Dynamic Spectrum Optimization for Internet-of-Vehicles with Deep-Learning-Based Mobility Prediction

Feng Li (fengli2002@yeah.net)
Zhejiang Gongshang University https://orcid.org/0000-0002-4896-8905

Zhongming Sun
Zhejiang Gongshang University

Kwok-Yan Lam
Nanyang Technological University

Lianzhong Sun
Zhejiang Gongshang University

Bowen Shen
Zhejiang Gongshang University

Bao Peng
Shenzhen Institute of Information Technology

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Dynamic Spectrum Optimization for Internet-of-Vehicles with Deep-Learning-Based Mobility Prediction

Feng Li[1,2] · **Zhongming Sun**[1] · **Kwok-Yan Lam**[2] · **Lianzhong Sun**[1] · **Bowen Shen**[1] · **Bao Peng**[3]

Abstract Internet-of-Vehicles (IoV) plays an important part of Intelligent Transportation Systems, and is widely regarded as one of the most strategic applications in smart cities development. Next generation wireless network is especially crucial for meeting the connectivity and bandwidth demands of IoVs. Smart spectrum resource management has received much attention of the research community as it is believed to be a promising approach for solving the spectrum resource challenge of IoV and Intelligent Transportation Systems. In this article, we propose a smart spectrum optimization technique based on a deep learning method for user mobility prediction. For this purpose, based on the Exploration and Preferential Return (EPR) model which can be used to investigate the movement trend and aggregation behavior of the target, we adopt the D-Exploration and Preferential Return (D-EPR) model as a deep learning technique to train a Long-Short Term Memory (LSTM) recurrent neural network (RNN) in order to predict the future locations of IoV nodes. With predicted user's mobility, a graph theoretic algorithm is then applied to achieve spectrum reuse and optimization. Besides, our proposed deep-learning-based user mobility prediction is able to identify the user position. This paper then compares the performances of mobility prediction by traditional method and our proposal. The outcomes of spectrum efficiency and network capacity are also provided to show the effectiveness of the proposed solution.

[1] School of Information and Electronic Engineering, Zhejiang Gongshang University, Hangzhou, 310018, China.

[2] School of Computer Science and Engineering, Nanyang Technological University, 639798, Singapore.

[3] School of Electronics and Communication, Shenzhen Institute of Information Technology, Shenzhen, China.

Corresponding author: Feng Li, fengli2002@yeah.net

Keywords Spectrum optimization · Internet of Vehicles · deep learning · mobility prediction

1 Introduction

Internet-of-Vehicles (IoV) play an important part of Intelligent Transportation Systems, and is widely regarded as one of the most strategic applications in smart cities development. Due to their heavy demand for communication bandwidth while travelling in high speed, next generation wireless networks are especially crucial for meeting the connectivity and bandwidth requirements of IoVs. For these reasons, IoV has become one of the most significant application scenario for next generation networks such as 5G [1]-[4]. In a typical intelligent transportation system, by deploying LTE-V or IEEE 802. 11p technology, vehicles can communicate with infrastructures (V2I), other vehicles (V2V) and even pedestrians. Besides, the on-board unit (OBU) deployed in smart vehicles also provide storage and computing capabilities for the vehicle to perform intelligent processing for safe navigation and routing, and even to serve as mobile edge nodes [5]-[8].

From the perspective of the wireless network, IoVs can be considered communication terminals or mobile computing devices. With the rapid development of IoV in recent years, many new techniques such as edge computing and cloud computing have been developed to enhance IoV by addressing the issues of time delay or energy efficiency [9]-[12]. When the number of IoV terminals proliferates with the development of 5G, the demand for wireless spectrum resource will continue to grow in a drastic manner, hence the challenges of optimizing spectrum resource has received much attention of the research community [13]-[16]. Besides, in a typical urban environment, the vehicular density in highly dynamic and heterogeneous with certain area in much higher density than some other areas at different times of the day. Hence, smart spectrum resource management is a key challenge that need to be tackled. In this connection, many techniques such as cognitive radio, dynamic spectrum sharing and cloud radio access networks (CRAN) have been widely investigated to enhance spectrum efficiency from various aspects [17]-[21].

One important direction in smart spectrum resource management is to explore the mobility characteristics of communication terminals. In the case of IoV, this is highly dependent on the travelling habit of IoV users, hence it will be useful to analyze IoV mobility data, identify the commuting patterns and, based on which, predict the movement and density of IoVs in order to optimize spectrum resource allocation in response to real world situations efficiently. For IoV, with its frequently changing network topology, a new approach to such analysis is needed in that traditional transmission mode or protocol designed for the static or low-speed scenarios cannot be applied effectively. In [22], a routing protocol for vehicular Ad Hoc networks based on terminal mobility analysis and prediction has been designed. A significant goal for this proposal is to cut the number of the usage of road beacon which is more practical for

