Optimal eNodeB Estimation for 5G Intra-Macrocell Handover Management

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ABSTRACT

In next generation 5G intra-macrocell deployment due to the high number of small cells existing in the network, one of the main concerns is the increased handover rate, followed by frequent, unnecessary and ping-pong handover challenges. That can also lead to high packet loss, dropped and blocked calls. Moreover, in 5G intra-macrocell deployments, due to the control and data channel separation handover operation must be executed in two tiers (both data and control channels). For these reasons, handover management in this specific 5G deployment becomes a challenging issue. We believe that,having an optimal and accurate eNodeB estimation, handover overhead in these deployments can be dramatically decreased. In this paper, we propose an optimal eNodeB selection mechanism for 5G intra-macrocell handovers based on spatio-temporal estimations. In this approach, Kriging Interpolator with Semivariogram Analysis is supported by the Autoregressive model for selecting the optimal eNodeB before the connection setup. The stochastic and statistical behaviors of Kriging Interpolation provide better modeling performance. These operations are performed by the proposed EnodeB Estimation Entity. Also, these estimations are applied to both the data and control channels independently. As a result of the proposed management scheme, unnecessary, frequent and ping-pong handover rates are decreased by %35, %37 and %17 respectively compared to the traditional handover method.

Keywords

5G; Intra-macrocell Handover; Kriging; Spatial Estimation; Temporal Estimation

1. INTRODUCTION

In the next generation 5G networks, a huge number of connected devices will generate massive amounts of data. According to Cisco's index report results, in 2020, there will be roughly 11.6 billion of mobile connected devices and mobile data traffic will reach 30.6 exabytes per month [1]. Therefore, network capacity must be remarkably increased to satisfy these high data rates and meet excessive demands of the users without reducing the service quality. Small-cells can be used as a solution to solve this capacity crunch in addition to the macrocell deployments. Moreover, in 5G technology, macrocells are used in the control plane for handling control channel traffic while a high number of the small cell are used in the data plane to operate massive amount of data channel traffic.

The existence of a large number of small cells in 5G intra-macrocell deployments enables high data rates and capacity, but on the other hand, they have posed some challenges from different aspects. The first challenge is the unnecessary and frequent handovers causing packet losses, dropped and blocked calls in high rates. Additionally, if these frequent handovers are executed between the target and serving cells continuously, then Ping-Pong handover problem occurs. Also, according to [2], these problems will accumulate with increasing number of deployed small cells. More specifically, executed handovers between the high number of small cells in the range of the same macrocell are called as the intra-macrocell handovers and the small cell selection is the more challenging issue in this special deployment. The second challenge is associated with the separated control and data planes architecture of the specific 5G deployment. Accordingly, control and data channels are connected to the macrocells and small cells, respectively. Thus, handover operation is executed for both channels in the two tiers. For these reasons, handover management becomes a problematic issue in this specific 5G deployment.

In the literature, there have been many handover algorithms proposed for optimizing the handover process by using different approaches. In [3], mobility management algorithm for 5G Technology was presented in the proposed Functionality as a Service platform and shown to decrease package loss percentage of 5G networks. In [4], handover approach was proposed for control/data channel separated architecture to handle mobility in 5G networks. Accordingly, user mobility and eNodeB location are modeled with random waypoint model and Poisson point process, respectively. On the other hand, in these works, the channel separation of the 5G architecture was not considered and only one channel is

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used promisingly. Moreover, the authors in [5], [6] and [7] respectively present an energy efficient handover approach, fuzzy-logic based handover decision algorithm and handover decision function, yet without considering Ping-Pong handover effect of the proposed methods. Handover mechanism presented in the survey [8] can decrease the number of Ping-Pong handover, however, fixed weights used in the algorithm are not suitable for changeable system requirements. Unnecessary handover probability which is one of the most important performances indicator are not taken into account in the cost based handover decision mechanisms presented in [9] and [10]. Also, in [11], estimation method similar to our proposed method is used to solve the problems of femtocell deployments. But, this work only focuses on the location estimation and accordingly, the variation of the attributes in timescale is not observed. Thus, selected femtocell cannot be the best choice for the user. So, this situation leads the growth in the handover number. In addition to the above works, handover mechanisms presented in [12], [13] and [14] decrease the Ping-Pong handover number by using reference signal received power, signal to interference noise ratio and reference signal received quality values. But, because of the rapidly changeable characteristic of the signal level, these works do not solve the mentioned challenges accurately.

