Vehicular Edge Computing: A Survey on Service Caching, Task Offloading, and Resource Allocation

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Abstract

Vehicular Edge Computing (VEC) is a transformative paradigm that integrates edge computing resources with vehicular networks to enhance computational capabilities at the network's edge. This survey paper comprehensively analyzes VEC, focusing on three critical components: service caching, task offloading, and resource allocation. VEC addresses the challenges of high mobility and dynamic network conditions by enabling efficient task distribution and minimizing latency. Key strategies include the integration of Mobile Edge Computing (MEC) with vehicular networks, the use of deep reinforcement learning (DRL) algorithms for dynamic task offloading, and the implementation of traffic-aware and cooperative caching architectures. Furthermore, the inclusion of High Altitude Platforms (HAPs) and Reconfigurable Intelligent Surfaces (RIS) enhances VEC systems' performance in heterogeneous environments, supporting real-time applications and reducing energy consumption. The survey highlights the significance of security and privacy in service caching, proposing blockchain technology and cryptographic techniques as potential solutions. Despite these advancements, challenges such as high mobility, dynamic network conditions, and resource constraints persist. Future research should focus on developing adaptive strategies and frameworks that leverage emerging technologies like Distributed Massive MIMO (DM-MIMO) systems, digital twin technology, and cognitive Software-Defined Networking (SDN) to enhance resource management efficiency, scalability, and network performance. In conclusion, VEC represents a significant advancement in vehicular networks, offering solutions to the challenges of high mobility, dynamic environments, and efficient resource management, thereby paving the way for future innovations in intelligent transportation systems and smart mobility initiatives.

1 Introduction

1.1 Concept of Vehicular Edge Computing (VEC)

Vehicular Edge Computing (VEC) represents a paradigm shift aimed at augmenting computational capabilities at the network's edge to meet the growing demands of vehicular users (VUs) for real-time data processing and service delivery [1]. By decentralizing processing, VEC efficiently manages the significant computation tasks generated by VUs, which often face challenges due to high mobility and dynamic wireless conditions [2]. This approach reduces service response times and mitigates core network traffic by bringing cloud functionalities closer to the edge [3].

A key aspect of VEC is the integration of Mobile Edge Computing (MEC) with vehicular networks, facilitating edge service caching and task offloading. Edge service caching pre-stores necessary programs at Multi-access Edge Computing (MEC) servers, enhancing task execution efficiency and significantly reducing latency by minimizing data travel distances. Task offloading, which distributes computational tasks from vehicles to edge servers, exemplifies VEC's capability to optimize task distribution and processing efficiency [4].

