Optimizing Channel Resource Allocation in Dynamic Vehicular Environments for Enhanced Throughput

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Abstract: In the rapidly evolving domain of intelligent transportation systems, the vehicular network is pivotal for achieving vehicle intelligence and road safety. This paper addresses the critical issue of optimizing channel resource allocation in dynamic vehicular environments to enhance communication stability and throughput. The proposed solution leverages a mixed-integer nonlinear programming (MINLP) framework to dynamically allocate subchannels and power among vehicles, ensuring high throughput and reliable communication. The algorithm integrates both V2V (vehicle-to-vehicle) and V2I (vehicle-to-infrastructure) communication types, adapting to the complex and changing road conditions. By utilizing the Link Expiry Time (LET) strategy and MIMO communication techniques, the approach ensures timely updates and robust data transmission. Through extensive simulations, the proposed method demonstrates significant improvements in system sum rate and transmission success rate compared to traditional schemes. This research advances intelligent transportation systems by providing a scalable and effective solution to meet the increasing demands of vehicular communications.

Keywords: Intelligent Transportation System; Vehicle Network; Channel Resource Allocation; Communication Stability; Throughput

1. Introduction:

With the swift progress of intelligent transportation systems, the Internet of Vehicles (IoV) has emerged as a key technology for achieving vehicle intelligence and road safety. In the IoV, vehicles can interconnect through wireless communication technologies and communicate with road infrastructure, enabling real-time information transmission and processing. However, due to the high-speed movement of vehicles and the complex and changeable road environment, the wireless communication channel in the network of vehicles is often congested and unstable, which seriously affects the reliability and efficiency of communication. Inaccurate or delayed vehicle sensor data can significantly impact the performance of algorithms that rely on real-time information. For instance, if a sensor reports false data or experiences latency, it can lead to erroneous decisions in navigation or collision avoidance systems. This can result in reduced safety, as the vehicle may react too late to obstacles or make inappropriate speed adjustments. Furthermore, the overall efficiency of autonomous systems may diminish, as algorithms designed to optimize route planning or energy consumption could miscalculate based on flawed inputs. Ultimately, ensuring accurate and timely sensor data is critical for enhancing algorithm performance and ensuring vehicle safety.

2. Organization of the Text

2.1 Using the Link Expiry Time(LET) strategy

The situation around the vehicles should be updated timely, the Link Expiry Time(LET)[1] strategy plays a role in adjusting the transmission intervals based on state and link lifetime, the Link Expiry Time(LET) between two vehicles can be calculated based on their current positions, speeds, and directions of movement:

$$\mathrm{LET} = \frac{-d+\sqrt{d^2-4ab}}{2a} \tag{1}$$

Where d is the distance equal to $\Delta x\Delta vx+\Delta y\Delta vy$, the sum of square of the v is equal to $\Delta v_x^2+\Delta v_y^2$, b is equal to $(\Delta x)^2+(\ \Delta y)^2$; Δx refers to the difference between the x-coordinates of the two vehicles , Δy refers to the difference between the y-coordinates of the two vehicles, Δv_x refers the difference in the x-components of the velocities between two vehicles whereas Δv_y refers the difference in the y-components of the velocities between two vehicles. The LET is the time until the link between two vehicles is expected to expire, given their current relative motion. This value is used to dynamically adjust the hello packet transmission intervals to ensure timely updates on surrounding vehicles. The first step of the LET strategy is to calculate the LET, and each car calculates the LET periodically according to the relative position and speed of neighboring vehicles. In addition, it is also important to adjust the interval, according to the calculated LET, each car adjusts the transmission interval of hello packets according to its current role status. Finally, we need to update the broadcast, with the vehicle broadcasting hello packets at adjusted intervals, ensuring timely updates on its status and surrounding network topology. This approach can significantly improve the communication efficiency of the in-vehicle network, ensuring that the network can maintain stability and high throughput even in a rapidly changing environment.

