Handover Enhancement in High-Speed Railway 5G Networks: A LSTM-based Prediction Method

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***Abstract*—This paper focuses on the handover performance enhancement of high-speed railway (HSR) 5G millimeter wave(mmWave) networks. As starting the handover at different time may yield very different performances, we propose a Long Short Term Memory (LSTM)-based prediction method to find a proper handover point in advance to alleviate the high handover delay and link interruption-prone problems of traditional A3 handover method. By learning the historical trend of Reference Signal Receiving Power (RSRP) and predicting the future changes of RSRP based on the LSTM encoder-decoder network, the proposed LSTM-based prediction method is able to enhance the handover performance of HSR 5G networks. Simulation results show that compared with traditional A3 method, our proposed LSTM-based prediction method reduces the probability of link interruption, improve the stability of the quality of service (QoS) during the handover process.**

***Index Terms*—High-speed rail, Millimeter wave, LSTM, Handover, 5G**

I. Introduction

In the HSR 5G mmWave networks, to guarantee continuous and uninterrupted train ground communications, the handover has to be fulfilled when high-speed trains go through the overlap region of two adjacent cells. However, with the increment of the moving speed of high-speed train, handover will become more frequent. Therefore, how to enhance handover performance is an urgent problem to be solved.

To enhance handover performance, some studies employed optimization of existing handover judgment conditions. In [1], a method was proposed to dynamically adjust the handover control parameters in heterogeneous networks (HetNet) with dense micro-areas, so that the time-to-trigger (TTT) and handover margin (HOM) can be adjusted according to the handover effect under different environments and speeds, thus the wireless link failure probability and ping-pong probability were minimized. In [2], a location-based handover method was proposed for LTE networks in high-speed mobile scenarios, supporting mobile scenarios of up to $500km/h$. In [3], an adaptive handover method based on random suppression was proposed, by establishing the elliptic function relationship between the hysteresis threshold and the train speed, introducing a normally distributed random variate to suppress reverse handover, which maintained a low ping-pong handover rate and a high handover success rate.

With the increase of machine computing power, machine learning and neural network techniques are widely applied in various domains. Many scholars have started to employ related techniques to solve the problem of high-speed handover. In [4], a machine learning-based handover method for HSR was proposed to reduce the RSRP gap between the original base station (BS) and the target BS and also help reduce the probability of wireless link failure, by initiating the handover earlier at the cell boundary. In [5], an adaptive optimization method based on the Q-Learning algorithm was proposed to achieve real-time estimation of the handover parameters of the LTE-R system, and a performance situation map for handover parameters for different speeds was established to improving handover performance. In [6], a time-difference-based reinforcement learning method was proposed to set up an agent that can interact with the environment, and a parameter adaptive handover mechanism for 5G in High-speed Rail Communication (HSRC) was established to find the optimal handover parameters by approximation functions to improve the handover performance and network performance.

However, although all aforementioned existing works are able to enhance the handover performance to some extent, in 5G HSR mmWave networks, due to the small coverage area and high propagation loss of mmWave BSs, the existing methods may be inefficient when they are applied to the scenarios with mmWave.

To fill the gap, this paper studies handover performance enhancement in HSR 5G mmWave networks, leverages mmWave characteristics and present a LSTM-based prediction method to find the optimal handover point to enhance handover performance. The contributions are summarized as follows

- To facilitate prediction with LSTM, we convert the RSRP signal variation trend into a time-series signal based on the characteristics of the cell distribution of the high-speed rail 5G network.
- To enhance handover performance, we propose a LSTM-based prediction method, in which, the LSTM encoder-decoder model is employed to study historical RSRP data and predict the RSRP data in the future, the one-dimensional search algorithm is employed to find the optimal handover point.
- Simulation results show that the proposed LSTM-based prediction method, compared with the traditional A3 one, can reduce the probability of link interruption, improve the stability of the QoS during the handover process.