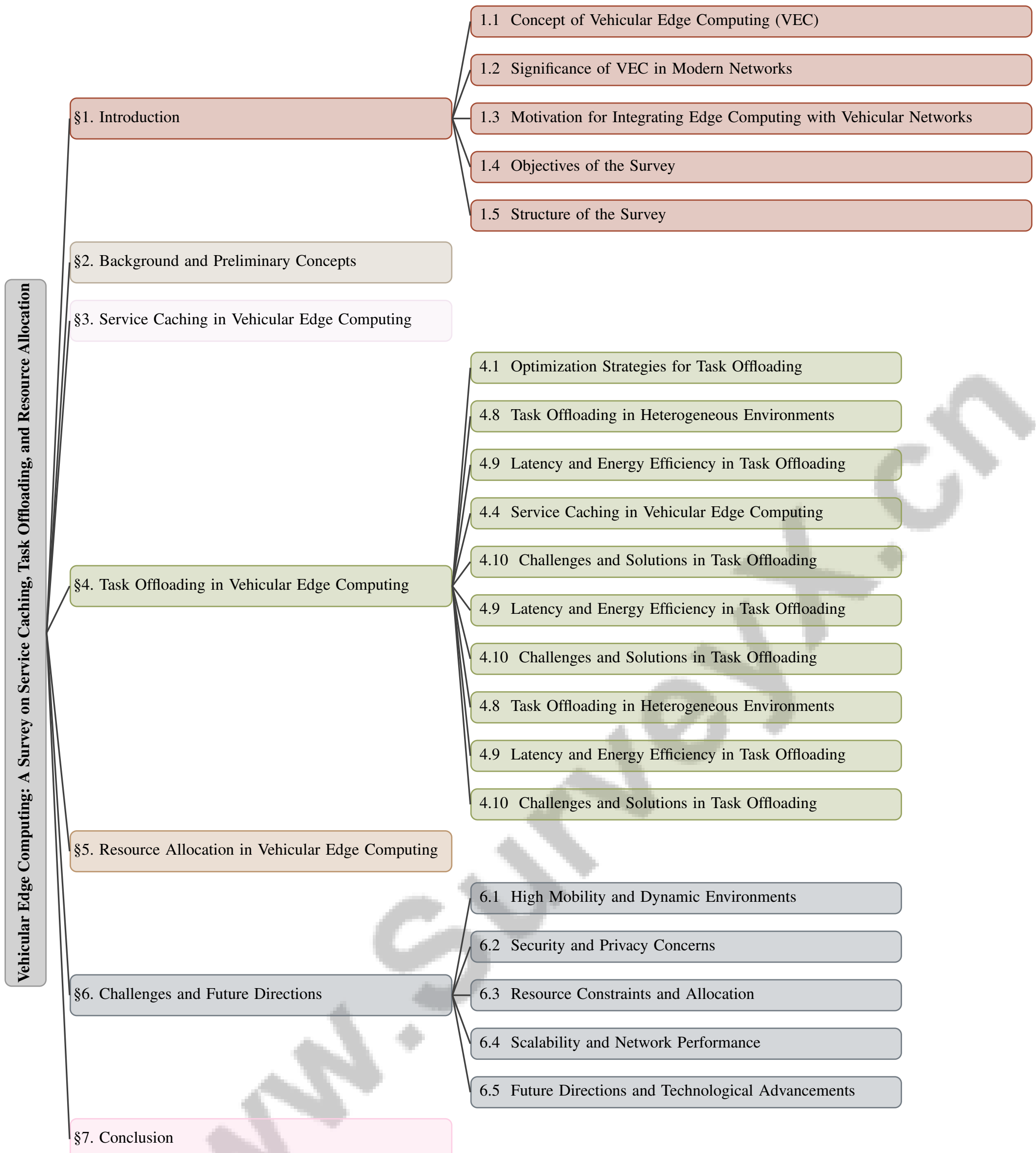

Figure 1: chapter structure

VEC supports real-time applications by caching content in roadside units (RSUs), enabling vehicles to quickly access requested information [5]. The inclusion of High Altitude Platforms (HAPs) in VEC frameworks, termed HAP-Assisted Vehicular Edge Computing (HAP-VEC), enhances processing efficiency by offloading tasks from ground vehicles to HAPs, particularly benefiting service delivery in rural areas [6]. Moreover, integrating satellite-terrestrial systems bolsters the reliability and scalability of VEC networks [7].

The architecture of VEC, where vehicles act as mobile edge servers providing computational resources to nearby User Equipments (UEs), underscores its transformative potential in modern vehicular networks [8]. Innovations such as the VEC-Sim simulation platform, designed for evaluating service caching and computation offloading policies, facilitate the optimization of VEC networks [9]. Collaborative Vehicular Edge Computing (CVEC) further enhances performance and resource utilization, addressing the complexities of networking operations and the increasing demands of service applications.

1.2 Significance of VEC in Modern Networks

The significance of VEC in modern networks is underscored by its capacity to enhance network capabilities and minimize latency, which is essential for the seamless functioning of autonomous vehicles and mission-critical Internet of Things (IoT) services. By integrating MEC with vehicular networks, VEC effectively addresses the challenges of balancing shared messages with limited bandwidth and computational resources, thereby improving the perception range and reliability of autonomous vehicles [10]. This integration alleviates the burden on smart vehicle CPUs and reduces network congestion [11].

Traditional communication protocols often incur latencies of 20 to 100 milliseconds, inadequate for the low-latency requirements of modern applications [12]. VEC mitigates these limitations by processing requests at the edge, reducing traffic on centralized cloud platforms and minimizing service delays, which is particularly crucial within 5G networks where ultra-low latency is vital [13].

Additionally, the integration of MEC enhances network capabilities by enabling dynamic and efficient content delivery systems through vehicular caching [14]. This approach improves channel spectrum efficiency and capacity while addressing challenges posed by uncertain channel conditions and stochastic task arrivals, which can significantly impact power consumption and latency [4]. In the context of UAV applications within 5G networks, dedicated MEC resources have been shown to significantly outperform traditional cloud solutions, highlighting the necessity of edge computing in modern vehicular networks [15].

Moreover, VEC enhances communication and computation in Internet of Vehicles (IoV) systems, addressing energy efficiency challenges [16]. The integration of blockchain and edge computing technologies further improves security, privacy, and operational efficiency in vehicular networks [17].

The three-layer architecture of VEC, comprising vehicular terminals, edge servers (RSUs), and cloud servers, emphasizes the role of edge servers in providing low-latency services [1]. Additionally, while many studies focus on energy consumption, the potential of edge computing to significantly reduce the carbon footprint in the information and communications technology (ICT) sector is noteworthy [18].

1.3 Motivation for Integrating Edge Computing with Vehicular Networks

The integration of edge computing with vehicular networks is driven by the need to overcome traditional network architecture limitations, such as high latency and inefficient resource management. The increasing complexity of vehicular networks, fueled by the proliferation of connected devices, necessitates optimization of energy efficiency and real-time communication capabilities [12]. This is particularly crucial in Internet of Vehicles (IoV) systems, where edge computing enables efficient utilization of heterogeneous architectures, supporting large-scale IoV deployments [19].

A core motivation is the challenge of joint resource allocation and cache placement in multi-user MEC systems, which requires effective management of computation resources and caching to enhance performance [20]. The integration of edge computing also aims to improve data freshness by optimizing task offloading strategies that account for vehicle-road interactions, thus enhancing overall service quality [21].

Furthermore, this integration addresses the need for energy-efficient caching and task offloading, vital for maintaining real-time updates and efficient cache refreshing [22]. The dynamic and harsh communication environments in vehicular networks, alongside limited edge resources, necessitate innovative solutions for effective task offloading and resource management [23].

Additionally, the integration seeks to mitigate communication interruptions caused by physical obstructions, employing technologies such as reconfigurable intelligent surfaces (RIS) to enhance service quality for low-latency applications [24]. The extensive coverage of satellites combined with the high capacity and low latency of terrestrial networks further motivates this integration, providing a robust framework for reliable vehicular communications [7].

Security and privacy are also paramount in this integration, focusing on minimizing false and malicious information exchanges within Vehicular Ad-hoc Networks (VANETs) [17]. The necessity for real-time updates and efficient management of cache refreshing and computation offloading highlights the importance of edge computing in improving the efficiency, reliability, and performance of vehicular systems [25].

1.4 Objectives of the Survey

This survey aims to provide a comprehensive analysis of VEC, focusing on three pivotal components: service caching, task offloading, and resource allocation within vehicular networks. The primary objective is to explore scalable system architectures and energy-efficient computing, crucial for optimizing VEC environments [19]. The survey seeks to enhance understanding of security mechanisms and resource management strategies vital in the context of MEC [26].

