daily=naija1
New Load.Ld33 phase=1 Bus=24.3.4 kv=0.24 kva=10.35 PF=0.88 model=1 daily=commercial
New Load.Ld34 phase=1 Bus=25.2.4 kv=0.24 kva=3.45 PF=0.88 model=1 daily=Semana
New Load.Ld35 phase=1 Bus=25.3.4 kv=0.24 kva=10.35 PF=0.88 model=1 daily=commercial
New Load.Ld36 phase=1 Bus=26.2.4 kv=0.24 kva=3.45 PF=0.88 model=1 daily=Semana
New Load.Ld37 phase=1 Bus=27.1.4 kv=0.24 kva=6.9 PF=0.88 model=1 daily=naija1
New Load.Ld38 phase=1 Bus=27.2.4 kv=0.24 kva=3.45 PF=0.88 model=1 daily=Semana
New Load.Ld39 phase=1 Bus=27.3.4 kv=0.24 kva=3.45 PF=0.88 model=1 daily=Semana
New Load.Ld40 phase=1 Bus=28.2.4 kv=0.24 kva=6.9 PF=0.88 model=1 daily=naija1
New Load.Ld41 phase=1 Bus=29.1.4 kv=0.24 kva=3.45 PF=0.88 model=1 daily=Semana
New Load.Ld42 phase=1 Bus=29.2.4 kv=0.24 kva=3.45 PF=0.88 model=1 daily=Semana
New Load.Ld43 phase=1 Bus=29.3.4 kv=0.24 kva=10.35 PF=0.88 model=1 daily=commercial
New Load.Ld44 phase=1 Bus=30.3.4 kv=0.24 kva=10.35 PF=0.88 model=1 daily=commercial
New Load.Ld45 phase=1 Bus=31.2.4 kv=0.24 kva=6.9 PF=0.88 model=1 daily=naija1
New Load.Ld46 phase=1 Bus=32.2.4 kv=0.24 kva=3.45 PF=0.88 model=1 daily=Semana
New Load.Ld47 phase=1 Bus=32.2.4 kv=0.24 kva=3.45 PF=0.88 model=1 daily=Semana
New Load.Ld48 phase=1 Bus=33.3.4 kv=0.24 kva=3.45 PF=0.88 model=1 daily=Semana
```

