ARTIFICIAL INTELLIGENCE(AI) BASED POWER SYSTEM STATE ESTIMTION

Major Project Report

Submitted in Partial Fulfillment of the Requirements

for Degree of

MASTER OF TECHNOLOGY

IN

ELECTRICAL ENGINEERING
(ELECTRICAL POWER SYSTEMS)

By

Kirtan K. Patel
(14MEEE14)

NIRMA UNIVERSITY
INSTITUTE OF TECHNOLOGY
NAAC ACCREDITED 'A' GRADE

DEPARTMENT OF ELECTRICAL ENGINEERING
INSTITUTE OF TECHNOLOGY
NIRMA UNIVERSITY
AHMEDABAD 382 481

MAY 2016

ARTIFICIAL INTELLIGENCE(AI) BASED POWER SYSTEM STATE ESTIMTION

Major Project Report

Submitted in Partial Fulfillment of the Requirements

for Degree of

MASTER OF TECHNOLOGY

IN

ELECTRICAL ENGINEERING
(ELECTRICAL POWER SYSTEMS)

By

Kirtan K. Patel
(14MEEE14)

DEPARTMENT OF ELECTRICAL ENGINEERING
INSTITUTE OF TECHNOLOGY
NIRMA UNIVERSITY
AHMEDABAD 382 481

MAY 2016

Undertaking for Originality of the Work

I, **Kirtan K. Patel** (**Roll.No.14MEEE14**), give undertaking that the Major Project entitled "**Artificial Intelligence (AI) Based Power System State Estimation**" submitted by me, towards the partial fulfillment of the requirements for the degree of Master of Technology in Electrical Power Systems of Nirma University, Ahmedabad, is the original work carried out by me and I give assurance that no attempt of plagiarism has been made. I understand that in the event of any similarity found subsequently with any published work or any dissertation work elsewhere; it will result in severe disciplinary action.

Signature of Student

Date :-

Place :- Ahmedabad

Endorsed by:

Project Guide

Prof. Vihang Dholakiya

Assistant Professor

Department of Electrical Engineering

Institute of Technology

Nirma University

Ahmedabad

CERTIFICATE

This is to certify that the Major Project Report (Part-II) entitled **"ARTIFICIAL INTELLIGENCE(AI) BASED POWER SYSTEM STATE ESTIMATION"** submitted by **Mr. Kirtan K. Patel (14MEEE14)**, towards the partial fulfillment of the requirements for Semester-IV of Master of Technology (Electrical Engineering) in the field of Electrical Power Systems of Nirma University is the record of work carried out by him under my supervision and guidance. The work submitted has in my opinion reached a level required for being accepted for examination. The results embodied in this major project work to the best of my knowledge have not been submitted to any other University or Institution for award of any degree or diploma.

Date:

Project Guide
Prof. Vihang M. Dholakiya
Assistant Professor
Department of Electrical Engineering
Institute of Technology
Nirma University
Ahmedabad

Head of Department
Department of Electrical Engineering
Institute of Technology
Nirma University
Ahmedabad

Director
Institute of Technology
Nirma University
Ahmedabad

Acknowledgement

"To achieve something it requires Perseverance, Diligence and Hard Work in right direction with Patience". On the moment of final Review of Major Project Part-I, it gives me abundant pleasure to express my gratitude to The Almighty and all the people who have supported me and contributed to my work.

I hereby seize the opportunity to express my indebtedness and deep sense of gratitude to **Prof. Vihang M. Dholakiya,** Assistant Professor, Electrical Engineering Department, Institute of Technology, Nirma University and **Prof. Dr. S. C. Vora,** Professor, Electrical Engineering Department, Institute of Technology, Nirma University for his continuous endeavor, co-operation, supports and encouragements. Their power of ratiocination and eloquence of writing report taught me a lot at every profound quirk. Continuous encouragements on all fronts are gratefully acknowledged. I am also thankful to **Prof. Dr. Sandeep Malhotra,** Assistant Professor, Mathematics and Humanity Department, Institute of Technology, Nirma University for his effort and co-operation.

I am also highly thankful to **Prof. Dr. P. N.Tekwani,** Director of Institute of Technology, Nirma University for providing all possible facilities and help.

Also I would like to thank the lab assistants Bhavesh Raval, Pratik Jani, Harshad Patel, Sajid Mohammad for their continuous support during my dissertation work.The help and support from the staff of Library is also greatly appreciated.

Finally, I would like to thank my family members for supporting and encouraging me in all possible ways. I would also like to thank my friends who have provided continuous encouragement in making this dissertation work successful.

- Kirtan K. Patel

14MEEE14

Abstract

For economic dispatch, load frequency control and to control the parameter of power system, data are acquired from the monitoring equipments or different metering device used in power system. Before any control action and security assessment carried out, reliable estimate of the existing state of the system has to be determined. However gross error in any of data causes the result to become useless data, which are analog or digital quantity measured by sensors. Analog measurements passes through analog to digital convertor which contains inaccuracies and free random errors like noise plus some unavoidable errors from instrumentation transformers. These errors ought to be quantified in statical sense. Best estimation are chosen which gives least sum. By using some modern technique like Artificial Intelligence more accurate data can be achievable. In this theses at first place as conventional method Weighted Least Square method is utilised to check and compare the result with standard result and afterwards Particle Swarm Optimisation as an advance technique is applied for power system state estimation in steady state condition. Adopted methods are subjected to WSCC 3-Machine 9-Bus standard test system to check effectiveness of each method. From the results of adopted methods it is discernible that Particle Swarm Optimization approach would be better option than conventional method as it has less computational process which leads to lesser consumption of time plus yields accurate result. Moreover power system state estimator has four basic operations: (1) Hypothesize structure, (2) Estimate, (3) Detect, (4) Identify. After extrapolating the state it is inevitable to detect and identify the errors in estimated results in order to have reliable data. Subsequently in this theses bad data detection and identification has been carried out by Chi-square method and Largest Normalized Residual(LNR) method. Both the methods are subjected to WSCC 3-Machine 9-Bus standard test system to detect and identify the errors from state estimation results and to check effectiveness of both methods.

List of Figures

List of Tables

Abbreviations

AI .... Artificial Intelligence
ADC .... Analog to Digital converter
Deg. .... Degree
DPSO .... Discrete Particle Swarm Optimization
EMS .... Energy Management System
Est. .... Estimated
GA .... Genetic Algorithm
Gbest .... Global Best
iter. .... Iteration
LNR .... Largest Normalised Residual
MSE .... Mean squared Error
N.E .... Normal Equation
Ortho. .... Orthogonal Transformation
Pbest .... Personal Best
PDF .... Probability Density Function
PU .... Per Unit
PSO .... Particle Swarm Optimisation
SE .... State Estimation
WLS .... Weighted Least Square
WSCC .... Western System Coordinating Council

Nomenclatures

H .... Hessian Matrix
G .... Gain Matrix
W .... Weighting Factor's Matrix
α .... Area under the $\chi^2_{k,\alpha} curve$
σ_i^2 .... Standard Deviation (Variance)
R .... Resistence
B .... Line Charging
G .... Conductance
v .... Velocity of particle
x .... Search point of particle
w .... Inertia weight
λ .... Penalty Factor
χ .... Constriction Factor
Ω .... Residual Covariance Matrix
b .... Decision Vector

Contents

Chapter 1

Introduction

A power system State Estimator has four basic operation such as, hypothesis modelling, estimation, detection and identification. In other words it typically provides outputs like estimated values of bus voltages, angle, measurement error for all metered and nonmetered quantity in order to maintain power system in normal and secure state.

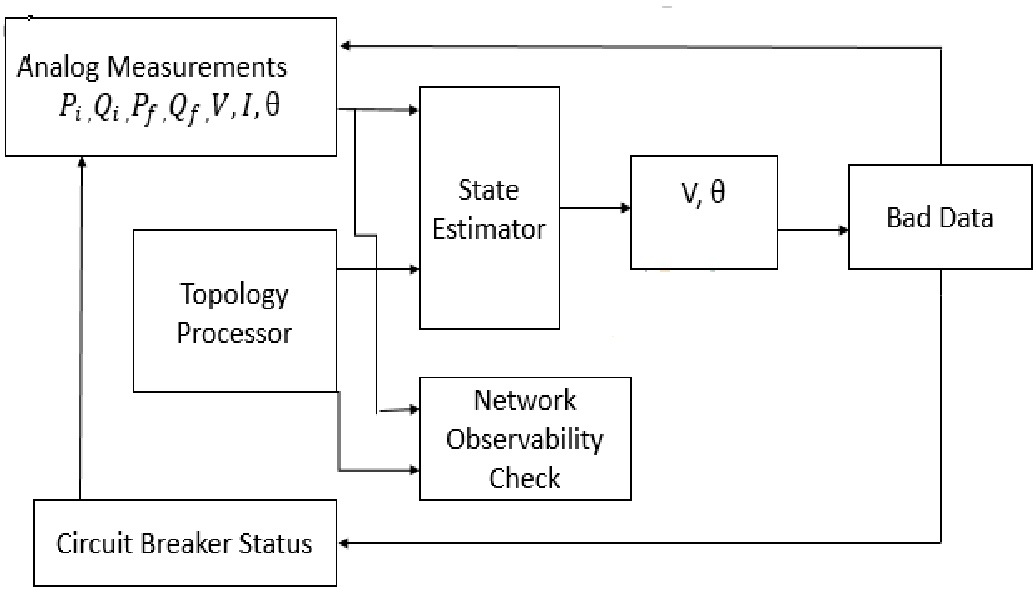

Figure 1.1: State Estimation

Despite real time measurement state estimation calculation is required for following reasons:

- For determining bus voltage and phase angle.
- To reduce the cost of metering and communication system.
- To have redundancy against the lost in metered data.
- To identify bad data.

The accuracy of power system measurements could be compromised by finite accuracy of components of data acquisition which are instrument transformer, Watt and Var transducers, Analog to digital converters. Accuracy of telemetered data could be influenced by unwanted interference in communication channels and noise as well.

1.1 Problem Identification

Many real time operations in electrical power system are carried out by state estimation. Particularly dynamic control action can not be carried out without proper state estimation of power system. Conventional state estimators utilizes Weighted Least Square (WLS) approach which converts non-linear equations into linear equations. Nowadays, system operator can visualize network using measurements available in supervisory control and data acquisition system. However, noise in the signal corrupts the data telemetered and hence leads to wrong estimates of operating state, implies that the conditioning of gain matrix, computational time, less robustness of conventional state estimation (SE) are some of the limitations. Artificial Intelligence (AI) can provide solution to all the limitations aforementioned and hence implementation of the same has carried out.

1.2 Objective of The Work

The objective of the dissertation is to extrapolate the state of power system by some modern technique as true values are never known and based on that operating state of the system can be known. Data should be accurate, reliable and incorporate less error as much as possible. After estimating the values by means of Artificial Intelligent (AI) technique comparison of it with the estimated values of conventional method has conducted.

1.3 Methodology

- Literature survey.
- WLS state estimation of standard test system.
- Identification of suitable AI technique.
- Development and verification on adopted technique for standard test system.
- Bad data detection.
- Comparison of conventional and AI based technique.

1.4 Scope of Work

The scope of project is to carry out the technique for state estimation which can have higher accuracy less computational time and can be outlined as below:

- To carry out study of conventional state estimation technique e.g. WLS.
- To develop AI based mathematical model and algorithm for state estimation.
- To verify the developed algorithm on standard test system.
- To identify and process bad-data for conventional state estimation.
- To develop and verify AI based technique suitable for bad-data detection.

1.5 Literature Survey

The literature survey is carried out to know about basic conceptualization of power system state estimation by conventional method and afterwards some basics of artificial intelligence technique.