A significant focus is on optimizing service caching and workload scheduling to minimize service response time and outsourcing traffic, essential in mobile edge computing environments [27]. This includes optimizing service caching placement and computation offloading decisions to reduce computation delay and energy consumption, thereby improving MEC system efficiency [7]. The survey also addresses data privacy challenges and proposes frameworks that enhance privacy protection in edge computing, particularly through federated learning.

Moreover, the survey aims to optimize task offloading and resource allocation for multiple tasks generated by vehicles within a single time slot, ensuring efficient utilization of VEC resources [7]. It explores optimizing the offloading of computational tasks from ground vehicles to high-altitude platforms (HAPs), maximizing real-time service probability while addressing latency and computational capacity constraints. Additionally, the survey focuses on optimizing resource allocation and task offloading to improve system utility and service satisfaction, critical for maintaining high performance in VEC environments.

The survey also aims to develop a specialized simulation platform, VEC-Sim, designed to enhance the assessment of diverse service caching and computation offloading strategies within VEC environments. By accurately modeling unique characteristics such as vehicle mobility, access patterns, and service dynamics, VEC-Sim facilitates the optimization and advancement of VEC networks, addressing key performance challenges and improving real-world service delivery [28, 29, 9, 30, 31]. It also addresses inefficiencies and environmental risks in applications such as oil extraction by leveraging edge computing to enhance task completion rates during high demand periods.

Finally, the survey aims to design an optimal content caching policy that adapts to the dynamic nature of vehicular networks while ensuring security and privacy. It explores joint optimization problems with multiple objectives in VEC, focusing on minimizing power consumption, propagation delay, and queuing delay [26]. Through these objectives, the survey intends to provide a comprehensive understanding of the current state and future directions of VEC, emphasizing the critical role of service caching, task offloading, and resource allocation in enhancing vehicular network performance.

1.5 Structure of the Survey

The survey is meticulously structured to provide a comprehensive analysis of VEC, focusing on key components such as service caching, task offloading, and resource allocation. It begins with an **Introduction** section that establishes foundational concepts of VEC, its significance in modern networks, and the motivations for integrating edge computing with vehicular networks, alongside outlining the primary objectives of the survey.

Following the introduction, the survey examines the section, investigating fundamental principles related to VEC. This includes comprehensive definitions and explanations of vehicular networks and edge computing, emphasizing their importance in addressing latency reduction challenges, which are crucial for the performance of Intelligent Transportation Systems (ITS) and the efficient operation of Autonomous Vehicles (AVs). The integration of MEC within VEC is highlighted, illustrating how this paradigm enhances communication, computation, and storage capabilities at the network's edge to meet modern vehicular application demands [12, 32, 28, 1, 17].

Subsequent sections delve into each key VEC component. The section on examines how service caching reduces latency and enhances service delivery efficiency by storing frequently accessed data closer to users [33]. It discusses traffic-aware and cooperative caching architectures, dynamic and adaptive caching strategies, and associated security and privacy concerns.

The section titled explores the distribution of computational tasks from vehicles to edge servers, emphasizing the advantages of enhanced processing efficiency and significant latency reductions critical for real-time applications in intelligent transportation systems. It reviews various architectures and techniques for task offloading and content caching, addressing challenges such as dynamic communication environments and energy consumption optimization, thereby contributing to the development of responsive and efficient vehicular networks [34, 28, 35, 36, 37].

In the survey titled , the authors explore challenges and innovative strategies for efficiently managing computational and network resources within VEC environments. These resources are essential for enhancing system performance and minimizing latency, particularly given the increasing demands from autonomous vehicles and advanced vehicular applications. The paper provides a comprehensive analysis of resource allocation schemes, addressing critical factors such as communication reliability, bandwidth optimization, and the integration of edge computing technologies to meet stringent Quality of Service (QoS) requirements in modern vehicular networks [38, 39, 28, 1].

The survey also includes a section on , identifying current challenges in implementing VEC, such as high mobility, security concerns, and resource constraints, while discussing potential future research directions and technological advancements to address these challenges.

Finally, the survey concludes with a section summarizing key findings and emphasizing the importance of service caching, task offloading, and resource allocation in enhancing vehicular network performance.

The structure of the paper includes an evaluation of methods such as the FSEC, assessing its performance against baseline heuristics and discussing its advantages and limitations [40]. This organized approach ensures a thorough understanding of VEC's current state and future potential.The following sections are organized as shown in Figure 1.

2 Background and Preliminary Concepts

2.1 Vehicular Networks and Edge Computing

Vehicular networks are pivotal in intelligent transportation systems, facilitating real-time communication between vehicles and infrastructure to enhance safety and traffic management [41]. These networks, characterized by high mobility and dynamic topologies, face challenges in computation-intensive task offloading and caching strategies [19]. The integration of Mobile Edge Computing (MEC) with vehicular networks mitigates these challenges by providing localized computing resources, thereby reducing latency and improving service quality [23].

MEC enables task offloading to nearby edge servers, reducing dependency on centralized cloud services and minimizing data processing latency, especially in high-density vehicular scenarios where congestion can impair performance [23]. The deployment of MEC infrastructure, such as Road Side Units (RSUs), supports efficient task offloading and data processing near the source [7].

Service caching, involving the pre-storage of frequently accessed data at the edge, is crucial for reducing latency and enhancing network efficiency [20]. However, despite its significance, this area requires further exploration to optimize edge computing performance. The dynamic nature of vehicular networks, marked by frequent handoffs and interruptions, complicates task continuity and resource management [27].

