AI-Based Optimization of Handover Strategy in Non-Terrestrial Networks

Abstract: Complicated radio resource management, e.g., handover condition, will trouble the user in non-terrestrial networks due to the impact of high mobility and hierarchical layouts which co-exist with terrestrial networks or various platforms at different altitudes. It is necessary to optimize the handover strategy to reduce the signaling overhead and improve the service continuity. In this paper, a new handover strategy is proposed based on the convolutional neural network. Firstly, the handover process is modeled as a directed graph. Suppose a user knows its future signal strength, then he/she can search for the best handover strategy based on the graph. Secondly, a convolutional neural network is used to extract the underlying regularity of the best handover strategies of different users, based on which any user can make near-optimal handover decisions according to its historical signal strength. Numerical simulation shows that the proposed handover strategy can efficiently reduce the handover number while ensuring the signal strength.

Keywords: convolutional neural network; directed graph; handover; low earth orbit; non-terrestrial network

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1 Introduction

The non-terrestrial network (NTN) has been regarded as a supplement to the 5G terrestrial mobile network since it provid global coverage and service continuity[1]. Compared with terrestrial networks, the handover in NTN is more frequent and complex. In this paper, a handover optimization method is proposed and applied to a typical NTN scenario, i. e. , a low earth orbit (LEO) satellite network. A LEO is an orbit around the earth with an altitude between 500 km and 2 000 km[1]. Compared with geostationary earth orbit satellites, the LEO satellites have much lower path-loss and propagation delay. Therefore, the third generation partnership project (3GPP) NTN study item has regarded the LEO satellites as the key to providing global broadband Internet access. Suppose the orbit is circular, the satellite will move around the earth at a constant velocity which is inversely proportional to the square root of the orbit altitude. Because of the low altitude, the LEO satellites have a high speed with respect to the earth, and terrestrial user equipment (UE) needs to frequently switch to new beams to keep connectivity. In order to ensure the quality of the Internet service, the optimization for NTN handover strategy needs to be carefully investigated.

Previous studies generally make handover decisions based on one or more predefined criteria. The most commonly used criteria include the elevation angle[2], remaining service time[3] and the number of free channels[4], which correspond to the signal strength, handover number and satellite burden, respectively. But these methods cannot get an overall optimization. In Ref. [5], an overall optimization method is proposed by modeling the handover process by a directed graph. Each satellite is denoted by a node, then the best handover strategy is obtained by searching the shortest path. However, in Ref. [5] each satellite node is invariable during the handover process.

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UE needs to perform handover as soon as entering the coverage of another beam and cannot choose an appropriate time. Besides, the UE needs to predict its coverage condition in a future time to construct the graph, which may bring unexpected error and is beyond the capability of standard 5G UE.

In recent years, some artificial intelligence (AI) techniques have been applied to search for overall optimization on handover. The most often used technique is Q-learning[6–8], which is typical model-free reinforcement learning (RL). In Q-learning, some properties of UE are defined as its state, and the handover operation is defined as its action. Numerical simulation is used to iteratively train the Q-table (the reward of each action for each state) until its convergence. Then the UE can decide whether to perform handover according to its state. Furthermore, the Q-table can be replaced by a neural network for an infinite number of states. In Ref. [8], the handover in a LEO scenario is optimized by Q-learning. The state of UE is composed by its position, accessible satellites and whether handover is processed in this time slot. In each time slot, the UE is required to know its state and will choose a satellite for handover, which is a really strong requirement for ordinary UE. Besides RL, a recursive neural network (RNN) can also be used for handover optimization. Refs. [9] and [10] apply RNN for handover optimization in terrestrial millimeter wave mobile systems and vehicular networks, respectively. However, in a LEO scenario, the beam switch is fast, and the signal series of one beam may be too short for the RNN to make decisions.

