**Joint Task Offloading and Resource Allocation for Mobile-Edge Computing Enable Vehicular Networks**

**Power Control and Task Offloading for Cloud Assisted MEC in Vehicular Networks**

**Abstract—**

原来的In order to support delay-sensitive applications of vehicle equipment (V-UE) in the Internet-of-Vehicles (IoV) systems, it is necessary to allow V-UEs to offload their computationally intensive applications to a cloud or edge computing server. Where the uplink channel is reused by multiple vehicles. For the current Mobile-Edge computing enable vehicular networks, interference in the dense vehicle arena often leads to acutely poor communication quality. In addition, a vehicle’s mobility leads to an uncertain channel state and further affects the stability of communication. The resulting optimization problem corresponds to nonconvex fractional programming, and the block coordinate descent (BCD) algorithm and the successive convex approximation (SCA) technique is proposed to solve it. Furthermore, we decompose the problem into two subproblems for distributed and parallel problem-solving. Numerical simulations are performed to evaluate the algorithm performances, and the results indicate that the proposed algorithm is effective in high mobility under uncertain channel MEC-enable vehicular network environments.

自己改的Mobile-edge computing (MEC) has been witnessed as a promising solution for vehicular networks under massive data processing in the future. In this paper, a novel scheme for maximizing network utility has been proposed to solve this problem. MEC has limited computing resources, and the cloud which has huge computing resources needs to be allocated to the MEC to support large-scale data processing. However, the channel reuse technology is adopted to deal with the poor spectrum resources of the Internet of Vehicles, but it can bring co-channel interference, and the vehicle’s mobility leads to an uncertain channel state and affects communication stability. The first-order Markov process and a convex approximation method namely Bernstein approximations are raised to solve problems respectively. Furthermore, the resulting optimization problem corresponds to nonconvex fractional programming, finding the optimal result to ensure the best performance is a difficult task, then the block coordinate descent (BCD) algorithm and the successive convex approximation (SCA) technique is proposed to solve it. Numerical simulations are performed to evaluate the algorithm performances, and the results indicate that the proposed algorithm is effective in high mobility under uncertain channel MEC-enable vehicular network environments.

后来的Cloud-assisted mobile-edge computing (C-MEC) has been witnessed as a novel solution for task offloading in vehicular networks, which is able to provide rich computing resources. In this paper, a robust power control scheme is proposed to offload the computation task and maximize the utility of C-MEC networks. However,

an uncertain channel state seriously affects the stable transmission of the offloading signal. The first-order Markov process is adopted to simulate channel uncertainty, where vehicular mobility is highly considered. Moreover, channel reusing is assumed due to the limited spectrum resources, which leads to complex co-channel interference and communication delay. To depress the above challenges, probability constraints of signal links are constructed to ensure communication quality. Furthermore, the Bernstein approximations method is adopted to transform the original constraints into solvable ones. Scrupulously, the block coordinate descent (BCD) method and the successive convex approximation (SCA) technique are further adopted to solve the nonconvex robust optimization framework. Furthermore, a robust power control algorithm is proposed to approach the optimal solutions. Numerical simulations are performed to evaluate the system performances, and the results indicate that the proposed algorithm is effective and outperform the benchmarks, especially in communication environments with channel uncertainty.

**Ⅰ INTRODUCTION**

原来的Urban traffic congestion is becoming more and more serious, traffic accidents are becoming more frequent, and many environmental and energy problems are also caused. Vehicular networks are envisioned to deliver data transmission services ubiquitously, especially in the upcoming autonomous driving era. Accordingly, the high data traffic load poses a heavy burden to the terrestrial network infrastructure. The vehicle speed is fast and the network topology constantly changes under the Vehicle-To-Infrastructure (V2I) environment. The transmission of low delay is also required in intelligent driving tasks, then the data can be transmitted through V2I to complete the intelligent driving task, the vehicle can communicate with the base station (BS) directly or the relay vehicle can help to forward the data.

Considering the rich computing resources provided by the Internet, cloud-based vehicular networks have been proposed to address the explosive growth of computing task requirements of vehicles. Traditional cloud computing can no longer meet the stringent low latency requirement of smart driving. Emerging computing mode represented by MEC is rising rapidly \cite{Pang2021}. Roadside units (RSUs), which have strong computing capability and are close to vehicle nodes, have been widely used to process delay and computation-intensive tasks of vehicle nodes. Edge computing, which is an information hinge for vehicles and roadside units, can enhance the level of vehicle intelligence in the scene of vehicle-road synergy sensing \cite{Cai2014}. Therefore, multiaccess edge computing (MEC) or formerly mobile-edge computing, as new architecture and key technology for the emerging 5G networks, has been proposed to address the V2I problem \cite{sym2019}. Different from traditional mobile cloud computing (MCC), MEC migrates remote cloud computing resources to the edge of the network to curtail the end-to-end transmission delay of data and to free the computing and storage pressure of vehicles or roadside units \cite{Wang2020}. Our objective is to design a comprehensive solution for joint task offloading and resource allocation in a multi-server MEC-enable vehicular network. Specifically, we consider a multi-cell ultra-dense network where each base station (BS) is equipped with a MEC server to provide computation offloading services to the mobile vehicles.

遇到问题

提出问题

解决问题

车联网中由于车辆本身计算能力有限，因此面临着越来越多的任务卸载的需求，云计算与边缘计算被越来越多的人提出来解决此问题。越来越多的研究使用边缘计算来辅助进行任务的卸载，边缘计算的优点是处于网络的边缘，距离较近所以时延更小，但是边缘计算的计算能力仍然有限。然后文献支撑，有人用云计算来进行更大数据量的卸载，云计算有着更加富足的计算能力，更能胜任未来大数据卸载的需求，但是云计算往往距离网络比较远，在高动态的车联网中，有些数据对时间是敏感的，于是跟云计算与边缘计算相结合有望解决这个问题。

在网络模型构建介绍之后，我们希望这样的网络结构可以解决车联网中的任务卸载的问题。但是这样的网络结构中仍然存在着共信道的干扰并且影响着系统的可靠性，系统对通信与卸载时延的容忍度也提出了新的要求。所以功率控制与计算资源的联合分配是个解决这两个问题的好方法

总结:面对任务卸载的需求，云和边缘计算相结合的方式致力于解决这个问题。最后这部分做一个总结，网络结构+资源优化提出了一个有希望能解决这篇文章想要解决的大问题

**but the Doppler effect in the high mobility of vehicles poses a challenge to V2I communication.**

SINR level of V2V links in order to satisfy the communication conditions. High reliable communication quality

硕士论文中参考

MEC 支持新型应用程序和资源管理，并且在云中心和终端用户之间建立了协同管理体系从而进行高效通信。

自己改的The high data traffic load poses a heavy burden to the Vehicular Networks because of the limitation of the computing resources.

