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SMART ARTIFICIAL INTELLIGENCE VOLTAGE INSTABILITY DETECTOR

M.Sc. Thesis

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DECLARATION

This thesis is submitted to Arab Academy for Science and Technology and Maritime Transport in partial fulfillment of the requirements of M.Sc. degree in Electrical and Control Engineering. I certify that all the material in this thesis that is not my own work has been identified, and that no material is included for which a degree has previously been conferred on me.

The contents of this thesis reflect my own personal views, and are not necessarily endorsed by the university.

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ABSTRACT

Voltage instability has been given much attention by power system researchers and planners in recent years because voltage instability problems in power systems have become one of the major concerns in power systems planning, operation and quality. The system which suffers from voltage instability can be easily exposed to fast failure due to voltage collapse. A neural network based voltage instability detector is proposed in this thesis utilizing wide area monitoring system and the measured angle of the installed Phasor Measurement Units (PMUs). Due to the strong correlation between the PMUs and the Global Positioning Satellites (GPS), PMUs began to spread widely after the great improvement in the satellite techniques and communications. PMUs are used in different electrical power engineering applications such as measurements, protection, control, and Voltage instability detection.

As proposed in this thesis the PMUs readings are used to detect voltage instability using Artificial Neural Network (ANN). This smart voltage instability predictor is developed through four stages. At the beginning The 14 and 30 bus IEEE systems are being simulated through MATLAB/power system toolbox program to get the system load flow results. Furthermore, the effect of different loading conditions is applied to the simulation system to get their corresponding bus angles values. About 1357 and 895 different studied cases for the 14 and 30 bus IEEE systems respectively are held for different loading values with different power factors on different buses. The results of these cases are tabulated, normalized and processed using the ANN.

The developed Feed-Forward Neural Network (FFNN) is designed and trained. The ANN is trained using about nine hundreds of these cases. The other values are used to test the performance of the developed system. The results of ANN are analyzed and considered to be satisfactory because of the high accuracy and reliable operation.

The main advantage of the smart developed system is that, it can detect the voltage instability of the whole power system buses in the same time.

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LIST OF SYMBOLS & ABBREVIATIONS

HVDC	:	High Voltage Direct Current
URVSLLC	:	Universal Radial Voltage Stability Loading Limit Curves
WECC	:	Western Electricity Coordinating Council
PV	:	Real Power against Voltage
ONS	:	Operador Nacional do Sistema Electrico “Brazilian System Operator”
FACTS	:	Flexible AC Transmission Systems.
DPSO	:	Discrete Particle Swarm Optimization
PMUs	:	Phasor Measurement Units
ANN	:	Artificial Neural Network
MPL	:	Multi-Layer Perceptron
AVRs	:	Automatic Voltage Regulators
DFIG	:	Doubly Fed Induction Generator
SVC	:	Static VAR Compensator
STATCOM	:	Static Synchronous Compensator
AI	:	Artificial Intelligence
PSS	:	Power System Stabilizer
SCADA	:	Supervisory Control and Data Acquisition
ES	:	Expert system
IEEE	:	Institute of Electrical and Electronics Engineers
QV	:	Reactive Power against Voltage
P_{ij}	:	Real Power from bus-i to bus-j

Q_{ij}	:	Reactive Power from bus-i to bus-j
Z	:	Transmission Line Impedance
Y_{ij}	:	the admittance magnitude of the line connected bus-i and bus-j.
θ_{ij}	:	the admittance angle of the line connected bus-i and bus-j.
δ_i	:	the angle of the bus-i voltage.
B_{capij}	:	the total line charging susceptance.
N	:	the total number of the network buses.
X normalized	:	The value of the main adjusted variable after Normalization
X	:	The main adjusted variable
X min	:	the min Value of the main adjusted variable
X max	:	The max Value of the main adjusted variable
GPS	:	Global Positioning Satellites
WAMS	:	Wide Area Monitoring System
PDC	:	Phasor Data Acquisition
a	:	Output of ANN
P_K	:	Number of Inputs
W_K	:	The weights
b	:	The bias
PF	:	Power Factor
P_{Load}	:	Load Power (MW)

CHAPTER ONE
INTRODUCTION

CHAPTER 1

INTRODUCTION

1.1 Overview.

This chapter presents an introduction of the voltage instability problem and the importance of studying it. The historical background and the literature review are cited. Also, thesis objective and the thesis outlines are stated at the end of the chapter.

1.2 Problem Description.

Severe and increasing strain has observed in the power system through the recent years due to incongruence between the generation and transmission infrastructure. Environmental issues, change in energy portfolio and deregulated energy markets are some of the prime factors. The kind of stress developed in the system affects the voltage instability. Voltage stability refers to the ability of a power system to maintain steady voltages at all buses in the system after being subjected to a disturbance from a given initial operating condition [1]. It is very closely related to load dynamics [2]. There are several studies focused on measures to accurately predict system conditions with respect to voltage stability and optimal control actions to avoid collapse in the online model [3]-[6]. Voltage instability problems in power systems have become one of the major concerns in power systems planning and operation [7]-[10]

Table 1.1 lists some severe voltage instability incidents over the past half century [9]. These events cause loss of billions of dollars. The main factors causing voltage instability are excessive loading of transmission lines, high transmission line losses, lack of reactive power supply, transmitting power over long distances and presence of non-linear loads.

Table 1.1 Voltage stability incidents

	Date	Location	Black out time frame
Short term	May. 17 1985	South Florida, USA	4 secs
	April 13 1986	Winnipeg, Canada Nelson River HVDC link	1 sec
	Nov. 30 1986	SE Brazil, Paraguay, Itaipu HVDC link	2 secs
Long term	Aug. 4, 1982	Belgium	4-5 mins
	Dec. 30, 1982	Florida, USA	1-3 mins
	Dec. 27, 1983	Sweden	55 secs
	July 23, 1987	Tokyo, Japan	20 mins
	Sep 2, 2003	Kuala Lampour, Malaysia	5 hours
	Feb 27 2014	Mindanao island, Philippines	6 hours
	Sep 4 2014	Cairo, Egypt	7 hours

Because of that, studying and searching in voltage instability issues became very important for most researchers and planners

1.3 Literature Review.

At any point of time, a power system operating condition should be stable, meeting various operational criteria and it should also be secure in the event of any credible contingency. Present day power systems are being operated closer to their stability limits due to economic and environmental constraints. Maintaining a stable and secure operation of a power system is therefore a very important and challenging issue. Voltage instability has been given much attention by power system researchers

and planners in recent years, and is being regarded as one of major resources of power system insecurity. Voltage collapse is the process by which the voltage falls to a low, unacceptable value as a result of an avalanche of events accompanying voltage instability and it does not come back even after setting restoring mechanisms such as VAR compensators, it also may continue to oscillate for lack of damping against the disturbances. Once associated the weak systems and long lines, voltage problems are now also a source of concern in highly developed networks as a result of heavier loading. Furthermore, the stable system contributes to reliability and reduction in system loss. For all these reasons the voltage stability problem has received a lot of attention not only from researchers but also from the industry. As a result, many techniques have been developed to identify critical power system, buses and lines.

1.3.1 Determining voltage stability techniques.

A voltage stability index for a stressed power station is derived using a reduced system model [11]. The index could identify how far a system is from its point of collapse. Line stability factors which could identify critical lines is also developed [11].

Another suggestion for a static voltage stability index is to use the minimum singular value of the power flow Jacobian matrix [12]. The use of this indicator, obtained from a (full) singular value decomposition of the power flow Jacobian matrix. The voltage stability index using the minimum singular value of the power flow Jacobian matrix is illustrated. This index determines how far the studied operating point is from the steady state voltage limit.

The topology space theory to describe the phenomena of voltage collapse and the bifurcation points, which are identified from the singularity of the power flow Jacobian matrix is used in [13]. The line voltage stability in a radial network using the Universal Radial Voltage

Stability Loading Limit Curves (URVSLLC) is studied in [14] and [15]. Reference [16] demonstrates how singularity in the Jacobian matrix could be avoided by slightly reformatting the power flow and applying a locally parameterized continuation technique to enable a power flow solution at and near the critical point to be computed. The voltage collapse at a load bus using the Thevenin equivalent circuit with respect to the load bus concerned and applying the concept of maximum power transfer theorem is discussed in [17]. A voltage collapse proximity indicator is derived from the ratio between the load impedance and the Thevenin impedance in the equivalent circuit.

An early prediction online voltage instability detector is discussed [18]. This voltage instability detector utilizes the voltage and current phasor readings of connected phasor measurement units to the distribution terminals. This detector works according to two parallel algorithms. The first algorithm is a comparison for terminal current and voltage phasors with an offline calculated Look-up table, in which particle swarm optimization technique is used. The second algorithm is based on the online computation of the ratio of the Thevenin equivalent system impedance to the terminal load impedance. The simulated voltage instability detector is applied to two unified power systems. The simulated detector gives effective results. It reacts with the systems changes in good and reasonable behavior.

A technique for determining voltage stability at a load bus and hence identifies critical buses (i.e buses which are prone to voltage collapse in power system) is presented in [11]. A voltage stability factor is derived from the voltage equation for a two bus network which is computed by applying it to a Thevenin equivalent circuit looking across each load bus. Buses with values of voltage stability factors close to 1 are identified as the critical buses.

Some works try to implement and present some voltage stability criteria [19]. For example, the Western Electricity Coordinating Council

(WECC) proposes a minimum real power against voltage (PV) margin requirement of 5% considering simple contingencies, 2.5% for double contingencies, and larger than zero for multiple contingencies. In a similar way, the ONS (Brazilian System Operator) has also initiated some studies and recommends a minimum PV margin requirement of 6% also considering simple contingencies. Both methods are based on PV curve computation. This is a good start for improving system security, but it has been always applied to system expansion studies, in terms of adding new capacitor banks, Flexible AC Transmission Systems (FACTS) devices, synchronous condensers, new generators or transmission lines in order to keep adequate stability margin for a selected set of credible scenarios [19].

1.3.2 Artificial Intelligence techniques.

Artificial Intelligence is one of the most important techniques that used in voltage instability detection such as, Particle Swarm Optimization Technique [18], Fuzzy Logic Technique, Artificial Neural Network [20],... etc

A Discrete Particle Swarm Optimization (DPSO) technique is developed to determine the optimal number and locations for Phasor Measurement Units (PMUs) in power system network for different depth of unobservability [18]. The PMUs' readings are to be utilized using a newly developed technique for on-line voltage stability monitoring. The predictor concept is tested and it gives an effective result.

Fuzzy Control Approach has been effectively presented in the Voltage Stability Enhancement too. The concept is as the same in reactive power planning and control which leads to better voltage profile. A new technique using fuzzy set theory for reactive power control with the purpose of improving the voltage stability of the power system presented in [20]. The voltage stability index and the controlling variables are translated into fuzzy set of notations to formulate the relation between

voltage stability level and controlling ability of controlling devices. Then a fuzzy ruled-based system is formed to select the controllers, their movement direction and the step size. The performance obtained from testing the above fuzzy controlled system was found to be encouraging.

Artificial Neural Networks (ANNs) have been proposed as an alternative method for solving certain traditional problems in power systems where conventional techniques have not achieved the desired speed, accuracy and efficiency. The application of ANN in the protection field has become very important since the concept of online protection is widely accepted. The voltage stability index has been popularly used for assessing voltage stability margin. Investigations are carried out on the influence of information encompassed in input vector and target output vector, on the learning time and test performance of Multi-Layer Perceptron (MLP) based ANN model.

Also, some of the factors that make load modeling for voltage stability a challenge and provide insight into key issues which must be considered when performing practical studies are discussed [21].

Automatic voltage regulators (AVRs) with synchronous machines are the most important means of voltage control in a power system. A synchronous machine is capable of generating and supplying reactive power within its capability limits to regulate system voltage [22]. For this reason, it is an extremely valuable part of the solution to the collapse-mitigation problem. Many research works have been undertaken in the area of voltage control using efficient excitation control.

Voltage instability is mainly associated with a reactive power imbalance. Improving a system's reactive power-handling capacity via FACTS devices is a remedy for the prevention of voltage instability and, hence, voltage collapse. FACTS devices are the right equipment to meet these challenges and different types are used in different power systems [22].

The transient and steady-state voltage issues of a distribution network with a distant doubly fed induction generator (DFIG)-based wind farm is investigated in [23]. Results show that a distant DFIG-based wind farm could improve the voltage stability of a distribution network with a large motor load in steady-state operating condition as well as following disturbances, like three-phase faults, sudden load tripping, and motor starting.

A comparative analysis of SVC and STATCOM in static voltage stability enhancement is presented in [24]. Both, SVC and STATCOM improve static voltage of the buses. STATCOM provides higher reactive power support with a faster response time but is expensive. SVC, on the other hand, is a cheaper substitute with relatively longer response time. But being capacitor based, the reactive power support to bus falls significantly at the time of fault. Hence, STATCOM provides a robust option. Hence comparison indicates STATCOM is suitable for static as well as dynamic voltage restoration.

Here, in this Thesis, the main objective is to introduce a new simulation for voltage instability alarming predictor based on Phasor Measurement Units (PMUs) readings and Power Voltage (PV) Curves of the system. The new alarming predictor is using Artificial Neural Networks (ANNs) as the new technique.

Artificial Neural Networks (ANNs) can play a richly significant potential role in electric power systems. As a branch of Artificial Intelligence, ANNs take problem-solving one step further. They can match stored examples against a new one, building on experience to provide better answers. On the field of AI, ANN computing shows great potential in solving difficult data-interpreting tasks.

ANN is biologically inspired and represented as a major extension of computation. They embody computational paradigms, based on

biological metaphor, to mimic the computations of the brain [25]. The improved understanding of the functioning of neuron and the pattern of its interconnection has enabled researchers to produce the necessary mathematical models for testing their theories and developing practical applications.

ANNs have attracted much attention due to their computational speed and robustness. They have become an alternative to modeling of physical systems such as synchronous machine and transmission line. Absence of full information is not a big as a problem in ANNs as it is in the other methodologies. A major advantage of the ANN approach is that the domain knowledge is distributed in manner. Therefore, they reach the desired solution efficiently.

Main applications of the ANN's can be divided into two principal streams. First stream among this is concerned with modeling the brain and thereby explains its cognitive behavior. The primary aim of researchers in the second stream is to construct useful 'computers' for real world problems of classification or Pattern Recognition by drawing on these principles. The application of ANN's in the power systems belongs to this category and is one of the most interesting topics in the Power System Engineering. These areas can be classified into Power System Stabilizer, Load Forecasting, Fault Diagnosis, Security Assessment, Protection, Load Modeling and Voltage Stability Assessment [20].

Real time timing of Power System Stabilizer is a complex task. An Artificial Neural network for this purpose is proposed [26]. Input to this ANN was the generator real power output P and the Power Factor. The outputs of ANN were the PSS gain settings. Another important application is the stable power system stabilizer based on inverse dynamics of the controlled system using an ANN. Enhancing the dynamic performance of power system is suggested in [27]. A novel Power System Stabilizer (PSS) controller based on a Multilayer Feed Forward Artificial Neural Network (ANN) is introduced in [28]. A feature of the proposed

controller is that the ANN parameters can be adapted online in real time according to generator loading conditions.

Load forecasting is perhaps the most important SCADA task and also one of the most popular areas for ANN implementation. The availability of historical load data on the utility databases makes this area highly suitable for ANN implementation. ANN schemes using perceptron networks and self-organizing feature maps have been successful in short-term as well as long-term load forecasting with impressive accuracy. Success of applying a class of recurrent neural network in short term load forecasting was tested in [29].

ANN's has recently invaded fault diagnosis, which has been a traditional area for ES (expert system) implementation. However, at present the ES implementations outnumber the ANN implementations. The explanatory abilities of ESs and their more powerful user interface make them a more attractive alternative. However, still there are certain areas, which require a quick response, and are still open to ANN implementation. A cascade structure of three three-layer perceptron networks for the identification of a faulted transmission section is proposed in [30]. A three-layer perceptron network to detect high impedance faults on distribution feeders is used [31]. ANNs were also successful in incipient fault detection of induction motors [32]. Multilayer perceptron networks for incipient fault detection in single-phase squirrel cage induction motors are used in [33].

In the field of protection, ANN can be effectively used effectively to achieve adaptive relaying for the above-mentioned problem as in [34]. Another method illustrated an adaptive protection technique based on neural networks with special emphasis on analysis of the first zone performance [35].

As seen by the sections above, Artificial Neural Networks are being successfully applied in a number of areas. One of the newest

important areas of using Artificial Neural Network is identifying critical power systems.

1.4 Thesis Objectives.

A newly developed Artificial Neural Network (ANN) based detector is used to predict different voltage instability cases in power systems. This detector utilized the voltage phasor readings of the Phasor Measurement Units (PMUs), which are connected to the terminals of the distribution systems. The work done in this thesis is developed through four stages. The first stage is the simulation of the power system using **MATLAB / Power System tools**. The data of the simulated systems is tabulated using **EXCEL** sheets. The second stage is the normalization of the output of the first stage. In the third stage, a feed-forward neural network is designed and trained utilizing the studied cases using **MATLAB/m-file**. In the final stage, the Phasor Measurement Units readings are entered to the trained artificial neural network to give the voltage stability status of the power system buses as stable, alarm or trip based on bus voltage angles. This predictor is tested on 14 and 30 Bus IEEE systems. The main advantage of this smart developed system is that, it can detect the voltage instability of the whole power system buses in the same time

1.5 Thesis Outlines.

This thesis consists of five chapters which explain the proposed method of an early voltage instability detector based on PMUs readings utilizing ANN. They are discussed as follows;

Chapter one: Introduction.

It presents an introduction of the voltage instability problem and the importance of studying it, also thesis objective, literature review and the thesis outlines stated at the end of the chapter.

Chapter two: Voltage Instability Studies.

It explains the fundamentals and basic theories for voltage instability detection methods for power systems. Besides it presents a new proposed technique for on-line voltage instability alarming detector based on Phasor measurement units and bus angle. At the end of this chapter the steps of this work are shown.

Chapter three: Phasor Measurement Units and Artificial Neural Network.

It presents Phasor Measurement Units which are used in detecting voltage instability problems with the help of Artificial Neural Network. This chapter presents as well the design of the Artificial Neural Network and how to train the network to detect the voltage instability.

Chapter four: Studied systems and Results.

It shows the simulation, testing and applying the work done to 14-bus and 30-bus IEEE standard power systems. The simulations are processed using MATLAB/m-file program. The simulation results and some case studies for the whole proposed system are discussed in this chapter.

Chapter five: Conclusion and recommendation.

It contains the conclusion and recommendation of the thesis which are stated, and discussed, and shows the advantage of the proposed method.

CHAPTER TWO
VOLTAGE INSTABILITY STUDIES

CHAPTER 2

VOLTAGE INSTABILITY STUDIES

2.1 Overview.

This chapter explains the fundamentals and basic theories for voltage instability detection methods for power systems. Besides it presents a new proposed technique for on-line voltage instability alarming detector based on Phasor measurement units and bus angle. The steps of this work are shown at the end of this chapter.

2.2 System Stability Studies.

Power system stabilities are classified into two distinct areas:

2.2.1 Synchronous (Inertial, or Angle) Stability: in which transient, dynamic and steady-state synchronous stability of power systems generators rotors inertial masses motions are their capability to operate stable without loss of synchronism after large or small disturbances respectively. Most of traditional power system stability studies were concerned by synchronous stability and were simply denoted by power systems stability. [36]

2.2.2 Voltage Stability: is serious concern to the electric utility industry. Several isolated and interconnected power systems are increasingly experiencing abnormal voltage problems, which can reach to voltage collapses or voltage failures leading to partial or complete blackouts. These voltage problems are mainly due to; (a) increased loading of transmission lines, (b) higher transmission impedance's, (c) insufficient local reactive supply, (d) shipping of power across long distances, and presence of induction motor loads, or HVDC systems, arc-furnaces, large welding machines or certain sensitive electronic devices, together with presence of 3-phase load unbalance or excessive amounts of harmonics penetrating in the network. Also voltage flickers may form certain voltage instability. [36]

The voltage dip, that occurs when the power system experiences sudden or gradual heavy loading or after excessive reactive power demand, is the main problem of voltage stability. It may lead to voltage oscillations or voltage collapse or both. Voltage instability occurs in four aspects, which are; voltage collapse, voltage oscillations, either modulated on each other, or voltage flickers. Voltage collapse is defined as a process by which voltage instability leads to very low voltage profile in a significant part of the system.