Advanced technologies like Distributed Massive MIMO (DM-MIMO) systems and High Altitude Platforms (HAPs) enhance vehicular communication by improving signal quality and processing capabilities for real-time data analysis, particularly in rural areas [7]. The Three-Tier Edge-Cloud Orchestration Architecture organizes existing research into scalable architectures, energy efficiency, and security mechanisms, underscoring the need for effective resource management in vehicular networks [26].

2.2 Latency Reduction in Vehicular Networks

Vehicular Edge Computing (VEC) plays a crucial role in reducing latency within vehicular networks by utilizing localized computing resources for data processing, thus decreasing reliance on distant cloud servers. This proximity significantly enhances response times, energy efficiency, and bandwidth management, essential for the reliable operation of modern vehicular networks, particularly regarding autonomous and connected vehicle technologies [12, 1].

A significant challenge in vehicular networks is the delay from network handoffs, which can lead to interruptions and service quality degradation. The Handoff-Aware Distributed Computing Scheme (HADCS) effectively mitigates these delays, ensuring seamless data transmission and improving user experience (QoE) [42]. By managing the temporal correlation between cached data freshness and task execution duration, VEC systems can further minimize latency, enhancing vehicular network performance [22].

Optimized communication protocols and task offloading strategies are vital for reducing energy consumption and improving the sustainability of vehicular networks [16]. Energy-efficient caching and task offloading mechanisms significantly contribute to latency reduction by ensuring timely data processing and delivery [22]. Additionally, optimizing age information in vehicular networks enhances latency reduction by maintaining information freshness and minimizing task execution duration [21].

Queuing delays at access points are a significant bottleneck in VEC systems, primarily due to limited service rates associated with wireless connections. This limitation can impede data transmission, increasing latency and adversely affecting real-time applications. As vehicles continuously generate and demand data, optimizing caching strategies and enhancing communication efficiency at RSUs are crucial for mitigating these delays and improving overall system responsiveness [12, 5, 32, 28, 1]. Thus, optimized communication protocols and offloading strategies are essential for addressing these challenges and enhancing vehicular network performance.

In the Internet of Vehicles (IoV) context, VEC's role in optimizing communication protocols and offloading strategies is critical for latency reduction [12]. Leveraging distributed massive MIMO systems and HAPs can further bolster vehicular communication, establishing a robust framework for reliable and low-latency data transmission. The strategic deployment of edge computing resources, combined with advanced task offloading mechanisms, is essential for tackling queuing delays, processing inefficiencies, and content access delays.

3 Service Caching in Vehicular Edge Computing

Category	Feature	Method
Traffic-Aware and Cooperative Caching Architectures	Collaborative Strategies	DSCM[43], OREO[31]
Dynamic and Adaptive Caching Strategies	Real-Time Optimization	TO&SC-CF[44], MEC-PS[45]
Challenges and Future Directions in Service Caching	Adaptive Caching Strategies	BECC[2], DL-OCP[20], DM-MIMO[7]

Table 1: This table provides a comprehensive summary of various methods and strategies employed in service caching within Vehicular Edge Computing (VEC) systems. It categorizes the methods into traffic-aware and cooperative caching architectures, dynamic and adaptive caching strategies, and examines the challenges and future directions in service caching. The table highlights key features and methodologies, offering insights into the current advancements and research trends in the field.

Service caching is pivotal in optimizing Vehicular Edge Computing (VEC) systems by enhancing content delivery and resource allocation. As illustrated in Figure 2, the hierarchical structure of service caching in VEC details key architectures, dynamic strategies, security measures, and challenges. This diagram categorizes traffic-aware and cooperative caching architectures, highlights dynamic and adaptive caching strategies, outlines security and privacy enhancements, and identifies current challenges and future research directions in the field. Techniques such as social-aware graph pruning, traffic-aware content recommendations, and Deep Reinforcement Learning (DRL) improve content delivery efficiency, reduce latency, and enhance user experience by ensuring timely access to relevant content amidst frequent communication interruptions [46, 28]. Table 1 presents a detailed summary of the methods and strategies utilized in service caching for Vehicular Edge Computing (VEC) systems, emphasizing the significance of traffic-aware architectures, dynamic strategies, and addressing future challenges. Additionally, Table 3 offers a detailed comparison of various methods and strategies employed in service caching for Vehicular Edge Computing systems, emphasizing their distinct optimization focuses, technological integrations, and performance enhancements.

