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Markov Renewal Prediction and Radial Kronecker Neural Network Based Handover for Seamless Mobility

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ABSTRACT

Prevailing personal mobile network architectures make use of streamlined mobility control system, where the complete understanding is concentrated on single-end that results in scarce of dynamic mobility support when data volume is found to be large. The present-day networks necessitate seamless connections regardless of node position and connectivity that has to be accomplished between personal are network (PAN). In this work, a novel method called, Markov Renewal Prediction and Radial Kronecker Neural Network (MRP-RKNN) based optimized handover for seamless mobility in PAN is proposed. By employing a Markov Renewal Prediction model for Seamless Mobility along with the two-hop network architecture, in this paper, we propose a transition probabilities (TP) function to mitigate the persistent handover issue in conventional wireless communication systems. The proposed Markov Renewal Prediction model for Seamless Mobility significantly reduces handover execution time and seamless mobility handover accuracy with efficient transition probabilities. In PANs, the unavoidable deployment of low power sink nodes permits the mobile nodes with many issues in terms of Quality of Service (QoS) due to complication of recurrent handovers due to high mobility. Addressing this issue of handover optimization in the deployment of PAN, this work proposes a model called to optimize the handovers in a cost-efficient manner. In this work, Radial Kronecker Delta Neural Network is utilized for handling frequent handovers based on received signal strength and cost metrics. Here, the resultant desired output is obtained using the Radial Kronecker function being a function of two variables with which optimized handover is performed. Simulation results presented in the study exhibits the performance and prediction rate of the proposed method in terms of handover execution time, seamless mobility prediction accuracy, mobility handover cost and packet loss rate.

1. INTRODUCTION

The small cell technologies have been considered as the high speed wireless standard based on GSM network with the objective of adapting traffic requirements in the fifth-generation (5G) era and beyond 5G. Handovers among various cell without interruption is the biggest challenge and it should be handled in an efficient way. The main idea of the work is to reduce the handover failures as a consequence of radio link failures (RLFs) and keeping back the number of ping-pongs as least as possible. A Machine learning based Mobility Robust Optimization (Machine learning-based MRO) was proposed in [1] with the purpose of optimizing handover factors towards seamless mobility under dynamic small-cell networks. Hence, the optimization of handover in dynamic environment is necessary in addition to user mobility. The algorithm involved in the work for the optimization are topology adaptation and mobility adaptation. As a first part of the work, topology adaptation was ensured by means of obtaining prior knowledge about the channel information and to resolve the congestion caused by the resources Second, fine tuning of the handovers was provided by means of reinforcement learning via information acquired from the first step. With these two factors model not only the adaptation time was reduced but also resulted in the improvement of user satisfaction rate. Even though, the proposed algorithm performs well, the handover execution time and seamless mobility prediction accuracy was not focused. To overcome these issues, the work introduces a Markov Renewal Prediction model for Seamless Mobility. With the renewal process, the Markov prediction handles handover in a computationally efficient manner.

A mobility-aware seamless handover method called, Multi Path Transmission Control Protocol (MPTCP) was proposed by Tong et al. [2]. The proposed MPTCP handover method was executed in software-defined HetNets (SDHetNets) that consisted of three steps, called, prediction of location, selection of the network and finally the actual execution of handover mechanism. To be more specific, the user's location was initially prediction. With the prediction location, Fuzzy Analytic Hierarchy Process (FAHP) was selected for obtaining the target network by taking into consideration the preferences of user, network attributes, and mobility patterns of the corresponding users. Finally, the seamless handover was modeled, therefore reducing the handover time. Though handover time was found to be reduced, there still remained room for improvement in terms of handling continuous state space owing to high mobility pattern. To address on this aspect, a Radial Kronecker Delta Neural Network-based Optimized Handover model is presented that with the aid of Kronecker Delta function not only improves the mobility handover cost but also the packet loss rate to a greater extent. Technological influence based on the investment cost, invention and extensive objectives of 6G was focused by Karam et al. [3]. A seamless content delivery method for mobile Consumers via Information Centric Network (ICN) based communication frameworks was proposed by Hernandez et al. [4]. The method applied the extended formulations from ICNs for serving mobile consumer for content flow and caching. Here, location update was obtained via remote mobility manager entity with the objective of improving content delivery to Consumers. However, it was found to be only suitable for horizontal handover. A vertical handover decision algorithm employing Fuzzy Logic (FL) algorithm was presented by Azzali et al. [5] to improve QoS performance in heterogeneous vehicular ad-hoc networks (VANET). However, mobility management one of the major issues faced by real time application was not focused. To concentrate on this issue, vision based localization was introduced by Pham et al. [6] via prediction algorithm. Artificial intelligence based framework was designed for mobile heterogeneous network [7].

Heterogeneous wireless networks that are utilized for seamless mobility are anticipated to face distinguished issues in 5G cellular networks. On account of their genuine pliability and adjustable preparation, Unmanned Aerial Vehicles (UAVs) could be of service to heterogeneous wireless network. However, the major issues of the prevailing UAV-assisted heterogeneous wireless networks comprise in having pertinent accessibility over wireless networks.

