Context-Aware Handover Skipping for Train Passengers in Next Generation Wireless Networks

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***Abstract*—5G spectral efficiency requirements foresee network densification as a potential solution to improve capacity and throughput to target next-generation wireless networks (NGWNs). This is achieved by shrinking the footprint of base stations (BSs), effective frequency reuse, and dynamic use of shared resources between users. However, such a deployment results in unnecessary handovers (HOs) due to the cell size decrements, and limited sojourn time on a high train mobility. In particular, when a train speedily passes through the BS radio coverage footprints, frequent HO rate may result in serious communication interruption impacting quality of service (QoS). This paper proposes a novel context-aware HO skipping that relies on passenger mobility, trains trajectory, travelling time and frequency, network load and signal to interference and noise ratio (SINR) data. We have modelled passenger traffic flows in cardinal directions i.e, north, east, west, and south (NEWS), in a novel framework that employs realistic Poisson point process (PPP) for real-time mobility patterns to support mobile networks. Spatio-temporal simulations leveraging NEWS mobility prediction model with machine learning (ML) where support vector machine (SVM) shows an accuracy of 94.51%. ML-driven mobility prediction results integrate into our proposed scheme that shows comparable coverage probability, and average throughput to the no skipping case, while significantly reducing HO costs.**

***Index Terms*—6G, artificial intelligence, context-aware, HO skipping, machine learning, mobility prediction, optimization, smart city planning.**

I. INTRODUCTION

WORLDWIDE increasing traffic demand entails the continuous use of electronic gadgets such as tablets, mobile phones, and other handheld devices. Such proliferation plays an active role in driving the evolution of small BSs, such as micro, pico, and femto, to traditional macro BSs in order to address the capacity crunch needs. For instance, the fifth-generation (5G) evolution for cellular networks brings mobile devices and cellular subscriptions more prevalent with increasing data traffic demand and subsequently straining out the available resources [1]. 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. The need to access mobile networks while travelling have been considerably expanded with the limitations from legacy wireless technologies, challenge high train mobility passengers without conforming their needs of modern day travel. Due to the rapid mobility of the high-speed trains, data transmission suffers from high HO rates, which has been a long-standing challenge for high-speed mobility passengers in cellular networks. Unnecessary frequent HOs incur a lot of communication and computational overheads and thus, affecting the overall quality of service (QoS) [2], [3]. Increasing traffic demands can be addressed by deploying more BSs under 5G wireless communications and beyond, as there is an expectation to serve more passengers providing tremendous data rates with resilience and support high-mobility passengers with low end-to-end latency. Densifying the BSs within the same geographical region shrinks the footprint of each BS, which results in the expansion of capacity with the increase in spatial-spectral efficiency and QoS. However, the increasing inclination of capacity gains is at the expense of a proportionally increased HO rates [1], [2].

Ultra-dense networks (UDNs) require more HO management due to their composition based on dense deployment nature of small cells (SC) [4]. HO executions occur more frequently along the passengers trajectory where users move inside each SC for a limited time at an expense of significant HO cost and resources and overall mobile users' performance (i.e., throughput). Such important negatives where the impact of BS densification (i.e., HO rate) and management of QoS to underline the overall benefits to stationary and mobile passengers are usually overlooked [5]. The cell dwell time for different shaped cells is characterized in [6]. Mobility prediction based HO management optimizatio is proposed in [7]–[9] to understand mobile traffic patterns, predicting human mobility, and travellers profiling. Self-organizing networks (SONs) driven HO management is proposed in [5], [10]–[12] to trim the needs of unnecessary HOs in multi-tier networks and fulfil passenger demands by running various distributed learning algorithms at the edge of the network.

Artificial intelligence (AI) based mobility prediction and encryption leveraging historical passengers data recorded via

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RFID sensors was discussed in [13]. By using machine learning (ML) classification, authors analysed London underground and overground (LUO) network user mobility to support and improve the railway operational performance which includes, QoS maintenance, HO optimization, effective resource management, etc. Bus passenger ridership mobility using multi-tier heterogeneous network (HetNet) is discussed in [14] with the main focus being adherent in the anticipation of the passengers mobility behavior crossing HetNet architecture. ML-based algorithms use geographic BS locations, user cell association, and number of passengers in peak and off-peak times have been modelled by using six ML algorithms. Several studies [15]–[23] use ML classifiers to present their model that discussed 5G limitations, opportunities, and directions. ML algorithms such as logistic regression (LR), support vector machine (SVM), and multilayer perceptron (MLP) are compared to predict passenger daily traffic. Some other algorithms such as reinforcement learning (RL), k-nearest neighbour (KNN), artificial neural networks (ANN), deep neural network (DNN), decision tree (DT), naive bayes (NB) and discriminant analysis (DA), are trained to classify inputs to obtain predicted intelligent outputs. However, none of the aforementioned works shed light on ML-driven HO skipping techniques in the context of load-awareness. Also, ther works are rare to use train data as inputs into ML model for data training. Therefore, a ML-driven context-aware HO management is required to intelligently drive the HO process in cellular networks.

For instance, efficient models to improve the HO performance along with the QoS have been extensively addressed in the mobility context of cellular network literature. In [3], data transmission suffers from severe penetration loss in high speed railways and when the train moves from one BS to another, there are huge amount of HO occurs. Using of mobile relay node (MRN) can improve the HO overheads in fixed-trajectory group pre-handover authentication mode with better security properties. A mobility model called self-similar least-action walk (SLAW) [24] is able to produce synthetic mobility traces containing statistical features such as, heavy-tail flight and pause-time distributions; heterogeneously bounded mobility areas; truncated power-law intercontact times; destinations of people in a self-similar manner; and users current waypoints where they are more likely to choose a destination. Due to the shrinking of the BSs led by network densification, the number of HOs increases. Therefore, a cooperative HO management scheme devising HO effect mitigation via cellular network densification is discussed in [25]. Several other techniques that discuss mobility predictions based HO management are studied in [26]–[31] for multi-tier downlink cellular networks.

Implementation of seamless HO between first tier (macro-cell layer) and second tier (small cells) is one of the key challenges to fulfill the QoS requirements. In [32], authors discussed HO procedure details for information gathering, decision strategies and the BS exchange process. In [33], authors presented a model of HO cost reduction is one of the important targets in LTE-Advanced SON based on a HO optimization algorithm on users mobility state. A comparison between HO reduction method and the traditional HO control algorithms was made. In [34] co-channel interference and HO management especially for cell edge users were discussed with the examination of HO management problems and cooperative interference mitigation in an HetNet small cell network. In [35], a relation between the desired link distance and the nearest interference sources has been discussed in the research that shows performance bounds for multi-tier and cognitive cellular wireless networks using stochastic geometry. User-centric BS cooperation and its complex HO patterns which are the contributors of user performance degrade are discussed in [36] with an aim to to quantify the number of HO in user-centric cooperative wireless networks. A systematic review of mobility communications high-speed railway systems has been discussed in [37], where key challenges and opportunities are summarized. Their survey includes, communication operations, high mobility channels, and signal processing techniques such as Doppler diversity along with the mitigation techniques high mobility systems. A cross-tier HO analysis between a macro cell (MC) and a SC in HetNet architecture, that can provide sojourn time expressions inside a SC by using tools from stochastic geometry has been proposed in [38]. For velocity estimation, the user's trajectory path is exploited by spatial randomness in [1], [2], [39]. HO skipping scheme and its alternatives have been introduced in [1], [2], [40] to reduce the HO rate which also proposed an alternative HO execution along the user's trajectory while associated with either its closest or second closest BS. This work is extended in [40] with the topology-based handover skipping concept on a user's distance from the target BS and the size of the cell. However, none of the aforementioned studies undertake the interaction between user throughput, multi-decision HO protocol as a function of the BS density. Nor the consideration was given to the train environment (underground and overground) where users move along a predefined trajectory. In addition, our NEWS framework examine multiple users simultaneously which fall short in the existing works such as [1], [2] where only a single user was considered.

