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Development of an Unattended Ionosphere–Geomagnetism Monitoring System with Dual-Adversarial AI for Remote Mid–High-Latitude Regions

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Abstract

To address coverage gaps in high-latitude space weather monitoring caused by constraints in energy, bandwidth, and labeled samples, this study presents a systematic solution deployed in Hailar, China. We constructed a Cloud–Edge–Terminal system featuring wind–solar hybrid energy and RK3588-based edge computing, achieving six months of stable ionospheric–geomagnetic observation under -40°C . Furthermore, we propose a Dual-Adversarial Recurrent Autoencoder (DA-RAE) for anomaly detection. Utilizing a single-source domain strategy, the model learns physical manifolds from quiet-day data, enabling zero-shot anomaly perception in the unsupervised target domain. Field tests in March 2025 demonstrated superior generalized anomaly detection capabilities, successfully identifying both transient space weather events and environmental equipment faults (baseline drifts). This work validates the value of edge intelligence for autonomous operations in extreme environments, providing a reproducible paradigm for global ground-based networks.

Keywords: space weather; unattended monitoring system; edge computing; dual adversarial recurrent autoencoder; domain generalization



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1. Introduction

As a crucial component of the Earth system, the space environment and its dynamic evolution are intrinsically linked to human activities and the safe operation of various technological systems [1–3]. As core manifestations of space weather, geomagnetic activities and ionospheric disturbances not only directly constrain critical fields such as satellite orbit maintenance, over-the-horizon communication, and the stability of power grids but also hold significant strategic value for space security assurance in high-latitude regions [4–7]. Ground-based observation stations serve as the primary sensing nodes for acquiring fundamental space environment data, providing irreplaceable in situ support for revealing magnetosphere–ionosphere coupling mechanisms and establishing early-warning models. However, existing ground-based observation networks suffer from significant spatial disparity where stations are predominantly clustered in populated areas with established

infrastructure at middle and low latitudes [8–11]. Conversely, remote high-latitude regions, which act as critical windows for solar wind energy injection and particle precipitation, suffer from substantial observational coverage gaps [12–14].

Bridging this observational gap requires addressing severe dual constraints regarding engineering and algorithms. The first challenge involves the dual pressure of energy and environment. Remote areas lack municipal power support, and single-source renewable energy supplies are prone to disruption by extreme high-latitude weather such as extreme cold and blizzards [15,16]. The second challenge stems from the conflict between high-volume data acquisition and limited transmission bandwidth. High-frequency sampling generates enormous amounts of raw data, while remote areas often rely on narrowband satellite communications. The traditional model of terminal-side acquisition followed by cloud-side processing faces risks including high latency, high costs, and data packet loss, creating an urgent need to shift computing power to the edge for in situ data cleaning and semantic transmission. The third challenge pertains to balancing lightweight deployment with robust generalization capability. Existing deep learning models typically rely on massive computational resources and are sensitive to training data distributions [17–19]. A critical unresolved issue involves enabling models to maintain robust cross-domain anomaly detection capabilities on edge terminals with limited computing power under cold-start conditions lacking local labeled data.

To address the aforementioned challenges, this paper focuses on the Hailar region of Hulunbuir, China, a typical high-latitude area, and presents a systematic study ranging from hardware system construction to edge intelligence algorithm innovation. First, we constructed an all-weather, autonomously operating integrated ionospheric–geomagnetic monitoring system. Addressing the extreme cold field environment, we solved system survival challenges through wide-temperature hardware selection and a wind–solar hybrid energy management design. Relying on this system, we completed six months of continuous observation and acquired a high-quality in situ dataset [20,21]. Second, we proposed a Dual-Adversarial Recurrent Autoencoder (DA-RAE) anomaly detection framework designed for edge deployment. To tackle the scarcity of labeled data and poor transferability at remote stations, this framework eliminates the reliance on complex supervised training. Instead, it adopts a single-source domain generalization strategy that utilizes quiet-day data from a mature station to learn the intrinsic physical manifold of the geomagnetic field. To achieve robust transfer from the source domain to the target domain under zero-shot conditions, the model introduces a dual-adversarial constraint mechanism. By using Critic_Z to regularize the distribution shape of the latent space and leveraging Critic_X to reinforce the topological consistency between the reconstructed signal and the real physical background field, the model ensures precise characterization of geomagnetic variation laws even without target domain training data. Finally, we achieved generalized anomaly perception based on edge intelligence. Cross-station validation and field deployment results indicate that the model can accurately capture the “sudden onset” of geomagnetic disturbances and effectively identify “persistent modal shifts” induced by extreme environments. This generalized detection capability, which accounts for both natural space weather events and non-physical equipment anomalies, fills the observational gap in the Hailar region and provides a reproducible technical paradigm for the intelligent operation and maintenance of global remote space environment monitoring networks [22–25].

2. System Architecture and Hardware Implementation

2.1. Cloud–Edge–Terminal Collaborative Framework

Targeting the three core bottlenecks hindering the construction of space weather observation networks in high-latitude remote areas—specifically the challenges of survival

in extreme low temperatures, discontinuous field energy supply, and limited real-time communication—this paper presents the design and deployment of an all-weather unattended ionosphere–geomagnetic monitoring system in the Hailar District of Hulunbuir (119.75° E, 49.20° N). As illustrated in Figure 1, the system adopts a Cloud–Edge–Terminal collaborative architecture that ensures high system availability and the physical fidelity of observational data through targeted designs across three specific dimensions.



Figure 1. Schematic diagram of the system architecture.

First, we implemented extreme environment adaptation and sensor thermal stability optimization. The Hailar region experiences extreme cold winters where minimum temperatures reach $-40\text{ }^{\circ}\text{C}$ and low-temperature conditions persist for over three months. Such an environment typically causes severe signal-to-noise ratio deterioration and electronic component drift in conventional sensors, directly threatening scientific data validity. To address this, the system adopts a wide-temperature range adaptation strategy where all core observation payloads undergo rigorous low-temperature calibration. This extends their operating temperature range to $-70\text{ }^{\circ}\text{C}$ to $+80\text{ }^{\circ}\text{C}$, a specification that far exceeds the standard $-40\text{ }^{\circ}\text{C}$ lower limit of conventional equipment. Through hardware-level temperature drift compensation and cold resistance optimization, the system effectively suppresses measurement errors induced by low temperatures, ensuring the acquisition of high-precision raw observational data for the geomagnetic field and ionospheric Total Electron Content (TEC) even under extreme cold conditions.

Second, we designed a resilient energy topology featuring wind–solar–storage complementarity. Addressing the lack of grid coverage in remote stations where traditional single-source energy solutions fail to meet the demands of continuous winter observation, this system constructs a hybrid microgrid comprising a photovoltaic array, a small wind turbine, and a battery storage pack. This design leverages the meteorological complementary characteristic of strong winds and weak sunlight typical of Hailar winters. By establishing a high-reliability energy flow control strategy, the system achieves a 24 h uninterrupted power supply, thereby fundamentally resolving the energy bottleneck constraining long-term observation and guaranteeing the temporal continuity of geomagnetic and ionospheric data streams.

Third, we engineered an in situ data processing design driven by edge computing. Given the constraints of narrow bandwidth and high latency inherent in remote satellite communication links, the traditional mode of full-volume backhaul is unfeasible. Consequently, the system introduces the RK3588 high-performance edge computing terminal

to reconstruct the data processing workflow, as shown in Figure 2. This design shifts computational tasks to the edge, where the terminal directly ingests massive raw data collected by sensors and performs local cleaning, preprocessing, and physical feature calculation. Simultaneously, it runs the lightweight DA-RAE model to conduct millisecond-level real-time anomaly discrimination. Ultimately, the system transmits only the filtered key status parameters, anomaly event fragments, and compressed scientific data to the cloud Network Attached Storage (NAS) via the satellite uplink. This architecture transforms raw data into high-dimensional semantic information at the edge, which significantly reduces dependence on scarce satellite bandwidth while realizing the millisecond-level real-time perception and alerting of generalized anomaly events.

