

Neural Network-aided Cell Selection and Handover in Cellular Networks with Carrier Aggregation

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Abstract—Carrier aggregation is one of the most important technologies for increasing data rates in current and future cellular network systems such as 5G and 6G. It combines multiple frequency channels, possibly from different bands such as bands under 6GHz and millimeter-wave bands, to send traffic between a base station and a user device at a faster speed. With carrier aggregation, a user device is simultaneously connected to multiple cells, one of them being the primary cell and the others being secondary cells. In environments where carrier aggregation is extensively used, the cell selection algorithm must take into account the performance of all potentially aggregated cells when selecting the best cell for a user device. However, the current cell selection method only considers the signal quality of primary cells, which may lead to sub-optimal performance when carrier aggregation is used. Modifying the cell selection algorithm to consider both primary and secondary cells may seem trivial, but faces new challenges such as increased measurement cost and delay. We present a simple and practical scheme for cell selection in carrier aggregation environments. First, the proposed scheme introduces new measurement configurations and events that can implement a cell group-based handover considering the combined performance of aggregated cells. Second, to reduce delay and overhead caused by measurements, we make use of neural networks that are trained to estimate the signal quality of neighbor cells at approximate user locations. Simulation results show that the proposed scheme achieves significant performance benefits over legacy methods, especially in dense network environments.

Index Terms—cellular networks, carrier aggregation, cell selection, handover, neural networks

I. INTRODUCTION

MOBILE communication systems strive to support high transmission rates to meet the ever-increasing user demand. As shown in the Shannon capacity theorem, providing high transmission rates requires a high signal-to-noise ratio (SINR) and large channel bandwidths. High SINR can be achieved by densely deploying cells and using antenna techniques such as beamforming. A large channel bandwidth can be allocated by using a single wide channel in the high-frequency band or combining multiple channels through carrier aggregation (CA) [1]. Future cellular systems will increasingly utilize these techniques to improve quality of service and support new applications.

This paper considers cell selection methods in this new environment where users see a high density of cells operating in various frequency channels and bandwidths combined using carrier aggregation. We do not assume a specific use of antenna configuration and techniques and assume that it is reflected in the shape and size of the cells. In this environment, the current standard cell selection method may incur high costs and lead the user equipment to a sub-optimal channel in terms of transmission rates. First, with CA, a user equipment (UE) simultaneously connects to multiple cells operated by the same base station. Among multiple cells, there is a primary cell that handles control signaling (as well as data transmission), and multiple secondary cells that supplement the capacity of the primary cell. Therefore, the cell selection method should choose a cell group consisting of primary and secondary cells, rather than a single cell. However, the legacy cell selection method only considers the signal quality of the primary cell. Second, with a large number of potential cell combinations in the vicinity, a UE must perform an increased number of measurements to choose the best cell. Since UE needs time to measure the reference signal of a cell, a large number of measurements would cause a high delay. Also, to measure cells operating in a channel different from the current primary cell, the UE has to temporarily switch to other channels, sacrificing the time used for data communication. Thus, an efficient technique is needed to select the best cell while minimizing the number of measurements. We propose a simple and practical cell selection method where cell selection is based on the estimated throughput of the cell group considering carrier aggregation. Measurement cost and delay are dramatically reduced by using neural networks trained to estimate inter-frequency cell measurements at their locations.

Since carrier aggregation was introduced, the need for cell-group-based cell selection was discussed. For example, a method was proposed that uses the multiplication of SINRs of all cells in a base station as a metric for cell selection [2]. More recently, Li et al. [3] identified, through real-world measurements, that UEs often choose sub-optimal base stations because they only consider the signal quality of primary cells. As a remedy, the authors tuned the handover parameters for each cell so that more UEs can select the base station where it can achieve the highest throughput. Later, Li et al. [4] proposed