In practical terms, a handover strategy with a low requirement for UE capability is desired to reduce the handover number while ensuring the reference signal received power (RSRP). In this paper, a convolutional neural network (CNN) based handover strategy optimization is proposed. Firstly, an amount of UE is randomly generated within the coverage of a satellite. The RSRP series of UE is generated based on the channel model in Ref. [1] and the simulation assumption in Ref. [11]. Secondly, the graph-based method in Ref. [5] is improved by setting each satellite in different time slots as different nodes. The improved method is used to find the best handover strategies for each piece of UE. Thirdly, the internal relation between the historical RSRP series and the best handover decision is extracted by a customized CNN. Since standard 5G UE needs to periodically measure the RSRP of the serving cell and adjacent cells, the UE can perform a sub-optimal handover strategy based on the historical measurements. The main contributions of this paper are summarized as follows.

• This paper proposes a novel directed graph model for the handover process. In this model, each beam in different time slots is viewed as different nodes, and the weight of an edge is determined by the RSRP and the beam identities of the two corresponding nodes. Suppose the beam coverage and the RSRP of UE are predictable, the best handover strategy for the UE can be found based on the model.

• A CNN is constructed based on the classical LeNet-5[12] for handover optimization. The results of the directed graph model are used to train the parameters of the CNN. Using the trained CNN, any UE in the LEO network can perform suboptimal handover based on its historical RSRP.

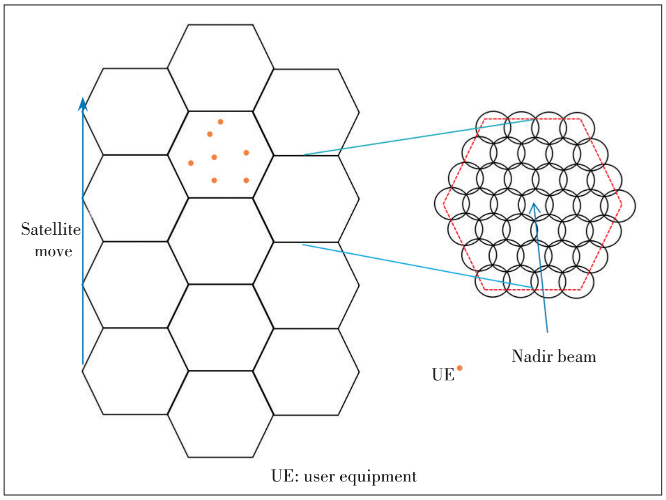
The rest of this paper is organized as follows. Section 2 describes the LEO network model and the motivation of handover optimization. In Section 3, a novel directed graph-based model is proposed for the handover process. A CNN structure is constructed and the results of the directed graph model are used to train the CNN. The effectiveness of the CNN is numerically evaluated in Section 4. Finally, Section 5 concludes this paper.

2 Background

2.1 System Model

A typical LEO satellite network consists of several circular orbits, and each orbit contains several evenly spaced satellites. This paper considers the scenario in Fig. 1 where each hexagon denotes the coverage of a satellite. Referred to the assumptions[11–13] used in 3GPP NTN study item, each satellite is assumed to have 37 beams that form the hexagon coverage. The UE is assumed to locate within a hexagon in the initial time, and the satellites in the three adjacent orbits are considered to evaluate the RSRPs on the UE. During the flight of the satellites, a piece of UE needs to periodically measure the RSRPs of different beams and make handover decisions.

The beam layout in Fig. 1 decides the center of the 37 beams[13]. Suppose the satellite is above a plane, then the diameter of the nadir beam on the plane can be computed based on the 3 dB angle. It is easy to compute the other 36 beam centers on the plane according to Fig. 1. Then the bore-sight directions of the 37 beams can be determined. The angles between co-orbital satellites and adjacent orbits are also calcu-



▲**Figure 1. Illustration of system model** lated to fulfill the coverage shown in Fig. 1.