参考一下其他文章，第一句话如何表达计算卸载的重要性

云计算与边缘计算是5G网络中的新技术，被越来越多的用来解决low-latency high-reliability computing services for Internet of Things (IoT) devices，尤其是车联网中的任务卸载，MEC距离网络中心较远，可以减少传输的时延并给车辆提供计算资源以缓解车辆本身的计算压力

MEC migrates remote cloud computing resources to the edge of the network to curtail the end-to-end transmission delay of data and to free the computing and storage pressure of vehicles or roadside units \cite{Wang2020}. 引用的原文

分别介绍完MEC和MCC后，应该着重强调一下我们的需求（我们希望得到一个既能克服MEC缺点的，又能克服MCC弱点的网络结构）

我们希望有一个既有强大的计算能力又能减少传输延时的网络结构

Mobile-edge computing (MEC) and mobile cloud computing (MCC), as two new architectures for the emerging 5G networks, have been increasingly proposed to solve the low-latency high-reliability computing services for Internet of Things devices, especially task offloading in the IoV system \cite{sym2019}. MEC at the edge of the network center, which can reduce the transmission delay and provide computing resources to the vehicle to relieve the computing pressure of the vehicles \cite{Wang2020}. But MEC's computing resources are still limited in large-scale vehicle computing environments. Considering the rich computing resources provided by the cloud computing, cloud-based vehicular networks have been proposed to address the explosive growth of computing task requirements of vehicles. However, cloud computing centers tend to be far from the network, in the high-dynamic Internet of Vehicles, the amount of data will be produced by vehicles, must be processed in a short period. \cite{Pang2021} Therefore, the (C-MEC) is expected to solve this problem, a network architecture that has both rich computing resources and reduced transmission latency

We explored and adopted a two-layer (C-MEC) vehicular network. Specifically, we consider a multi-cell network where each Base Station (BS) is equipped with a MEC server to provide computation offloading services for the mobile vehicles. For MEC layer, which has moderate computation capacity and deploys close to networks, can be used to assist the vehicles. Cloud computing layer, can be used to process the large-scale, delay-insensitive data that the MEC layer can not process. We hope that such a network structure can solve the problem of task offloading in the Internet of Vehicles. 这里对应上一段的需求，重点强调结合的优势（能够满足需求）

结合之后，既能拥有较大的计算能力又能减少端到端延时

Then the C-MEC vehicular network not only curtail the transmission delay of data but also free the computing pressure of MEC

However, for the current Mobile-Edge computing that enable vehicular networks, interference in the dense vehicle scenario often leads to acutely poor communication Quality of Service (QoS). In addition, a vehicle’s mobility leads to an uncertain channel state and further affects the stability of communication. So关联在哪里So joint power control and computing resource allocation in multi-vehicles, the multi-MEC system will resolve the task offloading problem in a C-MEC vehicular network and will guarantee the QoS.

**A. Related Works**

这里是解决的方法，也可以是对云计算与边缘计算的解释

总分总

总

首先是移动性带来的多普勒效应

信道的复用带来了干扰，尤其在高速移动情况下更难处理

车辆设备对时延与传输的可靠性提出了容忍度降低因此提出了更高的要求

所以有了边缘计算和云计算可以更好的提高稳定性，

面对任务卸载会遇到的这些情况，大家针对这些问题研究了什么，通过云边结合之后有什么好处，有什么优势

分

具体的挑战，展开这些挑战，文献的扩充

信道不确定性怎么带来的，稀缺的频谱资源导致了使用信道复用可以提高效率，然后是高动态环境下干扰与信干噪比问题更难以处理，因此使用了贝恩斯坦近似的方法求解，时延的问题也是一个关键性的指标，使用了概率约束的方式，结合积分变换进行了求解

总结 通过建立这样的网络结构，然后使用这样的资源分配与功率控制方案，有希望解决车联网中面临的这样的问题

重点应该是融合MEC和MCC，列举文献来突出两种结合的优势

原来的Recently, some works have been devoted to solving problems of computation offloading of mobile devices in MEC or MCC-enable vehicle network architectures. Several works have focused on exploiting the benefits of computation offloading in MEC network. Note that similar problems have been investigated in \cite{Dai2022}, the horizontal and vertical cooperations between MEC cloud servers are utilized for balancing the workload distribution in dynamic vehicular environment.

Some papers investigated the computation offloading of mobile terminals in single-user scenarios. Aliyu et al. \cite{Ahmed2016} proposed a systematic review of MCC energy-aware issues and grouped some research works on battery energy in MCC into dynamic and nondynamic energy-aware task offloading \cite{Dai2022}. Investigate the service scenario of cooperative computation offloading in MEC-assisted service architecture, where multiple MEC servers and remote cloud offload computation-intensive tasks in a collaborative way \cite{Pang2021}, propose a hybrid transmission and reputation management strategy to accommodate the fast-changing IoV topology and to meet the low latency requirements of intelligent driving tasks. In the V2I networks, the authorized vehicular users with spectrum resources can directly communicate to the RSU. However, the scarce spectrum resources appear inadequate in high-density vehicular networks \cite{Xie2020}. To realize more V2X communication under the limited spectrum resources, Chen et al. \cite{Chen2017} proposed a Device-to-Device (D2D) crowd framework where a massive crowd of devices at the network edge leverage network-assisted D2D collaboration for computation and communication resource sharing. D2D connects two geographically close devices to achieve low latency communication. D2D can improve spectrum efficiency, reduce cellular network pressure and optimize network performance \cite{Liu2015}. Zhou et al. \cite{Zhou2017} investigated dynamic sharing of the 5G spectrum and proposed a sharing architecture of DSRC and the 5G spectrum for immersive experience-driven vehicular communications. Tran et al. \cite{Tran2019} design a holistic solution for joint task offloading and resource allocation in a multi-server MEC-assisted network. As the vehicles transmitting to the same BS use different sub-bands, the up-link intra-cell interference is well mitigated. It can be see effective channel reusing is crucial \cite{Liang2021}, \cite{Liang2017} studies resource allocation problems under the one-to-one reusing mode, but the spectrum efficiency of the whole system is low. In order to address the defects of one to one reusing mode, the authors introduce a many-to-one reusing mode where the spectrum utilization is well improved \cite{Ren2015}.

