Spatiotemporal Mobility Prediction in Proactive Self-Organizing Cellular Networks

Hasan Farooq and Ali Imran

***Abstract*— Mobility prediction, one of the key enablers of proactive self-organizing networks, aims at efficient management of future cellular networks, which are envisaged to be extremely dense and complex due to conglomeration of diverse technologies. This paves the way for resource reservation prior to actual handover for seamless handover experience and for forecasting user traffic distribution. In this letter, we have utilized semi-Markov model for spatiotemporal mobility prediction coupled with steady state and gain analysis in cellular networks. Maximum prediction accuracy of 90% is achieved in the experimental evaluation leveraging on the real network traces generated by smartphone application.**

***Index Terms*— Semi-Markov, mobility prediction, self-organizing networks (SON), 5G.**

I. Introduction

THIS CENTURY has witnessed an exponential increase in mobile data usage - thanks to the proliferation of smart devices and diversity in mobile applications. This has prompted the need for future generation of wireless networks to provide unprecedented capacity gain and top notch quality of services. The ambitious requirements of zero latency and gigabit experience is driving the evolution of Fifth Generation (5G) cellular networks. The general consensus is that major capacity gain in 5G has to come from mostly impromptu network densification. It is not difficult to prognosticate that such a colossal deployment will become an enormous challenge in 5G aggravating several problems in terms of energy consumption, mobility management and OPEX to name a few. Fortunately, Self-Organizing Networks (SONs) are being researched extensively to cope with these challenges. SON automatizes the configuration, optimization and maintenance activities of the network. However, the state of the art research on SON has been carried out under the existing reactive networking paradigm, in which SON functions kick in after a problem has already occurred. The ambitious quality of service requirements for 5G dictate the proactive mode of operation for SON functions. This proactivity is achievable through anticipating user behavior and predicting a future network state by exploiting historical network information referred to as Big Data. Endowed with these proactive predictive capabilities, network resources can be pre-allocated more intelligently and in a more efficient manner than ever before [1].

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The authors are with the Department of Electrical and Computer Engineering, The University of Oklahoma, Norman, OK 73019 USA (e-mail: hasan.farooq@ou.edu; ali.imran@ou.edu).

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User Mobility Prediction is one of the core ingredients of the proactive SON paradigm which predicts the future locations of the users in terms of the associated Base Stations. This enables the reservation of network resources in future identified cells for seamless handover experience as well as for traffic forecasting purposes driving the energy saving SON functions. The mobility prediction rests on the notion that mobility patterns of mobile users are, to a certain extent, predictable as verified by the works [2] and [3] according to which despite the apparent randomness of individual trajectories, our daily mobility has a deep rooted regularity with a potential 93% average predictability along with a lack of variability across the population. Most of the existing studies relavent to mobility predictions such as [4] leverage Discrete Time Markov Chains (DTMC). However DTMC assumes human mobility is memory less with geometrically distributed sojourn time and each transition takes one unit time. As a result, most of the relevant works have utilized DTMC for only the spatial prediction, i.e., identification of future cell without any information about the time at which handover takes place. The same limitation is faced in the Continuous Time Markov Chain, which assumes cell sojourn time is exponentially distributed. Recent work in [5] found that the mobility pattern of mobile users in cellular networks exhibits a memory property that can be best approximated with power law (heavy tailed) distribution instead of memory less exponential distributions. Semi-Markov is a class of Markov models that allows for arbitrarily distributed sojourn times. Two meritorious works [6], [7] characterized the WLAN mobility traces available at Dartmouth College, collected in 2004 through the application of Semi-Markov models. Inspired by the usefulness of Semi-Markov models reported by these studies in building user mobility models, in this letter, we have also leveraged Semi-Markov based mobility prediction framework for spatiotemporal mobility prediction in future cellular networks, i.e., identifying future target Base Stations and the association duration. However, aforementioned relevant studies utilized historic publicly available WLAN traces, and not cellular network mobility traces. WLAN mobility traces exhibit large sojourn times due to relatively much lesser mobility dynamics in WLAN compared to cellular network. Therefore, conclusions drawn from these WLAN studies cannot be directly applied to current cellular network such as LTE, where device form factor and user behavior is drastically different than that of WLAN users of 2004. Study presented in this letter fills this gap. We gather real LTE network's mobility traces in live cellular network using a state-of-the-art application. These traces exhibit highly dynamic characteristics that are intrinsic to cellular network, and thus enable realistic evaluation of the prediction accuracy of the Semi-Markov based method, for cellular network mobility. Another contribution of this study is that instead of relying on historic public datasets, we use a novel methodology of utilizing smartphone application, based on the idea of participatory sensing, to collect real LTE network data for building, training and evaluating the performance of mobility prediction schemes in live network. We also present a method of quantifying gains of mobility prediction techniques in perspective of proactive SON-enabled cellular networks [1].

