

QATAR UNIVERSITY

COLLEGE OF ENGINEERING

OPTIMAL PLACEMENT OF PHASOR MEASUREMENT UNITS FOR POWER

SYSTEMS USING GENETIC ALGORITHM

BY

MOHAMED OSAMA MOHAMED ELHASSAN MAHGOUB

A Thesis Submitted to the Faculty of  
the College of Engineering  
in Partial Fulfillment  
of the Requirements  
for the Degree of  
Masters of Science in Electrical Engineering

January 2017

© 2017. Mohamed Osama Mahgoub. All Rights Reserved.

## COMMITTEE PAGE

The members of the Committee approve the Thesis of Mohamed Osama  
Mahgoub defended on 08/01/2017.

---

Adel Gastli  
Thesis/Dissertation Supervisor

---

Lazhar Ben-Brahim  
Committee Member

---

Ahmed Mohammed Massoud  
Committee Member

---

Hasan Mehrjerdi  
Committee Member

Approved:

---

Khalifa Al-Khalifa, Dean, College of Engineering

## ABSTRACT

MAHGOUB, MOHAMED, O., Masters : January : 2017,

Masters of Science in Electrical Engineering

Title: Optimal Placement of Phasor Measurement Units for Power Systems Using Genetic Algorithm

Supervisor of Thesis: Adel Gastli.

Power grids require monitoring to operate with high efficiency while minimizing the chances of having a failure. However, current monitoring scheme which consists of SCADA (Supervisory Control and Data Acquisition), accompanied with conventional meters distributed throughout the grid, is no longer sufficient to maintain an acceptable operation of the grid. This is evident from the multiple failures and blackouts that happened and are still happening in grids worldwide. This issue became more severe due to systems being operated near their limits (to reduce costs and due to the increase in electricity demands), as well as, the addition of renewable energy sources, which usually have abrupt changes. Smart grids were introduced as a solution to this issue by the inclusion of Wide Area Monitoring System (WAMS), which is mainly based on Phasor Measurement Units (PMU), which are measurement devices that provides synchronized time stamped measurements with high sending rate which significantly improves the monitoring of the grid. However, PMUs are relatively expensive (considering both direct and indirect costs incurred). Thus, it is desired to know the minimum number of PMUs required for achieving certain monitoring criteria. Thus, Optimal PMU Placement (OPP) formulates an optimization problem to solve this issue. In the literature of OPP, multiple objectives and constraints are considered, based on desired criteria. In this thesis, a

review of OPP is made, followed by the application of selected algorithms (Integer Linear Programming and Genetic Algorithm) on various test systems as a verification and then applying it to Qatar Grid, to compare between different considerations as well as gain insight about the possible PMU placements for Qatar Grid. The contribution of this thesis is introducing a modified fitness function for the Genetic Algorithm that provides more diverse results than previous papers, while incorporating for various considerations like Zero Injection Buses, Conventional Measurements and current branch limit. It also analyzes the results of current branch limit and provides new plots describing their effects.

## DEDICATION

*I dedicate this thesis to my father, mother, brother and sisters for their continuous support throughout my graduate studies, especially during the last months of my thesis work*

## ACKNOWLEDGMENTS

Special thanks to my thesis supervisor Prof. Adel Gastli and my co-supervisor Prof. Lazhar Bin Brahim for their patience, guidance, and encouragement throughout the thesis duration. My sincere gratitude goes to my friend Abdulrahman Alassi for his continuous support during my thesis work. Also, I would like to extend my gratitude to the Electrical Engineering Department for providing me with the needed technical background to finish this thesis. Finally, I thank the General Engineering Department (previously College Requirements Unit) for providing me with the opportunity to work with them as a Graduate Assistant and for their continuous support and understanding throughout the past two years.

# TABLE OF CONTENTS

<b>DEDICATION.....</b>	<b>v</b>
<b>ACKNOWLEDGMENTS .....</b>	<b>vi</b>
<b>LIST OF FIGURES .....</b>	<b>ix</b>
<b>LIST OF TABLES .....</b>	<b>xi</b>
<b>ABBREVIATIONS.....</b>	<b>xii</b>
<b>NOMENCLATURE.....</b>	<b>xiv</b>
<b>Chapter 1 Introduction.....</b>	<b>1</b>
1.1 Background .....	1
1.2 Problem Statement .....	4
1.3 Thesis Objectives .....	5
1.4 Thesis Scope.....	6
1.5 Thesis Organization.....	6
<b>Chapter 2 Literature Review .....</b>	<b>8</b>
2.1 Problem Formulation.....	8
2.2 Mathematical Algorithms.....	14
2.3 Heuristic and Metaheuristic Algorithms .....	17
2.4 Results for Commonly Used Systems.....	23
2.5 Solving OPP using Genetic Algorithm .....	25

<b>Chapter 3 Selected Methodology .....</b>	<b>32</b>
3.1 Selected Solvers and Test Systems .....	32
3.2 Description of Methodology .....	35
<b>Chapter 4 Case Studies and Results.....</b>	<b>42</b>
4.1 Application to Test Systems.....	42
4.2 Application to Qatar Grid.....	52
<b>Chapter 5 Conclusion and Future Work .....</b>	<b>57</b>
5.1 Conclusion.....	57
5.2 Future Work .....	58
<b>REFERENCES.....</b>	<b>59</b>
<b>APPENDIX A: USED IEEE SYSTEMS' DATA .....</b>	<b>76</b>
<b>APPENDIX B: PMU LOCATIONS.....</b>	<b>83</b>



## LIST OF FIGURES

Figure 1.1: PMU and conventional measurements connection with the grid .....	2
Figure 2.1: Algorithms used for solving OPP.....	14
Figure 2.2 Flowchart of the Genetic Algorithm.....	27
Figure 3.1: Flowchart for ILP to solving OPP .....	38
Figure 3.2: Flowchart for ZIB and IM observability allocation .....	41
Figure 4.1: Distribution of the results of 50 runs of GA – method1 for IEEE-300 .....	45
Figure 4.2: Results for OPP using GA method 2 for the IEEE-14 .....	47
Figure 4.3: Results for OPP using GA method 2 for the NE-39.....	47
Figure 4.4: Results for OPP using GA method 2 for the IEEE-57 .....	48
Figure 4.5: Results for OPP using GA method 2 for the IEEE-118 .....	48
Figure 4.6: Results for OPP using GA method 2 for the IEEE-300 .....	49
Figure 4.7: Results for GA method 2 case 4 for the IEEE-14 .....	49
Figure 4.8: Results for GA method 2 case 4for the NE-39.....	50
Figure 4.9: Results for GA method 2 case 4 for the IEEE-57 .....	50
Figure 4.10: Results for OPP using GA method 2 for the IEEE-118 .....	51
Figure 4.11: Results for OPP using GA method 2 for the IEEE-300 .....	51
Figure 4.12: OPP using GA method 2 for Qatar Grid case 1 and 2 (% of OBS).....	56
Figure 4.13: OPP using GA method 2 for Qatar Grid case 4 (% of OBS vs. NPMU) .....	56

Figure A.1 IEEE-14 bus system single line diagram [106] .....	76
Figure A.2 New England 345KV bus system single line diagram [106].....	77
Figure A.3 IEEE-57 bus system single line diagram [106] .....	78
Figure A.4 IEEE-118 bus system single line diagram [106] .....	79
Figure A.5 IEEE-300 bus system single line diagram – part 1 [106].....	80
Figure A.6 IEEE-300 bus system single line diagram – part 2 [106].....	81
Figure A.7 Qatar Grid single line diagram (obtained from Kahramaa).....	82

## LIST OF TABLES

Table 2.1 Number of PMUs required for full observability (base case).....	24
Table 2.2 Number of PMUs required for full observability (with contingencies).....	25
Table 3.1 Test systems overview .....	34
Table 3.2 Qatar Grid data.....	34
Table 4.1 Locations of the ZIB, IM and FM used in this paper .....	42
Table 4.2 Results for OPP using ILP for the test systems .....	43
Table 4.3 Results for OPP using GA method 1 for the test systems .....	44
Table 4.4 Comparison between ILP and GA method 1 results.....	45
Table 4.5 Results for OPP using ILP for Qatar Grid .....	52
Table 4.6 Results for OPP using GA method 1 for Qatar Grid .....	55

## ABBREVIATIONS

CM	Conventional Measurement device
CT	Current Transformer
FM	Flow Measurement device
GA	Genetic Algorithm
GPS	Global Positioning System
ICT	Information and Communication Technology
ILP	Integer Linear Programming
IM	Injection Measurement device
KCL	Kirchhoff's Current Law
NP	Nondeterministic Polynomial time
NPMU	Number of PMUs
NUOB	Number of unobservable buses
OBS	Observability
OPP	Optimal PMU Placement
PDC	Phasor Data Concentrator

PMU	Phasor Measurement Unit
SCADA	Supervisory Control and Data Acquisition
VT	Voltage (Potential) Transformer
WAMS	Wide Area Monitoring System
ZIB	Zero Injection Bus

## NOMENCLATURE

$a$	Connectivity matrix
$a_{nm}$	Connectivity of bus $n$ with bus $m$
$B$	Desired observability (as a vector)
$B_n$	Desired observability at bus $n$
$C$	Cost of PMU (as a vector)
$C_n$	Cost of PMU at bus $n$
$F$	Cost function (for ILP), fitness function (for GA)
$N$	Total number of buses in a power network
$O$	Actual observability (as a vector)
$O_n$	Actual observability of bus $n$
$S$	Apparent Power
$U_n$	Existence of PMU in bus $n$
$W$	Array of vectors of buses observable by ZIB and IM
$y_{nm}$	Observability of bus $n$ by the ZIB or IM in bus $m$

# **Chapter 1 Introduction**

## **1.1 Background**

Power grids around the world are witnessing remarkable development in recent years due to new challenges faced with the integration of renewables. This development is toward becoming smarter grids by integrating information and communication (ICT) layers above the conventional power layer allowing more accurate and faster control of the grid. Wide Area Monitoring System (WAMS) is one of the primary elements contributing to the development of smart grids. WAMS means the monitoring of the entire system by the control center, in other words, the system becomes observable by direct measurements rather than state estimations. WAMS can achieve this real-time monitoring through the usage of accurate synchronized time stamped measurement devices with high reporting rates, such as the Phasor Measurement Units (PMU). This monitoring, through PMUs, enhances the system in many aspects ranging from optimal power dispatch, monitoring tie line power, detecting unacceptable voltage profiles to prevent faults or minimize their effects. Although these features might appear to be already available in conventional power networks through Supervisory Control and Data Acquisition (SCADA), the efficiency and correctness of SCADA regarding giving real time data is relatively small due to many estimations, since there are many missing variables that SCADA needs to estimate. Another lacking in SCADA is the system's inability to properly react to major faults that might result in blackouts [1]. The previous is a common issue with SCADA

where by the time the estimations indicate that the grid is collapsing, many of the loads and generators throughout the system would already be disconnected, or worst a cascaded blackout might occur e.g. the 2003 northeast blackout in the USA [2].

Optimal power dispatch, active protection, and fault detection require real-time measurements or estimations of several system parameters such as the phasors of voltages and currents throughout the entire network to function properly and efficiently. Measurements could be provided by conventional measurement devices or PMUs (see Figure 1.1), while observers provide estimations.

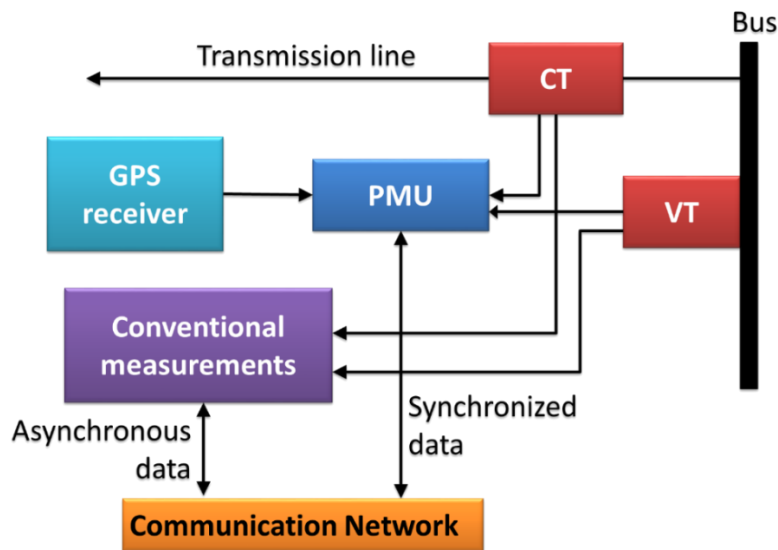


Figure 1.1: PMU and conventional measurements connection with the grid

However, having measurements instead of estimations is preferred, since it reduces errors (excluding the effects of bad data). Therefore, full observability, which means that the



phasors of voltages and currents throughout the entire network are known, would benefit the above applications and this status of full observability can be achieved using PMUs.

Thus, using PMUs as measurement devices provides more stability and security to the network. Also, PMUs should not necessarily mean the replacement of SCADA (although entirely WAMS system can replace SCADA), because PMUs can be utilized as a replacement or complement to the existing measurement devices while maintaining SCADA as the method for monitoring and controlling of the system. Also, the results demonstrated in this thesis would still be valid even if PMUs are considered as a complement measurement [3]. In addition, PMUs can generate profit by being able to do optimal power dispatch in real time, as well as, having accurate data about transmission line current, which give information regarding both the line losses and its power capacity. Another hidden profit is reducing the chances of a major blackout.

On the other hand, although PMUs are superior to conventional measurements in numerous aspects, they cannot be placed practically around the entire system at each bus, since they are relatively expensive (considering direct and indirect costs incurred) [4]. Thus, to fully make use of PMUs while minimizing the total number of needed PMUs to achieve full power system observability, Optimal PMU Placement (OPP) is introduced to solve this issue using different mathematical and heuristic algorithms.

Although full system observability was not the primary goal for incorporating PMUs into power networks, it soon became critical with the increase in PMU-based applications that require full system observability. Therefore, OPP refers to the problem of placing PMUs throughout the power network to provide full observability of the network (or any other

requirement) under certain constraints while minimizing the number or costs of the PMUs. To enhance the OPP, the formulation of the problem and the criteria required to be optimized are very essential. Surveying the literature showed that these criteria include different scenarios and considerations.

## **1.2 Problem Statement**

To solve optimization problems, Calculus-based and iterative techniques are mostly used since they provide reliable answers that are either the global minima (or maxima) in the case of calculus-based techniques, or a very likely to be the global minima (or maxima) in regard to iterative techniques. However, these techniques are vulnerable to fail in producing satisfactory solutions for nonlinear multivariable optimization tasks (due to numerous local minima and maxima, discontinuity, ...etc.). In addition, when the number of variables becomes enormous, the time required for solving the problems becomes impossibly large. In these aspects, bio-inspired optimization algorithms have outperformed these classical techniques; thus, these algorithms are used widely in applications with complicated, highly nonlinear multivariate problems, like the OPP.

From the literature survey, the complexity of the OPP comes from its nonlinearity, since the variables take values of 0 (no PMU) or 1 (with PMU). However, Integer Linear Programming (ILP) solves this issue since it deals with integers. Thus, the dominant method for solving the OPP is ILP. However, OPP does not refer to one problem only, because the various constraints, conditions, and objectives related to the OPP make the

problems varies considerably to the extent that some methods might not be able to solve some of these OPPs, i.e. it might not be possible to formulate it as an ILP problem. On the other hand, probabilistic and bio-inspired optimization techniques solve the issue of problem formulation, since these techniques only require an input-output relationship between the variables and the parameters to be optimized. Nonetheless, these techniques are not perfect and they suffer from a major problem which is the trapping in local minima since these algorithms try to look for solutions randomly but within a certain region around the current solutions.

As for the various constraints, conditions and objectives that occur in the OPP some of them are the consideration of existing measurement devices, the incorporation of the Zero Injection Bus (ZIB) effect, finding the maximum achievable observability given a specific number of PMUs, and allowing for multistage placement for PMUs. Hence, the problem of OPP is actually two problems: the selection of the suitable constraints, conditions and objectives, as well as, finding a solver for the formulated OPP problem.

### **1.3 Thesis Objectives**

The objectives of this thesis is to review the OPP techniques used in the literature and to apply selected algorithms (e.g. Integer Linear Programming and Genetic Algorithm) to various IEEE test systems as a verification and then to Qatar Grid, to compare between different considerations as well as to gain an insight about the possible PMU placements

for Qatar Grid. In addition it aims to propose a modified Genetic Algorithm to produce better results and to study the effects of current channel limit.

## **1.4 Thesis Scope**

This thesis considers the application of OPP to Qatar Grid as its primary goal. It also uses other benchmark IEEE test systems to verify the correctness of the obtained results.

However, the following are considered beyond the scope of the thesis along with a brief explanation of why these points are out of scope:

- The consideration of communication infrastructure as a criterion for OPP is excluded since it requires data that are not available, which are the Qatar Grid physical layout and the costs of communication infrastructures.
- This thesis focuses on the formulation of the OPP itself and using different algorithms, constraints and objectives to solve the OPP. However, the studying and modifying of the algorithms themselves (e.g. modifying Genetic Algorithm by adding additional steps or modifying the existing steps to increase convergence time or enhance the results) is beyond the scope of the thesis.

## **1.5 Thesis Organization**

The thesis is organized into five chapters. Chapter 1 is the introduction. Chapter 2 presents a literature review, which includes the review of the OPP considerations and

algorithms, as well as, providing a detailed explanation of the Genetic Algorithm and its uses in solving the OPP. Chapter 3 explains the selected methodologies to solve the OPP in this thesis. Chapter 4 presents and discusses all the obtained results for all the considered IEEE test systems and Qatar Grid cases. Finally, Chapter 5 concludes the thesis and proposes the future work.

## **Chapter 2 Literature Review**

The OPP mainly involves two separate parts.

1. The formulation of the OPP (the function to be optimized as well as the constraints and consideration)
2. The solving of the OPP

Section 2.1 shows the literature review of the formulation, while sections 2.2 and 2.3 represents the main ways to solve the OPP which are mathematical algorithms and heuristic algorithms respectively. A detailed literature review of OPP can be found in [6][7]. However, the literature review provided here is more extensive and includes more recent publications. Section 2.4 contains the typical results for the OPP of benchmark systems. Finally, Section 2.5 explains the Genetic Algorithm (GA) and its usage in solving the OPP.

### **2.1 Problem Formulation**

For a system to be observable, all the states of the system need to be either directly measured or can be calculated from the data available by the measurement devices using electric circuit equations. These states can be the voltages of each bus in the network because knowledge of the voltages (while knowing the admittance matrix) is sufficient to calculate the currents at all branches in the network, as well as, the power flow throughout

the network. Moreover, since PMUs measure the voltage of a bus and the currents of all branches connected to it (assuming that the PMU has enough current channels), then it can be shown that with the knowledge of the network's impedances and admittances it is possible to find the voltages of the buses connected to that PMU. A similar concept can be applied to Zero Injection Buses (ZIB) (A bus is considered a ZIB if it does not have any loads or generators attached to it, i.e.  $S = 0$ ). Let  $Z$  be a ZIB and connected to it are  $D$  buses, then there is a total of  $D+1$  buses, including the ZIB, for these  $D+1$  buses it is sufficient to find  $D$  voltages only, and the remaining one can be measured using direct application of Kirchhoff's Current Law (KCL). The mathematical proofs for the above assumptions can be found in [8], and are summarized as follows:

Assume that a PMU is installed in bus  $i$ , measuring both the voltage of the bus and the current of its branches including transmission line  $i$ - $j$ . Then, for bus  $j$ :

$$g(V_i, V_j) = \frac{D_{ij}}{B_{ij}} V_i + \left( C_{ij} - \frac{A_{ij} D_{ij}}{B_{ij}} \right) V_j = I_{ij} \quad (2.1)$$

where the parameters  $A$ ,  $B$ ,  $C$ ,  $D$  are the elements of the transmission matrix modeled as a two-port network, considering  $i$  as sending terminal. From (2.1) knowledge of  $V_i$  and  $I_{ij}$  (both obtained by the PMU) is sufficient to calculate the voltage at bus  $j$ . Thus, bus  $j$  becomes observable. Also, note that this formulation would work regardless of the type of the bus or what is connected to it (load, generator, PV farm, ...etc.), since it only requires the voltage at the bus and the transmission lines parameters.

As for ZIB and Injection measurement, using (2.2)

$$g(V_1, \dots, V_N) = \sum_{i \in B} Y_{ki} V_i = \frac{S_k^*}{V_k^*} \quad (2.2)$$

where bus  $k$  is a ZIB or a bus with injection measurement device,  $S_k$  is the apparent power at bus  $k$  and  $B$  is the set of all buses in the system and  $Y_{ki}$  is element  $k,i$  in the admittance matrix. Then, for ZIB or a bus with injection measurement device, the right-hand side would be known ( $I_{injected}$  or  $0$  respectively). Thus, it is possible to know one unknown voltage if all other voltages are known.

