VOLTAGE STABILITY ASSESSMENT AND ENHANCEMENT USING ANN AND OPTIMALLY PLACED PMUs

Thesis

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CERTIFICATE – I

This is to certify that the thesis entitled **Voltage Stability Assessment and Enhancement Using ANN and Optimally Placed PMUs** submitted in partial fulfillment of the requirements for the degree of **Master of Technology** in **Electrical Engineering** with major in **Electrical Energy System** of the College of Post Graduate Studies, G. B. Pant University of Agriculture & Technology, Pantnagar, is a record of bonafide research carried out by **Mr. Mohit Chandra Durgapal** ID. No. **57236** under my supervision and no part of the thesis has been submitted for any other degree or diploma.

The assistance and help received during the course of this investigation have been acknowledged.

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CERTIFICATE - II

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LIST OF NOMENCLATURES/ SYMBOLS

Symbols	Meaning
VSI	Voltage Stability Index
CPF	Continuation Power Flow
ANN	Artificial Neural Network
VCPI	Voltage Collapse Proximity Index
SNB	Saddle Node Bifurcation
PMU	Phasor Measurement Unit
MSE	Mean Square Error
GPS	Global Positioning System
SVC	Static VAR compensator
STATCOM	Static Compensator
FFBP	Feed Forward Back Propagation
FVSI	Fast Voltage Stability Index
LSI	Line Stability Index
PSO	Particle Swarm Optimization
GA	Genetic Algorithm
SA	Simulated Annealing
WSCC	Western System Coordinating Council
GUI	Graphical User Interface
PSAT	Power System Analysis Toolbox
FACTS	Flexible AC Transmission System
DFS	Depth First Search
BILP	Binary Integer Linear Programming
ZIB	Zero Injection Bus
SVM	Support Vector Machine
NVSI	Novel Voltage Stability Index
V	Voltage Magnitude
δ	Voltage Angle
L-index	A Voltage Stability Index

Introduction

CHAPTER 1 INTRODUCTION

1.1 Background

The electrical energy system is widely recognized as one of the largest systems created by humans. It is a complex network of generation, transmission, distribution, and utilization infrastructure designed to meet the demand for electrical energy in an efficient and reliable manner. With its extensive reach and continuous evolution, the electrical energy system is undergoing significant transformations. Factors such as economic growth, growing population, urbanization, technological advancements, the rise of the 4th industrial revolution, environmental concerns are responsible for these transformations. The growing energy needs of the digital economy with an increasing number of power electronic devices and internet-connected infrastructure requiring more power are also responsible for such a huge transformation. This has resulted in a huge demand for electrical energy, which is expected to persist in the future. The power system infrastructure must be planned to keep pace with the anticipated rise in energy demand, ensuring efficient and reliable operation. Advancements in renewable energy generation technologies have led to a substantial increase in electrical power generation but the transmission infrastructure is struggling to keep pace due to socio-economic factors, environmental considerations, and the aging of the existing transmission systems. As a result, the transmission infrastructure is facing challenges in accommodating the growing generation capacity, thereby creating a gap between the increased generation and the ability to efficiently transmit and distribute the electrical power. Therefore, in order to fully utilize the limited transmission capacity, the transmission infrastructure is usually operated under stressed conditions, i.e., very near to its maximum transfer capability.

The goal of power system operation and control is to maintain the equilibrium between the supply and the demand for electrical energy at the lowest cost while maintaining acceptable voltage, frequency levels, and other system security constraints. However, this can be a challenging task due to operational, economical, and environmental limitations. The power system is in quasi-steady state for most of the time. However, it is a dynamic system whose dynamics is nonlinear in nature. Various disturbances and contingent events occur regularly in the system which make it challenging to maintain efficient and secure operation of the power system.

Power system stability has been a major concern for secure system operation since the 1920s. Multiple blackouts across the world during the past few decades have caused significant load loss. Lack of adequate reserves and improper control actions have been identified as main reasons for such events. Power system stability traditionally meant synchronous operation of alternators with the grid, but modern technologies and operational constraints have introduced different types of instability. Stressed circumstances and unpredicted events can cause changes in power flow, frequency, voltage, and failure of information and communication systems, leading to instability.

One such issue is voltage instability which has gained major attention of researchers in the past few decades. This problem was known to engineers and researchers for a long time but was generally associated with long distance transmission lines and weak grids. The continuous growth of loads has resulted in the operation of the system under stressed conditions which again highlighted the problem of voltage instability as confirmed by post-mortem analysis of some major blackouts across the globe. When generation and transmission units are operating close to their operating limits, a slight increase in the load demand or a disturbance can cause voltage instability issues in the power system. If not monitored and controlled properly, these issues can lead to a series of cascaded events resulting in voltage collapse or total/partial failure of the grid.

There are several instances of significant blackouts caused by voltage instability worldwide. The operation of the power system becomes very complex when contingent events occur. These events may include the failure of a heavily loaded transmission line, or the sudden loss of a major generation unit or sudden power demands due to load dynamics. These disruptions in the system can lead to increased system stress and result in a heightened risk of voltage instability. The insufficient reactive power reserve worsens the situation and increases the likelihood of voltage collapse.

The occurrence of significant blackouts worldwide due to voltage instability underscores the critical nature of power system operation and control. To mitigate the occurrence of such events, it is necessary to continuously assess the voltage stability, plan adequate reactive power reserves, and monitor voltage stability indices in real time so that energy control centers may take preventive and corrective actions to mitigate the occurrence of voltage collapse event.

1.2 Voltage Collapse Phenomenon and Definitions

According to IEEE/CIGRE joint task force on stability terms and definitions "Voltage stability refers to the ability of a power system to maintain steady voltages close to nominal value at all buses in the system after being subjected to a disturbance" (**Kundur *et al.*, 2004)**. Voltage stability majorly depends on the ability of generation and transmission systems to fulfill the power demands requested by loads. It is also termed as load stability as it is associated with the load dynamics and ability of system to fulfill load demands. The load dynamics greatly influences the occurrence of voltage instability. The ability to fulfill the demands involves many constraints such as:

1. Inherent capabilities of various system equipment,
2. Voltage limits and frequency limits,
3. Thermal limits of transmission lines,
4. Generators over-excitation limiters,
5. Voltage drops and losses across the transmission lines.

Voltage instability results in loss of loads or tripping of stressed transmission lines and other system components, by the protection system, leading to cascading outages due to which some generators may lose synchronism. Voltage instability is initiated when load dynamics tries to restore power consumption beyond combined capacity of transmission and generation system.

The gradual and uncontrollable decline in system voltage level is termed as voltage collapse. The loading/operating conditions of the electrical system change as a result of increasing demands, causing a decrease in the voltage magnitude at various nodes. This, in turn, leads to an increase in reactive power losses across the network, depleting the system's reactive power reserves and reducing system voltage levels further. The situation gets worse when the demand for electrical power continues to grow. Which causes drops in voltage levels and increase in reactive power losses. Despite the use of voltage regulation equipment such as automatic voltage regulator of generators, reactive power support devices, and under-load tap changing transformers. Finally, the sources reach their operating limits in supplying sufficient reactive power due to inherent capacity constraints leading to uncontrollable and gradual decrease in voltage levels at some or all the nodes/buses of the system. It is primarily due to the power system's inability to meet the rising demand resulting in low voltage levels that results in a series of cascaded events leading to voltage collapse. This phenomenon is usually initiated by some form of minor or major disturbance or change in the system operating conditions or structure locally. Voltage instability is generally classified as shown in Fig 1.1.

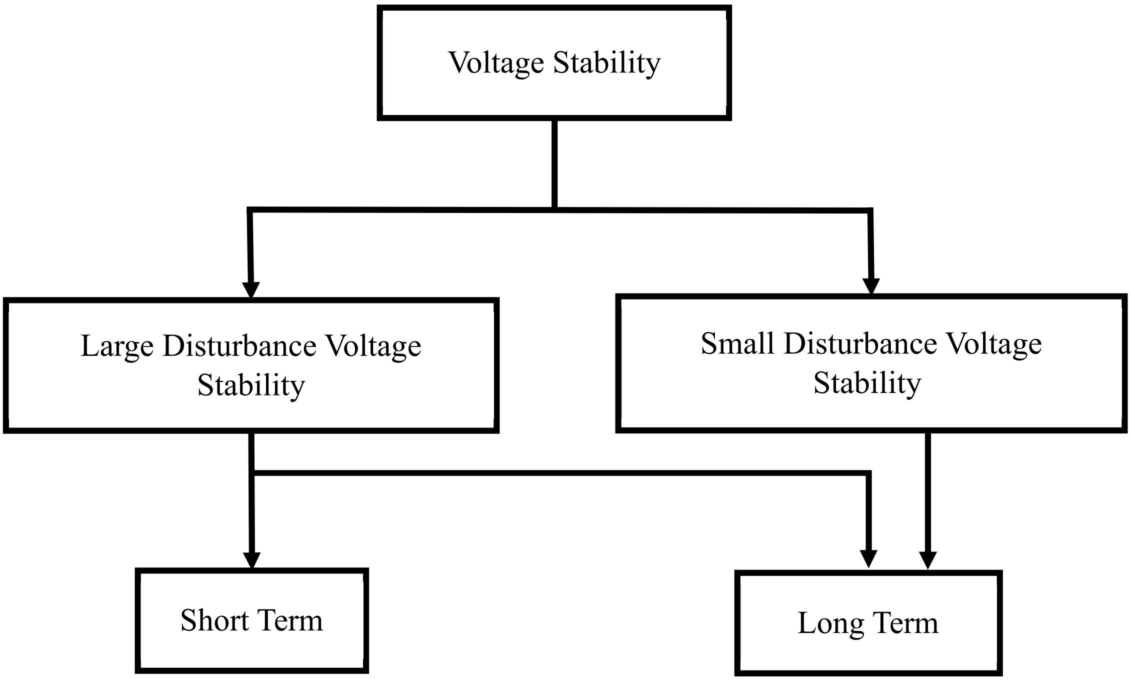


Fig. 1.1 Classification of voltage stability (Hatziargyriou *et al.,* 2020)

1.2.1 Large disturbance voltage stability

It is associated with the ability of the system to control voltages after being subjected to large disturbance such as loss of load, unexpected tripping of important transmission lines and sudden generator outages. Assessment of such events requires time-domain dynamic simulations involving nonlinear system and load dynamics which is based on proper mathematical modelling of system components and their interconnection.

1.2.2 Small disturbance voltage stability

It is generally concerned with the ability of the system to maintain acceptable voltages across system nodes following small variations in system conditions such as gradual changes in load. Its assessment involves linearization of differential equations and uses steady-state approaches such as load flow methods for the determination of system operating conditions.

1.2.3 Short-term voltage stability

It is associated with the dynamics of fast acting equipment and loads such as induction motors, electronically controlled loads, HVDC links, and inverter based generators associated with renewable generation. The study period for short term voltage stability is in the order of few seconds. Dynamic load models and time domain simulations are required for such analysis. For example, a most typical case of studying short-term voltage stability is stalling of induction motors following a large disturbance **(Hatziargyriou *et al.*, 2020)**.

1.2.4 Long-term voltage stability

It is associated with slower acting equipment such as ULTC transformers, thermostatically controlled loads, and generator over-excitation limiters. The study period for long-term voltage stability extends to several minutes. Steady-state simulations are needed for the study of this type of voltage stability. Analysis is done to study the post disturbance influence on voltage stability. Both large and small disturbances are considered in this study.

1.3 Voltage Stability Assessment

Voltage stability analysis is performed in order to identify the effect of various loading scenarios and disturbances on the system voltage security in order to plan and maintain a secure system operation. Voltage stability assessment involves:

a. The determination of system's vicinity to the point of voltage collapse in term of electrical distance, power margins, active and reactive power reserves, etc.
b. Determination of the mechanism that will be involved in the occurrence of voltage instability i.e., the key factors that will influence its occurrence.
c. Identification of weak buses and transmission lines.
d. Identification of most effective remedies for the mitigation of voltage instability.

1.3.1 Methods of voltage stability assessment

Voltage stability assessment is done using two major methods depending upon the objective of the analysis:

a. Dynamic analysis
b. Static analysis

1.3.2 Dynamic voltage stability assessment

Dynamic assessment requires time domain simulations and mathematical modelling of dynamic system components. It helps in determination of events and their chronological order leading to voltage instability. However, such simulations are time extensive and do not provide enough information about the relative stability. Dynamic analysis is usually performed for detailed study of a particular voltage collapse event, for coordination studies of protection and control devices, and for testing the effects of various corrective and preventive actions.

1.3.3 Static voltage stability assessment

Static assessment utilizes the results of steady state load-flow analysis of system across several operating points in the time scale. It is equivalent to capturing snapshots of the system across various operating points along the time domain trajectory. Static assessment is done either by manipulating and using the Jacobian matrices or by using load-flow results (real power (P), reactive power (Q), voltage magnitude (V), and voltage angle (δ)) to calculate voltage stability indices and voltage stability margins. System events influencing voltage instability usually progress slowly. Therefore, various aspects of voltage instability are analyzed using static methods. Wide range of operating conditions can be tested using static approach. It also helps in determination of viable equilibrium points. However, dynamic simulations can be used to complement the results of static analysis. Various voltage stability assessment methods using static approach have been proposed in literature. The most popular methods are:

1. P-V, Q-V curve tracing method
2. Continuation power flow method
3. V-Q sensitivity analysis
4. Modal analysis
5. Voltage stability indices
6. Local/ wide area measurement based methods

In this work, static voltage stability assessment methods are used. Voltage stability assessment of the test systems is done in MATLAB based simulation environment employing MATPOWER toolbox. The test system is simulated for a wide range of operating conditions and credible contingencies. The simulation results obtained are used to synthesize the phasor measurement unit (PMU) data and to calculate voltage stability indices. The data thus obtained is used to train, test, and deploy the artificial neural network (ANN) models. Voltage magnitudes (V) and voltage angles (δ) from some selected buses of the test systems are used as input features to ANN. The selection of buses whose measurements are used as input features to ANN is done based on optimal PMU placement strategies. The target and output features of ANN are voltage stability indices.

1.4 Voltage Stability Enhancement and Prevention of Voltage Collapse

To enhance the voltage stability and to mitigate the possibility of voltage collapse, the system design during planning phase and control measures during the operation phase need to be taken into consideration. Each aspect's contribution to voltage stability is described below.

1.4.1 System design approach

System design factors can enhance voltage stability if given proper attention during the planning phase. The system design factors influencing voltage stability are:

a. Sizing of generators and provision of secondary voltage control loop
b. Proper location and sizing of reactive power compensating devices
c. Proper coordination of protection and control devices
d. Under load tap changing transformers
e. Transmission line expansion planning

1.4.2 Control measures during operation

There are some predictive, preventive, and emergency control actions that can enhance voltage stability and prevent the occurrence of such events. These control actions are as follows:

a. Real time monitoring of voltage stability margins
b. Ensuring the availability of adequate reserves
c. Actions of energy control center and operators. Such as timely under-voltage load-shedding, generation rescheduling, and blocking the tap changing action of on-load tap changing transformers to deal with the extreme conditions.

1.5 Motivation behind the Proposed Work

It is very essential to monitor the power system continuously in real time to ensure voltage security of the system, which is undergoing huge changes in system infrastructure due to advent rise in power demands, grid integration of renewable generation, distributed generation, and system restructuring. So that energy control centers can take data driven intelligent decisions to maintain adequate reserves to mitigate occurrences of voltage instability events. Artificial neural networks (ANNs) are powerful tools used by many researchers for voltage stability assessment. ANNs can learn complex relationships and patterns from data due to which they are suitable for voltage stability assessment. Voltage instability is a complex phenomenon influenced by various nonlinear factors such as load characteristics, system topology, and control actions. ANNs can identify these patterns and correlations in large datasets which allow them to recognize the indicators of voltage instability. By training ANN on historical data and continuously analyzing system variables, such as voltage magnitudes, reactive power flows, and generator outputs in real time ANN can learn to identify system loading conditions that often appear before the voltage instability event. This can help system operators to take preventive actions in real time. With the advent of wide area measurement system employing PMUs for real time data acquisition and its application in real time power system monitoring makes integration of PMU and ANN based approach an ideal choice for voltage stability monitoring. In the literature survey it is found that there are various voltage stability assessment techniques using ANNs and phasor measurement units (PMUs). The major difference in proposed methods lies in:

a. The selection of input and output features
b. The selection of ANN model, and
c. The system operating conditions taken into consideration

Every proposed method has its own advantages and disadvantages. After going through the literature, it has been found that the research gap lies in effective utilization of real time PMU data for voltage stability assessment. The real time data which serves as input to ANN for continuous real time assessment is obtained from wide area measurement system employing phasor measurement unit. It has been found that researchers have not included the effect of various PMU placement strategies on the performance of voltage stability assessment using ANNs. In some literature employing ANN-PMU technique for voltage stability assessment PMUs were placed on every bus of the test system. PMU placement on every bus is economically not feasible so, optimal PMU placement is must to be taken into consideration. Also, the effect of contingencies on PMU placement was not considered. As system observability changes in case of contingencies, it is very important to consider its effect on real time voltage stability assessment. Global voltage stability indices were mostly used as output feature. These indices provide information about the overall stability of a system and do not provide any information about weak areas in the system. Only voltage stability monitoring was considered in the literatures employing ANN-PMU techniques. Voltage stability enhancement actions are not included based on voltage stability margins predicted by ANN. The above discussed research gap leads to the motivation for working on voltage stability assessment using ANNs utilizing different optimal PMU placements strategies. PMU data is synthesized using steady state simulations of test systems under various operating conditions considering critical and credible contingencies.

1.6 Research Objectives

1. To assess voltage stability of the test systems for various operating conditions using steady state repetitive power flows.
2. To synthesize the phasor measurement units (PMUs) data.
3. To find the optimal location of PMUs in the test system for complete system observability.
4. To assess voltage stability using artificial neural network (ANN) considering different PMU placement strategies.
5. To study the effect of various PMU placement strategies on the performance of voltage stability assessment using ANN.
6. To determine the location and optimal settings of static var compensator (SVC) for voltage stability enhancement.

1.7 Thesis Outline

Chapter 1 introduces the voltage stability problem associated with modern electrical energy system, need for voltage stability assessment, voltage stability assessment methods, factors influencing voltage stability, voltage stability enhancement methods, research gap and the research objectives.

Chapter 2 provides a brief literature review involving conventional and modern literature for voltage stability assessment and enhancement. Literature related to phasor measurement unit placement is also included in this chapter. The research gap identified is given in the summary part of this chapter.

Chapter 3 presents a comprehensive overview of the tools, procedures, and techniques used to carry out this thesis work.

Chapter 4 is dedicated to the presentation of the results obtained using the methodologies outlined in *Chapter 3,* including the performance of different PMU placement strategies and the impact of SVC deployment.

Chapter 5 Summarizes the findings of the research, highlights key contributions, and outlines potential avenues for future research in the field of voltage stability assessment and enhancement.

Review of Literature

CHAPTER 2 REVIEW OF LITERATURE

2.1 Background

The literature review offers a comprehensive understanding of existing ideas and approaches in the field of study, enabling the researcher to identify the gap and enhancing the researcher's knowledge of materials and methods. Electrical utilities have long recognized voltage stability concerns, but with increasing demand for electricity, they are gaining more attention. Post-mortem analysis of major events in the past few decades revealed voltage instability as the primary factor in network failures. Therefore, the term voltage instability or voltage collapse is more frequently appearing in power system operation and control literature. As the electricity demand continues to rise, it is crucial to understand and address the issue of voltage instability in power systems. With increasing concerns over system reliability and network redundancy, it is imperative to study the technical aspects of voltage stability and instability to ensure the stability and security of the power grid. The investigation of this issue will help to improve the overall performance of the power system and reduce the risk of network collapses, ensuring a stable and reliable electricity supply for consumers.

Consequently, numerous studies with varying objectives have been conducted to deepen our understanding of the subject. The useful findings of these studies are presented in this chapter in order to provide a comprehensive understanding of voltage stability using both conventional methods and artificial neural network (ANN) based methods. These studies also provide insight into future research directions. The goal of these studies is to improve our understanding of the underlying mechanisms of voltage instability and to develop more effective techniques for analyzing and mitigating voltage stability problems in power systems. By incorporating these findings into power system design and operation, we can enhance the reliability and stability of the power system.

2.2 Literature Review

Ajjarapu and Christy (1992) presented a method for preventing singularity in the Jacobian matrix by making slight modifications to the power flow equations and employing a locally parameterized continuation technique. By using this approach, known as "continuation power flow", the reformulated equations maintain good numerical properties, avoiding issues such as divergence and errors caused by a singular Jacobian. Predictor and corrector steps were employed in power flow so that solutions can be obtained at and around the critical point using single precision computations.

Gao *et al.* (1992) proposed a method for voltage stability assessment using modal analysis which involves computing eigenvalues and eigenvectors of a reduced Jacobian matrix derived from a steady-state system model. The eigenvalues represent different modes of voltage and reactive power variation, while the eigenvectors describe the mode shape and provide insights into the network elements and generators involved in each mode. By examining the eigenvalues, system operators can evaluate proximity to voltage instability and assess the overall system stability.

Morison *et al.* (1993) analyzed a small test system using static and dynamic approaches. Time domain simulations were used for dynamic analysis of the modeled system. These simulations effectively captured the sequence of events leading to voltage instability, providing the most accurate representation of system dynamics. Static analysis was conducted on the test system at three different load levels. This approach captured system conditions at specific points in time, providing snapshots that approximate different stages of the time domain trajectory. Modal analysis was then performed on each snapshot to assess the voltage stability. By comparing the results of dynamic and static approaches, it was demonstrated that results were consistent with each other and it was concluded that static approach offers some practical advantages over dynamic approaches.

Lee and Lee (1993) proposed a method for dynamic and static voltage stability enhancement of power systems. A modified criterion for static voltage stability was developed to accommodate a shunt compensator and a load dependent on voltage. The system was controlled to satisfy the static stability criterion. The control of static voltage stability involved the utilization of the shunt capacitor and online tap changing action of transformers. Simulation results demonstrated that employing these control measures increased the stability margin for static voltage stability. Furthermore, the enhancement of the stability margin led to an overall improvement in the voltage profile of the power system, effectively preventing a severe voltage decline. For an accurate analysis of dynamic voltage stability, the system model was expanded to include excitation systems, tap-changing transformers, capacitors, and power system stabilizers, into the system network equations.

Nallan and Rastgoufard (1996) conducted repetitive power flows in the test system for various operating conditions. System loading was increased from the base case to the maximum loading point. It was found that at the point of maximum loadability, power flow solutions were non-convergent due to the singularity of the Jacobian matrix. The proximity to the point of voltage collapse was determined using the eigenvalue analysis of the Jacobian matrix. Voltage stability margins (VSM) was given by the following formula:

$$\text{Voltage stability margin(VSM)} = \frac{\lambda_{\text{min}} - \lambda_{\text{cri}}}{\lambda_{\text{min}}}$$

Where λ_{min} is the minimum eigenvalue of the system at any operating point and λ_{cri} is the eigenvalue at the point of maximum loadability.

Popovic and Kulic (2001) proposed a methodology for the online monitoring and assessment of voltage stability margin in a power system using artificial neural networks (ANNs). This approach utilized a comprehensive vector of input variables, which includes bus voltage magnitudes (V), angles (θ), active powers (P), and reactive powers (Q). The ANN was trained to provide two important outputs: the voltage stability margin and the real part of the minimum eigenvalue derived from the linearized dynamic model of the system.

Musirin and Rahman (2002) proposed the fast voltage stability index (FVSI) which is a simplified index that provides a quick assessment of voltage stability in power systems. It was derived from voltage quadratic equation at the sending end of a simple two-bus power system representation. It was calculated for each transmission line in the the system, the index value ranges from 0 to 1, where a value close to 1 indicated that the line has reached its instability limit. Such a condition can lead to sudden voltage drops at the corresponding bus due to reactive load variations. It was also concluded that monitoring the FVSI values can help system operators to identify transmission lines that are close to their instability limits and take necessary actions to avoid potential voltage collapse.

Thukaram and Kashyap (2003) proposed an artificial neural network (ANN) based prototype to monitor and improve the power system voltage stability margin. The ANN focused on enhancing the voltage stability margin by utilizing Static Var Compensators (SVCs), generator excitation, and On-Load Tap Changer (OLTC) transformers as control parameters. The ANN was designed to accommodate various loading conditions for a practical extra high voltage (EHV) Indian power system.

Chakrabarti and Jeyasurya (2004) proposed a scheme for real-time monitoring of voltage stability utilizing artificial neural networks (ANNs). The ANNs were trained systematically using a specific approach. Multiple ANNs were employed to handle various contingencies and different load levels within each contingency. To improve the ANN's effectiveness, the results of contingency analysis were combined with principal component analysis (PCA) to select the significant input features for training. The incorporation of this feature selection scheme enhanced the overall utility and performance of the neural network in voltage stability monitoring.

Kundur *et al.* (2004) presented a report developed by a task force jointly set up by the CIGRE Study Committee 38 and the IEEE Power System Dynamic Performance Committee, to address the issues of definitions and classification of stability in power systems from a fundamental viewpoint and closely examine its practical consequences. The aim of the report was to define power system stability more precisely and provide a systematic basis for its classification. Finally, the report examined the interconnections between power system stability and other associated considerations, such as reliability and security.

Kamalasadan *et al.* (2006) proposed an artificial feed-forward neural network (FFNN) based approach for assessing power system voltage stability. A novel method was employed that utilized the input-output relationship between voltage stability index and real and reactive powers, as well as voltage vectors for generators and load buses to train the neural network (NN). The inputs of the feed-forward network were derived from offline training data that included diverse simulated loading conditions. These training conditions were generated using a conventional voltage stability algorithm based on the L-index. The neural network was then trained to predict the L-index output as the target vector for different system loads.

Chakrabarti (2008) presented a methodology for real-time voltage stability monitoring through the utilization of artificial neural networks (ANNs). The approach used separate ANNs for different contingencies. To select crucial features for training the ANN, a regression-based method was employed. The selection process leveraged the sensitivities of the voltage stability margins with respect to the inputs. These sensitivities were computed using regression models, which overcame the limitations associated with conventional methods of sensitivity computation.

Sodhi *et al.* (2010) introduced a novel method called Optimal PMU Placement (OPP) for achieving complete observability in a power system. This method consists of two stages: the first stage determines the minimum number of PMUs required for topological observability, and the second stage verifies if the resulting PMU placement leads to a fully ranked measurement Jacobian matrix. By utilizing this two-stage approach, the OPP method optimizes the placement of PMUs to ensure comprehensive observability of the power system.

Zhou *et al.* (2010) introduced a method based on artificial neural networks (ANN) for efficiently estimating the long-term voltage stability margin. The study revealed that node voltage magnitudes and phase angles serve as the most effective predictors of voltage stability margin. Furthermore, the proposed ANN-based approach successfully estimates the voltage stability margin not only during normal operation but also under N-1 contingency scenarios. By obtaining real-time voltage magnitudes and phase angles from phasor measurement units (PMUs) using the proposed method, the voltage stability margin can be estimated in real time, enabling the initiation of stability control actions.

Rahi *et al.* (2012) introduced a novel technique for determining the static voltage stability of load buses in a power system, aiming to identify buses that are close to voltage collapse. A voltage stability index was formulated for each load bus using the voltage equation derived from a simplified two-bus network. The index was computed based on the Thevenin equivalent circuit of the power system referenced to each load bus. Load buses with voltage stability index nearing 1.0 were identified as critical buses. Additionally, an ANN was developed for voltage stability monitoring.

Yang *et al.* (2012) proposed an improved voltage stability index (IVSI) and an optimization method for reactive compensation device settings. To solve the optimization problem, the hybrid differential evolution (HDE) algorithm was introduced which was utilized to determine tap settings of on-load tap changing (OLTC) transformers, excitation settings of generators or synchronous condensers (SCs), and locations with sizes of static var compensators (SVCs). To validate the performance of this technique, the IEEE 30-bus power flow test system was used. The results showed that the proposed method, incorporating the improved voltage stability index and the optimization approach, was able to effectively enhance the voltage stability of the system and reduce line losses.

Dasgupta *et al.* (2013) developed a model-free approach for the short-term monitoring of voltage stability in a power system. Finite time Lyapunov exponents were employed as indicators of stability. The time-series voltage data obtained from phasor measurement units (PMUs) was utilized to calculate the Lyapunov exponent, enabling real-time prediction of voltage stability. The practical implementation challenges, including phasor measurement noise, communication delays, and the finite window size for prediction, were addressed. The Lyapunov exponents serve as stability certificates, providing insights into the contributions of individual buses to overall system stability and facilitate the computation of critical clearing time.

Su and Liu (2015) proposed a novel method utilizing phasor measurement units (PMUs) to estimate the voltage stability margin in a power system, thereby enhancing operator situational awareness. The method incorporated a PMU measurement preprocessing technique to address data inconsistency and uncertainty resulting from random load disturbances. These preprocessed measurements are then employed to compute the voltage stability margin using a coupled single-port Thevenin equivalent model and cubic spline extrapolation technique. Furthermore, practical operating constraints, including generator reactive power limits, were considered to assess the method's performance in real-world scenarios.

Xu *et al.* (2015) proposed a multi-objective programming (MOP) model to simultaneously minimize investment cost, unacceptable transient voltage performance, and proximity to steady-state voltage collapse. The aim of the model was to identify Pareto optimal solutions, enabling flexible and multi-objective decision-making. To account for multiple contingencies and their probabilities, the study introduced risk-based metrics using respective voltage stability measures. These metrics were developed to handle different voltage stability criteria. A strategy based on the Pareto frontier was designed to identify critical contingencies and candidate buses for STATCOM connection. Subsequently, to solve the MOP model, an improved decomposition-based multi-objective evolutionary algorithm was developed. The proposed model and algorithm were demonstrated using the New England 39-bus test system and were compared with state-of-the-art solution algorithms.