II. SYSTEM MODEL

The system model of considered HSR 5G mmWave networks is shown in Fig. 1, where a number of Distribution Units (DU) are erected along both sides of the railroad, and each DU is connected to a set of BSs with horizontal spacing L. In the high-speed train, users communicate with an BS through an on-board Access Point (AP) and then access the internet. Because communication between users and APs is usually more stable, maintaining the communication quality between BSs and APs is essential for ensuring QoS for users. When the train travels through the coverage of two neighboring BSs, event A3 is triggered as the RSRP of the neighboring coverage is stronger than the current coverage by an offset and maintains TTT. Then, on-board APs connect to the BS with a stronger RSRP, which is named handover. If handover occurs between two BSs that belong to the same DU, it is called an Intra-gNB-DU handover, otherwise it is called an Inter-gNB-DU handover.

In the considered HSR 5G mmWave networks, signal transmission from BSs to the train is subject to fading by various influences. In this paper, both large-scale fading and small-scale fading are considered, including path loss, shadow effect and Rician fading.

A. Path Loss

Path loss is caused by the propagation characteristics of the channel and the diffusion of the transmitted power, which is a kind of large-scale fading and can represent the variation of the received power over a large area. This paper considers the calculation of the path loss of mmWaves based on the channel model proposed by 3GPP for the 0.5-100 GHz band. So, The path loss $PL_{\mathrm{RMa-LOS}}$ at the distance of d_{3D} from the BS can be expressed by

$$PL_{\mathrm{RMa-LOS}} = \begin{cases} PL_1 & 10 \text{ m} \le d_{\mathrm{3D}} \le d_{\mathrm{BP}} \\ PL_2 & d_{\mathrm{BP}} \le d_{\mathrm{3D}} \le 10 \text{ km}, \end{cases}$$

where PL_1 can be calculated by

$$\begin{aligned} &PL_1 = \\ &20\log_{10}\left(\frac{40\pi d_{\mathrm{3D}} f_c}{3}\right) + \min\left(0.03h^{1.72}, 10\right)\log_{10}\left(d_{\mathrm{3D}}\right) \\ &-\min\left(0.044h^{1.72}, 14.77\right) + 0.002\log_{10}(h) d_{\mathrm{3D}}, \end{aligned} \tag{1}$$

and PL_2 can be calculated by

$$PL_2 = PL_1\left(d_{\mathrm{BP}}\right) + 40\log_{10}\left(\frac{d_{\mathrm{3D}}}{d_{\mathrm{BP}}}\right). \tag{2}$$

In the above equations (1) and (2), h is the average height of the building, d_{BP} is break point distance that can be expressed by

$$d_{\mathrm{BP}} = \frac{2\pi h_{\mathrm{BS}} h_{\mathrm{UT}} f_c}{c}, \tag{3}$$

where f_c is a center frequency normalized to 1 GHz, c is the propagation speed in free space with a value of 3.0×10^8 m/s, h_{BS} and h_{UT} are the antenna heights at the BS and users, respectively. In addition, the standard deviation of shadow fading $\sigma_{\mathrm{SF}} = 4$ when $PL_{\mathrm{RMa-LOS}}$ is taken as PL_1 and $\sigma_{\mathrm{SF}} = 6$ when $PL_{\mathrm{RMa-LOS}}$ is taken as PL_2.

B. Shadow Effect

Inevitably, a small number of trees and other objects along both sides of the HSR track produces a degree of obscuration of the mmWave signal transmission path, creating the shadow effect and causing power fading. The shadow effect obeys a log-normal distribution. Let the ratio of transmit power and receive power be $\psi = P_t/P_r$, and its density function can be expressed by

$$p(\psi) = \frac{\xi}{\sqrt{2\pi}\sigma_{\psi_{\mathrm{dB}}}\psi}\exp\left[-\frac{\left(10\log_{10}\psi - \mu_{\psi_{\mathrm{dB}}}\right)^2}{2\sigma^2_{\psi_{\mathrm{dB}}}}\right], \psi > 0 \tag{4}$$

where $\xi = 10/\ln 10$, $\psi_{\mathrm{dB}} = 10\log_{10}\psi$. $\mu_{\psi_{\mathrm{dB}}}$ is the mean of ψ_{dB} and $\sigma_{\psi_{\mathrm{dB}}}$ is the standard deviation of ψ_{dB}.