Paper [1] authored by Lars Holtcn,Andcrs Gjelsvik, Svcrre Aam,Felix F. Wu, Wen-Hsiung E. Liu which is comparison of different methods for state estimation. This paper gives idea about comparison of different conventional method for state estimation. Which method is efficient and advantages and disadvantages of different methods on different criteria like numerical stability, computational efficiency, implementation complexity etc.

In [2] Bruce F. Wollenberg and Toshiaki sakaguchi has shown importance of artificial intelligence in power system and in which different areas of power system AI is useful, Major component of AI system, and authors have explain different type of knowledge representation scheme in AI.

In [3] & [4], Ali abur and Jhohn J. Grainger with William D. Stevenson, Jr have shown the basics of state estimation and why it is needed. Following to that authors have talked about WLS state estimation. How to carry out state estimation using WLS method. Afterwards authors have given some basics of bad data detection. Leading to that classification of bad data and measurements is also given.

In [6] & [7] J. F. Dopazo, O. A. Klitin, G. W. Stagg, L. S. Van Slyck have described the WLS state estimation method with some basics of it what is state estimation and what are the steps to carry out the same also have concluded the method of it after tested this method on 42 Bus system.

From [5], [8] & [9] data for WSCC 3-machine 9-bus has been taken.

Paper [10] authored by James Kennedy and Russell Eberhart who have developed the Particle Swarm Optimisation method in order to optimise the solution. This paper gives the basic and fundamental knowledge about the PSO. How this method is useful to optimise the solution and how it works.

In [11] authored by Daneiel Bartton and James Kennedy. Author of this paper have shown abstractness of PSO and its standard. How to select constants and its value.

Paper [12] authored by R. C. Eberhart and Y. Shi have shown comparison of weighting factor and constriction factor. How to select its value or find its value. From both the factors which is suitable plus when one of these factors will able to yield effective results is given in this paper.

Paper [13] authored by D.H. Tungadio, B.P. Nuimbi, M.W. Siti, J.A. Jordaan have implied WLS and PSO methods on IEEE six bus system for sate estimation. Afterwards authors have compared results of both the method with standard results from which it is clearly observable that which method is more reliable.

In [14] Edited by Kwang Y. Lee and Mohamed A. El-Sharkawi authors has given basic introduction of modern heuristic techniques so far used in power system and how it could be applied to power system problems.

In paper[15] authored by D.H. Tungadio, B.P. Nuimbi, M.W. Siti, A.A. Jimoh have implied WLS and PSO methods on IEEE six bus system for sate estimation. Afterwards authors have compared results of both the method with standard results from which it is clearly observable that which method is more reliable.

Paper[16] authored by Sara Nanchian, Student Member, IEEE, Ankur Majumdar, Student Member IEEE, and Bikash C. Pal, Fellow, IEEE proposes a method for three-phase state estimation (SE) in power distribution network including on-load tap changers (OLTC) for voltage control. The OLTC tap positions are essentially discrete variables from the SE point of view with details of acceleration coefficient.

In paper[17] authored by Ke-yan Liu, Member, IEEE, Wanxing Sheng, Senior Member, IEEE, Kaiyuan have shown Unbalanced three-phase state estimation for advanced distribution management system (DMS) in a smart distribution grid in detail from how to create initial swarm.

Paper[18] authored by E. Handschin, F. C. Schweppe, J. Kohlas, A Fiechter have shown the bad data analysis for power system state estimation and also have introduced to concept of interacting and non-interacting bad data and local redundancy as well.

In paper[19] authored by A. Monticelli and Felix F. Wu have shown the multiple bad data identification for state estimation by combinatorial optimization and features of Largest Normalized Residual method as well.

In paper[20] authors Eduardo N. Asada, Ariovaldo V. Garcia and R. Romero have shown the method for identifying multiple interacting bad data in power system state estimation for both conforming and non-conforming errors.
In paper[21] authors G.P. Granelli, M. Montagna have shown the method for identification of interacting bad dta in the framework of weighted least square method by LNR method, Chi-square method, Branch and Bound method as well.
Paper[22] authored by Jaratsri Khwanram and Parnjit Damrongkulkamjorn shows the method for multiple bad data identification in power system state estimation using particle swarm optimisation a method to improve the identification for bad data specially when errors are conforming and interacting.
Paper[23] authored by James Kennedy and Russell C. Eberhart shows the algorithm for discrete particle swarm optimization which is very much profitable when outcome is required in binary form.

1.6 Outline of Thesis

- **Chapter 1** introduce with the state estimation and its importance. It also includes problem identification and objective of the dissertation work.
- **Chapter 2** gives the basic idea of power system state estimation by Weighted Least Square(WLS) method and Bad data Detection and Identification by Chi-square and Largest Normalised Residual (LNR) methods.
- **Chapter 3** acquaints with the Artificial Intelligence.
- **Chapter 4** consists of power system state estimation and Bad data Detection and Identification by Artificial Intelligence method.

Chapter 2

State Estimation of Electrical Power Syatem

Power system state estimation is the interpolation of the state such as voltage magnitudes and voltage angles at each bus of network. Before direct measurement provided to system operator or telemetered to the EMS (Energy Management System) data has to be correct and accurate. If any input is inaccurate or not provided, it is difficult to know the operating point of system at given time such as, whether parameters of the system are within the predefine limits or not. Several method has been adopted for interpolation of the state of power system. Some of those are compared bellow.

2.1 Different Methods for State Estimation

a. Weighted Least Square (WLS)

b. Orthogonal Transformation

c. Hybrid Method

Different methods for state estimation are compared typically on several criteria such as,

- Numerical Stability
- Implementation Complexity

2.1.1 Comparison of Different methods

Orthogonal Transformation vs Normal Equation

- The QR Factorization H requires more computation[1]

$$\begin{bmatrix} Q_1 \\ Q_2 \end{bmatrix} H = \begin{bmatrix} R \\ 0 \end{bmatrix} \tag{2.1}$$

$$R\Delta x = Q_1 W^{1/2} \Delta z \tag{2.2}$$

- Where in WLS triangular factorization of G requires less computation[1]

$$G = H^T W H \tag{2.3}$$

$$G = U^T U \tag{2.4}$$

$$(U^T U)\Delta x = H^T W \Delta Z \tag{2.5}$$

Major drawback of orthogonal factorization is that it is not able to take advantage of efficient implementation using decoupling property. whereas fast decouple version of Weighted Least Square (WLS) has been very efficient and effective, and major advantage of Weighted Least Square (WLS) is its Intensive computation of G is performed only once at beginning also, as Q of Ortho. can be stored and compute again when we require but it is non-sparse and has higher dimension so require large space.[1]

Hybrid vs Orthogonal Transformation

Hybrid method solves the normal equation using the orthogonal factorization.

$$R\Delta x = Q_1 W^{1/2} \Delta z \tag{2.6}$$

Hybrid method is less stable than the Ortho. as it uses two measurement in given equation one is telemetered and second is virtual. When it is multiplied by r (residual) second term will dominates and RHS will become zero. Hybrid method does not require the storage of the matrix Q and can be efficient fast decouple.[1]

2.1.2 Summary

After performing different method in[1] author has concluded that Ortho. is mathematically most stable with heaviest computation and cannot be applied by decoupled version. Thereby WLS is efficient, stable, and requires less heavy computation as computation of gain matrix is not require in every step or iteration.

2.2 WLS State Estimation

Weighted least square (WLS) method often used in practice of power system state estimation.

2.2.1 Introduction

It refers as procedure of obtaining voltage magnitudes and angles at all of the system buses at a given point of time. state estimation can be used to filter out error and find optimal state by use of set of redundant measurement.

2.2.2 Assumptions in Method

- System is operating in steady state under balance condition i.e. power flow is balanced three phase, transmission line is fully transposed, all series and shunt devices are symmetrical, Which allows to use single phase positive equivalent circuit for modeling entire power system.all data and variable expressed in P.U.

- As starting to initiate WLS all bus voltage at 1.0 P.U and in phase with each other.

2.2.3 Gaussian Probability Density Function

If repeated measurement of any quantity under careful condition is carried out then it reveals certain statistical property by which true value of quantity can be estimated. A histogram is obtain if the measure values are plotted as the function of relative frequency of occurrence. To which a continues curve can be obtain as the number of measurement increases.
And defined as:

$$f(z) = \frac{1}{\sqrt{2\Pi\sigma}} e^{-1/2} \left(\frac{z-\mu}{\sigma}\right)^2 \tag{2.7}$$

z=random veriable
μ=mean value(expected value)
σ= standard deviation of z

According to the equation a continues curve encountered which looks like bell shaped as shown in figure This curve shown in figure2.1 obtained using matlab function:

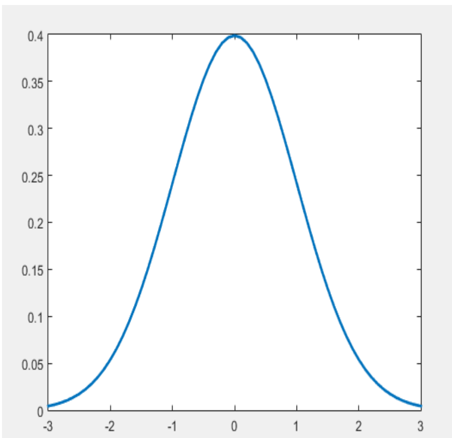

Figure 2.1: Gaussian Probability Density Function

pd = makedist(distname,name,value) creates probability distribution with μ and σ. It can be written as pd = makedist('Normal','mu',0,'sigma',1)

Probability associated with the corresponding interval of horizontal axis is given by area under the curve. Square of the deviation of z from mean is expected value or variance of z denoted by σ^2 .As the f(z) can not be directly integrated areas under the curve have been tabulated[4] for standard Gaussian density function u with $\mu = 0$ and $\sigma = 1$. The Shape of the curve is dependent on μ and σ

$$u = \frac{z - \mu}{\sigma} \tag{2.8}$$

$$E(u) = \frac{1}{\sigma}(E(z) - \mu) = 0 \tag{2.9}$$

$$Var(u) = \frac{1}{\sigma^2}var(z - \mu) = \frac{\sigma^2}{\sigma^2} = 1 \tag{2.10}$$

$$\phi(u) = \frac{1}{\sqrt{2\Pi}}e^{\frac{-u^2}{2}} \tag{2.11}$$

New scale y tells how many standard deviations from mean the corresponding values of z lies.

2.2.4 Weighted Least Square State Estimation Algorithm

- **STEP 1:**

  Start the iteration, Set the iteration index k=0

- **STEP 2:**

  Initialize the state vector x^k, Flat Start.

- **STEP 3:**

  Calculate the gain matrix(G).

$$G = H^T W H \tag{2.12}$$

$$W = R^{-1} = \begin{bmatrix} \frac{1}{\sigma_1^2} & & \\ & . & \\ & & \frac{1}{\sigma_n^2} \end{bmatrix} \tag{2.13}$$

- **STEP 4:**

  Decompose G and solve Δx^k

$$\Delta x = Z - \hat{Z} \tag{2.14}$$

$$\hat{Z} = H\hat{x} \tag{2.15}$$

$$\hat{x} = G^{-1}H^T WZ \tag{2.16}$$

- **STEP 5:**

  Check convergence $\mid \Delta x \mid \leqslant \varepsilon$?

- **STEP 6:**

  If no then update $x^{k+1} = x^k + \Delta x^k$ and repeat from step 3 else stop.