The main source of inspiration behind this work is the interplay of HO rate associated with the mobility of passengers within the metropolitan city of London where locations of BS deployment are known. Furthermore, rigorous analytical studies based on stochastic geometry [38], [40] exploit HO rates dependant on the cardinal passenger traffic flows in the LUO train network [1]. To achieve estimated results of coverage probability, the PPP is best [1], [2] in its ergodicity rate quantification for realistic BS deployment in the LUO train network. The coverage probability associated with passenger traffic flows and ergodic rate in multi-tier cellular network has been used by Poisson cluster process (PCP) where cell clustering captures and integrates the deployment of several SCs in congested regions [41]. The single and multi-tier scenarios were assumed to produce HO rates of user's mobility in PPP cellular networks in [38], [40], [42]. Some studies on HO rate analysis are conducted in [43]–[45]. However, none of the aforementioned studies investigates the combined effect

[1]LUO is the London Underground and Overground network with 270 stations and 11 train lines stretching deep into the Capital's suburbs, and beyond. For more details visit, https://tfl.gov.uk/corporate/about-tfl/culture-and-heritage/londons-transport-a-history/london-underground.

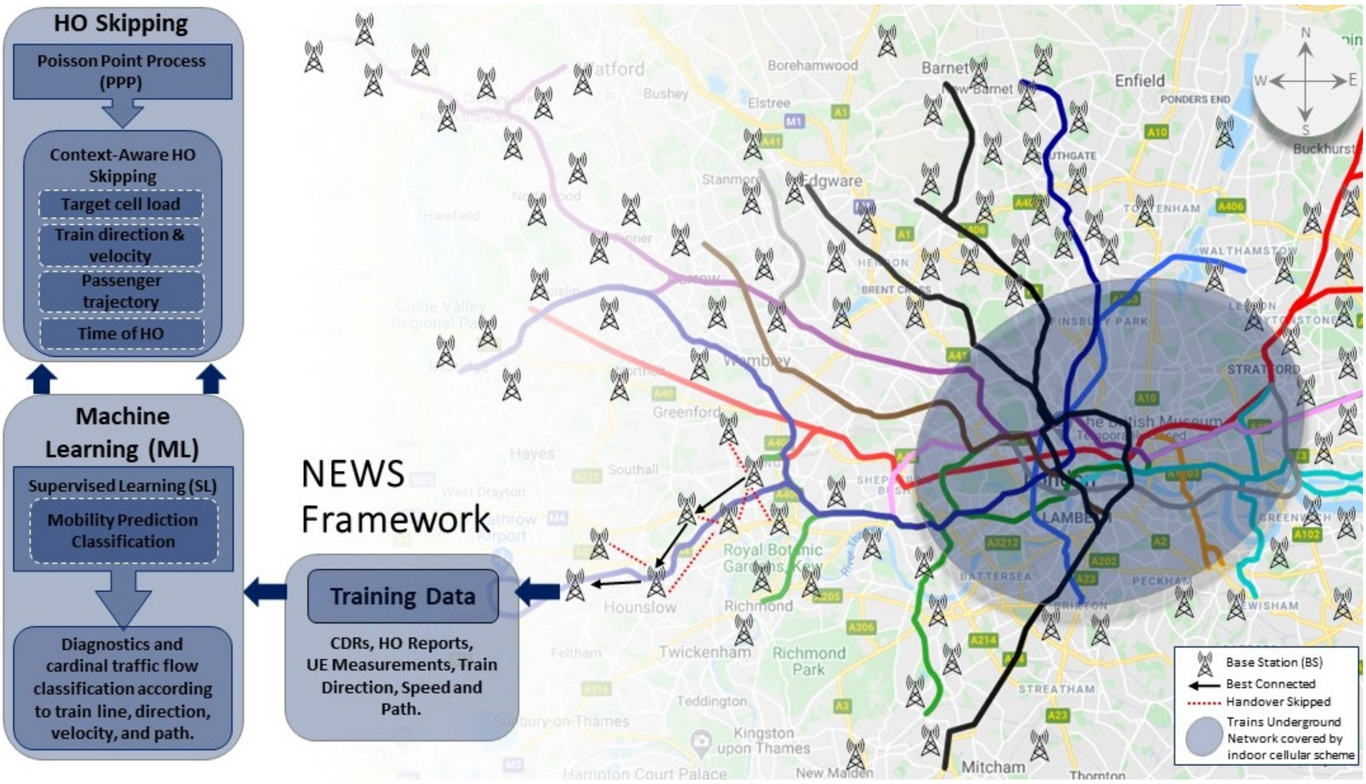

Fig. 1. NEWS Framework with LUO train map and assumed number of BSs plotted onto the image for indicative purposes. Multiple colours are representative of different train lines operate within LUO train network.

of network densification along with cardinal passenger traffic flows that exploit both the HO overhead and the throughput gains in the LUO train network.

In this direction of research, we study and model passenger traffic flows based on novel cardinal directions NEWS framework employing realistic PPP that can produce real-time mobility predictions to support LUO train infrastructure from overloading and congestion. For this, an intelligent HO skipping technique called context-aware HO skipping is proposed to efficiently manage HO rate associated with cardinal passenger traffic flows. Our paper contributions are as follows:

- Real dataset: To examine a real scenario, we utilised the dataset from Transport for London (TfL) in order to predict the passenger movements (number of passengers) at each train station. Multiple colours are representative of different train lines that operate within LUO train network as shown in Fig. 1. Dataset is comprised of 39 train lines that are operating in London region, out of which there are 13 London tube lines cardinally covering 272 stations in the extended London areas. Cardinal directions, such as northbound, southbound, eastbound, and estbound (NEWS) data was collected to form one big dataset which is detailed in Section IV-A.
- Mobility tracking and future location estimation: We propose mobility prediction classification by using ML algorithms for passenger traffic flows in cardinal directions. Realisation of passenger's mobility and trajectory in the LUO network that comprises of several train lines integrates with the HO skipping techniques.
- Context-aware HO skipping: Based on ML results obtained via classification and cell topologies (current cell and the cells which are going to be visited next), we analyse and present the passenger association with its closest BS while on the move. To address passenger's mobility, a context-aware HO management is required to intelligently drive the HO process in cellular networks. Therefore, we propose an intelligent HO skipping technique that exploits multi-decision protocol for taking automated decisions to carry out a necessary HO. In contrast to the proposed techniques in [1], [2], we not only manage to reduce the randomness of the passenger's association with the BSs but we also enhanced the overall performance of the HO skipping phase with improved SINR, and average throughput. A HO is skipped when BSs intelligently report their traffic states by issuing collective neighbouring reports. Context-aware technique takes multiple parameters into account such as passengers trajectories, velocities, path, travel direction, and cell load for a HO to be skipped, thus improving the overall performance of our NEWS framework.

