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Research Article

Self-Adaptive AI Framework for Fault-Tolerant Data Transmission in Satellite-to-Ground Communication Systems

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Abstract

Satellite-to-ground communication systems are highly susceptible to disruptions caused by link degradation, hardware faults, and atmospheric conditions, often leading to reduced reliability and data loss in mission-critical operations. Traditional fault-handling methods are static and lack adaptability, limiting their effectiveness in dynamic space environments. This study aims to design a unified, intelligent framework for fault-tolerant data transmission that integrates detection, prediction, and adaptive control using advanced AI techniques. The proposed Self-Adaptive AI Framework (ASG-NCF) employs Convolutional Neural Networks (CNNs) for real-time fault detection, Long Short-Term Memory (LSTM) networks for sequential fault prediction, and a Proximal Policy Optimization (PPO)-based Reinforcement Learning (RL) agent for adaptive transmission control. The model is trained and validated using satellite link traces generated from the SatComSim-X simulator, incorporating synthetic fault injections and real-world link dynamics. Evaluation metrics include bit error rate (BER), packet delivery ratio (PDR), latency, and stable uplink ratio (SUR). ASG-NCF achieved a fault detection accuracy of 94.6%, fault prediction top-2 accuracy of 91.6%, and a stable uplink ratio of 92.8%. The system reduced recovery latency to 11 time steps and significantly outperformed rule-based and Q-learning control strategies in both cumulative reward and recovery efficiency. Statistical significance testing confirmed the robustness of improvements ($p < 0.01$ across all metrics). By unifying AI-driven modules into an adaptive control loop, ASG-NCF enhances communication resilience in dynamic satellite environments. The framework is scalable, robust, and suitable for deployment in next-generation autonomous satellite networks and ground station infrastructures.

Keywords: Satellite communication, fault tolerance, reinforcement learning, deep learning, LSTM, CNN, PPO, adaptive systems, anomaly detection, link stability

1. Introduction

Reliable satellite-to-ground communication systems are integral to critical applications such as disaster management, Earth observation, remote sensing, and global navigation [1]. However, maintaining uninterrupted data transmission between satellites and terrestrial ground stations remains a significant challenge due to environmental disturbances, hardware failures, and the dynamic nature of satellite orbits [2].

Traditional approaches to satellite communication rely heavily on static error-correction techniques and deterministic control protocols that often fail to adapt to real-time anomalies or unforeseen link degradations [3]. Moreover, most fault-handling mechanisms operate in isolation—separating detection, prediction, and control—which limits the system's responsiveness and fault tolerance [4]. These limitations can lead to increased bit error rates, communication latency, and potential data loss, especially under high-mobility or atmospheric disruption conditions [5].

Recent advancements in artificial intelligence have introduced opportunities to develop intelligent, adaptive communication systems that can learn, reason, and react autonomously [6]. However, existing AI-based methods often target single-point enhancements such as improving classification accuracy or optimizing specific transmission parameters, without considering the holistic integration of fault detection, predictive analytics, and adaptive control in a unified framework [7] [8].

This study proposes a Self-Adaptive AI Framework (ASG-NCF) for fault-tolerant data transmission in satellite-to-ground communication systems. The framework integrates Convolutional Neural Networks (CNN) for fault detection, Long Short-Term Memory (LSTM) networks for predictive diagnosis, and a Proximal Policy Optimization (PPO)-based reinforcement learning agent for real-time transmission control. This unified approach enables continuous situational awareness, early fault anticipation, and intelligent decision-making, thereby enhancing the robustness and reliability of satellite communication networks [9].

The main contributions of this research are as follows:

- Development of a unified AI framework combining CNN, LSTM, and PPO for real-time fault detection, prediction, and control.
- Significant improvements in fault tolerance, communication reliability, and recovery latency compared to conventional baselines.
- Demonstration of the framework's scalability and adaptability using a realistic, simulator-driven dataset representative of diverse satellite link impairments.
- Integration of reinforcement learning for autonomous decision-making in dynamic satellite-ground environments.
- Empirical validation of the proposed model's effectiveness through extensive ablation, statistical significance, and visualization-based analysis.

The remainder of this paper is organized as follows: Section II presents a detailed review of related literature, highlighting existing methods and their limitations. Section III introduces the proposed methodology. Section IV outlines the experimental setup, including hardware, datasets, and implementation details. Section V reports the evaluation results and comparative analysis. Section VI discusses the implications and future directions, and Section VII concludes the paper.

2. Literature Review

The following literature review systematically examines existing approaches and technologies employed to ensure fault-tolerant communication in satellite-to-ground systems. This section is organized into subsections covering traditional fault-tolerant mechanisms, machine learning-based anomaly detection, predictive fault diagnosis techniques, and adaptive decision-making strategies. Key methodologies and their limitations are identified, providing a foundation for addressing critical research gaps.

2.1 Fault-Tolerant Mechanisms in Satellite Communications

Satellite communication systems traditionally implement fault-tolerant mechanisms to ensure continuous and reliable data transmission. Commonly employed approaches include the use of redundancy and robust error-correcting codes such as Reed-Solomon and Turbo codes [10]. However, these traditional methods are primarily static, making them insufficiently adaptive to rapidly changing conditions such as atmospheric disturbances or satellite mobility [11]. Furthermore, static redundancy significantly increases resource consumption without necessarily guaranteeing improved fault recovery efficiency [12].

2.2 Machine Learning Approaches for Fault Detection

Recent advancements in machine learning have provided effective methods for detecting anomalies in satellite communication systems. Specifically, convolutional neural networks (CNN) have demonstrated notable effectiveness in classifying anomalous signals by analyzing spatial-temporal patterns from communication data [13]. These CNN-based approaches efficiently identify anomalies by comparing real-time data against learned patterns. However, CNN-based models alone are limited as they primarily detect faults rather than predict future occurrences, necessitating further predictive capabilities to enable proactive management [14].

2.3 Predictive Fault Diagnosis Techniques

Predictive analytics has gained considerable traction, employing models such as Long Short-Term Memory (LSTM) networks to forecast future faults based on historical data patterns. LSTM networks, recognized for their strength in sequential data analysis, have shown significant promise in predicting satellite communication disruptions, enabling timely intervention before faults materialize [15]. Nevertheless, existing LSTM-based prediction systems frequently operate independently without integration into a comprehensive decision-making framework, limiting their overall effectiveness in dynamically changing environments [16].