Mouwafi *et al.* (2016) presented a multi-stage method for achieving complete observability in a power system through optimal placement of Phasor Measurement Units (PMUs), while considering the availability of PMU measuring channels. The method employed a two-stage approach. In stage-1, the ant colony optimization (ACO) algorithm was utilized to determine the optimal number and locations of PMUs to maximize the measurement redundancy (MR) under normal and emergency conditions. In stage-2, a reduction strategy (RS) was applied to achieve the minimum number of PMUs measuring channels while maintaining complete observability. The proposed method was evaluated on various standard test systems, including IEEE 14-bus, 30-bus, 57-bus, 118-bus, and New England (NE) 39-bus test systems.

Ratra *et al.* (2018) proposed a new accurate line voltage stability index (LVSI) based on ABCD parameters of transmission lines. This index also considered the effect of line resistance and line charging shunt parameters which were ignored in the previously proposed indices in the literature. In this method LVSI lies between 1 and 2. 'LVSI=1' represents that the system has reached its loadability limit and 'LVSI=2' represents a lightly loaded system. Simulation results clearly highlight the effectiveness of the proposed index in comparison to other voltage stability indices.

El-Araby and Yorino (2018) presented an approach for the effective management of reactive power reserves. The proposed method was deemed as an operational planning tool that simultaneously minimized the operating cost for a given forecasted load and the control cost of the likely disturbances, while ensuring effective VAR reserves to withstand credible severe contingencies without violating system security. The problem formulation included load shedding as a last resort control option to guarantee that voltage stability margins were maintained at a minimum control cost. The sensitivity of the load margin with respect to the generator VAR output was employed to determine the generator's relative worth for maintaining voltage security. The effectiveness of the proposed approach was validated through its implementation on a six-bus system and IEEE 57-bus system.

Pan *et al.* (2020) proposed a method that leverages phasor measurement unit (PMU) data to monitor static voltage stability in power systems. The approach utilized real-time information such as power, voltage, and phase angle measurements obtained from PMUs to estimate the power flow Jacobian matrix. By analyzing the minimum singular values (MSVs) of the Jacobian matrix, the static voltage stability of the system was monitored. This method was used to perform the online monitoring of static voltage stability solely based on PMU data, without any need for relying on a physical model or its parameters.

Hatziargyriou *et al.* (2020) presented extended definitions and classification of power system stability in accordance with the task force established in 2016 to re-examine and extend the classic definitions and classifications of the basic stability terms to incorporate the effects of fast-response power electronic devices as the dynamic behavior of power systems has gradually changed due to the increasing penetration of converter interfaced generation technologies, loads, and transmission devices.

Kumar *et al.* (2021) proposed a methodology for online voltage stability monitoring scheme using artificial neural networks (ANNs). The approach considered the worst-case contingency scenario along with the base case configuration to estimate the voltage stability margin. Separate ANN models were used for each configuration, and the meta-parameters of the ANN were tuned using particle swarm optimization (PSO). The inputs for the ANN model included voltage magnitudes and phase angles from PMUs. The effectiveness of the proposed approach was demonstrated on the IEEE 14-bus and 30-bus systems. The mean absolute percentage error (MAPE), mean percentage error (MPE), and root mean square error (RMSE) between the estimated and actual values of voltage stability margin were found to be negligibly small.

Nageswa Rao *et al.* (2021) presented a comprehensive review of the various methodologies commonly employed to determine voltage stability indices (VSI) in electrical energy System. The review encompassed an extensive survey of the available VSIs found in the literature. Multiple VSIs were listed, each serving different purposes such as assessing voltage collapse proximity, maximum loadability, voltage stability margin, identifying the weakest bus, contingency screening and ranking, identifying regions with reactive power deficiency, estimating critical branches and areas, evaluating system stability margin, and addressing data inconsistency in PMU measurements. The review investigated numerous VSIs based on the aforementioned studies. It highlighted that some indices are computationally intensive, while others may not provide accurate estimations in all scenarios.

Adetokun and Muriithi (2021) presented a comprehensive review on the application and control of flexible alternating current transmission systems (FACTS) devices to improve the voltage stability of power grids with a high share of renewable energy systems. The applications of FACTS devices for voltage stability improvement were explored in this research. This work also highlighted the future research directions in the area of voltage stability enhancement by FACTS devices for modern power grids characterized by increasing levels of renewable energy penetration.

Sandhya and Chatterjee (2023) proposed a two-stage artificial neural network (ANN) based technique to address the problem of complexity associated with optimization methods that rely on rigorous mathematical calculations. The approach used an ANN in the first stage to rank critical buses based on voltage stability indices. This ranking helped to determine the optimal location for the placement of distributed energy resources (DERs). In the second stage, another ANN was employed to assess the size of the DERs based on the location of the critical bus. This enabled the identification of the optimal sizing for the DERs.

2.3 Summary

Traditionally, two categories of techniques for the calculation of load margin were used, namely direct methods and indirect methods. Direct methods estimate the load margin directly, while indirect methods evaluate the voltage stability of the system for fixed load increments and restrict the evaluation after a series of increment steps. Static analysis using the Newton-Raphson method was commonly used for such voltage stability assessment (VSA). Indirect methods construct the PV curve by gradually increasing the load. Although these methods are effective, they may not be practical for real-time operations due to the need for frequent load adjustments. Direct techniques, on the other hand, estimate the load margin directly without calculating eigenvalues or subsequent load increases. However, there have been challenges in their application, including reliance on initial conditions near the voltage collapse point, inadequate system description, and failure to consider generator restrictions for reactive power generation. To address these issues, the continuation power flow (CPF) method has been employed to determine the stability margin. However, the accuracy of CPF diminishes when the step length is large. The main drawback of CPF and repetitive power flow techniques is their time-consuming nature, making them unsuitable for online voltage security assessment. Convergence may not always be ensured in real-time applications using these methods. Several voltage stability indices (VSIs) have also been proposed in the literature, but these indices mostly rely on traditional power flow methodologies. Modern Machine Learning (ML) techniques have also been utilized in literature to analyze the voltage stability. Artificial neural networks (ANNs) have been extensively studied for voltage stability monitoring, establishing associations between voltage stability indicators and power system parameters. Various feature selection techniques have been employed to reduce the input features of artificial neural networks (ANNs) for voltage stability assessment. These techniques aim to identify the most relevant and informative features from a large set of potential inputs, thus reducing the dimensionality of the input space. By selecting a subset of significant features, the computational complexity of the ANN gets reduced, and the training and prediction processes become more efficient.

The advancement of wide-area measurement systems using phasor measurement units (PMUs) has enabled real-time voltage stability monitoring in power systems. However, installing PMUs at every node in the system can be costly and impractical. To address this challenge, optimal PMU placement techniques have been developed to ensure the complete observability of the system while minimizing the number of PMUs required. These techniques aim to strategically select the optimal locations for PMU installation to achieve the maximum coverage and observability of the power system. By carefully selecting the nodes for PMU placement, the system can obtain sufficient measurements to accurately monitor voltage stability in real-time, without the need for PMUs at every node. Various voltage stability enhancement methods are also proposed in the literature which are helpful in maintaining a stable voltage profile in the system. Various voltage stability assessment methods using ANN and PMUs have also been proposed in the literature but, the effect of various PMU placement strategies on the performance of voltage stability assessment using ANN based method has not been studied. Also, the strategies for voltage stability enhancement based on the predictions made by these ANN-PMU based methods have not been studied in these works. Furthermore, the global voltage stability indices were mostly proposed in these works. Such indices are unable to identify weak areas in the system.

Thus, based on the above research gap identified, it can be observed that the accuracy and effectiveness of voltage stability assessment can be enhanced by strategically placing PMUs at critical locations. This approach will prove to be cost-effective by optimizing the number of PMUs required. It will provide flexibility to adapt to changing system conditions and enable proactive measures for maintaining stability. Overall, optimal PMU placement with ANN based assessment can improve efficiency, accuracy, and cost-effectiveness in voltage stability monitoring. Voltage stability of the system can be enhanced by the placement of reactive power support devices at weak areas identified using ANN and PMU based voltage stability assessment. Further, the effectiveness of voltage stability enhancement can be increased by determining optimal reactive power injections by reactive power support devices using meta heuristic optimization algorithms. So, it can be concluded that the voltage stability assessment and enhancement using ANN and optimally placed PMUs will try to fill the research gap as identified in this review of literature.

Materials and Methods

CHAPTER 3 MATERIALS AND METHODS

This chapter aims to elaborate on the methodology and tools adopted in this thesis work for voltage stability assessment and enhancement using artificial neural networks (ANN) and data acquired using optimally placed phasor measurement units (PMUs). This chapter is organized into different sections describing voltage stability assessment techniques, test systems used, simulation software used with associated libraries and toolboxes, and other materials employed in this work. This work utilizes artificial neural networks trained on data obtained from optimally placed PMUs to predict voltage stability indices. The data for training and testing of the ANN is synthesized using steady-state simulation of the test systems under diverse operating conditions and credible contingencies. The voltage stability indices predicted by trained ANN models are used for voltage stability enhancement of the test network.

3.1 Voltage Stability Assessment Techniques

There is a wide range of techniques available for voltage stability assessment, including both conventional and modern approaches. These methods can be categorized into two main groups: those based on mathematical modeling of the system and those relying on measurements from local measurement units or wide area monitoring systems. The following is a list of popular voltage stability assessment methods proposed and utilized in the literature:

1. PV and QV curve based method
2. V-Q sensitivity and modal analysis
3. Bifurcation analysis
6. Continuation power flow analysis
7. Voltage stability indices
8. Measurement and soft computing based techniques

3.1.1 PV and QV curve method for voltage stability assessment

PV (Power-Voltage) and QV (Reactive Power-Voltage) curve tracing methods are widely used for voltage stability assessment of electrical energy system. These methods help to analyze the voltage stability of a power system by plotting the relationship between real power (P) or reactive power (Q) and bus voltage (V) under varying loading conditions (λ). By examining these curves, the voltage stability limits, and potential risk of voltage collapse can be analyzed. Typical PV and QV curves are shown in Fig. 3.1.

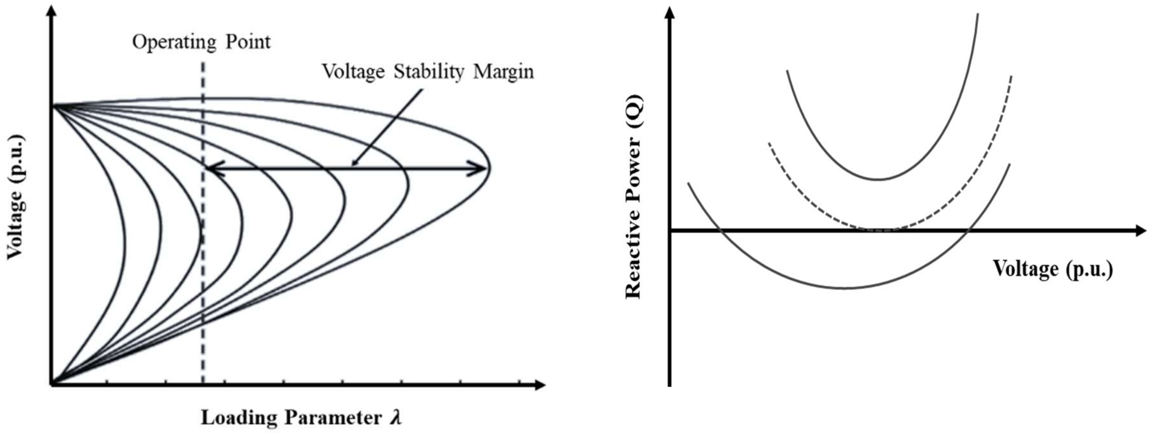


Fig. 3.1 Typical PV and QV curves

In the PV curve tracing method, the bus voltage (V) of a specific bus in the system is plotted against the real power (P) under incremental loading conditions (λ). The curve shows the region where the system operates in a stable manner. The upper limit of this region represents the maximum loading condition that the system can handle while maintaining stable voltage.

In the QV curve tracing method, the bus voltage (V) is plotted against the reactive power (Q) injection. The curve represents the system's ability to provide the reactive power support. If the curve shows a rapid decline in voltage for a given level of reactive power injection, it indicates that the system might be approaching a voltage collapse point.

Both PV and QV curve tracing methods help operators and planners understand the behavior of the power system as load increases and assess its ability to maintain stable voltage levels. By analyzing these curves, we can

- identify the critical points where voltage instability starts to become a concern,
- determine the available operating margin before the system becomes unstable, and
- design and implement control strategies such as adjusting generator set points, deploying reactive compensation devices, and load shedding to ensure voltage stability.

3.1.2 V-Q sensitivity and modal analysis method for voltage stability assessment

V-Q sensitivity analysis is a technique used in power system analysis to understand how changes in reactive power (Q) injections or withdrawals affect voltage (V) profiles within the system. The Newton-Raphson power flow equations can be used for this analysis. These equations are represented as:

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} J_{P\theta} & J_{PV} \\ J_{Q\theta} & J_{QV} \end{bmatrix} \begin{bmatrix} \Delta\theta \\ \Delta V \end{bmatrix}$$

where,

$\Delta P =$ incremental change in bus real power

$\Delta Q =$ incremental change in bus reactive power

$\Delta V =$ incremental change in bus voltage

$\Delta\theta =$ incremental change in bus voltage angle

Let $\Delta P = 0$, i.e., incremental changes in real power neglected. Then

$$\Delta Q = J_R . \Delta V$$

where, $J_R = \left[J_{QV} - J_{Q\theta} . J_{P\theta}^{-1} . J_{PV} \right]$

J_R is the reduced Jacobian matrix of the system

$$\frac{\Delta V}{\Delta Q} = J_R^{-1}$$

The ith diagonal element of J_R^{-1} is the V-Q sensitivity at bus i. A positive V-Q sensitivity indicates that an increase in reactive power injection leads to an increase in voltage magnitude, and a decrease in reactive power injection leads to a decrease in voltage. A negative sensitivity indicates the opposite behavior. Buses with high positive or negative V-Q sensitivity values are considered critical for voltage stability. High positive sensitivity indicates that small increases in reactive power injection can lead to significant voltage rises, making the bus prone to overvoltage issues. Conversely, high negative sensitivity suggests susceptibility to voltage collapse due to reactive power withdrawals. V-Q sensitivity analysis helps identify the buses that are more sensitive to reactive power changes, allowing operators to focus on those areas for proper control and mitigation strategies.

Modal analysis is an extension of V-Q sensitivity analysis technique to assess voltage stability. It involves studying the eigenvalues (modes) of the reduced system Jacobian matrix J_R^{-1} to understand the potential for voltage instability and identify critical modes that can lead to voltage collapse. If the minimum eigenvalue of J_R^{-1} is greater than zero then the system is voltage stable otherwise, unstable. The magnitude of eigenvalues indicates proximity of system to voltage instability.

3.1.3 Bifurcation analysis method for voltage stability assessment

It involves studying the behavior of a system as a system parameter is varied, specifically focusing on the points where the system's behavior changes abruptly or qualitatively. In the context of power systems, this analysis helps identify critical operating conditions, such as those leading to voltage instability, and provides insights into how the system's stability can be improved. Bifurcation analysis for voltage stability assessment involves following steps:

- Modeling the power system by identifying the equations that describe the relationships between various system parameters such as generator voltages, load demands, and network impedances.
- Selecting a Bifurcation Parameter. For voltage stability analysis, the bifurcation parameter is usually a control variable that can impact the system's voltage stability. This could be one of the factors like generator outputs, load levels, or transmission line parameters.
- Steady-State analysis of the power system for different values of the chosen bifurcation parameter. The steady-state analysis involves solving the power flow equations iteratively to determine the voltage magnitudes and angles at various buses in the system.
- Identifying points where the power system's behavior may exhibit sudden changes.

These methods track the system's behavior as the parameter is varied, identifying critical points and stability boundaries. By analyzing the bifurcation diagram (a graphical representation of the parameter values vs. system behavior), the conditions under which the system might experience voltage instability or collapse can be determined. This insight is crucial for preventing blackouts or voltage-induced failures.

3.1.4 Continuation power flow method for voltage stability assessment

The Continuation Power Flow (CPF) method is a numerical technique used for voltage stability assessment in power systems. It is a type of bifurcation analysis that tracks the system's behavior as the control parameter (often load demand) is varied. This method is particularly useful for identifying critical points where voltage instability or collapse might occur. The Jacobian matrix becomes singular at critical point in conventional power flow analysis. Continuation power flow solves this problem using prediction and correction steps. From a base solution a prediction step is used to determine the estimate of the next solution for a particular loading pattern. The corrector step is then used to determine the exact solution using the Newton-Raphson technique employed by a conventional power flow. After that a new prediction is made for a specified loading pattern based upon the new tangent vector. Then corrector step is applied again. This process goes on until critical point is reached. The critical point is the point where the value of tangent vector is zero. In CPF, power flow equations are reformulated by introducing a loading parameter.

let, $F(\theta, V) = 0$ defines initial load flow equations

then, $F(\theta, V, \lambda) = 0$ defines the reformulated equations

where,

θ denotes bus voltage angles,

V denotes bus voltage magnitudes, and

λ denotes the loading parameter introduced in reformulated power flow equations such that,

$$P_{Di} = P_{Di0} + \lambda(P_{\Delta_{base}})$$

$$Q_{Di} = Q_{Di} \ + \lambda(Q_{\Delta_{base}})$$

P_{Di} and Q_{Di0} are original load demands on bus i. $P_{\Delta_{base}}$ and $Q_{\Delta_{base}}$ are quantities of power to be scaled by λ.

The illustration of predictor-corrector based scheme is shown in Fig 3.2.

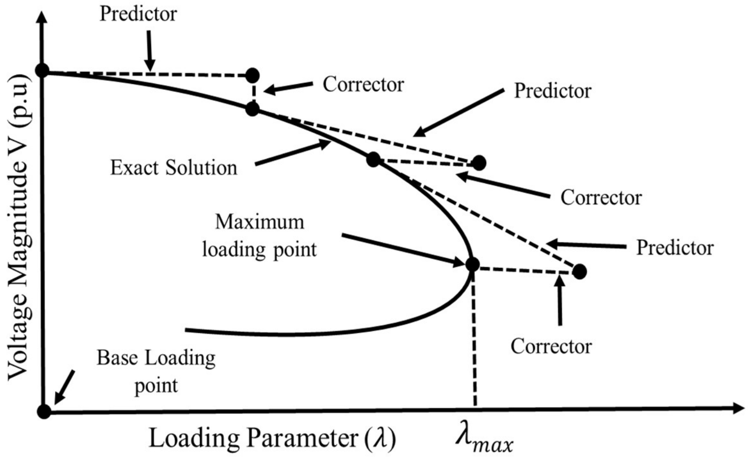


Fig. 3.2 Predictor-corrector based scheme in CPF

Steps involved in continuation power flow to identify the critical point are:

1. Base case power flow using conventional power flow approach
2. Predictor step by calculating tangent vector
3. Check if critical point reached
4. Select the continuation parameter
5. Perform correction
6. Repeat steps 2 to 5 till the critical point is reached

The flowchart of the above procedure is shown in Fig. 3.3

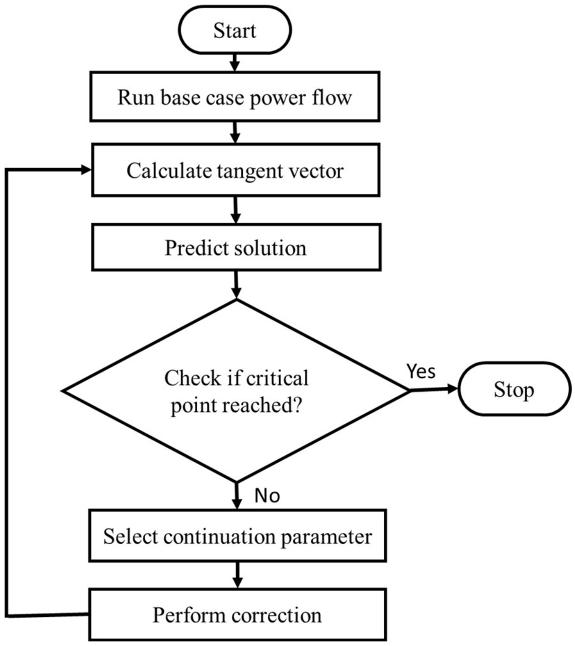


Fig. 3.3 Flowchart of the continuation power flow

3.1.5 Voltage stability indices method for voltage stability assessment

Voltage stability indices (VSIs) are methods used to quantify the proximity of a power system to voltage instability. These indices help power system operators and engineers identify potential voltage instability issues and take appropriate corrective measures in a timely manner. VSIs can be categorized into two main classes: Jacobian matrix based VSIs and system variables based VSIs. These two classes serve different purposes in voltage stability analysis.

1. **Jacobian matrix based VSIs:** Jacobian matrix based VSIs utilize the Jacobian matrix, which represents the partial derivatives of power flows with respect to voltage magnitudes and angles in a power system. These VSIs are capable of calculating the voltage stability limit and the voltage stability margin of power systems. However, due to their reliance on the Jacobian matrix, they are not well-suited for online or real-time voltage stability analysis. Any changes in the system configuration require recalculating the entire Jacobian matrix, which can be computationally intensive and time-consuming.
2. **System variables based VSIs:** System variables based VSIs, on the other hand, are designed to be more efficient for online and real-time assessment of voltage stability. They require fewer computations and rely on system variables such as bus voltages

and voltage angle differences. These VSIs use elements of the admittance matrix to estimate voltage stability. While they offer quicker analysis, they may not provide accurate estimates of the voltage stability margin as compared to Jacobian matrix based methods.

In addition to this classification, VSIs can be further categorized based on type and formulation concept.

- **Type:** This refers to the specific elements in the power system network that the VSI is concerned with. The types of voltage stability indices include:
    - Line Voltage Stability Indices: Focus on specific transmission lines and their impact on voltage stability.
    - Bus Voltage Stability Indices: Focus on individual buses and their voltage stability characteristics.
    - Overall Voltage Stability Indices: Provide a holistic assessment of the entire power system's voltage stability.
- **Formulation concept:** This refers to the underlying theories or methodologies used in formulating the VSI. The concept determines how the index is created and the factors it considers.

There are several voltage stability indices that have been developed over the years, each with its own approach and assumptions. Some of the commonly used indices include:

1. **Line stability index (LSI):** LSI is a voltage stability index derived by (**Moghavvemi and Omar, 1998)**, based on the concept of power flow in a simple 2-bus system. A simple 2-bus power system model is shown In Fig. 3.4. The reactive power injected at bus j is given by:

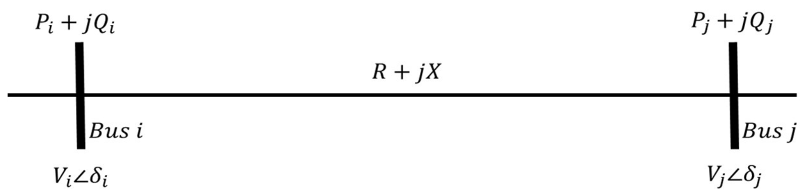


Fig. 3.4 A simple 2-bus power system model

$$Q_j = \frac{V_i V_j}{Z_{ij}} \sin(\theta_{ij} - \delta) - \frac{V_j^2}{Z_{ij}} sin\theta$$

where,

θ_{ij}= is the angle of (i, j) th element of system admittance matrix Y_{bus}.

$\delta_{ij} = \delta_i - \delta_j$

$Z_{ij} = R_{ij} + jX_{ij}$

Solving the above equation for V_j we get,

$$V_j = \frac{V_i \sin(\delta_{ij} - \theta_{ij}) \pm \sqrt{[V_i \sin(\delta_{ij} - \theta_{ij})]^2 - 4Z_{ij}Q_j sin\theta_{ij}}}{2}$$

To get real roots of V_j, the discriminant should be greater than zero so the line stability index is given as:

$$L_{ij} = \frac{4Q_j X_{ij}}{[V_i \sin(\delta_{ij} - \theta_{ij})]^2}$$

When L_{ij} values of a line approaches unity it means that the line is approaching its stability limits. The L_{ij} values of all the lines must be lower than 1 to assure the stability of the power system.

2. **Fast voltage stability index (FVSI):** The FVSI introduced by **(Musirin and Rahman, 2002)**, provides a fast and simplified way to assess the voltage stability of a system. This index is formulated using power flow equations through a line in a simple 2-bus system. For a standard transmission line, this index is computed as follows:

$$FVSI_{ij} = \frac{4Z^2 Q_j}{V_i^2 X}$$

Where,

Z represents line impedance,

X denotes line reactance,

Q_j stands for the reactive power flow at the receiving end,

V_i signifies the sending end voltage.

The computed FVSI can identify the system's weakest bus. This identification depends on the maximum load allowable on a load bus. The bus with the least permissible maximum load is considered the most vulnerable in the system. The line with an FVSI value closest to 1 is regarded as the most critical line for the respective bus, capable of inducing system-wide instability.

3. **Line stability factor (LQP):** (**Mohamed *et al.*, 1989)**, founded the line stability factor (LQP) based on the same principle as LSI and FVSI. LQP of a line between bus i and j is given by:

$$LQP_{ij} = 4\left(\frac{X}{V_i^2}\right)\left(Q_j + \frac{P_i^2 X}{V_i^2}\right)$$

To maintain stability, *LQP* must be less than 1. This index ignores shunt admittances and assumes that lines in the power system are lossless.

4. **Novel voltage stability index (NVSI):** (**Kanimozhi and Selvi, 2013**) formulated NVSI on the same principle as of FVSI and LSI, i.e., power flow in a simple two-bus system. In NVSI, transmission line resistance is assumed to be zero. NVSI must be less than 1, for the system to remain stable. NVSI is expressed as:

$$NVSI = \frac{2X\sqrt{P_j^2 + Q_j^2}}{2Q_jX - V_i^2}$$

5. **L-index:** The Voltage Stability Index "L", formulated by (**Kessel and Glavitsch, 1986)**, serves as a metric to monitor bus voltage stability in a power system. This index is derived from load flow outcomes in a simplified two-bus system and is expressed as:

$$L_j = \left|1 - \sum_{i=1}^{g} F_{ji}\frac{V_i}{V_j}\right|$$

Where,

g= Number of generators

V_i is the i^th bus voltage

V_j is the j^th bus voltage

F_{ji} is the element of the F^{LG} matrix

F^{LG} matrix is obtained as given below:

$$\begin{bmatrix} I^G \\ I^L \end{bmatrix} = \begin{bmatrix} Y^{GG} & Y^{GL} \\ Y^{LG} & Y^{LL} \end{bmatrix}\begin{bmatrix} V^G \\ V^L \end{bmatrix}$$

I^G, I^L and V^G, V^L represent currents and voltages at the generator buses and load buses. The matrix F^{LG} is calculated as:

$$[F^{LG}] = -[Y^{LL}]^{-1}[Y^{LG}]$$

The L-indices are calculated for all load buses. A value of L close to 1 indicates that the system is on the verge of instability. L-index aids in assessing the health of bus voltages by quantifying the influence of power flows and voltage magnitudes. Lower values of the L-index indicate a stable voltage condition, while higher values could imply potential voltage stability concerns. L-index calculation is simple, and results are usually consistent.

All the indices given above are calculated using system data such as load demands, generator reactive power capabilities, and network topology. However, these indices have limitations and assumptions, and they provide a simplified view of voltage stability. Voltage stability assessment usually involves monitoring these indices in real-time or through simulations to identify critical operating conditions and take necessary actions to prevent voltage collapse or instability.

3.1.6 Measurement and soft computing based methods for voltage stability assessment

Measurement based methods for voltage stability assessment involve using real-time data collected from power system measurements to analyze and predict the system's voltage stability conditions. These methods rely on monitoring voltage stability indices to identify potential voltage instability issues. Measurement devices play a crucial role in collecting real-time data for voltage stability assessment. These devices provide the necessary information to monitor key parameters, calculate stability indices, and identify potential voltage instability risks. Measurement devices, commonly used for voltage stability assessment, include supervisory control and data acquisition (SCADA) system and phasor measurement units (PMUs). PMUs are highly accurate devices that measure synchronized voltage and current phasors at high sampling rates, enabling fast and accurate calculation of voltage stability indices. PMUs are often preferred over SCADA systems for voltage stability assessment due to their capabilities in providing highly accurate and synchronized phasor measurements. A reliable communication infrastructure is also essential for transmitting measurement data from different devices to central monitoring and control centers. This infrastructure facilitates real-time monitoring and assessment of voltage stability.

Soft computing techniques can enhance the accuracy of voltage stability assessment by processing large amounts of historical and real-time measurement data and identifying complex patterns. Common soft computing methods for voltage stability assessment include:

- **Artificial neural networks (ANNs):** ANNs can learn the nonlinear relationships between various input parameters (e.g., load levels, reactive power injections) and voltage stability margins. Trained ANNs can predict voltage stability margins and assess potential risks.

- **Fuzzy logic systems:** Fuzzy logic allows for handling imprecise and uncertain data. A fuzzy inference system can be designed to evaluate the degree of voltage stability based on linguistic rules.
- **Support vector machines (SVMs):** SVMs are used for classification and regression tasks. They can be trained to classify the voltage stability status of a system based on features extracted from measurement data.
- **Neuro-Fuzzy systems:** These systems combine the learning capabilities of neural networks with the interpretability of fuzzy logic. They can be used to create accurate and understandable models for voltage stability assessment.