2.2 Motivation

In 3GPP simulation assumption Set-1[11], a satellite with an altitude of 600 km has a beam diameter of 50 km and a velocity of 7.56 km/s. Therefore, a piece of UE can only connect to one beam in 6.6 s at most. Because of the noise and the overlapping of different beams, the handover will happen more often. In addition, because of the long propagation time, each handover procedure needs a longer time and will consume more time-frequency resources. Therefore in a LEO network, the handover has a time lag and causes a large signaling overhead. To reduce the overhead and improve service continuity, the handover strategy needs to be optimized for the following targets.

• Predict the handover decision to compensate the time lag.

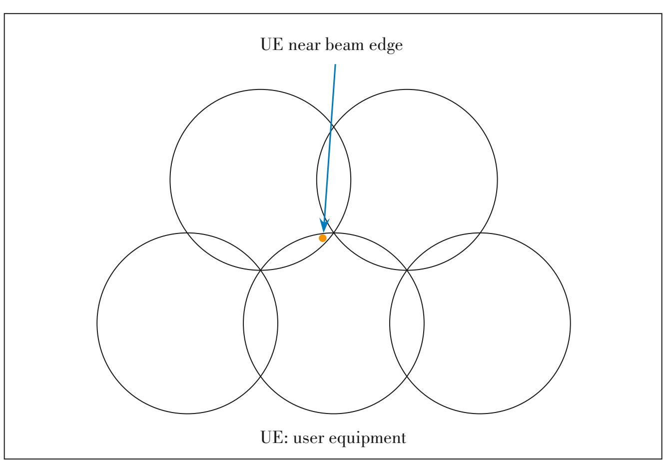
• Reduce the handover caused by noises, including shadow fading, multipath fading, and white Gaussian noise.

• Identify and suppress the handover in this situation. As shown in Fig. 2, a piece of UE near the beam edge may have a short serving time for some beams.

In this paper, an overall handover optimization is obtained in the directed graph model for each piece of UE. The common features of the optimized strategies for different UE are extracted using CNN to fulfill the targets without strong requirements for UE capability.

3 Handover Strategy Optimization Based on CNN

In a LEO satellite network, the satellites fly along predetermined circular orbits, so the change of the RSRP has strong regularity. The regularity can be used to improve the handover decision. Specifically, in each time slot, the previous N RSRP values of UE form a series, and some kinds of RSRP series imply that the UE should start handover. In this section, those kinds of RSRP series are found in two steps. First, the RSRP of each UE during a long period is measured and recorded. A directed graph model is proposed to search for the best handover decision in every time slot. Then the handover decision is regarded as the label for the previous N RSRP values of that time slot to be trained by the CNN. The proposed CNN can efficiently extract the common regularity of handover decisions for different UE.



▲Figure 2. An example of UE near beam edge

3.1 A Novel Directed Graph Based Model

The directed graph based model in Ref. [5] is designed to search the optimal handover strategy. However, the UE needs to start handover as soon as entering the coverage of the next satellite, which means it cannot choose a more appropriate handover time. This section proposes an improved directed graph based model to solve the problem.

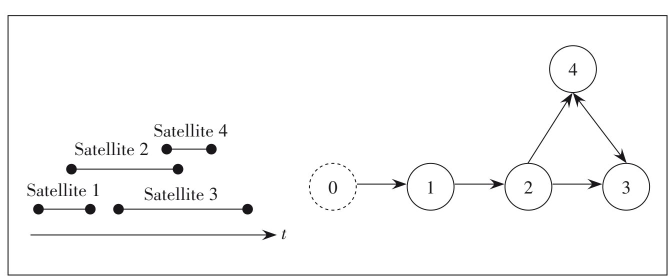
3.1.1 Referenced Model in Ref. [5]

In Ref. [5], every satellite is modeled as a node. If the beginning or end of the coverage of one satellite is between another satellite's coverage period, then there exists a directed edge between the two satellites, which means that a piece of UE can perform a handover between the two satellites. The weight of the edge is determined by the chosen criteria in the two satellites. For example, suppose only the criterion "handover number" is considered, then the weight of every edge should be set to 1. If other criteria such as "number of free channel" and "elevation angle" are considered, the weight can be set according to the two criteria of the target satellite. The Dijkstra's shortest path algorithm can be used to search the path with the smallest or largest weight. By choosing appropriate criteria, the resulting path becomes the overall optimal handover strategy.