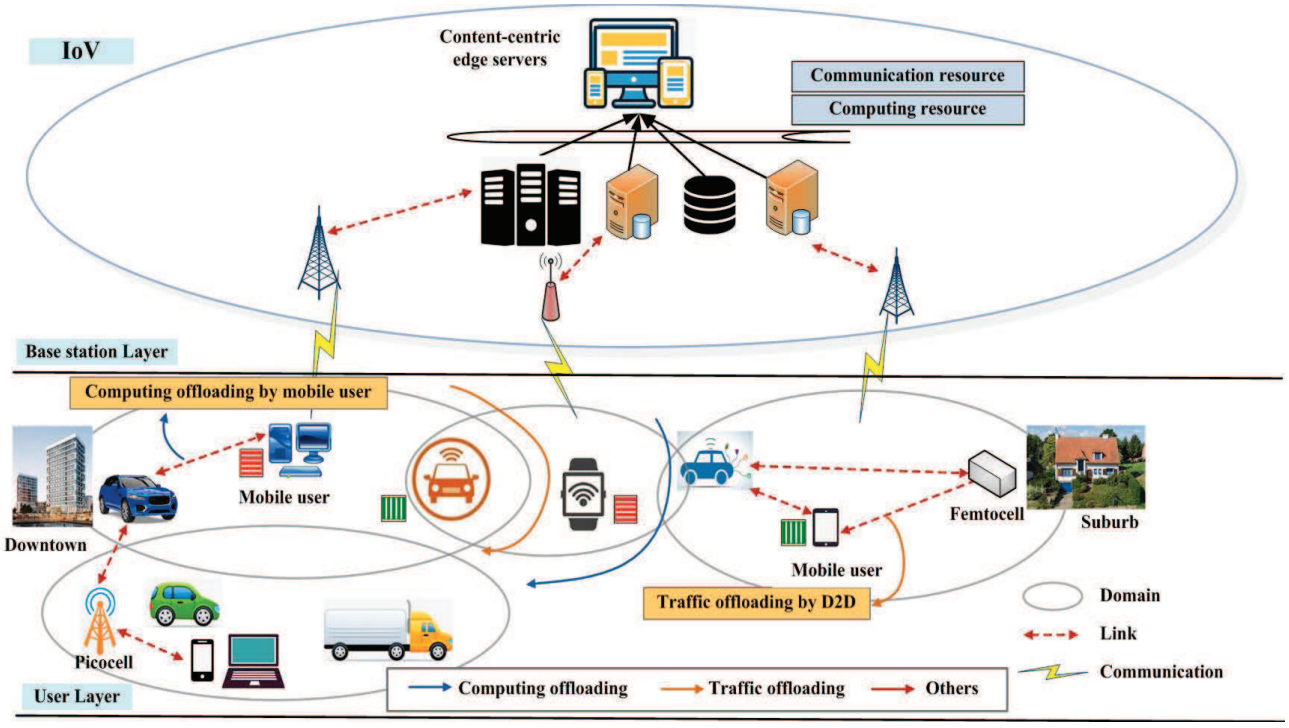

Fig. 1 IoV in smart city

IoV. Many researches have been conducted to evaluate the impacts on link performance and transmission capacity by various vehicular mobility characteristics including the uniform, normal, fixed moving speeds [23]-[26]. Many mathematical prediction methods or theories have been deployed in IoV or Internet of Things to predict flow or network changes [27]-[30]. In [27], a dynamic prediction method for vehicle to vehicle link duration in urban vehicular ad hoc networks was proposed in which a novel model for dynamically predict link duration was designed to adapt to the change of relative distance between two vehicles. In [28], a cognitive carrier resource optimization for IoV in 5G-enhanced smart cities was proposed wherein a concept of virtual networks was raised and the carriers in various cells can be centrally managed in CRAN networks. A user movement prediction was designed based on a traditional prediction model.

In this paper, a dynamic spectrum optimization method for IoV is proposed based on the deep-learning-oriented user moving prediction. To enhance the prediction precision of IoV terminal's moving, we introduce the D-Exploration and Preferential Return (EPR) model to train a Long-Short Term Memory (LSTM) recurrent neural network (RNN) to predict the future locations of IoV nodes. Unlike traditional EPR-model-based moving prediction in mobile

networks, we define a novel formula to use user moving data to represent the probability of a node going to another location at one location. Then, these probability values are sorted, and the two largest probability values and their corresponding positions are selected as part of the feature dimensions. The previous location and the dwell time of each history movement are also taken into consideration as feature dimensions. Based on the user mobility prediction, we further use the graph theory to complete the final spectrum optimization in IoV.

The main contributions of this paper can be highlighted as:

- A mobility-prediction-based dynamic spectrum optimization is proposed in this paper to enhance the energy efficiency for IoV.
- A deep-learning-oriented solution is designed to improve the prediction precision of IoV terminal's movement.
- Based on the future position of numerous of IoV terminals in dynamic IoV networks, the graph theory is utilized to perform the spectrum reuse and optimize the spectrum resource.
- Numerical results are provided containing the performances of user moving prediction and spectrum efficiency in our proposed method.

The rest of this article is organized as follows. A system model of IoV framework is presented firstly. Then, we propose a deep-learning-based mobility prediction method and a corresponding spectrum optimization solution with graph theory is raised in Section III. Besides, in Section IV, numerical results are provided to evaluate the performances of the proposed method in terms of user position prediction and spectrum efficiency. At last, we conclude this paper in Section V.