Future generation communication also necessitates reliability, seamless operations, and management of reconfiguration as far as heterogeneous wireless networks are concerned. Object mobility support algorithm was designed based on RSSI to handle seamless mobility [8]. A hybrid deep learning that consisted of convolution neural network (CNN) and long short term memory (LSTM) was presented by Khan et al. [9]. The CNN here allocated the resource in an efficient manner while the load balancing and error rate were handled using LSTM, therefore ensuring overall accuracy. Yet another uniform handover protocol using blockchain was designed by Haddad et al. [10] with the objective of reducing computation overhead.

1.1 Contributory remarks

The main contribution of this paper is that we propose a novel seamless mobility method taking into consideration Quality of Service (QoS) and guarantee service continuity during a vertical handover. Our key contributions include the following:

- To propose a method called Markov Renewal Prediction and Radial Kronecker Neural Network (MRP-RKNN) based optimized handover for seamless mobility to ensure QoS and seamless handoffs in PAN.
- To solve the problems of seamless mobility with minimum handover execution time and seamless mobility handover accuracy, we propose Markov Renewal Prediction-based Seamless Mobility model to improve the seamless mobility prediction accuracy by means of Markov Renewal Prediction kernel. Using the Markov Renewal Prediction kernel state transitions, the model can ensure accuracy with minimum time during handoffs.
- To design the Radial Kronecker Delta Neural Network-based Optimized Handover model with the objective of improving the mobility handover cost involved during handovers in PAN, that synthetically considers error evaluation, weight updates, handover data packet estimation and handover cost evaluation separately in four hidden layers. Then, we propose a seamless handover mechanism employing Kronecker Delta function, thus guaranteeing service continuity even during handover.
- The fundamental analysis on the performance of the proposed method is also evaluated. Simulation results show that the MRP-RKNN method can ensure seamless mobility with minimum handover time and maximum accuracy. Then, the handover cost results show that the proposed MRP-RKNN method is comparatively better than the state-of-the-art methods.

1.2 Organization of the paper

The rest of the paper is organized as follows: Section 2 provides a brief description of seamless mobility, addressing handover, personal area network, connectivity techniques, their pros and cons, finally, outlines some efforts to overcome them. Section 3 describes the method, Markov Renewal Prediction and Radial Kronecker Neural Network (MRP-RKNN) in PAN. Section 4 describes the experimental setup with a detailed discussion in Section 5 comparing MRP-RKNN method with the state-of-the-art methods. Finally, in Section 6 conclusions are drawn

2. RELATED WORKS

Radio access mechanisms are readily equipment with their own features, like, bandwidth, response time and coverage. These features are paramount owing to the deployment of applications that necessitate huge bandwidths, minimum latency. The main issues with the prevailing handover function are several unnecessary handovers occur due to low signal and large distance factor between device and Base Station.

To this end, a novel method was designed by Goudarzi et al. [11] on the basis of cooperative game theory that in turn identified the best UAV during handover process by reducing the end-to-end delay, handover latency and signaling overheads. Yet another method was proposed by Shi et al. [12] based on protocol oblivious forwarding to ensure flawless transmission in real environments. A review of application of machine learning and deep learning for seamless mobility to handle vertical handover was investigated by Kornaros [13]. A survey of machine learning methods was investigated by Ahmed and Diaz [14].

Mobile communication refers to the procedure of carrying out computations on a portable device and performing data transmission to single or several devices. Upon occurrences of geographical location changes of a mobile user, the network should be in a position to hand shift in data without loss in both signal quality and data. Handoff remains to be the only key for handling vigorous call transfer between access points.

A significant neural network-based handover trigger method for vehicular networks was proposed with the objective of accurately predicting handover trigger time utilizing time-series quality measurements of network [15]. Also, a recurrent neural network technique was presented with the purpose of predicting upcoming sequence of RSSI to derive handover trigger estimation. Artificial Neural Network was employed by Sasikala et al. [16] on the basis of user behavior for handling vertical handoff.

A new dynamic scheduling algorithm for heterogeneous wireless network while maintaining performance was proposed by Mansouri et al. [17]. The scheduling algorithm was specifically designed on the basis of link conditions of transmission from two distinct types of techniques namely, Media Independent Handover (MIH) and Handoff Call Prioritization. With these two techniques, average packet delay was reduced considerably.

A novel neural network named Driving Behavior Risk Prediction Neural Network (DBRPNN) was designed for performing prediction on the basis of the distracted driving behavior data [18]. Mobility prediction was performed in the studies of [19] by utilizing hidden Markov model. With this not only the network throughput was improved considerably but also resulted in the minimization of retransmission rate. Deep neural network and deep reinforcement learning were applied by Li and Li [20] in WSN for handling handover.

Motivated by the above materials in this work, a novel method for seamless mobility called Markov Renewal Prediction and Radial Kronecker Neural Network (MRP-RKNN) based optimized handover is proposed to ensure minimum handover time, cost and maximum accuracy between nodes in PAN. The elaborate description of the CK-DRN method is provided in the following sections.

3. METHODOLOGY

Handover management process is a predominant and essential aspect as far as wireless access communication is concerned. An insightful handover operation is necessitated enormously to accelerate the seamless communication of Mobile Nodes (MNs) for the sake of ensuring the indispensable Quality of Service (QoS). A method called, Markov Renewal Prediction and Radial Kronecker Neural Network (MRP-RKNN) based optimized handover for seamless mobility in PAN is designed. In this work first, users' or mobile nodes individual mobility is obtained by means of a Markov Renewal process. The Markov Renewal process being a stochastic process possesses discrete movements with arbitrary arrival time rather than the continuous time. Second, Radial Kronecker Delta Neural Network is applied for deciding upon optimized handover based on RSS and cost metrics. The elaborate description of MRP-RKNN method is provided followed by the system model.

