A Hybrid Model for User History-Based Prediction with Geolocation Assisted Handover in 5G

Safa E. Abdalla
safa@fkegraduate.utm.my

Sharifah Hafizah Syed Ariffin
sharifah @fkegraduate.utm.my

UTM-ATT Center of Excellence
Faculty of Electrical Engineering
University of Technology Malaysia
Johor- Malaysia

***Abstract* - The upcoming years promise an explosive growth in data traffic for mobile real-time applications. Femtocell networks seem to be the solution for the demanding traffic and coverage required in the next generation of telecommunication. However, the ultra-dense of the femtocellular networks bring additional delay overhead due to unnecessary handovers for the roaming Mobile Station (MS). This paper presents a hybrid model to predict the users movements accurately and eliminate the unnecessary handovers. The proposed model consider the behavioral patterns of MS movements which decreasing the delay to suit the real time application, and result of enhancing the performance in 5G networks.**

Keywords - Femtocell; 5G neworks; Handover; Hybrid Model; Prediction

I. INTRODUCTION

In recent years, and since the introduction of the smart mobile devices, the global data traffic has explosively increased in the cellular networks which are facing the challenges of coping with a rapidly increasing data traffic needs. Cisco reported a prediction of an 11-fold growth in worldwide mobile data traffic between 2013 and 2018 .[1]. This becomes an essential hot topic for the researchers to introduce the next generation of telecommunication (5G). The next generation (5G) networks are meant to keep a pack of the future networks demands in addition to overcoming the drawbacks of the 4G networks.

On the uprising to the (5G), the densification of heterogeneous networks (HetNets) and small cells are increasing capacity and satisfying the future mobile data needs [2]. Figure (1) illustrates the deployment of Femtocellular networks which consist of a large list of neighboring small-range cells that provide an excellent coverage, bandwidth, and capacity with a low cost and low power. In an open access mode, these extended lists of neighbors give the moving mobile user extended options of mobility management. However, the high dense of these cells create interference problems; increase the numbers of handover and unnecessary handover for the speedy user. The mobility management in femtocellular networks may result in a reduction of the QoS problems and may lead to a disconnect in real-timing services. [3]

The existing prediction methods aim to reduce the huge delay of handover through speeding up the phases of the process (scanning, authentication, and re-association). Since the scanning probe consume 90% of the whole delay[1], it's become the researcher target to reduce that delay by pre-scanning prediction of the next point of attachment (next cell). In our method, a hybrid smart handover method is proposed. The prediction method is considering both the randomness and regularity behaviour of the mobile terminals.in our previous work[2], we propose a prediction method for a regular user using Enhanced History-based Prediction (EHP) probabilistic method that conditioning a sufficient history tracking logging file. In EHP method the prediction of similar routes is resolved and the accuracy of the 1st prediction is increased. In this paper we continue the previous work by considering the regular user with insufficient history or new logging user, and the random behaviour of Mobile Station (MS).

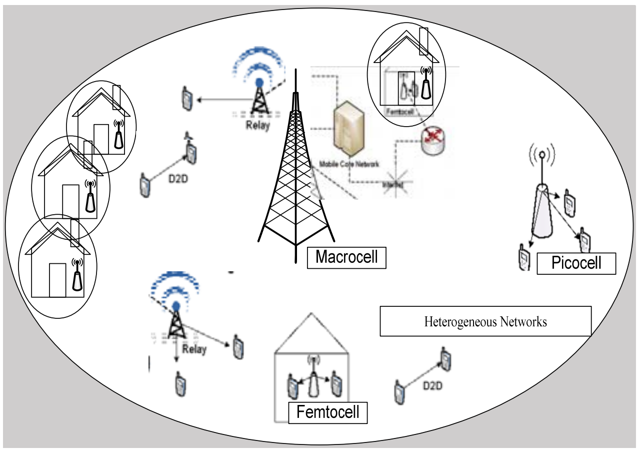

Figure 1. Example of Heterogeneous network

II. Relaed work

Many researches conducted to enhance the mobility management in the fifth generation of wireless communication by using wide variant methods. The methods might categorize into: a) geographic location based prediction, b) the link-based prediction, c) the traffic based prediction, d) the social based prediction. the four groups use different parameters to achieve seamless handover process.