The combination of measurement based and soft computing based methods can be employed for voltage stability assessment. Real-time measurements provide accurate data for analysis, and soft computing techniques process this data to generate insights and predictions about voltage stability conditions. Integrating these methods can enhance the reliability and efficiency of voltage stability assessment in power systems. A clear review of various models such as regression, classification, decision trees, support vector machines (SVM), artificial neural networks (ANN), ensemble machine learning models, and fuzzy logic based techniques employed in the literature is given by **(Amroune, 2021),** for predicting voltage stability indices, and maximum loadability, and assessing the relative state of the system in terms of voltage instability. Block diagram representation of measurement and soft computing-based voltage stability assessment is given in Fig. 3.5.

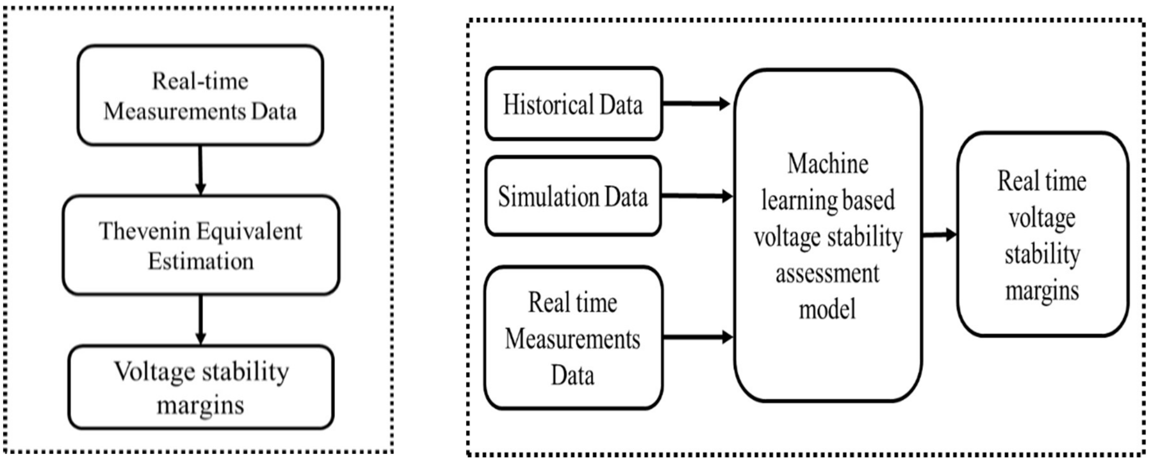


Fig. 3.5 Block diagram representation of measurement and soft computing based voltage stability assessment

Traditional voltage stability assessment methods rely on repetitive power flow calculations of test systems for different operating conditions. These methods are computationally expensive, time-consuming, and highly dependent on the network structure. As a result, they are typically used for offline assessments during power system planning and transmission line expansion planning. On the other hand, modern techniques based on measurements obtained from remote terminal units (RTU) or wide area monitoring systems (WAMS) offer real-time monitoring and control capabilities. These data-driven methods do not require mathematical modeling of the system and are independent of changes in the network structure. They are more time efficient, computationally less expensive, and utilize statistical and soft computing techniques to analyze and associate data from measurement devices. Due to these advantages offered by measurement and soft computing based methods for voltage stability assessment, an ANN-PMU based voltage stability assessment method is employed in this work.

3.2 Phasor Measurement Units and Their Optimal Placement

3.2.1 Phasor measurement units

Phasor Measurement Units (PMUs) are devices used in power systems to measure and monitor electrical quantities, such as voltage and current, in real-time. They provide synchronized phasor measurements, which are accurate representations of the amplitude and phase angle of the electrical quantities. The primary function of a PMU is to capture high-speed, time-synchronized measurements of the electrical waveforms at different points in the power system. These time-synchronized measurements are obtained using Global Positioning System (GPS) or other precise time synchronization methods to ensure accurate alignment of the phasor data from different locations. Block diagram representation of a typical phasor measurement unit is shown in Fig. 3.6.

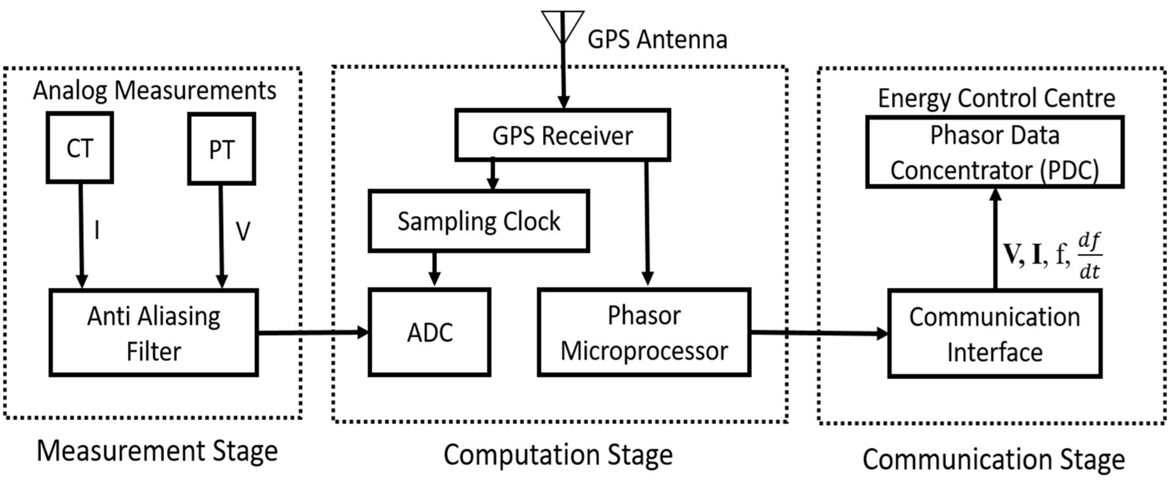


Fig. 3.6 Block diagram of phasor measurement unit (PMU)

A PMU typically measures the following quantities:

1. **Voltage phasors:** PMUs measure the magnitude and phase angle of the voltage waveforms at specific locations in the power system. These measurements help in assessing the voltage profile, stability, and quality of the system.
2. **Current phasors:** PMUs measure the magnitude and phase angle of the current waveforms flowing through specific points in the power system. These measurements are important for analyzing power flows, identifying faults, and monitoring system conditions.
3. **Rate of change of frequency (ROCOF):** PMU monitors the rate of change of frequency in a power system using phasor measurement techniques. The ROCOF provides information about the dynamic behavior of the power system, particularly during disturbances or events like faults or sudden changes in load.

PMUs provide a real-time view of the power system dynamics and enable system operators to detect and respond to abnormal conditions, such as voltage fluctuations, frequency deviations, or disturbances caused by faults or equipment failures. The synchronized phasor measurements from multiple PMUs are used for various applications, including system monitoring, state estimation, wide-area monitoring, oscillation detection, and control. The data collected from PMUs placed at different locations are telemetered to phasor data concentrators (PDC) installed at energy control centers. Analyzing the data collected at PDCs helps to improve the situational awareness of the power system, enhance grid stability, and facilitate efficient operation and control of the electrical network.

3.2.2 Optimal placement of phasor measurement units

It is not economically feasible to place PMUs at every node of the system. Optimal PMU placement strategies are used to identify the potential locations of PMUs to ensure complete observability of the system under normal operation and contingent situations. Complete observability means system variables defining system state (voltage phasors, current phasors, and complex powers) are known at every node of the system. There are various methods for optimal PMU placement depending on the goal of the system operator, the size and complexity of the network, and available resources. There are two ways to examine the complete network observability for optimal PMU placement:

1. Numerical observability based approach
2. Topological observability based approach

3.2.1.1. Numerical observability based approach

This approach involves the reconstruction of the Power flow Jacobian matrix using the PMU measurements. If the full Jacobian matrix can be evaluated based on available measurements, then the system is said to be completely observable. This approach involves calculations involving the Jacobian matrix due to which it requires complex calculations and is computationally expensive.

3.2.1.2. Topological observability based approach

These methods make use of a two-step process. The first step is to generate a network graph based on connections of various nodes by transmission lines, and the second step makes use of some set of rules listed below to determine the observability of the system.

a) If a PMU is placed at a specified bus then this bus and all its neighboring buses are fully observable.
b) By applying Ohm's law, the voltage phasor at one end of a branch can be calculated if the voltage phasor at the other end of the branch and the branch current are known.
c) If the voltages at both ends of a branch are known, the branch current can be computed by using Ohm's law.
d) When buses connected to an observable zero injection bus (ZIB) are all observable except one, the unobservable bus can be identified as observable by applying Kirchhoff's current law at the ZIB. ZIB is a bus that is not connected to any generator and load.
e) When buses connected to an unobservable ZIB are all observable, the ZIB will be identified as observable by applying the node equation.
f) A group of unobservable ZIBs, adjacent to observable buses, will be observable by obtaining the voltage phasors of ZIB through the nodal equations.

The voltage phasor at a PMU-installed bus and the current phasor of all the branches connected to the PMU-installed bus are direct measurements. A PMU-installed bus can help determine the remaining parameters of neighboring buses by using Ohm's law and Kirchhoff's Current Law (KCL). A bus adjacent to a PMU installed bus can have known values of its voltage phasor and branch currents using this indirect measurement technique. Indirect measurements are also known as pseudo measurements.

The objective of the optimal PMU placement is to find the minimum number of PMUs required and their locations in the system to achieve full network observability. Therefore, the objective function is formulated as below:

$$F = \min \sum_{k=1}^{n} c_k \times x_k$$

$$\text{Subject to: } [A] \times [X] \geq [b]$$

c_k = Cost of installation of PMU at bus k. This is usually constant for each bus if the same type of PMUs are installed.

[X] is a binary decision vector where $[X] = [\, x_1, x_2, x_3 \cdots x_n \,]^T$ and $x_k \in \{0,1\}$

x_k = Binary decision variable. $x_k = \begin{cases} 0, & \text{if PMU installed at bus k} \\ 1, & \text{if PMU not installed at bus k} \end{cases}$

[A] = Binary connectivity matrix based on systems network connections.

$$a_{ij} = \begin{cases} 1, & \text{if } i = j \\ 1, & \text{if } i^{th} \text{ bus is connected to } j^{th} \text{ bus} \\ 0, & \text{otherwise} \end{cases}$$

[b] is a unit column vector of dimension $(n \times 1)$

n = Number of buses in the test system.

The above-stated problem can be solved using different methods. The various topological observability based optimal PMU placement methods used in this work are listed below:

a) **Mixed integer linear programming for optimal PMU placement:** Mixed Integer Linear Programming (MILP) is a mathematical optimization technique used to solve optimization problems where the objective function and constraints are linear and some of the variables are required to take integer values. In the context of PMU (Phasor Measurement Unit) placement, MILP can be used to determine the optimal locations for placing PMUs in a power system. The problem of PMU placement can be formulated as a mathematical optimization problem using MILP. The objective of this optimization problem is to minimize the number of PMUs while satisfying complete observability of the power system as constraints. The decision variables in this problem are binary variables that represent whether a PMU should be placed at a particular bus in the power system. Solving this MILP problem using *intlinprog* function in MATLAB provides an optimal solution for PMU placement, which indicates the locations where PMUs should be installed in the power grid to achieve the desired level of observability and system stability.

b) Genetic algorithm: Genetic algorithm (GA) is a heuristic optimization technique inspired by the process of natural selection. It is used to find approximate solutions to complex optimization and search problems, especially when the search space is large, and the problem doesn't have a straightforward mathematical formulation. Genetic algorithms can be applied to solve the problem of optimal phasor measurement unit (PMU) placement in power systems. Steps involved in using genetic algorithm for optimal PMU placement are:

1. **Encoding:** In the context of PMU placement, each potential PMU location can be encoded as a binary string. Each bit in the string represents whether a PMU is placed at that particular bus or not.
2. **Initialization:** A population of potential solutions (PMU placements) is generated randomly or using some domain-specific knowledge. Each solution is represented as a binary string.
3. **Fitness function:** A fitness function is defined to evaluate the quality of each solution. The fitness function could consider observability metrics, system stability, voltage stability, and other relevant criteria. For instance, the objective might be to maximize observability while minimizing the number of PMUs placed.
4. **Selection:** Solutions are selected from the population based on their fitness scores. Solutions with higher fitness values have a higher probability of being selected.
5. **Crossover:** Crossover involves combining genetic information from two parent solutions to create new offspring solutions. This process mimics the genetic recombination that occurs in natural reproduction. In the context of PMU placement, crossover might involve swapping portions of the binary strings between two parent solutions to create one or more offspring solutions.
6. **Mutation:** Mutation introduces small random changes in the offspring solutions to introduce diversity into the population. In the PMU placement problem, mutation could involve flipping individual bits in the binary strings to potentially explore new PMU placement configurations.

7. **Replacement:** The offspring solutions replace some of the least fit solutions in the current population. This ensures that better solutions have a higher chance of being preserved.
8. **Termination:** The algorithm continues to evolve new generations of solutions through selection, crossover, and mutation until a stopping criterion is met. This could be a maximum number of generations, convergence of solutions, or reaching a satisfactory fitness level.

Genetic Algorithms can provide a set of potential PMU configurations that approximate the optimal solution, taking into account the observability constraints. However, GA is a meta-heuristic method, and the quality of the solution depends on parameter tuning, problem-specific considerations, and the complexity of the problem.

c) **Depth first search method:** Depth First Search (DFS) is a graph traversal algorithm commonly used in artificial intelligence and computer science for various tasks, including pathfinding and state space search. It can also be adapted for solving optimization problems, such as the placement of Phasor Measurement Units (PMUs) in power systems. Steps involved in using DFS algorithm for optimal PMU placement are:

1. **Problem formulation:** Define the objective function that needs to be optimized. For optimal PMU placements, the objective involves minimizing the PMU placement cost while ensuring the complete observability of the power system.
2. **State space representation:** Represent the state space as a graph where nodes represent potential PMU placement locations and edges represent connections between those locations.
3. **Initialization:** Start with an initial configuration of PMU placements. This could be randomly generated or based on some heuristic.
4. **DFS algorithm:** Start the DFS algorithm from the initial state. The algorithm explores deeper into the graph by selecting a node, expanding it, and then recursively exploring its children nodes.
5. **Expanding nodes:** At each step of the DFS, expand the current node by considering all possible PMU placement decisions that can be made from

that node. These decisions correspond to moving to neighboring nodes in the graph.

6. **Objective evaluation:** Evaluate the objective function for each expanded node to determine how well the power system's observability is improved and whether all constraints are satisfied.
7. **Pruning and backtracking:** If the objective function value does not meet certain criteria or if constraints are violated, prune that branch of exploration or backtrack to the previous node and explore other options.
8. **Termination conditions:** Decide termination conditions for the DFS. This could be a maximum depth of exploration, reaching a satisfactory solution, or a specified number of iterations.
9. **Solution selection:** Once the DFS algorithm terminates, select the best configuration of PMU placements based on the evaluated objective function values.

d) Simulated annealing algorithm: Simulated Annealing is a stochastic optimization algorithm inspired by the annealing process in metallurgy. It is a powerful technique for solving optimization problems, including the optimal placement of PMUs. Simulated Annealing tries to find the global optimum by starting with a high temperature "annealing" phase that allows exploration of the solution space and gradually lowering the temperature to focus on exploitation. Steps involved in utilizing simulated annealing for optimal PMU placement are:

1. **Problem formulation:** Define the objective function that needs to be optimized. This involves minimizing PMU placement cost while considering complete system observability.
2. **State space representation:** Represent the state space as a configuration of PMU placements, similar to the DFS approach.
3. **Initial solution:** Generate an initial configuration of PMU placements. This can be done randomly or using some heuristic.
4. **Simulated annealing algorithm:**

   a. **Parameters:**

      Initial temperature (high value)

      Cooling rate (how quickly temperature decreases)

      Maximum number of iterations or a stopping criterion

b. Loop:

i. Start with the initial configuration.

ii. Initialize the current temperature to the initial temperature.

iii. While the temperature is above a minimum threshold: Generate a neighboring configuration by making a small random change to the current configuration. This could involve moving a PMU to a different location.

iv. Evaluate the objective function for both the current and the neighboring configurations.

v. Calculate the "energy difference" between the two configurations.

vi. If the energy difference is positive (neighboring configuration is better), accept the new configuration.

vii. If the energy difference is negative (neighboring configuration is worse), accept the new configuration with a probability that decreases as the temperature decreases. This probability is determined by a function that considers the energy difference and the current temperature.

viii. Update the current configuration if a new configuration was accepted.

ix. Decrease the temperature using the cooling rate.

5. **Solution selection:** Once the annealing process is complete, select the final configuration that yielded the best objective function value during the iterations.
6. **Visualization and analysis:** Visualize and analyze the final PMU placement configuration, assessing its impact on observability and meeting the defined objectives.

e) **Graph theory procedure:** Graph theory for optimal PMU placement involves representing the power system as a graph and then applying graph algorithms to find the best locations for PMUs. Graph theory serves as a highly effective tool for analyzing power system networks. When aiming to attain full observability, the primary objective of this approach is to construct an optimal spanning tree that encompasses all nodes within the system. Steps involved in utilizing graph theory for optimal PMU placement are:

1. **Graph representation:** Representing the power system as a graph, where nodes represent buses or nodes in the power system, and edges represent the transmission lines connecting these nodes. Each edge may have associated attributes like impedance and distance.
2. **Define objective function:** Minimizing the number of PMUs.
3. **Create weighted graph:** Assign weights to the edges of the graph based on relevant factors. For example, edge weights could represent distance, line impedance, or other factors affecting PMU placement decisions. These weights influence the optimization process.
4. **Minimum spanning tree (MST):** Using minimum spanning tree algorithm. This algorithm finds a tree that spans all nodes with the minimum possible total edge weight.
5. **Solution interpretation:** The output of the algorithm is a set of nodes or locations for PMU placements.

PMUs are placed on the system buses fulfilling the complete observability criterion using the above discussed methods. PMUs placed at critical nodes in the system can help monitor real-time voltage stability. By measuring the voltage magnitude and phase angle at these points, operators can analyze the voltage profile and detect voltage instability conditions. This information is crucial for taking preventive and corrective actions to maintain voltage stability and prevent system-wide voltage collapse. PSAT toolbox, MATALB based mixed-integer linear programming solver, and genetic algorithm based optimization are used in this work for the optimal placement of PMUs in the test systems for normal conditions and considering network redundancy. The simulation data obtained from these optimally placed PMUs will be utilized for training, testing, and deployment of the artificial neural network models for evaluating the proximity to voltage instability.

3.3 Artificial Neural Networks

An artificial neural network (ANN) is a network of artificial neurons that are used to map the values of input features to the values of output features in order to make predictions. These networks are inspired by the way the human brain works. ANNs are designed to form the structure in which they associate input and output variables in a similar way the human brain performs and solve a problem. These networks are implemented using simulation software on a digital computer. A neural network has the capability to map the previously observed information and to generalize the relationship. They work in a distributed manner. ANN works like the human brain in two aspects. First, they observe the input information and adjust their network weights in the same manner as the human brain adjusts the synaptic weights according to the information they receive. Second, the trained network can make predictions on the new information given to them. A simple perceptron artificial neuron model is shown in Fig.3.7. The net input z is the weighted sum of inputs x_1, $x_{2...}x_{n,}$ along with a constant input bias b. the net input z is applied to the activation function ϕ and the output y is obtained. The activation function mimics the function of soma of a neuron in a biological neural network. It simulates the spiking phenomenon of biological neural networks. To achieve desired learning capabilities, a large network of such neurons is required. These networks are in the form of layers connected to each other by weighted links. The set of weights of these links is optimized during the training process in order to map the complex relationship between input and output data. During the training process, these weights are adjusted using various algorithms to minimize the error between the target and predicted output.

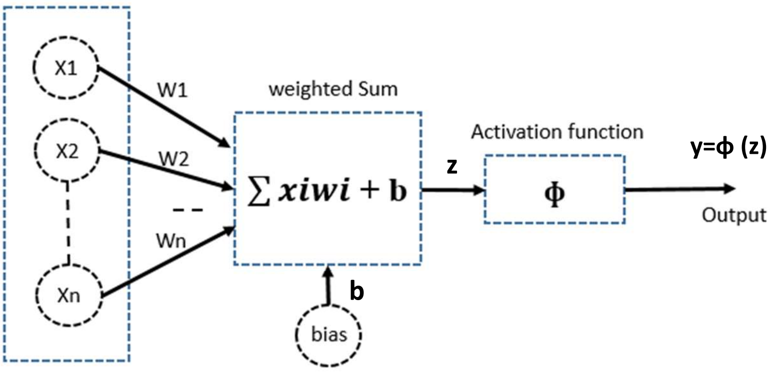


Fig. 3.7 Simple perceptron neural network

3.4 ANN and PMUs for Voltage Stability Assessment

As artificial neural networks (ANN) can learn complex relationships between input system parameters and voltage stability margins, which enable ANN to make predictions for voltage stability assessment. Once trained they can make predictions about voltage stability margins in real time using the real time measurements data acquired by phasor measurement units. They can make accurate and quick predictions, if trained properly, making them suitable for real time voltage stability monitoring. For voltage stability assessment using ANN, these few points need to be taken into consideration.

3.4.1 Input feature selection

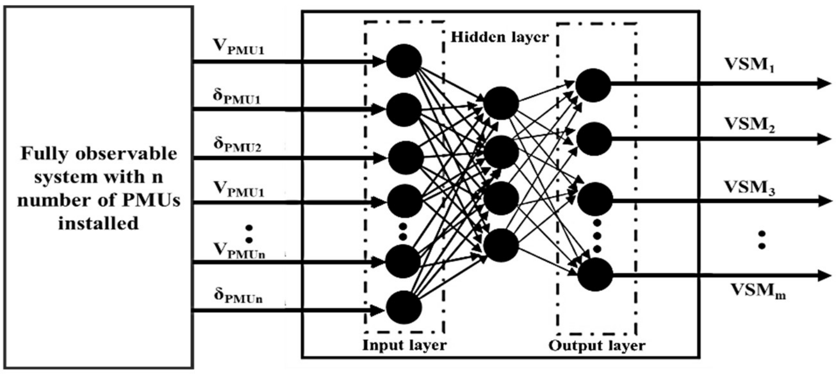
Voltage magnitude (V), voltage angle (δ), real power (P), and reactive power (Q) are the four important input features which can map the complex relationship between system variables and voltage stability margins. However, the combination of any two is sufficient to map this complex relationship. Voltage phasor data is easily available from strategically placed phasor measurement units. So, voltage angle and voltage magnitude from optimally placed PMUs are used as input features to ANNs in this work.

3.4.2 Output feature selection

Various voltage stability indices are available in the literature to comment on the status of system voltage stability. There are local and global voltage stability indices that can be used as target features for the ANN. Global voltage stability indices give information only about the overall stability which is not sufficient to determine the weak areas of the system. Therefore, in this work, local voltage stability index (L-index) at all the load buses in the test system are used as the outputs of the ANN. These indices will help in determining the weak areas of the system. This in turn can provide suggestions to system operators for voltage stability enhancement.

3.4.3 ANN model and related parameters

Use of ANN involves the selection of ANN architecture, number of hidden layers, number of neurons in hidden layers, activation functions, learning rate, and the training algorithm. Back propagation feed-forward artificial neural network has been used for voltage stability assessment in this work. A Schematic diagram of using ANN for voltage stability assessment is given in Fig. 3.8.



V: Voltage magnitude, δ: Voltage angle, VSM: Voltage stability margin, n: Number of PMUs, m: Number of load buses

Fig. 3.8 Schematic diagram of voltage stability assessment using ANN

3.5 Voltage Stability Enhancement

There exists a close coupling between voltage magnitude (V) and reactive power (Q) in a power system. Voltage stability problem generally arises due to inadequate reactive power reserves or the inability of generation and transmission system to fulfill reactive power demands. Therefore, the voltage stability of a system can be enhanced using proper reactive power planning. Voltage stability enhancement problem involves:

a) Determination of weak areas where reactive power support is required, and
b) Determination of optimal settings of voltage control devices

There are two types of methods for voltage stability enhancement. The first method is the system design approach during the planning phase, and the second one is the control of reactive power and voltage control devices. Such controls include automatic voltage regulation system of generators, on-load tap changing control of transformers, and control of devices used for reactive power support. The various devices used for reactive power support are:

a) Synchronous condensers
b) Fixed shunt capacitors
c) Static var compensators (SVC)
d) Static synchronous compensators (STATCOM)

3.5.1 Voltage stability enhancement using SVC

SVCs are flexible AC transmission system (FACTS) devices that regulate reactive power flow in transmission lines. An SVC consists of a combination of thyristor-controlled reactors (TCR) and thyristor-switched capacitors (TSC). These devices are capable of injecting or absorbing reactive power into the power system as needed. By controlling the reactive power flow, SVCs can help regulate voltage levels and maintain system stability. In addition to voltage regulation, SVCs can also provide damping to power system oscillations. SVCs can respond quickly to the changes in system conditions due to their fast-acting control mechanisms. They can continuously maintain voltage levels and respond within milliseconds, making them effective in mitigating voltage instability issues in real time. Due to above discussed advantages, SVC is used in this work for voltage stability enhancement of weak buses. Weak buses are identified by voltage stability assessment of the test systems using artificial neural networks. Optimal settings of SVC for reactive power compensation for a particular loading condition can be identified using the PSO algorithm in optimization toolbox of MATLAB. The functional diagram of SVC is given in Fig. 3.9 Reactive power injection by SVC is given by the formula:

$$Q_{svc} = V_n^2 \ . B_{svc}$$

Where,

V_n = bus voltage to which SVC is connected, and

B_{svc} = Susceptance of SVC,

By varying the firing angle of the thyristor valves, B_{svc} can be controlled which in turn helps in regulating the reactive power injections (Q_{svc}).

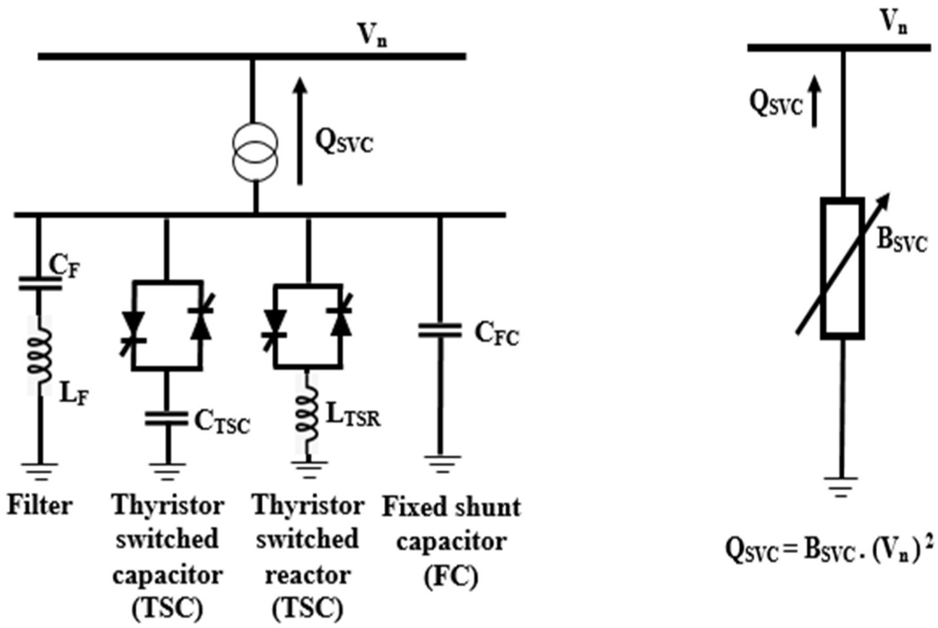


Fig. 3.9 Functional diagram of static VAR compensator (SVC)

As the reactive power demand at the bus varies, the susceptance of SVC is controlled by varying the firing angle of thyristor valves according to the amount of reactive power support required at that instant. The optimal value of reactive power support required at a particular loading point can be determined using particle swarm optimization algorithm for minimizing the squared sum of voltage stability indices as the objective function.

3.5.2 SVC location determination

Weak buses in the system serves as ideal location for the placement of SVC. These weak nodes/areas in the system are identified using voltage stability assessment. In this work weak buses of the test system are identified using the voltage stability indices predicted by PMU-ANN based voltage stability assessment. The load bus having the greatest value of voltage stability index is identified as the weakest node.

3.5.3 Application of PSO to find the optimal settings of SVCs for voltage stability enhancement

The application of particle swarm optimization (PSO) involves using the algorithm to find the best set of parameters for static var compensators (SVCs), aiming to improve voltage stability of the power system. Detailed procedure for using PSO to determine optimal parameters for SVCs to enhance voltage stability is as follows:

1. **Problem formulation:** Define the objective function that needs to be optimized. This could involve maximizing voltage stability margin, minimizing voltage deviations, or achieving a balance between multiple objectives. Minimizing the sum of squares of L-index is the formulated objective function in this thesis work given by:

$$F_{obj} = min\left(\sum_{i=1}^{n}(L_i^2)\right)$$

2. **Parameter configuration:** Determine the parameters of the SVC that are subject to optimization. These parameters could include the location of SVCs, their reactive power rating, control settings, and other relevant parameters. Reactive power injection by SVC (Q_{SVC}), installed at the weak buses in the system is selected as the optimization parameter in this thesis work.
3. **Particle representation:** Represent each particle in the PSO algorithm as a potential solution, which corresponds to a specific configuration of SVC parameters.
4. **Initialization:** Initialize a swarm of particles randomly within the feasible parameter space. Each particle's position represents a potential solution, and its velocity represents how it explores the solution space.
5. **Objective evaluation:** Evaluate the objective function for each particle's position. This involves simulating the power system with the chosen SVC parameters and assessing the voltage stability performance.
6. **Best position update:** For each particle, track its best position (solution) found so far. This is usually initialized with the particle's initial position.
7. **Global best update:** Identify the particle with the best objective function value among all particles. This particle's position represents the best solution found by the entire swarm.

