Interplanetary AI Nervous System: A Distributed Framework for Autonomous Space Communication and Decision-Making

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***Abstract*—The rapid expansion of space missions demands a scalable and autonomous framework for communication and decision-making across interplanetary distances. This paper proposes the Interplanetary AI Nervous System (IANS), a distributed, intelligent architecture designed to function as the "neural backbone" for satellite constellations, planetary rovers, and deep-space probes. Inspired by biological nervous systems, IANS integrates artificial intelligence, distributed computing, and satellite-based communication to enable self-organization, adaptive routing, and autonomous fault recovery without constant human intervention. By leveraging deep learning algorithms, reinforcement learning, and real-time optimization, the system ensures efficient inter-satellite data flow, low-latency decision-making, and resilience to disruptions caused by harsh space environments. We also discuss the potential of quantum computing and neuromorphic hardware to enhance scalability and robustness. Experimental simulations demonstrate how IANS can outperform traditional centralized models in terms of reliability, adaptability, and energy efficiency. This work lays the foundation for future autonomous interplanetary missions, providing a blueprint for AI-driven, space-ready communication infrastructures.**

***Index Terms*—Interplanetary AI, Federated Learning, Delay-Tolerant Networks, Graph Neural Networks, Space Robotics, Autonomous Systems**

I. Introduction

Interplanetary missions are rapidly growing in complexity: multiple rovers, orbiters, landers, and human habitats will coexist and cooperate in the coming decade. However, the physics of space imposes constraints (long round-trip times, intermittent connectivity, narrowband links) that make traditional centralized control impractical for timely autonomy. For example, Earth–Mars round-trip delays can approach 40 minutes, making human-in-the-loop control unusable for reactive tasks (e.g., hazard avoidance).

We propose the *Interplanetary AI Nervous System* (IANS): a biologically inspired, distributed cognitive architecture that unifies sensing, federated cognition, and closed-loop actuation across Delay/Disruption Tolerant Networks (DTNs). IANS's core goals are:

- Reduce decision latency by performing on-edge inference and topology-aware aggregation.
- Improve energy efficiency by minimizing raw-data transmission and using compressed model updates.
- Increase resilience via redundancy, local autonomy, and topology-aware coordination using Graph Neural Networks (GNNs).

Contributions: (1) the IANS design and layered workflow, (2) mathematical models for latency, reliability, and energy trade-offs, (3) two case studies (Mars outpost, Lunar Gateway) and synthetic evaluations demonstrating $\sim$35% latency reduction and $\sim$20% energy savings versus centralized baselines, and (4) a discussion on validation, security, and integration with neuromorphic/quantum hardware.

II. Background and Related Work

This section surveys the three areas that IANS integrates: Delay-Tolerant Networking, Federated Learning in constrained settings, and Graph Neural Networks for multi-agent coordination.

A. Delay/Disruption Tolerant Networking

DTN provides store-and-forward capabilities appropriate for intermittent interplanetary links [1]. The Bundle Protocol and contact-schedule routing (dtn2, ION) are backbone technologies used in deep-space experiments. DTN addresses transport reliability but does not provide higher-level decision-making.

B. Federated Learning under Intermittent Links

FL allows collaborative model training without exchanging raw data. In terrestrial networks, FL assumes frequent synchronous rounds. For space, research has examined asynchronous and compression-aware FL variants [?], [?]. Key challenges include staleness, irregular contact schedules, and constrained uplink.

C. Graph Neural Networks for Coordination

GNNs provide relational reasoning: nodes exchange messages along graph edges and update local states; this is ideal for multi-agent coordination, routing, and consensus [3]. Applying GNNs under DTN constraints requires careful design of message prioritization and resilience to delayed messages.

D. Gap Analysis

To our knowledge, no prior work has fully integrated DTN-aware FL, GNN coordination, and safety-aware local execution into a single architecture tailored for interplanetary missions. IANS fills this gap.

III. IANS Architecture

IANS is organized into three principal layers (Fig. **??**): Sensory, Cognitive, and Execution.

