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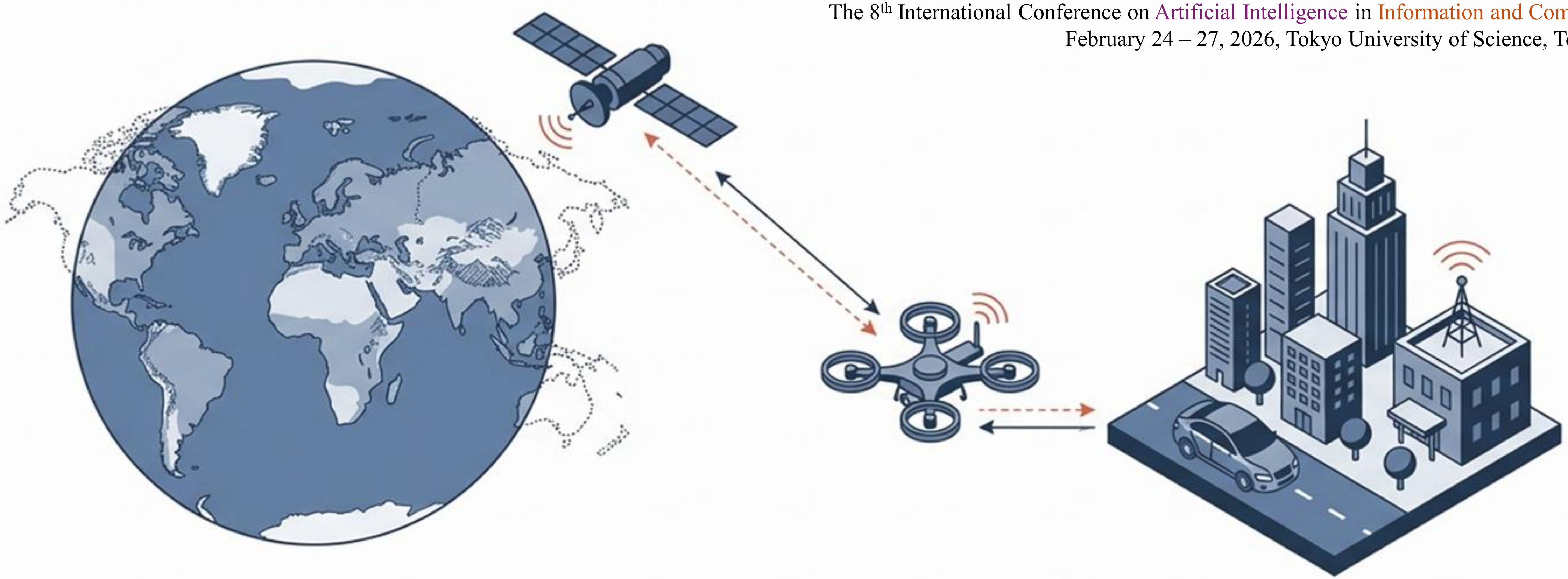
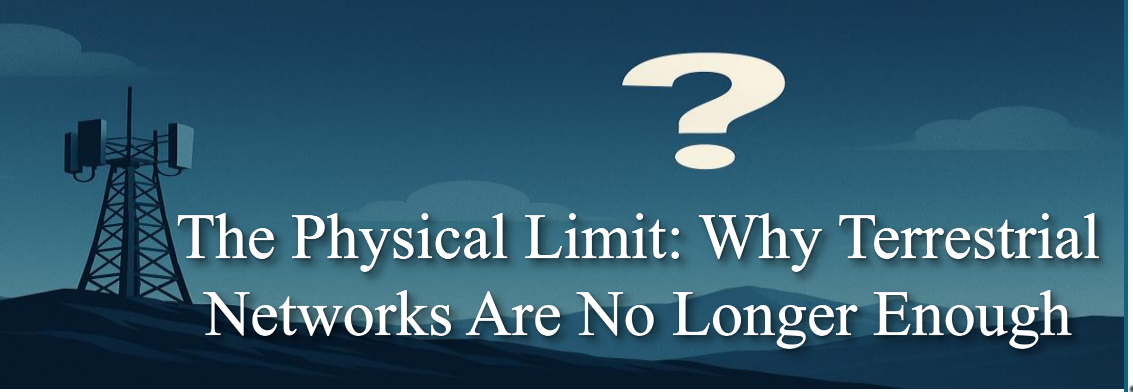


Deep Learning-Based Traffic Prediction for Non-Terrestrial Networks: A Hybrid Satellite-UAV Approach

Bridging the gap between global LEO coverage and local UAV adaptability.

