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An AI-based optimization of handover strategy in non-terrestrial networks

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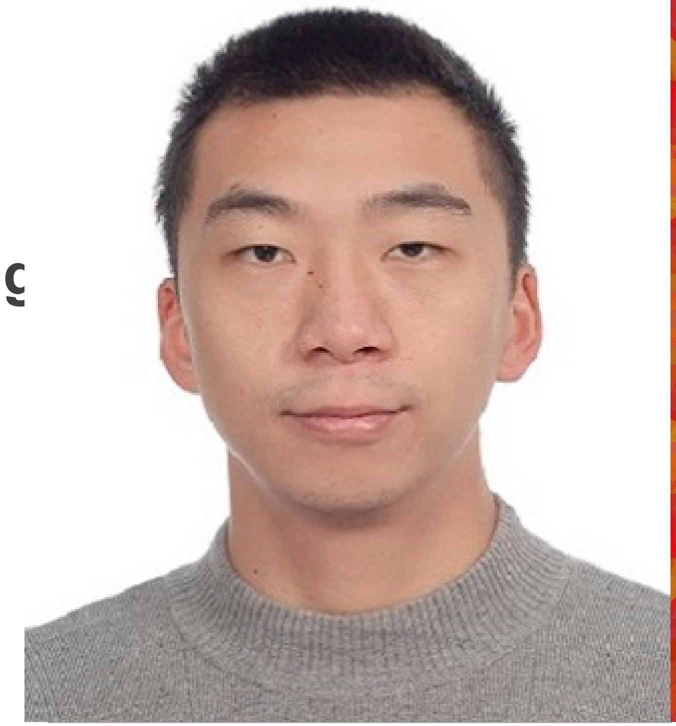
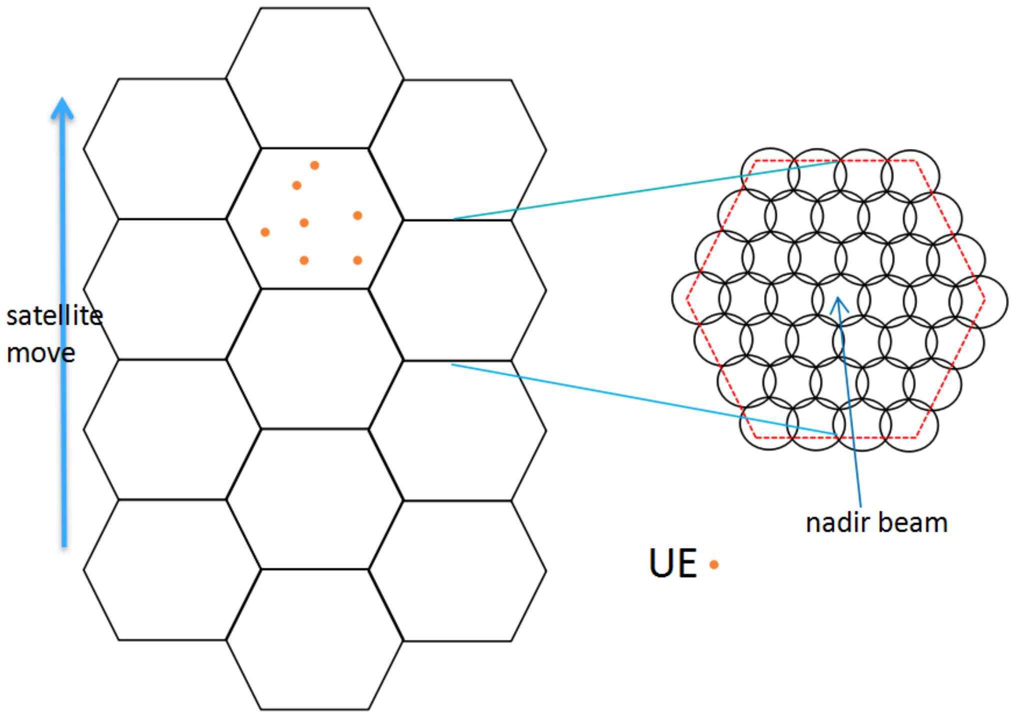
transformation

Paper S7.2



Background

- The low earth orbit satellite has better link budget, but also brings frequent handover.
- A typical diameter of a beam for 600km orbit satellites is 50km, and each satellite has 37 beams[1].
- A stationary UE can be served by one beam for at most 6.6s.