The location predictive methods are based on the MS history profile to provide the next AP, through exploit the history information of movement (the context) then train an statistical model (the prediction) to predict the target locations of the MSs and their channel conditions, finally solve an optimization problem that maximizes their Quality-of- Experience (QoE).[3] However, these methods need more investigations on the special characteristic of femtocells like the variant link quality, the high dense overlapped cells, and Mac contention. The regularity of MS is presented in many studies. it resulted in that people often show regular behavior and their routes are highly predictable [4]–[9]. The related mobility prediction techniques can be classified into the Geolocation and data mining categories.

The GPS proposed methods of prediction give an adequate estimation of the next serving cell, yet these proposed schemes have many drawbacks in terms of high cost, high energy consuming, long time procedure, besides it's not effective for the indoor communication. In[10] GPS framework calculate the distance between two points using Haversine formula and set the G threshold to 50% of the AP’s range. This minimizes the handoff latency in L2 and L3, but the latency of the initialization phase was surprised to 60ms due to GPS response time. The GPS has 10m error which affects the accuracy of prediction in the high overlapped cells, besides; MS does not allow to switch between indoor and outdoor Geolocation systems. In [11]the GPS server is used to reduce the discovery phase delay by doing only one probe during association step in the handover process. However, the method needs more value for the real scenario considering the security aspect to protect from the fake GPS servers. GPS methods seem to need for extra hardware to detect the next APs, also, consuming battery life. This considered negative aspects in targeting the optimization of the handoff scanning process.

The data mining methods extract and describe the patterns of users mobility. this done by tracing the mobility for good enough time in order to decrease the latency caused by scanning process [12][13][14]. AS much as collecting enough history of movement between location to be initiated in the database the better mine typical trajectory For a better prediction result. But, data-mining techniques drawbacks represented in consuming huge amount storage and the need for fast processors to catch the long-term mobility history. Also, this kind of techniques does not consider the randomness of MSs which results in lowering the utilization of the resources.

The probabilistic methods like Markov-based portability predictions, relay on the estimating the future movements In light of the present and past history [12], [15]–[18]. In a Markov mobility predictor , the historical locations, the most frequent visited location, of MSs are used in predicting the future locations of MSs [7]. The algorithms use Markov-based technique, can be found in[8], [9], [18], including ours. In [11] The GPC is proposed for Fast Handovers in wireless local area networks (WLANs) to speed up the handoffs process. In [18] Markov chain maintains only the regular movement, the problem is when the history dictates two equal prediction routes with the same probability this will confuse the scheme in choosing the target AP accurately .

In [19], a Hybrid Mobility Prediction (HMP) strategy has been proposed. It combines three different predictors, which are; probabilistic predictor (PP), group-based predictor (GP), and spatial predictor (SP). PP relies on Bayes theorem, GP uses ant colony optimization (ACO), while SP tries to detect the topological architecture of the current registration area to enhance the prediction process. HMP provides high accurate prediction of the next cell but the increase the computational process which consume the CPU times.

The proposed model has the advantages of manipulates all the computational process while the MS is offline, this benefits the energy savings and not add additional calculations overhead.

III. THE HYBRID PREDICTION METHODE

In order to satisfy the needs of the 5G, a hybrid smart handover method should be adopted. The model of prediction should consider both the randomness and regularity behavior of the mobile terminals. The smart handover technique keeps switches between the multiple methods of handover prediction techniques to meet the varying state of the mobile terminals. The basic Markov chain prediction collect the essential information for the prediction, this is to be used in the enhanced predictor after adding the behavioral characteristic. The time series model of the predictor is used to catch the short term movement behavior for insufficient history, while the GPS system is to be used if there is no history available for the MS or after the 1st mis-prediction to catch the random behavior.

A. *The Enhanced History-Based Prediction (EHP)*

EHP improve the accuracy of the prediction of the next point of attachment of the MS . This virtually eliminates the scanning process since it depends on tracking and extracting the behaviour patterns of a different group of user. In this section, we will discuss the basic EHP method. Table (1) and Fig.(2). In EHP the user information is tracked and kept in a log file [2] ,which contained a vital data like group, date, location, time, and transport method.