A formulation for the above description can be done using Integer Linear Programming (ILP) model since it is well suited for defining this type of problems. The ILP formulation is carried out as follows [8][9][10]. Assume that  $n$  is the  $n^{th}$  bus in a power grid with  $N$  buses. Then, we can consider the following rule:

$$u_n = \begin{cases} 1 & \text{if a PMU is placed at bus } n \\ 0 & \text{otherwise} \end{cases} \quad \text{for } n = 1, 2, 3 \dots N \quad (2.3)$$

where  $u_n$  indicates whether there is a PMU in the bus or not. Using (2.3), the optimal solution for the OPP should minimize the cost function  $F$  given in (2.4) and at the same time satisfy (2.5), (2.6), and (2.7):

$$F = \sum_{n=1}^N c_n u_n \quad (2.4)$$

$$O_n = \sum_{m=1}^N a_{nm} u_m + \sum_{m \in IM} a_{nm} y_{nm} \geq B_n \quad \text{for } n = 1, 2, 3 \dots N \quad (2.5)$$



$$a_{nm} = \begin{cases} 1 & \text{if } n = m \text{ or bus } n \text{ and } m \text{ are connected} \\ 0 & \text{otherwise} \end{cases} \quad (2.6)$$

$$\sum_{n=1}^N a_{nm} y_{nm} = 1 \quad \forall m \in IM \quad (2.7)$$

where  $c_n$  is the cost of the PMU at bus  $n$ ;  $O_n$  is the actual observability of bus  $n$ ;  $IM$  is the set of measured injection buses and ZIBs;  $y_{nm}$  is a variable that indicates that the bus is observable by an injection bus or a ZIB (1 if bus  $n$  is observed by the ZIB or IM in bus  $m$ , and 0 otherwise);  $B_n$  is the minimum required observability for bus  $n$ ; and  $a_{nm}$  is the connectivity matrix elements between two buses  $n$  and  $m$ . which can be directly found from the admittance matrix by assigning 1 to the nonzero elements in the matrix.

The cost of the PMU  $c_n$  is a general term that can include the price of the PMU itself, its network infrastructure costs, the cost of adding current and potential transformers if they are not available, the cost difference between installing a PMU at a low or high voltage levels and any other relevant cost. It can also be used to indicate the importance of a bus, by assigning low values to important buses and high values for other buses, making these important buses preferable locations for PMU placement. If it is assumed that all PMUs have the same cost and importance, then the cost can be normalized to be a vector of ones. As for the observability vector, it is typically a column vector of ones, since we need each bus to be observable by at least one PMU. However, the values of  $B_n$  (certain bus) or  $B$  (the entire network) can be  $> 1$  if a more reliable observability or a certain level of redundancy is needed for a specific bus or the entire system (e.g. a value of 2 allows resilience to  $N-1$  contingencies for the PMUs). On the other hand, the value can be

zero when a more relaxed constraint is needed (case of a system partially observable). As for the connectivity matrix, it is built based on the assumption that the impedances of transmission lines throughout the system are known. It should be noted that this is a basic formulation. However, other advanced formulation techniques exist in the literature. Moreover, the OPP is usually formulated using ILP, but solving it is not restricted to linear programming solvers. Nonetheless, this thesis uses ILP solvers, in addition to using the GA, since it is the direct approach to solve OPP.

As for computational complexity, OPP is considered to be NP-complete. Also, according to [24], the number of needed PMUs to solve the OPP for full observability is no more than 1/3 of the total nodes (for a typical OPP).

Other considerations can be included by modifying the problem formulation, for example the case of modifying the grid (adding extra transmission line, generation bus or distribution bus) can be approached by numerous methods, but the most direct is modifying the  $a$  matrix to reflect the changes (if any) and forcing  $u$  vector to have  $u_n = 1$  for any bus  $n$  that has a PMU. In addition, depending on the applications and their requirements, several additional considerations may be used in the problem formulations, such as:

1. Contingencies: failure of PMUs, transmission lines or both (N-1 contingency is the most used case but more severe cases can also be considered). [30] [45] [77]
2. Inclusion or exclusion of zero injection buses (ZIB). [5][47]
3. Consider PDC (Phasor Data Concentrator) and communication network cost. [77]

4. Minimizing current measurement branches in the PMU to reduce the PMU cost.[22]
5. Including errors due to faulty or imperfect measurement devices. [19] [60]
6. Aiming for state estimation enhancement rather than full observability.[23]
7. Ability to detect and eliminate bad data. [24]
8. Increasing redundancy of measurements in OPP. [5]
9. Including already placed PMUs in the OPP or reallocating them [46]
10. Including conventional measurements.[20]
11. Forcing certain buses into having or not having a PMU. [46]
12. Considering multistage placement of PMUs.[23]
13. Accounting for system reconfiguration [39]

Finally, as previously stated, the methods used to solve OPP are mainly classified into mathematical and heuristic algorithms. Figure 2.1 shows the algorithms associated with their classification (mathematical or heuristic).

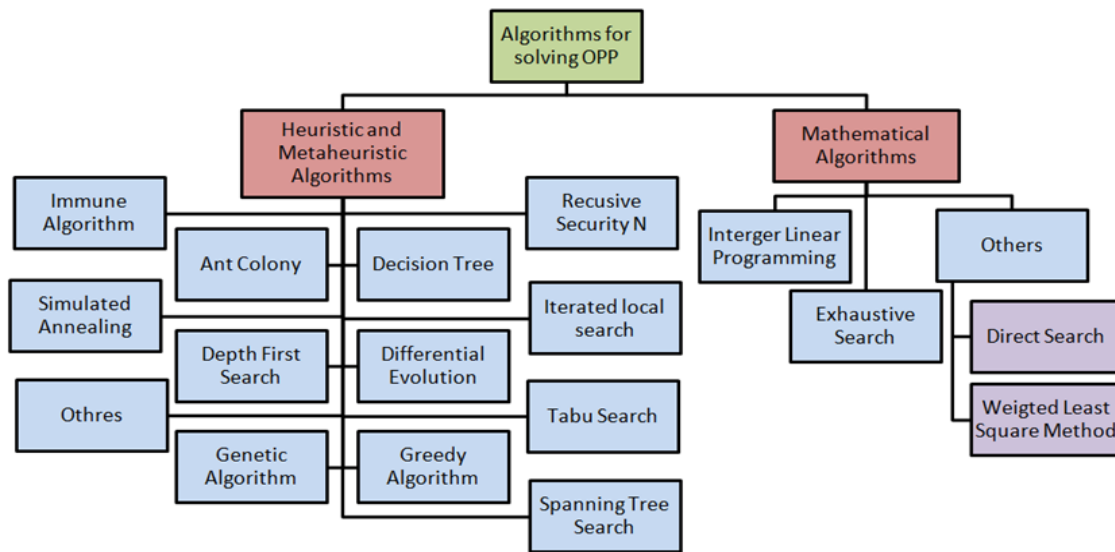


Figure 2.1: Algorithms used for solving OPP

## 2.2 Mathematical Algorithms

Different mathematical approaches are used in solving OPP most notably Integer Linear Programming and Exhaustive Search. Other used algorithms include Direct Search and Weighted Least Squares Algorithm. Mathematical algorithms have the advantage of being consistent and well defined. They provide accurate results, but depending on the complexity of the problem (e.g. discontinuity, nonlinearity) sometimes it is impractical or impossible to find or apply a mathematical algorithm.

### 2.2.1. Integer Linear Programming

Integer Linear Programming (ILP) refers to the type of problems where variables are restricted to integers only [11]. Thus, since the OPP is a discrete problem the

paradigm became formulating OPP using ILP. The previous led to the majority of papers either using ILP or one of its variants (e.g. Multiple Integer Linear Programming (MILP); Binary Integer Linear Programming (BILP)) to solve the OPP or use another algorithm while incorporating ILP to formulate the problem. Thus, only a few examples would be included in this section.

In [24]-[30], ILP is used. In [24] conventional measurements were incorporated in the solution. Another addition is that bad data detection was considered and an algorithm capable of transforming bad data detection into an ILP for OPP was introduced. From the versatility point of view, the algorithm provided in [25] is among the best of ILP based solutions to solve the OPP since it considered N-1 contingencies for both PMU and transmission lines, inclusion and exclusion of ZIB, and the number of current measurement branches in the PMU. In addition, [25] validated its proposed algorithm using six different test systems for multiple scenarios, whereas [26] differs from other papers by considering N-2 overlapping contingencies, instead of N-1. Also, the fact that it is a reliability based and incremental means that the method in [26] is practical regarding the addition of PMUs in multiple stages, while maximizing the reliability at each stage. In [27], Binary Integer Programming (BIP) is used for solving the observability problem as a binary integer minimization problem (BIMP), but the paper proposed its own algorithm for determination of critical buses in the system and to allow incremental (multistage) PMU placement and then the algorithm would re-call the BIMP. In [28], a novel algorithm considering minimizing PMUs and maximizing redundancy as conflicting objectives is used. Since practical systems are very large, ILP computational

burden becomes huge (>150000 seconds for 1000+ bus systems). Thus [29] introduced a novel community-based partitioning approach for solving the OPP by islanding the system and then solve for each island, while still maintaining a PMU count almost equal to the direct solving for the entire system. On the other hand, [30] introduced new approaches to consider the effects of both zero injection buses and conventional measurements. It also considers N-1 contingency for both PMU and transmission lines. The results in [30] matches and sometimes exceed previous papers.

### **2.2.2. Exhaustive Search**

Exhaustive search (also known as brute force search) means searching all possible permutations until finding the global optimum (since this method search all possible configurations then it guarantees that the global optimum solution is found). However, it is impractical to apply it to large systems. In [12], Exhaustive Search is used to solve the OPP while modifying the problem so that it is possible to do Exhaustive Search within a reasonable time even for large systems such as the Iranian National Grid. Also, [60] uses exhaustive search to validate its results. While [14] uses an algorithm based on Exhaustive Search to solve the OPP problem with multiple constraints and objectives while guaranteeing that the results are the global optima. As for [13], it proposes its own method while incorporating exhaustive search in the algorithm.

### **2.2.3. Others**

Direct Search is an optimization method that does not require derivative search, which makes them suitable for discontinuous functions [31]. In [15], Mesh Analysis Direct Search (MADS) algorithm, which is a modified version of Direct Search was implemented using NOMAD solver to solve the dynamic state estimation problem. Another new approach was incorporated in [32]. Since, instead of solving the typical OPP model, [32] introduced a new approach by transforming the integer/binary problem into a continuous optimization model of Weighted Least Squares Algorithm. In addition, [33] uses Revised Analytical Hierarchy Process to solve for OPP while also accounting for improving voltage stability, it also introduced the concept of having multistage PMU placement where the first stage targets critical buses regarding voltage stability, making the algorithm closer to industry demand.

Although, OPP is usually formulated as an ILP, in [34] a nonlinear programming NLP is used, and the OPP is solved using sequential quadratic programming algorithm. The paper states that this approach provides the advantage of having multiple solutions with the same number of PMUs but different PMU locations.

## **2.3 Heuristic and Metaheuristic Algorithms**

The second method is to use heuristic and metaheuristic algorithms. Heuristic refers to the type of algorithms that search for the solution among all possible points while following a particular pattern for this search, they are suitable for finding quick

solutions and can deal with complexities better than mathematical approaches, because they require minimal or no prior mathematical knowledge about the problem. However, the problem with these algorithms is that there is no guarantee that they provide the global optimum. As for the difference between heuristic and metaheuristic algorithms, it is that heuristic algorithms take into consideration the nature of the problem itself to solve it easily, but this might lead to trapping in local optima. Whereas, metaheuristic methods are heuristic methods that are independent of the nature of the problem, which can help in reducing the chances of being trapped in local optima since the algorithms do not make any specific assumptions regarding the problem. However, since the difference is quite subtle, they will both be in the same category [35][36].

### **2.3.1. Ant Colony Optimization**

Ant Colony is an optimization algorithm based on the behavior of ant colonies, and it is a part of the population algorithms [35]. In [37], Ant Colony optimization was used for the solution of the optimal PMU placement while maximizing redundancy. Other papers [38][39] show how to use ant colony accompanied with Greedy Algorithm to account for system reconfiguration. It should be noted that very few papers applied this optimization technique.

### **2.3.2. Decision Tree**

This algorithm constructs a treelike diagram representing the classification of data and is based on data prediction. Although no reviewed paper uses Decision Tree for full



system observability, there are notable articles that use Decision Tree Algorithm to optimally place PMUs for achieving security and stability objectives such as voltage security [40][41] and islanding detection [42].

### **2.3.3. Depth First Search**

Depth First Search is a searching algorithm that tries to explore the nodes around a root to find the optimal solution. In [43], multiple algorithms are used to satisfy both full system observability as well as fault detection. Among these algorithms is the Depth First Search Algorithm. Also, [44] improved the Depth First Search Algorithm to achieve a similar task but with three objectives: full observability; distribution of PMUs based on weighted values for each bus; and improving voltage stability.

### **2.3.4. Differential Evolution**

The algorithm is part of the population-based metaheuristic algorithm, aiming to improve and alter a candidate solution using certain criteria, until an optimal solution is reached. Multiple papers use Differential Evolution to achieve OPP among these papers the notables are [45]-[47]. In [45], PMU failure is considered, while [46] focuses on reallocation of PMUs and having some practical considerations such as specifying if a bus must be with or without a PMU.

### **2.3.5. Genetic Algorithm**

Genetic Algorithm (GA) is part of the population-based metaheuristic algorithm that mimics the process of reproduction and evolution. In [48] to [59], Genetic Algorithm is used to solve the optimal PMU placement problem. [49] introduces probabilistic criteria into the OPP, while [51] incorporates bad data detection. [53] and [59] improves the GA itself to make it more robust, [48] targets increasing redundancy and allow for N-1 contingency, [52] merges Fuzzy Weighted Average with the GA to improve the system security and account for multistage placement. [57] also accounts for multistage placement, but it also considers conventional measurement units, maximizing redundancy and introduces a new formulation for the GA population creation and mutation stage that is tailored for OPP. As for [58] it takes a step further and uses non-dominating sorting genetic algorithm-II to solve the OPP problem while accounting for communication infrastructure cost, maximizing redundancy, ZIB effect, actual costs, and channel limitations. It also applies its results to 5 systems ranging from IEEE 14-bus to Polish 2383 system.

### **2.3.6. Greedy Algorithm**

Similar to exhaustive search, the greedy algorithm tries to find the optimal solution through searching, but the search is limited to neighboring points of the current guess, whereas exhaustive search considers all possible cases. In [60], PMU phase angle mismatch is considered (due to imperfectly synchronized PMUs). The method takes into consideration the posterior Cramer-Rao bound on state estimation error and then uses it

finds the solution of the OPP. Actual OPP solution is obtained using Greedy Algorithm. Also, [39] incorporates greedy algorithm as previously stated.

### **2.3.7. Spanning Tree**

In [61]-[63], Spanning Tree Algorithm is used to solve or improve the solution for the OPP. In [61], a hybrid Genetic Algorithm uses Minimum Spanning Tree to improve the feasibility of the algorithm. While [62] study the validity of voltage stability assessment using PMUs, and the algorithm used for the OPP is a recursive spanning tree. Another novel approach introduced in [63], a new idea of The Depth of Observability indicates the percentage of observability in case of partial observability. Another addition is that the method also considers the minimization of current measurement branches in the PMU. Also, in [72], spanning tree algorithm is used for OPP, while also constructing voltage stability curve and limits using the information provided by the placed PMUs.

### **2.3.8. Particle Swarm Optimization**

Particle Swarm Optimization (PSO) is an optimization technique based on the social behavior of animals such as bird flocks. In [64]-[68], PSO is used to solve the OPP issue with emphasis on improving the algorithm itself to increase efficiency and convergence rate as well as reduce the trapping in local minima.

### **2.3.9. Simulated annealing**

Simulated Annealing is a probabilistic optimization technique that uses a scheme mimicking the heating and cooling of metals in metallurgy. Solving OPP using simulated annealing is in [70] and [71]. In [70], a novel multistage OPP algorithm is introduced, while [71] proposes a novel decomposition method for solving OPP

### **2.3.10. Tabu search**

Tabu Search, is a searching optimization method based on the idea of experience and oblivion of human beings. In [73], Tabu search is used to solve the OPP, while the Tabu search is improved in accordance with the nature of the OPP. Another addition in the paper is the inclusion of the redundancy as a criterion, i.e. even if the number of PMUs is the same through iterations while the redundancy is increasing, the method will continue iterating, thus providing better results even if they appear identical to other results.

### **2.3.11. Artificial Bee Colony**

Artificial Bee Colony (ABC) is a searching optimization method that is a part of the population-based metaheuristics algorithms. ABC is used in [74] -[76]. In [74], two algorithms are combined. Spanning Tree is first used to provide a graph-theoretic approach. The second phase is an ABC algorithm to search for the optimal solution. In [75], the Binary ABC is used to solve the OPP directly, the used method also incorporates Flow Measurements devices and takes contingencies into consideration.

While [75] uses a fuzzified ABC approach to solve the OPP while maximizing voltage stability level.

### **2.3.12. Others**

Multiple heuristic algorithms are applied in [43] which includes: Depth First Search; Graph Theoretic Procedure; Spanning Tree; And Simulated Annealing. It also tests these algorithms in seven different models. In [77], two optimization techniques are used simultaneously to find an optimal solution for both the PMU locations and their PDCs along with the communication infrastructure. For the first, Binary Imperialistic Competition Algorithm is used while Dijkstra's single source short path is utilized for the second task. The methods are also accompanied with practical considerations such as previously installed PMUs, communication infrastructures, and the actual cost of PMUs. Also, [53] uses a hybrid combination between minimum spanning tree and genetic algorithm. [78] uses a hybrid algorithm between Particle Swarm Optimization and Gravitational Search Algorithm to solve the OPP, to have a fast converging algorithm.

## **2.4 Results for Commonly Used Systems**

Throughout the literature, multiple test systems or actual power networks are used for OPP. Table 2.1 lists the best available results for these systems, as well as the references where these results are found. Another list of results single branch outage, single PMU outage, and single branch/PMU outage are given in Table 2.2.

It should be noted that these approaches do not necessary mean that this placement is the cheapest. For instance, in [77], an actual cost consideration of the PMUs, PMUs channels, PDC and communication infrastructure was made. In that paper, it was demonstrated that it is possible to have a cheaper solution with more PMUs.