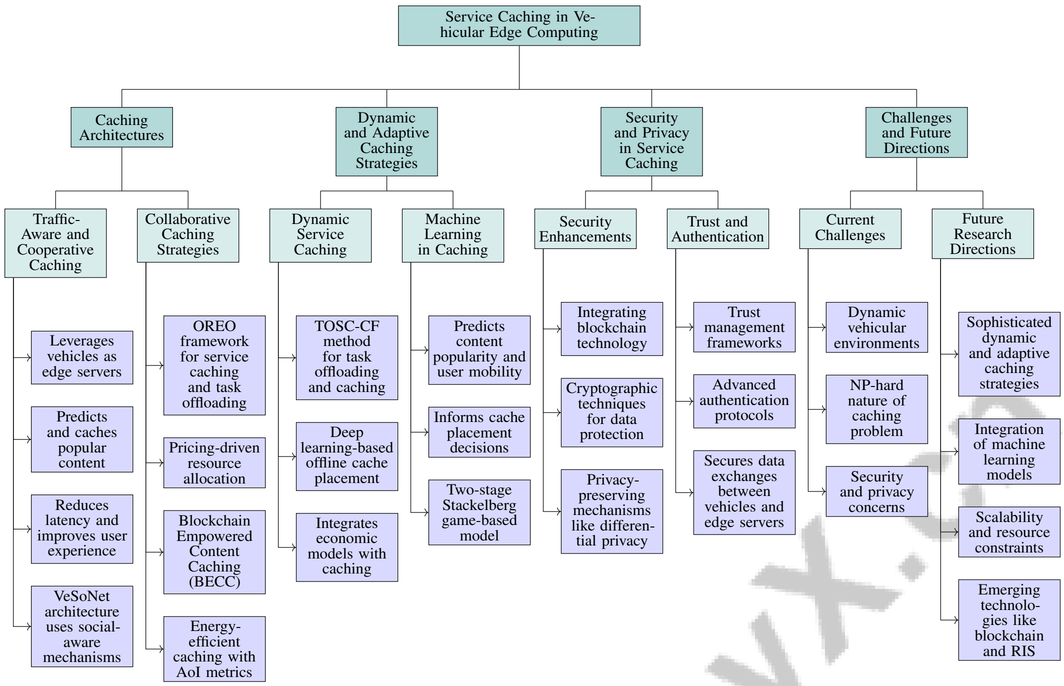

Figure 2: This figure illustrates the hierarchical structure of service caching in Vehicular Edge Computing (VEC), detailing key architectures, dynamic strategies, security measures, and challenges. The diagram categorizes traffic-aware and cooperative caching architectures, highlights dynamic and adaptive caching strategies, outlines security and privacy enhancements, and identifies current challenges and future research directions in the field.

3.1 Traffic-Aware and Cooperative Caching Architectures

Traffic-aware and cooperative caching architectures are crucial for enhancing content delivery in VEC environments, tackling challenges posed by high mobility and dynamic data requests. These architectures leverage vehicles as edge servers and employ advanced algorithms for predicting and caching popular content, significantly reducing latency and improving user experience in real-time applications [5, 28, 46, 14, 47]. The VeSoNet architecture exemplifies this approach, utilizing social-aware mechanisms that consider vehicular user movement patterns to optimize content distribution. By strategically caching frequently accessed content near users through predictive algorithms, VeSoNet reduces data retrieval times and improves service quality, employing traffic-aware recommendations and DRL for efficient content delivery in dynamic environments [46, 28, 5].

Collaborative caching strategies further enhance VEC performance. The OREO framework optimally determines services to cache and task offloading, addressing dynamic demand and resource limitations [31]. A collaborative caching approach by [43] combines service caching with workload scheduling, using a pricing-driven strategy to optimize resource allocation and ensure efficient content delivery across vehicular networks [45]. Blockchain Empowered Content Caching (BECC) integrates DRL with blockchain technology, optimizing caching strategies while enhancing security through decentralized transaction management [2]. Energy-efficient caching strategies, incorporating age of information (AoI) metrics, are crucial for maintaining optimal VEC performance by minimizing redundant data transmissions and optimizing cache placement [45, 48].

3.2 Dynamic and Adaptive Caching Strategies

Dynamic and adaptive caching strategies are essential for optimizing service delivery in unpredictable VEC environments. These strategies enhance data accessibility and reduce latency through intelligent cache management. As illustrated in Figure 3, which depicts the hierarchical structure of dynamic and adaptive caching strategies in VEC environments, various advanced methods, key challenges, and innovative solutions are highlighted. Table 2 provides a comprehensive examination of these

Method Name	Adaptive Techniques	Predictive Models	Economic Integration
TO Task Offloading	SC-CF[44]	Dynamic Adjustments	-
DL-OCP[20]	Adaptively Optimize Caching	Deep Neural Network	-
MEC-PS[45]	Adaptive Pricing Strategies	Machine Learning Techniques	Service Pricing Schemes

Table 2: Overview of dynamic and adaptive caching strategies in vehicular edge computing (VEC) environments, detailing the methods employed, their adaptive techniques, predictive models, and economic integration aspects. The table highlights the integration of task offloading, deep learning-based cache optimization, and economic models in enhancing VEC performance.

strategies, emphasizing their adaptive techniques, predictive models, and economic integration. The TO&SC-CF method, proposed by [44], exemplifies an advanced dynamic service caching strategy that integrates task offloading with caching to optimize resource utilization in VEC systems, underscoring the importance of adaptability for real-time adjustments based on fluctuating network conditions.

Deep learning techniques in cache management tackle challenges in dynamic vehicular networks. A deep learning-based offline cache placement scheme adapts to changing conditions, ensuring efficient data caching and retrieval in VEC systems [20]. By leveraging historical data, this approach predicts future data requests, enabling edge servers to pre-cache popular content, thus minimizing latency and improving service delivery.

Integrating economic models with caching strategies offers a novel perspective on enhancing VEC performance. The TO&SC-CF framework utilizes dynamic service caching strategies to optimize task processing, addressing the need for adaptive caching in vehicular networks [44]. This approach enhances service delivery efficiency and facilitates effective resource utilization by enabling dynamic adjustments in service pricing and caching strategies, guiding offloading decisions in a two-stage Stackelberg game-based model [45]. Advanced machine learning models help predict content popularity and user mobility patterns, leading to informed cache placement decisions crucial for VEC environments with frequent network topology changes [20].

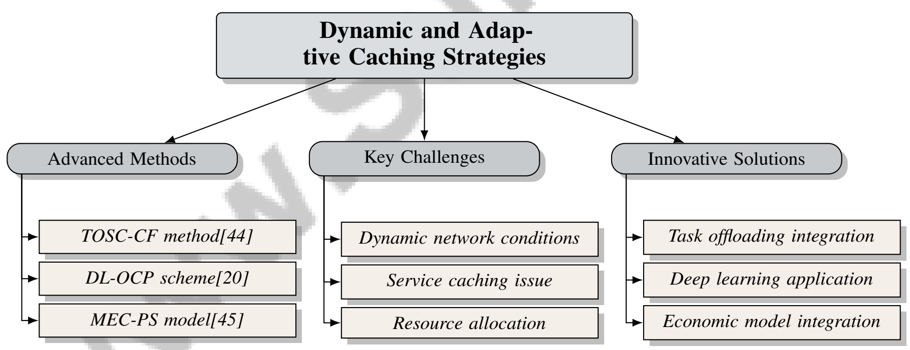

Figure 3: This figure illustrates the hierarchical structure of dynamic and adaptive caching strategies in VEC environments, highlighting advanced methods, key challenges, and innovative solutions.