2.3 Modes of Voltage Instability

As seen in Fig 2.1, the voltage instability studies are divided into two main areas [36-37], according to the duration taken by the voltage abnormality;

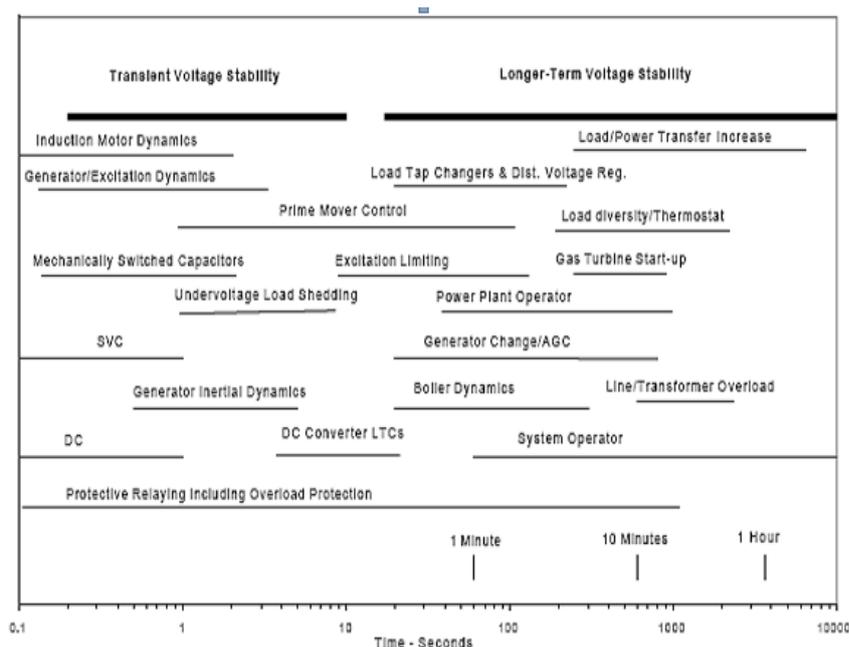


Fig 2.1 Voltage instability modes against their time duration

I. Steady-State (Long-Term) Voltage Instability.

It occurs gradually in minutes, hours or days and experienced in many countries in the form of voltage collapses. This thesis deals with such type of voltage instability.

II. Transient Voltage Instability.

It occurs suddenly in seconds or milliseconds, subsequent to network topology variations, short-circuits at induction motor, tripping of local generators or some parallel lines, at HVDC terminals with controller failures of either rectifiers or inverters, at certain operational conditions of repetitively variable loads, or due to presence of arc furnaces loads. This form of instability is the main cause of several blackouts in the systems worldwide. It occurs in the form of voltage oscillations, collapse modulated by oscillations, or as voltage flickers.

2.4 Voltage Instability Monitoring Techniques.

The classical relations and curves of real power against voltage (PV) and reactive power against voltage (QV) are used to determine the state of the system voltage stability [36-37]. **Fig. 2.4** shows the relation between the real power and the voltage magnitude. The relation between the real power and the voltage magnitude (PV) is derived from the system transmitted real and reactive power equations, which are clarified in both equations (2.1) and (2.2) respectively.

Two buses of an electrical network with voltage phasors $V_i \angle \delta_i$ and $V_j \angle \delta_j$ are shown in Fig 2.2. The two buses are connected through a transmission line with impedance $Z = R + jX$. The current phasor $I \angle \beta$ flows through the line from bus-i to bus-j. The phasor diagram of the two-bus system is presented in Fig 2.3

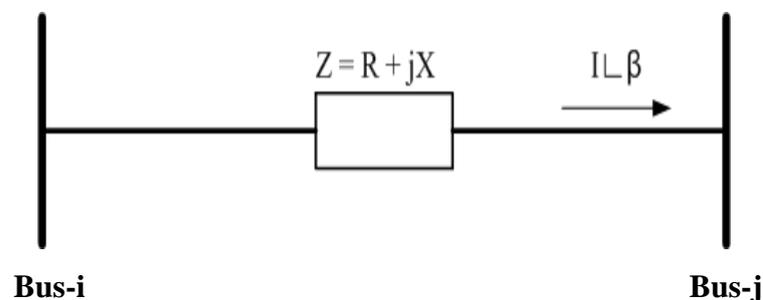


Fig 2.2 Simplified two-bus network

$$P_{ij} = V_i V_j Y_{ij} \cos (\delta_i - \delta_j + \theta_{ij}) - V_i^2 Y_{ij} \cos (\theta_{ij}) \quad (2.1)$$

$$Q_{ij} = V_i V_j Y_{ij} \sin (\delta_i - \delta_j + \theta_{ij}) - V_i^2 (Y_{ij} \sin (\theta_{ij}) + B_{capij}) \quad (2.2)$$

Where:

Y_{ij} : is the admittance magnitude of the line connected bus-i and bus-j.

θ_{ij} : is the admittance angle of the line connected bus-i and bus-j.

δ_i : is the angle of the bus-i voltage.

B_{capij} : is the total line charging susceptance.

N : is the total number of the network buses.

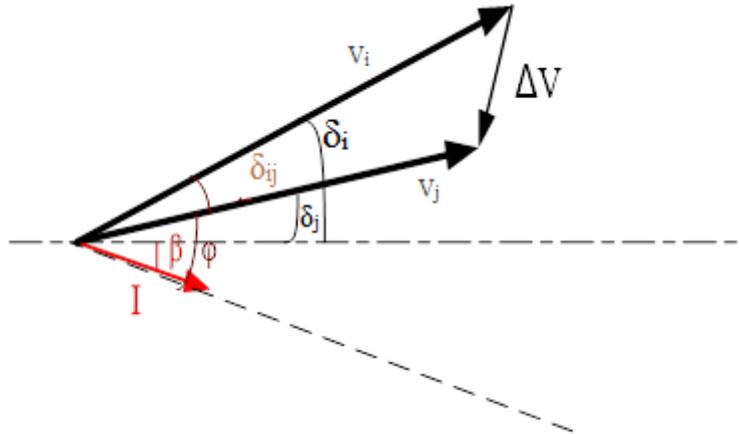


Fig. 2.3 Phasor diagram of the two-bus system

Since the total power transmitted from bus-i to bus-j is $S = P + jQ$,

so a direct relation between V_j , P and Q for certain V_i , can be expressed in equation (2.3).

$$V_j^4 + (2P_{ij}R_{ij} + 2Q_{ij}X_{ij} - V_i^2) V_j^2 + (R_{ij}^2 + X_{ij}^2) (P_{ij}^2 + Q_{ij}^2) = 0 \quad (2.3)$$

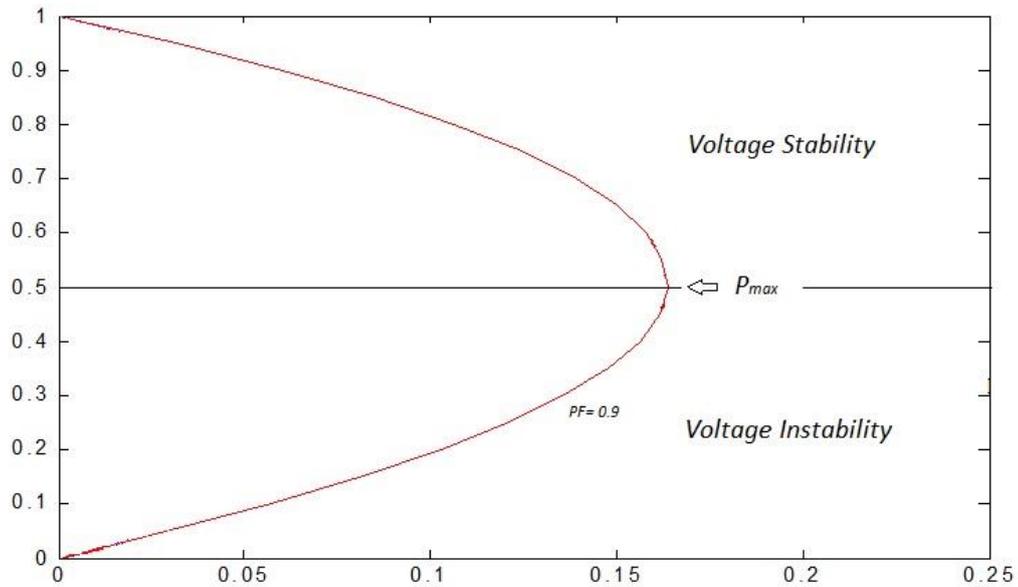


Fig 2.4 Two-bus system PV-curve

2.5 The Algorithm Procedures of the Voltage Instability Alarming Predictor Concept.

Depending on PMUs' readings, a simulation of real-time voltage instability alarming predictor using ANN is discussed. This predictor has been made using MATLAB program. This smart voltage instability predictor is developed through four stages as shown in Fig 2.5.

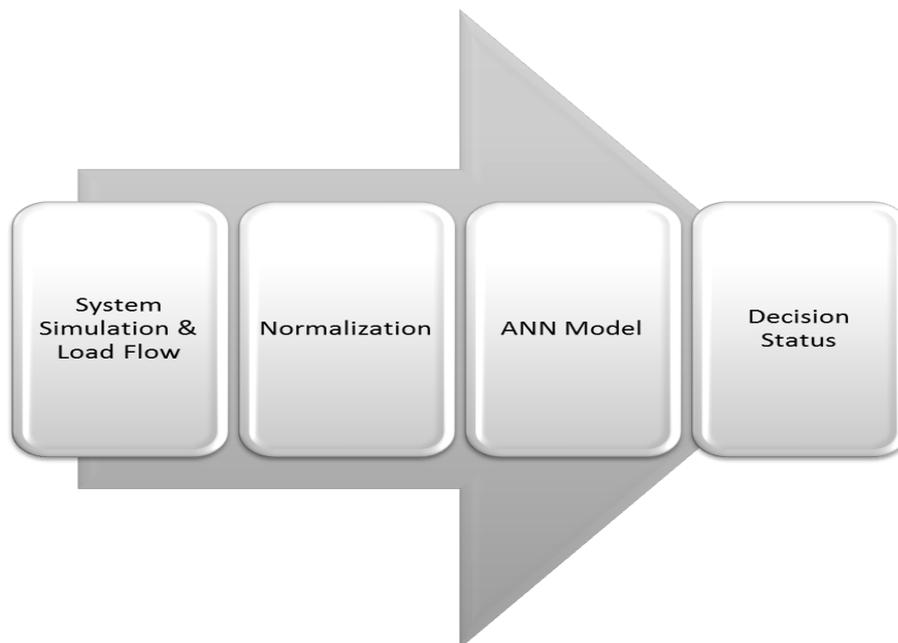


Fig 2.5 The four stages of the smart voltage instability detector

1) The first stage is the simulation of the power system using MATLAB/Power system toolbox. Different loading cases at different locations of the system are applied and studied in this stage. The load changing is applied through two strategies:

➤ The first strategy is by increasing the load while keeping the same power factor.

➤ The second strategy is by varying the power factor while fixing the total consuming apparent power of the load.

The output data of this stage is tabulated using Excel sheets to be used in the next stage.

2) In the second stage, the normalization of the output saved data of the first stage takes place. The equations which is used in the normalization process can be expressed in (2.4)

$$X \text{ normalized} = \frac{(X - X_{min})}{(X_{max} - X_{min})} \quad (2.4)$$

Where X is the main adjusted variable, such as: bus voltage, bus voltage angle, load active power, load reactive power, generation active power and generation reactive power.

3) The third stage is the design of a feed-forward neural network. The first stage data after normalization is used to train the neural network. The input information is connected to the hidden layers through weighted connections where the output data is calculated. The output data exits through the output layer. Each layer consists of number of neurons. The number of hidden layers and the number of neurons in each hidden layer controls the performance of the network.

4) The fourth stage is taking the decision after choosing the best construction of the ANN and testing it on the simulated system.

CHAPTER THREE
PHASOR MEASUREMENT UNITS & ARTIFICIAL
NEURAL NETWORK

CHAPTER 3

PHASOR MEASUREMENT UNITS & ARTIFICIAL NEURAL NETWORK

3.1 Overview.

Phasor Measurement Units which are became one of the most important and the most recent measurement devices in electrical power systems are being presented in this chapter, which are used to detect voltage instability problems depending on Artificial Neural Network. This chapter presents as well the design of the Artificial Neural Network and how to train the network to detect the voltage instability.

3.2 Phasor Measurement Units (PMUs).

Phasor measurement unit (PMU) is a device with capability of measuring the positive sequence of voltage and current phasors. Voltage phasors in power systems always interest to the power system engineers. It is well known that the active power flow in a given line in power system is proportional to the difference between the phase angles of terminals of that line [38]. Therefore, measuring the phase angles difference across the power system transmission lines is important to power system engineers.

PMUs were introduced in the mid-1980s. Since then, the subject of wide-area measurements in power systems using PMUs and other measuring instruments has been receiving considerable attention from researchers in the field. It points out that the PMU is a direct descendant of the Symmetrical Component Distance Relay introduced in late 1970s. Reference [39] also shows one of the early prototypes of PMU built at Virginia Tech as shown in **Fig 3.1** [38] a commercial product which has been installed in the field at various locations around the world.



Fig 3.1 First prototype PMU built at Virginia Tech

In reference [40], definitions for the phasors, PMUs, the sources of synchronization used for the synchronized PMUs, how to measure phasors magnitude and frequency, and state estimation using state estimator to monitor the state of the power system are explained. Authors aimed to use this in instability prediction, and in the protection field of the power systems.

Synchronized Phasor Measurement Unit (PMU) is, nowadays, one of the most important units in the applications of modern power systems and attractive measuring devices for the electrical engineering researchers. Due to the strong correlation between PMUs and the Global Positioning Satellites (GPS), PMUs began to spread widely after the great improvement in the satellite techniques and communications. In last decades, much research work has been concentrating on the exploration and introduction of GPS facilities. It is a group of 24 satellites which is placed into space orbits, as shown in **Fig. 3.2**, completing a network capable of providing position data to locate anything anywhere on Earth.

The satellites transmit timing signals and position data. At the beginning, it was used in different applications rather than in electrical engineering. GPS was used in geographical and military applications, then it was utilized in navigation and agricultural applications. Now, in engineering applications, GPS is continually spreading in civil engineering applications, in communications, and electrical power engineering. After the invention of PMUs, GPS plays a great role in the electrical power engineering

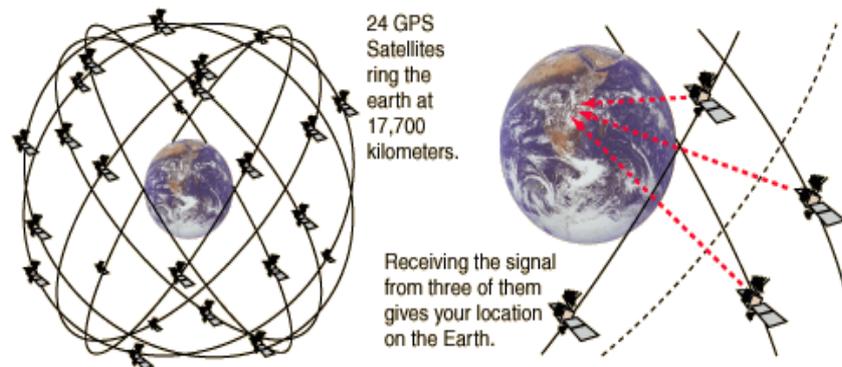


Fig. 3.2 GPS satellites rotating the earth

Since the middle of 1980's, some researchers have paid attention to the great subject of applying PMUs to power system monitoring and control, and there are others, everyday, who like to go through this way [41].

PMU are devices which are used in Wide Area Monitoring System (WAMS) technology that uses GPS satellite signals to accurately measure and analyze the condition of power grids and detect system instabilities as they appear [42], as shown in **Fig. 3.3**. A WAMS uses the satellite signals to ensure that the PMUs which monitor the condition of the power grid are synchronized with an accuracy of one microsecond. This enables system dynamics, such as frequency, voltage and power oscillations, to be observed in real time, regardless of the large geographical distances between the measurement points, and provides valuable early warning of potential network stresses.

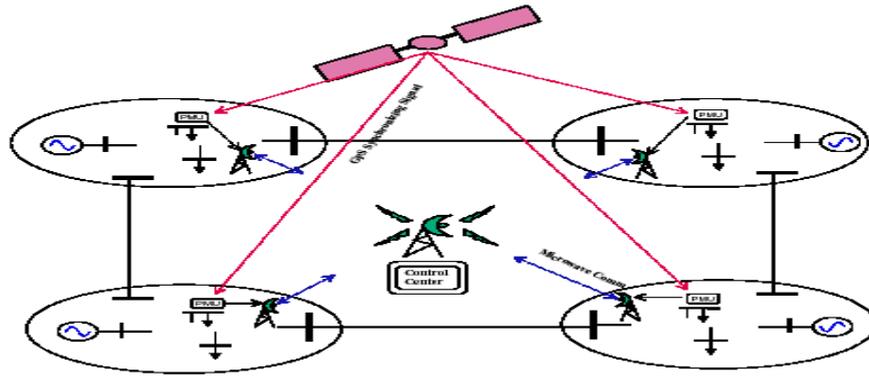


Fig. 3.3 A small Wide Area Monitoring System (WAMS)

Currently, PMUs are the most sophisticated device used in power systems which utilizes the high accuracy computation and the availability of GPS signal. Although advanced techniques in measuring and synchronizing measurements are basics for PMU operation, advances in other areas are also required to achieve the benefits of PMUs. One such area is data communication where faster and more reliable communication channels have created the chance of streaming from remote PMU site to the power system center.

PMU technology can track the network dynamics in micro-second rate. This is a great advancement to the SCADA/EMS measurements where the refreshment rate is seconds to minutes.

As mentioned in [43], the main purpose of new technologies in wide area monitoring, control and protection is to cover the following three directions:

- Monitor, control, and protect the transmission lines from disturbances and their negative impacts such as blackouts.
- Increase transmission line capacity in specific transmission area, mainly between two different electricity markets to reduce the congestion between networks.
- Improving the transmission assets utilization by enhancement of planning, control, operation, and protection process and modeling.

Researches and development of phasor measurements and their applications in power systems during the past two decades, show that a system designed based on utilizing these devices are very effective to meet the above three objectives, and can satisfy the new wide area operational constraints in the following three major areas [44]:

- Real-time wide area monitoring
- Real-time wide area control
- Real-time wide area adaptive protection

Generic architecture for a wide area monitoring, protection, and control contains four different layers:

- **Layer 1**, phasor data acquisition- synchronized phasor devices such as PMUs and digital fault recorders are installed at the substation and are capable of measuring the phasor voltage and current phasor and frequency at the substation. Basic phasor measurement process derives positive sequence, fundamental frequency phasors from voltage and current of the substation.
- **Layer 2**, Phasor data management – PDC collects data from different PMUs as well as other PDCs and correlates them into a single data set. It can also stream the data set to the appropriate application, using the data buffer.
- **Layer 3**, Data service – this layer contains a set of necessary services to provide data to different applications. The major role of this layer is to provide data in proper format for different applications. Both appropriate format and fast execution are important in this layer as providing data in appropriate format in a desired time frame can leave enough time for running the application within the sampling time.
- **Layer 4**, Applications- this layer contains the following three sections: real-time wide area control, real-time wide area monitoring and real-time wide area protection.

Four layers mentioned above forms one possible architecture which enables monitoring, control and protection of the system based on utilization of PMUs.

Utilizing phasor measurements in power systems has been popular for the past several years. As vendors and power utility companies show interest in using PMUs on their systems, investment on PMU and their applications in power systems has increased, as a result application of PMUs in power systems has received more attention in research as well.

With more than twenty utility companies, already using PMUs in North America and with the growing demand of PMU installation on power systems around the globe, different applications of phasor measurement units are of great value to researchers as well as industry. One of these applications is monitoring and control of the system in real-time. In this chapter, an Artificial Neural Network (ANN) is used to predict and detect the voltage instability problems in power systems depending on PMUs' readings.

3.2.1 PMUs placement.

Phasor Measurement Units' (PMUs) placement is the art of connecting bus-bars of the electrical power network to make use of a universal space monitoring communication system in control and protection. PMU placement in each substation allows direct measurement of the state of the network. However, a ubiquitous placement of PMUs is rarely conceivable due to cost and/or non-existence of communication facilities in some substations. The ability of PMUs to measure line current phasors allows the calculation of the voltage at the other end of the line using Ohm's Law. Optimal placement of PMUs requires only 1/4 to 1/3 of the number of network bus-bars to ensure observability is shown in [52].

It is possible to reduce the number of PMUs even further if they are placed for incomplete observability. PMUs are placed sparingly in such a way as to allow unobserved buses to exist in the system. PMUs are to be placed so that in the resulting system the topological distance of unobserved buses from those whose

voltages are known is not too great. The crux of this overall scheme is the interpolation of any unobserved bus voltage from the voltages of its neighbors.

3.2.2 Complete and Incomplete Observability.

Observability of the system from the topological point of view is the ability of observing all system buses either by measurement or direct calculation [52] – [53]. The simple system shown in **Fig 3.4** is an example for the complete observability. In **Fig 3.4**, it is seen that the buses 2 and 5 are equipped with PMUs, that can directly measure their voltage and current phasors. The voltages at buses 1, 3, 4 and 6 are calculated using the measured voltages V_2 , V_5 , and the PMUs line currents.