```
// CODE for lines//
```

```
New Line.L1  phases=1   Bus1=1   bus2=2    rmatrix=(0.0567)  xmatrix=(0.0085)  Length=0.05 units=km
New Line.L2  phases=1   Bus1=1   bus2=3    rmatrix=(0.0190)  xmatrix=(0.0040)  Length=0.05 units=km
New Line.L3  phases=1   Bus1=1   bus2=4    rmatrix=(0.0367)  xmatrix=(0.0055)  Length=0.05 units=km
New Line.L4  phases=1   Bus1=2   bus2=5    rmatrix=(0.0310)  xmatrix=(0.0065)  Length=0.05 units=km
New Line.L5  phases=1   Bus1=3   bus2=6    rmatrix=(0.0769)  xmatrix=(0.0180)  Length=0.05 units=km
New Line.L6  phases=1   Bus1=3   bus2=7    rmatrix=(0.0700)  xmatrix=(0.0105)  Length=0.05 units=km
New Line.L7  phases=1   Bus1=4   bus2=8    rmatrix=(0.0667)  xmatrix=(0.0100)  Length=0.05 units=km
New Line.L8  phases=1   Bus1=5   bus2=9    rmatrix=(0.0467)  xmatrix=(0.0070)  Length=0.05 units=km
New Line.L9  phases=1   Bus1=5   bus2=10   rmatrix=(0.1040)  xmatrix=(0,0053)  Length=0.05 units=km
New Line.L10 phases=1   Bus1=5   bus2=11   rmatrix=(0.2187)  xmatrix=(0.0105)  Length=0.05 units=km
New Line.L11 phases=1   Bus1=6   bus2=12   rmatrix=(0.2917)  xmatrix=(0.0140)  Length=0.05 units=km
New Line.L12 phases=1   Bus1=7   bus2=13   rmatrix=(0.0233)  xmatrix=(0.0035)  Length=0.05 units=km
New Line.L13 phases=1   Bus1=8   bus2=14   rmatrix=(0.1989)  xmatrix=(0.0098)  Length=0.05 units=km
New Line.L14 phases=1   Bus1=8   bus2=15   rmatrix=(0.1242)  xmatrix=(0.0098)  Length=0.05 units=km
New Line.L15 phases=1   Bus1=9   bus2=16   rmatrix=(0.0233)  xmatrix=(0.0035)  Length=0.05 units=km
New Line.L16 phases=1   Bus1=11   bus2=17  rmatrix=(0.2496)  xmatrix=(0.0053)  Length=0.05 units=km
New Line.L17 phases=1   Bus1=11   bus2=18  rmatrix=(0.0955)  xmatrix=(0.0075)  Length=0.05 units=km
New Line.L18 phases=1   Bus1=12   bus2=19  rmatrix=(0.0381)  xmatrix=(0.0080)  Length=0.05 units=km
New Line.L19 phases=1   Bus1=13   bus2=20  rmatrix=(0.1528)  xmatrix=(0.0120)  Length=0.05 units=km
New Line.L20 phases=1   Bus1=13   bus2=21  rmatrix=(0.4841)  xmatrix=(0.0158)  Length=0.05 units=km
New Line.L21 phases=1   Bus1=14   bus2=22  rmatrix=(0.1212)  xmatrix=(0.0255)  Length=0.05 units=km
New Line.L22 phases=1   Bus1=15   bus2=23  rmatrix=(0.2674)  xmatrix=(0.0210)  Length=0.05 units=km
New Line.L23 phases=1   Bus1=16   bus2=24  rmatrix=(0.0467)  xmatrix=(0.0035)  Length=0.05 units=km
New Line.L24 phases=1   Bus1=18   bus2=25  rmatrix=(0.1614)  xmatrix=(0.0053)  Length=0.05 units=km
New Line.L25  phases=1  Bus1=19   bus2=26  rmatrix=(0.0238)  xmatrix=(0.0050)  Length=0.05 units=km
New Line.L26  phases=1  Bus1=20   bus2=27  rmatrix=(0.1875)  xmatrix=(0.0090)  Length=0.05 units=km
New Line.L27  phases=1  Bus1=23   bus2=28  rmatrix=(0.0935)  xmatrix=(0.0210)  Length=0.05 units=km
New Line.L28  phases=1  Bus1=24   bus2=29  rmatrix=(0.1844)  xmatrix=(0.0060)  Length=0.05 units=km
New Line.L29  phases=1  Bus1=26   bus2=30  rmatrix=(0.0533)  xmatrix=(0.0040)  Length=0.05 units=km
New Line.L30  phases=1  Bus1=27   bus2=31  rmatrix=(0.2142)  xmatrix=(0.0105)  Length=0.05 units=km
New Line.L31  phases=1  Bus1=28   bus2=32  rmatrix=(0.3227)  xmatrix=(0.0105)  Length=0.05 units=km
New Line.L32  phases=1  Bus1=31   bus2=33  rmatrix=(0.3227)  xmatrix=(0.0105)  Length=0.05 units=km
```

```
new monitor.SSM1     element=Transformer.Tr1     terminal=1     mode=1     ppolar=no
new monitor.SSM2     element=Transformer.Tr1     terminal=1     mode=0

!//................Code For Line Monitoring................//
new monitor.snap1      element=Line.L1      terminal=1 mode=1      ppolar=no
new monitor.snap2      element=Line.L2      terminal=1 mode=1      ppolar=no
new monitor.snap3      element=Line.L3      terminal=1 mode=1      ppolar=no
new monitor.snap4      element=Line.L4      terminal=1 mode=1      ppolar=no
new monitor.snap5      element=Line.L5      terminal=1 mode=1      ppolar=no
new monitor.snap6      element=Line.L6      terminal=1 mode=1      ppolar=no
new monitor.snap7      element=Line.L7      terminal=1 mode=1      ppolar=no
new monitor.snap8      element=Line.L8      terminal=1 mode=1      ppolar=no
new monitor.snap9      element=Line.L9      terminal=1 mode=1      ppolar=no
new monitor.snap10     element=Line.L10     terminal=1 mode=1      ppolar=no
new monitor.snap11     element=Line.L11     terminal=1 mode=1      ppolar=no
new monitor.snap12     element=Line.L12     terminal=1 mode=1      ppolar=no
```