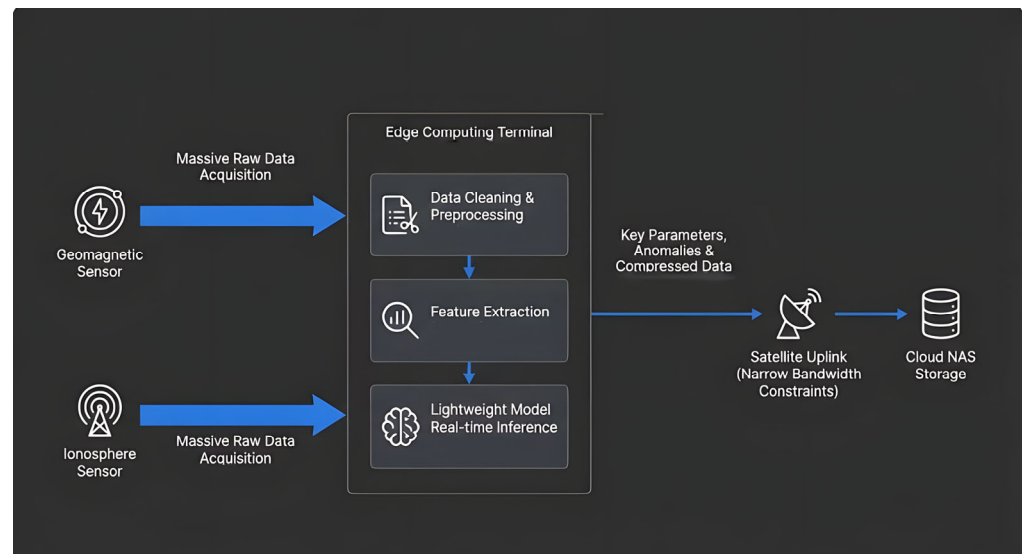


Figure 2. Data flow diagram.

2.2. Hardware Adaptation for Extreme Environments

To satisfy the rigorous demands for high data fidelity and system survivability imposed by the Cloud–Edge–Terminal collaborative architecture, the hardware selection process in this system adheres to three fundamental principles involving environmental adaptation priority, edge computing power redundancy, and the maximization of sensing precision. Consequently, this section elucidates the specific adaptation mechanisms across three dimensions that include energy flow control, the edge computing master controller, and high-sensitivity sensor integration.

2.2.1. Wind–Solar Hybrid Microgrid System

To overcome the limitations inherent in single-source energy generation, particularly the seasonal variability characterized by strong winds with weak solar irradiance in winter and high solar intensity with low wind speeds in summer, this study constructs an off-grid wind–solar–storage hybrid microgrid. By implementing a multi-energy complementary topology, the design ensures the system maintains energy autonomy even under extreme meteorological conditions. The detailed core parameters and topological architecture of the system are presented in Table 1.

The photovoltaic array topology system utilizes high-efficiency monocrystalline silicon modules with a total installed capacity of 4.6 kW. To address the issue of excessive line loss inherent in traditional low-voltage systems, the design incorporates a 2-series 4-parallel (2S4P) high-voltage DC topology. In this configuration, two 575 W modules are connected in series to elevate the bus voltage, while four sub-strings are subsequently connected in parallel to enhance current redundancy. This topological structure optimizes the

tracking efficiency of the Maximum Power Point Tracking (MPPT) controller and effectively mitigates the risk of hot spot formation caused by partial snow occlusion during winter, thereby guaranteeing basic power generation capabilities under low-light conditions.

Table 1. Key technical specifications of the wind–solar hybrid energy system.

Subsystem	Key Component	Topology	Key Performance Indicators	Selection Rationale
Photovoltaic Generation	Monocrystalline Silicon PV Modules	2-Series 4-Parallel (2S4P)	Rated Power: 4.6 kW Open Circuit Voltage > 48 V	High-redundancy design to address low solar altitude angles and snow occlusion during winter.
Wind Power Generation	Horizontal Axis Wind Turbine (HAWT)	Three-phase AC Rectification	Rated Power: 3 kW Cut-in Wind Speed: 3 m/s	Adapted to local wind speed distribution; utilizes strong winter wind resources to compensate for solar irradiance deficits.
Energy Storage Unit	Valve-Regulated Lead-Acid (VRLA) Battery	4-Series 16-Parallel (4S16P)	Total Capacity: 48 V/1200 Ah (57.6 kWh)	Wide temperature discharge characteristics; ensures system autonomy for over 10 days without sunlight.

To surmount the inherent diurnal intermittency of photovoltaic power generation, the system incorporates a horizontal axis wind turbine with a rated power of 3 kW as a complementary energy source. The selection strategy rigorously balances the startup threshold with wind resistance capabilities. Capitalizing on a low cut-in wind speed design of 3 m/s, the turbine efficiently captures the continuous class 3–4 winds typical of the Hailar region. Furthermore, the equipment integrates dual electronic and mechanical braking mechanisms to ensure a survival wind speed of up to 35 m/s. This wind–solar complementary mechanism effectively mitigates input fluctuations through the temporal coupling of multiple energy flows, thereby fundamentally guaranteeing the energy continuity required for long-term observation.

To mitigate the risk of lithium plating associated with lithium-ion batteries in low-temperature environments, this study employs Valve-Regulated Lead-Acid (VRLA) batteries, which exhibit superior low-temperature discharge characteristics, to construct a wide-temperature energy storage buffer pool. The system adopts a 4-series 16-parallel (4S16P) array configuration to establish a 48 V DC bus that provides a total capacity of 57.6 kWh. Assuming an average full-load power consumption of 200 W, this storage capacity theoretically supports an unassisted autonomy of more than 10 days. Such a high-capacity redundancy design constitutes a necessary guarantee for coping with prolonged continuous overcast and snowy weather conditions typical of extreme regions.

2.2.2. Edge Computing and Thermal Control Unit

The master control unit acts as the central hub the physical sensing layer and the intelligent decision-making layer. In light of the system's requirement to perform real-time cleaning, spatiotemporal alignment of high-frequency (20 kHz) multi-source data, and online inference of the DA-RAE model at the edge, traditional low-power Microcontroller Units (MCUs) prove insufficient to meet the requisite computational demands. Consequently, this study conducted a comparative analysis of current mainstream embedded

edge computing platforms as presented in Table 2 and ultimately constructed a heterogeneous computing architecture based on the RK3588 high-performance System on Chip (SoC) (Rockchip Electronics Co., Ltd., Fuzhou, China).

Table 2. Comparison of core parameters for embedded processors.

Model	Core Architecture	NPU Computing Power	Main Frequency	Application Scenario Analysis
RK3588	4 × Cortex-A76 4 × Cortex-A55	6 TOPS	2.4 GHz	High-performance data cleaning and complex model inference (Selected for this study).
RK3576	4 × Cortex-A72 4 × Cortex-A53	6 TOPS	2.2 GHz	Older architecture; exhibits bottlenecks in instruction throughput and memory bandwidth.
RK3568	4 × Cortex-A55	1 TOPS	1.8 GHz	Basic AI expansion scenarios; computing power is insufficient for running complex models.
NVIDIA Jetson Nano	4 × Cortex-A57	N/A	1.43 GHz	Entry-level AI applications; weak computing power due to the lack of an independent NPU.

The RK3588 leverages the advantages of heterogeneous CPU and NPU collaboration to achieve task decoupling. The eight-core high-frequency CPU provides sufficient computing power for high-throughput preprocessing tasks such as nanosecond-level spatiotemporal alignment, while the 6 TOPS NPU accelerates processing via INT8/FP16 mixed precision, controlling complex model inference latency to the millisecond level and effectively capturing transient magnetic storm events. In contrast, other solutions exhibit critical bottlenecks. The RK3568 is prone to data backlogs due to insufficient NPU computing power (1 TOPS); the Jetson Nano suffers from low energy efficiency ratios caused by the lack of an independent NPU; and the RK3576 faces limitations in instruction throughput and bandwidth due to its older CPU architecture. Consequently, the RK3588, with its superior computing density, I/O throughput, and industrial-grade wide-temperature stability, serves as the optimal platform for supporting “edge intelligence” in the extreme environments of this system.

Notably, in the face of deep freeze conditions in the Hailar region that persist for several months with minimum temperatures reaching −40 °C, relying solely on the intrinsic wide-temperature attributes of the chips is insufficient to completely eliminate the risk of cold-start failure. To address this, the system incorporates a dual thermal control architecture consisting of passive insulation and active compensation to ensure the survivability of core electronic systems at the lowest possible energy cost. Regarding passive insulation, the interior of the cabin is lined with customized insulation boards featuring high thermal resistance coefficients to establish a quasi-adiabatic space. This physical barrier effectively blocks heat exchange between the interior and exterior of the cabin and significantly retards the rate of internal temperature decay in response to plummeting external temperatures, thereby serving as a fundamental thermal retention protective measure. In terms of active compensation, the system integrates flexible electric heating pads as an emergency heat source. The unit employs a hysteresis control strategy where the relay activates the heating pad only when onboard sensors detect that the equipment temperature has fallen below the safe cold-start threshold, such as −30 °C. Conversely, the circuit is immediately disconnected once the temperature recovers to a safe range, such as −10 °C. This strategy, which prioritizes insulation with heating as a supplement, effectively resolves the cold-start

challenge under extreme low temperatures while minimizing the energy burden on the microgrid to the greatest extent possible.

