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Enhancing handover management in 5G networks with encoder-decoder LSTM for multistep forecasting

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ABSTRACT

The continuous evolution of wireless communication networks, fueled by advancements in 5G and the envisioned potential of 6G technologies, has introduced significant challenges in mobility management and handover (HO) optimization. The frequent HOs due to network densification, particularly at high frequencies like millimeter waves (mmWave) and terahertz (THz) bands, can lead to increased latency, and potential service disruptions. To address these issues, artificial intelligence (AI) driven approaches are emerging as promising alternatives. This paper explores the use of deep learning techniques for predictive HO management. An encoder-decoder long short-term memory (ED-LSTM) model is proposed to generate multistep predictions of future reference signal received power (RSRP) values. The model was trained and evaluated on two distinct real-world drive-test datasets. The results demonstrate that the proposed ED-LSTM model achieves lower prediction error, with a mean absolute error (MAE) of 2.07 for dataset 1 and 2.33 for dataset 2, and a mean absolute percentage error (MAPE) of 2.80% for dataset 1 and 2.96% for dataset 2. Overall, the ED-LSTM outperforms the bidirectional LSTM (BiLSTM) and standard LSTM (S-LSTM) model, achieving improvements of 33–38% on dataset 1 and 48-50% on dataset 2 in terms of MAE and MAPE, respectively.

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1. INTRODUCTION

The rapid evolution of wireless communication networks is driving different fields into being highly automated and data-centric. This transformation is particularly visible in environments, where the utilization of numerous data-intensive applications is crucial, enabling more efficient resource management and decisionmaking. In this context, next-generation networks must meet unprecedented demands for high-speed connectivity, low latency, and seamless mobility. To effectively address this growing data traffic demand, 5G networks have adopted several innovative solutions. These include network densification, which involves increasing the number of small cells to enhance coverage and capacity, and the implementation of heterogeneous networks that combine different types of technologies and infrastructures. Additionally, the use of high-frequency bands, such as millimeter waves (mmWave) [1]–[4], allows for significantly higher data rates, further supporting the performance requirements of modern applications. While these approaches offer high capacity and data rates, they also introduce significant challenges in mobility management and handover processes [5], [6].

As mobile users traverse dense 5G networks, frequent handovers can increase signaling, which may cause service interruptions and degrade user experiences, particularly for users in high-velocity scenarios. The evolution toward 6G networks with an emphasis on operating in the terahertz (THz) frequency bands, introduces more challenges [1], [7], [8]. This progression highlights the need for innovative solutions to manage mobility effectively as we move into the era of 6G. However, the complexity of mobility management in these networks necessitates innovative approaches to ensure efficiency and optimize handovers [9].

Artificial intelligence (AI) emerges as a critical enabler for overcoming the challenges associated with mobility management in advanced networks by leveraging AI-powered predictive handover management techniques. These approaches can significantly reduce latency, minimize costs, and ensure a seamless user experience [10]–[15]. The key to achieving these results lies in uncovering hidden correlations within a user's signal measurements history. By capturing dependencies in the data [16]. AI models can accurately predict user mobility patterns. This paper focuses on exploring AI-driven techniques for handover enhancing through multi-step ahead reference signal received power (RSRP) prediction in 5G networks.

The rest of the paper is structured as follows: section 2 provides a comprehensive literature review and details the methodology, including the key steps of the proposed model and a description of the datasets used. Section 3 presents the performance analysis, showcasing RSRP prediction using encoder-decoder long short-term memory (ED-LSTM), bidirectional LSTM (Bi-LSTM), and standard LSTM (S-LSTM) models, followed by a comparative evaluation based on mean absolute error (MAE) and mean absolute percentage error (MAPE) metrics. Finally, the paper concludes with a summary of findings and suggestions for future research directions.

2. METHOD

2.1. Literature review

Time-series forecasting algorithms (TSFAs) are responsible for generating reliable forecasts over a predefined horizon by modelling correlations between endogenous variables, the impact of exogenous variables, and structural data properties such as autocorrelation, periodicity, trend, pattern, and causality [17]. TSFAs include single-step and multi-step prediction tasks. While single-step predicts only the next value, multi-step forecasting extends further, capturing future trends [18], [19]. Despite challenges in preserving time-dependent patterns, multi-step forecasting is vital in areas like, energy consumption analysis, traffic load detection, and stock price prediction [20].