```
new monitor.snap13      element=Line.L13      terminal=1 mode=1      ppolar=no
new monitor.snap14      element=Line.L14      terminal=1 mode=1      ppolar=no
new monitor.snap15      element=Line.L15      terminal=1 mode=1      ppolar=no
new monitor.snap16      element=Line.L16      terminal=1 mode=1      ppolar=no
new monitor.snap17      element=Line.L17      terminal=1 mode=1      ppolar=no
new monitor.snap18      element=Line.L18      terminal=1 mode=1      ppolar=no
new monitor.snap19      element=Line.L19      terminal=1 mode=1      ppolar=no
new monitor.snap20      element=Line.L20      terminal=1 mode=1      ppolar=no
new monitor.snap21      element=Line.L21      terminal=1 mode=1      ppolar=no
new monitor.snap22      element=Line.L22      terminal=1 mode=1      ppolar=no
new monitor.snap23      element=Line.L23      terminal=1 mode=1      ppolar=no
new monitor.snap24      element=Line.L24      terminal=1 mode=1      ppolar=no
new monitor.snap25      element=Line.L25      terminal=1 mode=1      ppolar=no
new monitor.snap26      element=Line.L26      terminal=1 mode=1      ppolar=no
new monitor.snap27      element=Line.L27      terminal=1 mode=1      ppolar=no
new monitor.snap28      element=Line.L28      terminal=1 mode=1      ppolar=no
new monitor.snap29      element=Line.L29      terminal=1 mode=1      ppolar=no
new monitor.snap30      element=Line.L30      terminal=1 mode=1      ppolar=no
new monitor.snap31      element=Line.L31      terminal=1 mode=1      ppolar=no
new monitor.snap32      element=Line.L32      terminal=1 mode=1      ppolar=no

