Mobility Management in the Applications of 5G and Beyond: A Handover Skipping Topology Analysis

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***Abstract*—This paper introduces handover (HO) skipping topology analysis that adjust the HO Skipping of 5G and beyond applications to improve the overall network performance and diminish negative effects. We propose a novel Poisson point process (PPP) based context-aware HO skipping approach to focus on the impact of HO metrics such as, passenger's trajectory, different velocities, and a mean-time of a passenger within a BS to maintain a good quality of service (QoS). Our proposed scheme, context-aware HO skipping enables a dynamic HO skipping where the skipping decision is taken based on the load of the BSs along the passenger's trajectory. The parameters have been analysed and implemented in a dynamic simulator and have been investigated for different parameter sets in a high-speed railway simulation scenario. Our simulation results in the robustness of the framework show comparable coverage probability on various high train velocities and mean-times.**

***Index Terms*—5G and beyond applications, Context-Aware, HO Skipping, Mobility Prediction, Net-zero Carbon Target.**

I. Introduction

The fifth generation (5G) development in cellular communication systems is driven by the user demands to address capacity problems through the proliferation of mobile gadgets [1], [2]. Due to the increasing traffic in high mobility trains, a major consideration of cellular services need to be looked for all passengers at all times. For this to be satisfied, the vital player of the 5G and beyond is the network densification through heterogeneous small cell (SC) deployment. Densifying BSs increase spectral efficiency and offer more capacity which proportionally increases quality of service (QoS), but with the expense of shrinking the BSs footprints and the service area of each BS [3]–[5]. Having more BSs deployed with small footprints will, however, promote frequent handovers (HOs) and, the risk of disconnection and signaling overhead that lead to affect QoS of overall system [1], [3], [4], [6].

While HO signalling overhead is a concern on one side, existing HO procedures interrupt the data flow to the user on another. This interruption usually terminates the link between the user and the serving BS and affects the link establishment with the target BS [3], [7]–[10]. Due to the fast mobility of the trains, users are skipped to reduce excessive HOs which is an effective way in the densified SCs network. Data transmission suffers from high HO rates, especially when the demand is to maintain longer connection duration with a BS. Authors in [11] compared the cost of HO skipping techniques for user's mobility whereas in [12] nearest interference sources were analysed in terms HO management with multi-tier and cognitive cellular wireless networks. HO patterns and user-centric BS cooperation which affects user performance were discussed in [13] to reduce the number of HOs in user-centric cooperative wireless network through random BS deployment.

High-speed railway systems and HO executions have been discussed in [14], [15] with some lights on key HO challenges such as high mobility channels, signal processing techniques, Doppler diversity, etc. Sojourn time HO analysis and velocity estimation between a macro cell (MC) and a SC, for high mobility trains, using tools from stochastic geometry have been proposed in [16]–[18]. Some studies on HO rate analysis are conducted in [19]–[21]. However, none of the aforementioned studies examined comparative analysis of different high velocities in the context-aware domain discussing coverage probability, and time threshold along a predefined trajectory.

In order to improve the QoS with better sense of HO skipping, a trade-off is needed between the increased HO rate and the decreased data rate for high mobility trains. Our motivation behind this work is HO skipping when users are moving on high-speeds in densified SC environment. In this paper, we first examine and filter a train environment dataset for users mobility prediction in cardinal directions, i.e., North, East, West, and South. Then we analyse and compare multiple velocities on which train moves from one station to another using our novel context-aware HO skipping technique as opposed to traditional HO skipping techniques discussed in [1], [3]. Using Poisson point process (PPP) [22] mobility prediction, we provide an analysis framework for the two important metrics, i.e., coverage probability and time threshold. The remainder of the paper is organised as follows. Section II presents the system model. Section III presents the proposed method. Section IV discusses simulation results. Finally, Section V concludes the paper.

