Design and Development of a Handoff Management System in LTE Networks using Predictive Modelling

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Abstract

Handoff management is a key issue in mobile network to provide an efficient and low-cost service. Providing seamless connectivity in high speed data networks is a challenge due to user mobility and varying user traffic patterns. The major challenges with high user mobility are (1) Frequent handoff which causes call dropping (2) Unavailability of resources in the target base station which also may lead to call dropping. If the user behavior can be predicted, the network may proactively start the handoff procedure and thereby minimize the handoff delay, reduce call dropping and effectively manage network resources.

In this paper, a Handoff management system is designed and developed for LTE (Long Term Evolution) Networks using Predictive Modelling. The existing handoff procedure specified by 3GPP (3rd Generation Partnership Project) is modified to include a prediction part which will significantly reduce handoff overhead time, call dropping and utilize channel allocation. A Multilayer Feed - forward Neural Network (MFNN) model is designed and developed as a Predictive Model whose prediction is based on the history of mobility pattern of a mobile user recorded over several days. The MFNN is trained with the data obtained from the mobility pattern of a mobile user for making predictions. To test its functionality, this MFNN model is integrated with the LTE prototype code on ns2 (network simulator 2) by creating user movement scenarios.

The performance of the developed LTE Handoff Management System has been verified for prediction accuracy by considering mobility patterns of mobile user. The system simulation has achieved an average prediction accuracy of 93%. Handoff time overhead has reduced to 1 second which is significant as the current handoff process takes 6 seconds. The realized reduction in handoff time overhead has enhanced the Quality of Service (QoS).

Key Words: Handoff Management System, LTE, Predictive Model, Multilayer Feed Forward Neural Network, Back Propagation Algorithm

Nomenclature

3G	Third Generation
3GPP	3rd Generation Partnership Project
BER	Bit Error rate
CBQ	Class Based Queuing
eNB	Evolved Node B (Base Station in LTE)
LHMS	LTE Handoff Management System
LTE	Long Term Evolution
MAC	Medium Access Control
MFNN	Multilayer Feed-forward Neural Network
NN	Neural Network
ns2	Network Simulator 2
OFDM	Orthogonal Frequency Division Multiplexing
OTCL	Objected oriented TCL
PMBA	Predictive Modelling Based Algorithm
QoS	Quality of Service
TCL	Tool Command Language
UE	User Equipment
UMTS	Universal Mobile Telecommunications System
VoIP	Voice over Internet Protocol

1. INTRODUCTION

Long Term Evolution is a 3G mobile technology developed by a standards-developing body called the 3GPP. 3G LTE is a much advanced technology than the existing mobile technology which aims to provide mobile users with features like VoIP, high quality video conferencing, video messaging etc. The technology to be used in 3G LTE system has been a major issue because it aims for both high-quality service and reduction in cost. To meet this challenge of high-quality service at low cost, 3GPP has chosen Orthogonal Frequency Division Multiple Access (OFDMA) technology.

Handoff as used in mobile communication system is a process in which a UE (User Equipment) attached to a base station is transferred to another base station based on some conditions. Fast and seamless handoff is a major goal in the area of mobility management in wireless networks. It is also strongly required for a 3G LTE system in which soft handoff is not available due to its use of OFDM technology. However such handoff preparations have not been mentioned in the 3G LTE systems standards.

This paper aims at designing and developing a Handoff Management System in 3G LTE networks using Predictive Model. The handoff procedure for 3G LTE system as specified by 3GPP [17] is modified to include a NN (Neural Network) as a Predictive Model. This Predictive Model will predict a UE's next best cell location and best handoff time based on previous mobility pattern of that UE. For simulation of the system, the whole 3G LTE working functionality is realized in ns2 using C++ and OTCL programming languages interfaces. The Predictive Model is then included in the ns2 LTE prototype code to realize a Predictive Model based Handoff Management System for LTE networks. Different UE movement scenarios are created in ns2 to test the Predictive Model based handoff management system for LTE network. Simulation results and conclusions are presented at the concluding part of this report.

1.1 Handoff Basics

The fundamental concept of a cellular phone system is that a large number of base stations cover a small area (cells) and as a result frequencies are re-used. Cell phone systems can provide mobility. As a result it is a very basic requirement of the system that as the mobile handset moves out of one cell to the next, it must be possible to hand the call over from the base station of the first cell, to that of the next with no discernable disruption to the call. There are two terms for this process. "Cellular handover" is used within Europe, whereas "cellular handoff" is the term used in North America.