As G is not inverted. Instade of that decompose into it's triangular factors and following sparse linear set of equation are solved by forward and backwards substitution at each iteration k:

$$[G(x^k)]\Delta x^{k+1} = H^T(x^k)R^{-1}[z - h(x^k)] \tag{2.17}$$

In each iteration of above algorithm calculation given bellow is essential:

1. Calculation of righthand side of equation(2.17)

   a. Calculate the measurement function,h(x^k)

   b. Built the measurement jacobian, H(x^k)

2. Calculation of G(x^k) and solution of Equation(2.17)

a. Building the Gain Matrix,G(x^k)

b. Decomposing the G(x^k) into cholesky factors.

c. Performing forward/backward substitution to solve Δx^{k+1}

Measurement Function,h(x^k)

The most commonly measurements are line power flow, bus power injection, bus voltage magnitudes, and can be shown in the form of state variable using polar or rectangular forms. The state vector will be (2N-1) elements when using polar coordinate for N bus system. The state vector will be like following with assumption of bus no.1 as reference bus.

$$x^T = [\Theta_2, \Theta_3..., \Theta_n V_1, V_2..., V_n] \tag{2.18}$$

Assuming two port Π-model for network branches:

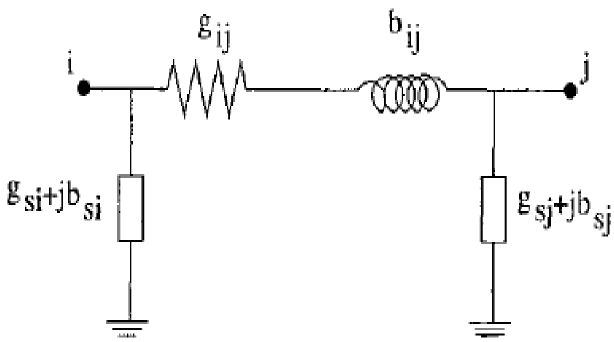

Figure 2.2: Two Port Π-Model

1.Real and Reactive power injection at bus i:

$$P_i = V_i \sum_{j \in N_i} V_j (G_{ij} \cos \Theta_{ij} + B_{ij \sin \Theta_{ij}}) \tag{2.19}$$

$$Q_i = V_i \sum_{j \in N_i} V_j (G_{ij} \sin \Theta_{ij} + B_{ij \cos \Theta_{ij}}) \tag{2.20}$$

2.Real and Reactive Power flow from bus i to j:

$$P_{ij} = V_i^2 (g_{si} + g_{ij}) - V_i V_j (g_{ij} \cos \Theta_{ij} + b_{ij} \sin \Theta_{ij}) \tag{2.21}$$

$$Q_{ij} = -V_i^2 (b_{si} + b_{ij}) - V_i V_j (g_{ij} \sin \Theta_{ij} - b_{ij} \cos \Theta_{ij}) \tag{2.22}$$

Where

V_i, Θ_i are Voltage Magnitude and phase angle at bus i

$\Theta_{ij} = \Theta_i - \Theta_j$

$G_{ij} + jB_{ij} = ij_{th}$ element of complex bus admittance matrix

$g_{ij} + jb_{ij}$=admittance of series branch connecting buses i and j

$g_{si} + jb_{si}$=shunt admittance at bus i

N_i=set of bus numbers directly connected to bus i.

The Measurement Jacobian,H

The structure of the Jacobian H is as follows:

$$H = \begin{bmatrix} 0 & \frac{\delta V_{mag}}{\delta V} \\ \frac{\delta P_{inj}}{\delta \Theta} & \frac{\delta P_{inj}}{\delta V} \\ \frac{\delta Q_{inj}}{\delta \Theta} & \frac{\delta Q_{inj}}{\delta V} \\ \frac{\delta P_{flow}}{\delta \Theta} & \frac{\delta P_{flow}}{\delta V} \\ \frac{\delta Q_{flow}}{\delta \Theta} & \frac{\delta Q_{flow}}{\delta V} \end{bmatrix} \tag{2.23}$$

1. Elements of real power injection measurements:

- $\frac{\delta P_i}{\delta \Theta_i} = \sum_{j=1}^{N} V_i V_j(-G_{ij} \sin \Theta_{ij} + B_{ij} \cos \Theta_{ij}) - V_i^2 B_{ii}$
- $\frac{\delta P_i}{\delta \Theta_j} = V_i V_j(G_{ij} \sin \Theta_{ij} - B_{ij} \cos \Theta_{ij})$
- $\frac{\delta P_i}{\delta V_i} = \sum_{j=1}^{N} V_j(G_{ij} \cos \Theta_{ij} + B_{ij} \sin \Theta_{ij}) + V_i^2 G_{ii}$
- $\frac{\delta P_i}{\delta V_j} = V_i(G_{ij} \cos \Theta_{ij} + B_{ij} \sin \Theta_{ij})$

2. Elements corresponding to reactive power injection measurements:

- $\frac{\delta Q_i}{\delta \Theta_i} = \sum_{j=1}^{N} V_i V_j(G_{ij} \cos \Theta_{ij} + B_{ij} \sin \Theta_{ij}) - V_i^2 G_{ii}$
- $\frac{\delta Q_i}{\delta \Theta_j} = V_i V_j(-G_{ij} \cos \Theta_{ij} - B_{ij} \sin \Theta_{ij})$
- $\frac{\delta Q_i}{\delta V_i} = \sum_{j=1}^{N} V_j(G_{ij} \sin \Theta_{ij} - B_{ij} \cos \Theta_{ij}) + V_i^2 B_{ii}$
- $\frac{\delta Q_i}{\delta V_j} = V_i(G_{ij} \sin \Theta_{ij} + B_{ij} \cos \Theta_{ij})$

3. Elements corresponding to real power flow measurement:

- $\frac{\delta P_{ij}}{\delta \Theta_i} = V_i V_j(g_{ij} \sin \Theta_{ij} - b_{ij} \cos \Theta_{ij})$
- $\frac{\delta P_{ij}}{\delta \Theta_j} = -V_i V_j(g_{ij} \sin \Theta_{ij} - b_{ij} \cos \Theta_{ij})$
- $\frac{\delta P_{ij}}{\delta V_i} = -V_j(g_{ij} \cos \Theta_{ij} + b_{ij} \sin \Theta_{ij}) + 2(g_{ij} + g_{si})V_i$
- $\frac{\delta P_{ij}}{\delta V_j} = -V_j(g_{ij} \cos \Theta_{ij} + b_{ij} \sin \Theta_{ij})$

4. Elements corresponding to reactive power flow measurements:

- $\frac{\delta Q_{ij}}{\delta \Theta_i} = -V_i V_j(g_{ij} \cos \Theta_{ij} + b_{ij} \sin \Theta_{ij})$
- $\frac{\delta Q_{ij}}{\delta \Theta_j} = V_i V_j(g_{ij} \cos \Theta_{ij} + b_{ij} \sin \Theta_{ij})$
- $\frac{\delta Q_{ij}}{\delta V_i} = -V_j(g_{ij} \sin \Theta_{ij} - b_{ij} \cos \Theta_{ij}) - 2(b_{ij} + b_{si})V_i$
- $\frac{\delta Q_{ij}}{\delta V_j} = -V_j(g_{ij} \sin \Theta_{ij} - b_{ij} \cos \Theta_{ij})$

5. Elements corresponding to voltage magnitude measurements:

- $\frac{\delta V_i}{\delta V_i}$=1
- $\frac{\delta V_i}{\delta V_j}$=0
- $\frac{\delta V_i}{\delta \Theta_i}$=0
- $\frac{\delta V_i}{\delta \Theta_j}$=0

Sate Estimation Result by WLS method of WSCC 3-Machine, 9-Bus System

Comparing results shown in below table with the standard voltage and phase angle table given in Appendix:B it can be concluded that output of the WLS state estimation is nearer to standard results. The results shown in table2.1 is obtained by following the algorithm stated in section2.2.4. To calculate time require to execute the program MATLAB function "tic-toc" is useful command. The tic command starts a stopwatch timer, MATLAB executes the block of statements, and toc stops the timer, displaying the time elapsed in seconds. Time elapsed to get the results by WLS method was 0.3501 seconds.

Table 2.1: Results of State Estimation by W.L.S

Sr.No.	Bus No.	Bus Type	**Voltages (P.U)**	**Angels (Deg.)**
1	1	Slack	0.981	0.00
2	2	P-V	0.958	10.35
3	3	P-V	0.950	3.72
4	4	P-Q	0.966	-1.81
5	5	P-Q	0.950	-1.81
6	6	P-Q	0.956	-2.44
7	7	P-Q	0.960	4.11
8	8	P-Q	0.956	1.18
9	9	P-Q	0.956	1.14

2.3 Bad Data Detection and Identification

Bad data identification is essential part of state estimation and function of state estimator. Bad data can be any error in data because of the finite accuracy of meter, telecommunication medium, meter biasing, wrong connection, noise and unexpected interference. Some can be eliminated by simple plausibility check i.e. negative voltage magnitude, large variation between incoming and out going currents. But not all errors can be eliminated in such easy way so, state estimator often have such function called bad data detection.

2.3.1 Classification of Bad Data

- Bad data can be classify into two main types:

a. **Single Bad Data:** Only one measurement comprises large error.

b. **Multiple Bad Data:** More than one measurement with error.

- Further Multiple bad data can be classify into following types:

a. **Multiple Non-Interacting Bad Data:** Bad data measurements with weakly correlated residual refers this type.

b. **Multiple Interacting but Non-Conforming bad data:** strongly correlated residuals with no-conforming bad data in measurements.

c. **Multiple Interacting and Conforming Bad Data:** With strongly correlated residual there are consistent bad data in measurements.

2.3.2 Classification of Measurement

Power system contains different type of measurements spread out in system which may affect the output of power system accordingly, depending upon the their value as well as location. Therefore measurements can be ramify into following categories:

a. **Critical Measurement:** A critical measurement is the one whose elimination from the measurement set will result in an unobservable system.

b. **Redundant Measurement:** A redundant measurement is a measurement which is not critical. Only redundant measurements may have nonzero measurement residuals.

c. **Critical Pair:** Two redundant measurements whose simultaneous removal from the measurement set will make the system unobservable.

2.4 Methods for Bad Data Detection

In this thesis there is a consideration of two conventional methods for bad data detection have been discussed which are Chi-square method and Largest normalized residual method.

2.4.1 Chi-square(χ^2) Distribution

Let us consider a set of N independent random variable $X_1, X_2, ..., X_n$ and distributed according to the standard normal distribution.So, new variable Y defined by:

$$Y = \sum_{i=1}^{N} X_i^2 \tag{2.24}$$

It will have χ^2 Distribution with N-degree of freedom $Y \sim \chi_N^2$.

Let us consider the Function written in terms of measurement Error.

$$f(x) = \sum_{i=1}^{m} R_{ii}^{-1} e_i^2 = \sum_{i=1}^{m} (\frac{e_i}{\sqrt{R_{ii}}})^2 = \sum_{i=1}^{m} (e_i^N)^2 \tag{2.25}$$

Where

e_i=i^{th}measurement error

m=total number of measurement

R_{ii}=diagonal entry of the measurement error covariance matrix.

So,f(x) will have to satisfy the power balance equation at most (m-n) degree of freedom(number of measurements - number of states).

2.4.2 χ^2 Test for Detecting Bad Data in WLS State Estimation

To approximate above function f(x) and detect bad data Objective Function J(x) is used.

$$J(\hat{x}) = \sum_{i=1}^{m} \frac{(Z_i - h_i(\hat{x}))^2}{\sigma_i^2} \tag{2.26}$$

Where

$\hat{x}$=estimated state vector of n dimension

$h_i(\hat{x})$= estimated measurement i

Z_i= measured value

σ_{ii}^2= R_{ii}= variance

m= number of measurements.

One can check the values of area under the curve from lookup table (values of α)[3] i.e. appropriate number of degree of freedom k=($N_m - N_s$) and a specified probability. check the value of Objective function less then the critical value corresponding to specified probability or not.

where

N_m= number of measurements

N_s= number of states.

The possible sets of measurements can be made for 'n' bus and 'l' branch system can be given by table 4.1[5]

Table 2.2: Max. No. of Measurements Table

Symbol	**Physical Quantity**	**Max.no. of Measurements**
P_{ij}, Q_{ij}	Real and reactive Power flow	4l
V_i	Voltage Magnitude	2l
P_i, Q_i	Real and Reactive Power injection	2n

2.4.3 Steps to Detect bad data from measurements by Chi-square Method

Bad data has been introduced in the measurement by using following equation:

$z_i = A_i + rand \times \sigma_{imeans}$

Where:

A_i is the true value of measurement

$rand$ is the random number between 0 to 1

σ_{imeans} is the standard deviation of measurement.