2 System Model

In this paper, we consider a traditional IoV model wherein multiple cells and numerous of IoV terminals coexist as shown in Fig. 1. Furthermore, essential edge computing and caching have been applied to enhance network performances and reduce time delay. In this circumstance, we focus on how to improve the spectrum efficiency in IoV when the IoV users are moving in predictable style as shown in Fig. 2. When IoV users' periodic movements occur, how to manage the carriers among various cells and allocate specific channels to each terminals deserve full investigations. In this work, we mainly discuss the spectrum allocation for numbers of moving terminals.

3 Mobility Prediction and Spectrum Optimization

This paper is based on the D-Exploration and Preferential Return (EPR) model to train a Long-Short Term Memory (LSTM) recurrent neural network (RNN) to predict the future locations of nodes in the Internet of Things (IoT).

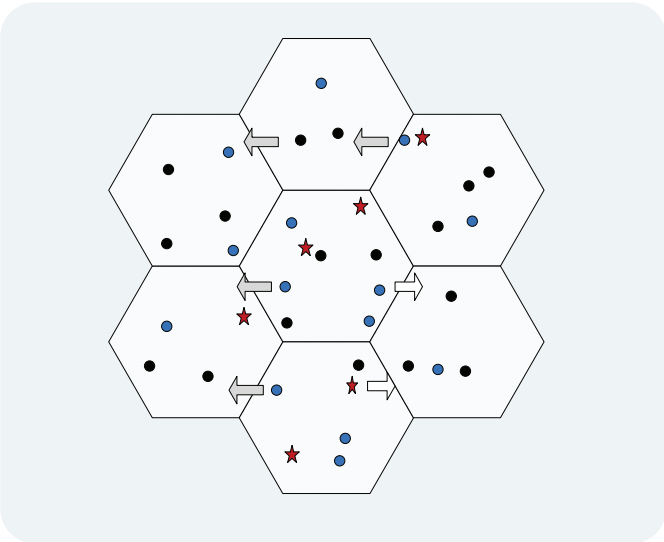

Fig. 2 Users' periodic movements in multi-cells

We first input the historical data of the nodes and record the visits number of the nodes to each location, the location of the nodes at each moment, time slots of the nodes in each location and the geographical distance between each location respectively. The number of times a node visits each point in history and the distance between two points are of great significance to the possible movement of the node at the next location. Thus, we define a formula to use these data to represent the probability of a node going to another location at one location. Then, these probability values are sorted, and the two largest probability values and their corresponding positions are selected as part of the feature dimensions. The previous location and the dwell time of each history movement are also taken into consideration as feature dimensions. After that, the processed information is organized as a sequence of LSTM neural network inputs to perform the prediction of future location. The whole framework can be divided into two phases, namely the data pre-processing phase and the model training phase. And we introduce the process and details of two phases in Section A and Section B.

A. Data Pre-processing Phase

The EPR model investigates the movement trend and aggregation behavior of the target, and the D-EPR movement model is built on the basis, which counts the frequency of nodes' visited locations. In the process of node movement, there are obvious differences in the frequency of each node for different visited locations, for example, many nodes visit few places, so that the upcoming locations can be predicted based on the visited time and location.

When analyzing and predicting the historical node movement data, an essential factor is to determine the important locations for the nodes based

on the historical data, which are also the locations frequently visited by the nodes. Analyzing the nodes movement process can lead to many patterns of the movement. For example, the dwell time slots of the node at each position, the order of the visited positions. Thus, we define the important position of each node in two aspects, which are the visits number of the node to each position and the time slots the node stays in each position. For each node, if the visited locations have a strong regularity, then we can find out the periodic pattern of node location visits according the location with high number of visits. However, the visited location of nodes does not always show regularity and periodicity. Usually, the visited locations of many nodes do not repeat too many times. Thus, the probability value function for a location to go to any location is defined, which can be given as

$$Pr(u_j) = \frac{r_j}{nd_{n1,n2}^2} \tag{1}$$

where u_j denotes the nodes, $d_{n1,n2}$ denotes the geographical distance between the current node position n_1 and the next position n_2, n denotes the normalization constants. r_j is the correlation between node visited locations, which we describe as the total visited number of a node for that location in historical data. And the $d_{n1,n2}$ can be expressed as

$$d_{n1,n2} = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \tag{2}$$

where x_1, x_2, y_1, y_2 are the coordinates of the geographic locations. Then, we sort the obtained probability value of each location going to any other location. Considering the computational power of edge nodes is limited, we select the highest two probability values and their corresponding positions as part of the input features of the LSTM model training in next phase.

Moreover, due to the dwell time slot and the previous location coordinates are closely related to the movement of the nodes, we also take these two as part of the input sequence. Therefore, the input sequence I_j can be defined as $I_j = [l_j^{prev}, s_j, l_j, Pr_j, l'_j, Pr'_j]$, where l_j^{prev} denotes the previous position coordinates, s_j denotes the dwell time. l_j, Pr_j, l'_j and Pr'_j express the first and second probability values of the position probability and their corresponding position coordinates respectively.