C. Rician fading

The mmWave signal is mainly propagated by Line of Sight (LoS) direct transmission which means that the direct path is the main component, in accordance with the Rician distribution.The probability distribution function (PDF) of the signal amplitude is

$$\begin{aligned} &f_p(\rho) = \\ &(1+K)e^{-K}\frac{\rho}{\bar{p}}\exp\left(-\frac{1+K}{2\bar{p}}\rho^2\right) I_0\left(\sqrt{\frac{2K(1+K)}{\bar{p}}}\rho\right), \end{aligned} \tag{5}$$

where local average power $\bar{p} = A^2/2 + \sigma^2$, Rician factor $K = A^2/2\sigma^2$, A is main signal amplitude peak and σ^2 is local average scattered power.

According to equation (5), PDF of signal power can be expressed by

$$\begin{aligned} &f_p(p) = \\ &\frac{(1+K)e^{-K}}{\bar{p}}\exp\left(-\frac{1+K}{\bar{p}}p\right) I_0\left(\sqrt{\frac{4K(1+K)p}{\bar{p}}}\right). \end{aligned} \tag{6}$$

III. THE LSTM-BASED PREDICTION METHOD FOR HANDOVER

A. Data Preparation And Processing

Given the specific HSR track, the overall RSRP trend for trains is similar to the historical trend. So, in order to adapt the LSTM-based model to a specific HSR track, the RSRP information from the train's previous period can be used as model input to predict the trend of RSRP in the future period. When the train is running, the RSRP measurement information of the BSs around the train is shown as Fig. 4(a). There are multiple constantly changing data sources, if they are employed as model input without being processed, the amount of data and complexity of training will increase significantly, so it must be simplified. Given that the handover only involves two BSs, this paper focuses on the RSRP change of the two BSs closest to the train. As shown in Fig. 2, when the train

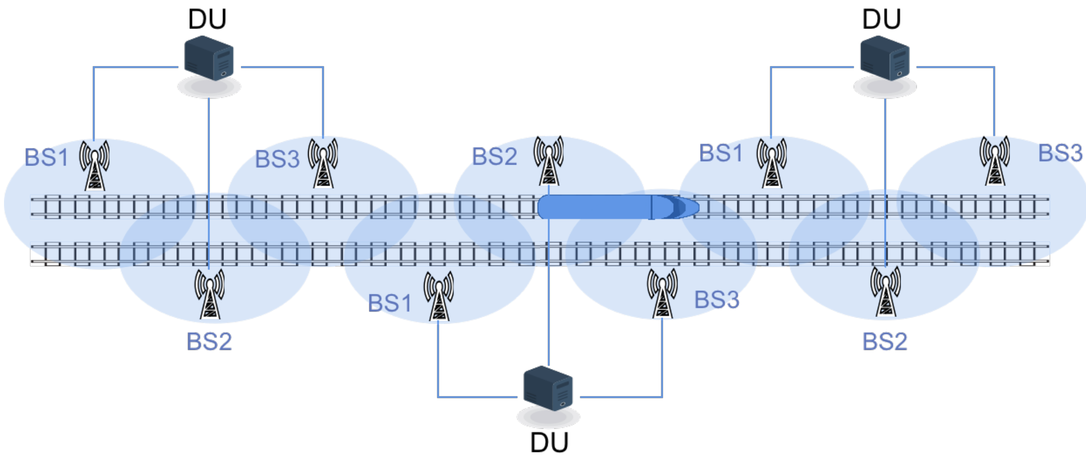


Fig. 1. HSR networks system model.

passes through railroad section d_{i-1}, only the RSRP changes of BS_{i-1} and BS_i need to be considered. Conversely, BS_i only needs to be considered on railroad sections d_{i-1} and d_i.

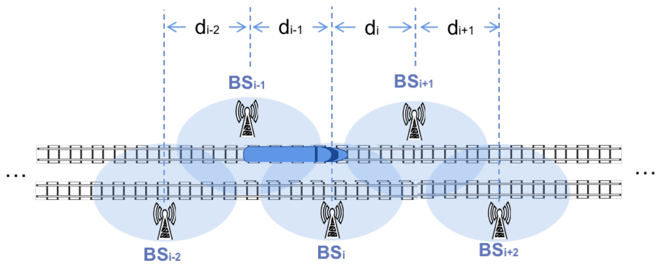


Fig. 2. Distribution of RSRP data source.