2.2.3. Sensor Integration and Signal Conditioning

To acquire scientific-grade data capable of satisfying the stringent requirements of space physics research, this system avoids standard configurations of commercial-grade sensors. Instead, a customized integration of the core payloads is executed, specifically targeting the extraction of weak magnetic fields and the characterization of polar ionospheric features.

Addressing the demand for broadband geomagnetic monitoring, the system constructs a dual-sensor heterogeneous array comprising both low-frequency and high-frequency units (Figure 3). This configuration covers full-spectrum fluctuations ranging from millihertz, corresponding to ring current decay, to kilohertz, corresponding to plasma waves. Regarding low-frequency vector magnetic field measurement, the system employs a Honeywell HMC1001 Anisotropic Magnetoresistance (AMR) sensor array to monitor the orthogonal B_x , B_y and B_z components. Considering the vulnerability of AMR sensors to zero-point drift caused by hysteresis effects, the design integrates a Set/Reset (S/R) pulse circuit. By periodically resetting the magnetic domain orientation via nanosecond-level high-current pulses, this mechanism effectively eliminates historical residuals from strong magnetic fields. Building on this foundation, the signal processing chain incorporates phase-sensitive demodulation technology. In conjunction with a high-precision 24-bit AD7734 Analog-to-Digital Converter (ADC), this setup successfully separates weak effective magnetic signals from environmental thermal noise. The nominal sampling rate of this unit is precisely locked at 10 Hz, ensuring a large dynamic range of $\pm 65,000$ nT while achieving a measurement precision superior to 1 nT. In terms of high-frequency micropulsation detection, the system introduces a Giant Magneto-Impedance (GMI) effect module based on AICHIMI sensors. This module utilizes the variation in the skin effect of amorphous wires under high-frequency excitation to detect weak magnetic fields. With a sampling rate as high as 20 kHz acquired by a 16-bit AD7606, this module is capable of sensitively capturing Electromagnetic Ion Cyclotron (EMIC) wave characteristics in the 1 Hz to 10 kHz frequency band, thereby effectively compensating for the insufficient high-frequency response inherent in traditional fluxgate magnetometers. To further eliminate Electromagnetic Interference (EMI), all magnetic sensing probes are encapsulated within multi-layer thermal insulation sleeves and suspended in a physical isolation zone situated 2 m away from the master control unit via non-magnetic telescopic booms.



Figure 3. Physical implementation of the geomagnetic monitoring system.

Targeting ionospheric monitoring requirements, the system integrates an extreme-environment-adapted TEC and scintillation monitor (Figure 4) that supports multi-

constellation signal tracking for BeiDou (B1C/B2a), GPS (L1/L2), and Galileo. To overcome the limitations regarding high code pseudorange noise inherent in consumer-grade receivers, the firmware layer incorporates a carrier phase-smoothed pseudorange algorithm. By applying long-sequence smoothing to geometry-free linear combinations, this algorithm eliminates frequency-independent noise, thereby achieving a relative observation precision for Total Electron Content (TEC) superior to 0.05 TECu. Furthermore, in light of the frequent ionospheric scintillation interference characteristic of high-latitude regions, the core components of the receiver have undergone wide-temperature calibration to extend the operating range to $-70\text{ }^{\circ}\text{C}$ to $+80\text{ }^{\circ}\text{C}$. Additionally, the bandwidth of its internal Phase-Locked Loop (PLL) has undergone adaptive optimization to ensure the maintenance of continuous signal locking even under strong disturbances characterized by an amplitude scintillation index of $S_4 > 0.8$, thereby guaranteeing the continuity and integrity of data during magnetic storms.



Figure 4. Photograph of the Ionospheric TEC and Scintillation Monitor.

2.3. Field Deployment and Operational Verification

To comprehensively evaluate the reliability and survivability of the system under authentic extreme environmental conditions, a six-month comprehensive in situ operational test was conducted at the Hailar Observation Station from January to June 2025. The testing period spanned the harshest local “deep winter-to-early spring” phase, characterized by seasonal freeze–thaw cycles. During this interval, the system was subjected to extreme cold temperatures and multiple episodes of strong winds and blizzards.

Regarding operational efficacy, the test results demonstrated that the system exhibited exceptional robustness, attributed to the aforementioned hardware–software co-design. Within the 181-day testing window, the system achieved stable operation characterized by zero power interruptions and zero freezing incidents. With the exception of transient fluctuations in the satellite link Signal-to-Noise Ratio (SNR) caused by sporadic extreme weather events, the geomagnetic and ionospheric data acquisition achieved all-weather quasi-continuous observation. This validates that the system possesses the engineering capability required for high-quality, continuous scientific observation under unattended conditions.

In terms of targeted deployment strategies and engineering design, as illustrated in Figure 5, the system adopts a modular distributed layout. Physically, the architecture is partitioned into four distinct functional units: the wind turbine generator group, the photovoltaic array, the energy control cabin, and the observation cabin. To overcome the specific geological and meteorological challenges inherent to high-latitude severe cold regions, this study implemented three critical engineering optimizations: (1) Omnidirectional Solar Harvesting Topology: Addressing the illumination characteristics of high latitudes—specifically the extremely low solar altitude angle and significant azimuth variation in winter—the photovoltaic array discards the traditional unidirectional alignment in favor of a matrix-style orthogonal layout. This topology maximizes the interception cross-section for surface diffuse reflection and atmospheric scattered radiation. Consequently, it ensures that the Maximum Power Point Tracking (MPPT) controller maintains high energy conversion gain even under weak light or hazy winter conditions, thereby guaranteeing the continuity of en-

ergy input at the source. (2) Multi-layer Composite Thermal Protection Architecture: Both the battery cabin and the observation cabin are constructed based on customized containers designed to establish a “thermally stable” environment. By lining the cabin walls with a polyurethane composite insulation layer featuring a high thermal resistance coefficient, the system constructs a dual protection mechanism comprising “passive thermal insulation shielding and active temperature control compensation.” This architecture leverages the high thermal inertia of the materials to effectively dampen severe thermal transients from the external environment, confining the operating environmental fluctuations of internal precision electronic components within safe thresholds and preventing thermal failure. (3) Anti-frost-heave Deep Anchoring Mechanism: Addressing the deep seasonal frozen soil layer in the Hailar region, the wind turbine tower base employs a deep anchoring scheme with embedded parts. The excavation depth of the anchor pit is designed to be 2.0 m, which strictly exceeds the local maximum frozen soil depth (approximately 1.8 m), anchoring the foundation into the stable soil layer beneath the frozen zone. This design eliminates the impact of soil frost heave and thaw settlement on the verticality of the tower, thereby ensuring the mechanical stability of the wind turbine under strong wind loads.

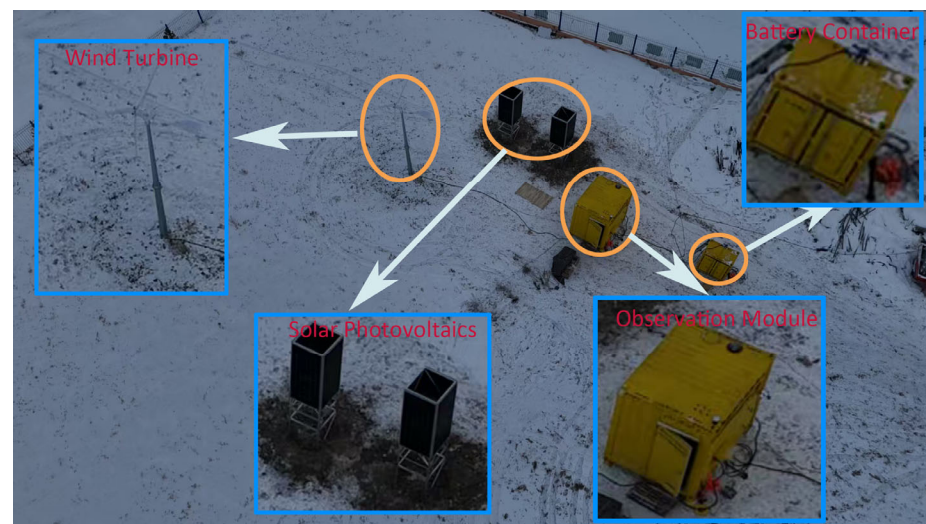


Figure 5. Layout of the field deployment.

