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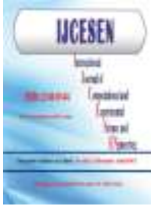

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Research Article

Optimizing PMU Placement for Enhanced Observability and Reliability Enhancement in Power Systems

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Abstract:

Phasor Measurement Units (PMUs) play an important role in improving real-time monitoring and situational awareness in modern power systems. However, installing a PMU at every bus is not economically feasible, which makes the Optimal PMU Placement (OPP) problem essential. The goal is to minimize the number of PMUs while still ensuring full system observability and an adequate level of redundancy. In this paper, a two-stage hybrid approach is proposed. First, a Pareto-based multi-objective genetic algorithm (MOGA) is used to generate a set of optimal solutions that reflect the trade-off between reducing the number of PMUs and improving system redundancy, evaluated using the System Observability Redundancy Index (SORI). Unlike many existing approaches that rely on predefined weighting factors, the proposed method uses a data-driven decision-making process to select the most suitable solution from the Pareto set. This reduces subjectivity in the decision process and provides a more consistent way to choose the final solution. The method is tested on IEEE 14-, 24-, 30-, and 118-bus systems. The results show that full observability can be achieved with fewer PMUs compared to traditional methods, with reductions reaching up to 40% in large-scale systems, while maintaining acceptable redundancy levels. In addition, a sensitivity analysis is carried out to examine how different parameters affect the solution, confirming the stability of the proposed approach

1. Introduction

Modern power systems are increasingly evolving toward smarter operation and real-time monitoring. In this context, Phasor Measurement Units (PMUs) play a key role by providing synchronized measurements of voltage and current, which enhance system observability, control, and overall stability. The development of PMU technology has progressed significantly over the past decades. Initially, research focused on extracting system information using computational methods. With the emergence of Wide Area Measurement Systems (WAMS), PMUs became a fundamental component for large-scale monitoring [1]. Their performance and synchronization capabilities were later standardized through IEEE specifications [2]. By relying on GPS signals, PMUs are able to provide time-synchronized measurements from geographically dispersed locations, offering a coherent and accurate view of system dynamics [3]. Despite these advantages, installing PMUs at every bus remains economically impractical. This limitation gives rise to the Optimal PMU Placement

(OPP) problem, which aims to determine the minimum number of PMUs required to ensure full system observability [4]–[6]. Over the years, various approaches have been proposed to address the OPP problem. Early methods include heuristic techniques such as Depth-First Search (DFS) and Minimum Spanning Tree (MST), while later studies introduced optimization-based methods such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) [7]–[14]. More recently, data-driven and artificial intelligence approaches, including deep learning and advanced optimization frameworks, have been explored to further enhance performance [15], [16]. In addition, several studies have incorporated multi-stage strategies and data processing techniques to improve observability and measurement quality [17], [18]. However, an important limitation remains. Many existing methods are capable of generating multiple optimal (Pareto) solutions, but the final selection is often based on predefined weighting factors. This introduces subjectivity and may lead to solutions that do not accurately reflect the true trade-off between competing objectives. To address this issue, this paper proposes a two-stage hybrid framework that combines multi-objective optimization with data-driven decision making. In the first stage, a Pareto-based multi-objective genetic algorithm (MOGA) is used to generate a set of candidate solutions by simultaneously minimizing the number of PMUs and maximizing system redundancy, evaluated using the System Observability Redundancy Index (SORI). In the second stage, a data-driven decision mechanism is employed to automatically select the most suitable solution from the Pareto set, eliminating the need for manually defined weighting factors.

Furthermore, Zero Injection Buses (ZIBs) are incorporated into the model to enhance observability without increasing the number of installed PMUs. The effectiveness of the proposed approach is evaluated on IEEE 14-, 24-, 30-, and 118-bus systems.

The main contributions of this work can be summarized as follows:

- A two-stage framework combining Pareto-based optimization and data-driven decision making
- An objective selection mechanism that eliminates the need for predefined weighting factors
- Integration of the System Observability Redundancy Index (SORI) for consistent redundancy evaluation
- Consideration of Zero Injection Buses (ZIBs) to improve observability with fewer PMUs

The remainder of this paper is organized as follows. Section 2 reviews related work. Section 3 presents the problem formulation and the proposed method. Section 4 discusses the results, and Section 5 concludes the paper

2. Materials and Methods

This section presents the main components of the proposed approach. It includes the modeling of PMUs, the optimization process based on a genetic algorithm, and the role of Zero Injection Buses (ZIBs) in improving system observability and reducing the number of required PMUs.