An example of satellite coverage time and the corresponding directed graph in the referenced model are shown in Fig. 3. Node 0 denotes the initial time and other nodes denote four satellites. In this model, the node and the edge weight are invariable during the handover process. The weights of the edges cannot reflect the change process of the elevation angles or other criteria of the satellites. The UE can only assume that the handover happens as soon as it enters the coverage of another satellite.

3.1.2 Proposed Model

By considering the variation of satellites during the handover process, a novel model can be constructed to generate



▲Figure 3. Directed graph in referenced model more reasonable optimization for handover. The basic idea is to regard a beam in different time slots as different nodes. As shown in Fig. 4, we assume that in each time slot the serving beam of UE is one of the K strongest beams. The beam$_{TK}$ denotes the K-th strongest beam in the T-th time slot. Every two nodes in adjacent time slots are connected by an edge, which means that the handover between them is possible.

Similar to Ref. [5], the weights of the edges can be set according to different criteria for overall optimization. For the sake of simplicity, this paper only considers the RSRP strength and handover number. Then the weight of the edge from beam$_{T1K1}$ to beam$_{T2K2}$ can be defined as

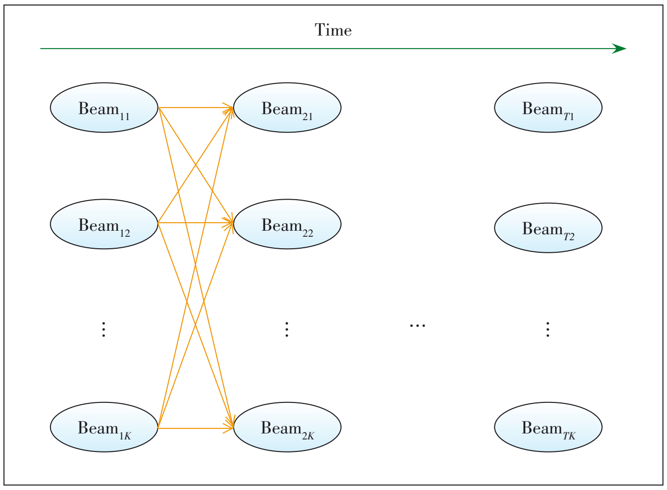
$$\mathrm{w}_1\times\mathrm{RSRP}_{T1K1}-\mathrm{w}_2\times\mathrm{handoverFlag}, \quad (1)$$

where RSRP$_{T1K1}$ denote the RSRP value of beam$_{T1K1}$, and handoverFlag = 1 if beam$_{T1K1}$ and beam$_{T2K2}$ are two different beams. When the signal-to-noise ratio is small, the channel capacity is proportional to the signal strength.

Therefore $w_1\times$RSRP$_{T1K1}$ in Eq. (1) denotes the benefit of connecting beam$_{T1K1}$ in T_1-th time slot, where w_1 is a predetermined parameter. Similarly, the parameter w_2 is chosen according to the degree of the negative impact of one handover. By using the Dijkstra's shortest path algorithm, we can find the longest path from the first time slot to the last time slot, which is actually the optimal handover strategy for this UE.

3.2 CNN Based Optimization for Handover

RSRP is defined as the linear average over the power of the resource elements that carry some predefined reference signals. Assume UE can predict the RSRP of different beams for a long period, then the method in Section 3.1.2 can be used to find the optimal handover strategy. However, in most cases, UE only knows its historical RSRP. Standard 5G UE needs to measure the RSRPs of detectable cells and handover to the strongest cell if its RSRP minus a predetermined threshold is larger than the serving RSRP. In this way, the information hidden in the historical RSRP is ignored. Actually, at least in the LEO scenario, the historical RSRP can help UE to make suboptimal handover decisions. The series of historical RSRPs of the strongest K beams in each time slot forms a two-dimensional matrix. A customized CNN is used to optimize the handover decision based on the matrix in this section.



