



LSTM Neural Network Architecture and Hyperparameter Exploration for Handover Simulation in 5G Network

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Abstract—This paper presents a machine learning model for optimizing a handover process in 5G networks. The data for learning and testing is simulated using NS3. By using RNN with LSTM layer, model is enable to decide which cell to handover to provide the highest download success rate. Key of this analysis is exploring the hyperparameter of the model such as hidden nodes, epoch, dropout rate to provide the highest download success rate.

Keywords—handover, RNN, LSTM, hidden nodes, epoch, dropout

I. INTRODUCTION

5G (Fifth Generation) is the fifth-generation technology standard for cellular networks, which began to be deployed worldwide in 2019, succeeding the 4G technology. It is designed to increase speed, reduce latency, and improve flexibility of wireless services. One of the key challenges in applying this technology is the handover process. Handover process occurs when a user equipment (UE) attempts to switch connections from one gNB to another. Near-RT RIC is one of the innovative systems used in 5G technologies. The Radio Access Network (RAN) is responsible for managing wireless communications between devices and the network. One of the methods that can be used to improve the handover process is by using machine learning that is used predict which cell to handover to provide seamless handover in 5G networks.

Recurrent Neural Networks (RNNs), especially with Long Short-Term Memory (LSTM) layers, in processing time series data. RNN is a type of artificial neural network architecture designed specifically to handle sequential or time-ordered data, such as time series data.[7]

The LSTM layers in RNN play a crucial role in addressing the vanishing gradient problem that often arises in conventional recurrent neural networks. LSTM allows the network to "remember" information for a longer period, making it more effective in processing sequential data with long-term dependencies.[7]

II. NEURAL NETWORKS FOR HANDOVER

A. Handover Scenario

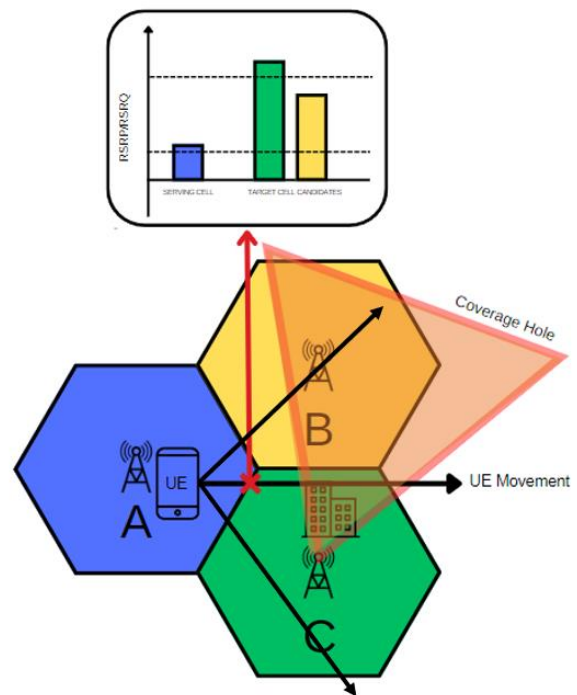


Fig. 1. Handover Scenario

In Figure 1, a mobile device is travelling from Cell A to Cell C. If the assumption is that traditional handover choose the one that has the highest number of RSRP and RSRQ, it will choose Cell C as handover target cell. Since the UE can't detect if there's a coverage hole ahead, the UE will be disconnected for a while. Sometimes in a non ideal network, relying solely on RSRP and RSRQ is not reliable because of the real condition of the network simetime cannot be represented by RSRP and RSRQ only. For example, if there is a coverage hole.

B. Open RAN Infrastructure

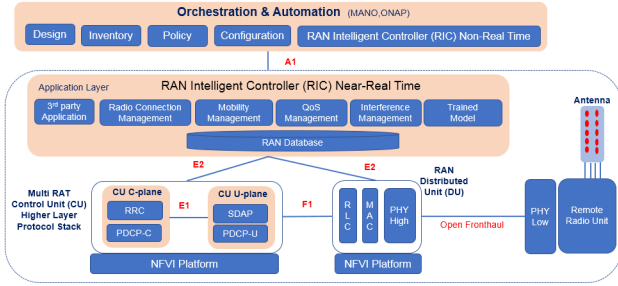


Fig. 2. Open RAN Architecture[2]

Open RAN adopts a system called cloudification [3], where all devices or units within Open RAN are stored in a cloud infrastructure. Open RAN introduces a new system called RAN Intelligent Controller (RIC), which is further divided into NonRealtime RIC and Near Realtime RIC. The NonRealtime RIC is used for processes that do not require real-time capabilities, such as MANO (Management and Orchestration). On the other hand, the Near Realtime RIC is utilized for processes that require near real-time capabilities, including the handover process [2]. Hence, the neural networks for the handover process in 5G networks can be implemented in the Near Realtime RIC system.