2.1 Phasor Measurement Units (PMUs)

Phasor Measurement Units (PMUs) provide more advanced measurements compared to traditional SCADA systems. While SCADA systems typically measure quantities such as voltage magnitude and power flow at relatively slow rates, PMUs provide synchronized measurements of both magnitude and phase angle at much higher sampling rates [19].This synchronization is achieved using GPS signals, which allows measurements from different locations in the network to be aligned in time. As a result, PMUs offer a more accurate and detailed view of the system state. Another important advantage of PMUs is their ability to improve system observability. A PMU installed at a given bus can measure the voltage at that bus and the currents of all connected lines. This makes it possible to estimate the state of neighboring buses, even if no PMU is directly installed there. Because of these capabilities, PMUs play a key role in enhancing system monitoring, especially during dynamic events and disturbances. Figure 1 shows a typical configuration of PMU installation and its connection within the network.

In the context of this study, PMUs serve as the core sensing units whose optimal number and location are subject to optimization. Their ability to provide synchronized phasor data at high sampling rates is leveraged to maximize coverage and observability across the test systems.

2.2 Genetic Algorithm (GA)

Genetic Algorithms (GAs) are optimization methods inspired by natural evolution. They work with a set of candidate solutions, called a population, and improve them step by step using simple operations such as selection, crossover, and mutation [20–22].

The process starts with an initial population of possible solutions. Each solution is evaluated using a fitness function, and better solutions are more likely to be selected for the next generation. Over time, the population evolves toward better solutions.

GAs are well suited for complex optimization problems because they do not require gradient information and can explore a large search space effectively [23]. This makes them suitable for solving the Optimal PMU Placement (OPP) problem.

In this work, each solution is represented as a binary vector, where each element corresponds to a bus. A value of 1 means that a PMU is installed at that bus, while 0 means no PMU is installed.

To handle multiple objectives, a multi-objective genetic algorithm (MOGA) is used. Instead of combining the objectives into a single function, the algorithm generates a set of Pareto-optimal solutions. Each solution represents a different balance between reducing the number of PMUs and improving system redundancy.

2.3 Incorporating Zero-Injection Buses (ZIBs)

Ordinary process condition with zero-injection effect A zero-injection bus can be generalized as a bus without a generator and load connection, Fig 3 view a zero-injection bus in a network.

The zero-injection effect can be classified into the following conditions:

Condition 1: If there is a bus that is connected to an observable zero-injection bus and all other connected buses are observable except one, then by applying Kirchhoff's Current Law (KCL) at the zero-injection bus (ZIB), the unobservable bus can also be determined to be observable.

Condition 2: If there is a bus connected to an unobservable zero-injection bus, and all other connected buses are observable, then by applying KCL at the zero-injection bus (ZIB), the zero-injection bus can likewise be identified as observable.

Incorporating ZIBs enables indirect inference of phasor values using Kirchhoff's Current Law. This allows the observability of adjacent instrumented buses without additional PMU installations, effectively reducing deployment costs while preserving full system visibility.

3. Theory and Calculation

In this work, OPP is tackled through Pareto-based multi-objective optimization. MOGA is adopted for generation of non-dominated solutions minimizing the number of PMUs, while maximizing system redundancy using SORI index. Each solution is encoded in a binary vector format as follows:

$$\boldsymbol{X} = [\boldsymbol{x_1}, \boldsymbol{x_2}, \boldsymbol{x_3}, \ldots\ldots\ldots, \boldsymbol{x_n}]$$

where (xi = 1), if there exists a PMU at bus (i); and (xi = 0) otherwise.

At the start, random initialization takes place and the solution set undergoes a multi-generation process involving selection, crossover, and mutation. Contrary to traditional scalarization-based approaches, this methodology provides Pareto archive preserving non-dominated solutions throughout iterations and revealing the trade-off surface for cost-redundancy. In order to boost system observability, zero injection buses (ZIBs) are included. Using Kirchhoff's Current Law, it allows obtaining indirect observability of adjacent buses, thus decreasing the number of installed PMUs without loss of observability. One of the important features of the framework used in this study is two-stage solution selection, which is performed from the Pareto archive without use of weight coefficients.