Table 2.1 Number of PMUs required for full observability (base case)

<b>System</b>	<b>No. of Buses</b>	<b>No. of Branches</b>	<b>No. of PMUs</b>	<b>Locations of PMUs</b>	<b>Reference</b>
<b>IEEE 14-bus</b>	14	20	3	2,6,9	[100]
<b>IEEE 24-bus</b>	24		6	2, 8, 10, 15, 22, 23	[100]
<b>IEEE 30-bus</b>	30	41	7	2, 3, 10, 12, 15, 18, 27	[30]
<b>IEEE 39-bus</b>	39	46	8	8, 11, 16, 18, 20, 23, 25, 29	[30][100]
<b>IEEE 57-bus</b>	57	80	11	1, 5, 13, 19, 25, 29, 32, 38, 42, 51, 54	[30]
<b>IEEE 118-bus</b>	118	186	28	1, 8, 11, 12, 17, 21, 25, 28, 33, 34, 40, 45, 49, 53, 56, 62, 72, 75, 77, 80, 85, 86, 91, 94, 102, 105, 110, 114	[30]
<b>IEEE 300-bus</b>	300		19	[100]	[100]
<b>Danish Power System</b>	470		53	[100]	[100]
<b>RTS 96</b>	96	-	19	309, 116, 209, 109, 321, 123, 210, 110, 220, 320, 310, 218, 213, 313, 203, 207, 307, 118, 301	[26]

Table 2.2 Number of PMUs required for full observability (with contingencies)

System	N-1 branches		N-1 PMUs		N-1 PMUs or branches	
	No. of PMUs	reference	No. of PMUs	reference	No. of PMUs	reference
<b>IEEE 14-bus</b>	7	[25][30][100]	7	[25][30]	8	[25][30]
<b>IEEE 24-bus</b>	12	[100]	12	[100]	-	-
<b>IEEE 30-bus</b>	13	[30]	14	[30]	16	[30]
<b>IEEE 39-bus</b>	16	[30][100]	17	[30]	18	[30]
<b>IEEE 57-bus</b>	19	[30]	22	[30]	22	[30]
<b>IEEE 118-bus</b>	53	[30]	61	[30]	61	[30]

## 2.5 Solving OPP using Genetic Algorithm

Many bio-inspired optimization techniques have emerged to solve difficult optimization problems. One example of these bio-inspired optimization techniques is the Genetic Algorithm (GA), which is based on the Natural Selection concept that comes from the “survival of the fittest” idea. In this idea, generations having better traits for survival will continue to live while those who are less fortunate will eventually die and disappear. Also, survival traits are passed from the parents to the new generations through their genes. This same idea is the building block for the GA. The formulation for GA is as follows (flowchart in Figure 2.2):

1. An initial dataset “population” is generated randomly, and their “fitness” are tested

2. The reproduction stage is initialized, where the “population” (which is currently the “parents”) “reproduce” to create the “offspring”. where the “genes” of the new “offspring” will be a combination of the parents’ genes
3. The crossover stage is initialized. The individuals with the best “fitness” survive and the others die (this happens to both the “parents” and the “offspring”)
4. In the mutation stage, some random “offspring” will then be subjected to random “mutations” that would slightly change their “genes”
5. Termination criteria are checked, these criteria include the generation count (how many generations have passed), generation stall (the generations are producing the same best fitness), or time limit (the simulation time exceeds the maximum allowed time).
6. If one of the termination criteria is reached, the algorithm terminates, and the “individual” with the best “fitness” in the last generation is the result of the optimization. Otherwise, set the current “offspring” as “parents” and go to step 2

To briefly explain the reason for each stage, and what makes the GA a robust algorithm:

1. “reproduction” is for quickly searching for minima/maxima if there are many variables
2. “Crossover” is intended to bring data closer to local minima/maxima
3. “Mutation” aims to diverge some offspring from these local points to look for global minima/maxima (or to avoid being trapped in local minima/maxima)



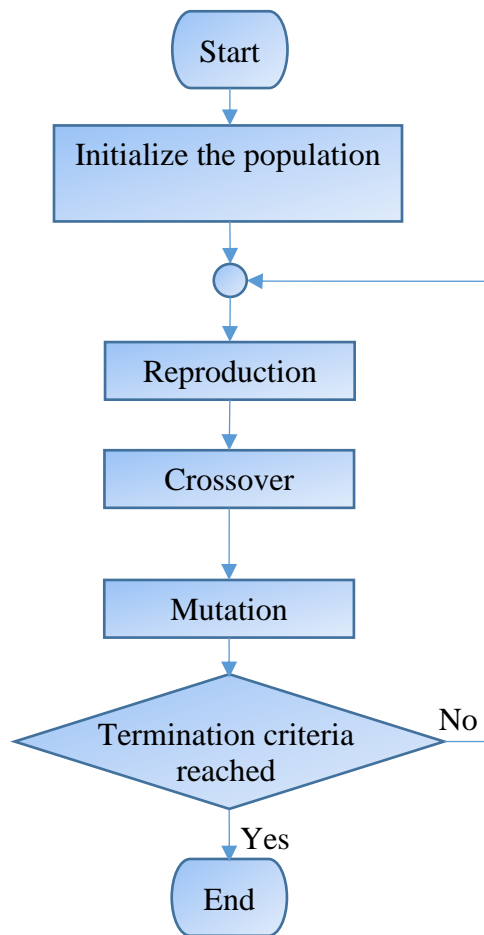


Figure 2.2 Flowchart of the Genetic Algorithm

As for the usage of GA in solving OPP, it can be classified as follows:

- Explanation of the typical formulation for OPP using GA
- Types of OPP used and the included constraints when using GA
- Modifying the GA algorithm to better suit the OPP
- Using GA as supplemental algorithm

### 2.5.1. Formulating OPP using Genetic Algorithm

Since the goal of OPP (in its basic definition/constraints) is to minimize the number of PMUs to achieve full observability, a typical formulation is to use Binary Genetic Algorithm. In Binary Genetic Algorithm, each “individual” has a “gene” made of  $n$  bits (or “chromosomes”), and each of these bits can have a value of either 0 or 1. Thus, for the OPP, each “individual” in the “population” is set to be a possible PMU configuration for the given network. This mapping from PMU placement to Genetic Algorithm is achieved by setting the number of bits in the gene equal to the number of buses in the system and then let “0” mean no PMU and “1” means that there is PMU. For example, an individual with the configuration 01011 would mean that we have a system of 5 buses (since the number of bits is 5) and this configuration would place PMUs in buses 2, 4, and 5 (since they are the bits with a value of 1). [79]

The second step is the formulation of the fitness function and the constraints. The fitness function is defined as a relation between the inputs and the desired characteristics. Since the goal of the OPP is to minimize the number of PMUs, the fitness function can be

$$fitness\ function = \sum_{1}^n Bit_n \quad (2.8)$$

As for the constraints function, it is used to make sure that individuals are conforming to certain rules. Since the only constraint for OPP (in the typical formulation) is to make the entire network observable, then the constraint is defined as (2.9). Finally, GA is applied as shown in the beginning of this section to obtain the final result.

$$Ax > B \tag{2.9}$$

Where  $x$  is the transpose of the PMU configuration of the individual

### **2.5.2. Types of OPP used and the included constraints**

Throughout the literature, multiple algorithms and techniques are used to solve the OPP. For the case of using GA, all papers containing the terms “Genetic Algorithm” and “Optimal PMU Placement” were reviewed, including both IEEE and Science Direct databases. In total 61 papers were found, but among them only 18 are using Genetic Algorithm as their main algorithm for solving the OPP. Regarding the used constraints and objectives, the reviewed papers included the following features:

1. Typical full observability is considered [79][93] [98]
2. Considers ZIB [80][95]
3. Considers Flow measurement devices (FM) [80]
4. PMU outages (N-1) [81][95]
5. Paper accounts for redundancies, and economic analysis [81]
6. Reliability (percentage that full OBS would be intact after contingencies) [82]
7. Partial observability [84]
8. limited current branches [84][89]
9. OPP for full observability and OPP given  $x$  PMUs [87]
10. OPP given  $x$  PMUs with one current channel and  $y$  PMUs with two current channels. [94]
11. Multistage placements [95]

### **2.5.3. Modifying the GA algorithm to better suit the OPP**

Multiple resources use different approaches to solve the OPP. Regarding using modified GA to solve the OPP better, the references listed here indicates how these modifications are done throughout the literature. In [80] the crossover, mutation and constraints in the GA were modified since the OPP is an Integer only problem. In [81][88] GA was changed to be tailored for OPP by using problem-related facts, such as the typical configurations in power systems. [83] introduces a simple yet new fitness function. In [85] a new step is added before reproduction to enhance results and convergence time. On the other hand, [87] presents Stepwise Mutation GA (SMGA) which forces the “randomness” to increase until the end of GA, once a threshold for PMU locations is reached, to enhance the ability of avoid local minima without affecting the convergence time significantly. While in [92] the mutation stage is adjusted by putting PMUs to maintain full observability when they are removed; also, the reproduction stage is also changed, by repairing the infeasible children. Finally, [96] puts new rules for the search space of the GA, to reduce the time and enhance convergence.

### **2.5.4. Using GA as supplemental algorithm**

In the literature, various papers use GA as a supplement algorithm. Since the main aim of this thesis is to have a mainly GA based OPP, only two resources that use this technique are mentioned here. In [86] Particle Swarm Optimization was used, but GA was incorporated within it to enhance the results and the simulation time. Whereas, [91] Introduces a new algorithm (Memetic algorithm) which is a combination of hill climbing

algorithm (which only has one initial solution, and keeps improving it, thus it is more prone to local trapping) and the GA (which has the issue of having too many redundant runs in case of using it to solve the OPP).

## Chapter 3 Selected Methodology

### 3.1 Selected Solvers and Test Systems

The selected solvers (algorithms), which are used in this thesis to solve the OPP, are the Integer Linear Programming (ILP) and the Genetic Algorithm (GA). The ILP solvers solve for linear optimization problems where the variables are restricted to integers. It is used since it provides results that depend on non-probabilistic methods. Thus, the ILP will always provide the same answer for the same problem. Also, it provides the global minima, unless the problem is ill-conditioned. Hence it is well suited to solve integer based problems like the OPP (the OPP is, in fact, a binary based problem, which is a subset of the integer based problems, where the values are limited to be between 0 to 1 inclusive). However, as the problem complexity increases, it becomes difficult or impossible to formulate it as a Linear Programming problem. Equation (3.1) shows a typical formulation for an ILP, and the OPP needs to be tailored to fit this function, otherwise ILP cannot be used (only the first two conditions are compulsory, the other two are optional).

$$\text{minimize } f^T x \text{ for } \begin{cases} x \text{ is an integer} \\ A \cdot x \leq b \\ A_{eq} \cdot x = B_{eq} \\ lb \leq x \leq ub \end{cases} \quad (3.1)$$

where  $x$  is the variable to be optimized,  $A$  matrix with  $b$  vector represents the linear inequality constraints,  $A_{eq}$  matrix and  $B_{eq}$  vector represents the equality constraints and

$lb$  and  $ub$  vectors are for the lower and upper boundary constraints, and  $f$  is the cost function vector while  $f^T x$  is the function to be minimized.

On the other hand, the reason for selecting GA as the main algorithm of the thesis is because it is preferable since the problem formulation is a straightforward relationship between the input and the output to be minimized. Thus, there is no requirement to put the problem in a particular structure, and there are no limitations regarding nonlinearities or discontinuities. In addition, the GA in comparison with other metaheuristic algorithms performs the same or better, and is both robust and adaptable [97]. Nonetheless, GA is not without disadvantages, and the main disadvantage of GA is that it has a probabilistic part which means that running the algorithm multiple times may generate multiple results. Another disadvantage is that there is no precise method for choosing the values for the variables in the GA (e.g. the mutation function, the mutation probability, the crossover percentage, the population count...etc). Also, the simulation time is large compared to other mathematical and metaheuristic algorithms [97]. Finally, GA does not provide any information regarding whether the solution is a global or a local minimum.

As for the tested systems, these include the IEEE-14, New England 345KV (39 buses), IEEE-57, IEEE-118, IEEE-300 and finally Qatar Grid 2016 version, which is the main testing system in this thesis. The single line diagram for each system is presented in Appendix A, while Table 3.1 provides a simple description for each system.

Table 3.1 Test systems overview

<b>System</b>	<b>Number of buses</b>	<b>Number of lines</b>	<b>Number of ZIBs</b>	<b>Number of IMs</b>	<b>Number of FMs</b>
<b>IEEE-14</b>	14	20	1	3	2
<b>NE-39</b>	39	46	10	6	3
<b>IEEE-57</b>	57	80	15	7	5
<b>IEEE-118</b>	118	186	10	10	7
<b>IEEE-300</b>	300	411	65	25	9

Regarding the network for Qatar, the network provided represents the full 2016 Qatar grid with both distribution and transmission level (6.6KV to 400KV). Information of the grid is provided in Table 3.2 (the grid data is obtained from Kahramaa). The importance of the application of OPP to Qatar Grid comes from its huge size (compared with the other test systems), which greatly increases simulation time. Also, the system has numerous ZIB which also increases the simulation time and can hugely affect the results of OPP.

Table 3.2 Qatar Grid data

<b>Number of buses</b>	<b>Number of lines</b>	<b>Number of ZIBs</b>	<b>Number of IMs</b>	<b>Number of FMs</b>
1572	2479	1112	0-414	-

Although OPP typically ignores distribution level and only focuses on transmission level, this selection is still valid for the following reasons. Firstly, Distributed Generation (DG)



which means that there can be generators in each house or town as a PV panel, wind turbine, or an electric car discharging to the grid, means that observing these buses will become necessary, which is the case in Qatar 2022. It should be noted that although the inclusion or exclusion of DG will not affect the modelling of PMU placement or how PMUs work, but it is the fact that these DGs will have a significant impact on the grid that makes observing them necessary. Moreover, the main reason for neglecting distribution in OPP is because it becomes economically infeasible solution, but since PMU prices are dropping, and communication infrastructures are now more widespread, it might become feasible in the near future. In addition, for Qatar 2022 the extra security provided by the full PMU observability, even if it means additional cost, will not be rejected, due to the importance of the World Cup event.

### **3.2 Description of Methodology**

The first part of the proposed methodology is solving the OPP using the ILP algorithm. Although solving OPP using ILP with the considerations applied here is already done in the literature, it was included here for three main reasons: to start this thesis from where the other have stopped; to verify the correctness of the later algorithm; and to verify that the results obtained for Qatar Grid are indeed correct, since there are no previous works for using OPP with Qatar Grid. As for the selected OPP cases, four cases are considered in this thesis.

Case 1: The basic case (minimum number of PMUs for full observability) while ignoring the ZIB effect

Case 2: The effect of including Zero Injection Buses (ZIB) effect

Case 3: Inclusion of Injection Measurement devices (IM). IM is a conventional measurement device that measures the active and reactive power at a bus.

Case 4: Inclusion of Flow Measurement devices (FM). FM is a conventional measurement device that measures the current flow at a transmission line.

The second proposed methodology in this thesis is the Genetic Algorithm, which is divided into two parts. The first part is the solving of the OPP using GA algorithm with a novel fitness function that has no constraints but still provides full observability. In addition, the same function is used to solve the following cases

Case 1. The basic case (minimum number of PMUs for full observability)

Case 2. The effect of including Zero Injection Buses (ZIB) effect

Case 3. Inclusion of Injection Measurement devices (IM)

Case 4. Number of PMUs to reach a certain level of partial observability

Case 5. Cost analysis (only the costs of PMUs is considered)

The second part solves the problem of “maximum observability given a certain number of PMUs”. The GA used here incorporates:

Case 1. The basic case (maximum observability with specific number of PMUs)

Case 2. The effect of including Zero Injection Buses (ZIB) effect

Case 3. Inclusion of Injection Measurement devices (IM)

Case 4. Limited number of current channels

### 3.2.1. Integer Linear Programming (ILP)

For the ILP, Figure 3.1 illustrates the flowchart for the typical case for solving the OPP. The simulation was carried out using MATLAB® software along with the MATPOWER package [103] while the solver for the ILP was from YALMIP package[104].

The equations describing this method are (2.3) to (2.6) which are listed in section 2.1. These equations describe case 2 for ILP. However, case 3 also uses the same equation, since IM has the same effect on observability as the ZIB. Case 1 is obtained by removing (2.7) as well as the  $y_{mn}$  from (2.5). Finally, Case 4 is obtained using (3.2) instead of (2.5) and adding (3.3) to the constraints.

$$O_n = \sum_{m=1}^N a_{nm}u_n + \sum_{m \in IM} a_{nm}y_{nm} + \sum_{m \in FM} a_{nm}r_{nm} \geq B_n \quad (3.2)$$

*for*  $n = 1, 2, 3 \dots N$

$$r_{mn} + r_{nm} = 1 \quad \forall m \in FM \quad (3.3)$$

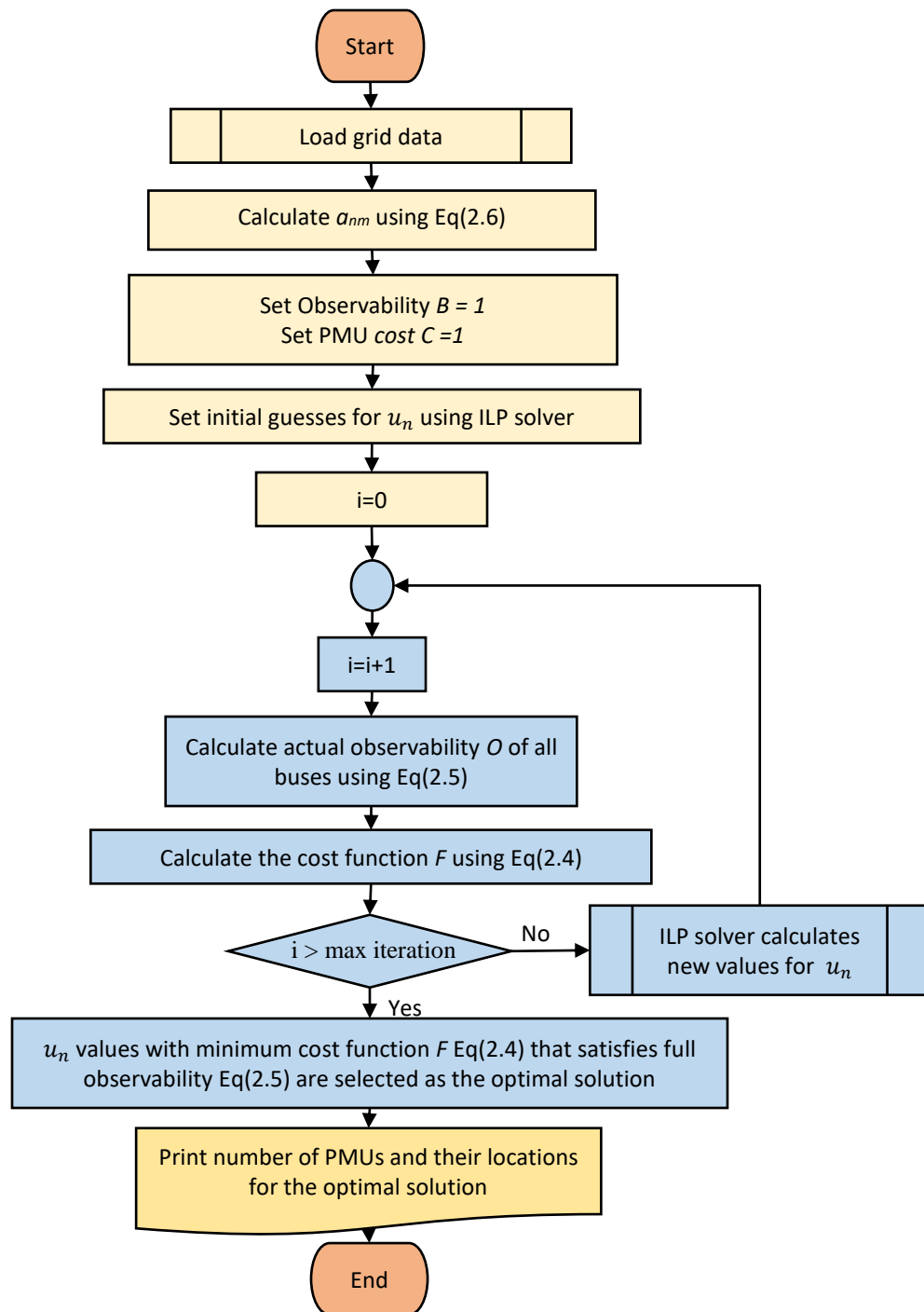


Figure 3.1: Flowchart for ILP to solving OPP

### 3.2.2. Genetic Algorithm (GA) - Method 1

The GA for both methods is applied using the optimization toolbox provided by MATLAB®. For method 1, the GA was restricted to binary values, and the number of variables was set to be the same as the number of buses in the system. The population was set arbitrary to 1000 to have a diverse population to avoid local minima, but this means also that, as a result, the simulation time substantially increases. The other tuning variables for GA were set to their default values (provided by the MATLAB toolbox). The main contribution of the work is that the GA has a novel fitness function and does not contain any constraint criteria.

$$\text{fitness function } (F) = NPMU + \text{modifier} * NUOB \quad (3.4)$$

The fitness function consists of two parts, the NPMU (number of PMUs) and the multiplication between the modifier and NUOB (number of unobservable buses). The modifier has a value between 0 and 1 and it is calculated using (3.5).

$$\text{modifier} = 1 - \text{allowed unobservability ratio} \quad (3.5)$$

By setting the modifier to 1, we find the solution for OPP for full observability (case 1). However, as the value of the modifier approaches zero, the algorithm only aims to satisfy partial observability, consequently minimizing the number of PMUs (case 4). Since, cases 2 and 3 are mathematically the same, they are both implemented by adding a simple algorithm that is similar to exhaustive search and greedy algorithm to decide which buses are to be observed by the ZIB effect or IM. The flowchart in **Figure 3.2** indicates how this algorithm allocates the buses, where  $W$  is an array of vectors (P.S.  $W$  is not a matrix

since the number of columns for each row is different). Each row in  $W$  corresponds to the  $i^{\text{th}}$  ZIB/IM in the network ( $i = 1, 2 \dots i_{\text{max}}$ .  $i_{\text{max}} = \text{total \# of ZIB/IM buses}$ ) and it has  $j$  columns ( $j = 1, 2 \dots j_{\text{max}}$ .  $j_{\text{max}} = \text{total \# of buses that can be observed by the } i^{\text{th}} \text{ ZIB/IM}$ ).

Finally, case 5 is achieved by modifying (3.5) to (3.6).

$$F = \frac{\sum_{i=1}^n \text{cost}PMU_i}{\text{average}PMU\text{cost}} + \text{modifier} * NUOB \quad n = 1, 2 \dots N \quad (3.6)$$

### 3.2.3. Genetic Algorithm (GA) - Method 2

The second method for the OPP using GA aims to find the best locations to place  $x$  PMUs in the network to achieve maximum possible observability. Unlike method 1, the variables here indicate the locations of the  $x$  PMUs; thus the GA is set to be integer restricted (instead of binary restricted), where the number of variables is the number of PMUs and each variable can take values from 1 to  $N$  inclusive. Cases 1,2 and 3 are applied the same way as the GA method 1, but the only difference is the fitness function.

$$\text{fitness function } (F) = NUOB \quad (3.7)$$

As for case 4, it is satisfied using an approach similar to the greedy-like algorithm used for cases 2 and 3 in method 1.

