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A Solar-Powered IoT Weather Monitoring Network with Big Data Architecture and Deep Learning Hyperlocal Forecasting: Design, Deployment, and Validation in Vietnam

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ABSTRACT: Vietnam ranks among the most climate-vulnerable countries in Southeast Asia, yet its operational weather monitoring network covers only approximately one station per 800 km², far below the World Meteorological Organization's recommended density. This paper presents the design, implementation, and field validation of a fully solar-powered IoT weather station network integrated with a Lambda/Kappa Big Data architecture and a Temporal Fusion Transformer (TFT) deep learning model for hyperlocal, multi-horizon weather forecasting. Fifty prototype stations were deployed across three climatically distinct provinces — An Giang (Mekong Delta flooding), Quang Nam (Central Vietnam typhoons/flash floods), and Dak Lak (Central Highlands drought/landslides) — collecting eight meteorological variables at six-minute intervals over twelve months. A Federated Anomaly Detection framework with differential privacy guarantees ($\varepsilon = 2.0$, $\delta = 10^{-5}$) identifies five classes of sensor faults without transmitting raw data. The TFT model, pre-trained on 23 years of ERA5 reanalysis and fine-tuned on local observations, achieves a 2-metre temperature RMSE of 0.81°C at 24-hour lead time, surpassing Kriging interpolation by 31% and the operational NWP baseline by 18%. System uptime reaches 99.3% over the evaluation period. All data and model weights are released as open datasets (CC BY 4.0) to support future research.

Keywords — *IoT; solar energy harvesting; Big Data; Apache Kafka; Apache Flink; Temporal Fusion Transformer; hyperlocal weather forecasting; federated learning; anomaly detection; Vietnam.*

Tóm tắt

Việt Nam là một trong những quốc gia chịu ảnh hưởng nặng nề nhất từ biến đổi khí hậu tại Đông Nam Á, song mạng lưới trạm quan trắc khí tượng hiện tại chỉ đạt mật độ xấp xỉ 1 trạm/800 km², thấp hơn nhiều so với khuyến nghị của Tổ chức Khí tượng Thế giới (WMO). Bài báo này trình bày thiết kế, triển khai và kiểm chứng thực địa của mạng lưới trạm quan trắc thời tiết IoT hoàn toàn sử dụng năng lượng mặt trời, tích hợp với kiến trúc Big Data Lambda/Kappa và mô hình học sâu Temporal Fusion Transformer (TFT) cho bài toán dự báo thời tiết siêu cục bộ đa chân trời. Năm mươi trạm nguyên mẫu được triển khai tại ba tỉnh đại diện ba vùng khí hậu đặc trưng của Việt Nam trong 12 tháng. Hệ thống phát hiện bất thường liên kết (Federated Anomaly Detection) với đảm bảo quyền riêng tư vi phân ($\varepsilon = 2{,}0$; $\delta = 10^{-5}$) xác định năm lớp lỗi cảm biến mà không cần truyền dữ liệu thô. Mô hình TFT đạt RMSE nhiệt độ 2 m là 0,81°C ở tầm xa 24 giờ, vượt trội hơn phương pháp nội suy Kriging 31% và mô hình NWP vận hành 18%. Toàn bộ dữ liệu và trọng số mô hình được công bố mở (CC BY 4.0).

Từ khóa — *IoT; thu hoạch năng lượng mặt trời; Big Data; Kafka; Flink; Temporal Fusion Transformer; dự báo thời tiết siêu cục bộ; học liên kết; phát hiện bất thường; Việt Nam.*

1. INTRODUCTION

Climate change represents one of the most pressing challenges for developing nations in Southeast Asia. Vietnam, with its 3,200 km coastline, extensive river deltas, and mountainous interior, is disproportionately exposed to meteorological extremes. According to the Global Climate Risk Index **[1]**, Vietnam ranked 9th globally in climate impact over the 2000–2019 period, with annual economic losses from weather-related disasters averaging 1–1.5% of GDP **[2]**. Accurate, high-resolution weather monitoring and forecasting are therefore not merely scientific pursuits but operational necessities underpinning disaster risk reduction, agriculture, and water resource management.

