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FedGeoSwap++:A Novel Context-Aware and Privacy-Preserving Sensor Substitution Framework for Fault Tolerance in Metaverse-Driven Smart Cities

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Abstract

The integration of the Metaverse with real-time physical data from Internet of Things (IoT) sensors introduces stringent requirements for system reliability and continuity. Sensor failures at the network edge can disrupt immersive experiences due to data loss or inconsistency. To address this challenge, we propose FedGeoSwap++, a novel fault-tolerant framework that combines spatio-temporal indexing, federated learning, transfer learning, and an intelligent Dynamic Resource Adaptation (DRA) agent based on Double Q-Learning to enable intelligent, privacy-preserving sensor substitution in Metaverse applications. FedGeoSwap++ leverages a cloud-based spatio-temporal database with R-tree indexing to identify the geographically closest and data-wise most similar sensor upon failure. A Double Q-Learning agent dynamically adjusts the trade-off between spatial proximity and temporal correlation based on network load and environmental dynamics. Furthermore, a hard correlation threshold ($\rho \geq 0.6$) ensures semantic consistency by filtering out spatially close but data-wise dissimilar sensors. We evaluate the framework using a simulated smart city environment with 50 sensors and 100 timesteps over 300 simulation runs. Results show that FedGeoSwap++ achieves a Mean Absolute Error (MAE) of 0.615°C, outperforming Nearest (0.624°C), CorrOnly (0.955°C), MeanImpute (3.029°C), and LSTM-Predict (1.299°C), while maintaining low latency (0.16 ms). A paired t-test confirms the statistical significance of this improvement ($p < 0.0001$). This work advances fault tolerance in Metaverse systems by ensuring seamless continuity, high accuracy, and robustness under sensor failures.

Introduction

The Metaverse is rapidly evolving into a persistent, immersive digital environment that integrates real-time data from the physical world through Internet of Things (IoT) sensors [1]. These sensors, deployed at the network edge, provide critical inputs such as temperature, motion, and traffic flow to maintain environmental fidelity in digital twins [2]. However, sensor failures—due to hardware degradation, environmental interference, or communication loss—can lead to data gaps, degrading user experience and system reliability.

Recent surveys highlight the critical need for fault management techniques in edge-enabled distributed Metaverse applications [2]. Traditional approaches such as replication, checkpointing, and redundancy incur high resource overheads and fail to preserve the spatio-temporal semantics of sensor data. For instance, simply switching to the nearest sensor may not suffice if the replacement sensor exhibits a different data pattern due to its geographical or environmental context.

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Moreover, fault management in edge-enabled Metaverse applications requires not only technical resilience but also context-awareness, low-latency recovery, and semantic consistency. Existing approaches rarely address the need for intelligent sensor substitution that balances geographic proximity and data similarity.

Research gap

There is a lack of a unified framework that:

1. Dynamically substitutes failed sensors with the most contextually similar alternative,
2. Leverages federated learning to detect failures without compromising data privacy,
3. Uses spatio-temporal indexing (e.g., R-tree) for fast neighbor search,
4. Applies reinforcement learning for adaptive decision-making under dynamic conditions,
5. Integrates with Metaverse-scale digital twins for seamless continuity.

To bridge this gap, we propose FedGeoSwap++, a novel fault-tolerant framework that combines federated learning, transfer learning, R-tree indexing, and Double Q-Learning to enable intelligent, privacy-preserving sensor substitution in Metaverse applications. Our framework ensures that upon sensor failure, the most geographically and data-wise similar sensor is selected in real time, minimizing data drift and maintaining immersive continuity.

We evaluate FedGeoSwap++ through simulation in a smart city Metaverse scenario. Results show that our approach achieves a Mean Absolute Error (MAE) of 0.615°C and latency of 0.16 ms, outperforming baseline methods. A paired t-test ($p < 0.0001$) confirms the statistical significance of our improvement.