3.1 System model

Personal Area Networks (PANs) are specifically split into mobile nodes, each mobile node served by at least one base station. Every mobile node in the network is identified by means of a unique ID that is utilized in tracking and identifying the mobile nodes. With this unique ID, the mobile node's mobility history patterns are said to be recorded recurrently by utilizing the unique ID representations. In this situation, each grid that is constructing a mobility pattern, documents the number of handovers made to adjacent mobile nodes in the grid as well as the random arrival times. This permits in estimating the mobile node transition probabilities '$Prob_{i,j}$' and random arrival times are given by '$K_{i,j}(t)$'. The system model considered in the proposed methodology for the mobile nodes 'MN_i' and 'MN_j' is illustrated in Figure 1.

As shown in Figure 1, let 'MN_i' be the source mobile node and 'MN_j' be the target or receiving mobile node and 'α_{Dis}' represents the distance between them. Let the user equipment 'UE' be positioned at coordinates '(X_{UE}, Y_{UE})' and presumed to propagate in a straight line making an angle of 'β' where '$\beta = 0^{\circ}$' denotes the straight line movement of user equipment 'UE' toward 'MN_j'. Then, the user equipment 'UE' is said to traverse from the 'MN_i' and toward the 'MN_j' in straight lines at arbitrary velocity and angle. At any instant, the user equipment 'UE' is considered to be at distance 'α_X' from 'MN_i' and 'α_Y' from 'MN_j'. The values of 'α_X' and 'α_Y' is then mathematically formulated as given below.

$$\alpha_X = \sqrt{(X_{UE} - X_i)^2 + (Y_{UE} - Y_i)^2} \tag{1}$$

$$\alpha_Y = \sqrt{\left(X_{UE} - X_j\right)^2 + \left(Y_{UE} - Y_j\right)^2} \tag{2}$$

From the above Eqns. (1) and (2), '(X_i, Y_i)' and '$\left(X_j, Y_j\right)$' denotes the position coordinates of mobiles nodes 'MN_i' and 'MN_j' respectively.

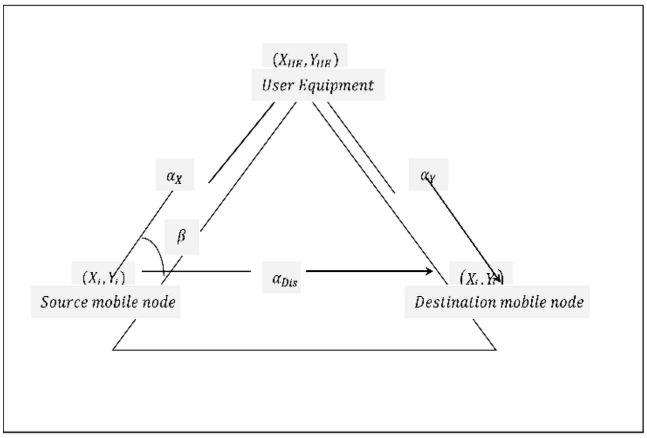

Figure 1. System model of Markov renewal prediction and radial Kronecker neural network

3.2 Markov renewal prediction-based seamless mobility model

Upcoming wireless networks will be designed by integrating heterogeneous networks over an IP-based infrastructure. This in turn has resulted in the deployment of handover to aid seamless mobility. These handover mechanisms hence have to be designed with the objective that the mobile nodes continue to receive communications without any disturbance during handover. In this work, user seamless mobility is modeled by a Markov Renewal Prediction process that permit for arbitrary distributed times and hence is said to be viewed as a process with random arrival times for each mobile nodes in PAN. Here, the random arrival times are the time instances when a user equipment or mobile attaches to a new grid. In a Markov Renewal Prediction process, the consecutive visited state of a mobile node represented by mobile node IDs are administered by the transition probabilities '$Prob_{i,j}$'. The random arrival times in any state depends on both the current position and the consecutive position where the user equipment of mobile node will move. Figure 2 shows the block diagram of Markov Renewal Prediction-based Seamless Mobility model.

As shown in Figure 2, the Markov Renewal Prediction-based Seamless Mobility model in PAN includes two processes, namely, mobility prediction and handover. In mobility prediction process, two predictions are made. They are state transition prediction and arrival prediction. According to these two predictions, handover mechanism is performed.

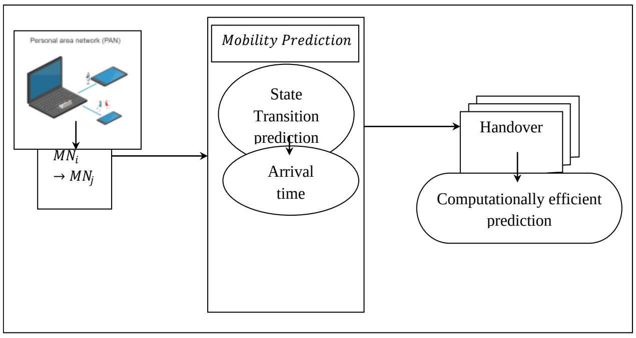

Figure 2. Block diagram of Markov renewal prediction-based seamless mobility model

