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Handover Prediction Integrated with Service Migration in 5G Systems

Hadeel Abdah
Instituto de Telecomunicações
Universidade de Aveiro
Aveiro, Portugal
hadeel.abdah@ua.pt

João Paulo Barraca
Instituto de Telecomunicações
Universidade de Aveiro
Aveiro, Portugal
jpbarraca@ua.pt

Rui L. Aguiar
Instituto de Telecomunicações
Universidade de Aveiro
Aveiro, Portugal
ruilaa@ua.pt

***Abstract*—As the research community inclines toward adopting increasingly complex techniques for future networks, and simple methods are often ignored, being labeled as trivial. In this paper, we argue that simple methods can sometimes outperform more sophisticated ones. We demonstrate that by evaluating two prediction mechanisms to forecast mobile user's handovers exploiting user-network association patterns. We perform a series of experiments on real-world data, evaluating the performance characteristics of such methods over more sophisticated and complex prediction techniques. Furthermore, we discuss how to easily bootstrap these mechanisms into the 5G network architecture. We suggest the use of these methods associated with Multi-access Edge Computing (MEC) scenarios, as a mean to identify favorable edge nodes to host the mobile applications, to best provide continuous and QoS-aware service for mobile users.**

I. Introduction

Unlike its predecessors, the fifth generation of networks (5G) is facing an unprecedented mobile traffic explosion, along with a proliferation of highly sophisticated services. enhanced Mobile Broad Band (eMBB), Ultra Reliability and Low Latency Communication (URLLC) and massive Machine Type Communication (mMTC) are among the types of traffic the upcoming 5G systems are expected to support. This instigated service providers to seek novel paradigms and techniques to enable not only continuous, but also QoS-aware services for mobile clients [1]. Fueled by the mounting pressure to meet Quality of Service demands, radical shifts in 5G networks architecture have been suggested e.g. network densification, control and data plane separation, and network virtualization. It also instigated the proposition of several new paradigms for 5G systems such as MEC, Fog Computing, and Cloudlet-based paradigm [2].

Taking advantage of the new features of 5G system and its innovative paradigms, novel techniques have been suggested as complementary methods to support mobility and enable latency-intolerant applications alongside the typical handover procedure. Some of these prominent techniques are application mobility or service migration [3], optimized low-delay handover [4], and dynamic and parallel offloading [5]. To enable such techniques, researchers are incorporating complex and computation intensive methods like machine learning algorithms.

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Understandably, complexity is a dominant theme of 5G networks. However, from the service provider point of view, the simpler the better, as operation costs may be reduced, and the predictability will be higher.

This work explores the potential of employing simple mechanisms for handover prediction, and compares them to more advanced ones proposed in the literature. As MEC is envisioned to play a significant role in providing an adequate platform for low-latency applications, we demonstrate the benefit of utilizing prediction techniques to identify the favorable node to host a set of services, which will be migrated proactively around MEC hosts.

The paper is structured as follows. The state of the art in the area of handover prediction is reviewed in section II. The evaluated mechanisms are described in section III. How the methods can be integrated into 5G cellular network and utilized in MEC for service migration is in section IV. The proposed solutions performance is analyzed in V. Section VI is dedicated to discuss some additional considerations. Finally, we conclude our study and present the future work in VII.

II. Related Work

Over the last few years, different studies have focused on enabling seamless mobility in wireless networks by exploiting handover prediction. Such studies rely on different techniques such as mobility prediction [6] , handover history [7], radio link characteristics [8], cross-layer optimization [9], machine learning [10], and mobile users profiling [11].

In this paper, the tested algorithms are closely related to the approaches proposed in [7] and [8]. Additionally, the evaluated mechanisms can be considered as extended works to [11]. The work presented in [7] evaluates the efficiency of utilizing statistics based on handover history to predict the future Base Station (BS). The prediction hit rate is found to vary between 20% and 47%.

