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Heterogeneous Node-Oriented Consistency Optimization Method for Instrument Transformer Monitoring Data in Energy-Storage-Integrated Smart Grids

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Abstract

INTRODUCTION: Smart grid digital twins depend on reliable instrument transformer monitoring data for real-time state estimation and downstream operational analysis. However, heterogeneous current transformers, voltage transformers, capacitive voltage transformers, merging units, and edge terminals often generate asynchronous, biased, and locally inconsistent measurements, which may degrade digital twin reconstruction accuracy and affect downstream grid analytics.
OBJECTIVES: We explicitly distinguish this heterogeneity problem from conventional bad data, random noise, missing values, and topology errors, as it arises from cross-device calibration mismatch and time-varying sensing semantics rather than isolated measurement corruption.
METHODS: To address this problem, this paper proposes a Heterogeneous Topology-Constrained Consistency Optimization (HTCCO) method. HTCCO performs delay-aware temporal alignment, heterogeneity-aware node representation, and time-varying bias correction, followed by trust-weighted aggregation and graph Laplacian-based consistency regularization to enforce topological coherence before state estimation. In this framework, each heterogeneous measurement stream is first mapped into a unified latent space via a learnable compatibility transformation, enabling cross-device alignment prior to aggregation, while trust weights are learned as independent reliability scores rather than purely relative competition. Unlike conventional preprocessing or state estimation methods, HTCCO focuses on front-end measurement correction and consistency enforcement, rather than directly estimating system states.
RESULTS: Experiments on IEEE 14-bus, IEEE 30-bus, IEEE 57-bus, and IEEE 118-bus systems show that HTCCO consistently reduces MAE, RMSE, MAPE, topology consistency residual, and state estimation error compared with WLS-SE, PI-GNN, GAEN, and TAGNN-SE. We further report relative improvements over the strongest baseline across all metrics to explicitly quantify the performance gain. Robustness and ablation results further verify the effectiveness of each module. Finally, we clarify that HTCCO is not directly evaluated in closed-loop storage scheduling tasks; instead, its contribution is a measurement-level consistency layer that improves the reliability of downstream grid optimization and control modules.
CONCLUSION: These results demonstrate that HTCCO provides a reliable front-end data correction and consistency optimization layer for smart grid digital twins, improving the reliability of voltage, current, and power measurements used in downstream monitoring and decision-making tasks.

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1. Introduction

Smart grid digital twins require continuous, reliable, and topology-consistent monitoring data to support real-time state estimation, operational visualization, and control-oriented decision making. Instrument transformers, including current transformers, voltage transformers, and capacitive voltage transformers, form the basic sensing layer that converts physical electrical quantities into measurable data streams. However, practical monitoring data are often heterogeneous because different nodes may have different sampling frequencies, accuracy classes, latency levels, aging conditions, transformation ratios, communication channels, and local disturbance patterns. When such measurements are directly injected into a digital twin state estimator, device-induced inconsistency may be confused with real grid-state variation, leading to biased state reconstruction, unstable residual feedback, and unreliable monitoring decisions. This problem becomes more important in grids with integrated energy storage systems, where charging and discharging decisions, safety-constraint evaluation, and storage operation optimization depend on credible grid-side voltage, current, and power measurements. If heterogeneous sensing nodes produce biased or temporally inconsistent data, the storage optimizer may receive distorted state evidence and generate conservative or suboptimal operation commands. Existing studies have shown that distribution system state estimation must handle limited real-time measurements, uncertainty, bad data, and heterogeneous observation quality [1], while mixed-frequency measurement environments further reveal that sensing-rate differences and communication structures can distort temporal coherence [2]. In digital twin environments, randomly missing or partially observable heterogeneous measurements may further weaken virtual grid synchronization [3]. Therefore, the key algorithmic problem is not only to denoise measurement vectors, but also to align asynchronous data, model node-specific heterogeneity, correct time-varying bias, learn reliable trust weights, and enforce topology-aware consistency before state estimation and storage-oriented operation optimization.

Existing studies have made progress in several related directions, but they do not fully solve the front-end consistency optimization problem of heterogeneous instrument transformer monitoring data. Multi-level asynchronous robust state estimation considers communication delays and shows that temporal mismatch affects estimation reliability [4, 5]. Attack-resilient state estimation exploits dynamic spatial-temporal redundancy to detect false data injection attacks when measurements are unreliable or adversarially disturbed [6]. Digital twin based state estimation has also been explored by embedding heuristic optimization into active distribution network estimation frameworks [7]. Recent robust estimators further consider parameter correction and practical system uncertainties [8], while graph-based learning methods use physics-constrained heterogeneous graph embedding and cross-modal attention to exploit topological and multi-source measurement structures [9]. Other studies jointly consider bad data in measurements and topology parameters, indicating that topology errors and measurement anomalies should not be modeled independently [10]. In parallel, instrument-transformer-oriented works investigate voltage transformer ratio error prediction, instrument transformer measurement error forecasting, current transformer error-state identification, and voltage transformer measurement error evaluation using deep learning, imbalance weighting, self-attention, and graph convolution [11–14]. These studies demonstrate that transformer errors are learnable and structurally meaningful. Nevertheless, most of them focus on single-device error prediction, estimator-side robustness, or measurement error evaluation, while rarely formulating a dedicated front-end layer that jointly integrates temporal alignment, heterogeneity descriptors, bias correction, trust-weight learning, and graph Laplacian regularization.