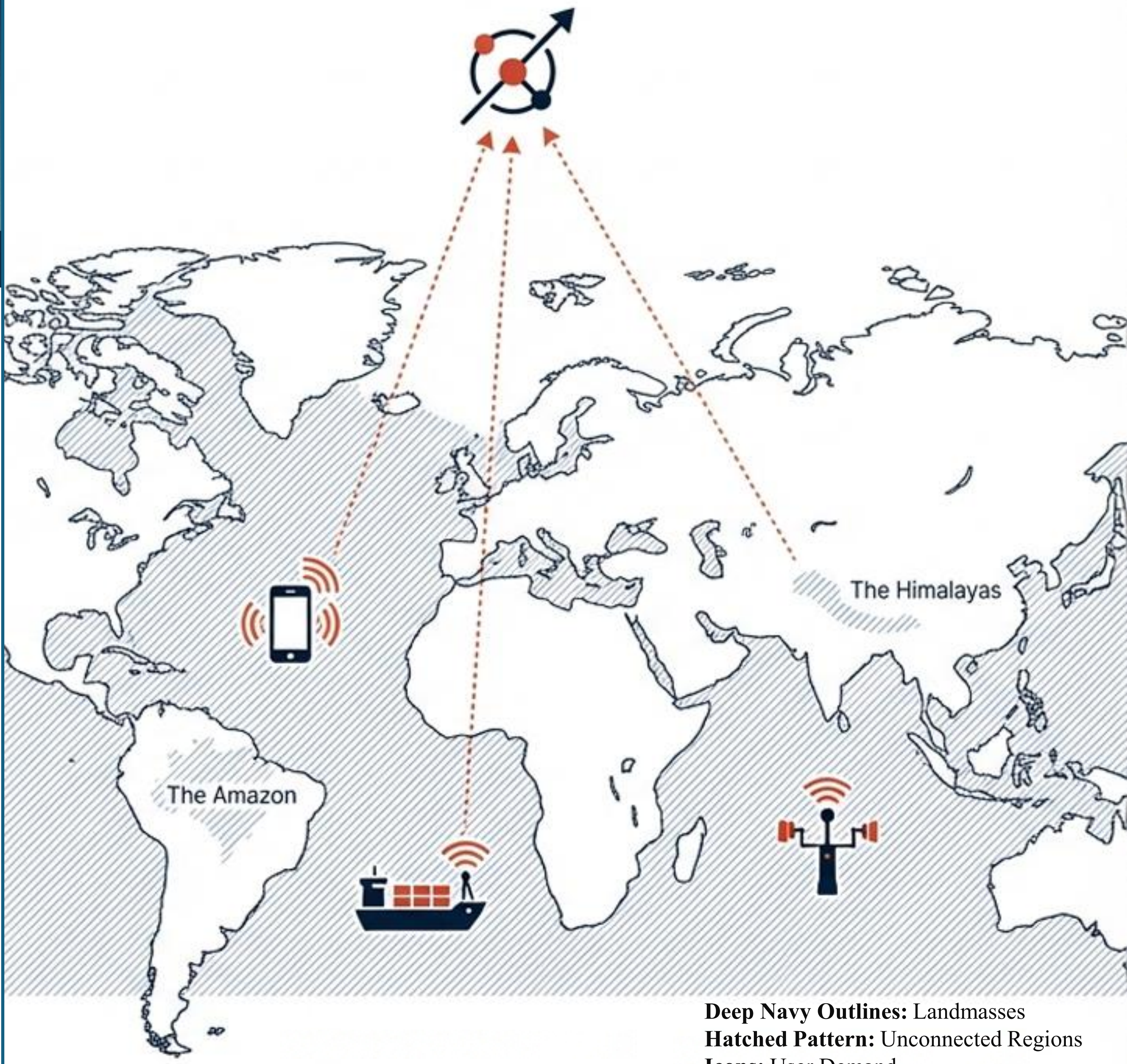
Vaskar Chakma[†], Seong-Yong Moon[‡], and Wooyeol Choi[†]
[†]Chung-Ang University, Seoul & [‡]Chosun University, Gwangju
Republic of Korea



The Physical Limit: Why Terrestrial Networks Are No Longer Enough

The explosive growth of IoT and mobile data has outpaced terrestrial infrastructure. Traditional cell towers are bound by geography; they cannot cover oceans, remote mountain ranges, or disaster zones where infrastructure is damaged.

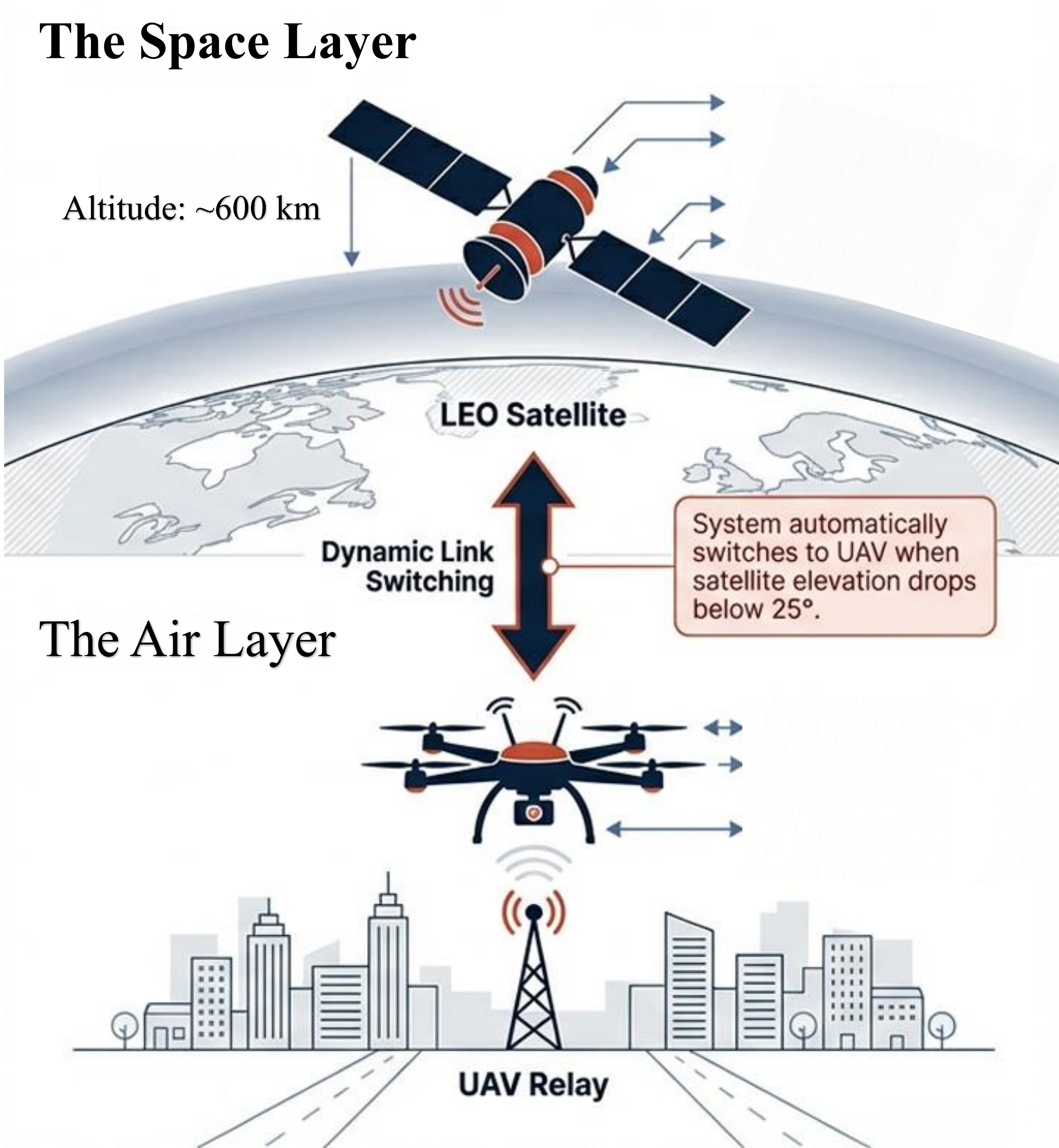
Global Data Surge: Exponential rise in mobile and loT sensor traffic.
The Coverage Gap: 70%+ of the Earth's surface (oceans/deserts) remains unconnected.
The Solution: Non-Terrestrial Networks (NTNSs) extend the internet's edge to the sky and space.



