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Cognitive Carrier Resource Optimization for Internet-of-Vehicles in 5G-Enhanced Smart Cities

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***Abstract*—Internet-of-Vehicles (IoV), an important part of Intelligent Transportation Systems, is one of the most strategic applications in smart cities initiatives. The mMTC and URLLC functions of 5G are especially crucial for ensuring the connectivity and communication needs of rapidly moving IoVs. In this backdrop, network virtualization, cognitive computing along with smart spectrum resource management to the virtual networks will play a key role in solving the spectrum resource challenge. In this article, we propose a dynamic carrier resource allocation scheme for supporting IoV systems in smart cities enabled by cloud radio access networks (CRAN)-based 5G carriers. In CRAN-based 5G networks, the carrier resource allocated to the virtual networks can be centrally managed and shared to meet the dynamic demand of cell capacities caused by the rapid movement of IoVs, and the response to this dynamic allocation will become more time critical. The proposed cognitive carrier resource optimization is achieved by enhancing the ability to predict movement of IoVs, hence the dynamically changing demand for carrier resources. As an enhancement of the traditional Markov Model, our prediction model introduces vehicles' mobility analysis in order to allow the construction of a more precise flow transition matrix to improve the prediction result. Numerical results are provided to show the performance improvement of the proposed method.**

***Index Terms*—Carrier allocation, Internet of Vehicles, smart city, mobility prediction**

I. INTRODUCTION

WITH its complex computing and sensing capabilities and is highly dynamic and mobile, Internet-of-Vehicles (IoV), an important part of Intelligent Transportation Systems, is one of the most strategic applications in smart cities initiatives. IoV, which may exist in the form of a semi-autonomous vehicle or even an autonomous vehicle, can be modelled as an IoT device with integrated sensing and control components for automated navigation and enhanced safety [1][2]. These IoT applications typically involve a massive number of IoT devices being deployed in field environment, which access some cloud platforms for big data analytics or intelligent decision making via a variety of wired and wireless networks. Such IoT devices can be deployed with high mobility when the Internet connectivity is available through the wireless channels [3][4].

Being a highly mobile IoT, IoV is a complex system to implement vehicular and intelligent transportation system. Typically, IoV is wirelessly connected to some road-side infrastructure, which in turn is connected to the backend control centre through broadband cables, for exchanging vehicular and traffic control information. Through constant communications with the roadside infrastructure, IoV also helps in efficient traffic management and enable intelligent transportation systems, and can potentially be used as an infrastructure platform for supporting other smart cities applications. Many remarkable research results on IoV have emerged. In [5], a new network architecture named IDT-SDVNs to extend the computation resources was proposed to address the limitations of current IoV. This architecture can help realize the iterative update of the networking schemes in an adaptive way. In [6], the authors proposed an efficient online sequential learning-based adaptive routing scheme for hybrid software-defined vehicular networks. This scheme can help fully utilize the computational power of edge servers and dynamically select a routing strategy for a specific traffic scenario.

Due to the very nature of vehicular systems, IoV is heavily dependent on network connectivity and bandwidth availability. In recent years, research advancement in cognitive radio network also allowed the massive deployment of bandwidth-hungry IoT devices in urban areas. In order for IoV to achieve its intended functionalities of enhanced navigation, safety and enabling efficient traffic management, IoV requires anytime anywhere connectivity which cannot be effectively satisfied by traditional networking technologies.

5G networks are widely believed to be the enabler of a broad range of smart city technologies [7]. To large-scale cyber system operators such as smart cities, the mMTC and URLLC functions of 5G are especially crucial to ensuring the connectivity and communication needs of rapidly moving IoVs. In technical terms, a 5G cellular mobile network must satisfy the three main, but distinct, use scenarios defined by the International Telecommunication Union (ITU). They are

- Enhanced Mobile Broadband (eMBB) i.e. to provide much higher transmission speed than 4G.

