

Article

Modeling and Calibration Using Micro-Phasor Measurement Unit Data for Yeonggwang Substation

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Abstract

Against the backdrop of high-proportion renewable energy grid integration, modeling accuracy for substations incorporating wind and solar power is critical. Traditional modeling methods rely on theoretical parameters and lack sufficient accuracy. This study uses the 154 kV/23 kV Yeonggwang Substation in Jeollanam-do, South Korea (connected to three wind farms and three solar power plants, with 35 Micro-Phasor Measurement Unit (μ PMU) measurement points deployed) as a case study. It investigates three-phase detailed modeling using Power System Computer Aided Design (PSCAD) and μ PMU data-driven calibration. Based on substation topology and equipment parameters, a simulation model encompassing main transformers, transmission lines, renewable energy units, and loads was established. A hierarchical calibration system of “data preprocessing—parameter identification—iterative correction” was constructed, employing an iterative optimization strategy of “main grid layer—renewable energy layer—load layer.” A multi-objective optimization function centered on voltage, current, and power was developed. Verification results show that after calibration, the mean relative error rates (MRE) for voltage, current, active power and reactive power are 2.46%, 2.57%, 2.52% and 3.96% respectively, with mean error reduction rates (MERRs) of 80%, 82.75%, 81.33%, and 74.94% compared to pre-calibration values. The uniqueness of the calibration method proposed in this study lies in its use of actual μ PMU measurement data to drive PSCAD model parameter calibration, achieving precise matching with the actual characteristics of the substation. This provides a reference method for modeling and digital twin construction of similar substations, demonstrating significant engineering application value.

Keywords: steady-state simulation; micro-phasor measurement unit data; substation modeling; data-driven calibration

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1. Introduction

Recent efforts in the power industry have increasingly focused on developing next-generation intelligent transmission grid platforms that leverage advanced sensing, communication, and control technologies to enable more reliable, efficient, and flexible system operation, particularly in the context of high renewable energy integration and real-time wide-area monitoring [1,2]. As the core hub for power conversion and dispatch, the

accuracy of substation simulation models directly determines the reliability of grid operation analysis, fault simulation, and dispatch optimization. PSCAD/EMTDC, as the core tool for power system electromagnetic transient simulation, has been widely applied in substation modeling. However, existing practices still face numerous challenges, struggling to meet the demands of complex power grids. Traditional PSCAD modeling heavily relies on design manual parameters and theoretical calculations, exhibiting issues such as strong parameter dependency, pronounced subjectivity, and excessive simplification of topologies. Furthermore, existing research predominantly focuses on theoretical parameter setting or limited measurement validation, with few explorations into full-station calibration under high penetration levels based on multi-point μ PMU data. Particularly for special voltage levels like 154 kV/23 kV, customized solutions are lacking for main transformer equivalent modeling and line impedance calculation, leading to significant deviations between models and actual operating conditions [3–5]. Concurrently, the high penetration of renewable energy sources (wind and solar) has introduced strong fluctuations and bidirectional power flow characteristics into substation operations. Existing modeling approaches inadequately characterize the coupled behavior of multiple renewable energy sources, further exacerbating model accuracy deficiencies. To enhance the accuracy of new energy-related models, existing research predominantly adopts hybrid technical approaches as follows: optimizing wind speed prediction accuracy through hybrid machine learning models provides precision support for modeling the fluctuating characteristics of wind power fed into substations [6]. The proposed hybrid optimization algorithm offers an algorithmic reference for optimizing model parameters in multi-energy coordinated dispatch at substations [7]. Focusing on improving photovoltaic system modeling accuracy, the approach combining topology simplification with intelligent algorithms offers valuable insights for precise modeling of the photovoltaic input side at substations [8].

Micro-Phasor Measurement Unit (μ PMU) Compared to traditional Supervisory Control and Data Acquisition (SCADA) systems with 4 s data acquisition cycles and lower synchronization accuracy, the μ PMU offers microsecond-level time synchronization capability. It enables real-time capture of critical electrical signals such as voltage magnitude, phase angle, and frequency, with a maximum data sampling rate of 256 times per power frequency cycle. This allows for precise detection of dynamic operational details within substations [9,10]. Therefore, μ PMU-based calibration is crucial in this study. Conducting model calibration using actual μ PMU measurement data to establish a closed-loop research system of “modeling-measurement-calibration” has become an important method for enhancing the accuracy of substation simulation models [11].

Current research on power system monitoring and microgrid modeling has established a solid foundation. μ PMU can address the limitations of SCADA systems, such as low accuracy and sampling rates, thereby enhancing the precision of state estimation [12]. Additionally, they can assist in transmission line loss monitoring and corona loss calculation [13]. Ensuring the performance of μ PMU in field applications is a critical issue. Related research has proposed a field testing and calibration framework incorporating calibrators and analysis centers, and has improved accuracy through methods such as signal denoising [14]. In the microgrid domain, PSCAD has been applied to model microgrids with multiple distributed resources. Related studies have explored grid-connected and islanded operation modeling, energy storage control, and other issues [15], laying the groundwork for research integrating PSCAD modeling with μ PMU data calibration.

The data-driven calibration method proposed in this study is tailored to the practical modeling needs of substations. By leveraging actual PMU measurement data to construct calibration logic, it accurately captures the dynamic characteristics of core parameters such as voltage and phase angle without requiring complex parameter iterations. This

approach effectively mitigates the interference of complex substation operating environments on calibration results, providing reliable support for subsequent simulation model optimization and fault analysis. Compared to existing PSCAD-PMU calibration research, this approach replaces traditional synchronous parameter estimation with hierarchical calibration. By decoupling core and secondary parameters, it resolves multi-parameter coupling interference, enhancing calibration specificity and computational efficiency [16]. It achieves deep alignment between PMU high-frequency, high-precision data and PSCAD modeling while balancing calibration accuracy and engineering practicality. This method can be implemented using existing substation data and adapts to real-world operational requirements.

The Yeonggwang Substation in South Jeolla Province, South Korea, serves as a critical node for regional voltage transformation, handling the conversion from 154 kV to 23 kV. This substation exemplifies South Korea's typical medium-voltage conversion standards and features a high penetration rate of renewable energy. Three wind farms and three photovoltaic power stations are connected to its transmission lines. Accurate modeling of this substation is crucial for ensuring the safe and stable operation of the regional power grid [17,18]. Therefore, we selected the Yeonggwang Substation as our research subject to conduct PSCAD modeling and μ PMU data calibration studies. First, we constructed a PSCAD model covering the entire line, including the main grid, new energy units, and transmission lines. Subsequently, based on data from 35 deployed μ PMU measurement points, we designed a hierarchical iterative calibration strategy to achieve precise optimization of model parameters. Finally, we quantitatively verified the calibration effectiveness by comparing metrics such as voltage, power, and relative error. The proposed "PSCAD modeling + multi-point μ PMU calibration" technical solution effectively addresses the limitations of traditional modeling accuracy. It provides a technical reference for precise modeling of substations at special voltage levels while offering a reliable simulation tool for operational optimization, fault prediction, and analysis/evaluation at the Yeonggwang Substation. This approach holds significant theoretical and practical engineering value [19,20].

The subsequent sections of this paper are organized as follows: Section 2 outlines the rationale for substation modeling and the fundamental parameters of μ PMU data. Section 3 details the implementation process of the full-line PSCAD modeling for Yeonggwang Substation. Section 4 proposes a hierarchical iterative calibration method based on 35 μ PMU data points, presenting and analyzing the modeling and calibration results. Finally, Section 5 summarizes the research conclusions and future directions.

