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

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***Abstract*—The rapid growth of mobile data and IoT devices demands seamless wireless coverage beyond terrestrial networks. Non-Terrestrial Networks (NTNs) combining Low Earth Orbit (LEO) satellites and Unmanned Aerial Vehicles (UAVs) offer promising solutions for remote and disaster-affected areas. However, efficient resource management in hybrid satellite-UAV systems requires accurate traffic prediction to handle dynamic topology changes, frequent handovers, and varying link conditions. We propose a long short-term memory (LSTM)-based deep learning framework that predicts network traffic using seven features, including satellite elevation, link type, SNR, latency, Doppler shift, and throughput. Our dual-layer LSTM architecture with batch normalization achieves 9.15% MAPE, outperforming ARIMA by 36.5% and vanilla RNN by 1.1%. Experiments on real 5G traffic data demonstrate stable prediction up to 30 minutes ahead with 8.72 Mbps MAE, enabling proactive resource allocation in next-generation NTNs.**

***Index Terms*—Non-Terrestrial Networks, LEO Satellites, UAV Communications, Traffic Prediction, LSTM, Deep Learning**

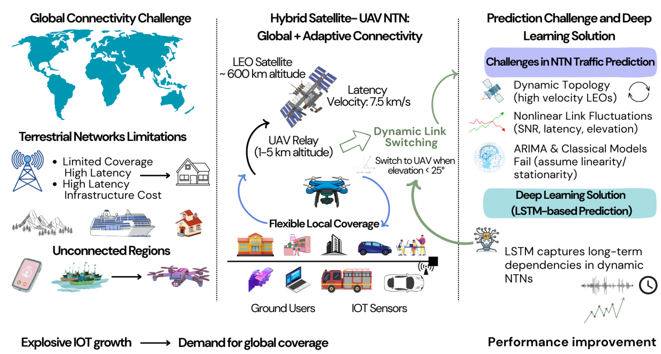

Fig. 1. Conceptual Overview and Motivation for Intelligent Traffic Prediction in Hybrid Satellite-UAV Non-Terrestrial Networks (NTNs).

I. Introduction

The explosive growth of mobile data and IoT devices has created unprecedented demand for worldwide wireless coverage. Traditional terrestrial networks struggle to provide seamless connectivity in remote areas, oceans, and disaster zones. Non-Terrestrial Networks (NTNs) comprising Low Earth Orbit (LEO) satellites and Unmanned Aerial Vehicles (UAVs) offer complementary solutions [1]. LEO constellations like Starlink provide wide coverage with low latency (30-40 ms) but face challenges from high velocities (∼7.5 km/s), frequent handovers, and elevation-dependent degradation. UAVs offer adaptive coverage with ultra-low latency (2-5 ms) but limited reach. A hybrid satellite-UAV architecture combining global LEO coverage with flexible UAV deployment is promising for next-generation NTNs [2]. Effective resource utilization critically depends on accurate traffic prediction for proactive allocation, congestion management, and improved QoS. However, NTN traffic prediction presents unique challenges: dynamic topology from high satellite velocities, satellite-to-UAV switching with fluctuating latency, and complex nonlinear relationships between orbital parameters and link quality that traditional statistical methods cannot model. Conventional forecasting models like ARIMA assume linearity and stationarity, invalid for dynamic hybrid NTNs. Deep learning, particularly long short-term memory (LSTM) networks, demonstrates superior ability to learn complex temporal dependencies through gating mechanisms. However, existing approaches target ground networks without considering NTN-specific characteristics like frequent handovers and elevation-dependent path loss. This paper presents an LSTM-based traffic prediction framework for hybrid satellite-UAV NTNs as shown in Fig 1. Main contributions include (i) A three-tier hybrid architecture with dynamic link selection, (ii) a seven-dimensional feature vector capturing traffic, orbital, and link quality parameters, (iii) a dual-layer LSTM network achieving 9.15% MAPE on real 5G data, and iv) comprehensive evaluation against ARIMA and RNN baselines.