II. Mobility Prediction Model

The human mobility is modeled as a Semi-Markov renewal process $\{(X_n, T_n) : n \geq 0\}$ with discrete state space $C = 1, 2, 3 \ldots, z$ where T_n is the time of nth transition, X_n is the state at nth transition and total of z cells. Each cell is represented by the state of the Semi-Markov process, and a handover from one cell to another is considered as state transition. It is assumed that the process is time-homogeneous during the time period in which the model is built. The associated time-homogeneous Semi-Markov kernel for user 'u' which is the probability of transition to jth cell if user has already spent time t in ith cell is defined as:

$$\begin{aligned} \zeta_{i,j}^{(u)}(t) &= Pr(X_{n+1}^{(u)} = j, T_{n+1}^{(u)} - T_n^{(u)} \leq t | X_n^{(u)} = i), \\ &= p_{i,j}^{(u)} \theta_{i,j}^{(u)}(t), \end{aligned} \tag{1}$$

where

$$\begin{aligned} p_{i,j}^{(u)} &= \lim_{t \to \infty} \zeta_{i,j}^{(u)}(t), \\ &= Pr(X_{n+1}^{(u)} = j | X_n^{(u)} = i), p_{i,j}^{(u)} \epsilon P^{(u)}, \end{aligned} \tag{2}$$

and

$$\theta_{i,j}^{(u)}(t) = Pr(T_{n+1}^{(u)} - T_n^{(u)} \leq t | X_{n+1}^{(u)} = j, X_n^{(u)} = i). \tag{3}$$

Here $p_{i,j}^{(u)}$ is the probability of the handover of user 'u' from cell i to j, $P^{(u)}$ is the probability transition matrix of the embedded Markov chain of user 'u' given as:

$$P^{(u)} = \begin{bmatrix} p_{1,1}^{(u)} & p_{1,2}^{(u)} & \cdots & p_{1,z}^{(u)} \\ p_{2,1}^{(u)} & p_{2,2}^{(u)} & \cdots & p_{2,z}^{(u)} \\ \vdots & \vdots & \vdots & \vdots \\ p_{z,1}^{(u)} & p_{z,2}^{(u)} & \cdots & p_{z,z}^{(u)} \end{bmatrix}, \tag{4}$$

and $\theta_{i,j}^{(u)}(t)$ is the sojourn time distribution of user 'u' in cell i when the next cell is j. It is important to note here that a handover from a cell to itself is not allowed; therefore, diagonal of the matrix $P^{(u)}$ will be all zeros, and the matrix will be a hollow matrix. Furthermore, direct handovers are possible between neighboring cells only. The probability distribution of sojourn time of user 'u' in cell i regardless of the next cell is defined as:

$$\begin{aligned} \mu_i^{(u)}(t) &= Pr(T_{n+1}^{(u)} - T_n^{(u)} \leq t | X_n^{(u)} = i), \\ &= \sum_{j=1}^{z} \zeta_{i,j}^{(u)}(t). \end{aligned} \tag{5}$$

Now the time-homogeneous Semi-Markov process of user 'u' is defined as $X = (X_t, t \epsilon \mathbf{R_0^+})$ with state transients as:

$$\begin{aligned} \mathbf{\Omega}_{i,j}^{(u)}(t) &= Pr(X_t^{(u)} = j | X_0^{(u)} = i), \\ &= (1 - \mu_i^{(u)}(t))\delta_{i,j} + \sum_{m=1}^{z} \int_0^t \mathbf{\Omega}_{m,j}^{(u)}(t-\tau) d\zeta_{i,m}^{(u)}(\tau), \\ &= (1 - \mu_i^{(u)}(t))\delta_{i,j} \\ &\quad + \sum_{m=1}^{z} \int_0^t \frac{d\zeta_{i,m}^{(u)}(\tau)}{d\tau} \mathbf{\Omega}_{m,j}^{(u)}(t-\tau) d\tau, \end{aligned} \tag{6}$$

where $\delta_{i,j}$ is the Kronecker function defined as:

$$\delta_{i,j} = \begin{cases} 0, & i \neq j \\ 1, & i = j. \end{cases} \tag{7}$$