8. **Particle movement update:** Update each particle's velocity and position using the PSO equations, which consider the particle's previous movement, its best position, and the global best position. This encourages particles to explore the solution space efficiently.
9. **Bound constraints:** Apply bound constraints to ensure that particle's positions remain within the feasible parameter space for SVCs.

$$Q_{svc\_min} \leq Q_{svc} \leq Q_{svc\_max}$$

10. **Iteration:** Repeat steps 5 to 9 for a defined number of iterations or until a convergence criterion is met.
11. **Solution extraction:** Extract the optimal SVC parameter configuration from the particle with the best position found in the final iteration.
12. **Simulation and validation:** Simulate the power system using the optimal SVC parameters to validate their effectiveness in enhancing voltage stability.

The important equations that constitute the PSO algorithm are:

Velocity Update Equation: $v_i^{t+1} = w.v_i^t + c_1 r_1 (p_{best_i} - x_i^t) + c_2 r_2 (g_{best_i} - x_i^t)$

Position Update Equation: $x_i^{t+1} = x_i^t + v_i^{t+1}$

where,

x_i^{t+1}= updated position of particle i in t+1 iteration.

x_i^t= current position of particle i in the t iteration.

v_i^{t+1}= updated velocity of particle i in t+1 iteration.

v_i^t= current velocity of particle i in the t iteration.

w = Inertia weight controlling the impact of the particle's previous velocity.

c_1, c_2 = Acceleration coefficients controlling the impact of personal best and global best.

r_1, r_2 = Random values between 0 and 1.

$pbest_i$ = Personal best position of particle i.

$gbest$ = Global best position among all particles.

Using PSO for optimizing SVC parameters involves iterative exploration of the parameter space, gradually converging towards a configuration that enhances voltage stability of the power system.

3.6 Description and Flowchart of the Methodology Adopted

The primary objective of this work is to assess the voltage stability status of the power system while exploring the influence of various phasor measurement placement strategies on the predictive capabilities of voltage stability indices using artificial neural networks (ANNs). Additionally, the study seeks to identify effective approaches for enhancing voltage stability.

The flowchart of the proposed methodology is given in Fig. 3.10 and the key steps involved in achieving these objectives are as follows:

Step 1: In this step a standardized test system is selected for the analysis, and a comprehensive database is constructed through steady-state simulations of test system within the MATLAB environment. The MATPOWER software package has been used to simulate diverse operational scenarios. The database preparation process involves two steps. Initially, voltage magnitudes and angles are recorded under a range of operating conditions. Subsequently, voltage stability margins are computed for each recorded condition, establishing a foundation for the subsequent analyses.

Step 2: In this step the optimal position of PMUs in the test system is determined using different PMU placement methods to ensure complete observability of the system. This includes identifying the strategic locations for installing PMUs that enable the monitoring of the system under normal operating conditions as well as during contingencies or disturbances. The goal is to maximize the coverage and effectiveness of PMU measurements in capturing the relevant information about the systems voltage stability.

Step 3: In this step input and output data for training and testing of ANN is acquired from the prepared database. Inputs to ANN are voltage phasors (V, δ) acquired from strategically placed PMUs at specific buses. Outputs of ANN are voltage stability indices (L-index), which were previously computed during the database creation process.

Step 4: In this step different ANN models are trained and tested for voltage stability assessment considering different PMU placement strategies and their performances are compared.

Step 5: In this step static var compensators (SVCs) are placed strategically at the weakest bus in the test system. The weakest bus in the system is determined based on maximum L-index value predicted by trained ANN model for voltage stability assessment.

Step 6: In this step optimal level of reactive power injection by the SVC is determined.

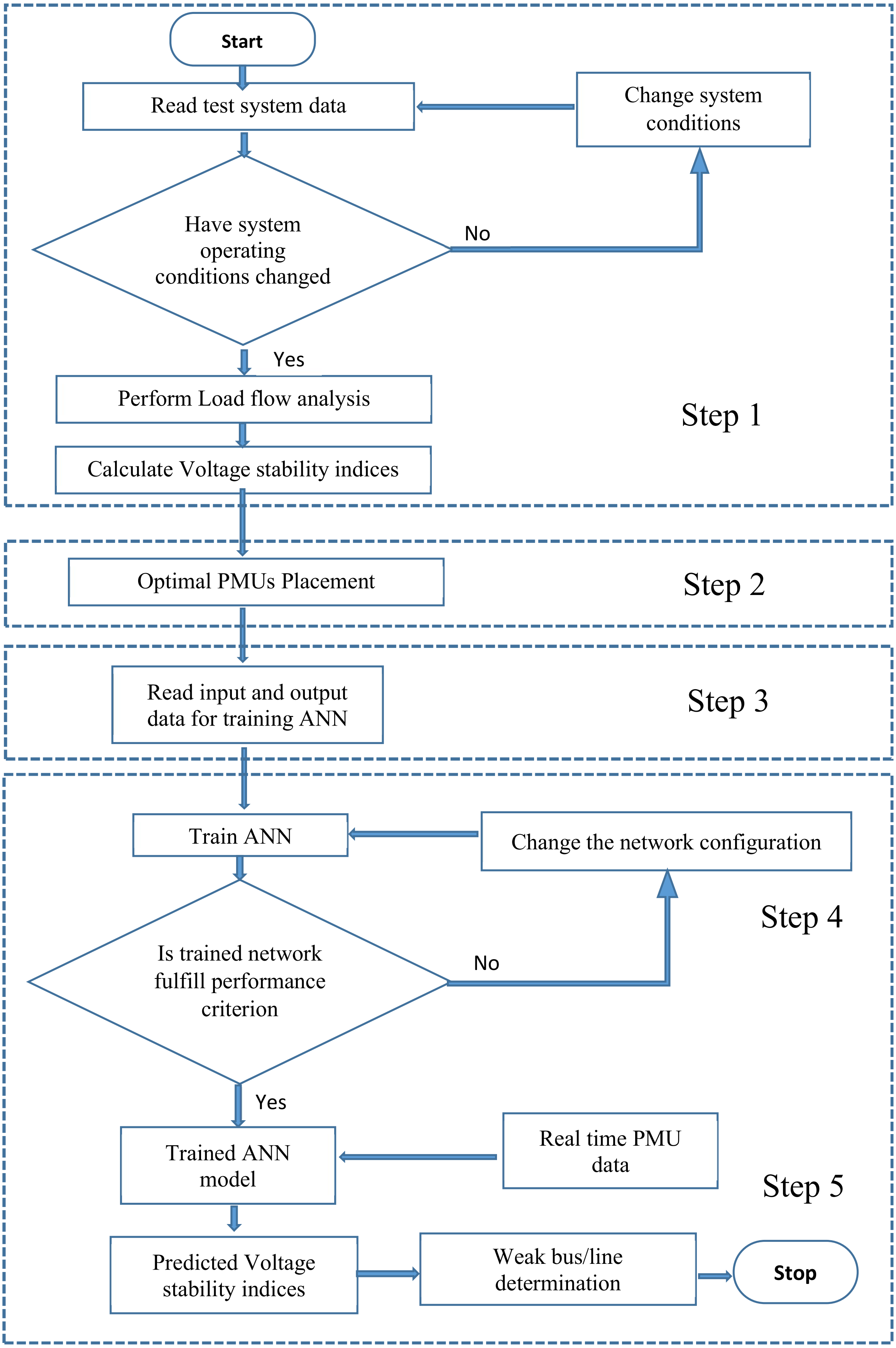


Fig. 3.10 Flowchart of the proposed methodology

3.7 Simulation Software and Associated Toolbox/Packages

All the required simulations have been performed in MATLAB R2021a simulation software, using MATPOWER 7.1, PSAT, and Neural Network Toolbox.

3.7.1 MATPOWER 7.1

MATPOWER 7.1 is an open-source MATLAB-based software package designed for power system analysis and optimization (**Zimmerman *et al.*, 2021**). It provides a set of tools and algorithms for performing power flow analysis, optimal power flow, contingency analysis, and voltage stability analysis using Continuation power flow. MATPOWER toolbox has been used in this research work for repetitive power flows and continuation power flow of the test system under various operating conditions and contingencies for generating the phasor measurement units data that has been used as inputs for artificial neural networks and target data in the form of voltage stability indices for training and testing the ANN for real-time voltage stability assessment.

3.7.2 PSAT toolbox

Power System Analysis Toolbox (PSAT) is another MATLAB based software toolbox designed for power system analysis, simulation, and optimization. PSAT provides a set of functions and tools for studying the behavior and performance of power systems, including generation, transmission, distribution, and control. PSAT can also be used for dynamic simulations and provides a Simulink library-based approach for power system analysis. It provides GUI based interface for power system simulations. In this thesis work, PSAT has been used for load flow analysis, CPF, and optimal placement of PMUs in test systems to generate input and target data for training and testing of artificial neural networks.

3.8 Test Systems

3.8.1 IEEE-9 bus test system

IEEE 9-bus test case represents a simple approximation of the Western System Coordinating Council (WSCC) to an equivalent system with nine buses and three generators. The base kV levels are 13.8 kV, 16.5 kV, 18 kV, and 230 kV. The line complex powers are around hundreds of MVA each. As a test case, the IEEE-9 bus test case is easy to control, as it has few voltage control devices. The single line diagram and general specifications of the test system are shown in Fig. 3.11 and Table 3.1, respectively.

Table 3.1 General specifications of IEEE-9 bus system

Sl. No.	Particular	Details
1	Buses	9
2	Lines	12
3	Generators	3
4	Transformers	3
5	Loads	3
6	Slack bus	1
7	PV buses	1,2,3
8	PQ buses	4,5,6,7,8,9

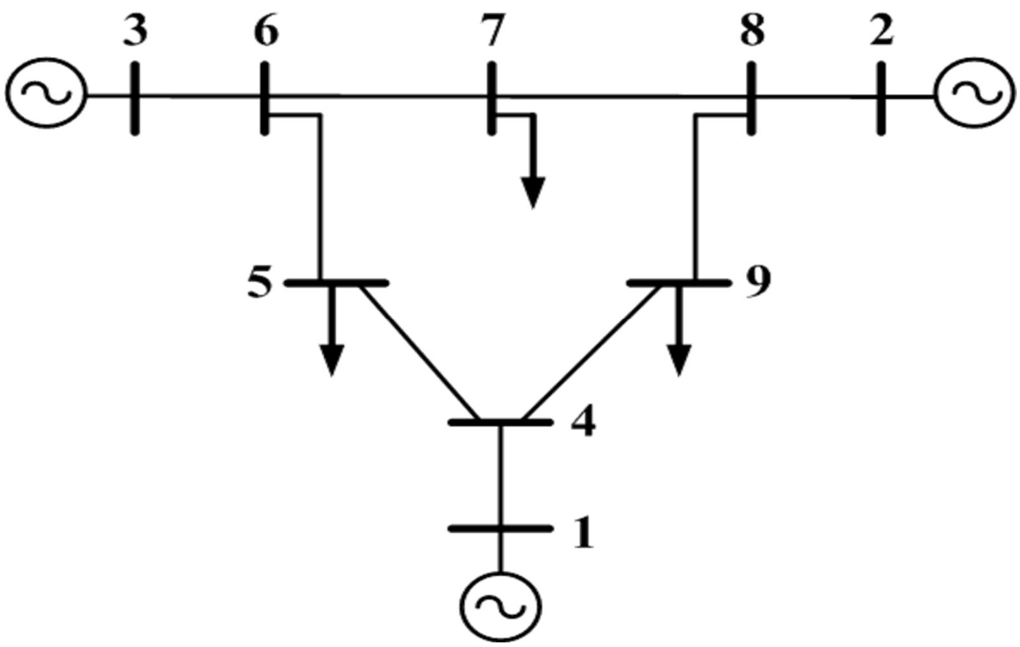


Fig. 3.11 Single line diagram of IEEE-9 bus system

3.8.2 IEEE-14 bus test system

This test system is a close approximation of a simple American electric power system as of February 1962. It consists of a total of 14 buses, 20 transmission lines, 5 generators, and 11 loads. The single line diagram and general specifications of this test system are shown in Fig. 3.12 and Table 3.2, respectively.

Table 3.2 General specifications of IEEE-14 bus system

Sl. No.	Particular	Details
1	Buses	14
2	Lines	20
3	Generators	5
4	Transformers	4
5	Loads	11
6	Slack bus	1
7	PV buses	2,3,6,8
8	PQ buses	4,5,7,9,10,11,12,13,14

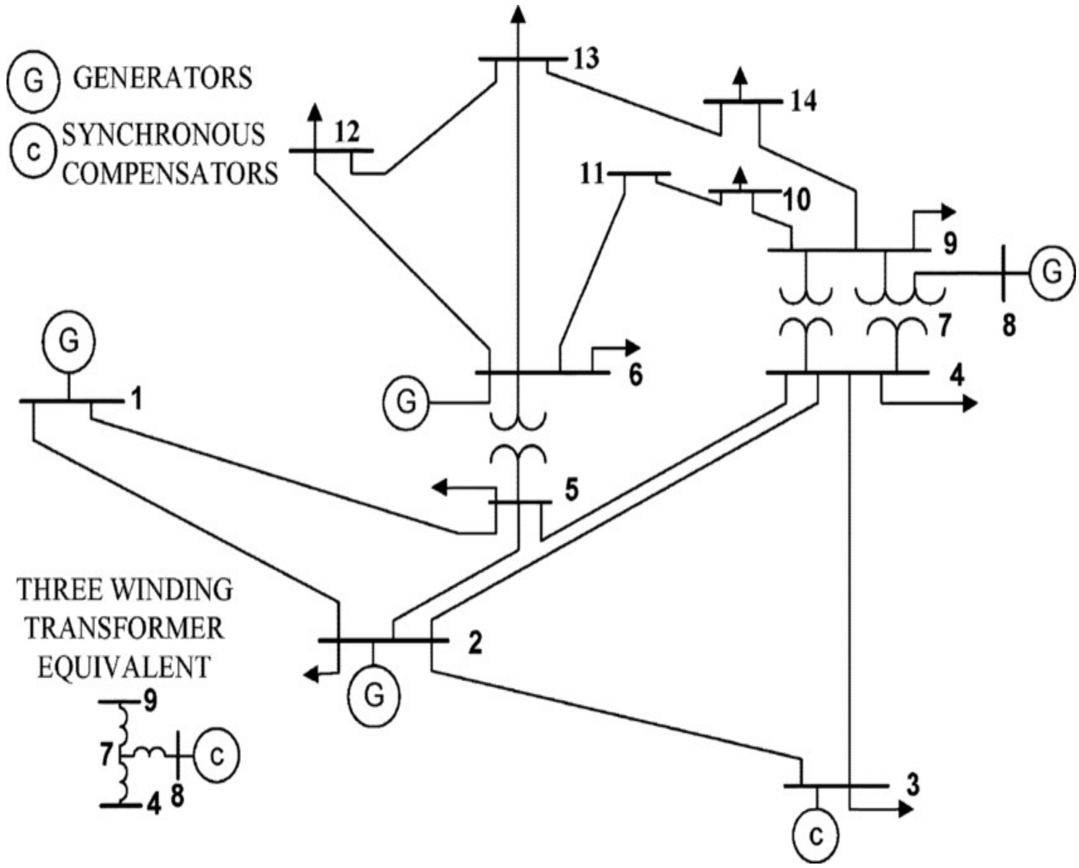


Fig. 3.12 Single line diagram of IEEE-14 bus system

These test systems play a crucial role in voltage stability assessment by providing a controlled environment for studying the behavior of power systems under varying operating conditions, aiding in the development, and validation of voltage stability prediction models. Hence, the proposed methodology is rigorously validated through its application to the IEEE-9 bus and IEEE-14 bus standard test systems. The comprehensive data sheets for these standard test systems are provided in *Appendix-I.*

Results and Discussion

CHAPTER- 4 RESULTS AND DISCUSSION

4.1 Background

In this chapter, the outcomes of the voltage stability assessment and enhancement study using artificial neural networks (ANN) and strategically placed phasor measurement units (PMUs) are presented and analyzed. The study encompassed data generation, ANN model training, PMU placement strategies, voltage stability enhancement using static var compensators (SVCs), optimal SVC placement, and optimization of reactive power injection.

4.2 Database Preparation

A comprehensive database considering diverse operating conditions has been prepared using steady-state simulations of standard test systems in MATLAB environment using MATPOWER package. This database covers a variety of operating scenarios, including normal, stressed, and contingent conditions. Voltage phasors at each of these operating conditions have been recorded and corresponding L-index values for each operating condition have been calculated. This database is crucial for training and testing of various artificial neural network (ANN) models for voltage stability assessment.

For IEEE-9 bus test system, a database considering 1400 different operating conditions has been prepared. Similarly, For IEEE-14 bus test system, a database considering 2700 different operating conditions has been prepared. Different operating conditions involve:

1. Load variation at individual load buses
2. Load variation at every load bus simultaneously
3. Load variations considering N-1 credible contingencies

4.3 Optimal PMU Placement Results

Result of the optimal phasor measurement unit (PMU) placement results for standard test systems, considering different PMU placement methods is given in this section.

4.3.1 Optimal PMU placement results for IEEE-9 bus test system

Optimal PMU placement for the IEEE-9 bus test system considering different PMU placement strategies are given in Table 4.1 and Table 4.2 under normal operating conditions and considering network redundancy respectively.

Table 4.1 Results of the optimal PMU placement for IEEE-9 bus system under normal operating conditions

S. No.	PMU placement method	Number of PMUs installed	Index of buses at which PMUs are installed
1	Depth search first method	3	4, 6, 8
2	Graph theory procedure	3	4, 6, 8
3	Simulated annealing method	2	8, 5 4, 7 9, 6
4	Binary integer linear programming	3	3, 4, 8
5	Genetic algorithm approach	3	1, 6, 8 4, 6, 8

Table 4.2 Results of the optimal PMU placement for IEEE-9 bus system considering network redundancy

S. No.	PMU placement method	Number of PMUs installed	Index of buses at which PMUs are installed
1	Binary integer linear programming	6	1, 2, 3, 4, 6, 8
2	Genetic algorithm approach	6	1, 2, 3, 4, 6, 8

4.3.2 Optimal PMU placement results for IEEE-14 bus test system

Results of the optimal PMU placement for the IEEE-14 bus standard test system considering different PMU placement methods are given in the tables below. Table 4.3 offers insights into PMU placements for the IEEE-14 bus system during regular operational conditions. In contrast, Table 4.4 outlines the outcomes of the PMU placement for the same system while considering network redundancy. These tables collectively offer a comprehensive view of how PMUs are strategically positioned in the test system to minimize the number of PMUs installed while ensuring complete observability of the test systems.

Table 4.3 Results of the optimal PMU placement for IEEE-14 bus system under normal operating conditions

S. No.	PMU placement method	Number of PMUs installed	Index of buses at which PMUs are installed
1	Depth search first method	6	1, 4, 6, 8, 10, 14
2	Graph theory procedure	5	1, 4, 6, 10, 14
3	Simulated annealing method	5 4	1, 4, 6, 10, 14 2, 6, 7, 9 1, 4, 11, 13 2, 4, 10, 13
4	Binary integer linear programming	4	2, 6, 8, 9
5	Genetic algorithm approach	4 3	2, 6, 7, 9 2, 6, 9 1, 4, 11, 13

Table 4.4 Results of the optimal PMU placement for IEEE-14 bus system considering network redundancy

S. No.	PMU placement method	Number of PMUs installed	Index of buses at which PMUs are installed
1	Binary integer linear programming	9	2, 4, 5, 6, 7, 8, 9, 10, 13
2	Genetic algorithm approach	9	2, 4, 5, 6, 7, 8, 9, 10, 13

4.4 ANN Training and Testing Data

During the database preparation process, a table similar to the one displayed in Table 4.5 for each test system has been created with the purpose of training and testing feedforward backpropagation artificial neural network (FFBP-ANN) models. This table has been prepared using steady-state simulations of the test systems, employing the Newton-Raphson power flow method, under various operating conditions, including normal, stressed, and contingent scenarios. Voltage magnitudes (V) and voltage angles (δ) for each bus in the test system have been recorded for every operating condition considered in this table during the database preparation process. Additionally, L-index values have been calculated at each load bus in the test system for every operating condition. These calculations were based on the power flow results and the test system admittance matrix, using the formula given by **(Kessel and Glavitsch, 1986)** expressed as:

$$L_j = \left|1 - \sum_{i=1}^{g} F_{ji} \frac{V_i}{V_j}\right| \ldots\ldots\ldots\ldots\ldots\ldots\ldots (4.1)$$

where, g represents the number of generator buses, V_i is the i[th] bus voltage, V_j is the j[th] bus voltage, F_{ji} is the element of the F^{LG} matrix. The F^{LG} matrix is obtained through the following equation:

$$[F^{LG}] = -[Y^{LL}]^{-1}[Y^{LG}]$$

where, Y^{LL}, Y^{LG} are the elements of system admittance matrix Y_{bus}.

Following the calculation of the L-index at all the load buses in the test system, these values have been recorded in the aforementioned table. The value of these calculated L-index ranged from 0.0019 in lightly loaded conditions to 1.0 in highly stressed conditions.

Table 4.5 Sample data table for training and testing of ANN models

	V_1	δ_1	V_2	δ_2	…	…	V_n	δ_n	L_1	L_2	…	L_m
OC-1												
OC-2												
OC-3												
…												
OC-Ns												

Here, V represent the voltage magnitude, δ represent the voltage angle, n represents the number of buses in the test system, m represents the number of load buses in the test system, OC represent the operating condition, and Ns represents the number of operating conditions considered i.e., Number of data samples taken.

Different operating conditions have been created through various scenarios. For instance, random load variations have been introduced at individual load buses, random load fluctuations have simultaneously been applied across all load buses, and random load variations at load buses have been considered while accounting for N-1 credible contingencies. The expressions for load variations at the load buses have been defined as follows:

$$P_{Di} = P_{Di0} + \lambda(P_{Di0})$$

$$Q_{Di} = Q_{Di0} + \lambda(Q_{Di0})$$

Where, P_{Di} and Q_{Di} denotes the actual real and reactive power loadings at bus i, P_{Di0} and Q_{Di0} denotes the base real and reactive power loadings at bus i. The variable λ denotes a random variable whose value has ranged from 0 to the maximum loadability point, determined through the continuation power flow analysis.

For IEEE-9 and IEEE-14 bus test systems the ANN models have been trained and tested using the prepared data table of the form as represented in Table 4.5, considering different PMU placement results as presented in section 4.3. For a specific PMU placement strategy, the inputs to the ANN consist of voltage magnitude (V) and voltage angle (δ) values obtained from the PMU-placed bus columns from this table and the outputs of the ANN encompass all the L-index columns from this table.

The available data has been divided randomly into two parts, with 70% of the data allocated for training purposes, and the remaining 30% reserved for testing of the trained FFBP-ANN model.

For example, the training and testing data table for IEEE-9 bus test system is of the form represented by Table 4.6

Table 4.6 Sample data table for training and testing of ANN models for IEEE-9 bus test system

	V_1	δ_1	V_2	δ_2	…	…	V_9	δ_9	L_1	L_2	…	L_6
OC-1												
OC-2												
OC-3												
…												
OC-1400												

In this table columns V_1, V_2, … V_9 represent the voltage magnitudes at all 9-buses in the system respectively and columns δ_1, δ_2, … δ_9 represent the voltage angles at all the 9 buses in this test system. There are 6 load buses in this test system and corresponding to each load bus L-index values are calculated using the formula given by equation 4.1 for every 1400 different operating condition considered in the database preparation process of IEEE-9 bus test system. From the optimal PMU placement results if PMUs has been placed at buses 4, 6, 8 then the voltage magnitude and voltage angles columns corresponding to these PMU placements i.e., V_4, V_6, V_8, δ_4, δ_6, δ_8 are given as inputs to the ANN for its training and testing. The targets and outputs of ANN include the L-index values calculated at all the load buses i.e., L_1, L_2, $L_3 \ldots L_6$. This process has been repeated for every distinct PMU placement result of IEEE-9 bus system and their performances have been compared.

Similarly, for the IEEE-14 bus test system and each distinct optimal PMU placement result, separate ANN models have been trained to predict the voltage stability index (L-index) and their performances have been compared.

4.5 Training and Testing of ANN Models

The architecture of FFBP-ANN models which has been trained in this work for voltage stability assessment considering different PMU placement methods is shown in Fig. 4.1

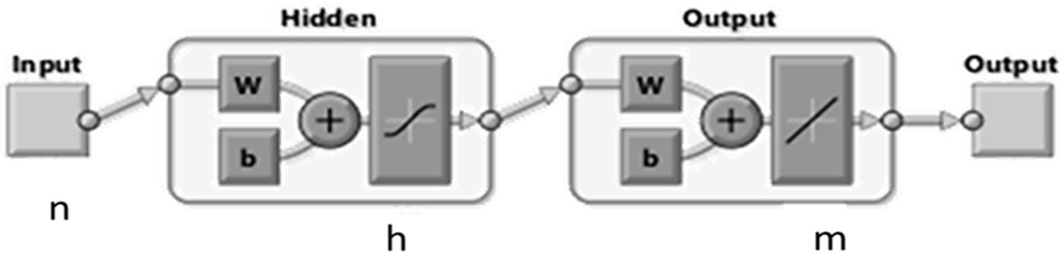


Fig. 4.1 FFBP-ANN architecture

In this architecture, the symbol *n* denotes the number of inputs, which is twice the count of PMUs strategically positioned within the system. The hidden layer of the network is composed of *h* neurons. The value of *h* has been determined through trial and error. In this approach, different values for *h* are tested to find the one that yields the best performance of the neural network. The output layer consists of *m* number of neurons, which is equal to the number of load buses in the test system.

The outcomes of training and testing of different ANN models are represented through regression plots and performance plots, providing comprehensive insights into their predictive capabilities.

The activation function utilized for the hidden layer of the network is the Tan-Sigmoid function and the output layer employs the purelin activation function, enabling the direct representation of network outputs.

For the training process, the Levenberg-Marquardt (LM) algorithm has been employed. This algorithm optimizes the network's parameters by iteratively adjusting the weights and biases, leading to the minimization of the error between target and actual outputs.

4.5.1 Training and Testing of ANN models for IEEE-9 bus system

a) PMUs placed at every bus in IEEE-9 bus system

Upon training the feedforward backpropagation artificial neural network (FFBP-ANN) with phasor measurement units (PMUs) placed at every bus in the IEEE-9 bus test system, a mean square error (MSE) of 1.893×10^{-4} has been achieved as the testing performance of FFBP-ANN. Furthermore, a substantial correlation coefficient (R) of 0.9966 has been obtained for the testing data. Fig. 4.2 depicts the training, and the testing regression plots and, Fig. 4.3 presents the training and the testing performance plots.

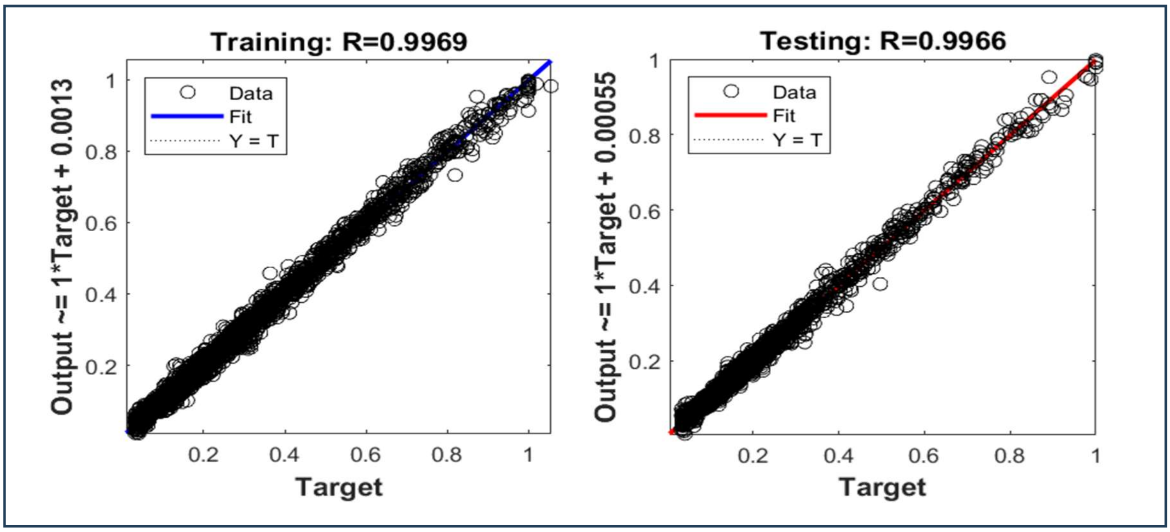


Fig. 4.2 Regression plots for the training and the testing of ANN with PMUs placed at every bus in IEEE-9 bus system

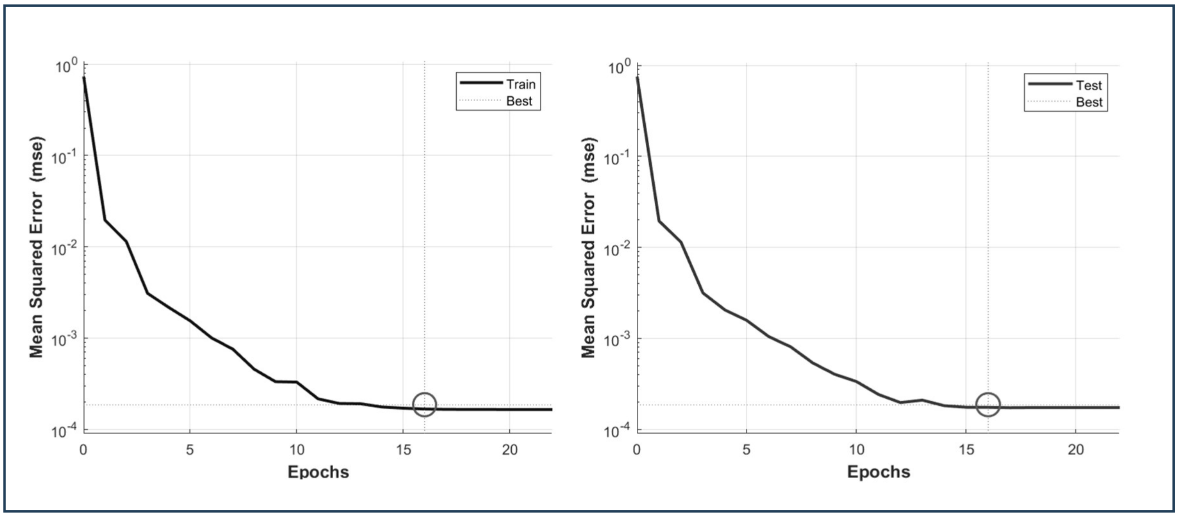


Fig. 4.3 Performance plots for ANN training and testing with PMUs placed at every bus in IEEE-9 bus system

b) PMUs placed at buses 4, 6, 8 in IEEE-9 bus system

After training the FFBP-ANN with PMUs strategically placed at buses 4, 6, and 8 within the IEEE-9 bus test system, an impressive testing MSE of 1.893 × 10^{-6} has been achieved, indicating the high precision of the FFBP-ANN model in its testing performance. Moreover, this achievement is complemented by a significant correlation coefficient (R) of 0.9999. This strong correlation coefficient underscores the model's ability to accurately capture the intricate relationships between input voltage phasor data and the L-index. Fig. 4.4 showcases the training and testing regression plots. Additionally, Fig. 4.5 presents the training and testing performance plots.