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- Ultra Reliable Low Latency Communications (URLLC) i.e. to support much lower air interface latency, which is to meet the requirements of using the network for mission critical applications that requires uninterrupted, real-time and robust data exchange. In IoV, the high-speed movement of terminals leads to stricter requirements for real-time response and information processing. URLLC is expected to meet the low latency requirements of cooperative communication among people, vehicles and roads.
- Massive Machine Type Communications (mMTC) i.e. to support much higher connection density than 4G in order to connect to a large number of devices in a small area.

This means that, at a first glance, given a fixed spectrum resource, 5G networks are expected to satisfy a number of seemingly conflicting requirements; that is, being able to connect a larger number of devices, with each connection supporting a much higher transmission speed and much lower communication latency. 5G network technology satisfies the aforementioned ITU requirements by making use of higher frequency spectrum ranges and achieving substantial improvement in spectrum management. Other techniques such as beaming and multiple antennae also contribute to the significantly enhanced capabilities of 5G.

In this backdrop, network virtualization, cognitive computing along with smart spectrum resource management to the virtual networks will play a key role in solving the spectrum resource challenge [8]-[10]. 5G technology adopts an architectural approach called slicing in order to meet the communication needs of specific 5G applications. To cater for a variety of mobile applications with differing communication requirements, 5G embraces the notion of network virtualization, with the extensive use of Software Defined Network (SDN) and Network Function Virtualization (NFV) techniques. Based on NFV technology, communication networks can realize the decoupling of software and hardware by introducing the cloud-based mode, and reducing the network operator's equipment cost while enhancing the utility efficiency of computation and wireless resources. Similar to NFV, the SND technology is designed to improve the system flexibility by decoupling the control plane and forwarding plane. These are key technologies to enable intelligent 5G communications. Slicing allows the same physical network infrastructure to implement different logical networks of various priorities in Quality of Services (QoS) in terms of transmission bit rates, connection density and air interface latency.

The trend of cognitive carrier resource optimization and edge computing will play a critical role in implementing the spectrum management capabilities of 5G carriers [11]-[13]. More recently, the adoption of cloud radio access networks (CRAN) architecture, which aims is to split the base stations into radio and baseband parts and pool the Baseband Units (BBUs) from multiple base stations into a centralized and virtualized BBU Pool, further enables mobile carriers to optimize their spectrum resources across multiple cells.

In CRAN-based 5G networks, the carrier resource allocated to the virtual networks can be centrally managed and shared to meet the dynamic demand of cell capacities caused by movement of mobile users. The response to this dynamic allocation will become more time critical in the case of IoV systems due to the rapid movement of mobile users. One of the key challenges caused by IoV's mobility is the fast-changing topology which easily leads to tidal effect in individual cell areas and difficulty for carrier resource allocation of core networks. In 5G-based smart city, CRAN-based architecture has shown its huge advantages and will be widely deployed to address the tidal effect and improve energy efficiency [14][15]. As such, the task of intelligently allocating carrier spectrum resource to various cells in the core network layer is a critical issue which requires the gathering of whole users' mobile information. Thus, in IoV, how to precisely predict the cells' flow change so as to optimize the wireless carrier resource deserves extensive investigations in 5G-oriented smart cities.

In this article, we propose a dynamic carrier resource allocation scheme for supporting IoV systems in smart cities enabled by CRAN-based 5G carriers. In smart cities, massive mobile users always exhibit certain regular mobility patterns, such as moving to CBD in daytime and to residence community in the evening, called tidal migration. To meet the peak capacity requirement in every cell, huge network resources need to be allocated to each cell area, even though the number of mobile users in CBD at the midnight could be very small. In such circumstances, the task of dynamically allocating network resource to match the users' regular movement patterns in smart cities has become a critical issue. In CRAN-based smart cities, where virtual spectrum resource can be centrally allocated in the cloud server, the tidal migration effect can be addressed.