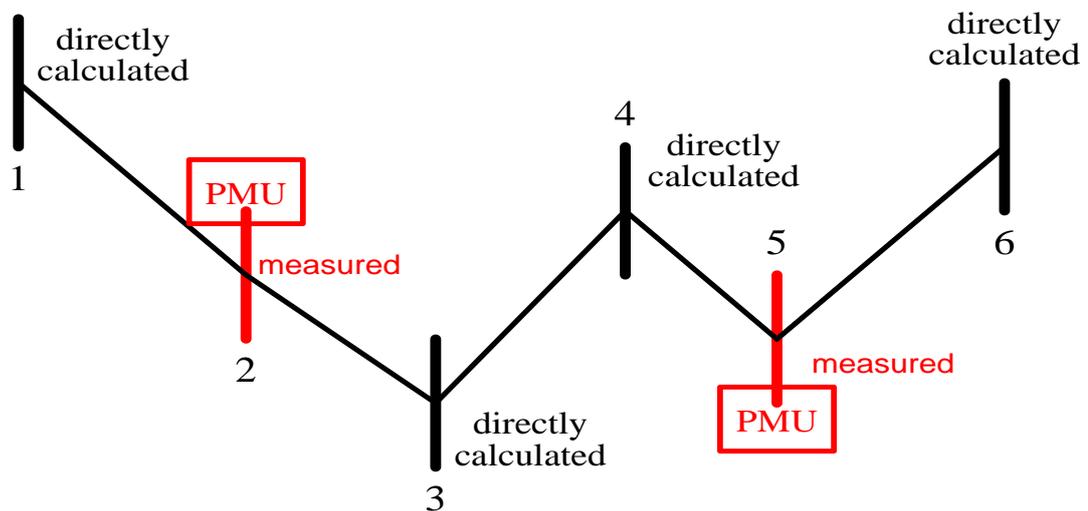


Fig 3.4 A complete observable simple system

Fig 3.5 and **Fig 3.6** illustrate the concept of depth of unobservability. In **Fig. 3.5**, the PMUs at buses 2 and 6 directly measure the voltages V_2 and V_6 respectively. The voltages at buses 1 and 3 are calculated using the voltage at bus 2, and the line currents as measured by the PMU. The voltages at buses 5 and 7 are also calculated in a similar manner. Buses 1, 3, 5 and 7 are defined as calculated buses. The voltage of bus 4 cannot be determined from the available measurements, since the injection at either bus 3 or bus 5 is not observed. Bus 4 is defined to be depth of one unobservable bus because it is bounded by two

observed (calculated) buses. One-unobservability depth system exists in **Fig. 3.5**. A depth of one-unobservability placement refers to the process of placing PMUs that strives to create depth of one unobservable buses in the system.

Fig. 3.6 characterizes a two unobservability depth system. Buses 2 and 7 are directly observed by the PMUs, while voltages at buses 1, 3 and 6 are calculated from the PMUs line current measurements. Buses 4 and 5 represent a depth of two unobserved buses. A two-unobservability depth condition exists when two observed buses bound two adjoining unobserved buses. It is important to realize that such condition exists if we traverse the path defined by the bus sequence 2-3-4-5-6-7.

The concept of unobservability depth and the aforementioned definitions are extendable for higher depths. Imposing an unobservability depth ensures that PMUs are well distributed throughout the power system and that the distances of unobserved buses from those observed is kept at a minimum.

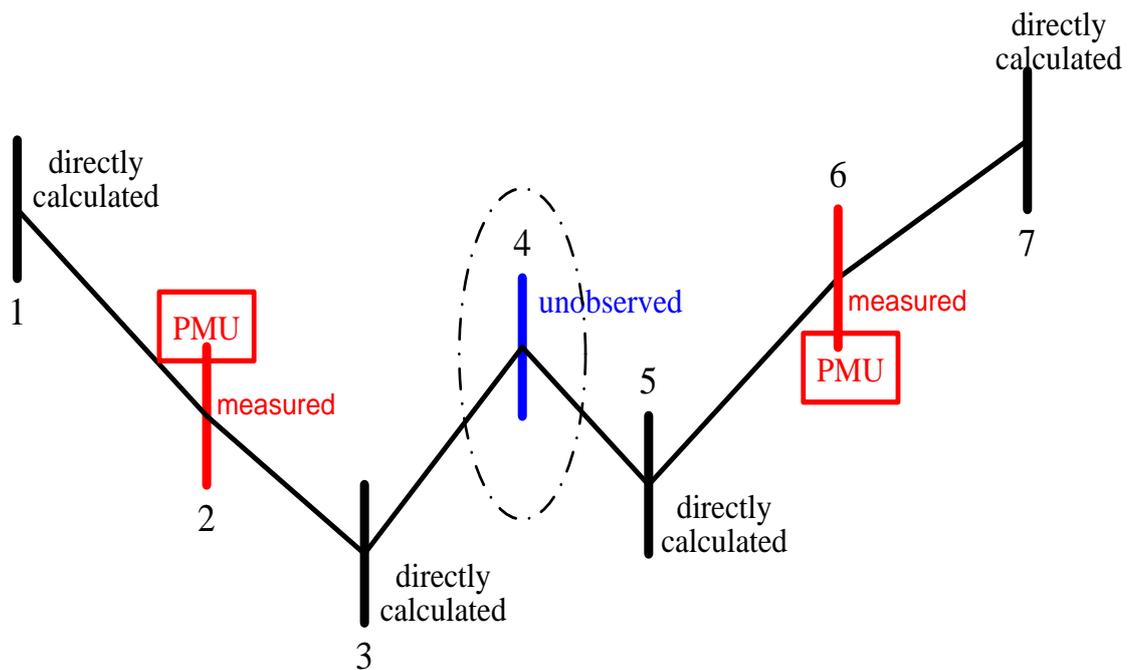


Fig. 3.5 One-Unobservability depth system

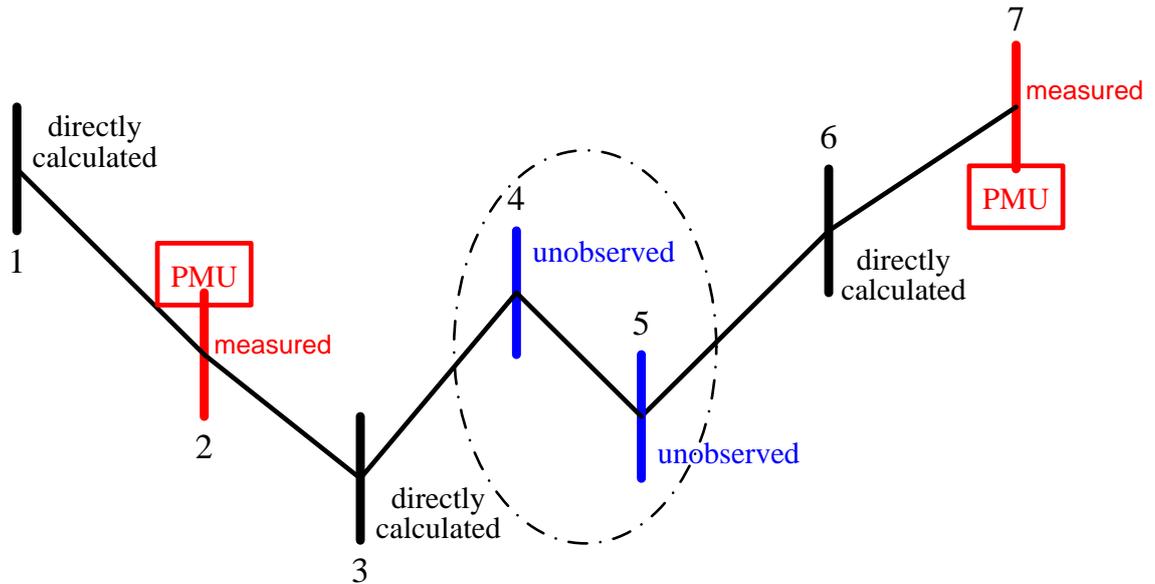


Fig. 3.6 Two-Unobservability depth illustrated

For any given unobservability depth, the voltages of unobserved buses can be estimated from the known voltages. Consequently, the vector of directly measured and calculated voltages augmented by the estimated voltages completes the state of the system. A streaming type of state exists with rate as fast as the speed of the PMU measurements.

3.3 Artificial Neural Network

ANNs can play a richly significant potential role in electric power systems. As a branch of Artificial Intelligence, ANNs take problem solving one step further. They can match stored examples against a new one, building on experience to provide better answers. On the field of AI, ANN computing shows great potential in solving difficult data-interpreting tasks.

ANNs can be defined as a set of processing units (neurons) interlinked with each other by means of a big number of interconnections (artificial synapses) as shown in **Fig. 3.7**. These synapses are responsible for storing information, i.e., for the learning of the network [46].

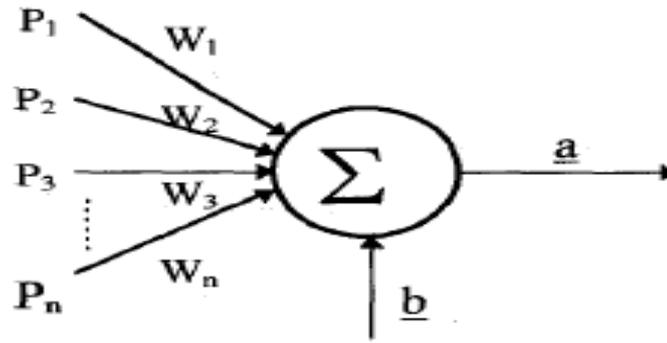


Fig. 3.7 Perceptron representation

Once trained, a network response can be, to a degree, insensitive to minor variations in its input. This ability to see through noise and distortion to the pattern that lies within is vital to pattern recognition a real world environment [45-47]. The neuron is the nervous cell and is represented in the ANN universe as a perceptron. **Fig 3.7** shows a simple model of a neuron characterized by a number of inputs P_1, P_2, \dots, P_n , the weights W_1, W_2, \dots, W_n , the bias adjust b and an output a . The neuron uses the input, as well as the information on its current activation state to determine the output a , given as in (3.1).

$$a = \sum_{k=1}^n W_k P_k + b \quad (3.1)$$

The neurons are normally connected to each other in a specified fashion to form the ANNs. These arrangements of interconnections could form a network which is composed of a single layer or several layers. As mentioned before, the ANN models must be trained to work properly. The desired response is a special input signal used to train the neuron. A special algorithm adjusts weights so that the output response to the input patterns will be as close as possible to the respective desired response. In other words, the ANNs must have a mechanism for learning. Learning alters the weights associated with the various interconnections and thus leads to a modification in their strength.

A neural network element is a smallest processing unit of the whole network essentially forming a weighted sum and transforming it by the activation function to obtain the output. In order to gain sufficient computing power, several neurons are interconnected together. The manner in which actually the neurons are connected together depends on the different classes of the neural networks. Basically neurons are arranged in layers. ANNs have parallel distributed architecture with a large number of nodes and connections.

3.3.1 ANN Architecture

The topology of the artificial neural network refers to its framework as well as its interconnection scheme. The number of layers and the number of nodes per layer often specify the framework.

The types of layer as shown in **Fig 3.8** [48] include:

- **Input Layer (X)** where the nodes are called input units, which do not process information but distribute information to other units.
- **Hidden Layers (V)** where the nodes are called hidden units, which are not directly observable. They provide into the networks the capability to map or classify nonlinear problems.
- **Output Layer** where the nodes are called output units, which encode possible concepts (or values) to be assigned to the instance under consideration.

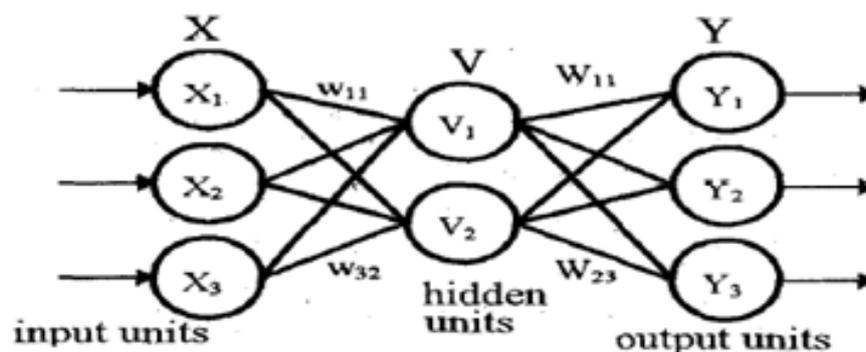


Fig. 3.8 Feed-forward neural network architecture

The main advantages of using the artificial neural network ANN controller are:

- A neural network can perform tasks that a linear program cannot i.e. very suitable for non-linear systems.
- When an element of the neural network fails, it can continue without any problem by their parallel nature.
- A neural network learns and does not need to be reprogrammed.
- It can be implemented in various applications.

The main disadvantages of using the artificial neural network ANN controller are:

- The neural network needs training to operate.
- The architecture of a neural network is sometimes complicated in design.
- Requires high processing time for large neural networks.

3.3.2 Collecting Data

The first step in designing an ANN is to collect historical data. In this thesis, the simulated data after normalization is used to train the neural network. These data is called (training points).

The obtained training points for this thesis model is shown in Appendix (C)

3.3.3 Selecting Network Structure

As mentioned before, the Artificial Neural Network consists of one input layer and a minimum of two layers (one hidden layer and another output layer). The input information is connected to the hidden layers through weighted connections where the output data is calculated. The number of hidden layers and the number of neurons in each layer controls the performance of the network.

Until now, there are no guidelines for deciding a way to choose the number of neurons along with number of hidden layers for a given problem to give the best performance. And it is still a trial and error design method.

In this thesis, there are two developed ANNs each one is used for one of the two simulated system. Both of them have the same number of inputs which are voltage angle degree, load active power, Load reactive power, generation active power and generation reactive power. Also, they have the same output which indicates the status of the system bus as stable, alarm and trip by giving an output of 1, 0, and -1 for each system bus. The hidden layers of the two developed ANNs consist of different number of neurons with tan-sigmoid activation function, as follows:

- **14 bus IEEE standard system**

The ANN of this system consists of two hidden layers, the first hidden layer has six neurons and the second hidden layer has eight neurons.

- **30 bus IEEE standard system**

The ANN of this system consists of two hidden layers, the first hidden layer has ten neurons and the second hidden layer has fifteen neurons.

The structure of both ANNs can be shown in **Fig 3.9**

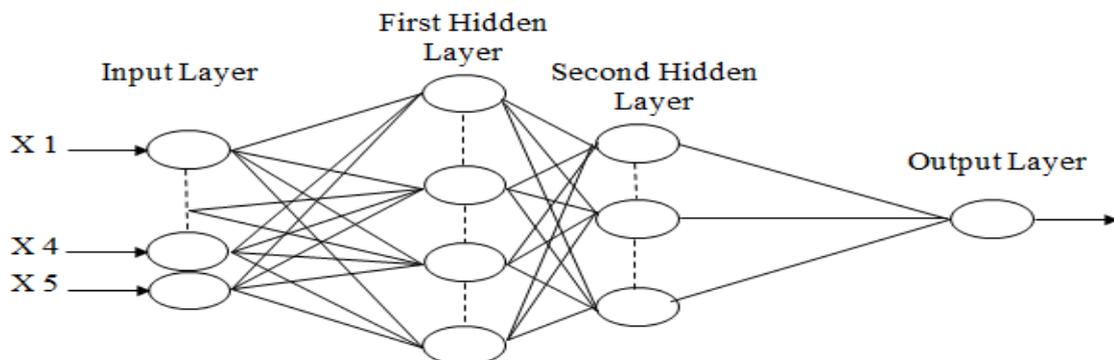


Fig.3.9 Proposed ANN structure for the simulated systems

3.3.4 Training the Network

The collected training points are passed into the designed network in order to teach it how to perform when different points than the training points are inserted to it. In this thesis, the training process of the ANNs is done using MATLAB/M-file program.

3.3.5 Testing the Network

Some of the collected test data is kept as test points. In order to find out how accurate the developed network is, these test data will be applied to the trained ANNs. This work will be presented briefly at next chapter. The test data can be found in Appendix (F)

CHAPTER FOUR
CASE STUDIES AND SIMULATION RESULTS

CHAPTER 4

CASE STUDIES AND SIMULATION RESULTS

4.1. Overview.

This chapter shows the simulation, testing and applying this work to 14-bus and 30-bus IEEE standard power systems. The simulations are processed using MATLAB/m-file program. The simulation results and some case studies for the whole proposed system are discussed in this chapter.

4.2. Voltage Instability Alarming Predictor Concept Procedures and Flowchart.

In this chapter, the simulation of a real-time voltage instability alarming predictor using Artificial Neural Network (ANN) depending on Phasor Measurement Units (PMUs) is progressed. This predictor is simulated using MATLAB program. The MATLAB program's algorithm program is explained under two main stages as shown in **Fig 4.1** which are the off-line stage and the on-line stage.

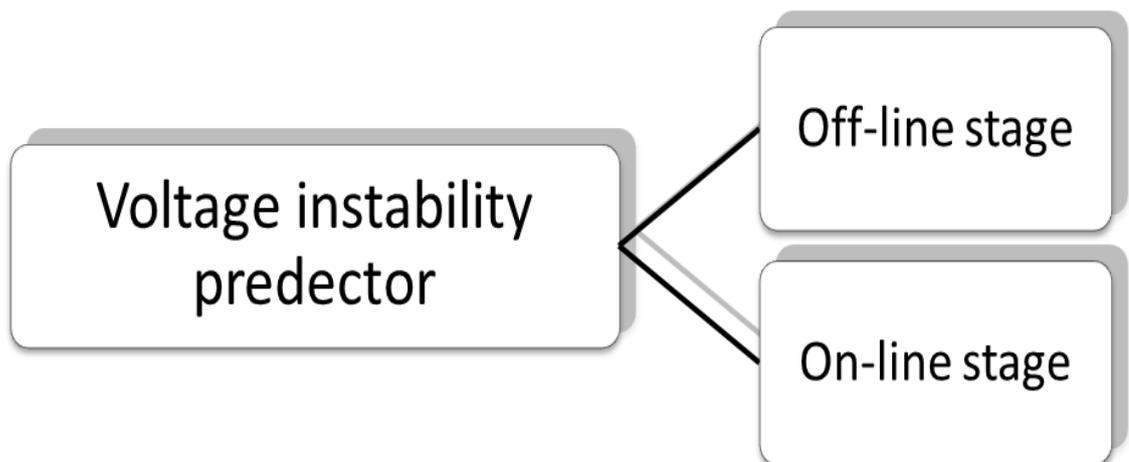


Fig 4.1 The voltage instability predictor main stages block diagram.

4.2.1. Off-line Simulations and Preparations.

In this stage, the steps of the preparation of the data for the Look-up table take place and can be summarized as follows:

- (1) Entering the system parameters and data.
- (2) Designing the system PV curves for different power factors (pf).
- (3) Determining the maximum P for V with 5% and 15% decreases.
- (4) Calculating different results of the system load-flow from the entered system data and parameters.
- (5) Normalizing the results and tabulating it into a look up table.
- (6) Designing the suitable architecture of the ANN.
- (7) Using the normalized data to train the ANN.

The flowchart of off-line simulations and preparations are illustrated in **Fig.4.2**. Also **Fig 4.3** shows some of the designed PV curves for different power factors.

4.2.2. On-line Alarming Prediction.

The process of this stage is presented in the following steps;

- (1) Reading the PMUs online data.
- (2) Entering the data to the trained ANN.
- (3) Checking the output of the ANN, whether it is 1, 0, or -1 which indicates the status of the system bus as stable, alarm and trip respectively.
- (4) Taking the suitable decision.

Figure 4.4 illustrates a flowchart of the on-line alarming prediction.

