Stochastic Model for Intelligent Cell Level Mobility Prediction in Next Generation Wireless Networks

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Abstract. Next-generation wireless networks (NGWN) are designed to support a very high data rate, minimal delay, jitter, seamless movement across operators and geographical regions with a much faster speed and more quality of services (QoS). More frequency spectrum in the medium to high band range has been allotted to meet the desired QoS in the 5G wireless networks. These high-frequency signals have smaller lengths and penetration, causing dense deployment of smaller cells for comprehensive coverage in NGWN. Smaller cells mean a more frequent handover of users between cells. This change of connecting cells, i.e. mobility of mobile users, is a matter of great concern to the service providers for resource management and maintaining desired QoS. In this article, a stochastic model based on connected mobile population in a base station for mobility prediction has been proposed to impart machine intelligence. The random motion of mobile devices and their connection status with an access point (AP) or base station (BS), also known as a cell, is studied at a different time interval of operation. The transition probabilities of a BS required to accommodate the handoff request of a mobile device at an interval is estimated from the BS records, and a Markov model-based mobility prediction method is proposed. The proposed prediction method does not add any traffic overhead for collecting data. It predicts the number of handoffs and fresh connection requests to serve at an interval and can facilitate resource reservation, congestion control and smooth handoff. Some practical application scenarios of mobility prediction are also discussed. The article also highlights the present open challenges and potential future research issues in this domain.

Keywords: Stochastic Model, Mobility prediction, next generation wireless networks, handoff management.

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1 Introduction

The convenience of use anywhere anytime for almost any service made the wireless mobile system very popular throughout the globe [?, ?, ?, ?, ?]. Because of this popularity, there is sharp growth in the number of mobile portable devices (like smart-phone, Laptops, Tabs, wearables etc.) connected to the network systems and the location-based tailored services offered through the next generation wireless networks [1]. This rapid increase in network customer population and the magnitude of multiple services, proposed quality of services (QoS), data rate, level of customer satisfaction, etc., have posed great challenges in NGWN [2]. To accommodate the large number of customers, more radio spectrum in the medium to the high range has been allocated to the networks operators, and the cell size has been reduced [3]. This reduction in cell size will definitely increase the handover of connected mobile devices to one of the neighbouring cells to get uninterrupted network services. Moreover, the permissible vehicular speed of the mobile customer is expected to be the common acceptable parameter for accessing uninterrupted services in 5G systems which are also expected to increase the number of handovers during a customer's service period [4]. Mobility is an implicit property of mobile wireless networks, and it is accompanied by the issues like handoff, frequency reuse, traffic shaping, paging, registration, beckoning, roaming, location updation, etc. [5]. Therefore, efficient mobility handling (handoff) is essential for maintaining the proposed QoS in 5G wireless network systems. Handoff means the process of transferring an ongoing wireless connection of a mobile device from one BS to another BS. Mobility prediction is one of the methods adopted for efficient handover management [6].

Mobility prediction is of utmost importance for a variety of emerging services and applications like customized data collections, city planning, intelligent transport system, traffic and public event management, object tracking, visual surveillance, mobility management, network resource planning, and many more in the NGWN [6]. To avoid the termination of the ongoing connection of the customer during actual handoff, generally, some resources are reserved in the base stations (BS) to accommodate ongoing connections that are handed over to this cell (BS) after handoff [2]. The ongoing connection is very unstable during the handover period. Radio resources in BS are limited. If resource reservations are not optimized dynamically at the different instants of time, resources will be underutilized, causing loss of revenues or ongoing connections will be forcefully terminated, or the attempts for new connection will be delayed/blocked, causing customer dis-satisfaction [7]. Considering the permissible high speed of mobile customers in 5G systems, it is necessary to estimate the expected number of connected devices in a cell at a future instance of time so that resource allocation and mobility management can be planned [5]. Because sometimes, handoff requests need to be addressed within a few seconds by allocating required resources in the new cell. If the number of expected handovers into a cell (BS) at a future instant of time can be forecasted, the adequate system resources can be reserved for that time interval to accommodate the smooth handoff of the ongoing active connection, and without causing waste of network resources through unnecessary extra reservation [8]. The success and efficiency of such schemes largely depend on the mobility prediction technique and its accuracy.