▲**Figure 4. Directed graph in the proposed model**

CNN is an effective tool to elicit information from two-dimensional data. It has been widely used to extract features from images. A classical CNN consists of one or more convolutional layers, pooling layers, and fully-connected layers. The features of the input data are extracted layer by layer, and are summarized in the last fully-connected layer to generate the final output. Compared with the fully-connected layer, the convolutional layer takes advantage of the strong local spatial correlation in natural images and only has a few parameters to be trained. It is worth mentioning that the matrix of RSRP also has the "local spatial correlation", i.e., the cooperation of the RSRP values in adjacent time slots and the RSRP values of the nearest 3 or 4 beams are more likely to contain information for handover decisions. Therefore it is suitable to apply CNN to the problem of handover.

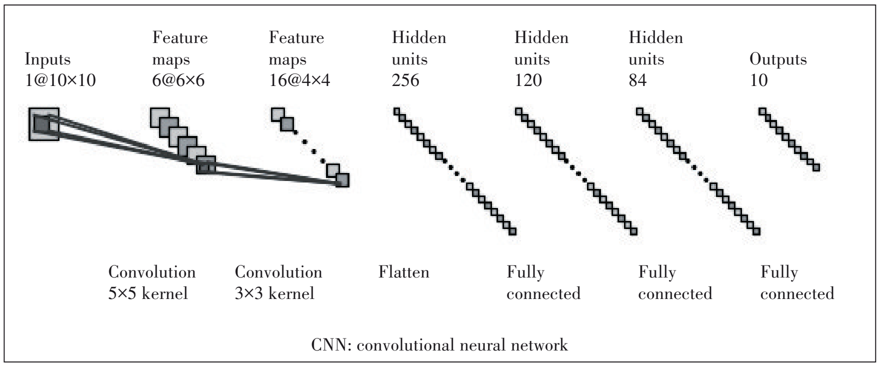
Intuitively, the RSRP series in the LEO network has strong regularity, so a relatively simple neural network structure should be chosen to reduce the training time and prevent overfitting. The LeNet-5[12] is firstly designed for character recognition and is a relatively simple modern CNN structure. The default input of LeNet-5 is a matrix of the size of 32×32. However, in the LEO network model presented in Section 2.1, the number of detectable beams for one piece of UE is generally smaller than 32. Therefore the size of the input data needs to be reduced. Actually, in the simulation, the number of considered beams in each time slot is set to be 10. The length of a time slot is set to be 0.5 s and the RSRP values in the previous 10-time slots are used to form the input. Then the input of the CNN is a matrix of the size of 10×10. In LeNet-5, two convolutional layers are used. The two convolution kernels both have the size of 5×5. Besides, two pooling layers are used to reduce the number of trained parameters. Because of the reduced input size, some layers in LeNet-5 need to be customized. First, one convolution kernel is reduced to the size of 3×3. Then the pooling layers are deleted since the number of parameters is not large. The structure of the resulting CNN is presented in Fig. 5. The output of size 10 corresponds to the 10 kinds of handover decisions, i. e., one of the 10 strongest beams is which the UE will connect in the next time slot.

The data preprocessing and the training procedure consist of four steps as follows.

1) For every piece of UE, generate the RSRP values of different satellites in every time slot. If one satellite is invisible or its signal is too weak to detect, the RSRP values are regarded as 0.

2) Compute the best handover strategy for every UE based on the proposed directed graph-based method in Section 3.1.2.

3) For every UE in every time slot, the previous 10 RSRP



▲**Figure 5. CNN structure for handover optimization**

values of the 10 strongest beams are used to form 10×10 input data. The best handover decision generated in the previous step is regarded as the corresponding label.

4) The input data and the corresponding labels from different UE are used to train the CNN in Fig. 5. After some epochs, the testing accuracy will converge.