Several studies have investigated classical auto-regressive (AR) models for multi-step time series forecasting, leveraging their capability to capture temporal dependencies in data. Approaches like vector autoregression (VAR), auto-regressive integrated moving average (ARIMA), and seasonal auto-regressive integrated moving average (SARIMA) have been widely applied. SARIMA and support vector regression (SVR) models have shown strong performance in forecasting environmental data, including temperature and humidity, for both short- and long-term predictions [17]. Similarly, ARIMA combined with seasonal decomposition techniques has been employed to predict bandwidth utilization in high-bandwidth networks [21].

Despite their effectiveness for stationary and moderately varying time series, with highly dynamic data due to their assumption of linearity and reliance on stationarity. They often require differencing techniques to handle non-stationary time series, but this approach becomes ineffective when abrupt changes in data occur. As a result, these models perform poorly when faced with rapid fluctuations and irregular patterns in data with intricate non-linear dependencies [18], [22].

In 5G networks, RSRP data pose a challenge for classical AR models due to their dynamic nature, influenced by user mobility, environmental obstructions, and network interference, resulting in rapid and unpredictable variations. These characteristics make it difficult for traditional models to accurately capture longterm dependencies and complex relationships inherent in 5G signal propagation. Given these limitations, more advanced machine learning and deep learning approaches are necessary to effectively model and predict RSRP fluctuations in multi-step forecasting tasks.

Deep learning models are widely adopted for multi-step and sequence-to-sequence (Seq2Seq) time series forecasting, capturing long-term dependencies and nonlinear patterns in complex data. Notably, in [23], Bi-LSTMs and ED-LSTMs outperformed S-LSTM and convolutional neural network (CNN). Diqi *et al*. [19] integrated an exponential moving average (EMA) smoothing algorithm to improve stability and robustness in noisy and non-stationary environments, addressing the shortcomings of conventional recurrent models, and improving consistency over longer forecast horizons. The integration of attention mechanisms into LSTM architectures [24] enhances Seq2Seq forecasting by improving focus on relevant time steps and better capture long-range dependencies. Transformer-based architecture has been explored in [25] as an alternative to S-LSTM models for multi-step forecasting, researchers have developed a hybrid model combining transformers with stacked Bi-LSTM in an encoder-decoder framework. This model uses self-attention mechanism to capture long-term dependencies in parallel while using Bi-LSTM layers to refine temporal relationships. This fusion approach has been particularly effective for multi-channel multi-step spectrum prediction, where complex nonlinear interference patterns are very challenging. The challenge of accurate multistep prediction of user trajectories a real-world user trajectory dataset collected from 5G cellular networks was addressed in [26] by integrating LSTM with transformer models.

2.2. Proposed model

The proposed method utilizes an ED-LSTM network to forecast future RSRP values based on past values in a Seq2Seq architecture. Figure 1 illustrates the general architecture of an ED-LSTM model.

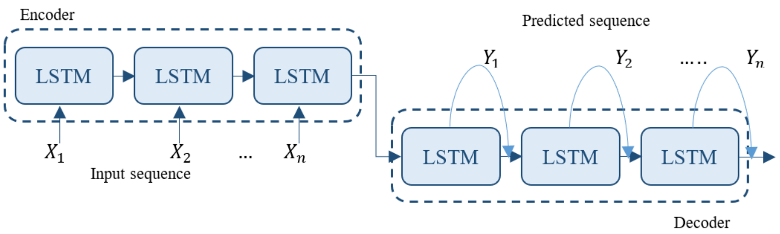


Figure 1. ED-LSTM general model architecture

- Encoder: the encoder consists of an LSTM layer that takes as input sequence of past RSRP values. This layer extracts temporal dependencies and encodes the information into a context vector. This vector serves as a compressed representation of the input sequence, which is passed to the decoder.
- Decoder: the decoder is another LSTM layer that receives the encoder's context vector as its initial state, then generates a sequence of future RSRP values iteratively.

To improve training stability and convergence, teacher forcing is applied. This involves shifting the ground truth values as inputs to the decoder during training rather than using only the model's own predictions. A Dense layer with a sigmoid activation function maps the decoder outputs to the final predicted RSRP values. The model is trained using the mean squared error (MSE) loss function, with the Adam optimizer and using an 80 to 20 train-test split and validation loss is monitored to prevent overfitting.