Deep Navy Outlines: Landmasses
Hatched Pattern: Unconnected Regions
Icons: User Demand
Dotted Lines: NTN Connection Path

The Hybrid Architecture: Combining Global Reach with Local Precision

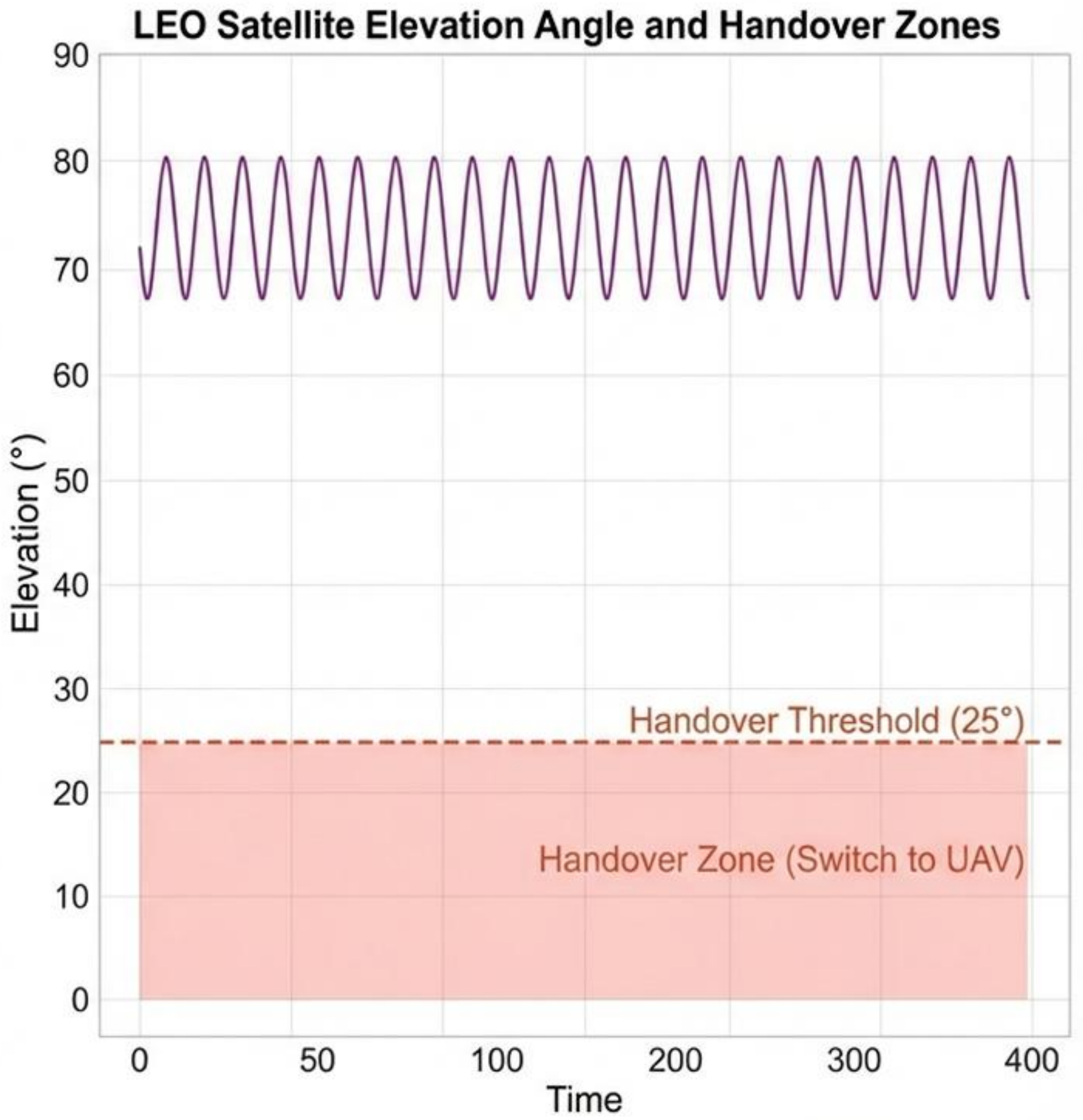
A hybrid approach integrates space-based global coverage with aerial-based local adaptability, ensuring uninterrupted, high-performance connectivity.