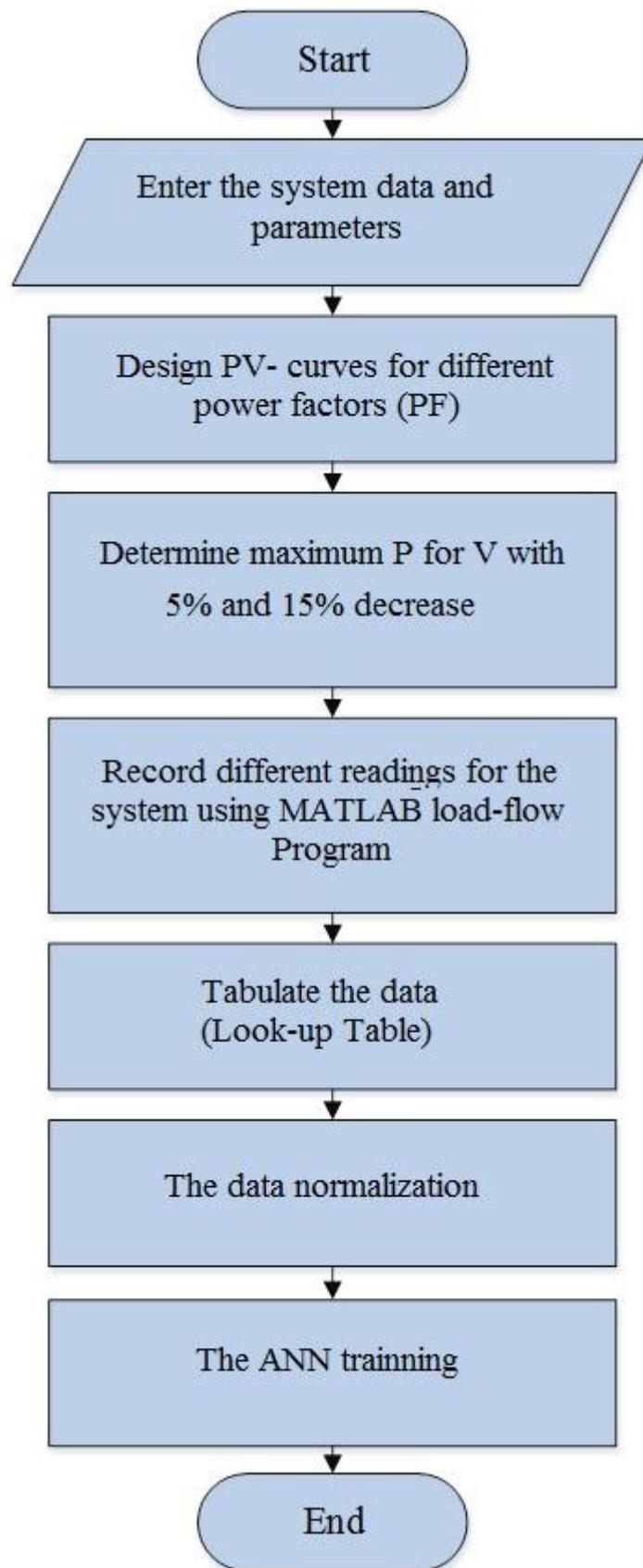


Fig 4.2 The voltage instability predictor off-line stage flowchart.

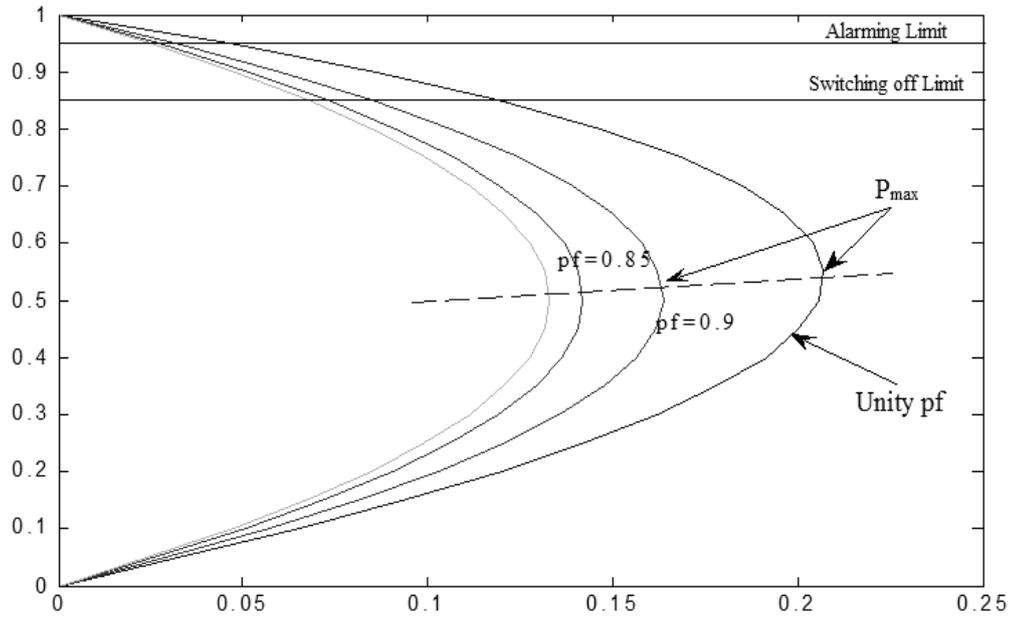


Fig 4.3 Designed PV curves for different power factors.

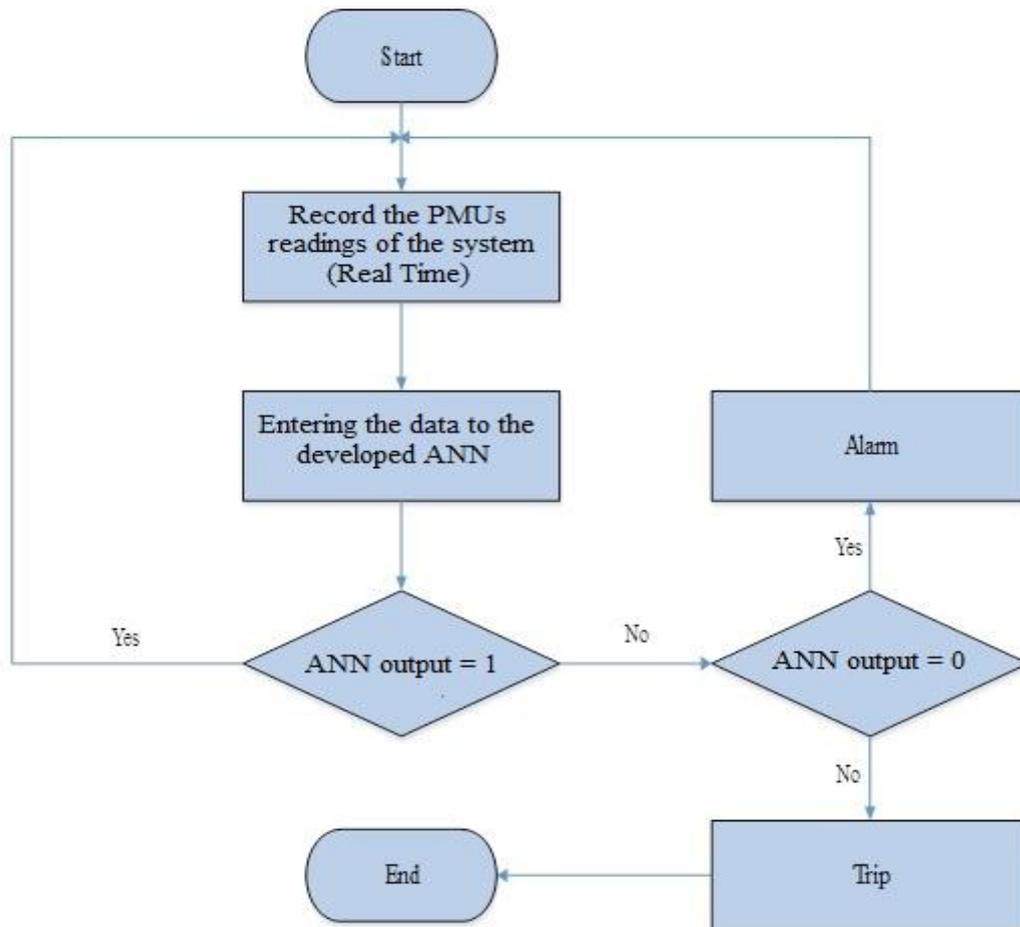


Fig 4.4 The voltage instability predictor on-line stage flowchart.

4.3. Studied Systems and Results.

The new voltage instability predictor concept is tested on both 14-bus and 30-bus IEEE standard systems. The simulation results of the studied systems will be discussed in the following subsections.

4.3.1. The 14-Bus IEEE Standard System

I. System Design.

The 14-bus IEEE standard system [49] (shown in **Fig 4.5**) is simulated using MATLAB/Power System toolbox program [50]. In the beginning, the system data and parameters are entered to the program. The equivalent system load-flow is executed. Different load-flow analysis for different loading cases is calculated. The load-flow results for a normal operating condition of IEEE 14-bus system are shown in **Table 4.1**. The first column of the table presents the system bus number. The second and third columns present the voltage magnitude and angle values respectively. The fourth and fifth columns present the active and reactive load power respectively. The last two columns present the active and reactive generation power. The IEEE 14-Bus system data and parameters are shown in Appendix (A).

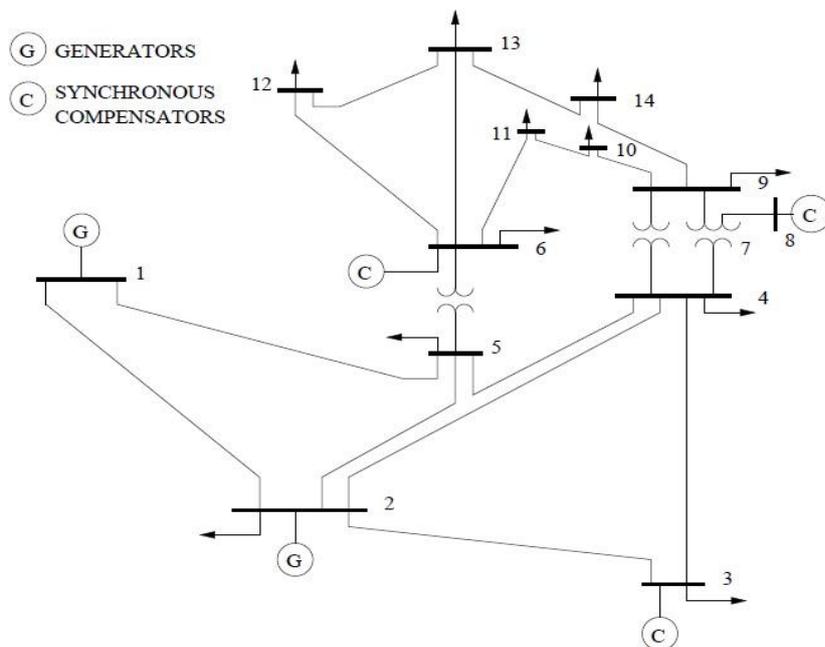


Fig 4.5 14-Bus IEEE standard system

Table 4.1 The 14-Bus IEEE standard system load-flow results for a normal operating condition

Bus No	Voltage Mag	Angle Degree	Load MW	Load MVAR	Generation MW	Generation MVAR
1	1.06	0	30.38	17.78	149.427	39.225
2	1.045	-1.31	0	0	232	-3.564
3	1.01	-13.313	131.88	26.6	0	62.16
4	0.994	-10.032	66.92	10	0	0
5	1.002	-8.289	10.64	2.24	0	0
6	1.07	-15.836	15.68	10.5	0	38.764
7	1.029	-14.759	0	0	0	0
8	1.09	-14.765	0	0	0	37.787
9	1	-17.281	41.3	23.24	0	0
10	1.003	-17.42	12.6	8.12	0	0
11	1.034	-16.782	4.9	2.52	0	0
12	1.05	-16.851	8.54	2.24	0	0
13	1.046	-16.795	18.9	8.12	0	0
14	0.951	-20.138	20.86	7	0	0

II. Load-flow Calculations

Various system load-flows are executed to give different results for the system by changing the load values. The load-flow of 1357 studied cases are calculated and tabulated. **Table 4.2** shows the load-flow results of the 14-Bus IEEE standard system when the load active power (P_{Load}) of bus 9 is changed to 165MW. The results of changing the loads which are connected to bus 12 and bus 5 to 50MW and 170MW respectively are shown in **Table 4.3**.

Table 4.2 The load-flow results when $P_{Load} = 165$ MW at bus 9

Bus No	Voltage Mag	Angle Degree	Load MW	Load MVAR	Generation MW	Generation MVAR
1	1.06	0	30.38	17.78	297.294	26.826
2	1.045	-4.592	0	0	232	67.289
3	1.01	-19.186	131.88	26.6	0	89.39
4	0.951	-17.232	66.92	10	0	0
5	0.967	-14.457	10.64	2.24	0	0
6	1.07	-27.11	15.68	10.5	0	67.263
7	0.979	-29.959	0	0	0	0
8	1.09	-29.962	0	0	0	68.548
9	0.933	-36.888	165	23.24	0	0
10	0.945	-35.195	12.6	8.12	0	0
11	1.006	-30.564	4.9	2.52	0	0
12	1.047	-28.427	8.54	2.24	0	0
13	1.038	-28.616	18.9	8.12	0	0
14	0.88	-40.203	20.86	7	0	0

Table 4.3 The load-flow results when $P_{Load} = 50$ MW at bus 12 and $P_{Load} = 170$ at bus 5

Bus No	Voltage Mag	Angle Degree	Load MW	Load MVAR	Generation MW	Generation MVAR
1	1.06	0	30.38	17.78	385.544	22.319
2	1.045	-6.235	0	0	232	82.341
3	1.01	-21.269	131.88	26.6	0	83.075

4	0.962	-20.017	66.92	10	0	0
5	0.957	-19.466	170	2.24	0	0
6	1.07	-31.381	15.68	10.5	0	77.051
7	1.015	-26.063	0	0	0	0
8	1.09	-26.06	0	0	0	46.602
9	0.988	-29.221	41.3	23.24	0	0
10	0.993	-30.197	12.6	8.12	0	0
11	1.029	-31.409	4.9	2.52	0	0
12	1.009	-35.454	50	2.24	0	0
13	1.038	-33.073	18.9	8.12	0	0
14	0.939	-32.16	20.86	7	0	0

III. Data Normalization.

The data of the 1357 studied cases are normalized in this stage and tabulated in Excel sheets. The load-flow results for the normal operating condition of the 14-Bus IEEE standard system after normalization are presented in **Table 4.4**.

Table 4.4 The 14-Bus IEEE standard system load-flow results for a normal operating condition after normalization

Bus No	Voltage Mag	Angle Degree	Load MW	Load MVAR	Generation MW	Generation MVAR
1	0.932584	0.995414	0.047843	0.668421	0.14845	0.10492
2	0.898876	0.97854	0	0	0.230484	0.035606
3	0.820225	0.823926	0.207685	1	0	0.142072
4	0.78427	0.866189	0.105386	0.37594	0	0.041379
5	0.802247	0.888641	0.016756	0.084211	0	0.041379
6	0.955056	0.791426	0.024693	0.394737	0	0.104173

7	0.862921	0.805299	0	0	0	0.041379
8	1	0.805222	0	0	0	0.10259
9	0.797753	0.772813	0.065039	0.873684	0	0.041379
10	0.804494	0.771022	0.019843	0.305263	0	0.041379
11	0.874157	0.779241	0.007717	0.094737	0	0.041379
12	0.910112	0.778352	0.013449	0.084211	0	0.041379
13	0.901124	0.779073	0.029764	0.305263	0	0.041379
14	0.68764	0.736011	0.03285	0.263158	0	0.041379

IV. ANN Design.

As stated before in chapter 3, the training points should be obtained in order to start the ANN training. A sample of the training points is shown in **Table 4.5**.

Table 4.5 Sample of the ANN training points

Bus No	Voltage Mag	Angle Degree	Load MW	Load MVAR	Generation MW	Generation MVAR	Target
1	0.932584	0.995414	0.047843	0.668421	0.086683	0.124438	0
2	0.898876	0.996522	0	0	0.230484	0.006975	1
3	0.820225	0.85609	0.207685	1	0	0.132213	1
4	0.806742	0.908272	0.015748	0.37594	0	0.041379	1
5	0.817978	0.921308	0.016756	0.084211	0	0.041379	1
6	0.955056	0.827803	0.024693	0.394737	0	0.09716	0
7	0.874157	0.846713	0	0	0	0.041379	1
8	1	0.846648	0	0	0	0.097502	0
9	0.811236	0.813724	0.065039	0.873684	0	0.041379	1
10	0.813483	0.81098	0.019843	0.305263	0	0.041379	1
11	0.878652	0.817034	0.007717	0.094737	0	0.041379	1

12	0.910112	0.814909	0.013449	0.084211	0	0.041379	0
13	0.901124	0.815759	0.029764	0.305263	0	0.041379	1
14	0.701124	0.77736	0.03285	0.263158	0	0.041379	1

The ANN is designed using MATLAB/m-file. A part of the MATLAB training program is shown in appendix (D). The proposed ANN has one input layer, two hidden layers and one output layer. The input layer consists of five inputs as follows:

- Voltage angles.
- Load active power.
- Load reactive power.
- Generation active power.
- Generation reactive power.

The output layer consists of one output for each system bus which indicates its status. The bus status may be stable \equiv 1, alarm \equiv 0 or trip \equiv -1. The construction of the ANN is shown in **Table 4.6**.

Table 4.6 The construction of the developed ANN for the 14-bus IEEE standard system.

No. of inputs	No. of neurons of 1 st layer	No. of neurons of 2 nd layer	No. of outputs
5	6	8	1

The developed ANN is trained using 900 of the study cases. The network is trained using the MATLAB/NNET tool box [51] as shown in **Fig 4.6**

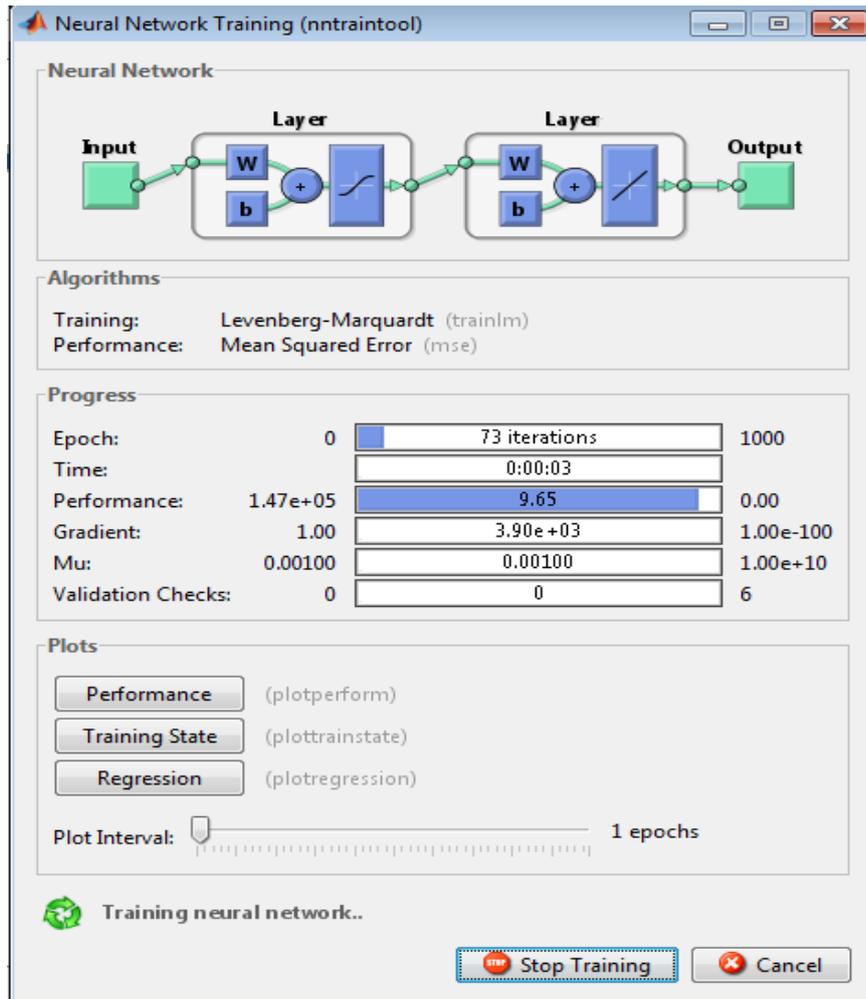


Fig 4.6 ANN training with MATLAB NNET toolbox

V. ANN Testing.

The generated ANN is then tested using 457 testing points. A part of the MATLAB testing program is shown in appendix (E). Samples of the results are shown in **Table 4.7** and **Table 4.8**.

Table 4.7 Sample of the testing points when $P_{Load} = 60$ MW at Bus 10.

Bus No	Voltage Mag	Angle Degree	Load MW	Load MVAR	Generation MW	Generation MVAR	Target	Output
1	0.932584	0.995414	0.047843	0.668421	0.203152	0.094191	1	1
2	0.898876	0.962966	0	0	0.230484	0.071422	1	1
3	0.820225	0.796669	0.207685	1	0	0.155171	1	1
4	0.755056	0.832286	0.105386	0.37594	0	0.041379	1	1

5	0.775281	0.858563	0.016756	0.084211	0	0.041379	1	1
6	0.955056	0.729982	0.024693	0.394737	0	0.120714	0	0
7	0.833708	0.739631	0	0	0	0.041379	1	1
8	1	0.739643	0	0	0	0.116006	0	0
9	0.757303	0.689986	0.065039	0.873684	0	0.041379	1	1
10	0.739326	0.668333	0.094488	0.305263	0	0.041379	1	1
11	0.842697	0.701579	0.007717	0.094737	0	0.041379	1	1
12	0.907865	0.714963	0.013449	0.084211	0	0.041379	1	1
13	0.892135	0.714074	0.029764	0.305263	0	0.041379	1	1
14	0.644944	0.651587	0.03285	0.263158	0	0.041379	0	0

Table 4.8 Sample of the testing points when $P_{Load} = 535$ MW at Bus 5.