All of the above works do not enable an accurate solution for the mentioned handover problems. However, we believe that these problems can be decreased by selecting an optimal eNodeB with correct estimation algorithm. Therefore, in this paper, we propose an optimal eNodeB selection approach for 5G intra-macrocell handovers by using spatio-temporal estimations. Details of this approach and our contributions can be explained as follows:

- For the optimal eNodeB selection, call drop rate, call block rate, packet loss rate, ping-pong, frequent and unnecessary handover rates are used as quality indicators in the proposed gain function with dynamic weights. By calculating this gain function, a certain number of the cell with the low gain value is selected as candidate cells.

- In spatial estimation phase of the proposed scheme, Kriging Interpolator is used with Semivariogram Analysis. With this stochastic approach unknown indicator values of the mobile user equipment (UE) are estimated by using certain values of the neighbor UEs.

- In temporal estimation phase by using autoregressive model, indicator values of the each candidate cell are monitored in a certain timescale. Thus, more stable eNodeB that has less fluctuation on indicator values is selected.

- All operations are implemented in the proposed eNodeB Estimation Entity which has a connection with all of the network nodes. The estimated optimal eNodeB information is sent to the mobility management entity for sending UEs.

- All of these procedures are executed for data and control channels separately to select the connected small cell and macrocell respectively. Also, in this scheme, quality indicator values are estimated before the connection setup. Accordingly, unnecessary, frequent and ping-pong handover risks are reduced. Moreover, packet losses, dropped and blocked calls are declined.

The rest of the paper organized as follows: In Section II, general system overview, considered network topology and quality indicators are presented. In Section III, the proposed optimal eNodeB estimation approach is investigated with details. The proposed mechanism is evaluated in section IV. Lastly, we conclude the paper in Section V.

2. THE PROPOSED SYSTEM

In this section, we first present our general system overview. Then, the considered network topology and eNodeB quality indicators are explained with details.

2.1 General System Overview

In our proposed system, as shown in the Fig. 1, new location information and eNodeB quality indicators are collected from the mobile UEs and eNodeBs respectively by the eNodeB estimation entity in the data acquisition phase. Then, in data processing phase, this received information is used in the spatio-temporal estimations for selecting the optimal macrocell and small cell during intra-macrocell handovers. In our topology, optimal eNodeB refers to the eNodeB with low gain value and less fluctuation in the eNodeB quality indicator values.

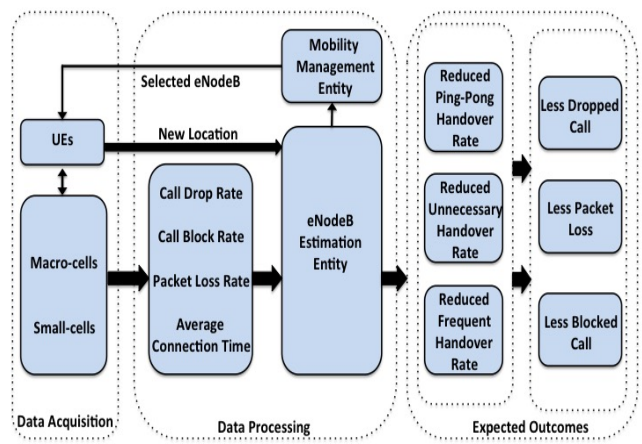

Figure 1: Proposed Optimal eNodeB Estimation Scheme Overview

By using this proposed scheme, any frequent, unnecessary and ping-pong handover risk is reduced. Also, a number of packet losses, dropped and blocked calls are decreased as expected outcomes.

2.2 Proposed Network Topology

In our proposed topology, control, and data channels are connected the macrocell and small cell respectively according to the specific 5G architecture. Furthermore, all operations related with the optimal eNodeB selection during the intra-macrocell handovers are executed in the proposed eNodeB estimation entity.

As shown in Fig. 2, this entity can communicate with all of the eNodeBs and UEs to collect quality indicators and location information. By using the collected information in the proposed scheme, optimal eNodeB is selected.