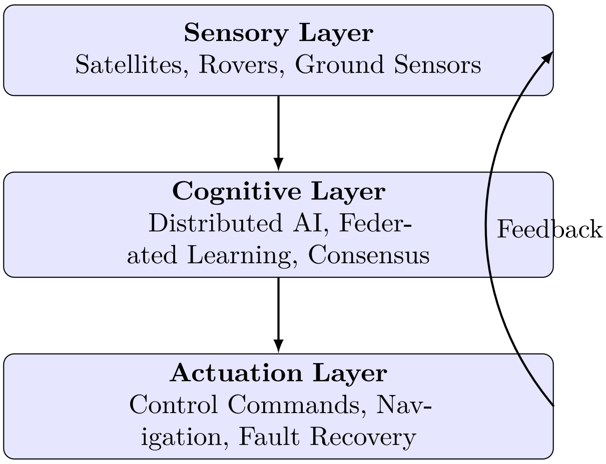

Fig. 1. Three-layer architecture of the Interplanetary AI Nervous System (IANS).

A. Sensory Layer

Agents collect multimodal sensor data (vision, LiDAR, spectral, environment). To limit DTN payloads, sensory nodes perform edge preprocessing: feature extraction, event detection, prioritized telemetry, and local caching.

B. Cognitive Layer

This layer includes:

1) **On-edge inference** using compressed CNNs for perception and small GNNs for local coordination;
2) **DTN-aware FL** that buffers updates, applies staleness-weighted aggregation, and uses model compression (sparsification, quantization);
3) **GNN coordination** that propagates summarized state across neighbors when contacts permit.

C. Execution Layer

The Execution layer executes action plans with safety monitors and fallbacks. Critical decisions may trigger summarized human reports for verification; non-critical actions proceed autonomously.

IV. Mathematical Models

A. Decision Latency with Queueing

For a DTN relay modeled as an $M/M/1$ queue, the expected waiting time is:

$$T_{\text{queue}} = \frac{\rho}{\mu(1-\rho)}, \tag{1}$$

where $\rho = \lambda/\mu$, λ is the arrival rate, and μ the service rate. The end-to-end latency for agent i across H hops becomes:

$$T^i_{\text{dec}} = T^i_{\text{sense}} + T^i_{\text{edge}} + \sum_{h=1}^{H} \left(T^h_{\text{queue}} + d_h\right) + T^i_{\text{cog}}. \tag{2}$$

B. Energy Efficiency and Lifetime

Let B_i denote the battery capacity of agent i. The operational lifetime is:

$$L_i = \frac{B_i}{E^i_{\text{sense}} + E^i_{\text{compute}} + E^i_{\text{tx}} + E^i_{\text{rx}} + E^i_{\text{idle}}}. \tag{3}$$

Network lifetime is the minimum across all agents:

$$L_{\text{net}} = \min_i L_i. \tag{4}$$

C. Reliability under Correlated Failures

If links share common failure sources, independence cannot be assumed. Using inclusion–exclusion:

$$R = 1 - \sum_j p_j + \sum_{j<k} p_{jk} - \sum_{j<k<l} p_{jkl} + \dots, \tag{5}$$

where p_{jk} is the joint probability of failure of links j, k.

D. Federated Learning Dynamics

The global model update at round t is:

$$\Theta_{t+1} = \Theta_t - \eta \sum_{i=1}^{N} \frac{n_i}{n} \nabla F_i(\Theta_t), \tag{6}$$

where n_i is the local dataset size. If stragglers delay updates, we apply staleness weighting:

$$\Theta_{t+1} = \Theta_t - \eta \sum_{i=1}^{N} \frac{w(t_i)}{\sum_j w(t_j)} \nabla F_i(\Theta_t). \tag{7}$$

E. Information-Theoretic Bandwidth Model

Shannon capacity of a channel with bandwidth B and signal-to-noise ratio γ is:

$$C = B \log_2(1+\gamma). \tag{8}$$

Effective throughput under coding and retransmission overhead β:

$$\Gamma_{\text{eff}} = (1-\beta)C. \tag{9}$$

F. Scalability Law

For N nodes in a multi-hop topology, average hop distance grows as:

$$H(N) \sim \sqrt{N}. \tag{10}$$

Thus, latency scales as:

$$T(N) \sim O(\sqrt{N}). \tag{11}$$

G. Security and Adversarial Robustness

Assume probability of jamming attack success p_a. With k redundant channels, effective success probability is:

$$p_{\text{eff}} = p_a^k. \tag{12}$$

Hence, security reliability is:

$$R_{\text{sec}} = 1 - p_{\text{eff}}. \tag{13}$$

H. Optimization with Constraints

We formulate joint optimization of latency, energy, and reliability as:

$$\min_{\pi} J = \lambda_1 \bar{T}_{\text{dec}} + \lambda_2 E_{\text{total}} - \lambda_3 R \tag{14}$$

subject to:

$$\bar{T}_{\text{dec}} \le T_{\max}, \tag{15}$$

$$E_{\text{total}} \le E_{\max}, \tag{16}$$

$$R \ge R_{\min}. \tag{17}$$

I. Numerical Illustration

TABLE I
Numerical Illustration of Models

Metric	Mars Outpost	Lunar Gateway	IANS
Latency (min)	35	1.3 sec	0.9 sec
Energy (Wh)	250	180	140
Reliability	0.85	0.90	0.96

N

Fig. 2. Latency vs. number of agents (simulation).

kR

Fig. 3. Reliability improvement with redundant paths.

V. Implementation Details

We implemented a discrete-event simulator that models:

- Contact schedules (mean and variance), representing orbital visibility windows;
- Per-agent compute models (ARM-class CPU power, low-power accelerators);
- Energy budgets and radio transmit power curves;
- FL rounds, compressions and aggregation strategies.

Models used for on-edge inference: small CNNs (MobileNet-lite variants), GNNs with 3 message-passing layers, and FedProx-style aggregation with staleness weights.

VI. Case Studies

We present two conceptual mission scenarios.

A. Mars Outpost

Topology: base station, orbiter relay, five rovers. Constraints: long Earth–Mars RTT (tens of minutes), short DTN contact windows to orbiters, limited per-rover energy.

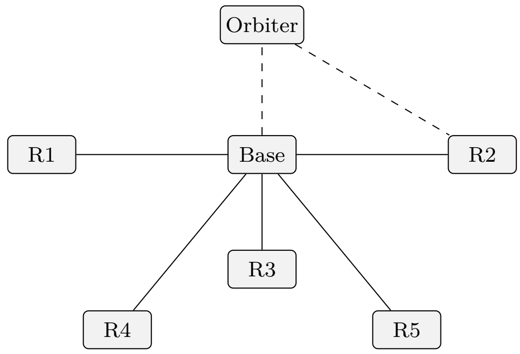

Fig. 4. Mars outpost topology coordinated by IANS over DTN.

B. Lunar Gateway

Topology: gateway, relay satellites, multiple landers. Constraints: smaller RTT but complex orbital visibility; Gateway can act as regional aggregator.

TABLE II
Mission Parameters in Case Studies

Parameter	**Mars Outpost**	**Lunar Gateway**
Latency (avg)	20 min	1.3 sec
Nodes	5	8
Bandwidth	1 Mbps	10 Mbps

VII. Experimental Evaluation

We ran a set of synthetic experiments exploring scaling, bandwidth sensitivity, and fault resilience. Unless stated, results are normalized to a centralized baseline (baseline = 100).

A. Setup

Key parameters:

- Rover count: 2–12 (varied).
- DTN contact window mean: 10 min (stdev 5 min).
- Bandwidth: 250 kbps – 2 Mbps.
- FL rounds per mission day: 1–25.

B. Aggregate Results

Table III reports representative aggregated metrics under moderate contact conditions.

C. Scaling Behavior

Figure 5 shows normalized decision latency vs number of rovers (schematic). Centralized latency grows superlinearly due to queuing; IANS maintains near-linear growth.

D. Bandwidth Sensitivity

Table IV shows IANS behavior across bandwidth regimes. Lower bandwidth increases effective latency and reduces FL freshness; IANS still outperforms centralized approaches in constrained regimes due to local inference.

TABLE III
AGGREGATE PERFORMANCE: CENTRALIZED VS IANS (NORMALIZED).