The moving vehicles, can communicate with different MEC servers in different time slots, and each MEC can only connect with vehicles within its coverage. For the high-speed V2I communication, the generated Doppler effect has a significant influence on the small-scale fading of CSI and thereby causes the fast channel variations. So the temporal correlation coefficient $$ is a function of the speed $$ and decreases as $$ increases, the average sum-rate degenerates as $$ grows larger, which means that a larger speed probably endows the acquisition of real-time CSI with more difficulty \cite{Chen2022}. In other words, the CSIs used are outdated. Therein, the Bernstein approximation method has commonly been used to deal with this difficult handling non-convex problem \cite{Wang2015}. To deal with the interference constraint, the probability constraint is constructed to depress the uncertain co-channel interference. And the Bernstein approximation method is used to transform it into a solvable closed form. To deal with the outage probability constraint, we assume the CSIs are obtained through channel estimation \cite{Xiao2020}. Therefore, the outage constraint is transformed according to the Bernstein-type inequality to make it a deterministic optimization problem. Based on the characteristics of our constraints, Bernstein method is also used in this paper.

Some papers focused on the problem of computation offloading in the multiple users’ scenario. Tan and Hu \cite{Tan2018} designed a joint communication, caching and computing problem for achieving the operational excellence and the cost efficiency of the vehicular networks. \cite{Wang2020} formulated the problem as a generalized NE problem and presented a game theory algorithm to analysis the equilibrium problem. It is assumed in \cite{Wang2020} that the vehicles use a constant transmit power while our approach optimizes vehicles’ transmit power. However, it seems like a new problem because the objective function is difficult to handle. Nemirovski and Shapiro have proposed a convex approximation approach in \cite{Nemirovski2007} that can solve it. In summary, most of the existing works did not consider a holistic approach that jointly power control and the computing resource allocation in a multi-vehicles, multi-MEC system as considered in this paper.

自己改的Related Works

构建这样的网络？研究什么问题？

都是哪些工作，要有文献支撑

Recently, some works have been devoted to an IoV edge computing network, consisting of a cloud computing layer and MEC layer vehicle network architectures. But the Doppler effect in the high mobility of vehicles poses a challenge to V2I communication. interference caused by channel reuse in the vehicle scenario often leads to acutely poor communication quality. Vehicle equipment has a reduced tolerance for delay and transmission reliability, so higher requirements are put forward. Aliyu et al. \cite{Ahmed2016} proposed a systematic review of MCC energy-aware issues and grouped some research works on battery energy in MCC into dynamic and nondynamic energy-aware task offloading \cite{Dai2022}. \cite{Zhou2019} Proposed a hierarchical computing framework for vehicular networks which is composed of the control layer, the VEC server layer, and the vehicular network layer. Investigate the service scenario of cooperative computation offloading in MEC-assisted service architecture, where multiple MEC servers and remote cloud offload computation-intensive tasks in a collaborative way \cite{Pang2021}, propose a hybrid transmission and reputation management strategy to accommodate the fast-changing IoV topology and to meet the low latency requirements of intelligent driving tasks.

In the V2I networks, authorized vehicles with spectrum resources can directly communicate to the RSU. However, the scarce spectrum resources appear inadequate in high-density vehicular networks \cite{Xie2020}. Zhou et al. \cite{Zhou2017} investigated dynamic sharing of the 5G spectrum and proposed a sharing architecture of DSRC and the 5G spectrum for immersive experience-driven vehicular communications. Tran et al. \cite{Tran2019} design a holistic solution for joint task offloading and resource allocation in a multi-server MEC-assisted network. As the vehicles transmitting to the same BS use different sub-bands, the up-link intra-cell interference is well mitigated. It can be see effective channel reusing is crucial \cite{Liang2021}.

When the fast-moving vehicles communicate with different MEC servers in different time slots, and each MEC can only connect with vehicles within its coverage, the generated Doppler effect has a significant influence on the small-scale fading of CSI and thereby causing fast channel variations. In other words, the CSIs used are outdated. The First-order Gauss-Markov process is adopted to describe the impacts of the Doppler frequency shift on the channel in \cite{Liu2019}. So the temporal correlation coefficient is a function of speed $$ and decreases as $$ increases, the average sum-rate degenerates as $$ grows larger, which means that a larger speed probably endows the acquisition of real-time CSI with more difficulty \cite{Chen2022}. Therein, the Bernstein approximation method has commonly been used to deal with this difficult handling non-convex problem \cite{Wang2015}. To deal with the interference constraint, the probability constraint is constructed to depress the uncertain co-channel interference. And the Bernstein approximation method is used to transform it into a solvable closed form. To deal with the outage probability constraint, we assume the CSIs are obtained through channel estimation \cite{Xiao2020}. Therefore, the outage constraint is transformed according to the Bernstein-type inequality to make it a deterministic optimization problem. Based on the characteristics of our constraints, the Bernstein method is also used in this paper.

Moreover, due to the outstanding performance in low communication delay and computing delay, Li et al. introduce the outage probability constraint to guarantee the reliability of vehicular links \cite{Li2020}. Considering that the exact expression contains the exponential integral function, to make it tractable, consider an approximate closed-form expression such that the computational complexity can be reduced.

Some papers focused on the problem of computation offloading in the vehicle computing scenario. Tan and Hu \cite{Tan2018} designed a joint communication, caching and computing problem for achieving the operational excellence and cost efficiency of vehicular networks. \cite{Wang2020} formulated the problem as a generalized NE problem and presented a game theory algorithm to analyze the equilibrium problem. In summary, most of the existing works did not consider a holistic approach that jointly power control and the computing resource allocation in a multi-vehicles, multi-MEC system as considered in this paper.