The remainder of the paper is organised as follows. Section II provides the background of the undertaken research. Section III presents the system model with the overview of HO procedure and multiple HO skipping techniques evaluation. Section IV presents the proposed method. Section V provides the analysis of our simulation results. Finally, Section VI concludes the paper.

II. BACKGROUND

A. HO Fundamentals

The arbitrary user association with the serving BS determines the need for HO when in motion. The criteria is for a user equipment (UE) to be associated with the serving BS based on the best serving participant which has high average received signal strength (RSS) level. A higher RSS level BS continues to serve a UE within its boundaries until the UE decides to change its association while moving from one BS to another domain. Traditionally, this method of user association was effective until the heterogeneity within cellular networks was introduced. Nowadays with increasing traffic demands, HetNets play a vital role in densifying cellular networks further to enhance the capacity. Increased demand for HetNets also brought developments in determining the best serving BS, cell load balancing, throughput maximizing, delay tolerance, and resilience recorded in the call detail records (CDRs) [1], [2], [9], [14], [15], [24], [46]. Despite of the selection rule, UE mobility requires an advanced level of intelligence to exploit the best HO rates with the densification of BSs. Hence, a trade-off is needed to utilise HO cost in line with the BS density.

There are three main phases of HO: Initiation, preparation, and execution. Initiation phase determines user reports that contain reference signals measured from serving BS neighbours. In the 4th generation (4G) long term evolution (LTE), but not limited to, the key point indicators (KPIs) consists of reference signal received power (RSRP) and reference signal received quality (RSRQ) [10], [40]. Downlink and/or uplink signal measurement reports also contribute to the HO initiation process. The preparation phase allows signalling to be exchanged between serving and targeted BSs along with the admission controller. The key player to decide whether HO is necessary is the admission controller which initiates the HO process based on a set of protocols defined in the HO criteria. Once the defined HO criteria is met, with the use of random access channel (RACH), the user discharges its association from the serving BS and attempts to synchronise and access the target BS. The UE then notifies the execution of HO, which is completed to the network by sending a confirmation message upon synchronisation. The HO procedure is performed but at the cost of some overheads which degrade the overall performance of the network. This involves the interruption of smooth data flow between UE and serving BS due to signalling. The occurrence of such interruptions depends on BS intensity and user velocity where the duration of each interruption is an important measure denoted as end-to-end HO jitter [47]. The aim is to decrease the frequency of such HO delays in user's mobility at both slow and high velocities. Usually, the slow user's movement doesn't trigger the HO due to the sufficient sojourn time. However, high mobility is incumbent upon setting up certain measures in order to avoid unnecessary HOs. UE speed has a great influence on HO rate and is an important aspect of the overall performance. Frequent cells and several BSs shift take place when a passenger moves in high mobility train leading to HOs, thus increasing call drop ratio and failure rate alongside [46]. Therefore, optimization of hysteresis and time to trigger (TTT) should be carefully monitored to satisfy passengers wireless communication requirement in high-speed train mobility. In our case, the LUO train network has high mobility trains that run on different speeds to cover distances. For instance, the average speed on the London underground (LU) is 20.5 mph (33.0 km/h) whereas, London overground (LO) trains tend to travel at over 40 mph (64 km/h) and can reach speeds of 62 mph (100 km/h) in the suburban and countryside areas [48]. For the multiple speeds and different time thresholds, we have made some empirical experiments and have chosen their values based on the best trade-off in terms of HO cost and user throughput.

B. State-of-Art in HO Skipping

The movement of the trains in cardinal directions require a strategy when they pass through SCs connected to macro base station (MBS) through backhaul as shown in Fig. 1. The main goal of the PPP mobility prediction model is to ensure that our novel NEWS framework defined context-aware HO skipping would produce best connected results when compared to other HO skipping techniques in LUO train environment. This means, to remain under mobile coverage footprint, when trains move from one BS to another, they receive coverage requests from several BSs located within the proximity of its movement. In our research we have discussed multiple HO skipping techniques such as, alternate HO, location-aware HO, size-aware HO [2], and context-aware HO. Preferring one SC to another requires a strategy to overcome unnecessary overheads, waste of resources and HO costs. PPP mobility prediction model driven HO skipping technique can maximize the throughput with the best SINR and reduced HO costs. The no skipping is shown in Fig. 2 (scheme a), where a black line indicates the train line, white circles indicate the train stations over the train line. BSs are represented by blue dots, with their coverage areas defined by the blue borders. In case a BS has its area painted in green, it means that the users have connected to that BS, whereas if it is in yellow, it means that the BS has been skipped.

1) Alternate cell switching based HO skipping: The alternate HO skipping scheme accounts for the alternate automated procedure for cell selection and HO skipping when a passenger is on the move in certain direction of travel [2]. The passenger's trajectory decides which BSs to latch and skip on alternating basis regardless of cell location, size, and load. The alternate HO skipping is illustrated in Fig. 2 (scheme b).

2) Location-aware HO skipping: The HO skipping technique based on location triggers skipping when shortest possible distance between the user trajectory and the target BS is accounted [2]. The users exceed the predefined threshold L when covering minimum distance along the trajectory to target a BS. In our work, threshold L can be designed in such a way that passengers skip the BSs along their cardinal directions through the cell edge only. HO skipping based on location scheme is illustrated in Fig. 2 (scheme c).

3) Size-aware HO skipping: When BSs' footprints are less than the predefined thresholds, s service areas, the passengers tend to skip the HOs based on BS cell sizes [2]. This HO

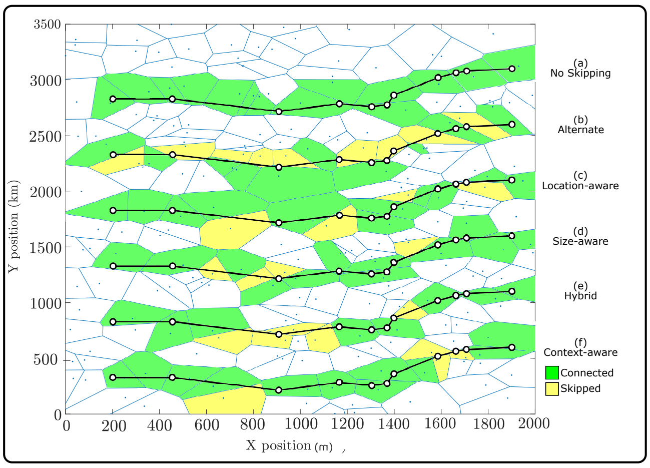

Fig. 2. Representation of PPP based single tier cellular network where green and yellow cells are indicative of connected and skipped cells. HO skipping schemes (a to f) represent no skipping, alternate, location-aware, size-aware, hybrid, and context-aware HO skipping schemes, respectively. Black line represents a specific train line moving east to west.

setting reduces the service area of the BS that leads moving passengers to skip the cell and form a connectivity to other cell. In this concept, cell dwell time is dependant on the BS footprint size that aims to avoid time duration for far-reaching blackouts. In this contingency, SCs are skipped by the passengers where large footprint-based cells serve the requirement and allocate resources. HO skipping based on cell sizes scheme is illustrated in Fig. 2 (scheme d). Service areas are assumed to be correct and known by the mobile network operators (MNOs) that deliver services around LUO train network.