The information gathered in the log file, after analysis process, is queued into Handoff History Table (HHT). the maintaining of the route request during each subsequent handoff is followed the same process used in [20]. Figure (2) shows MS moving across high overlapped cells with similar weight routes [5]. As the MS moving away from current AP, it is not clear which AP from the group of the adjacent cell will be the target AP, It may destine either to APz or APy. Since they have the same probability, the time factor filter is added to determine the target AP at that exact time.

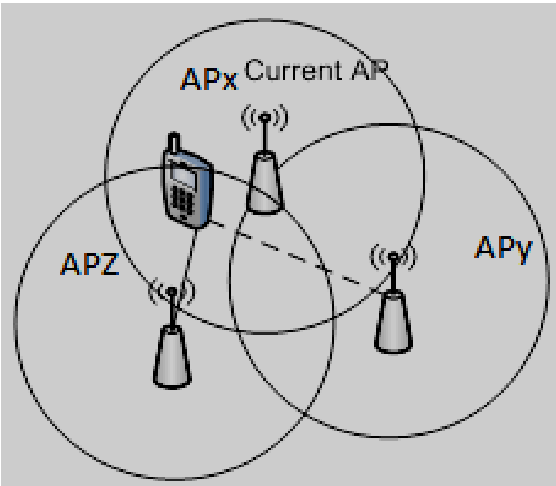

Figure 2. Example of EHP movement from APx to either APy or APz

The decision of the next cell depends on the time stamp in which the history of the movement is trapped. The time stamp is 2 hours length, while the day has a 12-time stamp starting from 6am to 4 am next day. For the regular behaviour of the MS it tends to visit several cells in exact time more than other cells (i.e. go to café at determined time stamp and visit the gem in another time stamp, but for the counter, both locations has the same number of visits). In the table (1) the EHP counted the same number of the visit for APy and APz, so the time stamp will be the decision tool for the prediction of the next AP.

TABLE 1. TIMESTAMP FILTER FOR SIMILAR TRAJECTORIES PREDICTION

Timestamp t5	APx	APy	APz
APx	0	1	0
Timestamp t8	APx	APy	APz
APx	0	0	1

Femtocell proactive actions are considered as a classification issue in order to estimate the target cell. The parameter defined in Table 2. used all together to find the mobility pattern of the mobile station that define the behavioural movement. The current position of the mobile user is determined by the five features mention in the table and used as a base of the prediction of the next serving cell.

TABLE 2. THE PARAMETERS OF EHP MOBILITY MODEL.

Parameter	Symbol
Source femtocell	Fs
Current femtocell	Fc
Destined femtocell	Fd
The set of neighbouring cells to Fc	N(Fc) = {f1,f2,f3,..fn}
The day of the week	D = {d1,d2,...dn}, n={1,2,....,7}, d={sunday, monday,.....satrday}
The month of the year	M = {ms} : m = { Jan.,Feb.,....Dec} , s= {1,2….12}
The ith time unit	Ui={u1,u2,..u12} where Ui assuming the time unit is 2 hours.
CP(MS)	The current position of the MS defined by :(Fc, Fs, U,D,M) for each MS.

The historical data of source cell Fs paired with the current cell Fc, filtered by time unit Ui, day and month D, M respectively, lead to decrease the mis-prediction of the regular movement behaviour:

$$P_{next} = \arg\max_{F_d \in N(F_c)} \frac{[P(CP(MS)\,|\,F_d).P(\mathrm{F}_d)]}{[\mathrm{P(CP(MS))}]} \qquad (1)$$

Where Pr_n is the prediction of the next cell , while P(CP(MS)|Fd) is the probability of the current position defined by $\{(f_s,f_c,u_i,d_s,m_s)\}$ given F_d , and $P(F_d)$ is the destined cell probability for F_d .

The probability of the current position is based on the HH Table can be represented by an order-k Markov process.

$$\mathrm{P(CP(MS)|F_d)}= \hat{P}(\mathrm{Xs+1=cs+1} \mid \mathrm{X(s\text{-}k+1,s)=(cs\text{-}k+1......,cs)}) \qquad (2)$$

$$\mathbf{P(CP(MS)} = \sum_{i=1}^{k} \mathbf{P(CP(MS)}|F_k).\mathbf{P}(F_k) \qquad (3)$$

Where, Xs+1 is the prediction of the next point of attachment k = 1 - 1, L is the overall observed history of mobility patterns.

