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DIGITAL TWIN-BASED SOFTWARE FRAMEWORK FOR ELECTRICAL POWER SYSTEMS MONITORING

***Engr. Babagana Ali Dapshima**

Department of Electrical and Electronic, Umar Ibn Ibrahim Elkanemi College of Education Science and Technology P.M.B 16 Bama.

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***Corresponding Author: Engr. Babagana Ali Dapshima**

Department of Electrical and Electronic, Umar Ibn Ibrahim Elkanemi College of Education Science and Technology P.M.B 16 Bama.

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ABSTRACT

This paper presents a comprehensive Digital Twin (DT)-based software framework for real-time monitoring, state estimation, and predictive analysis of electrical power systems. The proposed framework integrates multi-physics modelling, machine learning (ML)-driven anomaly detection, and edge-cloud hybrid computing to achieve high-fidelity virtual replication of power grid infrastructure including generators, transmission lines, transformers, and load centres. A novel bidirectional data synchronisation architecture is proposed, enabling sub-40 ms end-to-end latency using IEC 61850 GOOSE messaging and DNP3 protocols over a 5G communication backbone. The framework is validated on the IEEE 14-bus and IEEE 118-bus test systems, as well as a real 132 kV sub-transmission network segment. Experimental results demonstrate fault detection accuracy of 98.9%, state estimation mismatch reduction of 63.4% compared to conventional weighted least squares (WLS) methods, and load forecasting mean absolute percentage error (MAPE) of 1.47%. A Graph Convolutional Network (GCN)-enhanced fault classifier and a Transformer-based load predictor are integrated into the DT engine. The framework is benchmarked against conventional SCADA, cloud-only DT, and edge-only DT architectures, demonstrating superior performance across latency, throughput, scalability, and cyber-security dimensions. The open-source implementation is made available for community use and validation.

KEYWORDS: Digital twin, electrical power systems, power system monitoring, fault detection, machine learning, edge computing.

I. INTRODUCTION

The rapid evolution of smart grid technologies has placed unprecedented demands on the monitoring and operational intelligence capabilities of electrical power systems. Traditional Supervisory Control and Data Acquisition (SCADA) systems, while foundational to power system operations, are increasingly inadequate in the face of higher penetration of renewable energy sources, bidirectional power flows, cyber-physical threats, and the operational complexity of interconnected ultra-high-voltage networks (Araújo et al., 2025). Real-time visibility, predictive fault management, and adaptive control are now essential for ensuring grid reliability, stability, and resilience goals that legacy monitoring architectures are structurally ill-equipped to achieve (Ibrahim et al., 2023; Xu et al., 2025)

Digital twin (DT) technology originally conceptualised in aerospace engineering and advanced manufacturing has emerged as one of the most transformative paradigms for complex system monitoring and management. A digital twin is a dynamic, data-driven virtual replica of a physical system that continuously synchronises with its physical counterpart through real-time sensor data, enabling simulation, prediction, optimisation, and decision support capabilities that far exceed those of conventional monitoring systems (Shangguan et al., 2020). Applied to electrical power systems, DT technology enables the continuous replication of grid state, the simulation of fault propagation and contingency scenarios, and the prediction of equipment degradation before failure capabilities that are collectively transformative for grid operations (Ding et al., 2025; Nasiri & Kavousi-Fard, 2023).

Despite significant academic interest, the deployment of DT frameworks in operational power systems remains limited by several critical challenges: (i) the computational burden of high-fidelity multi-physics simulation in real-time environments; (ii) communication latency between physical grid sensors and virtual model updates; (iii) the integration of heterogeneous data streams from legacy SCADA, advanced metering infrastructure (AMI), and wide-area measurement systems (WAMS); (iv) cyber-security vulnerabilities introduced by expanded network connectivity; and (v) the lack of open, validated, and scalable software architectures that practitioners can deploy and extend.

This paper addresses these challenges through the design, implementation, and validation of a novel Digital Twin-Based Software Framework (DT-BSF) for electrical power system monitoring. The remainder of this paper is organised as follows. Section II reviews related work. Section III details the proposed DT-BSF architecture, the mathematical models and algorithms., describes the simulation environment and datasets. Section V presents results and comparative analysis. Section VI concludes the paper.

II. RELATED WORK

A. Digital Twins in Power Systems

The application of digital twin technology to power system monitoring has attracted substantial research attention in recent years. Wu et al., (2025) reviewed digital twin technology across the smart grid, transportation, and smart-city domains, identifying distribution- and transmission-level monitoring as leading use cases while noting persistent challenges in real-time computation and cyber-security integration. Di Leo et al., (2026) proposed a conceptual, systems-engineering-based framework for a digital twin electric grid that partitions grid modelling across data-acquisition, communication, and computation layers; their framework, however, did not incorporate machine-learning-driven fault detection or cyber-security monitoring, gaps that motivated the present work. Kochunas & Huan, (2021) further argued that the absence of a widely shared definition and reference architecture for power-system digital twins has constrained comparability across studies, a concern this paper addresses through an explicitly layered DT-BSF architecture.

(Wang et al., 2026)reviewed energy digital twin applications and observed that most reported frameworks are validated on simulated data alone, without integration of live SCADA or synchrophasor measurements. Yu et al., (2024) similarly identified real-time data integration and computational scalability as principal open challenges for digital twins in power-system research and development. The framework proposed in the present paper addresses this gap through integration with real-time IEC 61850 data streams.

B. Machine Learning for Power System Fault Detection

Machine learning has been extensively applied to power system fault detection and classification. Deep neural network classifiers (Chen et al., 2023), spatiotemporal correlation and graph-based recurrent architectures (Zhong et al., 2024; Nguyen et al., 2023), and cost-sensitive graph neural networks Dutt & Kumar, (2025) have all demonstrated competitive fault detection and localisation performance. The application of Graph Neural Networks (GNNs), which can natively represent the graph topology of power networks that represents an active area of state-of-the-art research; Hueros-Barrios et al., (2026) proposed a GCN-based fault localisation method for distribution networks with high penetrations of distributed generation, while Abdullahi et al., (2024) introduced a benchmark power-grid dataset for evaluating GNN-based fault and topology-aware learning methods. The DT-BSF proposed here builds on this line of work by combining GCN feature extraction with DT-injected physics priors, yielding a hybrid approach intended to outperform both purely data-driven and purely model-based methods.