The proposed cognitive carrier resource optimization is achieved by enhancing the ability to predict movement of IoVs, hence the dynamically changing demand for carrier resources. As an enhancement of the traditional Markov Model, our prediction model introduces vehicles' mobility analysis in order to allow the construction of a more precise flow transition matrix to improve the prediction result. In this connection, we investigate the behavior patterns of mobile vehicles based on their historical movement information, and then predict the flow change across various cells. The flow prediction serves as the basis for carrier resource allocation in the 5G network. Numerical results are provided to show the performance improvement of the proposed method.

The key contribution of this paper is to enhance the traditional Markov Model with a precise flow transition matrix. To achieve this, we introduce vehicles' mobility analysis to allow the construction of a more precise flow transition matrix to improve the prediction result. The main contributions of this paper can be highlighted as follows

- We propose a wireless carrier resource allocation scheme in CRAN-based 5G carriers. This carrier resource allocation optimization is based on the prediction of cell flows and adopt a Markov-based model to predict the cell flow change. Unlike to the classical flow prediction solutions, we introduce the IoV users' movement analyses to ensure the prediction accuracy.
- The movement analysis model is built for IoV terminals in smart city according to users' historical position in-

formation and QoS demands. To improve the accuracy of IoV user's position predicting at subsequent slots, vehicular terminal's behavior habit, service type along with QoS demand are considered in system model.
- Comparison simulated tests are performed to evaluate the performances of our proposed method in blocking probability and spectrum efficiency.

The rest of this article is organized as follows. A cloud-based IoV framework which can address the tidal effect and enhance spectrum efficiency is presented. Then, we propose a cognitive carrier optimization scheme for IoV in smart city on the basis of cell flow prediction. Unlike traditional flow prediction method, we improve the prediction accuracy by introducing the position analysis for IoV terminals which can refine the generation of flow transition matrix. Numerical results are then provided to show the performance improvement of the proposed method.

II. Cloud-Access-Based IoV Framework in Smart City

In this article, we consider IoV in smart cities enabled by CRAN-based 5G carriers as shown in Fig. 1. In this scenario, the cloud access mode is applied to enhance energy efficiency and spectrum usage for 5G networks, in which the management of network carrier resource is performed in the cloud layer. In addition, edge computing is supposed to be performed to guarantee real-time performance, as well as various kinds of task-hubs along the small cells serve. To address challenges in the complicated urban circumstances, fog computing and dynamic spectrum access have been considered to ensure user's Quality of Experience (QoE).

In the face of growing number of IoV connections in a massive scale, 5G carriers need to address many critical issues in order to ensure the high-quality transmissions in smart cities. These include:

1) The complex and dynamically changing traffic scenes due to the rapid movement of a massive number of vehicles will lead to frequent changes in the topology structure of IoV, hence the task of describing the impact of dynamic traffic flow topology on network performance has become one of the challenging issues in IoV.

2) The task of coordinating and scheduling key wireless resources, such as spectrum and computation resource, in order to cope with the impact of large-scale vehicle movement on existing wireless networks, and to meet the demand of large-scale data services, is a key problem to be addressed.

3) When using road beacon to improve the information collection and transmission, the route construction based on routing table of IoV transmission protocol usually has high transmission cost and slow convergence speed. However, the non-beacon transmission is easy to generate competitive requests, and the information interaction is disordered, which will weaken the system stability. How to establish an efficient and stable transmission routing mechanism for IoV is another key challenge.

4) In dynamic vehicle topology environment of IoV, how to assure the high-reliability information processing in vehicle emergency situation and large-capacity information transmission demand in common status still deserves deep investigations.

In this scenario, we consider to adopt CRAN technology in 5G-enabled smart cities to address the impact of massive IoV terminals' mobilities which bring huge challenges to resource management and energy efficiency for traditional cellular networks. As shown in Fig. 2, the cloud-access-based 5G networks are centralized framework, only antenna array is reserved at base stations, and the traditional control units in base station are canceled. All computation resources are centralized in the cloud and connected through optical fiber. The new architecture can greatly reduce the equipments in base stations, cut energy consumption and operating cost. In addition, CRAN-based 5G networks adopt collaborative and virtualization technology to achieve resource sharing and dynamic scheduling which effectively cope with the tide effect and improve spectrum utilization.