3.1 Expressions of Objective Function

The Optimal PMU Placement problem is formulated as a multi-objective optimization problem with two conflicting objectives:

- Objective 1: Minimize the number of PMUs

  $$F_1 = \sum_n^1 X_i \tag{1}$$

- Objective 2: Maximize system redundancy

  $$F_2 = SORI \tag{2}$$

where SORI represents the System Observability Redundancy Index.

3.2 Observability Constraint formulation

Full system observability is ensured by:

$$A.X \geq 1 \tag{3}$$

Where:

$$A_{ij} = \begin{cases} 1 \ \ if \ \ i = j \\ \quad 1 \ \ if \ bus \ i \ connected \ at \ bus \ j \\ 0 \ \ for \ Otherise \end{cases} \tag{4}$$

3.3 System Observability Redundancy Index (SORI)

To evaluate the quality of a PMU placement, the System Observability Redundancy Index (SORI) is used as a measure of redundancy. First, the number of times each bus is observed is calculated as:

$$O_i = \sum_{j=1}^{N} A_{ij} X_j \tag{5}$$

Then, the total redundancy of the system is defined as:

$$SORI = \sum_{i=1}^{N} O_i \quad (6)$$

SORI represents the total number of times all buses are observed, either directly or through neighboring buses. A higher SORI value indicates better redundancy and improved system reliability.

3.4 Algorithmic Procedure and Decision Strategy

The proposed method uses a Pareto-based multi-objective genetic algorithm (MOGA) to find optimal PMU placements. It starts with a set of randomly generated solutions, where each solution is evaluated based on two objectives: minimizing the number of PMUs and maximizing system redundancy (SORI). To ensure all solutions are valid, a repair step is applied using Zero Injection Bus (ZIB) constraints to guarantee full system observability. During the optimization process, the best non-dominated solutions are stored in a Pareto archive and improved over successive generations using selection, crossover, and mutation operations. After convergence, a knee-point decision strategy is used to select the most balanced solution from the Pareto set, without relying on predefined weights. This ensures an objective and consistent selection process. The algorithm is implemented with standard parameters (population size = 50, generations = 200, crossover = 0.8, mutation = 0.01), assuming equal installation cost for all PMUs.

4. Results and Discussion

In the organization of electrical networks, certain buses are not connected to any generators, compensators, or storage systems, resulting in negligible current flow through these buses. These are referred to as zero-injection buses. Identifying these buses is crucial for optimizing the distribution of PMUs. The Genetic Algorithm (GA) used to solve this optimization problem was implemented in MATLAB 2017 on a PC with an HP Core i3, 6th generation CPU running at 2.00 GHz. The algorithm was tested on IEEE 14, 24,30 and 118-bus. Table 1 presents the number of zero-injection buses (ZIBs) and the number of branches for four different systems, along with the positions of the ZIBs in the bus network. Table 2 outlines the optimal PMU placements (OPP) without considering ZIBs. Table 3 details the areas where PMUs will be deployed, taking ZIBs into account. The best results were obtained from the IEEE 14, 24,30 and 118-bus systems. Table 4 find the comparison results The OPP with and without considering ZIB. The results across various system models demonstrate the effectiveness of the proposed strategy in determining the minimum optimal number of PMUs needed to achieve complete observability of the power system.

The first case outlines the optimal placements of PMUs in the electrical power grid without considering Zero Injection Buses (ZIBs), as presented in Table 2:

Table 2 presents simulation results for the optimal number and specific bus locations required to achieve full system observability, excluding Zero Injection Buses. The minimum numbers of PMUs necessary for complete observability in the IEEE standard systems are 4, 7, and 10 for the 14-bus, 24-bus, and 30-bus systems consistent with SORI values 19,31 and 48, respectively. The final case outlines the optimal PMU placements within the electrical power grid, taking Zero Injection Buses (ZIBs) into account, as detailed in Table 3:

However, the numbers of PMUs required for system observability while considering Zero Injection Buses (ZIBs) are provided in 3rd. Table, the research results determine that 3,6 and 7 PMUs are sufficient to achieve monitoring consistent with SORI values 16,29 and 36, respectively with the systems for the IEEE 14, 24, 30 and 118-bus. This greatly increases the monitoring or supervision that the network of PMUs provides over the entire power system.