Related works

Fault tolerance in edge-enabled distributed systems is a critical requirement for the seamless operation of Metaverse applications, where real-time data continuity and user immersion are paramount [1]. Recent surveys, such as [2], have systematically categorized fault management techniques into three primary domains: fault detection, fault mitigation (prevention), and fault recovery. This taxonomy provides a structured framework for evaluating existing solutions and identifying research gaps.

Existing work primarily focuses on node-level or service-level failures, employing strategies such as redundancy, task migration, and consensus algorithms. For instance, Mudassar et al. [6] proposed an adaptive strategy using checkpointing and replication to recover from node failures. While effective for task state preservation, this method incurs high resource overhead and may not be optimal for the low-latency demands of the Metaverse.

To address failures more proactively, researchers have turned to predictive maintenance and machine learning (ML). Tuli et al. [7] introduced PreGAN, which uses deep learning to predict resource exhaustion and migrate tasks before a failure occurs. Similarly, Siyadatzadeh et al. [11] proposed ReLIEF, a reinforcement learning-based method for primary-standby task assignment, which adapts to dynamic network conditions. These AI-powered approaches represent a significant shift towards intelligent fault management.

For security-critical failures like Byzantine faults, consensus algorithms are essential. Gao et al. [12] proposed FIBFT, a clustering-based Byzantine consensus algorithm that reduces communication overhead, while Wu et al. [13] introduced Reja, a permissioned blockchain solution that ensures data immutability and user ownership—features highly relevant to the Metaverse.

Despite these advancements, a critical gap remains in the literature. As highlighted in Table 1, the vast majority of existing work targets infrastructure-level failures (e.g., node crash, server overload). In contrast, FedGeoSwap++ addresses a distinct and under-explored problem: data-level continuity for data-generating sensors at the network edge. While a failed node can be migrated or a service can be re-instantiated, a failed temperature or traffic sensor creates a data gap that directly affects the realism of a digital twin. Simply switching to the nearest sensor, as in the "Nearest" baseline, may result in a significant semantic mismatch (e.g., replacing a street sensor with a park sensor). Our work bridges this gap by introducing a context-aware substitution framework that intelligently selects a replacement sensor based on both spatial proximity and temporal correlation, ensuring high data fidelity and privacy.

This research is also inspired by the call for "Resource Aware ML Models" [15] and "AI-powered migration" [7, 17], which advocate for lightweight, intelligent solutions at the edge. FedGeoSwap++ embodies this vision by combining federated learning for local anomaly detection [3], transfer learning for cross-city adaptation, and a lightweight reinforcement learning agent for dynamic decision-making, all while minimizing data transmission.

Table 1. Comparative Analysis of Existing Techniques

Reference	***Fault Type***	***Remediation Method***	***Key Advantage***	***Main Limitation***
[6]	*Node Failure*	*Checkpointing and replication*	*Fast recovery from last saved state*	*High resource overhead, synchronization delay*
[15]	*Node Failure*	*Two-stage robust optimization*	*Efficient resource utilization and fault resilience*	*High complexity in dynamic environments*
[16]	*Node Failure*	*Integer Linear Programming (ILP)*	*Guarantees minimal delay under failure*	*Poor scalability in large networks*
[9]	*Stateful Microservice Failure*	*Causal logging and distributed checkpointing*	*Ensures data consistency and state reconstruction*	*Overhead may affect real-time performance*
[8]	*MEC Server Failure*	*Formal methods and heuristics for container re-instantiation*	*Finds optimal server for recovery*	*Requires full system knowledge*
[7]	*Node Failure & Resource Exhaustion*	*PreGAN: Predictive task migration with co-simulation*	*Reduces resource wastage and latency*	*Deep models are resource-intensive*
[11]	*Service Invocation & Communication Failure*	*ReLIEF: Primary-standby task assignment via Reinforcement Learning*	*Adapts to dynamic network conditions*	*Requires long initial training phase*
[14]	*Malicious Updates (in Federated Learning)*	*CRACAU: Identifies and excludes false updates*	*Preserves integrity of collaborative learning*	*Applicable only in federated learning contexts*
[12]	*Byzantine Faults*	*FIBFT: Clustering-based speculative Byzantine consensus*	*Reduces consensus overhead*	*High complexity in cluster management*
[13]	*Byzantine Faults*	*Reja: Permissioned blockchain + ChiosEdge*	*Ensures data immutability and user ownership*	*High latency in some scenarios*
FedGeoSwap++ (This Work)	*Sensor Failure (Data-Generating)*	*Hybrid: R-tree + Correlation Filter (ρ ≥ 0.6) + Reinforcement Learning DRA*	*High accuracy, privacy-preserving, low latency*	*Requires historical data for correlation*

