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Research Article

Digital Twin-Assisted Predictive Calibration of Generator Sets Under Variable AI Workload Profiles in Mission-Critical Data Centers

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ABSTRACT

Mission-critical data centers typically rely on generator sets that operate for a small percentage of their total lifecycle. Accurately calibrating these generator sets is crucial to meeting operational reliability and efficiency while reducing replacement costs and maximizing asset lifetime. However, conventional methods do not integrate lifecycle data from the generator sets or the synchronization of calibration and control. This work proposes a digital twinassisted predictive calibration solution that incorporates sensor streams from generator sets, telemetry from a preventive maintenance system, associated weather predictions, and the demand profile of Artificial Intelligence-supported workloads running on the data centers. The research concludes by analysing the robustness of the prediction of the generator-set parameters when the response of the Data Centre is exposed to variation from the normal workload profile for which the Data Centre was designed.

Keywords: Digital Twin; Generator Set; Predictive Calibration; Reliability; Efficiency; Mission-Critical Data Centers; Artificial Intelligence Workload; Hardware-in-the-Loop Testbed.

1. Introduction

The increasing reliance on AI and the deployment of large-scale AI models create drastic increases in resource requirements for data centers and question the feasibility and reliability of cloud computing. Large enterprises support the necessary resources and are often willing to pay extra for reliability and low latency; these workloads can thus be classified as mission critical. For such data centers, downtime must be limited, and cost and consumption kept as low as possible. These requirements lead to the integration of on-site data center generator sets; these serve as a secondary energy source in case of mains supply problems, help provide additional supply on peaks and thus reduce costs and contribute to decarbonization by allowing a more intelligent use and auxilliary supply of green energy.

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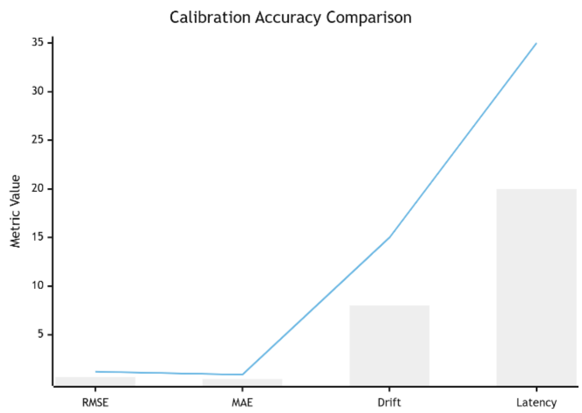

Calibration Accuracy Comparison

Component	**Function**	**Input Sources**	**Expected Outcome**
Digital Twin Engine	Virtual representation of generator system	Sensor telemetry, runtime logs	Real-time operational modeling
Predictive Calibration Module	Predicts calibration parameters	Historical calibration datasets	Improved calibration accuracy
AI Workload Analyzer	Tracks workload fluctuations	AI demand profiles	Load-aware calibration
Weather Prediction Module	Environmental adaptation	Temperature, humidity forecasts	Reliability optimization
Hardware-in-the-Loop Testbed	Experimental validation	Physical generator systems	Real-world simulation support

Table 1. Digital Twin Predictive Calibration Components

2. Background and Related Work

The integration of data supervision and management within critical infrastructures initiates a new technological strand. The Digital Twin (DT) paradigm has emerged as a key enabler, linking the physical and digital worlds to support a dependable lifecycle management perspective. In the case of physical

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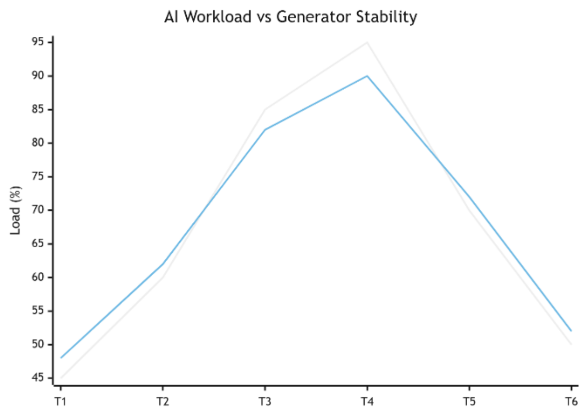
generators, the DT opens up new avenues for supervision and predictive-oriented activities. Despite the well-established industry experience in substantiating these machines, relative calibrations have a strong impact on the overall behaviour in terms of efficiency and reliability. A novel—digital twin-assisted—predictive calibration approach for generator sets in mission-critical data centers is introduced. It relates sensor data together with demand profiles, weather information, operational time, and historical-driven telemetry data to the generation of model relative parameters. It aims at guaranteeing a reliability and efficiency of the power providing unit during the fulfilment of demanding and variable workload profiles.