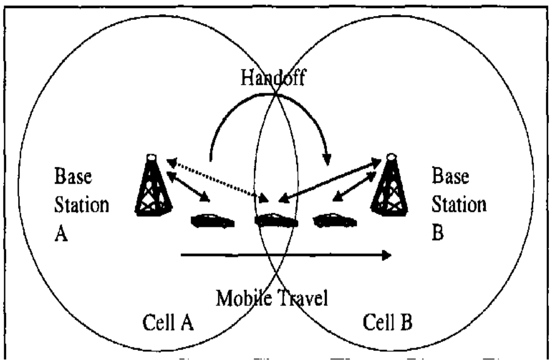

Fig. 1 Handoff in cellular systems [3]

1.2 Related Work

The method proposed in [4] aims to reduce signaling load resulting from location tracking. The idea is to take recent user movement information (called the paging information record) into account to determine which location area to page first. An effective location management strategy based on user mobility classes is tested and compared in [5] along with intelligent paging to reduce cost and paging delay. It shows that location management based on user mobility performs better. An optimal location registration area based on various mobility patterns of users and network architecture is designed to minimize the rate of location update, which in turn reduces the cost of tracking the mobile host [6]. In [7], the user profile (indicating the mobile host's identity and current location), replication mechanism for faster location lookup of a mobile user in a Personal Communication System (PCS) is presented with a minimum-cost maximum-flow-based algorithm to compute the set of sites at which a user profile should be replicated for given known calling and user mobility patterns [7]. A history-based location update scheme is considered [8] to reduce the number of unnecessary location updates by taking the recent mobility history of the mobile terminal into account to show that it results in a lower cost for mobility management. In [9], dynamic location areas are determined for each user on the basis of gathered statistics and incoming call patterns to reduce the average signaling cost to track a mobile user. Also, an optimal multi step paging algorithm is used to minimize the paging signaling cost.

An efficient heuristics to predict the location of a mobile user in a cellular network is presented in [10]. It assumes a hierarchy of location areas, which changes dynamically with traffic patterns. Depending on the movement profile of a user, it is possible to compute most probable location area and a future probable location area for the user. A mobile tracking scheme that exploits the predictability of user mobility patterns in wireless PCS networks is presented in [11]. In this scheme, a Gauss-Markov model is used and mobile's future location is predicted based on the information gathered from the mobile's last report of location and velocity. In [12], several basic prediction algorithms using real-life movement traces are verified, and a QoS adaptive mobility prediction is introduced to resolve the limitations of an individual's movement history for mobility prediction. The work carried out by introducing a dynamic velocity paging scheme based on semi-real-time movement information of an individual user, which allows a more accurate prediction of the user location at the time of paging, is reported in [13]. A novel predictive mobility management algorithm for supporting global mobile data accessing is introduced in [14]. This algorithm predicts the future location of a mobile user according to the user's movement history, i.e. previous mobility patterns.

2. DESIGN OF PMBA FOR LHMS

The design of PMBA for LHMS is discussed in the following sections.

2.1 Reason for Proposing a PMBA for LHMS

With the advent of high-speed, high-bandwidth mobile radio technologies and low-power, high-computing mobile devices, mobile phone users are becoming increasingly mobile, rather than remaining fixed. To migrate existing real-time applications of such users to these high-mobility networks, knowledge of user movement is essential. In the absence of this knowledge, re-establishing the network-side application context of users can be costly and lead to performance bottlenecks.

Fast and seamless handoff is also strongly required for a 3G LTE system in which soft handoff is not available due to its OFDMA technology [2]. However, such handoff preparation techniques have not been shown in UMTS or 3G LTE systems yet. Mobility prediction has been also considered an effective technique for fast and seamless handoff. It is usually based on the following two technologies. Time-series Analysis such as the Kalman filter [6] and Mobility Pattern Matching [7]. In spite of its usefulness, it has not appeared in the specifications of current mobile communication systems. The weaknesses of these mobility techniques result from the fact that their gains are not usually as high as their cost. Those techniques may be complex and may require more than simple change of the system. To overcome such weaknesses, a Predictive Modelling based handoff algorithm is proposed.