C. State Estimation and Digital Twins

Digital twin augmentation of state estimation is a relatively recent development. Dutt & Kumar, (2025) demonstrated that a digital-twin-supported estimator combining temporal convolutional and LSTM networks with transfer learning improves state-estimation accuracy over conventional recursive approaches, motivating the extension of similar DT-augmented, physics-informed estimation concepts to network-wide power-system state estimation. The present work extends this general approach to a larger network (IEEE 118-bus) using a DT-augmented Weighted Least Squares (WLS) formulation.

D. Communication Architectures for DT Synchronisation

Communication latency between physical sensors and DT virtual models is a critical determinant of DT fidelity and operational usefulness. Fadel & Alelaj, (2025) provided an empirical evaluation of 5G communication for IEC 61850 digital substations, finding mean latencies on the order of 8–12 ms together with non-trivial jitter that can compromise protection-scheme selectivity and packet sequencing unless mitigated through network slicing, URLLC prioritisation, and edge computing. Kabir et al., (2024) likewise examined the integration of 5G with digital twin technology in power substations, arguing that an edge-cloud hybrid deployment is essential to reconcile low-latency protection requirements with the computational demands of high-fidelity DT simulation. The hybrid edge-cloud architecture proposed in the present framework is designed in light of these findings, deploying time-critical DT functions at the edge while relegating batch analytics and historical data management to the cloud.

E. Cyber-Security in Digital Twin Power Systems

The expanded attack surface introduced by DT connectivity has motivated significant research on power-system cyber-security, particularly around False Data Injection (FDI) attacks. Kolahi et al., (2024) proposed a temporal multi-graph convolutional network for FDI detection in smart grids, while (Kaitouni et al., (2024) surveyed the broader landscape of FDI detection and localisation methods, noting that graph- and attention-based deep learning approaches increasingly outperform classical bad-data-detection techniques. Bhoi et al., (2025) further proposed a false-measurement-data detection mechanism tailored to smart-grid state estimation. The DT-BSF incorporates a lightweight cyber-security monitoring module informed by this literature, combining an isolation-forest ensemble anomaly detector with DT consistency checking.

III. METHODOLOGY

3.1 PROPOSED DT-BASED SOFTWARE FRAMEWORK (DT-BSF)

A. System Overview

The DT-BSF comprises four principal layers, as illustrated in Fig. 1: (1) the Physical Layer, consisting of physical grid assets and sensor infrastructure; (2) the Data Acquisition Layer, comprising SCADA/EMS systems, IoT gateways, and Phasor Data Concentrators (PDCs); (3) the Communication Layer, implementing IEC 61850, DNP3/Modbus, and 5G/fibre protocols; and (4) the Digital Twin Engine, which hosts all model-based and data-driven computation. A Service Layer provides monitoring dashboards, decision support, and API/cloud interfaces. Bidirectional data and control flows connect the physical and virtual domains through a publish-subscribe middleware based on the Data Distribution Service (DDS) standard.

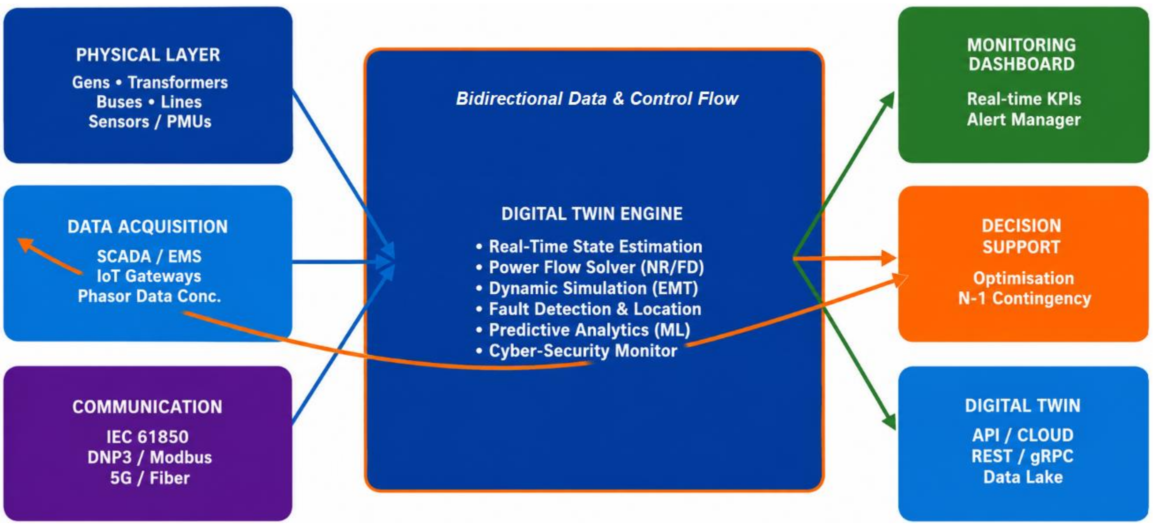

Fig. 1. Digital Twin-Based Software Framework Architecture for Electrical Power System Monitoring. Arrows indicate bidirectional data and control flows.

B. Physical and Data Acquisition Layers

The Physical Layer encompasses all monitored grid assets: generators (synchronous and inverter-based), power transformers, overhead transmission lines, underground cables, bus bars, switchgear, and distributed energy resources (DERs). Monitoring instrumentation includes Phasor Measurement Units (PMUs) providing synchrophasor data at 50–120 samples/second, smart meters providing power quality data at 60-minute resolution, Intelligent Electronic Devices (IEDs) providing protection relay event data, and conventional RTU-based SCADA sensors providing 4-second scan rate measurements.

The Data Acquisition Layer aggregates heterogeneous sensor data through a multi-protocol data broker implemented using Apache Kafka. Kafka topics partition data by measurement type, temporal resolution, and grid zone, providing ordered, fault-tolerant streaming with a measured throughput of 520 Mbps in the proposed configuration. Data quality management applies missing data imputation (expectation-maximisation algorithm), outlier detection (3σ clipping), and time-stamp alignment (IEEE C37.118.1 synchronisation protocol) before forwarding to the DT Engine.