4) Hybrid HO skipping: Alternate, location and size aware HO skipping techniques fall short to accurately observe the true cell dwell time. Therefore, on combining all techniques, more precision and enhanced inference about the cell dwell time can be achieved which is shown in Fig. 2 (scheme e) [2]. This way, the factor of improvement in the HO skipping decisions and performances can be handled more accurately and precisely. Consequently, the combination of all techniques set out the accountability of user location and cell areas while making the HO decision. One of the most important aspect is to estimate user's trajectory where we have used known trajectories associated with daily passengers on the LUO train network. This makes our HO skipping strategical which can be triggered on known passenger's location and cell size thresholds.

Fig. 2 also shows our proposed context-aware HO skipping (scheme f) which is presented in Section IV of this paper.

III. System Model

A. NEWS Framework

The proposed NEWS framework considers the downlink stream with number of BSs spread over an area based on the city of London. The area consists of a rectangle of sides L_1 and L_2 that covers one of the train lines for simplicity. In this area, a certain number of BSs are evenly deployed according to a PPP, with rate λ across several train lines as shown in Fig. 1. Moreover, we also assume that the city of London is covered by N_o distinct MNOs and that each operator is considered to have the same total available bandwidth W. Each BS is equipped with multiple directional antennas with constant gains and Tx powers, each BS has N_s sectors, with each sector supporting a fixed number of resource blocks (RBs), N_{RB}. In addition, a frequency reuse factor of 1 with constant bit-rate service is assumed. For context-aware HO skipping establishment, consideration has been given to a single-tier network model consisting of assumed BSs spread around multiple train lines in cardinal directions with their traffic information in separated control and data architecture (CDSA) [49]. In CDSA, macro cell (MC) controls the signalling with low data rate activities whereas data based stations (DBS) or simply small cells (SCs) offer high capacity services. In our NEWS framework, train lines move in specific direction using a specific path defined by the TfL as shown in Fig. 1 whereas, there are number of movements to define the trajectories of passengers such as boarders, alighters, station entry and exit passengers, link and passengers frequency, etc. For the movement of trains, each colour in Fig. 1 represents a train line. For instance, Piccadilly line which is represented by a blue colour in the figure moves in east-west (and vice-versa) direction. Northern line in black colour travels from North to South and vice-versa.

B. BSs Positioning Using PPP

Experiments yielding numerical values of random variable x, the number of outcomes occurring in a specific region in a given interval of time are referred as Poisson experiments. With the use of Poisson experiments, a number of observations can be generated for a random variable to formulate set of given values in a process called Poisson point process (PPP) [50]. NEWS framework employs PPP to model HO rate during passenger traffic flows in cardinal directions via topology-aware HO skipping techniques. The presented equation is to define how observations are calculated to perform Poisson experiments,

$$P(r; \lambda t) = \sum_{x=0}^{r} p(x; \lambda t) = \frac{e^{-\lambda t} \, (\lambda t)^x}{x!}. \tag{1}$$

The mean number of outcomes are computed from $\mu = \lambda t$, where t denotes the specific time of HO occurrence and λ is the rate of arrival that can be represented by a symbol $P(x; \lambda t)$. λ is the average number of outcomes per unit time and region, $x = 0, 1, 2, \cdots$, and $e = 2.718$. According to this model, in the proposed framework BSs are then evenly deployed in the rectangular area following a PPP.

C. User Parameters

To perform user association, our framework models passengers to associate with the BSs based on their distances with the set of all passengers $\mathbb{U} = 1, 2, \cdots, u$ and all BSs $\mathbb{B} = 1, 2, \cdots, b_k$. Once the distance is known, RSRP measurements are calculated by locating the passenger within a train, its association to the closest BS while on the move per each evolved node-B (eNB), and signal availability at a each location. Therefore from [2] we can calculate the RSRP of each user as,

$$\text{RSRP}_{u,b_k} = T_x \cdot h \cdot d_{u,b_k}^{-\alpha}\ , \tag{2}$$

where, T_x is the eNB transmit power, h is the channel power gain, which follows a Rayleigh distribution with unit variance, d_{u,b_k} is the distance between user u and BS b_k, and α is the path loss exponent. The average sum of the RSRP signal received from passengers (wanted reference signal) to the average sum of interference and noise N (unwanted signal) is measured by signal to interference and noise ratio (SINR), which is given as,

$$\text{SINR}_{u,b_k} = \frac{\text{RSRP}_{u,b_k}}{N + \sum\limits_{i=1, i\neq b_k}^{b_k} I_i}, \tag{3}$$

where, N corresponds to the additive white Gaussian noise (AWGN) and $\sum_{i=1,i\neq b_k}^{b_k} I_i$ is the interference from all other BSs, except the one that the user is trying to connect to.

In addition to SINR, the coverage probability is also determined. In general, coverage probability is dependant on the SINR where a UE exceeds a certain defined threshold. NEWS framework exploits coverage probability affected by SINR when the mobility of passengers outstrips by predefined threshold parameters. Therefore, the coverage probability can be calculated as [2],

$$C_{u,b_k} = \mathbb{P}\Big[\text{SINR}_{u,b_k} > T\Big], \tag{4}$$

where T is a predefined threshold.

Users are then allocated to specific BSs according to not only SINR, but also the available resource blocks (RBs) at each BS. Without loss of generality, it is assumed that each user consumes 1 RB when connecting to a BS and that for a user to associate to a BS, the following criteria must be met:

$$\Psi_{u,b_k} = \begin{cases} 1, & \text{if SINR}_{u,b_k} \geq \text{SINR}_{\min} \ \& \ \text{RB}_{rem} \geq 0, \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

where, Ψ_{u,b_k} is an association vector between UE and BS (b,k). If the user has a SINR above a minimum requirement SINR$_{min}$ and there are enough RBs available at the target BS, the user is associated with its preferred BS. Otherwise, if none of these conditions are met, the user then looks for the next best BS available. If none of these conditions are met, the user is then assumed to be out of service, until a new BS can be found that meets these criteria.

D. User Mobility

Since in this work it is considered that users are on-board trains, it is assumed that a train moves with a constant speed of v and that users inside the train are positioned in the center of mass of the train plus an additional random offset, defined by coordinates $(x_c, y_c) \pm (x_o, y_o)$ m. In addition, it is considered that the train travels in between a certain number of stations, and that whenever the train passes through a station certain passengers board, while others leave the train. It is also assumed that only a percentage of passengers, N_{active}, require connection while being on a train.

As the train moves through the considered area, it traverses the coverage zones of BSs. In case no BSs are skipped, passengers always associate to the best available BS, according to (5). When skipping is performed, whenever passengers skip a certain BS, they maintain their association with the previous serving BS and avoid looking out for nearest BSs regardless of their proximity. Alternatively, they tend to HO to the next target BS based on the relative distance. To simultaneously serve moving passengers by both serving and the next target BSs, mutually load dependant intelligent transmission is required, being the main focus of our NEWS framework, relies on full or partial coverage availability in the LUO network.