B. GPS Predictor Model

The prediction using GPS is set up in two cases, when the MS has no history or miss-prediction occurs due to random movements of the MS when the prediction is done by either the probabilistic or the time series predictor . in the proposed GPS predictor, theMS receives 4 signals from minimally 4 GPSs, which broadcasting beacon packets contain information like starting time, longitude and latitude [21]. This information updated every specified interval, while the exact location of the MS is the intersection of the 4 signals from the 4 GPSs, figure (3) represent the determination of the user location using GPS.

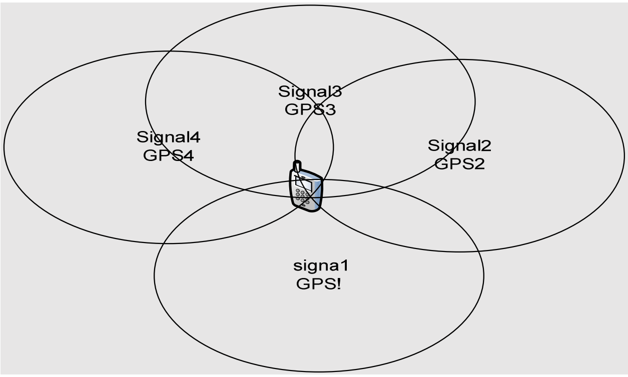

Figure 3. Ms Location Prediction using GPS

The MS activate the GPS device when GPS predictor is needed o avoid the power consumption, then all parameters(latitude (X), longitude (Y) and ellipsoid height (Z) calculated in order find the current location and direction and velocity of the MS. GPS server's DB keeps all maps locations of the neighboring APs to determine the headed AP. The predictor calculations are setup as in [24].

$$D_n = \sqrt{(x_n - x_{n-1})^2 + (y_n - y_{n-1})^2 + (z_n - z_{n-1})^2} \quad (4)$$

$$v = \frac{(D_n - D_{n-1})}{t} \quad (5)$$

The GPS is accurately determining the next point of attachment while it used either in the first stage of prediction when the user is new or without history , or in the second stage after the 1's misprediction. Our scheme enhances the 1'st and 2nd prediction. In fig (3) the flow chart of the hybrid proposed method is been represented.

IV. RESULTS AND ANALYSIS

In this section, the performance evaluated in term of accuracy of predictions. The results are compared with those in [8] and [11] Fig 6. The results show superior improvement against the mentioned schemes.

A. *Simulation Environment*

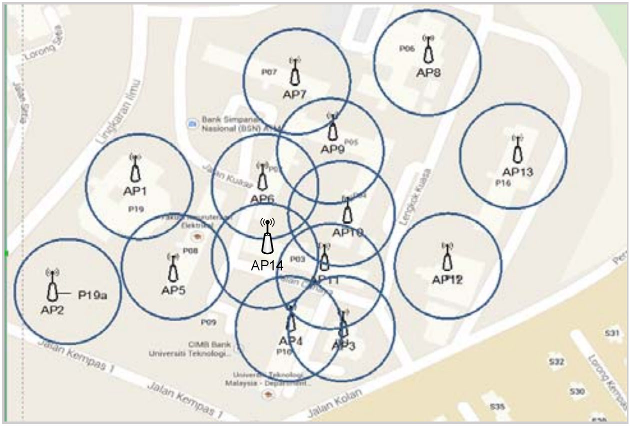

Figure 4. The Simulation Area in FKE .

In this study, we trace the history of 3 groups of users in UTM. The groups are undergraduate students, postgraduate students and staff, they reflect variety in ages, activities and mobility patterns. The14 APs in the simulated area are dense and overlapped. With pre-process on the log files original data to extract the mobility patterns of the users .In our case of femtocellular network we have the following key characteristic:

1- The APs is located in buildings those are close to and around the user's (MSs),i.e. labs, classrooms, cafes,...etc.

2- Some Access points are adjacent in a very small area like AP4 and AP11 see fig (3) result in a high overlapped coverage they may be highly interfered due to using the same channel1,6,and 11.

3- The transmitted signal is omnidirectional.

4- The quality of signal may vary over the time affected by the electromagnetic interference, load , and user mobility in and out the cells.

5- The mobility patterns to be most likely have a regular and repeated manner.

