Research Article

LOOP-BASED MARKOV CHAIN FOR NEXT CELL PREDICTION

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Atıf/Citation: YALIN, B. & YARKAN, S. (2022) Loop-Based Markov Chain For Next Cell Prediction, Journal of Technology and Applied Sciences 5(2), s. 31-40, DOI: 10.56809/icujtas.1133682

ABSTRACT

In this study, next possible cell for a User Equipment is predicted for Network Data Analytics Function (NWDAF) by using Markov Chain with novel loop-based approach. At the beginning, it is assumed that the prediction made for next state of a User Equipment will be more meaningful with our novel approach. As a result of the study, the transition states between the most visited cell after the last cell where a User Equipment is located were extracted and it was observed that the reliability of the prediction made is improved, when a semantic was established between two cells with the loop-based Markov Chain approach.

Keywords: 5G Network Functions, Markov Chain, Network Data Analytics Function, User Equipment Mobility

SIRADAKİ HÜCRE TAHMİNİ İÇİN DÖNGÜ TABANLI MARKOV ZİNCİRİ

ÖZET

Bu çalışmada Markov Zinciri, yeni bir döngü tabanlı yaklaşımla Ağ Veri Analitiği Fonksiyonu (NWDAF) için kullanılarak bir Kullanıcı Ekipmanı için bir sonraki olası hücre ya da hücre dizisi tahmin edilmektedir. Başlangıçta, bu yeni yaklaşımımız ile kullanıcının bir sonraki durumu için tahmininin daha anlamlı olacağı varsayımı yapılmıştır. Çalışmanın sonucunda ise, bir Kullanıcı Ekipmanı'nın bulunduğu son hücreden sonra en çok ziyaret ettiği hücre arasındaki geçiş durumlarının çıkarımı yapılmış ve bu iki hücre arasında bir ilişki kurulduğunda yapılan tahminin güvenilirliğinin, döngü tabanlı Markov Zinciri yaklaşımıyla arttığı gözlemlenmiştir.

Keywords: 5G Ağ Fonksiyonları, Ağ Veri Analitiği Fonksiyonu, Kullanıcı Ekipmanı Hareketliliği, Markov Zinciri

Geliş/Received	:	**21.06.2022**
Gözden Geçirme/Revised	:	**06.07.2022**
Kabul/Accepted	:	**18.07.2022**

1. INTRODUCTION

With the developing 5. Generation System (5GS), the number of mobile devices used will reach 12.3 billion and the traffic generated by smart devices will reach 132 GB per year approximately (H. Birkan, Meriç, Kerim, Salih, & Tuna, 2020). This increase in traffic should also bring data management with it. One of the ways that data can be managed is creating analytics. In this way, necessary data is used for certain operations, and redundant one is excluded. In order to provide this data analytics within 5GS, Network Data Analytics Function (NWDAF) was defined by the 3rd Party Partnership Project (3GPP) in Release 16 (3rd Generation Partnership Project [3GPP], 2019). NWDAF centrally collects data from other Network Functions (NFs), which are defined in the Service-Based Architecture (SBA) and process this data to create analytics. After these analytics are created by NWDAF, they are shared with NFs in synchronous or asynchronous way. In here, while synchronous refers to a request/response model, asynchronous refers to a subscription model.

Using NWDAF, other NFs are able to request analytics by specifying the required data to use in their own operations. Once these analytics are shared with the NF, this NF will be able to optimize its operation properly. In order for an NF Consumer to request these analytics from NWDAF, it shall use NWDAF's service (i.e., Nnwdaf). After an NF Consumer provokes this service (shown in Figure 1.), NWDAF receives the analytics request.