The Markov Renewal Prediction kernel for a random arrival times is given by '$K_{i,j}(t)$' that represents the probability that instantly after characterizing the transition into state 'i', the procedure makes a jump to state 'j' within 't' time. Then, the Markov Renewal Prediction kernel within 't' time is mathematically stated as given below.

$$K_{i,j}(t) = Prob\ \{P_{n+1} = j, T_{n+1} - T_n \le t | P_n = i\} \tag{3}$$

From the above Eq. (3), 'P_n' and P_{n+1} 'P_{n+1}' denotes the system state after 'n' and '$n+1$' transitions respectively. The Markov Renewal Prediction kernel state transitions are further manifested as given below.

$$KST_{i,j}(t) = PST_{ij} QST_{ij}(t) \tag{4}$$

$$QST_{ij}(t) = Prob\ \{T_{n+1} - T_n \le t |\ PST_{n+1} = j, PST_n = i\} \tag{5}$$

From the above Eqns. (4) and (5), '$QST_{ij}(t)$' denotes the conditional probability that a transition (from one mobile node to another mobile node) will take place within 't' time instances where the positioning movements are made between state 'i' state 'j' (i.e., movement between two states). Then, a random arrival times is said to be followed.

Let us further define the Markov Renewal Prediction kernel for a random arrival times '$KRA_{i,j}(t) = PRA_{ij} QRA_{ij}(t)$', where '$QRA_{ij}(t)$' defines the corresponding random arrival times and '$PM = [PRA_{ij}], \forall i,j \in [1,n]$' denotes the probability matrix mathematically stated as given below.

$$PM = \begin{bmatrix} PM_{11} & PM_{12} & \dots & PM_{1n} \\ PM_{21} & PM_{22} & \dots & PM_{2n} \\ \dots & \dots & \dots & \dots \\ PM_{m1} & PM_{m2} & \dots & PM_{mn} \end{bmatrix} \tag{6}$$

$$KRA_{ij}(t) = Prob\ \{PRA_{n+1} = j, T_{n+1} - T_n = t | PRA_n = i\} \tag{7}$$

$$QRA_{ij}(t) = Prob\ \{T_{n+1} - T_n = t | PRA_{n+1} = j, PRA_n = i\} \tag{8}$$

By means of past handover transaction of a mobile node via mobile node ID and date from the Computer Network Traffic dataset, the state transition probability matrix 'PM' and the Kernel random arrival time 'KRA', the dispersal matrix 'DM' are initialized as given below.

$$PST_{ij} = \frac{(HO_{ij})}{H_n} \tag{9}$$

$$DM_{ij}(\gamma) = \frac{(HO_{ij\gamma})}{HO_{ij}} \tag{10}$$

From the above Eqns. (9) and (10), 'HO_{ij}' represents the number of handovers from mobile node 'i' to mobile node 'j', and 'H_n' represents the total number of mobile node handovers. Next, 'HO_{ijt}' denotes the number of handovers from mobile node 'i' to 'j', with a random arrival time 'γ' respectively. Upon occurrence of a handover from mobile node 'i' to 'j', 'PST_{ij}', '$QST_{ij}(\gamma)$' and '$KRA_{i,j}(t)$' are updated. The grid with the highest '$KRA_{i,j}(t)$' is selected as the predicted destination when the time spent in mobile node 'i' falls within time interval 'γ'. The pseudo code representation of Markov Renewal Prediction model for Seamless Mobility is given below.

Algorithm 1 Markov Renewal Prediction-based Seamless Mobility

Input: Dataset 'DS', Mobile Nodes '$MN = MN_1, MN_2, \dots, MN_j$', user equipment '$UE$', coordinates '$(X_{UE}, Y_{UE})$'
Output: Computationally efficient prediction
1: Initialize time 't', mobile nodes 'MN_i' and 'MN_j' 2: Begin 3: For each Mobile Nodes 'MN', with 'MN_i' and 'MN_j' 4: For each user equipment 'UE' at a distance 'α_X' from 'MN_i' and 'α_Y' from 'MN_j' 5: Estimate the distance as given in Eqns. (1) and (2) 6: Formulate Markov Renewal Prediction kernel as given in Eq. (3) 7: Evaluate conditional probability between state 'i' state 'j' as given in Eqns. (4) and (5) 8: For each Mobile Nodes 'MN' with corresponding random arrival times 9: Estimate probability matrix as given in Eq. (6) 10: Evaluate Kernel random arrival time as given in Eqns. (7) and (8) 11: Return dispersal matrix as given in Eq. (9) 12: End for 13: End for 14: End

As given in the above algorithm, Markov Renewal Prediction-based Seamless Mobility is designed that with the aid of distance estimation first, obtains the grid for mobility. Next, Markov Renewal Prediction kernel is applied that first obtains state transitions, followed by which random arrival times are evaluated are results are stored in probability matrix. Finally, upon occurrence of a handover shifts between nodes, therefore ensuring prediction with minimum time and maximum accuracy

3.3 Radial Kronecker delta neural network-based optimized handover

In this section, we apply the Radial Kronecker Delta-based Neural Network as shown in figure. The advantage of this model is the application of Radial Basis Function (RBF) that depends on the distance between the input vector and centroid and has a simple structure. The basic structure comprises of three layers. They are input layer, hidden layer and output layer. The input nodes consist of number of handovers, received signal strength (RSS) and Flows (connection counts for that day) (i.e., six nodes). Four hidden layers are present that utilize a nonnegative function to connect them to all of the input mobile nodes.