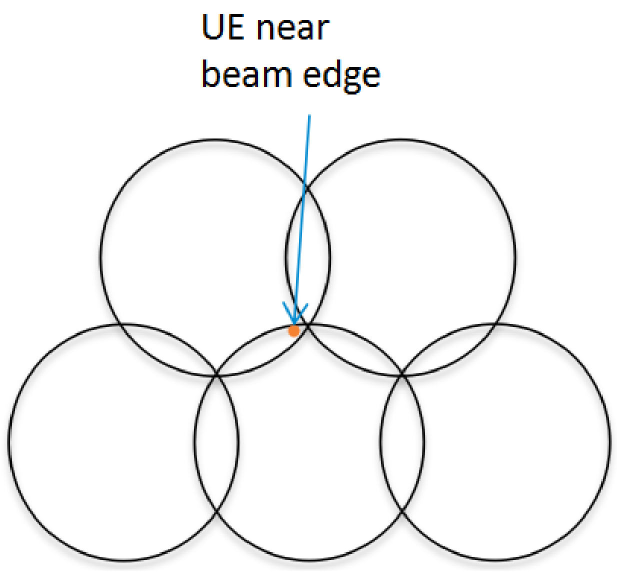


[1]. "Solutions for NR to support non-terrestrial networks (NTN)", 3GPP TR 38.821, Mar. 2019

Motivation

In this scenario, we hope to

- Predict the handover decision to compensate the time lag in satellite links.
- Avoid the handover caused by noise.
- As shown in the right figure, suppress the handover to the beams with short serving time.

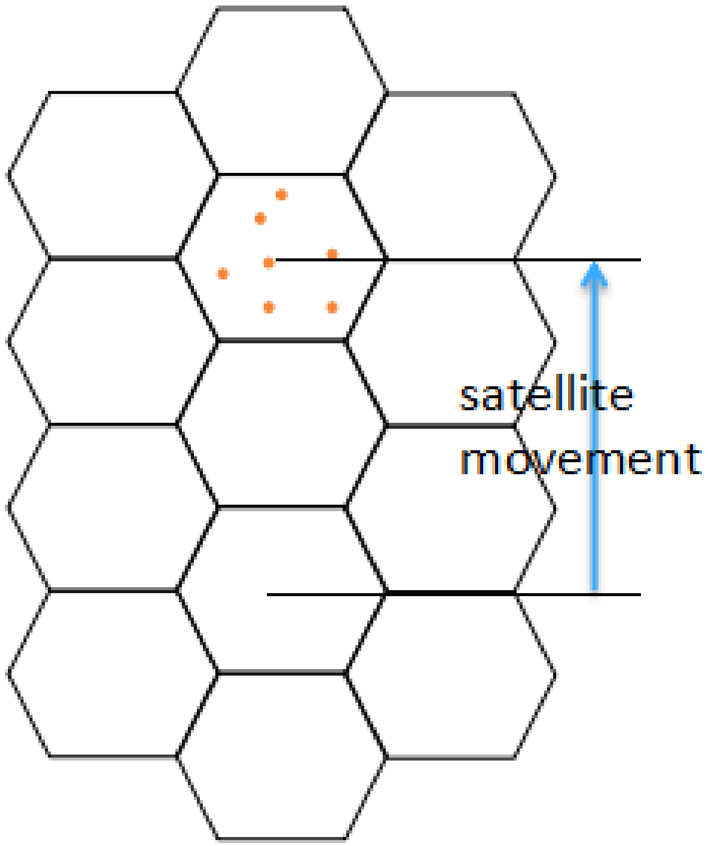


Solution

- Generally, a UE needs to preodically measure the strength of reference signals of different cells to always access a strong cell. It will make handover decision according to signal strength or some other parameters.
- The historical reference signal received power (RSRP) actually contains the information to avoid unncessary handover. For example, the historical RSRP of a cell with short serving time is obviously different with that of a cell with long serving time.
- The hidden rule is difficult to be systematically derived. However, it can be explored by machine learning.
- In this paper, a supervised learning based on convolutional neural network is employed.