March and April typically exhibit characteristic meteorological patterns in Hailar, featuring an overall warming trend punctuated by significant temperature fluctuations, frequent freeze–thaw cycles, and persistent snowfall accompanied by strong winds. To evaluate system stability under these transitional conditions, this study selected a data observation window from 15 March to 12 April. Figure 6 illustrates the temporal variations of the external environmental parameters alongside the system energy status during this period.

Figure 6 presents the time-series monitoring data of the environmental and energy system operational parameters for the period from 15 March to 12 April 2025. The dataset encompasses seven core indicators: atmospheric pressure, wind speed, AC/DC Power Distribution Unit (PDU) voltages, outdoor/indoor temperatures, and solar power generation.

During this monitoring period, the atmospheric pressure fluctuated within the range of 0.92–0.97 atm, approximating standard atmospheric pressure (1 atm). This falls within the typical near-surface range, with no extreme barometric events recorded. Wind speeds predominantly remained in the “light breeze” to “gentle breeze” range (0–10 km/h); however, significant gust peaks reaching approximately 50 km/h (corresponding to Beaufort force 6–7) were observed from 10 to 12 April, constituting a typical environmental disturbance scenario within the monitoring window. The outdoor temperature exhibited

dual characteristics of a seasonal warming trend and high-frequency diurnal fluctuations, whereas the indoor cabin temperature maintained stability.

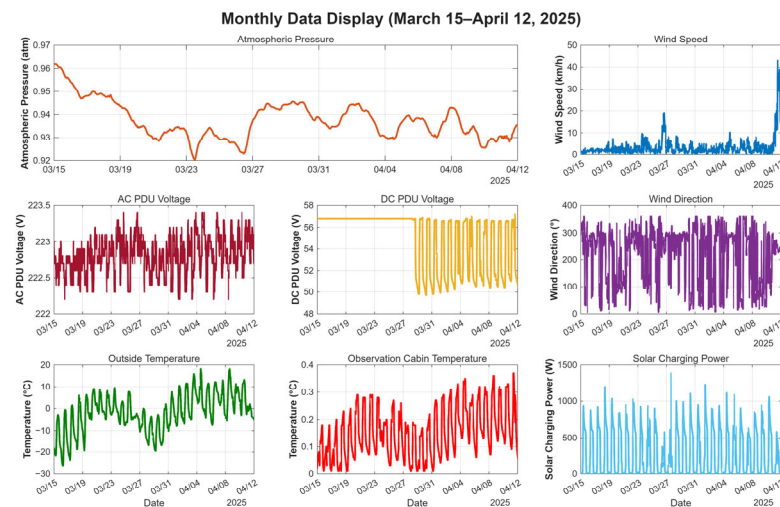


Figure 6. Profiles of environmental conditions and system energy data.

Regarding the energy system parameters, the AC PDU voltage fluctuated stably between 222 V and 223.5 V, demonstrating the high reliability of the system's AC power supply. The DC PDU voltage maintained its rated value (approximately 58 V) prior to 28 March, after which it exhibited periodic oscillations between 48 V and 58 V. This behavior reflects the system's active regulation strategy in response to varying load demands and fluctuations in photovoltaic input. Photovoltaic power generation displayed distinct diurnal cyclicity: charging power increased significantly during daylight hours, with peaks concentrated in the 800–1400 W range, while dropping to near 0 W during the night. This pattern is an inherent attribute of solar power generation and directly exemplifies the “diurnal intermittency” of photovoltaic energy sources.

2.4. Edge-Based Data Processing Pipeline

To resolve the inherent contradiction between high-spatiotemporal-resolution data acquisition and limited satellite communication bandwidth in remote middle-to-high-latitude regions, the system constructs an edge intelligence computing architecture centered on the RK3588 SoC. Adhering to the design principle of edge-side processing and on-demand transmission, this architecture realizes full-link hierarchical processing of observational data through the heterogeneous aggregation of multi-source data at the physical layer and on-board real-time inference at the application layer.

2.4.1. Heterogeneous Data Aggregation and Spatiotemporal Alignment

Given the significant heterogeneity between geomagnetic and ionospheric payloads regarding physical mechanisms, interface protocols, and sampling rates, the RK3588 master control terminal employs a multi-threaded concurrency mechanism to achieve synchronous acquisition and standardized encapsulation of data streams. Specifically, for high-frequency geomagnetic monitoring, the underlying Data Acquisition (DAQ) system encapsulates the 10 Hz background field vectors from the HMC1001 sensor and the 20 kHz micropulsation waveforms from the GMI sensor into a standardized binary frame format via a high-speed USB interface, pushing them to the master control memory in real time. Simultaneously, data from the TEC and scintillation monitor are accessed via the RS485 serial bus. Although this payload completes internal feature compression, its non-uniform update frequency presents a temporal mismatch with the continuously sampled geomagnetic data. To

construct a unified data baseline supporting multi-physical correlation analysis, the system establishes a circular buffer architecture at the software link layer. The master control unit utilizes the Pulse Per Second (PPS) signal output by the GNSS receiver as a hardware interrupt source to perform microsecond-level timestamp alignment on the heterogeneous data streams from the USB and RS485 buses. This mechanism effectively eliminates timing jitter in multi-source transmission, constructing a multidimensional observation tensor with a unified time base in memory in real time, thereby providing a strictly temporally aligned input source for subsequent AI inference.

2.4.2. On-Board AI Inference and Adaptive Telemetry

The software stack integrated into the RK3588 not only performs data persistence tasks but also functions as the real-time inference engine for the DA-RAE model, enabling closed-loop system control. Its processing pipeline comprises three cascaded stages: signal preprocessing, intelligent inference, and adaptive decision-making. Initially, the system executes denoising, downsampling (unified to a 30 s resolution), and Min–Max normalization on the raw geomagnetic waveforms, mapping physical quantities to a dimensionless interval adapted to the AI model input space. Subsequently, leveraging the built-in 6 TOPS NPU accelerator, the DA-RAE model performs online reconstruction and discrimination on the observation tensor within each 50 min sliding window. A single inference event requires only a millisecond-level response at the edge, completely eliminating reliance on cloud computing resources. Through this deep hardware–software integration, the system transforms originally independent hardware components into an organic intelligent sensing entity, effectively resolving the survival and observation challenges faced by unattended stations in extreme environments.

Ultimately, the system dynamically executes a hierarchical transmission strategy based on the anomaly score output by the model. When the space environment is determined to be in routine monitoring mode, the system writes only the downsampled low-frequency geomagnetic data (1 min averages) and TEC summary parameters to local storage for a scheduled daily batch upload, thereby significantly conserving satellite bandwidth. Conversely, once the anomaly score exceeds the threshold, the system immediately switches to an event-driven burst mode. It triggers a high-priority interrupt to lock the high-frequency raw waveform data (10 Hz geomagnetic vectors and high-frequency scintillation indices) surrounding the current time window, tagging this as high-value scientific data for immediate transmission. This deeply integrated hardware–software architecture transforms originally isolated physical components into an organic intelligent sensing entity with adaptive capabilities, fundamentally resolving the engineering challenge regarding the conflict between full-scale observation and limited transmission capacity in unattended stations under extreme environments.

3. Methodology: Deep Generalized Anomaly Detection Framework

3.1. Construction of Cross-Domain Experimental Datasets

This study focuses on three-axis magnetic field time series collected by fluxgate sensors. To verify the cold-start and generalization capabilities of the deep learning model on unlabeled target stations, a cross-latitude and cross-station monitoring network was constructed.

Source Domain Station: Mohe National Observatory of Geophysics. Located at the northernmost tip of China within the footpoint region of high-latitude magnetic field lines, this station is equipped with comprehensive observation instrumentation and long-term, stable background field records. Its high-quality geomagnetic data, with minimal anthro-

pogenic interference, provides standard statistical laws of the geomagnetic background field, serving as an ideal learning source for pure background patterns.

Target Domain Station: Hailar Field Unattended Station. Deployed autonomously by the research team, this station is located approximately 500 km south of the Mohe station, within the same geomagnetic longitude sector. This geographical layout ensures the capture of geomagnetic signals that possess physical correlations while exhibiting differences due to latitudinal effects.