The output layer comprises of one mobile node that is acquired by a weighted sum of outputs of hidden units. The output of the network in this work is to decide upon the factor whether handover is required or not. If the resultant value of Kronecker Delta 'δ' is '0', there is no handover. On the other hand, if the resultant value of Kronecker Delta 'δ' is '1', then the model handovers the mobile to the selected sink node. Figure 3 shows the structure of Radial Kronecker Delta Neural Network-based Optimized Handover model.

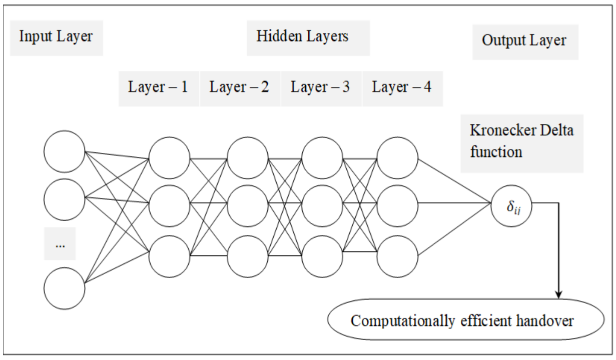

Figure 3. Structure of radial Kronecker delta neural network-based optimized handover

As shown in the above figure, there are one input layer, four hidden layers and one output layer. Six nodes (i.e., mobile nodes, data packets, Local IP, Remote ASN, RSS and flows) are provided as input in the input layer. The first hidden layer performs the actual tasks of evaluating the error, the second hidden layer updates the weight, the third hidden layer evaluates the handover data packets and the final fourth layer evaluates the handover cost. Finally, in the output layer, optimized handover is performed as output. Let us assume the initial value of center be 'C_{ij}' in the hidden layer for the '$i-th$' input mobile node and '$j-th$' hidden mobile node. Next, initialize the value of distance 'Dis_j' for the '$j-th$' hidden mobile node. Then, the output is formulated as given below.

$$Out = Exp\left[-\frac{\left(MN - C_{ij}\right)^2}{2Dis_j^2}\right] \tag{11}$$

From the above Eq. (11), the output unit is formulated 'Out' based on the exponential value of the input vector 'MN' with respect to the center vector for the '$i-th$' input mobile node and '$j-th$' hidden mobile node 'C_{ij}' and distance 'Dis_j^2' respectively.

$$Out_{kj} = \sum_{j=0}^{M} W_{kj} Out_j, where\ k = 1\ and\ M = 6 \tag{12}$$

With the obtained initialized weight and output, the error is mathematically stated as given below.

$$Err_k = DOut_k - Out_{kj} \tag{13}$$

From the above Eq. (13), the error is estimated 'Err_k' on the basis of the desired output '$DOut_k$' and the actual output 'Out_{kj}' respectively. On the basis of the error rate, the updated weight is mathematically stated with the aid of learning rate 'ϵ' as given below.

$$W_{kj}(n+1) = W_{kj}(n) + \epsilon\,(Err_k)Out_{kj} \tag{14}$$

Along with the updated weight as given in the above Eq. (14), transmitting handover data packets 'DP' results in an unavoidable delay in organizing the link. The total handover data packets 'DP' required to perform a handover is as follow.

$$DP = dp_{cons} + dp_{imp} + dp_{term} \tag{15}$$

From the above Eq. (15), 'dp_{cons}', 'dp_{imp}' and 'dp_{term}' denotes the data packets that are required to be exchanged during the handover construction, implementation and termination respectively. Then, the handover cost 'HO_{cost}' is formulated as given below.

$$HO_{cost} = DP + S * Del\left[MN_i, MN_j\right] \tag{16}$$

From the above Eq. (16), the handover cost 'HO_{cost}' is estimated based on the total handover data packets 'DP' required to perform a handover, link delay between two mobile nodes '$Del\left[MN_i, MN_j\right]$' and number of signals 'S' respectively. Finally, utilizing the Kronecker Delta function, the model either handovers the mobile node to the selected sink node and vice versa as given below.

$$Out_{kj} = \delta_{kj} = \begin{cases} 0, if\ k \neq j \\ 1, if\ k = j \end{cases} \tag{17}$$

From the above Eq. (17), results, with handover cost taken into consideration, optimized handover is said to be ensured. The pseudo code representation of Radial Kronecker Delta Neural Network-based Optimized Handover is given below.

Algorithm 2 Radial Kronecker Delta Neural Network-based Optimized Handover

Input: Dataset 'DS', Mobile Nodes '$MN = MN_1, MN_2, \ldots, MN_j$', user equipment '$UE$', coordinates '$(X_{UE}, Y_{UE})$', Data Packets '$DP = DP_1, DP_2, \ldots, DP_n$'
Output: Cost-efficient and optimized handovers
1: Initialize value of center 'C_{ij}', initialize 'Dis_j', weight vector '[0,1]', learning rate '$\epsilon = 0.05\ to\ 0.1$' 2: Begin 3: For each mobile nodes 'MN' 4: Formulate the output as given in Eq. (11) 5: Formulate the output with the initialized weight as given in Eq. (12) 6: Evaluate error with the initialized weight and output as given in Eq. (13)