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a cell-group-based handover method where a UE measures all cells that belong to neighbor base stations and chooses a target base station based on metrics such as aggregated bandwidth. Their focus was on reducing the measurement cost and delay, now that UEs need to measure primary cells as well as secondary cells. Their solution was to measure one of the cells that belong to a base station and estimate the signal quality of other cells that belong to the same base station, considering their difference in central frequency. However, the estimation could be inaccurate if the cells use remote radio heads and thus are located in different locations. In this paper, we propose to use neural networks which learn from historical measurements to predict neighbor cell signal qualities, for reducing measurement costs. By utilizing neural networks, a UE can find out when to measure which cells, and quickly handover to the best cell at its location. Also, we define new measurement configurations and measurement events that can be added to the current 3GPP standard, which can be used to associate UEs with the base station where they can receive the highest throughput through carrier aggregation.

II. SYSTEM MODEL

We consider a dense cellular network with multiple cells operated by each base station. Although controlled by the same base station, the cells can be placed at different locations using remote radio heads (RRHs). For example, as shown in Fig. 1, the base station BS operates three cells, one at the cell tower and two using RRHs. Cell 1 uses a sub-6GHz channel, while the other cells use millimeter-wave channels to provide high throughput to hot-spot users. The UE can have cell 1 as its primary cell and cell 2 as the secondary cell.

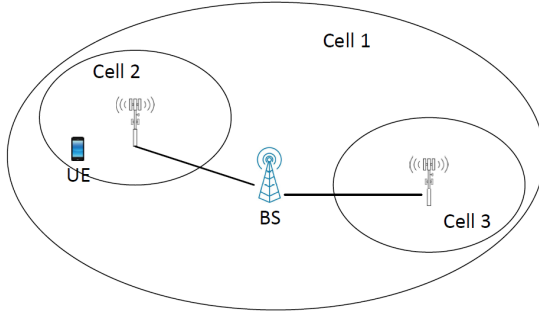


Fig. 1: An example scenario where a base station operates multiple cells with different frequency channels.

The system always tries to connect UEs to the “best” cell, through a cell re-selection process in the idle mode or handover in the connected mode. The best cell is determined based on UE measurements where a UE listens to reference signals sent by the cells, measures their signal quality, and reports the results to its serving cell. Instructions on when to measure which cells and what to report are given by the base station through measurement configurations.

UE measurements can be divided into intra-frequency measurements and inter-frequency measurements. If a neighbor

cell operates on the same frequency channel as the serving cell, the UE can measure its signal quality without switching channels. However, to measure a neighbor cell operating on a different channel, a UE needs to tune its receiver to the target channel, listen to the reference signal, and switch back to its original channel. Thus, the base station configures measurement gaps for inter-frequency measurements, where no traffic is scheduled for the UE.

Since inter-frequency measurements and measurement reporting need costs, they are controlled to be done only when necessary, through measurement events shown in Table I. For example, a UE can be configured to perform inter-frequency measurements only when the serving cell signal quality is below a certain threshold (A1, A2 event). Also, measurement reports are sent only when the signal quality of a neighbor cell is better than the serving cell by a certain offset (A3 event).

Event	Condition
A1	Serving becomes better than threshold
A2	Serving becomes worse than threshold
A3	Neighbor becomes offset better than Serving

TABLE I: Measurement events (partial)

The measurement event parameters affect performance and thus need to be carefully tuned. For example, a low A2 threshold means the UE will do inter-frequency measurements only when it needs to change cells. On the other hand, a high A2 threshold means the UE will do inter-frequency measurements even when its serving cell connection is stable. The parameter controls the trade-off between measurement cost and the chance of finding a better cell. In dense environments with carrier aggregation, a UE may benefit from choosing another base station even when the current connection is stable, because the aggregated cell throughput may be higher in the other base station. However, to find better cells, a large number of measurements need to be conducted to check all the potential target cells in the vicinity of the UE. Thus, we need to answer the following two questions: (1) How can we find the best cell group for UEs considering carrier aggregation? (2) How can we reduce inter-frequency measurement costs and delay? Our method seeks answers to these questions.