Bus No	Voltage Mag	Angle Degree	Load MW	Load MVAR	Generation MW	Generation MVAR	Tar get	Out put
1	0.932584	0.995414	0.047843	0.668421	0.858677	0.203564	1	1
2	0.898876	0.778287	0	0	0.230484	0.672039	1	1
3	0.820225	0.496586	0.207685	1	0	0.288361	1	1
4	0.494382	0.459424	0.105386	0.37594	0	0.041379	0	0
5	0.395506	0.417431	0.84252	0.084211	0	0.041379	-1	0
6	0.955056	0.310594	0.024693	0.394737	0	0.267341	0	0
7	0.725843	0.375953	0	0	0	0.041379	1	1
8	1	0.37594	0	0	0	0.163735	0	0
9	0.662921	0.334669	0.065039	0.873684	0	0.041379	0	0
10	0.694382	0.323617	0.019843	0.305263	0	0.041379	1	1
11	0.829213	0.312217	0.007717	0.094737	0	0.041379	1	1
12	0.903371	0.298717	0.013449	0.084211	0	0.041379	1	1
13	0.889888	0.301358	0.029764	0.305263	0	0.041379	1	1
14	0.54382	0.292586	0.03285	0.263158	0	0.041379	0	0

It is found from the tested cases that the accuracy of the developed ANN of the 14-bus IEEE system is 97.34%. It is obvious that the developed ANN results are very close to the actual one.

4.3.2. The 30-Bus IEEE Standard System.

I. System Design.

The 30-Bus IEEE standard system is simulated and presented in **Fig 4.7**. Different load-flow analysis for different loading cases is calculated. **Table 4.9** shows the load-flow results for a normal operating condition of IEEE 14-Bus system. The IEEE 30-Bus system data and parameters are shown in Appendix (B).

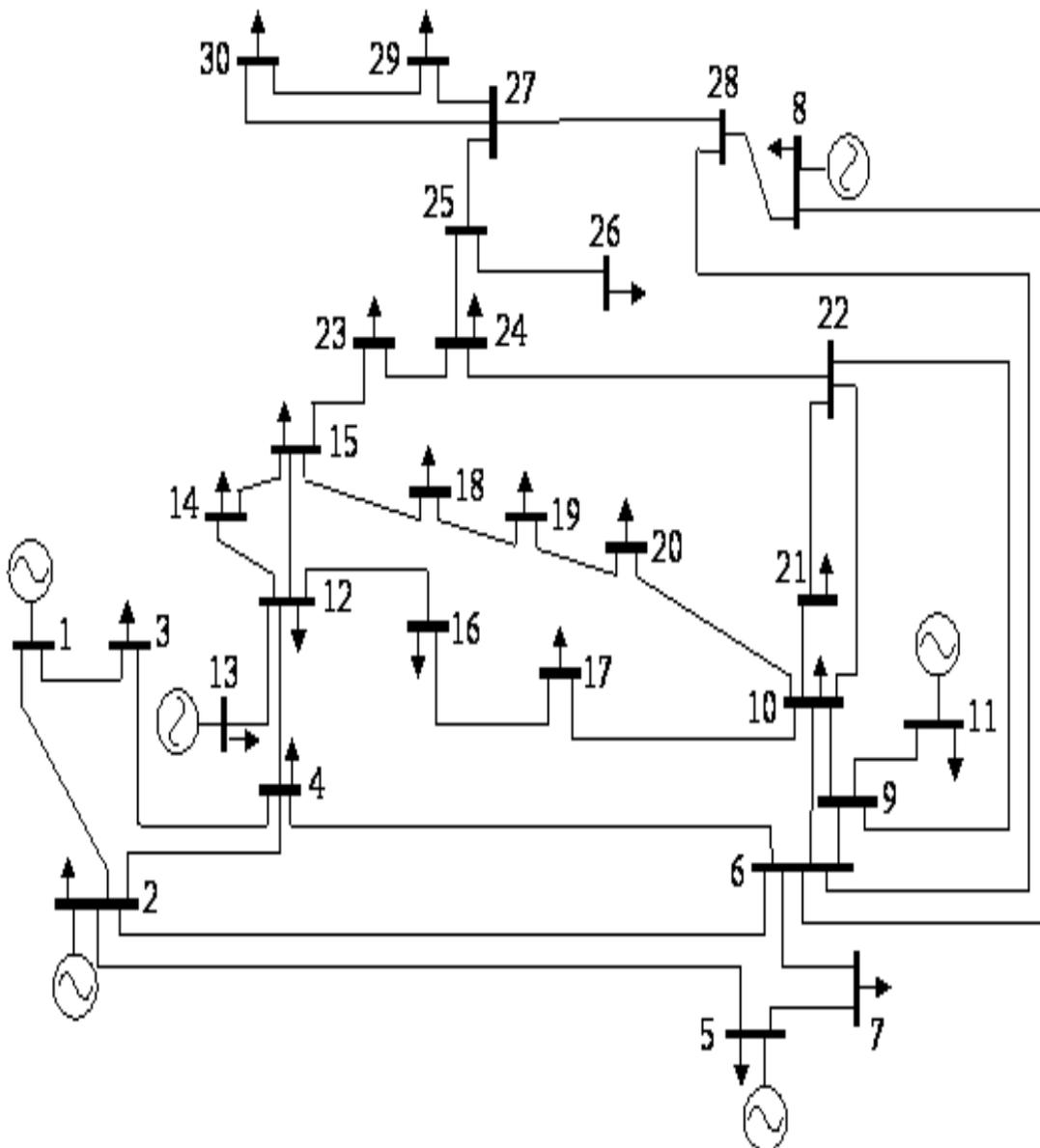


Fig 4.7 The 30-Bus IEEE standard system

Table 4.9 The 30-Bus IEEE standard system load-flow results for a normal operating condition

Bus No	Voltage Mag	Angle Degree	Load MW	Load MVAR	Generation MW	Generation MVAR
1	1.06	0	0	0	260.95	-17.01
2	1.043	-5.496	21.7	12.7	40	48.826
3	1.022	-8.002	2.4	1.2	0	0
4	1.013	-9.659	7.6	1.6	0	0
5	1.01	-14.38	94.2	19	0	35.995
6	1.012	-11.396	0	0	0	0
7	1.003	-13.149	22.8	10.9	0	0
8	1.01	-12.114	30	30	0	30.759
9	1.051	-14.432	0	0	0	0
10	1.044	-16.024	5.8	2	0	0
11	1.082	-14.432	0	0	0	16.113
12	1.057	-15.301	11.2	7.5	0	0
13	1.071	-15.3	0	0	0	10.406
14	1.043	-16.19	6.2	1.6	0	0
15	1.038	-16.276	8.2	2.5	0	0
16	1.045	-15.879	3.5	1.8	0	0
17	1.039	-16.187	9	5.8	0	0
18	1.028	-16.881	3.2	0.9	0	0
19	1.025	-17.049	9.5	3.4	0	0
20	1.029	-16.851	2.2	0.7	0	0
21	1.032	-16.468	17.5	11.2	0	0
22	1.033	-16.455	0	0	0	0
23	1.027	-16.66	3.2	1.6	0	0
24	1.022	-16.829	8.7	6.7	0	0

25	1.019	-16.423	0	0	0	0
26	1.001	-16.835	3.5	2.3	0	0
27	1.026	-15.913	0	0	0	0
28	1.011	-12.056	0	0	0	0
29	1.006	-17.133	2.4	0.9	0	0
30	0.994	-18.016	10.6	1.9	0	0

II. Load-flow Calculations.

After changing the load values, the new system load-flow is calculated to give new results of the system. The load-flow of 895 studied cases are calculated and tabulated. **Table 4.10** shows the load-flow results of the 30-Bus IEEE standard system when the P_{Load} of bus 15 changed to 135 MW. The results of changing the loads which are connected to bus 18 and bus 20 to 30MW and 105MW respectively are shown in **Table 4.11**.

Table 4.10 The load-flow results when $P_{Load} = 135$ MW at bus 15

Bus No	Voltage Mag	Angle Degree	Load MW	Load MVAR	Generation MW	Generation MVAR
1	1.06	0	0	0	420.822	49.824
2	1.008	-8.66	21.7	12.7	40	38.868
3	0.969	-13.815	2.4	1.2	0	0
4	0.953	-16.834	7.6	1.6	0	0
5	0.975	-20.382	94.2	19	0	43.777
6	0.963	-19.395	0	0	0	0
7	0.957	-20.4	22.8	10.9	0	0
8	0.981	-20.423	30	30	0	82.559
9	1.007	-26.876	0	0	0	0
10	0.987	-30.827	5.8	2	0	0

11	1.082	-26.918	0	0	0	38.852
12	0.972	-34.225	11.2	7.5	0	0
13	1.021	-34.226	0	0	0	35.917
14	0.932	-38.165	6.2	1.6	0	0
15	0.891	-40.802	135	2.5	0	0
16	0.971	-33.139	3.5	1.8	0	0
17	0.977	-31.768	9	5.8	0	0
18	0.908	-37.966	3.2	0.9	0	0
19	0.924	-36.117	9.5	3.4	0	0
20	0.938	-34.829	2.2	0.7	0	0
21	0.969	-31.645	17.5	11.2	0	0
22	0.968	-31.73	0	0	0	0
23	0.904	-37.785	3.2	1.6	0	0
24	0.934	-33.43	8.7	6.7	0	0
25	0.951	-30.147	0	0	0	0
26	0.931	-30.83	3.5	2.3	0	0
27	0.972	-27.671	0	0	0	0
28	0.965	-20.628	0	0	0	0
29	0.95	-29.239	2.4	0.9	0	0
30	0.938	-29.968	10.6	1.9	0	0

Table 4.11 The load-flow results when $P_{\text{Load}} = 30$ MW at bus 18 and $P_{\text{Load}} = 105$ at bus 20

Bus No	Voltage Mag	Angle Degree	Load MW	Load MVAR	Generation MW	Generation MVAR
1	1.06	0	0	0	442.991	49.618
2	1.008	-8.957	21.7	12.7	40	44.267
3	0.967	-14.189	2.4	1.2	0	0

4	0.946	-17.426	7.6	1.6	0	0
5	0.99	-21.655	94.2	19	0	68.883
6	0.954	-20.171	0	0	0	0
7	0.966	-21.268	22.8	10.9	0	0
8	0.967	-21.708	30	30	0	91.153
9	0.977	-30.163	0	0	0	0
10	0.936	-35.514	5.8	2	0	0
11	1.082	-30.116	0	0	0	54.639
12	0.971	-32.714	11.2	7.5	0	0
13	1.022	-32.65	0	0	0	35.369
14	0.936	-35.314	6.2	1.6	0	0
15	0.906	-36.731	8.2	2.5	0	0
16	0.944	-34.283	3.5	1.8	0	0
17	0.933	-35.387	9	5.8	0	0
18	0.815	-46.04	30	0.9	0	0
19	0.793	-48.898	9.5	3.4	0	0
20	0.789	-49.987	105	0.7	0	0
21	0.921	-35.937	17.5	11.2	0	0
22	0.922	-35.81	0	0	0	0
23	0.904	-36.304	3.2	1.6	0	0
24	0.911	-35.426	8.7	6.7	0	0
25	0.932	-31.764	0	0	0	0
26	0.912	-32.124	3.5	2.3	0	0
27	0.954	-29.474	0	0	0	0
28	0.952	-21.35	0	0	0	0
29	0.932	-30.696	2.4	0.9	0	0
30	0.919	-31.939	10.6	1.9	0	0

III. Data Normalization.

The data of the 895 studied cases are normalized in this stage and tabulated in Excel sheets. The load-flow results for the normal operating condition of the 30-Bus IEEE system after normalization is presented in **Table 4.12**.

Table 4.12 30-Bus IEEE standard system load-flow results for a normal operating condition after normalization

Bus No	Voltage Mag	Angle Degree	Load MW	Load MVAR	Generation MW	Generation MVAR
1	0.172228	0.499784	0	0	0.397345	0.192553
2	0.169447	0.484367	0.1085	0.423333	0.060907	0.24572
3	0.166012	0.477337	0.012	0.04	0	0.20629
4	0.16454	0.472689	0.038	0.053333	0	0.20629
5	0.16405	0.459446	0.471	0.633333	0	0.235359
6	0.164377	0.467816	0	0	0	0.20629
7	0.162905	0.462899	0.114	0.363333	0	0.20629
8	0.16405	0.465802	0.15	1	0	0.23113
9	0.170756	0.4593	0	0	0	0.20629
10	0.169611	0.454834	0.029	0.066667	0	0.20629
11	0.175826	0.4593	0	0	0	0.219302
12	0.171737	0.456862	0.056	0.25	0	0.20629
13	0.174027	0.456865	0	0	0	0.214694
14	0.169447	0.454368	0.031	0.053333	0	0.20629
15	0.168629	0.454127	0.041	0.083333	0	0.20629
16	0.169774	0.455241	0.0175	0.06	0	0.20629
17	0.168793	0.454377	0.045	0.193333	0	0.20629

18	0.166994	0.45243	0.016	0.03	0	0.20629
19	0.166503	0.451959	0.0475	0.113333	0	0.20629
20	0.167157	0.452514	0.011	0.023333	0	0.20629
21	0.167648	0.453589	0.0875	0.373333	0	0.20629
22	0.167812	0.453625	0	0	0	0.20629
23	0.16683	0.45305	0.016	0.053333	0	0.20629
24	0.166012	0.452576	0.0435	0.223333	0	0.20629
25	0.165522	0.453715	0	0	0	0.20629
26	0.162578	0.452559	0.0175	0.076667	0	0.20629
27	0.166667	0.455146	0	0	0	0.20629
28	0.164213	0.465965	0	0	0	0.20629
29	0.163395	0.451723	0.012	0.03	0	0.20629
30	0.161433	0.449246	0.053	0.063333	0	0.20629

IV. ANN design.

A sample of the training points is shown in **Table 4.13**. Some of the obtained training points are presented in Appendix (C).

Table 4.13 Sample of the ANN training points.

Bus No	Voltage Mag	Angle Degree	Load MW	Load MVAR	Generation MW	Generation MVAR	Target
1	0.172228	0.499784	0	0	0.410101	0.199913	0
2	0.168629	0.48417	0.1085	0.423333	0.060907	0.233974	1
3	0.165522	0.476184	0.05	0.04	0	0.20629	1
4	0.164213	0.47173	0.038	0.053333	0	0.20629	1
5	0.16405	0.458708	0.471	0.633333	0	0.238054	1
6	0.164213	0.466927	0	0	0	0.20629	1
7	0.162905	0.462074	0.114	0.363333	0	0.20629	1

8	0.16405	0.464851	0.15	1	0	0.234142	1
9	0.170592	0.458377	0	0	0	0.20629	1
10	0.169611	0.4539	0.029	0.066667	0	0.20629	1
11	0.175826	0.458377	0	0	0	0.219629	0
12	0.171573	0.455892	0.056	0.25	0	0.20629	0
13	0.174027	0.455892	0	0	0	0.215251	0
14	0.169284	0.453401	0.031	0.053333	0	0.20629	1
15	0.168466	0.453159	0.041	0.083333	0	0.20629	1
16	0.169611	0.454284	0.0175	0.06	0	0.20629	1
17	0.168629	0.453432	0.045	0.193333	0	0.20629	1
18	0.16683	0.451468	0.016	0.03	0	0.20629	1
19	0.16634	0.450999	0.0475	0.113333	0	0.20629	1
20	0.166994	0.451563	0.011	0.023333	0	0.20629	1
21	0.167484	0.452649	0.0875	0.373333	0	0.20629	1
22	0.167648	0.452688	0	0	0	0.20629	1
23	0.166667	0.452088	0.016	0.053333	0	0.20629	1
24	0.165849	0.451631	0.0435	0.223333	0	0.20629	1
25	0.165358	0.452781	0	0	0	0.20629	1
26	0.162414	0.4516	0.0175	0.076667	0	0.20629	1
27	0.166503	0.454225	0	0	0	0.20629	1
28	0.16405	0.465062	0	0	0	0.20629	1
29	0.163232	0.450781	0.012	0.03	0	0.20629	1
30	0.161269	0.448315	0.053	0.063333	0	0.20629	1

The construction of the ANN for the 30-bus IEEE standard system is shown in **Table 4.14**. The input and output layers have the same design of the 14-bus IEEE standard system. The hidden layers are changed into seven and eleven neurons

Table 4.14 The construction of the developed ANN.

No. of inputs	No. of neurons of 1 st layer	No. of neurons of 2 nd layer	No. of outputs
5	10	15	1

The developed ANN is trained using 615 study cases. The network is trained also using the MATLAB/NNET tool box

V. Testing the ANN.

The generated ANN is then tested using 280 testing points and two samples of the results are shown in **Table 4.15** and **Table 4.16**.

Table 4.15 Sample of the testing points when $P_{Load} = 200$ MW at Bus 3.

Bus No	Voltage Mag	Angle Degree	Load MW	Load MVAR	Generation MW	Generation MVAR	Target	Output
1	0.172228	0.499784	0	0	0.74805	0.248743	0	0
2	0.16454	0.474302	0.1085	0.423333	0.060907	0.244092	1	1
3	0.155054	0.445793	1	0.04	0	0.20629	1	1
4	0.15669	0.446654	0.038	0.053333	0	0.20629	1	1
5	0.159143	0.44128	0.471	0.633333	0	0.241822	1	1
6	0.158325	0.444935	0	0	0	0.20629	1	1
7	0.157998	0.441799	0.114	0.363333	0	0.20629	1	1
8	0.158816	0.44186	0.15	1	0	0.251209	1	1
9	0.167157	0.434979	0	0	0	0.20629	1	1
10	0.165522	0.42991	0.029	0.066667	0	0.20629	1	1
11	0.175826	0.435268	0	0	0	0.228404	0	0
12	0.167648	0.430853	0.056	0.25	0	0.20629	1	1
13	0.172391	0.430735	0	0	0	0.224122	0	0
14	0.165195	0.428289	0.031	0.053333	0	0.20629	1	1

15	0.164377	0.428292	0.041	0.083333	0	0.20629	1	1
16	0.165358	0.429731	0.0175	0.06	0	0.20629	1	1
17	0.164704	0.429271	0.045	0.193333	0	0.20629	1	1
18	0.162905	0.426777	0.016	0.03	0	0.20629	1	1
19	0.162251	0.426502	0.0475	0.113333	0	0.20629	1	1
20	0.163068	0.427178	0.011	0.023333	0	0.20629	1	1
21	0.163395	0.428634	0.0875	0.373333	0	0.20629	1	1
22	0.163395	0.428628	0	0	0	0.20629	1	1
23	0.162414	0.427534	0.016	0.053333	0	0.20629	1	1
24	0.161269	0.427445	0.0435	0.223333	0	0.20629	1	1
25	0.160124	0.429038	0	0	0	0.20629	1	1
26	0.157344	0.428126	0.0175	0.076667	0	0.20629	1	1
27	0.160942	0.430499	0	0	0	0.20629	1	1
28	0.158489	0.4431	0	0	0	0.20629	1	1
29	0.157671	0.427094	0.012	0.03	0	0.20629	1	1
30	0.155872	0.424039	0.053	0.063333	0	0.20629	1	1

Table 4.16 Sample of the testing points when $P_{Load} = 190$ MW at Bus 16.

Bus No	Voltage Mag	Angle Degree	Load MW	Load MVAR	Generation MW	Generation MVAR	Target	Output
1	0.172228	0.499784	0	0	0.827171	0.248342	0	0
2	0.163068	0.468268	0.1085	0.423333	0.060907	0.299617	1	1
3	0.152601	0.450548	0.012	0.04	0	0.20629	1	1
4	0.149002	0.438811	0.038	0.053333	0	0.20629	1	1
5	0.160779	0.428839	0.471	0.633333	0	0.270582	1	1
6	0.151783	0.430095	0	0	0	0.20629	1	1
7	0.15489	0.427924	0.114	0.363333	0	0.20629	1	1
8	0.15718	0.424847	0.15	1	0	0.317924	1	1
9	0.154236	0.395687	0	0	0	0.20629	1	1

10	0.14524	0.375182	0.029	0.066667	0	0.20629	1	1
11	0.175826	0.39668	0	0	0	0.261759	0	0
12	0.147857	0.366749	0.056	0.25	0	0.20629	1	1
13	0.168302	0.366185	0	0	0	0.2807	0	0
14	0.144913	0.36434	0.031	0.053333	0	0.20629	1	1
15	0.14475	0.366803	0.041	0.083333	0	0.20629	1	1
16	0.112202	0.31555	0.95	0.06	0	0.20629	1	1
17	0.132646	0.360053	0.045	0.193333	0	0.20629	1	1
18	0.143114	0.366096	0.016	0.03	0	0.20629	1	1
19	0.141642	0.368654	0.0475	0.113333	0	0.20629	1	1
20	0.142787	0.36935	0.011	0.023333	0	0.20629	1	1
21	0.143278	0.375013	0.0875	0.373333	0	0.20629	1	1
22	0.143278	0.374853	0	0	0	0.20629	1	1
23	0.143114	0.370626	0.016	0.053333	0	0.20629	1	1
24	0.142951	0.3759	0.0435	0.223333	0	0.20629	1	1
25	0.147203	0.390217	0	0	0	0.20629	1	1
26	0.144259	0.389331	0.0175	0.076667	0	0.20629	1	1
27	0.151783	0.398846	0	0	0	0.20629	1	1
28	0.151783	0.426247	0	0	0	0.20629	1	1
29	0.148348	0.395499	0.012	0.03	0	0.20629	1	1
30	0.146222	0.391541	0.053	0.063333	0	0.20629	1	1

It is found from the tested cases that the accuracy of the developed ANN of the 30-bus IEEE system is about 96.79%.