STEP 1:

Use the raw data Z_i from the system for determine the WLS $\hat{x}$,of system state.

STEP 2:

Substitute the $\hat{x}$ in the equation $\hat{z} = H\hat{x}$.By which one can find the $\hat{e}_i = z_j - \bar{z}_j$.

STEP 3:

calculate the sum of square of error.

$$\hat{f} = \sum_{j=1}^{m} \frac{\hat{e_i^2}}{\sigma_i^2} \tag{2.27}$$

STEP 4:

According to the value of α corresponding to values of k If the value of $\hat{f}$ larger then there has to be some bad data and should be removed.

$$P_r(\hat{f} < \chi^2_{k,\alpha}) = (1 - \alpha) \tag{2.28}$$

Based on this equation, the critical value of the statistic $\hat{f}$ can be determined using the tabulated values of $\chi^2_{k,\alpha}$ a given in[4]. For example, choosing $\alpha = 0.01$ and k $= (N_m - N_s) = 2$, one can conclude that the calculated value of $\hat{f}$ is less than the critical value of 9.21 with probability (1 - 0.01) or 99% confidence since $\chi^2_{2,0.01} = 9.21$ in [4]. Thus, the chi-square distribution of $\hat{f}$ provides a test for detection of bad measurements.

2.4.4 Largest Normalized Residual Method

As seen before Chi-square test is inaccurate due to the approximation of errors by residuals in equation (2.25). A more accurate test for detecting bad data can be devised by using the normalized residuals. Normalized value of the residual for measurement i can be obtained by simply dividing its absolute value by the corresponding diagonal entry in the residual covariance matrix:

$$r_i^N = \frac{|r_i|}{\sqrt{\Omega_{ii}}} \tag{2.29}$$

The normalised residual vector r^N will have standard normal distribution vector i.e.

$$r_i^N \sim \mathrm{N(0,1)}$$

The largest element in r^N can be compared against a statistical threshold to check the existence of bad data and can be selected based on the the desired level of sensitivity.

2.4.5 Steps to Detect bad data from measurements by Largest Normalised Residual method

STEP 1:

Solve the WLS estimation and obtain the elements of the measurement residual vector:

$$r_i = z_i - h_i(\hat{x}) \tag{2.30}$$

STEP 2:

Compute the normalized residuals:

$$r_i^N = \frac{|r_i|}{\sqrt{\Omega_{ii}}} \tag{2.31}$$

$$\mathrm{i = 1,...,m}$$

$$\sqrt{\Omega_{ii}} = \sqrt{R_{ii}S_{ii}} \tag{2.32}$$

$$S_{ii} = I - HG^{-1}H^TR^{-1} \tag{2.33}$$

Where:

I = identity matrix

S_{ii} = sensitivity matrix

The sensitivity matrix represents the sensitivity of the measurement residuals to the measurement errors.

STEP 3:

Find k such that r_k^N is largest among all r_i^N, i = 1,...,m.

STEP 4:

If $r_k^N > C$, then k^{th} measurement is suspected as bad data. Else, stop, no bad data is suspected. Here, C is a chosen identification threshold, for instance 3.0.[3]

STEP 5:

Eliminate the k^{th} measurement from measurement set and go to step 1.

2.4.6 Identification of Bad Data

In the pervious section ramification of bad data has been shown, after that it is incumbent to identify the bad data as well. Identification of bad data can be done by looking into the diagonal and off-diagonal entries of residual covariance matrix Ω and sensitivity matrix S as follows:

- $\Omega_{ij} \geq C$, i and j measurements are said to be strongly interacting, else those are weakly interacting or non-interacting.
- Ω should be real and symmetric, also off-diagonal entries can be verified to remain less then both the arithmetic and geometric mean of corresponding diagonal entries [3].
- When measurement is critical, column of corresponding measurement would be identically equal to zero in residual covariance matrix Ω, else measurement is redundant.
- In other way in sensitivity matrix $S_{ij} \approx 0$, then measurement i and j are said to be non-interacting.
- When S_{ij} is significantly large then measurement i and j said to be interacting.

- When in S_{ij} measurement i and j are mutually consistent or the error is mutually consistent in corresponding off-diagonal entry in S_{ij}, measurement is said to have conforming bad data

Both residual covariance matrix and sensitivity matrix are mentioned below, the matrix entries shown here is corresponding to estimated bus voltages as only bus voltage magnitudes and angles are estimated here.

$$S = \begin{bmatrix} 0.906 & -0.0918 & -0.090 & -0.094 & -0.094 & -0.093 & -0.092 & -0.090 & -0.090 \\ -0.0918 & 0.894 & -0.099 & -0.094 & -0.097 & -0.096 & -0.102 & -0.099 & -0.099 \\ -0.090 & -0.099 & 0.897 & -0.093 & -0.095 & -0.095 & -0.099 & -0.100 & -0.100 \\ -0.094 & -0.094 & -0.093 & 0.903 & -0.097 & -0.095 & -0.094 & -0.093 & -0.093 \\ -0.094 & -0.097 & -0.095 & -0.097 & 0.900 & -0.096 & -0.097 & -0.096 & -0.095 \\ -0.093 & -0.096 & -0.095 & -0.095 & -0.096 & 0.901 & -0.096 & -0.095 & -0.095 \\ -0.092 & -0.102 & -0.099 & -0.094 & -0.097 & -0.096 & 0.898 & -0.099 & -0.099 \\ -0.090 & -0.099 & -0.100 & -0.093 & -0.096 & -0.095 & -0.099 & 0.899 & -0.100 \\ -0.090 & -0.099 & -0.100 & -0.093 & -0.095 & -0.095 & -0.099 & -0.100 & 0.899 \end{bmatrix}$$

$$\Omega = \begin{bmatrix} 0.00906 & -0.00092 & -0.0009 & -0.00094 & -0.00095 & -0.00094 & -0.00092 & -0.00091 & -0.00091 \\ -0.00092 & 0.0089 & -0.00099 & -0.00095 & -0.00098 & -0.00096 & -0.00103 & -0.001 & -0.00099 \\ -0.0009 & -0.00099 & 0.00897 & -0.00093 & -0.00095 & -0.00095 & -0.00099 & -0.0010 & -0.0010 \\ -0.00094 & -0.00095 & -0.00093 & 0.00904 & -0.00097 & -0.00096 & -0.00095 & -0.00094 & -0.00094 \\ -0.00095 & -0.00098 & -0.00095 & -0.00097 & 0.00900 & -0.00097 & -0.00098 & -0.00096 & -0.00096 \\ -0.00094 & -0.00096 & -0.00095 & -0.00096 & -0.00097 & 0.00901 & -0.00096 & -0.00096 & -0.00096 \\ -0.00092 & -0.00103 & -0.00099 & -0.00095 & -0.00098 & -0.00096 & 0.00898 & -0.001 & -0.0009 \\ -0.00091 & -0.001 & -00010 & -0.00094 & -0.00096 & -0.00096 & -0.001 & 0.00899 & -0.001 \\ -0.00091 & -0.00099 & -0.0010 & -0.00094 & -0.00094 & -0.00096 & -0.00096 & -0.001 & 0.00899 \end{bmatrix}$$

2.4.7 Results after Bad Data Detection and Removal

Results tabulated has carried out after applying Chi-square algorithm shown in section 2.4.4 as well as using LNR algorithm shown in section 2.4.6. to the results of WLS state estimation. Time required by software to execute the Chi-square and LNR algorithm is 1.307 seconds and 1.219 seconds respectively.

Table 2.3: Results after Bad Data Detection and Removal

Sr.No.	Bus No.	Bus Type	**Voltages (P.U) (WLS)**	**Voltages (P.U) (Standard)**	**Voltages (P.U) (Chi square)**	**Voltages (P.U) (LNR)**
1	1	Slack	0.983	1.040	0.978	1.008
2	2	P-V	0.958	1.025	1.025	1.056
3	3	P-V	0.950	1.025	1.021	1.037
4	4	P-Q	0.966	1.025	0.974	1.005
5	5	P-Q	0.950	0.993	0.955	0.987
6	6	P-Q	0.956	1.007	0.963	0.992
7	7	P-Q	0.960	1.023	1.019	1.047
8	8	P-Q	0.956	1.013	1.016	1.028
9	9	P-Q	0.956	1.028	1.019	1.032

2.4.8 Computational Issues with Chi-square test and Largest Normalised Residual Test

a. Chi-square test fails to identify multiple interacting bad data.

b. Normalized residuals are calculated using the diagonal entries of the residual covariance matrix H.

c. Identified bad measurement with the largest normalized residual will be removed from the measurement set before repeating the state estimation procedure.

d. LNR method is able to identify the multiple interacting bad data in some cases when system doesn't have large number of measurements. However when system has large number of measurements and bad data is conforming type this method is unable to identify the bad data.