The operational network of the Vietnam National Center for Hydro-Meteorological Forecasting (VNMHA) currently comprises approximately 200 automatic rain gauges and 180 water-level stations distributed across a territory of 331,000 km² **[3]**. This translates to a mean station density of roughly one station per 800 km² — significantly below the WMO guideline of one station per 200–400 km² for lowland terrain and one per 100–200 km² for mountainous regions **[4]**. The resulting spatial interpolation errors fundamentally limit the accuracy of convective precipitation forecasts, which exhibit pronounced local variability driven by complex terrain.

The past decade has witnessed the convergence of three enabling technologies that collectively address this observational gap: (i) low-cost, low-power microcontrollers capable of embedded signal processing; (ii) long-range, low-power wireless protocols such as LoRaWAN and NB-IoT; and (iii) photovoltaic energy harvesting at sub-100-W scales suitable for autonomous field deployment **[5]**. Simultaneously, deep learning architectures have demonstrated skill exceeding numerical weather prediction (NWP) models at hyperlocal scales where coarse model resolution is a fundamental limitation **[6]**.

Despite growing interest in IoT-based environmental monitoring **[7,8]**, prior deployments in tropical developing-country contexts have been hampered by three persistent gaps. First, most systems rely on grid power or short-lived primary batteries, precluding deployment in the approximately 30% of Vietnam's territory lacking reliable electricity access. Second, existing data pipelines are engineered for low-throughput, high-latency applications and cannot support sub-minute, network-wide stream analytics across thousands of concurrent stations. Third, published deep learning weather models trained on global reanalysis products have not been systematically fine-tuned and validated for the distinct climatological regimes of mainland Southeast Asia — particularly the southwest monsoon, typhoon season, and dry-season haze events that characterise Vietnam's climate.

This paper makes the following original contributions:

i. A fully solar-powered IoT weather station design achieving station hardware cost below 5,000,000 VND (~USD 200) and system uptime exceeding 99% over a 12-month field trial in tropical monsoon conditions.

ii. A scalable Big Data pipeline — Kafka → Flink → InfluxDB/MinIO — capable of ingesting and processing 10,000 messages per second from 1,000 concurrent stations with end-to-end latency below 60 seconds.

iii. A Temporal Fusion Transformer model pre-trained on ERA5 reanalysis (2000–2022) and fine-tuned on local IoT observations, achieving 2-m temperature RMSE of 0.81°C and precipitation CSI of 0.46 at 24-hour lead time.

iv. A Federated Anomaly Detection framework with (ε, δ)-differential privacy that identifies five classes of sensor faults with F1-score 0.923 without transmitting raw observations beyond each gateway node.

v. An open dataset of 12 months of quality-controlled meteorological observations from 50 stations across three Vietnamese provinces, released under CC BY 4.0 on Zenodo.

The remainder of this paper is structured as follows. Section 2 reviews related work. Section 3 describes the system architecture. Section 4 presents the Big Data pipeline. Section 5 details the AI forecasting and anomaly detection models. Section 6 reports experimental results. Section 7 discusses implications and limitations. Section 8 concludes.

2. RELATED WORK

2.1 IoT-based Environmental Monitoring

The deployment of low-cost sensor networks for environmental monitoring has been extensively studied since the pioneering work of Akyildiz et al. **[9]**. Early wireless sensor network (WSN) systems focused primarily on reliability and energy efficiency in static deployments. The transition to IoT paradigms introduced cloud connectivity, real-time dashboards, and remote firmware management. Al-Fuqaha et al. **[7]** provide a comprehensive survey of IoT enabling technologies, protocols, and applications across domains including smart cities and precision agriculture. However, the majority of reviewed deployments rely on grid power or primary batteries with lifetimes measured in months rather than years.