2.2 Proposed PMBA for LHMS

Fig. 2 shows a sketch of basic handoff procedure used in the proposed PMBA for LHMS. The proposed handoff management system uses a prediction technique which tries to estimate the best handoff target cell and the best handoff time for fast and seamless handoff. This prediction is based on the mobility pattern of the UE, which has been recorded for certain time duration. MFNN (Multilayer Feed-forward Neural Network) with back propagation algorithm is used as a Predictive Model to predict the best handoff target cell and best handoff time.

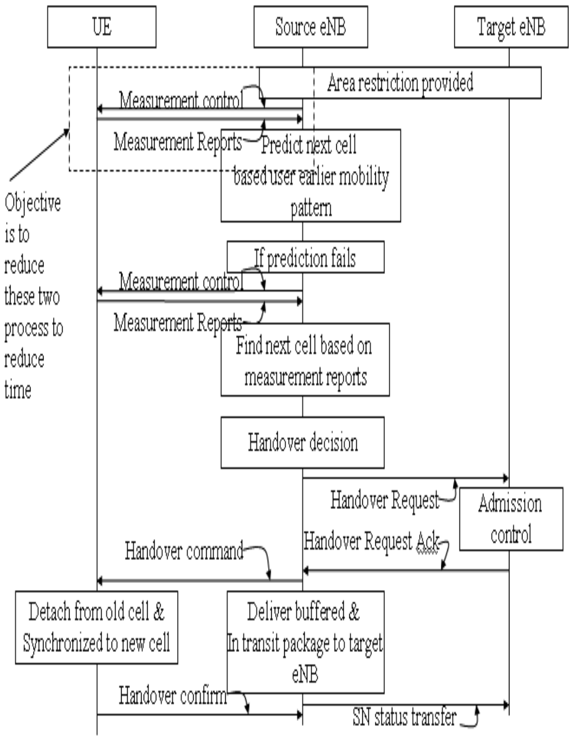

Fig. 2 Proposed handoff management system

The prediction starts as soon as a user initiates a call. The objective is to remove the measurement control and the measurements reports sending process of the 3GPP handoff procedure [17] as it is time consuming and sometimes leads to call dropping due to delay in delivery of measurement report. This delay may occur due to environmental interference or data packets lost on the way. In the proposed method, the source eNB predicts the next best cell location of a UE as well as the best handoff time based on the UE's earlier mobility pattern. Best handoff time is a time prior to the actual handoff time without prediction. So proactive handoff takes place in this way. But it may so happen that the prediction may fail. Prediction may fail when any of the following happens.

- The predicted target eNB is not in the neighborhood of the source eNB
- Sufficient number of UE mobility pattern is not found.
- The mobility pattern changes; however see discussion below how the proposed system is designed to handle such changes.
- Prediction process takes long time to make prediction and the UE has moved to some other eNB

In such situation when prediction fails, the normal handoff procedure will continue as specified by 3GPP [13]. The source eNB will take measurement reports from the UE and decides if handoff is required or not. If handoff is required, the source eNB will communicate with a target eNB to which the UE has to be handoff and thus the normal handoff procedure takes place. In case, the mobility pattern changed, the new mobility pattern will be learned by the MFNN so that it can predict a similar pattern later on. Thus the system is flexible enough to be trained dynamically.

2.3 Design of a MFNN as A Predictive Model

The design of a MFNN as a Predictive Model is described in this section.

Basics of Neural Network: A "Neural Network" (NN) is a mathematical model or computational model based on biological neural networks [15]. It consists of an interconnected group of artificial neurons. A NN with artificial neurons process information using a connectionist approach and perform computation.

Design of the MFNN Architecture: A MFNN Architecture as shown in Fig. 3 has an input layer (on the left) with three neurons, one hidden layer (in the middle) with three neurons and an output layer (on the right) with three neurons.

The MFNN model that is considered for prediction consists of three layers. input, hidden and output.

Finding the number of neurons in each layer:

The NN model that is considered for realizing a Predictive Model consists of three layers. input, hidden and output.

Some reports suggest that too few or too many input neurons can have significant impact on the learning and prediction ability of the network. In practice, the number of neurons is often chosen through experimentation by trial and error to have more generalization capability for the MFNN model. Also, while choosing the number of input and hidden layer neurons, care must be taken to avoid any under-learning or over-fitting of the training data.