The accuracy of the mobility prediction scheme has a big impact on network resource utilization, system efficiency, QoS and customer satisfaction [2]. Smooth handoff during the handover of the ongoing connection from the present connected cell to the new cell the customer moving into largely depends upon the availability of required resources (mainly channels, buffers etc.) in the new cell at that instant of time of handoff [2]. If resources are available in the new cell, smooth handoff will occur, and old cell resources will be released. Otherwise, handoff will be unsuccessful and ongoing connection will be forcefully terminated. Therefore, cell level mobility prediction is much more important for successful handoff than individual mobile device positional prediction [9]. Individual positional prediction is an important research issue for initiating the handoff process and avoiding ping-pong effects [10]. Moreover, high accuracy in cell level mobility prediction will help in designing more efficient resource distribution plans through the network system, which in turn improve the resource utilization, QoS, customers' satisfaction [9] [11]. In this article, a cell level mobility prediction model has been proposed. The article also addresses the future research issues that may arise in the orchestration of mobility prediction in NGWN.

2 Literature Survey

Mobility prediction has been one of the hot research issues since the beginning of the 21st century. Several works have been reported adopting different approaches to achieve different objectives like offering location-based services, optimum resource utilization and efficient handoff management. Ing-Ray Chen et al. [12] predicts the departure time of a mobile user from its movement pattern and travel histories. In contrast, Bhattacharya et al. [13] used a search tree-based approach for mobility prediction. Levine et al. used the concept of shadow cluster for predicting resource reservation in a cell, whereas Soh and Kim [14] used road topology for dynamic channel reservation in cells. This scheme needs BS to maintain a large dataset for road lengths, GPS and adds traffic overheads. The proposed model in this article has no extra cost; only control data typically recorded in BS can do the prediction. Balico et al. [15] predicted the future location of a moving vehicle in VANET using localization and time-series approaches. Fazio et al. [7] presented the different approaches of cell level mobility prediction for advance resource reservations to maintain connection continuity and to enhance QoS. With the advancement of technologies, deployment of smaller cells has been the necessity in 5G network systems that are accompanied by a higher number of handoffs, and more interference at the cell edges [3]. Therefore, mobility has more importance than ever before in maintaining the QoS in NGWN. Mobility prediction can help avoid undesired handoff, reduce forced terminations, and improve resource utilization and QoS. An entropy-based prediction algorithm is developed by [16] to estimate the individual user's future location. It shows that inspite of its random nature, a user's history of daily movement contains a higher degree of predictability. The entropy-based mobility prediction approach has also been applied in [17] for predicting a vehicle's future location. User group based cell prediction was done by Kuruvatti et al. [18] whereas authors in [19] predicted the user's future locality considering the direction of movement. The state transition is an important event in statistical prediction [20]. A state can represent the number of connected mobile devices in a BS, the status of buffer occupation, traffic load, or the status of free channels in a cell. Any change in the parameter representing the state makes a state transition, and every state transition occurs with a specific transition probability that can be estimated from the data collected in the operational system [21]. This article has adapted one such approach for cell level mobility prediction. Jin et al. [22] used mobility history to predict the user's next cell for advance resource reservation to handle real-time handoff. Trajectory based mobility prediction can also effectively improve the network efficiency through resource reservation at cell [23]. A log file-based mobility prediction algorithm is developed by authors in [24] to the user's next cell to meet the objective of seamless handoff.

3 Proposed Scheme

This section explains the cellular structure of the wireless system and the mathematical analysis adopted in this work.

3.1 System Model

A seven cell wireless system structure Fig.1 is considered where heterogeneous traffic is assumed to be independently and homogeneously distributed among the cells. Mobile devices (MD) are randomly and independently leaving a cell or BS, and some are entering into it from the neighbouring cells and vice versa. The movement of MDs among neighbouring BSs is collectively exhaustive.

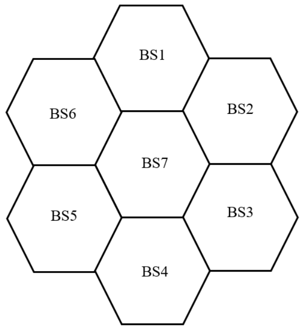

Figure 1: Layout for 7 Cell Cellular Wireless system Deployment

3.2 Mathematical Model

Because of the random mobile characteristics, some MDs come into a BS from their neighbouring BSs, and some leave it. The is represented by the number (X_n) of MDs connected with a BS at the nth instant or interval. Statistically, it can be proved that the movement of MDs between the BSs follows the discrete-state Markov process [20]. Hence, the next $(n+1)^{th}$ instant state of the connected MDs to a BS depends only on their previous (n^{th}) state.