The Challenge of 80 Dynamic Topology and Frequent Handovers

LEO satellites are not static cell towers; they 60 move at 7.5 km/s. This creates a highly dynamic environment where connection quality fluctuates rapidly.

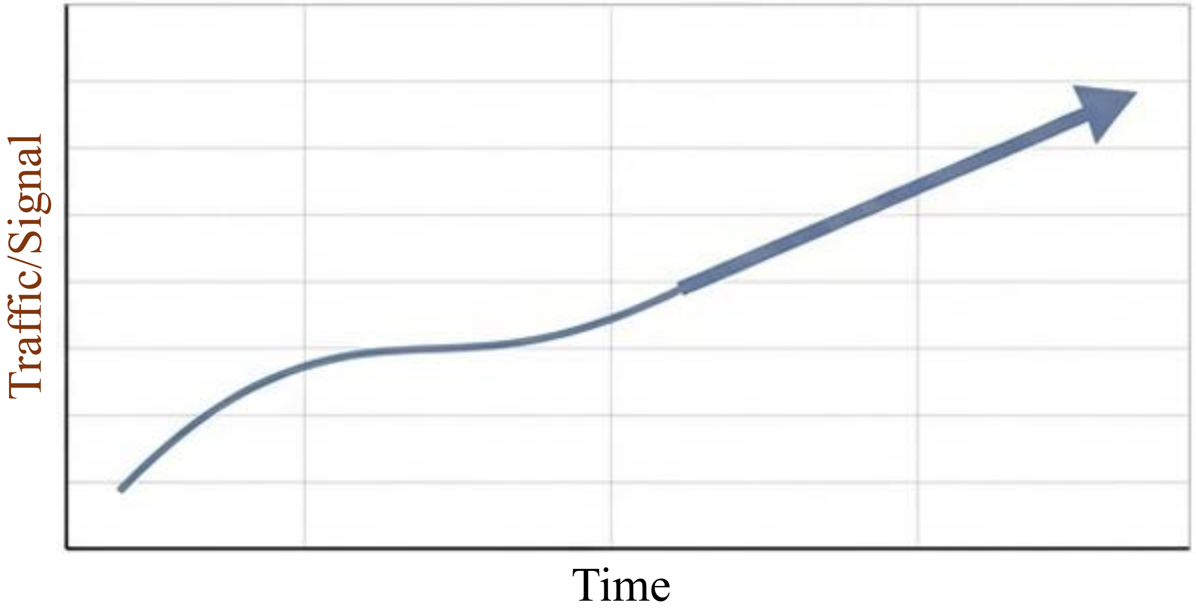
» **Oscillating Elevation:** Satellites rise and set 30 : relative to the User.
» **The Handover Zone:** When elevation < 25°, signal quality degrades.
» **Resource Friction:** Managing bandwidth is 9 impossible without predicting these physical movements.



Why Traditional Forecasting Models Fail in NTNs

Problem vs. Reality

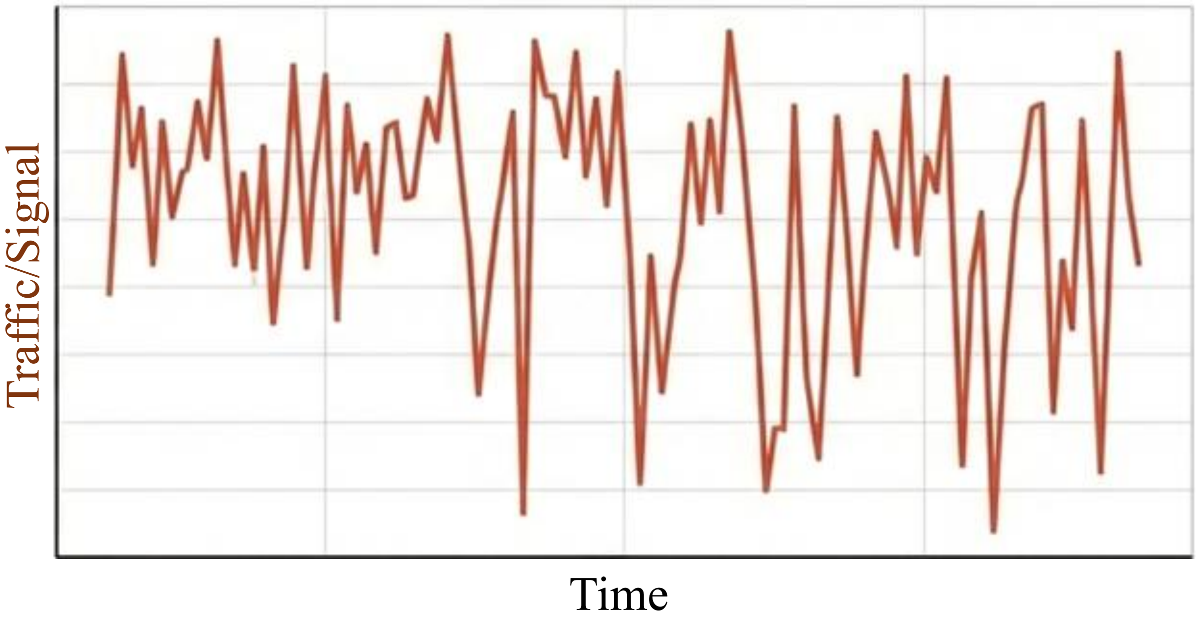
The Traditional Assumption (ARIMA*)



Assumes Linearity & Stationarity.

Traditional models expect traffic to follow predictable, static patterns, like a rush hour on a ground highway.