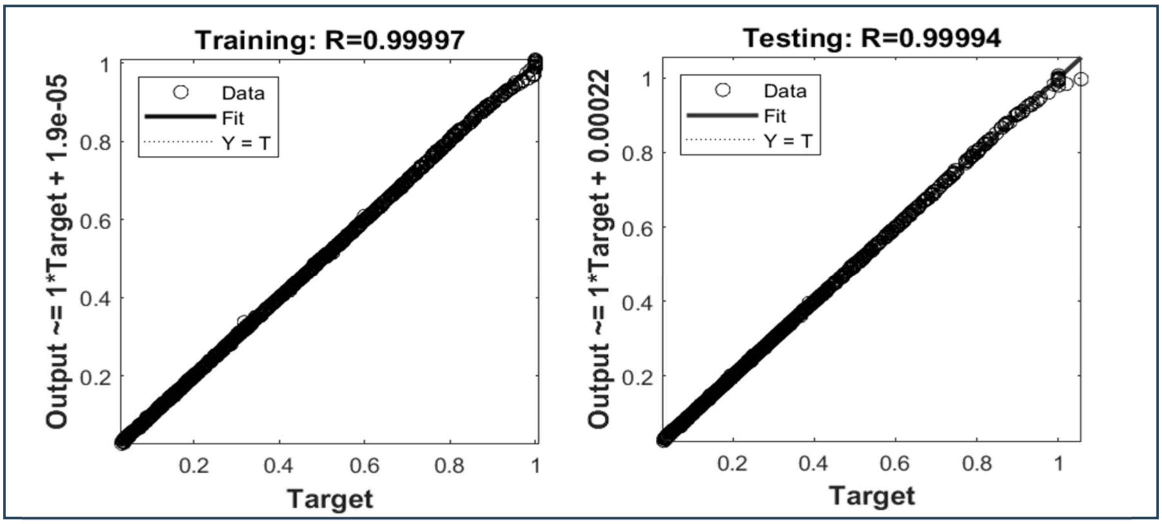


Fig. 4.4 Regression plots for the training and the testing of ANN with PMUs placed at buses 4, 6, 8 in IEEE-9 bus system

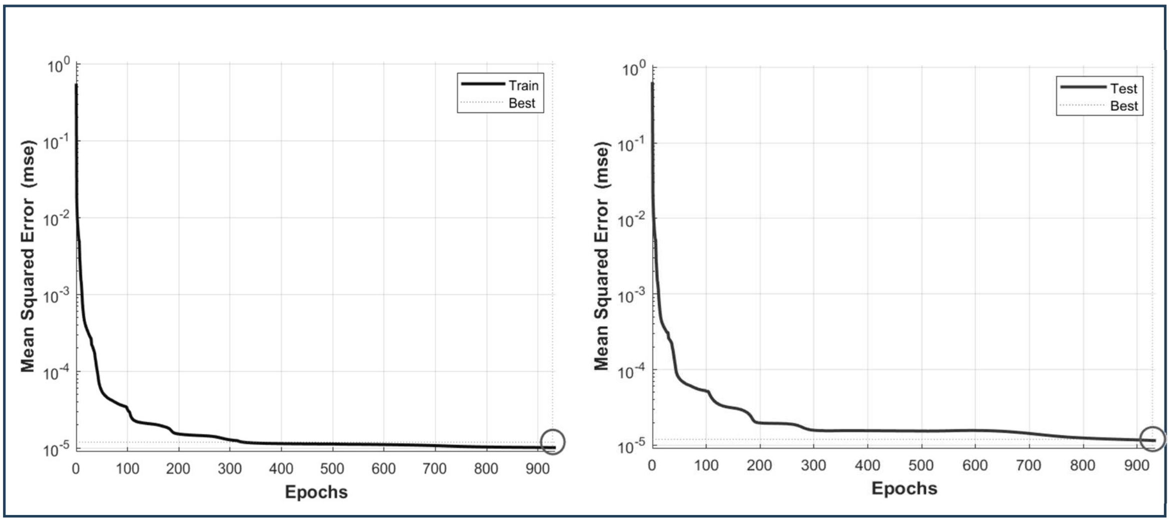


Fig. 4.5 Performance plots for ANN training and testing with PMUs placed at buses 4, 6, 8 in IEEE-9 bus system

c) PMUs placed at buses 5, 8 in IEEE-9 bus system

After training the FFBP-ANN with PMUs strategically placed at buses 5 and 8 within the IEEE-9 bus test system, a of 2.5975×10^{-4} has been achieved. Moreover, a correlation coefficient (R) of 0.99603 has been obtained.

Fig. 4.6 showcases the training and testing regression plots. Additionally, Fig. 4.7 presents the training and testing performance plots.

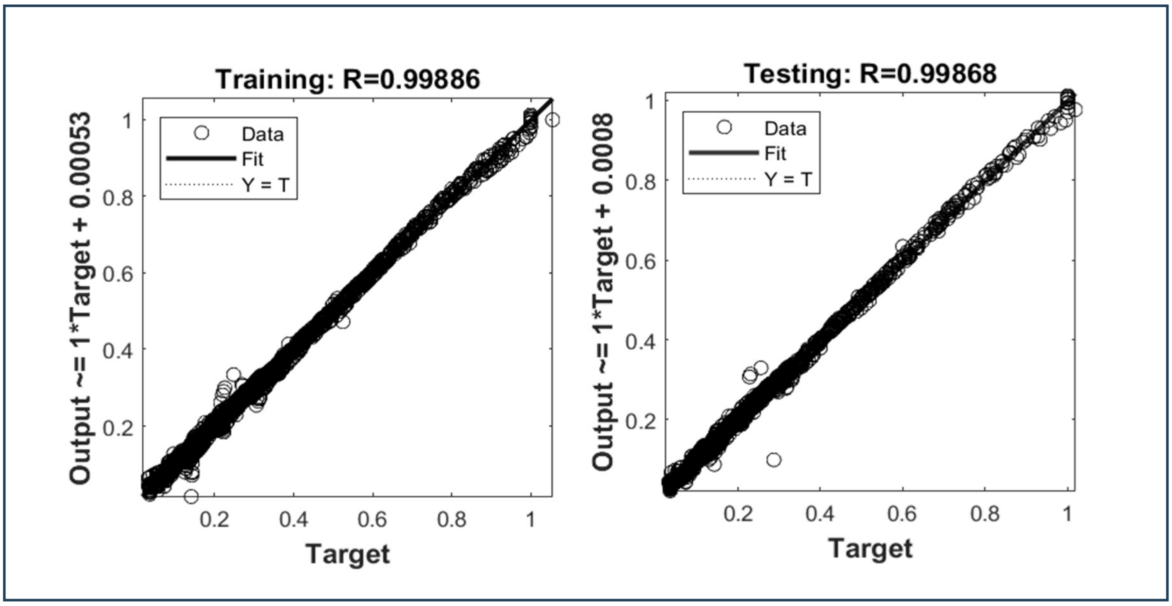


Fig. 4.6 Regression plots for the training and the testing of ANN with PMUs placed at buses 5, 8 in IEEE-9 bus system

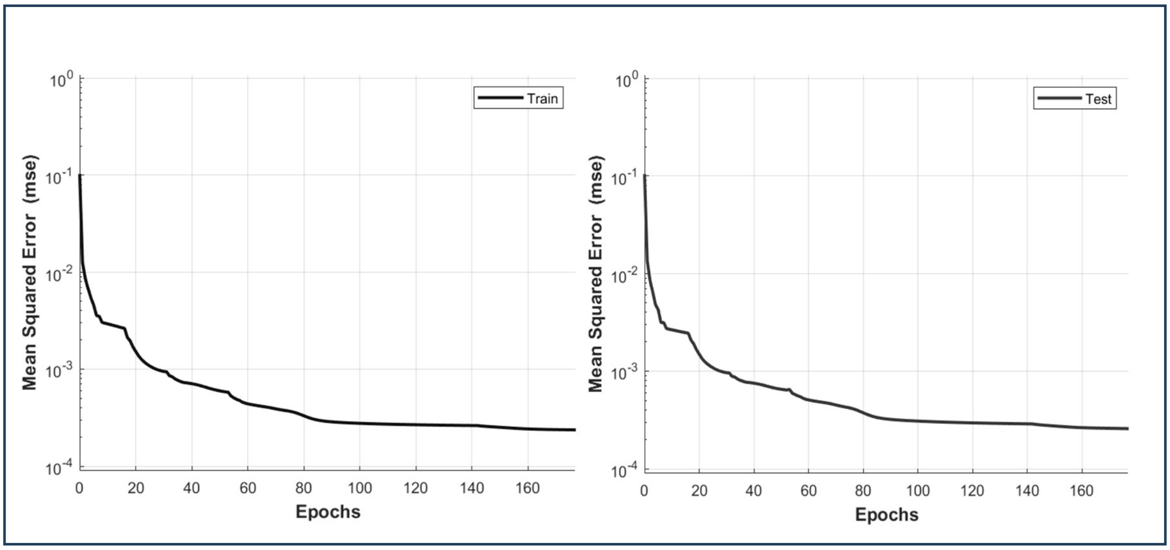


Fig. 4.7 Performance plots for ANN training and testing with PMUs placed at buses 5, 8 in IEEE-9 bus system

d) PMUs placed at buses 4, 7 in IEEE-9 bus system

After training the FFBP-ANN with PMUs strategically placed at buses 4 and 7 within the IEEE-9 bus test system, a testing performance MSE of 1.8420×10^{-4} has been achieved. Moreover, a correlation coefficient (R) of 0.9972 has been obtained.

Fig. 4.8 showcases the training and testing regression plots. Additionally, Fig. 4.9 presents the training and testing performance plots.

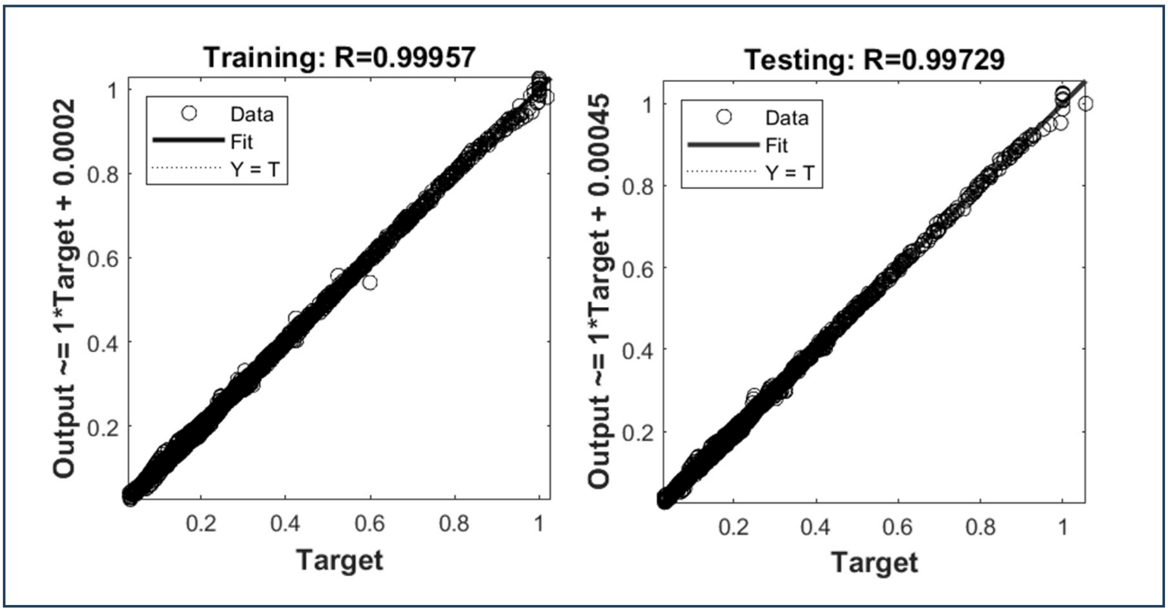


Fig. 4.8 Regression plots for the training and the testing of ANN with PMUs placed at buses 4, 7 in IEEE-9 bus system

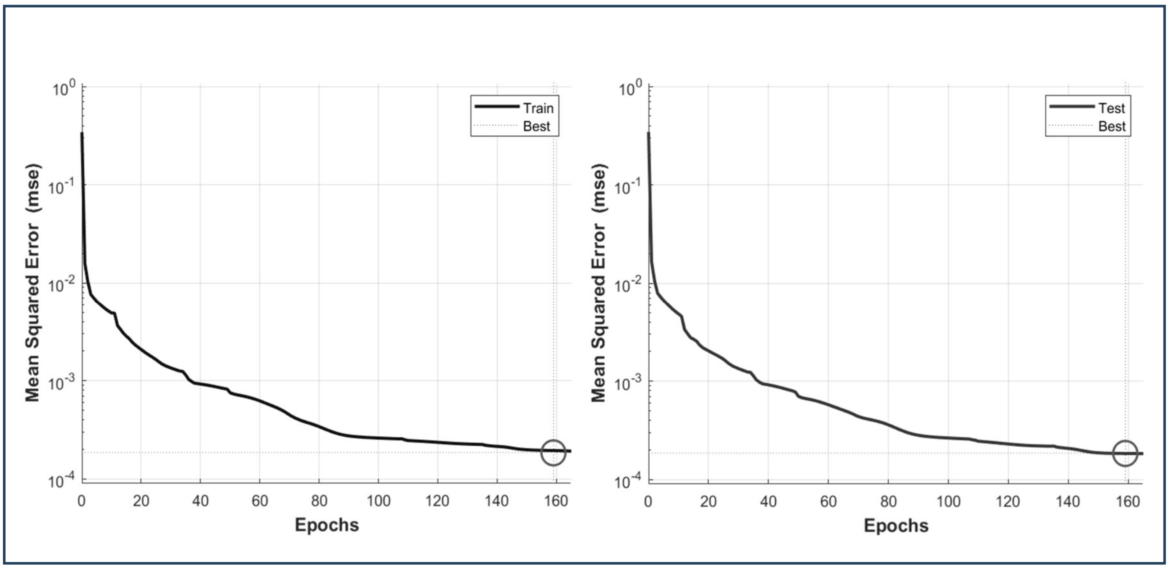


Fig. 4.9 Performance plots for ANN training and testing with PMUs placed at buses 4, 7 in IEEE-9 bus system

e) PMUs placed at buses 6, 9 in IEEE-9 bus system

Following training the FFBP-ANN with PMUs strategically placed at buses 6 and 9 within the IEEE-9 bus test system, a testing performance MSE of 1.8637×10^{-4} has been obtained. Moreover, a correlation coefficient (R) of 0.9975 has been achieved.

Fig. 4.10 showcases the training and testing regression plots. Additionally, Fig. 4.11 presents the training and testing performance plots.

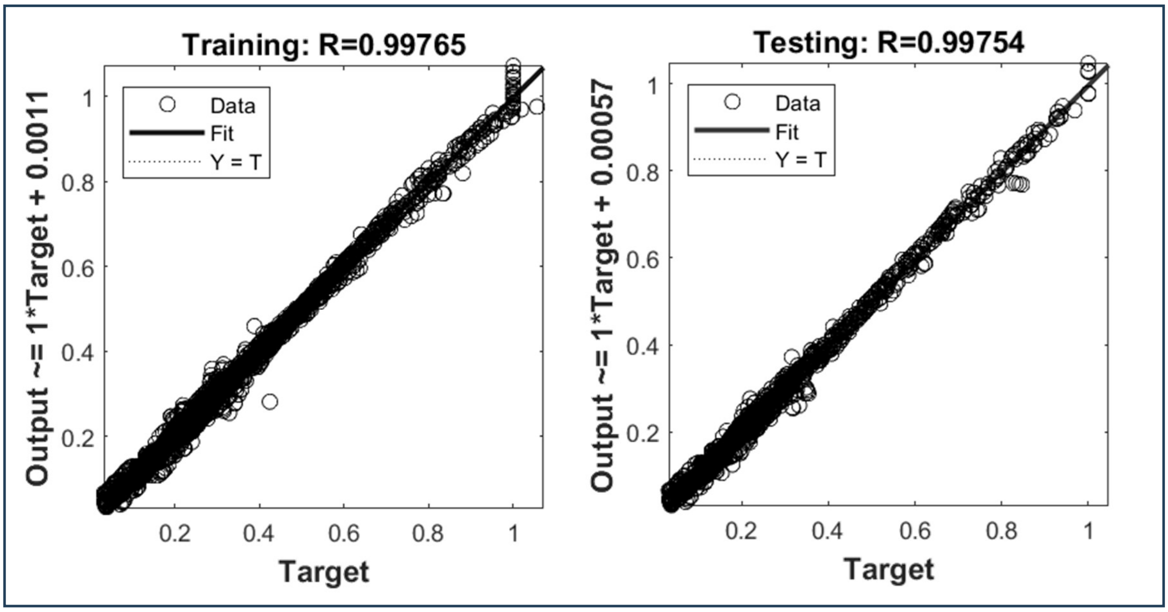


Fig. 4.10 Regression plots for the training and the testing of ANN with PMUs placed at buses 6, 9 in IEEE-9 bus system

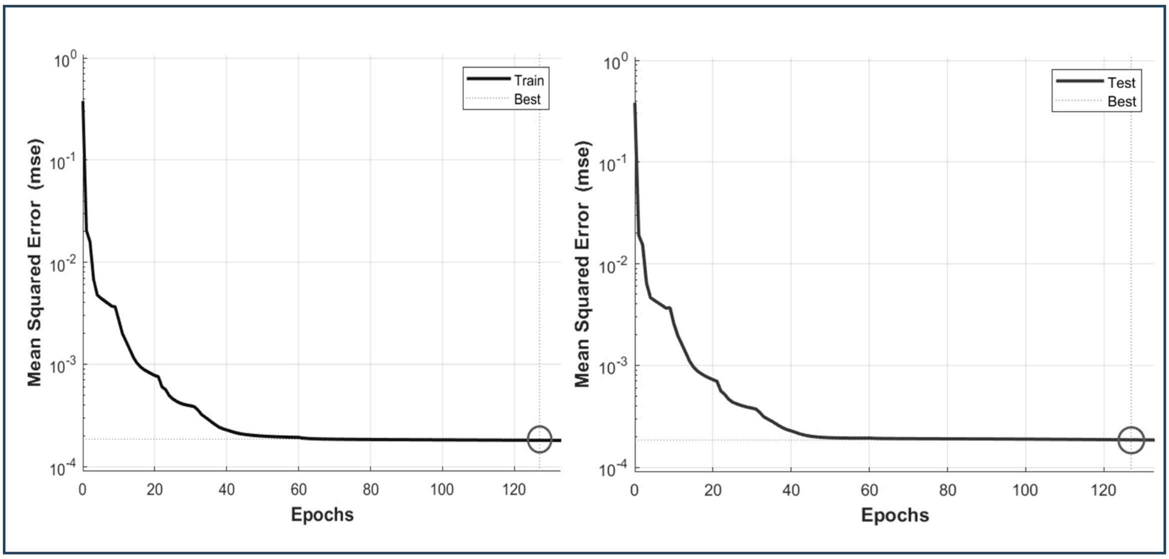


Fig. 4.11 Performance plots for ANN training and testing with PMUs placed at buses 6, 9 in IEEE-9 bus system

f) PMUs placed at buses 3, 4, 8 in IEEE-9 bus system

After training the FFBP-ANN with PMUs strategically placed at buses 3, 4 and 8 within the IEEE-9 bus test system, a testing performance MSE of 1.8686×10^{-3} has been achieved. Moreover, a correlation coefficient (R) of 0.9774 has been obtained.

Fig. 4.12 showcases the training and testing regression plots. Additionally, Fig. 4.13 presents the training and testing performance plots.

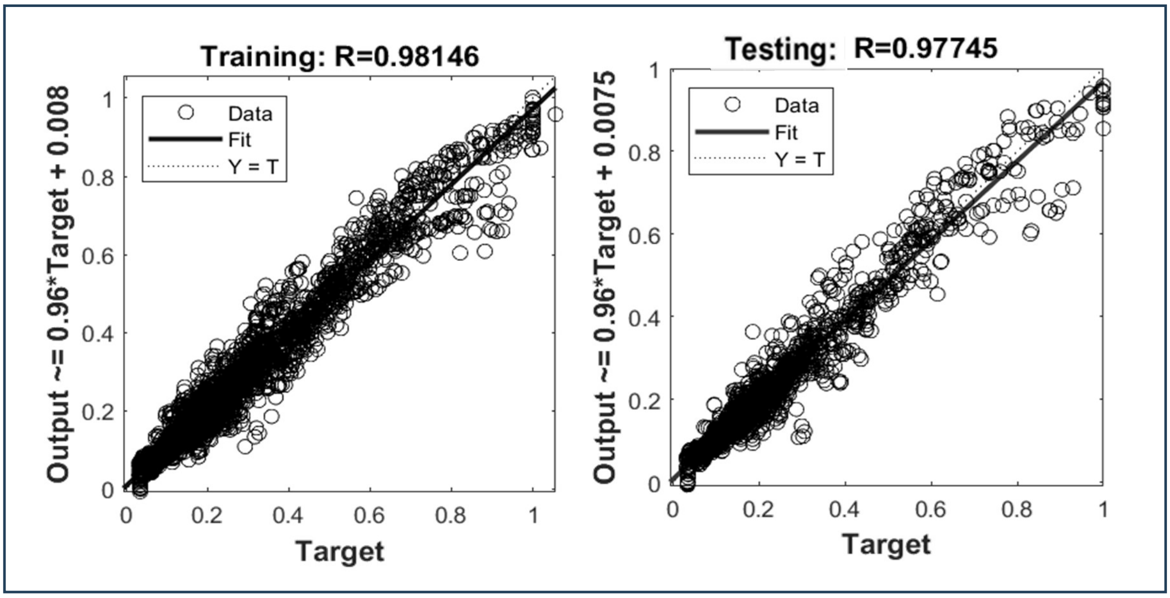


Fig. 4.12 Regression plots for the training and the testing of ANN with PMUs placed buses 3, 4, 8 in IEEE-9 bus system

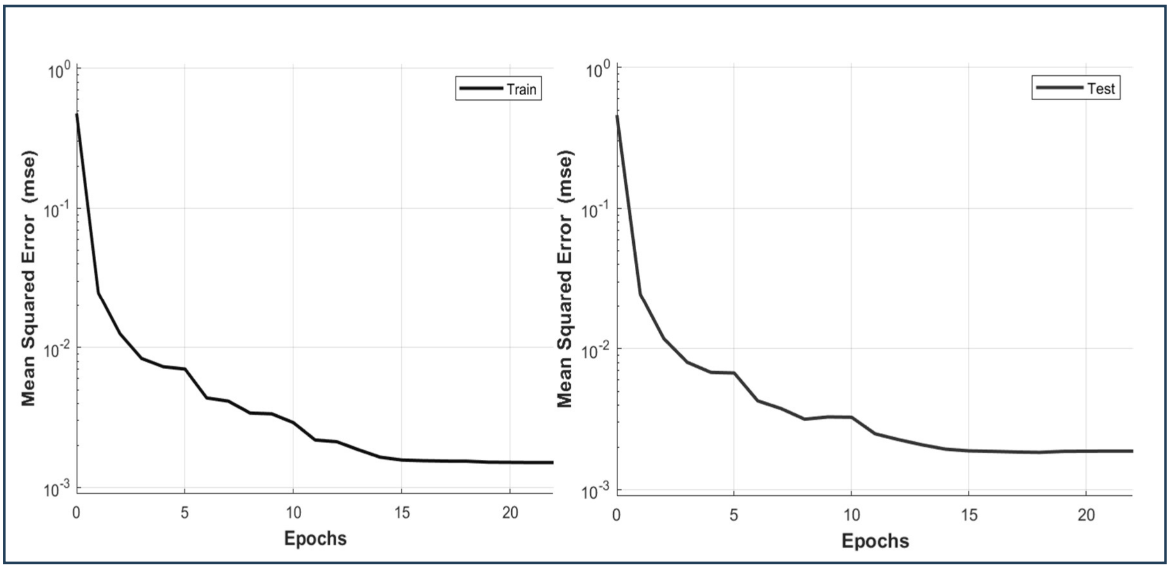


Fig. 4.13 Performance plots for ANN training and testing with PMUs placed buses 3, 4, 8 in IEEE-9 bus system

g) PMUs placed at buses 1, 6, 8 in IEEE-9 bus system

Following training the FFBP-ANN with PMUs strategically placed at buses 1, 6 and 8 within the IEEE-9 bus test system, a testing performance MSE of 3.9259×10^{-3} has been obtained. Moreover, a correlation coefficient (R) of 0.9928 has been achieved.

Fig. 4.14 showcases the training and testing regression plots. Additionally, Fig. 4.15 presents the training and testing performance plots.

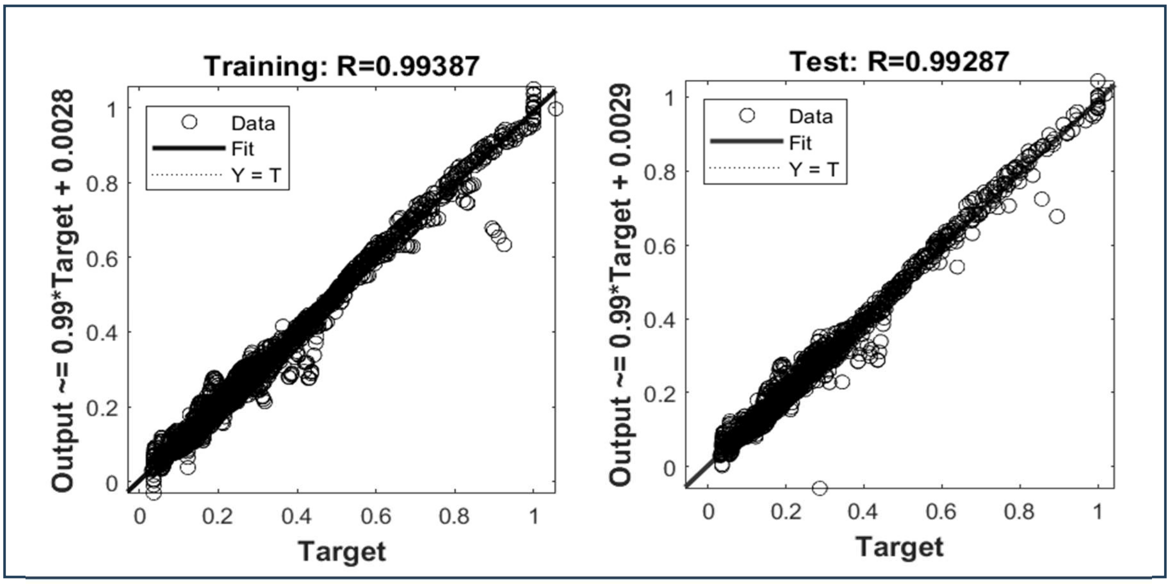


Fig. 4.14 Regression plots for the training and the testing of ANN with PMUs placed at buses 1, 6, 8 in IEEE-9 bus system

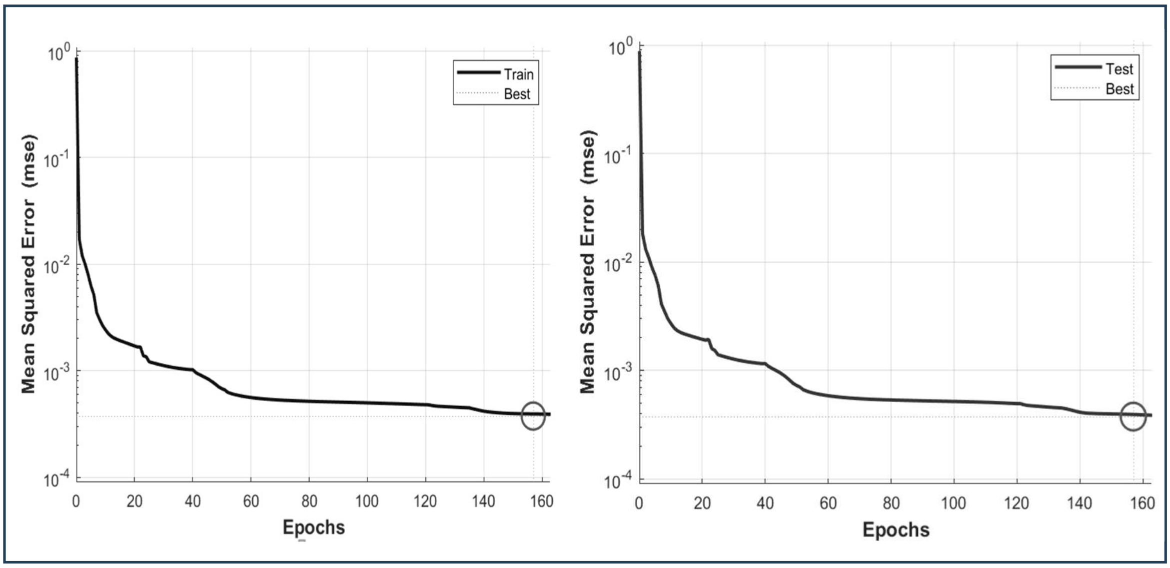


Fig. 4.15 Performance plots for ANN training and testing with PMUs placed at buses 1, 6, 8 in IEEE-9 bus system

h) PMUs placed at buses 1, 2, 3, 4, 6, 8 in IEEE-9 bus system

Following training the FFBP-ANN with PMUs strategically placed at buses 1, 2, 3, 4, 6 and 8 within the IEEE-9 bus test system, a testing performance MSE of 1.5460 × 10^{-3} has been obtained. Moreover, a correlation coefficient (R) of 0.9732 has been achieved.