Integral equation (6) is Volterra equation of second kind, and the integral is the convolution of $\zeta_{i,m}^{(u)}(.)$ and $\mathbf{\Omega}_{m,j}^{(u)}(.)$, i.e., $\zeta_{i,m}^{(u)} * \mathbf{\Omega}_{m,j}^{(u)}$. It gives the probability that user 'u' starting in cell i will be in cell j by t. The first part of the right-hand side is the probability that the user, being in cell i, never leaves cell i until the end of the period t. The second part of the right-hand side of equation accounts for all cases in which the transition from i to j occurs via another cell $m \neq i$ applying the renewal argument. The numerical solution to solve evolution equation (6) is given by [8] and we implemented the same approach. The evolution equation (6) can be re-written for discrete-time homogeneous Semi-Markov process as:

$$\mathbf{\Omega}_{i,j}^{(u)}(k) = \psi_{i,j}^{(u)}(k) + \sum_{m=1}^{z} \sum_{\tau=1}^{k} \sigma_{i,m}^{(u)}(\tau) \mathbf{\Omega}_{m,j}^{(u)}(k-\tau), \tag{8}$$

where $\psi_{i,j}^{(u)}(k) = (1 - \mu_i^{(u)}(t))\delta_{i,j}$ and $\sigma_{i,m}^{(u)}(k) = \frac{d\zeta_{i,m}^{(u)}(\tau)}{d\tau}$ can be approximated as follows assuming time step is equal to the unit:

$$\sigma_{i,m}^{(u)}(k) = \begin{cases} \zeta_{i,m}^{(u)}(1) & , k = 1 \\ \zeta_{i,m}^{(u)}(k) - \zeta_{i,m}^{(u)}(k-1) & , k > 1. \end{cases} \tag{9}$$

Here $\mathbf{\Omega}_{i,j}^{(u)}(k)$ gives the probability that the user 'u' is in cell j after k amount of time from the time instant when he/she made the transition from somewhere to cell i. As $P^{(u)}$ is a right stochastic matrix; therefore, $\zeta^{(u)}(k)$ and $\mathbf{\Omega}^{(u)}(k)$ will also be a right stochastic matrices, i.e., $\sum_{j=1}^{z} \zeta_{i,j}^{(u)}(k) = \sum_{j=1}^{z} \mathbf{\Omega}_{i,j}^{(u)}(k) = 1, \forall i, j \epsilon c$.

A. Steady State Distribution

In order to analyze the long-term average distribution of users in cells, we calculate the steady state distribution of the Semi-Markov $\Lambda^{(u)} = [\Lambda_1^{(u)}, \Lambda_2^{(u)}, \Lambda_3^{(u)}, ..., \Lambda_z^{(u)}]$ as:

$$\Lambda_j^{(u)} = \frac{\pi_j^{(u)} \gamma_j^{(u)}}{\sum_{i=1}^{z} \pi_i^{(u)} \gamma_i^{(u)}}, \tag{10}$$

where $[\pi_1^{(u)}, \pi_2^{(u)}, \pi_3^{(u)}, ..., \pi_z^{(u)}]$ is a positive solution to the following balance equations:

$$\pi_j^{(u)} = \sum_{i=1}^{z} \pi_i^{(u)} p_{i,j}^{(u)}, 1 \leq j \leq z,$$
$$\sum_{i=1}^{z} \pi_i^{(u)} = 1, \tag{11}$$

and $\gamma_j^{(u)}, 1 \leq j \leq z$ is the mean sojourn time of user 'u' in cell j.

B. Semi-Markov Based Mobility Prediction Framework (SMPF)

Utilizing the past handover history of user 'u' <time, Cell ID>, Probability transition matrix $P^{(u)}$ and sojourn time distribution matrix $\theta^{(u)}$ are initialized as follows:

$$p_{i,j}^{(u)} = \frac{N_{i,j}^{(u)}}{N_i^{(u)}},$$
$$\theta_{i,j}^{(u)}(k) = \frac{N_{i,j,k}^{(u)}}{N_{i,j}^{(u)}}, \tag{12}$$

where $N_{i,j}^{(u)}$ is the number of handovers of user 'u' from cell i to j, $N_{i,j,k}^{(u)}$ is the number of handovers of user 'u' from cell i to j with a sojourn time less than or equal to k, and $N_i^{(u)}$ is the total number of handovers of user ' u' from cell i. Whenever there is a handover from cell i to j, $p_{i,j}^{(u)}$ and $\theta_{i,j}^{(u)}(k)$ are updated and $\zeta_{i,j}^{(u)}(k)$ is updated. Finally $\Omega_{i,j}^{(u)}(k)$ is computed. The cell with the highest probability is chosen as the predicted future destination.