The NTN Reality



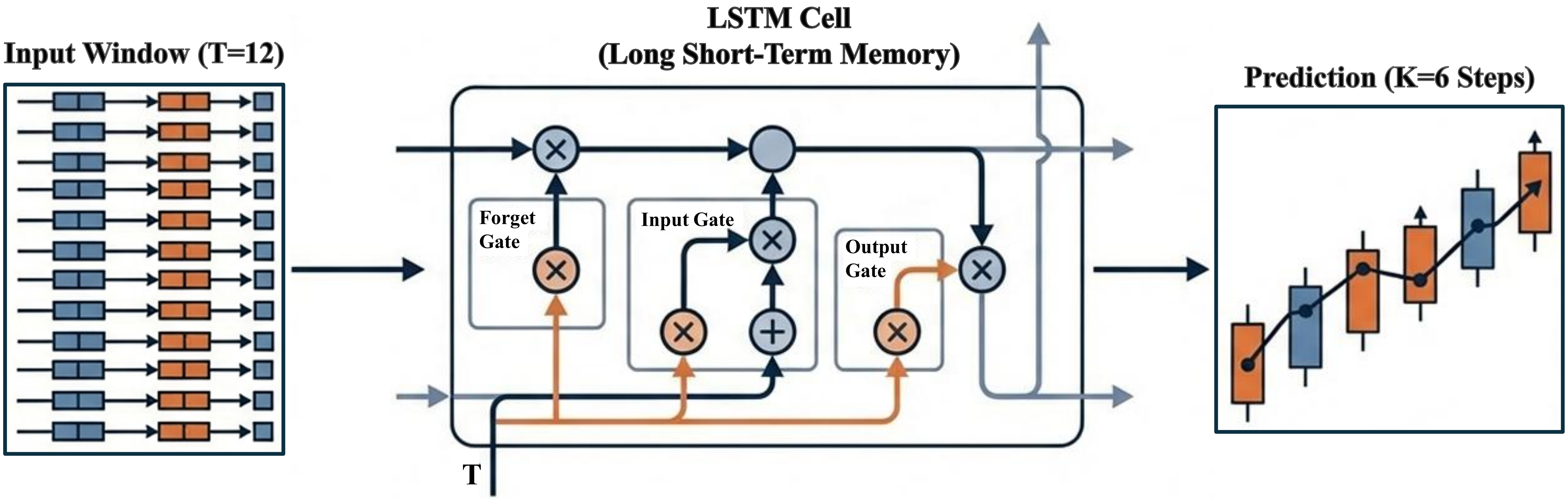
Non-Linear & Non-Stationary. NTN traffic is chaotic due to:

1. **Orbital Physics:** Path loss changes with elevation.
2. **Doppler Shifts:** Frequency changes due to high speed.
3. **Hard Handovers:** Instant switching between Satellite and UAV causes latency jumps.

Requirement:
We need a model that 'learns' the physics of the link, not just the history of the traffic.

* Autoregressive Integrated Moving Average

The Intelligent Agent: LSTM-Based Deep Learning Framework



Why LSTM?

- **Memory:** Captures long-term dependencies (traffic patterns from 60 mins ago).
- **Gating:** 'Forget' gates allow the model to ignore irrelevant noise while ‘Input’ gates capture sudden state changes (handovers).
- **Optimization:** Minimizes Euclidean error norm for a 30-minute future horizon.

Defining the Network State (Traffic Model): The 7-Feature Vector

The model ingests a snapshot of both traffic and physics at every time step t.

Normalized Traffic (x_{norm}):
Current load data.

Elevation Angle (θ_{elv}):
Satellite position in the sky.

Link Type (ltp):
0=Satellite, 1=UAV.

Latency (τ):
Transmission delay.

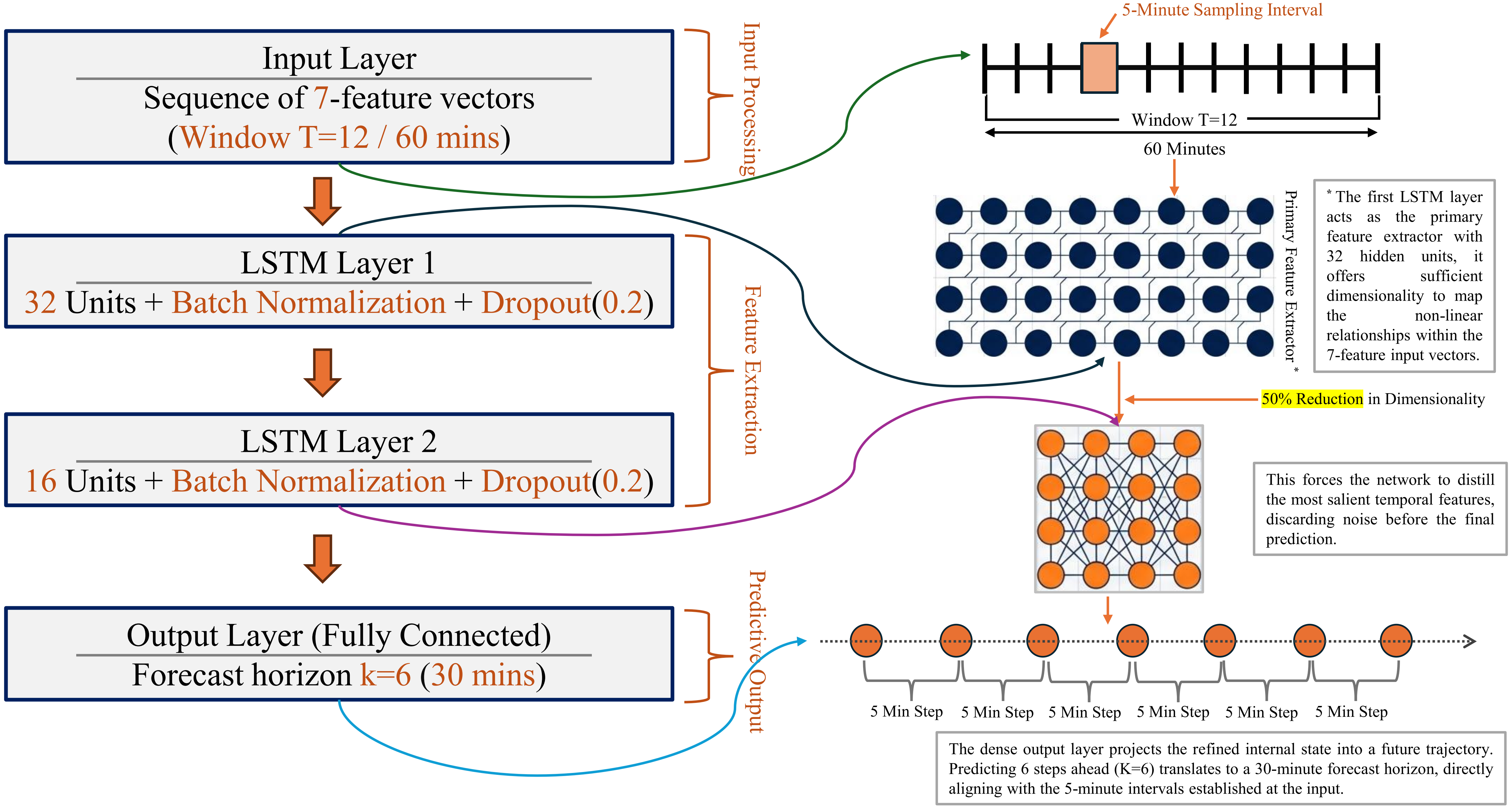
$$f(t) = \left[x_{norm}(t), \theta_{elv}(t), ltp(t), SNR(t), \tau(t), f_d(t), C(t) \right]$$