To ensure the rigor of the cross-domain validation, physical consistency alignment was implemented for both datasets. The observables at both stations consist of magnetic field components in the X, Y, and Z directions. The sampling frequency was standardized to 10 Hz to effectively reflect high-frequency magnetic field fluctuation characteristics. Prior to model input, data from both stations underwent unified standardization processing to adapt to the input distribution of the neural network.

3.2. Data Preprocessing

3.2.1. Unification of Temporal Resolution

Considering the high frequency of raw sampling and the substantial data volume, combined with the fact that engineering applications primarily focus on geomagnetic variation processes at the minute scale or greater, this study applied temporal resampling to both the training and testing datasets, unifying the temporal resolution to 30 s. Specifically, a mean value was calculated from multiple sampling points within a 30 s window to derive a representative magnetic field value for that interval. This strategy yields three key advantages:

1. It effectively smooths high-frequency noise and transient random disturbances.
2. It significantly reduces data volume, thereby enhancing the efficiency of model training and inference.
3. It ensures consistency in the time scale between the training and testing sets, facilitating the construction of a unified time-series model.

Upon completion of this processing, both the Mohe and Hailar datasets were represented as three-axis magnetic field sequences at 30 s intervals, with each time step containing three components.

3.2.2. Sliding Window Sample Construction

Following time alignment and 30 s resampling, this study employs a sliding window approach to transform the one-dimensional time series into sample formats suitable for deep learning model inputs [26]. Let the window length be $T = 100$, meaning each sample consists of three-axis magnetic field observations from 100 continuous time steps. With a 30 s sampling interval, a single window covers an actual duration of 50 min. Denoting the resampled three-axis magnetic field sequence as $\{\mathbf{x}_t\}_{t=1}^N$, where $\mathbf{x}_t = (\text{signal_}X_t, \text{signal_}Y_t, \text{signal_}Z_t)$, the corresponding time segment for any starting time t can be constructed as:

$$\mathbf{X}_t = [\mathbf{x}_t, \mathbf{x}_{t+1}, \dots, \mathbf{x}_{t+T-1}] \quad (1)$$

Here, the shape of $\mathbf{X}_t$ is $(T, 3)$, i.e., $(100, 3)$. By applying a sliding window with a stride of 1 along the time axis, $N - T + 1$ samples can be generated sequentially from a time series of length N , thereby maximizing the utilization of the long-term observational information.

In terms of implementation, the complete sequence first undergoes normalization. This study employs Min–Max normalization to map the three-axis magnetic field components into the $[-1, 1]$ interval. Subsequently, windows are extracted from the normalized

sequence according to the aforementioned method, with each window treated as an independent training or testing sample. In supervised scenarios, the label of a time window is defined as the annotation value at the terminal timestamp of the window. This approach ensures temporal semantic consistency, where each input segment corresponds to the historical observations leading up to that specific moment.

This sliding window construction strategy preserves evolutionary features on a scale of approximately 50 min, making it suitable for capturing slowly varying geomagnetic processes and their contextual information. Furthermore, it maintains the controllability of the input dimensions for each sample (100, 3), thereby facilitating the subsequent training and inference of the reconstruction-based anomaly detection model built upon Recurrent Neural Networks (RNNs) and Generative Adversarial Networks (GANs).

3.3. DA-RAE Model Architecture

Addressing the dual constraints of limited computational resources at the edge (RK3588 NPU) and the non-stationary nature of geomagnetic signals, this study proposes a Dual-Adversarial Recurrent Autoencoder (DA-RAE) framework. Regarding backbone network selection, the framework bypasses the computationally intensive Transformer architecture in favor of a Bi-LSTM foundation. This choice is motivated by the lower parameter count of Bi-LSTM and its superior suitability for processing short-term temporal dependencies, thereby reducing power consumption at the edge. Simultaneously, to mitigate the over-smoothing effect inherent in standard autoencoders constrained by Mean Squared Error (MSE) loss, the model innovatively introduces a dual-adversarial mechanism. Through adversarial training, this mechanism constrains the generated data to closely approximate the real physical fields in terms of both topological structure and latent distribution.

As illustrated in Figure 7, the overall architecture comprises four coupled sub-networks: a bidirectional LSTM encoder, an asymmetric deep bidirectional LSTM decoder, and two adversarial discriminators (Critic_Z and Critic_X) designated to constrain the latent space and the data space.

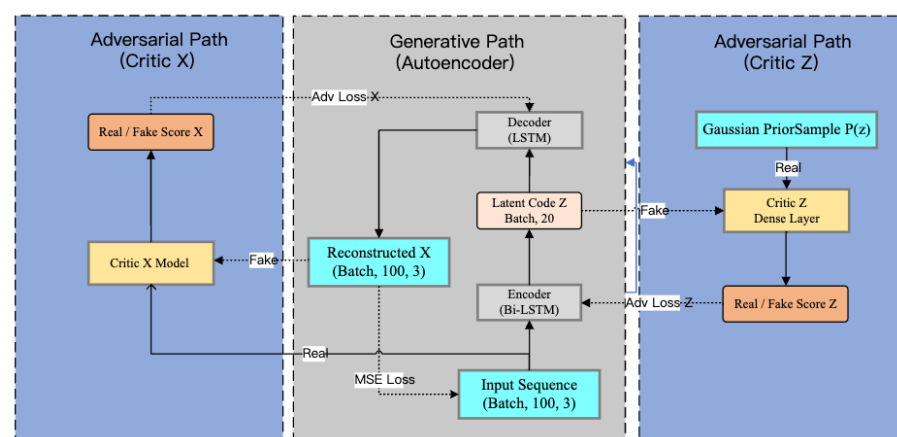


Figure 7. Algorithmic Architecture.

3.3.1. Bidirectional Temporal Encoder

The encoder E_ϕ serves as a feature extractor to map the high-dimensional input sequence $X \in \mathbb{R}^{B \times T \times F}$ to a latent vector $z \in \mathbb{R}^{B \times d}$, where B , T , F , and d represent the batch size, sequence length, number of features, and latent dimension, respectively.

To effectively capture temporal dynamics, a Bidirectional Long Short-Term Memory (Bi-LSTM) network is employed. Standard LSTMs process information unidirectionally, potentially failing to capture dependencies contingent on future context. In contrast, the

Bi-LSTM processes the sequence in both forward and backward directions. Let h_t denote the hidden state at time step t . The encoder aggregates temporal information by concatenating the hidden states from both directions at the final time step:

$$\mathbf{h}_{final} = \left[\vec{\mathbf{h}}_T \oplus \overleftarrow{\mathbf{h}}_T \right] \in \mathbb{R}^{2 \cdot d_{hidden}} \quad (2)$$

This concatenated vector $\mathbf{h}_{final}$ encapsulates the global contextual information of the input window. A subsequent linear transformation layer compresses this representation into the latent variable $\mathbf{z}$:

$$\mathbf{z} = \mathbf{W}_e \mathbf{h}_{final} + \mathbf{b}_e \quad (3)$$

This design ensures that $\mathbf{z}$ serves as a compact summary of the input time series on the normal manifold, compelling the model to filter out high-frequency noise from the input while retaining only the most representative background field features.

3.3.2. Deep Generative Decoder

The decoder G_θ maps low-dimensional latent representations $\mathbf{z}$ back to the original data space to generate reconstructed sequences $\hat{\mathbf{x}}_t$. In anomaly detection tasks, reconstruction quality directly determines detection sensitivity [27]. To address the challenge of recovering dynamic temporal features from a static vector, we first project $\mathbf{z}$ via a fully connected layer and reshape it into a tensor of shape $T \times d_{emb}$, “unfolding” the latent variable across the time dimension. The data then passes through a stacked 2-layer Bi-LSTM structure. An asymmetric architecture is adopted, with the decoder having deeper layers than the encoder, to enhance its stronger nonlinear expressive capacity for precisely capturing multi-scale fluctuations and fine-grained features in geomagnetic signals. Finally, LSTM outputs $\mathbf{O} \in \mathbb{R}^{T \times d_{out}}$ at each time step are mapped back to the original feature space via linear transformation:

$$\hat{\mathbf{x}}_t = \mathbf{W}_d \mathbf{o}_t + \mathbf{b}_d, \forall t \in \{1, \dots, T\} \quad (4)$$

3.3.3. Dual-Adversarial Regularization

To prevent the autoencoder from overfitting, we introduce dual-adversarial mechanisms to constrain model behavior, ensuring it generates only normal data compliant with physical laws.