2. Fundamentals of PSCAD Modeling for Yeonggwang Substation

PSCAD modeling theory forms the foundation for substation simulation modeling. Based on electromagnetic transient simulation mechanisms, it achieves precise replication of power system dynamic processes through core logic such as the node voltage method. Its applicability spans multiple power engineering domains, including transmission and transformation system component modeling and renewable energy integration simulation. This study clarifies the simulation principles and applicable boundaries of the software, with a focus on elucidating the core logic of power system component modeling. It provides a solid theoretical foundation for subsequent detailed modeling of key components and renewable energy units at the Yeonggwang Substation.

2.1. Topological Structure Analysis of Yeonggwang Substation

The Yeonggwang substation in South Jeolla Province, South Korea, has installed a 35- μ PMU (the device is a μ PMU manufactured by Korea's Green Information System Co., Ltd., Gwangju, Republic of Korea) [21,22], Figure 1 shows the single-line diagram of the

Yeonggwang substation. As shown in Figure 1, the high-voltage side of the substation is 154 kV, and the low-voltage side is 23 kV. Additionally, the installation locations of the 35 μ PMUs are marked in Figure 1 (#1–#35). The 154 kV area was connected to Baeksu WP, Jaewon PV, and Hamgumi PV. The 22.9 kV area was connected to Honam WP, DSE (PV), and Jeonnam TP (WP).

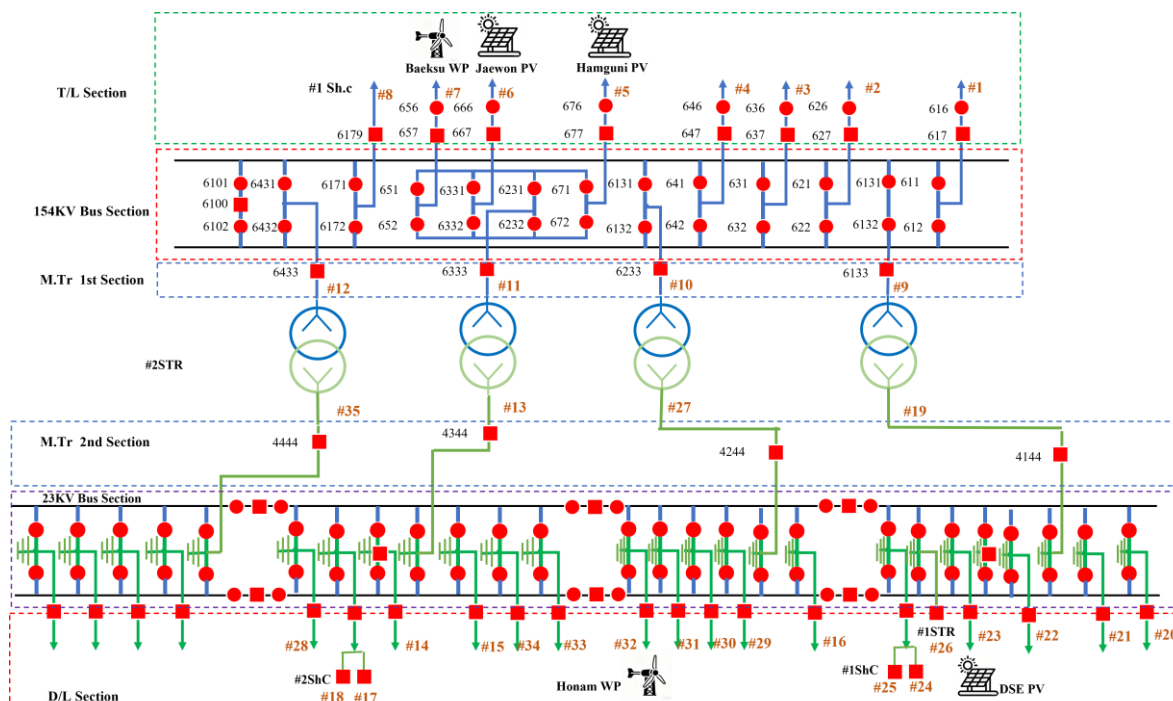


Figure 1. A single-line diagram of the Yeonggwang substation.

2.2. Analysis of Main Transformer Structure and Parameters

The four transformers at Yeonggwang Substation each have a rated capacity of 45 MW. These three-phase winding transformers are connected in a Y/Y/Delta configuration. Their high-voltage windings are connected in parallel to the 154 kV busbar, their medium-voltage windings are connected in parallel to the 23 kV busbar, and their low-voltage windings are connected in parallel to the 6.6 kV busbar. Specific parameters are shown in Table 1.

Table 1. Main transformer parameters of Yeonggwang Substation.

	#1 Transformer	#2 Transformer	#3 Transformer	#4 Transformer
Rated capacity	45 MW	45 MW	45 MW	45 MW
frequency	60 Hz	60 Hz	60 Hz	60 Hz
High Voltage	154 kV	154 kV	154 kV	154 kV
Medium Voltage	23 kV	23 kV	23 kV	23 kV
Low Voltage	6.6 kV	6.6 kV	6.6 kV	6.6 kV
Forward-Sequence Leakage Inductance (1–2)	10.2% AT 15 MW	14.6% AT45 MW	14.24% AT5 WM	15.2% AT45 MW
Forward-Sequence Leakage Inductance (1–3)	8.15% AT 5 MW	7.93% AT15 MW	7.44% AT5 MW	8.25% AT15 MW
Forward-Sequence Leakage Inductance (2–3)	2.75% AT 5 MW	2.10% AT15 WM	2.07% AT5 MW	2.18% AT15 MW

3. Detailed PSCAD Modeling Process for Yeonggwang Substation

3.1. Building PSCAD Models

3.1.1. A 154 kV Incoming Line and Busbar Modeling

Due to the lack of detailed resistance and reactance parameters for the incoming line, the unit length resistance and reactance values were estimated by referencing the general parameter ranges for 154 kV overhead lines in the “Electrical Design Manual for Power Engineering” and considering the line design length. This enabled the configuration of the line model parameters. The busbar employs the “Busbar” ideal busbar module, neglecting its inherent resistive and capacitive losses. The connection relationship between the 154 kV incoming busbar and the high-voltage side of the main transformer is explicitly defined.

3.1.2. Main Transformer Modeling

The “3 Winding Transformer” standard module in PSCAD was selected, with core parameters designed based on the specific transformer specifications in Table 1, including rated capacity, rated voltage ratio, and positive-sequence leakage reactance.

3.1.3. A 23 kV Feeder and Load Modeling

The outgoing lines also employ distributed parameter line modules, with resistance and reactance values estimated based on the 23 kV line design length and standard unit parameters. The load utilizes the “fixed_Load” composite load model, calculating actual active power P and reactive power Q from voltage, current, and phase angle data in the μ PMU. However, due to the unknown load power type, constant power (P), constant impedance (Z), and constant current (I) loads at 60%, 30%, and 10% respectively (matching typical distribution network load proportions at this voltage level). After initial calibration, precise adjustments are made using μ PMU data.

3.1.4. Detailed Construction of Wind Power and Photovoltaic Models

Due to confidentiality restrictions in practical power systems, detailed manufacturer-specific parameters of wind turbines and photovoltaic units—such as blade pitch control coefficients, rotor diameter, or PV module open-circuit and short-circuit characteristics—were not available. Only the rated power and rated voltage levels of each renewable unit were obtained.