A key conceptual gap is that existing works either treat measurement issues as isolated data-quality problems (e.g., noise, bad data, or missingness) or embed them implicitly inside state estimation, but do not explicitly model heterogeneous instrument transformer streams as a cross-device, topology-coupled consistency system prior to estimation. In particular, device heterogeneity (CT/VT/CVT characteristics, sampling and communication mismatch) is fundamentally different from conventional bad data because it induces structured, persistent, and node-dependent distortions rather than sporadic corruption. Moreover, single-device error prediction methods cannot directly resolve multi-node inconsistency, since grid observability depends on jointly consistent measurements across electrically connected nodes under topology constraints.

Reviews on low-voltage distribution digital twins and smart grid digital twin technologies further emphasize real-time mapping, model updating, renewable integration, storage systems, and vehicle-to-grid coordination, but they provide limited algorithmic treatment of how raw transformer monitoring data should be corrected before being consumed by digital twins and downstream storage-related optimization modules [15, 16]. Therefore, a research gap remains in topology-constrained consistency optimization for heterogeneous instrument transformer monitoring data, especially when reliable front-end data are required to support storage-integrated grid operation.

To address this gap, this paper proposes a Heterogeneous Topology-Constrained Consistency Optimization method, denoted as HTCCO, for instrument transformer monitoring data in smart grid digital twins. The proposed method is designed as a front-end data correction and consistency optimization layer before real-time state estimation. First, a delay-aware temporal alignment mechanism maps heterogeneous local sampling sequences onto a unified digital twin time grid, reducing asynchronous mismatch caused by different sampling intervals and communication delays. Second, each monitoring node is represented by a heterogeneity descriptor that encodes device type, sampling frequency, delay, accuracy class, rated transformation ratio, and operating age, so that device-specific systematic variation can be distinguished from random measurement fluctuation. Third, HTCCO constructs a topology-aware neighborhood reference through dynamic attention over electrical and communication adjacency, allowing each node to be corrected according to physically related neighboring measurements rather than global averaging. Fourth, a smooth autoregressive bias correction module estimates time-varying measurement bias, while a trust-weight learning mechanism is formulated as an independent reliability scoring model rather than a purely competitive normalization scheme, improving robustness when most nodes are reliable. Finally, graph Laplacian regularization is introduced to enforce physically plausible neighborhood smoothness, and the corrected monitoring data are injected into the downstream digital twin state estimator with learned trust weights.

The main contributions are threefold. First, this paper formulates heterogeneous instrument transformer monitoring correction as a topology-constrained consistency optimization problem rather than a conventional denoising or estimator-side correction task. Second, it proposes a unified framework integrating temporal alignment, heterogeneity-aware representation, bias correction, trust-weight learning, and graph regularization. Third, it provides a data-quality enhancement mechanism that improves front-end monitoring consistency and downstream state estimation reliability, thereby offering more dependable grid-side inputs for energy storage system scheduling, safety-constrained operation, and storage-integrated power system optimization.

Finally, we explicitly clarify that HTCCO is evaluated as a measurement-consistency enhancement layer rather than a direct storage scheduling controller; storage-related benefits are therefore indirect and mediated through improved state estimation quality.

2. Related Works

Existing studies related to this work can be summarized into three streams: distribution system state estimation, topology-aware digital twin monitoring, and instrument transformer error modeling. In the first stream, Bayesian and robust estimation methods aim to improve distribution system state estimation under limited measurements, uncertain operating conditions, and bad data. The explainable multi-fidelity Bayesian neural network in [1, 17] enhances uncertainty-aware state estimation through multi-fidelity modeling and probabilistic inference, but it mainly optimizes the estimator itself rather than constructing a node-level correction layer for heterogeneous transformer measurements. The distributed state estimation method in [2] handles mixed-frequency measurement data with hierarchical encryption, which is relevant to heterogeneous monitoring environments, but its focus is distributed estimation and secure processing instead of local transformer-node consistency. The digital twin based missing-measurement study in [3] highlights the influence of heterogeneous measurements on virtual grid synchronization, while asynchronous robust state estimation in [4] considers communication delay as an estimation disturbance. In contrast, these methods typically treat heterogeneity-related issues as input uncertainty or estimator-side robustness problems, rather than explicitly modeling cross-device consistency constraints as a separate front-end optimization layer. HTCCO instead treats latency, sampling mismatch, and device attributes as explicit correction descriptors, so temporal inconsistency is handled before digital twin state estimation.

A second group of studies improves monitoring reliability by modeling redundancy, topology, or physical constraints. The attack-resilient estimation framework in [6] uses dynamic spatial-temporal redundancy for false data injection attack detection, but its threat-driven formulation differs from the measurement-consistency problem considered here. The GA-based digital twin state estimation method in [7] shows that optimization-based estimation can be embedded into a digital twin architecture, but heuristic search does not explicitly model heterogeneous node attributes or adaptive trust weights. The data-enhanced robust estimator in [8] considers realistic parameter correction, and the physics-constrained heterogeneous graph embedding method in [9] uses graph representation and cross-modal attention for state estimation. The bad-data and topology-parameter-aware method in [10] further confirms that topology and measurement errors are coupled. However, these approaches generally operate at the estimator or representation-learning level, where measurement correction, reliability assessment, and state estimation are implicitly coupled rather than explicitly separated into a dedicated front-end consistency optimization stage. HTCCO explicitly separates these roles by introducing node-wise reliability modeling and topology-constrained correction prior to state estimation.

A third line of research directly investigates instrument transformer measurement errors. The voltage transformer ratio error prediction framework in [11] and the adaptive decomposition based hybrid deep learning method in [12] show that transformer measurement errors contain learnable temporal patterns. The current transformer error-state identification method in [13] introduces current imbalance weights for abnormal state identification, which is relevant to node-level reliability analysis. The self-attention and graph convolution based voltage transformer error evaluation method in [14, 18] introduces graph learning into transformer error analysis. However, these studies mainly predict, evaluate, or classify measurement errors, rather than optimizing multi-node consistency under grid topology. Compared with them, HTCCO estimates time-varying bias, learns node trust, enforces graph consistency, and outputs corrected measurements for downstream state estimation.