E. HO Cost

For HO skipping, we define HO cost associated with the coverage probability and SINR derivatives in light of multiple HO skipping techniques as [2],

$$\overrightarrow{HO_c} = \min(\hbar_t \ \cdot \ \tau, \ 1), \tag{6}$$

where, $\hbar_t$ is the rate of HO per unit time and τ denotes the delay tolerant of each HO in seconds. Therefore, the $\overrightarrow{HO_c}$, being unit-less, is used to observe the costs associated with the HO techniques to quantify the fraction of time along the passenger's trajectory. The time taken by a UE switching from serving BS to the targeted one due to HO signalling. Note that, if $\hbar_t \cdot \tau \geq 1$, this means that the HO delay is greater than the cell dwell time. Therefore, the entire time is wasted where $\overrightarrow{HO_c}$ is set to one. Now, PPP based HO rate for passenger's trajectory [42] is defined as,

$$\hbar_t = \frac{4v}{\pi}\sqrt{\lambda}, \tag{7}$$

where, v is the speed of the train, and λ is the PPP rate. The number of HOs per unit length have been calculated for HO rates followed by the velocity v multiplication. The number of HOs per unit length $\hbar_l$ is obtained from the the trajectory length. Thus, $\overrightarrow{HO_c}$ can be defined as,

$$\overrightarrow{HO_c} = \hbar_l \ \cdot \ v \ \cdot \ \tau. \tag{8}$$

F. User Throughput

The main performance metric of our NEWS framework is the average throughput of a passenger that exploits proposed HO techniques. Average throughput demonstrates the reciprocity between HO cost and capacity gain imposed by network densification. The average passenger throughput (bits/s (bps)) affected by HO rate and the impact of HO skipping techniques have been discussed in the following equation [2],

$$TP_{u,b_k} = W \cdot R_{u,b_k}(1 - \overrightarrow{HO_c}), \tag{9}$$

where, W denotes the overall bandwidth and R_{u,b_k} is the ergodic spectral efficiency which can be defined by Shannon formula for capacity by using (3) as,

$$R_{u,b_k} = \mathbb{E}(\ln(1 + \text{SINR})). \tag{10}$$

G. Context-Aware HO Skipping

In regards to the traditional HO skipping techniques shown in Fig. 2 (schemes a to d), neither the alternate, nor the location or size-aware HO skipping alone accurately reflects the true cell dwell time obtained from passengers location, travel direction, most chosen path, train load and speed etc. In addition, hybrid HO skipping shown in Fig. 2 (scheme e), which is the combination of location and size-aware techniques is unable to address true challenges of HO skipping associated with mobility of passengers in the LUO network. Challenging and complex LUO train network dynamics overburden traditional HO schemes to drive smooth and seamless HOs. Situation gets more complex when passengers location, travel direction, most chosen path, train load, and train speed are added as the key parameters to warrant real-time LUO train environment. This is where, context-aware methodology comes into play which has the ability to harvest LUO train network information about its environment at any given time and adapt behaviors accordingly. This intelligently acquires the best methodology according to the changing scenario with the accountability of real-time environment and radio parameters to develop the responses with best possible strategy. Context-aware methodology relies on complex LUO train network to automatically build load-aware dataset based on passengers location, their travel direction, most chosen path, train load, and train speed. In other words, context-aware cultivates its response by intelligently adapting to the transitional environment. Such a load-aware technique that intelligently addresses HO skipping in complex LUO train network is called context-aware HO skipping which is illustrated in Fig. 2 (scheme f).

IV. Proposed Method

We present an analytical model development of NEWS framework to optimise the passenger traffic flows in LUO train network. Following are the proposed elements;

- ML driven mobility predictions for future location estimation and planning.
- PPP mobility prediction.
- HO skipping.

Our proposed NEWS framework is based on the integration of ML [16]–[23], [51], [52] into PPP [50] mobility prediction model. Where, ML is first trained to classify north, east, west, and south directions along with LUO train lines from our dataset. The output of ML is then fed into the PPP simulation model for HO skipping examination using passenger's trajectory, velocity, path, load, train lines, train directions, travelling time, etc. Both ML classification and PPP simulation are presented in the following subsections.

A. Dataset

To examine a real scenario, we utilised the dataset from TfL to predict the number of passengers at each train station by classifying them into "high" or "low" passengers at a given the time of day. Multiple colours are representative of different train lines that operate within LUO train network as shown in Fig. 1. The dataset is comprised of:

- 39 train lines that are operating in London region, out of which there are 13 London tubes lines.
- 272 stations in the extended London areas in cardinal directions.
- Cardinal directions, such as northbound, southbound, eastbound, and westbound (NEWS) data was collected, merged, and classified into "high" or "low" passengers, i.e., Number of passengers are divided into two categories with labels "high" or "low".
- "High" passengers as being in the top 25% of all passenger values in our data set and "low" passengers as the bottom 25%. We have used these definitions to assign the labels "1" and "0" to the data points in our model.
- For instance, Label "1" has been assigned to instances of high passengers and the label "0" to instances of low passengers.
- Each train direction user numbers were collected in the 15-minute time intervals.

The availability of the data was dependant on each train line movement in cardinal directions in 15-minute time intervals. Hence, 15 minutes per hour per 21 hours: $(60/15) \times 21 = 84$ data points per day for one train line. This is, $84 \times 7 = 588$ data points (i.e., 1 week = 21 hours per day and for 1 train line). Therefore, multiplying data points with train lines and number of stations, i.e., $588 \times 13 \times 272 = 2,079,168$ data points (overall) of all stations in the LUO network. Now, number of passengers travelling in 1 week are, $469,680$ covering all train lines. Hence, w have, $469,680 + 2,079,168 = 2,548,848$ are overall data points in the training model.

As part of the pre-processing stage, we merged cardinal directions of the trains and passenger movements (number of passengers) into one big dataset followed by its conversion into csv file format to predict "high" and "low" passengers against 15-minute time intervals, being a binary classification. The "Nan" values are resolved by using simple function called imputer, an estimator used to fill the missing values in datasets.

For our dataset, we used several parameters comprising of (i) passenger movements, (ii) number of stations, (iii) train lines, (iv) train codes, (v) station names and codes, (vi) train direction, (vii) direction codes, (viii) train lines order numbers, (ix) link code, (x) time of passengers travelling such as: entry/exits, early, AM peak, midday, PM Peak, evening, and late, etc. Also, the number of passengers boarding onto train carriages called boarders and, passengers who alight on the stations called alighters are also considered. For binary classification predictions, we merged and classified multiple data streams mentioned above, into one large dimension dataset to train the ML model. Then the formulated dataset was plotted against 15-minute time intervals of each passenger movement in each train within LUO train network.

B. ML-Driven Mobility Training and Prediction

The proposed NEWS framework adopts supervised learning (SL) as a ML tool to predict the mobility prediction-based cardinal passenger traffic flows with the support of algorithms such as logistic regression (LR), support vector machine (SVM), and multilayer perceptron (MLP). For training ML algorithms, we divided our dataset into train, test and validation with 70% of data used for training the model, 20% for testing, and 10% for validation. Historical traces of passengers mobility which include direction, path, load, time of travelling, associated cell IDs, and reference signals received power (RSRP) are assumed to be available for training the framework. It is worth mentioning that all LUO train lines in cardinal directions with a huge dataset have been analysed and normalized prior to ML model fitting as shown in Fig. 1.