B. Model Training Phase

RNNs incorporate the concept of time in the network structure, making them dedicated to process data from time series, but if the sequences are too long, the problem of vanishing gradients can occur during optimization. To solve this problem, this paper users LSTM network as a variant of RNN. Based on RNN structure, forget gate, input gate and output gate are added to the hidden layer memory cell of the network, which not only solves the problem of vanishing gradients, but also effectively improves the network's ability to handle long-term related tasks. The structure of the LSTM memory cell is shown in Fig. 3. And the operation process of each unit can be expressed by the following formulas

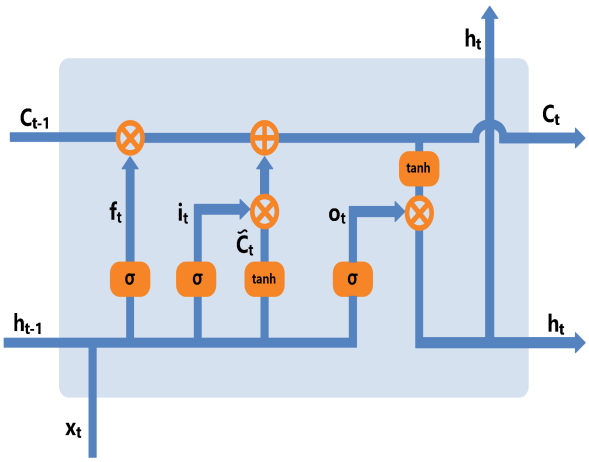

Fig. 3 Structure of LSTM memory cell

$$\begin{cases} f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \\ i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\ \tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_C) \\ C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \\ o_t = \sigma(W_o \cdot [h_{t-1,x_t} + b_o]) \\ h_t = o_t \cdot \tanh(C_t) \\ \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \\ \sigma(x) = \frac{1}{1+e^{-x}} \end{cases} \tag{3}$$

where f_t is the forget gate, which selectively filters out some useless things in learning based on the output of the last time. i_t and $\tilde{C}_t$ constitute the input gate to select which information will be added to the cell. C_t is used to update the state of the cell. o_t and h_t form the output gate, determining the output information. W_f, W_i, W_c and W_o are the weights of each gate. And b_f, b_i, b_C, b_o are the bias respectively. The input sequence obtained from the previous stage is passed into the LSTM network to predict the future location of the node.

The objective of the model training is to predict the future node location according to the historical data. We use the mean square error (MSE) function as the loss function which can be expressed as

$$MSE = \frac{\sum_{i=1}^{n}(y_i' - y_i)^2}{n} \tag{4}$$

where y_i' and y_i are the prediction data and truth data respectively for sample i. The training achieves the purpose of gradually optimizing the model by

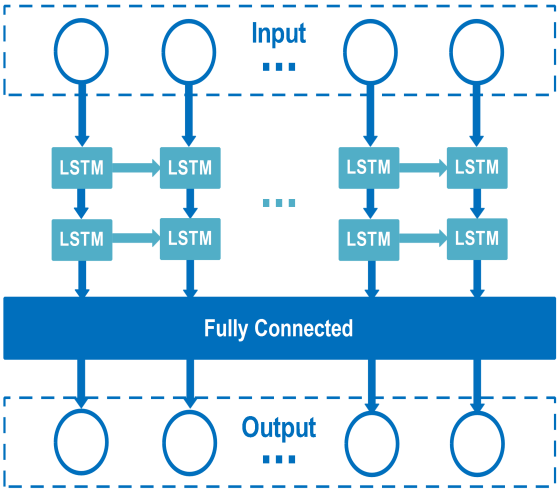

Fig. 4 LSTM model training process

iteratively minimizing the loss function. The LSTM model training process is as shown in Fig. 4 and the algorithm structure is given in Algorithm 1 as below.

Algorithm 1 Local Model Training Process

Input: the location of the node history visit
dwell time of each location
Output: possible next location for the node to go
Get the distance of each location to other locations based on (2).
Get the probability of the node going to other locations at each location based on (1).
Rank the probability of that node going to other locations at each location.
The first and second ranked positions and the corresponding probabilities are obtained, and a feature sequence is formed with the dwell time at the position and the previous position.
Store feature sequences in historical memory.
Update the prediction of the next position by LSTM model.

C. Graph-Theory-Based Spectrum Optimization

When using graph theory to perform the spectrum reuse in dynamic spectrum access circumstance, identifying the mobile user's position is a key which serves as the basis for interference range as shown in Fig. 5. In Fig. 5, we can obtain that the same spectrum band can be reused if the interference range does not overlap. In this case, we should figure out the user's transmit power and location.

Suppose there are N IoV users who are competing to use M available channels. The spectrum matrix and utility matrix can be ascertained by the