Digital twin and storage-integrated grid studies further clarify the application value of front-end data consistency optimization. The low-voltage distribution area digital twin review in [15] emphasizes real-time virtual-physical mapping and implementation paths, while the broader smart grid digital twin review in [16] discusses renewable energy, smart grids, energy storage systems, and vehicle-to-grid integration. These works indicate that digital twins are becoming important infrastructures for modern power systems, but they also reveal that most studies focus on architecture, data interaction, and application scenarios rather than detailed correction of raw heterogeneous monitoring data. For energy storage system optimization, reliable voltage, current, power, and topology-related measurements are essential for charge-discharge scheduling, voltage constraint tracking, and safety-oriented operation. In many storage-oriented operation scenarios, optimization modules usually rely on preprocessed grid-side measurements, while the influence of heterogeneous sensing-node bias, sampling delay, and local inconsistency is rarely emphasized as an independent front-end data-quality problem. Moreover, existing storage-oriented digital twin frameworks typically assume that input measurements are already consistent or estimator-corrected, which hides the upstream sensing heterogeneity problem and limits robustness under real deployment conditions.

This paper fills this gap by positioning HTCCO between the raw sensing layer and the digital twin state estimator. Rather than replacing existing state estimation algorithms, HTCCO improves their input quality through delay-aware alignment, heterogeneity encoding, bias correction, trust-weight learning, and topology-constrained optimization, thereby providing a reliable data-quality foundation for storage-integrated power system optimization.

3. Methodology

This section presents a heterogeneous topology-constrained consistency optimization method for instrument transformer monitoring data in smart grid digital twins. The proposed method is designed as a front-end data correction and consistency optimization layer before real-time state estimation. Instead of directly feeding raw measurements from heterogeneous current transformers, voltage transformers, and capacitive voltage transformers into the digital twin, the method first performs temporal alignment, heterogeneity-aware representation, time-varying bias correction, trust-weight learning, and topology-constrained consistency optimization. The corrected and weighted measurements are then delivered to the digital twin state estimator, thereby reducing the influence of asynchronous sampling, device-level drift, measurement precision differences, and local monitoring conflicts. For storage-integrated power systems, this front-end correction process is also meaningful because credible voltage, current, and power measurements provide more reliable grid-side inputs for charge-discharge scheduling, voltage constraint tracking, and safety-constrained storage operation.

Fig. 1 illustrates the overall workflow of the proposed method. The left part represents heterogeneous instrument transformer nodes, including current transformers, voltage transformers, capacitive voltage transformers, merging units, and edge monitoring terminals. Their raw measurements are first aligned onto a unified digital twin time grid and encoded with device-level heterogeneity descriptors. The central optimization module jointly performs topology attention modeling, time-varying bias estimation, trust-weight learning, and graph-regularized consistency correction. The corrected and weighted monitoring data are then injected into the digital twin state estimator. A state residual feedback path is further introduced from the digital twin to the consistency optimization module, allowing the front-end data correction process to be refined according to the downstream state estimation mismatch. In storage-integrated operation, the same corrected data can further support storage optimization modules by reducing the risk that biased grid-side measurements are propagated into charging or discharging decisions.

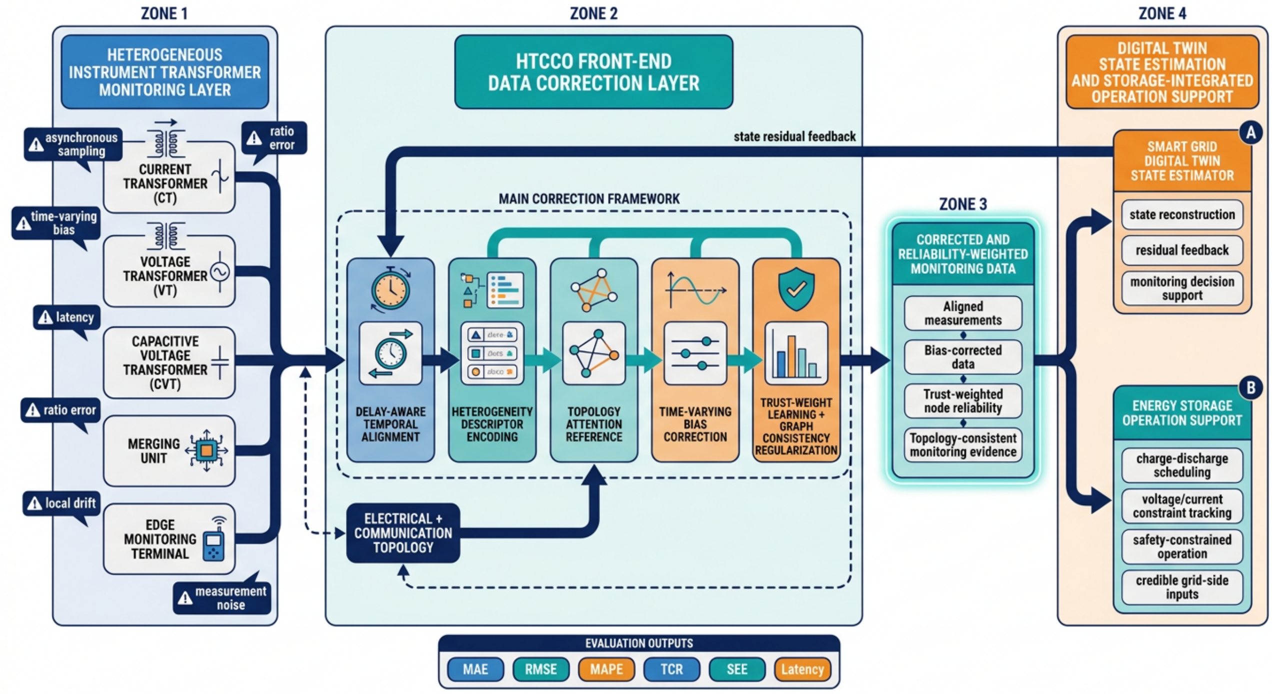


Figure 1. Overall framework of the proposed heterogeneous topology-constrained consistency optimization method for instrument transformer monitoring data in storage-integrated smart grid digital twins