!//.................Code For Load Monitoring................//
new monitor.camp1      element=Load.Ld1      terminal=1      mode=1      ppolar=no
new monitor.camv1      element=Load.Ld1      terminal=1      mode=0
new monitor.camp2      element=Load.Ld2      terminal=1      mode=1      ppolar=no
new monitor.camv2      element=Load.Ld2      terminal=1      mode=0
new monitor.camp3      element=Load.Ld3      terminal=1      mode=1      ppolar=no
new monitor.camv3      element=Load.Ld3      terminal=1      mode=0
new monitor.camp4      element=Load.Ld4      terminal=1      mode=1      ppolar=no
new monitor.camv4      element=Load.Ld4      terminal=1      mode=0
new monitor.camp5      element=Load.Ld5      terminal=1      mode=1      ppolar=no
new monitor.camv5      element=Load.Ld5      terminal=1      mode=0
new monitor.camp6      element=Load.Ld6      terminal=1      mode=1      ppolar=no
new monitor.camv6      element=Load.Ld6      terminal=1      mode=0
new monitor.camp7      element=Load.Ld7      terminal=1      mode=1      ppolar=no
new monitor.camv7      element=Load.Ld7      terminal=1      mode=0
new monitor.camp8      element=Load.Ld8      terminal=1      mode=1      ppolar=no
new monitor.camv8      element=Load.Ld8      terminal=1      mode=0
new monitor.camp9      element=Load.Ld9      terminal=1      mode=1      ppolar=no
new monitor.camv9      element=Load.Ld9      terminal=1      mode=0
new monitor.camp10      element=Load.Ld10      terminal=1      mode=1      ppolar=no
new monitor.camv10      element=Load.Ld10      terminal=1      mode=0
new monitor.camp11      element=Load.Ld11      terminal=1      mode=1      ppolar=no
new monitor.camv11      element=Load.Ld11      terminal=1      mode=0
new monitor.camp12      element=Load.Ld12      terminal=1      mode=1      ppolar=no
new monitor.camv12      element=Load.Ld12      terminal=1      mode=0
new monitor.camp13      element=Load.Ld13      terminal=1      mode=1      ppolar=no
new monitor.camv13      element=Load.Ld13      terminal=1      mode=0
new monitor.camp14      element=Load.Ld14      terminal=1      mode=1      ppolar=no
new monitor.camv14      element=Load.Ld14      terminal=1      mode=0
new monitor.camp15      element=Load.Ld15      terminal=1      mode=1      ppolar=no
new monitor.camv15      element=Load.Ld15      terminal=1      mode=0
new monitor.camp16      element=Load.Ld16      terminal=1      mode=1      ppolar=no
new monitor.camv16      element=Load.Ld16      terminal=1      mode=0
new monitor.camp17      element=Load.Ld17      terminal=1      mode=1      ppolar=no
new monitor.camv17      element=Load.Ld17      terminal=1      mode=0
new monitor.camp18      element=Load.Ld18      terminal=1      mode=1      ppolar=no
new monitor.camv18      element=Load.Ld18      terminal=1      mode=0
new monitor.camp19      element=Load.Ld19      terminal=1      mode=1      ppolar=no
new monitor.camv19      element=Load.Ld19      terminal=1      mode=0
new monitor.camp20      element=Load.Ld20      terminal=1      mode=1      ppolar=no
new monitor.camv20      element=Load.Ld20      terminal=1      mode=0
new monitor.camp21      element=Load.Ld21      terminal=1      mode=1      ppolar=no
new monitor.camv21      element=Load.Ld21      terminal=1      mode=0
new monitor.camp22      element=Load.Ld22      terminal=1      mode=1      ppolar=no
new monitor.camv22      element=Load.Ld22      terminal=1      mode=0
new monitor.camp23      element=Load.Ld23      terminal=1      mode=1      ppolar=no
new monitor.camv23      element=Load.Ld23      terminal=1      mode=0
new monitor.camp24      element=Load.Ld24      terminal=1      mode=1      ppolar=no
new monitor.camv24      element=Load.Ld24      terminal=1      mode=0
new monitor.camp25      element=Load.Ld25      terminal=1      mode=1      ppolar=no
new monitor.camv25      element=Load.Ld25      terminal=1      mode=0
new monitor.camp26      element=Load.Ld26      terminal=1      mode=1      ppolar=no
new monitor.camv26      element=Load.Ld26      terminal=1      mode=0
new monitor.camp27      element=Load.Ld27      terminal=1      mode=1      ppolar=no
new monitor.camv27      element=Load.Ld27      terminal=1      mode=0
new monitor.camp28      element=Load.Ld28      terminal=1      mode=1      ppolar=no
new monitor.camv28      element=Load.Ld28      terminal=1      mode=0
```