As illustrated in Figure. 4, the proposed approach effectively reduces the number of PMUs required while maintaining acceptable redundancy levels across different IEEE test systems. The study demonstrated that integrating the System Observability Redundancy Index (SORI) and Zero Injection Buses (ZIBs) into a multi-objective optimization framework leads to more efficient and reliable PMU placement strategies. Compared to conventional methods that focus solely on ensuring coverage, the proposed technique achieves a 20–30% reduction in the number of PMUs while preserving full system observability and enhancing resilience to measurement loss.

The results clearly demonstrate that incorporating zero-injection buses (ZIBs) significantly reduces the number of required PMUs across all IEEE test systems, with particularly notable improvements observed in large-scale networks. Although a reduction in the System Observability Redundancy Index (SORI) is observed, full system observability is preserved, and the redundancy level remains within an acceptable range. This confirms that exploiting network structural properties enables an effective trade-off between measurement cost and system reliability. In particular, the IEEE 118-bus system exhibits a substantial reduction in the number of PMUs, leading to a cost saving of approximately 56.57%. This reduction is economically significant while still ensuring comprehensive monitoring of the power system. Overall, the results confirm the scalability, efficiency, and practical applicability of the proposed method for large-scale power networks, maintaining reliable system performance with reduced measurement infrastructure.