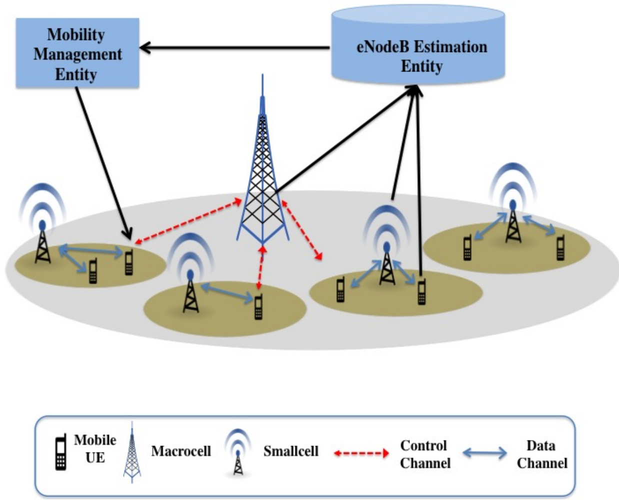

Figure 2: The Proposed Network Topology

2.3 eNodeB Quality Indicators

For generating the gain value for each eNodeB, quality indicators which are explained in the sequel are used in the gain function with dynamic weights. Details of this function are presented in Section 3.2.

1. Ping-Pong Handover Rate (Q_{PP}): To find the ping-pong handover rate, ping-pong handover number of the UE is divided into the total handover number of the UE.

2. Unnecessary Handover Rate (Q_{UH}): By dividing the unnecessary handover number of the UE with total number of handovers, unnecessary handover rate is reached.

3. Frequent Handover Rate (Q_{FH}): Frequent handover rate of the UE is found by dividing the number of frequent handovers by the total number of handovers of the UE.

4. Call Drop Rate (Q_{DR}): This parameter gives the dropping call ratio of the specific UE to the connected eNodeB. To find this parameter, the number of the dropping calls of the UE to the certain eNodeB is divided by the total number of calls of the UE.

5. Call Block Rate (Q_{BR}): This parameter is found similarly to the call drop rate and the number of blocked calls is divided by the total call number. In this way, the blocked call ratio of the UE to the specific eNodeB is calculated.

6. Packet Loss Rate (Q_{LR}): This parameter is found by dividing the number of lost packets by the total number of sending packets from UE to the certain eNodeB.

3. THE PROPOSED APPROACH

In our proposed scheme, the optimal eNodeB is selected by using spatio-temporal based estimation approach during the intra-macrocell handovers in 5G. Moreover, the required operations for the optimal eNodeB selection are executed by the proposed eNodeB estimation entity as shown in the Fig. 3. The collected information from eNodeBs and UEs are used in this entity and selected optimal eNodeB is reported to the mobility management entity for sending the UE. Details of this entity can be explained as follows in stages:

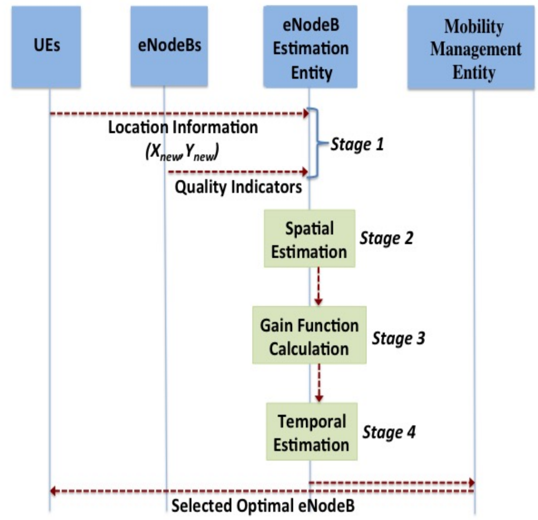

Figure 3: eNodeB Estimation Entity Procedure

- ***Stage 1:*** For the optimal eNodeB selection of the mobile UE in the new location (X_{new},Y_{new}), quality indicator values (Q_{PP}, Q_{UH}, Q_{FH}, Q_{DR}, Q_{BR}, Q_{PL}) of the UEs that have a connection with neighbor eNodeBs are collected.