II. Related Work

Wireless network traffic forecasting has progressed from traditional statistical approaches to advanced deep learning techniques. Azari et al. [3] compared LSTM and ARIMA for cellular traffic prediction, showing LSTM outperforms when sufficient training data is available. Recent work by Wu et al. [4] introduced CLPREM, combining LSTM with data augmentation for real-time 5G prediction. Yang et al. [5] developed Diviner to handle non-stationary patterns in 5G traffic for long-term forecasting. Belhadj et al. [6] applied LSTM for next-cell prediction in 5G IoT mobility management. These methods excel in terrestrial networks but do not

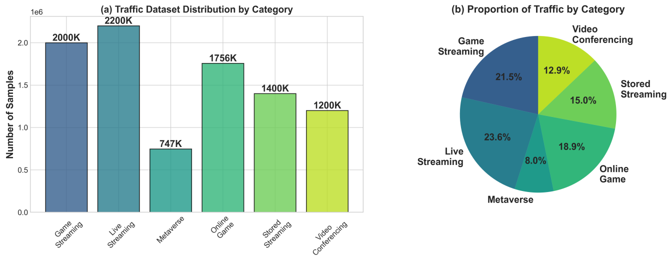

Fig. 2. Traffic dataset distribution: (a) Number of samples by application category showing live streaming and game streaming dominate the dataset; (b) Proportional distribution revealing balanced mix of real-time and stored content applications.

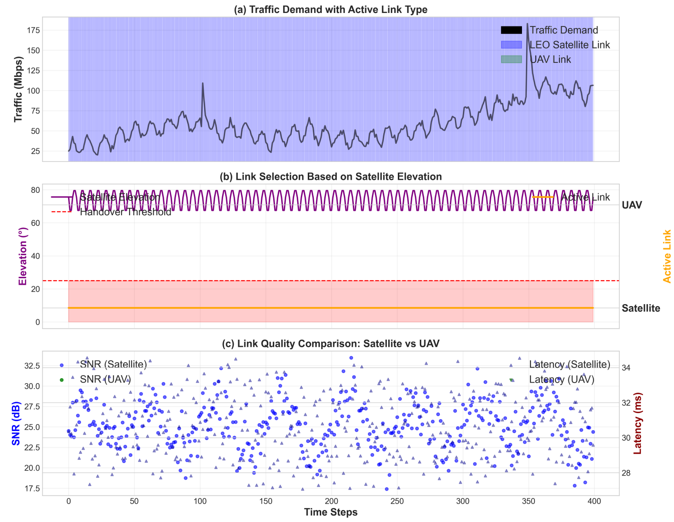

Fig. 3. Traffic and link characteristics: (a) Traffic demand overlaid with active link type showing satellite (blue) and UAV (green) periods; (b) Link selection based on satellite elevation with handover threshold at 25°; (c) Link quality comparison showing SNR and latency differences between satellite and UAV modes.

address unique NTN characteristics like orbital dynamics and handover complexity. NTN research has accelerated through 3GPP standardization. Lin et al. [7] surveyed Release 17 NTN specifications, introducing time-based and location-based conditional handovers for LEO satellites. Wang et al. [8] proposed hybrid LEO-UAV architecture for IoT data collection. Yao et al. [9] optimized multi-UAV communication in integrated satellite-aerial-terrestrial networks. Li et al. [10] designed authentication schemes for satellite-UAV integration in 6G systems. Jiang et al. [11] addressed privacy in satellite-terrestrial networks using federated split learning.

III. System Model and Problem Formulation

A. Hybrid Satellite-UAV Architecture

We propose a three-tier hybrid NTN architecture comprising LEO satellites at 600 km altitude with 90-minute orbital periods and 30-40 ms latency, UAVs operating at 1-5 km altitude with 2-5 ms latency, and ground users. The system implements dynamic link selection, switching to UAV when satellite elevation $\theta_{elev} < 25$ to ensure continuous coverage. Fig. 2 shows the traffic distribution across six application categories from our 5G dataset: game streaming (21.5%), live streaming (23.6%), metaverse (8.0%), online games (18.9%), stored streaming (15.0%), and video conferencing (12.9%).