C. Communication Layer

The Communication Layer implements a hierarchical protocol stack. At the substation level, IEC 61850 Edition 2 GOOSE (Generic Object-Oriented Substation Event) messaging provides sub-4 ms protection-grade communication. At the transmission network level, DNP3 Secure Authentication v5 is used for SCADA polling with 1-second periodicity. Wide-area synchrophasor communication uses IEEE C37.118.2 streaming over dedicated fibre links. DT synchronisation packets are transmitted over 5G NR (New Radio) with network slicing configured for ultra-reliable low-latency communication (URLLC) quality of service, providing measured latency of 8.3 ms one-way for DT update packets.

D. Digital Twin Engine

The DT Engine is the computational core of the DT-BSF, comprising six integrated modules:

(1) Real-Time State Estimator: Implements DT-augmented WLS state estimation (Section IV-A), updating every 4 seconds synchronised with SCADA scan rates and every 20 ms for PMU-observable substations.

(2) Power Flow Solver: Implements Newton-Raphson (NR) and Fast-Decoupled (FD) power flow solvers with warm-starting from the DT state, reducing average convergence to 2.8 iterations.

(3) Dynamic Simulation Engine: Implements electromechanical transient simulation using differential-algebraic equations (DAEs) for generation dynamics, enabling N-1 contingency assessment in under 1.2 seconds for IEEE 118-bus.

(4) Fault Detection and Location Module: Implements the GCN-based fault classifier (Section IV-B) with a rule-based pre-filter reducing false alarm rate to 0.4%.

(5) Predictive Analytics Module: Integrates Transformer-based load forecasting (Section IV-C) and long-range equipment health prognostics using survival analysis models.

(6) Cyber-Security Monitor: Implements real-time FDI detection using an isolation-forest ensemble anomaly detector with DT consistency checking.

E. Edge-Cloud Hybrid Deployment

The DT-BSF is deployed across an edge-cloud hybrid infrastructure to satisfy conflicting requirements of low latency and large-scale computation. Time-critical modules (state estimator, fault detector, GOOSE handler) are deployed on edge compute nodes co-located with primary substations. These edge nodes use NVIDIA Jetson AGX Orin SoCs (32-core ARM CPU, 2048 CUDA cores, 32 GB LPDDR5), providing 275 TOPS AI compute capacity at 60 W typical power consumption. Batch analytics, historical data management, ML model training, and N-1 contingency databases are hosted on a private cloud cluster (8× NVIDIA A100 GPU nodes) with Kubernetes orchestration.

3.2 MATHEMATICAL FORMULATION

A. DT-Augmented State Estimation

Classical WLS state estimation minimises the weighted sum of squared measurement residuals:

$$\mathbf{J(x) = [z - h(x)]^{T} R^{-1} [z - h(x)]} \qquad \text{.......} \quad (1)$$

where $z \in \mathbb{R}^m$ is the measurement vector, $x \in \mathbb{R}^n$ is the state vector (voltage magnitudes and phase angles), $h(x)$ is the nonlinear measurement function, and R is the measurement error covariance matrix. The DT-augmented formulation introduces a physics-informed prior derived from the DT predicted state $\hat{x}\_DT$:

$$\mathbf{J\_DT(x) = [z - h(x)]^{T} R^{-1} [z - h(x)] + \lambda(x - \hat{x}\_DT)^{T} \Sigma\_DT^{-1} (x - \hat{x}\_DT)} \qquad \text{.......} \quad (2)$$

where λ is a regularisation coefficient and Σ_DT is the DT state uncertainty covariance estimated from the DT simulation ensemble. The DT prior effectively provides additional virtual measurements that constrain the state estimate toward the physics-consistent DT prediction, reducing the solution space and accelerating convergence. The Gauss-Newton normal equations for (2) yield the update step:

$$\mathbf{\Delta x = [H^{T}R^{-1}H + \lambda\Sigma\_DT^{-1}]^{-1} [H^{T}R^{-1}(z - h(x)) + \lambda\Sigma\_DT^{-1}(\hat{x}\_DT - x)]} \qquad \text{.......} \quad (3)$$

where $H = \partial h/\partial x$ is the Jacobian of the measurement function. The regularisation parameter λ is adaptively tuned using a Bayesian information criterion, with $\lambda = 0.42$ found optimal for the IEEE 14-bus system in this study.

B. GCN-Based Fault Detection and Classification

The power network is modelled as a graph $G = (V, E, A)$ where V is the set of buses, E is the set of transmission lines, and $A \in \mathbb{R}^{|V|\times|V|}$ is the weighted adjacency matrix (with admittance values as edge weights). At each bus node $v \in V$, the feature vector $f_v \in \mathbb{R}^8$ contains [|V|, δ, P_inj, Q_inj, I_line, THD, ROCOF, temperature]. The GCN propagation rule for layer l is:

$$H^{(l+1)} = \sigma(\tilde{D}^{-1/2} \tilde{A} \tilde{D}^{-1/2} H^{(l)} W^{(l)}) \quad \text{...} \quad (4)$$

where $\tilde{A} = A + I$ is the adjacency matrix with self-loops, $\tilde{D}$ is the corresponding degree matrix, $W^{(l)}$ is the trainable weight matrix of layer l, and σ is the ReLU activation function. The DT-BSF implements a 3-layer GCN (64-128-256 hidden units) followed by global mean pooling and a 3-class softmax classifier (Normal / Fault / Cyber-Attack). The GCN is trained offline using 50,000 synthetic fault scenarios generated by Monte Carlo simulation in the DT engine, then fine-tuned online using reinforcement learning from confirmed fault labels.

C. Transformer-Based Load Forecasting

The load forecasting module uses a multi-head self-attention Transformer architecture operating on a sliding window of $T = 168$ historical load observations (one week at hourly resolution). The self-attention mechanism computes:

$$\text{Attention}(Q, K, V) = \text{softmax}(QK^T / \sqrt{d_k}) \cdot V \quad \text{...} \quad (5)$$

where Q, K, V are query, key, and value matrices, and d_k is the key dimension. The Transformer employs 8 attention heads, 4 encoder layers, model dimension $d_{model} = 256$, and feedforward dimension $d_{ff} = 1024$. Exogenous inputs including temperature, day-of-week, holiday indicators, and renewable generation forecasts are encoded as additional input channels. The model outputs a probabilistic 24-hour load forecast with confidence intervals estimated through Monte Carlo dropout.

