T.C.
ISTANBUL GEDİK UNIVERSITY
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ELECTRIC DISTRIBUTION NETWORK MANAGEMENT WITH NEURAL NETWORK METHODS

MASTER'S THESIS

Asaad Abdalkareem HAMEED

Engineering Management Department

Engineering Management Master in English Program

JANUARY 2022

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İSTANBUL GEDİK ÜNİVERSİTESİ
LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ MÜDÜRLÜĞÜ

Yüksek Lisans Tez Onay Belgesi

Enstitümüz, Engineering Management Department İngilizce Tezli Yüksek Lisans Programı 191281013 numaralı öğrencisi Asaad Abdalkareem Hameed'in "Electric Distribution Network Management with Neural Network Methods" adlı tez çalışması Enstitümüz Yönetim Kurulunun 05.01.2022 tarihinde oluşturulan jüri tarafından *Oy Birliği* ile Yüksek Lisans tezi olarak *Kabul* edilmiştir.

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DECLARATION

I, Asaad Abdalkareem Hameed, do hereby declare that this thesis titled as "Electric Distribution Network Management with Neural Network Methods" is original work done by me for the award of the masters degree in the faculty of Engineering Management. I also declare that this thesis or any part of it has not been submitted and presented for any other degree or research paper in any other university or institution. (05/01/2021)

Asaad Abdalkareem Hameed

DEDICATION

I'd want to dedicate my modest efforts to completing this work to my family, coworkers, and all of my friends for their unwavering support and encouragement throughout my academic, research, and life journeys. A particular thank you to Prof. Dr. Gözde Ulutagay, my father, mother, and family for their support and prayers throughout my research, as well as to my university, "Istanbul Gedik University".

PREFACE

I'd like to express my gratitude to everyone who has supported me over this journey's routinely prolonged period. I'd want to thank my advisor, Prof. Dr. Gözde ULUTAGAY, for being my compass even when I thought I was lost and for being an exceptional part of this work's pinnacle. I'd also like to express my gratitude to my boss for their encouraging words, which significantly improved the quality of this project. Finally, I believe that this institution has earned its place as my home by hosting me for these years. I owe a debt of gratitude to my parents, whose beliefs and education inspire me to continue moving forward, to my brothers and relatives for their unending love, and to my country, which, despite its suffering, remains steadfast and must rise.

January 2022 Asaad Abdalkareem HAMEED

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ABBREVATIONS

RESs	: Renewable energy sources
ES	: Energy storage
DSSE	: Distribution system state estimation
SCADA	: Supervisory control and data acquisition
WLS	: Weighted Least Squares
PSSE	: Power System Simulator for Engineering
OPF	: Optimal Power Flow
AC-OPF	: Alternating Current-Optimal Power Flow
NP-Hard	: Nondeterministic Polynomial-Hard
DC-OPF	: Direct Current-Optimal Power Flow
NR	: Newton-Raphson
SDR	: Special Drawing Rights
PSEE	: Power System State Estimation
EMS	: Energy Management System
V	: Voltage
I	: Current
P	: Power
Q	: Charge
PMUs	: Phasor Measurement Units
SE	: State Estimation
DG	: Distributed Generation
DSOs	: Distribution System Operators
PMU	: Phasor Measurement Unit
uPMUs	: High-Precision Micro Phasor Measurement Units
$\mathbf{V_n}$	: Total Nodal Voltages
$\mathbf{i_{lm}}$	: Current Flows
NN	: Neural network
GN	: Generation Network
R	: Resistor
jX	: Number of Line Inductor
CSP	: Constraint Satisfaction Problem
DNO	: Distribution Network Operator
DSM	: Demand Side Management
ANM	: Active Network Management
AuRA-NMS	: Autonomous Regional Active Network Management System
LIFO	: Last-In, First-Out Rule
PMUs	: Synchronized Phasor Measurement Units
VPNs	: Virtual Private Networks
ICS	: Internet Connection Sharing
HMI	: Human Machine Interface
KillDisk	: Free Data Destruction Program That Can Securely Erase Every File On a Hard Drive

UPS	: Uninterruptible Power Source
TDoS	: Telephony Denial of Service
WSNs	: Wireless Sensor Networks
PMU	: Phasor Measurement Unit
NPRTool	: Neural Pattern Recognition Tool
FACTS	: Flexible AC Transmission Systems

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ELECTRIC DISTRIBUTION NETWORK WITH NEURAL NETWORK METHODS

ABSTRACT

In the electric power distribution networks, the effective grid management represents the alternative solution to the traditional electric power management, as it provides the possibility of estimating and thus eliminating the stresses of irregular loading in the electric network as well as the ability of time and cost management process.

However, there are many limitations in this administration system. As the previous strategies focus on the generation aspect only. This work is a system based on neural networks used to estimate system variables very accurately, which in turn facilitates the process of managing the electrical network. The results of the proposed algorithm representation on several types of power systems showed good performance, and this is one of the features of neural networks, as it can be trained on huge numbers of information.

The percentage of error in both methods shows how accurate the algorithm is in estimation of system variables.

Keywords: *Electrical energy, Electrical transmission, Electrical network management*

NÖRAL AĞ YÖNTEMLERİYLE ELEKTRİK DAĞITIM ŞEBEKESİ

ÖZET

Elektrik enerjisi dağıtım şebekelerinde, etkin şebeke yönetimi, yönetim süreçleri sırasında, yanı zamanını, maliyeti ve elektrik şebekesindeki düzensiz yük streslerini tahmin etme ayrıca ortadan kaldırma olanağı sağladığından, geleneksel elektrik gücü yönetimine alternatif bir çözüm sunar. Ancak, şimdilik yönetim sisteminde birçok kısıtlamalar vardır. Önceki stratejiler hala yalnızca üretim yönüne odaklanır sadece. O araştırma çalışması, sistem değişkenlerini çok doğru bir şekilde tahmin etmek için kullanılan nöral ağlarına dayalı bir sistemdir ve bu da elektrik şebekesinin yönetimin ödevini kolaylaştırır. Önerilen algoritmanın çeşitli güç sistemleri üzerinde gayet iyi bir performans göstermiştir ve bilgilerin bu çok sayıları üzerinde eğitilebildiği için nöral ağlarının avantajlarından biridir. Her iki yöntemin hata yüzdesi, algoritmanın sistem değişkenlerini tahmin etmesi ne kadar doğru olduğunu gösterir.

Anahtar Kelimeler: *Elektrik enerjisi, Elektrik iletimi, Elektrik ağ yönetimi*

1. INTRODUCTION

The electricity grid is often regarded as the most significant engineering feat of the twentieth century. However, it has become clear over the last few decades that significant components of the power grid's operating capacities, including power generation operating capacities, transmission capacities, distribution capacities, and consumption capacities, will practically need to be revamped for meeting the unprecedented challenges which are the posed by the different demands of the 21st-century. The paradigm of smart grid takes advantage of modern developments and significant progress in technical of sensing and machine learning, signal processing, computational optimization, and dynamical system control to provide a quantum jump in our capability for monitoring, regulate, optimize, and learn power grid different operations.

Significant sizes and annoying complexities of that connected networks presents a number of obstacles to implementing the vision of smart grid:

1. The optimal networks of Low-latency communication provide the ability of meters distributed over the grid to continue the generation and send the measurements at unsuitable high gross rates, necessitating accurate processing at desired real-time to provide the ability for the network management at that real-time..
2. The nagging challenges complexities and the interconnections size these exceed a individual control center capabilities, apprehensions among regional operators, and exposure to failure/cyberattacks are all making centralized approaches to system operations increasingly unfeasible (This underscores the requirement to evolve a decentralized approaches for this purpose).
3. The operators of the various grid must take into consideration the increasing employ of the renewable energy sources (RESs), the decreasing the effectiveness of the cost required to deploy energy storage (ES) units, and shifting unsuitable/suitable electrical consumption patterns.

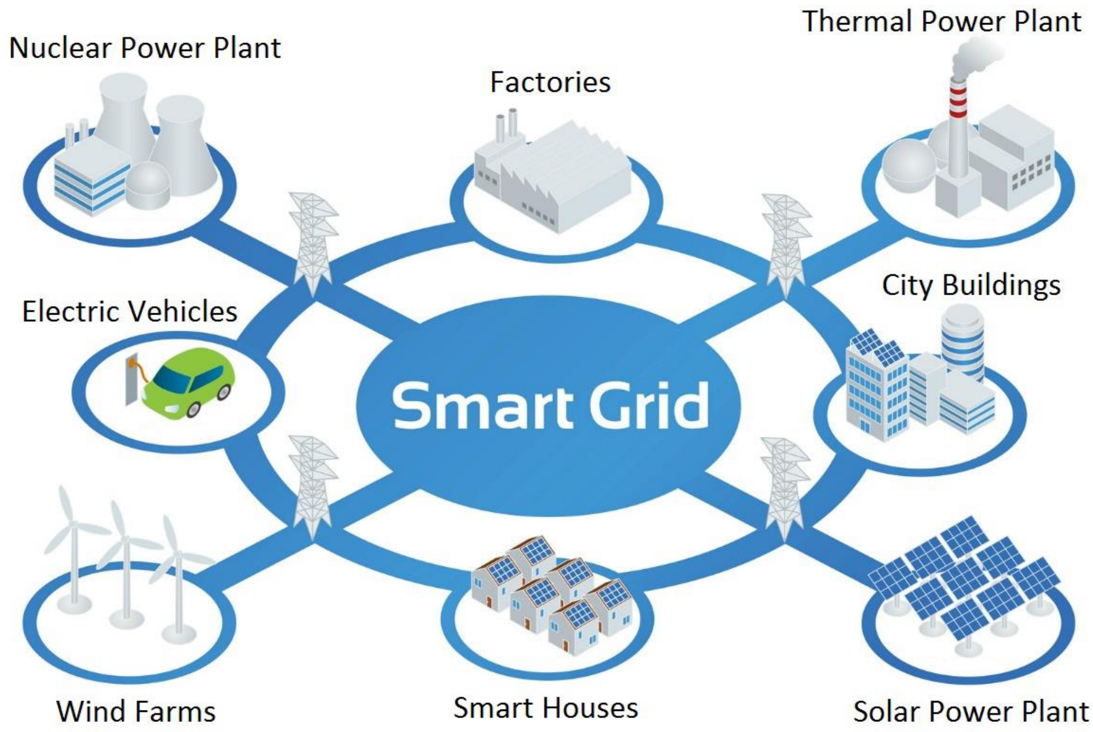

Figure 1.1: Main and practical components of the general smart grid

A smart grid generally comprises of electric power producers, smart meaurments, and different programmable devices of power; for an illustration, see Figure 1.1. Smart meters, which permit two-way communication among the utility and end users, are being installed on the appropriate buildings currently. The various techniques of mathematical optimization and machine learning are significantly justified in order to improve the both, performance and operation of electric distribution networks under the different conditions because the complicated of the smart grid, heterogeneity of its equipment, and the large amount of measurement readings to be analyzed.

1.1 Distribution System State Estimation

Distribution system state estimation (DSSE) is a critical activity for distribution network inspection and controlling. Distribution system state estimation (DSSE) takes a collection of network physical quantity measurements as inputs and/or outputs of the system state estimation, i.e., nodal voltages. Upgraded distribution grids are faced unique swings under the operation several and miscellaneous conditions as a result of the rapid adoption of variable renewable energy sources and regulated loads. As a result, accurate monitoring at determined real-time of different distribution grids is becoming growing important for ensuring the grid's operation with high level of the reliability and optimization. This is conceivable under certain circumstances because physical rules link the various quantities in the network Supervisory control and the gain of the data for SCADA (such as in the state of a power plants) and other upgraded systems that are dispersed across wide geographic. At various buses and grid lines, SCADA systems collect a variety of measurements on a regular basis. The many types of measurements that SCADA systems can acquire are depicted in Figure 1.2. Flow and injections, as well as voltage and current magnitudes in the field of electrical power, are all included in these measures. Future distribution networks will require even more adaptive monitoring, as equipment of an unsteady smart grid for instance, the renewable energy sources, scheduling of the demand and response, and smart meter technology pose a threat to situational awareness and control. A Any DSSE approach be complicated because of the nonlinear relationship among the values that was measured and the variables state. Furthermore, as demand-response, renewable energy sources grow more prevalent and implementation other techniques to improve efficiency and agility, the distribution grid practically will be more reacting and responsive but will be more unstable, needing similarly quick and robust DSSE routines.

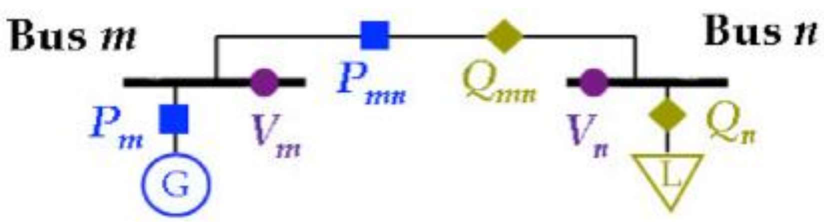

Figure 1.2: SCADA measurement system

Traditional SE various and different solvers are depending on the algorithm of Gauss-Newton and the WLS criterion, that are utilized to iterative solve the associated non convex problem. Extremely, this iterative solver of the gradient-type generally converges to undesired and unsuitable places, or even splaying, depending on the setup. This is especially representing an important problem when states of the system differ greatly between practical measurements which was got them or when there are errors in system data. The approach, moreover, enjoys quadratic convergence at the time a initialization is be at substantially close to the most perfect solution (Gomes *et al.*, 2006).

Many alternative ways to tackling the SE job have been presented, many of which utilize hidden convexity in some circumstances, motivating the relaxation of the more general problem to a convex one. Convex relaxations for PSSE, on the other hand, do not perform as well in difficult cases, especially when the size of data which was measured is small or at the buses when the available data does not involve the magnitude of voltage. In practice, this last is frequently the case (Giannakis *et al.*, 2013).

1.2 Multi-Phase Distribution Networks: Optimal Power Flow

The goal of the OPF challenge is to reduce a reasonable cost of the operation while keeping the network's engineering limits and physical in mind. The practical problem of the AC-OPF is a common mission in energy grid work optimization. It’s known the problem of the OPF is non-convex and generally NP-hard because of the quadratic feature of the equations of power flow (Lehmann, Grastien and Van Hentenryck, 2015). To deal with its non-convex character, several ways have been developed, such as DCOPF, which is a linear program produced by linearizing the equations of the power flow. The DC-OPF approach, on the other hand, is not guaranteed to be workable for the original situation. A variety of approaches have been developed for the real nonlinear issue (i.e., AC-OPF), stating with classical Newton-Raphson (NR) through Lagrange relaxation, algorithms of the evolutionary and methods of the interior point. Regrettably, except in a few circumstances, these methods do not ensure optimality or practicality, and they are highly dependent on the original prediction.

In a series of ground-breaking publications, fundamental and enough conditions for ensuring the strictness of SDR in solve mission of the AC-OPF to optimal level globally, which is accepting by specific networks through determined hypotheses, were established. used a simple 3-bus network to demonstrate the inexactness of SDR for a broad network. From the solution matrix, It is difficult to extract a physically significative solution when SDR is not tight; where the lower bound of the perfect cost is equipped only.

1.3 Thesis Outlines

This thesis includes five chapters, chapter one is an introduction about distribution networks and state estimation. The literature review discussed in chapter two, while third chapter contains the methodology of the work. Simulation results discussion is in chapter four. Finally, the conclusions and future works are in chapter five.

1.4 Purpose and Contributions

Because the equations regulating power flow in electrical grids are nonlinear, a variety of approximation approaches have been offered to address the related problems of all both, monitoring and control. The Gauss-Seidel and Newton-Raphson iterative methods are often used solvers, (Gómez-Expósito, Conejo and Cañizares, 2018).

When the beginning points lands inside a small neighborhood of the ideal solution, these repeated algorithms try to improve approximation in accuracy to the solutions of the appropriate to the problems of the nonlinear optimization, with the convergence of the quadratic. Because these algorithms' convergence is dependent on the first point, they may be more far if the initialization is cannot depend on it.