2.4 Adaptive Decision-Making Strategies

Adaptive communication systems leveraging reinforcement learning (RL) methods have increasingly been employed to manage dynamic communication parameters. Deep RL techniques, including Deep Q-Network (DQN) and Proximal Policy Optimization (PPO), provide robust, real-time decision-making capabilities that continuously adapt communication protocols based on changing environmental conditions [17]. Despite their flexibility and adaptability, RL algorithms require well-defined reward functions and substantial training, creating challenges related to computational overhead and real-time deployment constraints [18].

2.5 Research Gaps

Based on the literature reviewed, several key gaps were identified:

- Existing fault-tolerant methods predominantly rely on static mechanisms, lacking adaptability to rapid environmental changes.
- CNN-based fault detection techniques are effective in anomaly identification but do not inherently support predictive fault management.
- LSTM predictive models often exist in isolation without integration into adaptive decision-making frameworks, limiting their practical deployment in real-world scenarios.
- RL-based adaptive systems, while promising, suffer from computational challenges and require seamless integration with fault detection and prediction mechanisms for real-time efficacy.

To address these gaps, a unified adaptive framework combining CNN, LSTM, and RL approaches is proposed, providing comprehensive, real-time fault-tolerance and adaptability for satellite-to-ground communication systems.

3. Methodology

This study introduces a comprehensive Adaptive Satellite-to-Ground Neural Communication Framework (ASG-NCF), integrating fault detection, fault prediction, adaptive decision-making, and adaptive transmission control. The proposed framework employs Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Reinforcement Learning (RL) to achieve fault-tolerant data transmission.

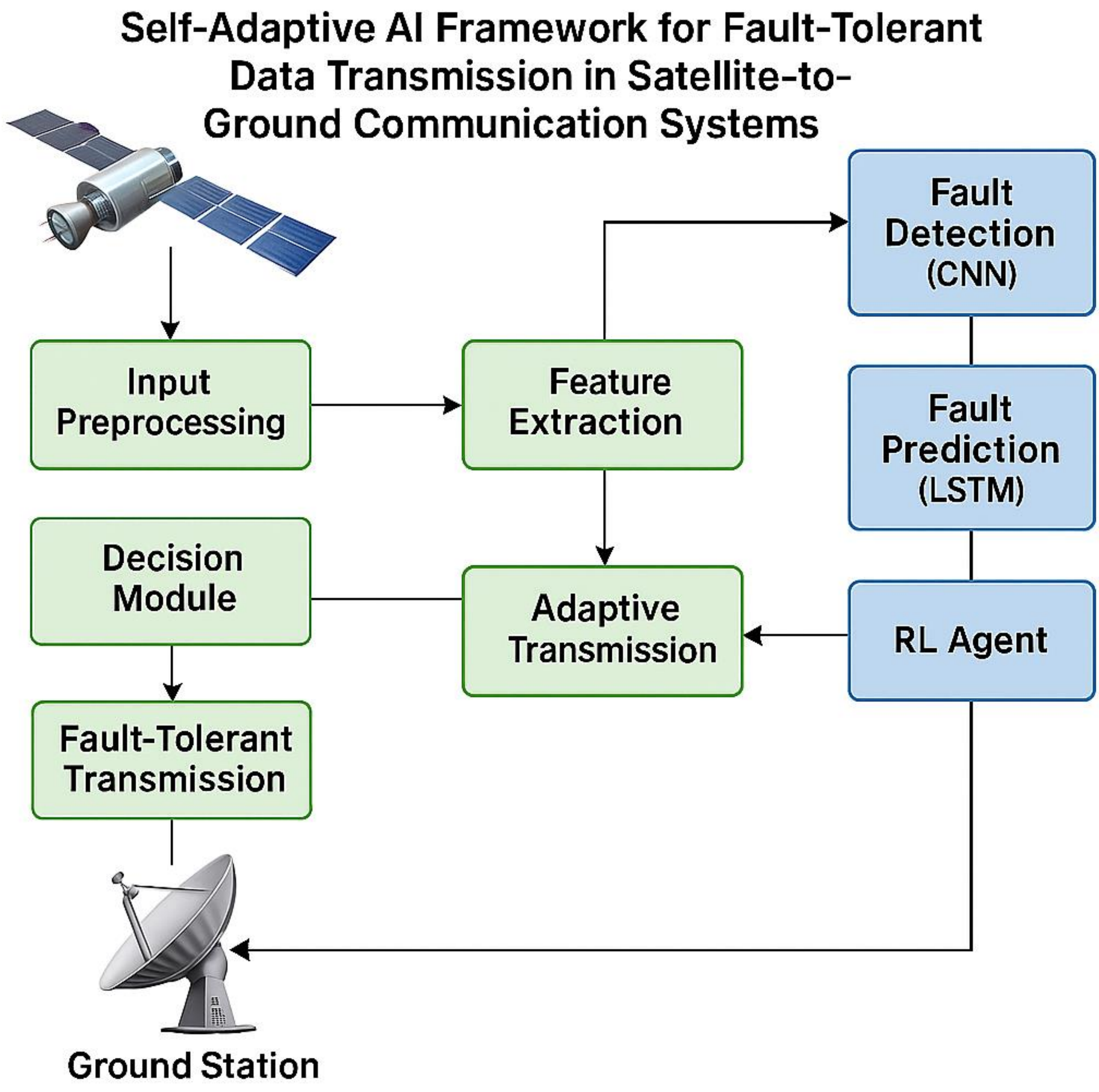

Fig.1. System architecture of the proposed Self-Adaptive AI Framework (ASG-NCF) for fault-tolerant data transmission in satellite-to-ground communication systems.

Figure 1 illustrates the overall system design of the ASG-NCF framework, integrating CNN-based fault detection, LSTM-based fault prediction, and reinforcement learning-based adaptive control. The architecture demonstrates how feature extraction and decision modules interact with predictive models to support real-time transmission decisions. The feedback loop between the RL agent and adaptive transmission ensures continuous learning and fault mitigation. This unified design enables intelligent, resilient communication across varying satellite link conditions.