B. Traffic Model

Let $x(t)$ denote traffic load in Mbps at time t. We define a seven-dimensional feature vector $\mathbf{f}(t)$ to capture the several features, and can be written as

$$\mathbf{f}(t) = [x_{norm}(t), \theta_{elv}(t), l_{tp}(t), \mathrm{SNR}(t), \tau(t), f_d(t), C(t)]^T,$$

where $x_{norm}(t)$ is the normalized traffic, $\theta_{elv}(t)$ is the satellite elevation angle, $l_{tp}(t)$ is the active link type (0=satellite, 1=UAV), $\mathrm{SNR}(t)$ is the signal-to-noise ratio, $\tau(t)$ is the latency, $f_d(t)$ is the Doppler shift, and $C(t)$ is the throughput capacity.

Fig 3 visualizes the relationship between traffic patterns and link dynamics. Traffic demand varies from 5 to 140 Mbps with clear peak periods, while satellite elevation oscillates between 70-80° with periodic drops below the 25° handover threshold triggering UAV activation. The link quality comparison reveals that satellite SNR fluctuates between 18-32 dB with fading effects, while latency remains stable around 30-32 ms for satellites versus 2-5 ms for UAVs.

C. Problem Statement

Given a historical observation window $\mathbf{X}(t) = [\mathbf{f}(t-11), \ldots, \mathbf{f}(t)]$ of $T = 12$ time steps (60 minutes with 5-minute intervals), our objective is to predict future traffic $\hat{x}(t+1:t+6)$ for $K = 6$ steps (30 minutes ahead). We formulate this as an optimization problem as

$$\min_{\theta} \mathbb{E}\left[\|\mathbf{x}(t+1:t+6) - g(\mathbf{X}(t);\theta)\|^2\right], \tag{1}$$

where $g(\cdot;\theta)$ represents the LSTM prediction function with learnable parameters θ, $\mathbf{x}(t+1:t+6)$ denotes the ground truth future traffic values, and $\|\cdot\|$ represents the Euclidean norm. The expectation $\mathbb{E}[\cdot]$ is taken over the training data distribution. This formulation allows the network to learn optimal parameters θ^* that minimize the expected prediction error across all training samples.

IV. Proposed LSTM Methodology

A. Network Architecture

Our LSTM network addresses the optimization problem formulated in (1) by leveraging gating mechanisms to capture long-term temporal dependencies [12]. Unlike vanilla RNNs that suffer from vanishing gradients, LSTM maintains a cell state $\mathbf{c}_t$ that selectively retains information through three control gates: (i) *Forget gate* $\mathbf{f}_t$ determines which information from the previous cell state $\mathbf{c}_{t-1}$ should be discarded, (ii) *Input gate* $\mathbf{i}_t$ controls what new information is added to the cell state, and (iii) *Output gate* $\mathbf{o}_t$ regulates what information is output from the cell state.

The cell state update mechanism is governed by

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tanh(\mathbf{W}_c \cdot [\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_c), \tag{2}$$

where $\odot$ denotes element-wise multiplication, $[\mathbf{h}_{t-1}, \mathbf{x}_t]$ concatenates the previous hidden state with current input features, $\mathbf{W}_c$ represents learnable weight matrices, and $\mathbf{b}_c$ is the bias term. The hidden state output is then computed as

$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t). \tag{3}$$

The gating mechanisms in (2) and (3) enable the network to learn which features among our seven NTN-specific inputs are most relevant for prediction at each time step. This is particularly important in hybrid NTNs, where the relevance of features like Doppler shift and link type varies depending on whether the satellite or UAV link is active. Our implementation consists of multiple layers as follows.

- LSTM layer 1 with 32 units and `return_sequences=True` to pass sequential information to the next layer.
- Batch normalization to stabilize training and accelerate convergence.
- Dropout layer 1 with rate 0.2 for regularization.
- LSTM layer 2 with 16 units for high-level feature extraction.
- Batch normalization layer 2.
- Dropout layer 2 with rate 0.2.
- Dense output layer with 6 units producing the multi-step forecasts $\hat{\mathbf{x}}(t+1:t+6)$ that minimize (1).