CHAPTER FIVE
CONCLUSION AND FUTURE WORK

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 CONCLUSION

As voltage instability is danger for power systems, this thesis has proposed an early voltage instability detector based on PMUs readings utilizing ANN. This detector is developed through four stages. The first stage is the simulation of the power system using MATLAB/Power system toolbox. In this stage, different loading cases at different locations of the system are applied, analyzed and studied. The load changing is applied through two strategies. The first strategy is by increasing the load while keeping the same power factor. The second strategy is by varying the power factor while fixing the total consuming apparent power of the load. A huge number of different studied cases are produced and tabulated using Excel files.

In the second stage, the normalization of the output saved data of the first stage takes place

The third stage is the design of a feed-forward neural network. In this thesis, there are two developed ANNs each one is used for one of the two simulated system. Both of them have the same number of inputs which are voltage angle degree, load active power, Load reactive power, generation active power and generation reactive power. Also, they have the same output which indicates the status of the system bus as stable, alarm and trip by giving an output of 1, 0, and -1 for each system bus respectively. The hidden layers of the two developed ANNs consist of different number of neurons with tan-sigmoid activation function. The ANN of the 14-Bus IEEE standard system consists of two hidden layers with six and eight neurons, respectively. The ANN of the 30-Bus IEEE standard system consists of two hidden layers with ten and fifteen neurons, respectively.

The smart enhanced technique is applied to IEEE 14-bus and 30-bus IEEE standard systems. The systems are simulated and 1357 studied cases are acquired for the 14-bus IEEE system and 895 studied cases are acquired for the 30-bus IEEE system. 900 studied cases for 14-bus IEEE system and 615 studied cases for the 30-bus IEEE system are used for training the ANNs and the rest are used for the examining stage. It is discovered that the accuracy of the ANN of the 14-Bus IEEE standard system is 97.34% and the ANN of the 30-Bus IEEE standard system is 96.79%.

5.2 FUTURE WORK

A set of suggestions may be presented here as a continuation of research in thesis area as have been observed throughout this work. Such suggestions may be summarized in the following points:

- Developing the work using different advanced Artificial Intelligence.
- Doing a comparison between the performance of different Artificial Intelligence techniques in solving voltage instability problems.
- Implementation of the voltage instability alarming predictor in a working power network

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APPENDICES

Appendix A

IEEE 14-BUS TEST SYSTEM

Table A.1 BUS DATA FOR IEEE-14 BUS SYSTEM

Bus No.	Bus Code	Voltage Magnitude	Angle Degree	Load		Generator				Injected MVAR
				MW	MVAR	MW	MVAR	Qmin	Qmax	
1	1	1.06	0	30	17.78	40	-40.0 0	0	0	0
2	2	1.045	0	0	0	232	0.0 -40	50	0	0
3	2	1.01	0	131.9	26.6	0	0.0 0	0	0	0
4	0	1	0	66.92	10	0	0.0 0	0	0	0
5	0	1	0	10.64	2.24	0	0.0 -40	40	0	0
6	2	1.07	0	15.68	10.5	0	0.0 0	0	0	0
7	0	1	0	0	0	0	0.0 0	0	0	0
8	2	1.09	0	0	0	0	0.0 -30	40	0	0
9	0	1	0	41.3	23.24	0	0.0 0	0	0	0
10	0	1	0	12.6	8.12	0	0.0 -6	24	19	0
11	0	1	0	4.9	2.52	0	0.0 0	0	0	0
12	0	1	0	8.54	2.24	0	0 0	0	0	0
13	0	1	0	18.9	8.12	0	0 -6	24	0	0
14	0	1	0	20.86	7	0	0 0	0	0	0

Table A.2 LINE DATA FOR IEEE-14 BUS SYSTEM

From Bus	To Bus	Resistance (p.u.)	Reactance (p.u.)	Line Charging (p.u.)	Tap ratio
1	2	0.01938	0.05917	0.0264	1
1	5	0.05403	0.22304	0.0246	1
2	3	0.04699	0.19797	0.0219	1
2	4	0.05811	0.17632	0.0187	1
2	5	0.05695	0.17388	0.017	1
3	4	0.06701	0.17103	0.0173	1
4	5	0.01335	0.04211	0.0064	1
4	7	0	0.20912	0	0.978
4	9	0	0.55618	0	0.969
5	6	0	0.25202	0	0.932
6	11	0.09498	0.1989	0	1
6	12	0.12291	0.25581	0	1
6	13	0.06615	0.13027	0	1
7	8	0	0.17615	0	1
7	9	0	0.11001	0	1
9	10	0.03181	0.0845	0	1
9	14	0.12711	0.27038	0	1
10	11	0.08205	0.19207	0	1
12	13	0.22092	0.19988	0	1
13	11	0.17093	0.34802	0	1

Appendix B

IEEE 30-BUS TEST SYSTEM

Table B.1 BUS DATA FOR IEEE-30 BUS SYSTEM

Bus No.	Bus Code	Voltage Magnitude	Angle Degree	Load		Generator				Injected MVAR
				MW	MVAR	MW	MVAR	Qmin	Qmax	
1	1	1.06	0	0	0	0	0	0	0	0
2	2	1.043	0	21.7	12.7	40	0	-40	50	0
3	0	1	0	2.4	1.2	0	0	0	0	0
4	0	1.06	0	7.6	1.6	0	0	0	0	0
5	2	1.01	0	94.2	19	0	0	-40	40	0
6	0	1	0	0	0	0	0	0	0	0
7	0	1	0	22.8	10.9	0	0	0	0	0
8	2	1.01	0	30	30	0	0	-30	40	0
9	0	1	0	0	0	0	0	0	0	0
10	0	1	0	5.8	2	0	0	-6	24	19
11	2	1.082	0	0	0	0	0	0	0	0
12	0	1	0	11.2	7.5	0	0	0	0	0
13	2	1.071	0	0	0	0	0	-6	24	0
14	0	1	0	6.2	1.6	0	0	0	0	0
15	0	1	0	8.2	2.5	0	0	0	0	0
16	0	1	0	3.5	1.8	0	0	0	0	0
17	0	1	0	9	5.8	0	0	0	0	0
18	0	1	0	3.2	0.9	0	0	0	0	0
19	0	1	0	9.5	3.4	0	0	0	0	0
20	0	1	0	2.2	0.7	0	0	0	0	0
21	0	1	0	17.5	11.2	0	0	0	0	0
22	0	1	0	0	0	0	0	0	0	0
23	0	1	0	3.2	1.6	0	0	0	0	0
24	0	1	0	8.7	6.7	0	0	0	0	4.3
25	0	1	0	0	0	0	0	0	0	0
26	0	1	0	3.5	2.3	0	0	0	0	0
27	0	1	0	0	0	0	0	0	0	0
28	0	1	0	0	0	0	0	0	0	0
29	0	1	0	2.4	0.9	0	0	0	0	0
30	0	1	0	10.6	1.9	0	0	0	0	0

Table B.2 LINE DATA FOR IEEE-30 BUS SYSTEM

From Bus	To Bus	Resistance (p.u.)	Reactance (p.u.)	Line Charging (p.u.)	Tap ratio
1	2	0.0192	0.0575	0.0264	1
1	3	0.0452	0.1852	0.0204	1
2	4	0.057	0.1737	0.0184	1
3	4	0.0132	0.0379	0.0042	1
2	5	0.0472	0.1983	0.0209	1
2	6	0.0581	0.1763	0.0187	1
4	6	0.0119	0.0414	0.0045	1
5	7	0.046	0.116	0.0102	1
6	7	0.0267	0.082	0.0085	1
6	8	0.012	0.042	0.0045	1
6	9	0	0.208	0.0 0.97	8
6	10	0	0.556	0 0.96	9
9	11	0	0.208	0	1
9	10	0	0.11	0	1
4	12	0	0.256	0 0.93	2
12	13	0	0.14	0	1
12	14	0.1231	0.2559	0	1
12	15	0.0662	0.1304	0	1
12	16	0.0945	0.1987	0	1
14	15	0.221	0.1997	0	1
16	17	0.0824	0.1923	0	1
15	18	0.1073	0.2185	0	1
18	19	0.0639	0.1292	0	1
19	20	0.034	0.068	0	1
10	20	0.0936	0.209	0	1
10	17	0.0324	0.0845	0	1
10	21	0.0348	0.0749	0	1
10	22	0.0727	0.1499	0	1
21	22	0.0116	0.0236	0	1
15	23	0.1	0.202	0	1
22	24	0.115	0.179	0	1
23	24	0.132	0.27	0	1
24	25	0.1885	0.3292	0	1
25	26	0.2544	0.38	0	1
25	27	0.1093	0.2087	0	1
28	27	0	0.396	0 0.96	8
27	29	0.2198	0.4153	0	1
27	30	0.3202	0.6027	0	1
29	30	0.2399	0.4533	0	1
8	28	0.0636	0.2	0.0214	1
6	28	0.0169	0.0599	0.065	1

Appendix C

IEEE 30-BUS SYSTEM TRAINING POINTS

Table C.1 TRAINING POINTS FOR IEEE-30 BUS SYSTEM

Bus No	Angle Degree	Load MW	Load MVAR	Generation MW	Generation MVAR	Target
1	0.172227674	0.499784003	0	0	0.397345044	0
2	0.16944717	0.484366848	0.1085	0.423333333	0.06090746	1
3	0.16601243	0.477337118	0.012	0.04	0	1
4	0.164540399	0.47268897	0.038	0.053333333	0	1
5	0.164049722	0.459445813	0.471	0.633333333	0	1
6	0.16437684	0.467816408	0	0	0	1
7	0.162904809	0.462898964	0.114	0.363333333	0	1
8	0.164049722	0.465802304	0.15	1	0	1
9	0.170755643	0.459299944	0	0	0	0
10	0.169610729	0.454834131	0.029	0.066666667	0	1
11	0.175825973	0.459299944	0	0	0	0
12	0.171736997	0.456862261	0.056	0.25	0	0
13	0.174026824	0.456865066	0	0	0	0
14	0.16944717	0.454368474	0.031	0.053333333	0	1
15	0.168629375	0.454127231	0.041	0.083333333	0	1
16	0.169774289	0.455240879	0.0175	0.06	0	1
17	0.168792934	0.45437689	0.045	0.193333333	0	1
18	0.166993785	0.452430109	0.016	0.03	0	1
19	0.166503108	0.451958843	0.0475	0.113333333	0	1
20	0.167157344	0.452514264	0.011	0.023333333	0	1
21	0.167648021	0.45358864	0.0875	0.373333333	0	1
22	0.16781158	0.453625107	0	0	0	1
23	0.166830226	0.45305005	0.016	0.053333333	0	1
24	0.16601243	0.452575978	0.0435	0.223333333	0	1
25	0.165521753	0.453714872	0	0	0	1
26	0.162577691	0.452559147	0.0175	0.076666667	0	1
27	0.166666667	0.455145504	0	0	0	1
28	0.164213281	0.465965003	0	0	0	1
29	0.163395486	0.451723209	0.012	0.03	0	1
30	0.161432777	0.449246254	0.053	0.063333333	0	1

1	0.172227674	0.499784003	0	0	0.410100589	0
2	0.168629375	0.484170486	0.1085	0.423333333	0.06090746	1
3	0.165521753	0.476184198	0.05	0.04	0	1
4	0.164213281	0.471729605	0.038	0.053333333	0	1
5	0.164049722	0.458708056	0.471	0.633333333	0	1
6	0.164213281	0.466927172	0	0	0	1
7	0.162904809	0.462074247	0.114	0.363333333	0	1
8	0.164049722	0.464851355	0.15	1	0	1
9	0.170592084	0.458377047	0	0	0	1
10	0.169610729	0.453900013	0.029	0.066666667	0	1
11	0.175825973	0.458377047	0	0	0	0
12	0.171573438	0.455891676	0.056	0.25	0	0
13	0.174026824	0.455891676	0	0	0	0
14	0.169283611	0.453400695	0.031	0.053333333	0	1
15	0.168465816	0.453159451	0.041	0.083333333	0	1
16	0.169610729	0.45428432	0.0175	0.06	0	1
17	0.168629375	0.453431551	0.045	0.193333333	0	1
18	0.166830226	0.45146794	0.016	0.03	0	1
19	0.166339549	0.450999478	0.0475	0.113333333	0	1
20	0.166993785	0.451563315	0.011	0.023333333	0	1
21	0.167484462	0.452648912	0.0875	0.373333333	0	1
22	0.167648021	0.452688184	0	0	0	1
23	0.166666667	0.45208788	0.016	0.053333333	0	1
24	0.165848871	0.451630639	0.0435	0.223333333	0	1
25	0.165358194	0.452780754	0	0	0	1
26	0.162414132	0.451599782	0.0175	0.076666667	0	1
27	0.166503108	0.454225411	0	0	0	1
28	0.164049722	0.465061742	0	0	0	1
29	0.163231927	0.450780676	0.012	0.03	0	1
30	0.161269218	0.448314941	0.053	0.063333333	0	1
1	0.172227674	0.499784003	0	0	0.426735939	0
2	0.168629375	0.483657142	0.1085	0.423333333	0.06090746	1
3	0.165194635	0.474711489	0.1	0.04	0	1
4	0.164049722	0.470531802	0.038	0.053333333	0	1
5	0.164049722	0.457914196	0.471	0.633333333	0	1
6	0.164049722	0.465869627	0	0	0	1
7	0.16274125	0.461126103	0.114	0.363333333	0	1
8	0.164049722	0.463774173	0.15	1	0	1
9	0.170592084	0.45728584	0	0	0	1
10	0.16944717	0.452791975	0.029	0.066666667	0	1
11	0.175825973	0.45728584	0	0	0	0
12	0.171573438	0.45473034	0.056	0.25	0	0
13	0.174026824	0.45473034	0	0	0	0
14	0.169120052	0.452242164	0.031	0.053333333	0	1

15	0.168465816	0.452009336	0.041	0.083333333	0	1
16	0.16944717	0.45314262	0.0175	0.06	0	1
17	0.168629375	0.452315098	0.045	0.193333333	0	1
18	0.166830226	0.45033185	0.016	0.03	0	1
19	0.166339549	0.449871804	0.0475	0.113333333	0	1
20	0.166993785	0.450441252	0.011	0.023333333	0	1
21	0.167484462	0.451540874	0.0875	0.373333333	0	1
22	0.167484462	0.451580146	0	0	0	1
23	0.166666667	0.450954596	0.016	0.053333333	0	1
24	0.165685312	0.450514186	0.0435	0.223333333	0	1
25	0.165358194	0.451681132	0	0	0	1
26	0.162414132	0.450502965	0.0175	0.076666667	0	1
27	0.166339549	0.45313701	0	0	0	1
28	0.163886163	0.463998586	0	0	0	1
29	0.163231927	0.449692274	0.012	0.03	0	1
30	0.161269218	0.447223734	0.053	0.063333333	0	1
1	0.172227674	0.499784003	0	0	0.435087874	0
2	0.168629375	0.483399068	0.1085	0.423333333	0.06090746	1
3	0.165031076	0.473973732	0.125	0.04	0	1
4	0.163886163	0.469928693	0.038	0.053333333	0	1
5	0.164049722	0.457518668	0.471	0.633333333	0	1
6	0.164049722	0.465339452	0	0	0	1
7	0.16274125	0.460649226	0.114	0.363333333	0	1
8	0.164049722	0.463232778	0.15	1	0	1
9	0.170592084	0.456738834	0	0	0	1
10	0.16944717	0.452236553	0.029	0.066666667	0	1
11	0.175825973	0.456738834	0	0	0	0
12	0.171573438	0.454146867	0.056	0.25	0	0
13	0.174026824	0.454146867	0	0	0	0
14	0.169120052	0.451661496	0.031	0.053333333	0	1
15	0.168302257	0.451431473	0.041	0.083333333	0	1
16	0.16944717	0.452570367	0.0175	0.06	0	1
17	0.168629375	0.451754066	0.045	0.193333333	0	1
18	0.166830226	0.449759598	0.016	0.03	0	1
19	0.166339549	0.449305162	0.0475	0.113333333	0	1
20	0.166993785	0.449877415	0.011	0.023333333	0	1
21	0.167484462	0.450982647	0.0875	0.373333333	0	1
22	0.167484462	0.45102192	0	0	0	1
23	0.166666667	0.450382343	0.016	0.053333333	0	1
24	0.165685312	0.449953154	0.0435	0.223333333	0	1
25	0.165194635	0.451131321	0	0	0	1
26	0.162414132	0.449950349	0.0175	0.076666667	0	1
27	0.166339549	0.452590004	0	0	0	1
28	0.163886163	0.463462801	0	0	0	1

29	0.163068368	0.449145268	0.012	0.03	0	1
30	0.161269218	0.446676728	0.053	0.063333333	0	1
1	0.172227674	0.499784003	0	0	0.451855698	0
2	0.168629375	0.482882918	0.1085	0.423333333	0.06090746	1
3	0.164703958	0.472481388	0.175	0.04	0	1
4	0.163722604	0.468708449	0.038	0.053333333	0	1
5	0.163231927	0.456856651	0.471	0.633333333	0	1
6	0.163886163	0.464259466	0	0	0	1
7	0.162414132	0.459726329	0.114	0.363333333	0	1
8	0.164049722	0.462102299	0.15	1	0	1
9	0.170428525	0.45561677	0	0	0	1
10	0.169283611	0.451097659	0.029	0.066666667	0	1
11	0.175825973	0.455619576	0	0	0	0
12	0.171409879	0.452951869	0.056	0.25	0	0
13	0.174026824	0.452951869	0	0	0	0
14	0.168956493	0.450469303	0.031	0.053333333	0	1
15	0.168302257	0.450250501	0.041	0.083333333	0	1
16	0.16944717	0.451397811	0.0175	0.06	0	1
17	0.168465816	0.450603951	0.045	0.193333333	0	1
18	0.166666667	0.448589846	0.016	0.03	0	1
19	0.16617599	0.448143826	0.0475	0.113333333	0	1
20	0.166830226	0.448721689	0.011	0.023333333	0	1
21	0.167320903	0.449840947	0.0875	0.373333333	0	1
22	0.167484462	0.44988022	0	0	0	1
23	0.166503108	0.449215397	0.016	0.053333333	0	1
24	0.165685312	0.448805844	0.0435	0.223333333	0	1
25	0.165194635	0.449998036	0	0	0	1
26	0.162250572	0.44881987	0.0175	0.076666667	0	1
27	0.16617599	0.45146794	0	0	0	1
28	0.163722604	0.462371594	0	0	0	1
29	0.163068368	0.448020399	0.012	0.03	0	1
30	0.161105659	0.445543444	0.053	0.063333333	0	1
1	0.172227674	0.499784003	0	0	0.460235042	0
2	0.168629375	0.482605207	0.1085	0.423333333	0.06090746	1
3	0.164213281	0.471782903	0.2	0.04	0	1
4	0.163231927	0.468158637	0.038	0.053333333	0	1
5	0.163231927	0.45639941	0.471	0.633333333	0	1
6	0.163395486	0.463810641	0	0	0	1
7	0.162087013	0.459271893	0.114	0.363333333	0	1
8	0.163231927	0.461732018	0.15	1	0	1
9	0.170264966	0.455111842	0	0	0	1
10	0.169120052	0.450567484	0.029	0.066666667	0	1
11	0.175825973	0.455111842	0	0	0	0
12	0.17124632	0.45235998	0.056	0.25	0	0