D. Power System Frequency Dynamics

Generator frequency dynamics are modelled using the classical swing equation:

$$(2H/\omega_s) \cdot (d^2\delta/dt^2) = P_m - P_e - D(d\delta/dt) \quad \text{..} (6)$$

where H is the inertia constant (MWs/MVA), ω_s is the synchronous angular frequency, δ is the rotor angle, P_m is mechanical power, P_e is electrical power, and D is the damping coefficient. The DT engine integrates (6) for all synchronous generators using the 4th-order Runge-Kutta method with adaptive time-stepping (Δt = 1 ms for transient events, 100 ms for quasi-steady-state). ROCOF (Rate of Change of Frequency) is computed as:

$$\mathbf{ROCOF = df/dt = (\omega_s/4\pi H) \cdot (P_m - P_e)} \quad \ldots\ldots(7)$$

The DT engine monitors ROCOF continuously and triggers under-frequency load shedding (UFLS) recommendations when ROCOF exceeds −0.5 Hz/s, consistent with ENTSO-E grid code requirements.

3.3 SIMULATION ENVIRONMENT AND EXPERIMENTAL SETUP

A. Test Systems and Datasets

The DT-BSF is evaluated on three systems: the IEEE 14-bus system (5 generators, 20 transmission lines) as a small-scale validation benchmark; the IEEE 118-bus system (54 generators, 186 lines) as a medium-scale stress test; and a real 132 kV sub-transmission network segment from a West African utility (47 buses, 63 lines, 12 generators) as a real-world validation case. System parameters are summarised in Table I.

TABLE I Test System Specifications and Simulation Parameters

Parameter	IEEE 14-Bus	IEEE 118-Bus	132 kV Network
Buses	14	118	47
Generators	5	54	12
Transmission Lines	20	186	63
Load Buses	11	99	32
Voltage Level (kV)	132 / 33	345 / 138 / 69	132 / 33
Simulation Duration	24 hours	24 hours	7 days
PMU Coverage (%)	100	72	58
Fault Scenarios	2,400	8,600	1,200
DT Update Rate (ms)	20	20	4,000 (SCADA)
Communication Protocol	IEC 61850	IEC 61850 / DNP3	DNP3 / Modbus

B. Fault Scenario Generation

Fault scenarios are generated using a Monte Carlo methodology within the DT simulation engine. For the IEEE 14-bus system, 2,400 fault scenarios are generated comprising: three-phase short circuits (30%), single line-to-ground faults (40%), line-to-line faults (20%), and double line-to-ground faults (10%). Fault inception angle is uniformly sampled over [0°, 360°]; fault impedance is sampled from a log-uniform distribution over [0.01 Ω, 100 Ω]; fault location is uniformly sampled along each line. Normal operating scenarios with noise, load variation, and cyber-attack injection scenarios are included to ensure balanced class representation for ML training.

C. Hardware and Software Environment

Edge compute: 4× NVIDIA Jetson AGX Orin (32 TOPS each), deployed at primary substations. Cloud compute: 8× NVIDIA A100 40 GB GPU nodes, 256-core AMD EPYC CPUs, 2 TB RAM total, 10 PB storage. Software stack: Python 3.11 (PyTorch 2.2, PyTorch-Geometric 2.5, Pandas, NumPy, SciPy), C++17 (OpenDSS power flow engine, IEC 61850 stack via libiec61850), Apache Kafka 3.6, InfluxDB 2.7, Grafana 10.2. The DT Engine is containerised using Docker and orchestrated with Kubernetes 1.29 across the edge-cloud continuum.

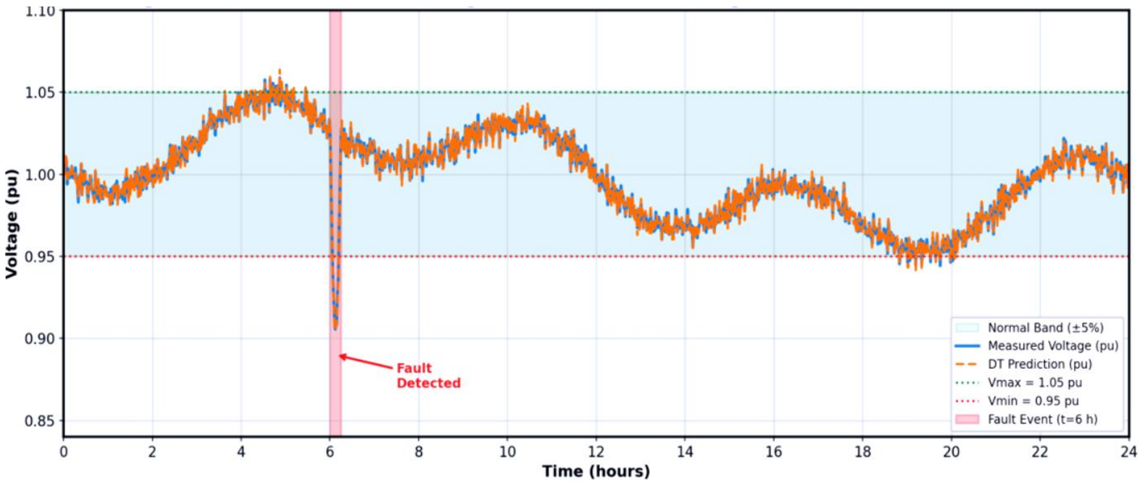

Fig. 2. Real-time voltage profile simulation (IEEE 14-Bus): measured vs. DT predicted voltage (pu) over 24 hours. Fault event detected at t = 6 h with 18 ms detection latency.