Energy harvesting for IoT has received sustained attention. Sudevalayam and Kulkarni **[5]** survey energy harvesting sensor nodes, identifying solar photovoltaic as the most mature and cost-effective harvesting modality for outdoor deployments. More recent work by Piñuela et al. **[10]** demonstrates perpetual operation of LoRaWAN nodes using 2W monocrystalline panels in Central European insolation conditions, corresponding to approximately 60% of Vietnam's annual solar irradiance. To our knowledge, no prior published system has demonstrated >99% uptime for a multi-sensor IoT weather station using solar harvesting under tropical monsoon conditions, where extended cloud cover periods of 5–7 days are common during the southwest monsoon season.

2.2 Edge Computing and Stream Processing for IoT

The concept of edge computing — processing data at or near the data source rather than in a centralised cloud — was formalised by Shi et al. **[11]**. For IoT time-series data, edge processing reduces latency, bandwidth consumption, and cloud storage costs while enabling graceful degradation during network outages through store-and-forward buffering. In the meteorological domain, edge QC (quality control) is particularly valuable: gross errors can be flagged and optionally suppressed before transmission, reducing downstream storage and processing load.

Apache Kafka has become the de facto standard for high-throughput event streaming in IoT pipelines **[12]**. Carbone et al. **[13]** describes Apache Flink's unified stream and batch processing engine, which we adopt for windowed aggregation, spatial interpolation triggers, and real-time anomaly scoring. The combination of Kafka and Flink has been validated at petabyte scales in industrial monitoring applications but has not previously been evaluated in the specific context of dense IoT weather networks in developing countries.

2.3 Deep Learning for Weather Forecasting

Significant advances in data-driven weather forecasting were achieved with the introduction of Pangu-Weather **[6]** and GraphCast **[14]**, which demonstrated that deep neural networks pre-trained on ERA5 reanalysis can outperform the ECMWF Integrated Forecasting System at medium-range lead times of 1–10 days. However, both models operate at global scales (0.25° × 0.25° resolution, approximately 28 km in the tropics) and do not leverage surface observations for sub-grid correction.

Lim et al. **[15]** introduced the Temporal Fusion Transformer, which achieves state-of-the-art performance on multi-horizon time-series forecasting benchmarks by combining variable selection networks, gated residual connections, and interpretable multi-head attention. TFT has been applied to electricity demand forecasting, financial time series, and hospital admission prediction, but its application to IoT-augmented meteorological forecasting in tropical climates remains unexplored.

For spatial downscaling, Neural Optimal Interpolation **[16]** extends classical data assimilation with learned residual corrections from a U-Net architecture, promising improved accuracy over Kriging when training data are available. Spatio-Temporal Graph Convolutional Networks (STGCN) **[17]** offer an alternative by explicitly modelling the station graph topology, learning spatially aware feature representations that outperform fully connected architectures when the observation network has stable geographic structure.

2.4 Federated Learning and Anomaly Detection

McMahan et al. **[18]** introduced Federated Averaging (FedAvg), demonstrating that deep models can be trained collaboratively across distributed edge devices without centralising raw data. Differential privacy integration for federated learning, formalised by Geyer et al. **[19]**, provides formal guarantees that individual device data cannot be inferred from shared model updates. In the context of IoT sensor networks, federated anomaly detection is particularly attractive because (i) raw meteorological data may be commercially sensitive or subject to data-sharing agreements, and (ii) uploading continuous multi-variable streams from thousands of stations would consume prohibitive bandwidth in many rural deployment contexts.

Audibert et al. **[20]** propose USAD (Unsupervised Anomaly Detection), a dual-autoencoder architecture for multivariate time series that achieves strong performance on industrial sensor datasets. We adapt this architecture for meteorological sensor fault detection and extend it with spatial consistency checks leveraging the Kriging neighbourhood, a combination not previously reported in the literature.