SNR (SNR):
Signal-to-Noise Ratio
(Link Quality)

Doppler Shift (f_d):
Frequency distortion
from speed.

Capacity (C):
Max Throughput
available

Architecture of the Dual-Layer LSTM Network



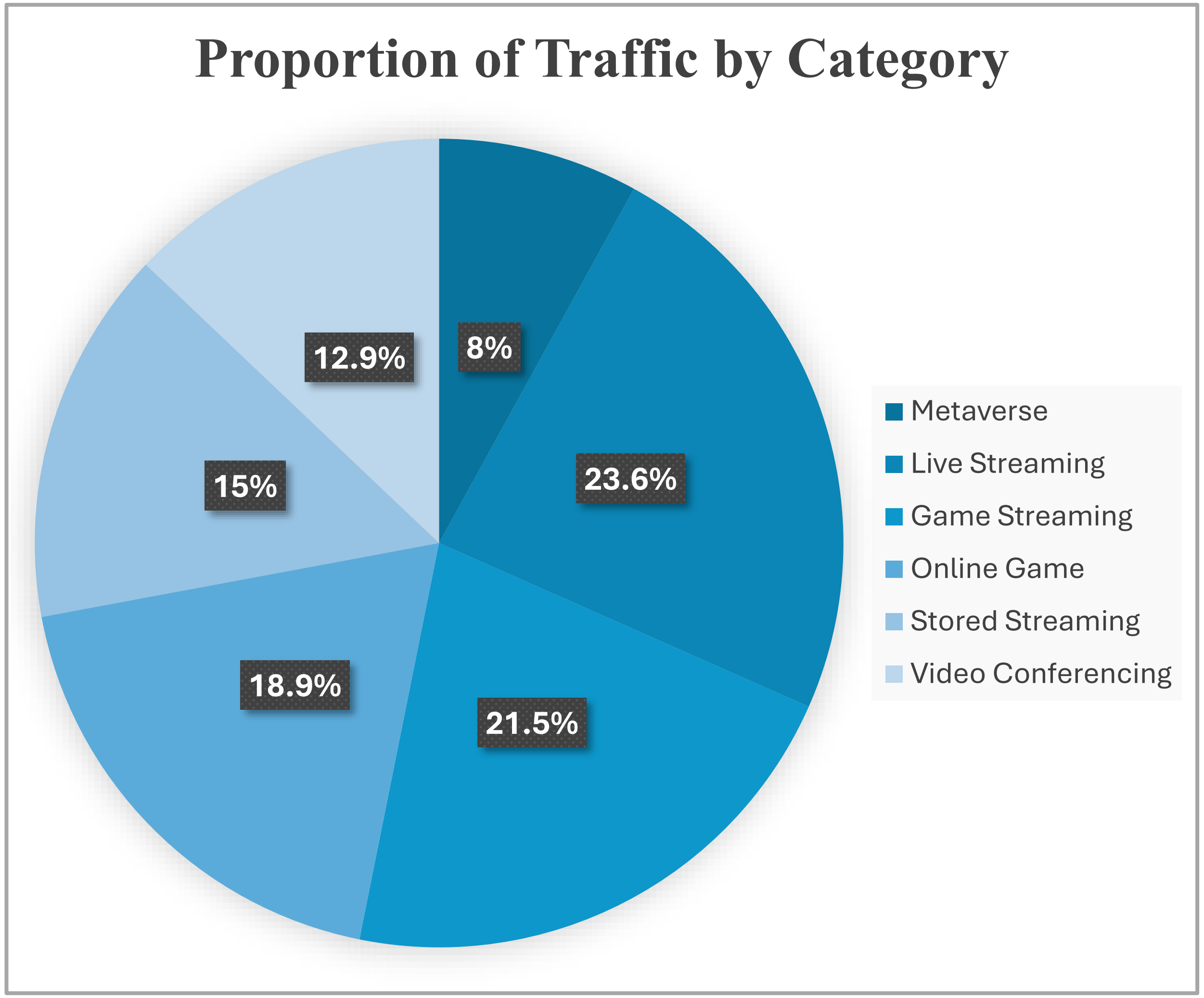
Experimental Validation: Real-World 5G Traffic Datasets

Dataset Overview

To validate the model, we utilized 328 hours of real network traces captured via **PCAPdroid**[1].