The total architecture contains 8,550 parameters, of which 8,454 are trainable (96 are non-trainable from batch normalization layers). This relatively compact architecture enables efficient training on limited data while maintaining sufficient capacity to capture complex NTN dynamics.

B. Training Procedure

Algorithm 1 outlines the training process. We create sequences where each input $\mathbf{X}_t$ contains 12 time steps of 7 features, and each output $\mathbf{y}_t$ contains 6 future traffic values. The dataset is split into 70% training, 15% validation, and 15% testing. We employ the Adam optimizer with learning rate $\alpha = 0.001$, mean squared error loss, and batch size of 32. Early stopping with patience of 20 epochs and learning rate reduction with a factor of 0.5 and patience 7 epochs prevent overfitting. Training runs for up to 150 epochs, terminating early if the validation loss does not improve.

V. Experimental Setup

We utilize the 5G Mobile Traffic Dataset[1] containing 328 hours of real network traces from gaming, streaming, and conferencing applications. Sampling yields 2,000 time steps at 5-minute intervals with traffic ranging from 5.2 to 180.3 Mbps (mean 52.9 Mbps, median 52.7 Mbps). Fig. 4 displays key NTN parameters, including satellite elevation with handover zones, SNR variations with fading effects, latency comparison between LEO (30-34 ms) and UAV (2-5 ms), and Doppler frequency shift patterns.

[1]A 5G traffic dataset measured by PCAPdroid: https://www.kaggle.com/datasets/kimdaegyeom/5g-traffic-datasets

Algorithm 1 LSTM Training for Hybrid NTN Traffic Prediction

Require: Traffic data $\mathcal{D}$, NTN features $\mathcal{F}$, window size $T = 12$, horizon $K = 6$

Ensure: Trained model parameters θ^*

Create sequences: $\mathbf{X}_t \leftarrow [\mathbf{f}(t-T+1:t)]$, $\mathbf{y}_t \leftarrow [x(t+1:t+K)]$
Split data: Train (70%), Validation (15%), Test (15%)
Initialize LSTM(32, 16 units) with batch normalization and dropout
Initialize Adam optimizer with $\alpha = 0.001$
for epoch = 1 to 150 **do**
  Forward pass: $\hat{\mathbf{y}} \leftarrow \text{LSTM}(\mathbf{X}; \theta)$
  Compute loss: $\mathcal{L} \leftarrow \text{MSE}(\mathbf{y}, \hat{\mathbf{y}})$
  Backward pass: $\theta \leftarrow \theta - \alpha \nabla_\theta \mathcal{L}$
  if validation loss not improved for 20 epochs **then**
    break (early stopping)
  end if
  if validation loss not improved for 7 epochs **then**
    Reduce learning rate: $\alpha \leftarrow 0.5 \times \alpha$
  end if
end for
return θ^* at best validation loss

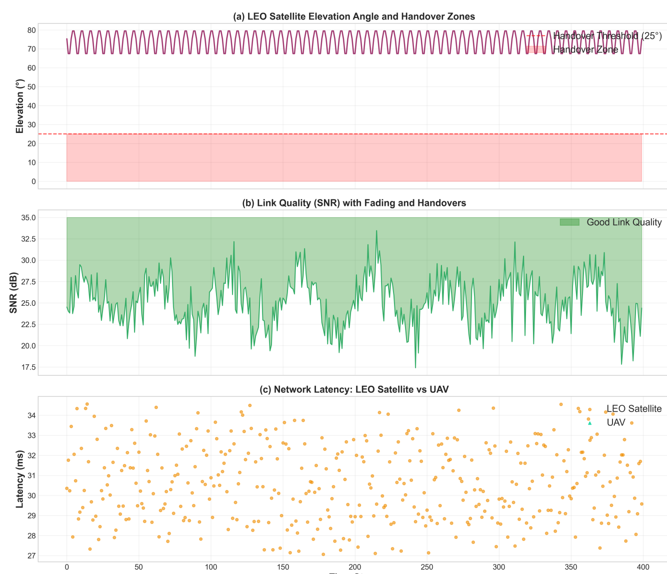

Fig. 4. Satellite and network parameters: (a) LEO satellite elevation angle showing periodic oscillations with handover zone below 25° highlighted; (b) SNR variations demonstrating fading effects in satellite link; (c) Network latency comparison between LEO satellite and UAV showing significant latency reduction with UAV deployment.