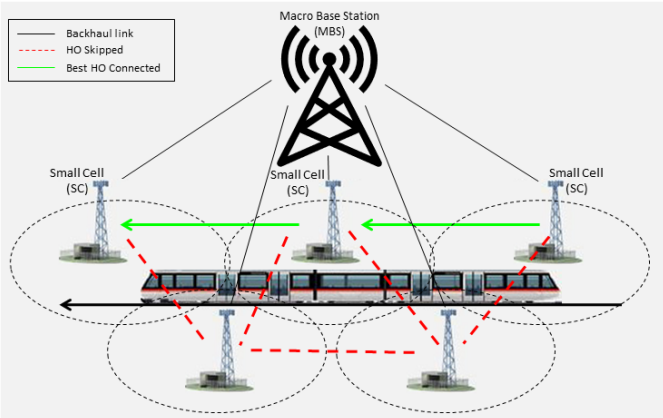

Fig. 1: Context-Aware HO skipping framework with assumed number of BSs plotted onto the image for indicative purposes.

II. System Model

Our system model relies on complex train network dataset based on passenger's trajectory, velocity, and a mean-time (sojourn time) of a passenger within a BS. The key mobility prediction metrics behind the simulation are, passenger's location and their travel direction, most chosen path, and train load and speed. Using this information, novel HO skipping approach and modelling is elaborated in the following sections.

A. Context-Aware HO Skipping

Trains trajectory require a strategy when passing through various SCs (connected to a MC through backhaul links) as shown in Fig. 1. Choosing one SC over the other is vital to avoid unnecessary overheads, waste of resources and HO costs. Therefore, we present a context-aware HO skipping framework to intelligently examine passenger's trajectory, velocity, and a mean-time (sojourn time) of a passenger within a BS. Our main realisation being PPP-modelled prediction architecture where our novel HO skipping technique compares with traditional HO skipping techniques such as, alternate HO, location-aware HO, size-aware HO, hybrid HO defined in [1], [3]. Through this, the PPP mobility prediction model is able to intelligently compare the crossing points of coverage probability on different train velocities, and CDF with different time thresholds. Traditionally, HO skipping methods struggled to accurately monitor and reflect true cell dwell time obtained from passenger's trajectory and velocity. That is why, context-aware methodology comes into play to process challenging train environments at any given time and location. Context-aware methodology builds a load-aware methodology by using real train dataset based on passenger's trajectory, velocity, and a mean-time (sojourn time) within a BS. *Notation*: $\mathbb{R}^2$ is the two-dimensional Euclidean space with $\mathcal{P}$ represents the probability with expected value $\mathbb{E}(X)$ where X being an event of the expected value and Γ is the complete Gamma function [22].

B. Framework Modelling

We have considered a downlink mobile network with random BSs distribution in the two dimensional Euclidean plane $\mathbb{R}^2$, according to a homogeneous PPP [22], $\phi = \{x_k \in \mathbb{R}^2\}, k \geq 1$, with density λ, where x_k represents the coordinates of the $k-th$ BS in the heterogeneous environment. Assumption has been made with antenna per BS with a transmit power P. As this is a centralised architecture which enables the employment of BSs cooperation to the backhaul network, we assume user associations with the closest BS in the network. Poisson Voronoi tessellation is used to sectorise the Euclidean plane $\mathbb{R}^2$ in the order K. There would be small-scale Rayleigh fading to the network with the channel gain h_k. The pathloss propagation exponent α follows the power-law function of $r_k^{-\alpha}$, where r_k is the distance from the $k-th$ BS to the origin. When BSs are in ascending order, the probability density function (PDF) of the distance r_k to the $k-th$ closest BS, is given by [1],

$$F = \frac{2(\pi\lambda)^k}{\Gamma(k)} r_k^{2k-1} exp(-\pi\lambda \cdot {r_k}^2), \tag{1}$$

The user related HO measurements are defined in [20] that models passengers to associate with the BSs according to their closest distance. Once the distance is known, reference signals received power (RSRP), R_s, measurements of the users at a each location can be derived as [3],

$$R_s = T_x \cdot h \cdot d^{-\alpha} \ , \tag{2}$$

where, T_x being eNB transmit power and Rayleigh distribution with unit variance, $d^{-\alpha}$. Thus, a best channel quality to serve a moving passenger is possible in each direction of travel which is called as reference signal received quality (RSRQ), R_{ss}, which is given as,

$$R_q = \text{RB} \cdot \frac{R_s}{R_{ss}} \ , \tag{3}$$

where, RB are number of resource blocks and relative received signal strength (RSSI),R_{ss}, is the wide-band carrier received signal strength indicator from all BS sources observed by passengers, including co-channel serving and non-serving cells, adjacent channel interference, thermal noise, etc. Hence, signal to interference and noise ratio (SINR) is calculated from the RSRP of the source eNodeB (R_s) and the RSRP of the target eNodeB (R_i) plus the additive white Gaussian noise (AWGN), N. The SINR values is as follows:

$$\mathbb{S} = R_s - R_i - N \ , \tag{4}$$

The coverage probability $\mathcal{P}$ determines the probability that a user's SINR is above a predefined threshold $\mathbb{T}$, i.e., $P(SINR > T)$. After general SINR expression has been derived, we deduce specific expressions for a user travelling