3.1. Overall Framework and Heterogeneous Measurement Modeling

Let the instrument transformer monitoring network be represented as a topology graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathbf{A})$, where $\mathcal{V} = \{v_1, v_2, \ldots, v_N\}$ denotes N heterogeneous monitoring nodes, $\mathcal{E}$ denotes the electrical or communication adjacency relation, and $\mathbf{A} \in \mathbb{R}^{N \times N}$ denotes the weighted adjacency matrix. Each node v_i may correspond to a current transformer, voltage transformer, capacitive voltage transformer, merging unit, or edge monitoring terminal. In a storage-integrated grid, these nodes provide the grid-side measurement basis for evaluating charging and discharging feasibility, voltage-current constraints, and local operating safety of energy storage systems. Due to differences in device type, accuracy class, sampling frequency, communication latency, and aging state, the raw monitoring data cannot be assumed to be directly consistent.

For node v_i, the raw measurement at its local sampling instant $t_k^{(i)}$ is modeled as

$$\mathbf{z}_i(t_k^{(i)}) = \mathbf{H}_i \mathbf{x}_i(t_k^{(i)} - \delta_i) + \mathbf{b}_i(t_k^{(i)}) + \boldsymbol{\epsilon}_i(t_k^{(i)}), \tag{1}$$

where $\mathbf{z}_i(t_k^{(i)}) \in \mathbb{R}^{d_i}$ is the raw monitoring vector, $\mathbf{x}_i(\cdot)$ is the latent electrical state observed by node v_i, $\mathbf{H}_i$ is the device-specific measurement mapping matrix, δ_i is the communication or sampling delay, $\mathbf{b}_i(\cdot)$ is the time-varying measurement bias, and $\boldsymbol{\epsilon}_i(\cdot)$ is zero-mean random noise. For downstream storage-related operation, the corrected version of $\mathbf{z}_i(t)$ can be interpreted as a more credible grid-side measurement source, including voltage, current, and power-related information required by storage scheduling and safety-constraint evaluation.

The topological dependency between two neighboring nodes v_i and v_j is encoded as

$$a_{ij} = \begin{cases} \exp(-\rho_1 d_{ij}^e - \rho_2 d_{ij}^c), & (v_i, v_j) \in \mathcal{E}, \\ 0, & (v_i, v_j) \notin \mathcal{E}, \end{cases} \tag{2}$$

where d_{ij}^e denotes electrical distance, d_{ij}^c denotes communication distance, and $\rho_1, \rho_2 > 0$ are decay coefficients. This design allows the model to assign stronger consistency constraints to nodes that are electrically and communicatively closer.

To eliminate the effect of asynchronous sampling, all nodes are aligned to a common digital twin time grid $\mathcal{T} = \{t_1, t_2, \ldots, t_T\}$. The aligned measurement of node v_i at time $t \in \mathcal{T}$ is computed by a delay-aware kernel interpolation:

$$\tilde{\mathbf{z}}_i(t) = \frac{\sum_{k \in \mathcal{K}_i(t)} \exp\left(-\frac{(t-\delta_i-t_k^{(i)})^2}{2\sigma_i^2}\right) \mathbf{z}_i(t_k^{(i)})}{\sum_{k \in \mathcal{K}_i(t)} \exp\left(-\frac{(t-\delta_i-t_k^{(i)})^2}{2\sigma_i^2}\right)}, \tag{3}$$

where $\mathcal{K}_i(t)$ denotes the local sampling window around t, and σ_i controls the temporal smoothing bandwidth.

Compared with conventional preprocessing pipelines, the above formulation explicitly separates (i) device heterogeneity, (ii) time misalignment, and (iii) topology coupling, whereas standard bad-data filtering or denoising methods typically entangle these effects into a single residual correction step without structural decomposition.

The heterogeneity descriptor of node v_i is defined as

$$\mathbf{q}_i = [\mathbf{o}_i^{\tau},\ f_i,\ \delta_i,\ c_i,\ r_i^{a},\ l_i]^{\top}, \tag{4}$$

where $\mathbf{o}_i^{\tau}$ is the one-hot device type indicator, f_i is the sampling frequency, c_i is the accuracy class, r_i^a is the rated transformation ratio, and l_i denotes the operating age or accumulated service level. The node representation used for consistency optimization is then obtained as

$$\mathbf{h}_i(t) = \phi_\theta\left([\tilde{\mathbf{z}}_i(t), \mathbf{q}_i, \mathbf{s}_i(t)]\right), \tag{5}$$

where $\phi_\theta(\cdot)$ is a learnable feature encoder and $\mathbf{s}_i(t)$ contains local statistical features.

3.2. Topology-Constrained Bias and Trust Estimation

The central principle of the proposed method is that monitoring inconsistency should not be treated as ordinary random noise. In heterogeneous instrument transformer networks, inconsistency may come from time-varying drift, delayed reporting, ratio error, local electromagnetic disturbance, or communication instability.