This normalization is done by using six features used for training the model based in order to obtain optimal results. These features are skew, percentile, square root (SR), standard deviation (SD), mean and kurtosis. The value for each feature is calculated individually for each window size. For example, the window size of 15 seconds (based on 15-minute time intervals) is selected, and the aforementioned features are calculated accordingly. Normalizing and using various features help to optimise the performance of the model fitting and learning. Below are the ML algorithms used to predict the mobility prediction-based cardinal passenger traffic flows;

- SVM is binary/multi-class classification algorithm with a polynomial kernel. However we used binary labelling for our dataset model training.
- A MLP is binary/multi-class classification algorithm which is a feed forward neutral network consisting of input, hidden and output layers. The classifier is trained for 100 epochs using back propagation and an Adam optimiser with a learning rate of 0.0003 which consists of one input layer and three hidden layers per feature, and an output neuron per positive class consisting of 2 nodes representing binary classification as "high" and "low" number of passengers in cardinal directions.
- LR is type of machine learning algorithms which is used for binary classification. The LR is used to find the best fitting model to describe the relationship between characteristic of interest and set of independent features.

The training of SVM and MLP are done by using Scikit Learn Python package based on binary classification predicting "high" and "low" passengers. The SVM algorithm works by constructing hyper planes and uses these hyper planes to separate the input data into different categories. Using mentioned features, data is used to train the hyper plane. The kernel for SVM is rbf whereas MLP is a feed forward neural network. It consists of three types of layers the input layer, output layer and hidden layer. The relu activation function and Adam optimizer were used.

We intended to evaluate the best possible outputs for the framework. The number of tests were conducted to achieve the suitable output from ML classifier for the input into context aware HO skipping. As NN are the functional unit of deep learning and are robust to mimic the behaviour of the real scenarios in order to solve complex data-driven problems. Similarly, we used NN architecture based on its capability to distinguish "high" and "low" number of passengers moving in cardinal directions out of a complex dataset. This is where our input data is processed through different layers of artificial neurons stacked together to produce the desired output mimicking real scenario of the LUO environment. Then we identified the best architecture by comparing different layers and we found the best optimal layers.

The number of neurons in the input layer equals the number of input variables in the data being processed where an input vector needs one input neuron per feature. Therefore, we have six neurons per six features to train our dataset. This has been carefully chosen as they contained identifying patterns of passengers to avoid overfitting. For a less complex dataset, fewer hidden layers are sufficient to produce desired results. However, in our case, complex dataset was rationalised and formulated from several data points as mentioned Section IV-A.Considering above complexities, we categorised complete dataset into two a binary form highlighting "high" and "low" passengers' categories in 15-minute time intervals in order to obtain an optimum solution. Normally, 1 or 2 hidden layers are used if data is less complex, however, due to our large-dimensioned dataset, 3 to 5 hidden layers were tested and carefully set to 3 which gave us best comparable result.

Similar size of hidden layers was not providing optimum results while tuning using our dataset and therefore overfitting. Hence, we chose to set hidden layers to 3 with unequal neurons. For number of neurons, we started training with 1–100 neurons initially followed by gradually increasing the numbers until we found overfitting. Hence, setting unequal neurons, i.e., 1500, 512, and 1500 provided optimal results with 3 hidden layers. This is due to the complex data set we rationalised and formulated considering large number of parameters.

ML-driven results are exploited to model PPP for HO skipping evaluation. To generate comparative analysis in terms of coverage probability (number of users covered vs SINR), average throughput, and HO costs, multiple HO techniques are simulated. Passengers trajectory, velocity, path, train load, directions & lines, travelling time, etc., are used as the key parameters for HO skipping techniques model simulation.

C. Context-Aware HO Skipping

Considering that the speed and trajectory of the trains are known beforehand, the proposed algorithm is able to calculate the time that the users spend in each cell traversed in the users' path. As such, given the time in each cell as t_{b_k}, and a given time-based threshold, defined as t_{thresh}, for a user to skip a cell according to the context-aware approach, the following conditions must be met,

$$\Omega_1 = \begin{cases} 1, & \text{if } t_i \leq t_{thresh}, \\ 0, & \text{otherwise}, \end{cases} \tag{11}$$

where, t_{thresh} is half the average time in cell spent through the trains entire journey. Since the train follows a specific path with a predefined maximum speed, it is natural to know the average time spent in cells throughout the entire route.

Condition 1 (Ω_1) states that if the time spent inside a cell is lower than a threshold, users opt to skip the cell. However, in the context-aware approach, the load and the quality of the signal (in terms of SINR) are also considered. Thus, another condition needs to be checked in order to decide who is going to skip the cell. Given $\mathbb{S} = \{s_{1,b_k}, s_{2,b_k}, \cdots, s_{u,b_k}\}$ as the set of measured SINRs of all passengers $\mathbb{U} = 1, 2, \cdots, u$ at base-station b_k, $\mathbb{SS}$ as the sorted set of measured SINRs, $\mathbb{SS} = \{ss_j, ss_{j+1}, \cdots, ss_{|j|}\} \mid ss_j < ss_{j+1}$, where $|j| = |u|$ and RB_{rem,b_k} as the available resource blocks at base-station i, condition 2 can be expressed as follows:

$$\Omega_2 = \begin{cases} 1, & \text{if } \Omega_1 = 1 \ \& \ j > \text{RB}_{rem,b_k}, \\ 0, & \text{otherwise}. \end{cases} \tag{12}$$

Condition 2 states that a user skips a base-station if condition 1 (Ω_1) is satisfied and if the index occupied by the user's sorted SINR is larger than the number of RBs available at the target BS. In other words, if the user has a good enough SINR when compared to other users and the number of RBs available at the target base-station can support at most $j-1$ users, user j should skip the target base-station. Alternatively, it can be said that not all the users skip at one time. Depends on the channel quality. some skip some do not. If the UE has a good channel, is not advantageous for him to skip. However, in bad channel quality, skipping makes no difference due to minimal impact on throughput and cost. Followed by condition 1, condition 2 checks the SINR and load for all UEs to have enough RBs to skip/no skip. During the phase of conditions 1 & 2 are in execution, UEs do not need to know the RBs availability. BS will schedule the cells with best SINRs against the ones with low SINRs, which don't need to be scheduled in conventional network system. Algorithm 1 shows an algorithm of the proposed context-aware skipping scheme.

Algorithm 1: Context aware HO skipping algorithm

Initialize area sizes L_1 and L_2;
Initialize train path, size, speed, initial position and stations' positions;
Initialize network parameters $W, N_o, N_s, N_{\text{active}}$,RB;
Initialize all thresholds;
for *counter = 1:*N_{runs} **do**
  Generate user positions inside train;
  Generate BS positions according to PPP and λ;
  while *Train is not in final station* **do**
    if *Train is in station* **then**
      SVM model predicts total number of users;
      Update number of users and positions;
    else
      Keep same number of users and positions;
    end
    Calculate RSRP via (2);
    Calculate SINR via (3);
    Determine user's cell association via (5);
    if *HO occurs* **then**
      Evaluate conditions Ω_1 and Ω_2;
      Update HO cost via (8);
    end
    Measure user throughput with (9);
    Update train and user positions;
  end
end
Calculate average coverage probability via (4);
Calculate average throughput;
Calculate average HO cost;

V. HO Skipping Simulation and Results

A. Simulation Scenario

In order to validate the proposed scheme, a simulation scenario is performed in MATLAB. Several BSs are positioned according to a random PPP in a rectangular area. It is also assumed that coverage is provided by 4 different operators, each having 20 bands of 10 MHz, each BS has 3 sectors and each sector has 50 resource blocks, resulting in a total of 150 resource blocks per base station. In this area, a total of 10 train stations, according to the underground map of London are positioned[2]. In addition, it is assumed that the train is moving west-bound with a fixed speed of 64 km/h and that at each station a certain number of users leave/board the trains. All simulation parameters are listed in Table I.