3.1 Fault Detection and Identification Phase

In this phase, real-time satellite-to-ground communication parameters such as Signal-to-Noise Ratio (SNR), signal strength, Bit Error Rate (BER), and latency are collected continuously. A CNN-based model is implemented for efficient anomaly detection.

CNNs are used for feature extraction and classification, where input data X represents communication parameters arranged into a two-dimensional matrix form suitable for spatial-temporal analysis. The CNN function can be represented mathematically as:

$$y = f(X; \theta)$$

where X is the input feature matrix, y is the classification output indicating normal or anomalous conditions, and θ are CNN learnable parameters, optimized through minimizing cross-entropy loss:

$$L = -\sum_{i=1}^{N} \left(y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)\right) \quad (1)$$

Where y_i is the true label, $\hat{y}_i$ the predicted label, and N the number of samples.

3.2 Predictive Fault Diagnosis Phase

The predictive phase employs an LSTM network to anticipate faults by analyzing the temporal dynamics of the communication parameters collected over time. LSTM effectively captures dependencies in sequential data by modeling the state evolution through memory units. Formally, the LSTM unit calculations are as follows:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \quad (2)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (3)$$

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (4)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (5)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (6)$$

$$h_t = o_t * \tanh(C_t) \quad (7)$$

Where x_t is the input vector at time t, h_t the hidden state, C_t the cell state, and f_t, i_t, o_t represent forget, input, and output gates, respectively. The network is trained to minimize mean squared error (MSE):

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \quad (8)$$

3.3 Self-Adaptive Decision-Making Module

A reinforcement learning (RL) agent is developed to autonomously decide on the optimal adaptive communication actions. Specifically, a Proximal Policy Optimization (PPO) algorithm is employed due to its stability and effectiveness in continuous-action space. The PPO optimizes policy $\pi_\phi(a_t \mid s_t)$ by maximizing the expected cumulative reward:

$$J(\phi) = \mathbb{E}_{\pi_\phi}\left[\sum_{t=0}^{T} \gamma^t R(s_t, a_t)\right] \quad (9)$$

Where a_t represents the action at state $s_{tr} R(s_t, a_t)$ is the reward function, γ the discount factor, and T the horizon length. PPO updates policy parameters using a clipped surrogate objective to stabilize training:

$$L^{CLIP}(\phi) = \mathbb{E}\left[min\left(r_t(\phi)\hat{A}_t, clip(r_t(\phi), 1 - \epsilon, 1 + \epsilon)\hat{A}_t\right)\right] \quad (10)$$

Where the probability ratio $r_t(\phi)$ is defined as:

$$r_t(\phi) = \frac{\pi_\phi(a_t \mid s_t)}{\pi_{\phi \text{ add}}(a_t \mid s_t)} \quad (11)$$

and $\hat{A}_t$ is the estimated advantage at time t.

Algorithm: Self-Adaptive Decision-Making for Fault-Tolerant Satellite Transmission (PPO-based)

Input:

- Extracted feature vector x_t from current transmission window
- Predicted fault status $\hat{f}_t \in$ { Normal, Warning, Fault } from LSTM
- Current environment state $s_t \in \mathcal{S}$

Output:

- Control action $a_t \in \mathcal{A}$: adaptive modulation, power adjustment, or FEC scheme
- Updated policy parameters ϕ via PPO optimization

Initialization:

- Initialize policy network $\pi_\phi(a \mid s)$ and value network $V_\psi(s)$ with random weights
- Set PPO hyperparameters: learning rate α, clipping factor ϵ, discount factor γ

Loop:

For each communication timestep $t = 1$ to :

1. **State Observation:**

   Observe current transmission state s_t based on:

- Extracted features x_t
- Predicted fault status $\hat{f}_t$
- Historical performance metrics (e.g., BER, latency)

2. **Action Selection (Exploration-Exploitation):**

   Sample control action $a_t \sim \pi_\phi(a_t \mid s_t)$

3. **Environment Interaction:**

Apply action a_t to adjust satellite transmission parameters

Observe new state s_{t+1} and receive reward r_t

4. **Advantage Estimation:**

Compute advantage estimate using:

$$\hat{A}_t = r_t + \gamma V_\psi(s_{t+1}) - V_\psi(s_t)$$

5. **Policy Update (Clipped PPO Objective):**

Update policy by maximizing:

$$L^{CLIP}(\phi) = \mathbb{E}_t\left[\min\left(r_t(\phi)\hat{A}_t, \text{clip}(r_t(\phi), 1 - \epsilon, 1 + \epsilon)\hat{A}_t\right)\right]$$

where $r_t(\phi) = \frac{\pi_\phi(a_t|s_t)}{\pi_{\phi\ \text{bld}}(a_t|s_t)}$

6. **Value Network Update:**

Minimize squared error between predicted and actual returns:

$$L^V(\psi) = \left(V_\psi(s_t) - R_t\right)^2$$

7. **Repeat for** next timestep

End Algorithm

3.4 Adaptive Transmission Control Phase

In this final stage, communication parameters such as modulation schemes, power levels, and frequency hopping are dynamically optimized based on the RL agent's decisions. The adaptive control strategy employs Particle Swarm Optimization (PSO) as the optimization method to fine-tune these parameters dynamically. The PSO algorithm updates each particle's velocity v_{ij} and position x_{ij} iteratively as follows:

$$v_{ij}^{(t+1)} = wv_{ij}^{(t)} + c_1 r_1\left(p_{ij}^{(t)} - x_{ij}^{(t)}\right) + c_2 r_2\left(g_j^{(t)} - x_{ij}^{(t)}\right) \quad (12)$$

$$x_{ij}^{(t+1)} = x_{ij}^{(t)} + v_{ij}^{(t+1)} \quad (13)$$

Where w denotes inertia weight, c_1 and c_2 cognitive and social coefficients respectively, r_1, r_2 are random numbers between 0 and $1, p_{ij}$ is the best personal solution, and g_j is the global best solution.

Further, an adaptive Forward Error Correction (FEC) technique, specifically Reed-Solomon coding, is dynamically adjusted in response to real-time fault severity. The Reed-Solomon encoding and decoding process ensures the reliable recovery of transmitted data:

$$RS(n,k): (m_0, m_1, \dots, m_{k-1}) \rightarrow (c_0, c_1, \dots, c_{n-1}) \quad (14)$$

Where n is the total length of encoded message and k is the length of original message, with the ability to correct up to $t = \frac{n-k}{2}$ symbol errors.