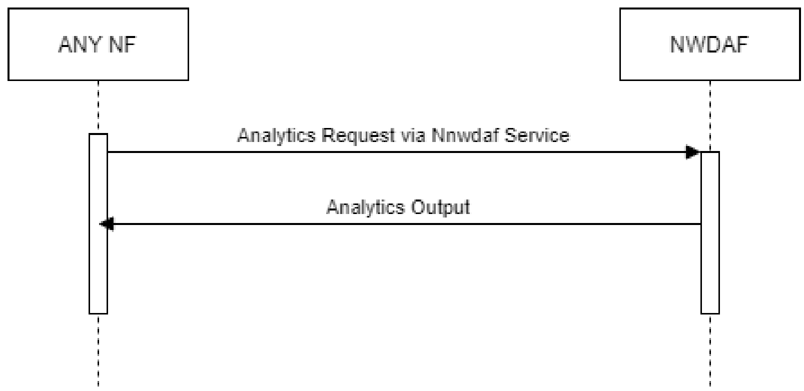

Figure 1. NF using NWDAF Service

NWDAF is able to create two types of analytics upon request sent by NF. One of the types is statistics based and the other one is prediction-based analytics. Statistics based analytics is basically collecting data from NF about its own operation (i.e., monitored event by NF), organizing it and sharing this data with the requester NF. In the prediction-based analytics, NWDAF collects historical data related to requested analytics, transforms this data into analytics by using Machine Learning (ML) and/or Artificial Intelligence (AI) algorithms and shares the result with the requester NF.

There are various analytics (or uses cases) that can be provided by NWDAF. Some of them are, Quality of Service (QoS) Sustainability, NF Load and User Equipment (UE) Mobility Analytics (3GPP, 2019). NWDAF shall interact with different NFs for each analytics to collect required data. Each NF is responsible for monitoring different events and collecting data for these events. In this way, NWDAF interacts with the NF that monitors the event related to data upon a received request and collects the required data to create the analytics. After required data is collected, NWDAF can create analytics by using ML/AI algorithms. ML/AI algorithms that are going to be used within NWDAF are generally related to the use cases.

In this work UE Mobility Analytics, creation scenario will be discussed. According to 3GPP standards, data of this analytics is collected via Access and Mobility Function (AMF) (3GPP, 2018). Unfortunately, since there is no AMF deployed for this work, data that needs to be collected was generated synthetically, with a similar format that generated by the AMF.

Lastly, after the synthetic data is created, our aim is to predict next possible positions, in cell granularity, with checking the last known cell. For that, simple Markov Chain was used firstly. For our problem, Markov Chain is implemented to predict next state considered the last state's earlier next states. So that, to make better prediction, contribution of this study is to check possible looping scenarios between last cell and its most visited (favorite) cell.

2. RELATED WORKS

In one of the studies which authors tried to predict UE mobility, ML Models were claimed to be problematic when used to predict UE's mobility with using locations of the user (Duong & Tran, 2015). According to this approach, when algorithm that is used for prediction is tried to be implemented for a new UE, prediction may fail. Therefore, implementation of data mining techniques can give better results. Authors aimed to predict the next step by gathering the mobility history of UEs who have similar trajectories, instead of using individual trajectories of the UEs in their study. According to methodologies they track on the paper, mobility prediction accuracy was improved.

On the other hand, some ML Models are also used in some previous research. For example, based on human mobility in the Long-Term Evolution (LTE) cellular network, mobility estimation of the individual user's evolved Node B (eNodeB) sequence was made with the help of Hidden Markov Model (HMM) method. Using the movement data of 2800 different users in Southern China, 53% prediction accuracy was achieved (Qiujian, Yuanyuan, Yufei, Zhenming & Zongshan, 2014).

On the other hand, more advanced methods than Markov Models in finer granularity than TA or cells were used in some studies (Ming, Wanfei, Wenhui, & Xiaoyan, 2021). In that study, in order to create mobility predictions, authors implemented and compared Long Short-Term Memory (LSTM), Attention Bidirectional Long-Short Term Memory (Bi-LSTM-attention) and Artificial Neural Network (ANN). They are used Geolife project of the Microsoft Research Asia as input. As a result of the mobility prediction, they tried to establish in GPS granularity, Bi-LSTM-attention improves the accuracy while the training time of it is almost twice of the LSTM. So as the output of their study, Bi-LSTM-attention was proposed as best method among two other for their work.

In another study, authors modeled the mobility data generated with the assumption that human mobility behavior is far from random (i.e., non-Gaussian). Using a Markov-based approach they aimed to predict the next movement of users (Fehmi, Jie, Xinyu, Yanting, Yuanyuan & Zhongwei, 2018). Authors kept the number of data (i.e., user trajectory) high they used to support their claims that human mobility behavior is far from random. Therefore, when they tested the non-Gaussian data of 3474 different users for 21 days with the model they created, they reached 56% accuracy.