VI. Results and Discussion

A. Performance Comparison

Table I presents quantitative results. The proposed LSTM achieves an MAPE of 9.15%, representing 36.5% improvement over ARIMA (14.41%), and 1.1% improvement over vanilla RNN (9.25%). For MAE, LSTM achieves 8.72 Mbps

TABLE I
PERFORMANCE COMPARISON OF PREDICTION METHODS

Method	MAE (Mbps)	RMSE (Mbps)	MAPE (%)
ARIMA	12.86	20.86	14.41
Vanilla RNN	9.24	13.84	9.25
Proposed LSTM	**8.72**	**13.03**	**9.15**

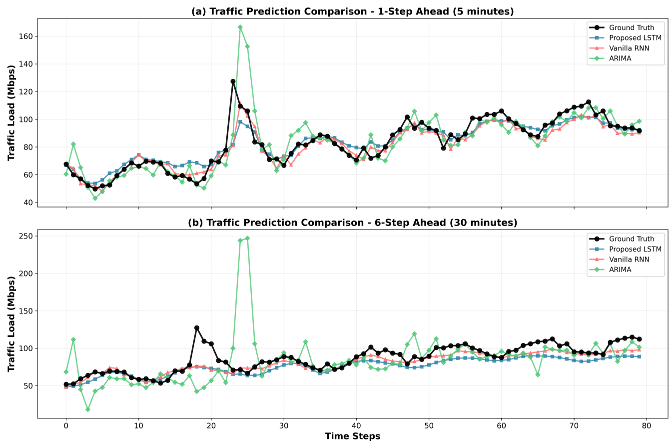

Fig. 5. Traffic prediction comparison over 80 time steps: (a) 1-step ahead (5 minutes) showing LSTM and vanilla RNN closely track ground truth while ARIMA shows larger deviations during peaks; (b) 6-step ahead (30 minutes) demonstrating increased uncertainty for all methods but superior stability for LSTM.

compared to ARIMA's 12.86 Mbps (32.2% improvement) and vanilla RNN's 9.24 Mbps (5.6% improvement). Similarly, RMSE shows LSTM at 13.03 Mbps outperforming ARIMA (20.86 Mbps) by 37.5% and vanilla RNN (13.84 Mbps) by 5.9%. The vanilla RNN performs competitively despite having fewer parameters (4,998 vs 8,550), suggesting that for this dataset size, simpler architectures may generalize better. However, LSTM's superior performance across all metrics demonstrates its effectiveness in capturing complex temporal patterns in hybrid NTN traffic. The substantial improvement over ARIMA validates the necessity of deep learning approaches for nonlinear, non-stationary NTN traffic prediction.

B. Prediction Analysis

Fig. 5 compares prediction performance across different time horizons. For 1-step ahead (5 minutes), LSTM tracks ground truth closely with occasional deviations during traffic spikes around 130 Mbps. ARIMA shows larger systematic errors, particularly overshooting peaks around time step 25. Vanilla RNN demonstrates smooth tracking similar to LSTM. For 6-step ahead (30 minutes), all methods show increased prediction variance, but LSTM maintains tighter bounds around ground truth. ARIMA exhibits significant overshooting during burst periods, while vanilla RNN and LSTM provide more stable predictions.

VII. CONCLUSION

We presented an LSTM-based traffic prediction framework for hybrid satellite-UAV NTNs using a seven-dimensional feature vector capturing traffic, orbital, and link quality parameters. Our dual-layer LSTM architecture with batch normalization achieved 9.15% MAPE on real 5G traffic data, demonstrating 36.5% improvement over traditional ARIMA methods and marginal improvement over vanilla RNN. The model maintains stable prediction accuracy up to 30 minutes ahead with 8.72 Mbps MAE, enabling proactive resource allocation for satellite handovers, beam steering, and congestion management in dynamic NTN environments.

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