Therefore, the state transition probabilities of the Markov chain [20] can be obtained as :

$$P[X_n = k | X_{n-1} = j] = p_{jk}. \quad (1)$$

i.e., MDs move from BS_j to BS_k with probability P_{jk}. It is assumed that the total population in a cluster (Fig. 1) of base stations is constant. In this context, the total population distribution of MDs over a cluster of base stations at any instant of time is represented by a vector

$$B(n) = [b_{n1}, b_{n2}, b_{n3}, b_{n4}, b_{n5}, b_{n6}, b_{n7}] \quad (2)$$

Where b_{ni} represents the fraction of total MD population of the cellular system present in BS_i at n^{th} instant of time and satisfy

$$\sum_{k=1}^{7} b_{nk} = 1 \quad (3)$$

Here, the interval instant n represents different slots of 15 minutes duration that are considered as transition steps. The vector B(0) is called the initial distribution vector and can be estimated from equation (4). To estimate b_{0i} (i.e. total mobile device population in base station i (BS_i) at time instant n=0). If X_1, X_2, X_3, X_4, X_5, X_6, X_7 are the mobile device population in BS_1, BS_2, BS_3, BS_4, BS_5, BS_6, BS_7 respectively at n = 0, then

$$b_{0k} = \frac{X_k}{\sum_{i=1}^{7} X_i}, k = 1, 2, 3....7 \quad (4)$$

Now, with passing time, every BS will retain a large fraction of its resident MD (known as retention) and release some fraction of its connected MDs to the neighbouring base stations. At the same time, it will receive some new connections from the neighbouring cells. The total MD population in the cluster remaining constant, 1-step Markov LossGain transition matrix P can be estimated from equation (5) as

$$P = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} & p_{15} & p_{16} & p_{17} \\ p_{21} & p_{22} & p_{23} & p_{24} & p_{25} & p_{26} & p_{27} \\ p_{31} & p_{32} & p_{33} & p_{34} & p_{35} & p_{36} & p_{37} \\ p_{41} & p_{42} & p_{43} & p_{44} & p_{45} & p_{46} & p_{47} \\ p_{51} & p_{52} & p_{53} & p_{54} & p_{55} & p_{56} & p_{57} \\ p_{61} & p_{62} & p_{63} & p_{64} & p_{65} & p_{66} & p_{67} \\ p_{71} & p_{72} & p_{73} & p_{74} & p_{75} & p_{76} & p_{77} \end{bmatrix} \quad (5)$$

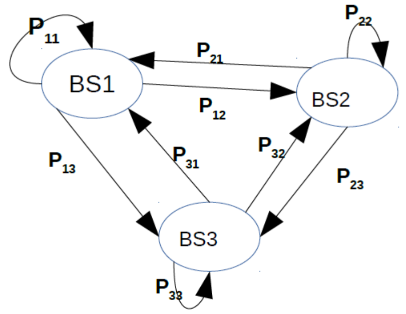

Figure 2: State transition diagram of Markov Chain with 3 BSs

Where each row in the transition matrix shows the retention and loss probabilities i.e., p_{ij} = probability of loss from i to j and each column shows the gain probabilities i.e., p_{ij}= probability of gain from i to j. When i j, p_{ij}= the probability of retention in the same cell. P satisfy the Markov Chain [20] properties given below:

$$0 \leq p_{ij} \leq 1 and \sum_{i=1}^{7} p_{ij} = 1; \quad (6)$$

p_{ij} can be estimated as given below:

For retention (i.e. p_{ii}), if A_i is the number of mobile devices that are connected to the i^{th} base station at the n^{th} interval and are still connected with the i^{th} base station in the $(n+1)^{th}$ interval, then $p_{ii} = A_k/X_i$, X_i = MD population connected with i^{th} base station at n^{th} interval. For loss, if L_{ij} is the number of mobile devices migrated to the neighboring jth base station from i^{th} base station, then $p_{ij} = L_{ij}/X_i$, X_i = MD population connected with i^{th} base station at n^{th} interval, j= 1 to 7 except $i = j$ that represents retention.

For gain, if G_{ij} is the number of mobile devices migrated to the neighbouring jth base station from ith base station, then $p_{ij} = G_{ij}/X_i$, X_i = MD population connected with i^{th} base station at n^{th} interval, j = 1 to 7 except $i = j$ that represents retention.

As per Chapman-Kolmogorov [25] analysis, the n^{th} interval LossGain transitional matrix can be estimated as

$$P(n) = P.P(n-1) = P^n. \quad (7)$$

The state of all the base stations is finite. So, the share of connected mobile devices among the considered cluster of base stations in our system after the nth interval can be expressed as

$$B(n) = B(0).P^n \quad (8)$$

For equilibrium state at the k^{th} interval, the LossGain transition matrix will remain constant, i.e.

$$P(k) = P(k+1) \quad (9)$$

This can be determined by using matrix algebra and solving simultaneous equations

$$B(k) = B(k).P \ and \ \sum_{i=1}^{7} b_{kj} = 1 \quad (10)$$

All the parameters used here are available in the database of the base station controller. Therefore, the prediction system can be designed for a flexible and suitable interval and can be performed automatically by the system if the intelligence is imparted into it.