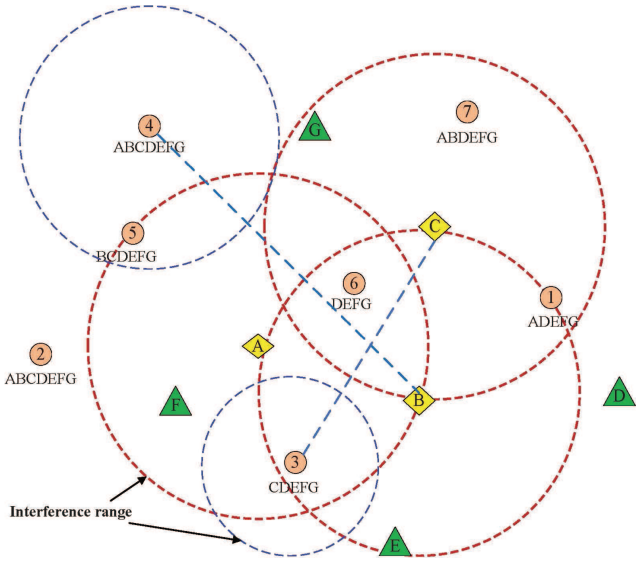

Fig. 5 Graph theoretic analysis

positions of licensed users and common users who wish to dynamically access the spectrum. The available spectrum matrix $L = \{l_{n,m} | l_{n,m} \in \{0,1\}\}_{N \times M}$ is a matrix with N rows and M columns, representing the spectrum interference. If $l_{n,m} = 1$, it shows this channel m can be used by user n. Otherwise, $l_{n,m} = 0$, the channel cannot be occupied by user n. $l_{n,m}$ can be ascertained by the following: If $d_s(n,m) < d_{min}$, then $l_{n,m} = 1$, otherwise $l_{n,m} = 0$, wherein $d_s(n,m) = Dist(n,x) - d_p(x,m)$. x denotes the communicating range for channel m with radius $d_p(x,m)$. $Dist(n,x)$ denotes the distance between user n and x. Thus, we can clearly achieve that it is critical to grab the position information for IoV users when using graph theory in dynamic spectrum optimization. In this case, we firstly design a mobility prediction method, then utilize the graph theory to complete the final resource allocation.

In this paper, we adopt three kinds of graph-theory-based solutions to optimize the spectrum in IoV as below.

1. Max-Sum-Reward (MSR) method, the utility function can be given as

$$U_{MSR}(R) = \sum_{n=1}^{N} r_n = \sum_{n=1}^{N} \sum_{m=1}^{M} a_{n,m} b_{n,m} \tag{5}$$

where $b_{n,m} = d_s(n,m)^2$ and we have $l_{n,m} = 0 \Rightarrow b_{n,m} = 0$. If the IoV systems allocate channel m to user n, then $a_{n,m} = 1$. In this utility function, the ultimate goal is to purse the maximal network capacity without considering the fairness among various IoV users.

2. Max-Min-Reward (MMR) method, the utility function can be defined as

$$U_{NMR}(R) = \min_{1 \le n \le N} r_n = \min_{1 \le n \le N} \sum_{m=1}^{M} a_{n,m} b_{n,m} \tag{6}$$

3. Max-Proportional-Fair (MPF) method, the utility function can be defined as

$$U_{MPF}(R) = \sum_{n=1}^{N} \log(r_n) = \sum_{n=1}^{N} \log(\sum_{m=1}^{M} a_{n,m} b_{n,m}) \tag{7}$$

In graph-theory-oriented spectrum optimization technology, the basic methods are MSR and MPF solutions. For MSR method, the overall network capacity can be achieved without consideration of user fairness. As a result, part of the users will obtain most of the available channels which the others cannot have the idle spectrum resource. If the systems want to balance the various users' demands, the MPF method should be taken into account which will reduce the channel variance to make every user having the chance to use spectrum.

Besides, in graph-theory-based technical solution, the labeling rule (LR) is also often used to optimize the spectrum allocation in which the labeling number denotes the value of the points in the graph. The points represent the mobile users. The labeling number depends on the allocation target and utility design, and every labeling responds to one kind of color. To achieve different goals, various network utility functions can be utilized.

The collaborative-Max-Min-Reward (CMMR) method can be given as

$$color_n = \arg\max_{m \in l_n} \frac{b_{n,m}}{D_{n,m} + 1} \tag{8}$$

where $D_{n,m}$ denotes the number of the users interfering with user n at channel m.

The Non-Collaborative-Max-Min-Reward (NMMR) method can be expressed as

$$label_n = -\sum_{m=1}^{M} a_{n,m} b_{n,m} \tag{9}$$

$$color_n = \arg\max_{m \in l_n} b_{n,m} \tag{10}$$

The Collaborative-Max-Sum-Reward (CMSR) rule can be expressed as

$$label_n = \max_{m \in l_n} \frac{b_{n,m}}{D_{n,m} + 1} \tag{11}$$

where l_n denotes the available channel set for user n. CMSR rule takes into account the maximal network utility for the whole systems and balances the interferences with the adjacent users. The CMSR method needs the cooperation of different users.

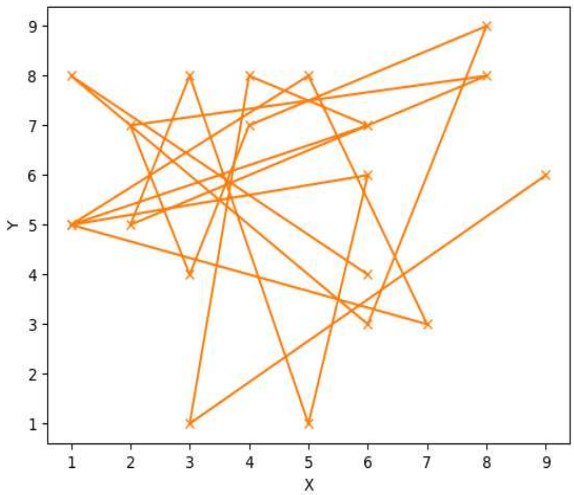

Fig. 6 Node history location

The Non-Collaborative-Max-Sum-Reward (NMSR) rule can be expressed as

$$label_n = -\sum_{m=1_n}^{M} b_{n,m} \tag{12}$$

$$color_n = \arg\max_{m \in l_n} b_{n,m} \tag{13}$$

The NMSE rule considers to increase the whole network utility for the systems without the burden of the interference to the adjacent users. Therefore, this rule is non-cooperative method.