2.3. Datasets description

The first dataset is an open access dataset from [27] contains real network data collected from drive test measurements in a real deployment in Belo Horizonte, Brazil, with a data granularity of 1 ms, the average velocity during the measurement campaign was 50 km/h. The dataset comprises 8896 data points capturing various metrics that assess network performance and coverage. The drive test dataset features contain geographic parameters (longitude and latitude) alongside network performance metrics (RSRP, reference signal received quality (RSRQ), and signal-to-interference-plus-noise ratio (SINR)). It also includes additional features that provide more information on measurements.

The second dataset [28] consists of drive test measurements derived from organized measurement drives covering a 25 km long Austrian highway section. The section consists of a mix of urban highway near the city of Salzburg and rural highway in the Salzkammergut region. The drive tests were conducted during rush hour when high cell loads could be expected. With 267199 data points from which we used 7.5 % worth 20000 data points featuring geographic location, network performance metrics (RSRP, RSRQ and SINR) alongside data rate and other features, this dataset presents more challenges in terms of mobility management due to high speed driving and cell load which makes it interesting to evaluate the robustness of the AI models.

According to 3rd generation partnership project (3GPP) standards [29], [30], handover (HO) triggering relies solely on the received signal condition, i.e., mainly on RSRP, RSRQ and SINR measurements. Among these, RSRP has been selected as the key input metric for the model due to its fundamental role in assessing signal strength. Table 1 provides a statistical summary of the RSRP for both datasets.

Table 1. Statistical summary of the RSRP for both datasets

Dataset	Parameter	Min.	Max.	Mean	Standard derviation
Dataset 1	RSRP	-101	-40	-75	9.57
Dataset 2	RSRP	-122	-51	-85	15.34

The minimum and maximum values indicate the range of signal strength variations. While the mean represents the average received power across the datasets. The standard deviation reflects the degree of fluctuation in RSRP values.

3. RESULTS AND DISCUSSION

To evatuate the performance of the ED-LSTM model and compare it to Bi-LSTM and S-LSTM models we present in this section the real vs. predicted RSRP values plots for both datasets alongside loss curves of the three models, we also compare the models in terms of MAE and MAPE across different prediction horizons ranging from 1 step ahead to 30 steps ahead.

The real vs. predicted RSRP plots in Figure 2 demonstrate the good performance of the ED-LSTM model in capturing signal variations for both datasets. Its observable on the left side of the Figures 2(a) and (b) that the model predictions closely follow the actual RSRP values, indicating its ability to learn temporal dependencies. The training and validation loss curves Figures 2(c) and (d) stabilize after 20 epochs, indicating effective convergence and good generalization without signs of overfitting.