4 Experimental setup and Results & Discussion

The simulation was performed with varying randomness with 7000 mobile nodes. From the traces, data are collected for movement, channel status, connection status during new connection setup and handoff. The arithmetic mean for all the collected data parameters are calculated and used for estimating the transition matrix. For simplicity, the LossGain matrix (P) with 3 base stations are presented here. The initial population distribution vector (B) obtained is given below. A comparison of the predicted and actual number of mobile devices at different intervals is presented too.

Initial probability matrix:

$$B = [0.143 \quad 0.142 \quad 0.141] \tag{11}$$

LossGain Transition Matrix:

$$P = \begin{bmatrix} 0.55 & 0.255 & 0.255 \\ 0.275 & 0.575 & 0.15 \\ 0.15 & 0.255 & 0.625 \end{bmatrix} \tag{12}$$

Table 1: Predicted and Actual connected MDs in BS1

N	Predicted	Actual	%Difference
1	975	978	0.31
2	970	974	0.41
3	971	976	0.51
4	971	975	0.41
5	967	963	0.42
6	968	972	0.41
7	972	967	0.52

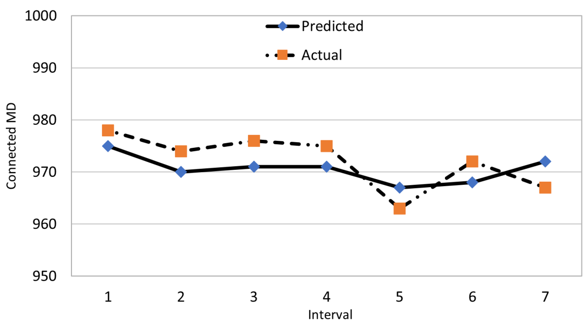

Figure 3: Predicted and Actual values in BS1

Table 2: Predicted and Actual connected MDs in BS2

N	Predicted	Actual	%Difference
1	1022	1024	0.20
2	1033	1035	0.19
3	1033	1032	0.10
4	1026	1021	0.49
5	1027	1030	0.29
6	1030	1033	0.29
7	1026	1030	0.39

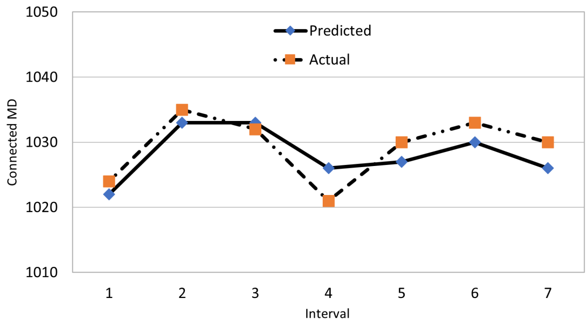

Figure 4: Predicted and Actual values in BS2

Table 3: Predicted and Actual connected MDs in BS3

N	Predicted	Actual	%Difference
1	1002	998	0.40
2	996	991	0.50
3	997	992	0.50
4	1003	1004	0.10
5	1006	1007	0.10
6	999	995	0.40
7	1002	1003	0.10

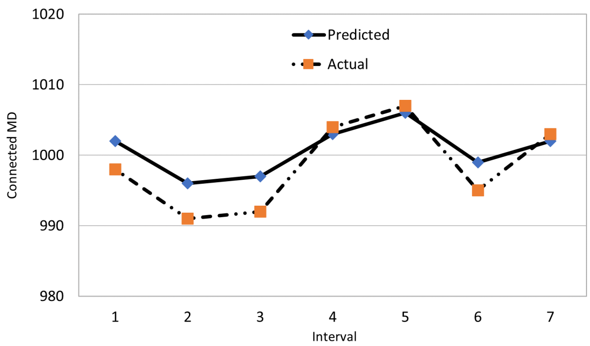

Figure 5: Predicted and Actual values in BS3

5 Conclusion

In this article, a statistical learning approach is used to forecast the expected client served by a cell in a future interval of time. The prediction is all within < 1% confidence level. The model may be used to plan the resource requirement of a base station for managing handoff and new connection requests, congestion control efficiently. The model works with the data collected at the base station controller, estimates the prediction parameters, so it can be extended for imparting prediction intelligence in the next-generation wireless networks with machine learning and Big data [26]. Cell dwell time, handoff initiation time, distributed (terminal device) handoff management, and prediction accuracy are important research areas for future works. Our future works will be towards this direction.

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