4 Numerical Results

In this section, we conduct the simulation to show the proposed framework's accuracy in predicting node location and its performance with some changing factors. We predict the mobility of one node, assuming that its access position is in the 10×10 rectangular coordinate system and its dwell time slot $s_j \in [1, 10]$. Then randomly generate its position and dwell time slot.

In Fig. 6 and Fig. 7, we set the length of the input sequence to 20. Fig. 6 is the node' history location and Fig. 7 is the prediction location of the node. It can be seen that the performance is good, and the accuracy reaches $85 - 90\%$. Fig. 8 presents the model's decrease of MSE with the increase of iteration times during training. We can see that the loss function of the model tends to be stable after about 150 iterations.

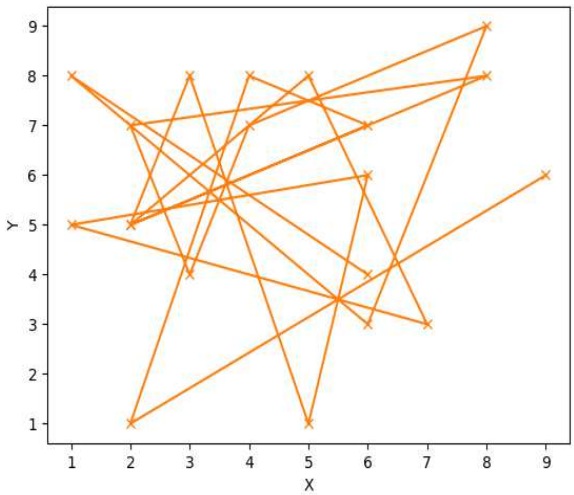

Fig. 7 Node prediction location

In Fig. 9, we compared the performance of different memory history sequence lengths in predicting node location under different hidden state sizes of the model. And we set the memory history sequence length to $[50, 100, 150, 200]$ and the hidden size to $[2, 4, 8, 16, 32, 64]$. With the increase of the input sequence length, the accuracy of node location predicted by the model with low hidden size decreases significantly, while the accurate value of high hidden size is still stable at a high level, which shows that the increase of hidden size is conducive to the training of models with long input sequences. However, the increase of hidden size also means the increase of model training complexity. Thus, it is necessary to select the appropriate hidden size according to different history length.

The simulation of the node dwell time's effect on the model's prediction is performed in Fig. 10. A parameter τ is given to set a random increase or decrease of the dwell time for the node. We define changed dwell time as $s'_j = s_j + \tau \times q$, where q is a random time slot in $[-1, 1]$. It is found that due to the change of dwell time, the pattern of node movement also changes. And thus, the accuracy of the model prediction decreases.

Considering the effect of node's location distribution mechanism on model prediction, we compare the accuracy of model prediction under three distribution mechanisms, namely passion distribution, normal distribution and random distribution in Fig. 11. To make the simulation closer to reality, the dwell time parameter τ is set to 0.2. We can see that the accuracy of the model's prediction is higher under the normal and passion distribution mechanisms compared to the random distribution mechanism. This is due to the fact that

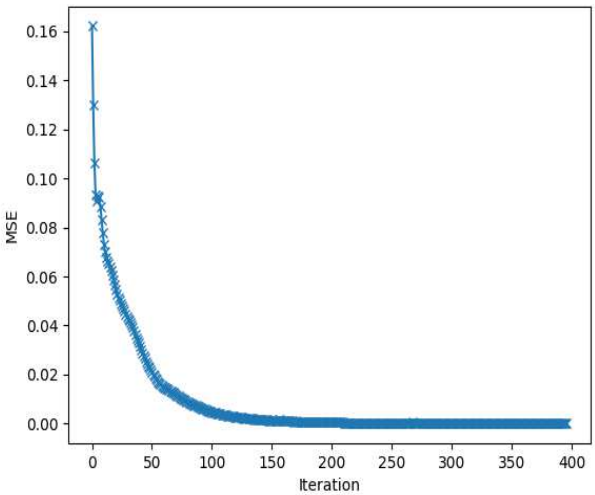

Fig. 8 The training loss of the model

nodes visit some locations more often than others, and the variance between location visit is larger, then the prediction accuracy is improved in such cases.

In Fig. 12, We compare the position prediction performance of the proposed scheme and the D-EPR approach without deep learning. As the history records increase, the accuracy of the D-EPR model is consistently 15 to 20 percent lower than that of the proposed scheme. This is because in the mechanism of random distribution, as the history visit records increase, the gap in the number of times a node visits other points at each location becomes smaller, and subsequently the gap in the probability value Pr of going to certain location at that location becomes larger by the distance between two locations, while the proposed scheme is more flexible through regular of deep learning, which is more flexible and thus makes the accuracy higher.