III. Mobility Analysis Based on IoV Users' Historical Position Information

Driven by the explosive growth in user demands, wireless networks have been evolving continuously. Optimized management of network resource, such as optimize wireless resource allocation, network planning, spectrum access and handoff, typically attempt to recognize and cater for the behavior characteristics of the majority users' mobile. For example, most classical schemes on wireless resource allocation are typically based on user QoS requirements, interference suppression, system profit and so on; whereas, thorough investigations of the mobility characteristics of mobile users are not carried out. For supporting IoV in smart cities, the strong mobility of IoV users makes the related research more important.

To address the tidal migration effect in smart cities, how to efficiently and dynamically manage the network resource among the various cells is a key challenge. Thanks to the CRAN networks, the framework of virtual spectrum pool realizes the goal of managing the spectrum resource centrally among cellular radio systems. In order to ensure a rational spectrum management in CRAN networks, knowledge about the users' mobility pattern is essential. In such circumstances, performing mobility analysis and establishing IoV users' mobility patterns are very significant to the task of efficient spectrum optimization in IoV.

Fortunately, in an actual communication process, there is a strong regularity in users' mobility. For instance, many users often commute within few places in a city. The tidal migration of massive users often occurs, such as gathering in several hot spots during daytime hours and the other places in resting time. Thus, the user's movement is usually highly purposeful and easy to show cyclical characteristics. These characteristics provide the possibility for mobility prediction which will benefit the spectrum optimization.

IoV user's every movement can be described as one hop, and there are two potential behavior modes for the next hop as: 1. The user moves to a new position; 2. The user moves back