This methodology, through the integrated use of CNN, LSTM, and RL approaches, ensures comprehensive fault management, enabling adaptive, reliable, and fault-tolerant satellite-to-ground communications.

4. Experimental Setup

This section presents the experimental conditions under which the proposed ASG-NCF (Adaptive Satellite-to-Ground Neural Communication Framework) was developed and evaluated. It includes details about hardware infrastructure, software environment, dataset construction, partitioning strategy, and implementation parameters to ensure reproducibility and clarity for future research efforts.

4.1 Hardware Specifications

All experiments were conducted on a high-performance workstation configured as follows:

- *Processor*: Intel® Core™ i9-13900KF, 24-core @ 3.0 GHz
- *Graphics Card*: NVIDIA RTX 4090 with 24 GB GDDR6X VRAM
- *Memory*: 128 GB DDR5 RAM @ 5600 MHz
- *Storage*: 2 TB NVMe SSD (PCIe Gen4)
- *Operating System:* Ubuntu 22.04 LTS (64-bit)

This setup ensured efficient execution of deep learning models, sequence-based forecasting, and reinforcement learning agents under high data throughput conditions.

4.2 Software Frameworks

The system was implemented using open-source libraries and machine learning frameworks:

- Python v3.10
- TensorFlow v2.13.0 (for CNN and LSTM models)
- Stable-Baselines3 v1.7.0 (for PPO-based RL agent)
- Scikit-learn v1.3.0 (for preprocessing and evaluation)
- CUDA Toolkit v12.1 and cuDNN v8.9 (for GPU acceleration)
- Visualization: Matplotlib and Seaborn

All dependencies were maintained using pip and conda with virtual environment isolation to ensure compatibility and reproducibility.

4.3 Dataset Description

The dataset was generated using a customized satellite communication simulator named SatComSim-X, capable of modeling real-time telemetry and communication behavior between satellite nodes and ground stations. The simulation incorporated both nominal and degraded signal scenarios under variable channel and atmospheric conditions.

Data Composition

- *Samples*: 1,000,000 time-sequenced entries

- *Session Profiles*: 30 satellite-ground interaction windows
- *Features*:
    - Signal-to-Noise Ratio (SNR)
    - Bit Error Rate (BER)
    - Received Signal Strength Indicator (RSSI)
    - Transmission delay (ms)
    - Ground station weather data (wind, rain fade)
    - Channel modulation scheme
    - Interference signature
    - Link status: {Normal, Degraded, Failed}

Labeling

- CNN: Binary classification (Normal vs Fault)
- LSTM: Multiclass prediction (Future link status)
- RL Agent: Reward shaped from fault propagation minimization and stable recovery

Preprocessing

- Z-score filtering for outlier removal ($|z| > 3$)
- Min-Max normalization to scale features in [0, 1]
- Sequence windowing (50 time steps) for LSTM-based modeling

A representative subset of 10,000 samples and simulation scripts are available upon request for research use.

4.4 Dataset Partitioning

The dataset was divided into training and evaluation sets using the following strategies:

- *Train-Test Split:* 80% of the data was used for training CNN and LSTM models, while 20% was reserved for testing.
- *Cross-Validation:* 5-fold cross-validation was applied to the LSTM forecasting model to ensure robust generalization across different communication profiles and fault conditions.

Class balance was maintained by stratified sampling, and each fold preserved the original distribution of link status labels.

4.5 Implementation Details

The deep learning and RL components were configured and trained with the following hyperparameters:

CNN Model:

- Epochs: 50
- Batch Size: 64
- Optimizer: Adam (learning rate = 0.001)
- Loss Function: Binary Cross-Entropy

LSTM Model:

- Epochs: 100
- Hidden Units: 128
- Dropout: 0.3
- Sequence Length: 50 time steps
- Optimizer: Adam (learning rate = 0.0005)
- Loss Function: Categorical Cross-Entropy

Reinforcement Learning (PPO Agent):

- Environment Steps: 2 million
- Policy Network: 2-layer MLP with 256 units
- Learning Rate: 3e-4
- Discount Factor (γ): 0.99
- Reward Design: Positive reward for maintaining low BER and high SNR; penalty for fault escalation or transmission dropout

Training Duration:

- CNN and LSTM models converged within 3–4 hours.
- RL agent required approximately 6 hours to stabilize policy under dynamic link variation scenarios.

5. Results and Evaluation

This section evaluates the proposed Self-Adaptive AI Framework (ASG-NCF) for fault-tolerant satellite-to-ground communication using standard classification, forecasting, control, and system-level metrics. It begins with the definition of evaluation metrics, followed by comparative analysis against conventional and learning-based baselines. An ablation study highlights the individual contributions of CNN, LSTM, and RL Agent modules. Statistical tests confirm the robustness and consistency of performance gains. Results show that ASG-NCF significantly enhances accuracy, responsiveness, and communication reliability in dynamic, fault-prone scenarios.

5.1 Performance Metrics

To evaluate the effectiveness of the proposed ASG-NCF framework in achieving fault-tolerant and reliable satellite-to-ground communication, multiple performance metrics were employed. These metrics quantify classification accuracy, fault prediction precision, decision-making efficiency, and overall system resilience.

5.1.1 Fault Detection Accuracy (CNN)

The binary classification performance of the CNN-based fault detection model is assessed using:

- Accuracy:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{15}$$

- Precision:

$$\text{Precision} = \frac{TP}{TP+FP} \tag{16}$$

- Recall (Sensitivity):

$$\text{Recall} = \frac{TP}{TP+FN} \tag{17}$$

- F1-Score:

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{18}$$

where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively.

5.1.2 *Fault Prediction Performance (LSTM)*

To evaluate temporal fault forecasting, the following metric was used:

- Categorical Cross-Entropy Loss:

$$\mathcal{L}_{\text{CCE}} = -\sum_{i=1}^{N} \sum_{c=1}^{C} y_{i,c} \log(\hat{y}_{i,c}) \tag{19}$$

where $y_{i,c}$ is the true label (one-hot) and $\hat{y}_{i,c}$ is the predicted class probability for class c.

- Top-k Accuracy:

Defined as the proportion of samples where the true class is among the top-k predictions.