The authors tracked the user's mobility behavior for a certain period of time to predict the next location by extracting the most visited locations (Marc-Oliver, Miguel, & Sébastien, 2012), for their study. In their work, they aimed to go beyond the Markov Property, which uses only current state for prediction. Accordingly, the model they use not only covers the last known location, but N historical information. As a result of their experimental approach, they reported that the accuracy rate of the algorithm they used was in the range of 75-95%. Moreover, they found that the computational cost of the algorithm for the case $N > 2$ is not optimized compared to the accuracy it gives.

In some studies, the Region of Interest (RoI) was also considered when estimating the user's mobility (Quannan, Xing, Yu, & Yukun, 2008) (Lizhu, Wei-Ying, Xing, & Yu, 2009). Shortly, the locations where a user has been in the past are collected, and the locations he/she visited more (e.g., home) and less (e.g., shopping mall) are called RoI. In one of the studies using this method, RoI points was used in a hierarchical order to predict user mobility with Markov Chain (Changchun, Ganke, Haichun, & Junjie, 2016). In their study, the authors deduced that the regions with historical data belong to the same RoI or different RoIs based on their proximity to each other. After this inference, they tried to predict the next location with the Markov Chain. At the same time, they aimed to extend the Markov Property concept by predicting the next location by using K states belong to past. When they tested the outcome evaluations for both Markov chain methods with entropy, they concluded that the Markov chain method using K prior data for their system reduces the uncertainty in the mobility estimation.

3. NETWORK DATA ANALYTICS FUNCTION (NWDAF)

NWDAF may interact with different NFs for different purposes (3rd Generation Partnership Project [3GPP], 2019). These purposes are as follows:

- With NFs that responsible for monitoring events and collecting data for different events,
- With repositories to collect required data, when data repositories are deployed (e.g., Analytics Data Repository Function (ADRF)),
- With Network Exposure Function (NEF) to collect information about NF(s),
- With NWDAF consumers who request analytics from NWDAF to share analytics it created.

In order for an NF to interact with NWDAF, they shall be on the same Public Land Mobile Networking (PLMN) (3GPP, 2018). When NF wants to get analytics, it shall send an HTTP POST or GET request to NWDAF by indicating the parameters. Among the HTTP methods, the POST method is used to receive analytics on a subscription basis, while the GET method is used on a request/response basis.

Upon the analytic request, if NWDAF does not have the necessary data to create analytics, it interacts with the NF over the POST request to obtain required data. When data is requested from Data (Event) Provider NF, it shares the data with NWDAF by using HTTP POST request. The POST request used by Event Provider NF is used for sharing data. Architecture of this operation is as in Figure 2.

Figure 2. NWDAF Data Collection Upon Analytics Request

Steps 2 and 3 will be skipped, if NWDAF already includes required data.

Prediction-based UE Mobility analytics, basically covers the predicting the next possible locations (e.g., cells) of a UE. When this type of analytics request is received by an NWDAF, it shall first collect the required data from AMF.

Since there is no deployed AMF to collect required data, parameters to be used in the model (i.e., UE ID and Cell ID) was parsed from the report in the same way as AMF sends. Detailly, value of “nrCellid” (Cell Identifier) and “supi” (UE Identifier) parsed and placed to model. After data model is created, aim is to predict possible next cell that UE will enter.

4. LOOP-BASED MARKOV CHAIN PREDICTION ANALYSIS

In this section, both Markov Chain prediction and novel Loop-based Markov Chain prediction is described. Firstly, our approach when modelling a system is presented. Then accuracies of two Markov Chain predictions are compared.

4.1. System Design

The synthetic data model was created in accordance with the real and synthetic data models used in the previous mobility prediction studies. For example, when students movement is considered for mobility prediction, they visit home and school more frequent than a cafe. In that sense, historical mobility data of a UE, some locations occur more than others. So, data model is created in that perspective.

When predicting the next cell of a UE, using the frequency of cells, that visited in the history, can be an approach. Because, when mobility patterns are considered next place predictors are based on the frequencies of occurrences rather than signal strength (Ben, Chansu, Myungchul, Seung-Min, Weetit, & Won-Tae, 2011). In order to predict next cell by using frequencies of occurrences, last cell of the mobility history can be used. In that sense, Markov Chain can be used to predict possible next cell. On the other hand, if last cell occurs first time in the dataset, prediction will fail because it has zero occurrences in the history. Therefore, this situation is out of prediction operation.