2. LITERATURE REVIEW

Since the late 1960s, the power system state estimation (PSEE) problem has been the focus of numerous studies. Prof. Schweppe of MIT's Power Systems Engineering Group was the first to suggest and develop the idea of state estimate for power system monitoring. Many scholars from universities, research centers, and industry have been drawn to the topic since then. The approach for integrating phasor measurements with the classic state estimate system was improved in 2006 by Ming Zhou, Virgilio A. Centeno, James S. Thorp, and Arun G. Phadke (Zhou *et al.*, 2006). A simple application of state estimation theory is discussed, which involves appending phasor measurements of currents and voltages as extra measures to the typical measurements now utilized in most of energy management system (EMS) state estimators. The calculated state estimator is nonlinear once more, necessitating considerable changes to existing EMS software.

In order to integrate phasor data into the conventional WLS algorithm, many methods have been suggested. The majority of working state estimators in modern control centers are acquired as part of a huge software package that is part of the control center computer's Energy Management Systems (EMS) functionality. It's necessary to translate the values of phasor V and I into similar measurements of P and Q for to accepting them as inputs in state estimation software. Adding measurements of the phasor as a post-processing step is one of the most ways of the efficient and effective. The technique for estimating the voltage magnitude and voltage angles of each bus in a power system at a given point in time is known as power system state estimation. This can be accomplished by taking direct measurements of all bus voltages in the system with very accurate synchronized phasors. Such measurements, however, would be extremely prone to measurement mistakes or telemetry failures, and Phasor Measurement Units (PMUs) are quite expensive. In order to filter out such mistakes and produce an ideal estimate, a typical state estimation process employs a set of redundant measurements. Other measurements, such as current magnitude or synchronized voltage phasor measurements, may be included in addition to the standard power and voltage data. Only the steady state bus voltage phasors (voltage magnitude and angle) are commonly included in the description of the system state.

2.1 Distribution System State Estimation

Power system State Estimation (SE) has been a critical aspect of the management and operation of systems of the transmission around this world since its inception in the early 1970s (Shweppe and Rom, 1969). Until not so long ago, at the distribution level, the application of (SE), i.e., Distribution System State Estimation (DSSE), had great arouse the interest of researchers. This is due to the fact that distribution grids have historically been maintained and designed as unfavorable systems, with unidirectional flows of power that are effortless to forecast and monitor relatively. Although that, various resources of the distributed energy for instance, small, medium or other Distributed Generation (DG), electric vehicles, loads of the demand-responsive and different devices of storage-capable are becoming more prevalent in distribution networks. This has necessitated increased monitoring in distribution grids, as well as the necessity significant role of the Distribution System Operators (DSOs) which should be play in network control and monitoring. In this situation, DSSE is quite important. Practically, much of the approaches or ways upgraded for "conventional" level of the transmission SE cannot be directly applied to DSSE because distribution grid has various properties than the networks of transmission (for instance, radial construction, high R/X ratios, the different imbalances that may happened in the phase, and the magnitude or quality of measurement data that was got them, be much low). As a result, in recent years, a grit of State Estimations built expressly for using on the level of distribution has been suggested through a literature. In spite of the increasing importance of DSSE, researchers have been unable to find a relevant survey in the literature that described the current state of art and analyzed research trends and future possibilities in the field. (Zhang, Liu and Xiao, 2012), but the literature survey that have been focused on it in this paper does not cover everything, and focuses on the publications with Chinese-language mainly. Although there have been various books and survey papers with various literature reviews within the public topics of the various power systems, none of them particularly address the advances and uses of DSSE.

For monitoring operations of the power grid at desired real time, state estimation (SE) techniques are required. Much operations of the control and automation, including as Volt/VAr restoration, optimization and reconfiguration of the feeder require accurate monitoring of the network operating point. SE estimates the different variables of the system state, such as magnitudes and angles of the bus-voltage over the network, by combining measurable quantities such as nodal voltages, power injections, and line power flows with physical laws, (Kekatos *et al.*, 2017). SE approaches have also proven beneficial in forensics of the network, for instance detecting erroneous measurements and detecting major modeling flaws.

The SE mission in the various systems of distribution is particularly difficult because of insufficiency measurements of the suitable and desired real-time, unlike the networks of transmission where units of the measurement are deployed at practically all nodes of grids. The using of so-called pseudo-measurements is frequently used to compensate for this. These virtual measurements, founded through short-term load and approaches of the renewable energy forecasting, are critical for estimating distribution system state Estimation (DSSE), (Džafić *et al.*, 2016). Several solvers of DSSE have been presented depending on the value of weighted least squares (WLS) transmission system state estimation approaches. In (Baran and McDermott, 2009) a WLS-based DSSE solver was developed by a formulation of the three-phase nodal voltage.

The authors of (Džafić, Jabr and Hrnjić, 2018), devised a modern method for state estimation of WLS in the undesired complex domain depending on Wirtinger calculus. The branch-based WLS model was suggested on (Baran and Kelley, 1995) to minimize computational complexity and storage requirements. Although, such gains are only possible when the system of the target power contains solely solidly grounded wye-connected loads. It's also widely acknowledged that using phasor measurements in DSSE improve desired accuracy of the estimation and observability. As a result, the DSSE methods described in this thesis take into account the both suitable measurements, phasor (linear) and classical (quadratic), as well as pseudo-measurements that be provided by the known algorithms of forecasting over short-term.

Continuing of work with a small numeral of measurements empirically makes the situation worse by introducing many local minima. WLS DSSE is a non-convex trouble with so much regional minima. In addition, Gauss-Newton methods may require a large number of iterations or possibly fail to converge. The problem of the distribution system state estimation (DSSE) formulation is presented in this chapter. We also go through the many sorts of metrics that are available in distribution systems.

Voltage, current, and power flows are routinely observed in a 33-kV primary substation; monitoring at the secondary substation (11 kV) level is almost non-existent. Instead of being measured, the loads are modeled as "pseudo measurements" based on historical and sample load profiles. Because pseudo measurements are high-variance load estimates, the accuracy of the estimated voltages and angles at each bus suffers when the number of pseudo measurements is considerable. Indeed, estimation errors are frequently too great for efficient network control; in this case, more real measurements are required, (Singh, Pal and Vinter, 2009).

The Optimal Power Flow issue (OPF) entails establishing the best operating levels for various generators within a transmission network in order to fulfill changing demand across time and place. OPF is used every day in the management and regulation of power grids all over the world. It is a well-established area of research in both power systems and operations, (Guha *et al.*, 2019).

2.2 DSSE Techniques and Applications

2.2.1 State estimation of classical power system

SE practically is employed in order to increase system ability for the note, detect and correct mistakes for various measurements of the system and network parameters, and reduce the undesired noise of the measurement and communication system. (Wu, 1990), provide elaborate explanations to the key methodologies with uses of traditional power systems SE. The essential operations and information flows are depicted graphically in Figure 2.1. First, a topology processor ensures that the parameters of specific network (such as various statuses of the line and switch) submitted to the estimator are accurate and up to date, guaranteeing provide the chrematistics of the accurate and upgrade for the network model.

Following that, an observability analysis determines whether the SE has enough measurement data. Testing the null items of the Jacobian matrix (Castillo *et al.*, 2005) can immediately calculate observability. If the network, or sections of it, are not inspected, estimated quantities of network inputs should be provided (also known as pseudo-measurements). SE finds a unique solution for the state of system depending on the available measurement data. Finally, poor data processing is treated to identify and eliminate data that has been tainted by the undesired errors and noise of large-scale, such as those caused by a failure of the measurement or communication system.

The voltages magnitude and voltage angles for each node of the system are represented by the vector x, which represents the network state. The group of measurements from the specific network, z, is used to estimate x. At system buses, injections measurements of power/current or the voltage magnitude, measurements of the effective and the flows of reactive energy in different branches of system , pseudo-measurements at system buses, the measurements of power/current injections or magnitudes of the voltage, while in the branches of system, measurements of the flows of active and reactive power and pseudo-measurements (for instance, estimates) of the proportions of network, or any one from the above combinations can be used to generate the values in z (Wu, 1990).

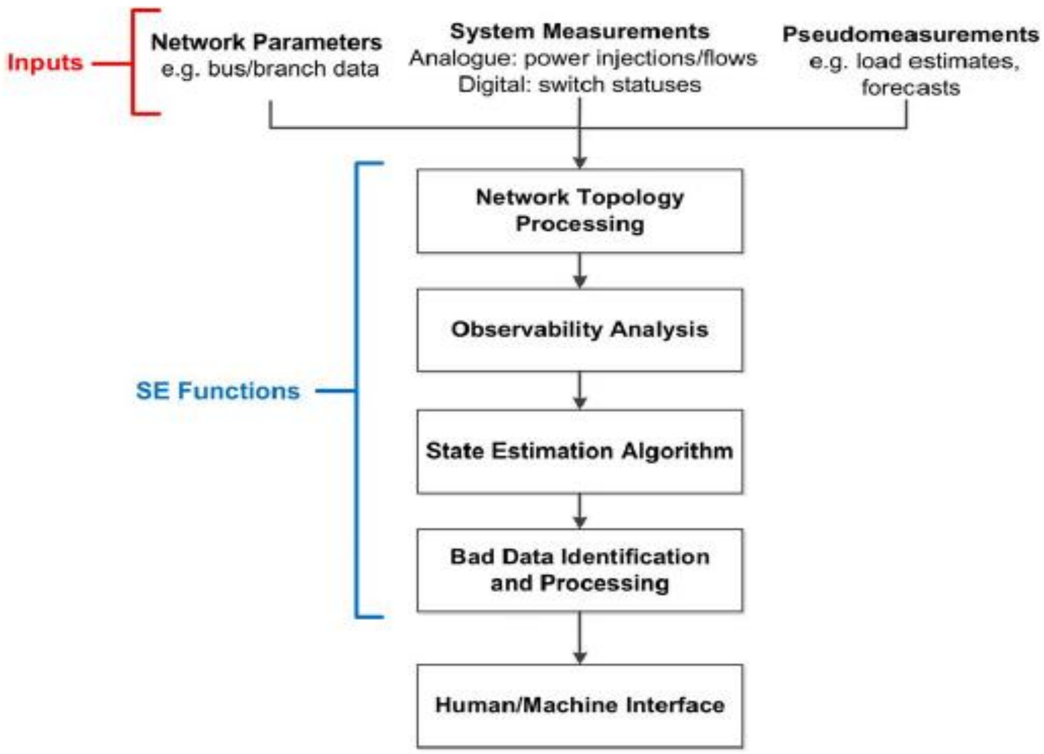

Figure 2.1: A visual representation of the major functions of power system status estimation.

2.3 Distribution System State Estimation

The first studies on DSSE were conducted in the 1990s. Because distribution grids vary principally from networks of transmission in the bellow respects, DSSE poses a number of unique challenges:

Construction: Most distribution networks are radial in design (in contrast to transmission systems, which are more meshed), for high R/X ratios.

Redundancy: The measuring points number in the distribution grids is substantially more low than in networks of the transmission for technological and economic reasons. Rather of being over-determined, systems are under-determined.

Measurement types: At the distribution level, the majority of the accessible input data are energy measurements (or pseudo measurements) or injections of the current. Direct voltage and power flow measurements are uncommon.

Scale and complexity: Distribution systems are diversified (for example, rural networks differ greatly from metropolitan networks) and feature a huge number of components. This leads to the meaning of that the approaches created for DSSE must be scalable, have a minimal computing overhead, and be adaptable to many types of networks.

Phase imbalances: Standard SE methods presume that the network is a well-balanced power system. Systems of distribution, on the other hand, might have large phase imbalances, necessitating the employ of the complete models of the three-phase system.

2.4 Available Measurements for DSSE

In comparison to the measures available in transmission systems, distribution networks often have a limited number of real-time metrics. As a result, pseudo-measurements are utilized to solve problems that are not well defined. Different latencies for various measurements sources always exist, which raises the issue of temporal skewness. Many techniques to dealing with the problem have been offered in the literature, (Zhang *et al.*, 2012). The following are the measuring functions:

- **phasor measurements** are expressed the total nodal voltages magnitudes V_n, or current value flows i_{lm}. In the state variable v, the associated measurement function is linear. Usually, these determined measurements are got through the PMUs and uPMUs. Every measurement of this sort is treated as two known measurements, with the two parts of complex values, which are real and imaginary, being treated separately.

- **real-valued measurements,** including voltage and current magnitudes, real and reactive power components measurements of the power flow. Intelligent Electronic Devices, Distribution Automation, SCADA systems and PMUs all collect these data. The state variable v is nonlinearly connected to the real-valued measurements. Active and reactive power flows, as well as the observed voltage magnitude square, can be represented as quadratic functions of the state variable v.

- **The available real-time metrics:** are frequently not enough to "pin down" the state of specific network. The system is considered to be unobservable in this instance. As a result, in DSSE, pseudo-measurements that supplement measurements of the determined real-time are critical for achieving network observability. Forecasting algorithms load and generation drive the pseudo-measurements, while try to estimate energy consumption rate or power generation based on historical data and information of location-based. They are given lower weights in the WLS formulation because they are regarded less precise than measurements of desired real-time (Dall'Anese, Zhu and Giannakis, 2013). Quadratic functions can be used to describe the mapping from variable of the state in order to predicted load and source injections of the renewable energy.

- **The Gauss-Newton** technique iteratively updates the state variables until convergence by linearizing the first order optimality requirements. Given that the procedure is initialized from a point near the genuine network state, it is known to implement completely in the practice, despite the lack of a demonstrable convergence result in theory. Using polar, rectangular, and complex representations of the state variables, several variants of the technique have been so much suggested in the literature. All of these techniques work to some extent, but failures do occur frequently. When the initialized valuses is close sufficiency to the desired and appropriate solution, stable convergence performance is observed (Džafić, Jabr and Hrnjić, 2018).

2.5 A DSSE Optimization Approach Assisted by Machine Learning

DSSE is substantially nonconvex in its weighted least-squares formulation. As a result, any local designed algorithm may converge to one of a number of different local minima. When utilizing different initializations, Gauss-Newton type algorithms react considerably differently. They may require several iterations or even when fail to converge. As a result, it's only natural to wonder if there's a smart way to initialize Gauss-Newton that avoids these difficulties. For a given distribution system, a wealth of historical data is frequently available. This information is typically saved and used for a variety of network management purposes, including load and injection forecasts. We can use this data to replicate network processes off-line even if we don't have a comprehensive record of the network status. Network states and measurements can thus be thought of as (output, input) training pairs that can be employ in order to train a neural network to learn a various function that maps a measurement to desired states. Following the learning of the mapping function, conjecting the states related to a new group of various measurements is as simple as sending the measurements through the learnt NN. This would considerably increase DSSE's efficiency, allowing for real-time state estimate. Accurate and inexpensive DSSE with a NN may appear to be better to be true, and it is in some ways (in its raw form); but there is a silver lining.

Neural networks, also known as approximators of a universal function, have made a spectacular resurgence in present, beating far more difficult (and disciplined) approaches in a variety of research fields (Jabr, 2006). One of the advantages of neural networks or other optimum techniques of machine learning systems is the ability to reduce the computing load in the stage of operation through employ transferring computationally taxing difficult work to training stage of the off-line. In our situation, the precision reached by convergent Gauss-Newton iterates (during suitable and desired initializations) is difficult to accomplish employment of the learning methodologies. The mapping is extremely complicated, demanding a wide and/or deep neural networks (NN)s that is difficult to train with sufficient data. Furthermore, training a deep neural network (DNN) is computationally intensive and necessitates significant processing resources. Also, because transmitting data via DNN's layers is a sequential operation that cannot be parallelized, real-time estimation is slowed. To get around these issues, we propose training a shallow neural network (NN) with the aim of learn to initialize, this is meaning, designation the available measurements around address be beside a real latent state, and then use that point to prepare Gauss-Newton. this can be illustrated in figure 2.2 for an example.