A set of input layer neurons is selected by experimentation results and correspondingly the length of the input training sub-patterns or window size k of the training data that is considered for a given mobility pattern.

For example, Table 1 shows that the number of movements considered in the input training data is 4, i.e. k = 4, and each movement P_j requires two quantities to represent cell number and time of a UE. But in this work, cell number and time are fed at a time to one neuron. Hence, the number of input layer neurons for the above representation is equal to k=4

The number of neurons in the hidden layer depends on the length of the sub-pattern and the number of sub-patterns provided for training. The number of neurons in the hidden layer is initially chosen to be 3. This is just a preliminary value and will be changed based on requirements.

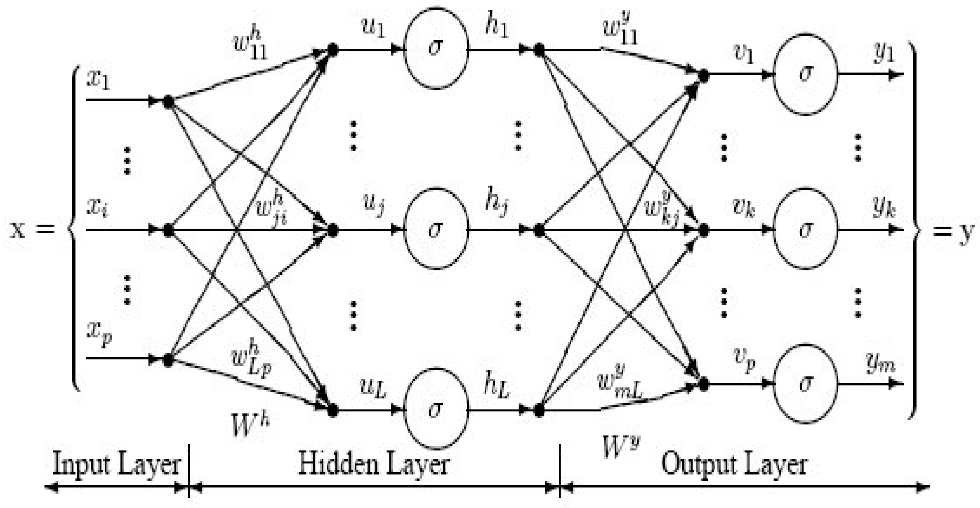

Fig. 3 MFNN architecture

The number of output layer neurons depends on the output movement parameters and their representation. In this case, cell number and time are considered as the movement parameter. Hence, there are two output neurons.

Finding MFNN parameters: The value of parameter is decided after trial and error. It is found that for the designed MFNN, the learning Parameter (input layer to hidden layer) is set to 0.7 and the learning parameter (hidden layer to output Layer) is set to 0.007. The activation function used is a tanh. This activation function is used because it gives value between -1 and 1. Sigmoid function was also used for comparison and it was found tanh gives more accurate results. The error tolerance is set to about 0.001. This error tolerance should not be set too low also as MFNN training will take more time and the network will be not be very efficient. Also setting the error tolerance high will lead to MFNN not learning properly. Sometimes the MFNN may get stuck at local minima during training period and may not be able to come out of it. To avoid the MFNN from getting stuck at local minima, numbers of iterations is chosen to be 20,000.

MFNN as a Predictive Model: Before discussing the designing part of MFNN as a Predictive Model, some of the definitions used in the latter sections are presented below.

Mobility pattern (Pn): Mobility pattern (Pn) is the history of recent movements' pattern of a mobile user recorded for a period of time T during which a UE makes a call. Let the mobility pattern $P_n= \{p_1, p_2,\ldots p_n\}$ be recorded for a UE, where p_i indicates the movement of a UE during time period t_i when the UE makes call. The mobility pattern P_n is defined in terms of the cell number and the time duration in seconds spend in that cell. P_i is represented by a pair (c_i, t_i).

- c_i is the possible cell number the UE is going to be after some time interval t_i. For example if the total cell number in a particular geographic area is considered to be 16, then $c_i \in \{1, 2, 3\ldots 16\}$. If a UE is in cell 2 then c_i=2;
- t_i is the time duration (in terms of seconds) a UE spends in a particular cell c_i while making active calls.

For example, if a mobility pattern is recorded for three cell transition (n=3) from cell no.1 to cell no.2 to cell no.3 with time spent in each cell as 10 minute,20 minute and 12 minutes respectively, then the mobility pattern is,
$P_3=\{p_1,p_2,p_3\}=\{(c_1,t_1),(c_2,t_2),(c_3,t_3)\}=\{(1,10),(2,20),(3,12)\}$.

