CNN-LSTM Based Prediction of LoS Duration in Satellite Communication Network

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***Abstract*—Satellite communication system is crucial to the advancement of sixth-generation (6G) networks, providing global connectivity and supporting applications that demand ultra-speed high and low latency. However, the high mobility of low Earth orbit (LEO) satellites poses significant challenges to maintaining consistent communication links, primarily due to the frequent handover required by user equipment. Traditional signal strength-based handover technique, which is effective in terrestrial networks, struggles in the satellite network due to the minimal signal strength variation across overlapping cells. This leads to frequent and unnecessary handovers, resulting in reduced network performance. To address these challenges, we propose an CNN-LSTM based predictive line-of-sight (LoS) duration estimation method that allows user terminals to anticipate satellite connection stability, minimizing unnecessary handovers and improving network efficiency in dynamic satellite environments.**

***Index Terms*—Satellite communication network, CNN-LSTM**

I. Introduction

Satellite communication system is a key component of sixth-generation (6G) communication system, complementing the limitations of existing terrestrial networks and playing a critical role in providing seamless connectivity anywhere in the world. These satellite networks are essential to overcome the infrastructure limitations of existing terrestrial networks and support next-generation applications that require ultra-high speed, ultra-connectivity and ultra-low latency [1]. The high mobility of satellite networks presents a significant challenge in maintaining consistent communication links, particularly with low Earth orbit (LEO) satellites, which travel at high velocities due to their low altitudes. This rapid movement necessitates frequent handovers by user equipment within short time intervals. Furthermore, in contrast to terrestrial networks, the elevated positions of satellite networks result in minimal signal strength variation between the centre and the edge of a cell. In regions where multiple cells overlap, the difference in signal strength between the two cells is very small. Therefore, The use of traditional signal strength-based handover techniques presents a challenge for ground terminals to identify the optimal target cell to handover to. This results in frequent handover processes and a reduction in network performance. Consequently, conventional handover technique that rely on signal strength is unsuitable for this dynamic satellite communication environment [2], [3].

To address these issues, we propose an convolutional neural network-long short term memory (CNN-LSTM) model based predictive line-of-sight (LoS) duration estimation technique. This enables user terminals to predict the connection duration for each satellite, thereby preventing unnecessary handover processes.

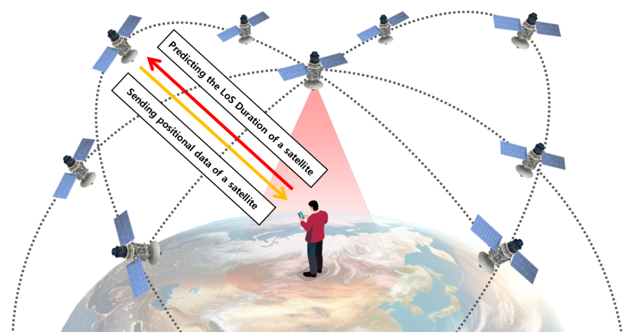

Fig. 1. Proposed CNN-LSTM-based satellite LoS duration prediction model

II. CNN-LSTM based Satellite LoS Duration Prediction Model

As shown in Fig. 1, We consider a constellation of N LEO satellites at different altitudes, each orbit having a different number of satellites. It is assumed that each satellite is equipped with a global navigation satellite system (GNSS) capability, enabling the transfer of its position data to the ground terminal at each time step. Given the high speeds at which LEO satellites move, the mobility of the ground terminal is disregarded. The terminal estimates the duration of the connection based on the satellite's position during the window time of the time step, the strength of the signal received from the satellite, and its own location.

A LSTM architecture is a class of learning techniques that has demonstrated efficacy in forecasting time series data. However, basic LSTM is constrained in their capacity to extract the most important features from a given input. Conversely, CNN architecture possess the benefit of local dependency. This local dependency refers to the capacity of CNN to correlate disparate signals, which is very useful for extract the important features from complex time series data. Therefore, the CNN-LSTM structure combines the advantages of both models to improve the prediction accuracy of time series data [4]. In particular, this structure can effectively reflect the spatial features of satellite orbits and learn the changes and patterns over time. In this paper, a CNN-LSTM model is employed to

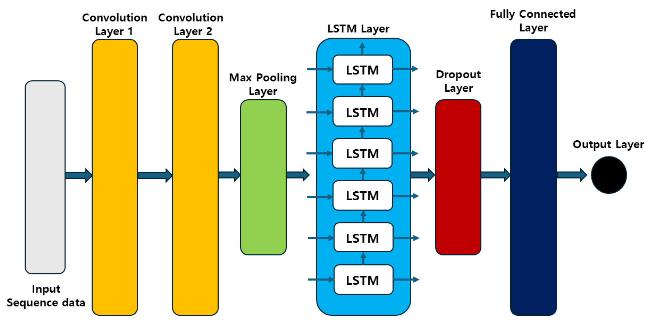

Fig. 2. CNN-LSTM model [5]