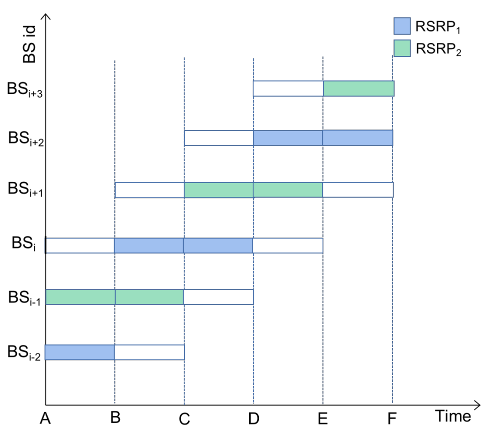
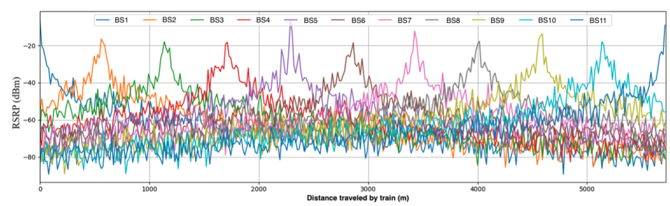
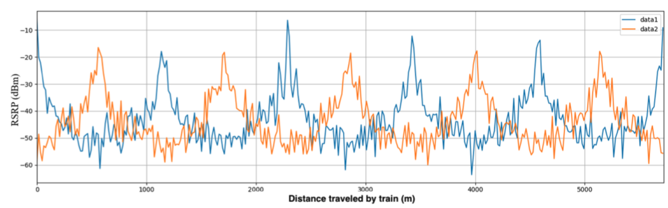


Fig. 3. An illustration of interception and splicing of raw RSRP data of BS.

The process of intercepting and splicing the raw RSRP data of the BS is shown in Fig. 3. Point A to point F indicates the times when the train travels to the nearest point of the railroad to the 5 BSs. The train starts from point A and travels to point F. Assuming the range radius of the on-board AP to obtain the change in RSRP of the BS is 2 times the BS spacing, at each point, RSRP changes can be measured for up to 5 BSs. The RSRP change of the BSs on the railroad side can be obtained by splicing the data in blue, which is set as RSRP_1. And by splicing the data in green, the RSRP change of the BSs on the another side can be obtained, which is set as RSRP_2.



(a) Raw RSRP data.



(b) Simplified RSRP data.

Fig. 4. Comparison of RSRP data before and after simplifying.

Fig. 4 visualizes the raw and simplified RSRP data.The blue and orange lines in Fig. 4(b) represent the trends of RSRP_1 and RSRP_2, respectively. Compared with the complicated and redundant raw RSRP data, the simplified RSRP data clearly and intuitively represents the RSRP changes received from the BSs. In addition, there are multiple intersection points in RSRP_1 and RSRP_2, and at each intersection point, if the handover condition is satisfied, a handover occurs. Therefore, after simplifying, multiple different data sources are integrated into two abstract data sources, and the problem of choosing the timing of handover between multiple BSs is transformed into the problem of predicting the trends of RSRP_1 and RSRP_2

and finding their intersection times, respectively.

B. The LSTM-based Predictive Handover Method

For sequence-to-sequence prediction of RSRP data trends, an LSTM-based encoder-decoder model is built. Fig. 5 portrays its structure, which is made up of two LSTMs. The first LSTM processes an input sequence and generates an encoded state which condenses the data in the input sequence and then the encoded state is used by the second LSTM to generate an output sequence. In addition, the propose method employs the mix teacher forcing method to accelerate model convergence and improve training effect. We sometimes give the LSTM decoder the true value as the next moment's input, just like a teacher, and other times we give it the predicted value. Each epoch of model training, the amount of teacher forcing is gradually reduced. At the start of training, mix teacher forcing can assist the model in learning the structure of the data, but it gradually transitions it to making predictions on its own.

