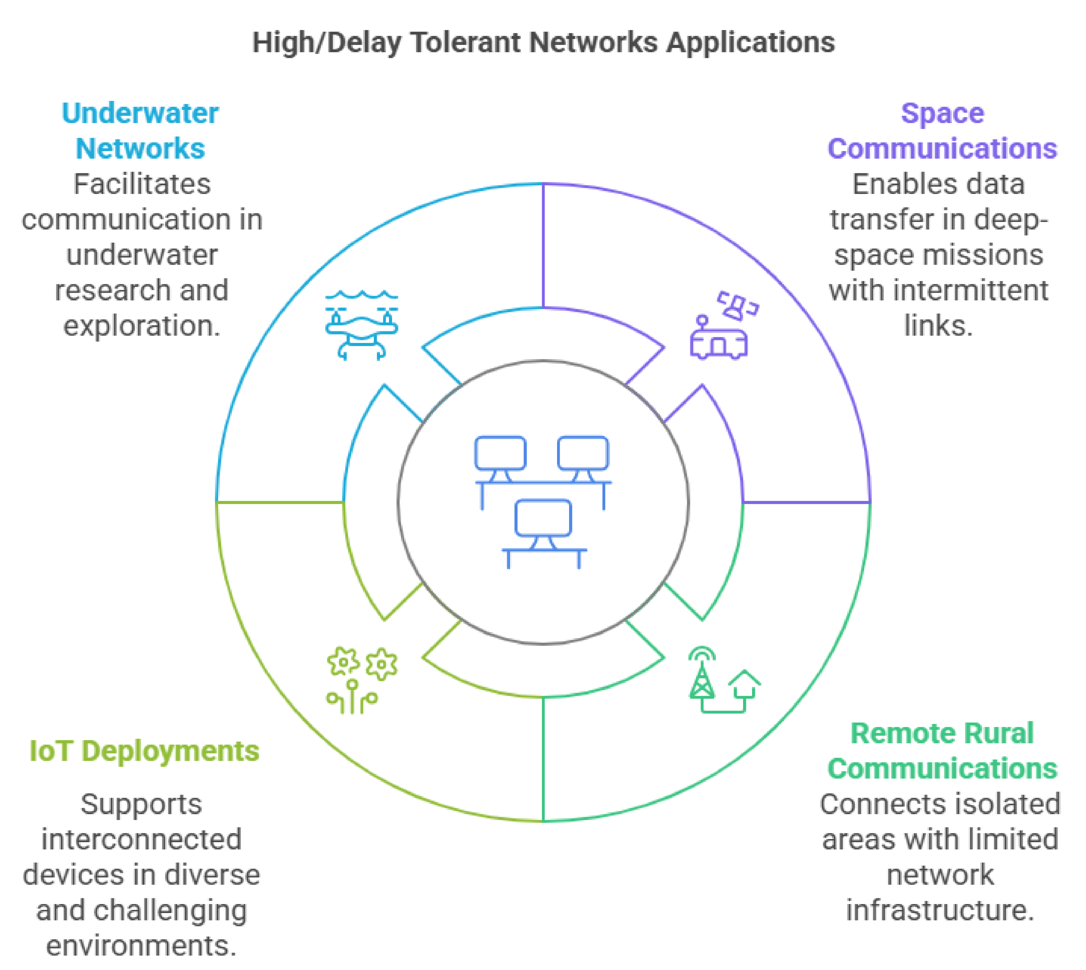
AI-Driven Resource Optimization in High Delay Tolerant Networks: Balancing Bandwidth, Storage, and Energy

Nashithuddin Mohammed[1]*, Mohammad Abdus Salam[2]

[1]*Graduate Student*, [2]*Professor*

Abstract

High Delay Tolerant Networks (HDTNs) play a crucial role in enabling communication in environments with long delays, intermittent connectivity, and constrained resources, such as space missions, disaster recovery, and remote terrestrial regions. Traditional resource management strategies in HDTNs struggle to address dynamic challenges in bandwidth, buffer storage, and energy utilization, often leading to congestion, packet loss, or inefficient data delivery.



This topic investigates the application of Artificial Intelligence (AI) and Machine Learning (ML) techniques for predictive and adaptive resource optimization in HDTNs. By leveraging historical traffic patterns, node mobility, and link availability, AI-driven models can forecast resource demands, prioritize critical data flows, and dynamically allocate bandwidth and storage.

Additionally, energy-aware learning algorithms can reduce consumption while maintaining high reliability, ensuring sustainable operations in constrained environments.