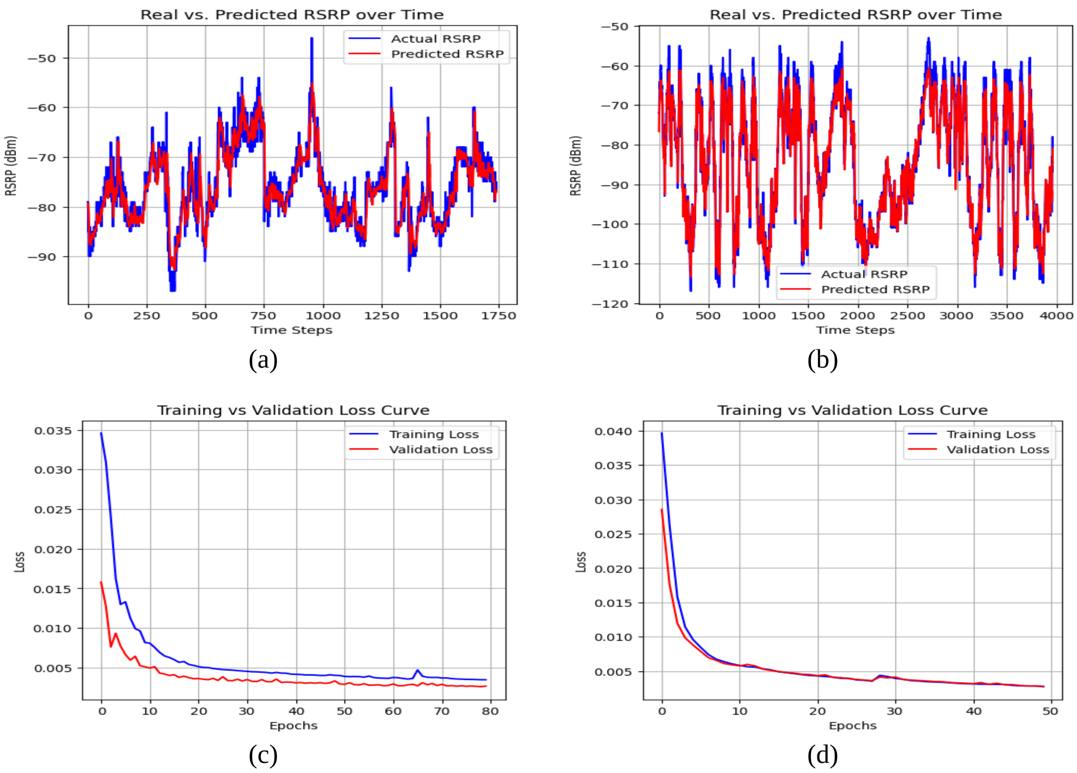


Figure 2. Performance evaluation of the ED-LSTM model on both datasets; (a) real vs. predicted RSRP for dataset 1, (b) real vs. predicted RSRP for dataset 2, (c) training vs. validation loss for dataset 1, and (d) training vs. validation loss for dataset 2

Figure 3 presents the real vs. predicted RSRP plots of the Bi-LSTM model for both datasets, high-lighting its ability to capture trends but with greater deviations than the ED-LSTM. The deviation between the real and predicted values is clearly observed on Figures 3(a) and (b). The loss curves Figures 3(c) and (d) indicate effective convergence, with validation loss closely following training loss after around 15 to 20 epochs. Despite moderate predictive performance, the Bi-LSTM model struggles with long-term forecasts.

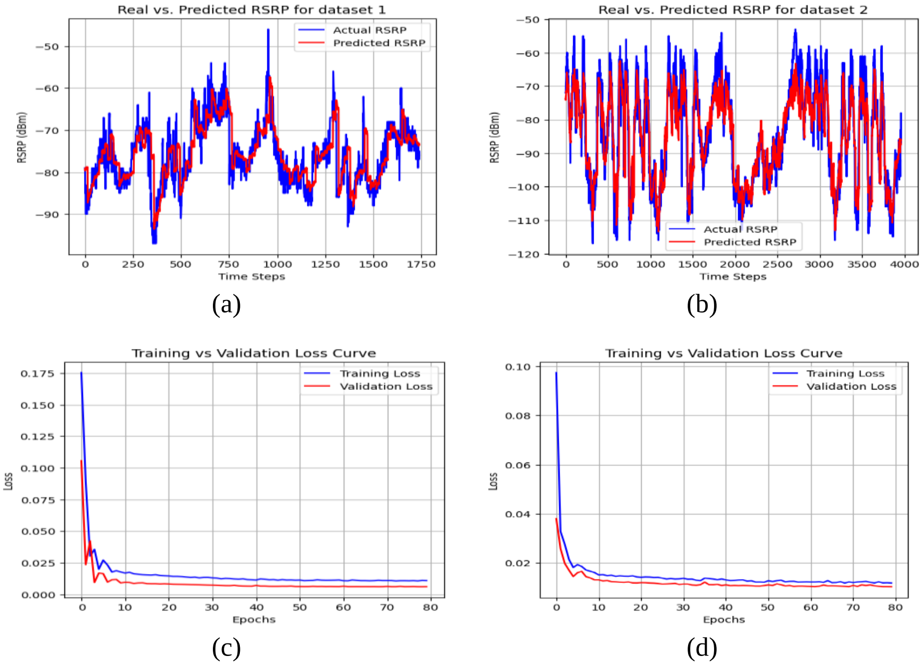


Figure 3. Performance evaluation of the Bi-LSTM model on both datasets; (a) real vs. predicted RSRP for dataset 1, (b) real vs. predicted RSRP for dataset 2, (c) training vs. validation loss for dataset 1, and (d) training vs. validation loss for dataset 2

The real vs. predicted RSRP plots Figures 4(a) and (b) of the S-LSTM model in Figure 4 resemble the Bi-LSTM model results and demonstrate that S-LSTM performs well to capture the general trends in the data, but struggles to accurately follow the rapid fluctuations in RSRP, leading to increased prediction errors. The training vs. validation loss curves presented in Figures 4(c) and (d), respectively, show successful convergence, stabilizing after approximately 10–15 epochs without signs of overfitting.