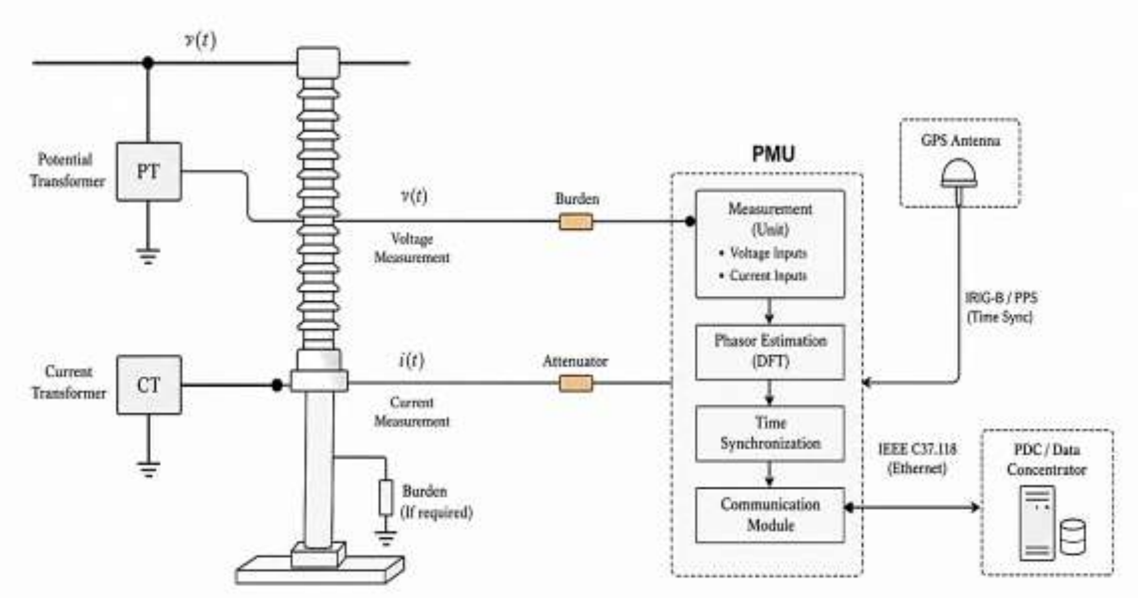

Figure 1. *PMU installation and connection diagram.*

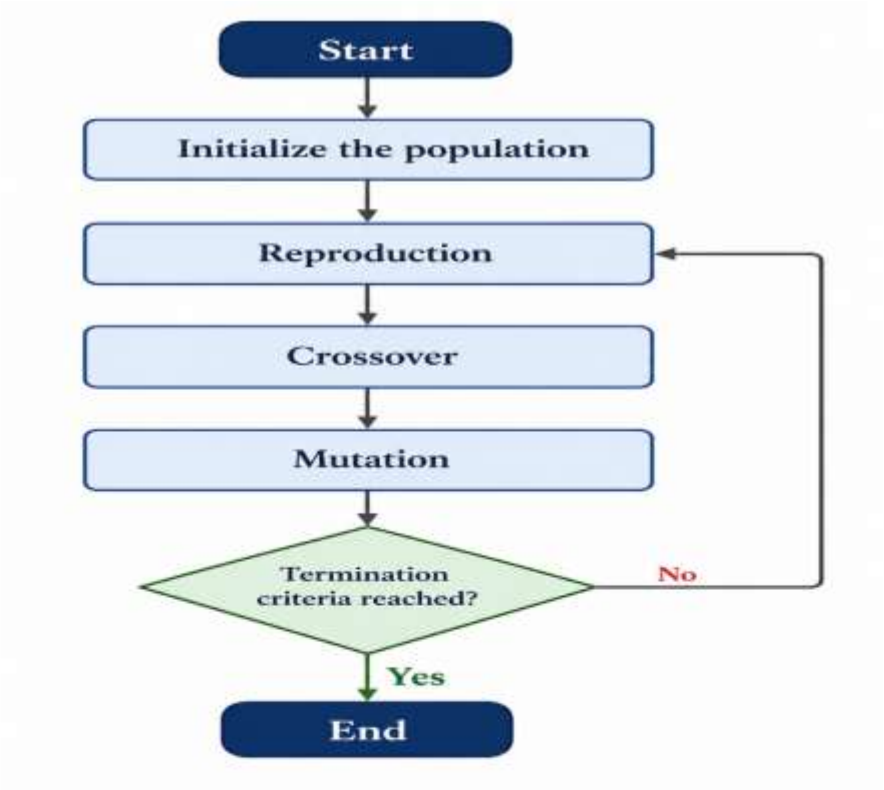

Figure 2*. The flowchart of genetic algorithm.*

Table 1. *The characteristics of a modern power grid.*

System	Number of Branch	Number of ZIB	Position of ZIB in Bus
IEEE 14_Bus [26]	20	1	7
IEEE 24 _Bus [26]	38	4	11-12-17-24
IEEE 30 _Bus [26]	41	6	5-6-9-11-25-28
IEEE 118 _Bus [26]	186	10	5-9-30-37-38-63-64-68-71-81