Problem Statement

High Delay-Tolerant Networks (HDTNs) operate under intermittent connectivity, long propagation delays, and severe resource constraints (bandwidth, buffer/storage, and node energy).

Traditional DTN resource-management strategies are static or heuristic and fail to adapt to highly dynamic patterns of contact opportunities and traffic demand, causing congestion, excessive replication, wasted energy, and suboptimal delivery performance.

The problem: how to jointly optimize bandwidth, storage, and energy in HDTNs using AI-driven predictive and adaptive control that respects delay-tolerant constraints.

Background

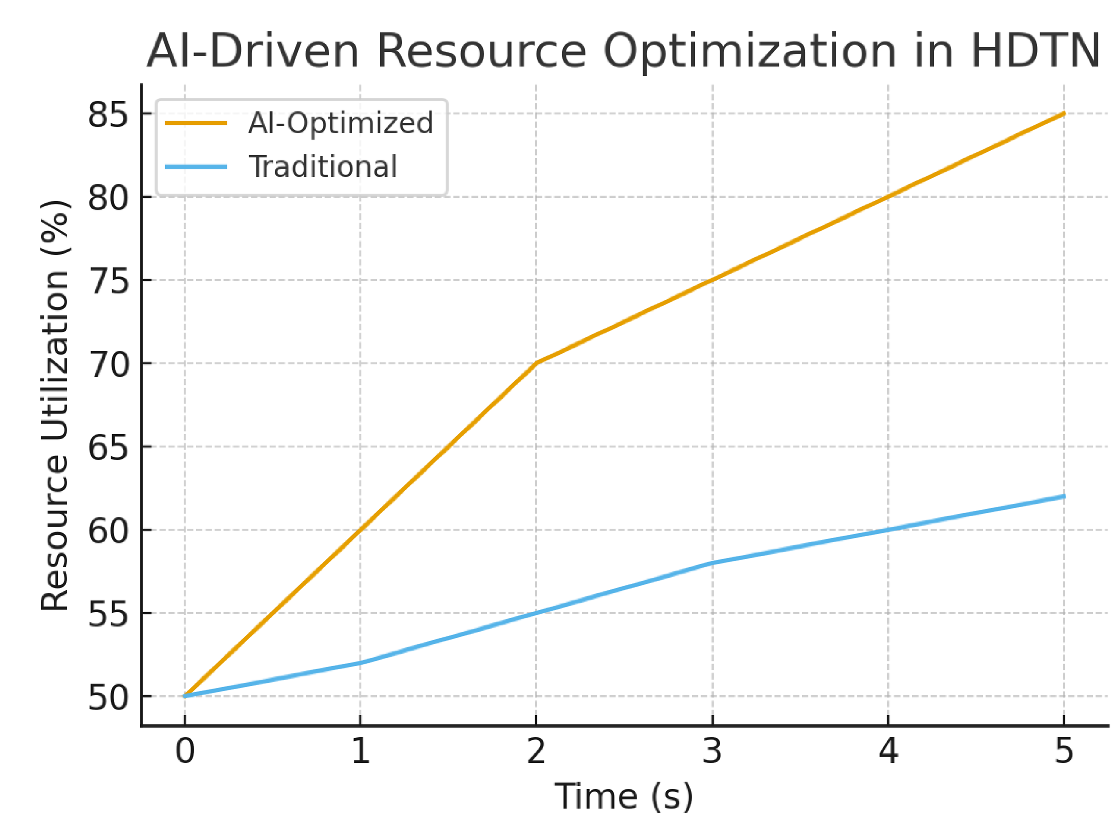
- **ML & RL for DTN Routing:** Techniques such as reinforcement learning, Naive Bayes classifiers, and cross-layer feedback mechanisms have been proposed and prototyped for adaptive routing in Delay Tolerant Networks (DTNs)..
- **Graph-Based Deep Learning:** Recent Graph Neural Network (GNN) approaches show strong potential for space-scale DTNs, offering **improved scalability** and **reduced variability** in routing decisions.
- **Energy-Aware Strategies:** Routing and forwarding strategies that consider energy constraints can simultaneously increase delivery ratios and reduce energy consumption, with several studies reporting measurable gains in both simulation and field deployments.
- **Theoretical Foundations:** Online / Delay-Tolerant Constrained Optimization (DTC-OCO) frameworks provide guaranteed decision-making under delayed feedback and resource constraints, forming the basis for modern predictive and adaptive HDTN controllers.