- ***Stage 2:*** In the spatial estimation phase, these collected values are used in the Kriging Interpolator with Semivariogram Analysis. Thus, by using certain values of the neighbor UEs, unknown indicator values ($\tilde{Q}_{PP}$, $\tilde{Q}_{UH}$, $\tilde{Q}_{FH}$, $\tilde{Q}_{DR}$, $\tilde{Q}_{BR}$, $\tilde{Q}_{PL}$) of the mobile UE is estimated for each eNodeB in the new location (X_{new},Y_{new}) before connecting the eNodeB.

- ***Stage 3:*** Estimated parameter values are used in the proposed gain function ($G(x)$) for generating a gain value for each eNodeB as selection criteria. In this way, comparison between eNodeBs are executed and according to the comparison results, certain number of cells with lower gain values are selected as candidate cells.

- ***Stage 4:*** Estimated parameter values of these candidate cells are monitored in timescale in the temporal estimation phase with the k-order autoregressive model as *AR(1), AR(2),...,AR(k)*. In this way, indicator value alterations are observed and more stable eNodeB that has less fluctuation on indicator values is selected. Then, this selected optimal eNodeB is sent to the mobility management entity for transfering the UE.

- The above stages are performed for control and data channels separately for macrocell and small cell selections.

Details of the spatial estimation, gain function, and temporal estimation are described in the below subsections.

3.1 Spatial Estimation

In the new location (X_{new},Y_{new}) of the mobile UE, quality indicator values which will be taken from eNodeBs are estimated spatially before the connection setup. To obtain this spatial estimation, the special type of statistical model ordinary kriging interpolation method is used with semivariogram analysis. In this way, each of the unknown quality indicator value ($\tilde{Q}_{PP}$, $\tilde{Q}_{UH}$, $\tilde{Q}_{FH}$, $\tilde{Q}_{DR}$, $\tilde{Q}_{BR}$, $\tilde{Q}_{PL}$) of the mobile UE is estimated by using spatial correlation among certain quality values (Q_{PP}, Q_{UH}, Q_{FH},Q_{DR}, Q_{BR}, Q_{PL}) of the number of neighbors UEs, N. Kriging formula can be defined as follows:

$$\begin{pmatrix} \tilde{Q}_{PP} \\ \tilde{Q}_{UH} \\ \tilde{Q}_{FH} \\ \tilde{Q}_{DR} \\ \tilde{Q}_{BR} \\ \tilde{Q}_{PL} \end{pmatrix} = \sum_{i=1}^{N} \lambda_i \begin{pmatrix} Q_{PP_i} \\ Q_{UH_i} \\ Q_{FH_i} \\ Q_{DR_i} \\ Q_{BR_i} \\ Q_{PL_i} \end{pmatrix}, \quad \forall\ i \tag{1}$$

In this formula, $\tilde{Q}_{PP}$, $\tilde{Q}_{UH}$, $\tilde{Q}_{FH}$, $\tilde{Q}_{DR}$, $\tilde{Q}_{BR}$, $\tilde{Q}_{PL}$ are the estimated quality indicator values, Q_{PP}, Q_{UH}, Q_{FH}, Q_{DR}, Q_{BR}, Q_{PL} are the known indicator values of the neighbor UEs and λ_i is the unknown kriging coefficient. Here, this Kriging formula is executed for each quality indicator separately. For example, firstly, Ping-Pong handover rate is estimated by using Eq. 1, then the same formula is executed with unnecessary handover rate and other parameters, respectively. Therefore, this summation is applied for each entry of the given vector separately to estimate the corresponding indicator value. Furthermore, the sum of Kriging coefficient values in Eq. 1 must be equal to the 1 as given in Eq. 2.

$$\sum_{i=1}^{N} \lambda_i = 1, \quad \forall\ i \tag{2}$$

These unknown kriging coefficients (λ_i) of N neighbor UEs (1,2,...,N) are calculated by using Eq. 3.

$$\begin{pmatrix} \lambda_1 \\ \lambda_2 \\ \vdots \\ \lambda_N \\ \mu \end{pmatrix} = \begin{pmatrix} \gamma_{11} & \cdots & \gamma_{1N} & 1 \\ \vdots & \vdots & \vdots & \vdots \\ \gamma_{N1} & \cdots & \gamma_{NN} & 1 \\ 1 & \cdots & 1 & 0 \end{pmatrix}^{-1} \begin{pmatrix} \gamma_{10} \\ \gamma_{20} \\ \vdots \\ \gamma_{N0} \end{pmatrix} \tag{3}$$