Training data set: It is the set of sub-patterns obtained from the mobility pattern p_n by partitioning into n-k sub patterns, where k+1 is the size of each sub pattern (k<<n). The sub pattern is a training data pair with cell number and time spent as input and the next cell location with time as a desired output. For example, the first training sub pattern is p_1, p_2 ….p_k as input and p_{k+1} as the desired output. The parameter k is the prediction order, which is chosen based on the movement characteristic of a UE and the size of the recorded mobility patterns.

Table 1 shows the training data set obtained from the mobility pattern of p_{10} and k=4.

Table 1 Prepared data format for the MFNN

Sub pattern	Input-1	Input-2	Input-3	Input-4	Desired output
1	P_1	P_2	P_3	P_4	P_5
2	P_2	P_3	P_4	P_5	P_6
3	P_3	P_4	P_5	P_6	P_7
4	P_4	P_5	P_6	P_7	P_8
5	P_5	P_6	P_7	P_8	P_9
6	P_6	P_7	P_8	P_9	P_{10}

2.4 Prediction Based on MFNN as A Predictive Model

This section discusses the prediction of future location of a mobile host by using MFNN model for mobile movement prediction.

The mobility pattern of a mobile user or UE traveled over a period of time is recorded and is processed to construct MFNN model for mobile movement prediction

If a UE is active and attached to a particular cell, the system predicts the UE next possible cell location along with the approximate amount of time likely to be spent in that cell based on previous mobility pattern of that UE. Approximate amount of time likely to be spent includes the handoff time and the duration for which the UE stays in that cell.

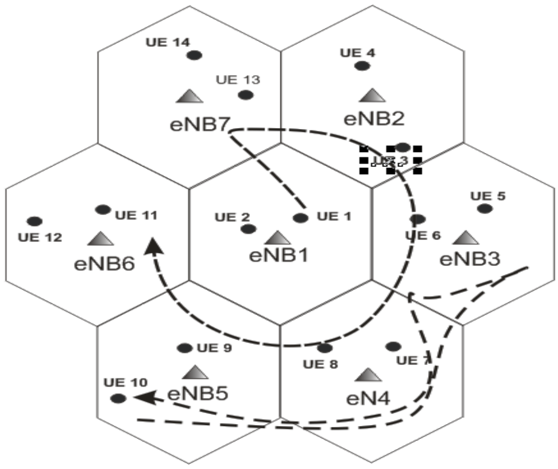

Fig. 4 Cell structure with mobile user movement

The process of predicting a UE next cell location is explained with the following example. For simplicity, without loss of generality, it is assumed that the cells are hexagonal shaped.

In this example, an array of 7 cells is considered, constituting the mobile network topology as shown in Fig. 4. Also, it is assumed that a central eNB is surrounded by the other 6 eNBs. The eNBs are assigned an eNBs number. In this example, it is assumed that eNB1 is surrounded by eNB2-eNB6.

The UE movements are recorded in terms of cell number and time spent in that cell at every handoff. The recorded mobile movements are pre-processed to obtain the mobility pattern, i.e. eNBs number and time spent, for training the neural network. From the cell-based mobility pattern, the pattern for UE1 and UE10 are derived for prediction as follows.

For UE1, the mobility pattern is

$P_i = \{(1, t_1), (7, t_2), (2, t_3), (3, t_4), (4, t_5), (5, t_6), (6, t_7)\}$, with seven handoffs. The time spent in the corresponding cell is taken some assumed values for explanation purpose. For UE10, the mobility pattern is $P_i = \{(5, t_1), (4, t_2), (3, t_3), (4, t_4), (5, t_5)\}$, with five handoffs.

By observing the patterns for each user, the corresponding sub patterns are obtained. These sub patterns are used for training the MFNN. Consider UE 1 to extract the training data set for the MFNN .The mobility pattern of UE1 is arranged in the form given in Table 2. It is arranged in a form suitable for training the MFNN

This training data is feed to the MFNN. Here, Pattern No.1 and Pattern No.2 are the training pattern while Pattern No.3 is considered as the test pattern. P_1 to P_4 are fed as the input to the MFNN while P_5 is considered to be the desired output. It is assumed that the above 3 patterns has occurred many times in the recorded mobility history of UE 1.