Based on this model, we propose temporal history-based mobility prediction algorithm. We used the Enhanced Markov predictor to predict future locations, especially in the case of similar routes probabilities.

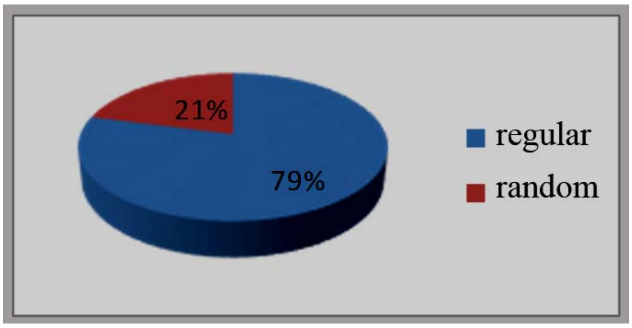

Figure 5. The Regularity of Mobility patterns in FKE.

B. The Simulation Result

The simulation work is done in Matlab. The mobility patterns in Figure 5 witness high regular behavior for the MSs versus randomness. The cell prediction is presented in Figure 6 for the total 15 AP, this prediction is very useful to fetch the next AP in case of lack information of the local history for users. Figure 7 shows the comparison of the accuracy in average between the pre-scanning scheme, the MCP, and EHP proposed method for the 3 groups. As can be seen, our method achieved a pretty much accuracy enhancement for the 1st prediction, while in the case of mis-prediction the 2nd prediction using GPS state 100% accuracy. In Figure 8 the accuracy is checked for the users in three subjected groups. The undergraduate group and staff group tends to have accuracy higher than postgraduate, this is because of the regularity of their movement since it is related to the lectures schedules. Figures 9 and 10 represent the histogram of the prediction after adding the parameters of time and day, this up raises the accuracy by 17% in average. The result in Figure 11 shows he improvement of adding the hybrid model with all parameters the 1st prediction .

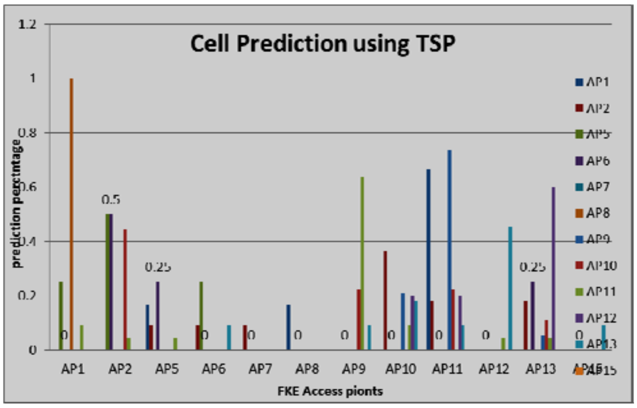

Figure 6. The Time Series Predictor for users with Insufficient History.

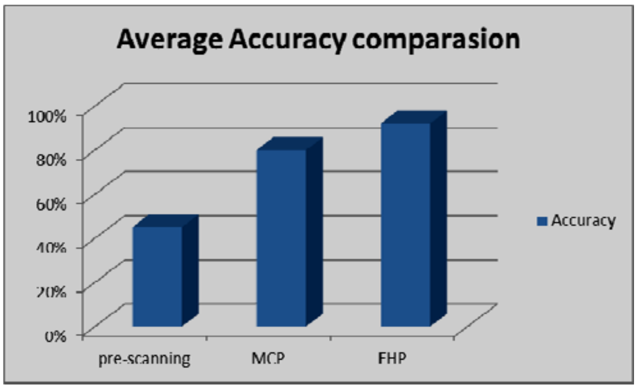

Figure 7. Prediction Accuracy Average Based On EHP Compared To Pre-scanning and MCP