3. SYSTEM ARCHITECTURE

3.1 Five-Layer Reference Architecture

Figure 1 illustrates the five-layer reference architecture of the proposed system. Layer 1 (Energy) provides autonomous power through a 30W monocrystalline photovoltaic panel, a Victron Energy MPPT 75/15 charge controller, and a 40 Ah $LiFePO_4$ battery, achieving a calculated autonomy of 6.2 days under zero-insolation conditions. Layer 2 (Perception) comprises eight sensors measuring temperature, relative humidity, atmospheric pressure, wind speed and direction, precipitation, UV irradiance, and solar radiation. Layer 3 (Network/Edge) implements firmware-level QC, MQTT packaging, and dual-path transmission via LoRaWAN (primary, up to 15 km range in open terrain) and NB-IoT 4G (failover). Layer 4 (Platform) encompasses the cloud-hosted Big Data pipeline described in Section 4. Layer 5 (Application) provides REST and MQTT APIs, a Grafana-based dashboard, and automated alerting via the Zalo OA business messaging platform.

The design philosophy prioritises three objectives: (i) operational autonomy — the system must continue collecting and locally storing data during network outages of up to 30 days; (ii) deployability — station hardware and installation must be within the capability of trained technicians without specialised electronics expertise; and (iii) extensibility — the platform must accommodate additional sensor types and new downstream applications without requiring core architecture changes.

3.2 Station Hardware

Table 1 summarises the station bill of materials. The primary microcontroller is an ESP32-S3-WROOM-1 (dual-core Xtensa LX7, 240 MHz, 8 MB flash), selected for its integrated Wi-Fi/BLE, support for FreeRTOS, and extensive driver ecosystem. A Raspberry Pi Zero 2W serves as the local edge gateway, running Mosquitto MQTT broker and executing Python-based QC Level 0–1 routine. Communication is handled by a RAK4631 LoRaWAN module (Semtech SX1262 radio, 14 dBm TX power) with a SIM7600G-H 4G Cat-4 module providing fallback connectivity. A NEO-M9N GNSS receiver provides time synchronisation with ±2.5 m positioning accuracy, eliminating dependency on internet time services during extended offline periods.

Table 1. Station bill of materials and unit costs.

Component	Model / Specification	Cost (VND)
MCU + Edge GW	ESP32-S3 + RPi Zero 2W	350,000
Temp. & Humidity	SHT31-D (±0.2°C, ±2% RH)	120,000
Pressure	BMP388 (±0.5 hPa)	80,000
Wind	Davis 7911 Anemometer	800,000
Precipitation	HS-TB3 (0.2 mm/tip)	600,000
UV + Solar rad.	ML8511 + BH1750	90,000
Comm. module	RAK4631 + SIM7600G-H	400,000
PV Panel	Mono 30 W, η=21%, IP67	350,000
Battery	$LiFePO_4$ 40 Ah / 12 V	800,000
MPPT Controller	Victron MPPT 75/15	500,000
GPS / RTC	NEO-M9N + DS3231	150,000
Enclosure	ABS IP66 + Inox 304 mast	400,000
Total		**~4,640,000**

3.3 Energy Budget Analysis

The energy budget was computed for the worst-case month (November, Central Vietnam monsoon season) with measured daily irradiance $H_d = 2.8$ kWh/m²/day. Daily energy harvested: $E_{in} = \eta_{panel} \times \eta_{MPPT} \times A_{panel} \times H_d = 0.21 \times 0.98 \times 0.167 \times 2.8 = 96$ Wh. Daily consumption: $E_{out} = P_{active} \times t_{active} + P_{sleep} \times t_{sleep} = 0.2\ \text{W} \times 4\ \text{h} + 0.001\ \text{W} \times 20\ \text{h} = 0.82$ Wh. Accounting for charge/discharge losses ($\eta_{bat} = 0.95$), net daily energy margin is $96 \times 0.95 - 0.82 = 90.4$ Wh, corresponding to a theoretical autonomy of $40\ \text{Ah} \times 12\ \text{V} \times 0.95 / 0.82 = 558$ hours (23.3 days) — comfortably exceeding the 5-day design target.

4. BIG DATA PIPELINE

4.1 Architecture Overview

The platform adopts a Kappa architecture **[21]** — a simplification of the Lambda architecture that uses a single replayable log (Apache Kafka) as the source of truth for both real-time and batch processing paths. This eliminates the operational complexity of maintaining parallel serving layers while retaining the ability to reprocess historical data when model or pipeline logic changes.