1. Latent Space Regularization (Critic_Z): Standard autoencoders often suffer from discontinuous or irregular latent spaces, rendering distance-based anomaly detection ineffective. To enforce smoothness and continuity in the latent space, we introduced Critic_Z (D_z). D_z is used to distinguish between the latent vector $\mathbf{z}$ generated by the encoder and the samples sampled from the standard normal prior distribution $p(\mathbf{z}) \sim N(\mathbf{0}, \mathbf{I})$. The objective is:

$$\min_E \max_{D_z} E_{\mathbf{z} \sim p(\mathbf{z})} [D_z(\mathbf{z})] - E_{\mathbf{x} \sim p_{data}} [D_z(E(\mathbf{x}))] \quad (5)$$

This regularization eliminates discontinuities in the latent space and ensures learned representations have statistical meaning.

2. Global Reconstruction Consistency (Critic_X): To overcome over-smoothing from mean squared error (MSE) and ensure reconstructed data conforms to geomagnetic physical properties in overall topology, we introduce a data-domain discriminator Critic_X (D_x). D_x uses a full flattening strategy, flattening time series and evaluating globally via a multi-layer perceptron (MLP):

$$Score = D_x(Flatten(X)) \quad (6)$$

Critic_X is trained to distinguish original normal samples from decoder reconstructions. For anomaly detection, it forces the decoder to produce outputs resembling normal data. Thus, when input contains anomalies, the decoder reconstructs toward normal form, amplifying differences between input (anomalous) and output (normal reconstruction), enhancing detectability.

3.3.4. Anomaly Score Definition

After the model training is completed, we use the trained DA-RAE to infer the test data. For any given test sequence x , the real-time anomaly score $A(x)$ is defined as the mean square error (MSE) between the input sequence and the reconstructed sequence $\hat{x}$.

$$A(x) = \frac{1}{T} \sum_{t=1}^T \|x_t - \hat{x}_t\|_2^2 \quad (7)$$

Low $A(x)$ indicates the input conforms to learned normal background patterns, and it is judged as normal. High $A(x)$ indicates the input cannot be explained by the normal manifold (e.g., geomagnetic storms, anthropogenic interference) and is judged as anomalous.

Automated anomaly detection can be achieved by setting the threshold τ :

$$\text{Label} = \begin{cases} \text{Anomaly, if } A(x) > \tau \\ \text{Normal, otherwise} \end{cases} \quad (8)$$

3.3.5. Network Configuration Details

Specific architecture hyperparameters are detailed in Table 1 (referred to as Table 3 in the original). The depth asymmetry between the encoder (1 layer) and decoder (2 layers) is intentional to prioritize enhanced generative reconstruction capability.

Table 3. Detailed network architecture configuration.

Component	Layer Type	Configuration/Dimension	Activation Function
Input	-	sequence: 100×3	-
encoder	Bi-LSTM	units : 20, layers : 1, bidirectional	Tanh
	Concatenated, fully connected	$\begin{matrix} \rightarrow & \leftarrow \\ [h_T, h_T] & \rightarrow 40 \\ 40 & \rightarrow 20 \end{matrix}$	- Linear
decoder	fully connected	20–2000 (Reshaping as 100×20)	-
	stack Bi-LSTM	units: 64, layers: 2, bidirectional	Linear
Critic_X	fully connected	128 $\rightarrow$ 3 (Time distribution))	Tanh
	Flatten	$100 \times 3 \rightarrow 300$	-
Critic_Z	fully connected	$300 \rightarrow 20$	ReLU
	fully connected	$20 \rightarrow 1$	Linear
	fully connected	$20 \rightarrow 1$	Linear

3.3.6. Training Paradigm and Anomaly Detection Logic

To comprehensively validate the effectiveness and generalization capability of the DA-RAE architecture in practical engineering deployments, this study established a rigorous cross-domain experimental strategy.

First, at the input feature construction level, the model input is defined as a multidimensional time-series tensor containing the three orthogonal vector components of the

geomagnetic field (B_x , B_y , B_z , with feature dimension $F = 3$). This design aims to fully preserve the vector physical properties of the geomagnetic field.

During the training phase, this study adopts a single-source domain generalization strategy, where the model is exposed exclusively to quiet-day data from the source domain. This strategy enables the encoder to compress the normal evolutionary patterns of the geomagnetic background field into the latent manifold while simultaneously utilizing discriminators to enforce physical constraints on the latent distribution and data reconstruction. The objective of this phase is to enable the model to learn the intrinsic physical consistency of the geomagnetic field under undisturbed conditions, rather than overfitting to site-specific numerical features of a specific station.

In the testing phase, the pre-trained model is directly transferred to an unseen target domain. The core validation logic of this experiment is as follows: if the input sample conforms to general geomagnetic background laws, the model should yield a low reconstruction error; conversely, for space weather disturbances or equipment anomalies occurring in the target domain, the feature distribution will deviate significantly from the learned manifold boundaries, resulting in high-amplitude reconstruction residuals. This strategy effectively validates the robustness of the system in overcoming cross-station environmental differences and sensor heterogeneity.

4. Results and Discussion

This section details the experimental deployment, training convergence characteristics, and cross-domain performance evaluation of the DA-RAE model. The core objective of the experiments is to verify the model's generalization robustness under zero-shot conditions through cross-station anomaly detection tasks. Specifically, the study focuses on assessing the model's generalized perception capabilities regarding natural space weather events and sudden equipment anomalies.

4.1. Experimental Environment and Hyperparameter Settings

In this study, model implementation was conducted on a hardware platform equipped with an NVIDIA RTX 3090 GPU (NVIDIA Corporation, Santa Clara, CA, USA) and 64 GB of RAM. The software framework was built upon Python version 3.8 (Python Software Foundation, Wilmington, DE, USA), PyTorch version 1.12 (Linux Foundation, San Francisco, CA, USA), and CUDA version 11.6 (NVIDIA Corporation, Santa Clara, CA, USA). The learning rates for the encoder and decoder were set to 1×10^{-3} , while the discriminator learning rate was set to 2×10^{-4} to balance the interplay between the generator and discriminator. The latent space dimension was fixed at $d = 20$, consistent with the architecture detailed in Table 3. Regarding the training strategy, the batch size was set to 64 with a maximum of 200 epochs. Early stopping mechanism (patience = 20) was employed to mitigate the risk of overfitting. To enhance the stability of adversarial training, a Gradient Penalty (GP) mechanism was introduced with a loss weight λ set to 10, which effectively accelerated model convergence and mitigated mode collapse.

4.2. Dataset Instantiation and Preprocessing Protocol

Based on the aforementioned cross-domain generalization strategy, this experiment instantiated specific experimental scenarios. The training set (source domain) was instantiated using the continuous three-axis geomagnetic observation sequence from the Mohe National Observatory of Geophysics (53.5° N, 122.3° E) spanning from 1 October to 31 December 2023. During this time window, the equipment operated stably with no known significant geomagnetic disturbance events. Consequently, this period is regarded as a typical quiet-period background field, constituting an ideal physical reference baseline.

The target domain was configured using field observation data from the Hailar Field Unattended Station (49.2° N, 119.7° E) covering the period from 24 February to 21 March 2025. This dataset not only contains long-duration quiet-day backgrounds but also records complex non-stationary signal fluctuations, serving as a blind test set.

To eliminate baseline differences caused by heterogeneous sensors and meet the input requirements of the deep learning model, raw data from both stations underwent a rigorous standardized preprocessing protocol. All observation sequences were first uniformly resampled to a 30 s temporal resolution to align the time base. Subsequently, Min–Max normalization was employed to scale the geomagnetic vector amplitudes to the dimensionless interval [0, 1], thereby accelerating optimizer convergence and eliminating dimensional effects. Finally, sliding window technology was utilized to slice the continuous stream data. Input sequences were constructed by setting a window length of $T = 100$ (corresponding to a 50 min observation window) with a stride of 1, generating multidimensional time-series tensors with a shape of (100, 3).