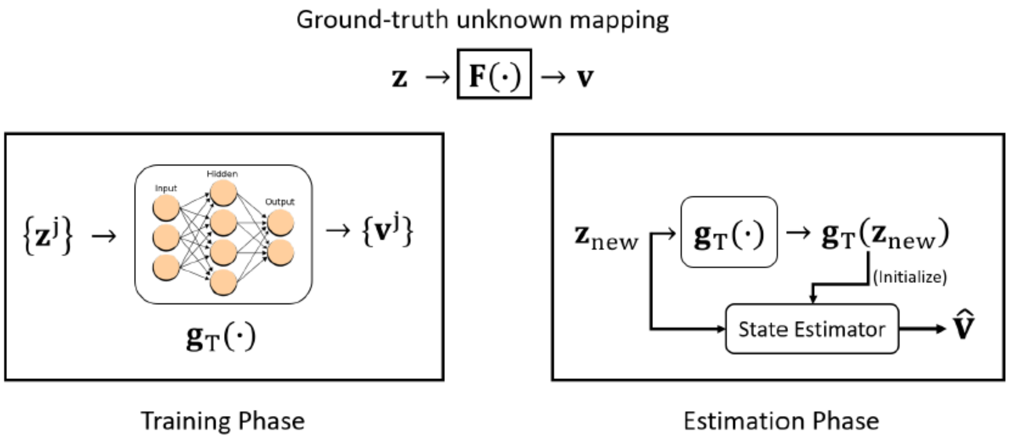

Figure 2.2: The proposed learning-based DSSE

In the power systems or smart grids different practical sectors, machine learning approaches are not wholly new. (O'Neill *et al.*, 2010), for example, used an online learning algorithm to modify domestic energy demand and save operational expenses. The power injection of sources of the renewable energy was forecasted using a multi-armed bandit online learning technique in, (Fang, Yang and Xue, 2011). (Amin *et al.*, 1997) provided an early example of employing NNs to solve guess difficulties as section about the ability for control of a damage-adaptive intelligent flight. (Manitsas *et al.*, 2012) advocated using an artificial neural network with observed power flows as input to evaluate injections of bus, that are then employed as pseudo-measurements over state estimation.

In contrast to a technique employed by NN for approximation of the network status, the authors of (Manitsas *et al.*, 2012) constructed an artificial NN for the production of pseudo-measurement from the existing power flow data. In order to anticipate the dynamic state estimation as well as for predicted state evaluation, (Rousseaux *et al.*, 1988), artificial neural networks were employed without traditional measures to anchor the solution, the state of the Network is inferred throughout the earlier concatenation of status. This is preferable for transmission systems that are more able to be predicted compared with time-changing distribution systems. The large volatility provided by these sources of energy is causing quick network changes when renewable energies are placed in the distribution grid, which often leads to a poor initialization of the next DSSE instance, (Schneider and Stuart, 2017). The previously estimated state. Machine learnings approaches to the fundamental DSSE optimization challenge, which is the subject of our study, have not been carried out to the best of our knowledge.

2.6 Neural Networks for DSSE physics-Aware

Distribution system state estimation (DSSE) is a critical activity in order to control and monitor the distribution network. DSSE takes a collection of physical quantity measurements of network as input and outputs for guess the system status, i.e., nodal voltages. Upgrade distribution networks faced a unique swing under various operational situations as a result of the rapid adoption of variable renewable energy sources and regulated loads. As a result, accuracy monitoring of appropriate real-time of distribution grids is becoming growing important in ensuring the perfect and dependable operation for the grid. A problem of the weighted least squares (WLS) optimization is frequently used to solve the DSSE task. Using a three-phase nodals voltage formulation, (Baran and McDermott, 2009) proposed a WLS-based DSSE solver. To reduce computing complexity, a Wirtinger calculus-based solution was recently devised in (Džafić, Jabr and Hrnjić, 2018) for getting suitable results of the problem in the complex domain. When the grid only has solidly-grounded wye-connected loads, branch current formulation based another DSSE solver was suggested in (Baran and Kelley, 1995), which minimizes the computing complexity of the issue.

Data driven techniques have the possibility of significantly improving accuracy for the desired monitoring and improving the execution of distribution systems by utilizing important data from plentiful real-time and known historic information. In order to do so, neural network techniques were employed in (Manitsas *et al.*, 2012) for guess the injections of bus from desired real-time observations. Compensation for the lack of online measurements, the bus injections that was estimated might be employed as pseudo-measurements. Furthermore, for predicting the grid status throughout the measurements in (Barbeiro *et al.*, 2014), basic feed-forward neural networks (NN) were developed. By moving the computational onus to training stage of an off-line using data that was be simulated or a specific date has been set for it, this technique minimize the complexity of the trouble of status guess to vector multiplications of the matrix. When training these feed-forward NNs, it might be difficult to avoid exploding or disappearing gradients, therefore the resulting estimates are less precise than any optimization-based strategy. The authors of (Zhang, Wang and Giannakis, 2019), invented a learning strategy in which a DNN is built throughout unfolding an frequent solver for the least-absolute-value formulation of the state estimation problem in networks of the transmission (Wang, Giannakis and Chen, 2019). All previous state estimation learning methods have ignored the physics of the implicit distribution grid, resulting in overparameterization of the mapping from observations to network states. We propose a unique neural network architecture that exploits the structure of the distribution grid for employing our understanding of the physical system that determines the link between the measurements and the grid status.

All of these algorithms rely only on physics-based models, which typically result in computationally expensive nonconvex optimization problems. Data-driven techniques hold the possibility of greatly improving monitoring accuracy and improving the execution of distribution systems by utilizing useful information from plentiful real-time and historical data. In order to do so, neural network techniques were utilized in (Manitsas *et al.*, 2012), for guess the bus injections using real-time observations. To compensate for the lack of real-time measurements, the bus injections that was estimated, might be employed as pseudo-measurements. Furthermore, for predicting the grid status throughout the measurements in (Barbeiro *et al.*, 2014), basic feed-forward neural networks (NN) were developed. By moving the computational onus to training stage of an off-line using historical or simulated data, this technique minimize the complication of the status guess problem to multiplications of matrix-vector. When training these feed-forward NNs, it might be difficult to avoid exploding or disappearing gradients, therefore the resulting assessments be low accuracy than other optimization-based strategy. (Zamzam, Fu and Sidiropoulos, 2019), presented a combined optimization/learning technique. Because GN performs well when properly initialized, the goal is to learn how to properly initialize a Gauss-Newton solver. It is necessitating of unique learning cost function, yet a shallow NN is all that is required to initialization learning, resulting in modest sample and runtime complexity while benefit from the great accuracy of correctly initialized GN. In contrast to (Zamzam, Fu and Sidiropoulos, 2019), the authors of (Zhang, Wang and Giannakis, 2019) presented a learning strategy for the minimum absolute-value formulation of the state estimation issue in power transmission networks (Wang, Giannakis and Chen, 2019), in which a deep NN is formed by finding an iterative solver. (Mestav, Luengo-Rozas and Tong, 2019) suggested a deep learning technique to Bayesian distribution power system state estimation. The collected measurements were mapped to the system state using a fully connected feed-forward neural network model in that study.

The suggested NN design in (Zamzam and Sidiropoulos, 2020) decreases the amount of trainable parameters, reducing the risk of overfitting. It also provides intrinsic robustness because any changes to the network topology would only influence the state estimations in the immediately affected areas. If the neural network comprises K layers, for example, any measurement contributes only to state estimates for buses that are at most K hops distant from the measurement point. Similarly, measurement outliers caused by faulty meters or communication failures will not affect the estimation of the state at remote locations based on the outliers measurements.

2.7 Dynamics of Power Systems

The electricity transmission system is primarily made up of three-phase alternating current transmission lines. An equivalent pi circuit is frequently used to depict a balanced phase transmission line. Figure 2.3 depicts the equivalent circuit for such a transmission line between bus k and bus m. The main cause of power loss in the transmission line is line resistance, which is depicted by resistor R. The line inductance jX is determined by the configuration of conductors, their spacing, and the material they are made of. The shunt capacitance B=2 simulates ac current leakage. It's caused by potential variations between conductors, as well as between conductors and ground. For a short transmission line, less than 80 kilometers in length, the capacitance element can be ignored.

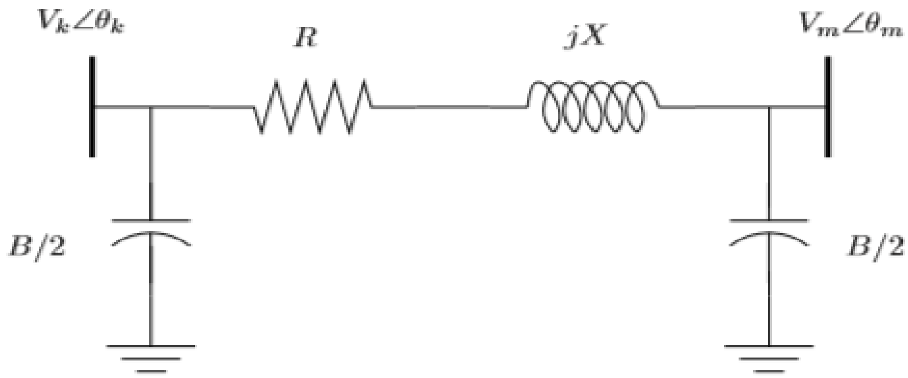

Figure 2.3: The transmission line π model

2.8 Voltage Control

Voltage difficulties are traditionally transcend by carefully choosing the both, reactance and resistance, of the line during the stages of plan (Currie *et al.*, 2004). Currently, the most accurate solution for supporting both power generation and loading in distribution power networks without significant capital expenditure appears to be arranged management of level of the voltage in the specific substation, profile of the voltage in distribution grid (e.g., voltage drop) and the minimization from generation. The voltage increasement impacts that happened by the connection of DGs are addressed in (Strbac *et al.*, 2002) by implementing the following measures: 1- generation curtailment of the active energy ; 2- management of the reactive energy; 3- controlling in area depending on the coordinated voltage of On Load Tap Changing Transformers; and 4- employing regulators of voltage. The most far customer can be kept overhead the low voltage boundary beneath the upper load situations, and all customers can be kept in the boundaries that be below the maximum voltage limit under lower load conditions, thanks to active voltage regulation. The load circumstances are taken for granted.

2.9 Power Flow Management

The control of DG outputs so that line ratings are not exceeded as a result of DG connections is referred to as power flow management, sometimes known as congestion management. The three forms of power flow management systems are pre-fault constraints, post-fault constraints, and real-time generation control. (Association, 2004). Generator controls must be based on accurate real-time measurements and a reliable Supervision Control And Data Acquisition system. (Currie *et al.*, 2004) in order to meet today's sophisticated management requirements. Power flow control, such as generator output restriction under particular network conditions, has been shown in (Currie *et al.*, 2007) to be more cost-effective than paying for network reinforcement in accommodating the needs of more D-G including within traditional power system planning methodologies.

The margins of the operating required for starting generator power output organization and tripping for desired security of the network are defined using a new approach (Currie, Ault and McDonald, 2006). Basic optimal power flow management incorporates coordinated voltage control, adaptive power factor regulation, and energy curtailment to maximize wind power potential in (Ochoa *et al.*, 2009). In (Hu and Li, 2012), sensitivity factors of power flow (the mathematical link between variations in grid power flows due to variations in D-G power outputs) are utilized to coordinate DG power outputs for avoiding thermal overloading. (Dolan *et al.*, 2013) proposes two strategies for managing power flows within static thermal restrictions, namely the current-tracing methodology and the technique of the constraint satisfaction problem (CSP). The current-tracing technique is demonstrated to provide the smallest D-G real power minimizing, but the CSP algorithm is much computationally effective and permits nodular conditions to be taken into account (Dolan *et al.*, 2013). The definition of the controllable devices of the grid, the parameters of the variable's control (that are assumed as domains), and the problem constraints are all part of modeling the power flow management problem as a CSP. The variables relate to the DG units that can be controlled, and the domains are the bands that limit their outputs. Constraints include power flow limitations, contractual obligations between the host DNO and the generator, and optimal solution preference needs (Hu and Li, 2010).

2.10 Demand Side Management

DSM's purpose is to dynamically balance load demand between peak and off-peak times of network congestion, lowering the system's total operating and planning expenses. (Luo, Ault and Galloway, 2010). DSM has the ability to deliver a wide range of benefits to distribution networks:

- The generation margin is shrinking. DSM can provide a less expensive alternative to traditional producing reserves by identifying households willing to forgo consumption extremely infrequently (for a fee).

- Improving the investment and operating efficiency of the transmission grid. DSM could minimize system operating costs and network and generation capacity by restricting some loads at appropriate areas in order to ensure transmission network security.

- Improving the distribution network's investment efficiency. By unlocking unused network capacity and providing system support services at the distribution level, DSM could also be used to alleviate voltage-constrained power transfer problems, reduce congestion in distribution substations, and improve telecommunications, going to result in advantages such as ceding new network investment, increasing distributed generation accessibility, and alleviating voltage-constrained power transfer problems.

- Balancing demand and supply in systems with intermittent renewables is difficult. When there's a lot of wind but not a lot of demand, using DSM as a form of standing reserve could assist bridge the gap.

- In-depth coverage of night-time heating with load switching, direct-load control, load limiters, commercial/industrial programs (supporting the system in the event of generation or network facility outages), frequency regulation, duration pricing, demand going to bid, and monitoring devices and appliances.(Strbac, 2008). Six basic DSM categories are depicted in figure 2.4, as discussed in (Luo, Ault and Galloway, 2010). Peak clipping and bottom filling are two ways for narrowing the gap between peak and valley load levels, resulting in a more stable and secure distribution network. Load shifting is used to flatten the demand curve by transferring load from peak to off-peak times. Conservation is a load-demand-reduction approach that involves lowering energy sales. As a result, DNOs must consider incentives to encourage customers to minimize peak-hour electricity consumption. Load building is a sort of conservation that operates in the opposite way from energy conservation. Its primary goal is to increase the market share of loads that use energy conversion and storage systems, as well as distributed energy resources. Customers with changeable loads who are ready to be controlled at key times in consideration for financial schemes must be identified by DNOs.

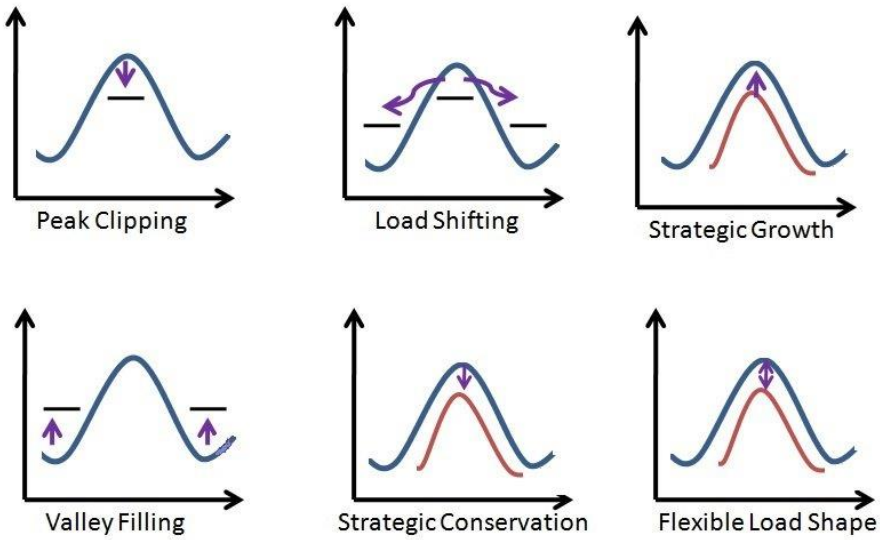

Figure 2.4: DSM loads classification

2.11 Autonomous Regional Active Network Management System

(Hu and Li, 2010) introduces one of ANM's projects, the Autonomous Regional Active Network Management System (AuRA-NMS), to solve new industrial difficulties posed by new DGs in distribution networks. Seven UK institutions, two DNOs, and a major manufacturer are all involved (Davidson *et al.*, 2010). Although AuRA-NMS is a heuristic and non-optimal algorithm, its findings are comparable to those of other optimization algorithms due to the use of sensitivity analysis. The term 'autonomous and regional' in AuRA-NMS refers to the fact that the algorithm is decentralized and devolved from a network control center, and that its operation spans a region rather than merely a feeder. The term "active" denotes a goal to improve primary infrastructure use and distributed generation integration, to embrace new control options such as energy storage, and to enable flexibility for various future uses (Green, 2009). A number of autonomous or cooperative network controls are carried out in AuRA-NMS to cope with a set of network operational difficulties such as a failure, an out-of-tolerance voltage, or a generator whose output is limited by particular network limitations.