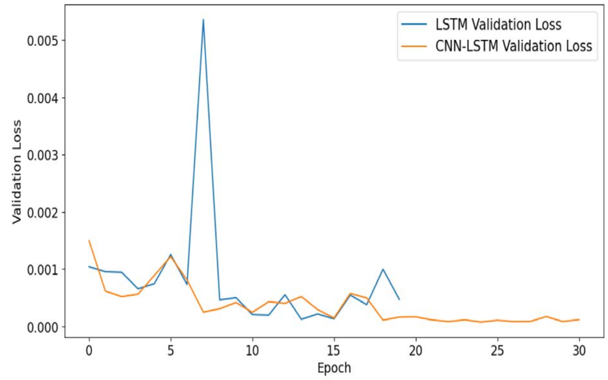

Fig. 3. Comparison of LSTM and CNN-LSTM Validation Loss

predict the satellite LoS duration. The structure of the CNN-LSTM model used is illustrated in Fig 2 [5].

III. System Evaluation

A. Evaluation Environment

The simulation was conducted for two distinct LEO satellite constellations. The first constellation has an altitude of 600 km and consists of 1,584 satellites. The second constellation has an altitude of 700 km and consists of 600 satellites. The time step for the simulation is set to 0.1 seconds. Our proposed model used an 60-20-20 split of the data into training, validation, and test sets. The CNN-LSTM prediction model comprises a one-dimensional CNN layer and six LSTM layers, while the LSTM prediction model is composed of six LSTM layers. The number of hidden state features for both models is 100. The input features include the reference signal received power (RSRP) of satellite, the Earth-centered Earth-fixed (ECEF) coordinates of both the satellite and the user terminal. The length of the time window is 100 to collect the position and RSRP information.

The simulation was implemented using the Python-based Pytorch framework. The learning rate was set to 0.001, and the batch size was set to 64. The optimizer was adaptive moment estimation (Adam), and the loss function used mean squared error (MSE). The model was trained on 100 epochs with early stopping, and its performance was evaluated using root mean square error (RMSE), a widely used performance metric for time series forecasting.

B. Evaluation Results

The Fig. 3 shows the validation loss graph, which depicts the convergence of the traditional LSTM model and the proposed CNN-LSTM based model during training. The proposed CNN-LSTM based prediction model exhibits enhanced convergence reliability in validation loss compared to the conventional LSTM-based model.

The Table 1 shows the RMSE metrics of both models on the test data. It can be observed that the proposed CNN-LSTM model achieves a 17.45% improvement in RMSE compared to the existing LSTM model.

TABLE I
Evaluation Result for Each Model

Metrics	**LSTM**	**CNN-LSTM**
RMSE	4.707	3.886

IV. Conclusions

This paper presents a CNN-LSTM model designed for predicting the LoS duration in satellite communication. The model utilises the location information of the terminal and satellites to avoid unnecessary handover processes of the terminal in a multi-low-orbit satellite constellation environment. The proposed model effectively estimates the LoS duration of satellites, even within a short observation window time of 10 seconds. The experimental results demonstrate that the learning performance is enhanced compared to the conventional LSTM model.

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References

[1] Z. Zhang et al., “6G wireless networks: Vision, requirements, architecture, and key technologies,” *IEEE Vehicular Technology Magazine*, vol. 14, no. 3, pp. 28–41, September 2019.

[2] E. Juan, M. Lauridsen, J. Wigard, and P. Mogensen, “Performance evaluation of the 5G NR conditional handover in LEO-based non-terrestrial networks,” in *Proc. IEEE Wireless Communications and Networking Conference (WCNC)*, Austin, Tx, USA, April. 2022, pp. 2488–2493.

[3] S. Mahboob and L. Liu, “Revolutionizing future connectivity: A contemporary survey on AI-empowered satellite-based non-terrestrial networks in 6G, ” *IEEE Communications Surveys & Tutorials*, vol. 26, no. 2, pp. 1279–1321, Second Quarter 2024.

[4] J. Wang, Y. Chen, S. Hao, X. Peng, and L. Hu, “Deep learning for sensor-based activity recognition: A survey, ” *Pattern Recognition Letters*, vol. 119, pp. 3–11, March 2019.

[5] M. Alhussein, K. Aurangzeb, and S. I. Haider, “Hybrid CNN-LSTM model for short-term individual household load forecasting,” *IEEE Access*, vol. 8, pp. 180544–180557, October 2020.