III. PROPOSED METHOD

A. CA-aware handover

In current measurement procedures, a UE measures and reports each cell independently, regardless of whether or not they belong to the same base station. For CA-aware handover, new measurement objects and events should be defined. A measurement object defines entities on which a UE performs measurements such as frequency, reference signal, and black-listed/whitelisted cells. We define a new measurement object that can indicate a cell group such as in Table II.

Also, new measurement events that are triggered when a condition is satisfied for a target cell group must be defined. We define a new measurement event that considers the total

Cell	PCID	ARFCN (Freq)	Bandwidth	Numerology
1	196	514000 (2.3GHz)	20	2
2	162	2079166 (28GHz)	200	2

TABLE II: Measurement object indicating cell group

transmission rate of cells in the group. The event is shown in Table III, and the quantity measured for the cell group is the transmission rate, in units of Mbps.

Event	Condition
AX	Target group becomes offset better than Serving group

TABLE III: New measurement event

The transmission rate of a cell can be estimated from measured SINR and cell information such as bandwidth and numerology. For example, an effective SINR is calculated from measured SINR using the exponential effective SINR mapping (EESM) technique [5], and mapped to block error rate (BLER) considering the number of resource blocks calculated from bandwidth and numerology. Then, a modulation and coding scheme (MCS) is selected which satisfies a target BLER. The transmission rate can be estimated from MCS and the number of resource blocks that can be scheduled for the UE. It is important to note that the cell load is another important factor in estimating the transmission rate provided to a UE. There are several indicators of cell load such as the number of active UEs in the cell, but accurately estimating cell load is a challenging problem [6]. Load estimation and balancing are considered as a separate function in this paper and are left for future work.

For example, a UE can be configured to report when the AX event with offset 50Mbps is triggered for target cell groups. When the event is triggered and the base station receives the measurement report, it starts the handover procedure and moves the UE to the target base station.

B. Neural network-aided cell selection

For CA-aware handover, UEs need to measure primary and secondary cells in the neighborhood, which leads to an increase in measurement costs. To measure inter-frequency channels, measurement gap repetition period (MGRP) and measurement gap length (MGL) are configured. In every MGRP, a UE tunes to the target channel during MGL and listens to the synchronization signals of the cell. Since a UE can listen to a single channel in an MGL, multiple MGRPs are needed to cover all inter-frequency cells in the vicinity of the UE. Thus, high measurement cost includes performance loss from measurement gaps and measurement delay. Li et al. [4] proposed to reduce this cost by measuring one cell and estimating the signal quality of other cells sharing the same cell tower. Here, we propose to use neural networks to reduce the measurement cost and delay. Specifically, we train neural networks that take intra-frequency cell measurements as input and predict the signal quality of inter-frequency cells.

A base station maintains a neural network model for each cell it operates. The input to the neural network is the

signal quality of the cell itself and intra-frequency cells in the neighborhood. The output of the network is the signal quality of inter-frequency cells in the neighborhood. The intra-frequency and inter-frequency cells used in a neural network are selected by the operator when a cell is deployed. An example is shown in Fig. 2. The neural network at cell C1 takes intra-frequency cell metrics such as RSRP, RSRQ, or SINR as input, and predicts the inter-frequency cell metrics. The intra-frequency cell metrics represent the current UE state, which is an approximation of UE location.