AuRA-NMS is part of a larger effort to create "intelligent" or "smart" networks. AuRA-NMS is also designed to be versatile and expandable, as detailed in (Davidson *et al.*, 2008). Flexibility refers to the ability to quickly reconstruct the control system if:

- Modifications to network topology and plant ratings;
- Installation of new generation or energy storage;
- Disconnection of generation or energy storage
- Modifications to protection and control systems;
- New measurement and monitoring equipment installation;
- measurement and monitoring equipment removal

From a technological aspect, AuRA-NMS implements four essential controls: power flow management, steady state voltage control, automated restoration, and network performance optimization approaches. (Davidson *et al.*, 2010). To decrease network congestion, this research focused on the power flow management component of flow control. Currently, the LIFO rule governs congestion control in the United Kingdom. When a network is overloaded, the rule states that the last-in DG will be the first to be tripped off or throttled (Jupe and Taylor, 2009). The disadvantage of this criterion is that the last-in DG may have little effect in reducing overloading problem. In the worst-case scenario, it may have no effect at all, resulting in waste of energy.

Unlike the LIFO rule, which frequently leads in excessive wind generation reduction, AuRA-NMS' load flow allows for the collection of real-time states and the selection of the most responsive busbar to relieve capacity problems. (Jupe and Taylor, 2009). Congestions can be avoided with the least amount of generation curtailment or load shedding.

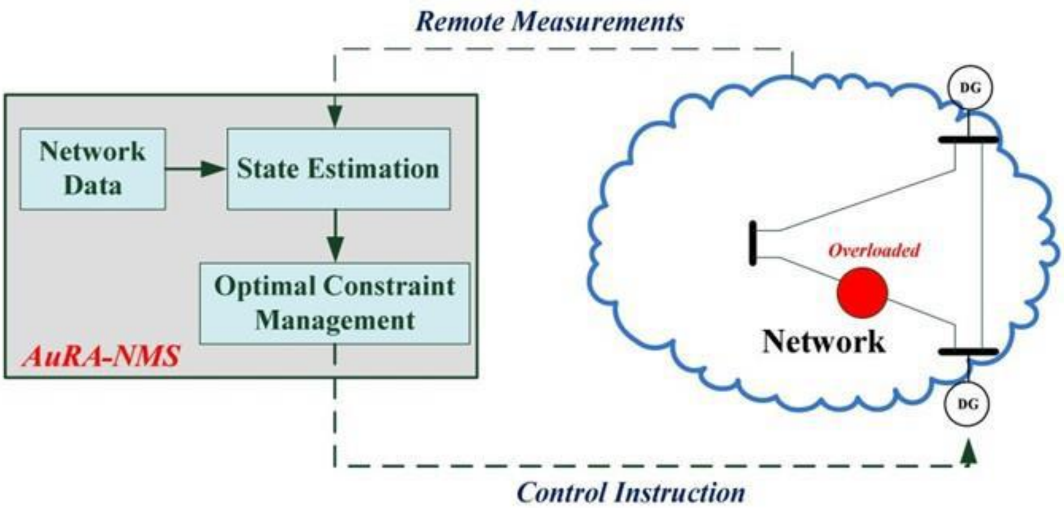

Figure 2.5: Schematic Illustration of AuRA-NMS Congestion Management

Once an overloaded condition is detected, AuRA-NMS will receive data via remote measurements. The system will then select the most susceptible generator and cut its output to ease stress using real-time data. Once the appropriate congestion management has been found, the system will return the control command to the network. It is assumed that it is equipped with state estimate software. The main flaw of AuRA-NMS congestion management is that it only looked at system optimization from the standpoint of generation. Because ANM approaches analyze generation and demand side management independently, this is the case. If congestion management can be enhanced with DSM, more generation curtailment can be avoided, particularly by employing flexible demand like as electric vehicles.

2.12 Synchronized Phasor Measurement Units (PMUs)

PMUs (phasor measurement units) were invented in the mid-1980s. Positive sequence voltage amplitudes at network buses and positive sequence current phasors in the line that connects those buses with GPS signals are synchronized by PMUs. The synchronization accuracy is less than one microsecond, and the data gathering offers a real-time snapshot of the state of the power system. Because the state vector of a power system is made up of positive sequence voltages for network buses, solving the state estimation problem solely with phasor measurements becomes quite simple. These data lead to a method that measures the system state rather than estimating it via nonlinear state measurements. However, because PMUs are so expensive, they are only used as a supplement to standard measurements. A functional block diagram of a typical PMU is shown in Figure 1.2.

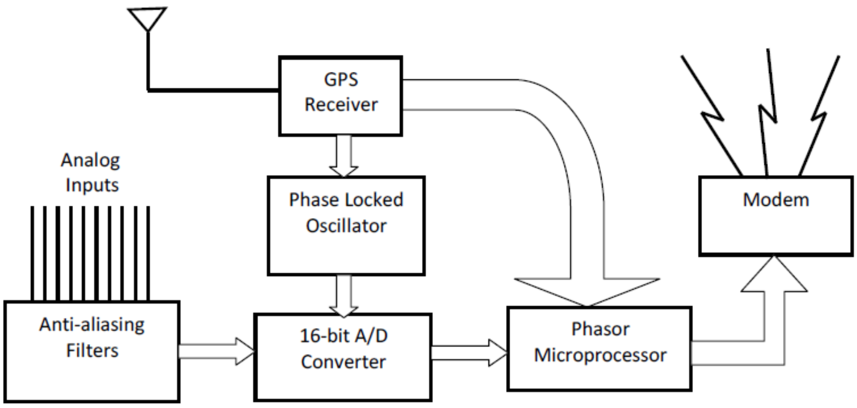

Figure 2.6: A functional block diagram of a typical PMU

However, a phasor-based state vector monitoring technique is a more accurate alternative to the conventional state estimators, it is recognized that PMU measurements are adequate to achieve this goal in many instances. The accuracy of state estimate is much improved when phasor data is added to the other measurements in adequate amounts. As a result, multiple approaches for incorporating phasor data into the standard measurement set are used. Appending phasor measurements of currents and voltages as extra measures to the usual measurement set is a simple solution. The resulting state estimator is nonlinear once more, necessitating considerable changes to existing EMS software. Another option is to keep the traditional state estimation software in place but use a post-processing linear estimator to incorporate the phasor measurements and the classic state estimator's results, (Karimi, 1986).

2.12.1 WLS state estimation with phasor measurements

In this method, phasor measurements are included to the state estimation after a post-processing phase. There are two phases to this operation. In the first technique, the WLS state estimation algorithm is developed to remove the state vector in polar coordinates from conventional data. The state vector using WLS state estimation and the measurement vector from phasor measurements are expressed in rectangular coordinates in the second operation, providing a new measurement set and a linear state estimation technique that does not depend on evolutionary algorithms, (Cheng, Hu and Gou, 2008). The block diagram of this method is shown in figure 2.7, and the details discussed in chapter three.

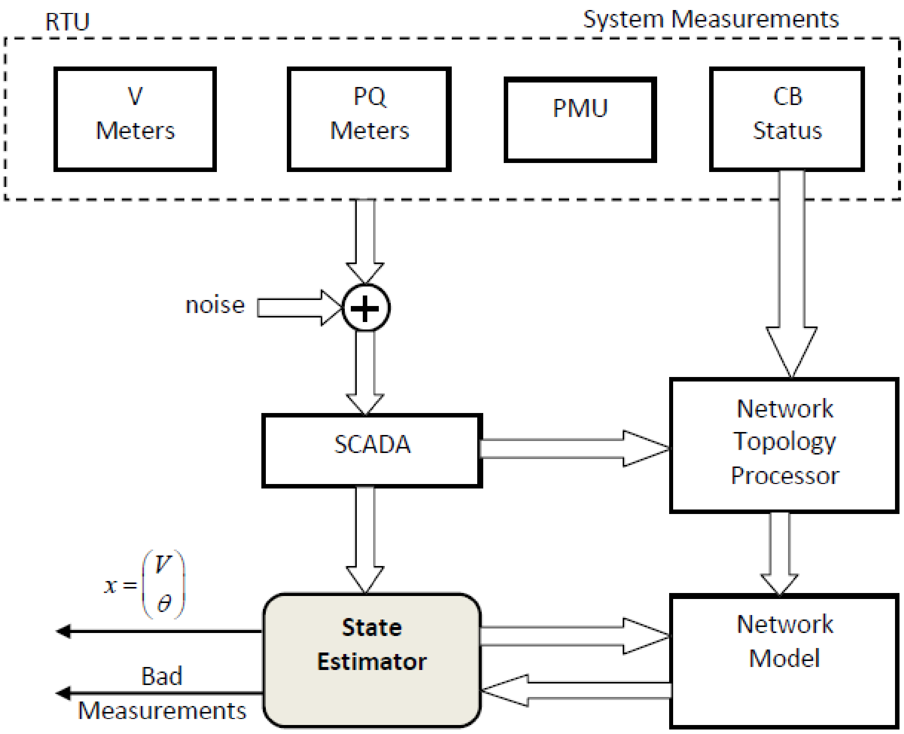

Figure 2.7: State Estimation Block diagram

2.13 The Challenges and the Resilience of Clectric Destribution Network Mamngement

The electrical distribution network considered as a main backbone for general critical services in the life. so, enabling the distribution networks in order to face the various challenges is one of the objects which has to be work on it, and this can be done by following steps:

- Support the resilience of distribution systems, which is a multi-steps process starts with the classification of the expected difficulties that faces the systems.
- Preparing the suitable quantification of the system resilience for taking it the ability to resistant the various current threats through identifying resilience metrics and development of them.
- Improving the system's resilience and, ultimately, developing a schedule for the resilience improvement strategy's evaluation.

Enabling resilience systems necessitates system-specific research and sophisticated analysis tools.

The term of resiliency can be defined as the "network's ability to faces the constant and frequent interruptions of power supply for the stressful loads under critical conditions of the various operating cases, with the ability to recover from the different types of flaws that can be result through the unfavorable events or external challenges". Some of these events and challenges can be illustrate in Table 2.1. These challenges may be happened at every time with very high occurrence rates. Therefore, from the desired concepts of systems resilience is the facing these threats, such as cyber challenges which may create high-impact of physical events.

Table 2.1: Illustration of the high affect, low probability events

Classification	Examples
Cyber challenges	Eavesdropping, injection of the bad data, service denial, modification for data packet, day zero vulnerabilities and man in the middle attack.
Physical – manmade	Warfare, vandalism, terrorism and the riots
Physical – natural	Earthquake, cyclone, storms, hurricane, snowstorm, avalanche and solar flares

Because the radial character of PDS's makes the restoration process difficult or impossible at times, high-impact events have a detrimental impact on the PDS stage by causing unforeseen and irreversible defects in assets. Other factors that have a negative impact on the system resilience of these networks include the rise in extreme weather threats, which have a direct negative impact on the infrastructure's health, the infrastructure's general age, and the significant support provided by the cyber equipment of the power distribution systems for automation and monitoring, which are considered more vulnerable to remote attacks (Kandaperumal and Srivastava, 2020).

The following aspects show some techniques and goals of cyber challenges:

- Phishing for gain access to the business networks (oblenergos) directly.
- Categorize the BlackEnergy 3 in every the impacted oblenergos.
- Theft of credentials from the business networks of the investor companies or national institutions.
- Using the virtual private networks (VPNs) to create loophole and access to the important ICS network.

- Using the remote access tools to issue directly orders from another far station which be same as an operator (HMI).
- Using the modified KillDisk in order to delete the main boot record for the impacted organization systems, added to the delete some logs16.
- Using the UPS systems for affecting connected load with outage of service continously.
- The challenge that can be represented by telephone denial-of-service attack which will cut the connections.
- in the other side, practically recommendations are varied, where it's must to focus on the following items:
- Creating the filtering and response abilities for the telecom providers and the capability to activate service through attacks of ongoing Telephony Denial of Service (TDoS).
- Stopping the service of remote management especially for the field devices.
- Stopping the connections of building control infrastructure systems with the important and practical ICS network.
- Consider the spares number which are required for embedded systems to appropriate reconnection or control in order to provide the desired protection (Assante, 2016).

Some of studies focused on the complication of electric system environment which pose significant difficulties in the efficiency of wireless sensor networks communications in the applications of smart-grids. The main technical challenges and threats of wireless sensor networks (WSN)s in the smart-grid applications can be illustrate as follows:

1. Difficult environmental situations: the topology and wireless connectivity of the network may fail. Added to that, sensors are impacted to RF interference, high humidity levels, different levels of vibrations, dirt and dust of the ambient environments, or other conditions that facing the performance of the WSNs. These impacts may cause the failure of portion of sensors or make the information much old.

2. Reliability requirements: The desired applications on WSNs of smart grid have various quality-of-service (QoS) requirements in terms of reliability, network throughput, etc., where the sensors data are sensitive with the time, it is very important to receive the information in the controller nodes at a timely manner.
3. Variable link capacity and packet errors: In WSNs, the bandwidth of wireless link based on the interference level at the receiver, in addition, the wireless links appear different properties during the time and space because of the noisy environment in power distribution systems.
4. Resource constraints: The implementation of WSNs depending on three types of resources (energy, memory and processing). Sensor nodes has a determined battery energy supply, therefore, the aim of strong design of communication protocols for WSNs is providing high power with significant efficiency (Sun, Guo and Gill, 2010).

3. METHODOLOGY

System state estimation is one of the important steps in power system management, since it gives an estimation for each effective parameter in the power system. In this work there are two parameters assumed to the most important parameters among the other in distribution power system, they are: the voltage magnitude and angle. There are many algorithms used in power flow solution such as Newton-Raphson NR, Range-Kutta RK, etc. In this work an estimation method is proposed to estimate the voltage magnitude and angle for each bus in the system. IEEE power systems are used to implement the proposed method, the estimated results are compared with the classical load flow algorithms results. Neural networks-based load flow algorithm also proposed for estimating the two mentioned parameters. IEEE-14 bus and IEEE-30 bus systems are the studied systems for the proposed work. Each of the two systems and the load flow algorithms are discussed in this chapter.

3.1 Load Flow Algorithms

3.1.1 Newton-raphson method

The Newton Raphson Method is an iterative method for resolving a set of nonlinear equations with an equal number of variables. Using the Newton Raphson Method, there are two solutions for the load flow. For the variables, the first technique employs rectangular coordinates, whereas the second method uses polar coordinates. The polar coordinate form is the most often utilized of these two techniques.

This method has: Advantages: rapid convergence as long as the starting guess is near to the solution; large convergence region. Drawbacks: Each iteration takes much longer than a Gauss-Seidel iteration, therefore it is more difficult to code. In power flow analysis, the Newton-Raphson algorithm is widely used. In the Newton-Raphson power flow Newton's method is used to determine the voltage magnitude and angle for each bus in the power system that satisfies power balance. It is needed to solve the power balance equation. From equation (3.1-3.3) or the power equations:

$$S_i = V_i I_i^* = V_i \sum_{k=1}^{n} V_{ik}^* \, Y_k^* \quad \textbf{(3.1)}$$

$$P_i = \sum_{k=1}^{n} V_i V_k Y_{ik} \cos(\delta_i - \delta_k - \theta_{ik}) \quad \textbf{(3.2)}$$

$$Q_i = \sum_{k=1}^{n} V_i V_k Y_{ik} \sin(\delta_i - \delta_k - \theta_{ik}) \quad \textbf{(3.3)}$$

Newton Raphson Method Procedure: first thing generating Y-bus matrix and line data matrix, calculating Jacobian matrix as in equation 3.4:

$$\Delta P_i = P_{i\,spec} - P_{i\,cal} \quad \textbf{(3.4)}$$

$$\Delta Q_i = Q_{i\,spec} - Q_{i\,cal} \quad \textbf{(3.5)}$$

The equations (3.4 & 3.5) can be expressed as follows (equation 3.6): where the subscripts *spec* and *cal* denote the stated and computed values, respectively.