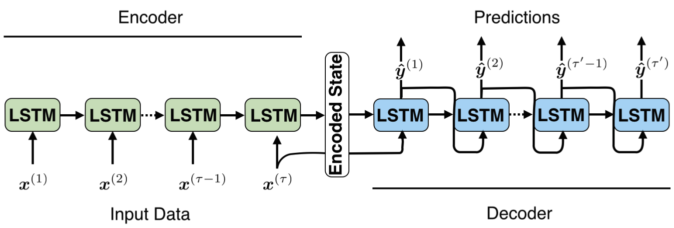


Fig. 5. The structure of LSTM encoder-decoder.

The sequence data should be windowed and divided into a series of shorter sequence data by strides in order to train the model, each of which includes n_o sequences of target values and n_i sequences of input values. The windowing process is visualized in Fig. 6. Beginning with the first y value, n_i values are gathered as input values, and the following n_o values are used as target values. The window then slides to the second y value as the stride is 1 and continues to do so until the window can no longer slide. Suppose that after windowing, a amount of n_w sequence data are obtained. Then both of matrix X with the shape (n_i, n_w) composed of the input values and matrix Y with the shape (n_o, n_w) composed of the target values are fed into LSTM encoder-decoder model for training.

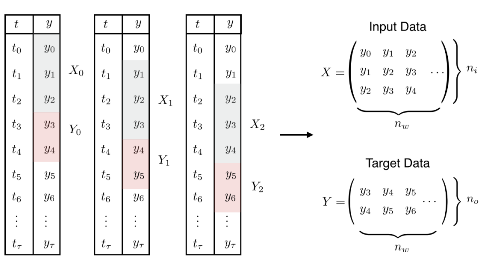


Fig. 6. Windowing of sequence data.

The data processing flow of the proposed method is shown in Fig. 7. First, the raw RSRP data is simplified to obtain RSRP_1 and RSRP_2, then they are windowed separately and the LSTM encoder-decoder model is trained independently. After that, we input the RSRP changes in the previous period to predict the short-term RSRP changes in the future. Finally, we search for the best handover point by one-dimensional search.

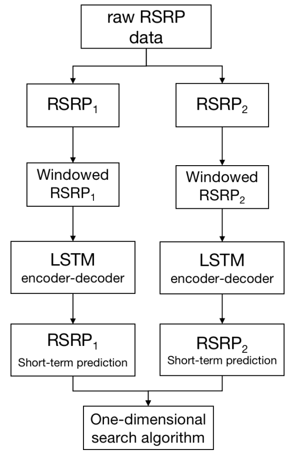


Fig. 7. Data processing flow of the proposed method.

One-dimensional search algorithm for handover points is summarized in Algorithm 1. The algorithm takes the prediction sequence of the LSTM-based predictive handover method as input and can find the best handover point from a global, a priori perspective via the one-dimensional search algorithm, effectively alleviating the handover delay problem of the A3 algorithm.

IV. NUMERICAL SIMULATIONS

We simulate a HSR 5G mmWave network with 100 BSs and 57km of railroad, where the train travels at a constant speed of 300km/h and measures the RSRP of the surrounding BSs every 0.2s. The simulation parameters are summarized in table.I.

We first observe the change of loss value versus epoch, shown as Fig. 8. The proposed method is able to converge to near zero with about 15 epochs. Fig. 9 visualizes the comparison of the predicted results of the proposed method with the real target results. The red line indicates the predicted value and the blue line indicates the target value. It can be seen that the predicted value is basically the same as the target value.