Under this constraint, the renewable generation units were modeled as grid-side equivalent power-controlled units, rather than detailed device-level physical models. The objective of the modeling was to accurately represent the power injection behavior at the point of interconnection, which is consistent with the spatial and temporal resolution of μ PMU measurements.

For wind power units, the DFIG Wind Turbine module from the PSCAD standard library was employed. To ensure reproducibility, the modeling procedure is summarized as follows:

- Rated capacity configuration: The rated active power of the DFIG model was set according to the known rated capacity of the wind power unit, ensuring that the steady-state active power output matches the actual operating level.
- Grid connection and voltage level: The wind turbine model was connected to the 154 kV substation bus through a step-up transformer. The modeling focus was placed on the electrical quantities at the grid connection point, including active power, reactive power, and voltage magnitude.
- Control mode selection: The wind power unit was operated in a constant active power control mode, while the reactive power (or voltage) control followed the

default configuration of the PSCAD standard model to match the observed μ PMU measurements.

- Default internal parameters: Parameters related to aerodynamic characteristics, mechanical dynamics, and internal control loops were retained at their PSCAD default values, due to the absence of verifiable field data. This avoids introducing unsubstantiated assumptions and ensures that the model can be reproduced directly using the standard library.
- For multiple wind power units, identical electrical and control parameters were used, with individual units distinguished only by their identifiers. This modeling strategy ensures consistency across units and facilitates replication. The wind power module is illustrated in Figure 2.

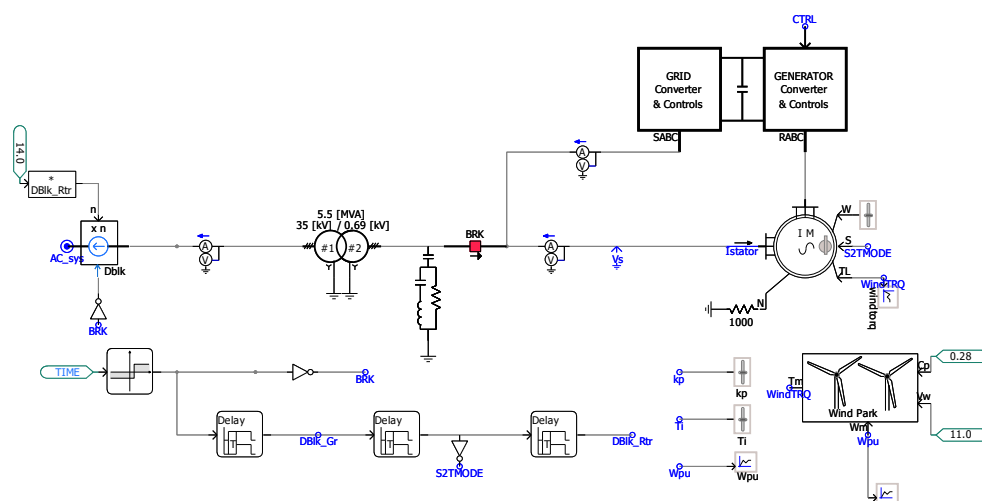


Figure 2. Wind power generation model.

The photovoltaic model is constructed using the “Simple Solar Farm” base module in PSCAD, which integrates core submodules including the PV array, inverter, and MPPT controller. Key modifications during modeling are as follows: ① calculate the number of series and parallel modules based on known PV rated power and rated voltage: assuming a single PV module has a rated power of 100 kW and rated voltage of 154 V, the number of series and parallel modules is estimated using the relationships: “Total rated power = Single module power $\times$ Number of parallel modules” and “Array rated voltage = Single module voltage $\times$ Number of series modules”. “Array rated voltage = single-module voltage $\times$ number of series connections.” (Due to the lack of detailed module parameters, this estimation is solely for matching rated power and voltage and does not involve modifying internal module characteristics); ② adjust the inverter’s rated output power and voltage to match the PV array’s rated parameters, ensuring the inverter can stably convert the array’s generated electricity into 154 kV AC for grid integration; ③ retain the standard model’s irradiance and temperature input defaults: standard irradiance 1000 W/m², standard temperature 25 °C. These parameters can be adjusted later to simulate PV output variations under different irradiance and temperature conditions. The key electrical waveforms at the PV array model’s common connection point (POC) are shown in Figure 3.



Figure 3. Photovoltaic module: (a) photovoltaic model circuit; (b) electrical waveform at the public connection point (POC) of a photovoltaic array.

3.2. Initial Model Construction and Validation

After completing the implementation of all components and control modules, an initial model verification was conducted to ensure topological integrity and numerical correctness of the PSCAD model. This step focused on verifying the connectivity logic and parameter consistency of key components, particularly the rated power and voltage levels of the main transformer and renewable generation units. The overall model topology exported from PSCAD is shown in Figure 4.