Dataset Specs:

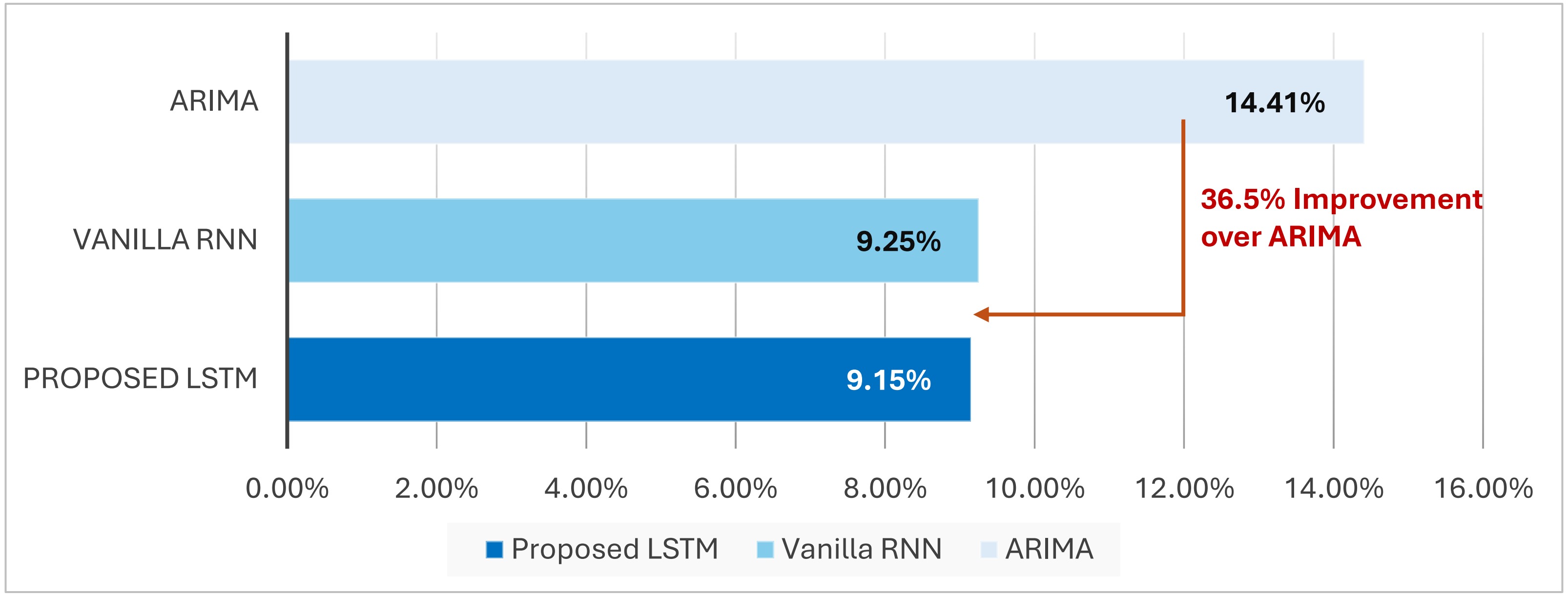
- ❑ 2,000 Time Steps (5-min intervals)
- ❑ Traffic Range: 5.2 Mbps – 180.3 Mbps