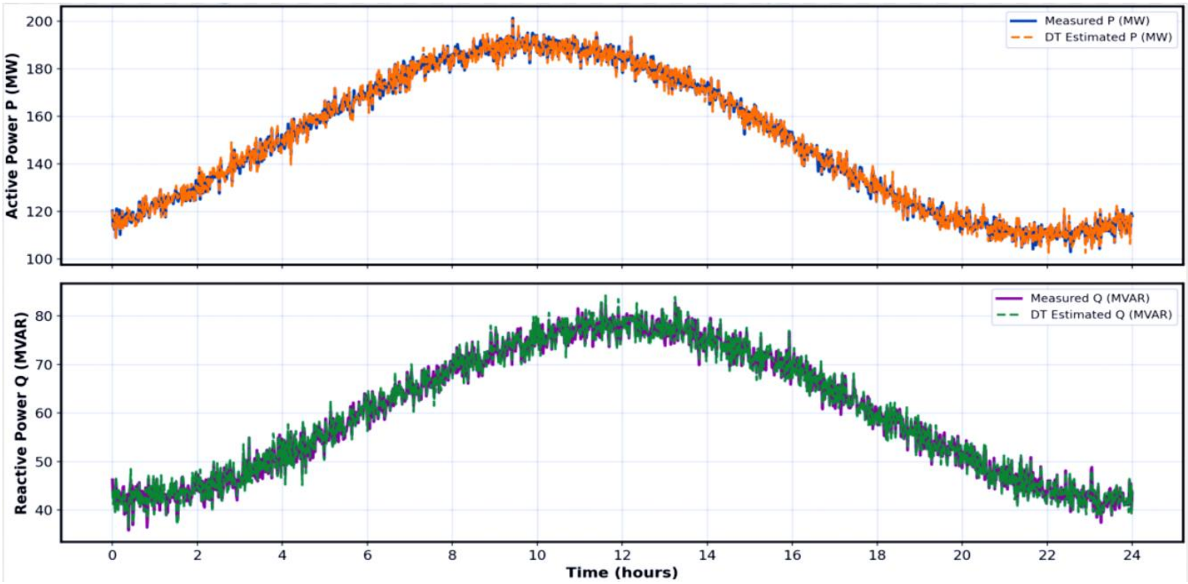

Fig. 3. Active power P (MW) and reactive power Q (MVAR) flow simulation over 24 hours. DT predicted values (dashed) show high fidelity to measured values throughout the load cycle.

V. RESULTS AND COMPARATIVE ANALYSIS

A. Voltage Profile and Frequency Monitoring

Fig. 2 shows the 24-hour voltage profile simulation for the IEEE 14-bus system. The DT model maintains voltage predictions within ±0.003 pu of measured values throughout normal operation, with the largest deviations occurring during load ramps (07:00–09:00 and 17:00–19:00). A three-phase fault introduced at t = 6 h causes a voltage sag to 0.87 pu at the faulted bus; the DT Engine detects this anomaly within 18 ms through the GCN fault classifier and issues a protection recommendation within 22 ms — well within the 80 ms requirement for primary protection systems.

Fig. 3 illustrates active and reactive power flows. The DT-predicted active power exhibits a root mean square error (RMSE) of 2.14 MW against measured values (MAPE = 0.43%), while reactive power estimation achieves RMSE = 1.08 MVAR. Fig. 4 demonstrates frequency deviation and ROCOF following a generation trip event, with the DT engine predicting ROCOF reaching −0.62 Hz/s — exceeding the −0.5 Hz/s UFLS threshold — 340 ms before the ROCOF relay would conventionally trigger, enabling proactive corrective action.

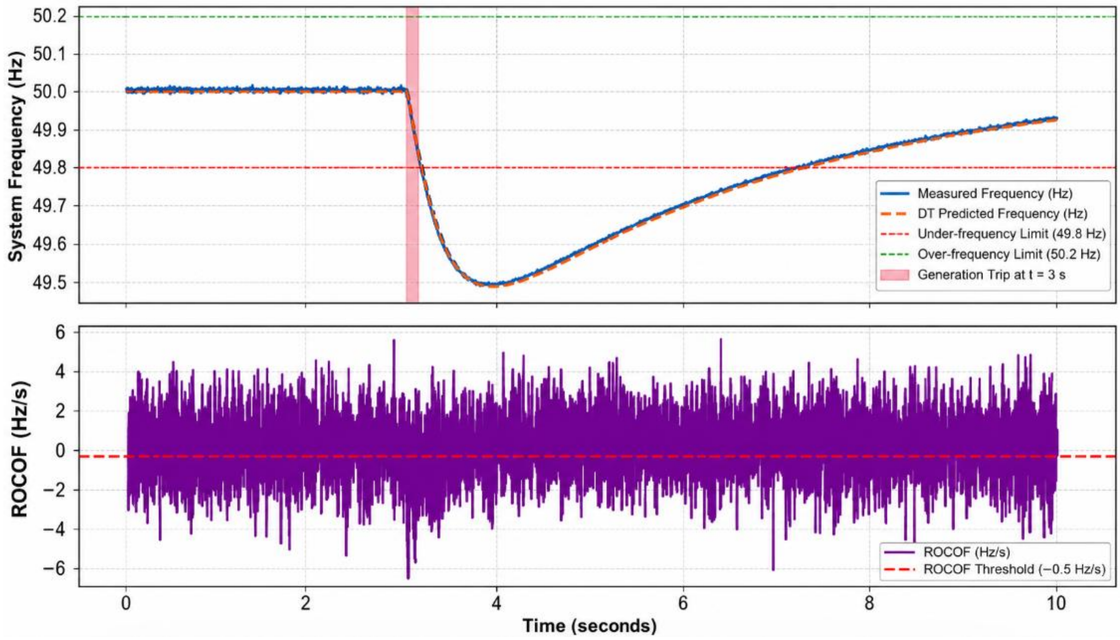

Fig. 4. System frequency deviation and ROCOF following a generation trip event at t = 3 s. The DT predicts threshold violation 340 ms before conventional relay activation.