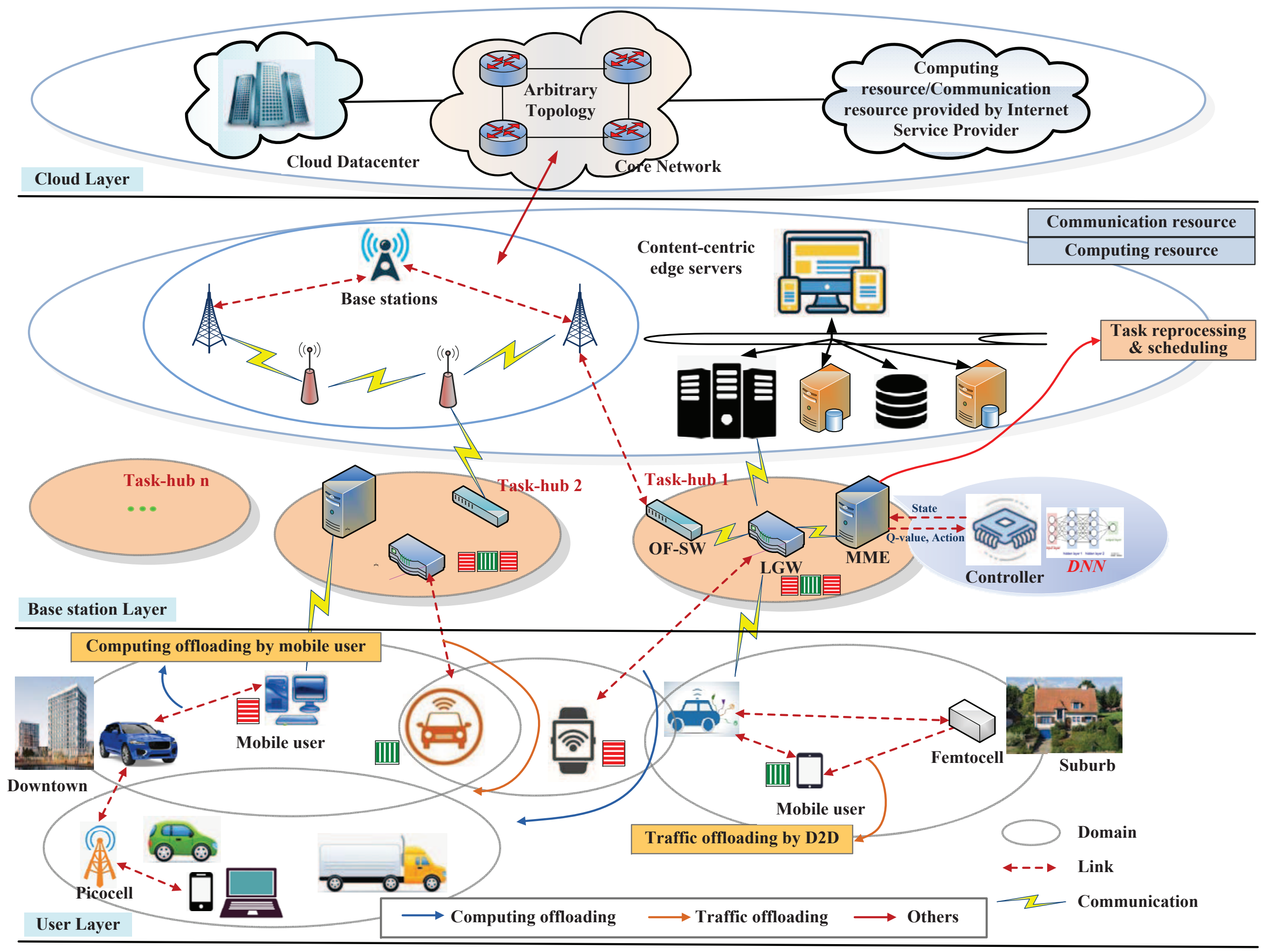

Fig. 1. CRAN-based VoI in smart city

to a previous position. The probability is $P_{re}(i) = \mu J(i) - k$ and $P_{new}(i) = 1 - \{\mu J(i) - k$. Wherein, $J(i)$ denotes the number of the positions visited, i is the hop number. In addition, before the user transfers to another position, it will stay at current position for a while. In (1), the probability of IoV user's visiting to previous position will rise when the visited positions increase. According to the visiting frequency to previous positions, we classify the IoV users into regular user or explore user. The radius for the most k popular visiting positions can be expressed as

$$\vec{r}_g = \sqrt{\frac{1}{n}\sum_{n1=1}^{n}\sum_{n2=1}^{n1}|\vec{r}_{n1} - \vec{r}_{n2}|^2} \tag{1}$$

where n denotes the overall hop number and $\vec{r}_g$ denotes the step number at g hop. The importance ranking for the visiting positions can be expressed as $Rank(L_0) = af_{n_0} + (1-\alpha)\triangle t_0$. Wherein, L_0 denotes the o important position for the IoV user, $\alpha \in [0, 1]$ is the impact factor, f_{n_0} is the visit frequency, $\triangle t_0$ is the stay time. In the process of user's behavior prediction, its future position and service type can be judged mainly by historic information on movement radius, important stop positions and used services. The probability of user's movement to next position is related to the key factors above.

IV. Carrier Resource Allocation with Cell Flow Prediction

The dynamic baseband pool technology of CRAN in 5G-based smart cities can optimize the whole baseband resource according to the traffic and data flow of the whole networks, dynamically allocating the carrier resources to base stations, which can address the effects of tidal coverage. In this process, how to accurately estimate the data flow characteristics for each base station area is the key for providing efficient resource scheduling solution.

As shown in Fig. 4, a CRAN-based 5G network with multiple cells is given. The service flow of each cell can be considered as a time sequence expressed by $Q_i(t)$. Furthermore, when using the time sequence, the user number, service overhead and cell number should also be taken into account. Furthermore, we need to describe the network flow condition in uniform time interval.