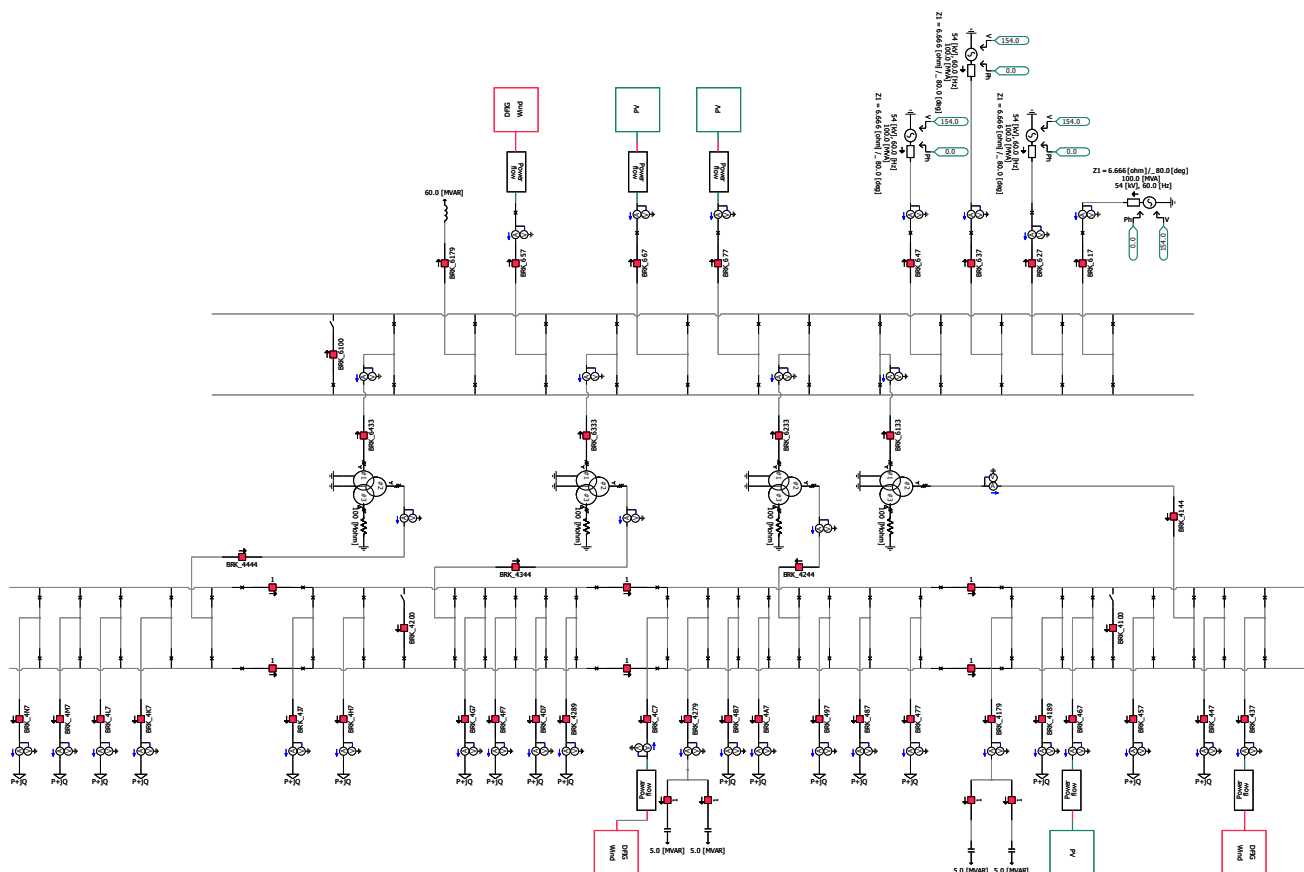


Figure 4. Yeonggwang Substation PSCAD model diagram.

Since the renewable generation units were developed based on modified PSCAD standard models and detailed manufacturer parameters were unavailable, the initial verification was limited to steady-state operating conditions, and complex dynamic performance tests were not conducted at this stage. The purpose of this initial verification was not to evaluate calibration accuracy, but to confirm that the model provides a physically reasonable baseline for subsequent μ PMU-based calibration.

Accordingly, no-load and rated-load tests were performed as sanity checks. The verification criteria included waveform quality, RMS magnitude consistency, and system frequency stability. Specifically, steady-state waveforms were required to exhibit no obvious numerical oscillations or abnormal harmonic distortion; RMS values were checked to ensure consistency in order of magnitude, with deviations within $\pm 15\%$ used solely as an indicator to identify gross modeling or configuration errors; and system frequency was required to remain stable within $60 \text{ Hz} \pm 0.5 \text{ Hz}$.

4. μ PMU Data-Driven PSCAD Model Calibration Method

4.1. Hierarchical Iterative Least-Squares Calibration for PSCAD Model with μ PMU Data

The core objective of model calibration is to refine PSCAD model parameters using μ PMU measurement data, ensuring simulation outputs closely match the actual operational characteristics of substations. This study employs a hierarchical iterative least-squares optimization method for calibration. Its core principle involves constructing a multi-objective optimization function using key electrical quantities—such as voltage, current, and power—synchronously measured by μ PMU as reference values. Through iterative adjustment of model parameters, the method minimizes the error between simulated and measured values while constraining parameter adjustments within the boundaries of equipment physical characteristics. Compared to traditional parameter-based calibration methods, this approach leverages synchronized multi-point measurement data from distributed μ PMU to achieve station-wide calibration without blind spots.

4.2. μ PMU Data Acquisition and Preprocessing

4.2.1. Data Collection Specifications

1. Time synchronization is achieved through GPS-based time stamping with microsecond-level accuracy, consistent with the IEEE C37.118 standard [23] for μ PMU measurements. The sampling rate is set to 60 Hz, which is sufficient to accurately capture steady-state operating characteristics, while also reflecting dynamic variations caused by renewable generation fluctuations and load changes.
2. Acquisition Parameters: A total of 35 μ PMU measurement data points encompass phase voltage, current, and phase angle for 154 kV/23 kV busbars and critical equipment. Active power P and reactive power Q are calculated. The μ PMU data used for calibration verification consists of one full month (1 July 2023–31 July 2023) of actual measurement data under all operating conditions. Tables 2 and 3 display raw data patterns from four μ PMUs at a specific moment, timestamped 10 July 2023, 12:00.
3. Acquisition Duration: Continuous collection of one month's full operational condition data, encompassing scenarios such as rated load operation, renewable energy output fluctuations (morning/evening peaks), load variations, and faults. This ensures μ PMU data comprehensively cover all operational states.

Table 2. Raw data for μ PMU frequencies, voltages, and voltage phasors #1–#4.

ID	f (Hz)	V_A (V)	δ_A (°)	V_B (V)	δ_B (°)	V_C (V)	δ_C (°)
#1	60.042	91,960.59	−47.23	92,150.64	−167.519	91,727.66	72.546
#2	60.041	91,849.45	−53.238	92,138.69	−173.521	91,651.93	66.496
#3	60.041	91,863.62	−53.341	92,068.79	−173.602	91,665.11	66.434
#4	60.042	91,878.20	−53.963	92,148.16	−174.268	91,657.13	65.748

Table 3. Raw data for μ PMU current and current phase angle #1–#4.

ID	I_A (A)	δ_A (°)	I_B (A)	δ_B (°)	I_C (A)	δ_C (°)
#1	294.879	−39.86	309.017	−161.479	298.132	75.486
#2	300.945	−44.901	312.034	−168.901	295.406	70.442
#3	50.46	152.319	49.817	19.767	31.087	−145.561
#4	104.022	123.802	128.044	−8.223	115.045	−125.41

4.2.2. Data Preprocessing Workflow

Raw μ PMU data may contain noise, outliers, and missing values that affect calibration accuracy. A standardized preprocessing workflow with clear and actionable steps is designed as follows:

1. **Outlier identification:** Considering the strong coupling characteristics of multiple indicators (e.g., voltage, current, phase angle, and power) in μ PMU data, the Mahalanobis distance method is adopted for multivariate outlier detection. Specifically, the Mahalanobis distance between each sample point and the center of the multivariate normal distribution constructed by voltage, current, phase angle, and power is calculated. Subsequently, the chi-square test is employed to determine the outlier threshold, so as to identify and eliminate abnormal data points caused by equipment faults, communication interference, and other factors (such as voltage sudden changes and current zero-crossing interruptions).
2. **Missing value imputation:** Use linear interpolation to fill sparse missing data, ensuring time series continuity.
3. **Data synchronization alignment:** Use the GPS timestamp in μ PMU data as the reference to adjust the time step and start time in PSCAD simulations, achieving one-to-one correspondence between simulated and measured data.

4.3. Calibration Metrics and Objective Functions

4.3.1. Core Calibration Metrics

To comprehensively evaluate model accuracy, key metrics were selected covering amplitude, power, and phase characteristics. All metrics employ relative deviation to eliminate the impact of different units of measurement:

1. **Three-phase average voltage relative deviation:**

$$\Delta U = \frac{|U_s - U_m|}{U_m} \quad (1)$$

2. **Three-phase average current relative deviation:**

$$\Delta I = \frac{|I_s - I_m|}{I_m} \quad (2)$$

3. **Active Power Relative Deviation:**

$$\Delta P = \frac{|P_s - P_m|}{P_m} \quad (3)$$

4. **Relative Deviation of Reactive Power:**

$$\Delta Q = \frac{|Q_s - Q_m|}{Q_m} \quad (4)$$

5. Relative deviation of phase angle:

$$\Delta \theta = \frac{|\theta_s - \theta_m|}{\theta_m} \quad (5)$$

where U_s , I_s , P_s , Q_s and θ_s represent the PSCAD model simulation values, while U_m , I_m , P_m , θ_m , and Q_m represent the μ PMU measured values.