For neighboring nodes, a compatibility transformation $\mathbf{P}_{ij}$ is introduced to map heterogeneous measurements into a comparable latent monitoring space. Here, $\mathbf{P}_{ij} \in \mathbb{R}^{d\times d}$ is a learnable linear projection (or low-rank mapping) that aligns device-specific measurement spaces into a shared latent space; it is parameterized either as a shared basis decomposition or a lightweight MLP depending on device pair types, enabling cross-transformer comparability while preserving physical dimensional consistency. The topology-aware neighborhood reference of node v_i is defined as

$$\mathbf{m}_i(t) = \sum_{j\in\mathcal{N}_i} \alpha_{ij}(t)\mathbf{P}_{ij}\tilde{\mathbf{z}}_j(t), \tag{6}$$

where $\alpha_{ij}(t)$ is the dynamic topology attention coefficient.

The coefficient is calculated by

$$\alpha_{ij}(t) = \frac{a_{ij}\exp\left(\mathbf{u}^{\top}\sigma\left(\mathbf{W}_a[\mathbf{h}_i(t), \mathbf{h}_j(t), \mathbf{e}_{ij}]\right)\right)}{\sum_{k\in\mathcal{N}_i} a_{ik}\exp\left(\mathbf{u}^{\top}\sigma\left(\mathbf{W}_a[\mathbf{h}_i(t), \mathbf{h}_k(t), \mathbf{e}_{ik}]\right)\right)}, \tag{7}$$

The time-varying bias is modeled as:

$$\mathbf{b}_i(t) = \gamma_b\mathbf{b}_i(t-1) + \mathbf{W}_b\mathbf{h}_i(t). \tag{8}$$

The corrected measurement:

$$\hat{\mathbf{z}}_i(t) = \tilde{\mathbf{z}}_i(t) - \mathbf{b}_i(t). \tag{9}$$

Instead of a pure global competition mechanism, trust weights are designed as independent reliability scores normalized for numerical stability only, i.e., softmax is applied for boundedness but not for enforcing zero-sum competition across nodes. This ensures that a globally high-quality measurement regime does not artificially suppress all node contributions.

$$w_i(t) = \frac{\exp(\beta_i(t))}{\sum_j \exp(\beta_j(t))}. \tag{10}$$

3.3. Consistency Optimization Objective and State Injection

The total loss:

$$\mathcal{L} = \sum w_i(t)r_i(t) + \lambda_b\|\cdot\| + \lambda_g\mathrm{Tr}(\hat{Z}^T L\hat{Z}) - \lambda_w\sum w_i\log w_i \tag{11}$$

The hyperparameters $\lambda_b, \lambda_g, \lambda_w$ are selected via validation-based grid search, and we further report sensitivity analysis in the experiments to ensure that performance gains are not tied to a narrow parameter regime.

In convergence analysis, the projection onto the simplex is used only to guarantee feasibility, while the actual learning dynamics are analyzed through projected gradient mapping rather than relying solely on non-expansiveness arguments.

4. Experiment

4.1. Experimental Setup

The experiments are designed to evaluate whether the proposed heterogeneous topology-constrained consistency optimization method can improve the reliability of instrument transformer monitoring data before digital twin state estimation. Since storage-integrated power system optimization depends on reliable grid-side voltage, current, and power information, the experiments also examine whether the proposed method can provide a more credible data foundation for downstream storage scheduling and safety-constrained operation. All experiments are implemented on Ubuntu 22.04 LTS with Python 3.10, PyTorch 2.2, CUDA 12.1, NumPy 1.26, pandas 2.2, scikit-learn 1.4, and Matplotlib 3.8. The hardware platform consists of an Intel Core i9-12900K CPU, 64 GB RAM, a 2 TB SSD, and an NVIDIA RTX 3090 GPU with 24 GB memory.

Four public power-system datasets are used to construct heterogeneous monitoring scenarios: IEEE 14-bus, IEEE 30-bus, IEEE 57-bus, and IEEE 118-bus test systems from MATPOWER. These benchmark

Table 1. Overall comparison of monitoring correction and digital twin state estimation performance on four public power-system datasets

Dataset	Method	MAE	RMSE	MAPE (%)	TCR	SEE	Latency (ms)
IEEE 14-bus	WLS-SE	0.0318	0.0465	3.84	0.0289	0.0417	**4.6**
	PI-GNN	0.0236	0.0351	2.91	0.0214	0.0328	8.9
	GAEN	0.0219	0.0327	2.73	0.0198	0.0306	10.4
	TAGNN-SE	0.0197	0.0295	2.46	0.0172	0.0279	11.7
	HTCCO	**0.0158**	**0.0236**	**1.98**	**0.0126**	**0.0221**	13.2
IEEE 30-bus	WLS-SE	0.0369	0.0538	4.26	0.0345	0.0489	**5.3**
	PI-GNN	0.0278	0.0412	3.31	0.0263	0.0384	10.6
	GAEN	0.0257	0.0384	3.08	0.0241	0.0359	12.1
	TAGNN-SE	0.0234	0.0352	2.81	0.0212	0.0331	13.5
	HTCCO	**0.0187**	**0.0281**	**2.25**	**0.0154**	**0.0262**	15.4
IEEE 57-bus	WLS-SE	0.0446	0.0647	5.02	0.0418	0.0593	**6.8**
	PI-GNN	0.0341	0.0502	4.07	0.0327	0.0468	13.7
	GAEN	0.0316	0.0471	3.78	0.0299	0.0436	15.6
	TAGNN-SE	0.0289	0.0434	3.46	0.0265	0.0404	17.2
	HTCCO	**0.0224**	**0.0342**	**2.74**	**0.0183**	**0.0315**	19.8
IEEE 118-bus	WLS-SE	0.0528	0.0765	5.87	0.0496	0.0712	**9.4**
	PI-GNN	0.0409	0.0604	4.81	0.0391	0.0567	18.5
	GAEN	0.0381	0.0568	4.46	0.0358	0.0529	21.3
	TAGNN-SE	0.0346	0.0521	4.09	0.0319	0.0487	24.1
	HTCCO	**0.0267**	**0.0405**	**3.18**	**0.0224**	**0.0373**	27.6