In the Eq. 3, μ is the Lagrange multiplier. γ_{ij} is the semivariogram value between (x_i, y_i) and (x_j, y_j) locations. Accordingly, $\lambda_1, \lambda_2, ..., \lambda_N$ values depend on this semivariogram value, semivariogram model and the h_{ij} distances between (x_i, y_i) and (x_j, y_j) locations.

$$h_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad , \quad \forall\ i, j \tag{4}$$

h_{ij} distances between (x_i, y_i) and (x_j, y_j) locations are found as given in the Eq. 4. These distances are used in Eq. 5 for calculating the semivariogram values (γ_{ij}) of the selected model. There are many semivariogram models in the literature as exponential, linear, spherical. In this paper, we choose exponential semivariogram model for kriging estimation of handover procedure as given in Eq. 5. Because, the mobile user moves away from the eNodeB coverage, indicator values are decreased exponentially.

$$\gamma_{ij} = \begin{cases} c_0 + c * (1 - \exp(\frac{-h_{ij}}{r})) & \text{if } h_{ij} > 0 \\ 0 & \text{if } h_{ij} = 0 \end{cases} \tag{5}$$

In Eq. 5, c_0, c and h are the sill, nugget and range values of the semivariogram model. Value of the variogram increases continuously until the range and reaches the maximum at that point. Accordingly, the sill is the reached maximum value of the semivariogram and variance remains constant on this sill value. Also, sill can be defined as the limit or upper bound for the semivariogram. Moreover, the nugget is the height from the origin and used for showing the measurement errors.

3.2 Gain Function

Gain function is defined by using eNodeB quality indicators as a parameter with dynamic weights. Accordingly, each spatially estimated indicator value is multiplied with corresponding weight and results of these multiplications are added as given in Eq. 6. In this way, gain values are calculated for each eNodeB as a comparison value.

$$\begin{aligned} G(x) = (W_1 * \tilde{Q}_{PP}) + (W_2 * \tilde{Q}_{UH}) + (W_3 * \tilde{Q}_{FH}) \\ +(W_4 * \tilde{Q}_{DR}) + (W_5 * \tilde{Q}_{BR}) + (W_6 * \tilde{Q}_{PL}) \end{aligned} \tag{6}$$

Also, W_1, W_2, W_3, W_4, W_5, W_6 are the dynamic weights and summation of these must be equal to the 1 as a normalization criteria as given in the Eq. 7. In this equation, M shows the number of quality indicators in the system.

$$\sum_{i=1}^{M} W_i = 1 \quad , \quad \forall\ i \tag{7}$$

Different weights can be chosen according to the priority levels of the quality indicators in the defined system. According to the priority, system can be designed to decrease the call drops or ping-pong handovers [12]. By considering these conditions, we define six cases by giving different priority levels for each quality indicator. Accordingly, ping-pong handover rate has high priority in case 1 and W_1 is chosen greater than the other weights. Similarly, W_2 has the greatest value in case 2 because of the unnecessary handover rate priority. Also, other four cases are defined in the same manner. Thus, high priority quality indicators have greatest weight value in each case. Furthermore, eNodeB quality indicators have highest values for non-optimal eNodeBs. Therefore, eNodeBs which have low gain values must be selected as candidate cells for temporal estimation.

3.3 Temporal Estimation

By using the spatially estimated values in gain function candidate cells are selected for temporal estimation. In temporal estimation, k-order autoregressive model *AR(k)* is used for observing indicator value alteration in timescale. By starting the spatially estimated quality indicator value, future values are estimated for each indicator of the candidate eNodeBs as *AR(1), AR(2),...,AR(k)*. Thus, by using the Eq. 8, first order auto-regression *AR(1)* is calculated.

$$\begin{aligned} \tilde{Q}_t = \phi_0 + \phi_1 * \tilde{Q}_{t-1} + \epsilon_t \\ \forall\ \tilde{Q}_t, \tilde{Q}_{t-1} \ \in \ \{\tilde{Q}_{PP}, \tilde{Q}_{UH}, \tilde{Q}_{FH}, \tilde{Q}_{DR}, \tilde{Q}_{BR}, \tilde{Q}_{PL}\} \end{aligned} \tag{8}$$