To quantify the improvement in accuracy before and after model calibration, the mean error reduction rate (MERR) is defined, calculated as follows:

$$MERR = \left(\frac{MRE_{before} - MRE_{after}}{MRE_{before}} \right) \quad (6)$$

where MRE_{before} , MRE_{after} represent the average relative error of each indicator before and after calibration.

4.3.2. Multi-Objective Optimization Objective Function

Construct a comprehensive deviation objective function, incorporating weighting coefficients to reflect the engineering priority levels of different indicators.

$$J = \omega_P \cdot \Delta P + \omega_Q \cdot \Delta Q + \omega_U \cdot \Delta U + \omega_I \cdot \Delta I + \omega_\theta \cdot \Delta \theta \quad (7)$$

where ΔP , ΔQ , ΔU , ΔI and $\Delta \theta$ represent the average relative deviations of the 35 measurement point indicators, respectively. Weighting coefficients: $\omega_P = 0.25$, $\omega_Q = 0.1$, $\omega_U = 0.25$, $\omega_I = 0.15$, $\omega_\theta = 0.3$. The weighting coefficients are selected based on the physical sensitivity of each quantity to network parameters. Higher weight is assigned to the positive-sequence voltage angle due to its strong dependence on network topology and reactance, while lower weight is assigned to reactive power considering its sensitivity to local control and measurement uncertainty.

4.3.3. Constraints

1. Parameter adjustment range constraints: The adjustment range for all model parameters (including line impedance, transformer leakage reactance, and rated power of new energy units) must not deviate excessively from actual physical parameters to prevent parameters from diverging from the actual operating characteristics of equipment.
2. Maximum deviation for core indicators ΔP , ΔU , $\Delta I \leq 3\%$; maximum deviation for non-core indicator $\Delta Q \leq 5\%$ (meeting engineering simulation accuracy requirements).

Objective function convergence threshold: the difference between the objective functions of two consecutive iterations satisfies $|J_{k+1} - J_k| \leq 10^{-3}$, where k denotes the current iteration number.

4.3.4. Identifiability Analysis

To verify the unique identifiability of the selected calibrated parameters, an analysis is conducted based on the existing configuration of 35 μ PMU measurement points and the calibration scheme: the 35 measurement points are evenly distributed across 154 kV/23 kV buses, the primary and secondary sides of main transformers, new energy grid-connected points, and load outgoing lines. Each point synchronously collects three-phase voltage, current, phase angle, active power, and reactive power, forming more than 350 independent measurement dimensions. In contrast, the number of parameters to be calibrated (including line impedance, transformer leakage reactance, new energy unit output parameters, and load proportion coefficients, etc.) is only about 40, providing significant

data redundancy that lays the foundation for the unique identification of parameters. Meanwhile, the hierarchical calibration strategy of “main grid layer → new energy layer → load layer” effectively decouples the parameter coupling between different components. Each parameter group is supported by dedicated measurement point data, avoiding ambiguity in identification caused by mutual interference among multiple parameters. Verified via numerical simulation, the Jacobian matrix of the objective function with respect to the calibrated parameters is non-singular, satisfying the mathematical condition for unique identifiability and ensuring that the selected parameters can be uniquely determined using the existing μ PMU measured data.

4.4. Layered Iterative Calibration Process

Given the criticality of substation equipment and the interdependence of its parameters, a three-tier iterative calibration process has been designed: “Main Grid Layer → Renewable Energy Layer → Load Layer.” This approach mitigates interference from multi-parameter coupling, enhancing calibration efficiency and precision. The specific steps are as follows:

4.4.1. Calibration Tier Classification and Adjustment Strategy

The calibration hierarchy, adjustment targets, core parameters, adjustment logic, and constraint conditions are clearly defined as shown in Table 4. The adjustment logic is designed based on the physical relationship between parameters and electrical quantities, ensuring each adjustment is targeted.

For three-winding transformer calibration, select leakage reactance parameters from the high-to-medium and high-to-low windings. These parameters directly influence power transmission and voltage distribution between the main grid and distribution network sides and can be precisely identified using power and voltage data from the main transformer’s high- and low-voltage side μ PMU measurement points. The leakage reactance between the medium- and low-voltage windings has a relatively minor impact on system steady-state characteristics. It is fixed using the manufacturer’s nameplate rated value, with the resulting error meeting engineering application requirements.

Table 4. Error-feedback-based hierarchical iterative parameter update rule.

Calibration Level	Adjustment Target	Core Adjustment Parameter	Adjustment Method
Main Grid	154 kV T/L	Resistance per unit length R , reactance X	Data-measured > Data-simulated Increase R/X (by 1% each time), or decrease it accordingly.
	Main Transformer	Positive-sequence leakage reactance (Phase 1–/Phase 1–3/Phase 2–3)	U -simulated < U -measured, Decrease leakage reactance (by 0.5% each time); conversely, increase it.
New Energy Sources	WP	Rated power of rotor	P -simulated < P -measured Increase (by 1% each time), or decrease
	PV	Inverter output voltage threshold, rated power	Fine-tune the voltage threshold in 0.5 kV increments; adjust the rated power in 1% increments.
Load	23 kV Load	Constant power P /Constant impedance Z /Constant current I ratio	P -simulated < P -measured, Increase the proportion of P by 5% and decrease the proportion of Z by 5%.

4.4.2. Iterative Calibration Steps

1. Initial Deviation Assessment: Run the initial PSCAD model to calculate the relative deviation of four metrics across 35 measurement points. Sort by descending deviation and identify critical measurement points with deviations exceeding 10%.
2. Main Grid Layer Calibration: Prioritize adjusting parameters of 154 kV lines and main transformers. After each parameter adjustment, run steady-state simulations to verify deviation changes at corresponding measurement points until core indicator deviations $\leq 3\%$ for all main grid layer measurement points.
3. Renewable Energy Layer Calibration: Based on the calibrated main grid layer model, adjust wind and solar unit parameters. Focus on matching renewable energy output fluctuation characteristics to ensure grid connection point power and voltage deviations meet standards.
4. Load Layer Calibration: Finally, adjust parameters of the 23 kV composite load model to adapt to the impact of load changes on busbar voltage.
5. Global Verification and Iteration: After completing one round of layered calibration, calculate the deviation of all measurement points. If any measurement point fails to meet standards, return to the corresponding layer for repeated adjustments.

4.4.3. Iteration Termination Criteria

Iteration terminates when any of the following conditions is met, ensuring balance between optimization accuracy and efficiency:

1. Error Convergence Criteria: The average relative deviation for core indicators across 35 monitoring points was $\leq 3\%$, while the average relative deviation for non-core indicators was $\leq 5\%$.
2. Convergence criterion for the objective function: The difference between the objective functions of two consecutive iterations satisfies $|J_{k+1} - J_k| \leq 10^{-3}$.
3. Maximum Iteration Threshold: When the iteration count within a single layer reaches the preset upper limit of 80 iterations (numerical experiments indicate that under typical operating conditions, the objective function typically converges within 50–70 iterations).

4.5. Test Results and Analysis

Based on the following configuration, Intel Core i7-13700K 2.4GHz + 32GB DDR5 RAM, the total computation time for a single full calibration cycle is approximately 2 h and 40 min.

Based on data from 35 μ PMU measurement points, statistical validation of key indicators for the calibrated model was conducted. All parameters demonstrated significant error reduction post-calibration, as shown in Figure 5, average voltage error decreased from 12.3% to 2.46%, average current error dropped from 14.9% to 2.57%, the average active power error decreased from 13.5% to 2.52%, and the average reactive power error decreased from 15.8% to 3.96%, significantly improving the model's accuracy.