Neural Networks are a computational approach used to enable a computer program to learn and improve itself based on data. It is inspired by the functioning of the human brain. Initially, a collection of software "neurons" is formed and interconnected, allowing them to communicate with each other. The system is then tasked with solving a problem, which is repeated iteratively, reinforcing connections that lead to success and weakening connections that may result in failure [4]. The success of using Machine Learning (ML) for automation in cellular networks has driven its adoption in 5G technology [5][6], as machine learning offers a cost-effective solution to achieve the required adaptability.

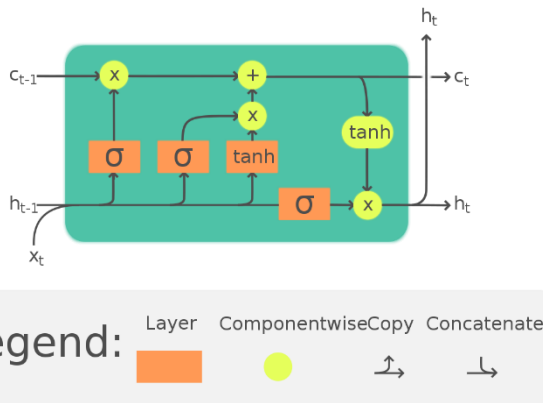


Fig. 3. Long Short-Term Memory Neural Network[1]

A Long Short-Term Memory (LSTM) network is a type of recurrent neural network (RNN) designed to address the vanishing gradient problem, which is a common issue with traditional RNNs. LSTMs are capable of learning long-term dependencies in sequential data, making them well-suited for tasks such as language translation, speech recognition, and time series forecasting.[1]

III. SIMULATION

This simulation is based on Figure 1 scenario, which will be simulated by NS3 as the source of data that will be used as training data as well as the testing data.

A. Datasets

The dataset is made using the NS3 application. Dataset is generated using the script from zoraze. There will be 2 sets of data, training data and testing data.

Training data is got by forcing the UE to handover to cell B and C. There are 100 forced handover data for each cell. The data collected is RSRP and RSRQ data which are measured in dB. Each of the data also has the download success parameter. UE will be moved to a straight line with a random release angle.

Testing data is 1000 times running the algorithm based on Figure 1. Scenario. In this simulation, UE will be moving within a straight line with a random angle. Data collected is RSRP, RSRQ, target cell, and download success parameter. The handover in the testing data use the traditional algorithm which measure by the strength of RSRP and RSRQ. This data will be the reference for Traditional Handover Download Success Rate which is 86% in this scenario.

B. Neural Network Architecture

This Neural network architecture is using RNN and expected to outperform the traditional handover methods which is 86% download success rate.

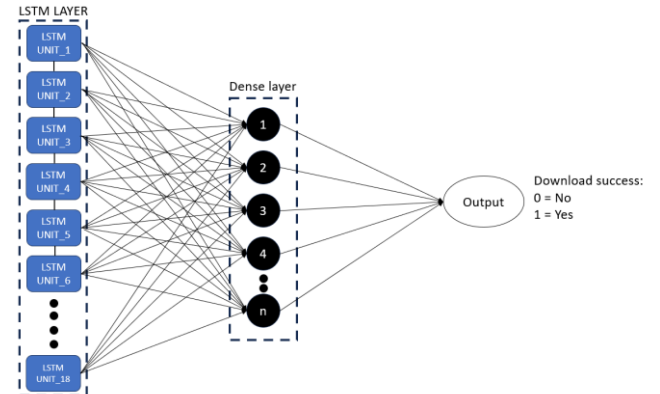


Fig. 4. Neural Network Architecture

This neural network architecture has an input of time series data. The data has 6 features and 30 timesteps as an input to each LSTM unit. The output from LSTM layer goes to dropout layer with the dropout amount will be tested from 0.1 to 0.5. The output from that dropout layer will go to the Dense Layer which consist of n number of nodes with relu function as connector. The output from that dense layer will go to the output layer and will predict if download is successful or no. There's 2 identical model for each input data, the one that's forced to handover to cell B and forced to handover to cell C.