Data generation

- Assume in each handover time slot, a UE measures the RSRP of beams, and only choose accessing beam from the K strongest beams.
- In the t-th handover time slot, we has a RSRP matrix of size (numOfBeams, t). Assume only T nearest RSRPs will affect the handover decision. For each UE, a submatrix of size (K, T) is regared as the training sample.
- The movement trace is wrapped by other satellites to generate interference.



Data labeling

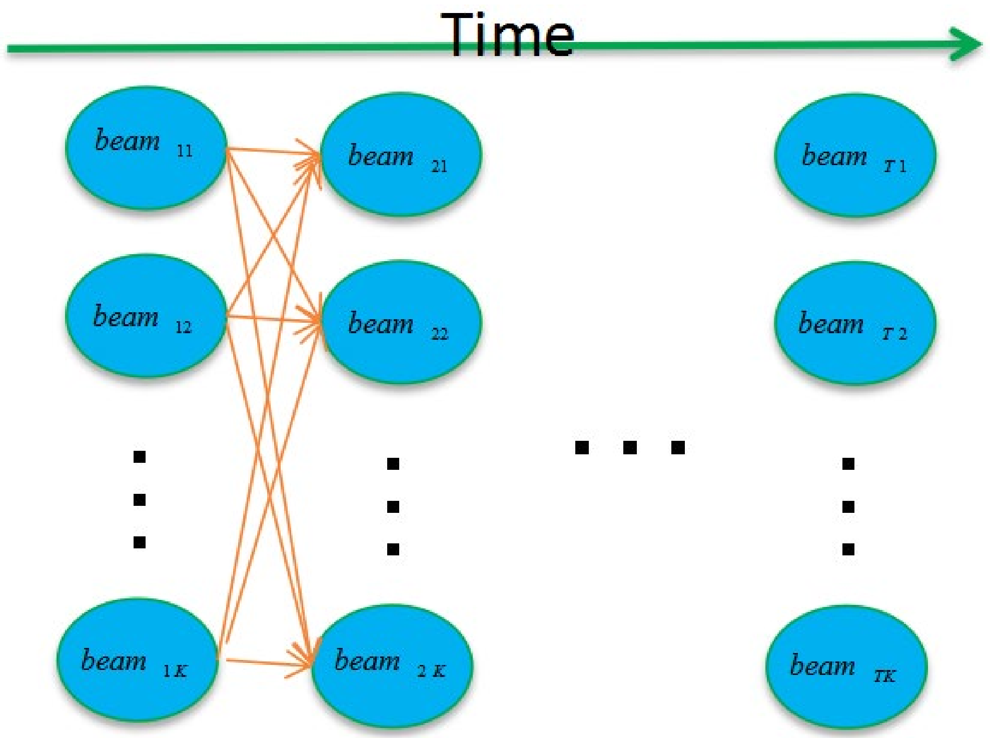
- For each training sample, we need to label it by their corresponding "good" handover decisions.

- For each UE, the handover procedure can be denoted by a directed graph. Each edge has the weight:

$$w1 * RSRP_{t_1 k_1} - w2 * handoverFlag$$

where $handoverFlag$ denotes whether the two ends are the same beam.

- Assume all the $RSRP_{t_1 k_1}$ in the whole process are known, then we can get the best handover strategey by the shortest path algorithm.