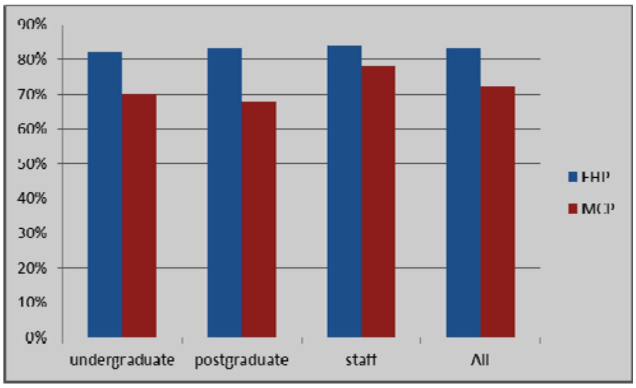

Figure 8. Prediction Accuracy Of Groups Based On EHP Compared To MCP

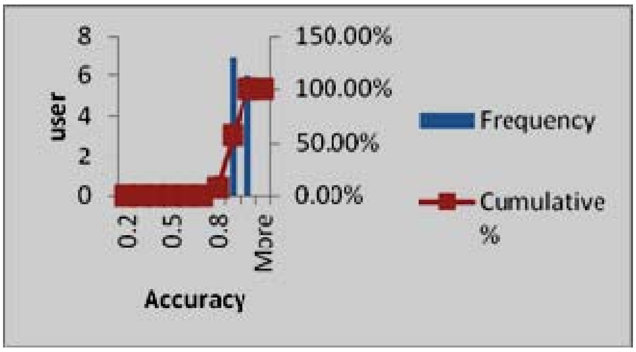

Figure 9. Histogram Of Prediction With Time Of Day Parameter

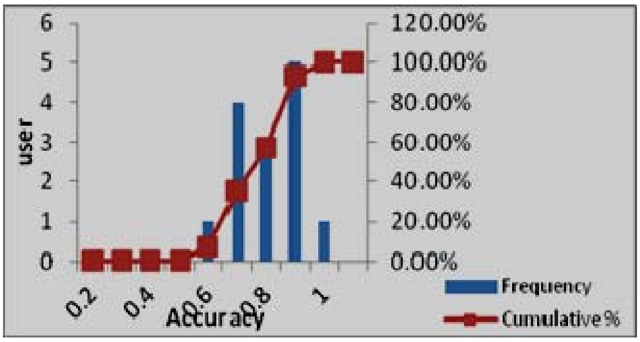

Figure 10. Histogram Of Prediction Without Time Of Day Parameter

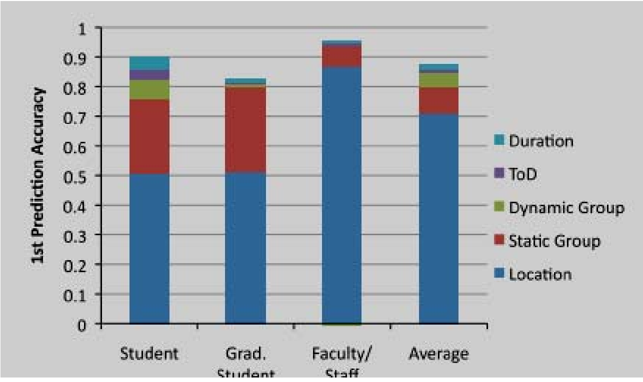

Figure 11. The prediction ccuracy for he hybrid model

V. CONCLUSION

This paper presented a Hybrid prediction for handover decision, the EHP technique to enhance mobility prediction is supported by GPS and TSP for a seamless handover in the next generation mobile networks. The proposed method based on extracting the behavior patterns of three groups of users. The added factors, to improve the accuracy of the first prediction of the next cell by85%. Our simulation study shows that the prediction of both random and regular manner of movement of MSs results in much lower delay and good QoS.