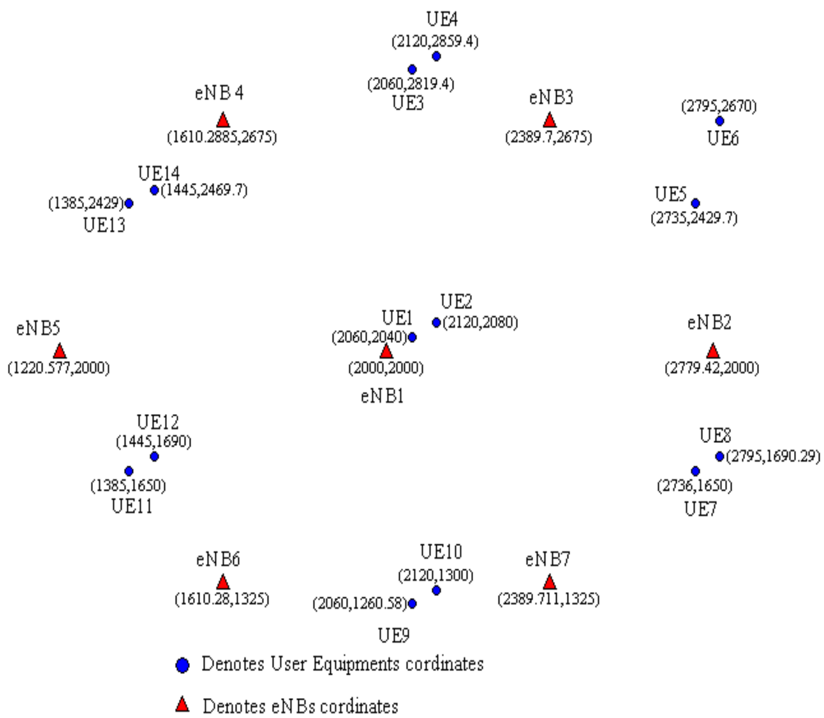

Fig. 5 Positions of UEs and eNBs

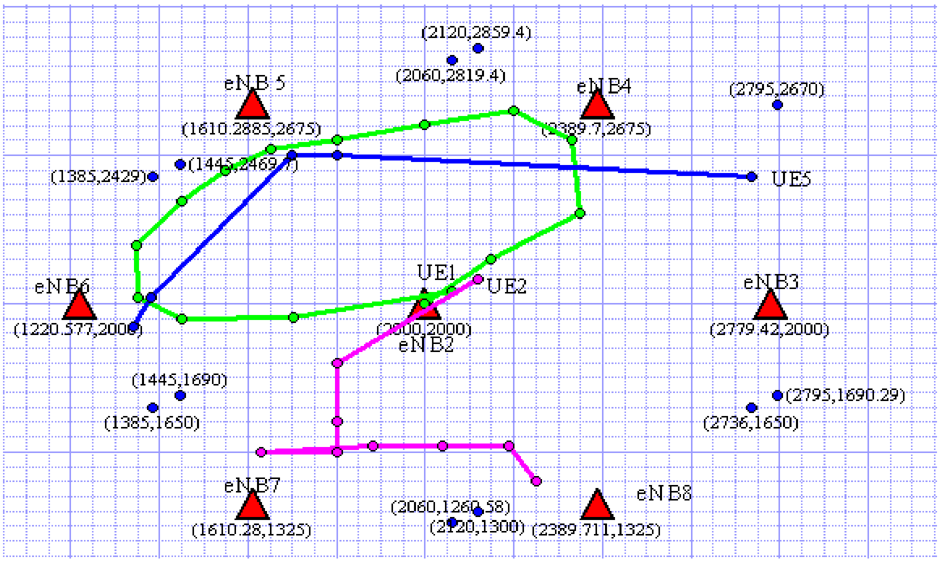

Fig. 6 UEs movement

Table 2 Prepared data format for the MFNN for UE1

Pattern No.	P_1	P_2	P_3	P_4	P_5
1	$(1,t_1)$	$(7,t_2)$	$(2,t_3)$	$(3,t_4)$	$(5,t_5)$
2	$(7,t_2)$	$(2,t_3)$	$(3,t_4)$	$(5,t_5)$	$(6,t_6)$
3	$(2,t_3)$	$(3,t_4)$	$(5,t_5)$	$(6,t_6)$	?