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} \frac{\partial P}{\partial \delta} & \frac{\partial P}{\partial V} \\ \frac{\partial Q}{\partial \delta} & \frac{\partial Q}{\partial V} \end{bmatrix} \begin{bmatrix} \Delta \delta \\ \Delta V \end{bmatrix} \quad \textbf{(3.6)}$$

The overall process can be summarized in the flowchart in figure 3.1(Mumtaz *et al.*, 2018):

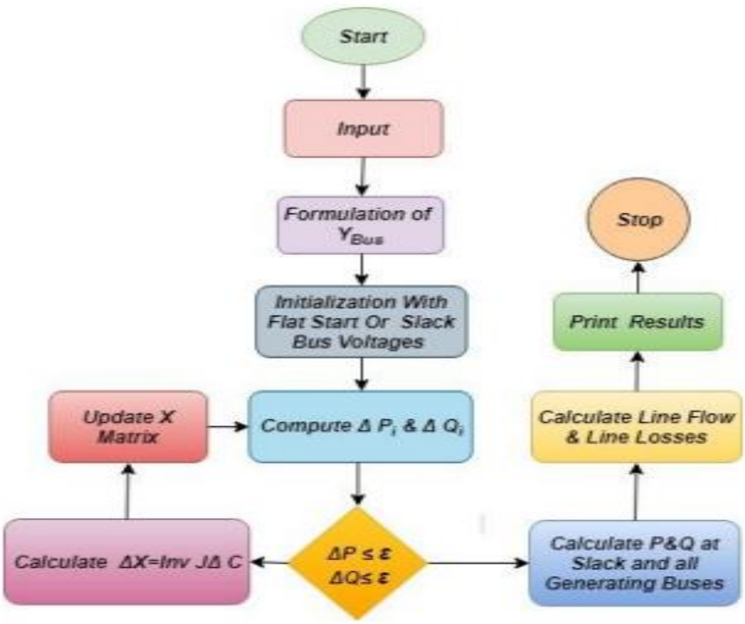

Figure 3.1: GS flowchart

In this work two methods are used to estimate the state variables of the distribution network (voltage magnitude and angle) for each bus or for selected buses. The two methods are discussed in this chapter. The simulation results for both methods compared with numerical power flow solutions (classical methods) like Gauss – Seidel method.

3.2 Phasor Measurement State Estimation Method

The method for predicting the state (voltage magnitude and angle) of all the buses in a power system based on measurements taken at a few buses is known as power system state estimation. In the past, measurement instruments could only provide you the magnitude of the quantity you were measuring. However, an efficient measurement device known as a Phasor measurement unit (PMU) is currently being used to measure the voltage phasor (both magnitude and angle) of a bus at which it is situated as well as the current phasors of the immediately connected lines, (Hurtgen and Maun, 2008).

Because PMUs are so expensive, they can't just be used to assess the state of a power system. As a result, phasor measurements are utilized in conjunction with other measures to determine the condition of a power system. The use of PMU measurements to estimate the condition of a power system has been explained, and a MATLAB application has been written, as well as a simulation of the method on IEEE-14 and IEEE-30 bus systems. The technique employs a distinct linear state estimator model based on the state estimate from WLS, as well as post-processed PMU voltage and current measurements. First, the model derives the state in polar coordinates using conventional data using the WLS state estimation approach. The final state of the system is estimated using this state and PMU measurements, both given in rectangular coordinates, (Melo *et al.*, 2017).

Consider a set of z1 measurements that includes non-synchronized (scanned) data on active and reactive power flows in network elements, bus injections, and bus voltage magnitudes. It is expected that faulty data has been removed from this measurement set using standard procedures. Nonlinear functions of the state vector x are used to make the measurements (a set of positive sequence voltages at all the buses of the network), (Karimi, 1986).

$$z_1 = h1(x) + e1 \quad \textbf{(3.7)}$$

where h1 denotes the nonlinear functions of the state vector x in polar coordinates, and e1 is the measurement error vector with R1 as the covariance matrix.

The Jacobian matrix, H1 can be written as :

$$H_1(x) = \frac{\partial h_1(x)}{\partial x} \quad \textbf{(3.8)}$$

While the gain matrix $G_1(x^k)$ is given by :

$$G_1(x^k) = [H_1^T(x_k)R_1^{-1}H_1(x_k)]^{-1} \quad \textbf{(3.9)}$$

The estimate x's error covariance matrix is given by:

$$COV([x]) = [H_1^T R_1^{-1} H_1] \quad \textbf{(3.10)}$$

The state vector, on the other hand, is derived from:

$$[x^{k+1}] = [x^k] + [G_1(x^k)]^{-1}[H_1^T R_1^{-1}][z_1 - h_1(x^k)] \quad \textbf{(3.11)}$$

This procedure is iterative, and iterations will continue until one of two conditions is met. The first requirement is that the maximum number of iterations allowed is exceeded, and the second condition is that the change in state variables is within an acceptable range.

$\max |\Delta x^k| \leq \epsilon$

The first proposed method is based on MTLAB m-file program. Four sub-programs are called by the main MATLAB program. The first returns the exact state vector obtained using the NRLF approach, while the second returns the estimated state vector as well as the covariance matrix obtained using classical measurement. The third calculates the state vector using the WLS output and phasor readings. The final one calculates estimation errors and plots voltage magnitude and angle estimation errors for each bus. While the second proposed method is based on neural networks, the neural network is designed using MATLAB Neural Pattern Recognition Tool NPRTool. The designed neural network trained using the 14-bus IEEE power system, bus number, buses voltages, generators, and load initial data are the used as a training dataset. The neural network output contains the voltage magnitude and angles for each bus. The obtained data compared with the data from classical NR load flow to show the accuracy of the proposed algorithm. The neural network design is shown in figure 3.2. the training performance is shown in figure 3.3 while training state is shown in figure 3.4.

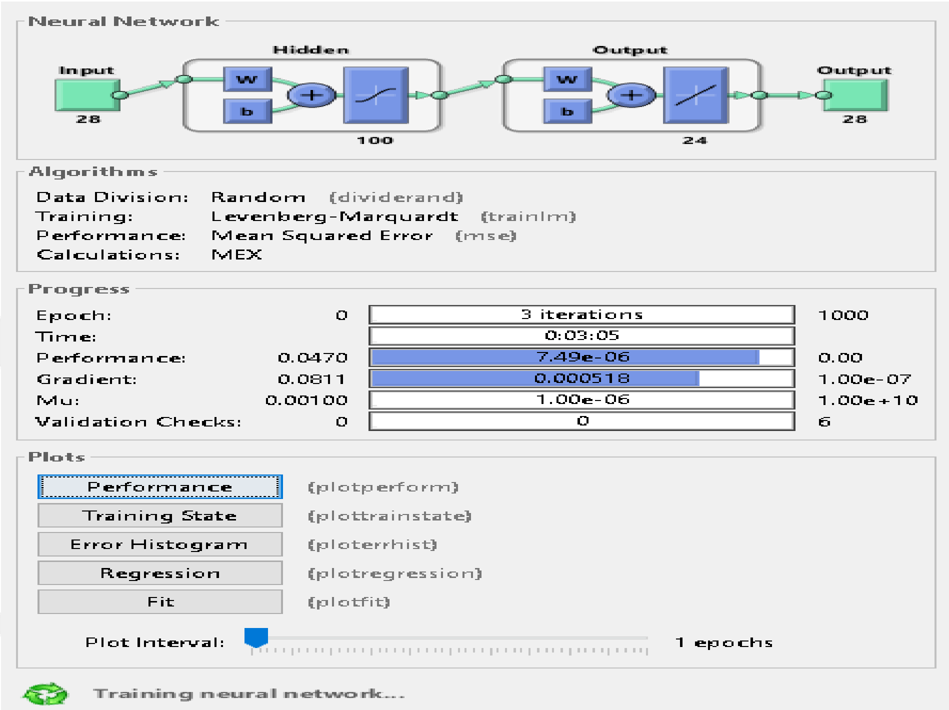

Figure 3.2: Neural network design

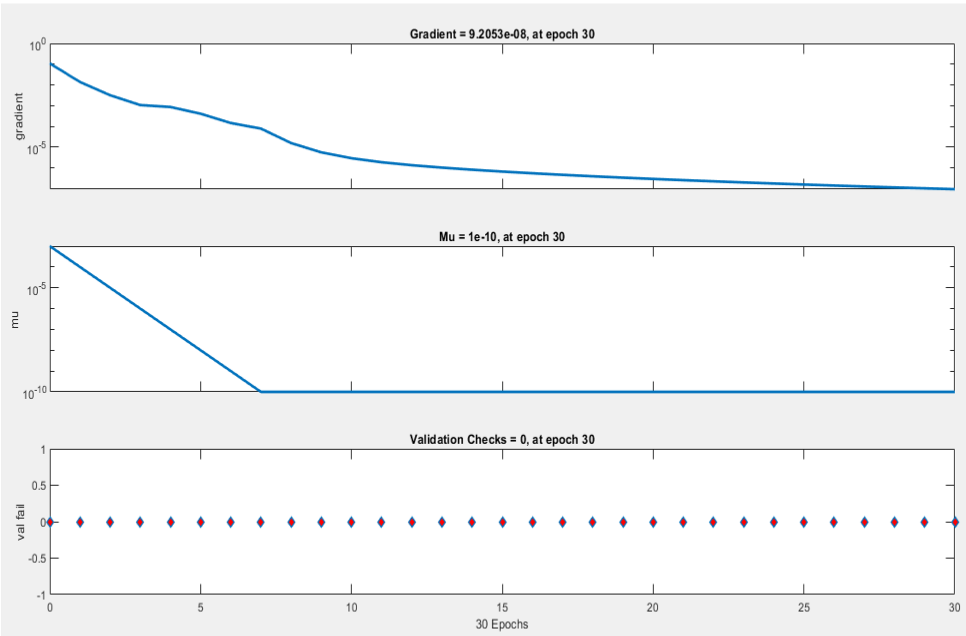

Figure 3.3: Neural network training state

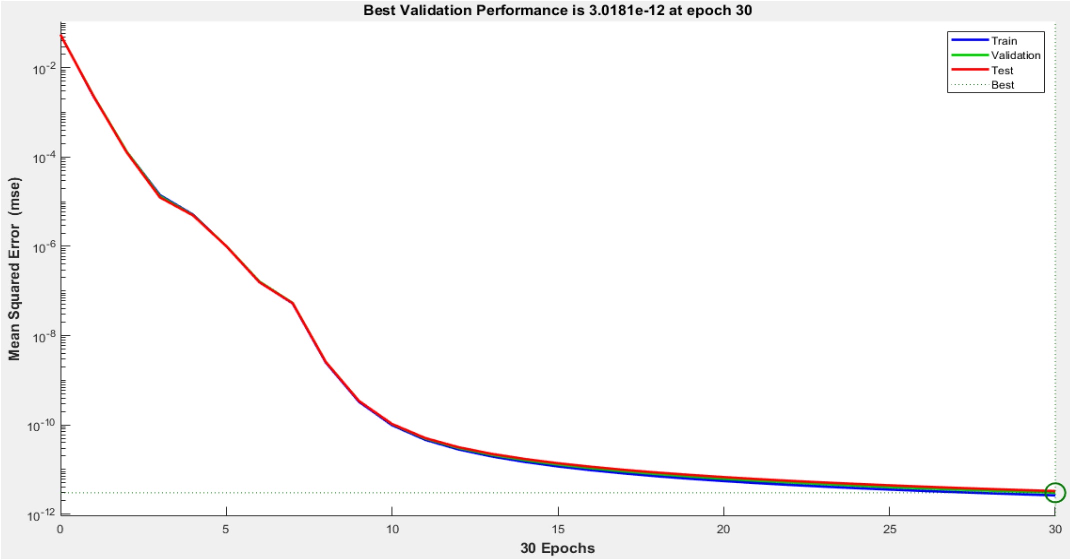

Figure 3.4: Neural network validation performance

The MATLAB code for the proposed neural network specifications is:

```
dimensions:

         num_Inputs: 1
         num_Layers: 2
        num_Outputs: 1
    num_InputDelays: 0
    num_LayerDelays: 0
 num_FeedbackDelays: 0
 num_WeightElements: 5224
        sample_Time: 1
connections:

       bias_Connect: [1; 1]
      input_Connect: [1; 0]
      layer_Connect: [0 0; 1 0]
     output_Connect: [0 1]

    subobjects:

             input: Equivalent to inputs{1}
            output: Equivalent to outputs{2}

            inputs: {1x1 cell_array of 1 input}
            layers: {2x1 cell_array of 2 layers}
           outputs: {1x2 cell_array of 1 output}
            biases: {2x1 cell_array of 2 biases}
      inputWeights: {2x1 cell_array of 1 weight}
      layerWeights: {2x2 cell_array of 1 weight}
```

```
functions:

     adapt-Fcn: 'adapt-wb'
   adapt-Param: (none)
     deriv-Fcn: 'default-deriv'
    divide-Fcn: 'divider-and'
  divide-Param: .train-Ratio, .valRatio, .testRatio
   divid Mode: 'sample'
      in_itFcn: 'initlay'
   perform-Fcn: 'mse'
 perform-Param: .regularization-, .normalization
     plot-Fcns: {'plot-perform', 'plot-trainstate', 'plot-errhist',
                'plot-regression', 'plot-fit'}
   Plot-Params: {1x5 cell array of 5 params}
     Train-Fcn: 'train-lm'
   Train-Param: .show-Window, .show-Command-Line, .show, .epochs,
                .time, .goal, .min_grad, .max_fail, .mu, .mu_dec,
                .mu_inc, .mu_max

weight and bias values:

            IW: {2x1 cell} containing 1 input weight matrix
            LW: {2x2 cell} containing 1 layer weight matrix
             b: {2x1 cell} containing 2 bias vectors

methods:

        adapt_: Learn - while -in continuous use
    configure_: Configure inputs & outputs
       genism_: Generate Simulink- model
         init_: Initialize weights- & biases
      perform_: Calculate -performance
          sim_: Evaluate -network outputs- given -inputs
        train_: Train network- with -examples
         view_: View -diagram
  un_configure: Unconfigure -inputs & -outputs

evaluate:       outputs = Net-Final-(inputs)
```

The studied systems are IEEE-14 -bus and IEEE-30- bus systems. The IEEE-14- bus data is listed

```
% %IEEE 14 bus system
%%       Bus No  Vm   Theta  Pg    Qg     P1     Q1     Qmax    Qmin  Type
busdata= [ 1    1.060   0     0    0     0      0      0      0     1;
           2    1.045   0   40.0 45.41  21.7   12.7   -40     50    2;
           3    1.010   0     0  25.28  94.2   19.0    0      40    2;
           4    1.000   0     0    0    47.8   -3.9    0      0     3;
           5    1.000   0     0    0    27.6   1.6     0      0     3;
```

```
        6   1.070  0    0  13.62  11.2   7.5    -6.0     24.0    3;
        7   1.000  0    0   0      0      0      0        0      3;
        8   1.090  0    0  18.24   0      0     -6.0     24.0    3;
        9   1.000  0    0   0     29.5   16.6    0        0      3;
        10  1.000  0    0   0      9.0    5.8    0        0      3;
        11  1.000  0    0   0      3.5    1.8    0        0      3;
        12  1.000  0    0   0      6.1    1.6    0        0      3;
        13  1.000  0    0   0     13.5    5.8    0        0      3;
        14  1.000  0    0   0     14.9    5.0    0        0      3];

% Line_Data_for_IEEE_14_bus_system
%        Line No   From to   R          X         B/2      T
Line_data=[ 1.0      1   2    0.01938   0.05917  0.02640    1;
        2.0      2   3    0.04699   0.19797  0.02190    1;
        3.0      2   4    0.05811   0.17632  0.01870    1;
        4.0      1   5    0.05403   0.22304  0.02460    1;
        5.0      2   5    0.05695   0.17388  0.01700    1;
        6        3   4    0.06701   0.17103  0.01730    1;
        7        4   5    0.01335   0.04211  0.00640    1;
        8        5   6    0.00000   0.25202  0.00000    0.932;
        9        4   7    0.00000   0.20912  0.00000    0.978;
        10       7   8    0.00000   0.17615  0.00000    1;
        11       4   9    0.00000   0.55618  0.00000    0.969;
        12       7   9    0.00000   0.11001  0.00000    1;
        13       9   10   0.03181   0.08450  0.00000    1;
        14       6   11   0.09498   0.19890  0.00000    1;
        15       6   12   0.12291   0.25581  0.00000    1;
        16       6   13   0.06615   0.13027  0.00000    1;
        17       9   14   0.12711   0.27038  0.00000    1;
        18       10  11   0.08205   0.19207  0.00000    1;
        19       12  13   0.22092   0.19988  0.00000    1;
        20       13  14   0.17093   0.34802  0.00000    1];
```