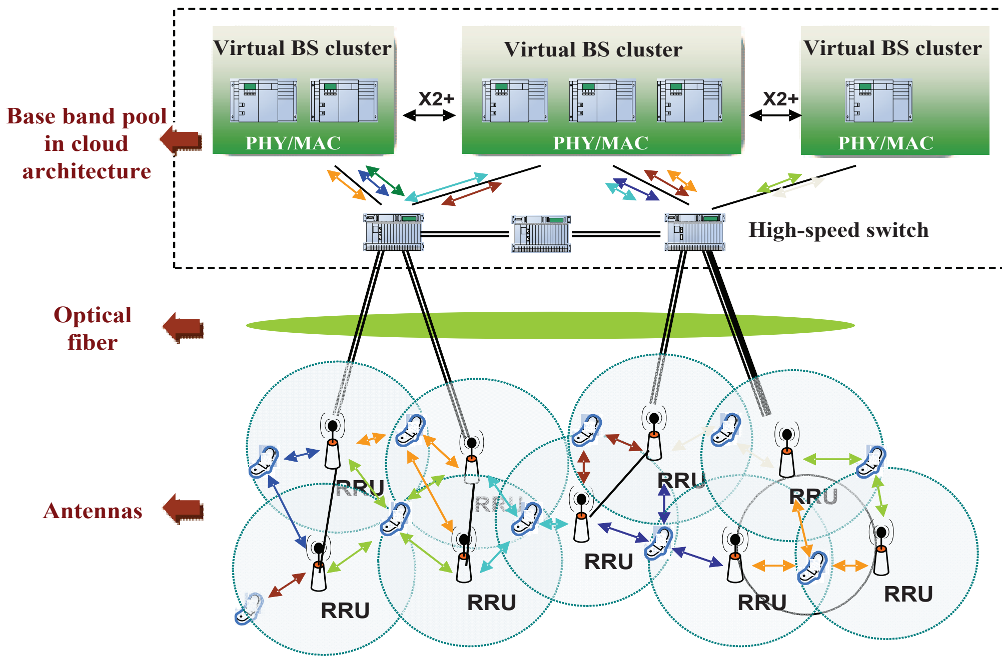

Fig. 2. CRAN architecture

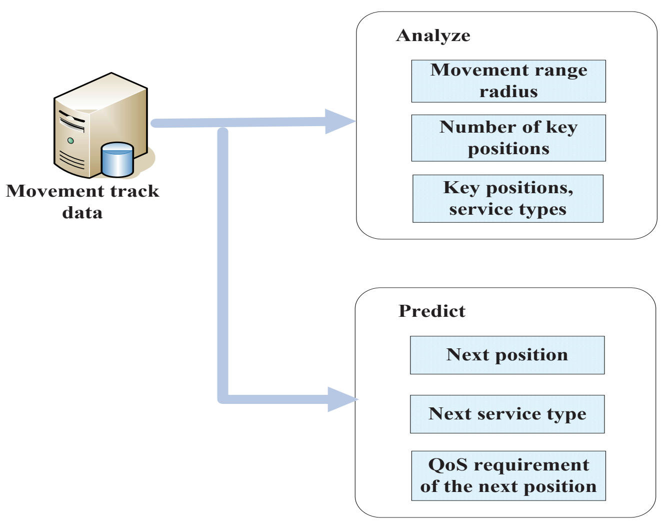

Fig. 3. Movement prediction model

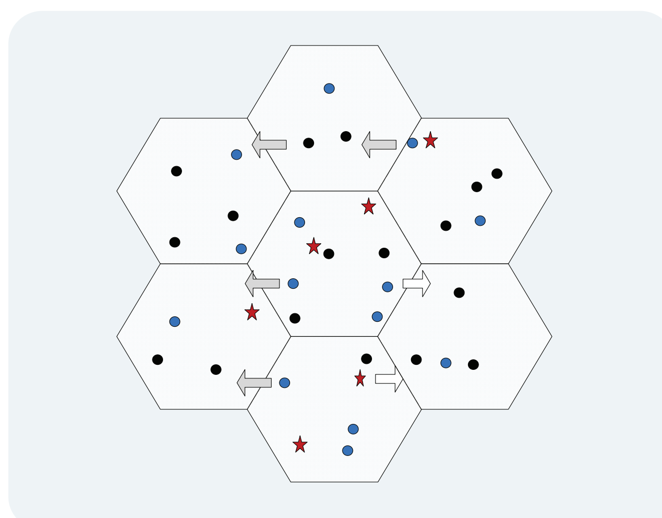

Fig. 4. Dense distribution of multi-cells

For two adjacent moment, the flow status change for a cell in CRAN has the following relation as $Q(n+1) = P(n) \times Q(n)$. Wherein, P denotes the transition matrix of network flow at n moment. The transition matrix can be expressed as

$$P(n) = \begin{pmatrix} P_{11}(n) & P_{12}(n) & \cdots & P_{1M}(n) \\ P_{21}(n) & P_{22}(n) & \cdots & P_{2M}(n) \\ \vdots & \vdots & \ddots & \vdots \\ P_{M1}(n) & P_{M2}(n) & & P_{MM}(n) \end{pmatrix} \quad (2)$$

In this scenario, by carrying out movement prediction for IoV users, we can obtain more precise transition matrix P to guarantee the cells' flow status estimation. On this basis, we optimize the carrier resource allocation for CRAN-based 5G networks in smart cities.

V. Performance Evaluation

In this section, we give the performance evaluation for our proposed carrier allocation method in the environment of 5G-enabled smart city where CRAN is deployed. In this case, we compare the performance of our proposal with the other two traditional flow prediction solutions, including Auto Regressive (AR) method and Markov method. For AR flow prediction, it estimate the flow change in near future according to mathematical model upon the past n time of flow status.