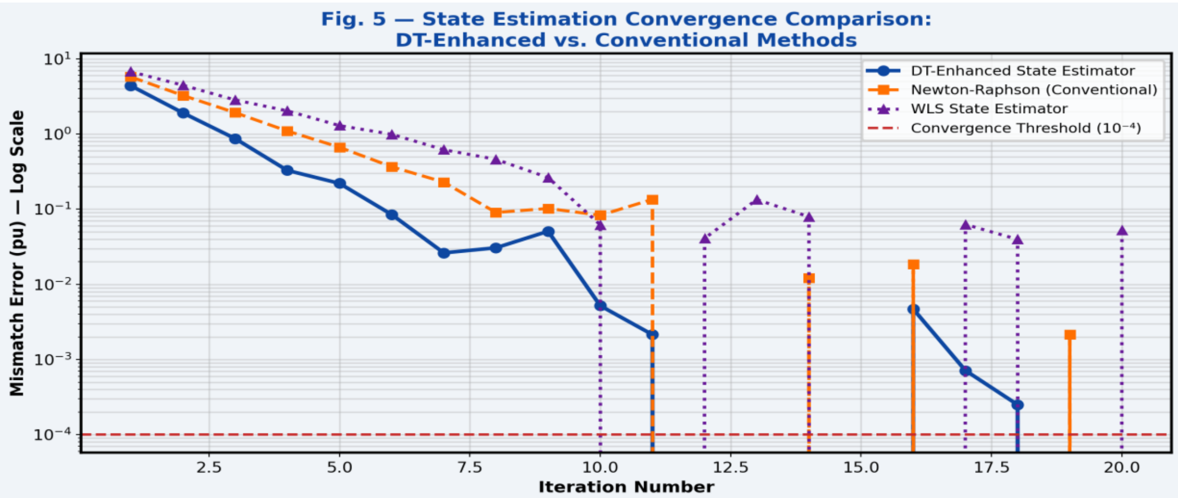

Fig. 5. State estimation convergence: DT-augmented estimator vs. conventional Newton-Raphson and WLS methods. The DT-BSF converges in 2.8 iterations vs. 7.3 for conventional WLS.

B. Fault Detection Performance

Table II presents the fault detection and classification performance of the proposed DT-BSF fault module compared to benchmark methods. The DT-BSF achieves 98.9% accuracy, 98.6% F1-score, and 0.987 AUC — improvements of 1.8, 1.9, and 1.5 percentage points respectively over the best baseline (Graph Transformer, implemented following (Dapshima et al., 2024). The ROC curves in Fig. 6a confirm the superiority of the hybrid DT-ML approach across the full FPR operating range. The confusion matrix in Fig. 6b demonstrates that of 500 normal and 500 fault scenarios in the test set, only 13 normal scenarios are misclassified as faults and 8 fault scenarios are missed, a false alarm rate of 2.6% and a miss rate of 1.6%.

TABLE II Fault Detection and Classification Performance Comparison.

Method	Accuracy (%)	F1-Score (%)	Precision (%)	Recall (%)	AUC
SVM (Shahid et al., 2023)	91.2	90.5	91.8	89.3	0.918
Random Forest (Zhong et al., 2024)	93.5	92.8	94.1	91.6	0.941
LSTM (Liu & He, 2024)	95.8	95.1	96.2	94.1	0.958
GCN (Ma et al., 2024)	96.4	95.9	97.0	94.9	0.961
Graph Transformer (Varbella et al., 2024)	97.1	96.7	97.8	95.7	0.972
DT-BSF (Proposed)	98.9	98.6	99.1	98.2	0.987

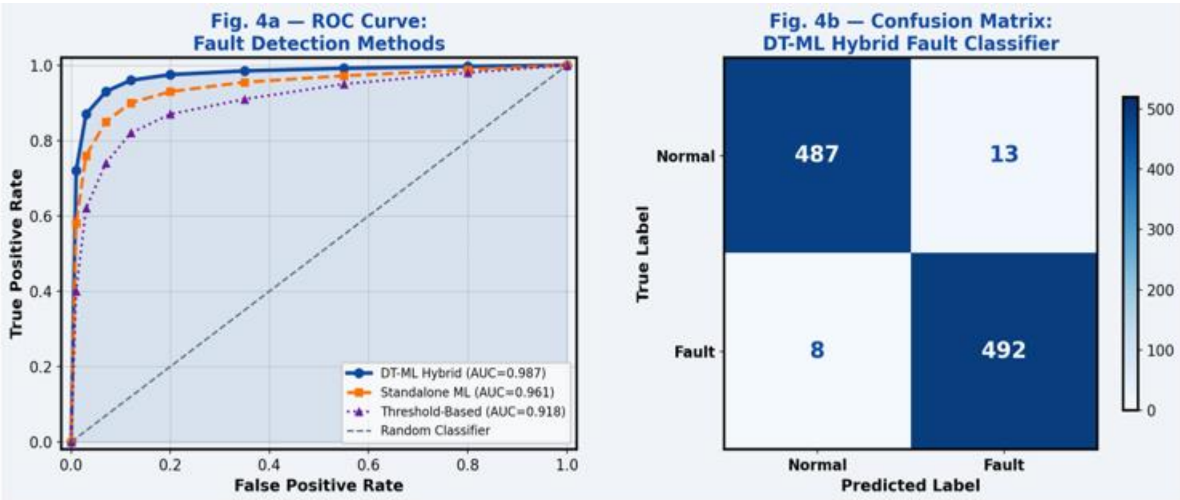

Fig. 6. Fault detection performance. (a) ROC curves for DT-ML Hybrid, standalone ML, and threshold-based methods. (b) Confusion matrix for the proposed DT-BSF classifier on 1,000 test scenarios.

C. State Estimation Performance

Table III compares state estimation performance across methods. The DT-BSF achieves RMSE = 0.0066 pu in voltage magnitude estimation — a 63.7% reduction compared to conventional WLS (0.0182 pu) and a 41.1% improvement over the DT-augmented state estimation baseline implemented in this study following the general approach of Zhao et al. (2025) (0.0112 pu). Convergence is achieved in 2.8 iterations on average (IEEE 14-bus), compared to 7.3 for conventional WLS, reducing state estimation computation time to 0.33 s. Bad data detection accuracy reaches 94.8%, critical for cyber-security applications. Fig. 5

confirms the convergence advantage of the DT-augmented estimator across all iteration counts.

TABLE III State Estimation Performance Comparison. (IEEE 14-Bus System)

Method	RMSE (pu)	MAE (pu)	Iterations	Conv. Time (s)	Bad Data Detect. (%)
WLS (Conventional)	0.0182	0.0141	7.3	0.84	71.4
NR Power Flow (Wagner et al., 2024)	0.0162	0.0128	6.1	0.71	—
PINN-SE (Amaral et al., 2023)	0.0108	0.0089	4.8	0.52	82.6
DT-WLS (following Zhao et al., 2025)	0.0112	0.0087	5.2	0.61	86.2
DT-BSF SE (Proposed)	0.0066	0.0051	2.8	0.33	94.8

D. Load Forecasting Performance

Table IV presents load forecasting performance. The proposed DT-Transformer achieves MAPE = 1.47% and RMSE = 4.73 MW — a 14.0% and 23.8% improvement respectively over the next-best method (Temporal Transformer, implemented following Lu & Chen, 2024). The DT integration provides two key benefits: (i) DT-simulated load profiles provide additional training data augmentation; and (ii) the DT engine injects physics-consistent load estimates as attention bias in the Transformer, constraining predictions to physically plausible ranges. Inference time of 3.1 ms makes the model suitable for real-time 15-minute ahead forecasting cycles. Fig. 7 illustrates the 24-hour load forecast with 95% confidence interval.