While IEEE-30 bus data is listed below :

```
%      IEEE 30-BUS TEST SYSTEM (American Electric Power)
%      Bus Bus  Voltage Angle   ---Load---- -------Generator----- Injected
%      No  code Mag.    Degree  MW     Mvar  MW   Mvar Qmin Qmax     Mvar
busdata=[1   1   1.06    0.0     0.0   0.0    0.0  0.0   0   0        0
     2   2   1.043   0.0    21.70  12.7   40.0  0.0 -40  50        0
     3   3   1.0     0.0     2.4   1.2    0.0  0.0   0   0         0
     4   3   1.06    0.0     7.6   1.6    0.0  0.0   0   0         0
     5   2   1.01    0.0    94.2  19.0    0.0  0.0 -40  40         0
     6   3   1.0     0.0     0.0   0.0    0.0  0.0   0   0         0
     7   3   1.0     0.0    22.8  10.9    0.0  0.0   0   0         0
     8   2   1.01    0.0    30.0  30.0    0.0  0.0 -10  40         0
     9   3   1.0     0.0     0.0   0.0    0.0  0.0   0   0         0
     10  3   1.0     0.0     5.8   2.0    0.0  0.0  -6  24        19
     11  2   1.082   0.0     0.0   0.0    0.0  0.0   0   0         0
     12  3   1.0     0       11.2  7.5    0    0     0   0         0
```

```
13   2    1.071   0       0    0.0    0    0    -6  24       0
14   3    1       0      6.2   1.6    0    0     0   0       0
15   3    1       0      8.2   2.5    0    0     0   0       0
16   3    1       0      3.5   1.8    0    0     0   0       0
17   3    1       0      9.0   5.8    0    0     0   0       0
18   3    1       0      3.2   0.9    0    0     0   0       0
19   3    1       0      9.5   3.4    0    0     0   0       0
20   3    1       0      2.2   0.7    0    0     0   0       0
21   3    1       0     17.5  11.2    0    0     0   0       0
22   3    1       0      0     0.0    0    0     0   0       0
23   3    1       0      3.2   1.6    0    0     0   0       0
24   3    1       0      8.7   6.7    0    0     0   0      4.3
25   3    1       0      0     0.0    0    0     0   0       0
26   3    1       0      3.5   2.3    0    0     0   0       0
27   3    1       0      0     0.0    0    0     0   0       0
28   3    1       0      0     0.0    0    0     0   0       0
29   3    1       0      2.4   0.9    0    0     0   0       0
30   3    1       0     10.6   1.9    0    0     0   0       0];


linedata=[ 1    2   0.0192  0.0575  0.0264  1
        1   3   0.0452  0.1852  0.0204  1
        2   4   0.057   0.1737  0.0184  1
        3   4   0.0132  0.0379  0.0042  1
        2   5   0.0472  0.1983  0.0209  1
        2   6   0.0581  0.1763  0.0187  1
        4   6   0.0119  0.0414  0.0045  1
        5   7   0.046   0.116   0.0102  1
        6   7   0.0267  0.082   0.0085  1
        6   8   0.012   0.042   0.0045  1
        6   9   0   0.208   0   1.078
        6   10  0   0.556   0   1.069
        9   11  0   0.208   0   1
        9   10  0   0.11    0   1
        4   12  0   0.256   0   1.032
        12  13  0   0.14    0   1
        12  14  0.1231  0.2559  0   1
        12  15  0.0662  0.1304  0   1
        12  16  0.0945  0.1987  0   1
        14  15  0.221   0.1997  0   1
        16  17  0.0824  0.1923  0   1
        15  18  0.107   0.2185  0   1
        18  19  0.0639  0.1292  0   1
        19  20  0.034   0.068   0   1
        10  20  0.0936  0.209   0   1
        10  17  0.0324  0.0845  0   1
        10  21  0.0348  0.0749  0   1
        10  22  0.0727  0.1499  0   1
        21  22  0.0116  0.0236  0   1
        15  23  0.1 0.202   0   1
```

```
22  24  0.115   0.179   0   1
23  24  0.132   0.27    0   1
24  25  0.1885  0.3292  0   1
25  26  0.2544  0.38    0   1
25  27  0.1093  0.2087  0   1
28  27  0   0.396   0   1.068
27  29  0.2198  0.4153  0   1
27  30  0.3202  0.6027  0   1
29  30  0.2399  0.4533  0   1
8   28  0.0636  0.2 0.0214  1
6   28  0.0169  0.0599  0.0065  1];
```

The depended procedure in this work is to estimate the operating condition for a specific bus and compare the results with the calculation-based method to verify the accuracy of the proposed method. The importance of the proposed method is that it has the ability to estimate the operating condition of each bus depending on the previous loading condition, that leads to network learning and management procedure. Selected operating and loading cases used in system simulation for each case the results compared with NR load flow, the loading case changes again and repeat the estimation process, this sequence repeated for more than one loading state. The variables to be estimated for the specific buses are the voltage magnitude and angle. The voltage magnitude gives an indication about the bus loading ability, while the voltage angle gives an indication about power flow controlling ability by means of flexible AC transmission systems FACTS, because the injected voltage angle is the most significant parameter in this case.

4. RESULTS DISCCUSION

4.1 Synchronized Phasor Measurements Method vs NR

4.1.1 IEEE-14 bus system

Loading case for bus-5 :

Bus voltage: 1p.u volt

Load power: 7.6 MW

Load reactive power: 1.6 MVAr, the simulation results for this case listed in table 4.1

Table 4.1: IEEE-14 system voltages and angles for the three methods

Bus No	NR		Without PMUs		With PMUs	
	Magnitude	Angle	Magnitude	Angle	Magnitude	Angle
1	1.0600	0.0000	1.0068	0.0000	1.0584	0.0000
2	1.0450	- 4.9891	0.9899	-5.5265	1.0451	-5.0258
3	1.0100	- 12.7492	0.9518	-14.2039	1.0046	-12.7546
4	1.0132	-10.2420	0.9579	-11.4146	1.0083	-10.2142
5	1.0166	-8.7601	0.9615	-9.7583	1.0118	-8.7264
6	1.0700	-14.4469	1.0185	-16.0798	1.0700	-14.4443
7	1.0457	-13.2368	0.9919	-14.7510	1.0457	-13.2372
8	1.0800	-13.2368	1.0287	-14.7500	1.0800	-13.2371
9	1.0305	-14.8201	0.9763	-16.5125	1.0305	-14.8206
10	1.0299	-15.0360	0.9758	-16.7476	1.0299	-15.0364
11	1.0461	-14.8581	0.9932	-16.5397	1.0461	-14.8553
12	1.0533	-15.2973	1.0009	-17.0203	1.0533	-15.2946
13	1.0466	-15.3313	0.9940	-17.0583	1.0466	-15.3285
14	1.0193	-16.0717	0.9647	-17.8967	1.0193	-16.0727

The voltage magnitude errors of estimation for both case (with and without PMUs method) are shown in figure 4.1, while the angle estimation errors are shown in figure 4.2.

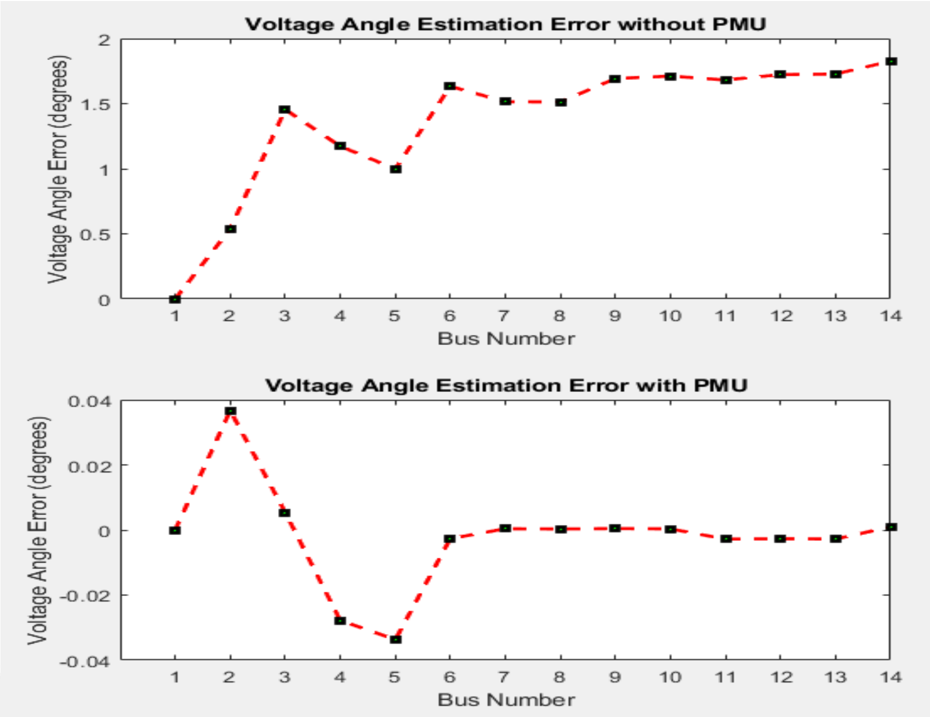

Figure 4.1: Angle estimation errors with and without PMUs

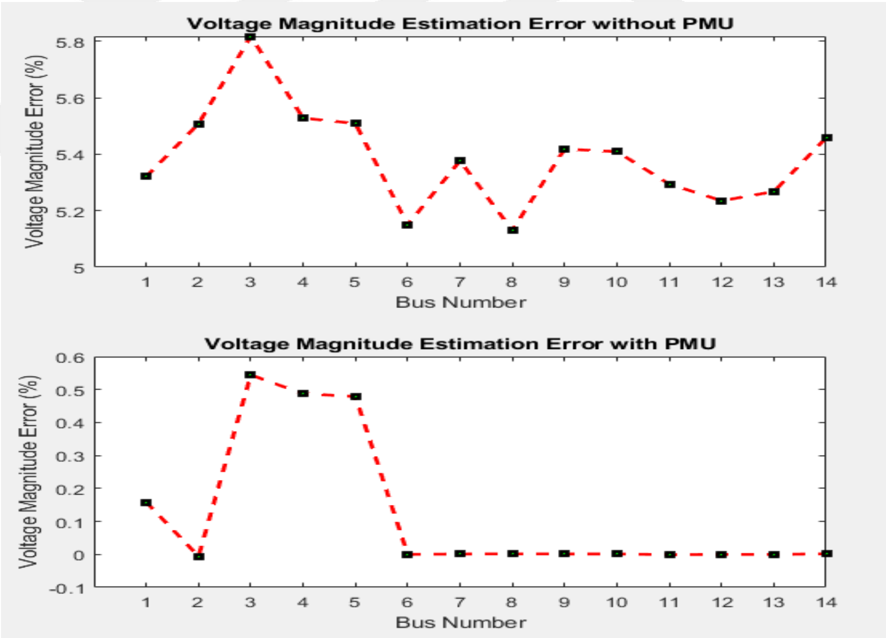

Figure 4.2: Voltage estimation errors with and without PMUs

The estimation process repeated for another loading case (for bus-5) for the studied bus, in this case bus-5 loading conditions are:

Bus voltage: 1p.u volt, Load power: 15 MW, Load reactive power: 1.6 MVAr. The system data is listed in table 4.2,

Table 4.2: IEEE-14 system voltages and angles for the three methods in other loading state

Bus No	NR		Without PMUs		With PMUs	
	Magnitude	Angle	Magnitude	Angle	Magnitude	Angle
1	1.0600	0.0000	1.0068	0.0000	1.0584	0.0000
2	1.0450	-5.1546	0.9899	-5.5265	1.0451	-5.0258
3	1.0100	-13.0072	0.9518	-14.2039	1.0046	-12.7546
4	1.0124	-10.5690	0.9579	-11.4146	1.0083	-10.2142
5	1.0166	-8.7601	0.9615	-9.7583	1.0118	-8.7264
6	1.0700	-14.4469	1.0185	-16.0798	1.0700	-14.4443
7	1.0457	-13.2368	0.9919	-14.7510	1.0457	-13.2372
8	1.0800	-13.2368	1.0287	-14.7500	1.0800	-13.2371
9	1.0305	-14.8201	0.9763	-16.5125	1.0305	-14.8206
10	1.0299	-15.0360	0.9758	-16.7476	1.0299	-15.0364
11	1.0461	-14.8581	0.9932	-16.5397	1.0461	-14.8553
12	1.0533	-15.2973	1.0009	-17.0203	1.0533	-15.2946
13	1.0466	-15.3313	0.9940	-17.0583	1.0466	-15.3285
14	1.0193	-16.0717	0.9647	-17.8967	1.0193	-16.0727

The voltage magnitude errors of estimation for both case (with and without PMUs method) are shown in figure 4.3, while the angle estimation errors are shown in figure 4.4.