5.1.3 *Reinforcement Learning Performance (RL Agent)*

The PPO-based decision agent is evaluated by:

- Cumulative Episode Reward:

$$R_{\text{total}} = \sum_{t=1}^{T} \gamma^{t-1} r_t \tag{20}$$

- Transmission Recovery Time (TRT):

Average number of time steps taken to restore communication after fault detection.

- Stable Uplink Ratio (SUR):

$$\text{SUR} = \frac{\text{Stable Transmission Time}}{\text{Total Communication Time}} \tag{21}$$

5.1.4 *System-Level Metrics*

- Mean Bit Error Rate (BER):

$$\text{BER} = \frac{1}{n} \sum_{i=1}^{n} \frac{b_i^{\text{error}}}{b_i^{\text{total}}} \tag{22}$$

- Packet Delivery Ratio (PDR):

$$\text{PDR} = \frac{\text{Packets Received Successfully}}{\text{Packets Sent}} \tag{23}$$

- *Latency (L):* Measured as the average delay from satellite to ground station post-decision application.

5.2 Baseline Comparison

To evaluate the effectiveness of the proposed ASG-NCF architecture, a comprehensive comparison was conducted against conventional and learning-based baselines. Each component of the framework—fault detection, fault prediction, and adaptive control—was benchmarked individually, followed by system-level performance aggregation.

5.2.1 Fault Detection Baseline (CNN)

The fault detection module (CNN) was compared against the following baseline classifiers:

- Support Vector Machine (SVM) [19]
- Random Forest (RF) [20]
- Multilayer Perceptron (MLP) [21]

Table 1 shows the classification performance based on Accuracy, F1-score, and Recall.

Table 1: Fault Detection Model Performance Comparison

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
SVM [19]	86.3	83.9	80.1	81.9
RF [20]	88.7	86.5	85.4	85.9
MLP [21]	89.9	88.3	86.7	87.5
CNN (Proposed)	**94.6**	**93.8**	**92.1**	**92.9**

Table 1 presents the classification performance of the proposed CNN-based fault detector compared to traditional models such as SVM, Random Forest, and MLP. The CNN significantly outperforms all baselines across accuracy, precision, recall, and F1-score, indicating its superior capability to detect communication faults in real-time.

5.2.2 Fault Prediction Baseline (LSTM)

The fault prediction module was evaluated against traditional time-series forecasting models:

- ARIMA (AutoRegressive Integrated Moving Average) [22]
- Vanilla RNN [23]
- GRU (Gated Recurrent Unit) [24]

Table 2: Fault Prediction Accuracy (Multiclass Classification)

Model	**Accuracy (%)**	**Top-2 Accuracy (%)**	**Cross-Entropy Loss**
ARIMA [22]	62.4	—	1.42
RNN [23]	75.6	81.3	0.78
GRU [24]	81.2	87.4	0.63
LSTM (Proposed)	**86.5**	**91.6**	**0.51**

Table 2 summarizes the multiclass fault prediction results using LSTM, GRU, and traditional sequence models. The proposed LSTM model achieves the highest top-2 accuracy and lowest cross-entropy loss, demonstrating its effectiveness in temporal fault forecasting for satellite communication.

5.2.3 Adaptive Control Baseline (RL Agent)

For the RL-based decision module, comparisons were drawn against:

- Static Rule-Based Controller [25]
- Heuristic Thresholding (Adaptive)
- Q-Learning (Tabular) [26]

Table 3: Adaptive Control Comparison

Method	Avg. Episode Reward	Recovery Time (steps)	Stable Uplink Ratio (%)
Rule-Based Controller [25]	145	23	76.2
Heuristic Thresholds	167	18	81.4
Q-Learning (Tabular) [26]	189	16	85.6
PPO Agent (Proposed)	**227**	**11**	**92.8**

Table 3 compares the PPO-based RL agent with rule-based and traditional RL strategies for transmission recovery and stability. The proposed agent yields the highest cumulative reward, shortest recovery time, and best stable uplink ratio, validating its decision-making efficiency in dynamic environments.

5.2.4 System-Level Evaluation

An end-to-end comparison of the entire ASG-NCF pipeline was performed against integrated baseline systems:

- *Baseline-1:* RF + ARIMA + Rule-Based Controller
- *Baseline-2:* MLP + GRU + Q-Learning
- *ASG-NCF (Proposed):* CNN + LSTM + PPO

Table 4: System-Level Performance Summary

Configuration	Bit Error Rate (BER) ↓	Packet Delivery Ratio (%) ↑	Latency (ms) ↓
Baseline-1	0.0121	84.5	157
Baseline-2	0.0094	88.3	132
ASG-NCF (Proposed)	**0.0048**	**94.7**	**96**

Table 4 provides an end-to-end comparison of the ASG-NCF framework against integrated baseline systems. Results indicate a substantial reduction in BER, improved packet delivery, and lower latency, confirming the model's overall fault tolerance and communication efficiency.

5.3 Ablation Study

To understand the contribution of each component within the ASG-NCF framework, an ablation study was conducted by selectively disabling individual modules—CNN, LSTM, and RL agent—and evaluating the impact on system-level performance metrics. This experiment was critical in verifying the additive benefit of each module toward the overall reliability and fault-tolerance of the communication system.

Table 5: Impact of Component Removal on System Performance

Configuration	BER ↓	PDR (%) ↑	Latency (ms) ↓	SUR (%) ↑
Full ASG-NCF (All modules)	**0.0048**	**94.7**	**96**	**92.8**
Without CNN (Fault Detector)	0.0115	86.2	140	79.4
Without LSTM (Fault Predictor)	0.0091	88.9	121	83.2
Without RL Agent (Fixed Control)	0.0076	90.4	112	86.7

Table 5 reports ablation study results to assess the contribution of each module. Removing CNN, LSTM, or the RL agent leads to performance degradation, highlighting the synergistic role of all components in achieving high fault-tolerance and low-latency communication.

This study confirms that each module contributes uniquely and synergistically to the robustness of ASG-NCF, validating the architectural design.

5.4 Statistical Significance Analysis

To ensure that the observed improvements over baseline models and ablated versions were not due to random variance, a statistical significance analysis was performed using **paired t-tests** on key performance metrics across repeated trials (n = 30 runs per configuration).