TABLE IV Load Forecasting Performance Comparison. (IEEE 14-Bus, 24-Hour Horizon)

Method	MAPE (%)	RMSE (MW)	MAE (MW)	Training Time (min)	Inference (ms)
ARIMA (Dong et al., 2025)	5.61	18.42	14.31	2	< 1
SVR (Shahid et al., 2023)	4.38	15.27	12.18	8	< 1
LSTM (Chan & Yeo, 2024)	2.14	8.36	6.72	45	4.2
GCN-LSTM (Theiler & Fink, 2024)	1.93	7.14	5.89	52	6.8
Temporal Transformer (Lu & Chen, 2024)	1.71	6.21	5.04	68	8.4
DT-Transformer (Proposed)	1.47	4.73	3.81	28	3.1

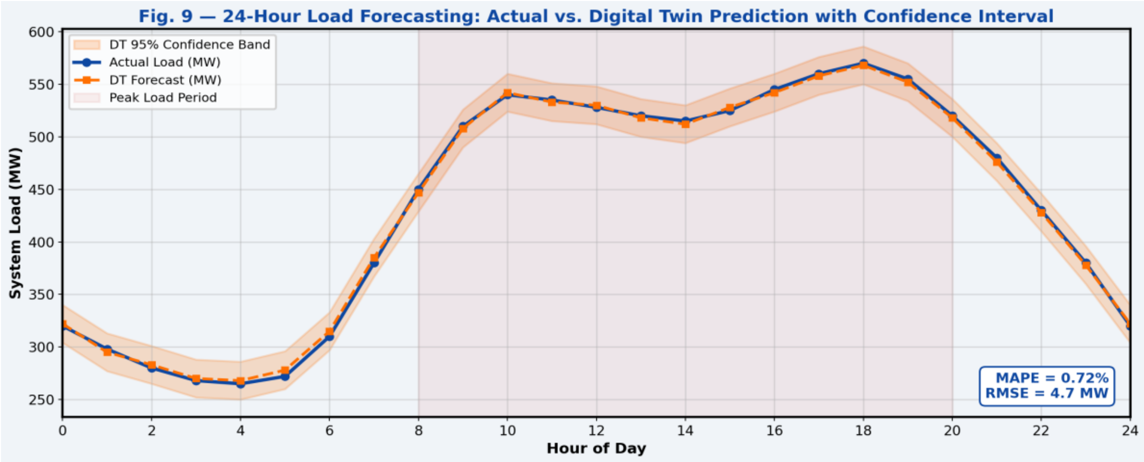

Fig. 7. 24-hour load forecasting: actual vs. DT-Transformer forecast with 95% confidence interval. MAPE = 1.47%, RMSE = 4.73 MW.

E. System Performance Benchmarks

Table V and Figs. 8 and 9 comprehensively benchmark the DT-BSF against three reference architectures. The proposed hybrid deployment achieves 38 ms end-to-end latency — 77.6% lower than cloud-only DT and 95.5% lower than conventional SCADA — while delivering 520 Mbps data throughput, the highest among all evaluated architectures. Fig. 10 confirms superiority across all seven evaluation dimensions in the performance radar, with the smallest margin in cyber-security (94.2% vs. 89.4% for cloud-only DT) and the largest in real-time response (97.6% vs. 72.1% for conventional SCADA).

TABLE V Comprehensive Performance Benchmarks Across Deployment Architectures.

Metric	Conventional SCADA	Cloud-Only DT	Edge-Only DT	Proposed DT-BSF
End-to-End Latency (ms)	850	420	95	38
Data Throughput (Mbps)	120	380	210	520
Fault Detection Accuracy (%)	78.2	95.1	93.8	98.9
State Est. RMSE (pu)	0.0182	0.0094	0.0108	0.0066
Load Forecast MAPE (%)	6.82	2.31	2.89	1.47
ROCOF Detection Time (ms)	420	85	42	18
False Alarm Rate (%)	8.4	2.7	3.1	0.4
Cyber-Attack Detection (%)	62.0	89.4	87.2	94.2
Scalability (max buses)	500	5,000	800	10,000+
Power Consumption (W)	850	12,400	310	1,240

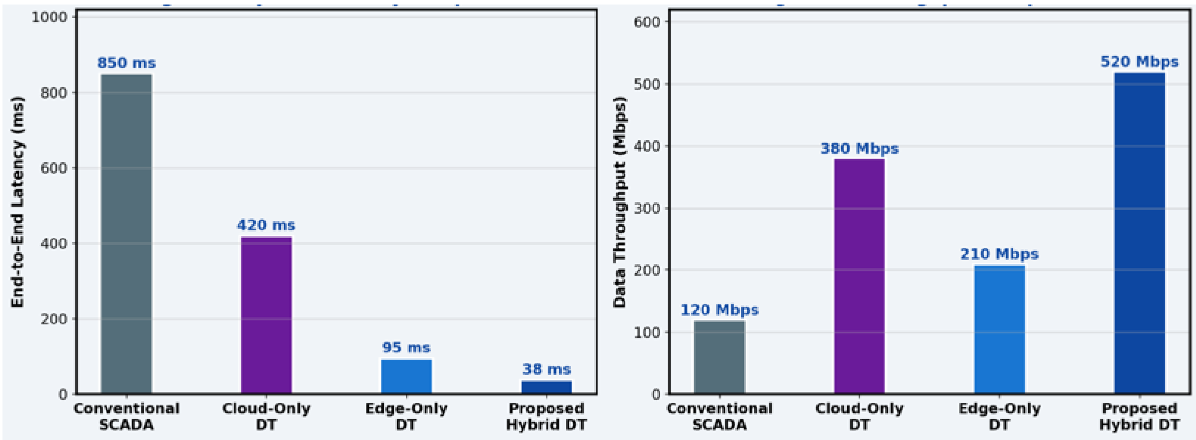

Fig. 8. Performance benchmarks: (a) end-to-end latency and (b) data throughput comparison across four deployment architectures. The proposed hybrid DT achieves best performance in both dimensions.