3.3 Security and Privacy in Service Caching

Security and privacy are critical concerns in service caching within VEC environments, where high mobility and frequent connectivity changes exacerbate risks to data integrity and confidentiality [17]. Integrating blockchain technology into VEC systems enhances security by providing a decentralized architecture that secures data transactions, mitigating unauthorized access and data tampering risks [2]. Cryptographic techniques further bolster data protection, enabling secure sharing among edge nodes while preserving user privacy, thus addressing interception and unauthorized access challenges [17]. Privacy-preserving mechanisms, like differential privacy, enhance security by ensuring individual user data confidentiality even in collaborative caching scenarios [1].

Adopting secure service caching strategies is vital for mitigating threats from malicious nodes within the network. Trust management frameworks can identify and isolate untrustworthy entities, maintaining cached data integrity and ensuring reliable service delivery [17]. Advanced authentication protocols enhance security during data exchanges between vehicles and edge servers, preventing unauthorized access and ensuring legitimate users access cached content [1].

3.4 Challenges and Future Directions in Service Caching

Service caching in VEC systems faces several challenges that must be addressed to optimize content delivery and enhance efficiency. The dynamic nature of vehicular environments, characterized by high mobility and fluctuating network conditions, complicates caching strategy implementation. This variability complicates decision-making for caching, as vehicles frequently move in and out of coverage areas, necessitating robust solutions that adapt to changing conditions for timely data access [46, 28, 47, 22]. The inherent variability in vehicle movement and network conditions complicates accurate prediction of data demands, highlighting the need for dynamic and adaptive caching strategies.

Another significant challenge is the NP-hard nature of the service caching problem, complicating cache placement and resource allocation optimization in multi-user environments [20]. The computational complexity involved in determining optimal caching strategies can be prohibitive, particularly in large-scale networks with diverse service demands and limited resources.

Security and privacy concerns further complicate service caching in VEC, necessitating robust security mechanisms to prevent unauthorized access and data breaches. Integrating blockchain technology with edge computing has been proposed to enhance data security and privacy within vehicular networks [17].

Future research directions should focus on developing sophisticated dynamic and adaptive caching strategies that respond to real-time network changes. Integrating machine learning models like reinforcement learning could enable intelligent cache management by predicting data access patterns and optimizing resource allocation [2]. Additionally, research could prioritize scalability of service caching methods and address resource constraints in diverse vehicular environments [2]. Emerging technologies, such as blockchain and reconfigurable intelligent surfaces (RIS), offer promising avenues to improve security and efficiency in service caching [7]. Innovative approaches, such as dynamic and adaptive caching strategies that utilize predictive analytics and machine learning models, could further enhance VEC systems' performance and efficiency [20].

Feature	Traffic-Aware and Cooperative Caching Architectures	Dynamic and Adaptive Caching Strategies	Security and Privacy in Service Caching
Optimization Focus	Content Delivery	Service Delivery	Data Integrity
Technological Integration	Social-aware Mechanisms	Deep Learning	Blockchain Technology
Performance Enhancement	Reduced Latency	Real-time Adjustments	Enhanced Security

Table 3: This table provides a comparative analysis of different service caching methods in Vehicular Edge Computing (VEC) systems. It highlights the optimization focus, technological integration, and performance enhancement of three key approaches: Traffic-Aware and Cooperative Caching Architectures, Dynamic and Adaptive Caching Strategies, and Security and Privacy in Service Caching. The table underscores the importance of content delivery, service delivery, and data integrity in optimizing VEC environments.

4 Task Offloading in Vehicular Edge Computing

In the context of Vehicular Edge Computing (VEC), the efficiency of task offloading is paramount for optimizing system performance and ensuring the seamless operation of vehicular networks. As vehicles become increasingly integrated with edge computing resources, understanding the strategies and methodologies for effective task offloading becomes essential. This section delves into various optimization strategies for task offloading, highlighting their significance in enhancing resource utilization, reducing latency, and improving overall system performance.

4.1 Optimization Strategies for Task Offloading

Task offloading in Vehicular Edge Computing (VEC) is a critical process that involves transferring computational tasks from vehicles to edge servers. This process is essential for optimizing resource utilization, improving processing efficiency, and reducing latency, which are crucial for supporting real-time applications in vehicular networks. Numerous optimization strategies have been proposed to improve task offloading effectiveness in VEC environments, focusing on various aspects such as task types, resource allocation, and communication dynamics. These strategies aim to enhance the quality of service (QoS) by minimizing total energy consumption and delay, addressing the challenges posed by rapidly changing network conditions and computational demands. For instance, approaches like adaptive learning-based algorithms and joint optimization techniques have been developed to dynamically adjust offloading parameters, ensuring efficient utilization of resources and improved performance in multi-tier VEC systems [34, 49, 30, 37, 7].

Figure 4: Key optimization strategies for task offloading in Vehicular Edge Computing (VEC), focusing on learning-based optimization, resource allocation and offloading techniques, and the integration of advanced technologies. Each category highlights specific methodologies and technologies that enhance task offloading efficiency and performance in dynamic vehicular environments.