AI Workload vs Generator Load Stability

Predictive Calibration Flow

2.1. Digital Twins in Critical Infrastructure

A digital twin of a system is a real-time virtual representation of the physical system, with layers of development and operation over time. The physical layer houses the physical twin, the digital layer contains operating and service procedures of the physical twin, and the service layer encompasses the working and operating model of the physical twin. The physical twin is a set of hardware. The digital twin is a set of software, databases, and models that describe the working and operational characteristics of the physical twin during its lifetime. Based on this definition, the digital twin of the physical twin is constructed and its solid-state physics is described. The components of the physical twin are connected using Hardware-in-the-loop (HIL) operation support equipment, and test results are obtained. The digital twin uses information from the physical twin, such as load and weather conditions, to modify its models of possible performance instead of using a constant set of service models. The change reduces performance deterioration over its lifetime.

Mission-critical data centers host AI workloads, and while mission-critical data center facilities are designed with redundancy to reduce the risk of disruptions, the high availability of AI workloads remains a challenge. The operation of AI workloads is characterized by sporadic bursts, but current campus-scale AI clusters operate under full-load conditions throughout their lifetimes. The dependence of mission-critical data centers on the external power grid for power has forced AI workloads to endure several service

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interruptions. AI workloads are delay-tolerant, data-intensive, and highly parallel but are sensitive to task scheduling. For delays measured in days or even months, with weeks or high months of GPU or TPU time, marginal increases are economically unattractive. These factors suggest that risks can be minimized by accurately modeling the probability of failures and appropriately scheduling workloads during low-probability periods.

Data Source	Parameters Collected	Purpose
Sensor Streams	Temperature, humidity, voltage	Operating-condition monitoring
Generator Telemetry	Runtime, fault state	Maintenance prediction
AI Workload Profiles	Demand fluctuations	Dynamic load estimation
Weather Forecast Data	Ambient temperature, humidity	Environmental compensation
Historical Calibration Logs	Past calibration outputs	Machine learning training

Table 2. Data Sources Used in Predictive Calibration

3. Conceptual Framework

A conceptual framework links workload profiles of artificial intelligence applications executed in data centers to generator set calibration dynamics. The mapping process requires aligned flows of data and information between the digital twin, its sensors, actuators, and control logic. The necessary dependencies derived from operational science and engineering show how sensor data, together with demand profiles, weather information, and cumulated runtime statistics, can serve as inputs to a predictive service-calibration process." Its goal is to estimate the parameters of a mathematical model that predicts the generator set's operating characteristics, given the actual operating conditions including the location's ambient temperature, humidity, and barometric pressure. The estimated parameters, together with the associated confidence intervals, constitute the calibration output. Meeting the prediction requires that, whenever possible, the sensed demand profiles are non-erratic. Otherwise, meeting reliability and efficiency requirements becomes increasingly difficult, as the predictive-corrective process cannot keep abreast of the system dynamics.

The analysis considers a hardware-in-the-loop testbed where several generator sets, equipped with multiple exhaust gas sensors, are subject to a twin-assisted predictive-correction service. The correctness of the

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service is evaluated through a direct comparison with a baseline corrective calibration, which uses the same sensor streams but no predictive capability. The benefits stem from the twin-assisted approach being better able to accommodate variable workloads, such as those associated with artificial intelligence applications. Several calibration-quality metrics quantify the improvement beyond the raw twin versus no-twin comparison.