In Fig. 13, the network utilities with changing user number have been provided where $M_g = 10$ denotes the available channel number is 10 in greedy algorithm, and $M_f = 15$ denotes the channel number is 15 in fairness algorithm. It can be obtained from Fig. 13 that the network utility will decrease with the increasing user number which means the excessive load will harm the network performances. Besides, in Fig. 13, the greedy algorithm can achieve more network utility due to its given objective. In Fig. 14, the variances of greedy algorithm and fairness algorithm have been shown. It is obvious that the fairness algorithm can balance the utilities for various mobile users.

In Fig. 15, the performances of two kinds of common-used labeling method for spectrum optimization are given. As shown in Fig. 15, the outcomes of labeling-based spectrum reuse outperform that of the random spectrum allo-

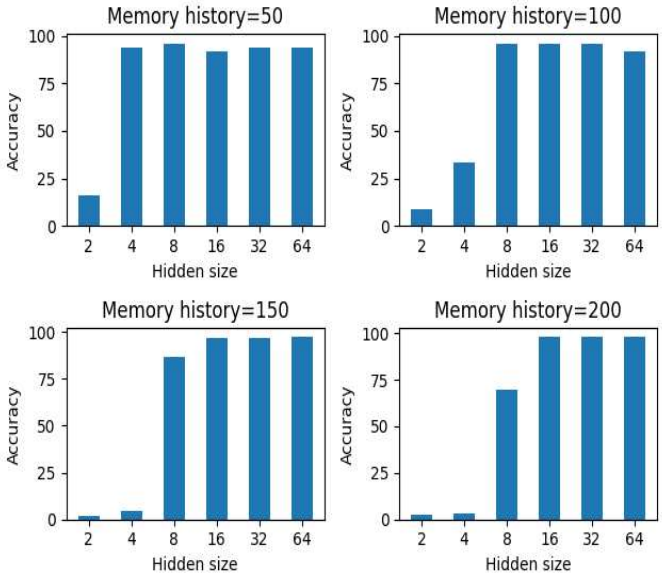

Fig. 9 The effect of the hidden layer size of the model on the prediction accuracy under different memory histories

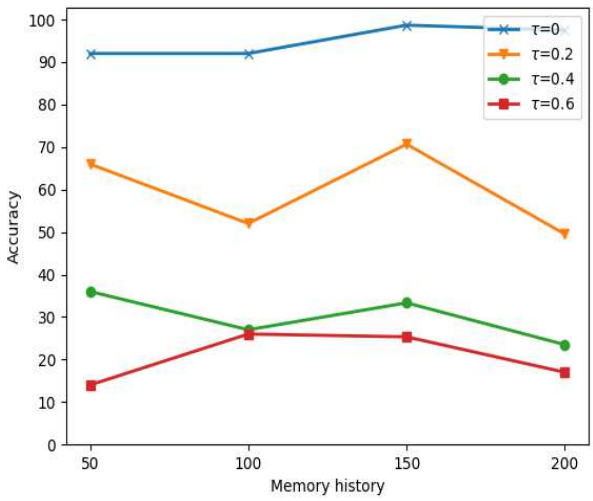

Fig. 10 Impact of node dwell time variation on prediction accuracy

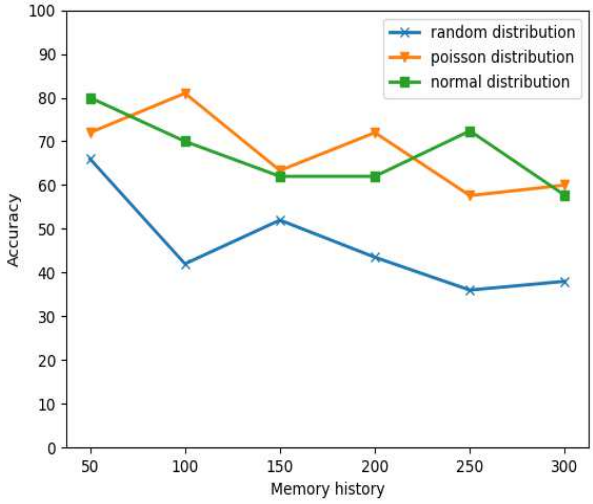

Fig. 11 Prediction accuracy under different node history distribution Mechanisms

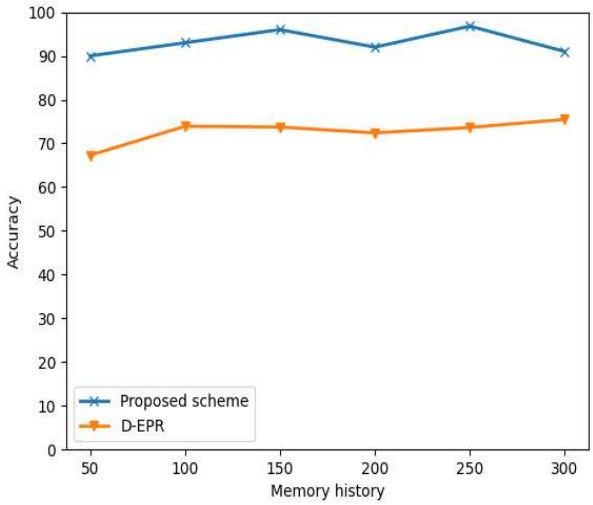

Fig. 12 Comparison of prediction accuracy between the proposed scheme and D-EPR without deep learning