C. Hyperparameter Exploration

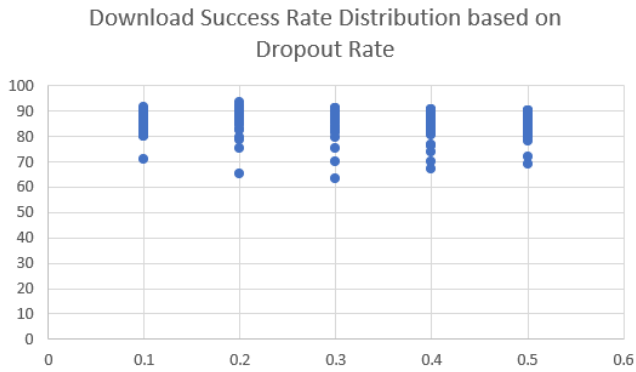


Fig. 5. Download Success Rate Distribution based on Dropout Rate

Dropout in the context of Long Short-Term Memory (LSTM) networks is a regularization technique used to prevent overfitting. It probabilistically excludes input and recurrent connections to LSTM units from activation and weight updates. In this model, dropout rate of 0.2 has the highest average download success rate which is 87.61%.

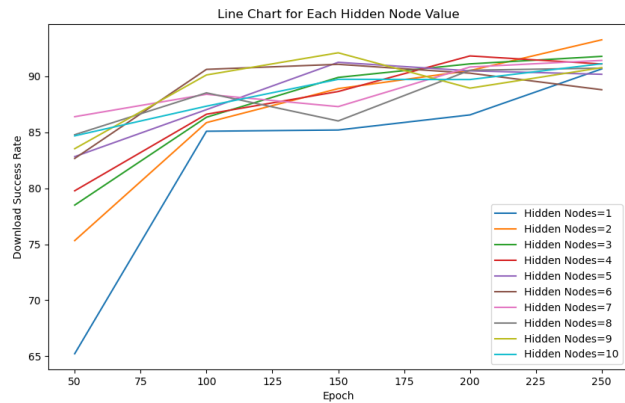


Fig. 6. Line Chart for Each Hidden Nodes Value

From the provided data, it can be observed that there is an increase in the download success rate after epoch 50. Beyond this point, the download success rate values need to be adjusted based on the number of hidden nodes. It is evident that the highest value occurs when the number of hidden nodes is 2 and the epoch is 250 which is 93.4% download success rate. There's not much correlation between it, because RNN is bi-directional machine learning so the LSTM layer it self already do most of the learning process.

Model: "sequential"

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 18)	1800
dropout (Dropout)	(None, 18)	0
dense (Dense)	(None, 2)	38
dense_1 (Dense)	(None, 1)	3

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 Total params: 1841 (7.19 KB)
 Trainable params: 1841 (7.19 KB)
 Non-trainable params: 0 (0.00 Byte)

Model: "sequential_1"

Layer (type)	Output Shape	Param #
lstm_1 (LSTM)	(None, 18)	1800
dropout_1 (Dropout)	(None, 18)	0
dense_2 (Dense)	(None, 2)	38
dense_3 (Dense)	(None, 1)	3

=====
 Total params: 1841 (7.19 KB)
 Trainable params: 1841 (7.19 KB)
 Non-trainable params: 0 (0.00 Byte)

Fig. 7. Neural Network Model Summary

Based on the parameter chosen, modelC2 and modelC3 have a total of 1841 parameters can be trained with 4 layers in each model.

Based on all the iterations conducted, the highest download success rate is observed when the number of hidden nodes is 2, epoch is 250, and dropout is 0.2 which is 93.4% download success rate.

IV. CONCLUSION

In this research, an optimization was conducted for a simulated handover process. The handover process was simulated using the NS3 application with a scenario as depicted in Figure 1. Using traditional handover algorithms, a download success rate of 86% was obtained. The author performed optimization of the download success rate during handover using a Recurrent Neural Network algorithm with LSTM layers. An exploration of hyperparameters, namely hidden nodes, epoch, and dropout rate, was carried out in the process.

Based on all the iterations conducted, the highest download success rate is observed when the number of hidden nodes is 2, epoch is 250, and dropout is 0.2 which is 93.4% download success rate. There's not much correlation between it, because RNN is bi-directional machine learning so the LSTM layer it self already do most of the learning process.

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