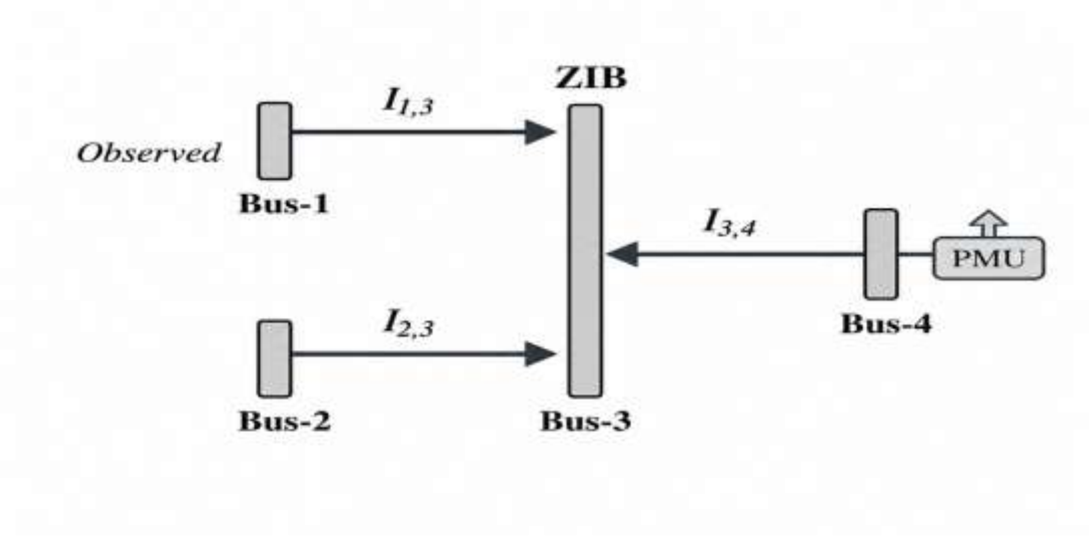

Figure 3. *Show a zero-injection bus in a network.*

***Table** 2. The OPP without considering ZIB*

Test system	**N# of PMUs**	**Location of PMUs**	**SORI**
IEEE 14_Bus	4	**2-6-7-9**	**19**
		2-6-8-9	17
		2-7-11-13	16
		2-8-10-13	14
IEEE 24 _Bus	7	**2-3-8-10-16-21-23**	**31**
		3-4-8-10-16-21-23	30
		2-3-5-7-13-16-19-21	29
		3-4-7-10-16-21-23	28
IEEE 30 _Bus	10	**2-3-6-10-11-12-15-19-25-27**	**48**
		2-3-6-9-10-12-19-23-26-27	46
		3-5-6-10-11-12-15-20-25-29	44
		3-5-8-9-10-12-18-20-25-27	43
IEEE118 _Bus	76	**1-2-3-4-5-7-10-11-12-13-15-17-18-19-21-23-25-26-27-30-31-32-34-36-37-38-40-41-42-43-44-46-47-49-50-51-52-54-56-57-59-61-62-64-65-68-69-70-71-74-75-76-77-78-80-82-83-85-86-89-91-92-93-94-95-96-97-98-100-101-103-105-109-110-114-118**	**335**
		2-3-5-7-8-9-11-12-15-17-19-21-22-23-24-27-28-30-31-32-34-35-36-37-40-41-42-43-45-46-47-49-52-54-56-57-58-59-60-61-62-63-65-66-68-69-70-71-73-74-75-77-79-80-81-84-85-87-88-90-92-94-96-99-100-101-102-103-105-106-107-108-109-110-116-118	332
		1-2-3-4-5-7-8-10-11-12-15-16-17-19-20-21-23-24-25-27-29-30-31-32-34-37-40-41-43-45-46-47-49-51-53-54-55-56-57-59-60-61-62-63-65-66-68-70-71-74-75-77-78-80-82-83-85-86-88-89-90-91-92-94-96-98-100-103-104-105-106-110-114-116-118	330

***Table 3.** The OPP with considering ZIB*

Test system	**N# of PMUs**	**Location of PMUs**	**TSORI**
IEEE 14_Bus	3	**3-6-9**	**16**
		2-6-9	15
		2-10-13	14
IEEE 24 _Bus	6	**1-9-10-16-21-23**	**29**
		2-3-10-16-21-23	27
		2-5-8-16-21-23	24
IEEE 30 _Bus	7	**3-6-10-12-18-24-27**	**36**
		3-6-10-12-19-23-27	35
		1-6-10-12-18-25-30	34
IEEE 118 _Bus	43	**3-4-6-9-12-15-17-21-23-24-27-30-33-35-**	**193**

		37-39-41-44-46-47-49-50-51-54-60-66-68-73-75-77-80-85-87-90-94-100-101-105-106-110-114	
		2-3-4-6-8-10-15-17-19-22-24-25-28-35-40-44-47-48-51-54-56-59-67-68-72-73-75-77-79-80-85-86-90-94-100-102-105-110-113-115-117	165
		4-7-9-12-15-17-20-23-25-27-29-32-36-40-42-44-46-49-50-51-54-59-66-70-71-75-78-80-83-84-87-88-90-92-93-96-102-105-109-111-112-116-118	189

Table 4. *Comparison results The OPP without considering ZIB*

Test system	**Cases**	**Proposed method**		**MOPSO [25]**		**SCA [6]**	
		N$^{\#}$ PMU	**SORI**	**N# PMU**	**SORI**	**N# PMU**	**SORI**
IEEE 14 _Bus	With ZIB	3	16	3	15	3	15
	Without ZIB	4	19	4	16	4	15
IEEE 24 _Bus	With ZIB	6	29	6	29	6	/
	Without ZIB	7	31	7	30	8	/
IEEE 30 _Bus	With ZIB	7	36	/	/	7	35
	Without ZIB	10	48	/	/	11	48
IEEE 118 _Bus	With ZIB	43	193	/	/	/	/
	Without ZIB	76	335	/	/	/	/