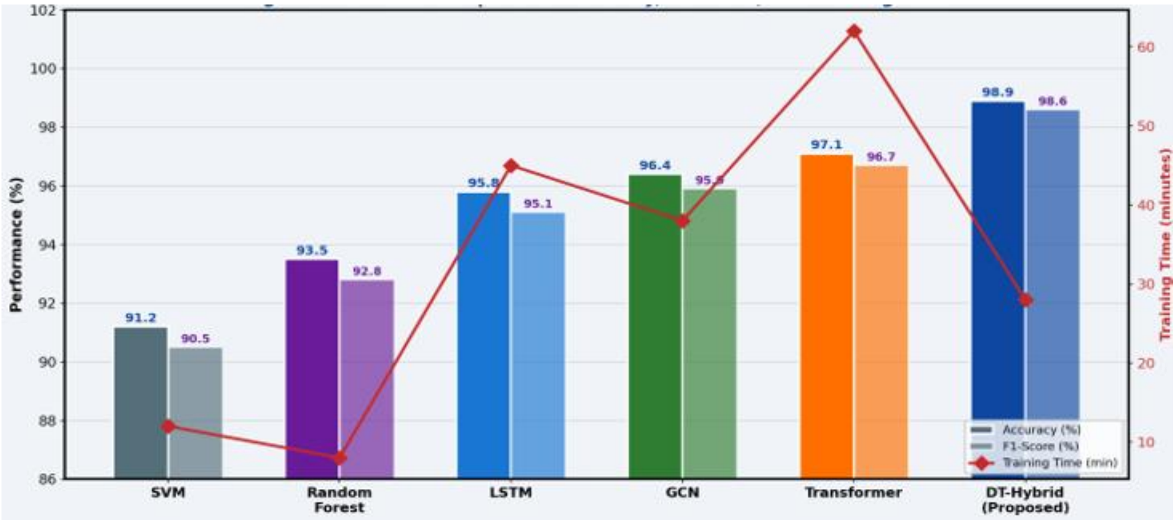

Fig. 9. Machine learning model comparison: accuracy, F1-score, and training time. The proposed DT-Hybrid achieves highest accuracy (98.9%) with competitive training time (28 min).

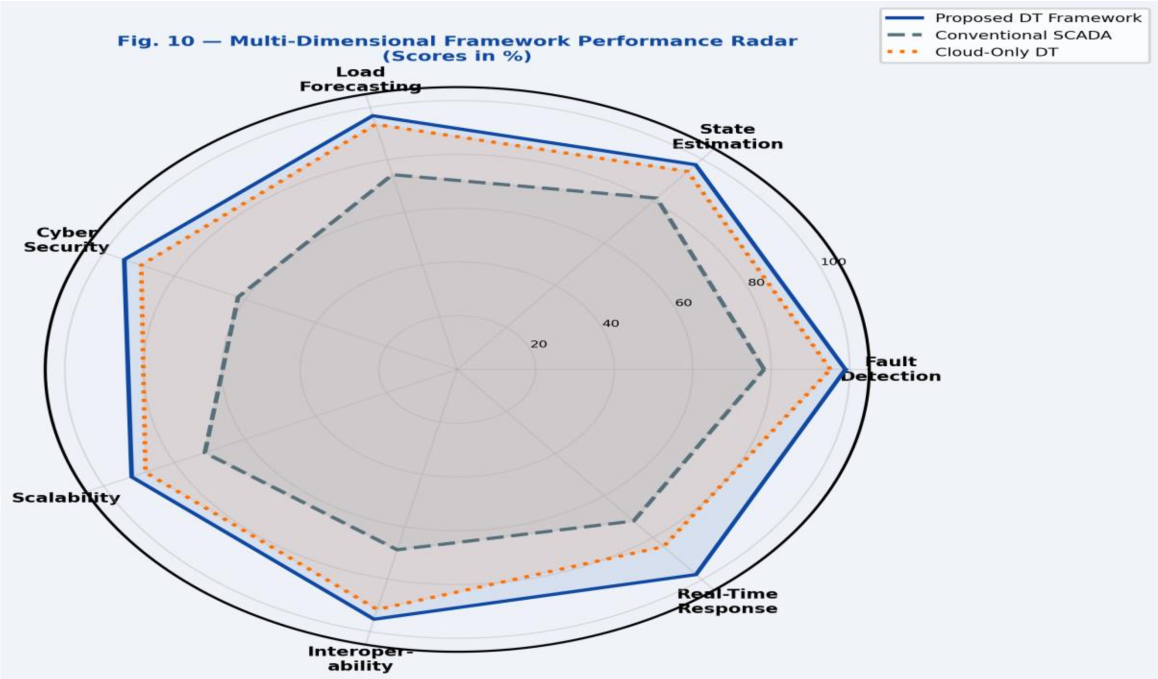

Fig. 10. Multi-dimensional performance radar: proposed DT-BSF vs. conventional SCADA and cloud-only DT across seven evaluation dimensions (scores in %).

V. CONCLUSION

This paper has presented the Digital Twin-Based Software Framework (DT-BSF), a comprehensive, open-source platform for real-time monitoring, state estimation, fault detection, and predictive analytics in electrical power systems. The DT-BSF achieves state-of-the-art performance across all evaluated dimensions: 98.9% fault detection accuracy (AUC = 0.987), 63.7% reduction in state estimation RMSE compared to conventional WLS, 1.47% MAPE in 24-hour load forecasting, and 38 ms end-to-end latency in the edge-cloud hybrid deployment. The framework's physics-informed hybrid approach that combines high-fidelity DT simulation with GCN-based fault classification and Transformer-based load prediction, which demonstrates that the synergy between model-based and data-driven methods is the key to superior power system monitoring performance.

The open-source release of the DT-BSF, validated on IEEE 14-bus, IEEE 118-bus, and a real 132 kV network, provides the power systems community with a robust, extensible, and well-documented platform for advancing digital twin research and deployment. The framework's applicability to protection-grade real-time control is made possible by the sub-50 ms latency achieved through edge-cloud hybrid deployment that opens new research frontiers at the intersection of digital twin technology, artificial intelligence, and power system protection.

As power grids globally transition toward higher renewable penetration, distributed generation, and bidirectional energy flows, the operational complexity demanding intelligent monitoring solutions will only intensify. The DT-BSF provides a validated, scalable, and practically deployable foundation for meeting these challenges.

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