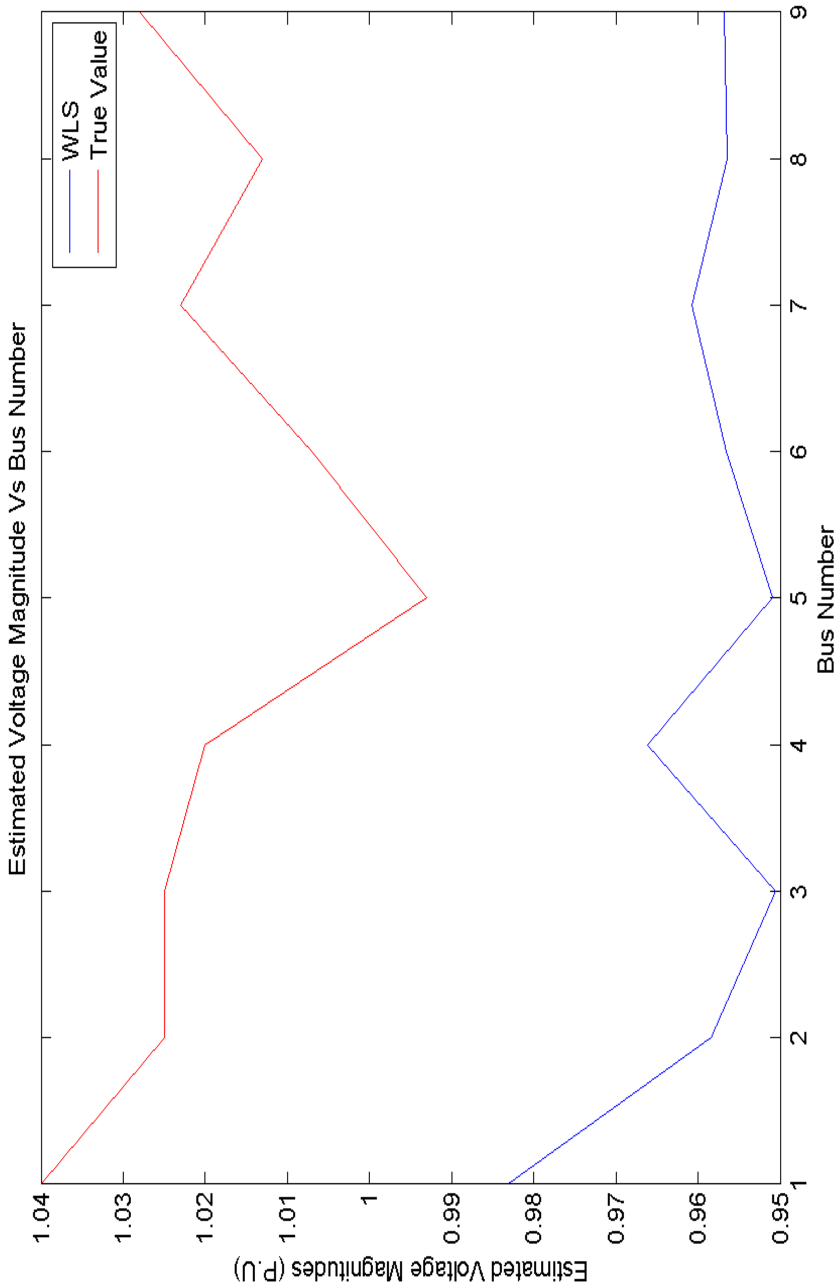

Figure 2.3: Estimated Bus Voltage Magnitudes by W.L.S

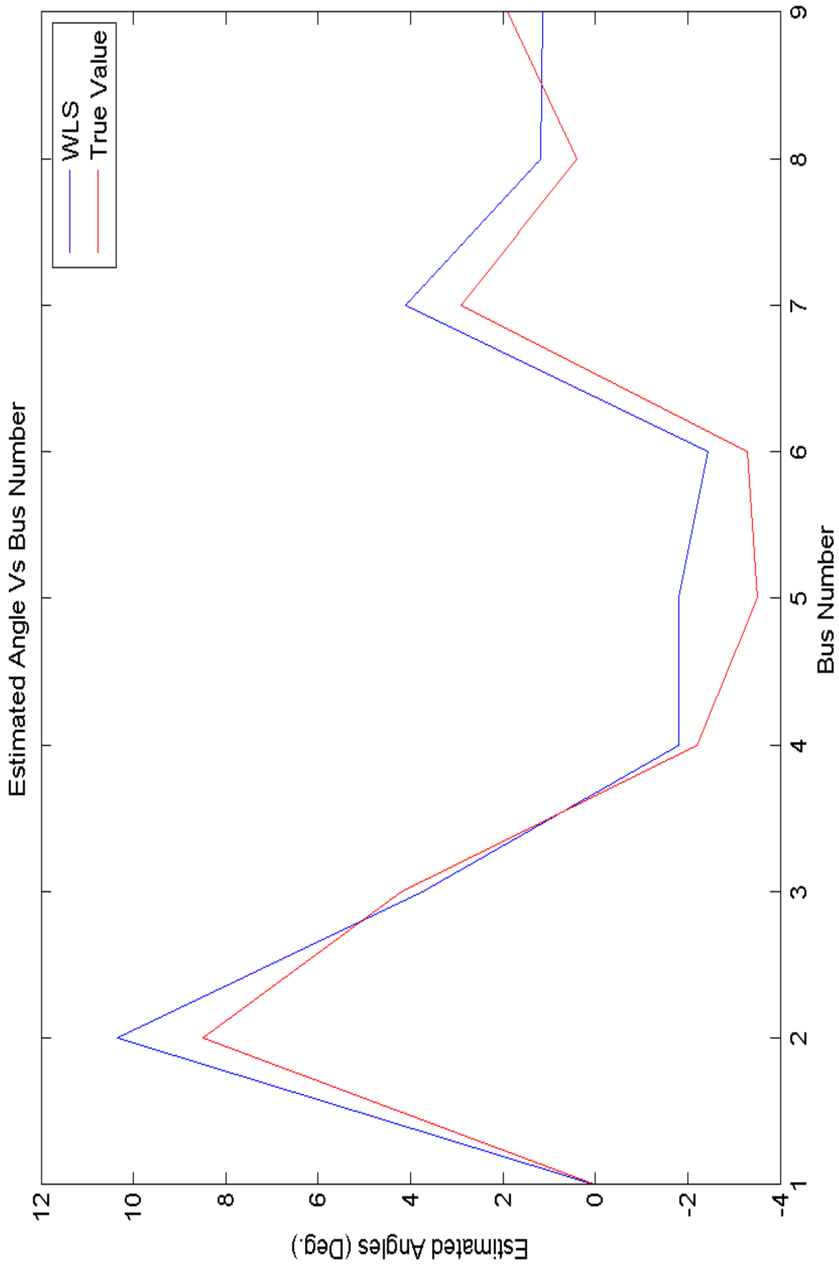

Figure 2.4: Estimated Bus Angle Results by W.L.S

Chapter 3

Application of Artificial Intelligence In Power System

Technology by which machine or computer can perform task equal to or batter than normal human computational ability with accuracy and efficiently consuming less time can be define as artificial intelligence.

3.1 Introduction

Human Operators more often faces cognitive barrier when information comes faster and can overwhelmed operator during emergency condition.
In such situation diagnosis of problem or to formulate the correct control scheme become difficult. With the help of AI technique some unforeseen event or failure of major component could be solved efficiently and faster, Because of various advantages of AI like high computational rates, robustness.
Coping with emergency event and diagnosis with decision making process and their solution heavily rests on experience and skill of human operator to react correctly.
There is need to incorporate heuristics in many area of power system which may fail to converge or economic analysis program may fail to meet constrains.

3.2 Approaches to AI

- System that think rationally
- System that think like humans
- System that acts like humans
- System that acts rationally

3.2.1 Intelligent Agents

In AI there are some entities which are working to make system autonomous called intelligent agents. Basically Agents receives percepts from environment and their action change the environment. Intelligent agent decide automatically which action to take in the current situation to maximize the progress towards the goal.
Performance measures are its speed, power usage, accuracy,etc. Intelligent agents can be classify as follows:

- State Based Agents
- Goal Based Agents
- Utility Based Agents
- Learning Agents

These intelligent agents should be able to do both ”mundane” and ”expert” tasks.
Mundane tasks which one is doing in everyday life for example:

- Interpreting sensor information.
- Recognising Faults.
- Communication.
- Fault Prevention.

These tasks are very hard to mechanise because of its dynamic nature and everyday changing facts. And expert tasks like:

- Mathematical calculation.

- Diagnostics of Machine.

These tasks are comparatively very easy to mechanise because of its logical and never changing facts.

3.3 Knowledge Representation in AI System

Depending upon the representation scheme an AI program become either rule-based, Logic based, or frame based.

3.3.1 Rule Based System

In this system a piece of knowledge is represented in form called premise part (if-clause) and action part (then-clause)
Here rule base system is based on rules that says what to do in given various conditions. In rule based system possibilities can be shown in between if else clauses.
Apart from adding fact other tasks like add an action part also can be performed. Rule base system can be fact or action or both. Various different schemes idea or logic or often heuristics are used as any human being cannot have outright knowledge of anything.
As with anyone's partial knowledge or based on logic(General knowledge) or thumb rule this method can be very effective system.
As figure 3.1 showing rule base system works first inference machine look into the rule base as shown in left block and then check in the fact base if any fact is matching with rule it takes action or the add the new fact in the fact base.

Inference machine

A machine that implements strategies to utilize the knowledge base(Fact Base) and derive new conclusion from it.
It will try to find a match by seeing in Rule Base and Fact Base which rule is triggered.

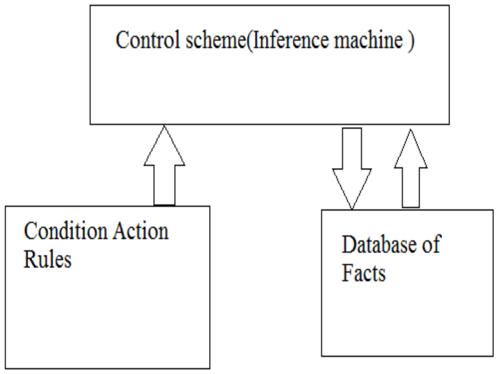

Figure 3.1: Basic Architecture of Expert System

If more then one rule is triggered then it will have to select one rule and it's fired and executed. Implies that it generate new fact.

Conflict Resolution

When more than one rule are triggered to decide which rule should be fired at what time conflict mechanism is used and strategies for doing same is as given below:

- FCFS(First Come First Start)
- Specify Ordering(Rule Ordering)
- Fire All
- Heuristic Measure

From all above strategies Heuristics technique is more often used.

3.3.2 Logic Based System

This method is more declarative type and not based on rule it is based on two possibilities If and else unlike Rule Based System. Moreover it shows proportional logic.

Syntax and Semantics

It should have proper Syntax(Grammar) and Semantics which is dose the rule is caring some meaning or not if or then system will not work.
Example of wrong syntax can be like this i.e Pen cut the road and Example of wrong semantics can be like this i.e Pen cuts the road.(In this statement the syntax is correct but one cannot map this in real world).

3.3.3 Frame Based System

There are always some relation in between objects in real world. Previous two techniques does not give facility to represent those relation or rather one can say those cannot provide facility to program relations.
Most of the time there are certain type of relation in between may problems. Frame base system allows to program these type of logic or knowledge. i.e substation operation depending upon the statues of breakers, switches, each bus can be split or energies or De-energise.

3.3.4 Heuristics Methods

- Gravitational Search
- Particle Swarm Optimisation
- Ruin and Recreate
- Harmony Method

3.3.5 Meta-heuristics Methods

- Genetic Algorithm
- Swarm Intelligent
- Simulated Annealing
- Ant Colony Optimisation

Chapter 4

State Estimation by Particle Swarm Optimisation

Artificial Intelligence comprises immense number of methods to train the system, optimize the system such as, Expert System, Fuzzy System, Artificial Neural network, Evolutionary Computation, etc. Among from all these methods Evolutionary Computation is most suitable for the optimisation problems. Evolutionary Computation further can be ramify into acclaimed or pronounced methods which are Genetic Algorithm (GA), Particle Swarm optimisation (PSO), Ant colony optimisation, etc. GA is incited by biological evolution such as mutation, selection, inheritance and crossover. GA requires high computation as compared to PSO which leads to high computation time implies that PSO could be better choice in some optimisation problem.

4.1 Introduction to Particle Swarm Optimisation

Particle Swarm Optimisation is usually used for optimising non-linear functions. Particle Swarm Optimisation is inspired from bird flocking, fish schooling and Swarm theory. Epitome of this method could be implemented in few lines of code with basic mathematical operators. Which entails that it is computationally inexpensive and require less memory requirement and higher computational efficiency.

Sociobiologist E.O. Wilson has written in reference of fish schooling, In theory at least, individual members of school can profit from the discoveries and previous experience of all other members of school during the search for food. This advantage can become decisive, outweighing the disadvantages of competition for food items, whenever food is unpredictably distributed in patches.[10]. This could be advantageous and was hypothesis of fundamental to the development of Particle Swarm Optimisation.

4.2 Fundamental of Particle Swarm Optimisation

Most commonly in Particle Swarm Optimisation each particle wanders in circumscribed search space. Each particle moves in search space outrightly using a combination of an attraction to the best solution that they individually have found and best solution that any particle in their neighbourhood has found.
An individual particle particle is formed of three vectors which are it's position in D-dimensional search space $\overrightarrow{x_i} = (x_{i1}, x_{i2}, ..., x_{iD})$, the best position that it has individually found $\overrightarrow{p_i} = (p_{i1}, p_{i2}, ..., p_{iD})$ and it's velocity $\overrightarrow{v_i} = (v_{i1}, v_{i2}, ..., v_{iD})$. Each particle were initialised in uniform random manner throughout the search space. Afterwards these particles move in entire search space using set of update equations. Velocity of particle is updated using following equation:

$$v_{id} = v_{id} + c\epsilon_1(p_{id} - x_{id}) + c\epsilon_2(p_{gd} - x_{id}) \tag{4.1}$$

Where:
c = constant with value 2.0
ϵ_1 and ϵ_2 = independent random numbers uniquely generated at every update for each individual dimension d = 1 to D
p_{gd} = best position found by any neighbour of particle
p_{id} = best position found by particle itself
x_{id} = search point of individual particle
As seen from equation (4.1) it has three terms and meaning of these terms can be

explained as follows[14]. The first term is previous velocity of the agent. The second and third term changes the velocity of the agent, without it agent will keep flying in same direction until it reaches to boundary, without the first term velocity of agent is only determined by using its best position in history and current velocity. Thus, it will try to converge at its *Pbest* and/or *Gbest* and will not try to explore further in search space. Search point update equation can be written as follows:

$$x_{id} = x_{id} + v_{id} \tag{4.2}$$

4.2.1 Swarm Communication Topology

Swarm communication comprises two topology (1) gbest topology and (2) lbest topology. The original PSO showed inferior performance when compared to gbest topology. lbest model allows to connect each particle with other two particle nearer to it unlike gbest model in which each particle can consolidate information from very best particle in entire swarm population. lbest model has slower convergence rate relative to gbest this prevents convergence at premature stage. Faster performance of gbest topology results in better performance on simple unimodal problems and even sometimes on complex multimodal problem [11].