B. Metrics

In this scenario the different HO skipping techniques are compared, mainly: No skipping (best connected), alternate skipping, location-aware, size-aware, hybrid, and the proposed context-aware approach. Depending on the technique adopted, different types of HO skipping are performed. For instance, the no kipping approach never skips any BSs, whereas the alternate skipping skips every other BS. The location-aware skipping [2] skips BSs if at the time the train enters the cell, the distance between the BS and the train is larger than a threshold.

$$\Omega_{b_k} = \begin{cases} 1, & \text{if } L > \text{d}_{\text{train},b_k}, \\ 0, & \text{otherwise}, \end{cases} \tag{13}$$

where, Ω_{b_k} indicates if BS b_k will be skipped or not. In the case of the size-aware skipping [2], a BS is skipped whenever

[2]In this work a 1:10 scale is adopted, meaning that the distance between train stations are scaled to a tenth of the actual distance.

TABLE I
SIMULATION PARAMETERS.

Parameter	Value
PPP rate (λ)	0.0001
Side of simulated area (L_1)	$2,000$ m
Height of simulated area (L_2)	$1,000$ m
Number of operators (N_o)	4
Bandwidth (W)	10 MHz
Noise spectral density (N_0)	-204 dBW
Active users (N_{active})	90%
Path loss exponent (α)	4 [2]
BS transmit power (T_x)	0 dBW [2]
Train speed (v)	64 km/h
RB per BS (RB)	150
Coverage probability threshold (T)	$[-15, \cdots, 15]$ dB [2]
Minimum SINR (SINR_{min})	0 dB
User offset X position (x_o)	± 5 m
User offset Y position (y_o)	± 2 m
HO delay (d)	1 s [2]
Size threshold (s)	9km^2
Location threshold (L)	85 m
Hybrid thresholds (s, L)	9km^2, 100 m

TABLE II
MOBILITY PREDICTION CLASSIFICATION WITH FEATURES.

Classifier	Accuracy	Precision	Recall	F-Score
LR	91.76	0.91	0.90	0.91
MLP	92.57	0.92	0.91	0.92
SVM	94.51	0.94	0.93	0.94

TABLE III
MOBILITY PREDICTION CLASSIFICATION WITHOUT FEATURES.

Classifier	Accuracy	Precision	Recall	F-Score
LR	78.63	0.78	0.77	0.78
MLP	80.80	0.80	0.79	0.80
SVM	83.56	0.83	0.82	0.83

TABLE IV
10 FOLD CROSS-VALIDATION.

Classifier	Accuracy	Precision	Recall	F-Score
LR	92.74	0.92	0.91	0.92
MLP	93.60	0.93	0.92	0.93
SVM	94.77	0.94	0.93	0.94

the size of a cell area is smaller than a threshold,

$$\Omega_{b_k} = \begin{cases} 1, & \text{if } s_{b_k} < s, \\ 0, & \text{otherwise.} \end{cases} \tag{14}$$

Lastly, in the case of hybrid-skipping [2], the two metrics are combined, meaning that a BS is skipped if either the distance between the BS and the train is larger than a threshold or if the cell area is smaller than a threshold. In other words,

$$\Omega_{b_k} = \begin{cases} 1, & \text{if } s_{b_k} < s \vee L > \text{d}_{\text{train},b_k}, \\ 0, & \text{otherwise.} \end{cases} \tag{15}$$

A total of 100 runs of each technique are performed in order to average out the results. The 6 techniques are compared in terms of:

- Coverage probability: The probability that the average SINR of the users are above a certain threshold;
- Handover cost: The total average cost to handover users to all BSs from the starting train station to the last one;
- Throughput: The total average throughput of users weighted by the HO cost;
- SINR CDF: The cumulative density function of the average SINR of all users, which represents the percentage of users that have an average SINR above a certain value.

C. Results Discussion

1) Machine Learning Classifiers: The experimental results in the Tables II and III are based on all ML train with/without features in Scikit Python package showing link load of one train line flowing in only one direction, i.e., east to west. In addition Table IV shows results from 10-fold cross-validation as a resampling procedure to estimate the skill of ML modelling. Since the SVM classifier presents the best performance among all other classifiers, the remainder of the simulations and evaluations are completed with the SVM model only.

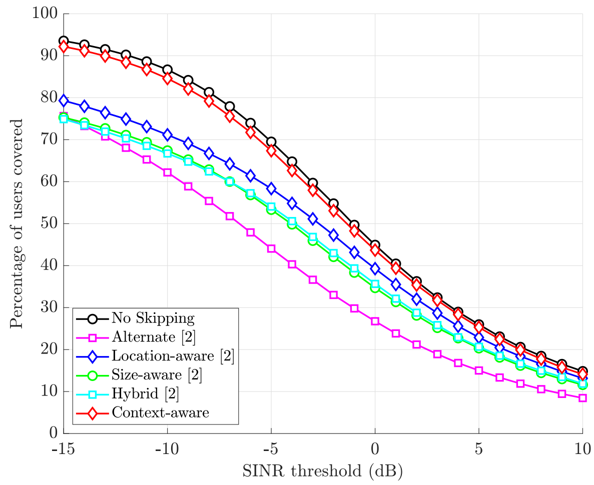

Fig. 3. Coverage probability comparison of different HO skipping techniques vs SINR threshold.

According to our empirical testing, it can be seen that the SVM achieved better results due its effectiveness on high dimensional spaces. In addition, SVM can performs better where the number of dimensions are greater than the number of samples. Also, SVM performs well when there is a clear margin to separate between data inputs according to their different attributes. Likewise, in our framework, the number of classes which supported SVM were; link direction, train trajectory, passengers movement, travelling time and frequency, carriage load, network load, etc.

2) Network Analysis: From Fig. 3, it can be seen that the best connected case offers the highest coverage probability, as expected, followed closely by the proposed context-aware scheme. This shows the robustness of the proposed scheme, as even by skipping certain cells, the context-aware approach is able to achieve a very similar performance in terms of cover-

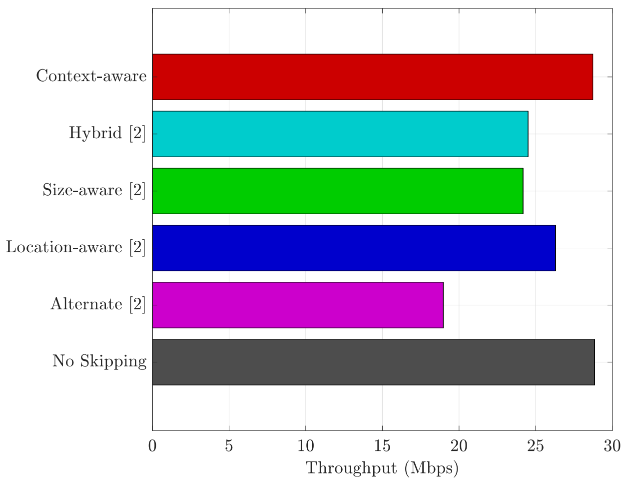

Fig. 4. Average throughput comparison of different HO skipping techniques.