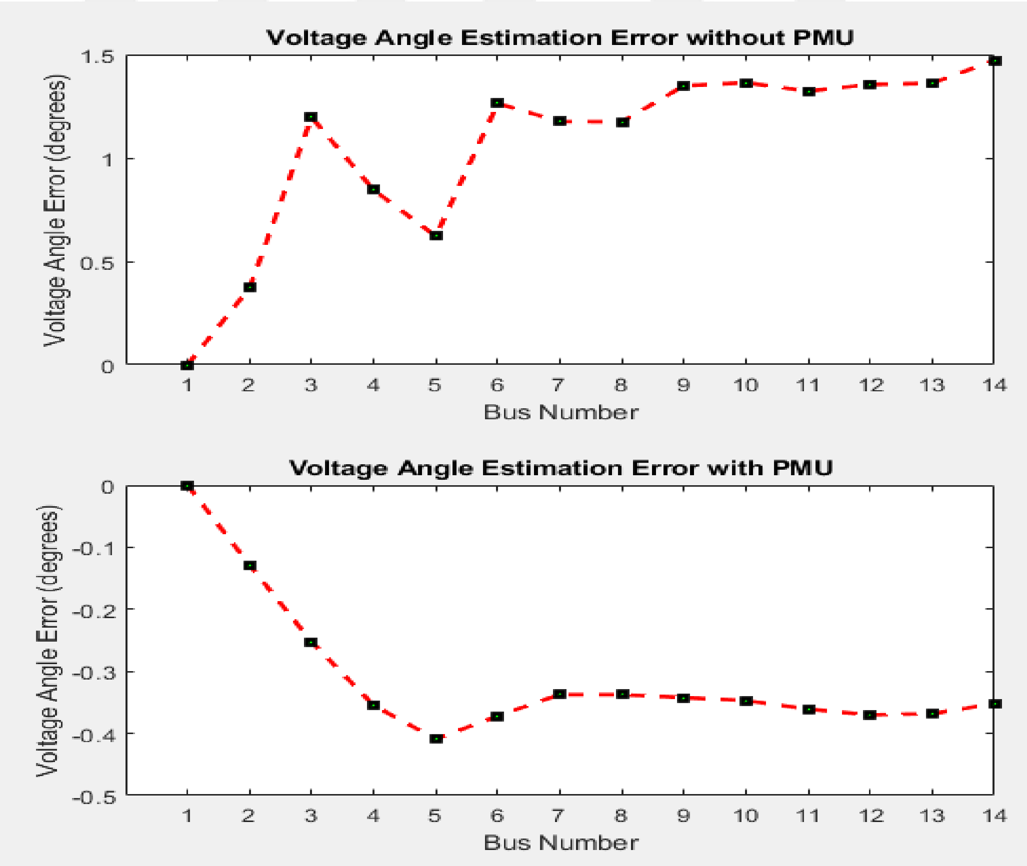

Figure 4.3: Voltage estimation errors with and withou PMUs

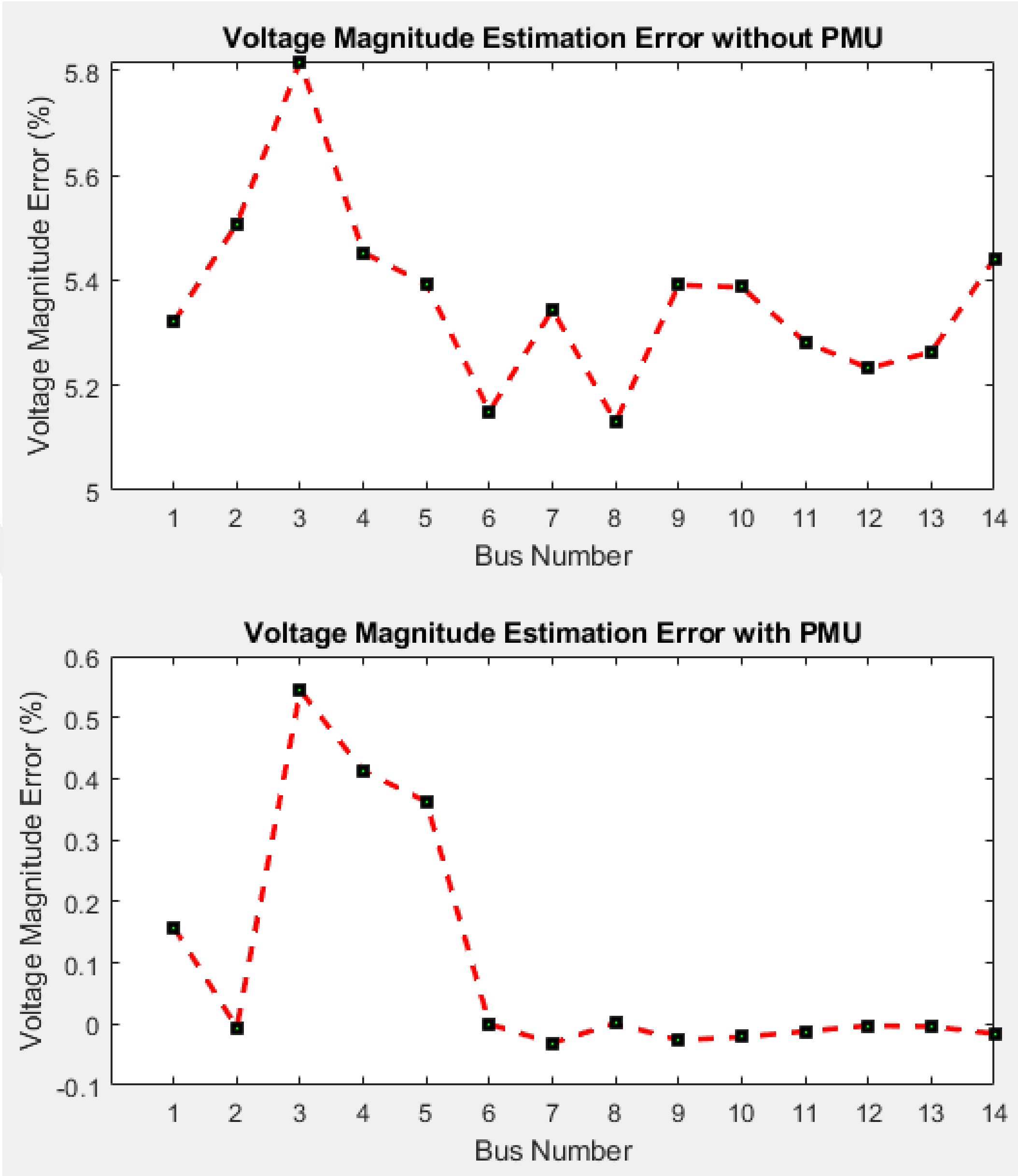

Figure 4.4: Angle estimation errors with and without PMUs

4.1.2 IEEE-30 bus system

The second studied case is the IEEE-30 bus system, in this case the the studied bus is bus-5, this bus is selected to show the accuracy of the estimation process. The estimation is done using PMU estimation method. Table 4.3 contains the system data.

Table 4.3: IEEE-30 system voltages and angles for the three methods

Bus No	NR		Without PMUs		With PMUs	
	V p.u	Angle	V p.u	Angle	V p.u	Angle
1	1.0600	0.0000	0.9865	0.0000	1.0574	0.0000
2	1.0430	-5.3543	0.9700	-6.2635	1.0430	-5.3904
3	1.0196	-7.5308	0.9474	-8.8420	1.0234	-7.6313
4	1.0104	-9.2840	0.9384	-10.9021	1.0141	-9.3750
5	1.0100	-14.1738	0.9335	-16.4941	1.0101	-14.1795
6	1.0096	-11.0581	0.9395	-12.9975	1.0152	-11.1708
7	1.0020	-12.8649	0.9287	-15.0443	1.0054	-12.9316
8	1.0100	-11.8193	0.9449	-13.9608	1.0201	-11.9941
9	1.0392	-14.0644	0.9667	-16.4813	1.0424	-14.1441
10	1.0215	-15.6706	0.9472	-18.3445	1.0248	-15.7384
11	1.0820	-14.0644	1.0093	-16.4813	1.0821	-14.1425
12	1.0496	-15.1245	0.9746	-17.6918	1.0517	-15.1645
13	1.0710	-15.1245	0.9954	-17.6918	1.0711	-15.1638
14	1.0320	-16.0018	0.9559	-18.7137	1.0344	-16.0404
15	1.0251	-16.0084	0.9491	-18.7299	1.0277	-16.0537
16	1.0304	-15.6251	0.9555	-18.2800	1.0331	-15.6746
17	1.0188	-15.8687	0.9441	-18.5714	1.0219	-15.9313
18	1.0114	-16.6067	0.9352	-19.4195	1.0144	-16.6575
19	1.0066	-16.7658	0.9306	-19.6063	1.0097	-16.8193
20	1.0095	-16.5502	0.9339	-19.3581	1.0127	-16.6068
21	1.0082	-16.2178	0.9328	-18.9821	1.0115	-16.2801
22	1.0120	-15.9811	0.9372	-18.7111	1.0156	-16.0477
23	1.0085	-16.2294	0.9331	-18.9957	1.0118	-16.2845
24	0.9991	-16.3007	0.9231	-19.0788	1.0030	-16.3609
25	1.0032	-16.0720	0.9270	-18.7784	1.0082	-16.1429
26	0.9852	-16.5038	0.9070	-19.2593	0.9904	-16.5709
27	1.0145	-15.6559	0.9395	-18.2962	1.0202	-15.7365
28	1.0078	-11.7163	0.9398	-13.7910	1.0143	-11.8374
`29	0.9944	-16.9077	0.9177	-19.7604	1.0003	-16.9710
30	0.9828	-17.8067	0.9051	-20.8172	0.9888	-17.8592

The voltage magnitude estimation results are shown in figure 4.5, and the voltage angle estimation results are shown in figure 4.6, it is clear that the using of PMUs in variable estimation process gives accurate results.

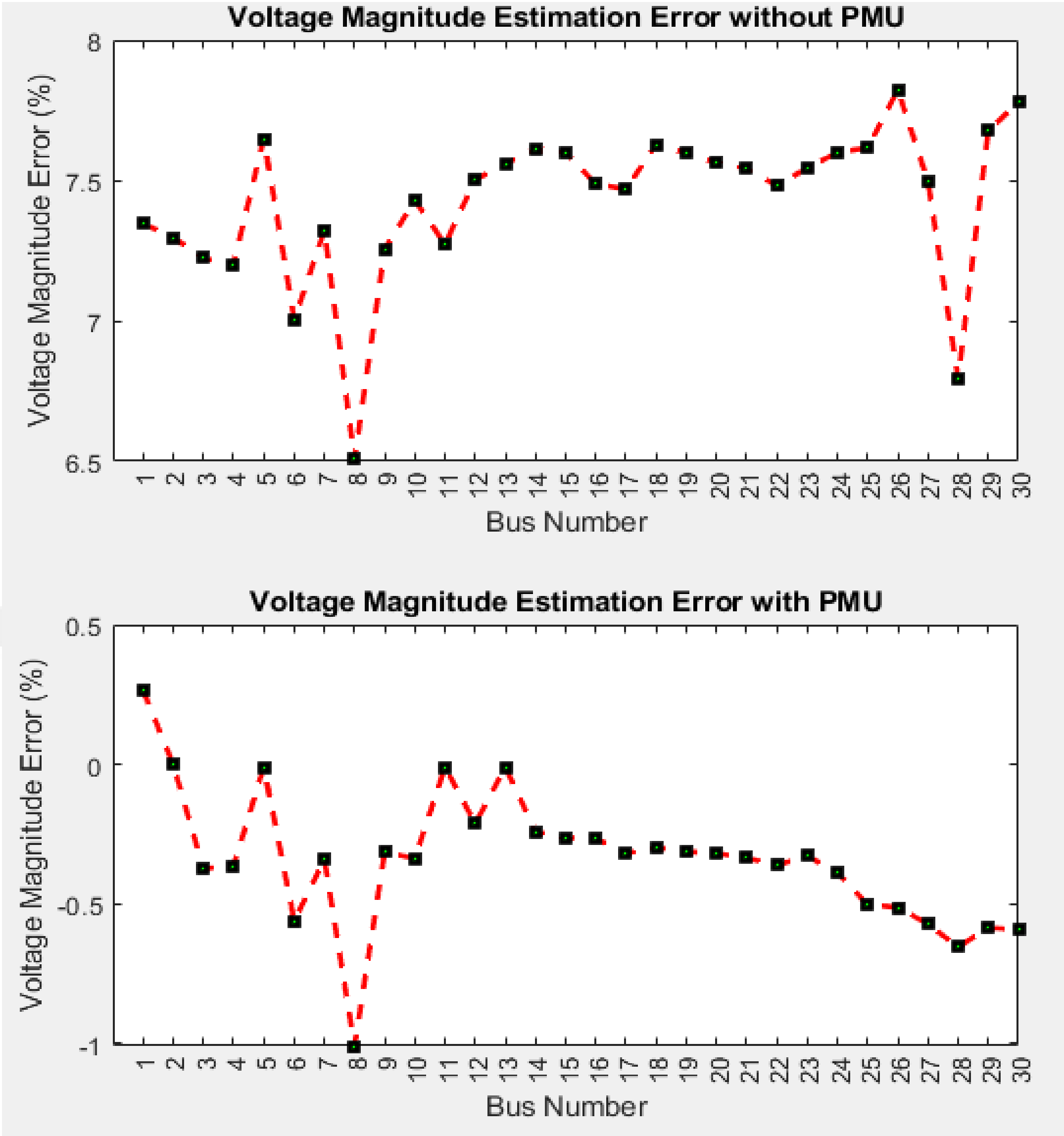

Figure 4.5: IEEE-30 bus voltage magnitude estimation

The maximum error in voltage magnitude in estimation without using PMUs method is 7.7% while the maximum error in case of using PMUs method is 0.4% as shown in figure 4.5, while the error in estimating the voltage angle in case without using PMUs is about 3.5 degrees while in case of using PMUs the error is about 0.175 degree as shown in figure 4.6.

Another estimation process implemented for other loading case (Bus 5) , the loading case is:

Bus voltage: 1.01p.u, voltage Angle: 0 degree, load real power: 57.0 MW, load reactive power: 94.2 MVAr. The results are shown in figures 4.7 and 4.8 respectively.

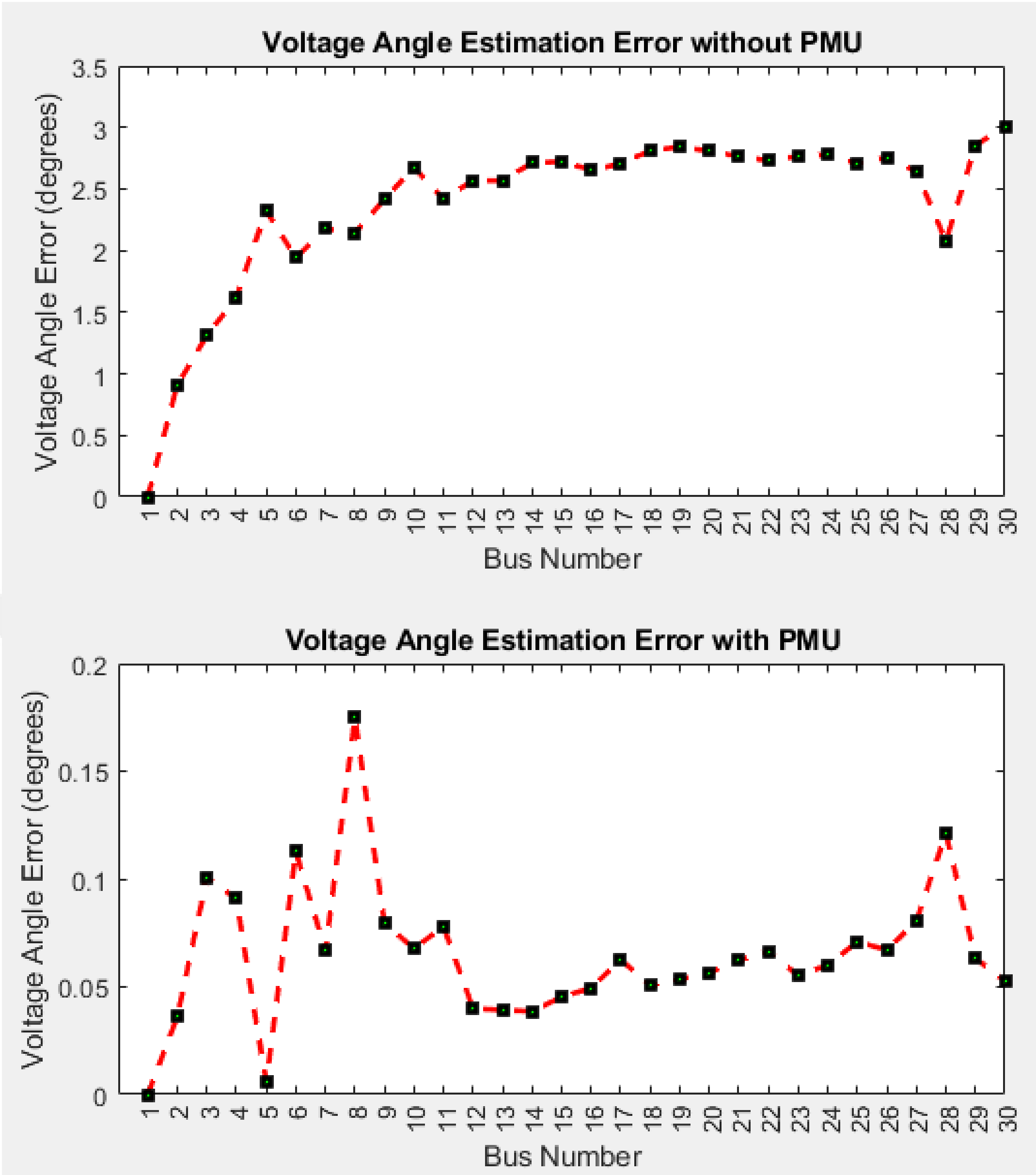

Figure 4.6: IEEE-30 bus voltage angle estimation

The estimation errors shown in figures 4.5 and 4.7 are very close to each other (the results for non-using PMUs are equal to that results when load is changed, and those when using PMUs are used are equal). Also, the errors in both figures 4.6 and 4.8 are close to each other.