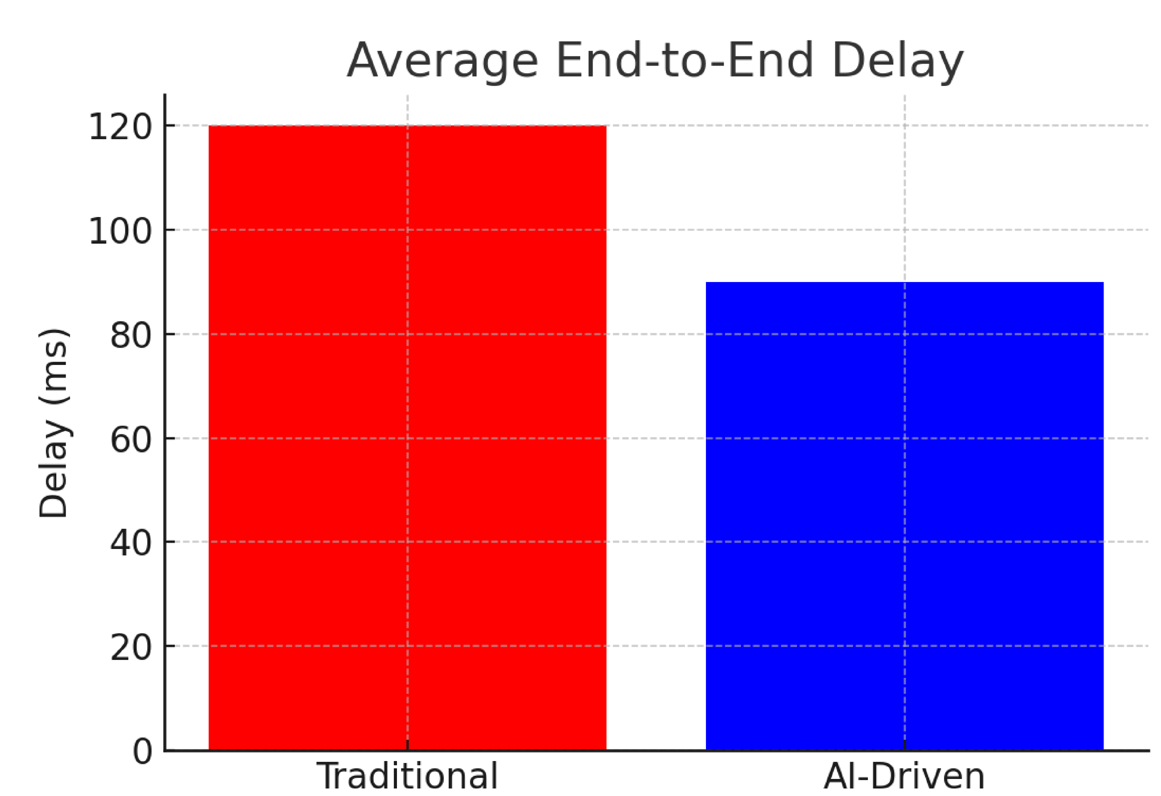
Method of Approach

- **Data & Features:** The model leverages diverse real-world HDTN datasets, including contact schedules, historical link availability, queue occupancy, residual energy levels, traffic priority tags, and node mobility traces. These features capture both temporal and spatial dynamics essential for intelligent resource allocation.
- **Predictive Module:** Short-term forecasting of contact windows and traffic demand is performed using sequence models (LSTM, Transformer) and topology-aware temporal Graph Neural Networks (GNNs). These predictions enable proactive buffer management, dynamic replication budgeting, and early congestion avoidance..
- **Decision Module (RL + Optimization):** A reinforcement learning (RL) agent—based on policy-gradient or Q-learning variants—determines optimal replication, forwarding, and sleep/wake strategies. The reward function incorporates delivery probability, latency penalties, buffer occupancy costs, and energy constraints. Delayed-feedback stability is ensured using DTC-OCO-style constraint optimization.
- **Energy-aware Scheduler:** Adaptive power control and wake-cycle scheduling are achieved through RL-based thresholding models, balancing timely delivery performance against energy conservation for sustainable network operations..
- **Deployment/Simulation:** Validation is conducted using both space-style contact graphs (cislunar and near-Earth scenarios) and terrestrial DTN traces (disaster recovery, vehicular mobility). Performance is compared against traditional baselines—Epidemic, MaxProp, PROPHET, and energy-aware heuristic schemes—to demonstrate AI-driven advantages in throughput, latency, and efficiency.