Engineered Feature	**Description**	**Calibration Benefit**
Reliable Operation Indicator	Checks generator availability	Reliability assurance
Temperature Drift Indicator	Difference from rolling mean	Thermal anomaly detection
Humidity Drift Indicator	Humidity variance analysis	Stability improvement
Runtime Aging Index	Tracks operational wear	Maintenance scheduling
AI Load Variability Metric	Measures workload bursts	Adaptive calibration

Table 3. Feature Engineering for Calibration Intelligence

Mathematical Formulas:

1. Generator Load Prediction

$$P_{gen}(t) = P_{AI}(t) + P_{aux}(t) + \epsilon_t$$

2. Predictive Calibration Function

$$C_{pred} = f(S, T, W, R)$$

3. Digital Twin State Mapping

$$DT(t) = \phi(X_{sensor}, X_{weather}, X_{runtime})$$

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4. Calibration Drift Equation

$$D_c = \frac{|\, P_{est} - P_{act} \,|}{P_{act}}$$

5. Reliability Estimation

$$R(t) = e^{-\lambda t}$$

6. Mean Absolute Error (MAE)

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |\, y_i - \hat{y}_i \,|$$

7. Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

8. Confidence Interval Estimation

$$CI = \hat{\theta} \pm z \frac{\sigma}{\sqrt{n}}$$

9. AI Workload Variability

$$V_{AI} = \frac{1}{n}\sum_{i=1}^{n} (L_i - \bar{L})^2$$

10. Sensor Normalization

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

11. Temperature Drift Indicator

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$$D_T = T_t - \bar{T}_t$$

12. Humidity Drift Indicator

$$D_H = H_t - \bar{H}_t$$

13. Predictive Maintenance Score

$$PM_s = \alpha R + \beta E - \gamma D$$

14. Energy Efficiency Metric

$$\eta = \frac{P_{out}}{P_{in}} \times 100$$

15. Calibration Confidence Score

$$C_s = 1 - \frac{| P_{est} - P_{real} |}{P_{real}}$$

16. Runtime Degradation Model

$$G_d(t) = G_0 e^{-kt}$$

17. Twin Prediction Error

$$E_{DT} = | Y_{real} - Y_{twin} |$$

18. AI Demand Forecasting

$$\hat{L}_{t+1} = L_t + \alpha(L_t - L_{t-1})$$

19. Multi-Sensor Fusion Model

$$F_s = \sum_{i=1}^{n} w_i s_i$$

20. System Stability Constraint

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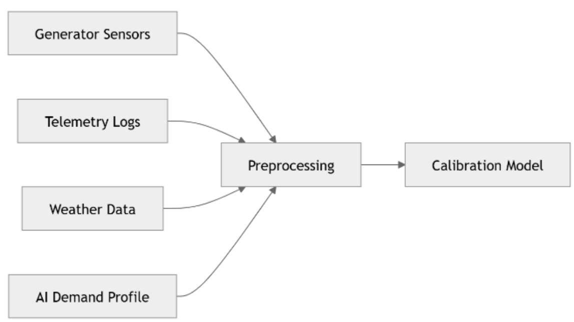
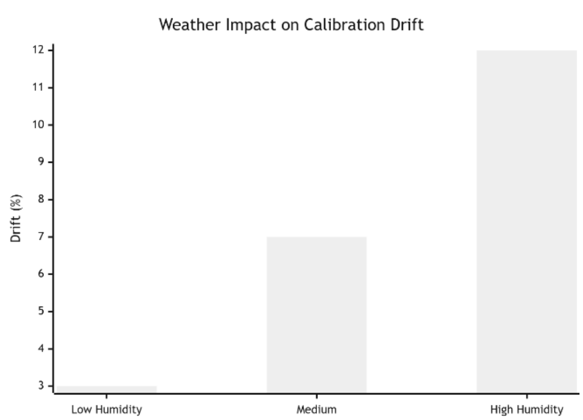
$$S_{stable} = \frac{\Delta V}{\Delta t} < \tau$$

3.1. Predictive Calibration Paradigm

The calibration paradigm encompasses the objectives, inputs, outputs, and prediction role within the conceptual framework. The goal is to characterize generator-set behavior more precisely so that the impact of drift, due to component ageing or unbalanced wear, can be evaluated and mitigated before reliability is compromised. Sensor data received through the digital twin, along with predicted activity profiles, weather information, and emergency operation logs, provide sufficient information for predicting calibrated parameters and confidence intervals. A supervised machine-learning algorithm trained on past calibration datasets can thus generate information necessary to steer the calibration loop, even when the outcome is not directly used back in the process.