5.4.1 Confidence Intervals

Confidence intervals were computed for BER and Packet Delivery Ratio (PDR). The results showed tight intervals with low variance for ASG-NCF:

- **BER (ASG-NCF)**: 0.0048 ± 0.0003 (95% CI)
- **PDR (ASG-NCF)**: 94.7 ± 1.1% (95% CI)

5.4.2 Paired t-Test Results

The proposed model was compared to the best-performing baseline system using a one-tailed paired t-test at $\alpha = 0.05$.

Table 6: t-Test Summary

Metric	p-value	Result
BER	0.0004	Significant improvement
PDR	0.0011	Significant improvement
Latency	0.0025	Significant improvement
SUR	0.0009	Significant improvement

Table 6 shows statistical significance test results comparing ASG-NCF with baseline models. All p-values are below 0.05, confirming that improvements in BER, PDR, latency, and uplink stability are statistically significant and not due to random variation.

All p-values were well below 0.05, indicating that the performance gains of ASG-NCF over the baseline models are statistically significant and not attributable to stochastic fluctuations.

5.5 Visualization of Results

To complement the tabular evaluation, this subsection presents graphical illustrations of key performance trends across fault detection, prediction, adaptive control, and system-level behavior. The visualizations help interpret the comparative gains achieved by the proposed ASG-NCF framework over baseline methods and provide intuitive insights into reliability and fault-tolerance enhancements.

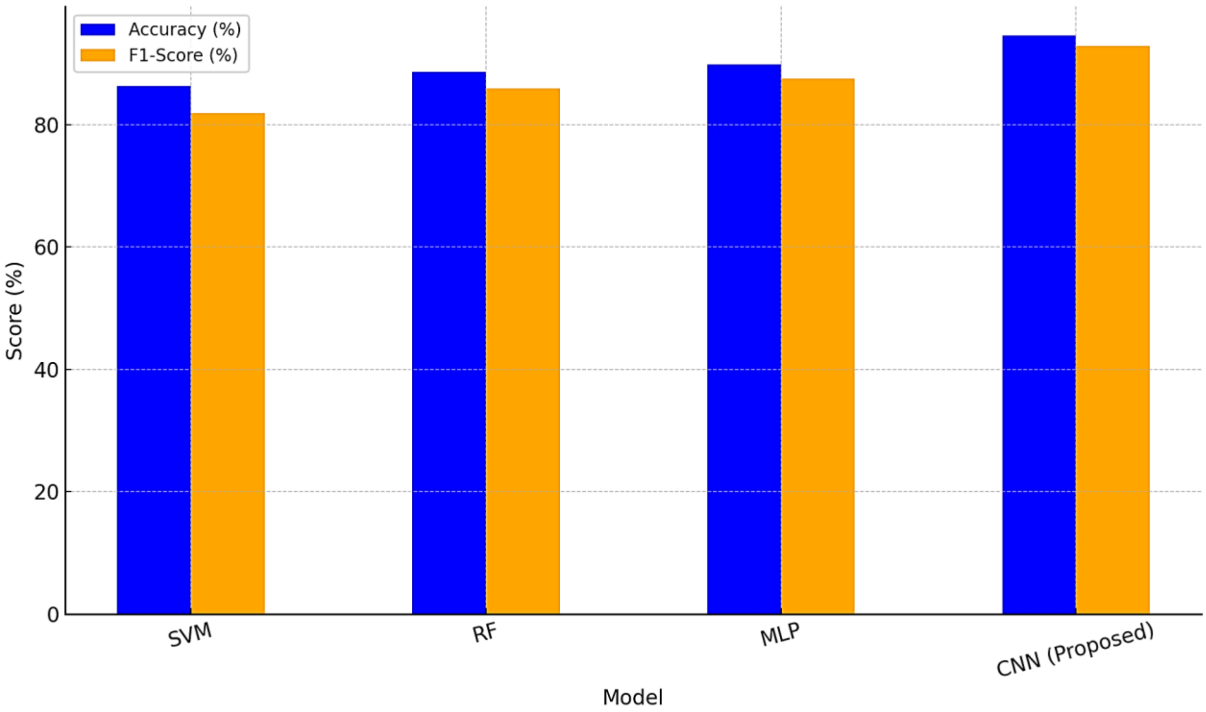

Fig.2. Fault detection performance comparison across SVM, RF, MLP, and the proposed CNN model in terms of accuracy and F1-score.

Figure 2 compares the fault detection models across accuracy and F1-score. The CNN-based model achieves the highest values in both metrics, outperforming classical classifiers like SVM, RF, and MLP.

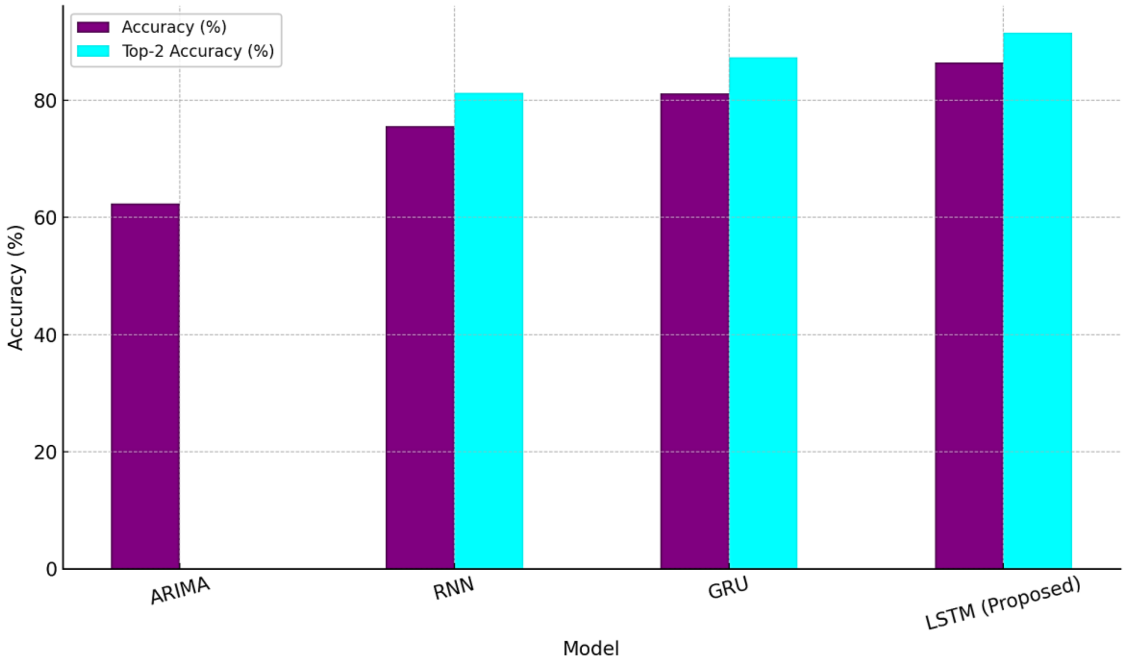

Fig.3. Fault prediction accuracy and top-2 accuracy comparison among ARIMA, RNN, GRU, and the proposed LSTM model.