The communication framework between the moving vehicle and the cluster head utilizes multiple-input multiple-output (MIMO) communication. This method, authorized by the Federal Communications Commission (FCC) in the 5.9 GHz band, allocates 75 MHz of spectrum under the Dedicated Short Range Communications (DSRC) protocol.[2] In vehicle-to-vehicle (V2V) communication scenarios, multipath propagation can significantly affect bridge performance due to reflection, diffraction, scattering, and shadows caused by numerous objects in urban areas. This results in signal distortion and requires advanced techniques to ensure high-quality communication. Each vehicle employs an Orthogonal Frequency-Division Multiplexing (OFDM) transceiver,which is compatible with the Dedicated Short Range Communications (DSRC) protocol. OFDM helps in managing the multipath effects by dividing the signal into multiple narrowband channels, thereby reducing inter-symbol interference (ISI). To exploit the multipath environment, spatial multiplexing MIMO technique is advocated. The key advantage of this approach is the improvement of Quality of Service (QoS) from a data rate perspective,which is directly proportional to both the number of transmit antennas (Nt) and the utilized bandwidth. Let Nt denote the number of antennas at the transmitter and Nr the number of antennas at the receiver. The communication link can be expressed as:

$$y = Hx + n \tag{2}$$

Where H represents the channel response matrix with dimensions N_r*N_t, x is the transmitted data vector, y is the received data vector, and n is the added noise vector due to channel phenomena. The channel response matrix H models the interaction of transmitted signals with the environment, capturing the effects of multipath propagation. At the receiver end, an additional phase of signal processing could be used to mitigate the effects of the channel. Techniques like Zero Forcing (ZF) and Minimum Mean Squared Error (MMSE) are applied to regenerate and process the received signals, effectively removing the distortions introduced by the channel.

2.2 IOV Work

The IoV represents a groundbreaking technological innovation that facilitates diverse automotive applications enabled through the integration of vehicles into the network.

By utilizing tactile Internet alongside V2I and V2V communication, task computing services can be delivered through roadside units (RSUs) or directly on vehicles, enhancing the efficiency in task handing in connected vehicle applications. However, the field faces numerous challenges, particularly concerning edge computing in V2I/V2V contexts. Several studies have tackled issues related to delegating tasks and distributing resources within vehicle edge computing architectures. Some researchers have concentrated on delegating tasks to the RSU. For example, The current body of research has explored various task offloading scenarios in vehicular networks, utilizing different approaches to optimize system performance. One study investigated a multi-edge-node-and-vehicle task offloading scenario with Vehicle-to-Vehicle (V2V) relays, proposing a novel routing scheme and a balanced task offloading strategy. However, this approach overlooked the computing resources of vehicles by offloading all tasks to edge nodes, thereby not fully utilizing local computational capabilities. Another study addressed a joint load balancing and task offloading problem to maximize system utilization in Vehicular Edge Computing (VEC) networks, by dynamically deploying tasks to either local vehicles or edge clouds.

Alternatively, a game-theoretic approach was employed to determine task offloading strategies in real-time dynamic vehicular systems. Additionally, another study proposed a model segmentation method, deploying models on vehicles and base stations to enable efficient task offloading and resource allocation strategies. While this method leveraged both local and edge computing resources, it did not consider the idle computing resources of nearby vehicles, potentially missing opportunities to further enhance system performance. These studies did not investigate the potential of task offloading among vehicles through V2V communication. By leveraging the additional computing resources of certain vehicles, task processing performance could be significantly improved by offloading tasks to these vehicles.

To address this gap, one study proposed a collaborative task scheduling framework among vehicles, incorporating a dynamic pricing scheme to incentivize vehicles to share their computing resources, thereby maximizing benefits through deep reinforcement learning techniques. Another study developed an optimization model focusing on minimizing computing delays for target vehicles, employing a particle swarm optimization algorithm. Similarly, a delay-optimal framework for V2V task offloading was presented, which aimed to reduce task processing delays for task vehicles by using a learning-based adaptive task offloading algorithm that dynamically determines the offloading position.

Although these studies optimized task offloading from V2V and Vehicle-to-Infrastructure (V2I) perspectives, the exclusive use of either V2I or V2V offloading limits the system's optimization flexibility. In scenarios with a high density of vehicles, reliance solely on V2I offloading may overwhelm Roadside Units (RSUs), whereas exclusive V2V offloading may not always ensure reliability due to vehicle mobility. Hence, a cooperative task offloading approach that integrates both V2I and V2V modes could effectively address these challenges, thereby enhancing overall system efficiency and ensuring the Quality of Service (QoS) for vehicular users.