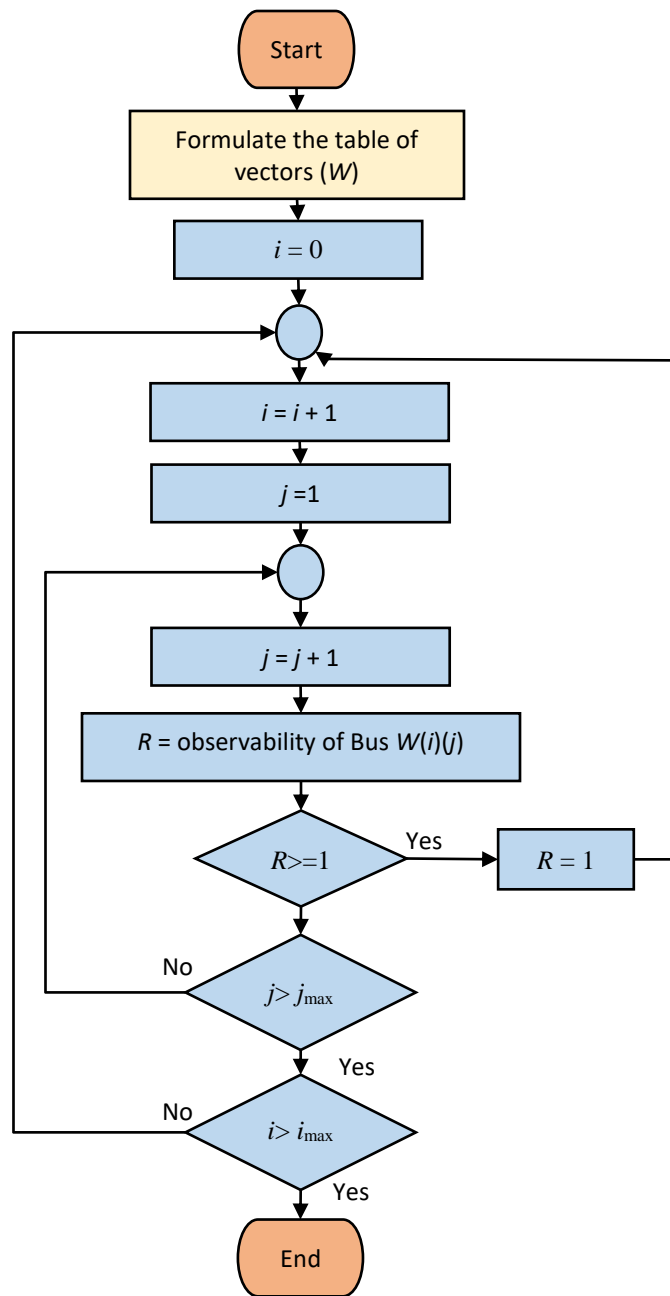


Figure 3.2: Flowchart for ZIB and IM observability allocation

## Chapter 4 Case Studies and Results

### 4.1 Application to Test Systems

The three methods presented in the previous chapter, which are ILP, GA method 1, GA method 2, were first applied to five test systems IEEE-14, New England 345KV (will be referred to as NE-39 in the remainder of the thesis), IEEE-57, IEEE-118, and IEEE-300. Since some cases require IM and FM, Table 4.1 describes the locations used. These locations for the FM and IM were selected arbitrary, but they remain the same throughout the thesis to be able to compare the results of the different methods easily. In addition, the table also includes the locations of the ZIB.

Table 4.1 Locations of the ZIB, IM and FM used in this paper

System	ZIB	IM	FM
<b>IEEE-14</b>	7	2, 6, 14	2-3, 4-9
<b>NE-39</b>	2, 5, 6, 10, 11, 13, 14, 17, 19, 22	4, 15, 17, 21, 25, 32	16-24, 4-14, 8-9
<b>IEEE-57</b>	4, 7, 11, 21, 22, 24, 26, 34, 36, 37, 39, 40, 45, 46, 48	18, 23, 43, 45, 46, 50, 57	37-39, 28-29, 4-18, 50-51, 42,56
<b>IEEE-118</b>	5, 9, 30, 37, 38, 63, 64, 68, 71, 81	12, 15, 33, 65, 75, 97, 107, 108, 113, 114	6-7, 27-28 114-115, 74-75, 77-80, 55-59, 103-105
<b>IEEE-300</b>	4, 7, 12, 16, 18, 23, 28, 29, 30, 33, 36, 39, 40, 52, 54, 56, 57, 62, 65, 68, 70, 71, 72, 73, 82, 94, 95, 96, 107, 108, 109, 110, 111, 112, 113, 123, 129, 130, 137, 139, 143, 144, 145, 147, 148, 153, 172, 173, 174, 189, 191, 198, 205, 216, 219, 223, 245, 246, 266, 270, 271, 272, 273, 276, 291	10, 11, 14, 30, 43, 48, 52, 84, 118, 127, 146, 197, 197, 204, 212, 223, 228, 238, 241, 255, 275, 281, 288, 288, 292	270-294, 276-279, 269-288, 22-253, 23-254, 222-224, 44-45, 49-50, 97-100



#### 4.1.1. ILP

Applying ILP to solve the OPP we obtain the results in Table 4.2. The results show that with the inclusion of IM and FM the number of needed PMUs decreases slightly. The same effect is also observed with the inclusion of the ZIB effect.

Table 4.2 Results for OPP using ILP for the test systems

System	Number of needed PMUs			
	Case 1 (no ZIB)	Case 2 (with ZIB)	Case 3 (with ZIB and IM)	Case 4 (with ZIB and FM)
<b>IEEE-14</b>	4	3	3	3
<b>NE-39</b>	13	9	7	8
<b>IEEE-57</b>	17	11	10	10
<b>IEEE-118</b>	32	28	26	27
<b>IEEE-300</b>	87	68	62	66

#### 4.1.2. Genetic Algorithm (GA) - Method 1

As for the GA, the same parameters from the ILP are used, and the best results for the cases (out of 50 trials) are shown in Table 4.3. The results show that the GA can achieve the same results as the ILP, but it is not guaranteed due to the probabilistic nature of the GA. In addition, since the GA produces different results with each run, which is a major disadvantage in this proposed algorithm and GA in general since the obtained results could be worse than the ILP results, Figure 4.1 shows the distribution of the results for 50 runs for the IEEE-300 case 1, indicating that the obtained results were in the worst case 106 PMUs which is worse than the ILP by 19 PMUs and worse than the best results of GA by 11 PMUs. Due to this variation, it is always recommended to run the GA

multiple times before assuming that the obtained results are the best ones. From the results, it is shown that the GA results are starting to slightly deviate from the optimal solution provided by the ILP as the system becomes larger (e.g. IEEE-118 case 1 requires 33 PMUs using GA, but according to ILP only 32 PMUs are required), Table 4.4 shows how the GA first gives similar results and then starts to deviate as the systems become larger. For the partial observability, the modifier was set to 0.7 and the results indicate that the partial observability becomes more significant as the system becomes larger. Finally, for the cost, the target was to minimize the cost of PMUs rather than their number. Nonetheless, the results show the same number of PMUs for these systems as the original Case 2. Which means that it is possible to have cheaper cost while maintaining the same number of PMUs.

Table 4.3 Results for OPP using GA method 1 for the test systems

System	Number of needed PMUs				
	Case 1 (no ZIB)	Case 2 (with ZIB)	Case 3 (with IM and ZIB)	Case 4* (partial OBS)	Case 5** (cost; with ZIB)
<b>IEEE-14</b>	4	3	3	3	3
<b>NE-39</b>	13	9	7	7	9
<b>IEEE-57</b>	17	11	10	10	11
<b>IEEE-118</b>	33	30	27	20	30
<b>IEEE-300</b>	95	77	73	52	77

\* For modifier = 0.7

\*\* assumption: placing PMUs in odd numbered locations is 50% more expensive

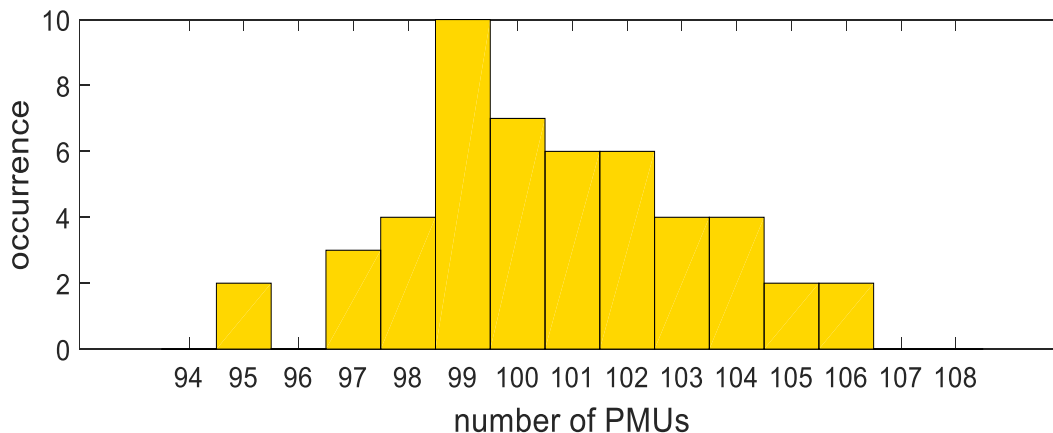


Figure 4.1: Distribution of the results of 50 runs of GA – method1 for IEEE-300

Table 4.4 Comparison between ILP and GA method 1 results

System	Number of needed PMUs					
	Case 1 (no ZIB)		Case 2 (with ZIB)		Case 3 (with ZIB and IM)	
	ILP	GA	ILP	GA	ILP	GA
<b>IEEE-14</b>	4	4	3	3	3	3
<b>NE-39</b>	13	13	9	9	7	7
<b>IEEE-57</b>	17	17	11	11	10	10
<b>IEEE-118</b>	32	33	28	30	26	27
<b>IEEE-300</b>	87	95	68	77	62	73

### 4.1.3. Genetic Algorithm (GA) - Method 2

The last algorithm deals with the observability given a certain number of PMUs, i.e. it answers the question of “what is the maximum observability achievable (4.1) given  $x$  PMUs and how can it be reached.” Each test system has a graph describing its results for cases 1 to 3 (Figure 4.2 to 4.6). As for case 4, they are shown in Figure 4.7 to 4.11.

$$\%observability = \frac{\text{number of observable buses}}{\text{number of total buses}} * 100 \quad (4.1)$$

The following observations can be realized from the figures. The probabilistic nature of the GA becomes more evident as the system becomes larger (this can be remedied by running the GA multiple times, as previously mentioned). For the ZIB and IM cases, the observability starts at a nonzero value, even at 0 PMU, since the ZIB and IM are already observing some buses, but as the number of PMUs increases, the difference between no ZIB and ZIB decreases. Also, as the number of channels increase the number of needed PMUs decreases, but the slope becomes gradual. Another observation regarding the number of channels is that the curve starts as a linear relation, but then it saturates. This happens because the PMUs with more current channels are only better while there are buses that do require the additional current branches, but after these buses are observed, then the additional buses will not benefit from the additional current branches. Finally, the graphs show that the 4 channels and 5 channels cases are almost similar and they are very close to the 3 channels results, thus it might not be needed to use PMUs with 3 channels or more in practical applications.