7: Update weight as given in Eq. (14)
8: Evaluate total handover data packets as given in Eq. (15)
9: Evaluate handover cost as given in Eq. (16)
10: Evaluate Kronecker Delta function as given in Eq. (17)
11: If '$\delta_{ij} = 0$'
12: No handover is performed
13: End if
14: If '$\delta_{ij} = 1$'
15: Handover is performed and the selected mobile node is sent to sink node for further processing
16: End if
17: End for
18: End

As given in the above Radial Kronecker Delta Neural Network-based Optimized Handover algorithm, the objective remains in improving both the mobility handover cost and packet loss rate. With this objective, a Kronecker Delta function is introduced in the Radial Basis Neural Network model. With the mobile nodes, data packets, Local IP, Remote ASN, RSS and flows provided as input in the input layer, the hidden layer (i.e., four hidden layers) performs the actual tasks of evaluating the error, updating the weight, estimating total handover data packets and handover cost. Finally, the output is evaluated using the Kronecker Delta function that in turn returns either '0' or '1', therefore resulting in cost efficient optimized handover.

4. EXPERIMENTAL SETTINGS

In this section, comprehensive experiments are operated to prove the efficiency of the Markov Renewal Prediction and Radial Kronecker Neural Network (MRP-RKNN) based optimized handover for seamless mobility in PAN using NS2.34 simulator. The experiment data called Computer Network Traffic Dataset are available online from https://www.kaggle.com/datasets/crawford/computer-network-traffic. The Computer Network Traffic Dataset [https://www.kaggle.com/datasets/crawford/computer-network-traffic] comprises of certain real network traffic data obtained from the past. The dataset consists of 21 rows, and covers a span of 10 local workstations, IPs collected over a period of three months. Table 1 lists the details of Computer Network Traffic Data with each row consisting of four columns as given below.

Table 1. Description of computer network traffic dataset

S. No	Feature	Description
1	Date	(yyyy-mm-dd)
2	I_ipn	Local IP
3	r_asn	Remote ASN
4	f	Flows)

First, we evaluate the handover execution time and seamless mobility prediction accuracy of the proposed MRP-RKNN method. Then, compared with the existing Machine learning based Mobility Robust Optimization (Machine learning-based MRO) [1] and Multi Path Transmission Control Protocol (MPTCP) [2], our method outperforms it a lot in time and accuracy. From the experiments, the significant enhancement is due to the less complicated mathematical operations in each stage of prediction. Second, we estimated the mobility handover cost and packet loss rate to ensure the efficiency of the method. In the experiments, the data are stored on a computer with an Intel(R) Core(TM) i5-7200 CPU @2.50GHz and 8.00GB of RAM.

5. DISCUSSIONS

In this section, the quantitative performance evaluation of the proposed MRP-RKNN method and the existing Machine learning-based MRO [1] and MPTCP [2] are compared with certain parameters such as handover execution time, seamless mobility prediction accuracy, mobility handover cost and packet loss rate with respect to distinct numbers of data packets and speed. The performance of proposed and existing methods is discussed with aid of table and graphical representation.

5.1 Comparative analysis of handover execution time

A considerable amount of time is said to consume during the process of handover. This time is said to be handover execution time. This is mathematically stated as given below.

$$HOET = \sum MN_i \rightarrow MN_j * Time\left[HO_{ij}\right] \tag{18}$$

From the above Eq. (18), handover execution time '$HOET$' is measured based on the mobile nodes and the time consumed in performing handovers between mobile nodes '$MN_i \rightarrow MN_j$'. It is measured in terms of milliseconds (ms). Table 2 presents the result comparison of our method MRP-RKNN with other previous seamless connectivity-based data transmission methods, Machine learning-based MRO [1] and MPTCP [2] in terms of handover execution time.

Table 2. Tabulation of handover execution time

Mobile nodes	Handover execution time (ms)		
	MRPRKNN	Machine learning-based MRO	MPTCP
50	23.25	31.45	48.35
100	35.15	48.35	60.45
150	45.35	62.15	85.35
200	51.25	78.35	105.45
250	68.35	90.45	120.25
300	75.45	115.15	135.15
350	82.15	135.25	155.35
400	105.35	148.25	175.35
450	125.45	160.45	210.25
500	135.35	185.35	225.25

Figure 4 given above illustrates the handover execution time towards seamless mobility between mobile nodes in PAN. From the above figure, the handover execution time is found to be directly proportional to the number of mobile nodes. In other words, increasing the number of nodes causes an increase in the handover processes and this results an increase in the handover execution time and vice versa. But simulations conducted with 5o mobile nodes saw 23.25ms of handover execution time using MRP-RKNN, 31.45ms using MRO [1] and 48.35ms using MPTCP [2] respectively. The handover execution time during the seamless mobility process using

MRP-RKNN method was found to be comparatively lesser than MRO [1] and MPTCP [2]. The reason behind the improvement was due to the application of Markov Renewal Prediction kernel state transition. By applying this transition mechanism, conditional probability that a transition will take place within 't' time instances between two states were made. Only after this measurement predictions were made. This Markov Renewal Prediction kernel state transition in turn managed in reducing the number of handoffs performed, therefore not only ensuring seamless mobility but also minimizing the handover execution time using MRP-RKNN by 29% compared to MRO [1] and 58% compared to MPTCP [2] respectively.