4.2. Prediction of Next Cell with Markov Chain

Markov models were used in various prediction tasks. Because they are efficient, easily implemented and require low computation complexity (Bui, Cesana, Hosseini, Liao, Malanchini & Widmer, 2016). The Markov-based model to be applied in this study uses the UE’s historical data in cell granularity (i.e., the cells that visited before) and presents a cell that has highest probability. Considering the cell list $C = [x_i, x_{i+1}, x_{i+2} \dots . x_n]$ visited by a UE in the past, x_n, is the last known cell. So, by using Markov Chain, prediction of next cell, x_{n+1}, in probabilistic manner is possible. Here, each x_i that , $0 \leq i \leq n$, represents a limited number of previously visited cells.

Starting point to calculate next possible cells is to evaluate the probability of what the next cell will be according to the last cell. When evaluating the possible next states, Markov Chain only considers the current state as in (2). This is known as Markov Property.

$$P(x_{n+1} \mid x_n, x_{n-1}, x_{n-2} \dots) = P(x_{n+1} \mid x_n) \tag{1}$$

Markov Chain for our problem is expressed in (2).

$$P(x_{n+1} = A \mid x_n = B) \tag{2}$$

Here, when $A, B \in \{x_i, x_{i+1}, x_{i+2} \dots . x_n\}$ is considered, while B represents the current visited state, A represents next possible cell (Korpipää, Koskinen, Mäkelä, Peltola & Seppänen, 2003). For example, a UE may have a mobility history in the cell set that has 5 different cells $\{S = S_1, S_2, S_3, S_4, S_5\}$. So that, a UE's mobility history can cover any variety of S set. Using a last element (cell) of UE mobility history, mobility prediction should return a cell which has the highest probability among all possible next cells. This can be seen from the state transition matrix in Table 1 for the last state.

Table 1. State Transition Matrix for Last Cell

	x_i	x_{i+1}	x_{i+2}	…	x_n
x_i	0	$P(x_{n+1} = x_{i+1} \| x_n = x_i)$	$P(x_{n+1} = x_{i+2} \| x_n = x_i)$	…	$P(x_{n+1} = x_n \| x_n = x_i)$

Here, probabilities between present and next state covers all the transitions between those states in the history. As it can be seen from the Table 1., $Pr(x_{n+1} = x_i \mid x_n = x_i) = 0$ because aim of this work is to predict only mobility, so stationary state is neglected.

Since Markov Chain gives a good approach for mobility prediction, it has some defects. For example, when semantics between cells is considered, Markov Chain does not create any relation. One can thing that, giving assumption at the beginning could solve the problem. For example, giving a threshold to probabilities, that calculated on the last step, so that if any interaction between cells is less than this threshold will not be given on the output can be thought. On the other hand, giving the threshold in-advance may not be a good approach for the mobility histories that are uniformly distributed. For that reason, using the frequencies of both cells and cells' transitions could be a better approach.

When calculating the frequencies of the cells and cell transitions, output should return a result that some cells and transitions have semantics. For example, cell that has the highest frequency (i.e., the most visited cell), can be identified as 'home' for a user. Also, the cell, which is the most visited after 'home', can be identified as 'office' or 'school'. It means, a mobility information has certain semantics (Jun, Ran, & Xihui, 2014).

Using the semantics of the cells leads the problem to our contributive approach, which is detecting a mobility between last cell and its next most visited cell (i.e., favorite next cell) and creating a loop between them.

4.3. Loop-based Markov Chain

In order to get better result than Markov Chain for the next cell prediction, giving a meaning to cells is the basis of our approach. Since the Markov Chain prediction computes all transition as in Table 1., aim of this paper is giving more meaningful outcome while reducing it.

Suppose that last cell is S_1 and after calculating its next cell possibilities in the history, favorite next cell is S_3. This also means, when this UE enters S_1, it tends to move to S_3. So that, there should be a semantic between S_1 and S_3.

As it is mentioned above, a UE tends to have more frequent transition between two distinct cells, when considering it has regular movement. Detailly, when checking the next possible cells of the last cell, the favorite next cell has a semantic with current one. This also means, maybe not in the next step but after some hops, this UE will tend to move to that cell. For example, if a UE enters cell S_3 after two steps from S_1, it means this UE did 2 hops to enter S_1. So, purpose is to check and calculate the hopping sequences between last cell, and its favorite next cell.

An example UE mobility history within the set S can be seen in Table 2.