13	0.174026824	0.45235998	0	0	0	0
14	0.168792934	0.449877415	0.031	0.053333333	0	1
15	0.167975139	0.449667028	0.041	0.083333333	0	1
16	0.169120052	0.450831169	0.0175	0.06	0	1
17	0.168302257	0.45005975	0.045	0.193333333	0	1
18	0.166339549	0.448020399	0.016	0.03	0	1
19	0.16601243	0.447582794	0.0475	0.113333333	0	1
20	0.166666667	0.448166267	0.011	0.023333333	0	1
21	0.166993785	0.449305162	0.0875	0.373333333	0	1
22	0.167157344	0.449344434	0	0	0	1
23	0.166339549	0.448648755	0.016	0.053333333	0	1
24	0.165358194	0.448261643	0.0435	0.223333333	0	1
25	0.164703958	0.449490303	0	0	0	1
26	0.161923454	0.448286889	0.0175	0.076666667	0	1
27	0.165848871	0.450991063	0	0	0	1
28	0.163231927	0.461931184	0	0	0	1
29	0.162577691	0.447507055	0.012	0.03	0	1
30	0.160614982	0.445030099	0.053	0.063333333	0	1
1	0.172227674	0.499784003	0	0	0.477187111	0
2	0.168629375	0.482080643	0.1085	0.423333333	0.06090746	1
3	0.163886163	0.470284948	0.25	0.04	0	1
4	0.163068368	0.466935588	0.038	0.053333333	0	1
5	0.163231927	0.455588719	0.471	0.633333333	0	1
6	0.163395486	0.462730654	0	0	0	1
7	0.162087013	0.458298503	0.114	0.363333333	0	1
8	0.163231927	0.4606352	0.15	1	0	1
9	0.170101407	0.453998193	0	0	0	1
10	0.168956493	0.449434199	0.029	0.066666667	0	1
11	0.175825973	0.453995388	0	0	0	0
12	0.17124632	0.451173398	0.056	0.25	0	0
13	0.174026824	0.451173398	0	0	0	0
14	0.168792934	0.448699248	0.031	0.053333333	0	1
15	0.167975139	0.448494471	0.041	0.083333333	0	1
16	0.169120052	0.449667028	0.0175	0.06	0	1
17	0.168138698	0.44891805	0.045	0.193333333	0	1
18	0.166339549	0.446861868	0.016	0.03	0	1
19	0.165848871	0.446432679	0.0475	0.113333333	0	1
20	0.166503108	0.447021762	0.011	0.023333333	0	1
21	0.166993785	0.448171878	0.0875	0.373333333	0	1
22	0.167157344	0.448208345	0	0	0	1
23	0.16617599	0.447487419	0.016	0.053333333	0	1
24	0.165194635	0.447122748	0.0435	0.223333333	0	1
25	0.164703958	0.448365434	0	0	0	1
26	0.161759895	0.447209708	0.0175	0.076666667	0	1

27	0.165685312	0.449857778	0	0	0	1
28	0.163231927	0.460834367	0	0	0	1
29	0.162414132	0.446413043	0.012	0.03	0	1
30	0.160614982	0.443896815	0.053	0.063333333	0	1
1	0.172227674	0.499784003	0	0	0.485759836	0
2	0.16781158	0.481993683	0.1085	0.423333333	0.06090746	1
3	0.163231927	0.469499503	0.275	0.04	0	1
4	0.162414132	0.466293206	0.038	0.053333333	0	1
5	0.162414132	0.455103426	0.471	0.633333333	0	1
6	0.162577691	0.462152791	0	0	0	1
7	0.161269218	0.457745886	0.114	0.363333333	0	1
8	0.162414132	0.460051727	0.15	1	0	1
9	0.169774289	0.453344591	0	0	0	1
10	0.168629375	0.448749741	0.029	0.066666667	0	1
11	0.175825973	0.453344591	0	0	0	0
12	0.170919202	0.450432836	0.056	0.25	0	0
13	0.174026824	0.450432836	0	0	0	0
14	0.168302257	0.44795027	0.031	0.053333333	0	1
15	0.167648021	0.447759519	0.041	0.083333333	0	1
16	0.168792934	0.448948907	0.0175	0.06	0	1
17	0.16781158	0.448219565	0.045	0.193333333	0	1
18	0.16601243	0.446132527	0.016	0.03	0	1
19	0.165521753	0.445711753	0.0475	0.113333333	0	1
20	0.16617599	0.446306447	0.011	0.023333333	0	1
21	0.166503108	0.447479003	0.0875	0.373333333	0	1
22	0.166666667	0.44751547	0	0	0	1
23	0.165848871	0.446766493	0.016	0.053333333	0	1
24	0.164703958	0.446418653	0.0435	0.223333333	0	1
25	0.164049722	0.447695001	0	0	0	1
26	0.161105659	0.446483172	0.0175	0.076666667	0	1
27	0.165031076	0.449229423	0	0	0	1
28	0.162414132	0.460256504	0	0	0	1
29	0.161759895	0.445717363	0.012	0.03	0	1
30	0.159960746	0.443215161	0.053	0.063333333	0	1
1	0.172227674	0.499784003	0	0	0.502824583	0
2	0.16781158	0.481457897	0.1085	0.423333333	0.06090746	1
3	0.162904809	0.467976302	0.325	0.04	0	1
4	0.162250572	0.465050521	0.038	0.053333333	0	1
5	0.162414132	0.454281515	0.471	0.633333333	0	1
6	0.162577691	0.461055974	0	0	0	1
7	0.161105659	0.456761275	0.114	0.363333333	0	1
8	0.162414132	0.458929663	0.15	1	0	1
9	0.169774289	0.452211307	0	0	0	1
10	0.168465816	0.44759682	0.029	0.066666667	0	1

11	0.175825973	0.452211307	0	0	0	0
12	0.170755643	0.449226618	0.056	0.25	0	0
13	0.174026824	0.449229423	0	0	0	0
14	0.168302257	0.446749662	0.031	0.053333333	0	1
15	0.167484462	0.446564521	0.041	0.083333333	0	1
16	0.168629375	0.44776513	0.0175	0.06	0	1
17	0.167648021	0.447058229	0.045	0.193333333	0	1
18	0.165848871	0.444951555	0.016	0.03	0	1
19	0.165358194	0.444539196	0.0475	0.113333333	0	1
20	0.16601243	0.445142306	0.011	0.023333333	0	1
21	0.166503108	0.446326083	0.0875	0.373333333	0	1
22	0.166503108	0.44636255	0	0	0	1
23	0.165685312	0.445585521	0.016	0.053333333	0	1
24	0.164703958	0.445260122	0.0435	0.223333333	0	1
25	0.164049722	0.446553301	0	0	0	1
26	0.161105659	0.445341472	0.0175	0.076666667	0	1
27	0.165031076	0.448098944	0	0	0	1
28	0.162414132	0.459151271	0	0	0	1
29	0.161759895	0.444584079	0.012	0.03	0	1
30	0.159797187	0.442079072	0.053	0.063333333	0	1
1	0.172227674	0.499784003	0	0	0.511353151	0
2	0.16781158	0.481188602	0.1085	0.423333333	0.06090746	1
3	0.162577691	0.467213299	0.35	0.04	0	1
4	0.162087013	0.464427776	0.038	0.053333333	0	1
5	0.162414132	0.453866351	0.471	0.633333333	0	1
6	0.162414132	0.460503358	0	0	0	1
7	0.161105659	0.456267567	0.114	0.363333333	0	1
8	0.162414132	0.458365826	0.15	1	0	1
9	0.169610729	0.45164186	0	0	0	1
10	0.168465816	0.447018957	0.029	0.066666667	0	1
11	0.175825973	0.45164186	0	0	0	0
12	0.170755643	0.448620703	0.056	0.25	0	0
13	0.174026824	0.448620703	0	0	0	0
14	0.168302257	0.446146553	0.031	0.053333333	0	1
15	0.167484462	0.445964217	0.041	0.083333333	0	1
16	0.168629375	0.447170436	0.0175	0.06	0	1
17	0.167648021	0.446474756	0.045	0.193333333	0	1
18	0.165848871	0.444359666	0.016	0.03	0	1
19	0.165358194	0.443952918	0.0475	0.113333333	0	1
20	0.16601243	0.444556027	0.011	0.023333333	0	1
21	0.166503108	0.445745415	0.0875	0.373333333	0	1
22	0.166503108	0.445781882	0	0	0	1
23	0.165685312	0.444993632	0.016	0.053333333	0	1
24	0.164703958	0.444676649	0.0435	0.223333333	0	1

25	0.164049722	0.445978243	0	0	0	1
26	0.161105659	0.444760804	0.0175	0.076666667	0	1
27	0.165031076	0.447535107	0	0	0	1
28	0.162414132	0.458593044	0	0	0	1
29	0.161759895	0.444011827	0.012	0.03	0	1
30	0.159797187	0.441515235	0.053	0.063333333	0	1
1	0.172227674	0.499784003	0	0	0.581075443	0
2	0.166993785	0.479163277	0.1085	0.423333333	0.06090746	1
3	0.160614982	0.460921327	0.55	0.04	0	1
4	0.160614982	0.459285919	0.038	0.053333333	0	1
5	0.161596336	0.450382343	0.471	0.633333333	0	1
6	0.161432777	0.455939364	0	0	0	1
7	0.160124305	0.452129957	0.114	0.363333333	0	1
8	0.161596336	0.453714872	0.15	1	0	1
9	0.169120052	0.446867479	0	0	0	1
10	0.16781158	0.442152006	0.029	0.066666667	0	1
11	0.175825973	0.446867479	0	0	0	0
12	0.170101407	0.443501288	0.056	0.25	0	1
13	0.174026824	0.443498482	0	0	0	0
14	0.167648021	0.441043968	0.031	0.053333333	0	1
15	0.166830226	0.440892489	0.041	0.083333333	0	1
16	0.167975139	0.442149201	0.0175	0.06	0	1
17	0.166993785	0.441557312	0.045	0.193333333	0	1
18	0.165194635	0.439346847	0.016	0.03	0	1
19	0.164703958	0.438973761	0.0475	0.113333333	0	1
20	0.165358194	0.439604921	0.011	0.023333333	0	1
21	0.165848871	0.440861633	0.0875	0.373333333	0	1
22	0.165848871	0.440895295	0	0	0	1
23	0.165031076	0.439980813	0.016	0.053333333	0	1
24	0.163886163	0.439759205	0.0435	0.223333333	0	1
25	0.163068368	0.441156174	0	0	0	1
26	0.160124305	0.439949956	0.0175	0.076666667	0	1
27	0.164049722	0.442769141	0	0	0	1
28	0.161269218	0.453975752	0	0	0	1
29	0.160778541	0.43922342	0.012	0.03	0	1
30	0.158815833	0.436684751	0.053	0.063333333	0	1

Appendix D

ANN MATLAB TRAINING PROGRAM

```
function rec_nn_train

INPUT30;
OUTPUT30;

f = IN;
f2 = OUT;

train_data = f
train_targets = f2
size(train_data)

P = con2seq(train_data')
T = con2seq(train_targets')
size(T)
size(P)

numOfHiddenNodes_11 = 10
numOfHiddenNodes_12 = 15
net = newff(P,T,{numOfHiddenNodes_11,numOfHiddenNodes_12})

net.trainParam.epochs = 5000;
net.trainParam.goal = 0.001;

net = train(net,P,T);

save net;

end
```

Appendix E

ANN MATLAB TESTING PROGRAM

```
function rec_nn  
  
INPUT30TEST;  
f3 = INTEST;  
  
load net;  
output = sim(net,f3);  
  
output = round(output')  
  
xlswrite('Comp2test.xlsx', output);  
  
save output;  
end
```

Appendix F

IEEE 30-BUS SYSTEM TESTING POINTS

Table F.1 TESTING POINTS FOR IEEE-30 BUS SYSTEM

Bus No	Voltage Mag	Angle Degree	Load MW	Load MVAR	Generation MW	Generation MVAR	Output	Target
1	0.172228	0.499784	0	0	0.397345	0.192553	0	0
2	0.169447	0.484367	0.1085	0.423333	0.060907	0.24572	1	1
3	0.166012	0.477337	0.012	0.04	0	0.20629	1	1
4	0.16454	0.472689	0.038	0.053333	0	0.20629	1	1
5	0.16405	0.459446	0.471	0.633333	0	0.235359	1	1
6	0.164377	0.467816	0	0	0	0.20629	1	1
7	0.162905	0.462899	0.114	0.363333	0	0.20629	1	1
8	0.16405	0.465802	0.15	1	0	0.23113	1	1
9	0.170756	0.4593	0	0	0	0.20629	0	0
10	0.169611	0.454834	0.029	0.066667	0	0.20629	1	1
11	0.175826	0.4593	0	0	0	0.219302	0	0
12	0.171737	0.456862	0.056	0.25	0	0.20629	0	0
13	0.174027	0.456865	0	0	0	0.214694	0	0
14	0.169447	0.454368	0.031	0.053333	0	0.20629	1	1
15	0.168629	0.454127	0.041	0.083333	0	0.20629	1	1
16	0.169774	0.455241	0.0175	0.06	0	0.20629	1	1
17	0.168793	0.454377	0.045	0.193333	0	0.20629	1	1
18	0.166994	0.45243	0.016	0.03	0	0.20629	1	1
19	0.166503	0.451959	0.0475	0.113333	0	0.20629	1	1
20	0.167157	0.452514	0.011	0.023333	0	0.20629	1	1
21	0.167648	0.453589	0.0875	0.373333	0	0.20629	1	1
22	0.167812	0.453625	0	0	0	0.20629	1	1
23	0.16683	0.45305	0.016	0.053333	0	0.20629	1	1
24	0.166012	0.452576	0.0435	0.223333	0	0.20629	1	1
25	0.165522	0.453715	0	0	0	0.20629	1	1
26	0.162578	0.452559	0.0175	0.076667	0	0.20629	1	1
27	0.166667	0.455146	0	0	0	0.20629	1	1
28	0.164213	0.465965	0	0	0	0.20629	1	1
29	0.163395	0.451723	0.012	0.03	0	0.20629	1	1
30	0.161433	0.449246	0.053	0.063333	0	0.20629	1	1
1	0.172228	0.499784	0	0	0.410101	0.199913	0	0
2	0.168629	0.48417	0.1085	0.423333	0.060907	0.233974	1	1
3	0.165522	0.476184	0.05	0.04	0	0.20629	1	1

4	0.164213	0.47173	0.038	0.053333	0	0.20629	1	1
5	0.16405	0.458708	0.471	0.633333	0	0.238054	1	1
6	0.164213	0.466927	0	0	0	0.20629	1	1
7	0.162905	0.462074	0.114	0.363333	0	0.20629	1	1
8	0.16405	0.464851	0.15	1	0	0.234142	1	1
9	0.170592	0.458377	0	0	0	0.20629	1	1
10	0.169611	0.4539	0.029	0.066667	0	0.20629	1	1
11	0.175826	0.458377	0	0	0	0.219629	0	0
12	0.171573	0.455892	0.056	0.25	0	0.20629	0	0
13	0.174027	0.455892	0	0	0	0.215251	0	0
14	0.169284	0.453401	0.031	0.053333	0	0.20629	1	1
15	0.168466	0.453159	0.041	0.083333	0	0.20629	1	1
16	0.169611	0.454284	0.0175	0.06	0	0.20629	1	1
17	0.168629	0.453432	0.045	0.193333	0	0.20629	1	1
18	0.16683	0.451468	0.016	0.03	0	0.20629	1	1
19	0.16634	0.450999	0.0475	0.113333	0	0.20629	1	1
20	0.166994	0.451563	0.011	0.023333	0	0.20629	1	1
21	0.167484	0.452649	0.0875	0.373333	0	0.20629	1	1
22	0.167648	0.452688	0	0	0	0.20629	1	1
23	0.166667	0.452088	0.016	0.053333	0	0.20629	1	1
24	0.165849	0.451631	0.0435	0.223333	0	0.20629	1	1
25	0.165358	0.452781	0	0	0	0.20629	1	1
26	0.162414	0.4516	0.0175	0.076667	0	0.20629	1	1
27	0.166503	0.454225	0	0	0	0.20629	1	1
28	0.16405	0.465062	0	0	0	0.20629	1	1
29	0.163232	0.450781	0.012	0.03	0	0.20629	1	1
30	0.161269	0.448315	0.053	0.063333	0	0.20629	1	1
1	0.172228	0.499784	0	0	0.418407	0.199641	0	0
2	0.168629	0.483915	0.1085	0.423333	0.060907	0.234827	1	1
3	0.165358	0.475449	0.075	0.04	0	0.20629	1	1
4	0.16405	0.471132	0.038	0.053333	0	0.20629	1	1
5	0.16405	0.458313	0.471	0.633333	0	0.238143	1	1
6	0.164213	0.4664	0	0	0	0.20629	1	1
7	0.162905	0.4616	0.114	0.363333	0	0.20629	1	1
8	0.16405	0.464313	0.15	1	0	0.234618	1	1
9	0.170592	0.457833	0	0	0	0.20629	1	1
10	0.169447	0.453347	0.029	0.066667	0	0.20629	1	1
11	0.175826	0.457833	0	0	0	0.219681	0	0
12	0.171573	0.455314	0.056	0.25	0	0.20629	0	0
13	0.174027	0.455314	0	0	0	0.215372	0	0
14	0.16912	0.452823	0.031	0.053333	0	0.20629	1	1
15	0.168466	0.452584	0.041	0.083333	0	0.20629	1	1
16	0.169611	0.453715	0.0175	0.06	0	0.20629	1	1
17	0.168629	0.452873	0.045	0.193333	0	0.20629	1	1

18	0.16683	0.450901	0.016	0.03	0	0.20629	1	1
19	0.16634	0.450436	0.0475	0.113333	0	0.20629	1	1
20	0.166994	0.451002	0.011	0.023333	0	0.20629	1	1
21	0.167484	0.452096	0.0875	0.373333	0	0.20629	1	1
22	0.167648	0.452136	0	0	0	0.20629	1	1
23	0.166667	0.451521	0.016	0.053333	0	0.20629	1	1
24	0.165685	0.451072	0.0435	0.223333	0	0.20629	1	1
25	0.165358	0.452234	0	0	0	0.20629	1	1
26	0.162414	0.451053	0.0175	0.076667	0	0.20629	1	1
27	0.166503	0.453681	0	0	0	0.20629	1	1
28	0.16405	0.464532	0	0	0	0.20629	1	1
29	0.163232	0.450236	0.012	0.03	0	0.20629	1	1
30	0.161269	0.447771	0.053	0.063333	0	0.20629	1	1
1	0.172228	0.499784	0	0	0.426736	0.199386	0	0
2	0.168629	0.483657	0.1085	0.423333	0.060907	0.235695	1	1
3	0.165195	0.474711	0.1	0.04	0	0.20629	1	1
4	0.16405	0.470532	0.038	0.053333	0	0.20629	1	1
5	0.16405	0.457914	0.471	0.633333	0	0.238233	1	1
6	0.16405	0.46587	0	0	0	0.20629	1	1
7	0.162741	0.461126	0.114	0.363333	0	0.20629	1	1
8	0.16405	0.463774	0.15	1	0	0.235102	1	1
9	0.170592	0.457286	0	0	0	0.20629	1	1
10	0.169447	0.452792	0.029	0.066667	0	0.20629	1	1
11	0.175826	0.457286	0	0	0	0.219734	0	0
12	0.171573	0.45473	0.056	0.25	0	0.20629	0	0
13	0.174027	0.45473	0	0	0	0.215496	0	0
14	0.16912	0.452242	0.031	0.053333	0	0.20629	1	1
15	0.168466	0.452009	0.041	0.083333	0	0.20629	1	1
16	0.169447	0.453143	0.0175	0.06	0	0.20629	1	1
17	0.168629	0.452315	0.045	0.193333	0	0.20629	1	1
18	0.16683	0.450332	0.016	0.03	0	0.20629	1	1
19	0.16634	0.449872	0.0475	0.113333	0	0.20629	1	1
20	0.166994	0.450441	0.011	0.023333	0	0.20629	1	1
21	0.167484	0.451541	0.0875	0.373333	0	0.20629	1	1
22	0.167484	0.45158	0	0	0	0.20629	1	1
23	0.166667	0.450955	0.016	0.053333	0	0.20629	1	1
24	0.165685	0.450514	0.0435	0.223333	0	0.20629	1	1
25	0.165358	0.451681	0	0	0	0.20629	1	1
26	0.162414	0.450503	0.0175	0.076667	0	0.20629	1	1
27	0.16634	0.453137	0	0	0	0.20629	1	1
28	0.163886	0.463999	0	0	0	0.20629	1	1
29	0.163232	0.449692	0.012	0.03	0	0.20629	1	1
30	0.161269	0.447224	0.053	0.063333	0	0.20629	1	1
1	0.172228	0.499784	0	0	0.435088	0.199148	0	0