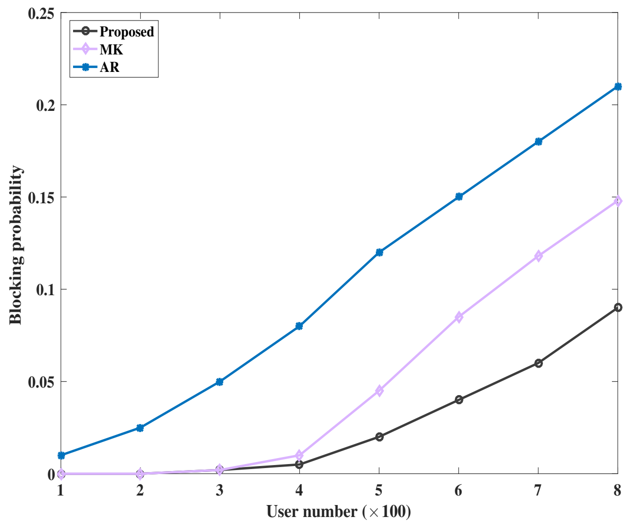

Fig. 5. Blocking probability

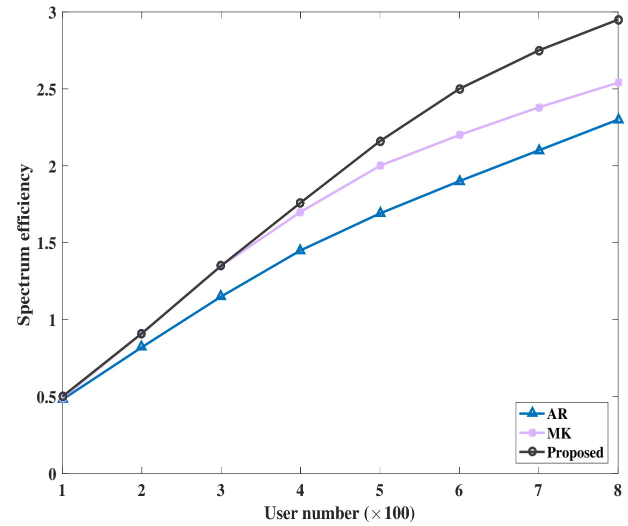

Fig. 6. Spectrum efficiency

Markov method assumes the flow change is steady, then ascertain the flow transition matrix which is similar to our proposal. Yet, our proposal adopt movement-predicting-based method to obtain more precise flow transition matrix in the cost of more computation consumption. The related computing task can be completed in edge nodes or cloud servers. In the following tests, the user number changes from 100 to 800 and the visiting position number is set to be 50. The access location is fixed in a 10×10(km) area. The total moving time is 100 slot and each slot equals 10s. We suppose there are 80 channels to be allocated among various cells. Furthermore, we set the QoS requirements for all the terminals to be uniform value 10dB and the user distribution is stochastic.

In Fig. 5, we give the performances of blocking probability for IoV users in this cloud-access-based networks. As shown in Fig. 5, with the increase of user number in a given cell, the blocking probability rises. In this scenario, we consider the massive users' movements are random. When the network load grows up. Fig. 5 shows that our proposal has better network capacity compared with the methods of Auto Regressive and Markov flow predictions. It can be envisioned that a precise carrier optimization solution is called for especially when the cell load changes sharply.

In Fig. 6, we give the performances of spectrum efficiency for the three methods in cloud-access-based networks. As shown in Fig. 6, with the increase of IoV user number, the spectrum efficiency in a given cell becomes better. Yet, when the user number exceeds 500, the spectrum efficiency changes slowly. In general, the difference between the three methods is not very obvious. When the carrier allocation scheme can be further optimized, the spectrum efficiency will be enhanced.

VI. Concluding Remarks and Future Works

In this article, we proposed a dynamic carrier resource allocation scheme for supporting IoV systems in smart cities enabled by CRAN-based 5G carriers. The proposed cognitive carrier resource optimization is achieved by enhancing the ability to predict movement of IoVs, hence the dynamically changing demand for carrier resources. As an enhancement of the traditional Markov Model, our prediction model introduces vehicles' mobility analysis in order to allow the construction of a more precise flow transition matrix to improve the prediction result. In this connection, we investigated the behavior patterns of mobile vehicles based on their historical movement information, and then predict the flow change across various cells. The flow prediction serves as the basis for carrier resource allocation in the 5G network. Numerical results are provided to show the performance improvement of the proposed method. The key contribution of this paper is to enhance the traditional Markov Model with a precise flow transition matrix. To achieve this, we introduce vehicles' mobility analysis to allow the construction of a more precise flow transition matrix to improve the prediction result.

The main contributions of this paper include, firstly, we proposed a wireless carrier resource allocation scheme for CRAN-based 5G carriers which, with the introduction of IoV users' movement analyses, is based on the prediction of cell flows by adopting a Markov-based model to predict the cell flow change; secondly, the movement analysis model is built for IoV terminals in smart cities according to users' historical position information and QoS demands. To improve the accuracy of IoV user's position predicting at subsequent slots, vehicular terminal's behavior habit, service type along with QoS demand are considered in system model.

In our future research, we aim to extend the scope of our efforts to more complicated scenario and take into account more critical factors for spectrum optimization in IoV. In particular, towards upcoming 6G, we consider the mobile scenario of integrating with satellite systems for continuous connectivity of IoV. Wherein, we plan to adopt federated learning (for cognitive carrier resource optimization) between mobile terrestrial networks and satellite systems to distribute the computation tasks and maintain good data governance by avoiding sending user mobility data across network operators.

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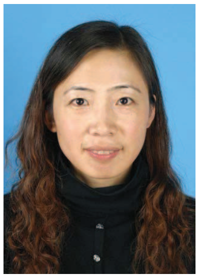

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