Table 2. Example Mobility History Sequence

S_1	S_2	S_3	S_1	S_4	S_2	S_1	S_3	S_4	S_2	S_4	S_5	S_3	S_1	S_2	S_4	S_1	S_2	S_3	S_1

In the UE mobility history in Table 2., the last cell is S_1 and by calculating next possible cells with using the Table 1., the favorite next cell is S_2. So, what needs to be calculated is how S_1 transits to S_2 in different hops. By looking at the Table 2., different hopping sequences between S_1 and S_2 can be seen. For example, after fourth step, UE did two hops to reach S_2. Since this should be considered in the prediction, the probability of passing from S_1 to S_4 and from S_4 to S_2 are calculated. For both situation, their corresponding state transition matrices shall be calculated. Calculation for the two hops probability for given example can be seen from (3).

$$P(x_{n+2} = S_2 \mid x_n = S_1) = P(x_{n+2} = S_2 \mid x_{n+1} = S_4) * P(x_{n+1} = S_4 \mid x_n = S_1) \tag{3}$$

For any other hops (i.e., more than one hop), (3) can be transformed into the appropriate format of problem and calculated as it is in (4) where $S_n \in S$ and n = [1,2,3,4].

$$P(x_{n+k} = S_n \mid x_n = S_n) = \prod_{l=1}^{k} P(x_{n+l} = S_n \mid x_{n+l-1} = S_n) \tag{4}$$

According to (4), k upper limit decides the hopping sequence (k=1 for Markov Chain). Since, as in Table 2., there can be more than one hop, using a loop for all possible hops results all possible hopping scenarios between S_1 and S_2. Also, any other hopping scenarios (i.e., between last and any next) can be implemented. On the other hand, since, for the example above, S_1 and S_2 have a relation in terms of their semantics, using their hopping transitions is more meaningful for prediction.

So, by creating a loop-based approach between last cell and its favorite next cell by means of their semantics, Markov's property can be extended to predict some relational loops between cells.

5. CONCLUSION

In this study, UE Mobility prediction, was first implemented with a Markov Chain. Then, as the contribution of this article, the Loop-based Markov Chain was implemented. When implementing two methods, data is prepared in accordance with the AMF report. Background for creating and using loops between cells is, there should be a semantic information between cells that are in the UE mobility sequence. In that perspective, result of the Markov Chain has less information than the result of Loop-based Markov Chain. Because, by checking the possible next cells given the last cell information, Markov Chain computes all possible next cells in every step. Hence, any random movement occurred in the UE mobility history isn't eliminated in the simple Markov Chain.

On the other hand, since novel method of this article creates semantics between two cells, unnecessary information can be eliminated. For example, if one cell after next cell occurs only once in the history, loops of it won't be calculated. Therefore, for the synthetically generated UE mobility pattern, the Loop-based Markov Chain has succeeded for giving more meaningful results. In here, meaningful result refers to the prediction that was created by the hopping schemes of two cells.

In order to test our approach, different hops between the last and the favorite next cell using 3 different synthetic datasets were extracted firstly. When different loops are calculated within datasets, one of the loop length can be longer (e.g., 2-loop is occurred more than 3-loop). So, first thing to compute is comparing the occurrences of loops in new dataset, given that the most frequent loop is computed in-advance (in train set). Therefore, if most frequent loop (e.g., 2-loop) has different hopping schemes (e.g., S_1, S_3, S_2 and S_1, S_4, S_2), the one with highest probability shall be given as prediction result. Loop distribution between 3 different dataset can be seen from Figure 3. Black, blue, red, and purple bars represent 1-loop (simple Markov Chain), 2-loop, 3-loop, and 4-loop, respectively.