III. Experimental Evaluation

In order to realistically evaluate the proposed framework, we conducted an experimental study based on participatory sensing to analyze the applicability of the proposed model. In this letter, we will only present the results of phase one of this experimental evaluation under which mobility pattern of a graduate student at the University of Oklahoma, Tulsa Campus, was logged for a one-month period in the Tulsa Campus region. The data gathered through the student's phone was used to build a Semi-Markov model. This model was then used to predict his mobility pattern for the next whole week. Android application " LTE Discovery" was installed on the student's smartphone to continuously log the handover information of the user. The application once activated continued to run in the background and updated the handover log whenever the user moved to some new cell. The logged information contains a time stamp and a new cell ID. At some places like indoor offices and cell overlapping regions, the test subject's equipment experienced ping pong effect. The mobility history log was preprocessed to remove such entries as has been done in [7] and only stable entries were utilized to build the Semi-Markov model. Based on the recorded data set, four Base Stations were identified in the campus region hereby anonymously named as A, B, C and D. Two Semi-Markov models were built (I and II) with time intervals of one hour and quarter hour (15 minutes), respectively. A mobility pattern was predicted up to next 3-hour period. The sojourn time distribution matrix $\theta^{(u)}$ was computed for the test subject as done in [9]. Network scenario settings are given in Table I.

TABLE I
Network Scenario Settings

No.	Parameter	Value
1	No. of Cells	4
2	Mean Sojourn Time (hours)	A: 0.33, B: 0.07, C: 2.95, D: 13.98
3	Speed (miles/hour)	max: 20
4	Prediction Interval (hour)	1/4, 1
5	Avg. no. of HOs (per day)	9
6	Area (sq. meters)	3000

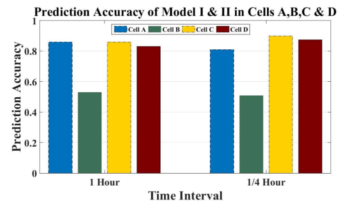

Fig. 1. Prediction accuracy.

For prediction accuracy, each of the times the user entered a new cell, we calculated the probability of future locations for the next 3-hour period using the two Semi-Markov models and compared it with actual mobility pattern. The prediction accuracy results for each individual cell are presented in Fig. 1. As per the results, minimum accuracy achieved was around 50% and maximum of 90%. The test subject had the least amount of sojourn time in cell B corresponding to the parking area, around 2 min on average, that affected the training of sojourn time matrix and, therefore, its prediction accuracy was lowest. The user spent a relatively larger amount of time in rest of the cells, and prediction accuracy was above 80% for all of the test cases. Comparing models I and II with time intervals of 1 hour and ¼ hour respectively, model I with a larger time interval had slightly better accuracy for the cells with small sojourn times. As number of predictions made, each time user entered a new cell, was small (3 hour / 1 hour = 3) so effect of small sojourn time was smoothened out. Model II with relatively smaller time intervals exhibited better accuracy for cells with larger sojourn time. The number of predictions made at each instant of transition was large (3 hour / (1/4 hour) = 12) so cells with large sojourn times effectively had better accuracy. A smaller time interval effectively gave better resolution, but it increased the operational complexity for the same prediction period and the number of matrix multiplications increased. The difference in prediction accuracies for the two models having prediction time windows of one hour and quarter hour is not significant. This observation highlights a potential advantage of using Semi-Markov based mobility prediction model as in such a model the variation in the prediction accuracy turns out to be almost insensitive to the choice of prediction window size, at least for the scenario represented by our case study, and so the search for optimal prediction window size can be avoided. Choosing the next two destinations with maximum probabilities instead of only one significantly increases the prediction accuracy, almost 100% in our test cases; however, this comes at the cost of decreased resource efficiency as

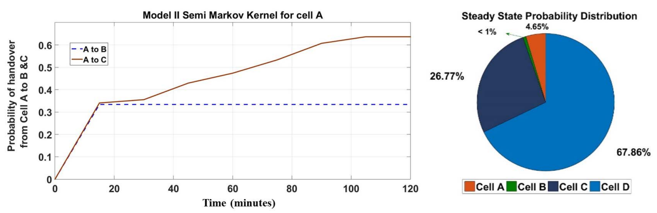

Fig. 2. (a) Semi-Markov kernel for Model II (b) Steady state distribution.

resources need to be reserved in more than one cell, and this factor amplifies in case of incorrect predictions.