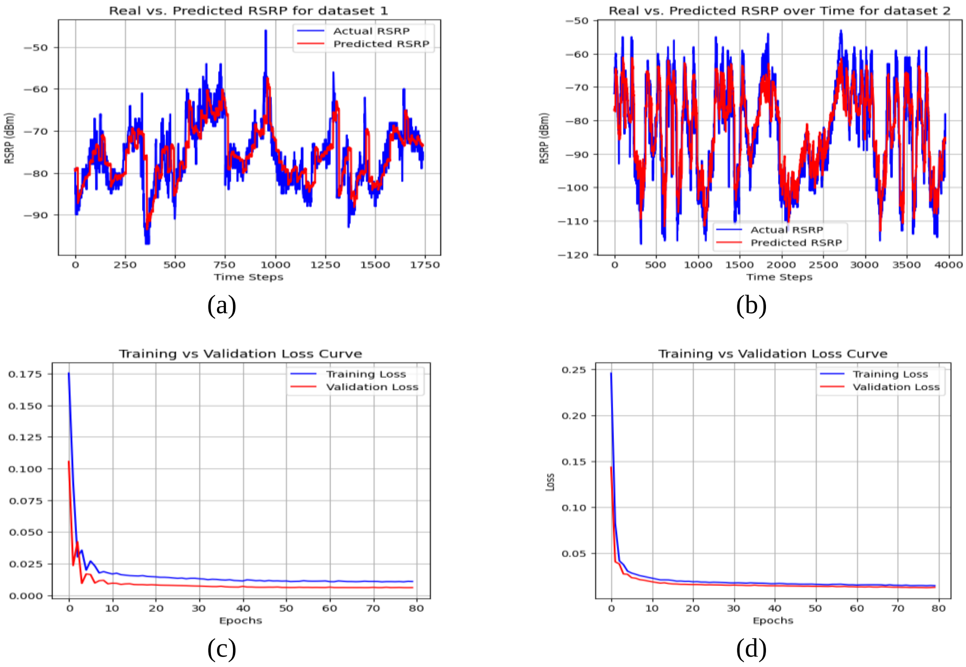


Figure 4. Performance evaluation of the S-LSTM model on both datasets; (a) real vs. predicted RSRP for dataset 1, (b) real vs. predicted RSRP for dataset 2, (c) training vs. validation loss for dataset 1, and (d) training vs. validation loss for dataset 2

All of the three models demonstrate good convergence and achieve low final loss values, indicating effective learning without signs of overfitting. The training and validation losses curves remain closely aligned across epochs for each model, suggesting strong generalization performance. However, when comparing the actual versus predicted RSRP plots, the ED-LSTM model clearly provides more consistent and accurate tracking of signal variations over time, outperforming both the Bi-LSTM and S-LSTM models.

Figure 5 illustrates the performance evaluation of ED-LSTM, Bi-LSTM, and S-LSTM across prediction horizons from 1 to 30-time steps, using MAE and MAPE as metrics. It is evident that the ED-LSTM consistently outperforms the other models across all prediction horizons. The model maintains a relatively low stable MAE and MAPE demonstrating superior generalization capability, with MAE ranging between 1.92 and 2.23 for dataset 1 (Figure 5(a)) and between 2.24 and 2.50 for dataset 2 (Figure 5(b)). The slightly higher errors in dataset 2 align with its higher variability. The MAPE values remain below 3.5% for both datasets Figures 5(c) and (d), highlighting the model's robustness in multistep forecasting. In contrast, Bi-LSTM and S-LSTM models exhibit higher errors, which increase progressively with longer prediction horizons, where for Bi-LSTM model in dataset 1, the MAE increases from 1.95 at t=1 to 4.38 at t=30, while in dataset 2, the increase is more pronounced, reaching 6.88 at t=30. Whereas for S-LSTM model the MAE goes from 1.92 at t=1 to 3.98 at t=30 in dataset 1, while for dataset 2, the increase is more pronounced, reaching 7.22 at t=30. Similarly, the MAPE values show a significant rise, particularly for dataset 2, where it exceeds 8.5% for longer prediction horizons in Bi-LSTM model and 9% for S-LSTM model (Figure 5(d)). The overall error is higher for the larger dataset. This is due to its higher variability, yet both datasets show similar MAE and MAPE trends: errors rise with prediction length, and ED-LSTM remains superior. The ED-LSTM model outperforms Bi-LSTM and S-LSTM by 33–38% in terms of MAE for dataset 1 and 48-50% in terms of MAPE for dataset 2.