2	0.168629	0.483399	0.1085	0.423333	0.060907	0.236577	1	1
3	0.165031	0.473974	0.125	0.04	0	0.20629	1	1
4	0.163886	0.469929	0.038	0.053333	0	0.20629	1	1
5	0.16405	0.457519	0.471	0.633333	0	0.238326	1	1
6	0.16405	0.465339	0	0	0	0.20629	1	1
7	0.162741	0.460649	0.114	0.363333	0	0.20629	1	1
8	0.16405	0.463233	0.15	1	0	0.235593	1	1
9	0.170592	0.456739	0	0	0	0.20629	1	1
10	0.169447	0.452237	0.029	0.066667	0	0.20629	1	1
11	0.175826	0.456739	0	0	0	0.219789	0	0
12	0.171573	0.454147	0.056	0.25	0	0.20629	0	0
13	0.174027	0.454147	0	0	0	0.21562	0	0
14	0.16912	0.451661	0.031	0.053333	0	0.20629	1	1
15	0.168302	0.451431	0.041	0.083333	0	0.20629	1	1
16	0.169447	0.45257	0.0175	0.06	0	0.20629	1	1
17	0.168629	0.451754	0.045	0.193333	0	0.20629	1	1
18	0.16683	0.44976	0.016	0.03	0	0.20629	1	1
19	0.16634	0.449305	0.0475	0.113333	0	0.20629	1	1
20	0.166994	0.449877	0.011	0.023333	0	0.20629	1	1
21	0.167484	0.450983	0.0875	0.373333	0	0.20629	1	1
22	0.167484	0.451022	0	0	0	0.20629	1	1
23	0.166667	0.450382	0.016	0.053333	0	0.20629	1	1
24	0.165685	0.449953	0.0435	0.223333	0	0.20629	1	1
25	0.165195	0.451131	0	0	0	0.20629	1	1
26	0.162414	0.44995	0.0175	0.076667	0	0.20629	1	1
27	0.16634	0.45259	0	0	0	0.20629	1	1
28	0.163886	0.463463	0	0	0	0.20629	1	1
29	0.163068	0.449145	0.012	0.03	0	0.20629	1	1
30	0.161269	0.446677	0.053	0.063333	0	0.20629	1	1
1	0.172228	0.499784	0	0	0.443457	0.199068	0	0
2	0.168629	0.483141	0.1085	0.423333	0.060907	0.239901	1	1
3	0.164868	0.473225	0.15	0.04	0	0.20629	1	1
4	0.163723	0.469314	0.038	0.053333	0	0.20629	1	1
5	0.163232	0.457258	0.471	0.633333	0	0.23456	1	1
6	0.163886	0.464795	0	0	0	0.20629	1	1
7	0.162414	0.460206	0.114	0.363333	0	0.20629	1	1
8	0.16405	0.462649	0.15	1	0	0.237218	1	1
9	0.170429	0.456169	0	0	0	0.20629	1	1
10	0.169447	0.451659	0.029	0.066667	0	0.20629	1	1
11	0.175826	0.456169	0	0	0	0.219962	0	0
12	0.171573	0.453541	0.056	0.25	0	0.20629	0	0
13	0.174027	0.453541	0	0	0	0.215861	0	0
14	0.16912	0.451056	0.031	0.053333	0	0.20629	1	1
15	0.168302	0.450831	0.041	0.083333	0	0.20629	1	1

16	0.169447	0.451976	0.0175	0.06	0	0.20629	1	1
17	0.168466	0.451171	0.045	0.193333	0	0.20629	1	1
18	0.166667	0.449165	0.016	0.03	0	0.20629	1	1
19	0.166176	0.448716	0.0475	0.113333	0	0.20629	1	1
20	0.16683	0.449288	0.011	0.023333	0	0.20629	1	1
21	0.167321	0.450405	0.0875	0.373333	0	0.20629	1	1
22	0.167484	0.450441	0	0	0	0.20629	1	1
23	0.166503	0.44979	0.016	0.053333	0	0.20629	1	1
24	0.165685	0.44937	0.0435	0.223333	0	0.20629	1	1
25	0.165195	0.450556	0	0	0	0.20629	1	1
26	0.162251	0.449375	0.0175	0.076667	0	0.20629	1	1
27	0.16634	0.452018	0	0	0	0.20629	1	1
28	0.163886	0.46291	0	0	0	0.20629	1	1
29	0.163068	0.448573	0.012	0.03	0	0.20629	1	1
30	0.161106	0.446096	0.053	0.063333	0	0.20629	1	1
1	0.172228	0.499784	0	0	0.451856	0.198864	0	0
2	0.168629	0.482883	0.1085	0.423333	0.060907	0.240813	1	1
3	0.164704	0.472481	0.175	0.04	0	0.20629	1	1
4	0.163723	0.468708	0.038	0.053333	0	0.20629	1	1
5	0.163232	0.456857	0.471	0.633333	0	0.234657	1	1
6	0.163886	0.464259	0	0	0	0.20629	1	1
7	0.162414	0.459726	0.114	0.363333	0	0.20629	1	1
8	0.16405	0.462102	0.15	1	0	0.237726	1	1
9	0.170429	0.455617	0	0	0	0.20629	1	1
10	0.169284	0.451098	0.029	0.066667	0	0.20629	1	1
11	0.175826	0.45562	0	0	0	0.220018	0	0
12	0.17141	0.452952	0.056	0.25	0	0.20629	0	0
13	0.174027	0.452952	0	0	0	0.215989	0	0
14	0.168956	0.450469	0.031	0.053333	0	0.20629	1	1
15	0.168302	0.450251	0.041	0.083333	0	0.20629	1	1
16	0.169447	0.451398	0.0175	0.06	0	0.20629	1	1
17	0.168466	0.450604	0.045	0.193333	0	0.20629	1	1
18	0.166667	0.44859	0.016	0.03	0	0.20629	1	1
19	0.166176	0.448144	0.0475	0.113333	0	0.20629	1	1
20	0.16683	0.448722	0.011	0.023333	0	0.20629	1	1
21	0.167321	0.449841	0.0875	0.373333	0	0.20629	1	1
22	0.167484	0.44988	0	0	0	0.20629	1	1
23	0.166503	0.449215	0.016	0.053333	0	0.20629	1	1
24	0.165685	0.448806	0.0435	0.223333	0	0.20629	1	1
25	0.165195	0.449998	0	0	0	0.20629	1	1
26	0.162251	0.44882	0.0175	0.076667	0	0.20629	1	1
27	0.166176	0.451468	0	0	0	0.20629	1	1
28	0.163723	0.462372	0	0	0	0.20629	1	1
29	0.163068	0.44802	0.012	0.03	0	0.20629	1	1

30	0.161106	0.445543	0.053	0.063333	0	0.20629	1	1
1	0.172228	0.499784	0	0	0.460235	0.199338	0	0
2	0.168629	0.482605	0.1085	0.423333	0.060907	0.243917	1	1
3	0.164213	0.471783	0.2	0.04	0	0.20629	1	1
4	0.163232	0.468159	0.038	0.053333	0	0.20629	1	1
5	0.163232	0.456399	0.471	0.633333	0	0.235888	1	1
6	0.163395	0.463811	0	0	0	0.20629	1	1
7	0.162087	0.459272	0.114	0.363333	0	0.20629	1	1
8	0.163232	0.461732	0.15	1	0	0.233212	1	1
9	0.170265	0.455112	0	0	0	0.20629	1	1
10	0.16912	0.450567	0.029	0.066667	0	0.20629	1	1
11	0.175826	0.455112	0	0	0	0.220712	0	0
12	0.171246	0.45236	0.056	0.25	0	0.20629	0	0
13	0.174027	0.45236	0	0	0	0.216734	0	0
14	0.168793	0.449877	0.031	0.053333	0	0.20629	1	1
15	0.167975	0.449667	0.041	0.083333	0	0.20629	1	1
16	0.16912	0.450831	0.0175	0.06	0	0.20629	1	1
17	0.168302	0.45006	0.045	0.193333	0	0.20629	1	1
18	0.16634	0.44802	0.016	0.03	0	0.20629	1	1
19	0.166012	0.447583	0.0475	0.113333	0	0.20629	1	1
20	0.166667	0.448166	0.011	0.023333	0	0.20629	1	1
21	0.166994	0.449305	0.0875	0.373333	0	0.20629	1	1
22	0.167157	0.449344	0	0	0	0.20629	1	1
23	0.16634	0.448649	0.016	0.053333	0	0.20629	1	1
24	0.165358	0.448262	0.0435	0.223333	0	0.20629	1	1
25	0.164704	0.44949	0	0	0	0.20629	1	1
26	0.161923	0.448287	0.0175	0.076667	0	0.20629	1	1
27	0.165849	0.450991	0	0	0	0.20629	1	1
28	0.163232	0.461931	0	0	0	0.20629	1	1
29	0.162578	0.447507	0.012	0.03	0	0.20629	1	1
30	0.160615	0.44503	0.053	0.063333	0	0.20629	1	1
1	0.172228	0.499784	0	0	0.468675	0.199166	0	0
2	0.168629	0.482344	0.1085	0.423333	0.060907	0.244859	1	1
3	0.16405	0.471034	0.225	0.04	0	0.20629	1	1
4	0.163232	0.467547	0.038	0.053333	0	0.20629	1	1
5	0.163232	0.455995	0.471	0.633333	0	0.235975	1	1
6	0.163395	0.463272	0	0	0	0.20629	1	1
7	0.162087	0.458789	0.114	0.363333	0	0.20629	1	1
8	0.163232	0.461179	0.15	1	0	0.233735	1	1
9	0.170265	0.454556	0	0	0	0.20629	1	1
10	0.16912	0.450001	0.029	0.066667	0	0.20629	1	1
11	0.175826	0.454556	0	0	0	0.220769	0	0
12	0.171246	0.451768	0.056	0.25	0	0.20629	0	0
13	0.174027	0.451768	0	0	0	0.216865	0	0

14	0.168793	0.449288	0.031	0.053333	0	0.20629	1	1
15	0.167975	0.449081	0.041	0.083333	0	0.20629	1	1
16	0.16912	0.450251	0.0175	0.06	0	0.20629	1	1
17	0.168139	0.44949	0.045	0.193333	0	0.20629	1	1
18	0.16634	0.44744	0.016	0.03	0	0.20629	1	1
19	0.165849	0.447008	0.0475	0.113333	0	0.20629	1	1
20	0.166503	0.447594	0.011	0.023333	0	0.20629	1	1
21	0.166994	0.448741	0.0875	0.373333	0	0.20629	1	1
22	0.167157	0.448778	0	0	0	0.20629	1	1
23	0.166176	0.448068	0.016	0.053333	0	0.20629	1	1
24	0.165195	0.447692	0.0435	0.223333	0	0.20629	1	1
25	0.164704	0.448929	0	0	0	0.20629	1	1
26	0.16176	0.447723	0.0175	0.076667	0	0.20629	1	1
27	0.165685	0.450438	0	0	0	0.20629	1	1
28	0.163232	0.46139	0	0	0	0.20629	1	1
29	0.162578	0.446949	0.012	0.03	0	0.20629	1	1
30	0.160615	0.444475	0.053	0.063333	0	0.20629	1	1
1	0.172228	0.499784	0	0	0.477187	0.19901	0	0
2	0.168629	0.482081	0.1085	0.423333	0.060907	0.245813	1	1
3	0.163886	0.470285	0.25	0.04	0	0.20629	1	1
4	0.163068	0.466936	0.038	0.053333	0	0.20629	1	1
5	0.163232	0.455589	0.471	0.633333	0	0.236135	1	1
6	0.163395	0.462731	0	0	0	0.20629	1	1
7	0.162087	0.458299	0.114	0.363333	0	0.20629	1	1
8	0.163232	0.460635	0.15	1	0	0.234325	1	1
9	0.170101	0.453998	0	0	0	0.20629	1	1
10	0.168956	0.449434	0.029	0.066667	0	0.20629	1	1
11	0.175826	0.453995	0	0	0	0.220835	0	0
12	0.171246	0.451173	0.056	0.25	0	0.20629	0	0
13	0.174027	0.451173	0	0	0	0.217001	0	0
14	0.168793	0.448699	0.031	0.053333	0	0.20629	1	1
15	0.167975	0.448494	0.041	0.083333	0	0.20629	1	1
16	0.16912	0.449667	0.0175	0.06	0	0.20629	11	11
17	0.168139	0.448918	0.045	0.193333	0	0.20629	1	1
18	0.16634	0.446862	0.016	0.03	0	0.20629	1	1
19	0.165849	0.446433	0.0475	0.113333	0	0.20629	1	1
20	0.166503	0.447022	0.011	0.023333	0	0.20629	1	1
21	0.166994	0.448172	0.0875	0.373333	0	0.20629	1	1
22	0.167157	0.448208	0	0	0	0.20629	1	1
23	0.166176	0.447487	0.016	0.053333	0	0.20629	1	1
24	0.165195	0.447123	0.0435	0.223333	0	0.20629	1	1
25	0.164704	0.448365	0	0	0	0.20629	1	1
26	0.16176	0.44721	0.0175	0.076667	0	0.20629	1	1
27	0.165685	0.449858	0	0	0	0.20629	1	1

28	0.163232	0.460834	0	0	0	0.20629	1	1
29	0.162414	0.446413	0.012	0.03	0	0.20629	1	1
30	0.160615	0.443897	0.053	0.063333	0	0.20629	1	1
1	0.172228	0.499784	0	0	0.397345	0.192553	0	0
2	0.169447	0.484367	0.1085	0.423333	0.060907	0.24572	1	1
3	0.166012	0.477337	0.012	0.04	0	0.20629	1	1
4	0.16454	0.472689	0.038	0.053333	0	0.20629	1	1
5	0.16405	0.459446	0.471	0.633333	0	0.235359	1	1
6	0.164377	0.467816	0	0	0	0.20629	1	1
7	0.162905	0.462899	0.114	0.363333	0	0.20629	1	1
8	0.16405	0.465802	0.15	1	0	0.23113	1	1
9	0.170756	0.4593	0	0	0	0.20629	0	0
10	0.169611	0.454834	0.029	0.066667	0	0.20629	1	1
11	0.175826	0.4593	0	0	0	0.219302	0	0
12	0.171737	0.456862	0.056	0.25	0	0.20629	0	0
13	0.174027	0.456865	0	0	0	0.214694	0	0
14	0.169447	0.454368	0.031	0.053333	0	0.20629	1	1
15	0.168629	0.454127	0.041	0.083333	0	0.20629	1	1
16	0.169774	0.455241	0.0175	0.06	0	0.20629	1	1
17	0.168793	0.454377	0.045	0.193333	0	0.20629	1	1
18	0.166994	0.45243	0.016	0.03	0	0.20629	1	1
19	0.166503	0.451959	0.0475	0.113333	0	0.20629	1	1
20	0.167157	0.452514	0.011	0.023333	0	0.20629	1	1
21	0.167648	0.453589	0.0875	0.373333	0	0.20629	1	1
22	0.167812	0.453625	0	0	0	0.20629	1	1
23	0.16683	0.45305	0.016	0.053333	0	0.20629	1	1
24	0.166012	0.452576	0.0435	0.223333	0	0.20629	1	1
25	0.165522	0.453715	0	0	0	0.20629	1	1
26	0.162578	0.452559	0.0175	0.076667	0	0.20629	1	1
27	0.166667	0.455146	0	0	0	0.20629	1	1
28	0.164213	0.465965	0	0	0	0.20629	1	1
29	0.163395	0.451723	0.012	0.03	0	0.20629	1	1
30	0.161433	0.449246	0.053	0.063333	0	0.20629	1	1



الأكاديمية العربية للعلوم والتكنولوجيا والنقل البحري
كلية الهندسة والتكنولوجيا - القاهرة
هندسة الكهرباء والتحكم

الكاشف الذكي عن عدم استقرار الجهد الكهربائي باستخدام الذكاء الاصطناعي

إعداد

أحمد كمال علي

رسالة مقدمة للأكاديمية العربية للعلوم والتكنولوجيا والنقل البحري
لاستكمال متطلبات نيل الماجستير في

هندسة الكهرباء والتحكم

إشراف

الأستاذ الدكتور / سعيد فؤاد مخيمر
هندسة القوى والآلات الكهربائية
جامعة عين شمس

الدكتور / نهى هانى العماري
هندسة الكهرباء والتحكم
الأكاديمية العربية للعلوم والتكنولوجيا والنقل البحري

الدكتور / عمرو محمد ابراهيم
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فبراير ٢٠١٦

وتحتوي الرسالة على خمسة فصول تم تناولها على النحو الآتي:

الفصل الأول: المقدمة

ويشمل مقدمة الرسالة حيث يلقي الضوء على مشكلة عدم استقرار الجهد الكهربى فى انظمة الطاقة الكهربائية والتي تعد واحدة من الاهتمامات الرئيسية فى مجال التخطيط والتشغيل والجودة لانظمة الطاقة الكهربائية. كما يتم عرض مقدمة عن الشبكات العصبية الاصطناعية واستخدامتها فى المجالات المختلفة وقد اختتم هذا الفصل بالاهداف والخطة المقترحة فى هذا البحث مع عرض ملخص بسيط لكل باب.

الفصل الثانى: دراسة استقرارية الجهد الكهربى

ويتناول هذا الفصل الأسس والنظريات الأساسية لطرق الكشف عن عدم استقرار الجهد الكهربى للشبكة الكهربائية. كما انه يقدم تقنية جديدة مقترحة للتنبؤ والانداز عن عدم استقرار الجهد الكهربى وذلك بالاستفادة بقراءات اجهزة القياس الاتجاهية التى يتم تثبيتها بشبكة القوى الكهربائية. وفى نهاية هذا الفصل يتم عرض خطوات القيام بهذا العمل.

الفصل الثالث: اجهزة القياس الاتجاهية والشبكة العصبية الاصطناعية

فى هذا الفصل يتم القاء الضوء على وحدة القياس الاتجاهى والتي تعد واحدة من اهم وأحدث اجهزة القياس بنظم القوى الكهربائية الحديثة والتي تستخدم للكشف عن عدم استقرار الجهد الكهربى بالاعتماد على الشبكات العصبية الاصطناعية. بالإضافة الى انه يناقش تصميم الشبكة العصبية الاصطناعية وكيفية تدريبها للكشف عن عدم استقرار الجهد الكهربى.

الفصل الرابع: محاكاة النظام والنتائج

هذا الفصل يعرض خوارزمات وخريطة برمجة لبرنامج MATLAB مصمم لحساب قيم التحميلات المختلفة والحصول على قيم زوايا جهد قضبان النظام وتسجيلها لحين استخدامها فى المراحل القادمة. كما يقدم النتائج التي تم دراستها بعد اختبار اداء الشبكة العصبية الاصطناعية المصممة على كلا نظامى IEEE القياسيين ذوي الـ 14 والـ 30 قضيب، بالإضافة الى عرض الجداول المبرمجة الناتجة من البرنامج ومناقشتها فى نهاية هذا الفصل.

الفصل الخامس: الاستنتاجات والتوصيات

ويشمل خلاصة البحث والتوصيات المقترحة. كما يعرض اقتراحات للاعمال المستقبلية وأخيرا تضم الرسالة ملحق اضافى يعرض البيانات المستخدمة الخاصة بكلا نظامى الـ IEEE القياسيين ذوي الـ 14 والـ 30 قضيب.

ملخص

في السنوات الاخيرة، أعطى الباحثون والمخططون في مجال نظم القوى الكهربائية الكثير من الأهتمام لمشكلة عدم إستقرار الجهد الكهربى حيث ان مشاكل عدم إستقرار الجهد فى أنظمة الطاقة الكهربائية تعتبر واحدة من الاهتمامات الرئيسية فى مجال التخطيط والتشغيل والجودة لأنظمة الطاقة. حيث يتعرض النظام الذى يعاني من عدم استقرار الجهد الكهربى الى انهيار سريع مما ادى الى دراسة مقترح لكاشف عدم استقرار الجهد الكهربى اعتمادا على الشبكة العصبية الاصطناعية (ANN) بالاستفادة من نظام المراقبة واسع النطاق والزاوية المقاسة لأجهزة القياس الاتجاهية بالشبكة الكهربائية. بدأت اجهزة القياس الاتجاهية فى الانتشار على نطاق واسع المدى فى تقنيات الاقمار الصناعية والاتصالات وذلك نظرا للارتباط القوى بين اجهزة القياس الاتجاهية والاقمار الصناعية العالمية لتحديد المواقع. ثم استخدمت فى مختلف تطبيقات هندسة القوى الكهربائية من قياس وتحكم وحماية لأنظمة القوى.

وتستخدم اجهزه القياس الاتجاهية للكشف عن عدم استقرار الجهد الكهربى كما هو مقدم فى هذه الرسالة بالاعتماد على الشبكات العصبية الاصطناعية. وقد تم هذا العمل من خلال مجموعة من الخطوات وهي:

في البداية تم تمثيل الأنظمة القياسية IEEE ذات الـ ١٤ والـ ٣٠ قضيب من خلال برنامج MATLAB للحصول على نتائج وقيم توزيع الطاقة الكهربائية فى المسارات المختلفة بالأنظمة. علاوة على ذلك تم وضع استراتيجيات مختلفة لتغيير تحميل النظام الكهربى والحصول على قيم زوايا جهد القضبان المناظرة، حيث تم تسجيل حوالي ١٣٥٧ و ٨٩٥ حالة مختلفة لقيم التحميلات المختلفة فى مختلف الظروف لكلا النظامين، ثم تمت جدولة هذه النتائج استعدادا للمرحلة الاخيرة وهي معالجتها باستخدام الشبكة العصبية الاصطناعية. بالمرحلة الثالثة والاخيرة تم تصميم الشبكة العصبية الاصطناعية وتدريبها. حيث تم هذا التدريب بالاستعانة بثلاث نتائج الحالات التى تم دراستها بالمرحلة الاولى، كما استخدمت باقى النتائج فى اختبار اداء الشبكة العصبية الاصطناعية المصممه. وتحليل نتائج الشبكة العصبية الاصطناعية وجد ان هذه النتائج تعتبر مرضية بسبب الدقة العالية فى التشغيل. وتعد الميزة الرئيسية لنظام الذكاء الاصطناعى المستخدم فى هذه الرسالة هى استطاعته الكشف عن عدم استقرار الجهد الكهربى بكل قضبان الشبكة الكهربائية المدروسة فى نفس الوقت.