The network is trained using a number of iterations until the error reduced below the error tolerance value of 0.001. The trained network is tested on the testing data for prediction.

3. TESTING OF THE PROPOSED PMBA FOR LHMS

Testing of the proposed PMBA for LHMS is done on ns2 by developing the C++ code and OTCL code for it.

3.1 Network Simulator - 2

ns2 is an object-oriented, discrete event driven network simulator developed at UC Berkely. It is written in C++ and OTcl [16]. It implements network protocols such as TCP and UPD, traffic source behavior such as FTP, Telnet, Web, CBR and VBR, router queue management mechanism such as Drop Tail, RED and CBQ, routing algorithms such as Dijkstra, and more. NS also implements multicasting and some of the MAC layer protocols for LAN simulations.

3.2 Description of the Scenarios Developed in Ns2 Used For Testing the Developed LHMS

The scenarios created to test the developed Predictive Modelling based LHMS consists of 7 eNBs and 2 UE attached to each eNB. So a total of 14 UEs are considered. It is assumed that handoff takes place among these 7 eNBs. All the 7 eNBs and 14 UEs are assigned the x-y coordinate value which will define their position in a geographical area. It is assumed that eNB1 will be in the centre surrounded by the remaining 6 eNBs forming an eclipse formation. The positions of eNBs are configured as fixed nodes while the UEs are configured as movable nodes.

eNB1 is assigned x_pos=2000, y_pos=2000.

Radius of radius= 450 units is taken for the eNBs eclipse formation.

eNB2=(x_pos+(2*cos 30),y_pos)=(2779.42,2000)

eNB3=((x_pos+cos 30),(y_pos+radius*3/2))=(2389.7, 2675)

eNB4=((x_pos-cos 30),(y_pos+radius*3/2))=(1610.28,2675)

eNB5=((x_pos-(2*cos 30),y_pos))=(1220.577,2000)

eNB6=((x_pos-cos 30),(y_pos-radius*3/2))=(1610,1325)

eNB7=((x_pos+cos30),(y_pos-radius*3/2))=(2389.71, 1325)

The positions of the eNBs along with their corresponding UEs attached to it are plotted in the Fig. 5

Fig. 6 shows the position of the eNBs along with the positions of the UEs. The green line shows the movement of UE1. Initially UE1 is attached to eNB2. The blue line shows the movement of UE5 which is initially attached to eNB3. The pink line shows the movement of UE2 which is initially attached to eNB2.

3.3 Test Pattern Generation for Testing the Developed PMBA

Patterns for testing the developed PMBA for the LHMS are generated from the scenarios developed on ns2. During the time interval 1 to 190 seconds, the handoff procedure taking place without prediction in the developed scenarios is kept track of by storing the relevant information in an excel file. This information stored consists of source eNB Id, time spent in source eNB and the target eNB Id. This information is arranged in patterns in a form that can be fed to the MFNN based Predictive Model. The test pattern is obtained from the arranged pattern.

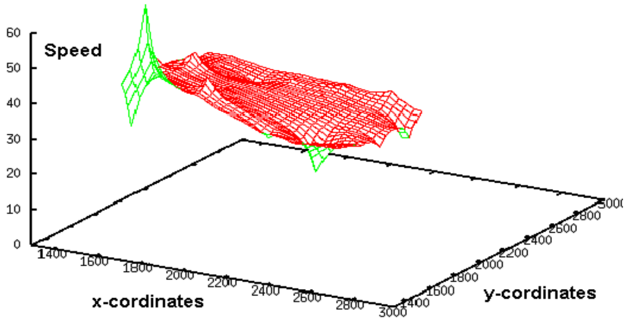

Fig. 7 3-D plot showing variation of speed with x-y coordinates for the scenario

4. DISCUSSION OF RESULTS

Figure 7 shows the 3-D plot of x-coordinates, y-coordinates and speed of a UE in the scenario.