Markov based mobility prediction was proposed in [11], in which user mobility patterns are modeled using a continuous-time Markov process with the network cells represented as the discrete states. A second order Markov-based prediction is used to perform the predictions. Thus, the probability of the future cell to be likely visited by a user depends on both the current node and previously visited one. Authors of [8] try to predict the next cell the user connection will be handed over to using a machine learning based prediction system. The metrics taken into consideration are the Channel State Information (CSI) and the user's handover history. In some cases, the prediction algorithm accuracy reached 95 to 100%. The accuracy is found to be highly related to the geometric complication of the cell, in terms of the number of paths that cross through it. In addition to the proportion of CSI values used, out of all CSI values a user reports in its current cell [8]. The main problem of this approach is its dependence on periodic feedback of channel gain from the users. Indeed, CSI values are reported to the base station (BS) by the user. However, the typical CSI values do not include channel gain, and are reported periodically or episodically from the user to the station, with time and frequency controlled by the eNodeB [12]. This raises the question of the time interval needed to report and calculate the channel gain for this approach to be feasible and how much overhead such reporting imposes on the network.

Machine learning algorithms were also utilized for handover prediction as in [13], where a Long Short Time Memory (LSTM) neural network was employed, and [14] which used multi-layer perception neural network for direction prediction assisted handover. The accuracy achieved by these methods was quite high. However, solutions based on neural networks have a major drawbacks of reduced scalability and high computation overhead.

For this study, we examine simple prediction techniques which can be executed mostly offline, thus, avoiding any extra delay. And, contrary to the aforementioned works which exploit the individual behavior of a user, we investigate a collective strategy where the behavior of multiple users are considered. We then compare it to the individual user profiling. The evaluated handover prediction methods are further detailed in section III.

III. Solutions for Handover Predictions in MEC

We consider handover prediction methods that take advantage of two facts. Firstly, roads have a defined and mostly fixed topology. Thus, we can model the movements of a mobile user through each road as a sequence of the cells he associates with during his journey. Secondly, people display significant regularity in their movements since they tend to revisit a few highly frequented locations, such as home, a shopping center, a restaurant, or work. Thus, mobile users within vehicles will likely follow the same streets frequently in their daily life. The following subsections further details the prediction mechanisms considered.

A. Method 1: Probabilistic Handover Prediction Approach

In this method, to predict the future cell mobile user, each user is capable of storing its previous cell identifier, and every BS knows the probability of handing over the

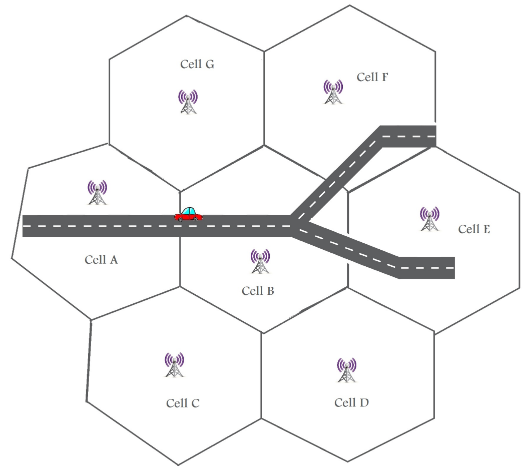

Fig. 1: Mobility scenario.

user's connection to each neighboring BS given the user's previous cell. These probabilities are derived from the user's handover history, stored locally in each BS, or in a centralized orchestrating entity at an upper layer of the network.

Assuming the scenario illustrated in Fig 1, the mobile user currently is associated with BS_B, and previously was associated with BS_A. BS_B has the probabilities of handing over the user's connection to each of the adjacent cells given the user past association is BS_A. The equation that represents these probabilities is given in (1):

$$P(X|BS_A, BS_B) \ \ where\ X \in \left\{BS_A, BS_C, BS_D, BS_E, BS_F, BS_G\right\} \tag{1}$$

The prediction method assumes the cell with the highest probability to be the future cell the user is heading to.

In our experiment, we deducted these probabilities by globally monitoring the users'-network association patterns over a period of time. In a real cellular network, these probabilities can be easily deducted at every base station individually, as the traditional handover procedure involves communication between the source cell initiating the connection handover, and the target cell receiving the connection. Thus, each base station can deduct the transitions probabilities locally. In such configuration, the prediction mechanism does not require any computation, as it only requires a lookup to a dataset containing these probabilities.