A key strategy for enhancing performance in dynamic vehicular networks involves the application of deep reinforcement learning (DRL) algorithms, which are utilized to optimize task offloading decisions by considering various factors such as resource availability, user mobility, and data dependencies. This approach not only enables efficient allocation of computational tasks to edge nodes but also adapts to changing network conditions, thereby improving overall task completion times and system stability. Recent advancements in DRL techniques, including multi-agent diffusion models and hierarchical learning frameworks, further enhance the decision-making process, allowing for more effective handling of complex, interdependent tasks in vehicular edge computing environments [8, 50, 51, 52, 53]. These algorithms leverage real-time data to make informed decisions about task allocation, considering factors such as network conditions, vehicle mobility, and computational resources. By employing DRL, VEC systems can adapt to changing network conditions and optimize task offloading processes, thereby reducing latency and improving overall network performance.

Another significant approach involves the joint optimization of resource allocation and computation offloading strategies. The Joint Resource Allocation and Cache Placement (JRACP) framework, for instance, addresses the challenges of dynamic resource allocation and cache management in multi-user MEC systems [20]. By optimizing the allocation of computation resources and caching strategies, this framework enhances the efficiency and performance of VEC environments.

Furthermore, the integration of software-defined networking (SDN) with VEC is proposed as a means to improve the adaptability and scalability of task offloading strategies [12]. The SDVEC framework, for example, allows for dynamic configuration and optimization of network resources, enabling more efficient task offloading and resource allocation in vehicular networks [12].

In addition, the optimization of task offloading strategies in heterogeneous vehicular environments is crucial for ensuring seamless communication and data processing [23]. The integration of advanced technologies such as Distributed Massive MIMO (DM-MIMO) systems and High Altitude Platforms (HAPs) further enhances the performance of VEC systems by providing improved signal quality and processing capabilities in rural areas [7].

Moreover, the implementation of energy-efficient task offloading strategies, which consider the dynamic nature of vehicular networks, is essential for reducing latency and improving the overall performance of VEC systems [22]. These strategies aim to optimize the distribution of computational tasks from vehicles to edge servers, ensuring efficient resource utilization and minimizing energy consumption [21].

4.2 Task Offloading in Heterogeneous Environments

The implementation of task offloading strategies in heterogeneous vehicular environments introduces a complex array of challenges, such as latency due to network congestion and the dynamic nature of vehicle mobility, while also offering significant opportunities for enhancing low-latency Intelligent Transportation Systems (ITS) applications through innovative solutions like on-line learning algorithms and effective base station selection. [28, 36]. Heterogeneous environments are characterized by diverse network technologies, varying computational resources, and dynamic mobility patterns, which necessitate adaptable and efficient task offloading strategies to ensure optimal performance in Vehicular Edge Computing (VEC) systems .

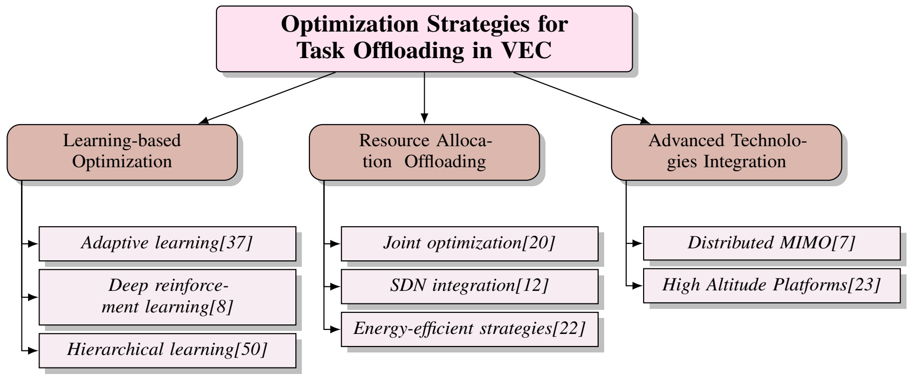

Figure 5: This figure illustrates the key optimization strategies for task offloading in Vehicular Edge Computing (VEC), focusing on learning-based optimization, resource allocation and offloading techniques, and the integration of advanced technologies. Each category highlights specific methodologies and technologies that enhance task offloading efficiency and performance in dynamic vehicular environments.

One of the primary challenges in heterogeneous environments is the need to address the heterogeneity of resources, which can lead to varying levels of service quality and performance [20]. To address this, researchers have proposed various solutions, including the use of software-defined vehicular edge computing (SDVEC) frameworks, which enable dynamic resource allocation and management in response to changing network conditions [12]. These frameworks leverage the capabilities of software-defined networking (SDN) and network function virtualization (NFV) to provide flexible and efficient resource allocation, ensuring optimal task offloading and service delivery [12].

The integration of High Altitude Platforms (HAPs) with VEC systems, as explored by [7], offers an innovative approach to extending the coverage and capacity of vehicular networks, particularly in rural areas. HAP-assisted VEC systems can offload computational tasks from ground vehicles to HAPs, thereby improving service delivery and reducing latency in areas with limited infrastructure [6]. This approach enhances the overall performance and reliability of vehicular networks, ensuring seamless communication and data processing in diverse environments.

Moreover, the integration of Reconfigurable Intelligent Surfaces (RIS) within VEC systems has been proposed as a means to enhance service quality and reduce latency by optimizing wireless communication channels [24]. RIS technology enables the dynamic reconfiguration of wireless channels, improving signal quality and reducing interference, which is crucial for maintaining reliable communication in heterogeneous vehicular environments [24].