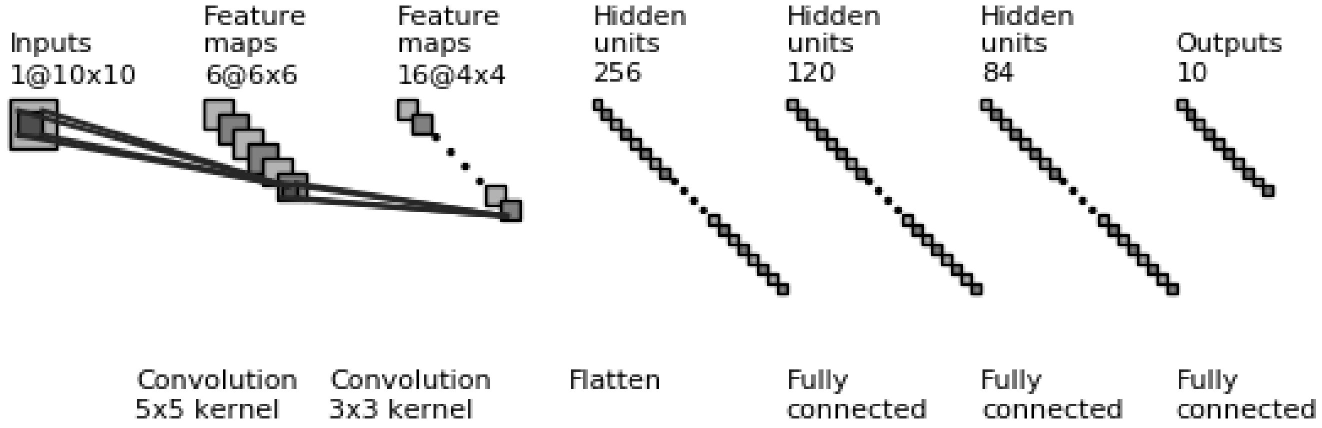


Neural network structure

- With the data labeling, the handover decision is coverted to a classification problem.

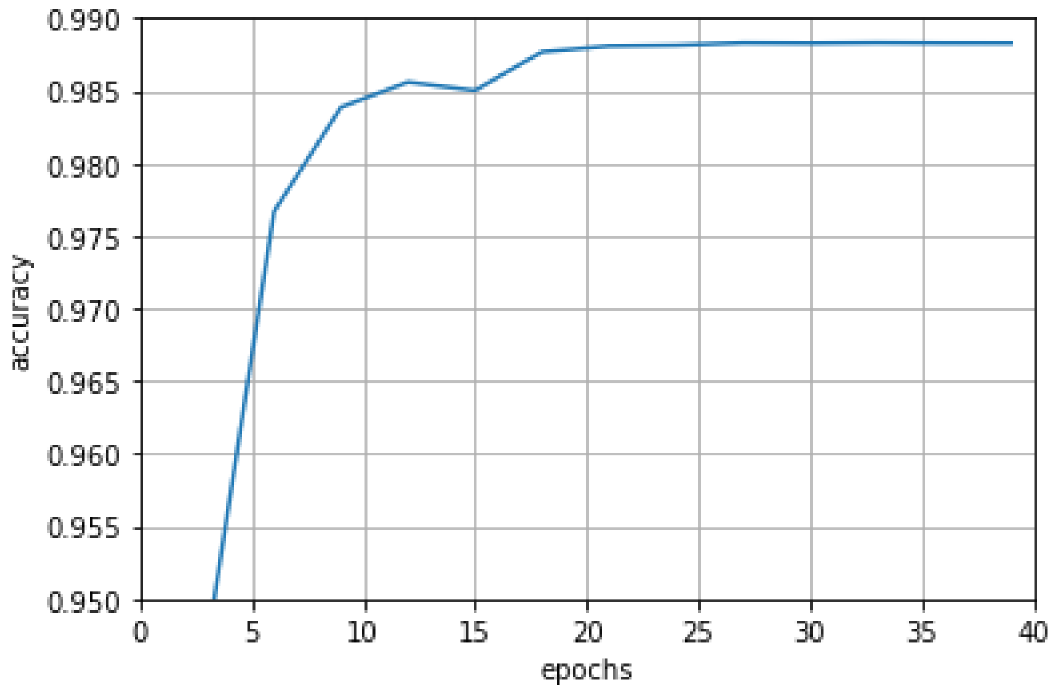
- In RNN, a decision will largely affect the next decision. To avoid a series of wrong decision, we haven't choose RNN/LSTM although the historical RSRP is a time series.