Research on cooperative task offloading between vehicles and RSUs remains limited. One study identified resource-rich vehicles as service providers and proposed a federated Q-learning approach to minimize communication and computing costs, as well as to reduce offloading failure probabilities. Another study classified vehicles into client and fog vehicles, utilizing machine learning and coded computing technologies to address delay-sensitive data offloading challenges. A further investigation introduced a decentralized deep reinforcement learning (DRL) algorithm to maximize the sum capacity during offloading, but this method was confined to V2V and V2I communication modes. Additionally, a study focused on joint optimization of task offloading and resource allocation, considering only V2I offloading, with tasks relayed via V2V transmission for vehicles outside RSU coverage. Another study considered a two-step task offloading process, where tasks were first offloaded to vehicles through RSUs and then further relayed to other vehicles, excluding the V2V offloading mode.

The use of fixed task offloading modes is impractical in Internet of Vehicles (IoV) scenarios, where vehicles may act as both providers and consumers of computing resources, requiring or offering task computing services at different times. An effective task offloading strategy should dynamically combine V2I and V2V modes, harnessing the full potential of all available resources to ensure optimal performance and flexibility under varying vehicular network conditions.

2.3 Algorithm

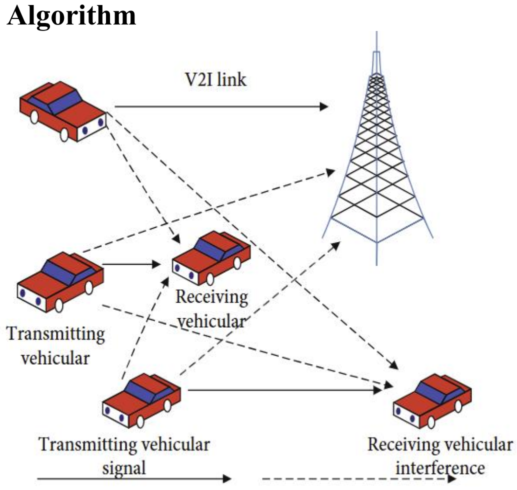

Figure 1. The Model of Communication

In a dynamic vehicle environment, efficient channel resource allocation is the key to ensure high throughput and reliable communication. This paper presents a new algorithm for optimizing sub-channel and power allocation in vehicle-networking, with special attention to vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication. The algorithm utilizes a mixed integer nonlinear programming (MINLP) framework, which is challenging due to the non-convexity of the problem and the real-time constraints of the vehicle network. Resource allocation problems in vehicle networks aim to maximize the sum rate of the system, including V2V and V2I communication. The main constraints include ensuring a minimum transfer rate for each V2V and V2I link, adhering to maximum power limits, and ensuring that each subchannel is occupied by a limited number of V2V links. Specifically, the optimization problem can be formulated as:

The performance of the proposed algorithm is evaluated through a large number of simulations in a dynamic vehicle environment. Key metrics considered include system and rate, transfer success rate, and computational complexity. The results show that compared with the traditional resource allocation scheme, the proposed algorithm significantly improves the throughput. It effectively balances the tradeoff between V2V and V2I links between maximum and minimum interference. [4] The novel subchannel and power allocation algorithm proposed in this paper provides a robust solution for optimal resource allocation in dynamic vehicle environments. By dividing MINLP problem into manageable sub-problems and adopting efficient matching and optimization techniques, the algorithm improves the overall throughput and reliability of the system. This approach is critical to advancing intelligent transportation systems and supporting the growing demand for high-throughput vehicle communications.

The dynamic nature of vehicle environment poses a major challenge to channel resource allocation, which directly affects the stability and throughput of communication. New algorithms for optimizing subchannels and power allocation in this study address these challenges by integrating advanced techniques such as mixed integer nonlinear programming (MINLP) and MIMO communication. The key innovation lies in its ability to dynamically adjust to changing vehicle network conditions, ensuring high throughput and reliable communication.

The use of the Link Expiration Time (LET) policy to adjust the hello packet transmission interval based on the vehicle state and link lifetime is particularly effective in maintaining timely updates of the vehicle's surroundings. This dynamic adjustment helps mitigate the effects of rapid vehicle movement and changes in road conditions, thereby improving the stability of the entire network.