Fig. 10 visualizes the location of the handover points of the proposed method and the A3 handover method, where the blue vertical line indicates the handover point of the proposed method and the red vertical line indicates the handover point of the A3 handover method. It can be seen that the handover point of the proposed method is earlier than that of the conventional A3 handover method and is closer to the intersection of RSRP_1 and RSRP_2, which indicates that the proposed method can effectively alleviate the handover delay caused by the offset and TTT conditions in A3 handover. In addition, the difference between RSRP_1 and RSRP_2 before and after

Algorithm 1: One-dimensional Search Algorithm For Handover Points

Input: RSRP prediction arrays r_1,r_2 and threshold t;
Output: Set of handover points S_h;
if $r_1[0] > r_2[0]$ **then**
    $strong, weak \leftarrow r_1, r_2$;
else
    $strong, weak \leftarrow r_2, r_1$;
end
while $i < len(r_1)$ **do**
    if $weak[i] > strong[i]$ **then**
        $counter = 0$;
        for $i \leftarrow 1$ ***to*** $t + 1$ **do**
            if $weak[index + i] \leq strong[index + 1]$ **then**
                $index \leftarrow index + counter$;
                $break$;
            else
                $counter \leftarrow counter + 1$;
            end
        end
        if $counter == t$ **then**
            Put $index$ into set S_h;
            $strong, weak \leftarrow weak, strong$;
            $r_1, r_2 \leftarrow r_2, r_1$;
            $index \leftarrow index + t - 1$;
        end
    end
    $index \leftarrow index + 1$;
end

TABLE I
SIMULATION PARAMETER SETTING

Parameter	Meaning	Value
f	mmWave signal frequency	30GHZ
$\mu_{\psi_{\text{dB}}}$	The mean of ψ_{dB}	0
$\sigma_{\psi_{\text{dB}}}$	The standard deviation of ψ_{dB}	4
p	BS transmit power	46dbm
d_0	Distance between BS and railroad	5-25m
L	Horizontal spacing of neighboring BSs	576m
v	Train speed	300km/h
t	RSRP measurement interval	200ms

handover is closer to the proposed method, which indirectly reflects that the proposed method has more stable received power and better handover effect.

Fig. 11 compares the link interruption probability of the two methods with the link interruption threshold. From the figure, it can be seen that the link interruption probability of the proposed method is always lower than that of the A3 handover. With the increase of the link interruption threshold, the link interruption probabilities of both methods keep increasing, and the proposed method increases at a lower rate than the A3 handover. Simulation result shows that the proposed method has a 21.1% lower link interruption probability than the A3 handover, which indicates that the proposed method has more stable performance and can better guarantee the service quality of users.

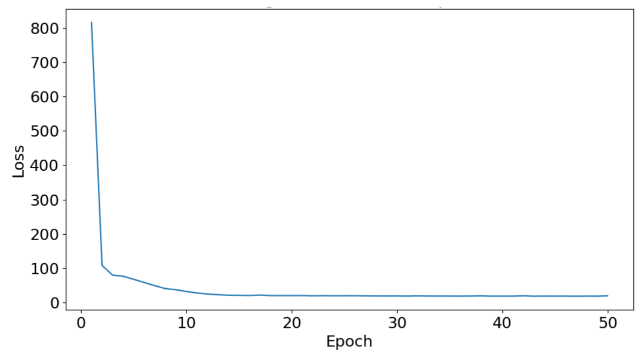


Fig. 8. Change of loss versus epoch.

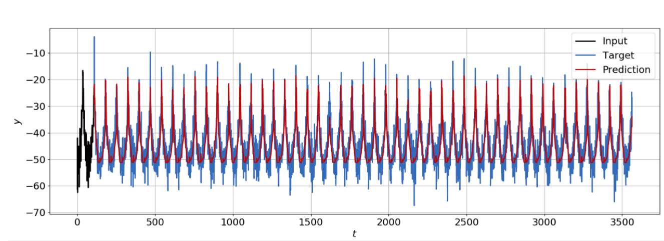


Fig. 9. Prediction result.

In addition, we tested and compared the two methods in terms of more metrics, including the handover delay, the average received power, and the difference between the average received power before and after the handover. The three are employed to evaluate the handover efficiency, the average QoS, and the stability of the QoS during the handover process, respectively.

Fig. 12 compares the handover delay of the two methods, from which we can conclude that compared to A3 handover method, the proposed LSTM-based prediction method is able to reduce the handover delay by 33.9%, and each handover is $837.5ms$ earlier on average, which effectively alleviates the handover delay, provides more time for handover preparation, and makes the triggered handover more timely.