B. Method 2: Enhanced Handover Prediction Algorithm

Method 2 is an enhanced version of method 1. As it stands, method 1 is only able to perform the prediction when it has already performed handovers with the user's past cell i.e the sequence (previous cell, current cell, future cell) is present in the dataset used to deduct the probabilities and $P(X|BS_{current}, BS_{previous})$ can be calculated.

As a further enhancement in method 2, we avoid this limitation by calculating the probability of transitioning to the next cell given only the user's current cell $P(X|BS_{current})$ when the probability $P(X|BS_{current}, BS_{previous})$ can not be deducted.

When neither of these values are known to the BS, radio characteristics methods can be exploited. As an example, the predicted next cell can be considered as the neighboring cell correspondent to the highest recorded received power by the mobile device. The workflow of this possible enhancement is illustrated in Fig 2. The grey-colored parts of the workflow highlight the enhancements of this method compared to workflow of method 1 which is tinted black.

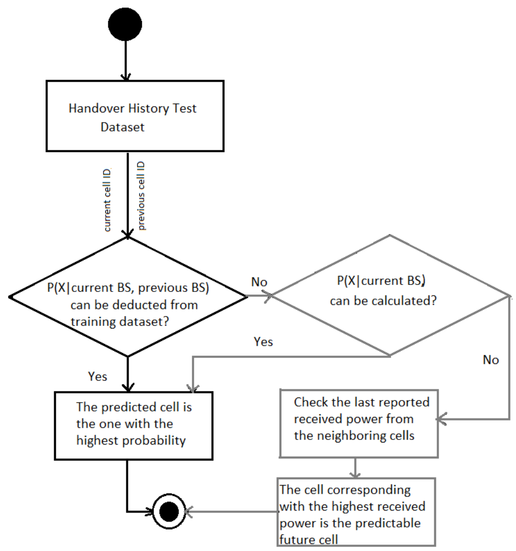

Fig. 2: Enhanced handover prediction algorithm workflow.

C. Forecasting Strategy

We consider that the handover prediction methods can use two strategies.

1) Forecasting based on the existence of Global Knowledge: the probabilities of the user transitions to the next cell, given its last and present cells, are deducted from the movement history of all users in the dataset. These histories are stored in the BS, independently of the generating user. The basic assumption, in this case, is that people often tend to have similar behavior. Thus, individuals tend to follow common streets/paths. This knowledge should be available at a somewhat wide scale, that includes the movements of users. It doesn't mean that there should be a globally coherent database, which may be impractical, but only local or partially valid information.

2) Forecasting based on Individual Profiling: where the probabilities are user dependent i.e different for each user and dependent on his own handover history. This will present higher complexity for implementation, as each user will have a different profile. Although techniques to compress data, or to have a hierarchical classification and storage, which will improve scalability, the worst case corresponds to a user specific movement dataset.

D. Time of day based clustering

To capture the impact of repetitive user behavior on the proposed methods, we define a time window concept and consider four different levels of granularity. In our case the windows relate to the behavior of typical commuting professionals. For other scenarios, the actual window granularity and number should be determined. These are:

1) 24 hours: where the probabilities are deducted from the complete handover history, independent of the time of the day (no time clustering).
2) 12 hours: where the probabilities are dependent on the time of the handover history. We consider two time domains with different probabilities (00am to 12pm) and (12pm to 24pm). Prediction execution timing determines the time domain to be used and its corresponding probabilities. For example, when the individual movement occurs during the first time domain, the probabilities of the corresponding domain is taken into consideration when handover prediction is needed.
3) 6 hours: in which the day is divided into four time intervals (00am to 6am), (06am to 12pm), (12pm t0 18pm) and (18pm to 24pm). Each interval has different probabilities deducted from previous handover histories occurring on the same time interval.
4) 2 hours: in which the probabilities considered are deducted from previous handover histories at the same hour of the individual movement and the hour before.

IV. Integrating the prediction mechanisms in 5G MEC environments

The vision of services driving the development and deployment of 5G systems has forced companies to think of radical changes to the traditional point-to-point core architecture which was adopted in previous cellular network generations. This motivated the design of a service-based architecture for cloud-based 5G systems. This was standardized by 3GPP working group as illustrated in Fig 3.