It is assumed in \cite{Wang2020} that the vehicles use a constant transmit power while our approach optimizes the vehicle’s transmit power. However, it seems like a new problem because the objective function is difficult to handle. Nemirovski and Shapiro have proposed a convex approximation approach in \cite{Nemirovski2007} that can solve it. Aiming at the non-convex of the problem with two variables, Some research decouples the original problem into two subproblems and deploys the block coordinate descent (BCD).

**B. Challenges and Contributions**

**Generally, for the low-speed V2I communication case, the Doppler effect is not noticeable, thereby being ignored, but the high mobility of vehicles poses a challenge to V2I communication. it is analyzed that the original stochastic optimization problem with two variables can be transformed into a deterministic non-convex optimization problem. It is likely to bring a new difficulty.**

**In this paper, The main contributions are summarized as follows:**

* The Doppler effect in the process of high-speed movement of vehicles will affect the communication quality between vehicles and roadside units, different from previous studies, this paper considers the mobility of vehicles in the research of the edge computing system of the Internet of Vehicles, and verifies the adverse effects of vehicle mobility through comparative simulation
* We propose an efficient hybrid transmission task scheduling strategy. The transmission mode is predicted, and the task is scheduled according to the vehicle context. V2V transmission is adopted to minimize the delay when the task-initiating vehicle cannot complete the task independently
* Considering the channel uncertainty caused by the high-speed movement of vehicles in the scenario of the Internet of Vehicles, the first-order Markov process is introduced. A reasonable and feasible IoV network scenario is constructed to more realistically describe the dynamic characteristics of the Internet of Vehicles. The Bernstein approximation method previously used in interference constraints is improved and generalized, and it is applied to the matrix form of interruption probability to deal with non-convex outage constraint in large-scale dynamic vehicle network environments to ensure the quality of network communication services
* 贡献点
* 不同于以往的研究新意是什么，什么被提出，考虑解决了什么，建立了什么样的模型
* 云边协同的好处是什么
* 不同于以往的研究，本文研究了云计算与边缘计算协同情况下的车联网，提出了鲁棒的功率控制算法与计算资源分配方案，考虑了低时延与高可靠性的网络结构，建立了(C-MEC)模型辅助车辆完成任务卸载并保证通信的质量。

The remainder of this article is organized as follows: the model of computation offloading in MEC-assisted vehicular networks is established defines in Section II. In Section III, the probability constraints and the objective function of the primal problem are formulated, and the optimization is proposed. In Section IV, simulation results and performance analysis are presented. Finally, we draw a conclusion in Section V.

自己改的贡献点 **In this paper, a robust power control and task offloading algorithm is proposed for the cloud assisted MEC in vehicular networks with highly dynamic vehicles. The communication delay and computing delay are guaranteed by probabilistic constraints, and vehicle QoS is also guaranteed in the framework. The main contributions of this paper include the following aspects:**

**We present a C-MEC vehicular networks for computation offloading architecture. For MEC layer, which has moderate computation capacity and deploys close to networks, can be used to assist the vehicles. Cloud computing layer, can be used to process the large-scale, delay-insensitive data that MEC layer can not process.**

**Considering the channel uncertainty caused by the high-speed movement of vehicles in the scenario of the Internet of Vehicles, the first-order Markov process is introduced. A reasonable and feasible IoV network environment is constructed to more realistically describe the dynamic characteristics of the Internet of Vehicles. The Bernstein approximation method previously used in interference constraints is improved and generalized, and it is applied to the matrix form of interruption probability to deal with non-convex outage constraint in large-scale dynamic vehicle network environments to ensure the quality of network communication services.**

**Our proposed algorithm considers cross-layer computation and communication resources to guarantee the vehicle QoS and various task requirements under C-MEC vehicular networks.**

The remainder of this article is organized as follows: the model of power control and task offloading for cloud assisted MEC in vehicular networks is established deﬁnes in Section II. In Section III, the probability constraints and the objective function of the primal problem are formulated, and the optimization is proposed. In Section IV, simulation results and performance analysis are presented. Finally, we draw a conclusion in Section V.

**Ⅱ SYSTEM MODEL**

系统模型就不要再解释了，直接说我建立了什么样的模型

原来的In this paper, we consider a IoV edge computing network, consisting of a cloud computing layer, MEC layer, as shown in Fig. 1. For MEC layer, which has moderate computation capacity and deploys close to networks, can be used to assist the vehicles. Cloud computing layer, can be used to process the large-scale, delay-insensitive data that MEC layer can not process. \cite{Cui2021} Numerous vehicle-to-RSU (V2I) cells underlay a cell. In which each RSU is equipped with a MEC server to provide computation offloading services to the vehicles. To avoid inter-cell interference, the time division multiple access (TDMA) communication technology is adopted. Time resource is divided into multi-frames, and each frame is divided into several time slots. Different vehicles access its time slots when they communicate with the RSU, and signal transmission in different time slots will produce no interference [10]. We denote the set of vehicles and MEC servers in the mobile system as $$ and $$, respectively. Some notations are given in Table I.

自己改的In this work, the road network is divided into multiple geographic zones within the RSU’s coverage in Fig. 1, which is composed of the MEC layer, and the cloud computing layer hierarchical architecture of computation offloading, numerous vehicle-to-RSU (V2I) cells underlay a macro cell. In which each RSU is equipped with a MEC server to provide computation offloading services to the vehicles. The detailed offloading process is described as follows. Firstly, the vehicles offload request messages by the wireless interface, which includes required communication resources, the task ID and submission time, and the expected service delay of the task to the cloud. Secondly, the MEC server makes scheduling according to the received request messages, including the task upload server and task computation server. Finally, after task upload, the task waits in the computation queue until one of the processors is available. We denote the set of vehicles and MEC servers in the mobile system as $$ and $$, respectively. Some notations are given in Table I.

Remark1

**In this paper, we only consider the simplified single-segment case in order to derive a tractable solution. The more complicated multi-segment case is beyond the scope of this paper and will be investigated in future works. Nevertheless, the proposed solution can be easily extended to the multi-segment scenario by adopting a** time division multiple access communication technology**. That is, the number of vehicles in each segment remains constant within a slot and varies across different slots. Hence,** time resource is divided into multi-frames, and each frame is divided into several time slots. Different vehicles access its time slots when they communicate with the RSU**.**

**A. Communication Model**

Different from the traditional cellular communication, Due to the fast mobility of vehicles, their CSIs are hard to be estimated precisely. In particular, RSU can only achieve the accurate knowledge of large-scale fading $$ of vehicular to RSU links while the small-scale fading $ $ is greatly influenced by the fast channel variations caused by the Doppler effect. We assume the CSIs are obtained through channel estimation \cite{Xiao2020}, Therefore, we model the small-scale fading channel estimation of $$ by using the first-order Gauss-Markov process \cite{Kim2011} in each transmission time interval (TTI) as follows.