The trained CNN can be used to make suboptimal handover decisions for new UE. In each time slot, the UE extracts the historical RSRP values of the 10 strongest beams as the input of the trained CNN. The output contains 10 values and the index of the largest value is regarded as the serving beam in the next time slot. It is worth noting that the handover decision is actually a prediction for the next time slot, so the time lag in the handover procedure can be compensated.

4 Simulation

The proposed methods are numerically evaluated in this section. The simulation parameters are mainly referred to as the parameter Set-1 in Ref. [11]. Some important parameters are shown in Table 1.

As described in Section 2.1, the LEO network in simulation consists of three orbits. Each satellite has 37 beams which form a hexagon. Some points are randomly generated within one hexagon in the UV plane. The projection of the points on the earth is calculated as the positions of the UE.

4.1 Optimal Handover Strategy Based on Directed Graph Model

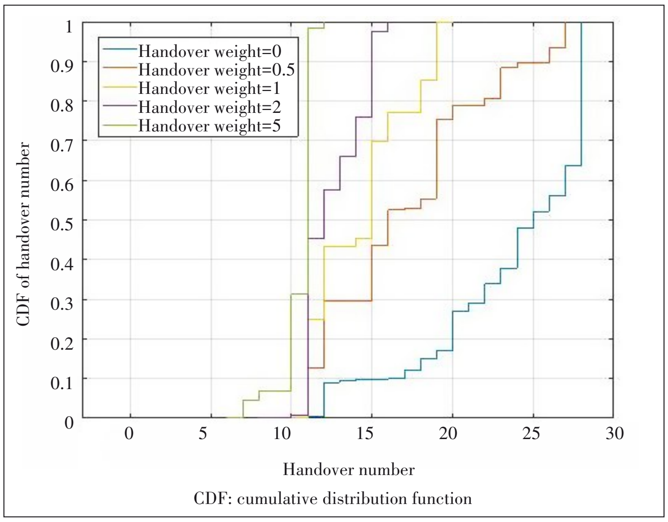
With the constructed LEO network, the RSRP values for each UE are calculated in each time slot. The length of a one-time slot is set to be 0.5 s, and about 140-time slots are considered in the whole simulation. The optimal handover strategy for each UE is generated by using the directed graph-based model in Section 3.1.2.

▼**Table 1. Simulation parameters**

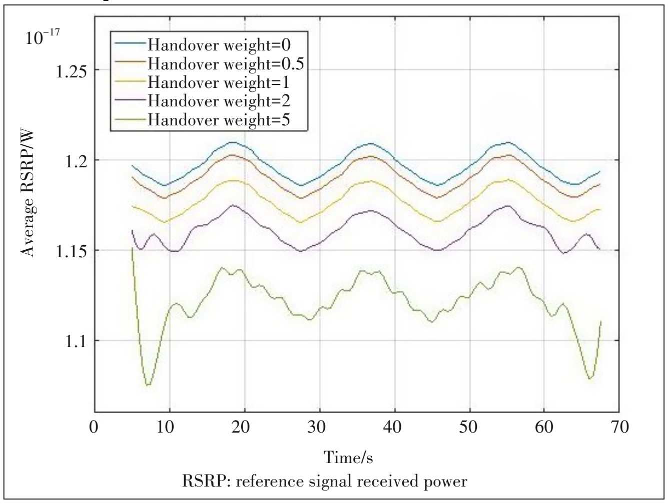
Parameter	Value
Orbit altitude	600 km
Simulation scenario	Rural
Carrier frequency	2 GHz
Antenna type	Bessel antenna
Antenna aperture	2 m
EIRP	34 dBW/MHz