Authentication Server Function (AUSF) provides information for authenticating the user. Session management and IP addresses allocation is the responsibility of Session Management Function (SMF). The Access and Mobility Function (AMF) functional entity in this architecture provides authentication, authorization and mobility management. Meanwhile, Application Function (AF) provides information on the packet flow to the Policy Control Function (PCF) which controls the policies in order to support Quality of Service (QoS) [15]. The User Plane Function (UPF) has multiple functionalities, such as, being an uplink flow classifier, an interconnect point between the mobile infrastructure and the Data Network (DN), and Protocol Data Unit (PDU) session anchor point for providing mobility within and between radio access technologies [16].

These new functionalities of 5G networks serve as enablers for MEC, in which software-based applications and cloud computing services are provided at the network edge. Hosting applications at the edge optimizes the performance for ultra-low latency and high bandwidth services. However, a direct consequence of such deployment is the exposure of those applications to User Equipment (UE) mobility. Users

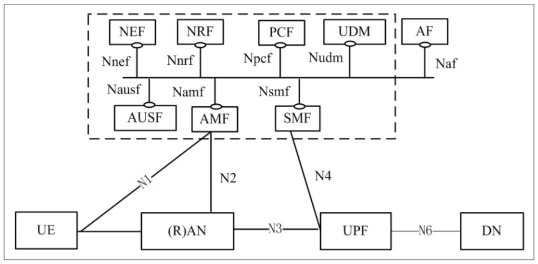

Fig. 3: 5G Service-based Architecture [21].

movements may render the location of the currently used edge application host non-optimal in the long run. For the MEC system to maintain the application quality requirements in a mobile environment, utilizing 5G complementary procedures for MEC environment is suggested, e.g application mobility [17], dynamic and parallel offloading [18] [19].

The service instance utilized by the user can be relocated to a new location to maintain certain quality. Before moving the application, it is necessary to identify the target host which can provide optimal service for the mobile user. In a typical reactive application migration, the application moves in harmony with the user and relocates to one of the nearby hosts following the user movement. In a proactive strategy, the application migration is executed in advance preceding to the user's mobility [20]. This calls for a mechanism to predict user's mobility and direction, and to evaluate the nearby hosts suitability to host the service. For this purpose, we exploit the handover prediction mechanisms proposed to foresee the user's direction. This helps identifying the edge nodes best fitted to host the mobile service.

The proposed mechanisms can be bootstrapped with MEC easily due to the Location Service (LS) already defined in MEC standardization [22]. LS supports sending both geolocation (i.e. geographical coordinates), and logical location, such as a Cell ID, for a single UE and for a certain category of UEs periodically or based on specific events, such as location change. The information on the user-network association can be sent to the service consumers which can be mobile edge application or mobile edge platform that communicates with the Location Service over the LS API. Moreover, the LS supports anonymous location reporting (without the related UE ID information) enabling statistics collection, which is helpful for the global knowledge strategy. By exploiting this service, the network can easily build the transition probability data structures, needed for the proposed prediction mechanisms to be executed in the edge node, without requiring the user to report its handover history.

As the enhanced approach relies on radio characteristic as well as probabilities, the user shall be able to measure the received power of the neighboring cells. This capability is also already standardized in 5G networks [23]. Furthermore, the user reporting of these measurements to the network is also considered.

After utilizing the proposed mechanisms to forecast the user's future cell, a user aware service migration is initiated by the network orchestrator placed at the core or the edge of the network. The traffic routing and steering to the new application host is then managed by the PCF and the SMF [15]. SMF manages the session and allocates the necessary IP addresses to the user. Meanwhile, AF provides the PCF with information on the packet flow. The PCF, then, controls the mobility and session management policies for SMF in order to support QoS.

V. Analysis of the solutions proposed

We analyse our solutions taking in consideration a real world mobility dataset, that is further enhanced to support cellular handover information. We utilize the dataset described in [24], which was collected by volunteers, using a specially crafted android application on smartphones, placed on the dashboards of their cars. Each monitoring device would store information about location, speed, and timestamp whenever the car is moving, at around 20Hz (device dependent). The dataset contains all trajectories followed by all users over a period of three months in the city of Aveiro, Portugal, with a total of 1971 trajectories.