Fig. 4.16 showcases the training and testing regression plots. Additionally, Fig. 4.17 presents the training and testing performance plots.

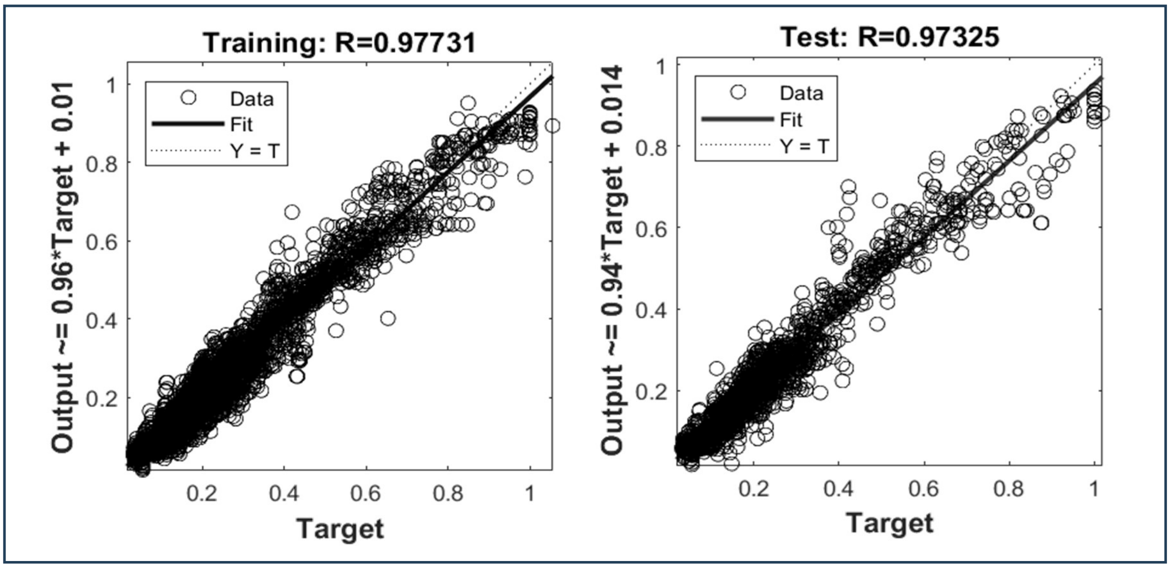


Fig. 4.16 Regression plots for the training and the testing of ANN with PMUs placed at buses 1, 2, 3, 4, 6, 8 in IEEE-9 bus system

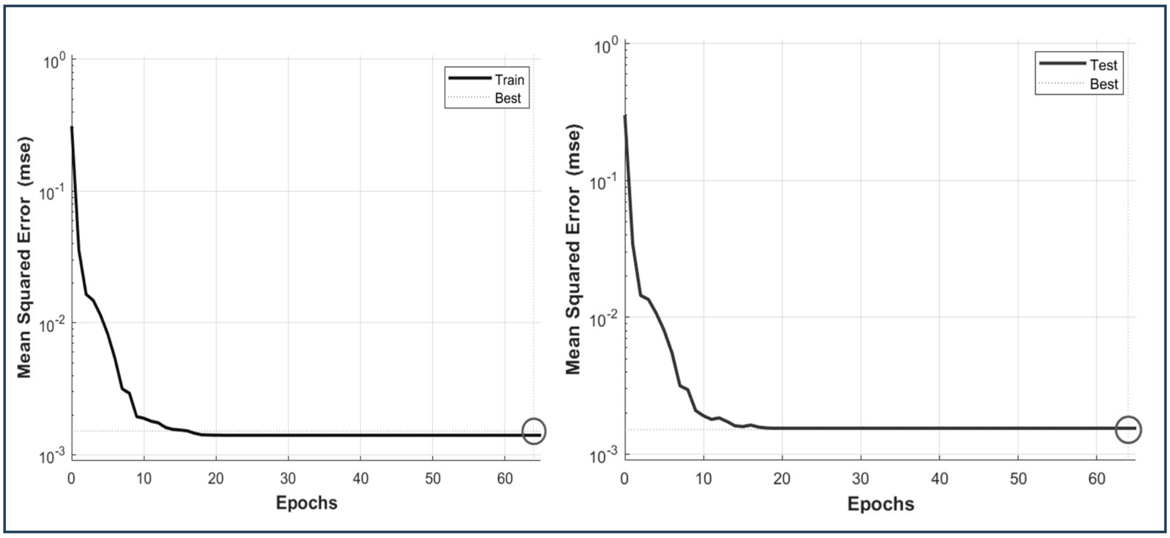


Fig. 4.17 Performance plots for ANN training and testing with PMUs placed at buses 1, 2, 3, 4, 6, 8 in IEEE-9 bus system

4.5.2 Training and Testing of ANN Models for IEEE-14 bus system

a) PMUs placed at every bus in IEEE-14 bus system

After training the FFBP-ANN with PMUs strategically placed at every bus in the IEEE-14 bus test system, a testing performance MSE of 1.502×10^{-4} has been achieved. Moreover, a correlation coefficient (R) of 0.9933 has been obtained.

Fig. 4.18 showcases the training and testing regression plots. Additionally, Fig. 4.19 presents the training and testing performance plots.

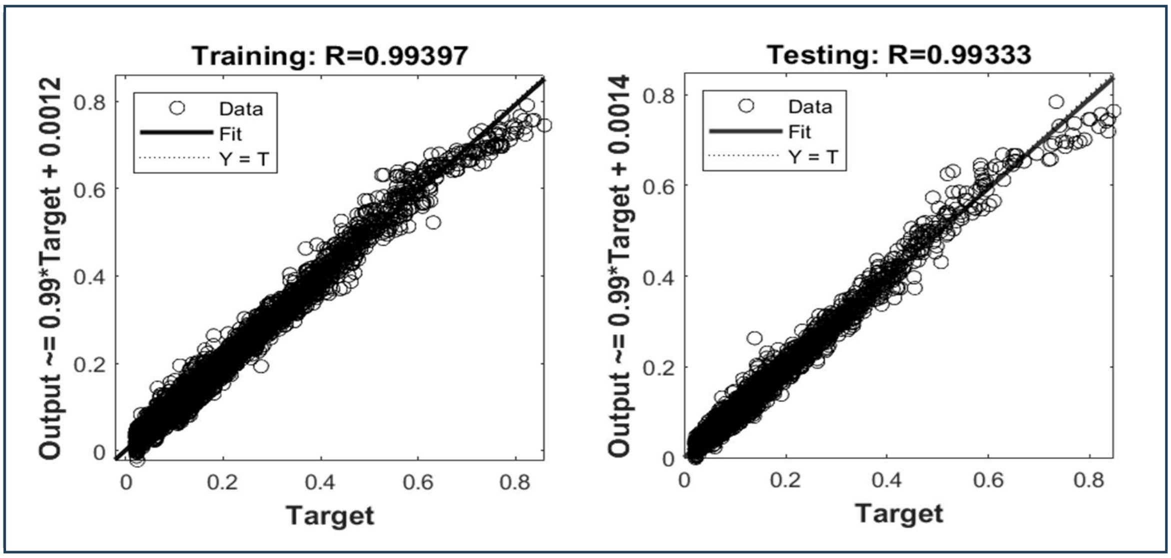


Fig. 4.18 Regression plots for the training and the testing of ANN with PMUs placed at every bus in IEEE-14 bus system

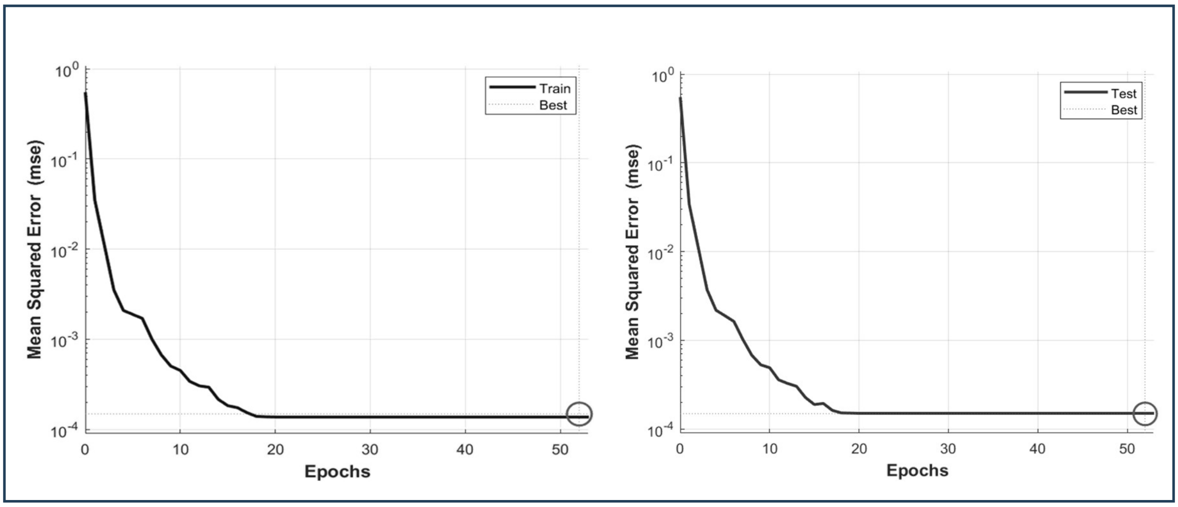


Fig. 4.19 Performance plots for ANN training and testing with PMUs placed at every bus in IEEE-14 bus system

b) PMUs placed at buses 1, 4, 6, 8, 10, 14 in IEEE-14 bus system

After training the FFBP-ANN with PMUs strategically placed at buses 1, 4, 6, 8, 10, and 14 within the IEEE-14 bus test system, a testing performance MSE of 1.638×10^{-4} has been achieved. Moreover, a correlation coefficient (R) of 0.9928 has been obtained.

Fig. 4.20 showcases the training and testing regression plots. Additionally, Fig. 4.21 presents the training and testing performance plots.

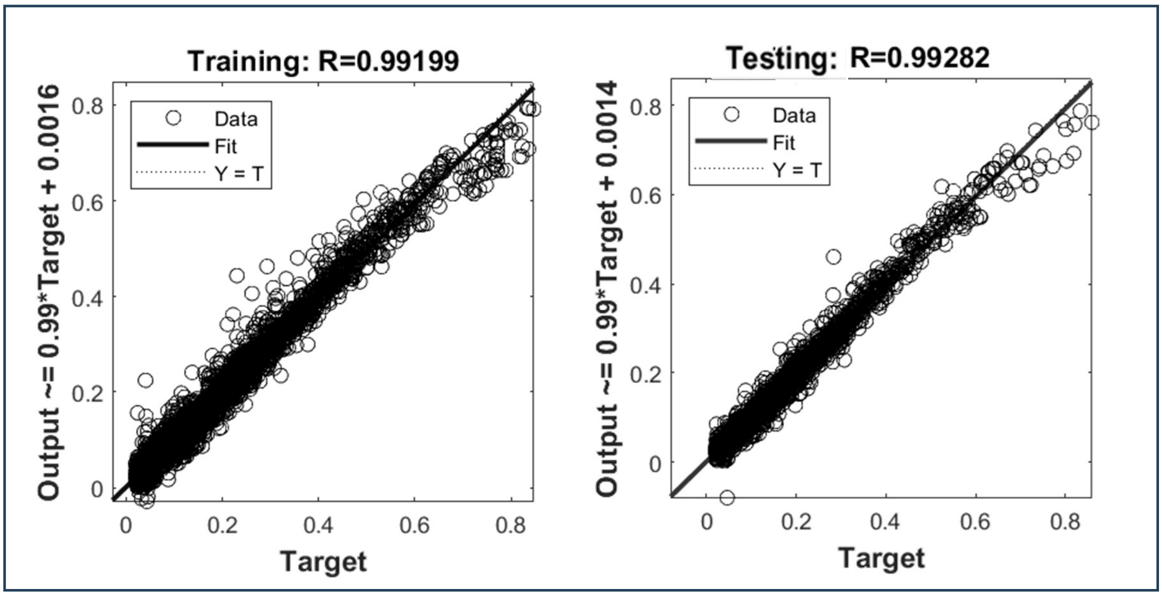


Fig. 4.20 Regression plots for the training and the testing of ANN with PMUs placed at buses 1, 4, 6, 8, 10, 14 in IEEE-14 bus system

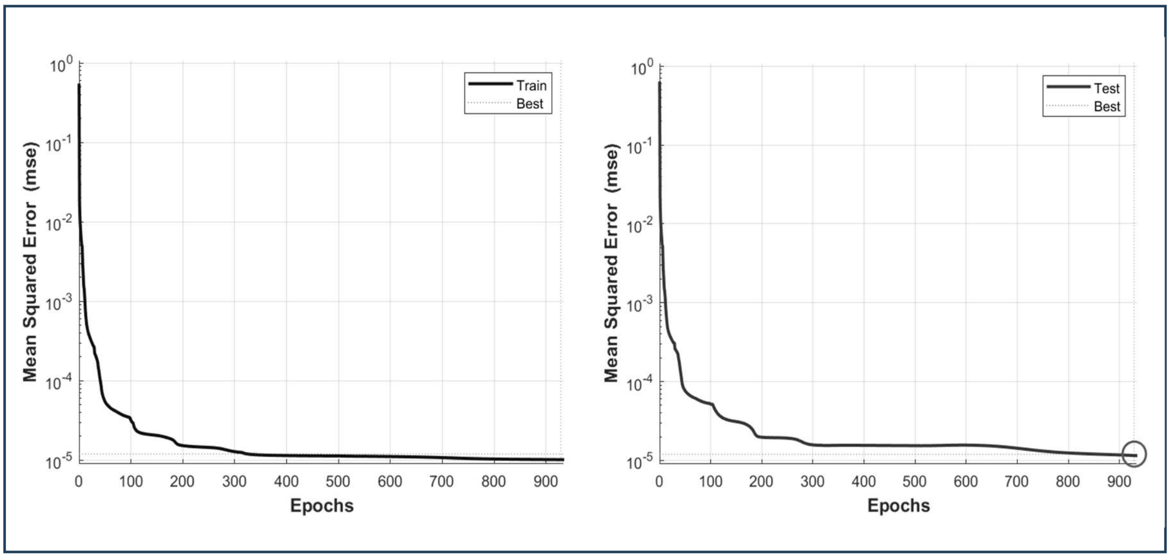


Fig. 4.21 Performance plots for ANN training and testing with PMUs placed at buses 1, 4, 6, 8, 10, 14 in IEEE-14 bus system

c) PMUs placed at buses 1, 4, 6, 10, 14 in IEEE-14 bus system

After training the FFBP-ANN with PMUs strategically placed at buses 1, 4, 6, 10, and 14 within the IEEE-14 bus test system, a testing performance MSE of 2.440×10^{-4} has been achieved. Moreover, a correlation coefficient (R) of 0.9891 has been obtained.

Fig. 4.22 showcases the training and testing regression plots. Additionally, Fig. 4.23 presents the training and testing performance plots.

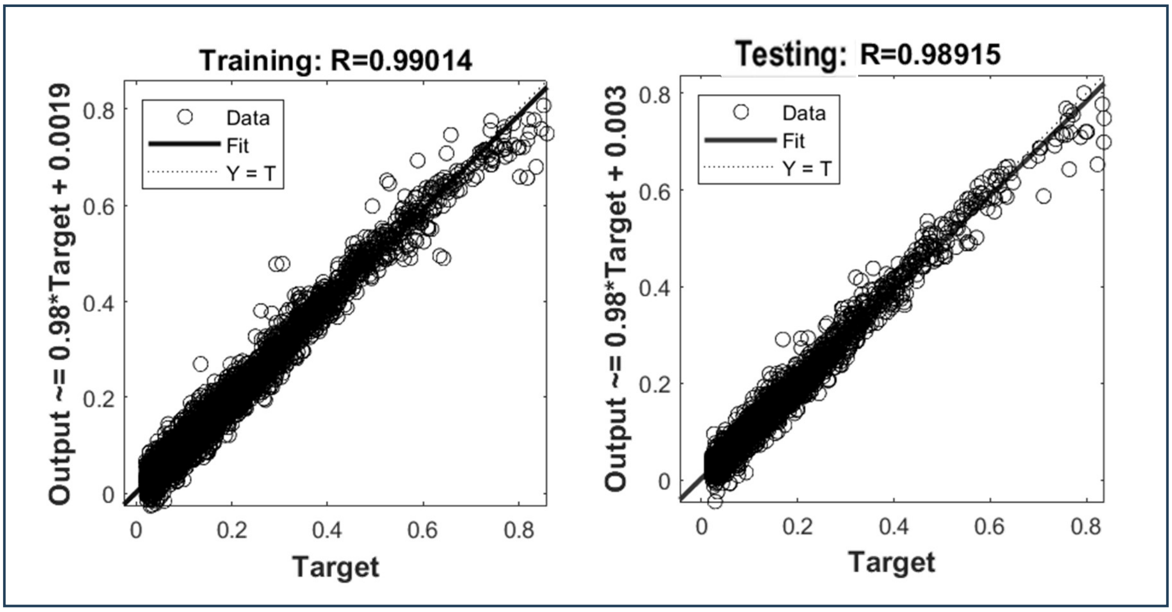


Fig. 4.22 Regression plots for the training and the testing of ANN with PMUs placed at buses 1, 4, 6, 10, 14 in IEEE-14 bus system

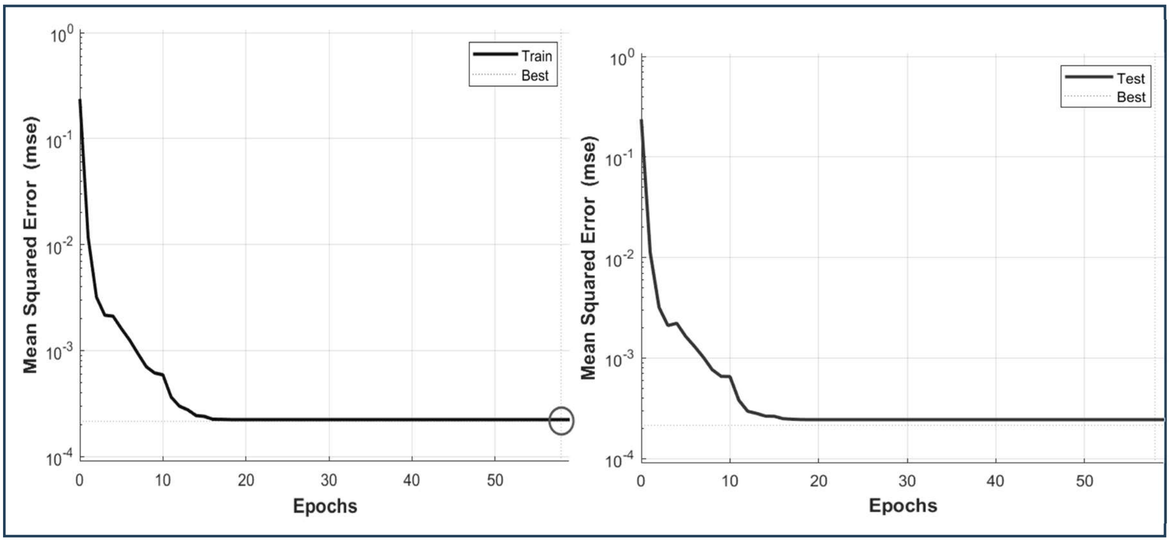


Fig. 4.23 Performance plots for ANN training and testing with PMUs placed at buses 1, 4, 6, 10, 14 in IEEE-14 bus system

d) PMUs placed at buses 2, 6, 8, 9 in IEEE-14 bus system

After training the FFBP-ANN with PMUs strategically placed at buses 2, 6, 8 and 9 within the IEEE-14 bus test system, a testing performance MSE of 1.393×10^{-3} has been achieved. Moreover, a correlation coefficient (R) of 0.9367 has been obtained.

Fig. 4.24 showcases the training and testing regression plots. Additionally, Fig. 4.25 presents the training and testing performance plots.

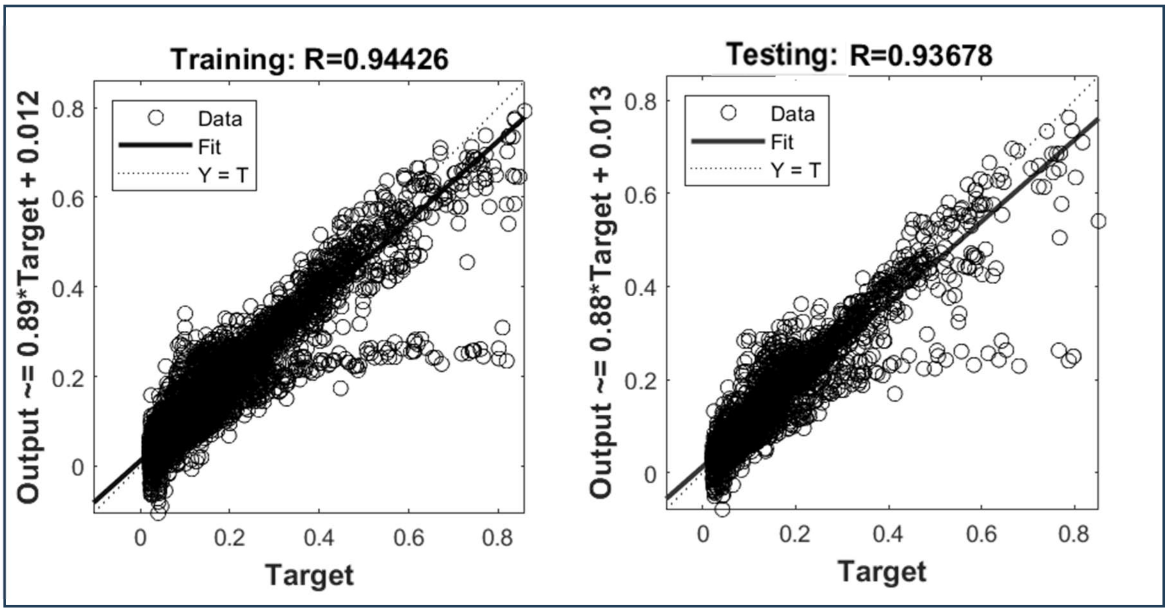


Fig. 4.24 Regression plots for the training and the testing of ANN with PMUs placed at buses 2, 6, 8, 9 in IEEE-14 bus system

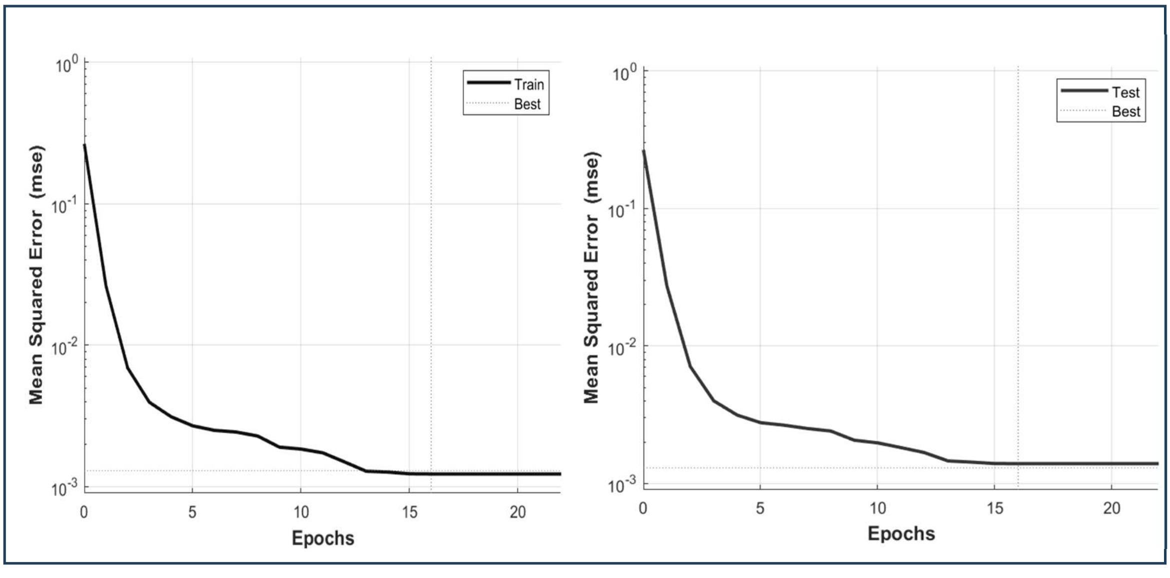


Fig. 4.25 Performance plots for ANN training and testing with PMUs placed at buses 2, 6, 8, 9 in IEEE-14 bus system

e) PMUs placed at buses 2, 6, 7, 9 in IEEE-14 bus system

After training the FFBP-ANN with PMUs strategically placed at buses 2, 6, 7 and 9 within the IEEE-14 bus test system, a testing performance MSE of 1.275×10^{-3} has been achieved. Moreover, a correlation coefficient (R) of 0.9444 has been obtained.

Fig. 4.26 showcases the training and testing regression plots. Additionally, Fig. 4.27 presents the training and testing performance plots.