The pipeline comprises five components. (1) Kafka Cluster (3 brokers, replication factor 3) ingests station messages partitioned by station_id with 7-day retention. A Schema Registry enforces Avro schemas versioned per firmware release. (2) Apache Flink DataStream API performs windowed aggregation (1-min, 5-min, 1-hour tumbling windows), spatial consistency cross-checks against Kriging estimates from the three nearest stations, and real-time anomaly score computation. Flink checkpoint interval is 30 seconds, enabling recovery from failure within one checkpoint period. (3) InfluxDB 2.x cluster stores processed observations as time-series for dashboard queries and alerting, with 90-day hot retention. (4) MinIO object storage receives Parquet-encoded raw data for long-term preservation, with lifecycle rules tiering data to lower-cost storage after 90 days. (5) Apache Spark batch jobs run nightly to compute climatological baselines, retrain the anomaly detection models, and generate daily QC reports.

4.2 Data Quality Control Framework

Four QC levels are applied sequentially, consistent with WMO No. 8 guidelines **[4]**. QC Level 0 (on-device): syntactic validation, timestamp plausibility, and physical range checks (e.g., temperature ∈ [−10°C, 50°C] for Vietnam). QC Level 1 (edge gateway): internal consistency checks — e.g., dew point ≤ dry-bulb temperature, pressure variance < threshold over 1 min. QC Level 2 (Flink stream): spatial consistency cross-check against Kriging estimate from five nearest stations; deviations exceeding 3σ_spatial are flagged. QC Level 3 (Spark batch): temporal consistency using climatological percentile bounds and persistence detection (variance < 0.01 over 30-min window). Each observation is assigned a Quality Flag (QF) from 0 (raw/unknown) to 4 (verified by independent reference).

Table 2 summarises observed data recovery and QC statistics across the 12-month evaluation period. Overall data recovery reached 96.7%, with the principal cause of data loss being extended LoRaWAN outages during Typhoon Noru (October 2022), which affected 11 stations in Quang Nam province for up to 72 hours. The store-and-forward mechanism successfully recovered 94.3% of data lost during connectivity interruptions upon reconnection.

Table 2. Data recovery and quality control statistics by deployment province.

Metric	An Giang	Quang Nam	Dak Lak
Stations deployed	20	20	10
Data recovery (%)	98.1	93.8	98.8
QF ≥ 2 observations (%)	97.3	96.1	97.9
Anomalies detected (n)	1,241	2,189	678
Confirmed faults (n)	183	312	91
False positives (%)	3.8	4.2	3.1
Mean uptime (%)	99.5	98.8	99.6

5. AI MODELS FOR FORECASTING AND ANOMALY DETECTION

5.1 Temporal Fusion Transformer

The forecasting model is a Temporal Fusion Transformer (TFT) **[15]** adapted for multi-station, multi-variable meteorological forecasting. The model receives as input: (i) a look-back window of $\tau = 72$ time steps (7.2 hours at 6-min resolution) of observed station variables; (ii) ERA5 reanalysis fields at 0.25° resolution downsampled to the station grid via bilinear interpolation; (iii) Himawari-9 cloud-top temperature composites; and (iv) static geographic covariates (elevation from SRTM-30m DEM, land cover class, distance to coastline). Temporal covariates include time-of-day and day-of-year encoded as sine-cosine pairs to respect their circular nature.

The Variable Selection Network (VSN) assigns learned importance weights to each input variable at each time step, enabling post-hoc interpretation of which inputs drive each forecast. The model is trained to minimise the multi-quantile loss:

$$L = (1/|Q||H||N|) \cdot \Sigma\_q\ \Sigma\_h\ \Sigma\_t\ QL\_q(y(t+h), \hat{y}\_q(t+h))$$

with quantile set $Q = \{0.1, 0.5, 0.9\}$, forecast horizon $H \in \{6, 12, 24, 48, 72\}$ time steps, and N training samples. The 10th and 90th percentile outputs define an 80% prediction interval whose coverage is post-hoc calibrated using Conformalized Quantile Regression **[22]** on a held-out calibration set, achieving empirical coverage of 80.8% versus the nominal 80% target.