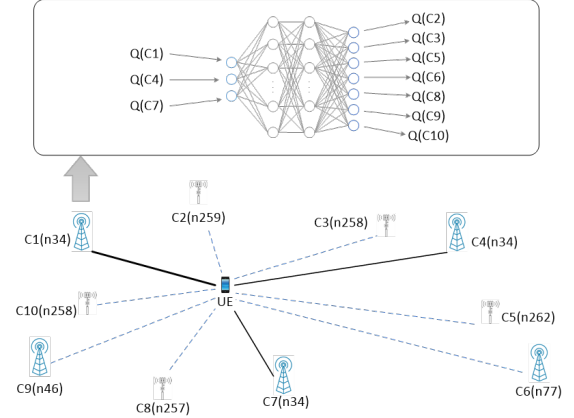
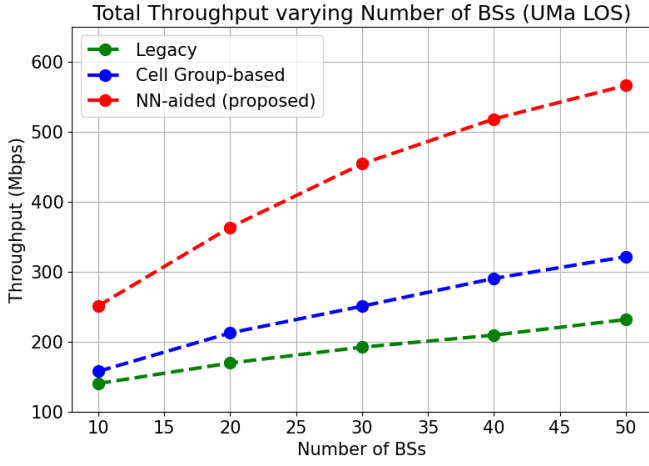


Fig. 2: A base station maintains a neural network for each cell which takes intra-frequency measurements as inputs and outputs predicted signal quality of inter-frequency cells.

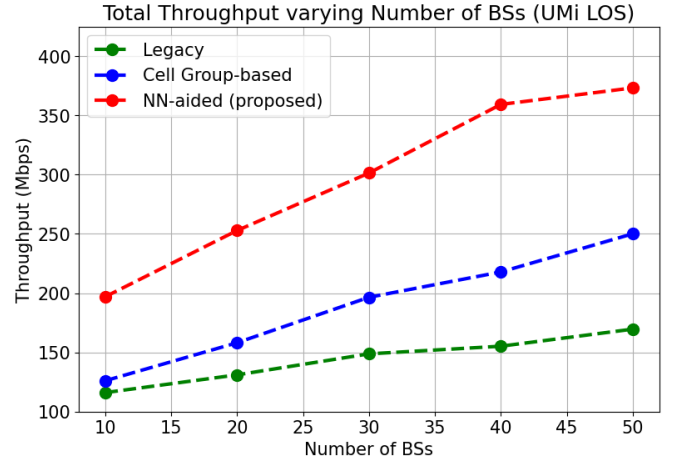
A neural network can be trained through offline walk or drive test before service, and further updated in service through UE measurements. For online measurements, the UEs include intra-frequency measurements when reporting inter-frequency measurements. The base station collects measurement reports and updates the neural network using the MSE loss as in Eq. 1, where y is the inter-frequency cell metric, $\hat{y}$ is the predicted value, and N is the number of samples in the batch.

$$L = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (1)$$

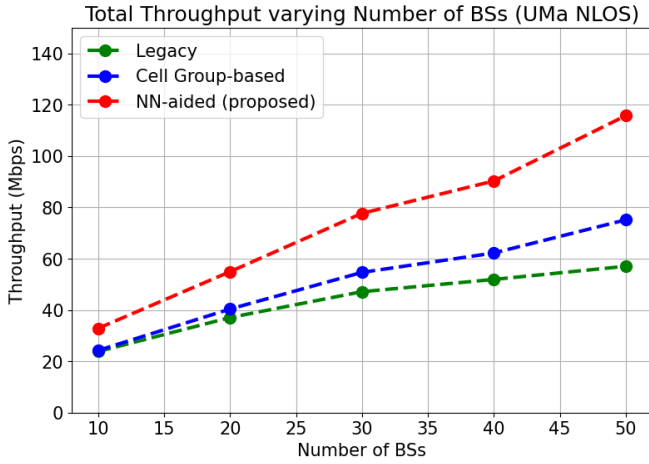
Since UE needs to know when to send measurement reports, the base station sends the neural network to the UE as a part of measurement configurations. Instead of performing inter-frequency measurements, the UE can use the neural network to predict the cell metrics in its current location. Note that the UE can be configured to use both the neural network and actual measurements for better accuracy. In this case, the measurement gap repetition period can be set longer to reduce throughput loss, and the UE can measure first the cells that are predicted by the neural network to provide the best performance.