Fig. 13 compares the average received power of the two handover methods. From the figure, it can be seen that the average received power of the proposed method increases

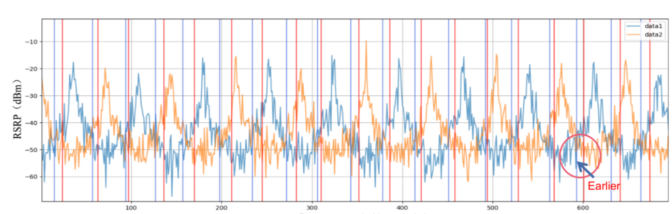


Fig. 10. Comparison of handover points between the proposed and A3 handover method.

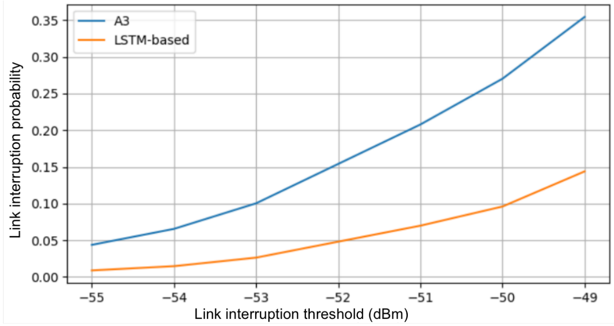


Fig. 11. The influence of link interruption threshold on link interruption probability of two methods.

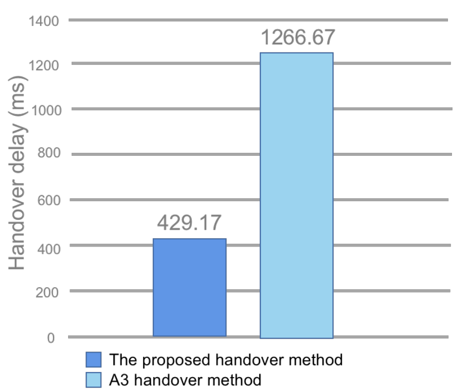


Fig. 12. Comparison of handover delay.

by $0.5dBm$ compared to the A3 handover method, which indicates that the proposed method is able to improve the overall QoS.

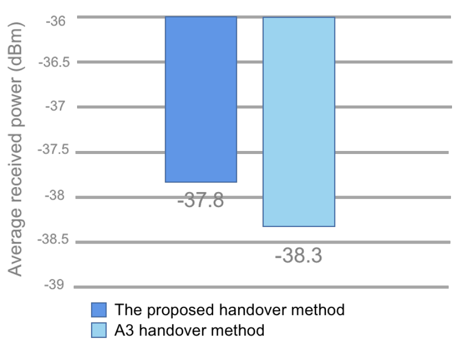


Fig. 13. Comparison of average received power.

Fig. 14 compares the received power difference before and after handover for the two methods. It can be seen that the proposed method reduces the average difference of received power before and after handover by 85.14% and the average received power difference by $5.9dBm$, which indicates that the proposed method can make the difference between received power before and after handover smaller and enhance the stability of the service during the handover process.

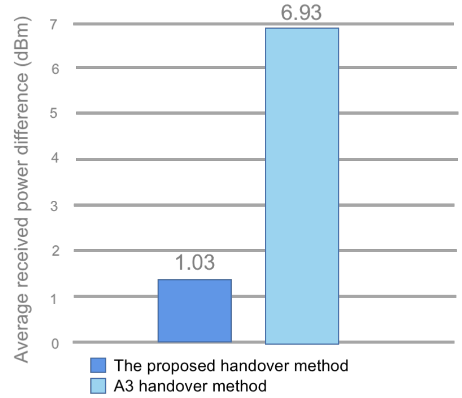


Fig. 14. Comparison of average received power difference.

V. CONCLUSION

This paper studied the handover performance enhancement in the HSR 5G mmWave networks. Leveraging the characteristics of the networks, we proposed a LSTM-base prediction method. The simulation results show that compared with traditional A3 method, the proposed LSTM-base prediction method can reduce the probability of link interruption by 33.9 percent and the difference in received power before and after handover by 85.14 percent, increase the average received power by 0.5dBm, and effectively enhance handover performance.

VI. ACKNOWLEDGMENT

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