Spatially estimated value and result of Eq. 8 are used in Eq. 9 for the second order auto-regression *AR(2)*.

$$\tilde{Q}_t = \phi_0 + \phi_1 * \tilde{Q}_{t-1} + \phi_2 * \tilde{Q}_{t-2} + \epsilon_t$$
$$\forall\ \tilde{Q}_t, \tilde{Q}_{t-1}, \tilde{Q}_{t-2} \ \in\ \{\tilde{Q}_{PP}, \tilde{Q}_{UH}, \tilde{Q}_{FH}, \tilde{Q}_{DR}, \tilde{Q}_{BR}, \tilde{Q}_{PL}\} \tag{9}$$

According to the observing timescale, k-order auto-regression *AR(k)* which is given by Eq. 10 in the general form is used for temporal estimation.

$$\tilde{Q}_t = \phi_0 + \sum_{j=1}^{k} \phi_j * \tilde{Q}_{t-j} + \epsilon_t \tag{10}$$
$$\forall\ \tilde{Q}_t, \tilde{Q}_{t-j} \ \in\ \{\tilde{Q}_{PP}, \tilde{Q}_{UH}, \tilde{Q}_{FH}, \tilde{Q}_{DR}, \tilde{Q}_{BR}, \tilde{Q}_{PL}\}$$

In these equations, ϵ_t is defined as the random error and this value can be taken as 0. Moreover, ϕ_0, ϕ_1 and ϕ_k are the regression coefficients and these coefficient values are found with least squares estimation (LSE) by using Eq. 11 and Eq. 12.

$$\phi_k = \frac{\sum_{i=1}^{k}(Q(t-i)Q(t) - kE[Q(t-i)Q(t)])}{\sum_{i=1}^{k} n(Q^2(t-i) - nE[Q_2(t-i)])} \tag{11}$$

$$\phi_0 = E[Q(t)] - \sum_{i=1}^{k} \phi_i * E[Q(t-i)] \tag{12}$$
$$\forall\ Q(t) \ \in\ \{\tilde{Q}_{PP}, \tilde{Q}_{UH}, \tilde{Q}_{FH}, \tilde{Q}_{DR}, \tilde{Q}_{BR}, \tilde{Q}_{PL}\}$$

With these operations, the eNodeB which has less fluctuation on indicator values in the certain time range is selected for connection establishment during the intra-macrocell handovers.

4. PERFORMANCE EVALUATION

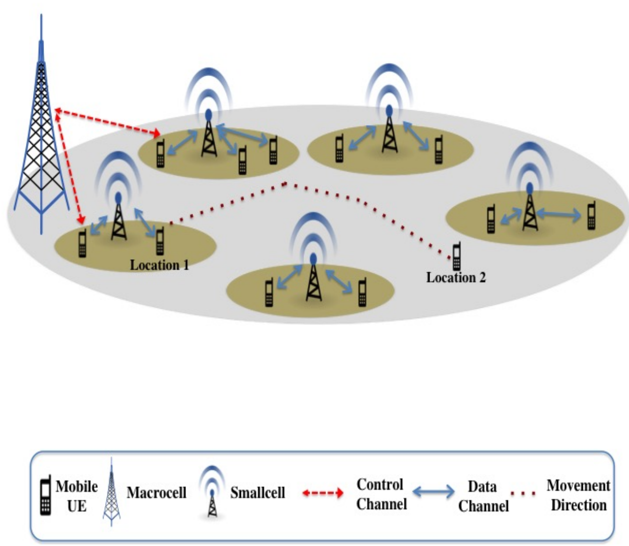

Figure 4: Example Scenario

The proposed optimal eNodeB estimation scheme is evaluated on Matlab environment with example scenario as given in Fig. 4. In this scenario, 1 macrocell, 50 small cells, and 100 UEs are deployed on the network randomly. The certain number of small cells, UEs, and data channel connections which belong to this scenario are shown in Fig. 4 to eliminate the complexity of the figure. Here, all of the UEs move randomly in the coverage of the macrocell and one of the movement is showed in Fig. 4. During this movements, intra-macrocell handovers are executed and mobile UEs are connected to the different small cells. Details of the other simulator parameters are given in Table 1.