After calibration, the average relative voltage error remained below 3%, as shown in Figure 6. The relative errors at each measurement point clustered within the range of 1.65% to 2.95%, exhibiting uniform distribution with no significantly outlying high-error points. The maximum error was 2.95%, the minimum was 1.65%, and the average was only 2.57%. This result demonstrates that the model achieves stable voltage calibration accuracy across all 35 measurement points at the substation, with all points meeting standards. It enables “precision matching without blind spots” for substation voltage parameters, fully validating the model's comprehensive coverage and reliable accuracy.

To verify the stability of the model voltage, one measurement point was selected for each of the busbar, transformer side, and load side. After 60 s of steady-state operation, the voltage output remained stable within the error range, as shown in Figure 7. The voltage fluctuation trends of the three measurement points were highly consistent, exhibiting the characteristic of periodic minor fluctuations; the deviation between the simulated values and measured values remained consistently within a narrow range, with only slight numerical differences observed. This result confirms that the established PSCAD simulation model can accurately reproduce the quasi-static fluctuation characteristics of three-phase voltages in actual substations, demonstrating a high degree of dynamic consistency between the model outputs and field measurement data.

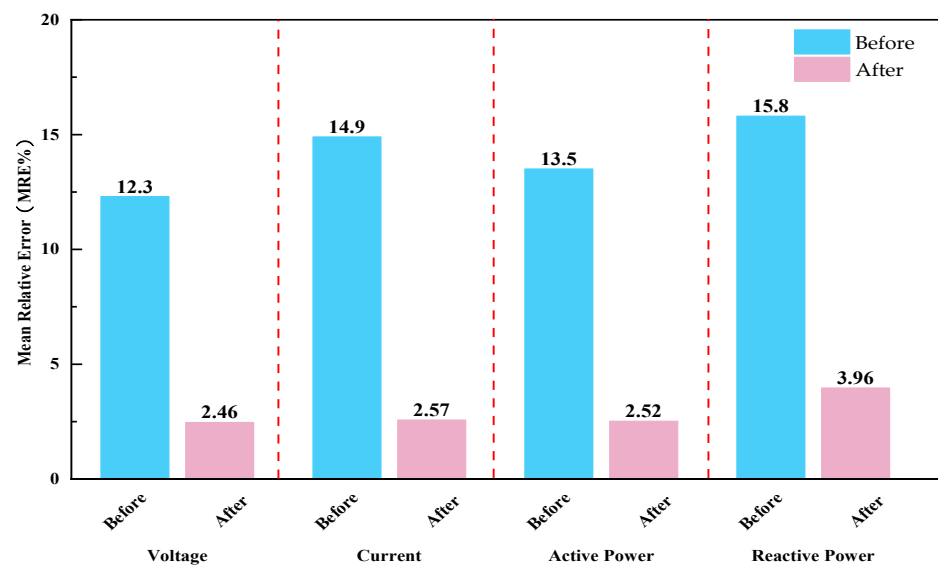


Figure 5. Comparison of average error for each parameter before and after calibration.

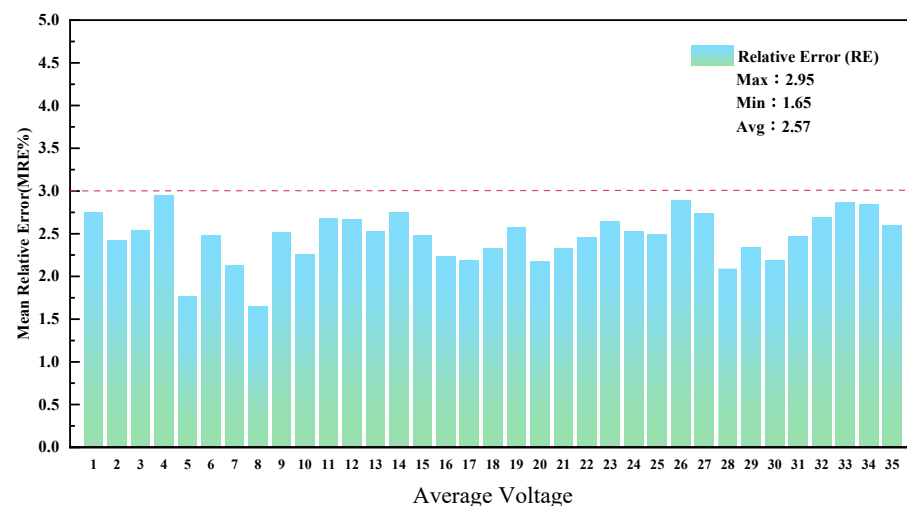


Figure 6. Average voltage error chart.

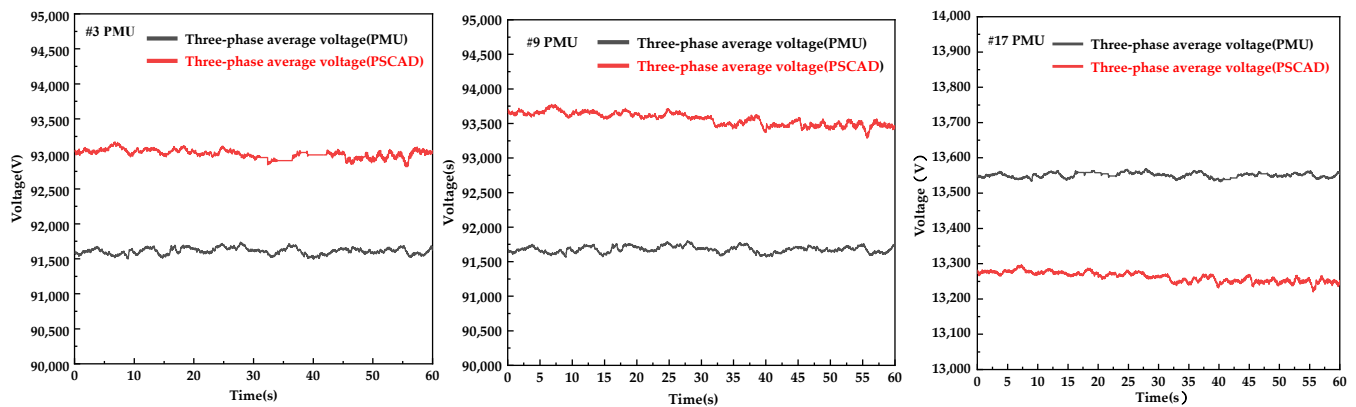


Figure 7. Comparison of μ PMU and simulated voltage under steady-state conditions.

Figure 8 illustrates the dynamic changes in phase angle errors between measured data and PSCAD simulation results for three Micro-Phasor Measurement Units (μ PMUs), namely #3, #9, and #17, over a 0–60 s time window. The blue curves represent real-time fluctuations in phase angle error, while the red horizontal lines indicate the average error values for the corresponding periods. Overall, the phase angle errors of the three μ PMUs exhibit good consistency, with the phase angle error being less than 3° for the vast majority of the time and maintaining a low average error level: the error fluctuation of #3 μ PMU is the smallest, with an average error of only 0.709° ; the average error of #9 μ PMU is 0.986° ; although the error fluctuation of #17 μ PMU is relatively significant, it remains within 3° for most periods, with an average error of 1.075° . This overall indicates that the established PSCAD simulation model has a high phase angle matching degree with the measured data, and the overall error level is controllable.