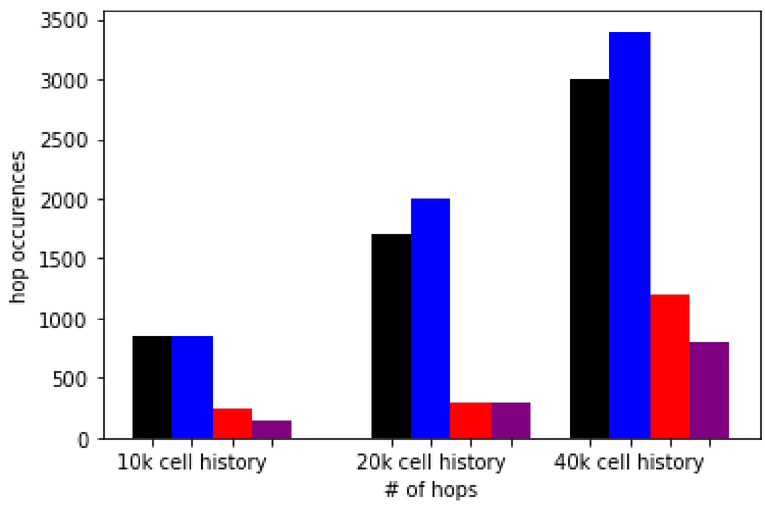

Figure 3. Loop distribution of 3 dataset

As it can be seen from Figure 3., this UE tends to move to its favorite next cell in one or two hops. Since the output of the system gives sequence as prediction, it should be the 2-hop loop, according to movement characteristic of this UE. After 2-loop with highest probability is extracted, the accuracy of it shall be calculated. This accuracy is calculated via $\frac{extracted\ sequence\ between\ S_1\ and\ S_2\ in\ two\ hops}{all\ sequences\ between\ S_1\ and\ S_2\ in\ two\ hops}$ .When 0.8 of all 3 dataset is used for training and 0.2 of them for testing, accuracy results between 1-hop and 2-hop can be seen from Figure 4.

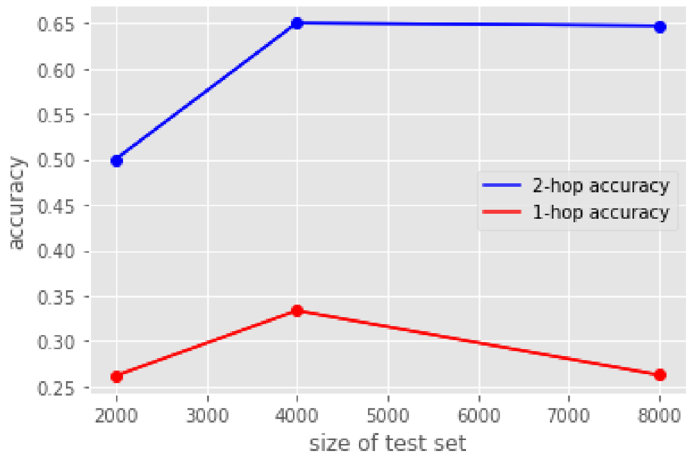

Figure 4. Accuracy of 1 and 2 hops

As result indicates, creating a semantic between two cells can give more accurate prediction. For our data and approach, accuracy result shows that, this UE moves to its favorite next cell of the last cell in 2 hops. In other words, it moves mostly in a loop between three cells, that are last cell, favorite next cell, and a cell between them. But, for any other UE movement characteristics, result can be changed. On the other hand, since regular UE movement is assumption of the study, a UE doesn't create 5 or more loops often. Because the number of cells between the last and the favorite next cell is not expected to be very large. Also, if mobility of this UE will have different characteristic in the future, prediction may fail. For example, if new dataset includes 4-hops more than 2-hops, since the training set includes the opposite, prediction will provide less accuracy. That's why, adding one more feature to the UE mobility list (e.g., timestamps) may be a solution.

6. FUTURE WORKS

In that work, we tried to create loops between last and its favorite next cell in order to predict next state. In order for us to improve our idea, first future work can be to increase the order of the Markov Chain, which means checking not only last cell but last k cells. With that approach, creation of loops can be more meaningful. For example, if favorite next cell is just visited before the last cell, then there might be a hopping sequence to enter that cell again. Also, since, the study given in that article covers only the history cell sequences (i.e., mobility traces) of a UE, adding the timestamps of cells entry moment, as another feature for prediction, gives higher resolution. Therefore, to predict the cells that a UE will enter in the next t period, it is necessary to consider the timestamps of the cells that was entered previously.

With both development, prediction can be more precise. Also, for a random movement of a UE, our model would not give good results, because our assumption, is regular UE movement.

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ACKNOWLEDGEMENT and DECLARATIONS:

The contributions of the authors to the article are equal. There is no conflict of interest between the authors. Research and publication ethics were complied with in the study.

Note: *This publication was produced from the Master thesis of Bahadır YALIN in the Electronics and Communications Engineering Program of Istanbul Commerce University, Engineering Faculty.*