- We choose CNN because
  1. The feature map of historical RSRP has strong local spatial correlation
  2. CNN can save computation comparing with DNN



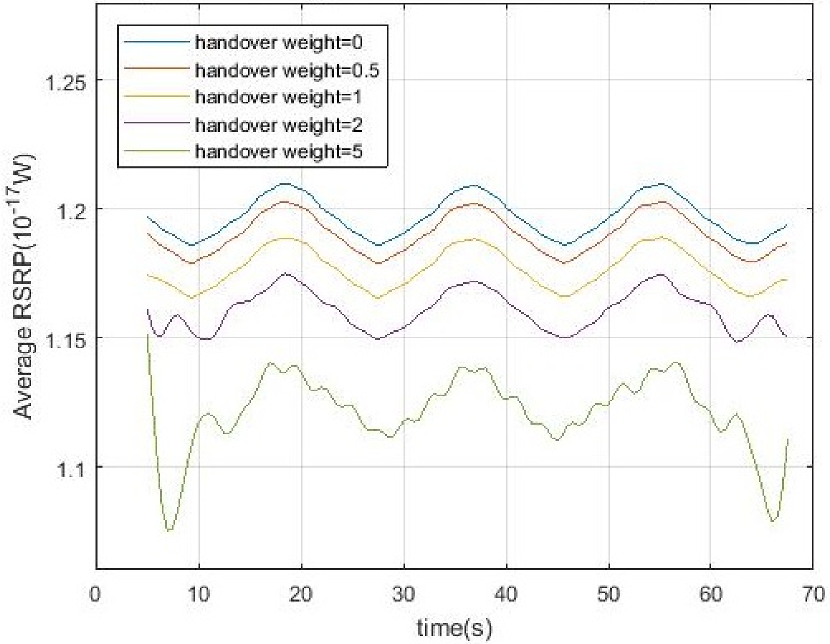
Training settings

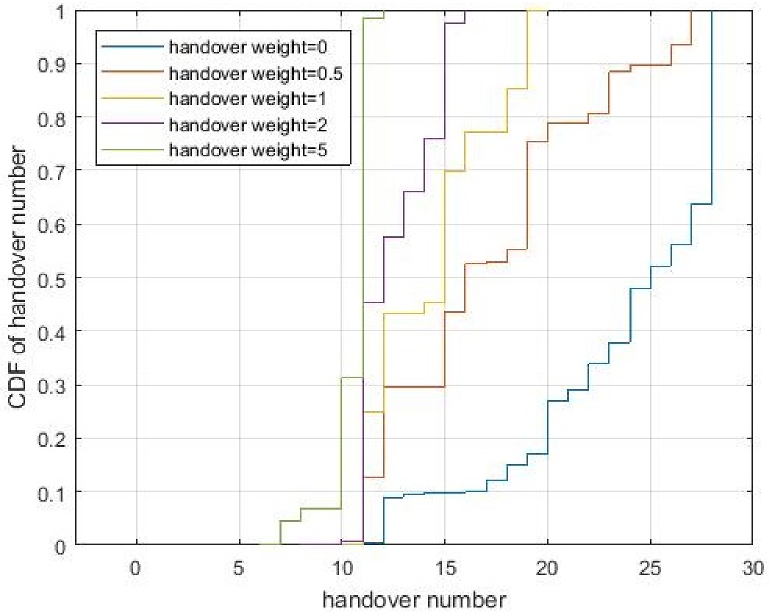
- batch size 100
- 2450000 training samples
- 615000 testing samples
- learning rate 0.001, decay by 10 every 15 epochs
- SGD optimizer
- crossentropyloss



Simulation results

- With the increase of handover weight w_2 , the average handover number will decrease.