We assume that the estimated channel gain $$ denotes the estimate of $$ and $$ is exponentially distributed with unit mean \cite{Sakr2014}. Furthermore, $$ represents the correlation coefficient over $$ link, and $$ stands for the channel gain and follows a complex Gaussian distribution $$ and independent and uncorrelated of $$. The coefficient $$ quantifies the channel correlation between the two consecutive time slots and we assume that time correlation coefficient $$ is same for all VUEs. According to the Jakes statistical model for the fading channel \cite{Kim2011}, $$ is given as $$ , where $$ is the zero-order Bessel function of the first kind. $= $ is the maximum Doppler frequency, where $$ indicates the vehicle speed, $$ indicates the carrier frequency at 5.9 Ghz, and $$, $$ is a period feedback latency. erally, both transmitter vehicles and RSU can know the accurate $$.

Based on the aforementioned discussion, the mobile V2I channel power gain of the effective links and interference links in $$ time slot from $$ transmitter to $$ receiver can be expressed as a shared expression:

Where $ $, $ $, and $ $ denotes the kth time slot large-scale fading effects including shadow-fading and path loss from $$ transmitter to $$ receiver on the road section. Moreover, $$ is an observed value. $$ denotes an exponential random variable with parameter,

$$

To improve the spectrum utilization and realize multi-vehicles joint communication, V2I communications reuse the same uplink channel. In this case, the Signal-to-Interference-plus-Noise Ratio (SINR) from vehicle $$ to RSU can be formulated as,

$$

Where $$ denotes the transmit power of the $$ vehicles, where $$ is the background noise. Therefore, the deterministic equivalent transmission rate of VUEs calculated by Shannon’s theorem is,

$ $

Hence, the transmission time of vehicle $$ when sending its task input $$ in the uplink can be calculated as,

$ $

Where $$ is the bandwidth of the reused channel. Therefore, the upload time of each V2I link can be formulated as,

$ $

And $$ is the amount of input data including system settings, program codes, and input parameters, which is necessary to transfer the program execution.

Communication delay is another significant index that affects the performance of wireless networks. The packets to V2I receivers must be in the queue before they transmit at the speed of $$. It is assumed that the process of a packet arriving at the $$ V2I receiver is a Poisson process with parameter $$, and the length of the data packet obeys the exponential distribution of parameter $$. We develop the M/M/1 model instructions the relationship between the expected delay and transmission rate of the $$ V2I links can be expressed as,

$$

**B. Vehicle Computation Mode** l

We consider that each vehicle $$ has one different computation task at a time. denoted as $$ [cycles] specifies the workload, i.e. the amount of computation to accomplish the task, that is atomic and cannot be divided into subtasks. The values of $$ can be obtained through carefully profiling of the task execution \cite{Yang2015}. Each task should be offloaded to the MEC server and then transmission to the cloud server. By offloading the computation task to the MEC server, the vehicles would get more computing resources, however, it would consume additional time for sending the task input in the uplink.

The MEC server at each RSU is able to provide computation offloading service to a vehicle at a time slot. The computing resources are quantified by the fixed rate $$, expressed in terms of number of CPU cycles/s. the vehicle $$ uploads the input data of task to the nearest RSU, the RSU process the small-scale, delay-sensitive data first, then the RSU forward the remaining data to the remote cloud server, the cloud is able to provide computation offloading service to multiple RSU concurrently. The computing resources made available by cloud to be shared among the associating users are quantified by the computational rate $$, it is still expressed in terms of number of CPU cycles/s. Thus, the latency for computing offloading can be written as,

$ $

**C. Problem Definition**

Given the computing resource allocation $$, the total delay experienced by vehicle $$ when offloading its task is given by,

$ $

The transmission latency between RSU and cloud server is defined as $$, usually it is set to a fix value \cite{Xiao2020}, so the relative improvement in task completion time is characterized by,

$$,

Where $$ is the maximum tolerable threshold of the task completion time, if a task can be completed ahead of deadline $$, the vehicle can get a higher utility, otherwise, it will produce the corresponding loss. Therefore, we define the offloading utility of vehicle u as, $$ denote offloading time cost utilities at a unit.

The joint task offloading and resource allocation will be formulated as an optimization problem in this section. And the goal is to obtain the minimum total system cost composed of latency and transmission rate for all vehicles in the networks. For a given uplink power allocation $$, and computing resource allocation $$, we define the system utility as the weighted-sum of all the vehicles’ offloading utilities,

$ $.

This utility means getting a more enormous execution time utility with a minor upload time cost. We now formulate the Joint Resource Allocation and Task Offloading Problem as a system utility maximization problem, i.e. The robust optimization problem is formulated as follows,

优化函数

3

4

Where $$ denotes the network utility, the constraints in the formulation above can be explained as follows: Constraints (13a) is used to guarantee the QoS requirements of VUEs, however, due to Large amount of computation caused by time varying network topologies, the real-time SINR is hard to obtain in vehicular communication scenario, and it can be replaced with the long-term SINR since the CSI feedback time interval is very small. $$ denotes the average SINR of the $$ V2I link when a small CSI feedback time interval is used, in order to ensure that the task is successfully offloaded to the RSU, the SINR should be guaranteed to be no less than the SINR threshold \cite{liu2021}. $$ is the SINR threshold for successful detecting the V2I communication. $$ defines the probability of the input. In this case, we introduce the outage probability constraint (13a) to guarantee the reliability of vehicular links \cite{Li2020}. $$ is the delay bound of the $$ V2I link in the process of data transmission. $$, $ $ are the outage probability thresholds of SINR and delay constraint respectively, where $$. constraints (13c) state that each MEC server must allocate a positive computing resource to each user associated with it and that the total computing resources allocated to all the associated users must not excess the server’s computing capacity, in another word, the number of applications served by a particular edge cloud should be within its capacity. (13b) denote the total latency of communication and computing should be guaranteed to be no less than the time threshold, $$ is the maximum transmit power of the transmit vehicle in vehicle communication network, and the transmit power is greater than zero in (13d).