We enhanced this dataset with the approximate location of all base stations in Portugal, as available in [25], which provides information about the location of each base station, range and frequencies in use. Using the Free-space path loss formula [26], the frequency of each BS, and the range extracted from the location information captured in the dataset, we derived the maximum pathloss as follows:

$$Lu_{max} = 20\, log_{10}(ran) + 32.44 + 20\, log_{10}(f) \quad (2)$$

Where *ran* refers to the range, f to the frequency and are measured in kilometers and megahertz, respectively.
Consequently, we calculated each base station Equivalent Equivalent Isotropically Radiated Power (EIRP) using the typical Long-Term Evolution (LTE) parameter values of macrocells given in [27], and illustrated in the following table:

Parameter	Symbol	Value
UE equipment sensitivity	S	-107.5 dBm
UE Height	h_{ue}	1 m
eNodeB Antenna Height	h_b	30 m

TABLE I: LTE Setup Parameters

Where the BS *EIRP* can be calculated as follows:

$$EIRB = Lu_{max} + S \quad (3)$$

We used the coordinates of each user and BS provided by the datasets to calculate the distance between the two, at each timestamp, by using Haversines, which determines the great-circle distance between two points on a sphere given their coordinates.

The distance between the user and eNodeB is then used to calculate the path loss *Lu*, taking in consideration the *COST-231* data model for urban areas, which is widely used to predict the path loss in the mobile wireless system as described below [28]:

$$Lu = 69.55 + 26.16\ \log_{10}(f) - 13.82\ \log_{10}(h_b) - Ch + [44.9 - 6.55\ \log 10(h_b)]log_{10}(D) \tag{4}$$

For urban environment Ch is determined as [28]:

$$Ch = 0.8 + (1.1\ \log_{10}(f) - 0.7) * h_{ue} - 1.56\ \log_{10}(f) \tag{5}$$

The UE received power P_r can then be calculated as follows:

$$P_r = EIRB - Lu \tag{6}$$

After calculating the UE received power from each BS, we associate it to the station with the best signal (highest received power) in each instant, mimicking the procedure followed in cellular networks. The sequence of user-network associations representing handover procedures are considered spatio-temporal points, which describe the individual movement.

In the learning phase of the proposed algorithms, 80% of the generated dataset is used as a training set, where the trajectories in this set are used to extract the probabilities described in (1). The remaining 20% of the dataset is used to evaluate the accuracy of the prediction methods.

A. Strategy Comparison

To forecast the handovers based on global knowledge, we used the movement traces of all users in the dataset. Meanwhile, to forecast handovers based on individual profiling, the models were applied to two different individuals. User A with a dataset of 126 traces and their corresponding user-network associations, and User B with a dataset of 179 traces and corresponding associations. The results of forecasting based on global knowledge and individual profiling, using the proposed methods are illustrated in Fig 4. Fig 5 demonstrates the relationship between the total number of predictions the models were able to perform and the time window considered.

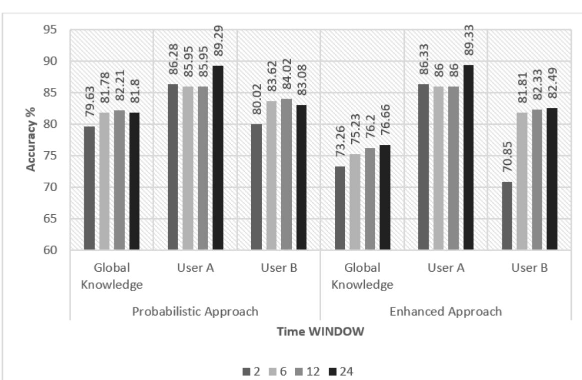

Fig. 4: Methods 1 and 2 Achieved Accuracy.

The results illustrated in Fig 4 show that both methods scored significantly better accuracy utilizing individual profiling strategy, than compared to the global knowledge strategy. However, employing the global knowledge strategy can be a better approach for large scale scenarios, especially if it

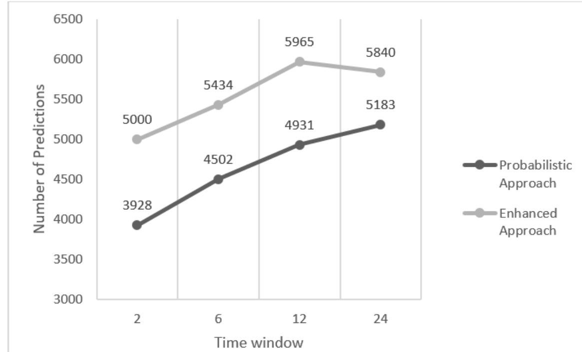

Fig. 5: Number of Predictions vs Time Window

is possible to cluster people based on certain criteria. For example, university students living in the same area tend to have similar trajectories when going to university and coming back.
Furthermore, as suggested in [29], using a collective strategy can dramatically minimize the quantity of information to be transmitted from each individual, while guaranteeing specific privacy protection for users.