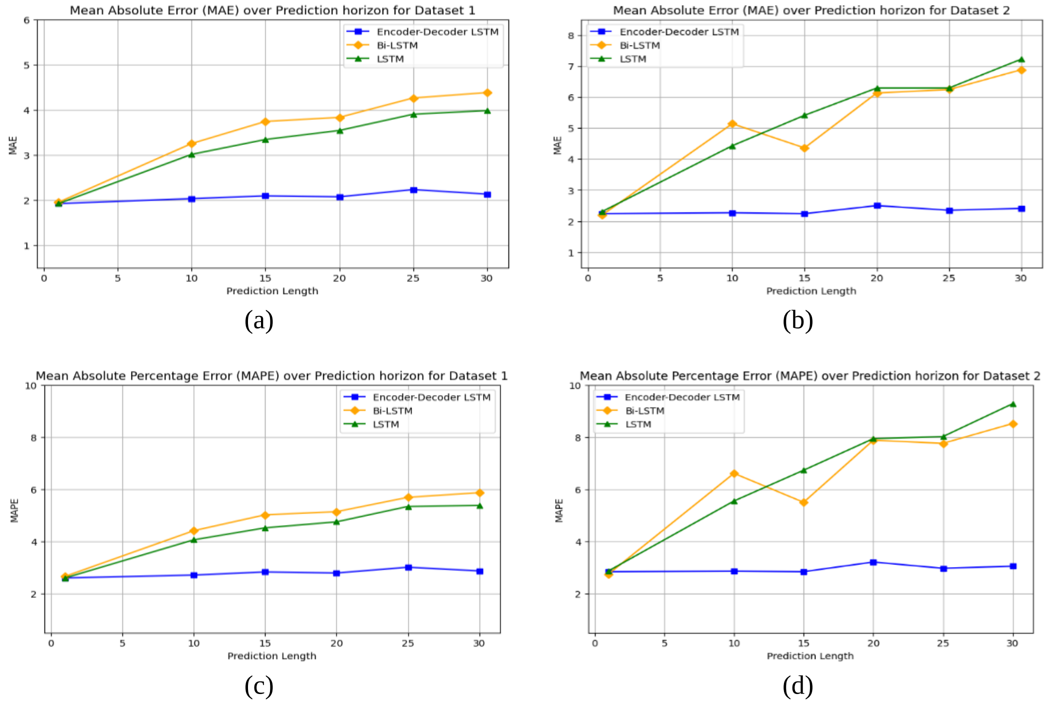


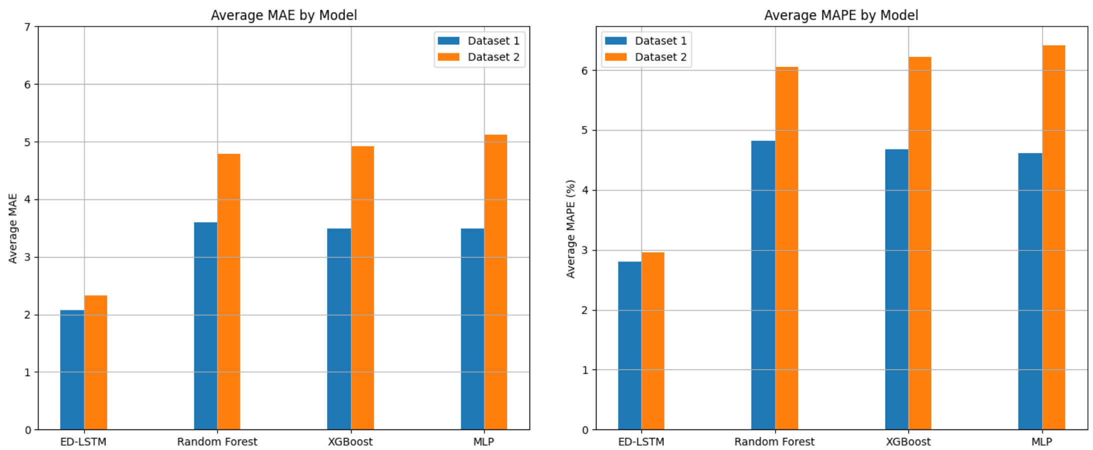
Figure 5. Performance evaluation of the ED-LSTM, Bi-LSTM, and S-LSTM models over different prediction horizons; (a) MAE across prediction horizons for dataset 1, (b) MAE across prediction horizons for dataset 2, (c) MAPE across prediction horizons for dataset 1, and (d) MAPE across prediction horizons for dataset 2