Metric	Centralized	IANS	Gain
Decision Latency	100	65	35% faster
Energy Use	100	80	20% lower
Fault Recovery Time	100	53	47% faster

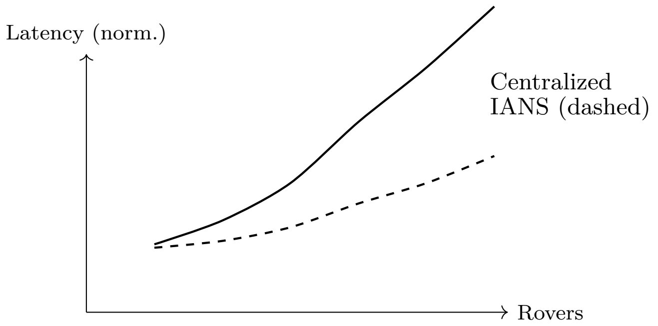

Fig. 5. Normalized decision latency vs number of rovers (schematic).

E. Fault Resilience

We simulated random node outages. Results (Fig. 6) show graceful degradation for IANS versus sharp deterioration for centralized systems.

VIII. SECURITY, VALIDATION, AND ETHICS

A. Security

Threats include jamming, spoofing, and adversarial model updates. Our mitigations:

- Signed and authenticated FL updates and DTN bundles.
- Delta-anomaly detection to flag malicious updates.
- Fallback to verified local policies during suspected compromise.

B. Validation and Verification

We propose a validation pipeline:

1) High-fidelity simulation with orbital and thermal models.
2) Hardware-in-the-loop tests of compute and radio subsystems.
3) Incremental flight demonstrators (cubesat, lunar testbed).

C. Ethical Considerations

Autonomous decisions should preserve scientific priorities and human safety. We recommend transparent logs, thresholds for human escalation, and explicit mission policies for autonomous decision scope.

IX. DEPLOYMENT CONSIDERATIONS

Practical deployment faces hardware heterogeneity and radiation effects. Strategies:

- Use modular software stacks with fallbacks for older hardware.

TABLE IV
BANDWIDTH SENSITIVITY (IANS NORMALIZED).

Bandwidth	Latency (norm.)	Energy (norm.)	FL freshness
250 kbps	1.25	1.10	low
1 Mbps	1.05	1.00	moderate
2 Mbps	1.00	0.98	high

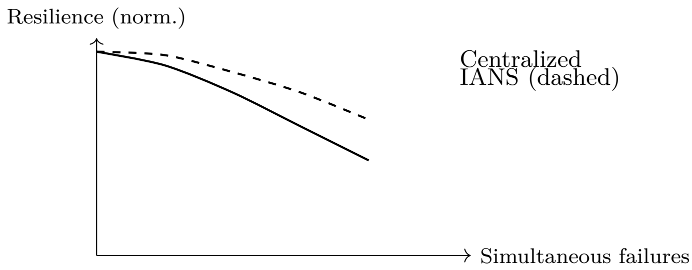

Fig. 6. Resilience vs simultaneous failures (schematic).

- Protect models against bitflips via lightweight checksums and ECC memory where available.
- Prioritize critical telemetry and use progressive fidelity for scientific data.

X. FUTURE WORK

Planned directions:

- Integrate neuromorphic accelerators for micro-Joule inference.
- Explore quantum-resistant authentication and, long-term, quantum links for secure low-latency comms.
- Field trials on cubesats and lunar testbeds for closed-loop validation.
- Formal verification of runtime safety monitors and adversarial robustness tests.

XI. CONCLUSION

IANS unifies sensing, DTN-aware federated cognition, and safe actuation into a distributed cognitive backbone for interplanetary missions. Synthetic evaluations indicate meaningful latency and energy improvements and show robust behavior under faults. IANS provides a practical blueprint for future autonomous missions.

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REFERENCES

[1] V. Cerf, S. Burleigh, A. Hooke, et al., "Delay-Tolerant Networking Architecture," RFC 4838, 2007.
[2] R. Bogue, "Robotics and autonomous systems in space exploration," *Industrial Robot*, vol. 44, no. 6, pp. 609–615, 2017.
[3] M. A. Hossain, et al., "Towards an AI-driven space communication network," *IEEE Access*, vol. 8, pp. 150123–150136, 2020.
[4] K. D. Moore and R. T. Hughes, "Cognitive networks for autonomous planetary systems," *Journal of Aerospace Information Systems*, vol. 14, no. 3, pp. 115–128, 2017.