```
new monitor.camp29    element=Load.Ld29    terminal=1    mode=1    ppolar=no
new monitor.camv29    element=Load.Ld29    terminal=1    mode=0
new monitor.camp30    element=Load.Ld30    terminal=1    mode=1    ppolar=no
new monitor.camv30    element=Load.Ld30    terminal=1    mode=0
new monitor.camp31    element=Load.Ld31    terminal=1    mode=1    ppolar=no
new monitor.camv31    element=Load.Ld31    terminal=1    mode=0
new monitor.camp32    element=Load.Ld32    terminal=1    mode=1    ppolar=no
new monitor.camv32    element=Load.Ld32    terminal=1    mode=0
new monitor.camp33    element=Load.Ld33    terminal=1    mode=1    ppolar=no
new monitor.camv33    element=Load.Ld33    terminal=1    mode=0
new monitor.camp34    element=Load.Ld34    terminal=1    mode=1    ppolar=no
new monitor.camv34    element=Load.Ld34    terminal=1    mode=0
new monitor.camp35    element=Load.Ld35    terminal=1    mode=1    ppolar=no
new monitor.camv35    element=Load.Ld35    terminal=1    mode=0
new monitor.camp36    element=Load.Ld36    terminal=1    mode=1    ppolar=no
new monitor.camv36    element=Load.Ld36    terminal=1    mode=0
new monitor.camp37    element=Load.Ld37    terminal=1    mode=1    ppolar=no
new monitor.camv37    element=Load.Ld37    terminal=1    mode=0
new monitor.camp38    element=Load.Ld38    terminal=1    mode=1    ppolar=no
new monitor.camv38    element=Load.Ld38    terminal=1    mode=0
new monitor.camp39    element=Load.Ld39    terminal=1    mode=1    ppolar=no
new monitor.camv39    element=Load.Ld39    terminal=1    mode=0
new monitor.camp40    element=Load.Ld40    terminal=1    mode=1    ppolar=no
new monitor.camv40    element=Load.Ld40    terminal=1    mode=0
new monitor.camp41    element=Load.Ld41    terminal=1    mode=1    ppolar=no
new monitor.camv41    element=Load.Ld41    terminal=1    mode=0
new monitor.camp42    element=Load.Ld42    terminal=1    mode=1    ppolar=no
new monitor.camv42    element=Load.Ld42    terminal=1    mode=0
new monitor.camp43    element=Load.Ld43    terminal=1    mode=1    ppolar=no
new monitor.camv43    element=Load.Ld43    terminal=1    mode=0
new monitor.camp44    element=Load.Ld44    terminal=1    mode=1    ppolar=no
new monitor.camv44    element=Load.Ld44    terminal=1    mode=0
new monitor.camp45    element=Load.Ld45    terminal=1    mode=1    ppolar=no
new monitor.camv45    element=Load.Ld45    terminal=1    mode=0
new monitor.camp46    element=Load.Ld46    terminal=1    mode=1    ppolar=no
new monitor.camv46    element=Load.Ld46    terminal=1    mode=0
new monitor.camp47    element=Load.Ld47    terminal=1    mode=1    ppolar=no
new monitor.camv47    element=Load.Ld47    terminal=1    mode=0
new monitor.camp48    element=Load.Ld48    terminal=1    mode=1    ppolar=no
new monitor.camv48    element=Load.Ld48    terminal=1    mode=0
C:\Users\Abdulkareem\Documents\my code\master.dss
```

```
%Matlab Code for state estimation.
Clear all;
```

APPENDIX C

```
fbus=Idata(:,3);
tbus=Idata(:,4);
nbus =max(max(fbus),max(tbus));
nbranch =nbus-1;
Ir=Idata(:,6);
Ii=Idata(:,7);
Imod=Ir-(1i*Ii);
Iflow = Imod./696;
Ibus = zeros(nbus,nbus);         % Initialise IBus...

% Formation of the Off Diagonal Elements...
for k=1:nbranch
Ibus(fbus(k),tbus(k)) = Ibus(fbus(k),tbus(k))+ Iflow(k);
Ibus(tbus(k),fbus(k)) = Ibus(fbus(k),tbus(k));
end

% Formation of Diagonal Elements....
for m =1:nbus
for n =1:nbranch
iffbus(n) == m
Ibus(m,m) =0;
elseiftbus(n) == m
Ibus(m,m) = 0;
end
end
end
Ibus;                  % branch current Matrix
```

APPENDIX D

```
num = 33; % Test case feeder code...
ybus = ybusppg(num); % Get YBus..
zbus=1./ybus;
Current=imatrix; Calling the branch current matrix
Volt = Voltage; Calling measurement function equations
zdata = zdatas(num); % Get Measurement data..
bpq = bbusppg(num); % Get B data..
busdata=busdatas(num);%Get Bus data
nbus = max(max(zdata(:,4)),max(zdata(:,5))); % Get number of buses..
type = zdata(:,2); % Type of measurement, Vi - 1, Pi - 2, Qi - 3, Pij - 4, Qij - 5, Iij - 6..
z = zdata(:,3); % Measuement values..
fbus = zdata(:,4); % From bus..
tbus = zdata(:,5); % To bus..
Ri = diag(zdata(:,6)); % Measurement Error..
current = zdata(:,7); % Initial current data measuremnt
I= ones(nbus-1) & Initialize the current vector
angI = zeros(nbus-1); % Initialize the current angle angles.
V = ones(nbus,1); % Initialize the bus voltages...
del=zeros(2:nbus,1)
E = [ang1; I];   % State Vector..
R=real(imatrix);
Im=imag(imatrix);
G = real(zbus);
B = imag(zbus);