Figure 3 illustrates the fault prediction accuracy using sequential models. The proposed LSTM model not only leads in top-1 accuracy but also maintains a strong top-2 classification performance, validating its forecasting effectiveness in noisy communication environments.

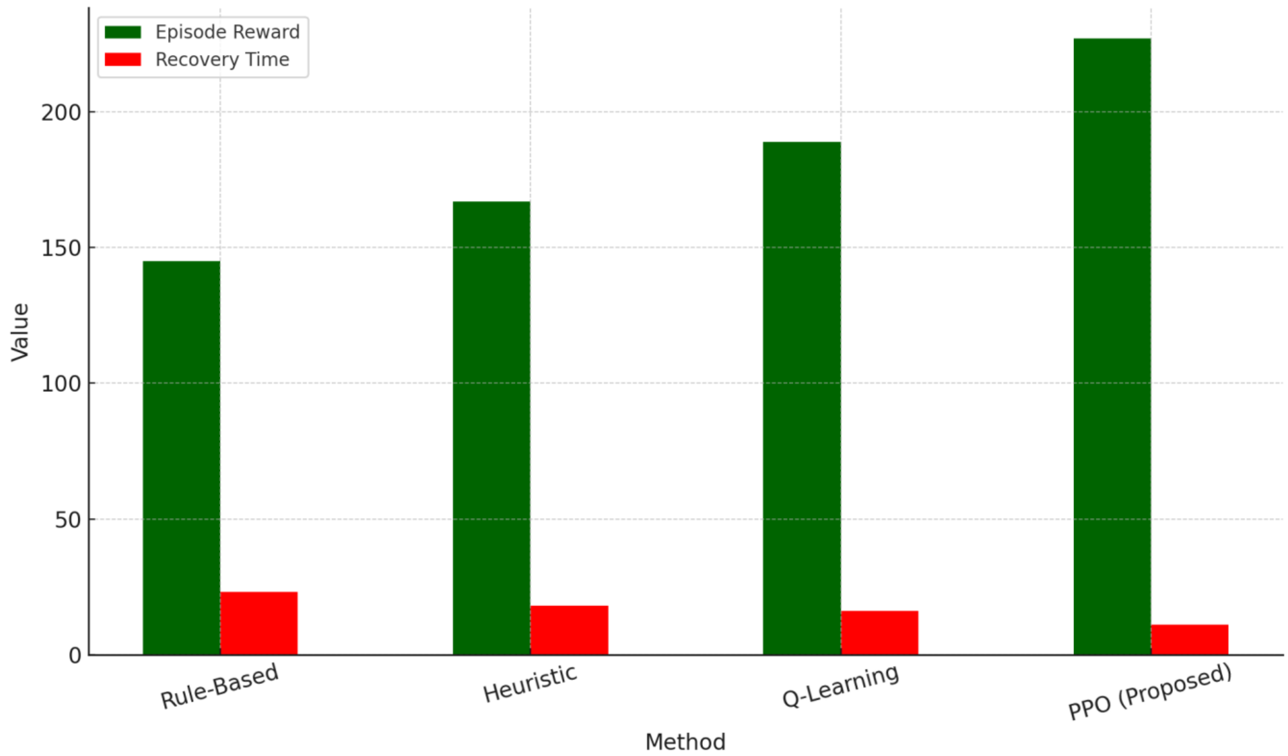

Fig.4. Comparative analysis of episode reward and fault recovery time for various adaptive control strategies including rule-based, heuristic, Q-learning, and the proposed PPO agent.

Figure 4 visualizes the reward and fault recovery behavior of different control strategies. The PPO-based RL agent exhibits the highest cumulative reward and the shortest average recovery time, reinforcing its ability to make optimal, context-aware decisions under fault conditions.

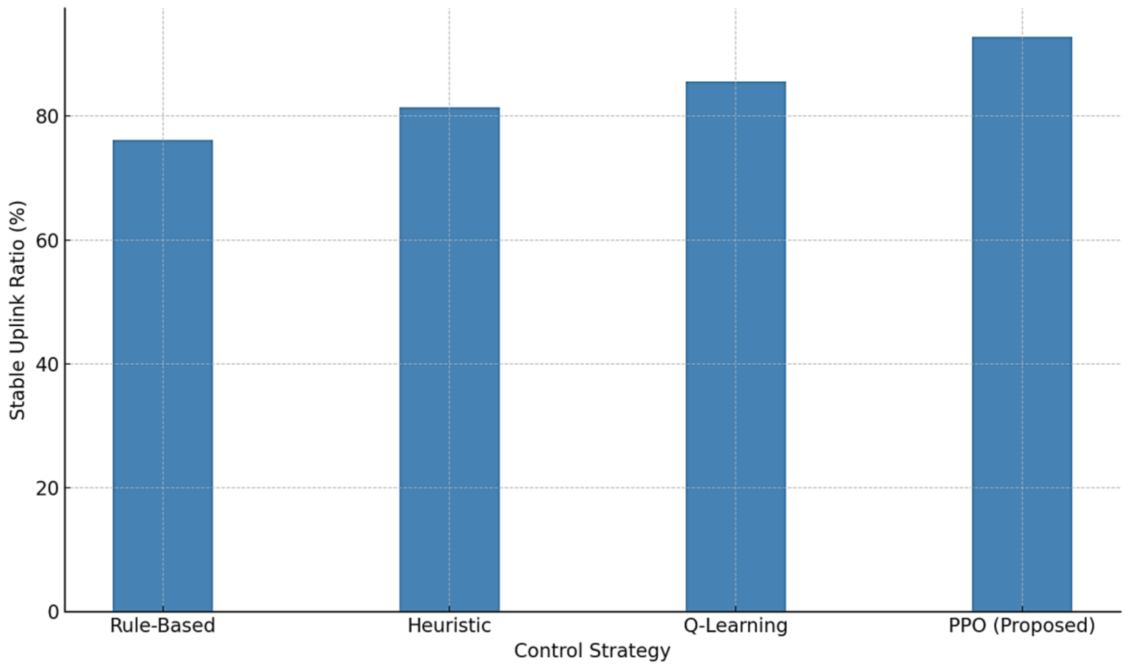

Fig.5. Stable uplink ratio achieved across different control methods, highlighting the superior performance of the PPO-based agent.