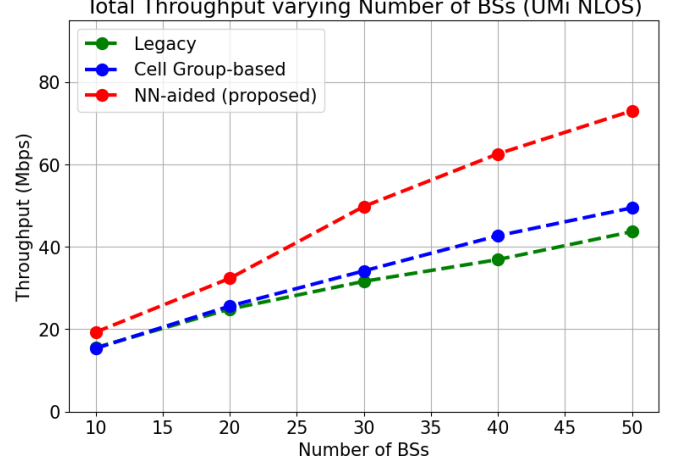
(a) UMa LOS



(b) UMi LOS



(c) UMa NLOS



(d) UMi NLOS

Fig. 3: Throughput varying number of base stations for environments described in 3GPP TR 38.901 [7]

IV. PERFORMANCE EVALUATION

A. Simulation Setup

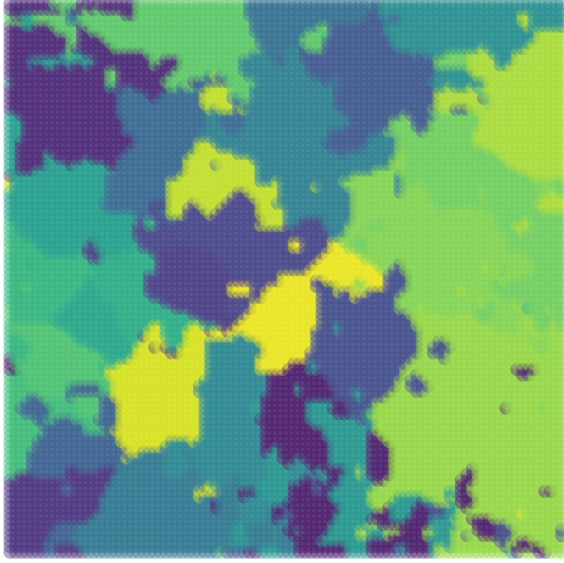
The performance of the proposed method was evaluated using a simulator written in python¹. Then channel model implements Urban Macro (UMa) and Urban Micro (UMi) environments with line-of-sight (LOS) and non-line-of-sight (NLOS) conditions, described in the 3GPP standard [7]. Base stations are randomly deployed within the 1km² simulation area. Each base station operates two cells, one in the sub-6GHz band (FR1) and one in the millimeter wave band (FR2). For each band, the frequency channel is randomly selected from 5 channels. The channel bandwidth is 20MHz for a FR1 channel, and 200MHz for a FR2 channel. We assume that all cells use TDD frame structure with numerology 2, with 60kHz subcarrier spacing, 16.7 μ s symbol duration, and 0.25ms slot length. This numerology is used for both FR1 and FR2 band.

A UE is initially positioned in a random location and moves with a speed of 30m/s according to a random waypoint mo-