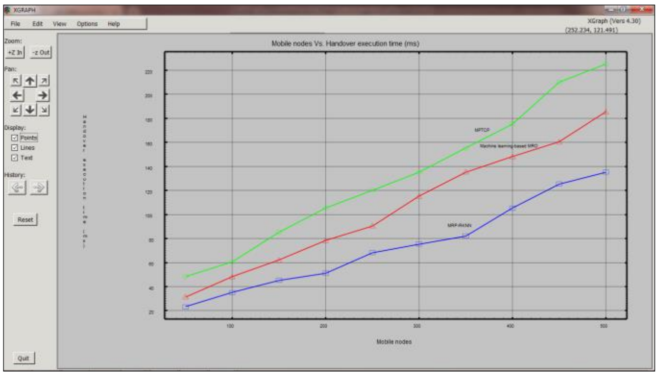

Figure 4. Graphical representation of handover execution time

5.2 Comparative analysis of seamless mobility prediction accuracy

The efficiency of the method can be learnt from the accuracy rate. The seamless mobility prediction accuracy is mathematically stated as given below.

$$SMPA = \frac{DP_{rec}}{DP_{sent}} * 100 \tag{19}$$

From the above Eq. (19), the seamless mobility prediction accuracy '$SMPA$' is measured based on the data packets sent 'DP_{sent}' and the data packets received 'DP_{rec}'. It is measured in terms of percentage (%). Table 3 presents the result comparison of our method MRP-RKNN with other previous seamless connectivity-based data transmission methods, Machine learning-based MRO [1] and MPTCP [2] in terms of seamless mobility prediction accuracy.

Table 3. Tabulation of seamless mobility prediction accuracy

Mobile nodes	Seamless mobility prediction accuracy (%)		
	MRPRKNN	Machine learning-based MRO	MPTCP
50	93.25	90.45	88.15
100	91.15	88.15	84.35
150	90.35	86.35	82.15
200	89.25	85.15	82.00
250	88.15	85.00	81.35
300	86.25	81.25	81.00
350	86.00	81.00	78.25
400	84.15	79.55	75.00
450	83.00	78.00	73.15
500	82.55	76.25	72.00

Figure 5 shows the graphical portrayal of seamless mobility prediction accuracy in the y axis with 500 distinct numbers of mobile nodes simulated for 10 different simulation runs to obtain the results. With high speed transmitting all-round the continuous network makes wireless communications exceedingly demanding owing to the purpose that the rate of handover grows with the equivalent speed. As a result there result in a high call of data packet dropping probability. In our work by employing a Markov Renewal Prediction-based Seamless Mobility, distance between the nodes is first evaluated. Followed by which, Markov Renewal Prediction kernel is applied to the obtained distance to measure state transitions. Next, the random arrival times are taken into consideration and stored in probability matrix. Finally, upon occurrence of a handover shifts between nodes, prediction is made. This in turn results in the improvement of seamless mobility prediction accuracy using MRP-RKNN by 5% compared to MRO [1] and 10% compared to MPTCP [2] respectively.

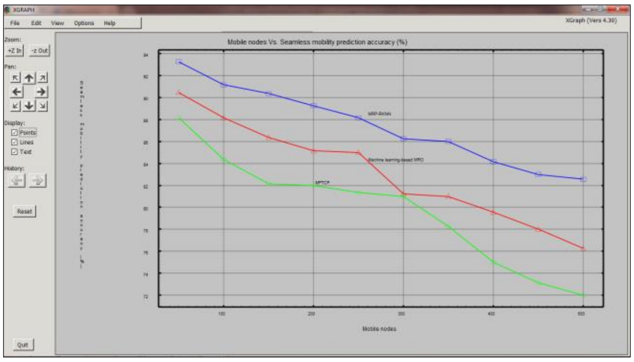

Figure 5. Graphical representation of seamless mobility prediction accuracy

5.3 Comparative analysis of mobility handover cost

The mobility handover cost in our work is evaluated on the basis of the bandwidth being utilized. Hence, the amount of data that are said to be transmitted in a given amount of time instance is measured to obtain mobility handover cost. The mobility handover cost is mathematically stated as given below.

$$Bandwidth\ utilization\ = Dp_i\ (bits)/t \tag{20}$$

From the Eq. (20), the mobility handover cost is measured based the data or data packets being transmitted 'DP_i' and the time taken to transmit 't'. It is measured in terms of milliseconds (ms). Table 4 presents the result comparison of our method MRP-RKNN with other previous seamless connectivity-based data transmission methods, Machine learning-based MRO [1] and MPTCP [2] in terms of seamless mobility handover cost.

Figure 6 given below illustrates the graphical representation of mobility handover cost analysis with respect to speed ranging between 2m/s and 20m/s from mobile nodes involved in the simulation process for 10 different simulation runs performed under diversified environments. From the above figure, a linear increase is found in the seamless mobility handover cost by applying all the three methods. In other words increasing the mobile nodes speed causes an increase in the network traffic in PAN, therefore resulting in the increase in the seamless mobility handover cost also. However, simulations performed with speed 2m/s using the proposed MRP-RKNN method was observed to be 145bps, 190bps using MRO [1] and 235bps using MPTCP [2] respectively. From this, the seamless mobility handover cost with the proposed MRP-RKNN method was found to be comparatively lesser than MRO [1] and MPTCP [2]. The reason behind the minimization of seamless mobility handover cost using MRP-RKNN method was due to the application of Kronecker Delta function in the Radial Basis Function (RBF) that depends on the distance between the input vector and centroid. With this measurement only further processing was carried out in the hidden layers. As a result, the seamless mobility handover cost was said to be reduced considerably by 26% compared to MRO [1] and 39% compared to MPTCP [2] respectively.