REFERENCES

[1] D. Xenakis, N. Passas, L. Merakos, and C. Verikoukis, “Mobility management for femtocells in LTE-advanced: Key aspects and survey of handover decision algorithms,” *IEEE Commun. Surv. Tutorials*, vol. 16, no. 1, pp. 64–91, 2014.
[2] S. E. Abdalla and S. H. Syed Ariffin, “The Enhanced User History - Based Prediction In 5G,” no. August, pp. 0–5, 2016.
[3] N. Bui, S. Member, M. Cesana, S. Amir Hosseini, Q. Liao, I. Malanchini, J. Widmer, and S. Member, “Anticipatory Networking in Future Generation Mobile Networks: a Survey.”
[4] M. Tao, H. Yuan, X. Hong, and J. Zhang, “SmartHO: mobility pattern recognition assisted intelligent handoff in wireless overlay networks,” *Soft Comput.*, 2015.
[5] B. Sas, K. Spaey, and C. Blondia, “Classifying Users Based on Their Mobility Behaviour in LTE Networks,” in *10th International Conference on Wireless and Mobile Communications (ICWMC)*, 2014, pp. 198–205.
[6] N. W. Sung, N. T. Pham, H. Yoon, S. Lee, and W. J. Hwang, “Base station association schemes to reduce unnecessary handovers using location awareness in femtocell networks,” *Wirel. Networks*, vol. 19, no. 5, pp. 741–753, 2013.
[7] A. Ulvan, R. Bestak, and M. Ulvan, “Handover procedure and decision strategy in LTE-based femtocell network,” *Telecommun. Syst.*, vol. 52, no. 4, pp. 2733–2748, 2013.
[8] Z. B. -, “Efficiency of Handover Prediction Based on Handover History,” *J. Converg. Inf. Technol.*, vol. 4, no. 4, pp. 41–47, 2009.
[9] W. Wanalertlak and B. Lee, “Global Path-Cache technique for fast handoffs in WLANs,” *Proc. - Int. Conf. Comput. Commun. Networks, ICCCN*, pp. 45–50, 2007.
[10] M. K. N. D. S. J. B. T. J. S. K. S. Utpal Biswas3, “Minimization of Handoff Latency by Angular Displacement Method Using GPS Based Map,” *IJCSI Int. J. Comput. Sci. Issues*, vol. 7, no. 3, pp. 29–37, 2010.
[11] J. Montavont and T. Noel, “IEEE 802.11 handovers assisted by GPS information,” *IEEE Int. Conf. Wirel. Mob. Comput. Netw. Commun. 2006, WiMob 2006*, pp. 166–172, 2006.
[12] N. A. Amirrudin, “Mobility Prediction via Markov Model in LTE Femtocell,” *Int. J. Comput. Appl. (0975 – 8887)*, vol. 65, no. 18, pp. 40–44, 2013.
[13] M. N. Hindia, A. W. Reza, and K. A. Noordin, “Investigation of a new handover approach in LTE and WiMAX,” *Sci. World J.*, vol. 2014, 2014.
[14] T. Duong and D. Tran, “An Effective Approach for Mobility Prediction in Wireless Network based on Temporal Weighted Mobility Rule,” *Int. J. Comput. Sci. Telecommun.*, vol. 3, no. 2, 2012.
[15] M. Prediction, M. For, V. Network, and U. Markov, “Jurnal Teknologi MOBILITY PREDICTION METHOD FOR VEHICULAR NETWORK USING MARKOV,” vol. 2, pp. 7–13, 2016.
[16] N. A. Amirrudin, S. H. S. Ariffin, N. N. N. A. Malik, and N. E. Ghazali, “User’s mobility history-based mobility prediction in LTE femtocells network,” *RFM 2013 - 2013 IEEE Int. RF Microw. Conf. Proc.*, pp. 105–110, 2013.
[17] A. Ben Cheikh, M. Ayari, R. Langar, G. Pujolle, and L. A. Saidane, “Optimized Handoff with Mobility Prediction Scheme Using HMM for femtocell networks,” *IEEE Int. Conf. Commun.*, vol. 2015–Septe, pp. 3448–3453, 2015.
[18] D. Barth, S. Bellahsene, and L. Kloul, “Combining local and global profiles for mobility prediction in LTE femtocells,” *Proc. 15th ACM Int. Conf. Model. Anal. Simul. Wirel. Mob. Syst. - MSWiM ’12*, p. 333, 2012.
[19] A. I. M. Saleh, “A Hybrid Mobility Prediction (HMP) strategy for PCS networks,” *Pattern Anal. Appl.*, vol. 19, no. 1, pp. 173–206, 2016.
[20] W. Wanalertlak, B. Lee, C. Yu, M. Kim, S. M. Park, and W. T. Kim, “Behavior-based mobility prediction for seamless handoffs in mobile wireless networks,” *Wirel. Networks*, vol. 17, no. 3, pp. 645–658, 2011.
[21] K. Regin Bose and V. Sankaranarayanan, “GPS Based Location Prediction and Authentication during Inter-MSC Handover,” *Appl. Mech. Mater.*, vol. 602–605, pp. 2326–2329, 2014.