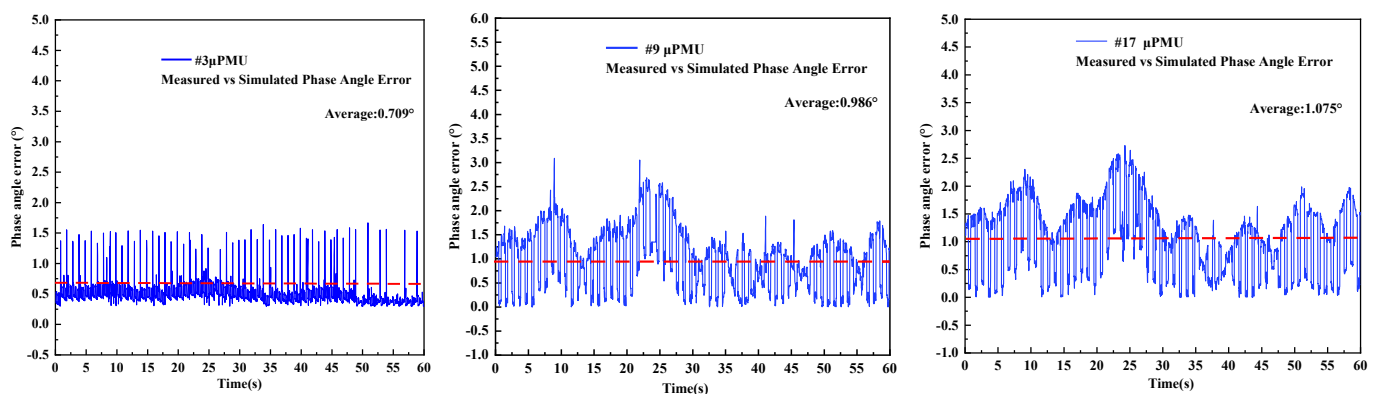


Figure 8. Phase angle error plot: measured vs. simulated data.

To verify that the average power error complies with calibration standards, it is characterized via Figure 9. Power errors are primarily concentrated within the 2.3–2.9% range, with the 2.4–2.5% interval exhibiting the highest relative frequency approaching 30%, while frequencies in marginal intervals are lower. Simultaneously, the red Gaussian fitting curve closely aligns with the histogram distribution trend, indicating that the power error distribution approximates a normal distribution. The results reveal a concentrated and stable distribution pattern for power errors, with no extreme outliers. This confirms the model's consistency and stability in power parameter calibration accuracy.

Finally, to visually represent the average relative errors of key parameters after model calibration, Figure 10 presents a box plot. As shown, the error ranges for ΔU , ΔI ,

and ΔP are all concentrated within the 1.5–2.5 interval. The narrow box and low data dispersion indicate that the error distributions for these three parameters are more compact, demonstrating superior precision stability. In contrast, the error range for ΔQ is significantly broader, concentrated between 3.0 and 4.5, with relatively higher data dispersion. Overall, the errors in voltage, current, and active power exhibit stronger concentration and stability. Only the error dispersion for reactive power is slightly higher. This reflects that after model calibration, the error states of most core electrical parameters are controllable, and their accuracy performance is consistent.

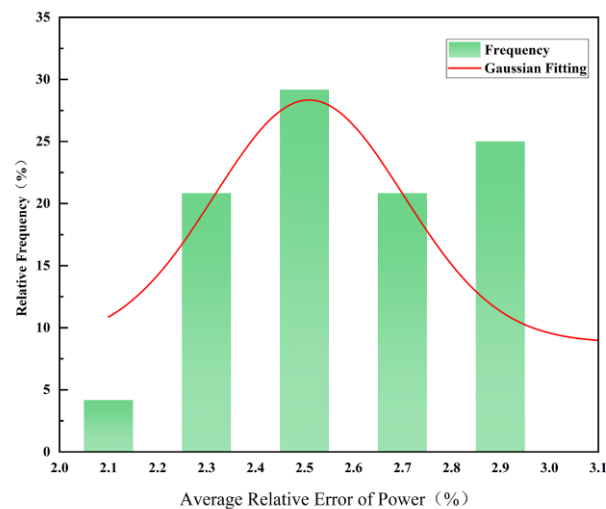


Figure 9. Voltage mean relative error distribution.

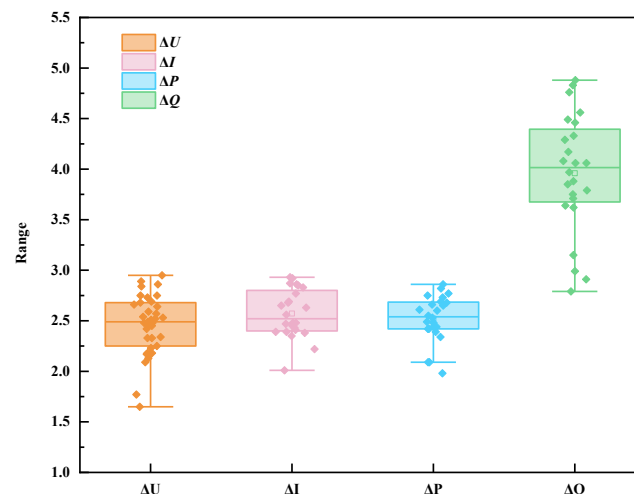


Figure 10. Mean relative error of each key parameter.

5. Conclusions

This study focused on the Yeonggwang Substation, completing PSCAD modeling and μ PMU data-driven calibration research. Based on μ PMU measurement point data, a hierarchical calibration system was established, controlling deviations in core parameters such as voltage, current, and power within 3% of actual measurements. This model provides a reliable tool for substation operation optimization and fault analysis, while the

proposed calibration method offers a generalizable reference for modeling similar substations.

Although this study established a data-driven hierarchical calibration method for substation PSCAD models using μ PMU data and validated its effectiveness, several limitations remain. The method was only validated at the Yeonggwang Substation, which possesses comprehensive measurement equipment, and is not applicable to sites with sparse measurement points. The capability to simulate harmonics and sub-synchronous oscillations was neither discussed nor validated, limiting its support for complex dynamic scenarios. Furthermore, the offline calibrated simulation model does not equate to a digital twin, as the latter requires real-time interconnection and predictive capabilities that remain unachieved. The measurement uncertainty inherent to μ PMUs themselves was also not thoroughly investigated. Future work will explore transient and fault scenarios while addressing these shortcomings to enhance the method's applicability and engineering utility.

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Abbreviations

μ PMU	Micro-Phasor Measurement Unit
PV	Photovoltaic
MRE	Mean Relative Error
MERR	Mean Error Reduction Rates
PMU	Phasor measurement units
SCADA	Supervisory Control and Data Acquisition
T/L	Transmission Line
D/L	Distribution Line
M.Tr	Main Transformer
WP	Wind Power
RESs	Renewable Energy Sources
URTDMS	Unified Real Time Dynamic State Measurement System

References

1. Park, J.; Yun, S.-J. Social determinants of residential electricity consumption in Korea: Findings from a spatial panel model. *Energy* **2022**, *239*, 122272. <https://doi.org/10.1016/j.energy.2021.122272>.
2. Chu, K.H.; Lim, J.; Mang, J.S.; Hwang, M.-H. Evaluation of strategic directions for supply and demand of green hydrogen in South Korea. *Int. J. Hydrog. Energy* **2022**, *47*, 1409–1424. <https://doi.org/10.1016/j.ijhydene.2021.10.107>.