Table 1: Simulation Parameters

Time to Trigger (TTT)	200 ms
Simulation Time	600 ms
Receiving Bandwidth	4096 MHz
Noise Rise	6 dB
Maximum/Minimum UE Tx power	21 dBm / -44 dBm
Tx power for macrocells/small cells	30 dBm /20 dBm
Transmission power for macrocells	30 dBm
Transmission power for small cells	20 dBm
Small-cell Range	25 m
Macro-cell Coverage Distance	1 km

In the implementation of the proposed approach as explained in Section 3, firstly, we implement Kriging interpolation with semivariogram analysis for estimating the indicator values spatially. Then, these estimated values are used in the gain function for candidate cell selection. Lastly, we use the autoregressive model in temporal estimation for selecting the optimal eNodeB among the candidate cells. Also, numbers of the Ping-Pong, unnecessary and frequent handovers, dropped and blocked calls are assigned to zero at the starting of the simulation. Then, the value of the each indicator is updated at the end of the each simulation. After that, these reached values are divided by the related total numbers to find the required eNodeB quality indicators. For example, to find the Ping-Pong handover rate quality (Q_{PP}) indicator, reached Ping-Pong handover number is divided by the total handover number as a result of all of the simulations.

Table 2: Selected Weight Values

	W_1	W_2	W_3	W_4	W_5	W_6
Case 1	0.65	0.09	0.08	0.02	0.10	0.06
Case 2	0.10	0.55	0.07	0.05	0.20	0.03
Case 3	0.10	0.09	0.60	0.05	0.10	0.06
Case 4	0.15	0.10	0.06	0.50	0.10	0.09
Case 5	0.03	0.05	0.20	0.04	0.60	0.08
Case 6	0.07	0.10	0.03	0.10	0.05	0.65

Moreover, all implementations are performed according to the Case 3, so frequent handover is the most important criteria in eNodeB selection. Therefore, W_3 takes the highest weight value in all implementations as given in Table 2.

In the new locations of the UEs, optimal eNodeBs are selected by using the proposed mechanism and traditional handover methods. Accordingly, the performance of the proposed mechanism is compared with the traditional handover mechanism results. In traditional handover method, Time to Trigger (TTT) and hysteresis values are used for handover decision. In this scheme, if the signal level of the target cell is greater than the serving cell up to the hysteresis value during the Time to Trigger duration, then this target cell is selected to establish a connection. Accordingly, any estimation method is not used for selecting the optimal eNodeB.

With all of these in mind, in our proposed mechanism, unnecessary, frequent, and Ping-Pong handover rates are decreased. Due to these parameter values of the eNodeBs are considered during the selection as given in the Eq. 1 and Eq. 10. These equations are used for estimating and observing the long-term behaviors of these quality indicators of the eNodeBs and in this way, most optimal eNodeB is selected.