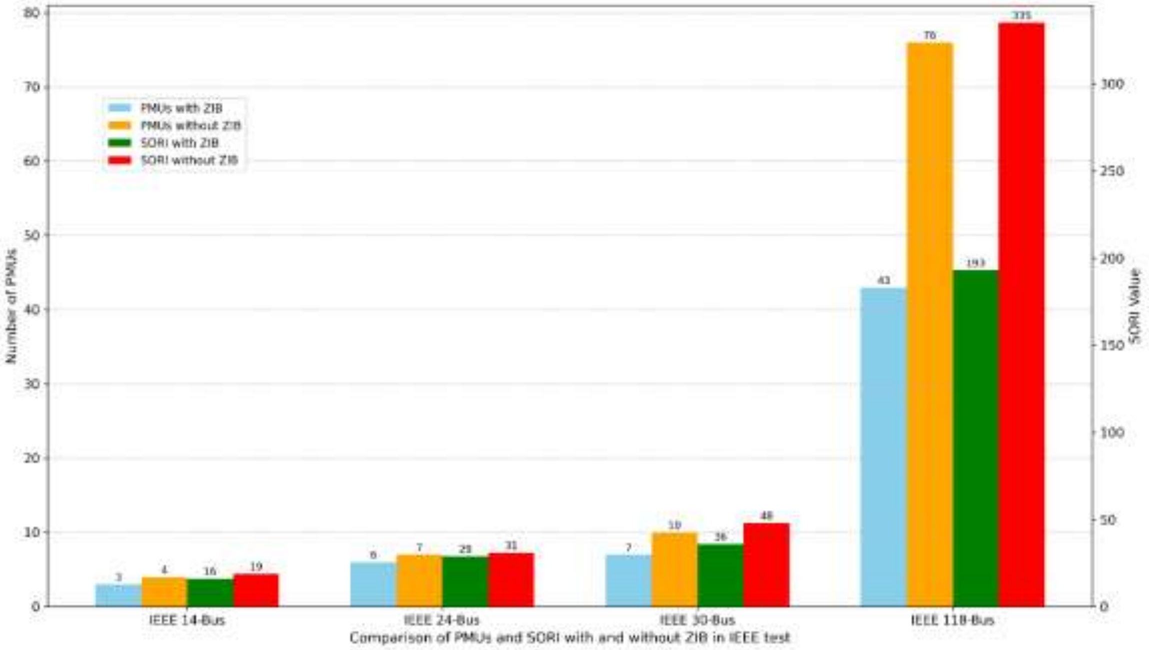

Figure 4. *Unified Comparison of PMUs and SORI with and without ZIB in IEEE test.*

5. Conclusions

This paper presented a two-stage hybrid framework for solving the Optimal PMU Placement (OPP) problem in power systems. The proposed approach combines Pareto-based multi-objective optimization with a data-driven decision-making process to address the challenge of selecting a suitable solution from multiple alternatives. The method was evaluated on IEEE 14-, 24-, 30-, and 118-bus test systems. The results show that full system observability can be achieved with a reduced number of PMUs, with reductions reaching up to 40% in larger systems, while maintaining acceptable redundancy levels. This demonstrates that the proposed framework provides an effective balance between measurement cost and system observability. In addition, incorporating Zero

Injection Buses (ZIBs) into the observability model further improves efficiency by enabling indirect monitoring of certain buses, reducing the need for additional PMU installations. Compared to conventional approaches that rely on predefined weighting factors, the proposed method offers a more consistent and objective way to select the final solution from the Pareto set, reducing subjectivity in the decision process. Overall, the results confirm that combining multi-objective optimization with data-driven decision support is a promising direction for improving PMU placement strategies. Future work will focus on extending the model to more realistic scenarios, including contingency conditions (e.g., PMU outages), network topology changes, communication constraints, and cybersecurity considerations such as false data injection attacks.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
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- **Use of AI Tools:** The authors used a generative language tool for grammar polishing only; all technical content and conclusions were authored and verified by the authors.

Nomenclature and Abbreviations

PMUs — Phasor Measurement Units
WAMS — Wide Area Measurement Systems
OPP — Optimal PMU Placement
IEEE — Institute of Electrical and Electronics Engineers
GPS — Global Positioning System
DFS — Depth-First Search
MST — Minimum Spanning Tree
GA — Genetic Algorithms
PSO — Particle Swarm Optimization
MOGA — Multi-Objective Genetic Algorithm
SORI — System Observability Redundancy Index
ZIBs — Zero Injection Buses
SCADA— Supervisory Control and Data Acquisition
KCL — Kirchhoff's Current Law

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