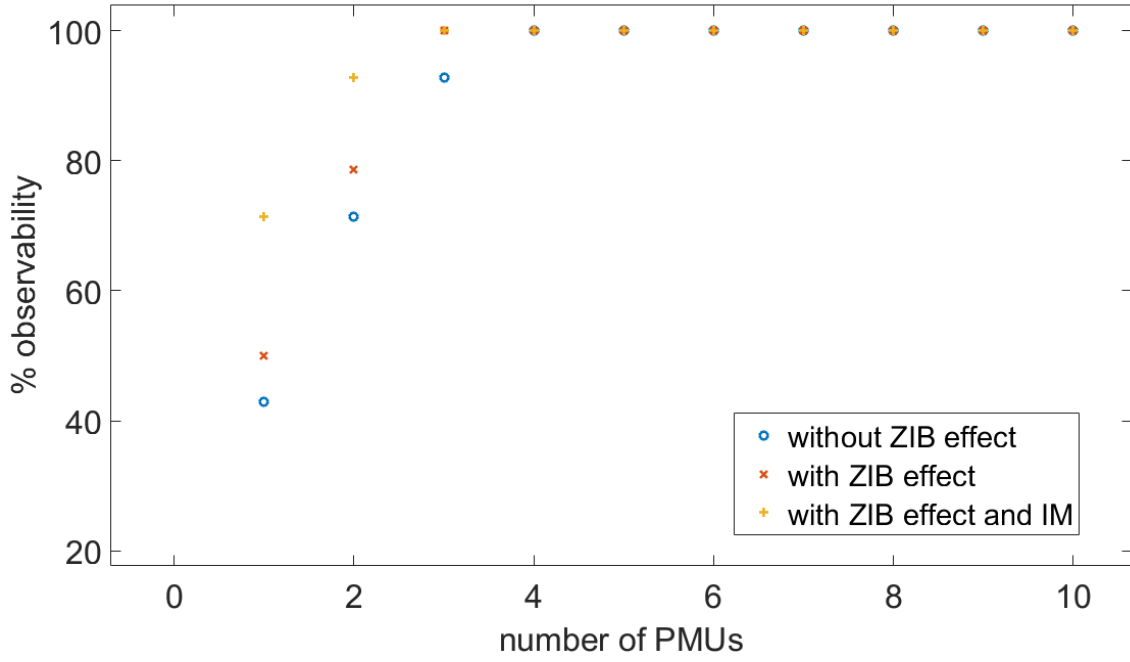


Figure 4.2: Results for OPP using GA method 2 for the IEEE-14

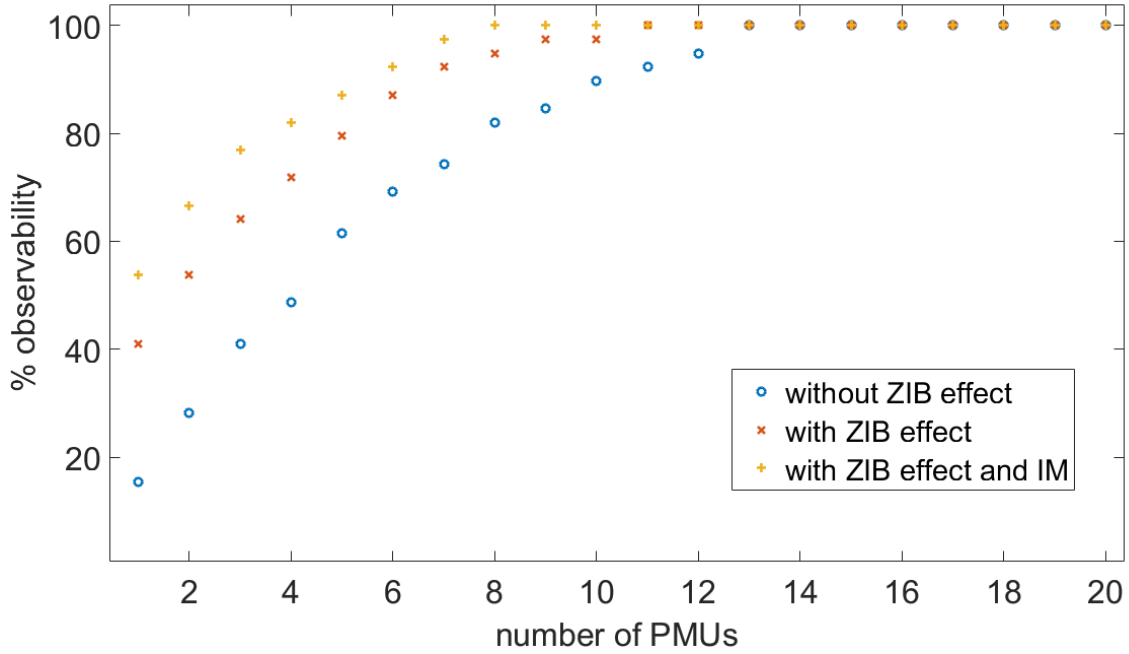


Figure 4.3: Results for OPP using GA method 2 for the NE-39

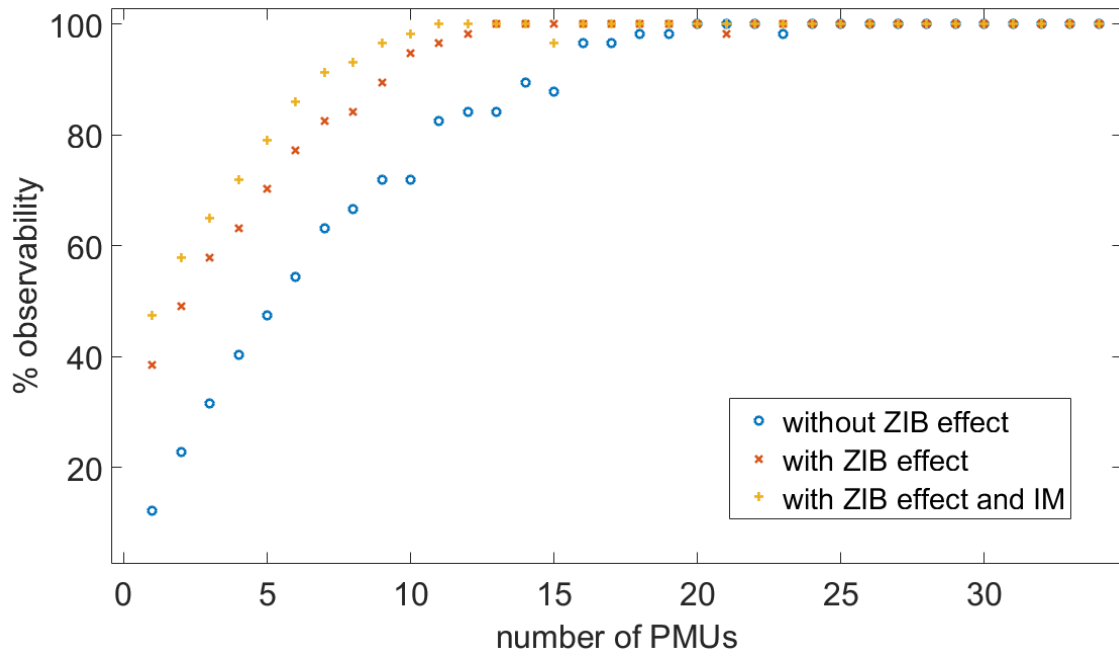


Figure 4.4: Results for OPP using GA method 2 for the IEEE-57

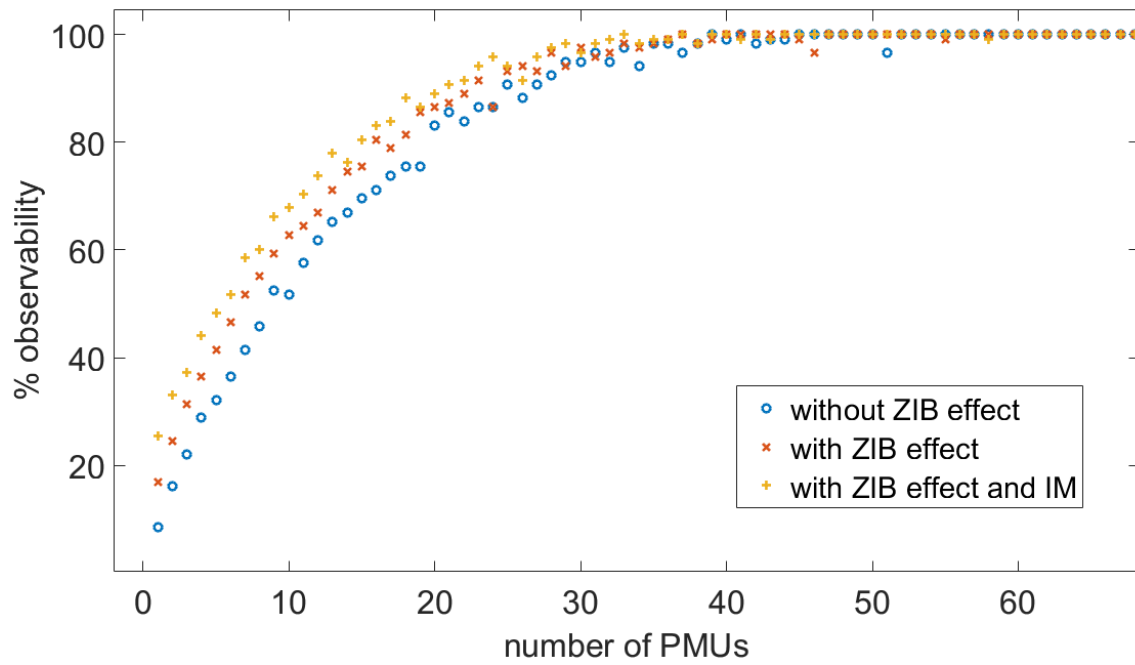


Figure 4.5: Results for OPP using GA method 2 for the IEEE-118

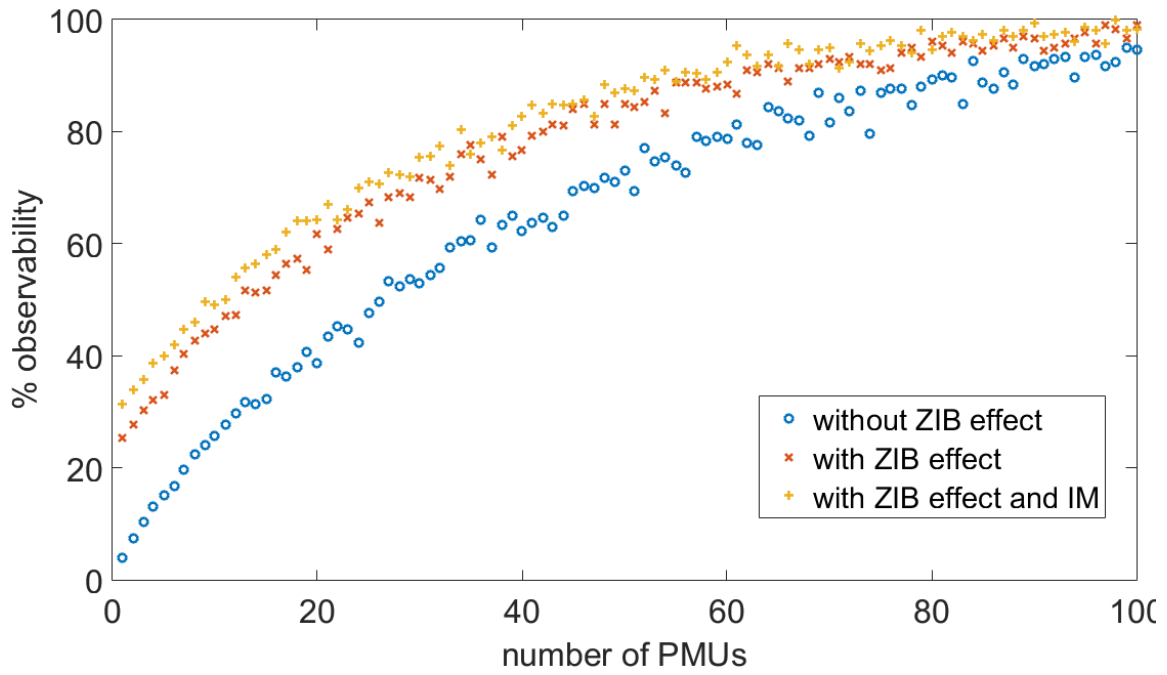


Figure 4.6: Results for OPP using GA method 2 for the IEEE-300

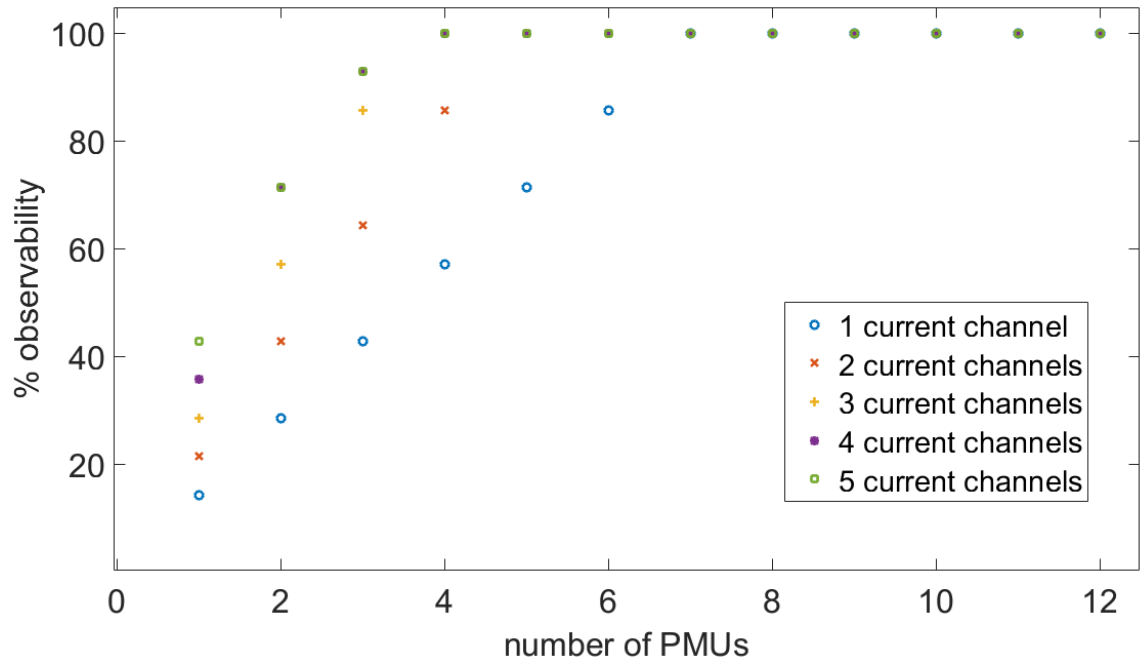


Figure 4.7: Results for GA method 2 case 4 for the IEEE-14

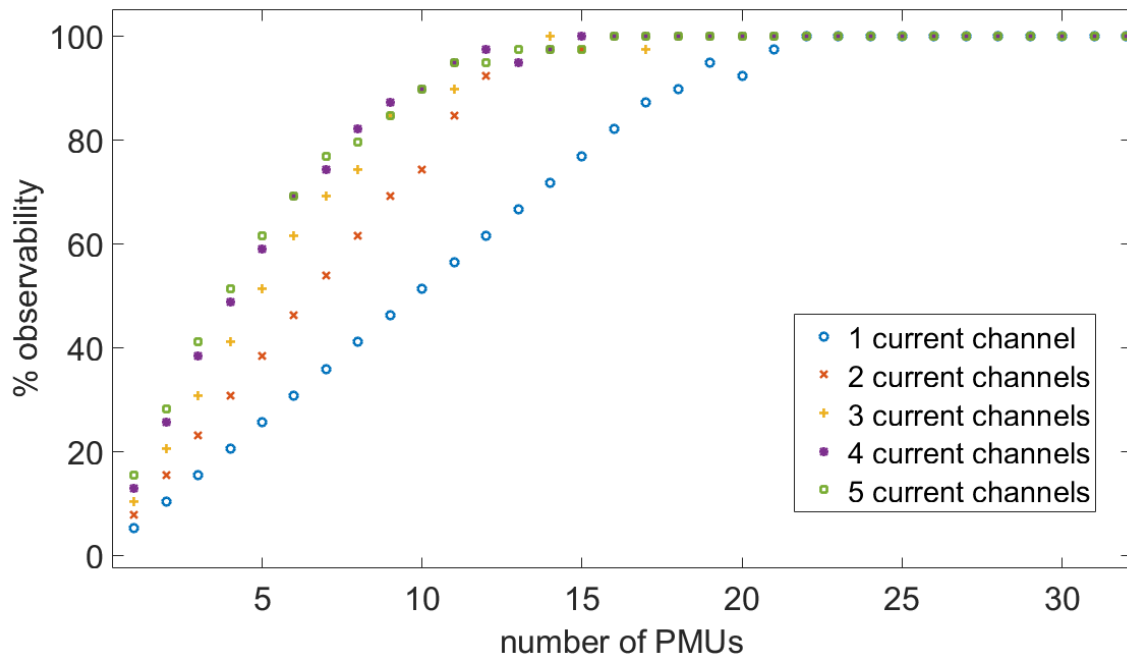


Figure 4.8: Results for GA method 2 case 4 for the NE-39

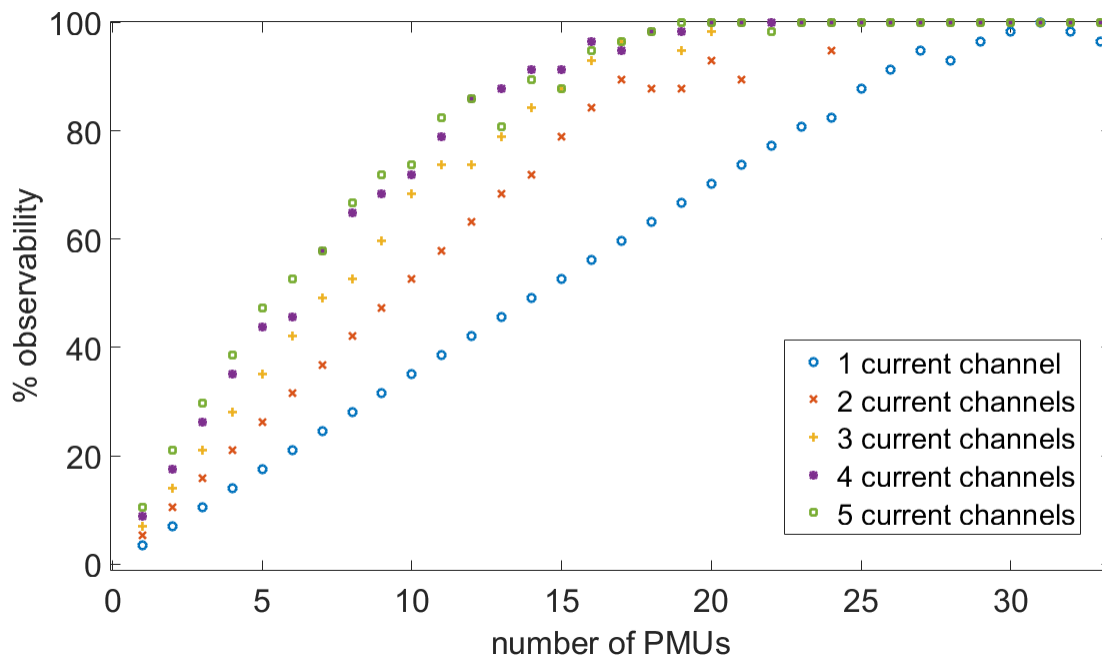


Figure 4.9: Results for GA method 2 case 4 for the IEEE-57



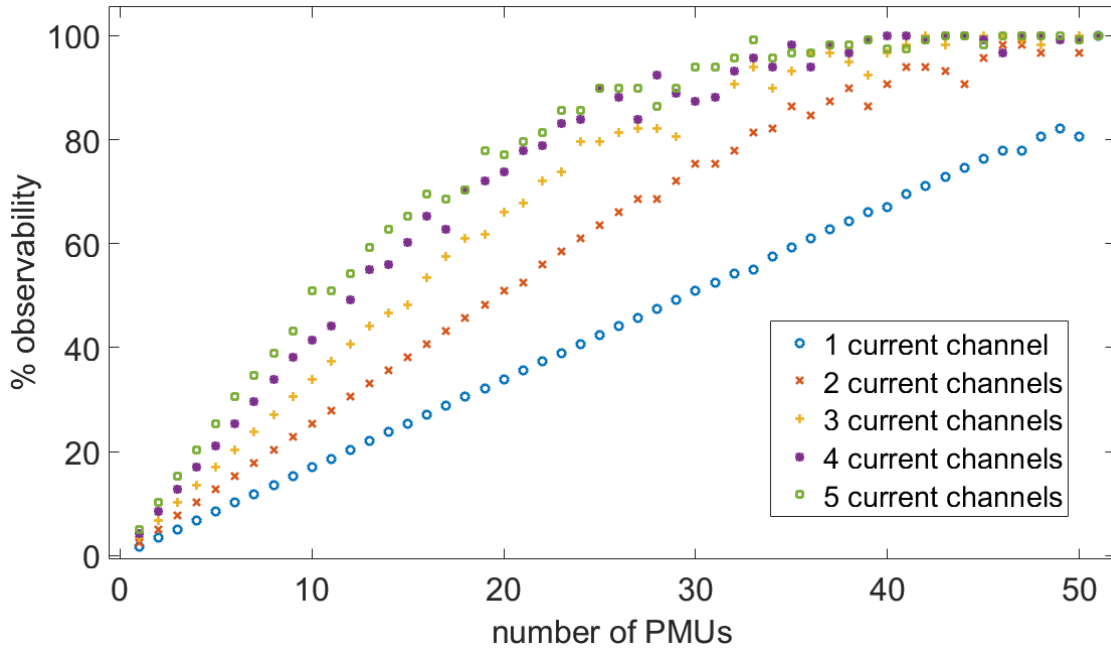


Figure 4.10: Results for OPP using GA method 2 for the IEEE-118

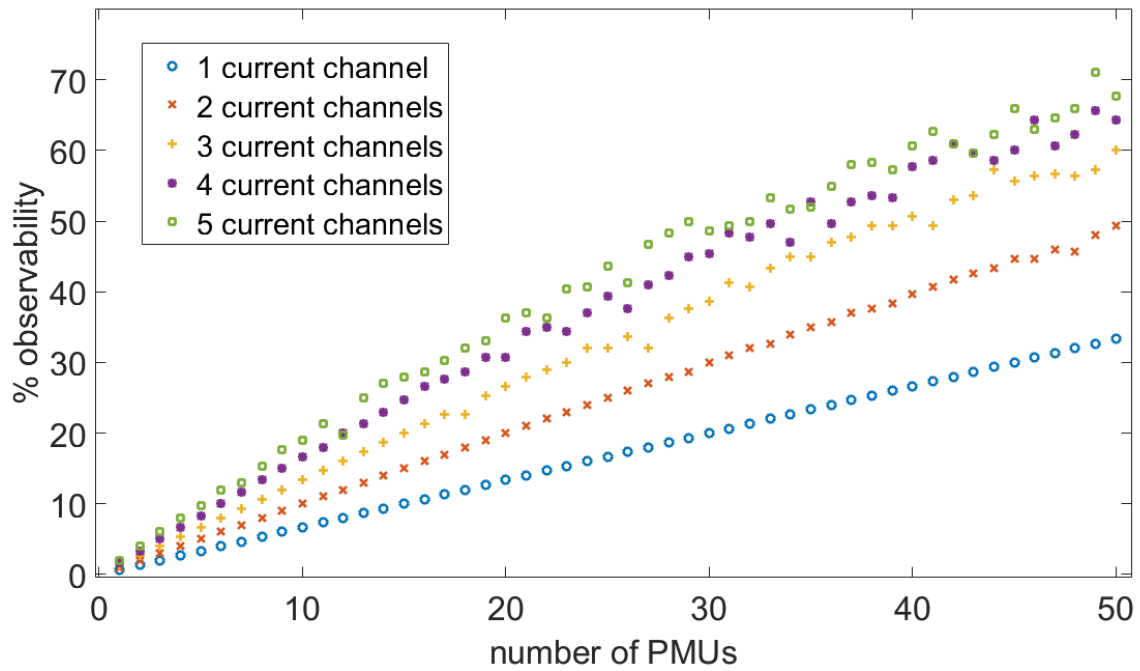


Figure 4.11: Results for OPP using GA method 2 for the IEEE-300

## 4.2 Application to Qatar Grid

### 4.2.1. ILP

For Qatar Grid cases 1-3 were applied, but instead of applying case 4, case 3 was applied with multiple scenarios. The reason for this selection is because it was more practical and the results would be easier to analyze. The study applied here would include the cases shown in Table 4.5.

Table 4.5 Results for OPP using ILP for Qatar Grid

Case	Number of IM	% of none ZIB observed by IM	PMU needed
Case 1 (no ZIB)	0	0%	615
Case 2 (with ZIB)	0	0%	144
Case 3.1 (with ZIB and IM)	46	10%	131
Case 3.2 (with ZIB and IM)	115	25%	108
Case 3.3 (with ZIB and IM)	230	50%	77
Case 3.4 (with ZIB and IM)	345	75%	44
Case 3.5 (with ZIB and IM)	414	90%	17
Case A.1 (N-1, with ZIB)	0	0%	603
Case A.2 (N-1, with ZIB and IM)	414	90%	401

Cases 1 and 2, using ZIB effect and without using it respectively, indicates the number of PMUs required if the Qatar grid is to be observed by PMUs alone. Cases 3.1 to 3.5 show how many PMUs are required in case injection measurements (IM) are included in the OPP, alongside the number of IM in each case. Finally, Case A.1 and A.2 demonstrates the results of the OPP in case N-1 contingency is considered.

Analyzing the results, it is clear that the required PMUs for full observability significantly decrease when including IMs; however, this assumption comes with a very critical disadvantage. Buses that are being observed using these conventional measurements will send data at a much lower rate and with less accuracy when comparing them to the ones observable by PMUs. To look at it from a different perspective, buses observed by PMUs would send data with a high rate but the network as a whole would be fully observable only when all measurements are received from both conventional measurements and PMUs [101]. Hence, practically it would be preferable not to consider conventional measurement with very low data sending rate even if they are available in the system. Another important notice is that the case when all the buses in the system have measurement devices is excluded since it brings a redundant result, which is that 0 PMUs are needed.

The results of the OPP algorithm indicate that, for full system observability, the number of needed PMUs is 144, which is 9.1% of the total number of buses (31.3% of the non-ZIB buses). Thus, it is clear that for monitoring Qatar Grid a far lower value than the assumption of “each bus requires a PMU”, in fact, it is shown that for practical systems the needed ratio is 1/3 of the total buses at maximum [24]. As for the cases 3.1 to 3.5, it is concluded that with the addition of IMs the number of PMUs keeps on decreasing with a rate of around 0.26-0.39 PMU/IM. The result of Case 3.5 also shows how the number of PMUs is almost one-eighth of the number of needed PMUs in Case 2 which proves that, in case more IMs are considered, the full observability can be obtained with a significantly lower number of PMUs.

Finally, cases A.1 and A.2 indicate how many PMUs are needed in case N-1 contingencies are considered (N-1 contingency includes the failure of a single PMU or IM, or the tripping of a single line). This is carried out by setting the  $Bn$  in (2.5) to be a vector of twos (instead of a vector of ones) which effectively makes each bus observable by at least two PMUs [102]. Thus, a single contingency will not affect its observability. However, the number of required PMUs becomes almost three times the needed PMUs in the typical case, which shows that maybe the accommodation for N-1 contingency might not be a feasible solution for practical systems.

Moving from the theoretical results, practically each non-ZIB has its own IM to monitor the consumed/injected power, and to make sure that the power factor is within acceptable operation region. Thus, another approach towards solving the OPP is to assume that all buses are observable, but some critical buses are important enough to have the high monitoring rate of PMUs, in this case, the OPP would only need to find the optimal placement to make these selected buses observable by PMUs. Such approach can even make the PMUs only limited to monitoring large scale industrial loads and similar critical buses that are more probable to cause various problems in the network. Another approach is to generate a  $Bn$  vector that matches the importance of the bus. Thus, the  $Bn$  would be either 2 or 1 depending on whether a bus is critical or not (values  $>2$  can be considering if needed). Thus, the system would benefit from both withstanding some N-1 contingency while maintaining a small PMU count.

### 4.2.2. Genetic Algorithm (GA) - method 1

The same parameters from the ILP are used, and the best results for the cases (out of 50 trials) are shown in Table 4.6. The results show that the results are worst than the ILP results, for the cases that are applied by both methods, this can be improved by running the GA multiple times or increasing the population count. However, since the system is large, the algorithm already takes a long time, and by increasing the population count, the needed time drastically increases.

Table 4.6 Results for OPP using GA method 1 for Qatar Grid

Case 1 (no ZIB)	Case 2 (with ZIB)	Case 3 (with IM and ZIB)	Case 4* (partial OBS)	Case 5** (cost)
656	210	74	181	326

\* for modifier = 0.7

\*\* assumption: placing PMUs in odd numbered locations is 50% more expensive

### 4.2.3. Genetic Algorithm (GA) - method 2

Cases 1 and 2 are shown in Figure 4.12, and case 4 is shown in Figure 4.13. For case 1 and 2 the number of PMUs only slightly increase the observability, since the system is large. As for case 4, it shows that even with 100 PMUs, the relationship between current branches and observability is still in the linear region due to the size of the system.