vi = find(type == 1); % Index of voltage magnitude measurements..
ppi = find(type == 2); % Index of real power injection measurements..
qi = find(type == 3); % Index of reactive power injection measurements..
pf = find(type == 4); % Index of real powerflow measurements..
qf = find(type == 5); % Index of reactive powerflow measurements..
Iij= find(type==6); % Index of branch current flow measurement....

nvi = length(vi); % Number of Voltage measurements..
npi = length(ppi); % Number of Real Power Injection measurements..
nqi = length(qi); % Number of Reactive Power Injection measurements..
npf = length(pf); % Number of Real Power Flow measurements..
nqf = length(qf); % Number of Reactive Power Flow measurements..
nIb = length(Iij); % Number of branch current floe mesurement..

iter = 1;
tol = 5;

while(tol> 1e-4)

   %Measurement Function, h
   h1 = zeros(nvi,1);
   h2 = zeros(npi,1);
   h3 = zeros(nqi,1);
   h4 = zeros(npf,1);
   h5 = zeros(nqf,1);
   V1 = 0.9


for i = 1:npf
       m = fbus(pf(i));
       n = tbus(pf(i));
       h4(i) = h4(i) + v(m)*I(m,n)*cos(del(m)-del(m,n));

end
```

```
for i = 1:nqf
      m = fbus(qf(i));
      n = tbus(qf(i));
      h5(i) = V(m)*I(m,n)*sin(del(m)-del(m,n));
end

   h = [h1; h2; h3; h4; h5];
   r = z – h;
   H11 = zeros(nvi,nbus-1);
   H12 = zeros(nvi,nbus-1);
for k = 1:nvi
      m=fbus(vi(i));

for n = 1:nbus
if n == k
H12(k,n) = 1;
end
end
end

   H21 = zeros(npi,nbus-1);
for i = 1:npi
      m = fbus(ppi(i));
for k = 1:(nbus-1)
if k+1 == m
for n = 1:nbus
            H21(i,k) = H21(i,k) + I(m,n)*(-G(m,n)*sin(del(m)-del(n)) + B(m,n)*cos(del(m)-del(n)));
end
H21(i,k) = H21(i,k) - V(m)^2*B(m,m);
else
         H21(i,k) = V(m)* V(k+1)*(G(m,k+1)*sin(del(m)-del(k+1)) - B(m,k+1)*cos(del(m)-del(k+1)));
end
end
end

   H22 = zeros(npi,nbus);
for i = 1:npi
      m = fbus(ppi(i));
for k = 1:(nbus)
if k == m
for n = 1:nbus
            H22(i,k) = H22(i,k) + V(n)*(G(m,n)*cos(del(m)-del(n)) + B(m,n)*sin(del(m)-del(n)));
end
H22(i,k) = H22(i,k) + V(m)*G(m,m);
else
         H22(i,k) = V(m)*(G(m,k)*cos(del(m)-del(k)) + B(m,k)*sin(del(m)-del(k)));
end
end
end

   % H31 - Derivative of Reactive Power Injections with Angles..
   H31 = zeros(nqi,nbus-1);
for i = 1:nqi
      m = fbus(qi(i));
for k = 1:(nbus-1)
if k+1 == m
for n = 1:nbus
            H31(i,k) = H31(i,k) + V(m)* V(n)*(G(m,n)*cos(del(m)-del(n)) + B(m,n)*sin(del(m)-del(n)));
end
H31(i,k) = H31(i,k) - V(m)^2*G(m,m);
else
         H31(i,k) = V(m)* V(k+1)*(-G(m,k+1)*cos(del(m)-del(k+1)) - B(m,k+1)*sin(del(m)-del(k+1)));
```