The model was pre-trained for 50 epochs on ERA5 data for the Vietnam bounding box (8°N–24°N, 100°E–110°E) from 2000 to 2022, then fine-tuned for 20 additional epochs on local IoT observations from the first six months of deployment. Transfer learning was implemented by freezing the bottom 70% of parameters (embedding and LSTM encoder layers) and applying a cosine-annealing learning rate schedule ($\eta\_max = 1\times10^{-3}$, $\eta\_min = 1\times10^{-5}$).

5.2 Federated Anomaly Detection

Each gateway node maintains a local LSTM Autoencoder trained exclusively on quality-controlled ($QF \geq 2$) observations from the stations it supervises. The reconstruction error for a window of $w = 12$ steps defines the anomaly score;

observations exceeding μ_e + 3σ_e (3-sigma rule estimated on a clean training window) are flagged as candidate anomalies and passed to the spatial consistency module for confirmation.

Model weights are aggregated every 24 hours using FedAvg **[18]** with client sampling fraction C = 0.5. Differential privacy is enforced by clipping each weight update to L_2 norm C_clip = 1.0 and adding Gaussian noise with standard deviation σ_DP = 1.12, corresponding to privacy budget ($\varepsilon = 2.0$, $\delta = 10^{-5}$) per Abadi et al. **[23]**. The resulting global model is used to initialise all local models at the next round, preventing drift in stations with intermittent connectivity.

6. EXPERIMENTAL RESULTS

6.1 Forecasting Performance

Table 3 presents deterministic forecast skill scores for 2-metre temperature (T2m), precipitation (Precip.), and 10-metre wind speed (WS10m) across lead times of 6 to 72 hours on the held-out test set (months 7–12 of the deployment period). All metrics are spatially averaged across the 50 station locations and compared against three baselines: (i) Ordinary Kriging interpolation of station observations to the target location; (ii) the VNMHA operational NWP product (3 km WRF-based); and (iii) ERA5 reanalysis nearest-grid-cell extraction.

Table 3. Forecast skill scores on held-out test set (months 7–12). Bold row = proposed method. CSI threshold: 1 mm/h. Best values in each column underlined.

Model	T2m 24h RMSE (°C)	T2m 72h RMSE (°C)	Precip CSI 24h	WS10m 24h RMSE (m/s)	ACC 24h
Kriging	1.17	1.89	0.31	1.52	0.71
ERA5 (0.25°)	1.43	2.01	0.24	1.88	0.63
WRF-3km	0.99	1.51	0.38	1.31	0.79
TFT (Ours)	0.81	1.24	0.46	1.08	0.87
TFT + STGCN	0.79	1.21	0.48	1.05	0.88

The TFT model reduces 24-hour T2m RMSE by 31% relative to Kriging and by 18% relative to the operational WRF-3km product. The improvement is most pronounced at 72-hour lead time, where the advantage over WRF-3km widens to 21%, consistent with the hypothesis that data-driven models leveraging dense surface observations maintain skill longer than physics-based NWP at short ranges. Precipitation CSI of 0.46 at the 1 mm/h threshold is competitive with state-of-the-art downscaling products for Southeast Asia documented by Baño-Medina et al. **[24]**. The combined TFT + STGCN ensemble achieves marginal additional gains (0.02 CSI, 0.01°C RMSE) at the cost of 3.7× inference latency.

6.2 Anomaly Detection Performance

The Federated Anomaly Detection system was evaluated against a manually labelled ground-truth dataset of 586 confirmed sensor fault events across the 12-month period, spanning five fault classes: spike (n=187), persistence (n=142), drift (n=98), range violation (n=89), and spatial inconsistency (n=70). Table 4 reports per-class and aggregate detection metrics.

Table 4. Federated anomaly detection performance by fault class on 586 labelled events.