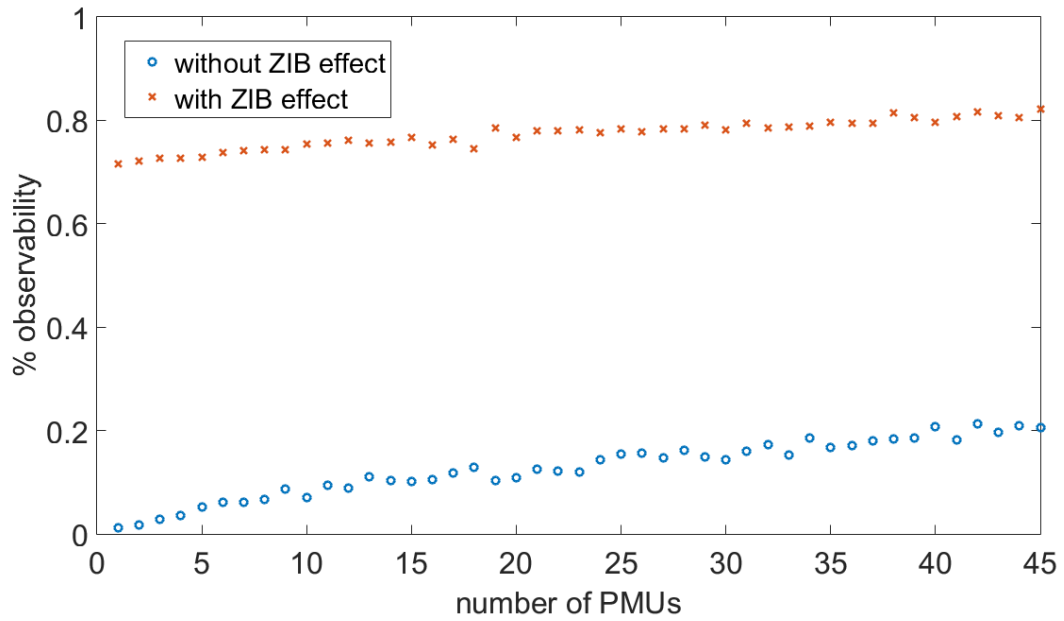


Figure 4.12: OPP using GA method 2 for Qatar Grid case 1 and 2 (% of OBS)

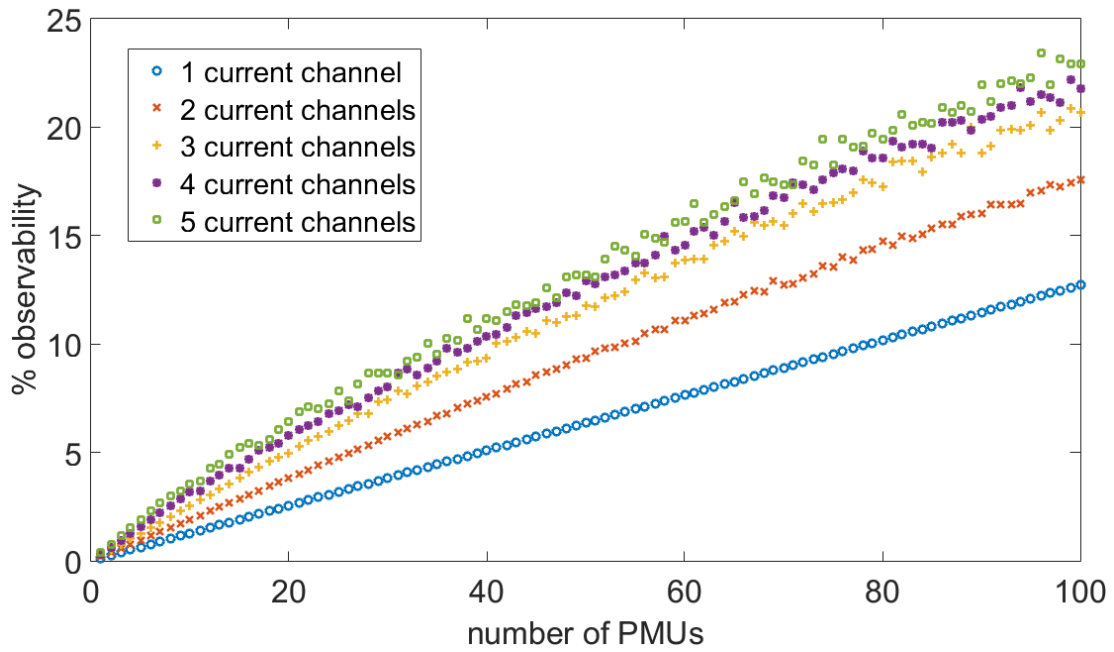


Figure 4.13: OPP using GA method 2 for Qatar Grid case 4 (% of OBS vs. NPMU)

## **Chapter 5 Conclusion and Future Work**

### **5.1 Conclusion**

PMUs greatly improves power systems' observability. However, they are relatively expensive, thus it is needed to use OPP to find the least number of PMUs needed to achieve full observability. The literature review shows that several techniques and algorithms were used for OPP with different degrees of complexity depending on adopted constraints and considerations and that the latest published articles show a clear shift towards more realistic considerations. As for the contribution of this thesis to the OPP, using the proposed GA with modified fitness function, new results are obtained for partial observability and other considerations. The results of the GA are the same as the results obtained by the ILP for small systems. However, one major disadvantage of the method is that the difference between ILP and GA results become larger as the studied system becomes larger, but this can be remedied by increasing the population count. Another disadvantage is that, due to its probabilistic nature, the proposed method requires multiple trials to get better results. Also, the GA requires much longer simulation time than GA for the included cases. However, the inferiority of the GA in terms of providing answers similar to ILP is balanced by the two main advantages of the GA. Firstly, since the formulation is simple, modifying the proposed algorithm to accommodate to newer constrains and objectives is much easier than ILP. Secondly, some objectives and constraints cannot be modeled as ILP. Thus, GA becomes superior to ILP in that aspect.

Another important contribution of the thesis, is that the number of required PMUs greatly changes when the current branch limits are considered, which is very important observation since actual PMUs only have limited number of current branch. In addition, the results showed that once the number of branches is 3 or more the results become equal or very close, hence the usage of PMUs with more than 3 current channels might not be needed. Finally, applying the OPP (full observability with ZIB) to Qatar Grid shows very promising results that can be feasible practically, since the number of needed PMUs to observe the grid is only 9.1% of the total number of buses.

## **5.2 Future Work**

As a future work, the study can be extended to cover transient observability, as well as, observability with device failures and faulty measurements. Another approach is to have more financial data regarding the prices of the PMUs (total installation cost and not the unit itself) and compare it with the possible gains from having full system observability, to come to a financial conclusion regarding the validity of having full observability. As for the GA, it can be extended by adding more cases and considerations. It can also be improved by analyzing the effects of modifying the population size and the mutation percentage to enhance the results and the convergence time for the GA to reduce the effects of its inherent disadvantages.



## REFERENCES

- [1] Azizi, S.; Dobakhshari, A.S.; Nezam Sarmadi, S.A.; Ranjbar, A.M., "Optimal PMU Placement by an Equivalent Linear Formulation for Exhaustive Search," in *Smart Grid, IEEE Transactions on* , vol.3, no.1, pp.174-182, March 2012
- [2] U.S.-Canada Power System Outage Task Force, "Final Report on the August 14, 2003 Blackout in the United States and Canada: Causes and Recommendations", 2004.
- [3] A. Mao, J. Yu, and Z. Guo, "PMU placement and data processing in WAMS that complements SCADA," in *IEEE Power Eng. Soc. Gen. Meet.*, 2005.
- [4] Bei Xu; Abur, A., "Observability analysis and measurement placement for systems with PMUs," in *Power Systems Conference and Exposition, 2004. IEEE PES* , vol., no., pp.943-946 vol.2, 10-13 Oct. 2004
- [5] Aghaei, J.; Baharvandi, A.; Rabiee, A.; Akbari, M.-A., "Probabilistic PMU Placement in Electric Power Networks: An MILP-Based Multiobjective Model," in *Industrial Informatics, IEEE Transactions on* , vol.11, no.2, pp.332-341, April 2015
- [6] Manousakis, N.M.; Korres, G.N.; Georgilakis, P.S., "Taxonomy of PMU Placement Methodologies," in *Power Systems, IEEE Transactions on* , vol.27, no.2, pp.1070-1077, May 2012
- [7] Manousakis, N.M.; Korres, G.N.; Georgilakis, P.S., "Optimal placement of phasor measurement units: A literature review," in *Intelligent System Application to Power*

*Systems (ISAP), 2011 16th International Conference on* , vol., no., pp.1-6, 25-28  
Sept. 2011

- [8] S. Azizi, G. B. Gharehpetian and A. S. Dobakhshari, "Optimal Integration of Phasor Measurement Units in Power Systems Considering Conventional Measurements," in *IEEE Transactions on Smart Grid*, vol. 4, no. 2, pp. 1113-1121, June 2013.
- [9] Esmaili, M.; Gharani, K.; Shayanfar, H.A., "Redundant Observability PMU Placement in the Presence of Flow Measurements Considering Contingencies," in *Power Systems, IEEE Transactions on* , vol.28, no.4, pp.3765-3773, Nov. 2013
- [10] Lei Huang; Yuanzhang Sun; Jian Xu; Wenzhong Gao; Jun Zhang; Ziping Wu, "Optimal PMU Placement Considering Controlled Islanding of Power System," in *Power Systems, IEEE Transactions on* , vol.29, no.2, pp.742-755, March 2014
- [11] Schrijver and er Schrijver, *Theory of linear and integer programming*. United Kingdom: Wiley, John & Sons, 1998.
- [12] Azizi, S.; Dobakhshari, A.S.; Nezam Sarmadi, S.A.; Ranjbar, A.M., "Optimal PMU Placement by an Equivalent Linear Formulation for Exhaustive Search," in *Smart Grid, IEEE Transactions on* , vol.3, no.1, pp.174-182, March 2012
- [13] Bao, W.; Guo, R.; Han, Z., "A substation-oriented approach to optimal phasor measurement units placement". In *Journal of Electrical Engineering and Technology*, vol.10, no.1, pp.18-29, Jan. 2015

- [14] S. Chakrabarti and E. Kyriakides, "Optimal Placement of Phasor Measurement Units for Power System Observability," in *IEEE Transactions on Power Systems*, vol. 23, no. 3, pp. 1433-1440, Aug. 2008.
- [15] Junjian Qi; Kai Sun; Wei Kang, "Optimal PMU Placement for Power System Dynamic State Estimation by Using Empirical Observability Gramian," in *Power Systems, IEEE Transactions on* , vol.30, no.4, pp.2041-2054, July 2015
- [16] U.S.-Canada Power System Outage Task Force, "Final Report on the August 14, 2003 Blackout in the United States and Canada: Causes and Recommendations", 2004.
- [17] Bei Xu; Abur, A., "Observability analysis and measurement placement for systems with PMUs," in *Power Systems Conference and Exposition, 2004. IEEE PES* , vol., no., pp.943-946 vol.2, 10-13 Oct. 2004
- [18] Aminifar, F.; Fotuhi-Firuzabad, M.; Safdarian, A.; Davoudi, A.; Shahidehpour, M., "Synchrophasor Measurement Technology in Power Systems: Panorama and State-of-the-Art," in *Access, IEEE* , vol.2, no., pp.1607-1628, 2014
- [19] M. Göl and A. Abur, "Optimal PMU placement for state estimation robustness," *Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), 2014 IEEE PES*, Istanbul, 2014, pp. 1-6.
- [20] N. Manousakis; G. Korres, "Optimal Allocation of PMUs in the Presence of Conventional Measurements Considering Contingencies," in *IEEE Transactions on Power Delivery* , vol.PP, no.99, pp.1-1

- [21] A. Schrijver and er Schrijver, *Theory of linear and integer programming*. United Kingdom: Wiley, John & Sons, 1998.
- [22] V. Rokkam and R. Bhimasingu, "A novel approach for optimal PMU placement considering channel limit," *Power System Technology (POWERCON), 2014 International Conference on*, Chengdu, 2014, pp. 1164-1171.
- [23] J. Hao, R. J. Piechocki, D. Kaleshi, W. H. Chin and Z. Fan, "Multistage PMU placement scheduling for robust state estimation in power systems," *Communication Workshop (ICCW), 2015 IEEE International Conference on*, London, 2015, pp. 1952-1957.
- [24] Bei Gou; Kavasseri, R.G., "Unified PMU Placement for Observability and Bad Data Detection in State Estimation," in *Power Systems, IEEE Transactions on* , vol.29, no.6, pp.2573-2580, Nov. 2014
- [25] Aminifar, F.; Khodaei, A.; Fotuhi-Firuzabad, M.; Shahidehpour, M., "Contingency-Constrained PMU Placement in Power Networks," in *Power Systems, IEEE Transactions on* , vol.25, no.1, pp.516-523, Feb. 2010
- [26] Yang Wang; Caisheng Wang; Wenyan Li; Jian Li; Feng Lin, "Reliability-Based Incremental PMU Placement," in *Power Systems, IEEE Transactions on* , vol.29, no.6, pp.2744-2752, Nov. 2014
- [27] Pal, A.; Sanchez-Ayala, G.A.; Centeno, V.A.; Thorp, J.S., "A PMU Placement Scheme Ensuring Real-Time Monitoring of Critical Buses of the Network," in *Power Delivery, IEEE Transactions on* , vol.29, no.2, pp.510-517, April 2014

- [28] J. Aghaei, A. Baharvandi, M. Akbari, K. Muttaqi, M. Asban and A. Heidari, "Multi-objective Phasor Measurement Unit Placement in Electric Power Networks: Integer Linear Programming Formulation", *Electric Power Components and Systems*, vol. 43, no. 17, pp. 1902-1911, 2015.
- [29] A. Pal, G. Sánchez-Ayala, J. Thorp and V. Centeno, "A Community-based Partitioning Approach for Phasor Measurement Unit Placement in Large Systems", *Electric Power Components and Systems*, vol. 44, no. 12, pp. 1317-1329, 2016.
- [30] Gharani Khajeh, K.; Bashar, E.; Mahboub Rad, A.; Gharehpetian, G.B., "Integrated Model Considering Effects of Zero Injection Buses and Conventional Measurements on Optimal PMU Placement," in *Smart Grid, IEEE Transactions on* , vol.PP, no.99, pp.1-1
- [31] Kolda T.G., Lewis R.M. and Torczon V. (2003), "Optimization by direct search : New perspectives on some classical and modern methods," *SIAM Review*, vol.46, 385–482.
- [32] Manousakis, N.M.; Korres, G.N., "A Weighted Least Squares Algorithm for Optimal PMU Placement," in *Power Systems, IEEE Transactions on* , vol.28, no.3, pp.3499-3500, Aug. 2013
- [33] K. Sadanandan Sajan, A. Kumar Mishra, V. Kumar and B. Tyagi, "Phased Optimal PMU Placement Based on Revised Analytical Hierarchy Process", *Electric Power Components and Systems*, vol. 44, no. 9, pp. 1005-1017, 2016.

- [34] N. Theodorakatos, N. Manousakis and G. Korres, "Optimal Placement of Phasor Measurement Units with Linear and Non-linear Models", *Electric Power Components and Systems*, vol. 43, no. 4, pp. 357-373, 2015.
- [35] M. H. Tayarani-N, Xin Yao and Hongming Xu, "Meta-Heuristic Algorithms in Car Engine Design: A Literature Survey," in *IEEE Transactions on Evolutionary Computation*, vol. 19, no. 5, pp. 609-629, Oct. 2015.
- [36] Z. Michalewicz, D. B. Fogel, and Z. Michalewicz, *How to solve it: Modern Heuristics*. Germany: Springer-Verlag Berlin and Heidelberg GmbH & Co. K, 1999.
- [37] Bo Wang; Dichen Liu; Li Xiong, "An Improved Ant Colony System in Optimizing Power System PMU Placement Problem," in *Power and Energy Engineering Conference, 2009. APPEEC 2009. Asia-Pacific*, vol., no., pp.1-3, 27-31 March 2009
- [38] Abdelsalam, H.A.; Abdelaziz, A.Y.; Osama, R.A.; Salem, R.H., "Impact of distribution system reconfiguration on optimal placement of phasor measurement units," in *Power Systems Conference (PSC), 2014 Clemson University*, vol., no., pp.1-6, 11-14 March 2014
- [39] H. A. Abdelsalam, A. Y. Abdelaziz, and V. Mukherjee, "Optimal PMU placement in a distribution network considering network reconfiguration," *2014 International Conference on Circuits, Power and Computing Technologies [ICCPCT-2014]*, Mar. 2014.

- [40] Nuqui, R.F.; Phadke, A.G.; Schulz, Richard P.; Bhatt, N., "Fast on-line voltage security monitoring using synchronized phasor measurements and decision trees," in *Power Engineering Society Winter Meeting, 2001. IEEE* , vol.3, no., pp.1347-1352 vol.3, 2001
- [41] Mahmoodianfard, F.; Mohammadi, M.; Gharehpetian, G.B.; Askarian Abyaneh, H., "Optimal PMU placement for voltage security assessment using decision tree," in *PowerTech, 2009 IEEE Bucharest* , vol., no., pp.1-5, June 28 2009-July 2 2009
- [42] Rui Sun; Zhongyu Wu; Centeno, V.A., "Power system islanding detection & identification using topology approach and decision tree," in *Power and Energy Society General Meeting, 2011 IEEE* , vol., no., pp.1-6, 24-29 July 2011
- [43] Kumar, G.N.; Kalavathi, M.S., "Implementation and comparison of state estimation techniques for optimal placement of PMU'S in interconnected power networks," in *Computational Intelligence and Information Technology, 2013. CIIT 2013. Third International Conference on* , vol., no., pp.532-539, 18-19 Oct. 2013
- [44] Xiaolin Gao, "An optimal PMU placement method considering bus weight and voltage stability," in *Environment and Electrical Engineering (EEEIC), 2013 12th International Conference on* , vol., no., pp.124-129, 5-8 May 2013
- [45] Venkateswaran, V.B.; Kala, V.S.C., "Observability analysis and optimal placement of PMU using Differential Evolution algorithm," in *Emerging Trends in Electrical Engineering and Energy Management (ICETEEEM), 2012 International Conference on* , vol., no., pp.205-209, 13-15 Dec. 2012

- [46] Al-Mohammed, A.H.; Abido, M.A.; Mansour, M.M., "Optimal PMU placement for power system observability using differential evolution," in *Intelligent Systems Design and Applications (ISDA), 2011 11th International Conference on* , vol., no., pp.277-282, 22-24 Nov. 2011
- [47] Rajasekhar, B.; Chandel, A.K.; Vedik, B., "Differential evolution based optimal PMU placement for fault observability of power system," in *Engineering and Systems (SCES), 2013 Students Conference on* , vol., no., pp.1-5, 12-14 April 2013
- [48] Müller, H.H.; Castro, C.A., "Genetic algorithm-based phasor measurement unit placement method considering observability and security criteria," in *Generation, Transmission & Distribution, IET* , vol.10, no.1, pp.270-280, 1 7 2016
- [49] Kumar, S., "Optimal placement of PMU using probabilistic approach," in *Engineering and Computational Sciences (RAECS), 2014 Recent Advances in* , vol., no., pp.1-6, 6-8 March 2014
- [50] Theodorakatos, N.P.; Manousakis, N.M.; Korres, G.N., "Optimal placement of PMUS in power systems using binary integer programming and genetic algorithm," in *MedPower 2014* , vol., no., pp.1-6, 2-5 Nov. 2014
- [51] Kolosok, I.; Korkina, E.; Paltsev, A.; Zaika, R., "Genetic algorithms for bad data detection at decomposition of state estimation problem," in *Energy Conference (ENERGYCON), 2014 IEEE International* , vol., no., pp.400-406, 13-16 May 2014
- [52] Linda, Ondrej; Manic, Milos; Giani, Annarita; McQueen, Miles, "Multi-criteria based staging of Optimal PMU Placement using Fuzzy Weighted Average,"



in *Industrial Electronics (ISIE), 2013 IEEE International Symposium on* , vol., no., pp.1-8, 28-31 May 2013

- [53] Zhu Hui-Ling; Duan Yuan-Xiu; Zhang Xiao-Pan; Qi Huan; Huang Cheng-Xun, "Hybrid of MST and Genetic Algorithm on Minimizing PMU Placement," in *Intelligent System Design and Engineering Applications (ISDEA), 2013 Third International Conference on* , vol., no., pp.820-823, 16-18 Jan. 2013
- [54] Kimiyaghalam, A.; Mahdavi, M.; Ashouri, A.; Bagherivand, M., "Optimal placement of PMUs for reliable observability of network under probabilistic events using BABC algorithm," in *Electricity Distribution (CIRED 2013), 22nd International Conference and Exhibition on* , vol., no., pp.1-4, 10-13 June 213
- [55] Khiabani, V.; Erdem, E.; Farahmand, K.; Nygard, K., "Genetic algorithm for instrument placement in smart grid," in *Nature and Biologically Inspired Computing (NaBIC), 2013 World Congress on* , vol., no., pp.214-219, 12-14 Aug. 2013
- [56] Allagui, B.; Ben Aribia, H.; Hadj Abdallah, H., "Optimal placement of Phasor Measurement Units by genetic algorithm," in *Renewable Energies and Vehicular Technology (REVET), 2012 First International Conference on* , vol., no., pp.434-439, 26-28 March 2012
- [57] P. Gopakumar, M. Jaya Bharata Reddy and D. Mohanta, "A Novel Topological Genetic Algorithm-Based Phasor Measurement Unit Placement and Scheduling