**Ⅲ PROBLEM SOLUTIONS**

In this section, we proposed a BCD-based algorithm to solve the problem (13). The BCD method enables the complex original problem to be decomposed into a succession of simpler subproblems \cite{Bertsekas1999}. Motivated by this fact, all variables are divided into two blocks and optimized alternatively.

By fixing $$, the problem (13) can be transformed into the following problem.

优化函数

4

**A．Successive Convex Approximation of the Objective Function**

Since the original problem is a non-convex and NP-hard because of the logarithmic function in the objective function, here, the method of successive convex approximation is adopted to relax the original problem and make objective function solvable. We can use the lower bound to approach the original function as follows.

Each term of (14) can be represented by $$ through successive convex approximation, where $$ and $$ can be chosen as $$, $$, $$=1, $=0, and each term of objective function can be written as follows,

It is still hard to directly calculation because of fractional from of SINR, we use variable substitution, i.e. $$, $$, then

**B．Approximate of the Outage Probability Constraint**

中断概率约束表示为

It is obvious that the constraint (14a) includes uncertainties and the objective function is a non-convex problem in (14), so the objective function and constraints are difficult to deal with when determining the optimal solutions. It is necessary to design an algorithm with lower complexity to solve the problem. In this paper, For the uncertain channel gain. Considering the fast fading. Two common forms are adopted to describe the uncertainty mentioned above, i.e. the statistical constraints and deterministic constraints. to pursue a simple form of (14a), a matrix form is introduced, the general form the channel gain is described as,

Where$ $,

Furthermore, the Bernstein method is adopted to approximate the probability constraint with channel uncertainty

Theorem 1: The outage probability of all cochannel V2I links $$

is reformulated as the separable constraints (14a)

Where $$, these parameters (i.e. $$ and $$) are deduced to be positive in \cite{Liu2019}. Suppose that the truncated distributions of $$ have bounded supports $$, $$ is an estimate of $$, Introduce constants $$, $$ to normalize the supports to $$ as follows,

In the last term of (19), the variables $$ are coupled nonlinearly. Hence, directly finding an acceptably good solution to (14a) by the Bernstein method is time consuming when the K increases and the number of vehicles is large. Therefore, it is necessary to Introduced a $$ approximate problem for any $$. Hence, the last term in (19) containing $$ of the vector is further approximated by $$. Based on these, the constraint in (14a) is further formulated as fellow with lower complexity and higher reliability,

$ $

To pursue a simple form of (21), we define $ $.

The constraint (14b) can be handled by an Integral transformation method, According to constraint (14b), where $$, $$, $$, $$, $$ is an exponential random variable with unit mean, i.e., $$.

we can get the feasible power region of the communication delay probability as follows,

The proof of the feasible region can be found in Appendix B

The probability constraint of (14b) can be transformed to the deterministic one according to the following inference

Then, we have the equivalent result of the inequality function in (24) as

Where

In summary, we can obtain a deterministic optimization problem of robust power allocation by transforming the objective function, outage probability constraints, delay constraints. It is expressed as,

P1

2

4

**C．Optimal Power Control Algorithm**

To pursue an iterative algorithm for solving the problem, Lagrange method is used to maximize the lower bound of the original objective under given coefficients $$ and $$. It is noted that these two coefficients should be updated to guarantee a monotonic increase in the lower bound performance.

Hence, the Lagrangian function of (26) under fixed coefficients $$ and $$ can be expressed as,

Where $$ and $$ are the Lagrangian multipliers, and $$, $$.

The power vector $$ iteration function is obtained by

28

Based on (28), the iteration for the power allocation, can be formulated as,

29

The Lagrangian multiplier $$, $$, are updated through the sub-gradient method, which are formulated as,

Where $$, $$ denote the step-size, and $$, $$. $$ denotes the iteration index. $$.

**D. Computing Resource Allocation**

After obtaining $$, the formulated problem with respect $$ reformulated by:

max

3

Notice that the constraints in (32a) and (32b) are convex, by calculating the second-order derivatives of $$, the Lagrangian function is constructed to seek the optimal powers. Hence, (32) is a convex optimization problem and can be solved using Karush-Kuhn-Tucker (KKT) conditions. The Lagrangian function of (32) is formulated as,

目标函数求导了

Based on (33), the iteration for the computing resource allocation, can be formulated as,

In order to prove the concavity of (32), the following research is taken. The first-order derivative of $ with respect to $$ is,

in which, for simplicity

The second-order derivative of is obtained further as,

it is obvious that the second-order derivative of $ with respect to $$ is always less than zero. Therefore, $ is a concave function about $$, Hence, (32) is a convex optimization problem and can be solved using Karush-Kuhn-Tucker (KKT) conditions.

Let, the optimal computing resource allocation is obtained by

The iterative expression is as follows,

The Lagrangian multiplier $$, $$, are updated through the sub-gradient method, which are formulated as,

With the above efforts, we successfully transform the original problem into two convex subproblems. Then, an alternative iterative algorithm which is summarized in Algorithm 1 is proposed to solve them.

**算法伪代码**

where P∗ and F can be obtained through Algorithm 1

Algorithm 1: Joint Robust Power Control and Task Offloading Scheduling Algorithm

Input Set the maximal iterative number Tmax, the fixed price C and the step size φ.

Initialize the log-domain power vector,computing resource allocation and the Lagrangian multiplier vector

repeat

Calculate

Given feasible points ,

Solve problem P4, and obtain the current optimal solution .

Update ˜ p and λ using (20) and (23), respectively.

Given feasible points ,

Solve problem P4, and obtain the current optimal solution .

Update ˜ f and λ using (20) and (23), respectively.