Fault Class	n	Precision	Recall	F1	Latency (s)
Spike	187	0.961	0.968	0.964	< 6
Persistence	142	0.934	0.943	0.938	< 12
Drift	98	0.891	0.878	0.884	< 60
Range violation	89	1.000	1.000	1.000	< 1
Spatial inconsistency	70	0.871	0.857	0.864	< 60
All (macro avg.)	**586**	**0.931**	**0.929**	**0.930**	—

Aggregate F1-score of 0.930 meets the design target of >0.90. Range violations achieve perfect detection by construction (hard physical bound checks). Drift and spatial inconsistency exhibit lower F1, consistent with the inherent ambiguity between slow sensor degradation and genuine regional meteorological anomalies —

a limitation discussed in Section 7. The differential privacy mechanism reduced aggregate F1 by 0.031 relative to a non-private federated baseline, within the acceptable range for operational use.

6.3 System Performance

End-to-end latency (station measurement → dashboard update) was measured as 42.3 ± 8.7 seconds (mean ± SD) across 10,000 sampled events during peak load. Kafka consumer lag remained below 500 messages (< 50 seconds of backlog) under sustained 8,000 msg/s ingestion, confirming the pipeline's headroom for network expansion to 1,000+ stations. Mean station uptime across all 50 nodes over 12 months was 99.3%, with the primary failure mode being LoRaWAN gateway power interruptions (rather than station hardware failure), representing 71% of all downtime events.

7. DISCUSSION

7.1 Contributions and Practical Implications

The results demonstrate that a network of solar-powered IoT weather stations costing approximately USD 200 per node can achieve data quality and forecasting accuracy exceeding the current operational NWP standard for hyperlocal applications. The cost differential is substantial: a conventional automatic weather station from established meteorological instrument manufacturers typically costs USD 2,000–15,000 per unit excluding installation. The proposed system's 10–75× cost reduction makes nationwide densification economically tractable within existing VNMHA budget frameworks.

The federated learning approach for anomaly detection has broader implications for data governance in developing-country IoT deployments. Many provincial authorities in Vietnam are reluctant to share raw observational data with external cloud providers for commercial sensitivity and sovereignty reasons. By keeping raw data on-premise at the edge gateway, the federated approach satisfies these constraints without sacrificing the benefit of network-wide learning.

7.2 Limitations

Several limitations warrant acknowledgement. First, the 50-station pilot network, while sufficient for model training and validation, remains below the density needed to resolve convective cells of typical diameter 5–20 km that drive the most severe flash-flood events. Network expansion to 500+ stations is planned for Phase 2 but was outside the scope of the current evaluation. Second, the TFT model's performance degrades substantially at 72-hour lead times during typhoon intensification events (RMSE increases by 0.6°C relative to non-typhoon periods), likely because ERA5's 0.25° resolution inadequately represents rapidly evolving cyclone structure. Integration with the Japan Meteorological Agency's typhoon track ensemble would be a productive future direction. Third, $LiFePO_4$ cell capacity degradation under repeated deep discharge cycles during the wet season may shorten effective battery lifetime below the manufacturer's 2,000-cycle specification in the most cloud-intensive deployment locations.

8. CONCLUSION

This paper has presented the end-to-end design, deployment, and validation of a solar-powered IoT weather station network integrated with a scalable Big Data pipeline and deep learning forecasting system for Vietnam. Fifty stations deployed across three climatically distinct provinces over 12 months achieved 99.3% system uptime, 96.7% data recovery, and a 2-metre temperature RMSE of 0.81°C at 24-hour lead time — a 31% improvement over Kriging interpolation. The Federated Anomaly Detection framework achieved macro-average F1-score of 0.930 with formal differential privacy guarantees, enabling trust-preserving collaborative learning across distributed edge nodes.

The system demonstrates that the technological and economic barriers to high-density weather monitoring in climate-vulnerable developing nations are now surmountable. Future work will focus on network expansion to 500 stations covering all 63 Vietnamese provinces, integration of soil moisture and water-level sensors for multi-hazard early warning and coupling with national emergency management information systems. All data, firmware, and model weights are publicly available at https://zenodo.org/record/[DOI] under CC BY 4.0.

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