Model II Semi-Markov kernel for cell A, plotted in Fig. 2(a), gives the probability of transition of user to neighboring cells B and C from cell A w.r.t time. Effectively from 0 to 15 minutes, probabilities of transition to cell B and C are the same while from 15 minutes and onwards, probability of transition to cell C increases compared to cell B. This can be utilized to decide when, where and for how long resources need to be reserved for each user for successful and seamless handover between the cells. For instance, the necessary amount of resources could be initially reserved in both cells B and C during the first 15 minutes of transition to cell A. If the user stays in the cell A for more than 15 minutes then this could prompt the network to limit its resource reservation thereafter in cell C only since that is the most likely handover to take place from the current cell.

The results for steady state probability distribution are given in Fig. 2(b). Accordingly, the user spends 67.86% of the time in cell D followed by C with 26.77%, A with 4.65% and B with only 0.7%. This information can be utilized by the operator to identify the cells that are most likely to exhibit maximum traffic and plan the resources accordingly. For example, if the other users of the region exhibit the same steady state distribution similar to our test subject then the network operator should have maximum capacity resources provision in cell D as compared to the other cells. It's important to highlighting that presented results are valid only for the considered network in which data is gathered. To be applicable to another network and set of users, the proposed mobility prediction model needs to be trained for that network and set of users. The parameter investigated in this letter is mobility prediction accuracy as the holistic performance of a proactive-SON-enabled Cellular System (CS) depends on how accurate are its predictions. The Gain of SMPF based CS can be evaluated as follows [4]:

$$Gain = \frac{\lambda_{np} - \lambda_{smpf}}{\lambda_{np}}, \tag{13}$$

where λ_{np} is the resource utilization cost in conventional non-predictive CS and λ_{smpf} is the expected resource utilization cost for SMPF-enabled CS given as:

$$\lambda_{smpf} = \alpha(RUC_c) + (1 - \alpha)(RUC_{ic}). \tag{14}$$

Here α is the prediction accuracy and RUC_c and RUC_{ic} are the resource utilization costs for correct and incorrect predictions. These can be handover resources reservation costs, resource block reservations for capacity, caching, waking up next BS etc. An incorrect prediction may degrade the overall system performance since it reserves resources that could

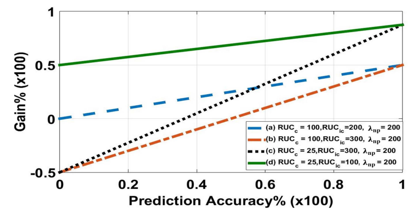

Fig. 3. Gain of SMPF vs prediction accuracy.

otherwise be used for other users. The gains for different RUCs with prediction accuracy are plotted in Fig. 3. A fixed value of 200 is considered for λ_{np}. In (a), when RUC_c is half of non-predictive CS (λ_{np}) and RUC_{ic} is the same as λ_{np}, then Gain is always positive and lies in range of (0 to 50%). When RUC_{ic} is increased to 300 in (b) then Gain can be negative and at 50% prediction accuracy, we get Gain of 0% (same performance as that of non-predictive CN). When RUC_c is decreased to 25 in (c) then Gain achieved rises to maximum. When RUC_{ic} is also decreased to half of λ_{np} as in (d) then Gain is always positive and $\geq$ 50% for all prediction accuracies. While Gain is a generic measure and evaluation of specific values is beyond the scope of this letter, it provides a framework for assessing the gain of SMPF and its minimum accuracy needed to achieve any gain.

IV. Conclusions & Future Work

The presented spatiotemporal mobility prediction framework can empower SON functions like Mobility Robustness Optimization, Energy Saving and Mobility Load Balancing. Experimental evaluation using two different models with different prediction time intervals achieved high prediction accuracy of above 80% for the majority of the cells. For future work, the effect of ping-pong on prediction accuracy will be investigated and additional improvement to the model will be devised to consider edge user movement. Moreover, Gain of the proposed framework will be evaluated for different SON use cases.

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