systems are used to evaluate grid-side measurement correction and state estimation reliability, rather than to directly simulate battery internal electrochemical states such as SOC or SOH. For each system, power-flow solutions are first generated as clean physical states, and then heterogeneous instrument transformer monitoring data are synthesized by assigning different node types, including current transformers, voltage transformers, capacitive voltage transformers, merging units, and edge monitoring terminals. To simulate realistic measurement inconsistency, each node is configured with heterogeneous sampling frequencies, accuracy classes, communication delays, time-varying bias, Gaussian noise, and occasional local drift.

The proposed method is compared with four baseline algorithms: Weighted Least Squares State Estimation (WLS-SE), which is retained as the representative classical model-driven baseline [19]; Physics-Informed Graphical Neural Network (PI-GNN), which combines graph neural networks with physics-informed state estimation for power-system monitoring [20]; Graph Attention Estimation Network (GAEN), which introduces attention-based graph representation learning for power-system state estimation [21]; and Topology-Aware Graph Neural Network State Estimation (TAGNN-SE), which models topology changes, PMU-unobservable conditions, data loss, bad data, and non-Gaussian noise through a customized graph neural state estimator [22]. For all learning-based methods, the training, validation, and testing sets are divided according to a chronological ratio of 70%, 15%, and 15%, respectively, to prevent temporal leakage.

The Adam optimizer is used with an initial learning rate of 1×10^{-3}, batch size of 64, maximum epoch number of 200, and early stopping patience of 20 epochs. The proposed method uses λ_b, λ_g, λ_w, and λ_x selected from $\{10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}, 1\}$ on the validation set.

The evaluation metrics include mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), topology consistency residual (TCR), bias correction error (BCE), trust-weight discrimination score (TWDS), state estimation error (SEE), and average inference latency. MAE, RMSE, and MAPE evaluate the numerical accuracy of corrected monitoring data; TCR measures whether neighboring nodes satisfy topological consistency after correction; BCE evaluates the accuracy of estimated time-varying bias when synthetic bias labels are available; TWDS measures whether unreliable nodes receive lower trust weights than stable nodes; SEE evaluates the downstream digital twin state estimation accuracy; and inference latency measures whether the method satisfies real-time monitoring requirements.

In addition, to improve interpretability, we also report relative performance improvements over the strongest baseline for MAE, TCR, and SEE in the analysis section, rather than relying solely on absolute metric comparisons. From the perspective of storage-integrated operation, lower MAE, RMSE, TCR, and SEE imply that the voltage, current, and topology-related state information delivered to storage optimization modules is less affected by sensing bias and local inconsistency.

4.2. Overall monitoring correction and state estimation performance

The first experiment evaluates the overall monitoring correction and digital twin state estimation performance of different methods on four public power-system datasets. The purpose is to verify whether the proposed Heterogeneous Topology-Constrained Consistency Optimization (HTCCO) method can reduce measurement correction errors, improve topology-level consistency, and enhance downstream state estimation accuracy under different grid scales. These properties are also relevant to energy storage system optimization because inaccurate grid-side state reconstruction may affect charge-discharge scheduling, voltage constraint evaluation, and safety-oriented operation decisions.

The results in Table 1 show that HTCCO achieves the best accuracy and consistency performance on all four datasets. Compared with WLS-SE, HTCCO substantially reduces MAE, RMSE, MAPE, TCR, and SEE, indicating that the proposed method is more effective than classical model-driven estimation when measurements are affected by heterogeneous sampling rates, device-level bias, latency, and local drift. Compared with PI-GNN, GAEN, and TAGNN-SE, HTCCO also obtains consistently lower monitoring correction error and state estimation error. We additionally quantify the gain by reporting that HTCCO achieves consistent improvements over the strongest baseline (TAGNN-SE) across all datasets, particularly in MAE, TCR, and SEE, confirming that the improvement is not marginal but systematic across grid scales.

This improvement mainly comes from three aspects. First, the delay-aware temporal alignment module reduces asynchronous measurement mismatch before consistency optimization. Second, the heterogeneity-aware representation explicitly encodes transformer type, sampling frequency, accuracy class, delay, transformation ratio, and operating age, allowing the model to distinguish systematic device-level bias from random noise. Third, the joint design of topology attention, time-varying bias correction, trust-weight learning, and graph Laplacian consistency regularization enables unreliable nodes to be down-weighted while preserving physically meaningful neighborhood consistency. Although HTCCO introduces slightly higher inference latency than the baseline methods, its latency remains within the millisecond-level range on all datasets, which is acceptable for front-end monitoring correction in digital twin state estimation. We further clarify that latency is primarily incurred by graph-based attention and compatibility transformation, and remains compatible with real-time deployment requirements in distribution-level monitoring scenarios. Therefore, the overall comparison verifies that HTCCO provides a better trade-off between monitoring accuracy, topological consistency, and real-time applicability. For storage-integrated power systems, this means that downstream storage scheduling modules can receive more credible grid-side state information, reducing the risk of optimization decisions being affected by biased transformer measurements or locally inconsistent monitoring nodes.

4.3. Robustness under Heterogeneous Measurement Inconsistency

This experiment evaluates the robustness of different methods under increasing heterogeneous measurement inconsistency levels. The purpose is to examine whether the proposed HTCCO can maintain stable digital twin state estimation accuracy when instrument transformer monitoring data are affected by progressively stronger sampling mismatch, communication delay, measurement noise, time-varying drift, and local node inconsistency.