Until synchronously converge to the optimal solutions  **f p**

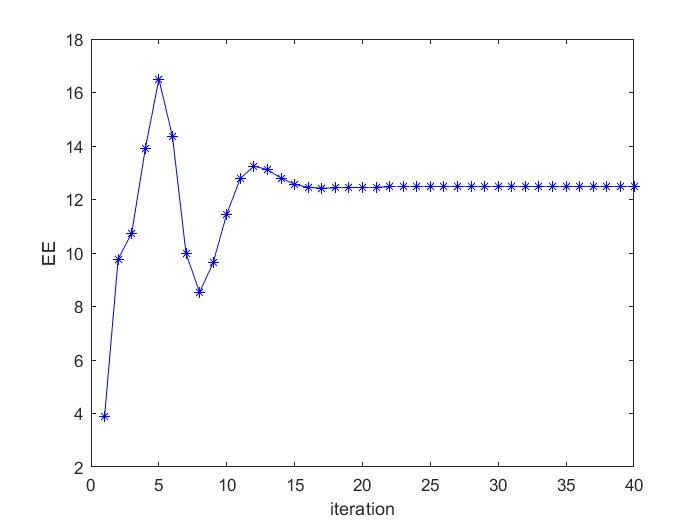
Output:

**Ⅳ SIMULATION AND PERFORMANCE EVALUATION**

In this section, numerical simulations are presented to evaluate the performance of the proposed Algorithm1. A MEC-based vehicular network system which includes five clusters under a certain time slot is selected as our fundamental simulation scenario. The major system parameters are listed in Table II. It is noted that the carrier frequency f and the bandwidth W are set as 10 MHz in the numerical simulations. We assume that both the vehicles and RSUs use a single antenna for uplink transmission and reception, respectively, and the variation of the vehicles’ speed is negligible within the reference time interval. Unless stated otherwise, the parameter value of $$ is set to $$, the outage probability threshold $$.

假设车速在某个较小的时隙内为常数[85]。

Assume the variation of the vehicles’ speed is negligible within the reference time interval,

除非特别说明，车辆速度与计算所需要的CPU周期数如下表所示task workloads.

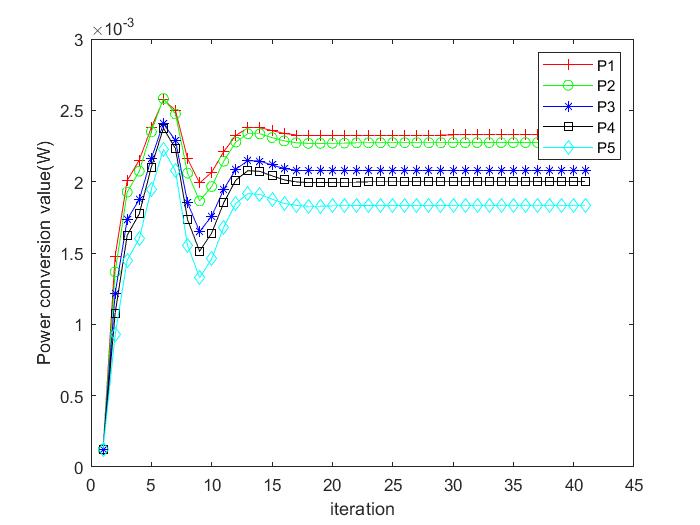
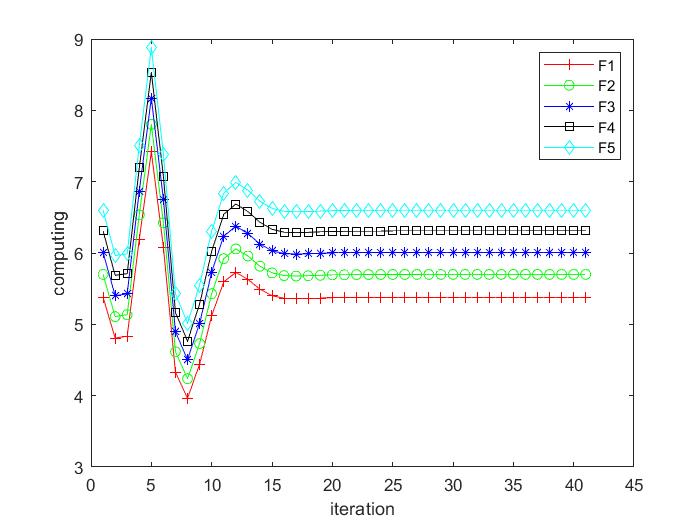
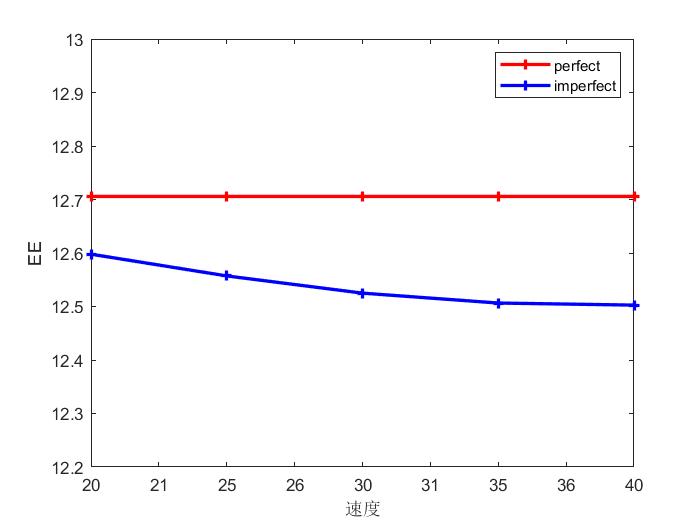


Fig. 1 and Fig. 2 show that the power allocation of each vehicle transmitter and the corresponding computing resource which cloud allocation to RSU in Algorithm1, respectively. It can be seen that the computing resources allocated in the cloud peak at the fifth iteration and begin to decline because of the limitation of total computing resources $$ from the cloud. The corresponding power resource allocation also changes due to computing resources allocation under Joint Robust Power Control and Task Offloading Scheduling.