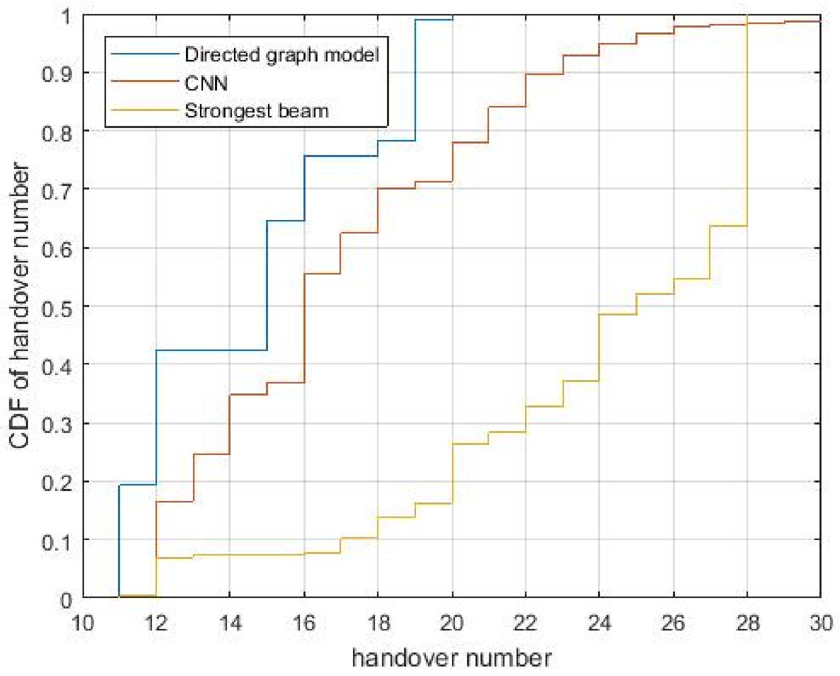


- With the increase of handover weight w_2, the average RSRP will decrease. Actually, the parameter w_2 is a tradeoff between RSRP strength and handover number

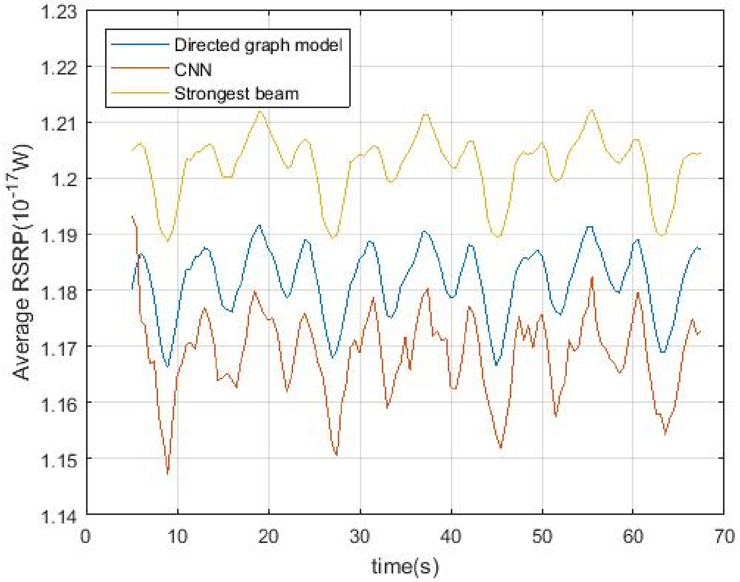
Simulation results

- In the AI-based method, the handover number of more than 70% of the UEs are reduced by more than 1/4.

- The directed graph model can only be used when all the RSRP in future is known.



- Compared with the “strongest beam” method, the average RSRP of AI-based method is only reduced by 3%.



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Thank you!