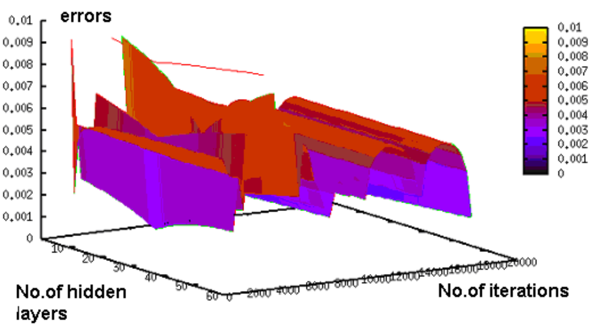

Fig. 8 3-D plot showing the variations of errors with the no. of hidden layers and no. of iterations

Fig. 8 shows the 3-D plot of errors as a function of the number of hidden layers and number. of iterations. It is inferred from the plot that if the no. of hidden layers is between 3 and 20, the error reduces and the number of iterations decreases. It is always desirable to reduce the error and no. of iterations when the numbers of hidden layers are small. The optimal value of the number of hidden layers is chosen to be 6.

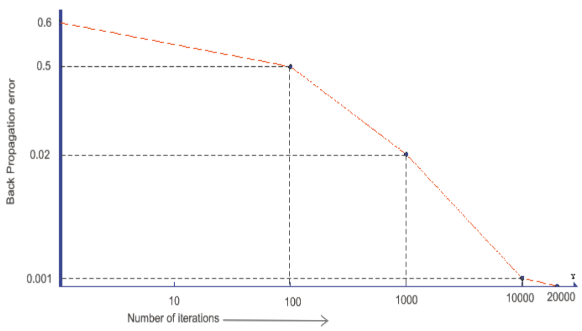

Fig. 9 Back propagation error versus number of iterations plot

Fig. 9 shows the plot of Back Propagation error versus Number of iterations. It is observed that at around 10,000 iterations, the error has reduced to around 0.001.

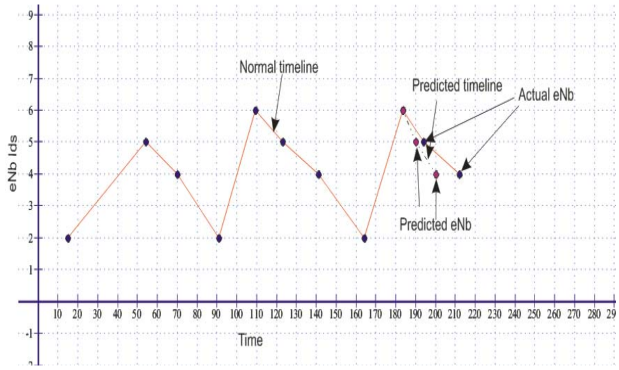

Fig. 10 Movement of a UE (with and without prediction) from one eNb /eNB ids to another with respect to time (seconds)

Figure 10 shows the plot of the eNBs id with time for UE 1. Initially, UE 1 is attached to eNB 2. At time 53 seconds, handoff takes place and it attached to eNB 5. During the time interval 1 to 185 seconds, the movement of UE1 is recorded. At time = 185 seconds, a prediction step is performed to find UE1 next possible cell location and time at which handoff should take place. As per the prediction UE1 should move to eNB5 after 21 seconds. The objective is to perform proactive handoff and so handoff should take place before 21 seconds. Hence, handoff is allowed to take place from eNB2 to eNB5 for UE 1 at time = current time – (21 seconds-5 seconds). This means that handoff takes place 5 seconds before the actual handoff time and UE1 moves to eNB4.

Prediction Accuracy: It is a measure in terms of percentage of how accurate a prediction is, and is taken to be

Prediction accuracy =

$$\frac{\text{Number of times accurate prediction of target eNBs of a UE}}{\text{Number of times prediction is performed for that U E}}$$

The scenario was run 30 times and the prediction was correct 28 times

Prediction accuracy = 28/30 *100 = 93%

5. CONCLUSION

The handoff procedure specified by 3GPP [17] was successfully modified to add a prediction part. A Predictive Model based on MFNN was designed and developed for making predictions about the next eNB Id as well as the optimal time for a proactive handoff to take place. It is observed that for the MFNN used as a Predictive Model, 6 neurons in the hidden layers are sufficient to obtain accurate predictions. The average prediction accuracy was measured to be around 93 %. It is observed that the proposed method helps in reducing the time of handoff by proactively performing the handoff. The system is able to predict the next best handoff cell location as well as the best handoff time. Handoff time overhead has reduced to 1 second which is significant as the current handoff process takes 6 seconds. The realized reduction in handoff time overhead has enhanced the Quality of Service (QoS).

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