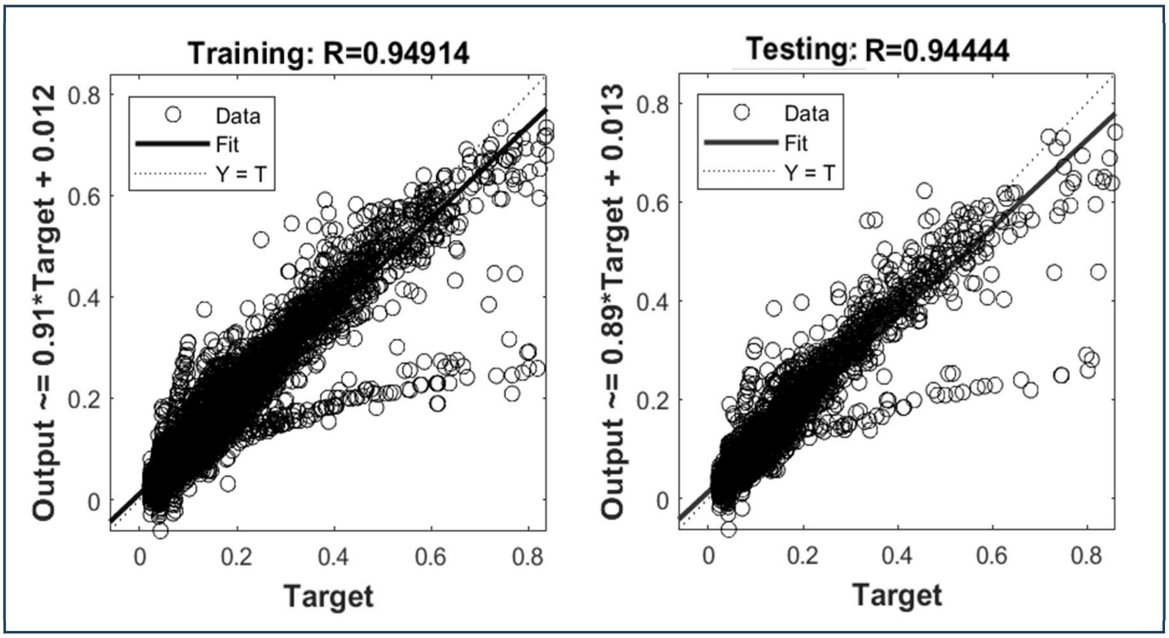


Fig. 4.26 Regression plots for the training and the testing of ANN with PMUs placed at buses 2, 6, 7, 9 in IEEE-14 bus system

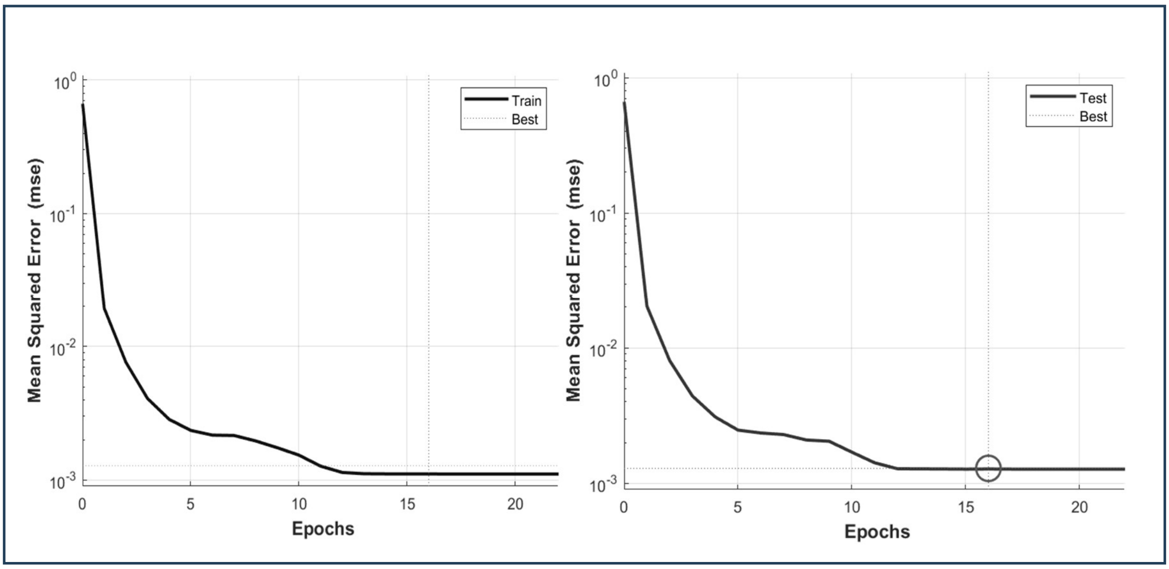


Fig. 4.27 Performance plots for ANN training and testing with PMUs placed at buses 2, 6, 7, 9 in IEEE-14 bus system

f) PMUs placed at buses 1, 4, 11, 13 in IEEE-14 bus system

After training the FFBP-ANN with PMUs strategically placed at buses 1, 4, 11, and 13 within the IEEE-14 bus test system, an impressive MSE of 1.808×10^{-6} has been achieved, indicating the high precision of the FFBP-ANN model in its testing performance. Moreover, this achievement is complemented by a significant correlation coefficient (R) of 0.9999. This strong correlation coefficient underscores the model's ability to accurately capture the intricate relationships between input voltage phasor data and the L-index. Fig. 4.28 showcases the training and testing regression plots. Additionally, Fig. 4.29 presents the training and testing performance plots.

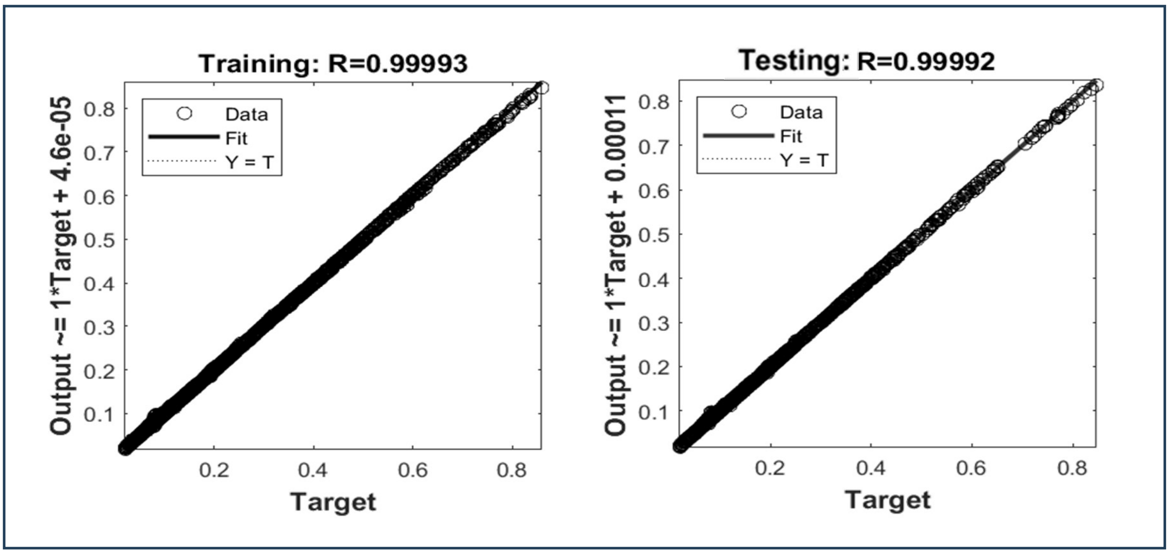


Fig. 4.28 Regression plots for the training and the testing of ANN with PMUs placed at buses 1, 4, 11, 13 in IEEE-14 bus system

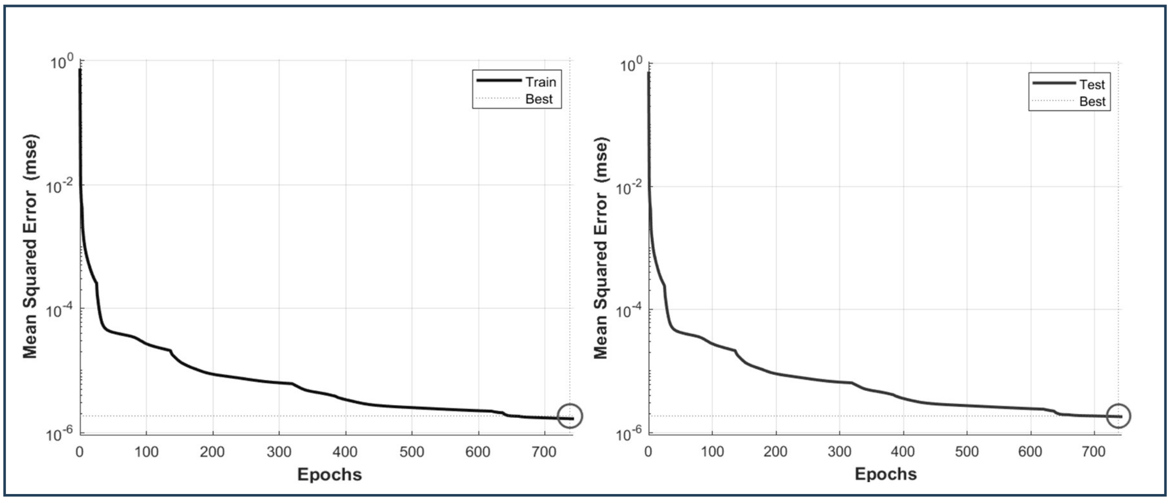


Fig. 4.29 Performance plots for ANN training and testing with PMUs placed at buses 1, 4, 11, 13 in IEEE-14 bus system

g) PMUs placed at buses 2, 4, 10, 13 in IEEE-14 bus system

After training the FFBP-ANN with PMUs strategically placed at buses 2, 4, 10 and 13 in the IEEE-14 bus test system, a testing performance MSE of 1.577×10^{-4} has been achieved. Moreover, a correlation coefficient (R) of 0.99352 has been obtained.

Fig. 4.30 showcases the training and testing regression plots. Additionally, Fig. 4.31 presents the training and testing performance plots.

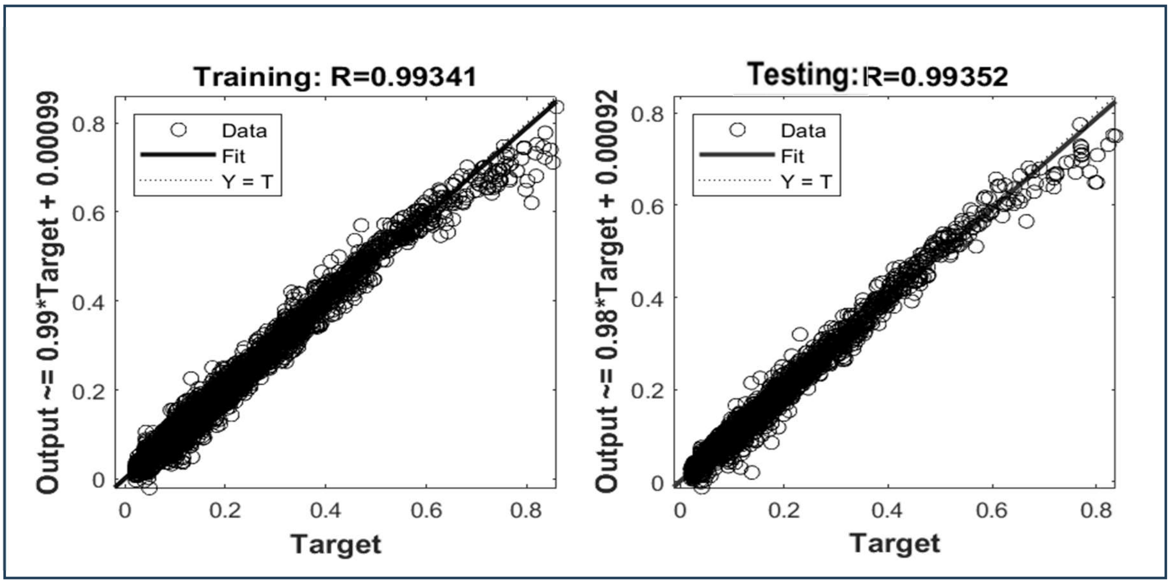


Fig. 4.30 Regression plots for the training and the testing of ANN with PMUs placed at buses 2, 4, 10, 13 in IEEE-14 bus system

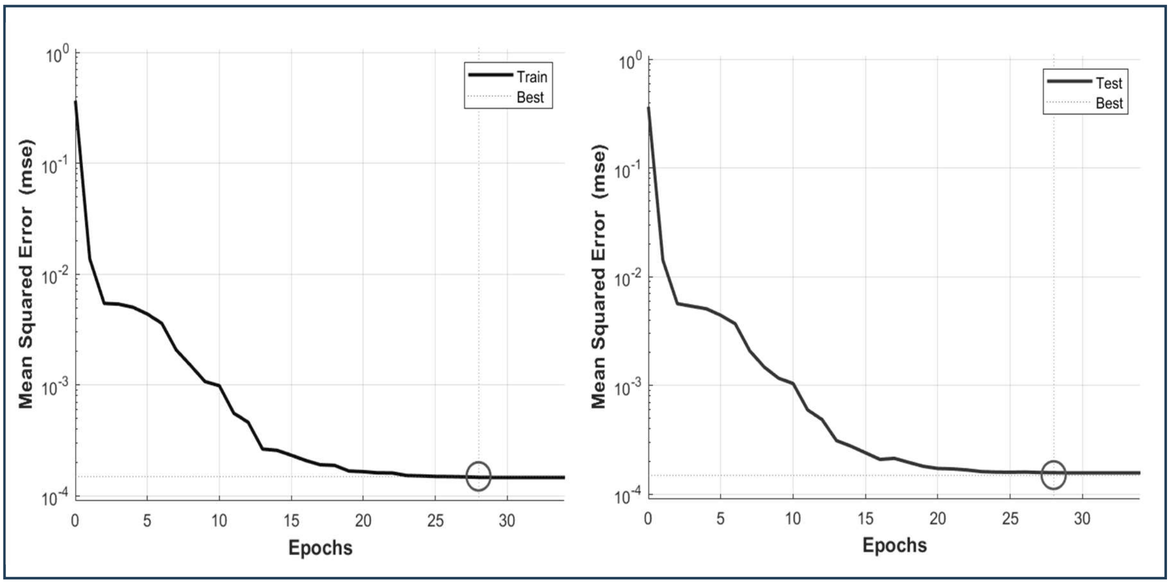


Fig. 4.31 Performance plots for ANN training and testing with PMUs placed at buses 2, 4, 10, 13 in IEEE-14 bus system

h) PMUs placed at buses 2, 6, 9 in IEEE-14 bus system

After training the FFBP-ANN with PMUs strategically placed at buses 2, 6 and 9 in the IEEE-14 bus test system, a testing performance MSE of 3.976×10^{-4} has been achieved. Moreover, a correlation coefficient (R) of 0.98341 has been obtained.

Fig. 4.32 showcases the training and testing regression plots. Additionally, Fig. 4.33 presents the training and testing performance plots.

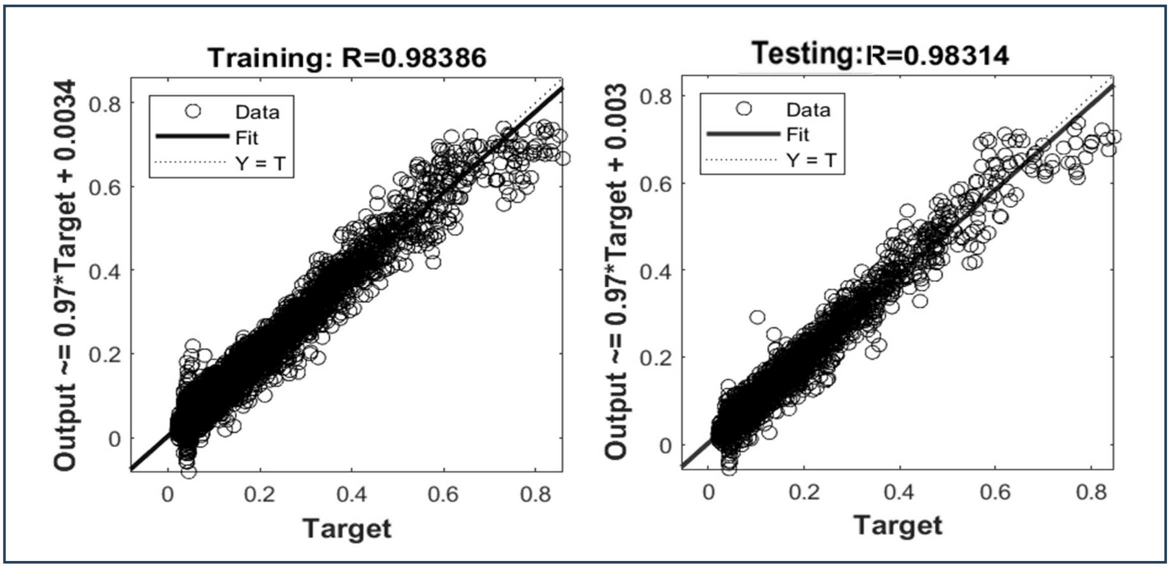


Fig. 4.32 Regression plots for the training and the testing of ANN with PMUs placed at buses 2, 6, 9 in IEEE-14 bus system

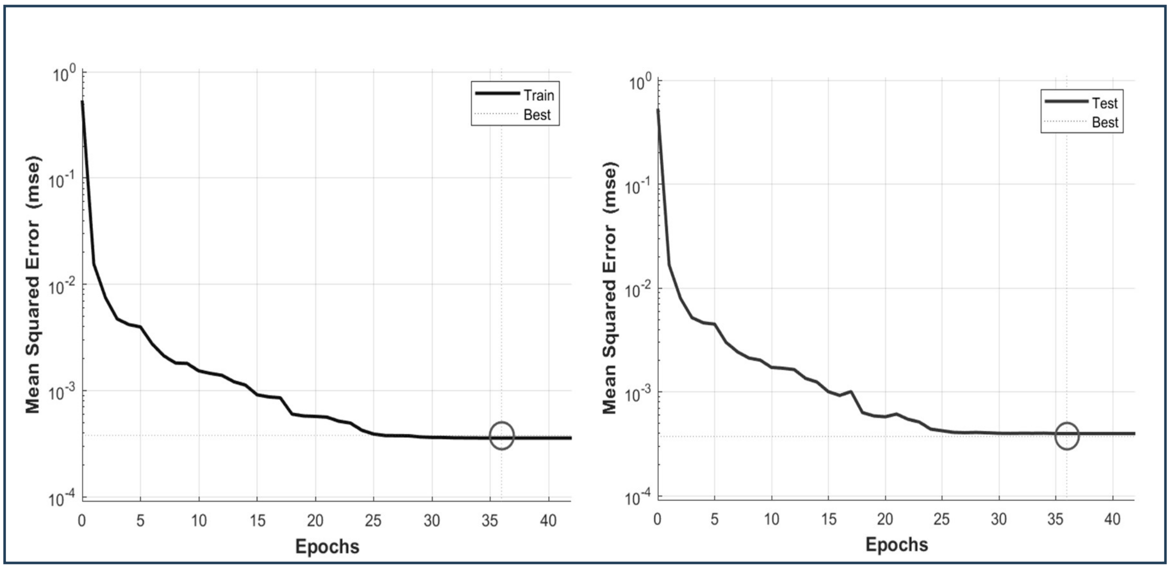


Fig. 4.33 Performance plots for ANN training and testing with PMUs placed at buses 2, 6, 9 in IEEE-14 bus system

i) PMUs placed at buses 2, 4, 5, 6, 7, 8, 9, 10, 13 in IEEE-14 bus system

After training the FFBP-ANN with PMUs strategically placed at buses 2, 4, 5, 6, 7, 8, 9, 10 and 13 within the IEEE-14 bus test system, a testing performance MSE of 2.317×10^{-4} has been achieved. Moreover, a correlation coefficient (R) of 0.9891has been obtained.

Fig. 4.34 showcases the training and testing regression plots. Additionally, Fig. 4.35 presents the training and testing performance plots.

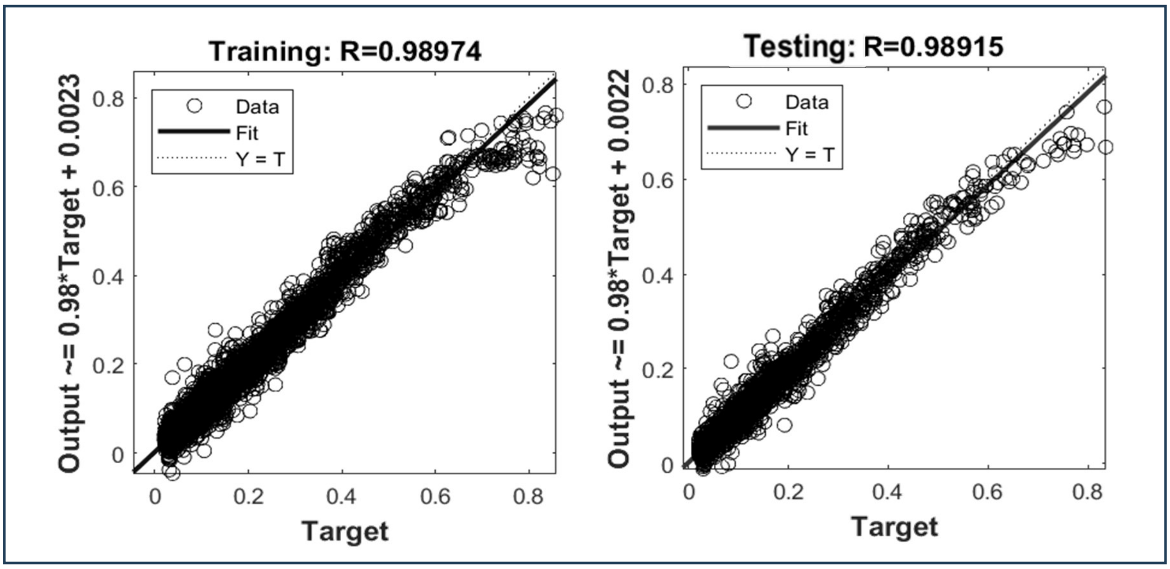


Fig. 4.34 Regression plots for the training and the testing of ANN with PMUs placed at buses 2, 4, 5, 6, 7, 8, 9, 10, 13 in IEEE-14 bus system

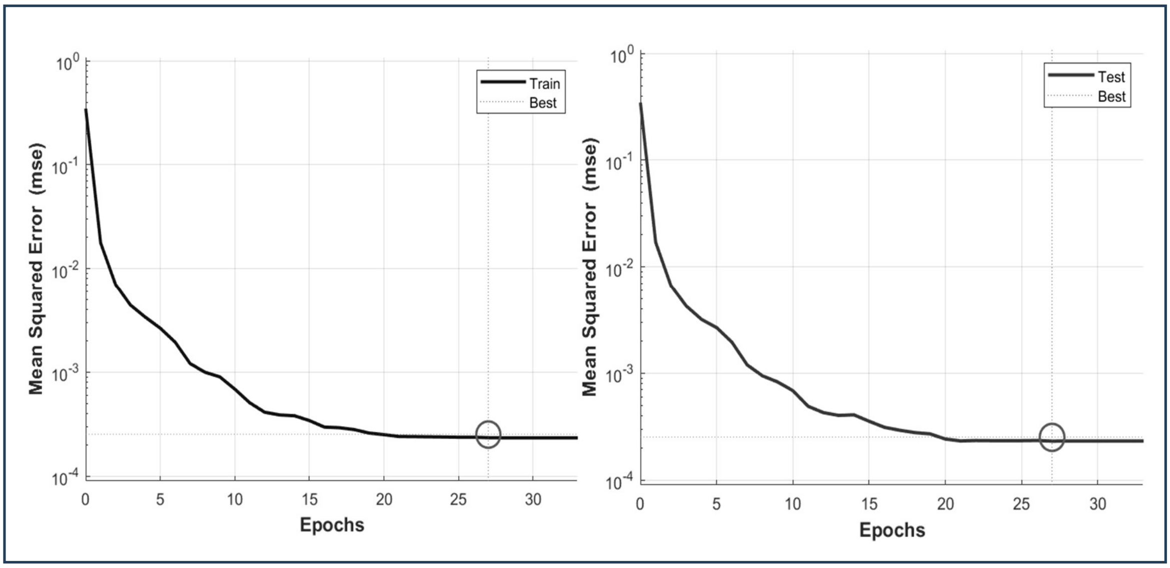


Fig. 4.35 Performance plots for ANN training and testing with PMUs placed at buses 2, 4, 5, 6, 7, 8, 9, 10, 13 in IEEE-14 bus system

4.6 Performance Comparison of Trained ANN Models

The accuracy of voltage stability assessment using the PMU-ANN approach was thoroughly examined for each PMU placement strategy. The performance of each model was evaluated using mean squared error (MSE) and correlation coefficient (R) for the testing data. The result of the performance comparison of trained ANN models considering different PMU placements for IEEE-9 bus system and IEEE- 14 bus system are given in Table 4.7, Table 4.8 respectively.

Table 4.7 Performance comparison of trained ANN models considering different PMU placements for IEEE-9 bus test system.

S. No.	Index of PMU Placed Buses	MSE	R
1	All buses	1.893×10^{-4}	0.9966
2	**4, 6, 8**	$\mathbf{1.51 \times 10^{-6}}$	**0.9999**
3	1, 6, 8	1.745×10^{-4}	0.9928
4	3, 4, 8	3.95×10^{-4}	0.9934
5	8, 5	1.066×10^{-5}	0.9960
6	4, 7	2.27×10^{-5}	0.9972
7	6, 9	1.863×10^{-4}	0.9975
8	1, 2, 3, 4, 6, 8	1.546×10^{-3}	0.9732

Table 4.8 Performance comparison of trained ANN models considering different PMU placement for IEEE-14 bus test system.

S. No.	Index of PMU Placed Buses	MSE	R
1	All buses	1.502×10^{-4}	0.9939
2	1, 4, 6, 8, 10, 14	1.638×10^{-4}	0.9928
3	1, 4, 6, 10, 14	2.440×10^{-4}	0.9891
4	2, 6, 8, 9	1.393×10^{-3}	0.9367
5	2, 6, 7, 9	1.275×10^{-3}	0.9444
6	**1, 4, 11, 13**	$\mathbf{1.808 \times 10^{-6}}$	**0.9999**

S. No.	Index of PMU Placed Buses	MSE	R
7	2, 4, 10, 13	1.577×10^{-4}	0.9935
8	2, 6, 9	3.976×10^{-4}	0.9831
9	2, 4, 5, 6, 7, 8, 9, 10, 13	2.317×10^{-4}	0.9891

These results demonstrated varying levels of accuracy across different strategies. Notably, specific PMU placements highlighted in the tables have demonstrated a significant improvement in the accuracy of predicting voltage stability indices. The accuracy of voltage stability predictions increased, especially when PMUs are strategically placed at critical buses with high generation and load parameter variations.

4.7 Selection of Best Model for Voltage Stability Assessment

For the IEEE 9-bus system, PMUs positioned at buses 4, 6, and 8 have proven to be superior in assessing voltage stability, highlighting bus-9 as the weakest bus in the system. Similarly, in the IEEE 14-bus system, the PMUs strategically placed at buses 1, 4, 11, and 13 have shown exceptional capabilities in assessing voltage stability, leading to the identification of bus-14 as the system's weakest bus. By accurately pinpointing the weakest buses, these models provide actionable insights that empower decision makers in power system management and control.

4.8 Voltage Stability Enhancement Using SVC

The application of static var compensators (SVCs) for voltage stability enhancement is investigated in this section. For the IEEE-9 bus system bus-9 has been found to be the weakest bus. Similarly, bus-14 has been found to be the weakest bus in IEEE-14 bus system. So, SVCs are placed at these weak buses for voltage stability enhancement.

4.8.1 Voltage stability enhancement using SVC in IEEE-9 bus test system

This thesis work showcases voltage stability enhancement in the IEEE-9 bus test system through the exploration of two distinct random loading scenarios. Bus-9 has been identified to be the weakest bus. So, SVC is placed at bus 9 for voltage stability enhancement in IEEE-9 bus test system. The optimal reactive power injection by SVC is determined using the particle swarm optimization algorithm.

Loading case 1: Both active and reactive power loads at bus-9 are increased by twice the system base loading condition.

Base load at bus-9: P_{base9}=125 MW, Q_{base9}=50 MVAr

Actual load at bus-9: P_9=250 MW, Q_9=100 MVAr

Optimal reactive power injection by SVC= 122.4297 MVAr

Results of the voltage stability enhancement have been demonstrated through the visible improvement in the voltage profile, as depicted in Fig. 4.36. Additionally, the implementation of measures has led to reductions in both real power losses and reactive power losses. These improvements are further validated by the reduction in L-index values, as highlighted in Table 4.9

Table 4.9 Voltage stability enhancement in loading case-1 of IEEE-9 bus system

Parameter	Without compensation	With compensation	% Reduction in parameter values
P_{loss}(MW)	8.7	6.9	20.69 %
Q_{loss}(MVAr)	102.57	84.75	16.82 %
L_{max}	0.3154	0.2371	24.83 %

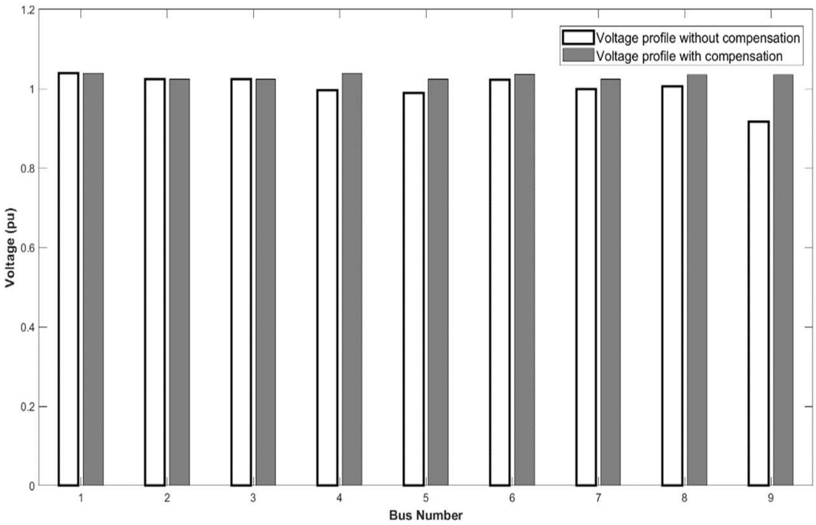


Fig. 4.36 Voltage profile of IEEE-9 bus system without and with compensation in loading case-1

In this loading scenario before the placement of SVC, bus-9 voltage magnitude was 0.918 per unit (pu) that is very near to the lower voltage limits of 0.9 pu. However, following the installation of the SVC, the voltage magnitude at bus-9 significantly improved by 12.7 % to 1.035 pu which is now within the acceptable range and below the upper voltage limit of 1.1 pu.

Loading Case-2: Reactive power load at bus-9 is increased by thrice the system base loading condition.