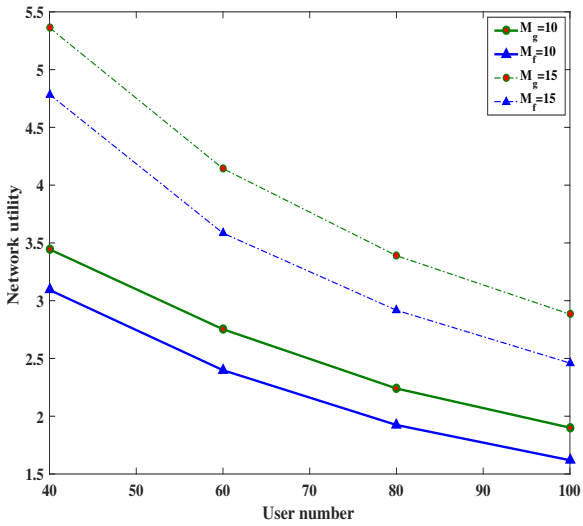

Fig. 13 Network utility for greedy and fairness algorithms

cation. Thus, it can be concluded that effective spectrum reuse can obviously improve the spectrum efficiency. Besides, compared with the NMMR method which does not require the collaboration among various IoV users, the CMMR method can achieve better performance.

5 Conclusions

In this paper, we a dynamic spectrum optimization method for IoV based on the user mobility prediction. The main contribution of this paper lies in that we introduce the deep-learning-oriented solution to refine the IoV users' moving rules which serve as the basis for graph-theory-based spectrum optimization in IoV. Compared with the traditional movement prediction solutions, our proposed method can reach more ideal accuracy. In specific, we adopted the D-Exploration and Preferential Return (EPR) model to train a Long-Short Term Memory (LSTM) recurrent neural network (RNN) to predict the future locations of IoV nodes. Unlike traditional EPR-model-based moving prediction in mobile networks, we define a novel formula to use user moving data to represent the probability of a node going to another location at one location. Besides, based on the mobility prediction, we further use graph theory to complete the spectrum optimization in IoV. Numerical results including the outcomes of mobility predictions and spectrum optimization have been provided.

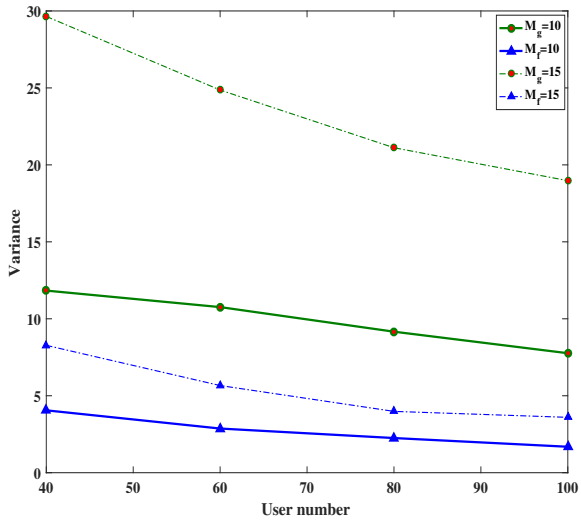

Fig. 14 Variance

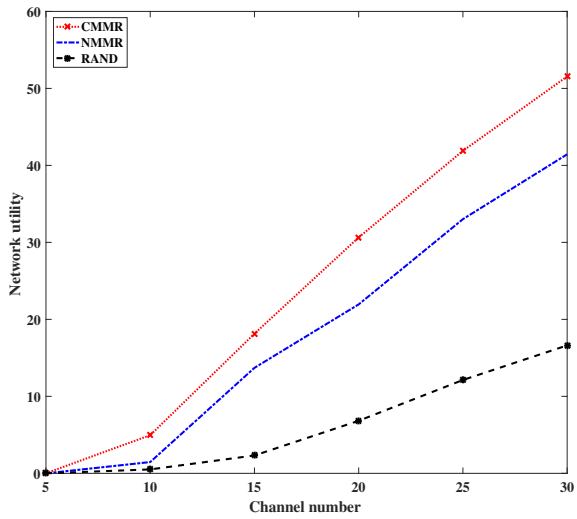

Fig. 15 Network utility for CMMR, NMMR and random spectrum optimization

Declarations

-Ethical Approval: All listed authors have approved the manuscript before submission, including the names and order of authors.

-Consent to Participate: All listed authors agreed with the content and that all gave explicit consent to submit and that they obtained consent from the responsible authorities at the institute/organization where the work has been carried out, before the work is submitted.

-Consent to Publish: All listed authors approved the version to be published.

-Authors Contributions: Dr. Feng Li, Prof. Lam and Dr. Bao Peng proposed the framework of this work, Zhongming Sun and Lianzhong Sun formulated the algorithm, Bowen Shen performed the simulation tests.

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-Competing Interests: No competing Interests.

-Availability of data and materials: The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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