Table 4. Tabulation of mobility handover cost

Mobile nodes	Mobility Handover Cost (bps)		
	MRPRKNN	Machine learning-based MRO	MPTCP
2	145	190	235
4	170	215	270
6	195	235	315
8	215	280	365
10	235	345	390
12	240	355	425
14	275	390	445
16	300	415	485
18	325	435	515
2	145	190	235

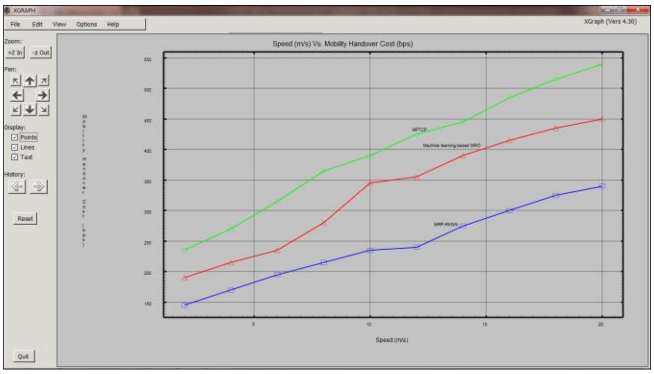

Figure 6. Graphical representation of seamless mobility handover cost

5.4 Comparative analysis of packet loss rate

Packet loss rate is defined as the percentage ratio of number of data packets dropped to the total number of data packets send. The packet loss rate is mathematically formulated as given below.

$$PLR = \frac{DP_{drop}}{DP_{sent}} * 100 \quad (21)$$

From the Eq. (21), packet loss rate 'PLR' is measured by means of data packets dropped 'DP_{drop}' and the total data packets send 'DP_{sent}'. It is measured in terms of percentage (%). Finally, Table 5 provides result comparison of our method MRP-RKNN with other previous seamless connectivity-based data transmission methods, Machine learning-based MRO [1] and MPTCP [2] in terms of packet loss rate.

Finally, Figure 7 given below shows the packet loss rate with respect to distinct numbers of packets ranging between 10 and 100. From the figure it is inferred that the packet loss rate is neither increasingly proportionate nor decreasingly proportionate to the data packets concerned. However, from the above illustrations the packet loss rate using MRP-RKNN method is found to be comparatively lesser than MRO [1] and MPTCP [2]. The reason behind the minimization of packet loss rate using MRP-RKNN method was owing to the application of Radial Kronecker Delta Neural Network-based Optimized Handover algorithm. By applying this algorithm, four distinct hidden layers were utilized, error evaluation in first hidden layer, weight update in second hidden layer, evaluating total handover data packets in third hidden layer and finally, estimating handover cost in the fourth layer. Only upon successful evaluation of each distinct process the procedure is continued and forwarded to the next stage. As a result, the packet loss rate using MRP-RKNN method is said to be reduced by 21% compared to MRO [1] and 37% compared to MPTCP [2].

Table 5. Tabulation of packet loss rate

Mobile nodes	Packet loss rate (%)		
	MRPRKNN	Machine learning-based MRO	MPTCP
10	7	9	12
20	9	12	14
30	11	14	16
40	12	15	18
50	10	13	17
60	10	13	16
70	11	14	18
80	11	14	18
90	10	12	16
100	9	11	13

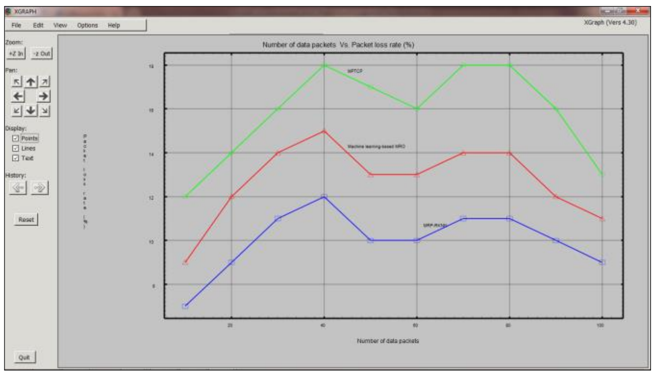

Figure 7. Graphical representation of packet loss rate

6. CONCLUSIONS

Seamless mobility has the capability in replacing the nodes position of association to a network designed on the basis of an Internet Protocol (IP) without any interruption in the persuading connections and disturbance throughout the communication process. With the high rate of network traffic, one of the most challenging tasks as far as PAN is provisioning of continuous network access. In this work, a novel method called, Markov Renewal Prediction and Radial Kronecker Neural Network (MRP-RKNN) for seamless mobility in presence of handover in PAN is proposed. The MRP-RKNN method ensures seamless mobility even in case of handover by means of two different phases, Markov Renewal Prediction-based Seamless Mobility model and Radial Kronecker Delta Neural Network-based Optimized Handover. Extensive simulation results were provided to demonstrate that the proposal can boost the performance of seamless mobility even during handover in PAN. The performance of the proposed method was analyzed in terms of mobility handover cost, packet loss rate, handover execution time and seamless mobility prediction accuracy and it was compared to the state-of-the-art methods. Numerical results validated that the proposed method outperforms the state-of-the-art methods and obtains lower mobility handover cost, packet loss rate, handover execution time and ensuring better prediction accuracy for seamless mobility in PAN.

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