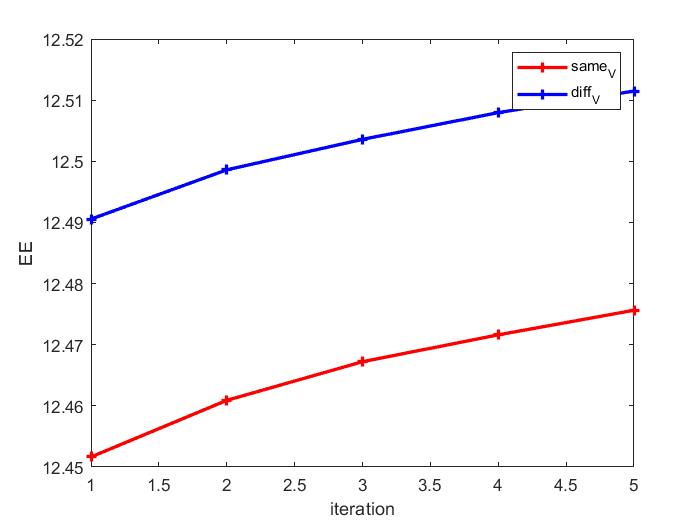
This phenomenon is reasonable due to the definition of $$ in (12). $$ increases logarithmically as the power vector $$ increases, the upload time $$, as the denominator of $$, will decrease with the increase of power vector $$ and as the executive utility of the numerator part, $$ decreases inversely proportional with the increase of computing power $$,causing the numerator to increase with the increase of $$.

As the upload time of the $$ denominator part, $$ increases logarithmically with the increase of the power vector $$, causing the denominator to decrease with the increase of power,

 In the MEC-Enabled vehicular cloud system. It is unrealistic not to take into account the mobility of the vehicle. We then investigated the impact of vehicle mobility on system performance, Assume the variation of the vehicles’ speed is negligible within the reference time interval,

In order to further illustrate the influence of speed-induced Doppler shift on system performance, the comparison experiment between the benchmark value and the increasing speed measurement under the condition of constant vehicle speed is simulated in the system.

Since the relative speed in the V-RSU link is zero, And the speed of all vehicles is the same in the same network there is no Doppler effect. Then the vehicle speed on the road is set to 20 m/s, 30 m/s, 40 m/s, 50 m/s and 60 m/s, respectively，It can be seen from Fig. 5 that with the increase of vehicle speed, the utility value of the V2E network decreases, This is because the higher speed will cause a greater Doppler frequency shift in the network, increase channel uncertainty, The solid blue line result also proves that methods that tend to obtain a better utility when the vehicle speed Is low.



In order to further verify the performance of the proposed scheme after considering the mobility of the vehicle, the figure. 6 describes the effect of the same speed and different speeds of each vehicle under different $$ on the total utility, and it can be seen from the figure that with the change of $$, the system utility also changes, and the utility at different speeds of each vehicle is higher than that of all vehicles at the same speed, which characterizes the high robustness of the proposed method in complex dynamic vehicle networks.

In terms of computing resources allocation, we choose the default task input size as $$ (following [4], [10]), We now evaluate the system utility performance against different benchmark schemes. The purpose of this section is to show the convergence of our proposed algorithm and its performance is better than three benchmark schemes through some simulation results. The benchmark schemes are described as follow

“Independent Offloading and power control” (denoted as “IOP”), the vehicles independently make power control and the computing resources allocation

“Without vehicle power control” (denoted as “Without-VPC”): The transmit power of the vehicles is set as average power during the offloading.

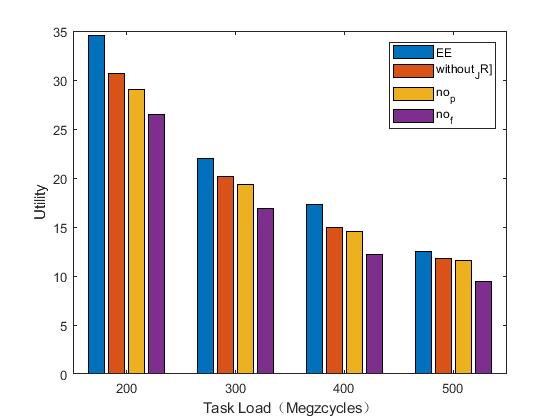
“Without computing resources allocation”: Similar to [? ] (denoted as “Without-CRA”),The transmit power of the vehicles is set as average power during the offloading.

图表, 折线图

描述已自动生成 Fig. 6 is the iterative convergence of the total utility of the system in different cases, and it can be seen from the figure that the robust joint optimization performance is better than the other three cases. It can be seen that with the increase of the number of iterations, the four methods converge to a stable value, among which the performance of proposed scheme is the best.

In order to reflect a more realistic situation, the CPU task lode (Megzcycles) required for each vehicle are often different, so we set the CPU task lode (Megzcycles) of the five vehicles to 1600, 1700, 1800, 1900, 2000.

As we can see, with the increase of the ratio of iteration, the average system utility of vehicles changes gradually and tends to be stable. In the independent optimization process, the computing resource allocation is carried out first, and the optimal power allocation is not known at this time, and the power and computing resource alternate optimization method is used, and the corresponding optimal value can be obtained for each iteration. Individual optimization is to first optimize the power $$, and after obtaining the result, the result is used for the optimization of computing resources, and then the computing resources are optimized, and finally, the utility of the system is obtained.However, if joint optimization is used, then both variables can get the optimal value.



The average system utility of the four competing schemes are plotted in Fig. 6(a) with different values of $$. It can be seen that the average system utilities of all schemes decrease with the task input size. Moreover, we observe that the performance gains of the proposed scheme over the other schemes also follow the similar trend.

图表, 条形图

描述已自动生成

我们注意到，当云端有更强大的计算能力时，也会使得系统总效用提升

The total system cost comparisons with different $$ are shown in Fig. 5. Due to the limited computation capability at the cloud, when the computation capability is small, the system utility tend to small.

图表, 条形图

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We can clearly see that as the data size increases, the system utility tend to small. This is because when the tasks require more upload time with more data size.

**Ⅴ CONCLUSION**

This paper focuses on the Joint Task Offloading and Resource Allocation for Mobile-Edge Computing Enable Vehicular Networks with channel uncertainty and co-channel interference.

The optimization scheme attempt to guarantees vehicles’ QoS when there exists a maximized utility requirement. Due to the existence of channel uncertainty, the probability forms of interference, delay, and delivery rate constraints are performed. The underlying optimization problem was formulated as a Mixed-Integer Non-linear Program (MINLP), which is very difficult to solve to optimal, then the SCA technique is applied to transform the non-convex problem of variables coupling into a treatable convex problem. The Task Offloading and power allocation algorithm is developed to achieve practical execution scheme. Simulation results showed that our heuristic algorithm performs closely to the optimal solution and significantly improves the average system offloading utility over traditional approaches.