TABLE I: Simulation parameters

Parameter	Value
PPP rate (λ)	0.0001
Bandwidth (W)	10MHz
Noise spectral density (N_0)	-204 dBW
Active users (N_{active})	90%
Path loss exponent (α)	4 [3]
BS transmit power (T_x)	0dBW [3]
RB per BS (RB)	150
Coverage probability threshold (T)	[-15, ..., 15] dB [3]
Minimum SINR (SINR$_{min}$)	0 dB

at multiple train speeds. Thus, the coverage probability of a user served by the set of BSs is [3],

$$\mathcal{P} = \mathbb{P}\left[\frac{\left|\sum_{x_i \in \mathcal{N}} \sqrt{P h_i r_i^{-\alpha}}\right|^2}{N_k^2} > T\right], \tag{5}$$

where, $\mathcal{N}$ is a set of BSs, and $P h_i r_i^{-\alpha}$ refers to the aggregate interference occurring from the $n-th$ closest BS and onwards. As $h_i \sim exp(1), |\sum_{x_i \in \mathcal{N}} \sqrt{P h_i r_i^{-\alpha}}|^2$ is an exponential random variable with mean $\sum_{x_i \in \mathcal{N}} \sqrt{r_i^{-\alpha}}$. By using the complementary CDF of an exponential random variable, we have [1],

$$\mathcal{P} = \mathbb{E}_\phi\left[exp\left(-\frac{T}{P} \cdot \frac{N_k^2}{\sum_{x_i \in \mathcal{N}} \sqrt{r_i^{-\alpha}}}\right)\right], \tag{6}$$

III. Performance Evaluation

A. Simulation Scenario

Simulation results were carried out to evaluate the proposed HO skipping technique for which the simulation parameters are shown in Table I. We used MATLAB to simulate train dataset at different train velocities and time thresholds. For this, BSs are positioned according to a random PPP deployment in rectangular fashion.

B. Metrics

Three different metrics, namely passenger's trajectory, velocity, and a mean-time (sojourn time) within a BS, are used to evaluate the performance of the developed context-aware HO skipping technique. When passengers are on the move, the given time they spend in each cell depends on the train velocity. The dwell time t_i shall be less than or equal to the defined time threshold t_{thresh} for a user to decide HO skipping. For context-aware approach, the following conditions must be met,

$$\eta_1 = \begin{cases} 1, & \text{if } t_i \leq t_{thresh}, \\ 0, & \text{otherwise}, \end{cases} \tag{7}$$

where, the mean time $t_i \sim (\bar{t}, \frac{1}{4}\bar{t}, \frac{1}{2}\bar{t}, \frac{3}{4}\bar{t})$ is the comparison of four different time thresholds that a user spent in one BS

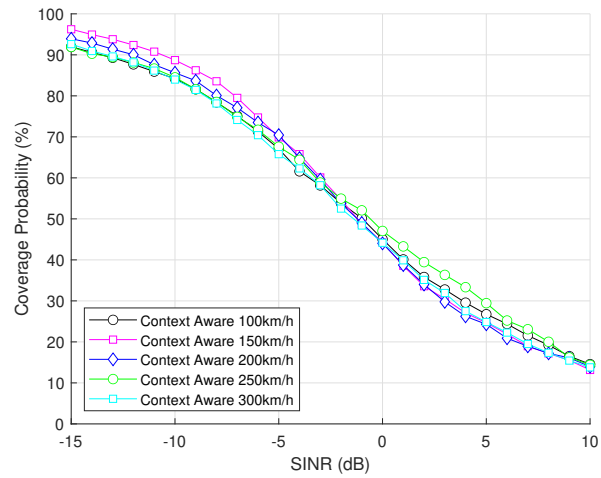

Fig. 2: Coverage probability comparison of various train speeds HO skipping vs SINR threshold.