4.2.2 Inertia Weight and Constriction Factor

Inertia Weight

After few years of original PSO a new parameter was introduced to have better balance between global exploration and local exploration avoiding clamping the particle velocity through vmax method simultaneously. The new parameter called Inertia Weight (w) was replaced with vmax. Inertia weight could be adjusted by the influence of previous particle velocities on the optimization process. Velocity equation is altered by following equation:

$$v_{id} = wv_{id} + c_1\epsilon_1(p_{id} - x_{id}) + c_2\epsilon_2(p_{gd} - x_{id}) \tag{4.3}$$

Where:

w = Inertia Weight

$c_1 = c_2 =$ acceleration factor

c_1 and c_2 affect the maximum step size of a particle in a single iteration. c_1 regulates the maximum step size of a particle in the direction of the *Pbest* while c_2 regulates the maximum step size in the direction of the *Gbest*. The particle velocity is limited by V_{max} to minimize the possibility of the particle escaping the search space. If the search space is defined by the bounds $[X_{min}, X_{max}]$, the value of V_{max} is typically set to:

$$V_{max} = K \times (X_{max} - X_{min}) \tag{4.4}$$

Where:

$0.1 \leq K \leq 1.0$

Before w was set to 1.0 to encourage the early exploration, then decreased eventually to less then 1.0 to focus the efforts of swarm on the best area found in exploration[11]. Inertia weight is set to 0.9 at the beginning of the run and decreased linearly to 0.4 at the maximum number of iteration. This settings of inertia weight has provided improved performance in number of application[12].

Constriction Factor

An alternative way to balance the global and local searches acclaimed as "Constriction Factor" method. As name entails this method introduce a new parameter constriction factor χ derived from existing constants in velocity update equation.

$$\chi = \frac{2}{|2 - \psi - \sqrt{\psi^2 - 4\psi}|} \tag{4.5}$$

Where :

$\psi = c_1 + c_2$

$c_1 = c_2 =$ acceleration factor

It was found that when $\psi < 4$, the swarm would slowly spiral toward and around the best found solution in the search space with no guarantee of convergence, while for $\psi > 4$ convergence would be quick and guaranteed [11]. New velocity update equation can be written as follows:

$$v_{id} = \chi v_{id} + c_1\epsilon_1(p_{id} - x_{id}) + c_2\epsilon_2(p_{gd} - x_{id}) \tag{4.6}$$

Best approach to use particle swarm optimisation is to utilize the constriction factor approach while limiting V_{max} to X_{max} or utilize the inertia weight approach while selecting w, c_1, c_2. Employing latter method instead former is easy and straightforward particularly when particle swarm paradigm requires the specification of X_{max} [12].

4.3 Power System State Estimation by Particle Swarm Optimization

Particle Swarm Optimization does not need any gradient information about the objective or error function and it can obtain the best solution independently and also less dependent on initial starting point in order to get global solution [13]. From an initial position, each particle in swarm starts wandering in search space to explore optimal points and Spot of each particle shows the potential solution. Purpose here is minimisation, the particle is one with a lower fitness value. During the search (iteration), the best value (position), for each particle is stored and acquaint as Personal Best (*Pbest*) and the lowest value among all the *Pbest* is assigned as Global Best (*Gbest*) of the swarm. Fitness value can be find by employing following equation:

$$F(X_i) = J(x) + P(x) \tag{4.7}$$

$$J(x) = \sum_{i=1}^{m} w_i^2(z_i - h_i(x))^2 = \sum_{i=1}^{m} \frac{e_i^2}{\sigma_i^2} \tag{4.8}$$

Where:

e_i=i^{th}measurement error

m=total number of measurement

σ =veriance of i^th measurement.

z = measured value

h(x) = measurement function

$$P(x) = \lambda_1 \sum_{i=1}^{NV} [max(0, x_i - x_i^{max})]^2 + \lambda_2 \sum_{i=1}^{NV} [max(0, x_i^{min} - xi)]^2 \tag{4.9}$$

Where:

NV = number of state variable

$\lambda_1 = \lambda_2 = 10000$

λ_1 and λ_2 are problem dependent and hence usually found experimentally [13].

4.3.1 Algorithm for Power System State Estimation by Particle Swarm Optimization

- **Step 1:**

  Initialize the swarm by assigning a random position in search space to each particle. Initial population of state variables can be expressed as follows:

  $$X = [X_1, X_2, X3, ..., N_s] \tag{4.10}$$

  Where: N_s = number of state variables

  $$X_{id} = [X_j]_{1\times N} \tag{4.11}$$

  Where: id = 1, 2, 3,..., N_s

  $$X_j = rand(0, 1) \times (X^j_{max} - X^j_{min}) + X^j_{min} \tag{4.12}$$

Where: j = 1, 2, 3,..., N

- **Step 2:**

  Evaluate the fitness function for each particle by utilising the equation(4.6)

- **Step 3:**

  For each individual particle, compare the particle's fitness value with it's *Pbest*. If *Pbest* is better then previous *Pbest* then set that value as new *Pbest* and set current particle's Position x_i as P_i.

- **Step 4:**

  Identify particle with best fitness value identified as *Gbest* and it's position as P_g.

- **Step 5:**

  Update velocity and position of particles.

  Velocity update equation:

$$v_i^{t+1} = wV_i^t + c_1r_1(X_i^{pbest} - X_i^t) + c_2r_2(X^{Gbest} - X_i^t) \tag{4.13}$$

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter. \tag{4.14}$$

Where:

$c_1 = c_2 =$ acceleration factors

$w_{max} = 0.9$

$w_{min} = 0.4$

$r_1 = r_2 = rand(0, 1)$

$X^t =$ State Vector

Position update equation:

$$X_i^{t+1} = X_i^t + v_i^{t+1} \tag{4.15}$$

- **Step 6:**

  Identify best value of each particle and set as *Pbest*. Identify best value among all the particles and set as *Gbest*.

- **Step 7:**

  Has convergence criteria match ? or Has maximum iteration reached ? If yes then Stop, else go to step 5 and repeat the process.

4.3.2 Flow Chart for Basic Particle Swarm Optimization

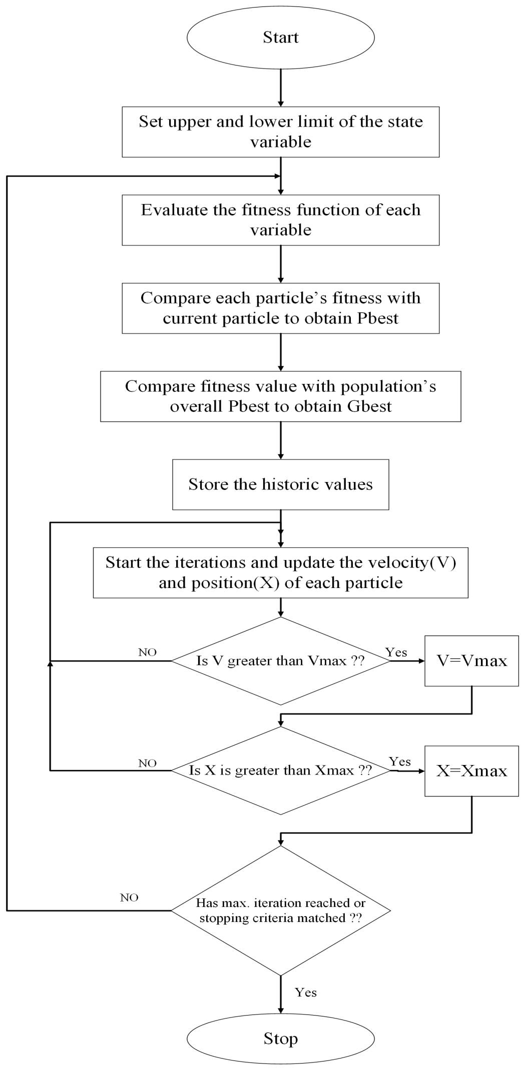

Figure 4.1: Flowchart of Basic P.S.O

4.3.3 Results of Power System State Estimation by Particle Swarm Optimization

Results showed below are obtained by following algorithm given in section 4.3.1. To calculate time require to execute the program MATLAB function "tic-toc" is useful command. The tic command starts a stopwatch timer, MATLAB executes the block of statements, and toc stops the timer, displaying the time elapsed in seconds. Time elapsed to get the results by P.S.O was 0.0314 seconds which is apparently lesser then time taken by the conventional method.

Table 4.1: Estimated Voltage and Phase Angle by PSO

Sr.No.	**Bus no.**	**Type**	**True Value Voltage Mag. (P.U)**	**True Value Theta (Deg.)**	**Est. value Voltage Mag. (P.U)**	**Est. value Theta (Deg.)**
1	1	Slack	1.04	0.00	1.042	0
2	2	P-V	1.025	9.3	1.027	8.3
3	3	P-V	1.026	4.7	1.022	4.035
4	4	P-Q	1.026	-2.2	1.022	-2.023
5	5	P-Q	0.996	-4.0	0.99	-3.682
6	6	P-Q	1.013	-3.7	1.0072	-3.098
7	7	P-Q	1.026	3.7	1.025	2.9
8	8	P-Q	1.016	0.7	1.015	0.3
9	9	P-Q	1.032	2.0	1.03	1.881

4.4 Bad Data Detection and Identification by Particle Swarm Optimization

In the previous section introduction and fundamentals of Particle Swarm Optimization has discussed. The purpose here is to detect and identify the bad data, thus the same PSO method can not be applicable here. The algorithm required is to operate on discrete binary variable. As any problem discrete or continuous, can be expressed in a binary notation, such as in this problem bad data can be noted with digit 1 else 0. Thus method required here is Discrete Particle Swarm Optimization (DPSO).

4.4.1 Discrete Particle Swarm Optimization

The original PSO described in previous section deals with non-linear optimization problem with continuous variable. Despite, practical engineering problems are often formulated as combinatorial optimization problems. Discrete PSO developed by Kennedy and Eberhart in [23] deals with these type of problems.
The parameter v, tendency of an agent to make one or other choice will determine the probability of threshold. If v is higher, chances of choosing 1 by an agent is higher and in contrary with the lower value of v agent will choose 0. Thus threshold should required to be in the range [0,1] and to accomplish this sigmoid function is used.

$$sig(v_i^k) = \frac{1}{1 + exp(-v_i^k)} \tag{4.16}$$

The only change here is in the velocity update equation, where change in particle's position is made by using equation (4.15). However in this algorithm change in position of particle is made through sigmoid function by comparing its value to the threshold as follows:

$$v_i^{k+1} = v_i^k + rand_1 \times (pbest_i - S_i^k) + rand_2 \times (gbest - S_i^k) \tag{4.17}$$

$$\rho_i^k < sig(v_i^{k+1}) \rightarrow S_i^{k+1} = 1;$$

else

$$S_i^{k+1} = 0,$$

Where:
rand is the positive random number drawn from the uniform distribution with predefined limits. ρ_i^k is the vector of random number between [0.0, 1.0].
Thus the particle moves in restricted search space of 0 and 1 on each dimension. If $v_{id} = 0.20$ because of the random number multiplying in initialization of swarm then there is twenty percent chance is that particle will select 1 as its position i.e $x_{id} = 1$ [23].