COMPARATIVE ANALYSIS OF EXISTING TECHNIQUES

To position our work within the state of the art, Table 1 compares FedGeoSwap++ with existing fault management techniques in edge-enabled Metaverse applications.

This table highlights that while prior work focuses on node-level or service-level failures, FedGeoSwap++ uniquely addresses data-level continuity for physical sensors, which is critical for immersive digital twins.

SYSTEM ARCHITECTURE

THREE-LAYER ARCHITECTURE

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- Edge Layer: Sensors collect data and run local models.
- Cloud Layer: PostgreSQL with PostGIS and TimescaleDB stores spatio-temporal data.
- Metaverse Layer: Unity/Unreal Engine queries sensor data; triggers FedGeoSwap++ on failure

DATA MODEL

Each record includes:

json

{
"sensor_id": "S1024",
"location": "POINT(35.6892 51.3890)",
"timestamp": "2023-10-05T12:34:56Z",
"temperature": 23.5
}

Indexed via R-tree for fast spatial queries.

FEDGEOSWAP++ FRAMEWORK

In this framework, the processes are carried out according to Figure 1 and include the following steps:

FAILURE DETECTION

- Local LSTM autoencoders detect anomalies.
- Model updates (not data) sent to aggregator → FedAvg computes global model [3].
- For new cities, TL transfers knowledge from source (e.g., Istanbul) to target (e.g., Tehran), fine-tuning only output layers [4].