Additionally, the results illustrated in Fig 4 indicate that using a time window decreases the accuracy for both methods. This is basically due to the decreased number of the predictions performed when complying to a more limited time window. Owing to the fact that narrowing the time window resulted in decreasing the corresponding dataset used to deduct the probabilities, ergo the decreased number of predictions the algorithms were able to perform as shown in Fig 5.

B. Comparative Analysis of the Solutions Proposed

We evaluated the proposed handover prediction methods performance against two machine learning algorithms namely, K-nearest neighbors [30] and Decision Tree classification algorithms [31]. Fig 6 illustrates the evaluation outcomes. For this test, the information used as features from the dataset are only the user's past and current cells IDs. The future cells is considered to be the target. The value of K for the nearest neighbors algorithm is equal to 1 since it scored the best accuracy.

In order to achieve a fair comparison, the times where the proposed mechanisms failed to execute predictions are considered as wrong predictions.

Using the same handover history datasets of all users and of a single user, the proposed approaches surpassed both K-nearest neighbors and decision tree classification algorithms in terms of accuracy. The enhanced approach scored 70% when using the global knowledge strategy, and up to 79% and 89% when using the individual profiling strategy. Thus, surpassing both the probabilistic and the machine learning algorithms.

Although the probabilistic approach scored less accuracy compared to the enhanced approach, still yielded better results than machine learning algorithms. Both K-nearest neighbors and decision tree algorithms performed better incorporating more features such as the hour of the day and user's speed. However, this lead to doubling the dataset in size. Moreover, acquiring such data raises problems related to the user privacy and may requires the user's approval or even participation.

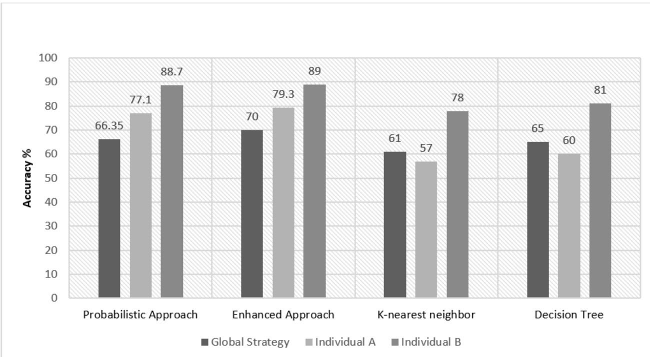

Fig. 6: Proposed algorithms vs Machine learning approaches

C. *Employing the Proposed Solutions for MEC Migration*

For evaluation, we formulated a mathematical model to estimate the effect of implementing the proposed handover prediction mechanisms as complementary methods for user-aware service migration in MEC. The prediction mechanisms are utilized to determine the best fitted edge node to move the application to preceding to the user mobility. We performed our evaluation considering data from individual user movements. We divided the dataset into a test and training sub-datasets, with a ratio of 1:4. We considered a service encapsulated in a virtual machine with 2GB of storage, being transmitted over a 1Gb/s network link. Each of the pre-migration and the post-migration phases is considered to be of 1s, and all edge nodes are capable of hosting the migrated service. We employed a "always migrate" strategy, where the service is moves in harmony with the UE, disregarding other migration decision-making factors such as load balancing and power consumption. Based on the user's current and previous Cell IDs, we predicted its future cell using one of the proposed mechanisms. Once the future cell is identified, we performed a proactive service migration to the identified cell. We used a reactive service migration to compensate for the cases of incorrect predictions, in which the user will be connected to a different base station than the one predicted.