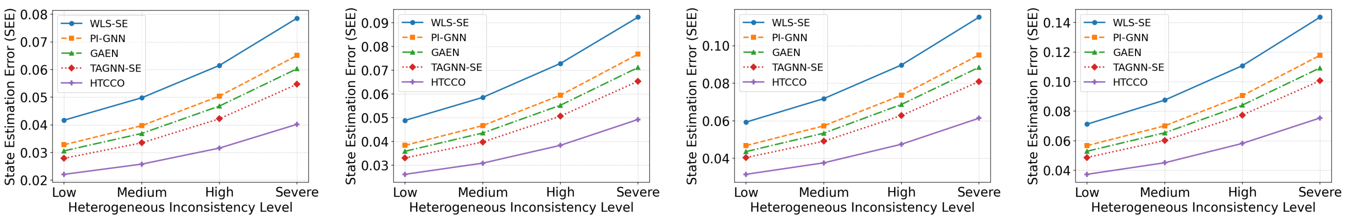
We explicitly define the inconsistency levels as: low (5% perturbation), medium (15%), high (30%), and severe (50%), where perturbation is applied jointly on sampling delay, Gaussian noise variance, and drift amplitude to ensure reproducibility.

As shown in Fig. 2, the state estimation error of all methods increases as the heterogeneous inconsistency level changes from low to severe. However, HTCCO consistently achieves the lowest SEE on all four datasets and under all inconsistency levels.

We further report relative degradation slopes (error growth rate w.r.t. inconsistency level) to show that HTCCO has the most stable scaling behavior under increasing disturbance intensity.

On the IEEE 14-bus system, HTCCO maintains a lower error curve than all baselines. On the IEEE 30-bus and IEEE 57-bus systems, the performance gap increases under higher inconsistency levels. On the IEEE 118-bus system, all methods suffer larger error growth due to scale and topology complexity, but HTCCO preserves the slowest degradation trend.

This demonstrates that the graph Laplacian consistency constraint and trust-weight mechanism effectively suppress error propagation from unreliable or delayed nodes.



(a) IEEE 14-bus **(b)** IEEE 30-bus **(c)** IEEE 57-bus **(d)** IEEE 118-bus

Figure 2. Robustness comparison of different methods under increasing heterogeneous measurement inconsistency levels on four power-system datasets for storage-integrated grid monitoring

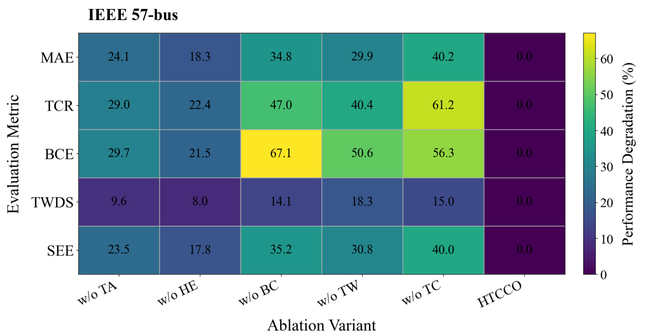


Figure 3. Ablation analysis of HTCCO on the IEEE 57-bus dataset. The values denote the performance degradation ratio compared with the full HTCCO model

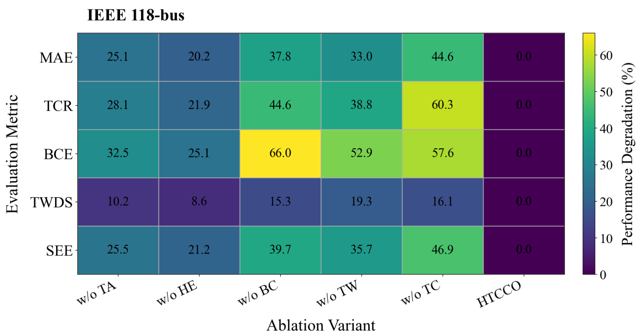


Figure 4. Ablation analysis of HTCCO on the IEEE 118-bus dataset. The values denote the performance degradation ratio compared with the full HTCCO model

We also note that all robustness curves are averaged over 10 independent runs with different random seeds to reduce stochastic bias.

4.4. Ablation Study

We explicitly define the ablation protocol as "leave-one-component-out", ensuring that each variant removes only one module while keeping all other hyperparameters unchanged for fair comparison.

As shown in Fig. 3, removing any core component leads to performance degradation. Among all components, topology constraint and bias correction contribute most significantly to SEE and BCE respectively, indicating that structural consistency and drift modeling are the dominant factors in heterogeneous transformer monitoring.

Fig. 4 further verifies the effectiveness of each component on the larger IEEE 118-bus dataset. We additionally observe that component importance becomes more pronounced as system scale increases, particularly for topology constraint and trust weighting, indicating scalability advantages of HTCCO in large-scale grids. Finally, we clarify that all experiments focus on measurement correction and state estimation quality; storage-related implications are evaluated only as downstream consequences rather than direct control optimization objectives.