[1] https://www.kaggle.com/datasets/kimdaegyeom/5g-traffic-datasets

Performance Results: LSTM vs. The Baselines

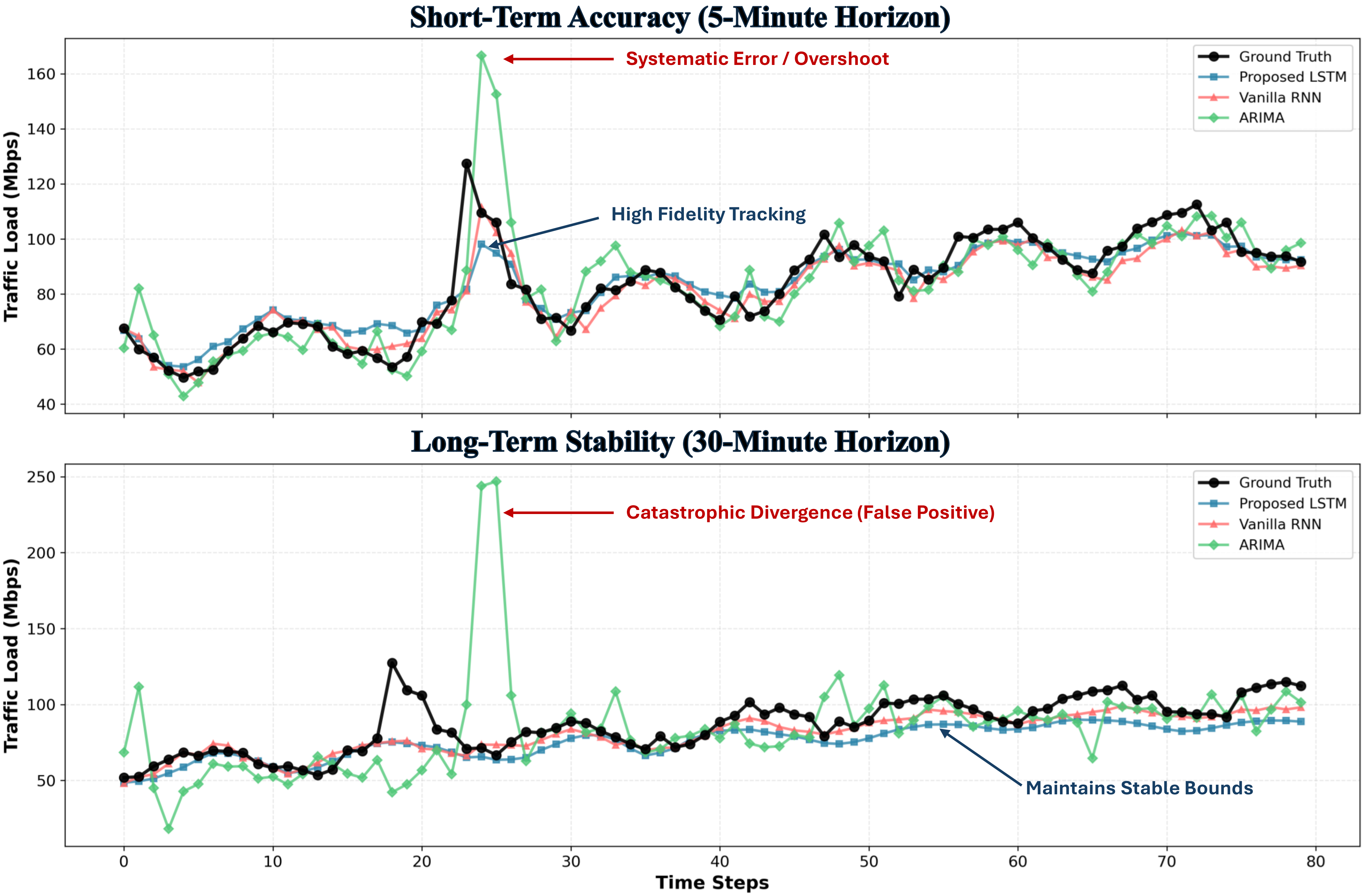
MAPE (Mean Absolute Percentage Error)



MAE (Mean Absolute Error)

ARIMA: 12.86 Mbps **Proposed LSTM: 8.72 Mbps**

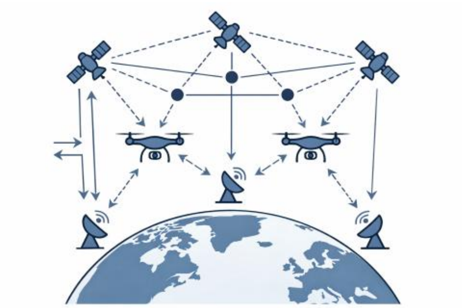
The Deep Learning approach fundamentally solves the non-linearity problem that breaks statistical models like ARIMA.


Short-Term Accuracy (5-Minute Horizon)
Systematic Error / Overshoot
High Fidelity Tracking
Ground Truth
Proposed LSTM
Vanilla RNN
ARIMA
Traffic Load (Mbps)
160
140
120
100
80
60
40
Long-Term Stability (30-Minute Horizon)
Catastrophic Divergence (False Positive)
Maintains Stable Bounds
Ground Truth
Proposed LSTM
Vanilla RNN
ARIMA
Traffic Load (Mbps)
250
200
150
100
50
0
10
20
30
40
50
60
70
80
Time Steps

Summary of Contributions

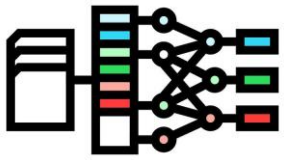
01 | Hybrid Architecture

Validated a multi-tier model combining LEO satellite and UAV relays with dynamic link switching.



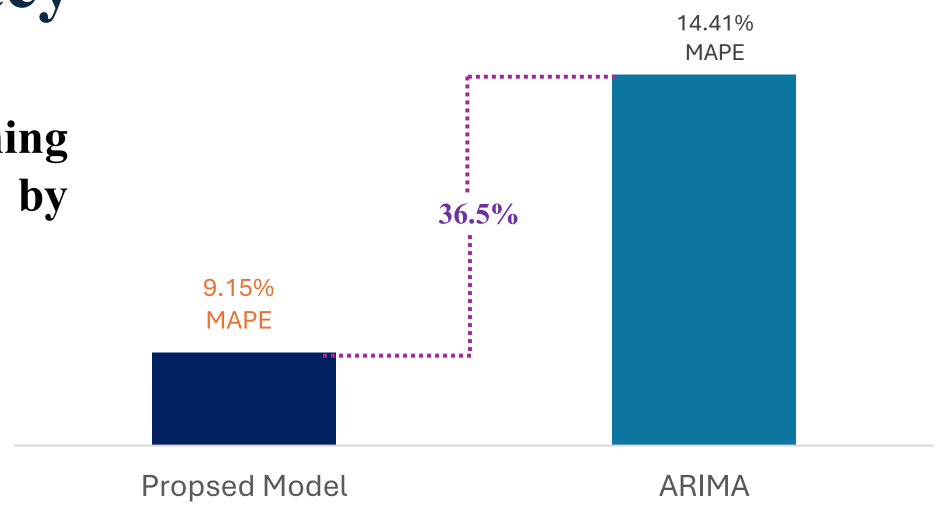
02 | Physics-Aware Inputs

Developed a novel 7-dimensional feature vector integrating orbital mechanics (Doppler, Elevation) with digital traffic data.



03 | Superior Accuracy

Achieved **9.15% MAPE**, outperforming industry-standard ARIMA models by **36.5%**.



Thank You!

Intelligent Networking Lab (INL)
School of Computer Science and Engineering, Chung-Ang University
Seoul, Republic of Korea

vaskar@cau.ac.kr