4.4.2 Bad Data Identification by Particle Swarm Optimization

In [19] and [22] the identification of interacting bad data is done through combinatorial problem using framework theory. Decision variable of i^{th} measurement can denoted by:

$$b_i = 1 \text{ if the } i^{th} \text{ measurement is bad}$$
$$b_i = 0 \text{ if the } i^{th} \text{ measurement is good}$$

There are 2^m possible elements which are good and bad measurement in decision vector. Decision vector can be define as $b = [b_1, b_2, b_3, ..., b_m]$ where $b_i = 1$ or 0. The decision vector is feasible if after removal of bad data in b, the resulting network S(b) is still observable also the result of state estimation does not detect any bad data. S(b) denotes the corresponding measurement set that only good data are applied and no bad data have been suspected. Removal of bad data can be done through Chi-square test mention in section 2.4.4, and the decision vector can be defined as follows after performing bad data identification by Chi-square test and LNR test respectively.

$$b_{\chi^2} = [0\ 1\ 1\ 0\ 0\ 0\ 1\ 1\ 1\ 1\ 1\ 0\ 0\ 0\ 1\ 1\ 1] \tag{4.18}$$

$$b_{LNR} = [1\ 1\ 1\ 0\ 0\ 0\ 1\ 1\ 1\ 1\ 1\ 0\ 0\ 0\ 1\ 1\ 1] \tag{4.19}$$

The problem of interacting multiple bad data identification can be formulated as follows [22].

$$min\ F(b) = \sum_{i=1}^{m} b_i \tag{4.20}$$

subjected to S(b) is observable, $J(\hat{x}(b)) < C(b)$ where C is detection threshold. As mentioned in section 2.4.4 bad data has been introduced in all the measurement yet both conventional method for bad data detection is not able to identify all the bad data from measurement set as it can be seen from table (2.4) and above decision vectors, which manifest the computational issues discussed in section 2.4.9. To abolish those issues Particle Swarm Algorithm can be useful.

Algorithm of Bad Data Detection and Identification by Particle Swarm Optimization

Step 1:

Solve the state estimation problem by conventional WLS method.

Step 2:

Check the presence of bad data by Chi-square test. If $J(\hat{x}) < C$, go to step 3 else quit the program.

Step 3:

Set k=1. Initialize the population of particles with random positions, set the decision vector $b = [b_1, b_2, b_3, ..., b_m]$ where $b_i = 1$ or 0, here in this algorithm equation (4.19) is used as decision vector, which is problem dependent, also set the velocities v_i^k.

Step 4:

For each particle, evaluate desired fitness function $F(b_i^k)$ as follows, where state estimation is solved to obtain $J(\hat{x}(b_i^k))$ by equation (2.27) or equation (2.32), here equation (2.27) is used.

$$min\ F(b) \ = \ \sum_{i=1}^{m} b_i \ + \ K_1[J\hat{x}(b)] \ + \ K_2 \tag{4.21}$$

where K_1 is penalty coefficient and K_2 is large penalty coefficient when b makes system unobservable.

Step 5:

Compare each particle fitness $F(p_i^K)$ value with $F(p_{i^{k-1}})$ (for k = 1, $p_i^k = b_i^k$). If $F(b_i^k)$ is better than $F(p_i^{k-1})$, then $p_i^k = b_i^k$, else $p_i^k = p_i^{k-1}$.

Step 6:

Select the best p_i^k (based on the fitness value) to be p_g^k.

Step 7:

Update the velocity and position of every particle using equation (4.16) and equation (4.17).

Step 8:

If $k <$maximum iteration, then $k = k + 1$ and go to step 4, else go to next step.

Step 9:

Stop the program once bad data has identified.

Discussion of results

By applying the proposed algorithm the best particle b_pso = [0.775 1 1 0.9327 1 1 1 0.7673 1 1 1 1 0.8990 1 1 1 1] is obtained i.e introduced all the bad data in measurement set has identified and detected. According to the degree of freedom in this problem i.e. $(N_m - N_s)$ is 28 the value of threshold is 48, after performing aforementioned algorithm value of $J(\hat{x}(b))$ which was before 208 now has become 0.048 i.e. $J(\hat{x}(b)) < C(b)$. Which entails this is a feasible solution and the optimal one. Time required to execute this algorithm by software is 0.1200 seconds which is certainly leas then the conventional method of bad data detection.

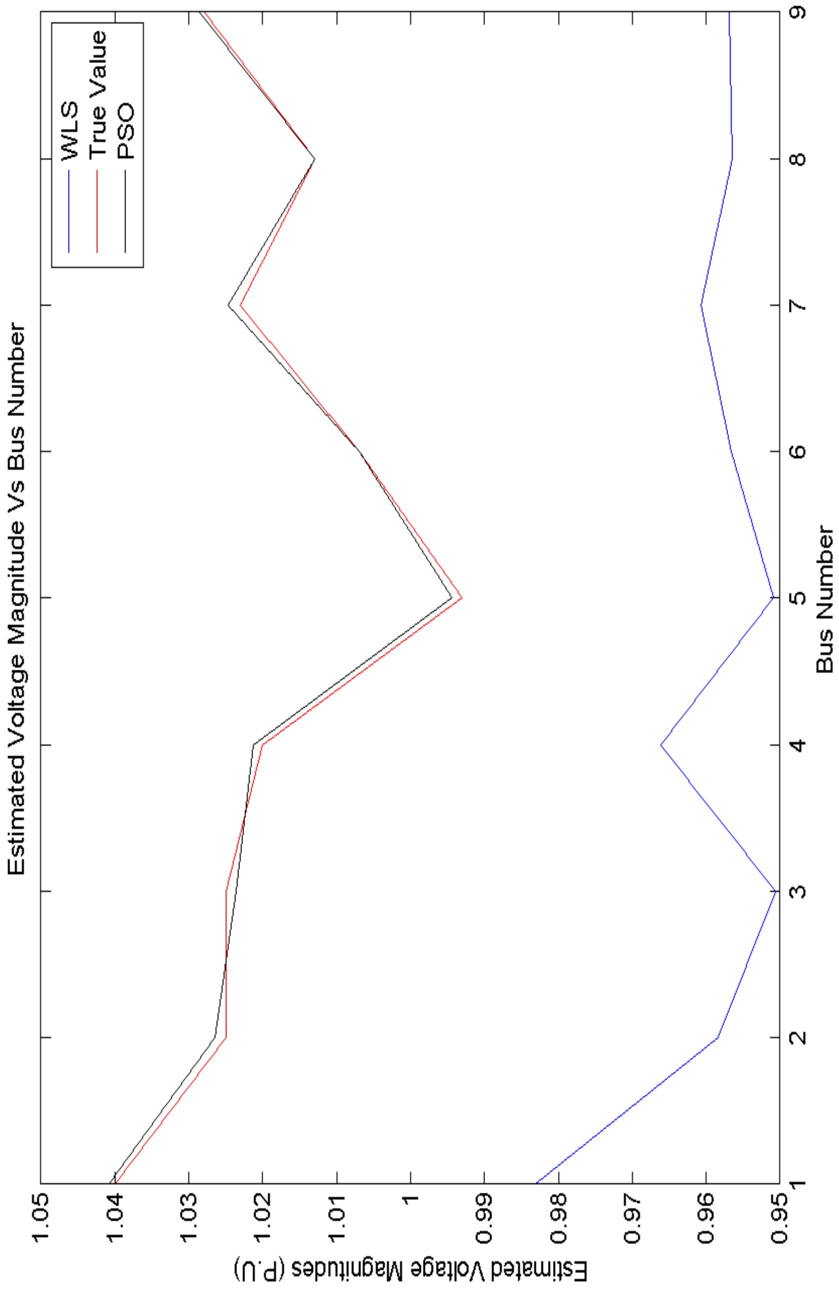

Figure 4.2: Estimated Bus Voltage Magnitude Results by P.S.O

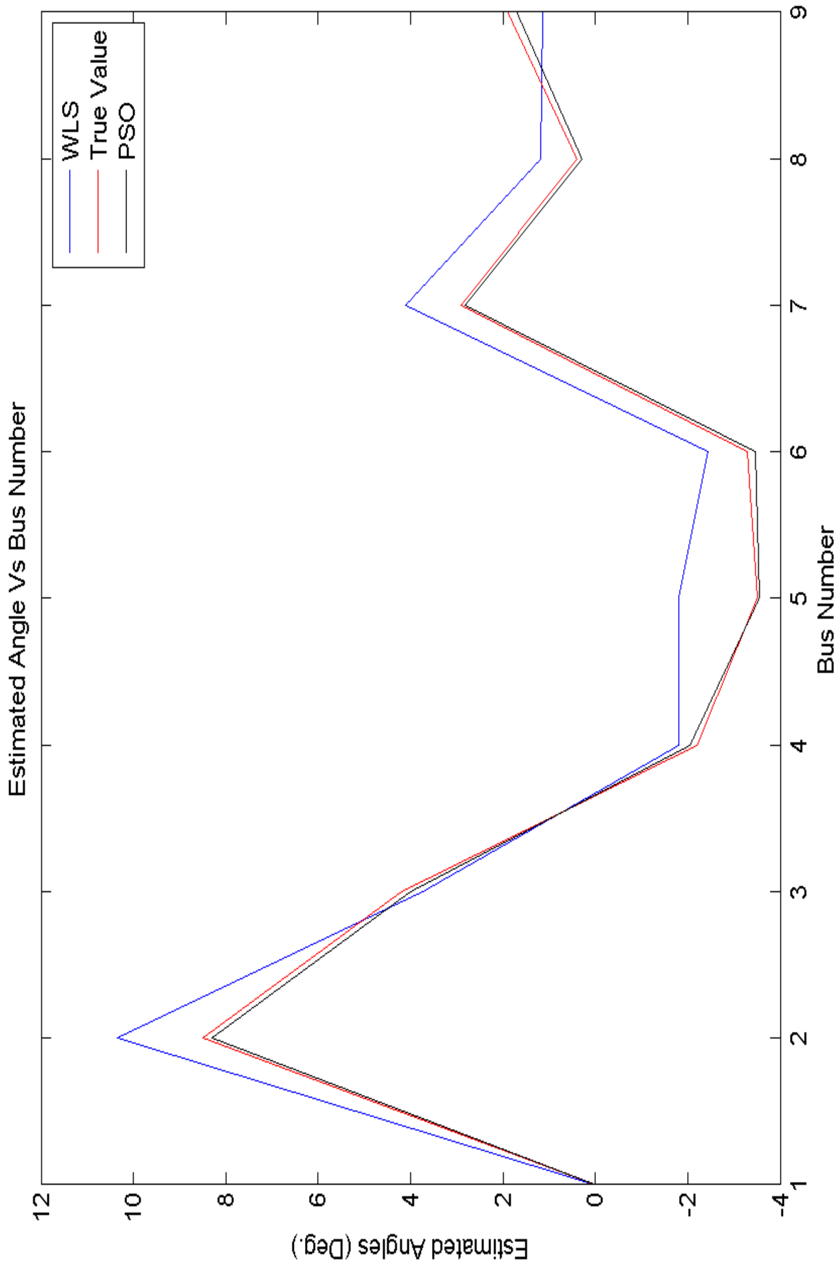

Figure 4.3: Estimated Bus Angle Results by P.S.O

Chapter 5

Conclusion and Future Work

5.1 Conclusions

The extract of the work can be concluded as follows-

- literature survey shows the comparison of different method for W.L.S state estimation, methods for bad data detection and an artificial intelligence method for state estimation.
- After testing Weighted Least Square Sate Estimation on standard test system (WSCC 3-Machine 9-Bus System) and comparing the results with the true value it seems that results obtained by this method is nearer to the true value, but still it was deficit in accuracy and the method is bit of time consuming.
- Moreover to improve the results one of the advance method from Artificial Intelligence technique called Particle Swarm Optimisation has had applied on the same test system. It appears that despite of having subtle disadvantage this method works fine and yields remarkable results by consuming much lesser time than previously applied method.
- Furthermore out of several methods for bad data detection two widely used methods has been discussed here and also applied to the state estimation results of WSCC 3-Machine 9-Bus test system.