- Methodology for Enhanced State Estimation", *Electric Power Components and Systems*, vol. 43, no. 16, pp. 1843-1858, 2015.
- [58] V. Basetti and A. Chandel, "Simultaneous Placement of PMUs and Communication Infrastructure in WAMS using NSGA-II", *IETE Technical Review*, pp. 1-17, 2016.
- [59] Jian-ming Wang; Li Chuandong; Jian Zhang, "Optimal Phasor Measurement Unit Placement by an Improved PSO Algorithm," in *Power and Energy Engineering Conference (APPEEC), 2012 Asia-Pacific*, vol., no., pp.1-4, 27-29 March 2012
- [60] Peng Yang; Zhao Tan; Wiesel, A.; Nehorai, A., "Placement of PMUs Considering Measurement Phase-Angle Mismatch," in *Power Delivery, IEEE Transactions on*, vol.30, no.2, pp.914-922, April 2015
- [61] Z. Hui-Ling, D. Yuan-Xiu, Z. Xiao-Pan, Q. Huan, and H. Cheng-Xun, "Hybrid of MST and genetic algorithm on minimizing PMU placement," *2013 Third International Conference on Intelligent System Design and Engineering Applications*, Jan. 2013.
- [62] P. Prabhakar and A. Kumar, "Voltage stability assessment using Phasor measurement technology," *2014 IEEE 6th India International Conference on Power Electronics (IICPE)*, Dec. 2014.
- [63] Mandava, S., Vanishree, J., Ramesh, V. A, "spanning tree approach in placing multi-channel and minimum channel PMU's for power system observability," in *International Journal of Electrical and Computer Engineering*, vol.5, no.3, pp. 518-524, June 2015

- [64] Rather, Z.H.; Chengxi Liu; Zhe Chen; Thogersen, P., "Optimal PMU Placement by improved particle swarm optimization," in *Innovative Smart Grid Technologies - Asia (ISGT Asia), 2013 IEEE* , vol., no., pp.1-6, 10-13 Nov. 2013
- [65] Jian-ming Wang; Li Chuandong; Jian Zhang, "Optimal Phasor Measurement Unit Placement by an Improved PSO Algorithm," in *Power and Energy Engineering Conference (APPEEC), 2012 Asia-Pacific* , vol., no., pp.1-4, 27-29 March 2012
- [66] Rahman, N.H.A.; Zobaa, A.F.; Theodoridis, M., "Improved BPSO for optimal PMU placement," in *Power Engineering Conference (UPEC), 2015 50th International Universities* , vol., no., pp.1-4, 1-4 Sept. 2015
- [67] Mishra, C.; Jones, K.D.; Pal, A.; Centeno, V.A., "Binary particle swarm optimisation-based optimal substation coverage algorithm for phasor measurement unit installations in practical systems," in *Generation, Transmission & Distribution, IET* , vol.10, no.2, pp.555-562, 2 4 2016
- [68] Peppanen, J.; Alquthami, T.; Molina, D.; Harley, R., "Optimal PMU placement with binary PSO," in *Energy Conversion Congress and Exposition (ECCE), 2012 IEEE* , vol., no., pp.1475-1482, 15-20 Sept. 2012
- [69] Ben Kilani, K.; Ben Hamouda, H.; Elleuch, M., "Detection of inter area oscillations in the Tunisian interconnected power system using phasor measurement units," in *Systems, Signals and Devices, 2009. SSD '09. 6th International Multi-Conference on* , vol., no., pp.1-6, 23-26 March 2009

- [70] Gopakumar, P.; Reddy, M.J.B.; Mohanta, D.K., "Novel multi-stage simulated annealing for optimal placement of PMUs in conjunction with conventional measurements," in *Environment and Electrical Engineering (EEEIC), 2013 12th International Conference on* , vol., no., pp.248-252, 5-8 May 2013
- [71] Xiaoqin Li; Jing Wu; Chengnian Long; Shaoyuan Li, "A novel decomposition of power systems for PMU placement," in *Control Conference (CCC), 2015 34th Chinese* , vol., no., pp.8975-8980, 28-30 July 2015
- [72] Prabhakar, P.; Kumar, A., "Voltage stability assessment using Phasor Measurement technology," in *Power Electronics (IICPE), 2014 IEEE 6th India International Conference on* , vol., no., pp.1-6, 8-10 Dec. 2014
- [73] Ki-Seon Cho, Joong-Rin Shin and Seung Ho Hyun, "Optimal placement of phasor measurement units with GPS receiver," *Power Engineering Society Winter Meeting, 2001. IEEE*, Columbus, OH, 2001, pp. 258-262 vol.1.
- [74] Chung-Shou Liao, Tsung-Jung Hsieh, Xian-Chang Guo, Jian-Hong Liu and Chia-Chi Chu, "Applying power domination with hybrid search to optimal PMU placement problems," *Power and Energy Society General Meeting (PES), 2013 IEEE*, Vancouver, BC, 2013, pp. 1-5.
- [75] A. Kimiyaghalam, M. Mahdavi, A. Ashouri and M. Bagherivand, "Optimal placement of PMUs for reliable observability of network under probabilistic events using BABC algorithm," *Electricity Distribution (CIRED 2013), 22nd International Conference and Exhibition on*, Stockholm, 2013, pp. 1-4.

- [76] K. Arul jeyaraj, V. Rajasekaran, S. Nandha Kumar and K. Chandrasekaran, "A multi-objective placement of phasor measurement units using fuzzified artificial bee colony algorithm, considering system observability and voltage stability", *Journal of Experimental & Theoretical Artificial Intelligence*, vol. 28, no. 1-2, pp. 113-136, 2015.
- [77] Mohammadi, M.B.; Hooshmand, R.-A.; Fesharaki, F.H., "A New Approach for Optimal Placement of PMUs and Their Required Communication Infrastructure in Order to Minimize the Cost of the WAMS," in *Smart Grid, IEEE Transactions on* , vol.PP, no.99, pp.1-1
- [78] H. Aminzadeh & M. Miri, "Optimal placement of phasor measurement units to obtain network observability using a hybrid PSO–GSA algorithm," *Australian Journal of Electrical and Electronics Engineering*, vol. 12, no. 4, pp. 342-349, 2015
- [79] S. S. Geramian, H. Askarian Abyane and K. Mazlumi, "Determination of optimal PMU placement for fault location using genetic algorithm," *2008 13th International Conference on Harmonics and Quality of Power*, Wollongong, NSW, 2008, pp. 1-5.
- [80] N. P. Theodorakatos, N. M. Manousakis and G. N. Korres, "Optimal placement of PMUS in power systems using binary integer programming and genetic algorithm," *MedPower 2014*, Athens, 2014, pp. 1-6.
- [81] H. H. Müller and C. A. Castro, "Genetic algorithm-based phasor measurement unit placement method considering observability and security criteria," in *IET Generation, Transmission & Distribution*, vol. 10, no. 1, pp. 270-280, 17 2016.

- [82] V. Khiabani, E. Erdem, K. Farahmand and K. Nygard, "Genetic algorithm for instrument placement in smart grid," *Nature and Biologically Inspired Computing (NaBIC), 2013 World Congress on*, Fargo, ND, 2013, pp. 214-219.
- [83] O. Linda, M. Manic, A. Giani and M. McQueen, "Multi-criteria based staging of Optimal PMU Placement using Fuzzy Weighted Average," *Industrial Electronics (ISIE), 2013 IEEE International Symposium on*, Taipei, Taiwan, 2013, pp. 1-8.
- [84] K. S. Sajan and B. Tyagi, "Optimal placement of PMU with optimal branch current phasors for complete and incomplete observability," *2011 IEEE Power and Energy Society General Meeting*, San Diego, CA, 2011, pp. 1-5.
- [85] F. Aminifar, C. Lucas, A. Khodaei and M. Fotuhi-Firuzabad, "Optimal Placement of Phasor Measurement Units Using Immunity Genetic Algorithm," in *IEEE Transactions on Power Delivery*, vol. 24, no. 3, pp. 1014-1020, July 2009.
- [86] Yang Gao, Zhijian Hu, Xixiong He and Dong Liu, "Optimal placement of PMUs in power systems based on improved PSO algorithm," *2008 3rd IEEE Conference on Industrial Electronics and Applications*, Singapore, 2008, pp. 2464-2469.
- [87] Xiaomeng Bian and Jiaju Qiu, "General Solutions to Multi-objective Optimization of PMU Placement," *2006 6th World Congress on Intelligent Control and Automation*, Dalian, 2006, pp. 7641-7645.
- [88] B. Milosevic and M. Begovic, "Nondominated sorting genetic algorithm for optimal phasor measurement placement," in *IEEE Transactions on Power Systems*, vol. 18, no. 1, pp. 69-75, Feb 2003.

- [89] F. J. Marin, F. Garcia-Lagos, G. Joya and F. Sandoval, "Genetic algorithms for optimal placement of phasor measurement units in electrical networks," in *Electronics Letters*, vol. 39, no. 19, pp. 1403-1405, 18 Sept. 2003.
- [90] A. S. Deese, T. Nugent and S. Coppi, "A comparative study of optimal PMU placement algorithms for cost minimization," *2014 IEEE PES General Meeting / Conference & Exposition*, National Harbor, MD, 2014, pp. 1-5.
- [91] O. Linda, D. Wijayasekara, M. Manic and M. McQueen, "Optimal placement of Phasor Measurement Units in power grids using Memetic Algorithms," *2014 IEEE 23rd International Symposium on Industrial Electronics (ISIE)*, Istanbul, 2014, pp. 2035-2041.
- [92] Z. Hui-Ling, D. Yuan-Xiu, Z. Xiao-Pan, Q. Huan and H. Cheng-Xun, "Hybrid of MST and Genetic Algorithm on Minimizing PMU Placement," *Intelligent System Design and Engineering Applications (ISDEA), 2013 Third International Conference on*, Hong Kong, 2013, pp. 820-823.
- [93] B. Allagui, H. Ben Aribia and H. Hadj Abdallah, "Optimal placement of Phasor Measurement Units by genetic algorithm," *2012 First International Conference on Renewable Energies and Vehicular Technology*, Hammamet, 2012, pp. 434-439.
- [94] Zheng Zhao and E. B. Makram, "Optimal PMU placement considering number of analog channels," *North American Power Symposium (NAPS), 2011*, Boston, MA, 2011, pp. 1-5.

- [95] S. Mousavian and M. Feizollahi, "An investment decision model for the optimal placement of phasor measurement units", *Expert Systems with Applications*, vol. 42, no. 21, pp. 7276-7284, 2015.
- [96] Y. Zhao, P. Yuan, Q. Ai and T. Lv, "Optimal PMU placement considering topology constraints", *International Journal of Electrical Power & Energy Systems*, vol. 73, pp. 240-248, 2015.
- [97] W. Yuill, A. Edwards, S. Chowdhury and S. P. Chowdhury, "Optimal PMU placement: A comprehensive literature review," *2011 IEEE Power and Energy Society General Meeting*, San Diego, CA, 2011, pp. 1-8.
- [98] K. Kumar and M. Sydulu, "Optimal PMU Placement Techniques for the Topological Observability of a Partial network of the Southern Grid of India", *IFAC Proceedings Volumes*, vol. 47, no. 1, pp. 1044-1048, 2014.
- [99] K. Jamuna and K. Swarup, "Optimal placement of PMU and SCADA measurements for security constrained state estimation", *International Journal of Electrical Power & Energy Systems*, vol. 33, no. 10, pp. 1658-1665, 2011.
- [100] Z. H. Rather, Z. Chen, P. Thøgersen, P. Lund and B. Kirby, "Realistic Approach for Phasor Measurement Unit Placement: Consideration of Practical Hidden Costs," in *IEEE Transactions on Power Delivery*, vol. 30, no. 1, pp. 3-15, Feb. 2015.
- [101] Gol, M., Abur, A.: 'A hybrid state estimator for systems with limited number of PMUs', *IEEE Trans. Power Syst.*, 2015, 30, (3), pp. 1511–1517



- [102] K. S. K. Reddy, D. A. K. Rao, A. Kumarraja and B. R. K. Varma, "Implementation of Integer Linear Programming and Exhaustive Search algorithms for optimal PMU placement under various conditions," *2015 IEEE Power, Communication and Information Technology Conference (PCITC)*, Bhubaneswar, 2015, pp. 850-855.
- [103] MATPOWER: A MATLAB Power System Simulation Package [Online]. Available: <http://www.pserc.cornell.edu/matpower/>
- [104] J. Löfberg.; "*YALMIP : A Toolbox for Modeling and Optimization in MATLAB*" in *Proceedings of the CACSD Conference*, Taipei, Taiwan, 2004.
- [105] Bills, G.W. *On-Line Stability Analysis Study, RP 90-1*. United States: N. p., 1970. Print.
- [106] "Power Systems Test Case Archive - UWEE", *Www2.ee.washington.edu*, 2017. [Online]. Available: <http://www2.ee.washington.edu/research/pstca/>. [Accessed: 12-Jan- 2017].

## APPENDIX A: USED IEEE SYSTEMS' DATA

This appendix includes the single line diagrams for the IEEE-14, New England 345KV (39 buses), IEEE-57, IEEE-118, and IEEE-300 bus systems' single line diagram. These single line diagrams are available from Power Systems Test Case Archive (retrieved online: <http://www2.ee.washington.edu/research/pstca/>), except the New England 345KV which is described in [105]. The provided diagrams are either the original files of the authors or a clearer reprint (or a redraw) of these documents in case the original files were not clear. The actual data files used in this thesis are from [103].

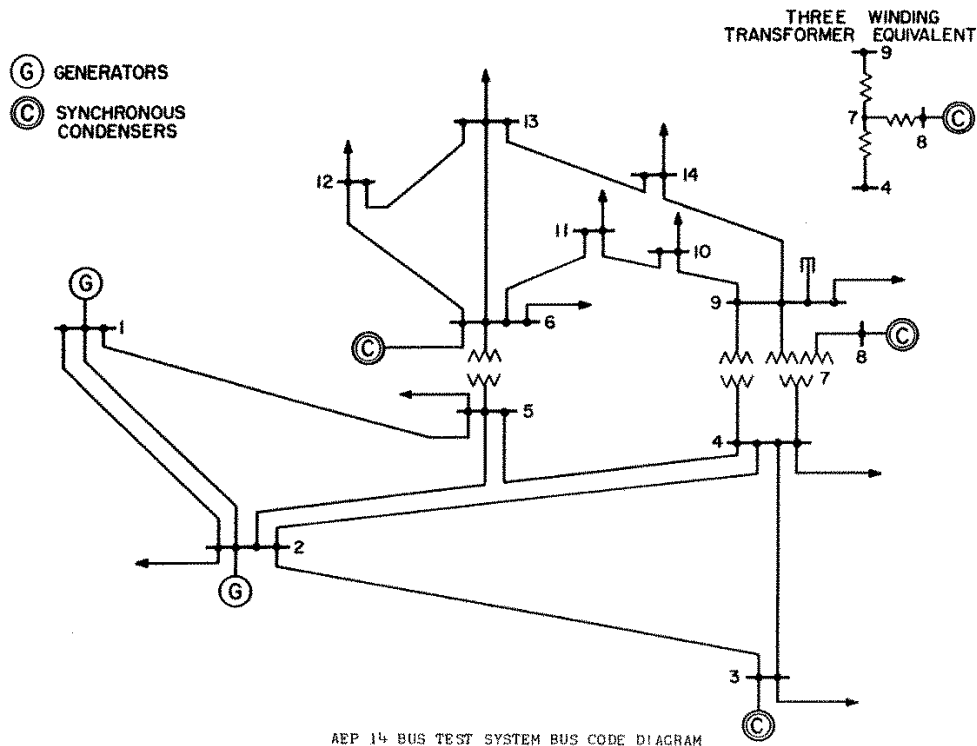


Figure A.1 IEEE-14 bus system single line diagram [106]

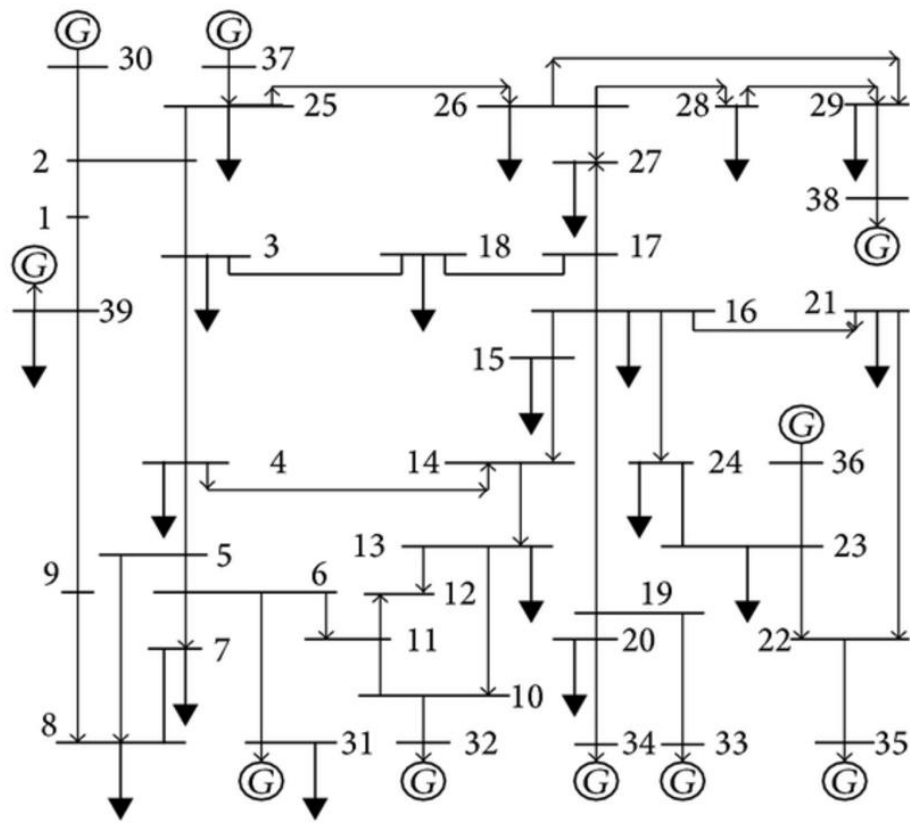


Figure A.2 New England 345KV bus system single line diagram [106]

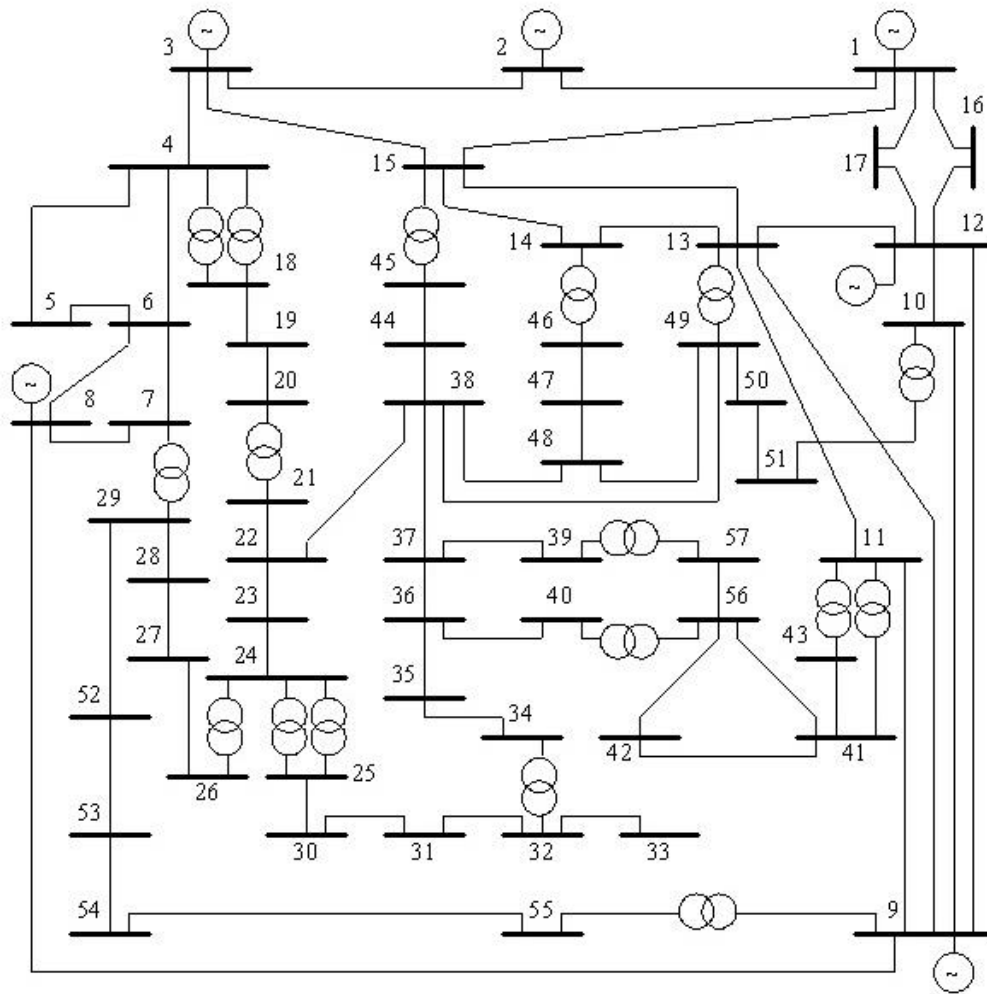


Figure A.3 IEEE-57 bus system single line diagram [106]