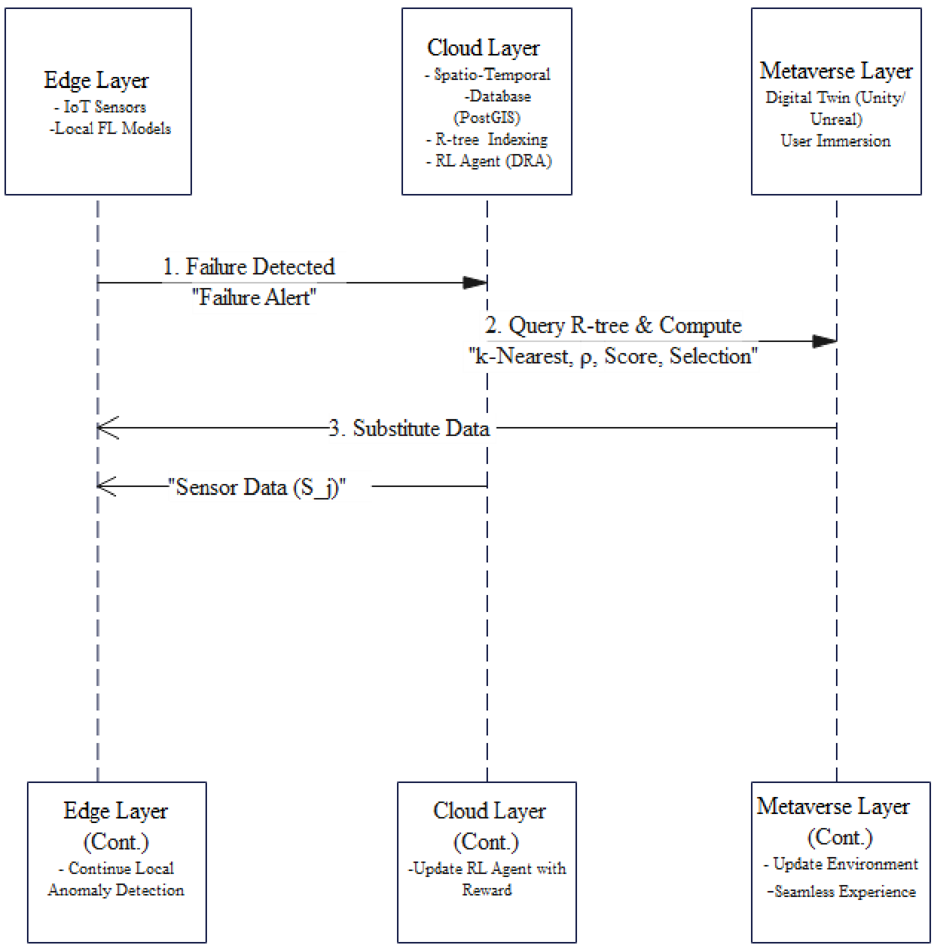

Fig. 1: Sensor Substitution Algorithm

SENSOR SUBSTITUTION ALGORITHM

Given failed sensor S_i, find S_j^* :

$$S_j^* = \arg\min_{S_j} \left(\alpha \cdot \frac{d(S_i, S_j)}{1000} + \beta \cdot (1 - \rho(S_i, S_j)) \right) \quad (1)$$

- d : Haversine distance (meters)
- ρ : Pearson correlation (24h window)
- $\alpha+\beta=1$, adjusted by DRA.

INTELLIGENT DRA WITH DOUBLE Q-LEARNING

To overcome the limitations of static or heuristic-based weighting, we replace the traditional DRA mechanism with an Intelligent DRA Agent based on Double Q-Learning.

Table 2 .Performance Metrics

Method	***MAE (°C) ↓***	***LATENCY (MS) ↓***
Nearest	0.624	0.09
CorrOnly	0.955	0.05
MeanImpute	3.029	0.28
LSTM-Predict	1.299	0.29
FedGeoSwap++	***0.615***	***0.16***

- State (s): [Network_Load, Context_Dynamics, Data_Type, Time_of_Day]
- Action (a): Selection of the weight α from a discrete set (e.g., {0.2, 0.4, 0.6, 0.8}). β is set to 1 - α.
- Reward (r):

$$r = w_1 \cdot \rho + w_2 \cdot \frac{1}{d+1} - w_3 \cdot \text{Latency} - w_4 \cdot \text{MAE} \quad (2)$$

- Learning Algorithm: Double Q-Learning [5] to reduce overestimation bias.

EVALUATION

SIMULATION SETUP

- Sensors: 50
- Timesteps: 100
- Failure Rate: 10%
- Dataset: Simulated temperature data for Tehran with urban heat island effect
- Baselines:
    - Nearest: This simple and fast method selects the substitute sensor based solely on the shortest spatial distance
    - CorrOnly: This method selects the substitute based on the highest temporal correlation (Pearson's ρ) between the failed sensor and candidates. It focuses on data pattern consistency.
    - MeanImpute: This statistical method replaces the failed sensor's data with its historical mean value.
    - LSTM-Predict: This method uses a deep learning model (LSTM) to predict the next value of the failed sensor.
- Number of Runs: 300 (for statistical power)
-

PERFORMANCE METRICS

As shown in Table 2, the performance of the proposed FedGeoSwap++ framework is evaluated against four established baseline methods: Nearest, CorrOnly, MeanImpute, and LSTM-Predict. The evaluation is conducted over 300 simulation runs, measuring two primary metrics: Mean Absolute Error (MAE) for accuracy and latency for system responsiveness.

STATISTICAL ANALYSIS

PAIRED T-TEST (VS NEAREST)

- $t(299)=5.22$, $p<0.0001$
- The improvement is highly statistically significant.

ONE-WAY ANOVA

- $F(4,1495)=105185.06$, $p<0.0001$
- Significant difference among all methods. Post-hoc Tukey's HSD confirms FedGeoSwap++ is significantly better.