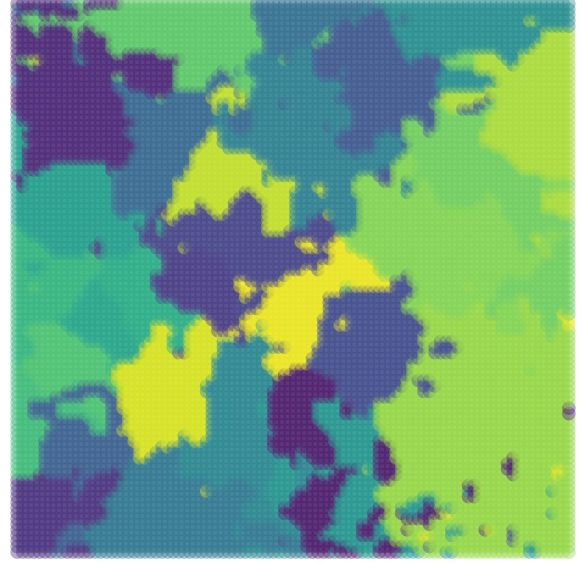
bility model. At the beginning of simulation, the UE connects to a cell with the best signal quality. Once connected, the UE always downloads traffic from its serving cell. For inter-frequency measurements, a 6ms gap (MGL) is used in every 40ms period (MGRP). The handover interruption time is 50ms.

We have compared three different methods. The “Legacy” method selects cells based on the signal quality of the primary cell, which is an FR1 cell. Once a primary cell is chosen, the secondary FR2 cell is added to the UE for throughput boost. Measurement gaps are configured for the FR1 cells only, and one inter-frequency channel is measured from the set of channels. For the handover condition, we use the A3 event with 3dB offset. The “Cell Group-based” method selects cells based on the estimated throughput of cell groups. Measurement gaps are configured for FR1 and FR2 cells. The handover condition is the AX event with 30Mbps offset. Finally, the “NN-aided” method is the proposed method which uses the neural network instead of inter-frequency measurements. The neural networks are trained with a total of 10,000 measurement samples at offline. Thus, if there are 20 cells, each cell is updated with an

¹<https://github.com/GaHyeK/5gSim>



(a) actual best BS



(b) predicted best BS

Fig. 4: Actual and predicted best BSs at the UE locations

average of 500 measurement samples. The handover condition is the same as the Cell Group-based method.

B. Results

Fig. 3 shows the average throughput of UE while moving within the simulation area for 1 minute. We have varied the number of base stations from 10 to 50. Each point in the graph is a result of 35 runs with different BS locations and UE movement paths. Simulations were conducted in four different environments: (a) UMa LOS, (b) UMi LOS, (c) UMa NLOS, and (d) UMi NLOS. As shown in the graphs, the proposed NN-aided cell selection method achieves significantly higher throughput compared to other methods. For example, the NN-aided method achieves 80% higher throughput compared to the Legacy method and 60% compared to the Cell group-based method, with 10 BSs in the UMa LOS environment. When the density of cells is higher, the NN-aided methods benefit more than other methods, achieving 140% and 75% over Legacy and Cell Group-based methods with 50 BSs, respectively. Similar patterns can be seen in other environments as well. The Cell Group-based method improves the UE throughput by selecting target BSs that could offer the best transmission rate through carrier aggregation. However, the benefit is reduced by increased measurement costs. Also, since the inter-frequency measurements are done sequentially for each channel, the UE can select a sub-optimal BS, while a better choice of BS exists operating on channels not measured yet. On the other hand, the UE can select the best target BS without delay in the NN-aided method, through the use of neural network models.

The performance of the NN-aided method depends on the prediction accuracy of neural network models. The intra-

frequency measurements may not reflect the actual position of UE due to shadowing and multipath fading effects. In Fig. 4, we have visualized the actual and predicted best BSs at each location of the simulation area with 30 BSs. The prediction accuracy in this case is 89.1%. In our simulations with 10 to 50 BSs, the prediction accuracy of neural networks was 75% to 90% for most cases. This level of accuracy was enough to achieve gains over other methods as shown in Fig. 3.

V. CONCLUSION

In this paper, we have proposed a neural network-aided cell selection method for mobile communication networks with carrier aggregation. The method involves new measurement configurations and events to select BSs that can offer the best transmission rate, as well as the use of neural networks to reduce measurement costs and quickly move to the best BS. The simulation results show that the proposed method can achieve significantly higher throughput over the legacy cell selection method, especially with high network density.

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