3. Yue, C.; Wang, D.; Qi, Q. Simulation Analysis of Wind Turbine Grid Operation Based on PSCAD. *IOP Conf. Ser. Mater. Sci. Eng.* **2019**, *631*, 042027. <https://doi.org/10.1088/1757-899X/631/4/042027>.
4. Wu, H.; Wang, L.; Xing, H.; Liu, Z.; Zhang, A. Modeling and simulation of extra high voltage magnetically controlled shunt reactor based on PSCAD. *J. Phys. Conf. Ser.* **2023**, *2584*, 012077. <https://doi.org/10.1088/1742-6596/2584/1/012077>.
5. Rusina, A.G.; Serohvostov, D.A.; Kolesnikov, D.I.; Arestova, A. PSCAD as a Tool for Development of a Simulation Model for a Power System with Renewable Energy Sources. In Proceedings of the 2020 Ural Smart Energy Conference (USEC), Yekaterinburg, Russia, 13–15 November 2020; pp. 39–42. <https://doi.org/10.1109/USEC50097.2020.9281187>.
6. Hou, Z.; Liu, J.; Shao, Z.; Ma, Q.; Liu, W. Machine Learning Innovations in Renewable Energy Systems with Integrated NRBO-TXAD for Enhanced Wind Speed Forecasting Accuracy. *Electronics* **2025**, *14*, 2329. <https://doi.org/10.3390/electronics14122329>.
7. Liu, J.; Hou, Z.; Wang, B.; Yin, T. Optimizing Microgrid Energy Management via DE-HHO Hybrid Metaheuristics. *Comput. Mater. Contin.* **2025**, *84*, 4729–4754. <https://doi.org/10.32604/cmc.2025.066138>.
8. Adar, M.; Babay, M.-A.; Boussif, M.; Khaouch, Z.; Abbassi, Z.; Najih, Y.; Mabrouki, M. Optimization of Photovoltaic System Modelling: A Comparative Study and Experimental Validation Using Bond Graph Methodology and a Genetic Algorithm. In *Applied Mathematics, Modeling and Computer Simulation*; IOS press: Amsterdam, The Netherlands, 2024. <https://doi.org/10.3233/atde240825>.
9. Zhu, J.; Gao, W.; Li, Y.; Guo, X.; Zhang, G.; Sun, W. Power System State Estimation Based on Fusion of PMU and SCADA Data. *Energies* **2024**, *17*, 2609. <https://doi.org/10.3390/en17112609>.
10. Rehman, H.U.; Ritschel, U. DC-Link Voltage Control and Power Management of BESS Integrated Wind Power System Using PSCAD. In Proceedings of the 2024 IEEE 4th International Conference on Power, Electronics and Computer Applications (ICPECA), Shenyang, China, 26–28 January 2024; pp. 776–781. <https://doi.org/10.1109/ICPECA60615.2024.10471133>.
11. Gupta, P.; Gajbhiye, R.; Gajjar, G.; Navalkar, P.; Soman, S. Towards a Three Phase Local Substation IT Calibrator using PMU Data. In Proceedings of the 2022 22nd National Power Systems Conference (NPSC), New Delhi, India, 17–19 December 2022; pp. 1–6. <https://doi.org/10.1109/NPSC57038.2022.10068914>.
12. Wakti, M.H.; Putranto, L.M.; Hadi, S.P.; Yasirroni, M.; Marsiano, A.F.D. PMU Location Determination in a Hybrid PMU-SCADA System. In Proceedings of the 2020 12th International Conference on Information Technology and Electrical Engineering (ICITEE), Yogyakarta, Indonesia, 6–8 October 2020; pp. 245–250. <https://doi.org/10.1109/ICITEE49829.2020.9271728>.
13. Pavičić, I.; Holjevac, N.; Ivanković, I.; Brnobić, D. Model for 400 kV Transmission Line Power Loss Assessment Using the PMU Measurements. *Energies* **2021**, *14*, 5562. <https://doi.org/10.3390/en14175562>.
14. Xu, S.; Liu, H.; Bi, T. Field PMU Test and Calibration Method—Part I: General Framework and Algorithms for PMU Calibrator. *J. Mod. Power Syst. Clean Energy* **2022**, *10*, 1507–1518. <https://doi.org/10.35833/MPCE.2021.000526>.
15. Blackwelder, A.; Niraula, P.; Brescia, J.; Kelk, L.; Ramabhotla, S. Modeling and Simulation of a Microgrid Using PSCAD. In Proceedings of the 2025 57th North American Power Symposium (NAPS), Knoxville, TN, USA, 26–28 October 2025; pp. 1–6. <https://doi.org/10.1109/NAPS66256.2025.11272353>.
16. Lin, L.; Wu, W.; Shangguan, Z.; Wshah, S.; Elmoudi, R.; Xu, B. HPT-RL: Calibrating Power System Models based on Hierarchical Parameter Tuning and Reinforcement Learning. In Proceedings of the 2020 19th IEEE International Conference on Machine Learning and Applications (ICMLA), Miami, FL, USA, 14–17 December 2020; pp. 1231–1237. <https://doi.org/10.1109/ICMLA51294.2020.00194>.
17. Masmali, M.; Elimy, M.I.; Fterich, M.; Touti, E.; Abbas, G. Comparative Studies on Load Frequency Control with Different Governors connected to Mini Hydro Power Plant via PSCAD Software. *Eng. Technol. Appl. Sci. Res.* **2024**, *14*, 12975–12983. <https://doi.org/10.48084/etasr.6722>.
18. Li, A.; Liu, C.; Su, C.; Wang, Y.; Xu, Y.; Kong, L. Study on the Topological Transformation of Electromagnetic Transient Models in PSCAD and ADPSS. In Proceedings of the 2024 IEEE 8th Conference on Energy Internet and Energy System Integration (EI2), Tianjin, China, 29 November–2 December 2024; pp. 931–935. <https://doi.org/10.1109/EI264398.2024.10991848>.
19. Sandhya, K.; Chatterjee, K. Study the impact of renewable and non-renewable energy sources on micro-grid using time series data based information transfer. *Energy Rep.* **2024**, *11*, 4957–4966. <https://doi.org/10.1016/j.egy.2024.04.051>.
20. Lee, J.S.; Kang, S.H. A study on a current transformer modelling method considering core magnetic saturation characteristics for PSCAD/EMTDC. In Proceedings of the 18th International Conference on Developments in Power System Protection (DPSP APAC 2025), Melbourne, Australia, 8–11 January 2025; pp. 495–500. <https://doi.org/10.1049/icp.2025.0572>.
21. Lee, K.-M.; Park, C.-W. High-Precision Analysis Using μ PMU Data for Smart Substations. *Energies* **2024**, *17*, 4907. <https://doi.org/10.3390/en17194907>.

22. An, J.; Jung, D.; Jeong, K.; Ji, C.; Hong, T.; Lee, J.; Kapp, S.; Choi, J. Energy-environmental-economic assessment of green retrofit policy to achieve 2050 carbon-neutrality in South Korea: Focused on residential buildings. *Energy Build.* **2023**, *289*, 113059. <https://doi.org/10.1016/j.enbuild.2023.113059>.
23. Martin, K.E.; Benmouyal, G.; Adamiak, M.G.; Begovic, M.; Burnett, R.O.; Carr, K.R. IEEE Standard for Synchrophasors for Power Systems. *IEEE Trans. Power Deliv.* **1998**, *13*, 73–77. <https://doi.org/10.1109/61.660853>.

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