4.3. Training Process Convergence Monitoring

During the training process, we monitored three specific loss components:

1. Critic_X Loss (denoted as CX): This represents the Wasserstein distance between real normal samples and decoder-reconstructed samples. Upon the conclusion of training, CX converged to near-zero values with only minor oscillations, indicating that the discriminator could no longer effectively distinguish between reconstructed sequences and real quiet-period sequences.
2. Critic_Z Loss (denoted as CZ): This represents the Wasserstein distance between the encoder's latent vectors and the standard normal prior $N(0, I)$. CZ exhibited minimal fluctuation throughout the process, indicating that the latent space matched the target prior distribution to a high degree.
3. Generator Loss: This synthesizes reconstruction error and adversarial objectives. It ultimately stabilized at a low value, demonstrating that the generator possesses both high-quality reconstruction capabilities and the ability to successfully deceive the dual discriminators.

4.4. Cross-Domain Anomaly Detection and Generalized Robustness Evaluation

To quantify the blind testing performance of the model in the Hailar target domain, this study constructed a multi-dimensional physical feature validation system integrating geomagnetism and the ionosphere. We calculated three metrics: reconstruction error, Critic_X raw score, and the comprehensive anomaly score (as illustrated in Figure 8).

Furthermore, raw geomagnetic waveforms (as shown in Figure 9) were temporally aligned with ionospheric Total Electron Content (TEC) observation data (as shown in Figure 10) to conduct rigorous physical cross-validation.

4.4.1. Zero-Shot Generalization Verification Under Quiet Backgrounds

During the geomagnetic quiet period from 24 February to 8 March, despite the approximately 500 km geographical span and the 14-month temporal offset between the Hailar station and the training source domain, the DA-RAE model demonstrated exceptional adaptability. As shown in Figure 8, the reconstruction error remained consistently at a very low baseline ($MSE < 0.005$), and the comprehensive anomaly score remained below the 0.1 threshold. Simultaneously, the concurrent TEC data exhibited smooth diurnal variation patterns with no observed anomalous disturbances. This high consistency between model inference and multi-source physical observations compellingly demonstrates that DA-RAE successfully captured the Universal Statistical Manifold of the mid-to-high-latitude geo-

magnetic background field under zero-shot conditions, achieving reliable cross-domain zero false positives.

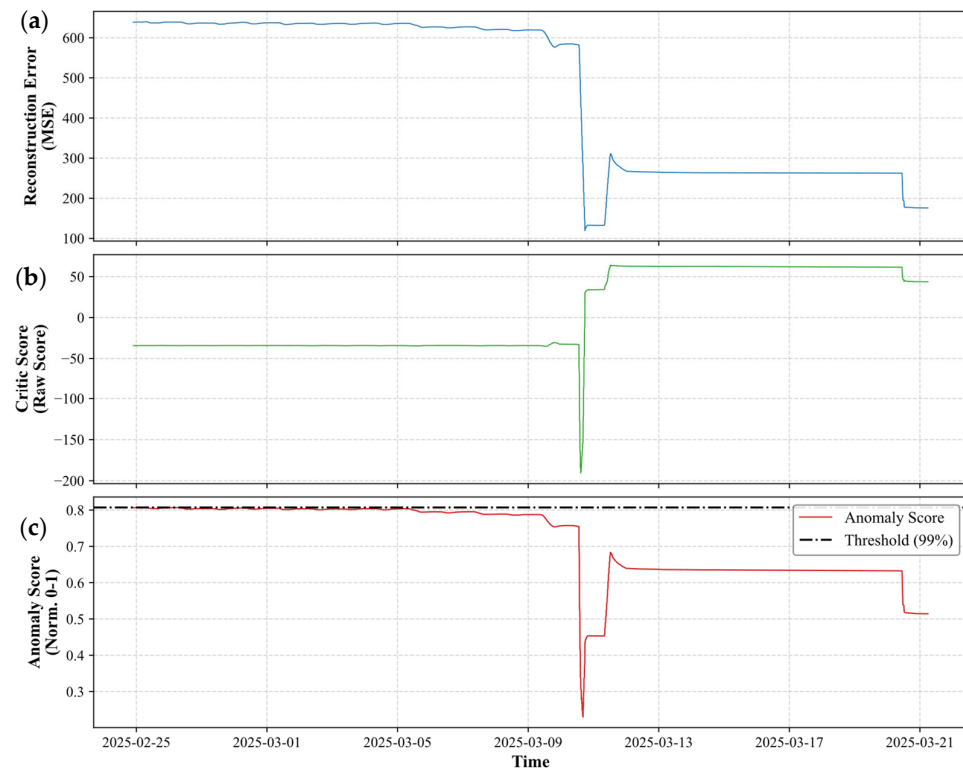


Figure 8. Model metrics: (a) Reconstruction error; (b) Critic score; (c) Anomaly score.

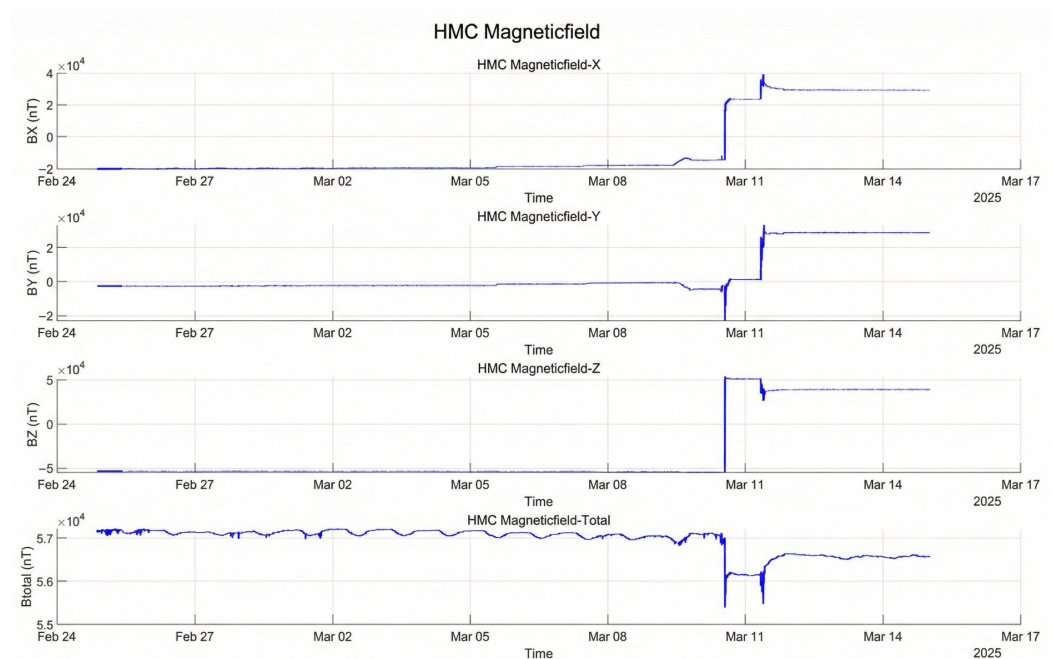


Figure 9. Geomagnetic observations at the Hailar target station.

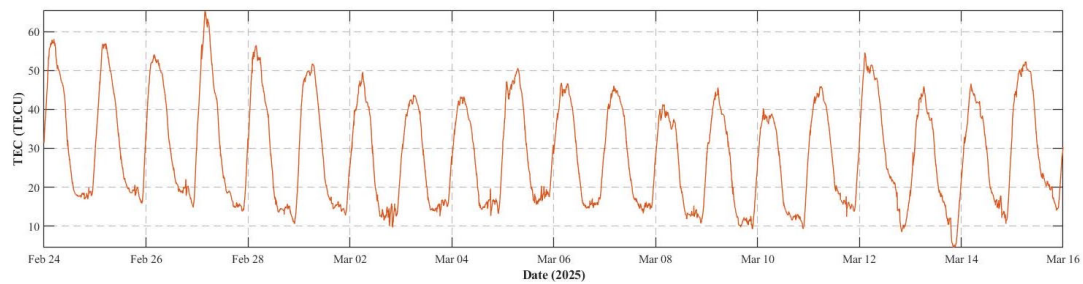


Figure 10. Concurrent Ionospheric TEC observations.

4.4.2. Physical Discrimination Between Transient Disturbances and Persistent Anomalies

During the experiment, the system recorded two types of anomalous events with distinct time-frequency characteristics. Through the joint analysis of geomagnetic and ionospheric data, we confirmed that the model accurately responded to both natural space weather events and non-physical equipment faults.