Utilizing the probabilistic approach, the future cell was correctly identified 1448 times (77%), and was wrongly identified for 429 (23%). The average service downtime experienced by the user for each migration reached 1.62 seconds. USing the enhanced prediction approach, the future cell was correctly identified for 1488 times (82%), and was wrongly identified for 389 (28%). The service downtime experienced by the user for each migration reached 1.54 seconds. On the other hand, when relying on a reactive service migrations alone, the user experienced an average of 4 seconds of service downtime per individual migration. These results further emphasize the benefits of integrating the proposed handover prediction mechanisms within 5G systems architecture, when using the MEC paradigm.

VI. Further Considerations

As the aim of this work is to present an efficient forecasting mechanisms, which can be implemented in real networks. We try to answer some key questions concerning the mechanisms implementation such as a) what is the appropriate size of the dataset needed to accurately build the transitions probabilities, b) what is the effect of considering more than one former cell from the user movement trace.To answer these questions, we dedicate this section to examine the outcomes of varying the training dataset size and the number of anterior cells considered from the trajectory.

A. *Accuracy vs training set size*

Fig 7 illustrates the relationship between the proposed methods accuracy and the training set proportion considered to compute the probabilities.

For a proper assessment, we considered all the instants in which the mechanisms were unable to perform a prediction to be wrong predictions and we calculated the accuracy accordingly. The results show that, at first, the prediction accuracy increases in accordance to the increase of the training set proportionally up until a certain threshold, from there onward the accuracy tends to have steadier value. In this case, the training set proportion required to obtain sufficient accuracy is approximately 60% of the traces dataset, and is equivalent to monitoring this particular individual movements for 669 minutes over several days. To avoid repetition, the dataset considered in this test is of a single individual. We obtained similar results for global knowledge strategy and for other individuals as well. However, we found the threshold to be user-dependent.

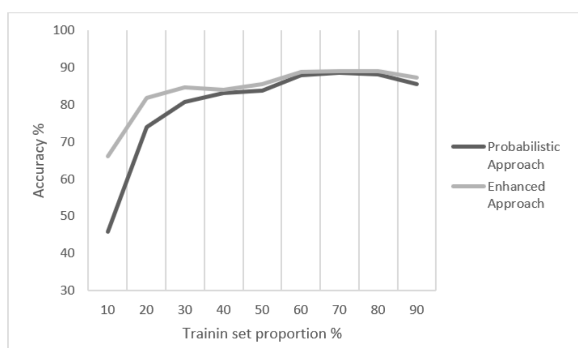

Fig. 7: Accuracy vs Training Set Proportion.

B. *Accuracy vs number of former Cells*

Earlier on, we considered the user's current and past cell ids to predict the future cell. Tables II and III clarify the effect of taking more than one antecedent cell on the proposed methods performance. The results show that taking more than one former cell increases accuracy. Understandably, the number of achievable predictions decreases for the probabilistic approach as deducting probabilities from the dataset becomes harder as less number of matching cells sequences exists. However, the enhanced approach performed better as its coping mechanism compensate to the prediction failures by relying on radio characteristics as well.

Case	User A		User B	
	Accuracy	Nº predictions	Accuracy	Nº predictions
One past cell	89.29%	299	83.08%	1744
Two past cells	90.57%	297	85.72%	1695

TABLE II: Probabilistic Approach: Accuracy Vs the Number of antecedent cells

Case	User A		User B	
	Accuracy	Nº predictions	Accuracy	Nº predictions
One past cell	89.33%	300	82.49%	1805
Two past cells	90%	300	83.37%	1804

TABLE III: Enhanced Approach: Accuracy Vs the Number of antecedent cells

VII. Conclusions and Future Work

We proposed two handover prediction mechanisms, which can be easily adopted in future networks architecture. The results showed that both methods yielded a quite high prediction accuracy compared to k-nearest neighbors and decision tree classification algorithms. We further demonstrated how the algorithms can be integrated into 5G service-oriented architecture and the potential benefits of utilizing them for a proactive service migration in MEC paradigm.

We intend to explore the handover prediction mechanisms presented in this paper in a complete framework, which aims at preserving the QoS for latency-intolerant applications employed in MEC paradigm. This framework is intended to provide mobile users with uninterrupted services by performing dynamic offloading accompanied with proactive service migration and timely optimized handover.

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