The ED-LSTM model demonstrated superior ability to capture temporal dependencies and map complex sequences, particularly over longer prediction horizons. While an increase error trends with extended horizons is expected due to the accumulation of prediction uncertainty, which was also mentioned in [31], where the LSTM based model suffered in a situation with a growing prediction horizon and could only have good performance at a prediction 9 steps ahead. However, the ED-LSTM consistently maintained low and stable error levels across different prediction horizons reaching 30 timesteps ahead, the long prediction horizon is a key aspect for practical usability if we want to optimize handover decision making and minimize handover latency. In contrast the performance of the other models degraded as the prediction horizon extended. This superior performance largely be attributed to encoder-decoder architecture, where the encoder compresses the input sequence into a fixed-length context vector that captures essential temporal features, and the decoder generates the forecast step-by-step based on this rich representation. This design allows the model to focus on learning a meaningful representation of past data, which better informs future predictions, especially over extended horizons.

A key factor enhancing the decoder's robustness is the use of teacher forcing during training. By feeding the true previous output as input for the next step, teacher forcing helps the decoder handle sequential dependencies in the data more reliably and reduces error accumulation in multistep predictions, particularly over longer horizons where compounding errors are common. In contrast, the S-LSTM processes the sequence only once and outputs predictions directly, which limits its ability to capture distant dependencies. Similarly, although Bi-LSTM's bidirectional processing is advantageous for classification tasks or understanding past context, it is less suited for long-horizon future forecasting.

The higher variability observed in dataset 2 results in larger errors for the Bi-LSTM and S-LSTM models, suggesting that these models struggle to maintain performance in noisy or volatile environments. This outcome aligns with the nature of dataset 2, which spans a mix of urban highways and rural highways, featuring varying cell loads and higher mobility speeds that contribute to fluctuating RSRP measurements. The differences in error rates across datasets highlight how dataset variability affects model generalization. Notably, the relatively stable performance of the ED-LSTM across both datasets demonstrates its robustness and superior ability to handle diverse and more challenging network conditions.

To further evaluate the model's performance, we compare it to three widely used machine learning models random forest, XGBoost and MLP for the same prediction horizons, the average MAE and MAPE for each model is compared to the ED-LSTM's MAE and MAPE as illustrated in Figures 6(a) and (b) respectively, the ED-LSTM clearly surpasses these models in performance and presented the lowest error.



(a) (b)

Figure 6. Performance evaluation of ED-LSTM against ML models RF, XGBoost and MLP; (a) average MAE of models and (b) average MAPE of model

4. CONCLUSION

This study explored the application of deep learning techniques for predictive HO management in 5G networks, with a focus on multi-step forecasting of RSRP values using an ED-LSTM model. The results demonstrated that ED-LSTM significantly outperforms Bi-LSTM and S-LSTM architectures in terms of MAE and MAPE across different prediction horizons. The model effectively predicts future RSRP values, which can contribute to more informed and proactive HO decision-making. There are several avenues for future research that could explore the integration of RL-based decision-making models with predictive deep learning approaches to dynamically optimize HO policies based on realtime network conditions and incorporating additional radio parameters such as RSRQ, SINR, and network load. Future studies may also explore hybrid deep learning architectures to further improve predictive performance.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in https://github.com/jpshlima/lstm-handover and https://github.com/mherlich/wireless-data-set at http://doi.org/10.1109/ICC45041.2023.10279195 and http://doi.org/10.1109/OJCOMS.2022.3210289 respectively.

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