EIRP: effective isotropic radiated power

In the graph-based model, the two parameters w_1 and w_2 form a trade-off between RSRP strength and handover number and need to be predetermined. In this section, w_1 is fixed and different w_2 is evaluated to show the change of handover number and average RSRP strength. Because of the large path loss, the received power of the strongest beam in one resource element is near 10^{-17} W. Therefore, the w_1 in Eq. (1) is set to be 10^{17}, which means that the benefit of accessing the strongest beam in one-time slot is around 1. Meanwhile, the value of w_2 is set to be 0, 0.5, 1, 2, and 5. When w_2 =0, the UE will always connect to the strongest beam. As shown in Figs. 6 and 7, with the increase of w_2,



▲ **Figure 6. Cumulative distribution function of handover number for different w_2**



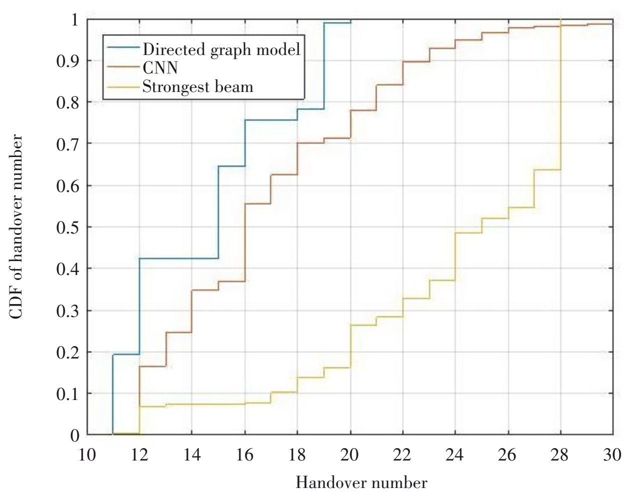
▲**Figure 7. Average RSRP during simulation for different w_2**

the handover number and average RSRP will both decrease.

4.2 Performance of CNN in Handover Optimization

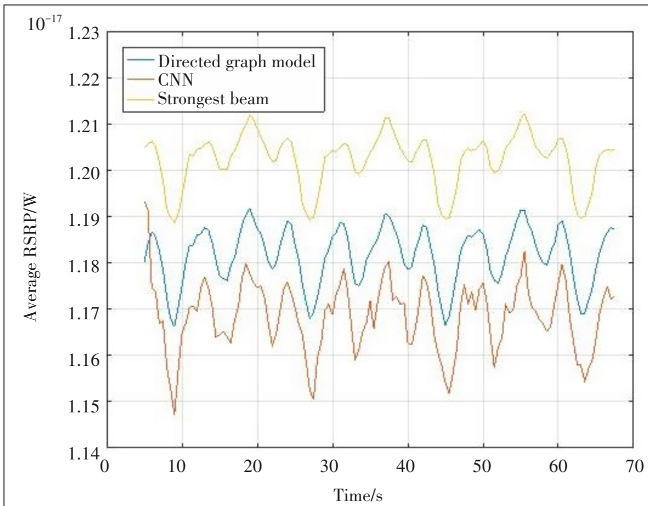
Three methods for handover optimization are compared in this section. The first method assumes the UE can predict its RSRP and make handover decisions based on the directed graph model. The second method means that the UE uses the trained CNN to make handover decisions. The CNN is trained by the results of the directed graph model with w_2 =1. In the third method, the UE is always served by the strongest beam.

Compared with the "strongest beam" method, the CNN can largely reduce the number of handovers without a requirement for UE capability. Figs. 8 and 9 show that the handover number of more than 70% of the UE is reduced by more than 1/4, while the average RSRP is only reduced by 3%.



CDF: cumulative distribution function CNN: convolutional neural network

▲Figure 8. Cumulative distribution function of handover number for different handover optimization methods



CNN: convolutional neural network RSRP: reference signal received power

▲Figure 9. Average RSRP during simulation for different handover optimization methods

5 Conclusions

This paper proposes a CNN-based handover optimization method for the LEO satellite network. The CNN structure is customized based on LeNet-5 and is used to extract the hidden information in the historical RSRP. In order to produce the training data for CNN, a novel directed graph-based model is proposed to find the optimal handover strategy when the UE knows its future RSRP. After the training, the CNN can be used to find a suboptimal handover decision based on its historical RSRP. In the simulation, the CNN is verified to be effective in handover optimization. The number of handovers is significantly reduced while the average RSRP is only reduced by 3%.