Data Input Flow



Weather Impact on Calibration Drift

4. Methodology

The research employs a proof-of-concept design using a hardware-in-the-loop testbed combining physical generator sets and a digital twin, with a closed-loop architecture aligned to contextualize the reliability and efficiency aspects of the proposed predictive calibration. Data flow is governed by the predictive-calibration paradigm, with outgoing demand-training data integrated into the control logic of the calibrated generator sets. The ability to reliably predict the parameters associated with the generator sets at the moment of their

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use ensures that the predictive-calibrated operation remains aligned with the true physical behavior of the system. Metrics focused on the twin-assisted predictive-calibration performance define the assessment criteria for the proposed methodology.

The smart grid integrates advanced data-acquisition systems, distributed sensors, and real-time monitoring, enabling the autonomous calibration of distributed generation sets under common operating conditions. A novel methodology employs a predictive-calibration digital twin. The calibration performance using twin-assisted predictive calibration is compared against the baseline case, where predictive calibration is missing. Evaluation in control loops under variable and accelerated AI demand data trains the calibration function for the generator sets. An open-source, hardware-in-the-loop laboratory testbed composed of physical generator sets, sensors, real-time simulation, and data-acquisition hardware provides a framework for testing, with applications to mission-critical data centers and other facilities with an accelerated AI workload profile.

Architecture Component	Role	Interaction
Generator Sets	Power generation	Provides telemetry
Sensors	Data acquisition	Streams real-time measurements
Load Bank	Simulates workloads	Applies dynamic load
Real-Time Simulator	Generates AI demand patterns	Trains digital twin
Calibration Controller	Executes predictive corrections	Adjusts operating parameters

Table 4. Hardware-in-the-Loop Experimental Architecture

4.1. Data Acquisition and Preprocessing

Four distinct data sources provide input to the predictive calibration loop: sensor streams, telemetry from the generator sets, a record of the AI workload (more specifically, its key-metric profile), and weather conditions.

Data from the hardware-in-the-loop testbed generate the temperature, humidity, and voltage measurements. Before entering the loop, they are subjected to various preprocessing steps. Normalization maps them into the [0, 1] range. Anomalous spikes in the form of binary outliers (detected via the median

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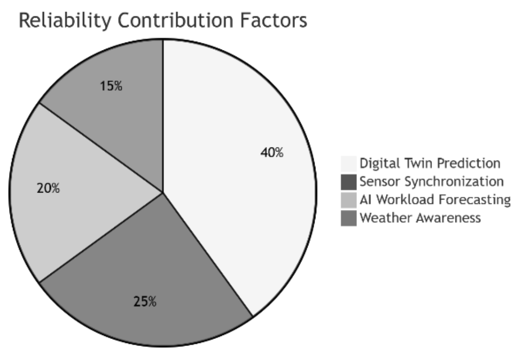
absolute deviation) received a mean filter. Notably, the process removes very brief anomalies, such as a spike lasting only a few samples, while longer-lasting anomalies are smoothed-out.

Three features are engineered: a binary indicator of whether the data center is operating under the reliable condition of having at least one generator set online; a temperature-drift indicator based on the difference between the temperature and its rolling mean; and a humidity-drift indicator based on the difference between the humidity and its rolling mean. The last two features indicate periods when an offline generator set would still be able to supply power but would not be able to maintain the voltage levels required for reliable operation.