```
end
end
end

   % H32 - Derivative of Reactive Power Injections with Iij..
   H32 = zeros(nqi,nbus);
for i = 1:nqi
      m = fbus(qi(i));
for k = 1:(nbus)
if k == m
for n = 1:nbus
                 H32(i,k) = H32(i,k) + V(n)*(G(m,n)*sin(del(m)-del(n)) - B(m,n)*cos(del(m)-del(n)));
end
H32(i,k) = H32(i,k) - V(m)*B(m,m);
else
             H32(i,k) = V(m)*(G(m,k)*sin(del(m)-del(k)) - B(m,k)*cos(del(m)-del(k)));
end
end
end

   % H41 - Derivative of Real Power Flows with Angles..
   H41 = zeros(npf,nbus-1);
for i = 1:npf
      m = fbus(pf(i));
      n = tbus(pf(i));
for k = 1:(nbus-1)
if k+1 == m
             H41(i,k) = V(m)* V(n)*(-G(m,n)*sin(del(m)-del(n)) + B(m,n)*cos(del(m)-del(n)));
else if k+1 == n
             H41(i,k) = -V(m)* V(n)*(-G(m,n)*sin(del(m)-del(n)) + B(m,n)*cos(del(m)-del(n)));
else
H41(i,k) = 0;
end
end
end
end

   % H42 - Derivative of Real Power Flows with V..
   H42 = zeros(npf,nbus);
for i = 1:npf
      m = fbus(pf(i));
      n = tbus(pf(i));
for k = 1:nbus
if k == m
             H42(i,k) = -V(n)*(-G(m,n)*cos(del(m)-del(n)) - B(m,n)*sin(del(m)-del(n))) - 2*G(m,n)*V(m);
else if k == n
             H42(i,k) = -V(m)*(-G(m,n)*cos(del(m)-del(n)) - B(m,n)*sin(del(m)-del(n)));
else
H42(i,k) = 0;
end
end
end
end

   % H51 - Derivative of Reactive Power Flows with Angles ..
   H51 = zeros(nqf,nbus-1);
for i = 1:nqf
      m = fbus(qf(i));
      n = tbus(qf(i));
for k = 1:(nbus-1)
if k+1 == m
             H51(i,k) = -V(m)* V(n)*(-G(m,n)*cos(del(m)-del(n)) - B(m,n)*sin(del(m)-del(n)));
```

```
else if k+1 == n
        H51(i,k) = V(m)* V(n)*(-G(m,n)*cos(del(m)-del(n)) - B(m,n)*sin(del(m)-del(n)));
else
H51(i,k) = 0;
end
end
end
end

   H52 = zeros(nqf,nbus);
for i = 1:nqf
     m = fbus(qf(i));
     n = tbus(qf(i));
for k = 1:nbus
if k == m
        H52(i,k) = -V(n)*(-G(m,n)*sin(del(m)-del(n)) + B(m,n)*cos(del(m)-del(n))) - 2*V(m)*(-B(m,n)+
bpq(m,n));
else if k == n
        H52(i,k) = -V(m)*(-G(m,n)*sin(del(m)-del(n)) + B(m,n)*cos(del(m)-del(n)));
else
H52(i,k) = 0;
end
end
end
end

   H = [H11 H12; H21 H22; H31 H32; H41 H42; H51 H52];

   % Gain Matrix, Gm..
Gm = H'*inv(Ri)*H;

   %Objective Function..
   J = sum(inv(Ri)*r.^2);

   % State Vector..
dE = inv(Gm)*(H'*inv(Ri)*r);
   E = E + dE;
del(2:end) = E(1:nbus-1);
   V = E(nbus:end);
iter = iter + 1;
tol = max(abs(dE));
end

CvE = diag(inv(H'*inv(Ri)*H)); % Covariance matrix..

Del = 180/pi*del;
E2 = [Iij Del]; % Branch current and angles..
disp('-------- State Estimation ------------------');
disp('--------------------------');
disp('| Branch |  Iij   |  Angle  | ');
disp('| No     |   pu   |  Degree | ');
disp('--------------------------');
for m = 1:n
fprintf('%4g', m); fprintf('  %8.4f', V(m)); fprintf('   %8.4f', Del(m)); fprintf('\n');
end
disp('---------------------------------------------');
```