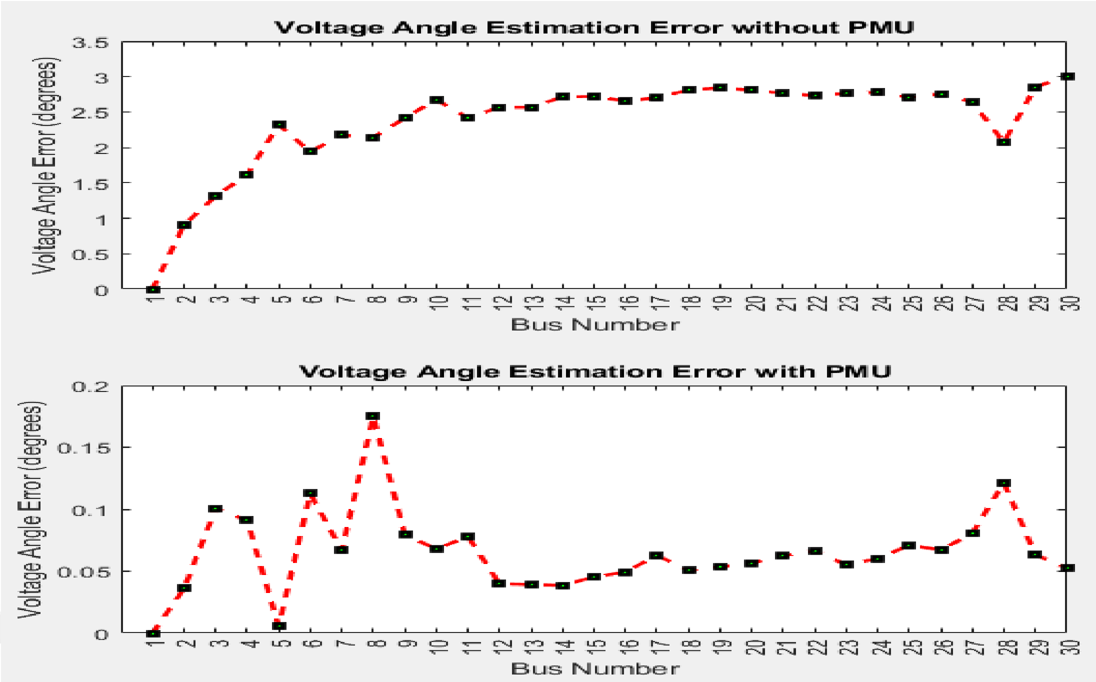

Figure 4.7: IEEE-30 bus voltages angles

4.2 Neural Networks Estimation Method vs NR

The NN based estimation method is implemented for IEEE-14 bus system, the estimation results are compared with NR numerical load flow results for the same system the process repeated for two times depending on bus-5 loading.

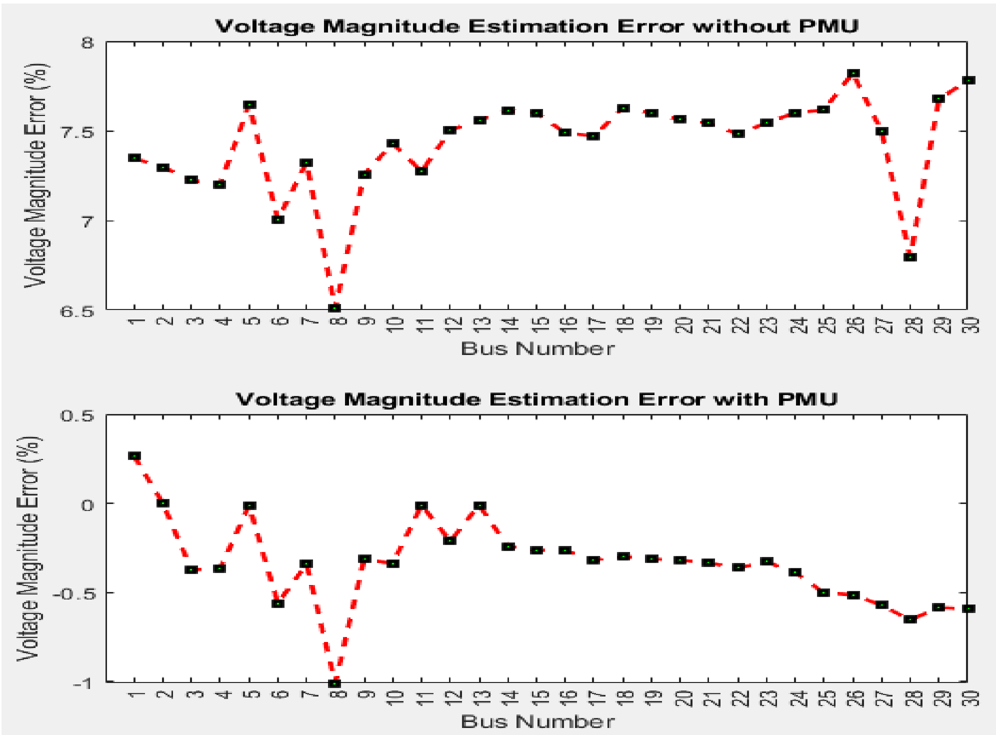

Figure 4.8: IEEE-30 bus voltages magnitudes

4.2.1 Normal loading case

The system voltages magnitudes and angles are listed in table 4.3, also figures 4.9 and 4.10 show the voltage magnitude and voltage angle for each bus respectively using NR and NN load flow methods.

Table 4.4: IEEE-14 bus voltages magnitudes and angles for NR and NN

Bus No	NR Load flow		NN Load flow	
	V_magnitude p.u	V_angle degree	V_magnitude p.u	V_angle degree
1	1.06	0	1.06	0
2	1.045	-0.093749	1.045	-0.093273
3	1.01	-0.2303	1.01	-0.22941
4	1.039	-0.19854	1.0389	-0.20113
5	1.0472	-0.17755	1.0464	-0.17994
6	1.0716	-0.27444	1.0715	-0.27126
7	1.047	-0.24918	1.0466	-0.24843
8	1.0768	-0.24918	1.0767	-0.24807
9	1.0213	-0.27688	1.0209	-0.27771
10	1.0226	-0.28134	1.0223	-0.28437
11	1.0432	-0.27982	1.0436	-0.28105
12	1.054	-0.28912	1.0535	-0.28665
13	1.0467	-0.28926	1.0466	-0.28794
14	1.014	-0.30041	1.0141	-0.30222

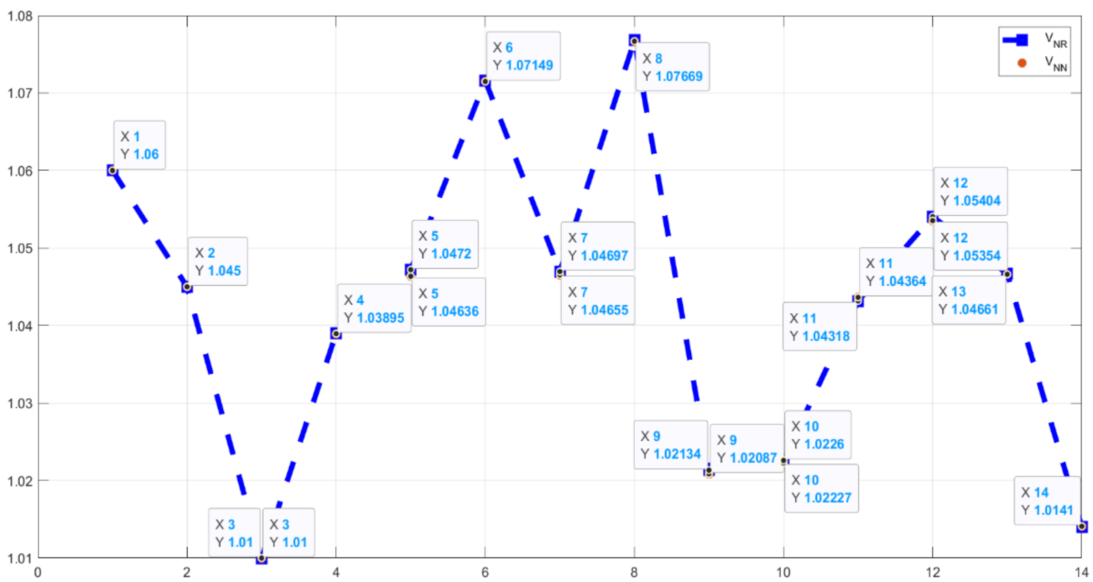

Figure 4.9: Voltage magnitudes for each bus using NR and NN methods

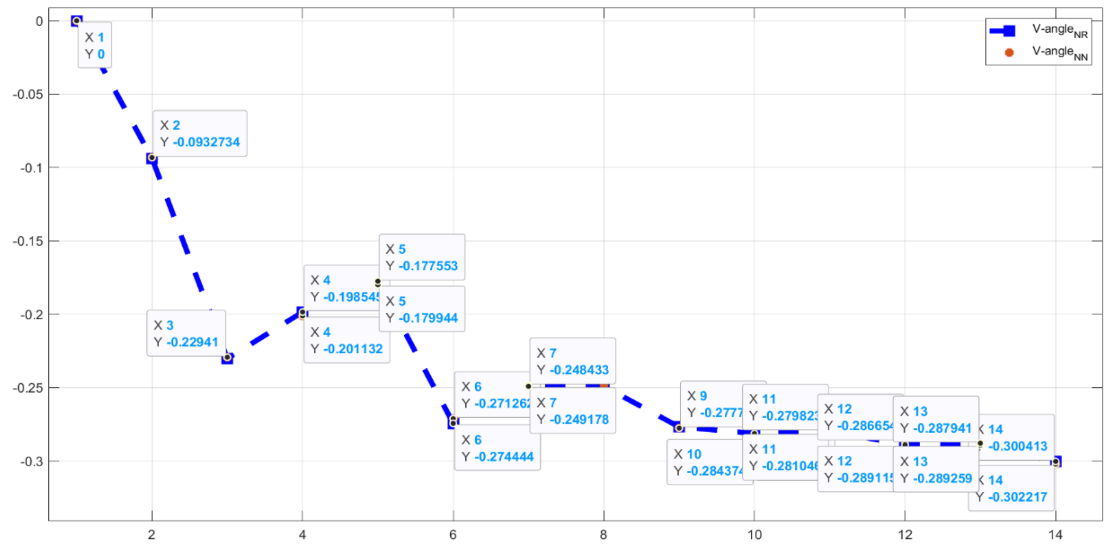

Figure 4.10: Voltage angles for each bus using NR and NN methods

The differences between calculated bus voltages and estimated bus voltages using NR and NN estimation method are listed in table 4.5, and plotted in figure 4.11, while the differences between calculated (NR) bus voltages angles and estimated bus voltages angles (NN) are shown in figure 4.12.

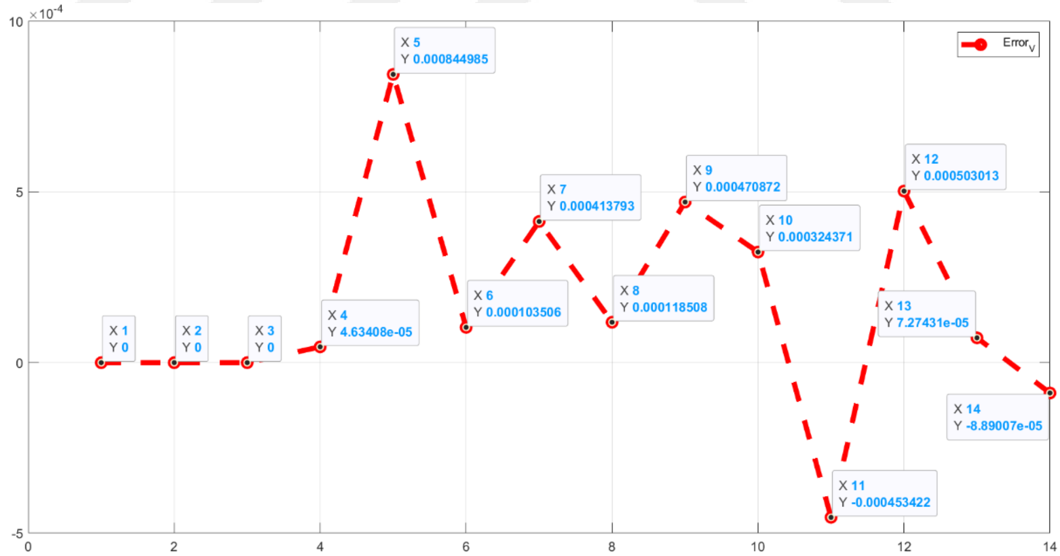

Figure 4.11: Voltage error between calculation and estimation methods

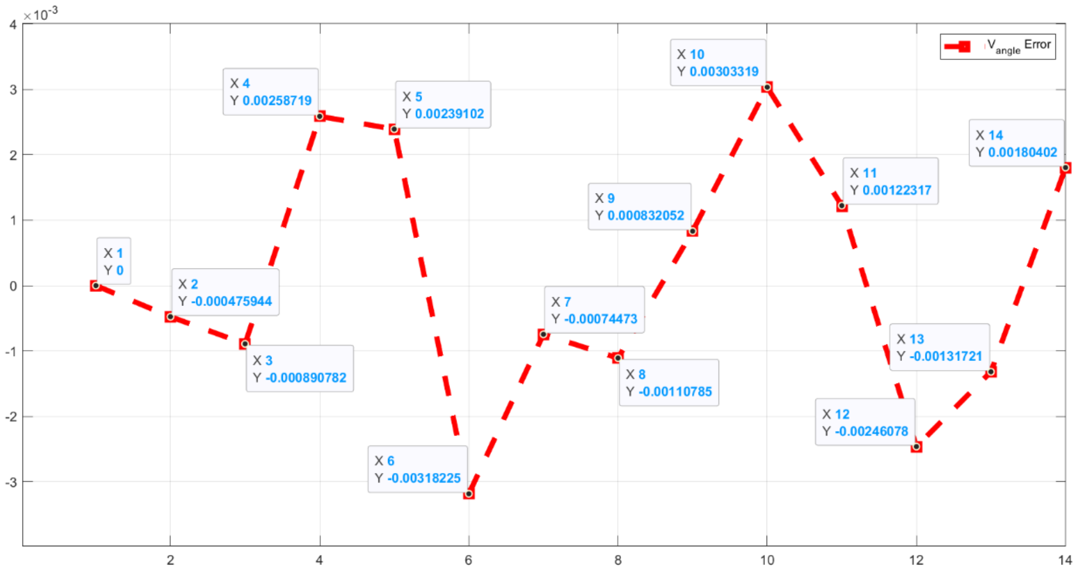

Figure 4.12: Voltages angles errors between calculation and estimation methods

5. CONCLUSIONS AND FUTURE WORKS

5.1 Conclusions

Distribution networks management can be achieved by estimating system state variables (in our case voltage magnitude and voltage angle for each bus). When the state variables estimated in correct way and precise manner the power management can be implemented easily. The proposed estimation methods (PMUs and NN) give a high performance in system state estimation since the error range was in less than 0.001 in voltage magnitude and in range of less than 0.5 degree in voltage angle estimation. NN has the advantage of retraining ability which gives it more flexibility to be used with more than one type of power systems. NN estimation system training data repaired using NR load flow algorithm. NR load flow analysis implemented for wide range of loading case in specific bus (bus-5), the calculation results collected and used as training set for NN training. NN designed using MATLAB platform (m-file software).

Simulation results showed that NN-based estimation system can be used as robust network learning system, while it has the ability to estimate distribution network parameters in a high accuracy. Also, the ability of implementation of NN in microcontrollers gives it the ability to be integrated with the power controller (circuit breakers CBs or FACTS components) in distribution grids which is very important thing in smart grids applications.

5.2 Future Works

The proposed system state estimation method can be implemented using real distribution system or including renewable energy power sources in the estimation process.

The proposed algorithm can be modified to overcome the problem of voltage absence case which can be occurred in some unstable electric power distribution system.

The proposed system can be simulated using another platform or program languages such as python, or C.

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