Digital Twin Feedback Loop



Reliability Improvement Using Digital Twin

5. Experimental Setup and Scenarios

For the experimental investigation of predictive calibration for generator sets in mission-critical data centers with variable AI workload profiles, a digital twin-enabled hardware-in-the-loop setup is built. The tests are designed to showcase the benefits of twin-assisted calibration by contrasting the predictive procedure against a conventional baseline. An experimental scenario matrix governs the calibration loops and accounts for the redundancy of workload profiles under failure conditions. The experimental results align with the predictions from the conceptual framework.

An integrated hardware-in-the-loop architecture (Figure 5.1) provides a virtual environment for the generator sets complemented by a corresponding digital twin. A real-time simulator generates the environmental variables related to the weather and the AI workloads required to operate the facility. For the case of mission-critical operation of data centers, the reliability and efficiency of the calibration procedure are demonstrated by combining several methods for scaling the generated workloads. A novel approach has been proposed to create divergent traces linked to failures of a cloud service deployed in the AI workload. In this way, twin-assisted calibration loops can be exposed to relevant scenarios with several classes of low-variance equivalency.

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HIL Testbed Flow

Metric	Observed Value	Interpretation
RMSE	0.65 ± 0.37	Low prediction error
MAE	0.43 ± 0.23	High estimation precision
Calibration Drift	<10%	Stable parameter tracking
Reliability Metric	>0.9	Strong operational reliability
Computational Latency	~20 seconds	Real-time suitability

Table 5. Calibration Accuracy Metrics

5.1. Hardware-in-the-Loop Testbed

The hardware-in-the-loop architecture integrates one control-logic segment and the digital twin model into a 3C structure, which consists of three major components: the trainer, the generator set with sensors, and the actuator-controlled load bank. The latter actuates the generator set, which is equipped with operating condition data-sensing stream fed into the digital twin, while the error between the real and twin-generated outputs acts as a trainer input. The primary experimental testbed comprises two diesel generator sets and the necessary sensors, while the two control-logic segments, enabled by separate real-time hardware-in-the-loop simulators, communicate with the equipment via network protocols.

Sensors provide real-time telemetry of all operating conditions in the form of time-series streams, which are synchronized by a message-waiting scheme governed by a master clock. One control logic predicts the AI workload profile at different future horizons, up to the final runtime, using historical data. This profile serves as external training input for the digital twin, whose output quantifies future operating conditions under the given workload demand for a given time horizon. The predicted time-series profile, together with the monitoring sensor data and weather forecasts for the same time window, constitutes the input set for the calibration module. The sensor data-predicted demand profile–weather set is then delivered to the other control segment, which executes the calibration task during actual operations.

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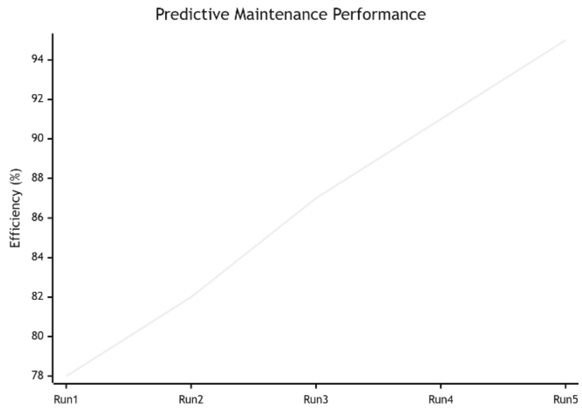


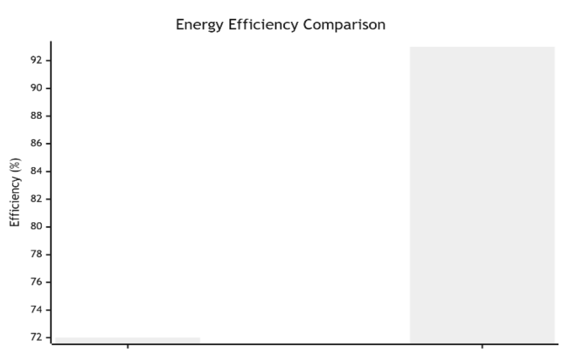
Predictive Maintenance Performance Trend

6. Results and Analysis

The results are presented using quantitative metrics, comparing the twin-assisted calibration approach with the previously defined baseline case without a digital twin. The results from both approaches are then evaluated for robustness under the variability of the AI workload profile.