In addition, the implementation of MIMO and OFDM technologies within the framework of DSRC protocol provides a powerful solution to the multipath propagation problem that is prevalent in urban environments. The spatial multiplexing capabilities of MIMO, combined with the ability of OFDM to handle multipath effects, significantly increase data rates and reduce intersymbol interference, thereby improving quality of service (QoS).

However, the algorithm's reliance on precise real-time data on the vehicle's position and speed is a potential limitation. Inaccuracies in these data can lead to sub-optimal resource allocation and reduced communication efficiency. In addition, although the collaborative task offloading scheme between vehicle and rsu proposed in this paper effectively balances V2V and V2I communication modes, its success depends largely on the availability of sufficient computing resources in the vehicle network.

Future work could explore integrating machine learning techniques to predict vehicle movement patterns and further optimize resource allocation. In addition, in order to verify the algorithm's performance in various traffic conditions and ensure its scalability in large vehicle networks, a large number of real-world tests are essential. In summary, this study provides a promising method for enhancing vehicle communication networks and contributes to the development of intelligent transportation systems.

This study is expected to significantly enhance the stability and efficiency of communication within the Internet of Vehicles (IoV), providing technological support for efficient communication in intelligent transportation systems. Additionally, the findings of this research are anticipated to offer both theoretical and practical foundations for the standardization and commercialization of IoV applications.

One of the primary challenges in applying MINLP to VANETs is the non-convex nature of the optimization problem, which can lead to multiple local optima and hinder the search for a global solution. To address this challenge, several strategies can be employed. First, incorporating relaxation techniques can simplify the problem by temporarily ignoring certain constraints, allowing for an initial feasible solution that can be iteratively refined. Second, heuristic methods, such as genetic algorithms or particle swarm optimization, can be utilized to explore the solution space more effectively, providing a way to escape local optima. Additionally, using decomposition techniques can break down the MINLP problem into smaller, more manageable subproblems, each of which can be solved with greater efficiency. By leveraging these approaches, the MINLP framework can significantly enhance the performance of algorithms in VANETs, ultimately improving network reliability and vehicle communication efficiency.

3. Conclusion

This study proposes a novel channel resource optimization allocation algorithm for dynamic vehicular environments, significantly improving communication stability and throughput. The algorithm utilizes a Mixed-Integer Nonlinear Programming (MINLP) framework to address the complex non-convex resource allocation problems in vehicular networks, with a particular focus on Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communications. By incorporating strategies such as timely updates using Link Expiry Time (LET) and Multiple Input Multiple Output (MIMO) communication to enhance data rates, the method effectively adapts to rapidly changing vehicular environments.

Extensive simulations demonstrate that the proposed algorithm substantially improves system sum rate and transmission success rate while maintaining manageable computational complexity. Achieving a balance between maximizing throughput and minimizing interference is crucial for the effective operation of Intelligent Transportation Systems (ITS). The algorithm dynamically adjusts to vehicular network conditions, optimizing resource allocation for V2V and V2I communication modes, thereby ensuring network robustness and efficiency even in high-density, high-mobility traffic scenarios.

While the proposed MINLP-based channel resource optimization algorithm offers significant improvements in communication stability and throughput in dynamic vehicular environments, it is not without limitations. One key challenge is the computational complexity inherent in solving MINLP problems, which can lead to longer processing times, particularly in real-time applications where rapid decision-making is crucial. Additionally, the reliance on timely updates using Link Expiry Time (LET) may be compromised in scenarios with high mobility or rapidly changing traffic conditions, potentially affecting the accuracy of resource allocation.

Moreover, while Multiple Input Multiple Output (MIMO) technology enhances data rates, its implementation can be resource-intensive and may require additional infrastructure support, which might not be feasible in all environments. Finally, the algorithm's performance could be sensitive to the accuracy of input parameters, such as vehicle density and channel conditions; inaccuracies in these estimations could degrade the optimization results. Addressing these limitations will be essential for ensuring robust performance in diverse vehicular networks.

The findings provide a solid theoretical and practical foundation for the standardization and commercial application of vehicular networks, fostering the development of ITS and supporting the growing demand for high-throughput vehicular communications. Future work may explore further refinements to the algorithm and its deployment in real-world settings, contributing to the ongoing evolution of the smart connected vehicle ecosystem.

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