The optimization of handover in satellite communication is relatively simple because of the strong regulation of the movement of satellites. But the deep learning-based method can also be used in more complex scenarios. In order to extract the hidden regulation, a more advanced neural network structure may be needed, such as the attention-based neural network. The deep Q-learning is also worth investigating for a dynamically changing environment.

References

[1] 3GPP. Study on new radio (NR) to support non terrestrial networks: 3GPP TR 38.811 [S]. 2018
[2] GKIZELI M, TAFAZOLLI R, EVANS B. Modeling handover in mobile satellite diversity based systems [C]//The 54th Vehicular Technology Conference. Atlantic City, USA: IEEE, 2001: 131 – 135. DOI: 10.1109/VTC.2001.956570
[3] DEL RE E, FANTACCI R, GIAMBENE G. Handover queuing strategies with dynamic and fixed channel allocation techniques in low Earth orbit mobile satellite systems [J]. IEEE transactions on communications, 1999, 47(1): 89 – 102. DOI: 10.1109/26.747816
[4] DEL RE E, FANTACCI R, GIAMBENE G. Efficient dynamic channel allocation techniques with handover queuing for mobile satellite networks [J]. IEEE journal on selected areas in communications, 1995, 13(2): 397 – 405. DOI: 10.1109/49.345884
[5] WU Z F, JIN F L, LUO J X, et al. A graph-based satellite handover framework for LEO satellite communication networks [J]. IEEE communications letters, 2016, 20(8): 1547 – 1550. DOI: 10.1109/LCOMM.2016.2569099
[6] YAJNANARAYANA V, RYDÉN H, HÉVIZI L. 5G handover using reinforcement learning [C]//IEEE 3rd 5G World Forum (5GWF). Bangalore, India: IEEE. 2020: 349 – 354. DOI: 10.1109/5GWF49715.2020.9221072
[7] CHEN Y, LIN X Q, KHAN T, et al. Efficient drone mobility support using reinforcement learning [C]//IEEE Wireless Communications and Networking Conference (WCNC). Seoul, South Korea: IEEE, 2020: 1 – 6. DOI: 10.1109/WCNC45663.2020.9120595
[8] CHEN M T, ZHANG Y, TENG Y L, et al. Reinforcement learning based signal quality aware handover scheme for LEO satellite communication networks [M]//Human Centered Computing. Cham: Springer International Publishing, 2019: 44 – 55. DOI: 10.1007/978-3-030-37429-7_5
[9] ALKHATEEB A, BELTAGY I, ALEX S. Machine learning for reliable mmwave systems: Blockage prediction and proactive handoff [C]//IEEE Global Conference on Signal and Information Processing (GlobalSIP). Anaheim, USA: IEEE, 2018: 1055 – 1059. DOI: 10.1109/GlobalSIP.2018.8646438
[10] ALJERI N, BOUKERCHE A. An efficient handover trigger scheme for vehicular networks using recurrent neural networks [C]//The 15th ACM International

Symposium on QoS and Security for Wireless and Mobile Networks. New York, USA: ACM. 2019: 85 – 91. DOI: 10.1145/3345837.3355963

[11] 3GPP. Solutions for NR to support non-terrestrial networks (NTN): 3GPP TR 38.821 [S]. 2019

[12] LECUN Y, BOTTOU L, BENGIO Y, et al. Gradient-based learning applied to document recognition [J]. Proceedings of the IEEE, 1998, 86(11): 2278 – 2324. DOI: 10.1109/5.726791

[13] 3GPP. On beam layout definition for NTN system level simulations [EB/OL]. [2021-04-16]. https://www.3gpp.org/DynaReport/TDocExMtg--R1-97--32823.htm

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