- Furthermore, after applying the conventional method one of the method from Artificial Intelligent techniques has applied for bad data detection and it gives remarkable results compared to conventional method in much lesser time.

- For verifying the accuracy of the estimated values, relative voltage magnitude error ($REL-VE$) and relative voltage angle error ($REL-AE$) have been calculated as follows:

$$REL-VE \;=\; max\left|\frac{V_i^{true}-V_i^{est}}{V_i^{true}}\right| \times 100 \tag{5.1}$$

$$REL-AE \;=\; max\left|\frac{\delta_i^{true}-\delta_i^{est}}{\delta_i^{true}}\right| \times 100 \tag{5.2}$$

Table 5.1: Relative Errors

Sr.No.	Methods	Relative Error (%) Voltage Magnitude (V)	Relative Error(%) Voltage Angle (δ)
1	WLS	7.15	8.87
2	PSO	0.13	2.35

- Time required by software in seconds to execute the algorithm of all discussed methods are as tabulated.

Table 5.2: Time Consumed by Software to Execute the Algorithms

Sr.No.	Methods	Time Required (Sec.)
1	WLS	0.35
2	PSO	0.031
3	Chi-square	1.037
4	LNR	1.21
5	Bad-Data (PSO)	0.120

5.2 Future Work

- The results aforementioned of both the methods could be further improved by employing another advance technique from artificial intelligence such as Genetic Algorithm Artificial Neural Network, as PSO some time coverage prematurely to a local optimum, without considering more promising areas of search space depending upon the problem.

- Otherwise more advance version of PSO methods can be used to solve Power System State estimation such as Guaranteed Convergence PSO (GPSO), Hybrid PSO (HPSO), Full Informed PSO (FPSO), etc.

- Other than that, the state estimation carried out here is static type. The AI method used here can be applicable for Dynamic state estimation also, else static state estimation can be carried out by using other AI method such as Artificial Neural Network, Genetic algorithm, etc. and results of these methods can be compared with the PSO method carried out here to check the accuracy.

References

[1] Comparison of Different Methods of State Estimation by Lars Holtcn, Andcrs Gjelsvik, Svcrre Aam, Felix F. Wu, Wen-Hsiung E. Liu IEEE Transactions on Power Systems, Vol. 3, No. 4, November 1988.

[2] Artificial Intelligence in Power System Operations by Bruce F. Wollenberg and Toshiaki Sakaguchi invited paper.

[3] Power System State Estimation Theory and Implementation by Ali Abur.

[4] Power System Analysis by Jhon J. Grainger and William D. Stevenson,Jr.

[5] Power Syatem State Estimation: Implimentation and Evaluation by P.M Jaltare.

[6] State Calculation of Power System from Line Flow Measurement by J. F. Dopazo, O. A. Klitin, G. W. Stagg, L. S. Van Slyck IEEE Transections on Power Apparatus And Systems, Vol. Pas-89, No. 7, September/October 1970.

[7] State Calculation of Power System from Line Flow Measurement Part-II by J. F. Dopazo, O. A. Klitin, G. W. Stagg, L. S. Van Slyck.

[8] Power System Stability and Control by P.M.Anderson.

[9] Power System Dynamic and Stability by P.Sauer and M.A.Pai.

[10] Particle Swarm Optimization by James Kennedy and Russell Eberhart IEEE International Conference on Neural Networks, 1995.

[11] Defining a Standar for Particle Swarm Optimization by Daneiel Bartton and James Kennedy Proceedings of the 2007 IEEE Swarm Intelligence Symposium(SIS 2007).

[12] Comparing Inertia Weights and Constriction Factors in Particle Swarm Optimization by R. C. Eberhart and Y. Shi Evolutionary Computation, 2000. Proceedings of the 2000 Congress.

[13] Weighted Least Squares and Iteratively Reweighted Least Square Comparison using Particle Swarm Optimization Algorithm in Solving Power System State Estimation by D.H. Tungadio, B.P. Nuimbi, M.W. Siti, J.A. Jordaan IEEE Conference Publication AFRICON 2013.

[14] Modern Heuristic Optimization Techniques - Theory And Applications To Power Systems Edited by Kwang Y. Lee and Mohamed A. El-Sharkawi.

[15] Particle Swarm Optimization for Power System State Estimation by D.H. Tungadio, B.P. Nuimbi, M.W. Siti, A.A. Jimoh. Tshwane University of Technology, Department of Electrical Engineering, Pretoria 0001, SouthAfrica. Contents listsavailableat ScienceDirect Neurocomputing 148(2015)175180.

[16] Three-Phase State Estimation Using Hybrid Particle Swarm Optimization by Sara Nanchian, Student Member, IEEE, Ankur Majumdar, Student Member IEEE, and Bikash C. Pal, Fellow, IEEE. IEEE Transection on Smart Grid.

[17] Unbalanced Three-Phase Distribution State Sstimation using cooperative Particle Swarm Optimization by Ke-yan Liu, Member, IEEE, Wanxing Sheng, Senior Member, IEEE, Kaiyuan He.

[18] Bad Data Analysis For Power System State Estimation by E. Handschin, F. C. Schweppe, J. Kohlas, A Fiechter. IEEE Transactions on Power Apparatus and Systems, vol. PAS-94, no. 2, March/April 1975.

[19] Multiple Bad Data Identification for State Estimation by Combinatorial Optimization by A. Monticelli and Felix F. Wu 1985 Pica Conference July 1986, pp. 361-369.

[20] Identifying Multiple Interacting Bad Data in Power System State Estimation by Eduardo N. Asada, Ariovaldo V. Garcia and R. Romero. IEEE 2005.

[21] Identification of interacting bad data in the framework of the weighted least square method by G.P. Granelli, M. Montagna. Electric Power Systems Research 78 (2008) 806814

[22] Multiple Bad Data Identification in Power System State Estimation using Particle Swarm Optimization by Jaratsri Khwanram and Parnjit Damrongkulkamjorn. IEEE 2009.

[23] A Discrete Binary Version of The Particle Swarm Algorithm by James Kennedy and Russell C. Eberhart. IEEE 1997.

Appendix A

Basic Definitions

Random Variables:

A real value function that defined on sample space i.e. Outcome of rolling dice.

P.D.F:

A non-negative function that is defined on the real line called probability density function.

M.S.E:

The value of Z that will minimize the expected value of squared error.

Variance:

Square of Standard deviation of random or measured value from it's mean and is denoted by σ^2.

$$\sigma^2 = \sum_{i=1}^{n} \frac{(x_i - \bar{x})^2}{n-1} \tag{A.1}$$

Mean:

Mean is sum of total measurements divided by number of measurements.

$$\bar{x} = \sum_{i=1}^{n} \frac{x_i}{n} \tag{A.2}$$

Appendix B

Data of WSCC 3-Machine, 9-Bus System

- **WSCC 3-Machine, 9-Bus System**

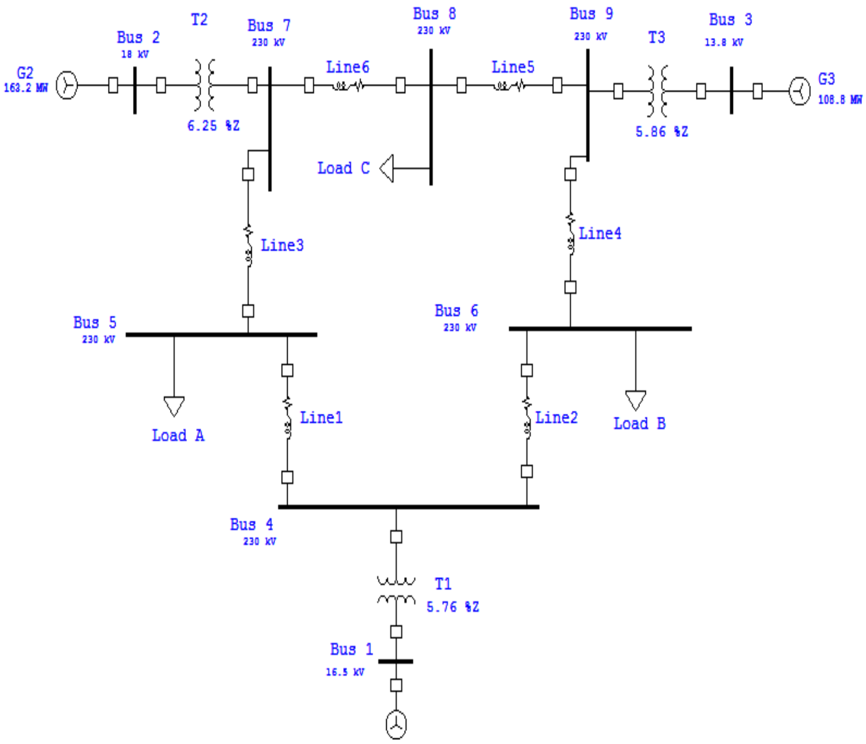

Figure B.1: WSCC 3-Machine, 9-Bus System

All reactance, resistance, Voltage Magnitudes and admittance values are in P.U and on 100 MVA base.

- **Line Data of WSCC 3-Machne, 9-Bus System**

Table B.1: Line Data

Sr.No.	**From Bus**	**To Bus**	**R(P.U)**	**X(P.U)**	$\frac{\mathbf{B}}{\mathbf{2}}$	**Transformer Tap (a)**
1	1	4	0.00	0.0576	0	1
2	2	7	0.00	0.0625	0	1
3	3	9	0.00	0.0586	0	1
4	4	5	0.01	0.071	0.065	1
5	4	6	0.017	0.078	0.0065	1
6	7	5	0.032	0.137	0.12	1
7	9	6	0.039	0.14	0.149	1
8	7	8	0.0085	0.084	0.087	1
9	9	8	0.0119	0.006	0.062	1

Table B.2: Bus Data of WSCC 3-Machine, 9-Bus System

Sr.No.	**Bus no.**	**Type**	**Voltage Mag.**	**Theta**	$\mathbf{P_{Gi}}$	$\mathbf{Q_{Gi}}$	$\mathbf{P_{Li}}$	$\mathbf{Q_{Li}}$	$\mathbf{Q_{min}}$	$\mathbf{Q_{max}}$
1	1	Slack	1.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	2	P-V	1.025	0.00	1.63	0.00	0.00	0.00	-0.50	1
3	3	P-V	1.026	0.00	0.85	0.00	0.00	0.00	-0.50	1
4	4	P-Q	1.026	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5	5	P-Q	0.996	0.00	0.00	0.00	1.25	0.50	0.00	0.00
6	6	P-Q	1.013	0.00	0.00	0.00	0.87	0.29	0.00	0.00
7	7	P-Q	1.026	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8	8	P-Q	1.016	0.00	0.00	0.00	0.96	0.33	0.00	0.00
9	9	P-Q	1.032	0.00	0.00	0.00	0.00	0.00	0.00	0.00

- **Voltage and Phase Angle WSCC 3-Machine, 9-Bus System**

Table B.3: Voltage and Phase Angle

Sr.No.	**Bus no.**	**Type**	**Voltage Mag. (P.U)**	**Theta (Deg.)**
1	1	Slack	1.04	0.00
2	2	P-V	1.025	9.3
3	3	P-V	1.026	4.7
4	4	P-Q	1.026	-2.2
5	5	P-Q	0.996	-4.0
6	6	P-Q	1.013	-3.7
7	7	P-Q	1.026	3.7
8	8	P-Q	1.016	0.7
9	9	P-Q	1.032	2.0