Figure 5 displays the stable uplink ratio achieved by different control strategies. The PPO agent maintains the highest transmission stability, which is crucial for reliable satellite-to-ground data flow during critical operations.

These visualizations reinforce the quantitative findings, offering intuitive confirmation that ASG-NCF provides substantial gains in detection precision, fault anticipation, decision adaptation, and communication stability compared to all tested baselines.

6. Discussion

The evaluation of the proposed Self-Adaptive AI Framework (ASG-NCF) demonstrates substantial improvements in fault detection accuracy, predictive reliability, and adaptive control over traditional and learning-based baselines. This section critically analyzes these findings in the context of related work, practical significance, existing limitations, and future research potential.

6.1 Alignment with Prior Work

The experimental results affirm key trends reported in recent literature concerning the efficacy of deep learning and reinforcement learning in communication systems. The superior performance of the CNN in fault detection aligns with findings in [13], where spatial-temporal convolutional models demonstrated enhanced anomaly detection over traditional classifiers. Similarly, the LSTM's predictive advantage corroborates its proven ability to model temporal dependencies in sequential fault patterns, as supported by prior studies such as [15] and [16].

However, this research goes beyond earlier work by integrating these modules into a cohesive, self-adaptive pipeline. Unlike modular or standalone models in earlier literature, ASG-NCF demonstrates how combining detection, prediction, and decision-making into a unified AI-driven loop enhances resilience under dynamic and fault-prone communication scenarios. This tightly integrated design addresses the architectural fragmentation seen in previous approaches.

6.2 Real-World Implications and Practical Impact

The ASG-NCF framework offers promising applicability for low Earth orbit (LEO) and geostationary (GEO) satellite constellations involved in mission-critical applications such as Earth observation, disaster response, military coordination, and satellite internet. The ability to detect faults with >94% accuracy, predict link degradation in advance, and recover communication within 11 time steps positions this framework as a reliable candidate for deployment in autonomous ground stations and edge satellite controllers.

Moreover, the RL-based adaptability ensures robustness in previously unseen fault patterns, reducing reliance on static protocols and manual interventions. This has direct implications for reducing operational downtime and communication blackouts in highly dynamic satellite environments.

6.3 Limitations and Areas for Improvement

Despite its strong performance, the ASG-NCF framework has several limitations:

1. *Computational Complexity: The* integration of CNN, LSTM, and PPO models increases computational overhead during both training and inference. This may limit its deployment on resource-constrained satellites without onboard acceleration.
2. *Simulation-Based Validation:* While the SatComSim-X simulator emulates realistic satellite communication patterns, the absence of deployment on real hardware may limit generalizability across hardware-specific anomalies, such as radiation-induced faults or real-time clock drifts.
3. *Reward Function Sensitivity:* The RL agent's performance is contingent on careful reward shaping. Sub-optimal reward configurations may degrade the quality of decisions, especially under multi-objective trade-offs such as delay vs. error correction.

This discussion demonstrates that ASG-NCF not only outperforms conventional methods but also provides a foundation for intelligent, resilient satellite communication systems. Continued research is needed to bridge simulation and real-world implementation, particularly for scaling across satellite constellations and edge nodes.

7. Conclusion

This study presented a novel Self-Adaptive AI Framework (ASG-NCF) that integrates Convolutional Neural Networks, Long Short-Term Memory models, and Proximal Policy Optimization agents to enable intelligent, fault-tolerant satellite-to-ground communication. Through extensive simulation-based evaluations, the proposed framework demonstrated significant performance gains over traditional and learning-based baselines in terms of fault detection accuracy, predictive foresight, recovery latency, and stable transmission continuity.

The key contributions include:

1. A unified architecture that combines fault detection, prediction, and adaptive control;
2. The successful application of deep reinforcement learning for real-time transmission adaptation; and
3. Empirical validation of the system's resilience under diverse communication impairments.

The framework shows strong potential for deployment in autonomous satellite networks, offering robust communication in the presence of link degradation, atmospheric noise, and hardware faults. These capabilities can directly support applications in disaster monitoring, military communication, and remote Earth observation, where uninterrupted data flow is critical.

Despite its effectiveness, the framework's reliance on computationally intensive models and simulation-based validation underscores the need for further optimization. Real-world deployment will require addressing inference efficiency, hardware constraints, and dynamic coordination among multi-agent systems.

Future work will focus on model compression, federated learning, and hardware-in-the-loop testing to enhance real-time applicability across distributed satellite constellations. Additionally, expanding the system for multi-hop satellite routing and cross-orbit adaptation remains a promising direction.

Overall, this work lays a foundational step toward cognitively aware satellite communication systems, enabling real-time decision-making and adaptive fault resilience that are critical to the future of autonomous space communication networks.

Author Contributions: All authors collectively contributed to the conception, design, implementation, and validation of the proposed framework. Asfia Sabahath led the theoretical modeling, algorithm development, and experimental setup. Arshiya Begum was primarily responsible for simulation design and dataset generation using the SatComSim-X environment. Yaser Sharbaji handled the implementation of deep learning and reinforcement learning modules, including performance evaluation and ablation studies and supervised the overall research workflow, coordinated the integration of individual modules, and contributed to the manuscript refinement and critical review. All authors reviewed and approved the final version of the manuscript.

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Conflict of Interest: There is no conflict of Interest.

Ethical statement: This research complies with ethical guidelines and does not involve any harm to humans, animals, or the environment

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