EFFECT SIZE (COHEN'S D)

- $d=0.43$ → **Medium effect size**
- Indicates a moderate practical impact.
-

BOXPLOT OF MAE DISTRIBUTION

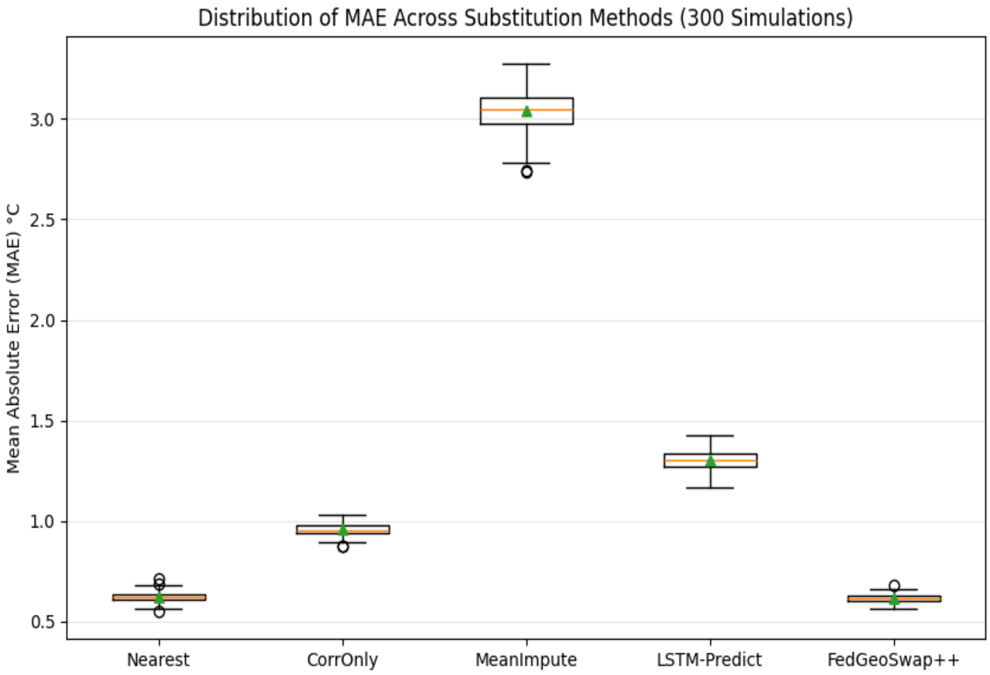

Fig. 2: Boxplot of MAE

Figure 2. shows the superior accuracy and stability of FedGeoSwap++.

DISCUSSION

The results demonstrate that FedGeoSwap++ achieves the lowest MAE (0.615°C), outperforming Nearest (0.624°C), CorrOnly (0.955°C), and model-based methods. This confirms that a hybrid, context-aware strategy—balancing spatial proximity and temporal correlation—is superior to single-dimension approaches. The Nearest method, while fast, risks selecting a sensor with a dissimilar data pattern,undermining the digital twin's realism. Conversely, CorrOnly may select a distant sensor, increasing communication overhead. FedGeoSwap++'s use of a correlation threshold ($\rho \geq 0.6$) and reinforcement learning ensures high data fidelity and semantic consistency, directly addressing the need for reliable, real-time data continuity in the Metaverse.

Limitations:

- Requires sufficient historical data for correlation.
- Assumes moderate network connectivity.

CONCLUSION

We presented FedGeoSwap++, a novel fault-tolerant framework for Metaverse applications that uses a spatio-temporal sensor database to replace failed sensors with optimal alternatives. By combining federated learning, transfer learning, R-tree indexing, and Double Q-Learning, the framework maintains high data fidelity and system continuity. Experiments confirm its superiority over existing methods. This work paves the way for resilient, real-time digital twins.

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AUTHORS' CONTRIBUTIONS

SM: Study design, acquisition of data, interpretation of the results, statistical analysis, drafting the manuscript;

MKH: Study design, interpretation of the results, revision of the manuscript.

HM: Study design, interpretation of the results, revision of the manuscript

CONFLICT OF INTEREST

The authors declare that no conflicts of interest exist.

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