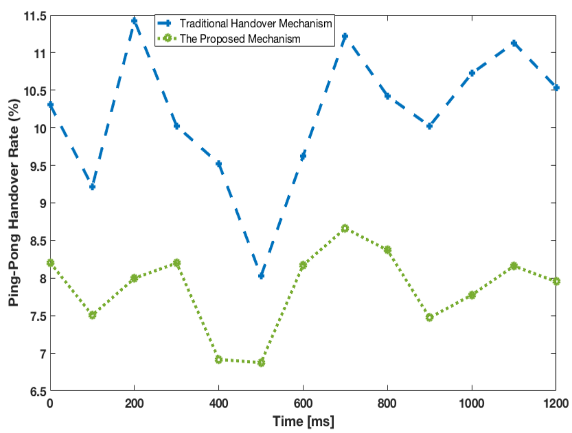

Figure 5: Ping-Pong Handover Rate Comparison

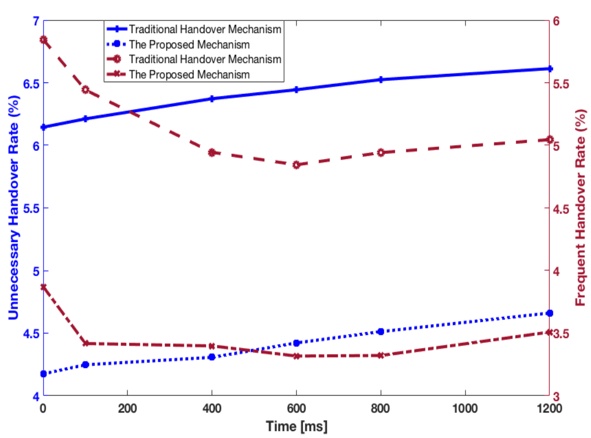

Figure 6: Unnecessary and Frequent Handover Rate Comparison

Comparison results of the traditional and proposed handover mechanisms in terms of unnecessary, frequent and ping-pong handover rates are given in the Fig. 5 and Fig. 6.

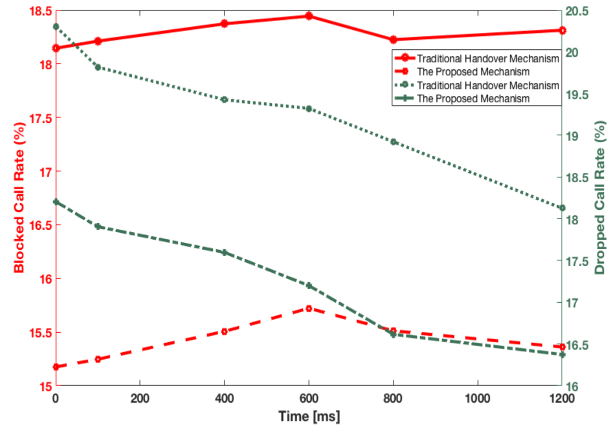

Figure 7: Dropped and Blocked Calls Rates Comparison

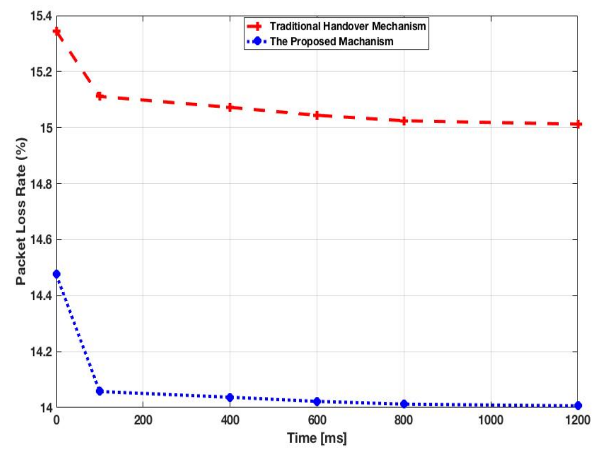

Figure 8: Packet Loss Rate Comparison

In these figures, unnecessary, frequent, ping-pong handover numbers are decreased by %35, %37 and %17 respectively compared to the traditional handover mechanism. Furthermore, the rate of the packet losses, dropped and blocked calls are investigated for the two mechanisms as shown in the Fig. 7 andd 8. As shown in these figures, packet loss, dropped and blocked call rates are reduced by the %7, %9 and %14 respectively for medium-scale networks in our proposed approach. Similar to the above mentioned, by using Eq. 1 and Eq. 10, eNodeB with fewer packet losses, dropped and blocked calls are preferred in the selection, therefore rate of these problems are decreased. Also, the best improvement results are obtained from the frequent handover rate, because, it is assumed that this parameter has the highest priority (Case 3) in the implementation scenario as a selection criterion.

5. CONCLUSION

The high number of small cells is one of the main features of the 5G technology, which can improve the network capacity. Yet, together with that, the probability of frequent, unnecessary and ping-pong handover problems also increases. In 5G networks, handover operation must be executed in two tiers architecture because of the control and data channel separation. To solve these problems, in this paper, we were proposed optimal eNodeB selection mechanism by using spatio-temporal estimation methods. In spatial estimation, Kriging Interpolator was used with Semivariogram Analysis because of the stochastic behavior. Then, this spatial estimation was followed by temporal estimation by using autoregressive model. All of these operations are executed by the EnodeB estimation entity for two channels before the connection setup and thus; any unnecessary, frequent and ping-pong handover risk were reduced by the %35, %37 and %17 respectively.

Acknowledgment

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