Regarding transient geomagnetic disturbances, a weak perturbation occurred in the magnetic field on 9 March. DA-RAE acutely captured this transient sudden commencement feature, with the comprehensive anomaly score showing a brief pulse-like increase. Meanwhile, concurrent TEC data displayed typical ionospheric negative phase response characteristics, where the daily peak showed an amplitude suppression of approximately 5–8 TECU compared to quiet periods. This synchronous micro-perturbation across multi-physical fields validates the model's extremely high detection sensitivity to real, weak geophysical signals under low signal-to-noise ratio conditions.

Regarding persistent equipment modal shifts, on 11 March, the magnetometer recorded a step-like anomaly with an amplitude exceeding 10^4 nT in components such as B_z , and the anomaly score was instantly saturated (see Figure 9).

While Figure 9 effectively illustrates the magnitude of the anomaly on 11 March, the extreme scale of the baseline drift ($>10^4$ nT) compresses the Y-axis, obscuring the fine-scale details of the normal geomagnetic variations. To address this and validate the data fidelity during the operational period, we present a magnified view of the quiet period (24 February–8 March) in Figure 11.

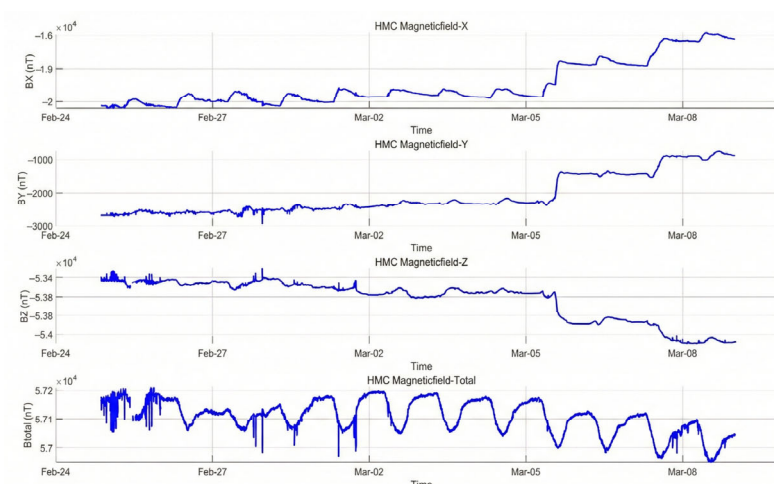


Figure 11. Detailed visualization of the geomagnetic field components during the quiet period.

As observed in Figure 11, the magnetometer data exhibits clear and smooth diurnal variations (Sq curves) across all three components and the total intensity. These regular daily fluctuations, with amplitudes of approximately 30–80 nT, are consistent with standard ionospheric quiet-day currents. The clarity of these waveforms confirms that the system

maintains high-precision sensing capabilities and that the subsequent anomaly was not due to signal noise, but a genuine physical displacement event.

To determine the physical attributes of this signal, TEC data was introduced for cross-validation. As shown in Figure 10, during the period from 11 to 14 March when the magnetic field underwent a massive jump, the ionospheric TEC maintained a continuous and stable diurnal variation cycle, exhibiting no ionospheric storms or large-scale traveling disturbances corresponding to the drastic magnetic variations.

This pronounced decoupling of the magnetosphere–ionosphere response provided strong physical evidence that the anomaly did not originate from a global storm in solar-terrestrial space. Instead, detailed analysis suggests that this persistent modal shift was induced by mechanical displacement of the sensor foundation rather than electronic failure. Meteorological data (Figure 6) confirms that the station was undergoing a seasonal transition with frequent freeze–thaw cycles and strong winds during this period. Under these conditions, the thawing of the permafrost layer likely caused a slight tilt in the magnetometer’s mounting mast. Given the vector nature of the fluxgate sensor, a tilt of merely 0.5° in the presence of the local geomagnetic background ($\sim 56,000$ nT) can result in a projection component jump exceeding 500 nT. This physical decoupling from the ionospheric TEC further validates the system’s capability to identify non-space-weather equipment anomalies. The model’s instantaneous rapid detection of this non-physical fault further confirms its engineering robustness as a generalized anomaly detector.

It is important to emphasize that while the large-amplitude anomaly observed on 11 March might appear detectable via simple thresholding, the specific deployment context of remote, unattended stations underscores the necessity of the proposed AI approach. In a “cold-start” scenario for a newly established station, local statistical baselines are inherently unknown, rendering it difficult to establish accurate thresholds without extensive historical data. In contrast, the DA-RAE model demonstrated robust cross-domain adaptability by learning the intrinsic topological manifold of geomagnetic variations from the source station. The successful detection of the anomaly without site-specific calibration validates the system’s “plug-and-play” capability, which is essential for expanding observation networks into previously uncovered remote regions where manual calibration is impractical.

4.5. Edge-Side Real-Time Performance and Resource Overhead

To verify the deployment feasibility of the algorithm in resource-constrained environments, the quantized DA-RAE model was deployed onto an RK3588 edge computing unit, and continuous inference tests were conducted in single-core NPU mode.

Experimental results demonstrate that the model demonstrates high computational efficiency at the edge. For a single-frame input sample, the average end-to-end inference latency is only 8.4 ms, with a throughput reaching 119 fps. This processing speed is significantly faster than the geomagnetic data sampling interval (30 s), implying that the system requires only a negligible processor duty cycle ($<0.1\%$) to complete real-time monitoring tasks, leaving ample remaining computational power for data cleaning or communication transmission.

Regarding resource overhead, the storage footprint of the quantized model is merely 1.8 MB, and the runtime system memory usage is approximately 145 MB. Benefiting from the high-efficiency architecture of the NPU, the average power consumption of the device during inference is maintained at around 2.1 W. These low-latency and low-power characteristics make it well-suited for the stringent energy constraints of field stations relying on solar power, validating the engineering viability of the DA-RAE architecture for all-weather, unattended monitoring at the edge.

5. Conclusions and Outlook

5.1. Conclusions

To address the critical challenges imposed by hostile environments, power scarcity, and limited communication in space weather monitoring across mid-to-high-latitude regions, this paper presents a comprehensive solution integrating ruggedized hardware architecture with cross-domain edge intelligence. Based on long-term deployment data from the unmanned Hailar station, we draw three primary conclusions.

First, we established a robust autonomous observation architecture for extreme environments. Targeting operating conditions of $-40\text{ }^{\circ}\text{C}$, we constructed a cloud–edge–end collaborative system for integrated ionosphere–geomagnetic monitoring. Through wide-temperature hardware selection and hybrid energy management, the system achieved continuous, uninterrupted operation for six months. This enabled reliable and successful acquisition of high-quality, synchronous observation data, effectively filling coverage gaps in key coupling regions of the ground-based monitoring network.

Second, we demonstrated the efficacy of a single-source domain generalization strategy for unsupervised anomaly detection. The proposed DA-RAE model utilizes a quiet-day manifold learning approach to overcome the lack of fault labels and cross-domain distribution shifts. Experiments demonstrated that the model, trained solely on source domain data, achieved high-precision zero-shot monitoring at the target domain. The low reconstruction error during quiet periods validates the model's inherent capability to capture the universal physical laws of the geomagnetic background field.

Finally, we achieved generalized anomaly detection coupled with efficient edge deployment. The system demonstrated exceptional robustness in differentiating between physical and non-physical anomalies, accurately capturing both transient geophysical perturbations and sensor baseline drifts as validated by ionospheric cross-checks. Furthermore, deployment tests on the RK3588 platform confirmed the feasibility of embedding complex deep learning capabilities into low-power edge devices. With minimal power consumption and low latency, this provides solid technical support for the paradigm shift from raw data transmission to semantic intelligent perception in field scenarios.

5.2. Future Work

Future research will focus on three primary directions to advance the construction of globalized, intelligent space environment monitoring networks.

First, we will implement multi-modal fusion. Current detection relies primarily on unimodal geomagnetic data. Future iterations will incorporate all-sky imaging data or GNSS-TEC data into the model input. Leveraging multi-modal complementary information will improve the distinction between local interference and global space weather events, thereby enhancing physical interpretability.

Second, we aim to transition the system from diagnosis to self-healing. Currently limited to fault identification, the next phase involves embedding adaptive calibration algorithms at the edge. Upon detecting baseline drift, the model will automatically trigger sensor reset or parameter compensation mechanisms, achieving a truly autonomous, closed-loop maintenance system.

Third, we plan to expand deployment to polar environments. We intend to deploy the system to higher-latitude regions, such as the Antarctic Zhongshan Station. This will verify the model's generalization boundaries under complex electromagnetic environments—including polar nights and auroral substorms—ultimately contributing to the development of more accurate global space weather prediction models.

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