Base load at bus 9: P_{base9}=125 MW, Q_{base9}=50 MVAr

Actual load at bus 9: P_9=125 MW, Q_9=150 MVAr

Optimal reactive power injection by SVC = 139.3465 MVAr

Results of the voltage stability enhancement in this loading scenario are represented in Fig. 4.37 and Table 4.10

Table 4.10 Voltage stability enhancement in loading case-2 of IEEE-9 bus system

Parameter	Without compensation	With compensation	% Reduction in parameter value
P_{loss} (MW)	6.865	4.495	34.52 %
Q_{loss} (MVAr)	69.43	46.98	32.33 %
L_{max}	0.2453	0.1387	43.46 %

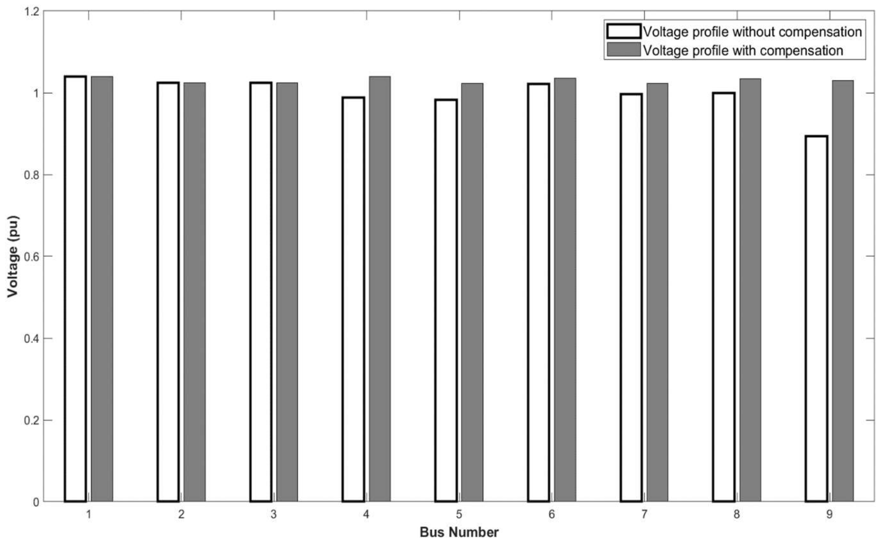


Fig. 4.37 Voltage profile of IEEE-9 bus system without and with compensation in loading case-2

The voltage magnitude at bus-9 was 0.894 pu initially, which is below the lower voltage limits of 0.9 pu before the placement of the SVC. However, following the installation of the SVC, the voltage magnitude at bus-9 significantly improved by 15.21 % to 1.030 pu which is now within the acceptable voltage range.

4.8.2 Voltage stability enhancement using SVC in IEEE-14 bus test system

This thesis work showcases voltage stability enhancement in the IEEE-14 bus test system through the exploration of two distinct random loading scenarios. Bus-14 has been identified to be the weakest bus. So, SVC is placed at bus-14 for voltage stability enhancement in IEEE-14 bus test system. The optimal reactive power injection by SVC is determined using the particle swarm optimization algorithm.

Loading case-1: Both active and reactive power loads at bus-14 are increased by five times the system base loading conditions.

Base Load condition at bus 14: P_{base14}=14.9 MW, Q_{base14}=5 MVAr

Actual loading at bus 14: P_{14}=74.5 MW, Q_{14}=25 MVAr

Results of the voltage stability enhancement in this loading scenario are represented in Fig. 4.38 and Table 4.11

Table 4.11 Voltage stability enhancement in loading case-1 of IEEE-14 bus system

Parameter	Without compensation	With compensation	% Reduction in parameter value
P_{loss} (MW)	28.298	26.920	4.76 %
Q_{loss} (MVAr)	114.34	109.48	4.25 %
L_{max}	0.2660	0.2100	21.05 %

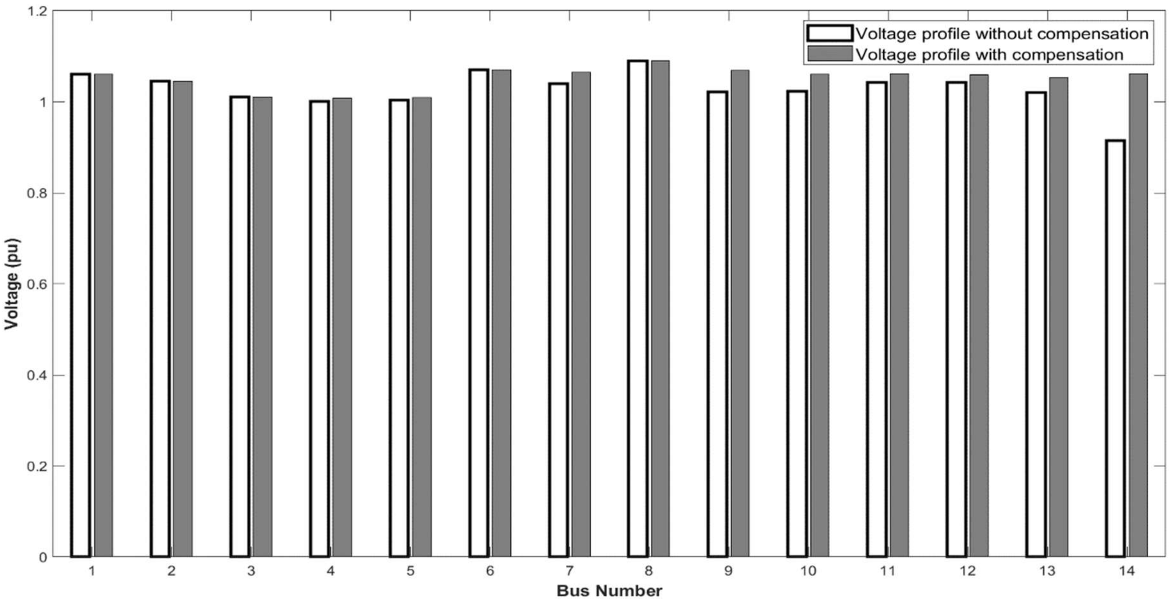


Fig. 4.38 Voltage profile of IEEE-14 bus system without and with compensation in loading case-1

The voltage magnitude at bus-14 was 0.915 pu initially, that is very close to the lower voltage limits of 0.9 pu before the placement of the SVC. However, following the installation of the SVC, the voltage magnitude at bus-14 significantly improved by 15.8 % to 1.06 pu which is within the acceptable voltage range.

Loading case-2: Reactive power load at bus-14 increased by eighteen times the system base loading conditions.

Base Load condition at bus 14: P_{base14}=14.9 MW, Q_{base14}=5 MVAr

Actual load at bus 14: P_{14}=14.9 MW, Q_{14}=90 MVAr

Results of the voltage stability enhancement in this loading scenario are represented in Fig. 4.39 and Table 4.12

Table 4.12 Voltage stability enhancement in loading case-2 of IEEE-14 bus system

Parameter	Without compensation	With compensation	% Reduction in parameter value
P_{loss} (MW)	26.699	13.499	49.44 %
Q_{loss} (MVAr)	90.57	54.68	39.63 %
L_{max}	0.3603	0.0730	79.74 %

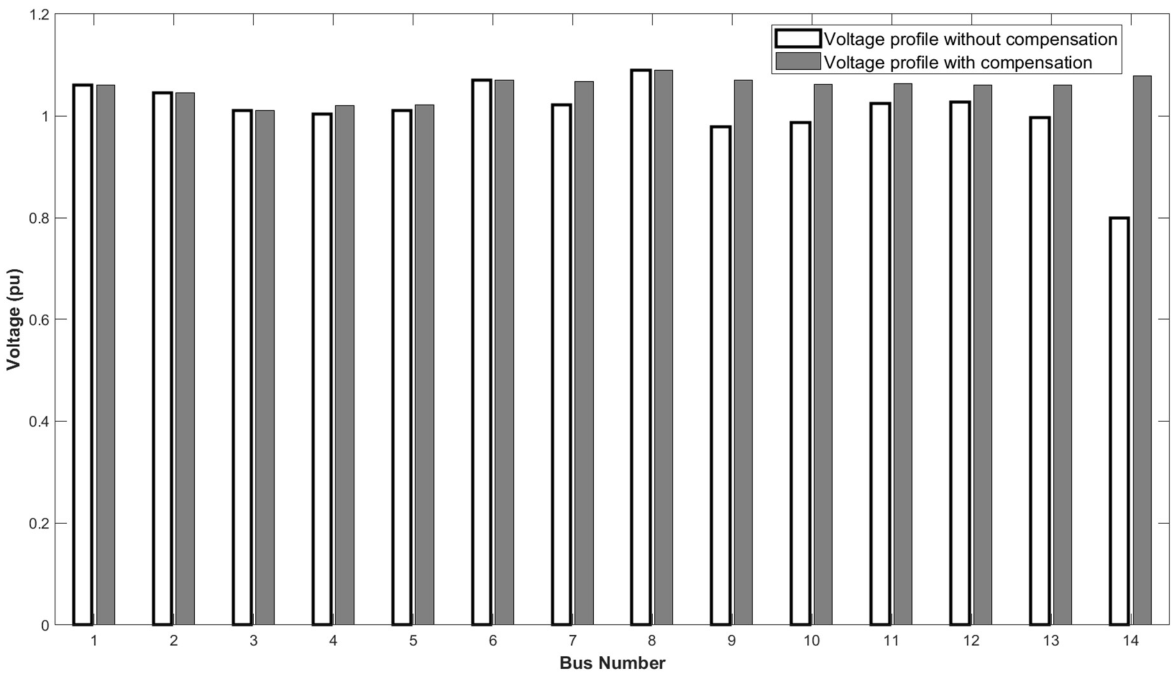


Fig. 4. 39 Voltage profile of IEEE-14 bus system without and with compensation in loading case-2

The voltage magnitude at bus-14 was 0.8 pu initially, that is below the lower voltage limit of 0.9 pu. However, after the installation of the SVC, the voltage magnitude at bus-14 significantly improved by 17.8 % to 1.06 pu, which is now within the acceptable range and below the upper voltage limit of 1.1 pu.

It has been observed that SVCs placed at the weakest bus could effectively mitigate the voltage instability issues by providing the optimized amount of reactive power support at the weakest bus location. The integration of SVCs has resulted in the improvement of voltage stability during both normal and stressed operating conditions.

In summary, the key findings from these results includes:

1. The accuracy of voltage stability predictions increased, especially when PMUs are strategically placed at critical buses with high generation and load parameter variations. For the IEEE-9 bus system, these buses are 4, 6, and 9, and for the IEEE-14 bus system, these buses are 1, 4, 11, 13, and 14.
2. For the IEEE 9-bus test system, ANN trained on data obtained from PMUs positioned at buses 4, 6, and 8 demonstrate superior performance with a remarkably low mean square error (MSE) of 1.51×10^{-6} for the testing data and an impressive testing correlation coefficient of 0.9999 for voltage stability assessment.
3. For the IEEE 14-bus test system, PMUs placed at buses 1, 4, 11, and 13 offer the highest capabilities for assessing the voltage stability with a remarkably low MSE of 1.808×10^{-6} for the testing data and an impressive testing correlation coefficient of 0.99991.
4. Bus-9 has been identified as the weakest bus in the IEEE-9 bus test system using PMU-ANN based voltage stability assessment.
5. Bus-14 has been identified as the weakest bus in the IEEE-14 bus test system using PMU-ANN based voltage stability assessment.
6. By providing the optimized amount of reactive power support at the weakest bus using SVC could effectively mitigate the voltage instability issues.
7. The voltage levels on the vulnerable buses were alarmingly closer to the lower voltage limits of 0.9 pu prior to the installation of SVC. However, after the SVC was implemented, there was a significant enhancement in the voltage levels of these critical buses, with the increments ranging from 12% to 18%.
8. Improvement in voltage profile, reduction in real power losses, reduction in reactive power losses, and the reduction in L-index values substantiate the effectiveness of the SVC deployment strategy in mitigating the voltage instability concerns.

Summary and Conclusions

CHAPTER- 5 SUMMARY AND CONCLUSION

In modern society, electrical power systems play an indispensable role in providing reliable and uninterrupted electricity supply to meet the ever-growing demand. As the scale of power systems continues to expand and the integration of renewable energy sources increases, ensuring the stability and reliability of these systems becomes very important. Voltage stability is a critical aspect of power system operation, referring to the ability of the system to maintain acceptable voltage levels under various operating conditions, including normal and abnormal scenarios. Voltage instability can lead to cascading failures, blackouts, and widespread disruption of services, making its assessment and enhancement crucial for maintaining the integrity of power grids. The increasing complexity and interconnectivity of power systems pose challenges for conventional methods of voltage stability assessment and control. Traditional methods often rely on linear approximations and simplified models, which may not accurately capture the intricate dynamics of modern power systems. Additionally, the uncertainty introduced by renewable energy sources and varying load patterns necessitates innovative approaches that can provide more accurate and real-time assessments of voltage stability.

5.1 Summary

This thesis work presents a comprehensive approach for voltage stability assessment and enhancement through the utilization of artificial neural networks (ANN) in conjunction with strategically placed phasor measurement units (PMUs). This PMU-ANN methodology based analysis involves generating synthetic PMU data and computation of voltage stability indices (L-index) via steady-state repetitive power flow simulations in MATLAB environment using the MATPOWER package. These simulations encompass a range of operational scenarios, including normal, stressed, and contingent conditions. The synthesized dataset serves as the foundation for training of various feedforward backpropagation artificial neural network (FFBP-ANN) models employing distinct PMU placement strategies. By comparing the impact of different PMU locations on the performance of voltage stability assessment using the PMU-ANN methodology, optimal placements are identified. Furthermore, voltage stability enhancement is explored by integrating a static var compensator (SVC). The optimal locations for SVC installation are determined by identifying weak buses using voltage stability indices projected by the trained ANN model. To determine the optimal reactive power injections by the SVC for specific loading conditions, the Particle Swarm Optimization (PSO) algorithm is employed. The objective function for the PSO algorithm to be minimized is the squared sum of the L-index, reflecting a quantified metric for voltage stability enhancement.

The proposed methodology is rigorously validated through its application to the IEEE-9 bus and IEEE-14 bus standard test systems. The PMU and ANN approach, with ANN models trained on diverse PMU placement strategies, has been applied to these systems. The comparative analysis of different PMU placement strategies on the performance of voltage stability assessment using ANN reveals the methodology's sensitivity to PMU location. Optimal PMU locations have been identified for both the IEEE-9 and IEEE-14 bus systems, ensuring optimal coverage for accurate voltage stability assessment. Notably, in the IEEE 9-bus test system, PMUs positioned at buses 4, 6, and 8 demonstrate superior performance with a remarkably low mean square error (MSE) of 1.51×10^{-6} and an impressive correlation coefficient of 0.9999 for the voltage stability assessment. Similarly, in the IEEE 14-bus test system, PMUs placed at buses 1, 4, 11, and 13 offer the highest capabilities for assessing the voltage stability with a remarkably low mean square error (MSE) of 1.808×10^{-6} and an impressive correlation coefficient of 0.9991. The accuracy of the methodology is notably enhanced when PMUs are strategically placed at critical buses, such as those with low voltage stability margins or high values of L-index. These findings emphasize the pivotal role of optimal PMU placement in achieving reliable and precise voltage stability assessment.

The use of SVC for voltage stability enhancement is validated through simulations on the IEEE-9 and IEEE-14 bus systems. Weak buses within the system are effectively identified using voltage stability indices (L-index) predicted by the trained ANN model. The bus having L-index value closest to unity is identified as the weakest bus. For IEEE-9 bus system bus-9 has been found to be the weakest bus. Similarly, bus-14 has been found to be the weakest bus in IEEE-14 bus system. SVCs are then placed at these weak buses. This resulted in the tangible improvements in voltage stability as shown through the simulation results.

For loading case-1 in IEEE-9 bus system when real and reactive power load at bus-9 has been increased twice the system base load condition using the proposed methodology the real power losses reduced by 20.69%, reactive power losses reduced by 16.82%, and maximum L-index value reduced by 24.83%. Similarly for loading case-2 when reactive power load at bus-9 has been increased thrice the system base load condition using the proposed methodology the real power losses reduced by 34.52%, reactive power losses reduced by 32.33%, and maximum L-index value reduced by 43.46%.

In the context of loading case-1 in the IEEE-14 bus system, where the real and reactive power load at bus-14 has been augmented to five times the system's base load condition using the proposed methodology, noteworthy improvements have been observed. Specifically, the real power losses exhibited a reduction of 4.76%, while the reactive power losses experienced a decrease of 4.25%. Additionally, the maximum L-index value, a critical metric, displayed a substantial reduction of 21.05%. Similarly, in the scenario of loading case-2 where the reactive power load at bus-14 was elevated to eighteen times the system's base load condition utilizing the proposed methodology. The real power losses encountered a significant reduction of 49.44%, accompanied by a noteworthy decline of 39.63% in reactive power losses. Moreover, the maximum L-index value, a parameter of high importance, showcased an impressive reduction of 79.74%.

Improvement in voltage profile, reduction in real power losses, reduction in reactive power losses, and the reduction in L-index values substantiate the effectiveness of the SVC deployment strategy in mitigating the voltage instability concerns. The PSO algorithm has been employed to determine the optimal reactive power injections by the SVCs under various loading conditions. By minimizing the squared sum of the L-index values at load buses, the PSO algorithm successfully optimized the reactive power settings. The results underscore the significance of this optimization step, as the fine-tuned SVC settings led to substantial enhancements in voltage stability.

Collectively, the validation results on the IEEE-9 and IEEE-14 bus systems affirm the potential of the proposed methodology in addressing voltage stability challenges. The improved accuracy in voltage stability assessment due to strategic PMU placement, coupled with the demonstrated enhancement of voltage stability through SVC deployment and the optimization of reactive power settings reflects the robustness and versatility of the approach.

5.2 Conclusion

The simulation results consistently demonstrated the improved accuracy of proposed methodology in voltage stability assessment. This improvement is attributed to the ability of ANN models to capture non-linear relationships and complexities present in modern power systems, leading to more precise predictions of voltage stability indices. The results provide compelling evidence of the effectiveness of the approach in improving the accuracy of voltage stability assessment, showcasing the significance of strategic PMU placement, and demonstrating the enhancement of the system's voltage stability through SVC deployment. In the IEEE 9-bus test system, PMUs positioned at buses 4, 6, and 8 demonstrate superior performance with a remarkably low mean square error (MSE) of 1.51×10^{-6} and an impressive correlation coefficient of 0.9999 for the voltage stability assessment. Similarly, in the IEEE 14-bus test system, PMUs placed at buses 1, 4, 11, and 13 offer the highest capabilities for assessing the voltage stability with a remarkably low mean square error (MSE) of 1.808×10^{-6} and an impressive correlation coefficient of 0.9991.

Improvement in voltage profile, reduction in real power losses, reduction in reactive power losses, and the reduction in L-index values establish the effectiveness of the SVC deployment strategy in mitigating the voltage instability concerns. The integration of the PSO algorithm further highlights the method's capability to determine optimal reactive power injections, resulting in substantial improvements in voltage stability. The use of SVCs at identified weak buses exhibits tangible improvements in voltage stability, as validated by the reductions in the L-index, the real power losses, and the reactive power losses. Thus, the work presented in this thesis establishes a robust methodology for voltage stability assessment and enhancement using advanced technologies like ANN, PMUs, and the use of SVCs. The methodology's effectiveness has been validated on IEEE-9 and IEEE-14 bus standard test systems, demonstrating improved accuracy in voltage stability assessment through strategic PMU placement, enhanced voltage stability via SVC deployment, and optimized reactive power settings using the PSO algorithm.

5.3 Future Scope

The successful validation of the methodology on standard test systems opens avenues for its application to larger and more complex real-world power systems. The following aspects present promising directions for future research:

a. **Hyper-tuning of ANN network parameters:** While this research employed FFBP-ANN models, exploring the hyper-tuning of network parameters can potentially enhance the accuracy of voltage stability assessment.

b. **Neuron models beyond FFBP:** Investigating alternative neuron models beyond Feedforward Backpropagation (FFBP), can potentially enhance the accuracy of voltage stability assessment.
c. **Multiple SVC placements:** Extending the SVC deployment strategy to include placement on multiple identified weak buses could offer greater flexibility in voltage stability enhancement.
d. **Alternative meta-heuristic algorithms:** While this research utilized the PSO algorithm, investigating other meta-heuristic optimization algorithms, such as Genetic Algorithm (GA) or Simulated Annealing (SA), could provide insights into their comparative performance in determining optimal reactive power injections by SVCs.
e. **Real-time digital simulators:** Taking the methodology from simulated validation to real-time digital simulators would offer a more accurate representation of the complexities and dynamics of real-world power systems. Implementing and testing the methodology in a real-time environment would validate its feasibility for practical application.
f. **PMU measurement errors:** Research into accounting for measurement errors and their impact on the accuracy of voltage stability assessment would enhance the methodology’s robustness.

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Appendices

I.1 Data Sheet for IEEE-9 Bus Test System

Table I.1 Bus Data for IEEE-9 Bus Test System

BUS No.	Voltage		Generation		Load	
	Mag (p.u.)	Angle (deg.)	P (MW)	Q (MVAr)	P (MW)	Q (MVAr)
1	1.040	0	71.64	27.04	0	0
2	1.025	9.28	163	6.65	0	0
3	1.025	4.66	85	-10.85	0	0
4	1.025	-2.21	0	0	0	0
5	1.012	-3.68	0	0	90	30
6	1.032	1.966	0	0	0	0
7	1.015	0.727	0	0	100	35
8	1.025	3.719	0	0	0	0
9	0.995	-3.988	0	0	125	50

Table I.2 Branch Data for IEEE-9 Bus Test System

Line No.	From bus	To Bus	R (pu)	X (pu)	½ B (pu)	MVA rating
1	1	4	0	0.0576	0	250
2	4	5	0.01700	0.0920	0.1580	250
3	5	6	0.03900	0.1700	0.3580	150
4	3	6	0	0.0586	0	300
5	6	7	0.01190	0.1008	0.2090	150
6	7	8	0.00850	0.0720	0.1490	250
7	8	2	0	0.0625	0	250
8	8	9	0.0320	0.1610	0.3060	250
9	9	4	0.0100	0.0850	0.1760	250

I.2 Data Sheet for IEEE-14 Bus Test System

Table I.3 Bus Data for IEEE-14 Bus Test System

BUS No.	Voltage		Generation		Load	
	Mag (p.u.)	Angle (deg.)	P (MW)	Q (MVAr)	P (MW)	Q (MVAr)
1	1.06	0	232.40	-16.90	0	0
2	1.045	-4.980	40.00	43.56	21.70	12.70
3	1.01	-12.72	0.00	25.08	94.20	19
4	1.019	-10.33	0.00	0.00	47.80	-3.90
5	1.020	-8.78	0.00	0.00	7.60	1.60
6	1.070	-14.22	0.00	12.73	11.20	7.50
7	1.062	-13.37	0.00	0.00	0	0
8	1.090	-13.36	0.00	17.62	0	0
9	1.056	-14.94	0.00	0.00	29.50	16.60
10	1.051	-15.10	0.00	0.00	9	5.80
11	1.057	-14.79	0.00	0.00	3.50	1.80
12	1.055	-15.07	0.00	0.00	6.10	1.60
13	1.050	-15.16	0.00	0.00	13.50	5.80
14	1.036	-16.04	0.00	0.00	14.90	5

Table I.4 Branch Data for IEEE-14 Bus Test System

Line No.	From bus	To Bus	R (pu)	X (pu)	½ B (pu)	MVA rating
1	1	2	0.01938	0.05917	0.0528	120
2	1	5	0.05403	0.22304	0.0492	65
3	2	3	0.04699	0.19797	0.0438	36
4	2	4	0.05811	0.17632	0.0340	65
5	2	5	0.05695	0.17388	0.0346	50
6	3	4	0.06701	0.17103	0.0128	65

7	4	5	0.01335	0.04211	0	45
8	4	7	0	0.20912	0	55
9	4	9	0	0.55618	0	32
10	5	6	0	0.25202	0	45
11	6	11	0.09498	0.19890	0	18
12	6	12	0.12291	0.25581	0	32
13	6	13	0.0661	0.13027	0	32
14	7	8	0	0.17615	0	32
15	7	9	0	0.11001	0	32
16	9	10	0.03181	0.08450	0	32
17	9	14	0.12711	0.27038	0	32
18	10	11	0.08205	0.19207	0	12
19	12	13	0.22092	0.19988	0	12
20	13	14	0.17093	0.34802	0	12

This data is taken from Literature-Based Power Flow Test Cases section of website https://icseg.iti.illinois.edu/power-cases/

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ABSTRACT

The modern power system is undergoing significant transformations due to growing energy demands, technological advancements, and a rising level of environmental concerns. Thus, maintaining voltage stability is a critical concern in modern power systems operation, ensuring the secure and reliable operation of electrical networks. This thesis presents an approach for voltage stability assessment and enhancement leveraging the real-time measurement capabilities of phasor measurement units (PMUs) and the pattern recognition abilities of artificial neural networks (ANNs). To achieve this, ANN models are trained using simulated PMU data encompassing diverse system operating scenarios and corresponding L-indices. The trained ANN models are then used to predict voltage stability margins using real time voltage phasor data acquired by strategically placed PMUs. Various optimal PMU placement methods are employed in this work to identify potential PMU locations in the network where PMUs can capture critical voltage stability issues, thus enhancing the accuracy of voltage stability assessment. The effects of different PMU placement strategies on the performance of voltage stability assessment using ANN have also been compared in this work. Furthermore, this work utilizes static var compensator (SVC) for voltage stability enhancement. The proposed methodology is validated on IEEE-9 bus and IEEE-14 bus standard test systems, demonstrating improved accuracy in voltage stability assessment, particularly due to the strategic placement of PMUs. Moreover, the reinforcement of the system's voltage stability has been demonstrated by placing SVC at the weakest buses in the system. The utilization of the particle swarm optimization (PSO) algorithm has further emphasized the methodology's efficacy in determining optimal reactive power injections, thereby leading to significant improvements in voltage stability.

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मुख्य विषय	:	इलेक्ट्रिकल एनर्जी सिस्टम	**विभाग**	:	इलेक्ट्रिकल इंजीनियरिंग
शोध शीर्षक	:	**कृत्रिम तंत्रिका नेटवर्क और श्रेष्ठतम रूप से अवस्थित पीएमयू का उपयोग करके वोल्टेज स्थायित्व का आकलन और संवर्धन**			
पृष्ठों की संख्या	:	87	**सलाहकार**	:	डॉ० अभिषेक यादव

सारांश

आधुनिक विद्युत् प्रणाली, में ऊर्जा की बढ़ती मांग, प्रौद्योगिकी में प्रगति, और पर्यावरण से संबंधित चिंताओं के कारण, महत्वपूर्ण परिवर्तनों का सामना कर रही है। इस प्रकार आधुनिक विद्युत् प्रणाली के संचालन में वोल्टेज स्थायित्व की देखभाल करना महत्वपूर्ण बिन्दु है। विद्युत नेटवर्कों की सुरक्षित और विश्वसनीय प्रणाली सुनिश्चित करते हुए, यह थीसिस वोल्टेज स्थायित्व मूल्यांकन और सुधार के लिए एक दृष्टिकोण प्रस्तुत करती है जिसमें फेजर मापन इकाइयों (पी०एम०यू०) की वास्तविक समय मापन क्षमताओं और कृत्रिम तंत्रिका नेटवर्क (ए०एन०एन०) की कृत्रिम संज्ञान क्षमताओं का उपयोग किया जाता है। इसे प्राप्त करने के लिए, कृत्रिम पी०एम०यू० डेटा का उपयोग करके ए०एन०एन० को प्रशिक्षित किया जाता है जिसमें विविध प्रणाली संचालन परिदृश्यों और संबंधित एल०-सूचकांक शामिल होते हैं। प्रशिक्षित किए गए मॉडल फिर रणनीतिक रूप से स्थानित पी०एम०यू० इकाइयों द्वारा प्राप्त वोल्टेज फेजर डेटा का उपयोग करके वोल्टेज स्थायित्व मार्जिन्स का पूर्वानुमान करने के लिए प्रयुक्त किए जाते हैं। इस कार्य में आदर्श पी०एम०यू० स्थापन विधियों का उपयोग किया जाता है ताकि नेटवर्क के क्षेत्रों में ऐसे संभावित पी०एम०यू० स्थानों की पहचान की जा सके जहाँ पी०एम०यू० महत्वपूर्ण वोल्टेज स्थायित्व समस्याओं को संज्ञान में ले सकते हैं, इससे वोल्टेज स्थायित्व मार्जिन्स की गुणवत्ता में सुधार होता है। इस कार्य में विभिन्न पी०एम०यू० स्थापन की रणनीतियों के प्रदर्शन पर भी ध्यान दिया गया है जो ए०एन०एन० का उपयोग करके वोल्टेज स्थायित्व मार्जिन्स की प्रदर्शन क्षमता पर प्रभाव डालती है। इसके अलावा, इस कार्य में वोल्टेज स्थायित्व में सुधार के लिए स्थिर वार कॉम्पेंसेटर (एस०वी०सी०) का उपयोग किया गया है। प्रस्तावित मेथडोलॉजी को आई०ई०ई०ई०-9 बस और आई०ई०ई०ई०-14 बस मानक परीक्षण प्रणालियों पर प्रमाणित किया गया है, जिससे वोल्टेज स्थायित्व मार्जिन्स के मूल्यांकन में सुधार प्रदर्शित किया गया है, विशेष रूप से पीएमयू के रणनीतिक स्थापन की वजह से। इसके साथ ही, प्रणाली की वोल्टेज स्थायित्व को मजबूती देने के लिए एस०वी०सी० को प्रणाली की सबसे दुर्बल बसों पर स्थापित करके प्रदर्शित किया गया है। आवश्यक प्रतिकूल शक्ति संचालन की अवश्यकता को निर्धारित करने के लिए पार्टिकल स्वार्म ऑप्टिमाइजेशन (पी०एस०ओ०) एल्गोरिदम का उपयोग किया गया है, जिससे आवश्यक रिएक्टिव पावर इंजेक्शन की अवश्यकता को निर्धारित करने में महत्वपूर्ण सुधार हुआ है और इससे वोल्टेज स्थायित्व में भी काफी सुधार हुआ है।

(अभिषेक यादव)	**(मोहित चंद्र दुर्गापाल)**
सलाहकार	लेखक