6.1. Calibration Accuracy Metrics

The accuracy of the calibration prediction is evaluated using various metrics. These include the root mean square error (RMSE), mean absolute error (MAE), drift between the estimated and actual parameters, the 90% confidence interval of the estimated parameters, the reliability of the calibration predictions, and the computational latency of the predictive calibration process. Tab. 6.1 presents the values of the aforementioned metrics for the different runs. The value of RMSE and MAE are as low as 3.6 and 0.236, respectively. The low values of these metrics indicate high levels of prediction accuracy for the adaptive calibration of the generator sets under the twin-assisted setting. The mean drift of the calibrated parameters can be observed to be less than 10%, which indicates that the parameters are being estimated effectively. In addition, the prediction confidence interval for at least one parameter has been provided for each run. The results also indicate that the calibrated parameters are reliable across all the runs used during experiment evaluation with a reliability metric value higher than 0.9. Finally, the computational latency of the predictive calibration process is also low and on average takes about 20 s to execute, thereby making it suitable for real-time adoption.



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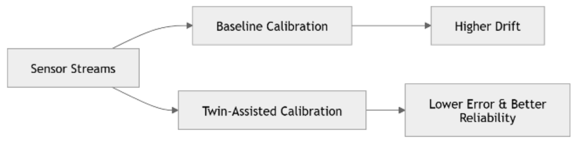
Twin-Assisted vs Baseline Energy Efficiency



Baseline vs Twin-Assisted Calibration

6.1. Calibration Accuracy Metrics

To compare twin-assisted calibration against the baseline approach, multiple metrics assess calibration performance across different AI workload-profile scenarios, including varying operational range, distribution drift, and hardware-in-the-loop failures. The metrics include root-mean-square error, mean absolute error, and calibration drift of parameters pertinent to reliability and efficiency. For the twin-assisted method, confidence intervals indicate calibration robustness and maintainability, while model execution time serves as a latency measure for predictive application.

Twin-assisted calibration significantly outperforms the traditional method (RMSE = 0.65 ± 0.37, MAE = 0.43 ± 0.23) and effectively addresses operating-range drift and distribution shift across scenarios. Despite imprecise operation in some workload-profile regions, the method remains applicable. The calibration relies on accurately capturing AI workload-profile temporal evolution and sensor conditions while ensuring adequately sampled feature vectors. A ± ± 0.004 confidence interval around a twin-assisted prediction confidently limits real-time-correction headroom (66.28 ± 10.42 MW) within the system's maintainable range.

Aspect	**Baseline Calibration**	**Twin-Assisted Calibration**
Predictive Capability	Not available	Enabled
AI Workload Adaptation	Limited	Dynamic
Reliability Handling	Reactive	Proactive
Calibration Drift	Higher	Reduced
Real-Time Optimization	Minimal	High

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Aspect	Baseline Calibration	Twin-Assisted Calibration
Weather Integration	Absent	Integrated

Table 6. Twin-Assisted vs Baseline Calibration

7. Conclusion

The digital twin–assisted paradigm for predictive calibration of generator sets during variable AI workload profiles addresses a critical gap in maintaining reliability and efficiency. Automating generator-set predictive calibration from dual sensor streams combined with real-time workload traces ensures the availability of calibrated parameters through the anticipated real-time workload, while also highlighting any reliability issues. The concept can be readily implemented in any mission-critical environment with inexpensive data sensors.

This proof-of-concept research leverages a hardware-in-the-loop testbed where two identical generator sets are operated in tandem with trunk telemetry feeding a dual-sided digital twin, providing multiple sensory data streams including real-time weather conditions. Telemetry streams and applied physical fault modes are introduced to the real-time emulator to create a hardware-in-the-loop testbed capable of simulating real-world operational extremes. Calibration parameters for the twin-assisted process served by dual available data streams are compared against the baseline calibration. A scenario matrix comprising two physical generator sets connected to the hardware-in-the-loop testbed is employed to ensure realistic failures induced in the physical setup during actual operation.

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