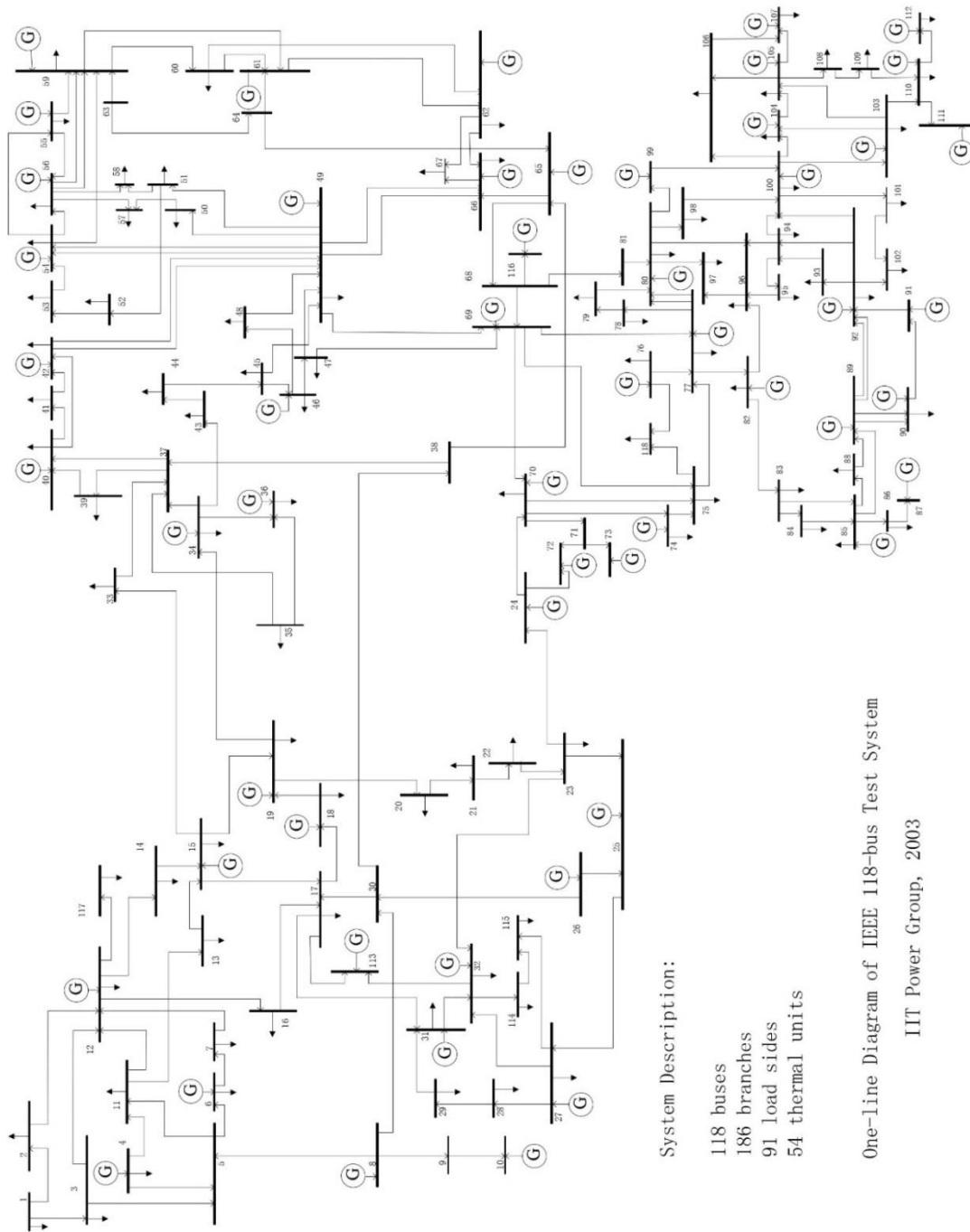


Figure A.4 IEEE-118 bus system single line diagram [106]

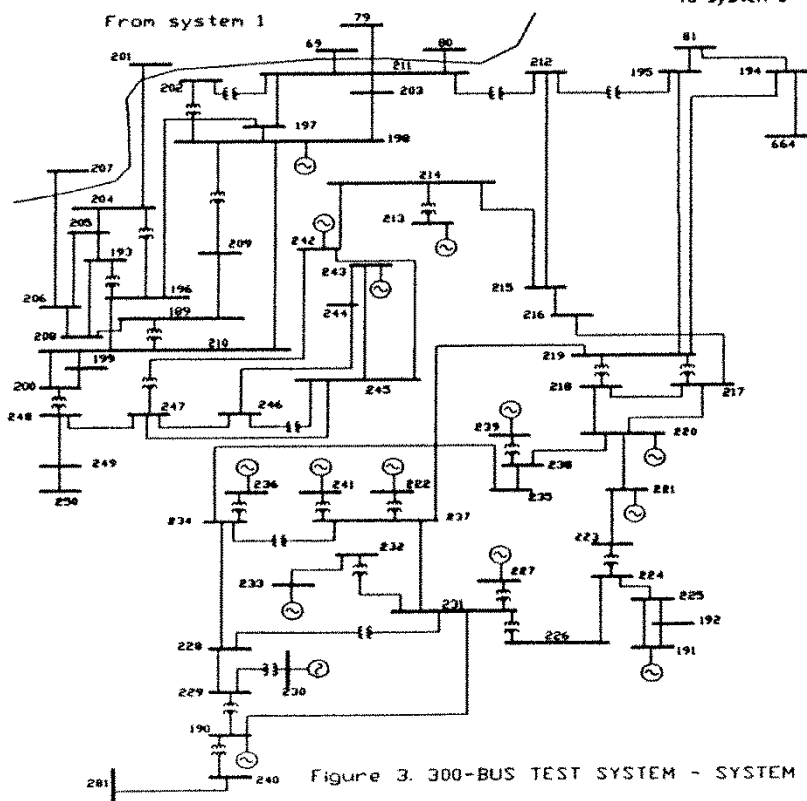
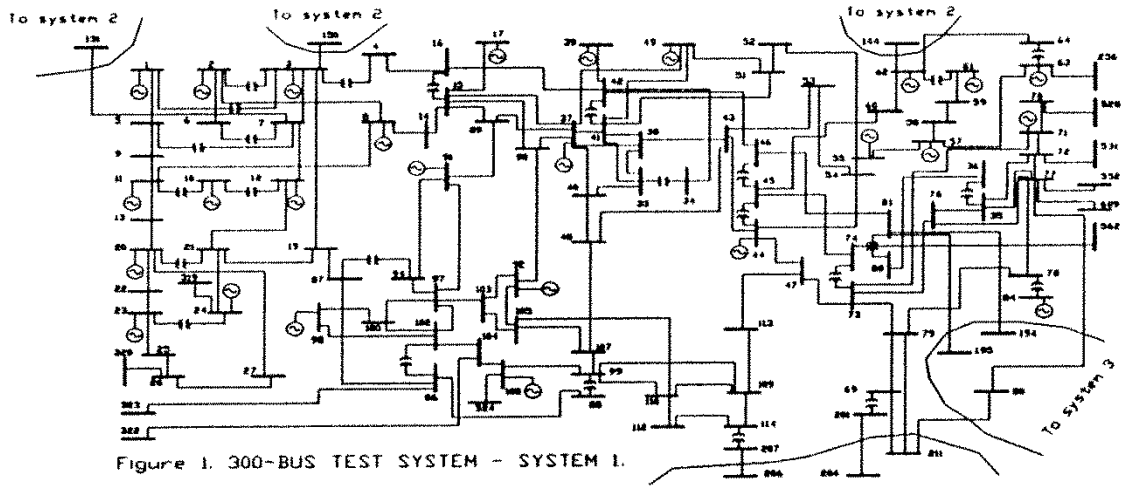


Figure A.5 IEEE-300 bus system single line diagram – part 1 [106]

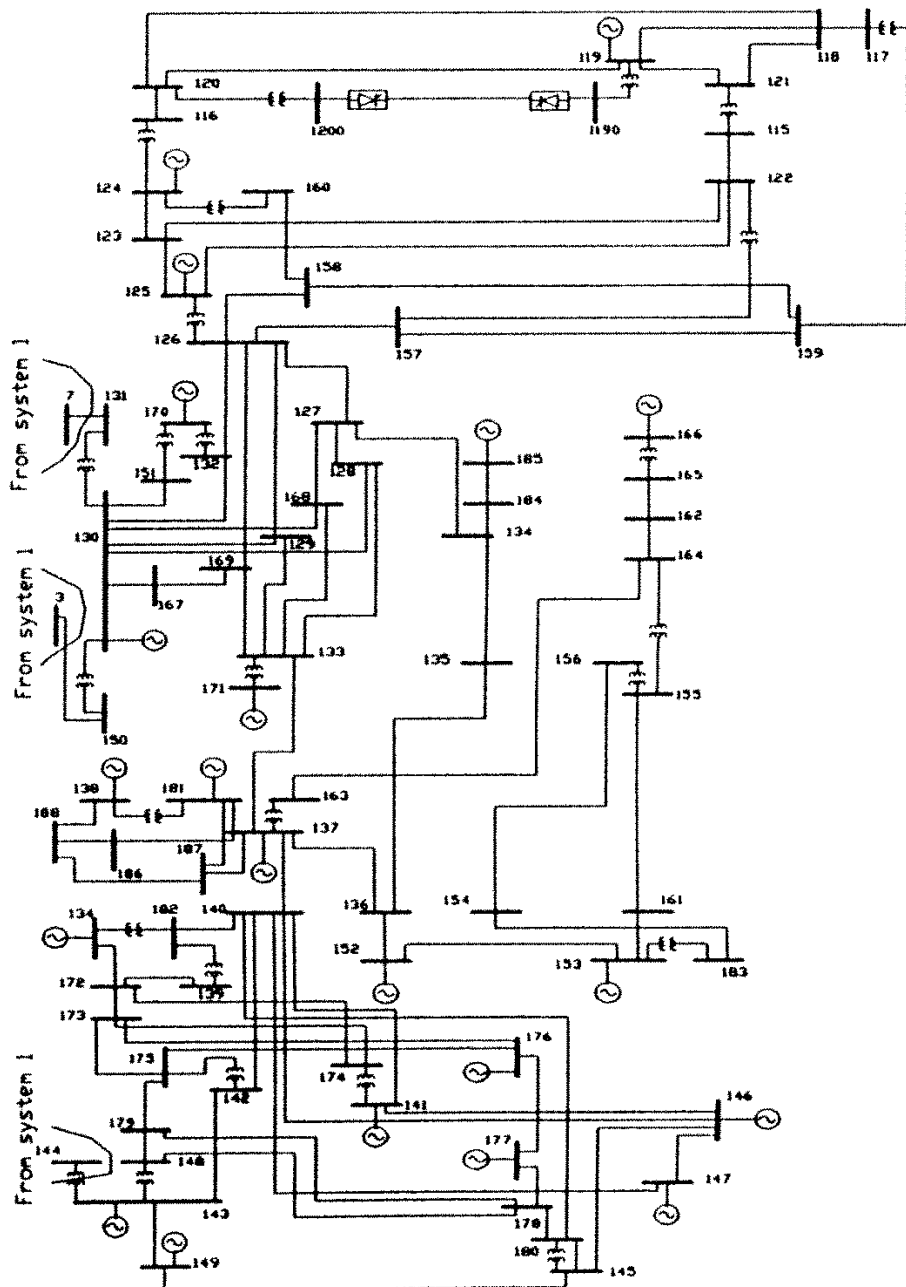


Figure 2. 300-BUS TEST SYSTEM - SYSTEM 2.

Figure A.6 IEEE-300 bus system single line diagram – part 2 [106]





## APPENDIX B: PMU LOCATIONS

### ILP:

#### IEEE-14:

No ZIB	With ZIB	With IM	With FM
2, 8, 10, 13	2, 6, 9	11, 14	1, 6, 9

#### NE-39:

No ZIB	With ZIB	With IM	With FM
2, 6, 9, 12, 14, 17, 22, 23, 29, 32, 33, 34, 37	3, 7, 23, 29, 34, 37	2, 6, 17, 20, 23	3, 6, 16, 23, 29, 34, 37, 39

#### IEEE-57:

No ZIB	With ZIB	With IM	With FM
1, 4, 9, 20, 23, 27, 29, 30, 32, 36, 38, 41, 45, 46, 50, 54, 57	1, 13, 19, 25, 29, 32, 38, 42, 54	1, 13, 25, 29, 32, 42, 51, 54	1, 6, 15, 20, 25, 32, 42, 53

#### IEEE-118:

No ZIB	With ZIB	With IM	With FM
2, 5, 10, 12, 15, 17, 21, 25, 29, 34, 37, 41, 45, 49, 53, 56, 62, 64, 72, 73, 75, 77, 80, 85, 87, 91, 94, 101, 105, 110, 114, 116	, 2, 10, 15, 17, 21, 25, 29, 34, 40, 45, 49, 53, 56, 62, 75, 77, 85, 87, 91, 94, 101, 105, 110, 114	, 1, 10, 11, 17, 21, 27, 29, 34, 40, 45, 49, 53, 56, 62, 80, 85, 87, 91, 94, 101, 105, 110, 117	, 2, 8, 12, 15, 18, 21, 26, 29, 32, 34, 40, 45, 49, 53, 56, 62, 72, 75, 77, 85, 87, 91, 94, 101, 105, 110

IEEE-300:

No ZIB	With ZIB	With IM	With FM
1, 2, 3, 11, 15, 21, 23, 25, 27, 30, 33, 37, 38, 41, 43, 48, 49, 53, 54, 64, 68, 69, 71, 79, 83, 86, 88, 93, 96, 98, 99, 101, 109, 111, 112, 113, 116, 119, 128, 132, 135, 139, 141, 152, 157, 160, 164, 170, 183, 187, 188, 189, 190, 193, 196, 202, 209, 210, 212, 215, 216, 217, 222, 224, 228, 230, 233, 236, 237, 238, 240, 242, 251, 252, 253, 262, 264, 265, 268, 269, 270, 272, 275, 276, 277, 299, 300	1, 2, 3, 11, 15, 21, 23, 25, 34, 37, 38, 41, 43, 48, 49, 53, 64, 79, 86, 88, 93, 98, 102, 118, 119, 124, 132, 135, 145, 160, 163, 170, 177, 180, 184, 189, 192, 195, 202, 209, 210, 212, 215, 216, 217, 224, 228, 230, 233, 236, 237, 238, 244, 252, 253, 262, 268, 269, 270, 275, 277, 278, 297, 300	1, 3, 11, 19, 25, 31, 37, 38, 41, 45, 49, 53, 64, 79, 86, 88, 93, 98, 102, 116, 119, 122, 132, 135, 155, 159, 160, 163, 170, 192, 195, 202, 209, 210, 215, 217, 220, 224, 227, 230, 231, 233, 236, 237, 244, 248, 252, 253, 262, 265, 267, 268, 269, 270, 278, 297, 300	1, 2, 3, 11, 19, 25, 34, 37, 41, 43, 53, 79, 86, 88, 99, 104, 118, 132, 135, 160, 163, 170, 177, 184, 189, 192, 195, 202, 209, 210, 212, 215, 216, 217, 224, 228, 230, 231, 233, 236, 237, 238, 243, 252, 258, 262, 265, 268, 269, 270, 274, 277, 297, 300

GA

IEEE-14:

No ZIB	With ZIB	With IM	Partial OBS	cost
2, 6, 9	2, 6, 9	1, 6, 9	2, 6, 9	2, 6, 9

NE-39:

No ZIB	With ZIB	With IM	Partial OBS	cost
2, 4, 6, 9, 10, 13, 16, 17, 20, 22, 29, 33, 36, 37	1, 3, 8, 10, 20, 23, 25, 27, 29	2, 6, 9, 16, 20, 26, 36, 38	2, 8, 11, 17, 20, 23, 29	3, 8, 10, 16, 20, 23, 25, 29, 39

IEEE-57:

No ZIB	With ZIB	With IM	Partial OBS	cost
2, 6, 12, 19, 21, 24, 28, 32, 35, 37, 43, 45, 46, 49, 53, 55, 56	, 3, 9, 12, 15, 19, 28, 29, 30, 33, 38, 50, 54, 56	, 1, 6, 12, 15, 25, 29, 32, 38, 42, 50, 54	1, 4, 9, 27, 29, 30, 32, 38, 41, 50, 54	, 1, 9, 15, 18, 24, 29, 32, 38, 41, 50, 54

## IEEE-118:

No ZIB	With ZIB	With IM	Partial OBS	cost
5, 9, 12, 15, 17, 20, 23, 25, 28, 36, 40, 44, 49, 52, 56, 61, 65, 71, 75, 77, 80, 85, 91, 96, 101, 107, 109, 110, 114, 116	2, 11, 12, 19, 21, 26, 29, 30, 32, 33, 35, 42, 43, 48, 49, 52, 56, 62, 69, 70, 80, 83, 87, 89, 92, 105, 110, 118	1, 9, 11, 17, 20, 23, 27, 34, 40, 44, 46, 49, 52, 56, 60, 66, 71, 75, 77, 80, 84, 86, 88, 91, 93, 95, 102, 103, 110	5, 12, 17, 20, 23, 27, 37, 44, 49, 53, 56, 60, 70, 76, 79, 85, 92, 96, 100, 105, 110	2, 9, 11, 12, 17, 21, 24, 27, 28, 34, 40, 45, 49, 53, 56, 62, 68, 70, 77, 80, 85, 91, 92, 94, 100, 108, 111, 112, 115

## IEEE-300:

No ZIB	With ZIB	With IM	Partial OBS	cost
2, 3, 5, 8, 10, 13, 16, 17, 23, 25, 28, 31, 38, 41, 43, 48, 50, 53, 54, 55, 57, 58, 60, 62, 64, 65, 68, 71, 73, 77, 79, 81, 87, 93, 96, 98, 99, 101, 109, 112, 113, 116, 117, 119, 121, 124, 127, 132, 135, 137, 143, 145, 149, 153, 156, 161, 166, 172, 173, 175, 179, 184, 188, 190, 193, 196, 200, 204, 207, 210, 215, 216, 218, 219, 221, 223, 229, 233, 250, 251, 253, 255, 259, 262, 268, 269, 270, 273, 274, 278, 279, 297, 298, 300	2, 3, 11, 15, 17, 20, 22, 25, 35, 37, 48, 49, 53, 55, 58, 59, 61, 64, 79, 86, 88, 89, 90, 99, 101, 105, 109, 116, 118, 119, 124, 127, 132, 133, 134, 144, 155, 163, 166, 168, 175, 178, 186, 190, 193, 196, 199, 203, 204, 206, 208, 212, 213, 216, 219, 225, 228, 233, 234, 247, 257, 261, 268, 269, 270, 272, 274, 276, 300	5, 11, 15, 22, 23, 26, 37, 38, 42, 45, 49, 53, 54, 59, 64, 68, 72, 79, 86, 88, 92, 98, 99, 101, 105, 116, 118, 121, 126, 128, 132, 133, 134, 145, 150, 152, 155, 159, 160, 163, 168, 173, 184, 186, 190, 193, 194, 200, 201, 204, 209, 210, 213, 218, 222, 227, 230, 232, 233, 236, 248, 249, 257, 263, 267, 268, 269, 270, 279	1, 2, 3, 11, 15, 19, 22, 27, 38, 44, 49, 53, 55, 57, 64, 79, 81, 85, 86, 93, 99, 101, 105, 109, 114, 116, 118, 122, 126, 132, 135, 144, 154, 156, 167, 171, 177, 187, 192, 195, 199, 202, 208, 212, 213, 216, 226, 227, 232, 237, 246, 262, 268, 269, 270, 274	3, 8, 9, 11, 17, 20, 22, 25, 31, 38, 42, 43, 46, 48, 49, 50, 55, 59, 61, 64, 78, 83, 84, 88, 91, 92, 98, 99, 104, 112, 115, 116, 118, 119, 130, 133, 138, 140, 144, 152, 157, 160, 164, 170, 175, 178, 185, 190, 196, 202, 208, 210, 215, 217, 219, 220, 221, 225, 228, 233, 237, 247, 255, 260, 261, 267, 268, 269, 270, 275, 278, 294