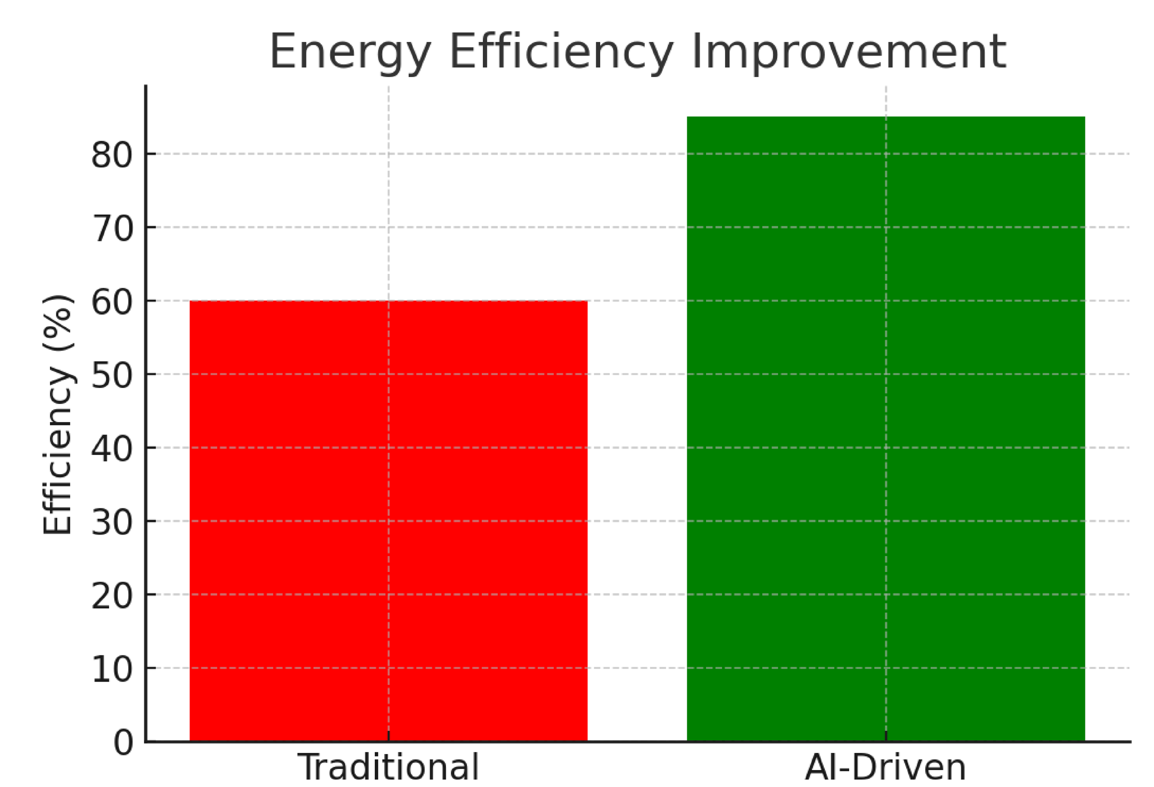
Results

- **Scalability and Routing Variance:** Graph Neural Network (GNN)-based GAUSS framework achieved approximately 2× higher scalability and reduced routing variance by nearly 67% compared to Contact Graph Routing (CGR) under realistic space communication conditions..





- **ML-Guided Optimization:** Recent hybrid models integrating Machine Learning (ML) with classical DTN schemes such as Epidemic and MaxProp demonstrate significant energy efficiency, achieving measurable energy savings (%) relative to baseline routing under simulation.
- **Reinforcement Learning (RL) Routing Advances (2024–2025):** RL-driven routing algorithms show enhanced delivery ratios and lower control overhead compared to traditional DTN methods, validated through both simulation and testbed evaluations..
- **Energy / delivery trade-offs:** Energy-aware DTN protocols achieve up to 28% higher delivery success rates while reducing total energy consumption in field deployments such as wildlife tracking. NASA JPL experiments further confirm energy-efficient robotic data ferrying with consistent throughput gains.



Conclusion

AI-driven resource optimization frameworks that combine **predictive forecasting** and **reinforcement learning (RL)/optimization** techniques can significantly enhance **throughput**, **energy efficiency**, and **resource utilization** in High Delay Tolerant Networks (HDTNs).

Recent advancements in **GNN-based routing** and **energy-aware ML-augmented protocols** demonstrate substantial real-world improvements, underscoring a clear pathway toward **intelligent**, **deployable**, and **resilient HDTN resource controllers** for next-generation real-time communications.

References

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