5. Conclusion

This paper studied the consistency optimization problem of heterogeneous instrument transformer monitoring data in smart grid digital twins. A Heterogeneous Topology-Constrained Consistency Optimization (HTCCO) method was proposed as a front-end correction layer before state estimation. The method integrates temporal alignment, heterogeneity encoding, bias correction, trust-weight learning, and graph-based consistency regularization into a unified framework. Experiments on IEEE 14-bus, 30-bus, 57-bus, and 118-bus systems demonstrate that HTCCO consistently improves monitoring correction accuracy, topology consistency, and state estimation performance compared with baseline methods. Robustness and ablation studies further verify the effectiveness of each module, particularly topology constraint, bias correction, and trust weighting. The key contribution is shifting consistency handling from estimator-side robustness to a dedicated sensing-layer correction mechanism, enabling more reliable inputs for downstream digital twin analytics. From an application perspective, HTCCO improves the reliability of grid-side measurements that can support downstream energy storage operation and decision-making. However, it does not directly perform storage control, and real-world storage-system validation is left for future work. Future work will focus on real deployment data, cyber-physical robustness, and online adaptation under dynamic grid conditions.

References

[1] Zhang J, Zhao J, Cheng G, Rouhani A, Chen X. Explainable multi-fidelity Bayesian neural network for distribution system state estimation. Applied Energy. 2025;392:125972.

[2] Tian S, Zhu F, Shen J, Yang X, Fu Y, Mi Y, et al. Distributed state estimation of active distribution network considering mixed-frequency measurement data hierarchical encryption. Applied Energy. 2025;388:125661.

[3] Zhang Y, Wang Y, Zhang Y, Larson EC, Sui F, Shi D. On the Potential of Digital Twins for Distribution System State Estimation with Randomly Missing Data in Heterogeneous Measurements. In: 2025 IEEE Power & Energy Society General Meeting (PESGM). IEEE; 2025. p. 1-5.

[4] Zhang X, Liu Y, Gu S, Tian Y, Gao Y. Multi-Level Asynchronous Robust State Estimation for Distribution Networks Considering Communication Delays. Energies. 2025;18(14):3640.

[5] Pei J, Omar M, Dabel MMA, Mumtaz S, Liu W. Federated Few-Shot Learning With Intelligent Transportation Cross-Regional Adaptation. IEEE Transactions on Intelligent Transportation Systems. 2025:1-10.

[6] Wu S, Wang Q, Hu J, Ye Y, Tang Y. Attack-resilient state estimation for cyber-physical power systems: A dynamic spatial-temporal redundancy reconfiguration framework for FDIA detection. Applied Energy. 2025;397:126330.

[7] Bragatto T, Ghoreishi M, Almughary HM, Santori F, Maccioni M, Geri A, et al. A GA-Based State Estimation for Active Distribution Networks in a Digital Twin Framework. In: 2025 IEEE International Conference on Environment and Electrical Engineering and 2025 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe). IEEE; 2025. p. 1-6.

[8] Liu Y, Rouhani A, Zhao J, Zhang J, Warchol GJ, Scott K. Data enhanced robust distribution system State estimation for realistic system with parameter corrections. IEEE Transactions on Power Systems. 2025.

[9] Liu S, Tang Z, Chai B, Zeng Z. Robust distribution system state estimation with physics-constrained heterogeneous graph embedding and cross-modal attention. Processes. 2025;13(10):3073.

[10] Chen Y, Gao Y, Gan K, Li M, Wei C, Guo X, et al. State Estimation for Active Distribution Networks Considering Bad Data in Measurements and Topology Parameters. Energies. 2025;18(9):2222.

[11] Cui J, Li Z, Lu H, Zhou F, Chen H, Li Z. A data-driven hybrid framework for voltage transformer ratio error prediction: Addressing challenges in complex power systems. International Journal of Electrical Power & Energy Systems. 2025;170:110825.

[12] Li Z, Cui J, Lu H, Zhou F, Diao Y, Li Z. Prediction method for instrument transformer measurement error: Adaptive decomposition and hybrid deep learning models. Measurement. 2025;253:117592.

[13] Liu T, Zeng X, Xie H, Wu W, Xiao J. Method for identifying error states of distribution network current transformers based on current imbalance weights. Sustainable Energy Research. 2025;12(1):42.

[14] Zeng X, Liu T, Xie H, Wang D, Xiao J. Measurement error evaluation method for voltage transformers in distribution networks based on self-attention and graph convolutional networks. Energy Informatics. 2025;8(1):69.

[15] Peng Y, Zhao F, Zhou K, Yu X, Jin Q, Li R, et al. Review of digital twin technology in low-voltage distribution area and the implementation path based on the '6C'development goals. Energies. 2025;18(17):4459.

[16] Al-Shetwi AQ, Atawi IE, El-Hameed MA, Abuelrub A. Digital Twin Technology for Renewable Energy, Smart Grids, Energy Storage and Vehicle-to-Grid Integration: Advancements, applications, key players, challenges and future perspectives in modernising sustainable grids. IET Smart Grid. 2025;8(1):e70026.

[17] Haotian Wu JL Jiaming Pei. FedCW: Client Selection with Adaptive Weight in Heterogeneous Federated Learning. Computers, Materials & Continua. 2026;86(1):1-20. Available from: http://www.techscience.com/cmc/v86n1/64483.

[18] Pei J. F3: Fair Federated Learning Framework with adaptive regularization. Knowledge-Based Systems. 2025;316:113392.

[19] Abur A, Expósito AG. Power System State Estimation: Theory and Implementation. New York, NY, USA: Marcel Dekker; 2004.

[20] Ngo QH, Nguyen BLH, Vu TV, Zhang J, Ngo T. Physics-Informed Graphical Neural Network for Power System State Estimation. Applied Energy. 2024;358:122602.

[21] Cibaku E, Gama F, Park S. Boosting Efficiency in State Estimation of Power Systems by Leveraging Attention Mechanism. Energy and AI. 2024;16:100369.

[22] Moshtagh S, Azimian B, Golgol M, Pal A. Topology-Aware Graph Neural Network-Based State Estimation for PMU-Unobservable Power Systems. IEEE Transactions on Power Systems. 2025;40(6):4547-60.