through the entire journey. Condition 1 (η_1) states that if the time spent inside a cell is lower than a threshold, considering load and the quality of the signal, users are skipped. Another condition based on the available resource blocks (RBs) and which users to skip, is expressed as follows:

$$\eta_2 = \begin{cases} 1, & \text{if } \eta_1 = 1 \ \& \ i > \text{RB}, \\ 0, & \text{otherwise}. \end{cases} \tag{8}$$

Condition 2 (η_1) states that a user skips a BS while satisfying condition 1 (η_1) and the significant number of RBs to serve the user are available. A total of 100 runs are performed to perform the averaged simulation. The 3 metrics are evaluated in terms of:

- Passenger's trajectory: A path which every user takes to reach his destination out of cardinal directions in a train network.
- Coverage probability: he probability that the SINR received by the test user exceeds a certain time threshold;
- SINR CDF: the cumulative density function is the percentage of users with average SINR above a certain value.

C. Results

Fig. 2 presents the context-aware coverage probability versus the threshold SINR, T, in dB (decibels), for BS association scenarios in various train speeds. It was expected to have highest coverage probability when the user is travelling at higher speeds at lowest SINR and vice versa. It can be seen that, as the user's velocity increases, the average SINR remains closer to the one with lower velocities. This shows the robustness of the proposed scheme where at different train velocities all the curves are pretty close to each other but with some crossing points. This is expected, since the context-aware approach takes into account passenger's trajectory, velocity, and a mean-time (sojourn time) within a BS, it doesn't let the higher velocities behaving abruptly as traditional HO

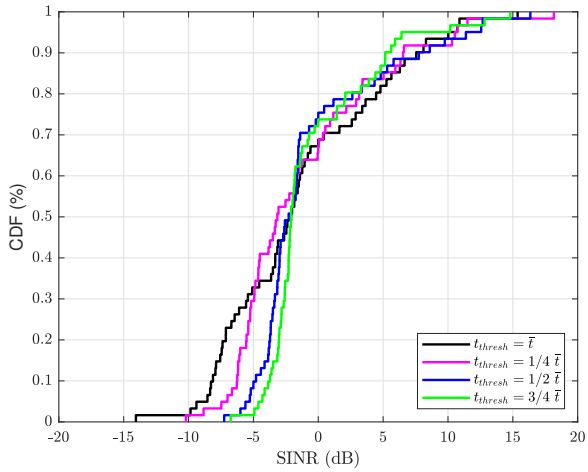

Fig. 3: CDF of SINR for different mean-times (sojourn time).

techniques did. In traditional cases [1], [3], higher velocities were subject to higher HOs rates and HO costs which had a major impact on the average throughput and SINR. Also, when the cells are shrinked in terms of their footprints, context-aware approach able to maintain QoS without handing over to a different cell on high train speeds. This result suggests that context-aware approach performs better when it finds sufficient BSs for the users to connect to in comparison with traditional methods of HO skipping.

Fig. 3 shows results in terms of the CDF of the average SINR of the users at different time thresholds as explained in eq. (7). As expected, similar pattern can be seen from the figure that even at different mean-times, curves do not vary too much, proving context-aware scheme robustness. When observing the curves, we can clearly see that mean-time affect concentrate users from -5 to -2dB at 70% of the CDF. It further follows the same trend while going up the percentage. This proves the context-aware does have an intelligent threshold in comparison with traditional methods where users able to maintain their connectivity with best available BSs. If not, they tend to skip to second closest BS and so on.

IV. Conclusion

This paper proposed an intelligent HO skipping approach, that allows the passenger to dynamically skip upcoming HO executions by considering topological characteristics of the network deployment. For this, our novel context-aware HO skipping framework focuses on the analysis of various train velocities HO scenarios at different mean-times. We have compared our novel approach with conventional mobility approaches that left a gap to address all the challenges occurring in the train environment considering load-awareness. We first developed a PPP-based HO skipping topology framework with multiple HO skipping scenarios through simulation. Then, we examined coverage probability behavior with different train velocities and CDF of SINR for different mean-times. Our framework proved its robustness when analysing metrics among all traditionally equipped HO schemes.

Acknowledgment

This work was partially funded by Deanship of Graduate Studies and Research (DGSR), Ajman University under the grant number 2021-IRG-ENIT-2.

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