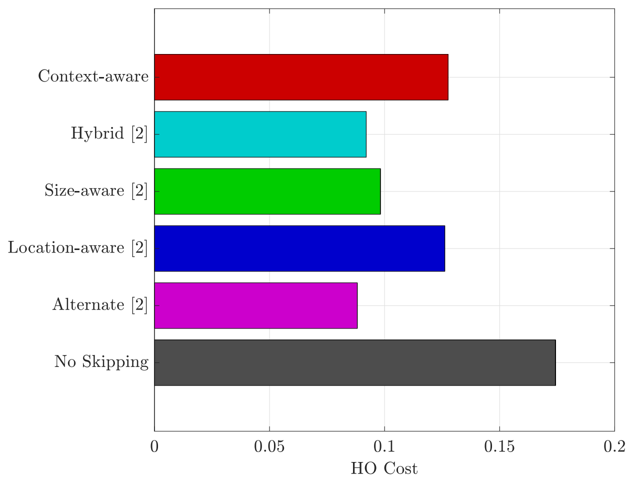

Fig. 5. Average HO cost comparison of different HO skipping techniques.

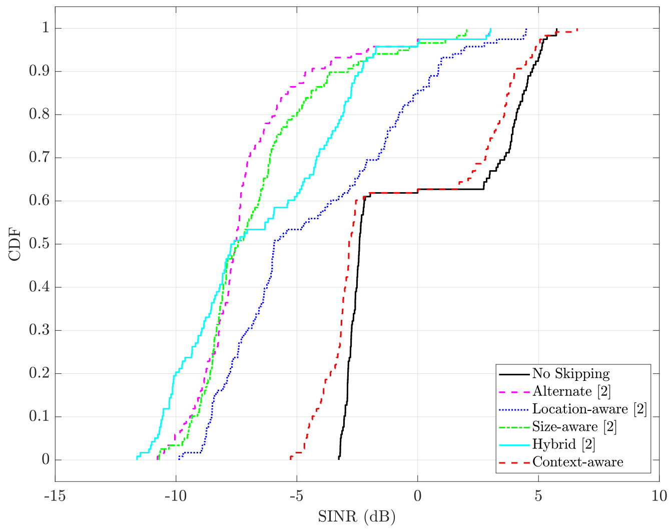

Fig. 6. CDF of SINR for different HO skipping techniques.

age probability. These 2 solutions are followed by the location-aware, size-aware and hybrid, which all have a very similar performance, and lastly the one with the worst performance is the alternate skipping method that skips every other cell. In addition we can also see that the gap between the no skipping, the proposed context-aware and the other solutions is larger when the SINR threshold is lower. This result suggests that both no skipping and context-aware approaches are able to find good enough BSs for the users to connect to, whereas the other approaches cannot. This happens since the location-aware, size-aware, hybrid and alternate schemes have a hard threshold in terms of skipping BSs, in which if that condition is met the target base station is skipped. This results in BSs that could potentially be the first or second best BS for users to connect to being skipped, resulting in a very poor SINR. In case of the context-aware approach, since both load and SINR information of the users are taken into account, this effect is mitigated, as users that have very poor SINR are forced to connect to these BSs, whereas users that have a good enough SINR can skip it. Lastly, the no skipping case is expected to be the best, as users always connect to the best available BS.

The average throughput results using (9) are extrapolated by SINR dependant spectral efficiencies as shown in Fig. 4. The HO cost impact on average throughput is directly proportional i.e., when velocity increases, due to the frequent HOs, cost increases as well. From Fig. 4, it can be seen that NEWS framework employed context-aware HO skipping outperforms with the minimum difference benchmarked against the no skipping case. Our proposed scheme has the best average throughput compared to other PPP HO skipping techniques.

In terms of HO cost and average throughput, it can be seen from Figs. 4 and 5 that the no skipping approach has the highest cost among all schemes and the best average throughput. This occurs as expected, since users do not skip any BSs in this scheme, thus users are always connected to the best BSs available. However, despite producing the highest throughput of all schemes, this also result in the highest cost. When comparing the alternate skipping approach, we can also see that its performance work as expected, as in this scheme every other BS is skipped, resulting in a percentage difference of around 50% when compared to the no skipping case. However, despite reducing the cost by almost 50%, the difference in terms of throughput is not as big, resulting in a loss of around 34% when compared to the no skipping case. Next, the location-aware approach is the one that performs best in terms of throughput when compared to other conventional skipping schemes, with a throughput degradation of only around 9% when compared to the no skipping case. However, this comes at a price, as the location-aware needs to connect to more cells, thus reducing the HO costs by only around 28%. The other approaches, such as size-aware and hybrid have very similar performance, in which they are able to significantly reduce the HO cost by around 44% and 47%, respectively, achieving a cost reduction similar to the one seen in the alternate scheme. However, their performance in terms of throughput is not as bad as the alternate, having a throughput degradation of around

16% and 15% for the size-aware and hybrid approaches, respectively. Lastly, the context-aware approach is the one that achieves the best average throughput among all other skipping techniques, being worse only than the no skipping base by only around 0.4% and with a HO cost similar to the one of the location-aware approach. These results really demonstrate the benefits of skipping techniques, as all of them are able to significantly reduce HO costs (by more than 1/4) with different levels of throughput reduction. In addition, when load and SINR information from users are taken into account, the benefits are even greater, as it can be seen from the proposed context-aware approach, which is able to reduce HO costs by around 27% with a minimal throughput reduction.

Lastly, Fig. 6 shows results in terms of the CDF of the average SINR of the users. This figure follows a similar pattern to the one from coverage probability, with the no skipping approach yielding the best results, as expected, followed closely by the proposed context-aware approach. In addition, when observing these two curves we can clearly see two regions where the SINR of users was concentrated: from -5 to -2 dB and from around 0 to 7 dB. This can be explained as in the proposed scenario, sometimes BSs would be overloaded, not being able to accommodate all users. As such, these regions show two groups of users, the ones that were able to connect to the best available BS, and another group of users, which had to connect to other BSs. Since in the context-aware approach some users are able to connect to the best available BS while others skip that BS, the SINR of the users are far greater than the ones from the other skipping methods. As previously explained, since the other methods have a hard threshold in terms of skipping and do not consider the load or the SINR information in their decision, all users are forced to skip their preferred BSs at some point, thus drastically reducing the users' SINR. In terms of the other methods, we can see that the performance of the location-aware is slightly better than the other schemes and that the performance of both size-aware and hybrid are very similar. Lastly, the alternate approach presents the worst results in terms of SINR. It is important to note that our framework has been assessed with multiple velocities and different time thresholds and performed some empirical experiments where we have chosen their values based on the best trade-off in terms of HO cost and user throughput.

VI. CONCLUSION

This paper proposed a novel NEWS framework that exploits an intelligent HO skipping scheme, context-aware HO skipping. The proposed technique allows train passengers to dynamically skip HOs by considering challenging and complex LUO train network dynamics over-burden traditional HO schemes to drive smooth and seamless HOs. To this end, NEWS framework first analyzes mobility prediction and future passenger directions for maximizing futuristic optimization by using ML. Secondly, through ML classification results, PPP-based HO skipping model is trained and simulated. The paper discussed topology-aware multiple HO skipping schemes for effective HO management. HO schemes take passenger location, cell-size, velocities, path, travel direction, and cell-loads into account to make HO decisions, for the avoidance of unnecessary HOs along the passengers trajectory. Our novel scheme, context-aware HO skipping outperformed among all traditionally equipped HO schemes in terms of coverage probability, average throughput, and HO costs. For future works, intelligent schemes can be modelled/designed in such a way that they may consider passengers' smarter HO skipping in a multi-tier network for different train velocities.

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