4.3 Latency and Energy Efficiency in Task Offloading

The optimization of latency and energy efficiency in task offloading is a critical aspect of Vehicular Edge Computing (VEC), as it directly impacts the performance and sustainability of vehicular networks. By offloading computational tasks from vehicles to nearby edge servers, Vehicle Edge Computing (VEC) systems can significantly alleviate the processing burden on on-board CPUs, thereby improving overall network efficiency and minimizing latency and bandwidth consumption, which are critical for supporting the increasing demands of vehicular applications and ensuring rapid response times in Intelligent Transportation Systems (ITS). [28, 1]

One of the key challenges in achieving latency and energy efficiency in VEC lies in the dynamic nature of vehicular networks, where high mobility and varying network conditions can lead to increased latency and energy consumption . To tackle the challenges associated with task offloading in vehicle-to-infrastructure (V2I) networks and mobile edge computing systems, a variety of innovative strategies have been developed, notably those leveraging deep reinforcement learning (DRL) algorithms. These algorithms facilitate real-time adaptation of vehicle edge computing (VEC) systems to fluctuating network conditions, thereby optimizing task offloading decisions. For instance, a hierarchical offloading scheme utilizing DRL has been proposed to effectively manage interdependent computation tasks represented as directed acyclic graphs (DAGs), addressing concerns related to processing delays, energy consumption, and edge computing costs. Additionally, a model-free DRL-based distributed algorithm has been introduced to enable mobile devices to autonomously determine their offloading strategies, minimizing the expected long-term costs while accounting for edge load dynamics. Simulation results indicate that these approaches can significantly reduce task delays and the number of dropped tasks, showcasing their potential for enhancing the efficiency of task offloading in dynamic environments. [52, 50]

Moreover, the integration of reconfigurable intelligent surfaces (RIS) with VEC systems has been explored as a means to enhance signal quality and reduce latency in vehicular networks [24]. By dynamically adjusting the reflection coefficients of RIS elements, VEC systems can improve communication efficiency and ensure reliable data transmission even in challenging environments with high mobility and varying network conditions .

In addition to DRL-based strategies, other innovative approaches such as the use of blockchain technology have been proposed to address security and privacy concerns in VEC systems [17]. Blockchain technology can enhance the trustworthiness and transparency of data exchanges within vehicular networks, mitigating potential security risks and ensuring the integrity of transmitted information [23].

Moreover, the integration of satellite-terrestrial systems with VEC has been explored as a means to enhance the reliability and scalability of vehicular networks [7]. By leveraging the extensive coverage of satellites and the high capacity of terrestrial networks, VEC can provide a robust framework for reliable and low-latency data transmission in vehicular networks, addressing the challenges of dynamic environments and high mobility [7].

4.4 Service Caching in Vehicular Edge Computing

Service caching in Vehicular Edge Computing (VEC) plays a pivotal role in minimizing latency and improving the efficiency of service delivery by strategically storing frequently accessed data in proximity to users. This approach leverages the capabilities of roadside units (RSUs) to cache popular content, thereby enabling vehicles to quickly retrieve requested information, which is essential given the high mobility of vehicles and the dynamic nature of user demands. By utilizing advanced techniques such as asynchronous federated learning, VEC can effectively predict and update cached content, ensuring that the most relevant data is readily available, thus enhancing the overall performance of real-time applications in connected and autonomous vehicle environments. [12, 28, 5]. The dynamic and unpredictable nature of vehicular networks, characterized by high mobility and varying data demands, necessitates the development of efficient caching strategies that can adapt to changing network conditions .

One of the key benefits of service caching in Vehicular Edge Computing (VEC) is its capacity to significantly decrease data retrieval times by strategically storing frequently accessed content at roadside units (RSUs). This approach minimizes the distance that data must travel to reach users, thereby enhancing the responsiveness of real-time applications. Additionally, the use of advanced techniques such as Asynchronous Federated Learning enables RSUs to predict and cache popular content based on the dynamic data requests of vehicles, further optimizing the efficiency of data delivery while addressing privacy concerns associated with user data sharing. [28, 54, 5]. This is particularly crucial in vehicular networks, where low-latency data access is essential for supporting real-time applications and improving the overall quality of service .

Various strategies and algorithms have been developed to optimize service caching in vehicular networks, each with its own advantages and limitations. Traffic-aware and cooperative caching architectures, such as the VeSoNet architecture, have been proposed to enhance content delivery efficiency by considering the movement patterns of vehicular users and dynamically adjusting cache placement . Other dynamic and adaptive caching strategies focus on optimizing cache placement based on real-time network conditions and user demands, ensuring efficient data retrieval and minimizing latency [2].

In addition to improving service delivery efficiency, service caching in VEC also addresses critical security and privacy concerns. The integration of blockchain technology with caching strategies has been proposed as a means to enhance data security and privacy in vehicular networks [17]. By leveraging blockchain's decentralized architecture, VEC systems can ensure secure data transactions and protect user privacy, even in dynamic and distributed network environments [2].

4.5 Challenges and Solutions in Task Offloading

Task offloading in Vehicular Edge Computing (VEC) systems presents several challenges that must be addressed to optimize computational efficiency and reduce latency. One of the primary challenges is the dynamic nature of vehicular networks, characterized by high mobility and varying network conditions, which can lead to unpredictable task execution times and resource allocation complexities. The dynamic and unpredictable nature of vehicular networks, characterized by rapidly changing network topologies, varying wireless channel states, and fluctuating computational workloads, necessitates the development of robust and adaptive task offloading strategies. These strategies should effectively manage resource allocation and minimize offloading delays, ensuring efficient utilization of computing resources while addressing challenges such as latency and energy consumption in energy-limited vehicles. By leveraging advanced algorithms, such as adaptive learning-based approaches and multi-armed bandit theory, these strategies can optimize task offloading decisions in real-time, thereby enhancing the overall performance of vehicular edge computing systems. [34, 28, 36, 37]

The integration of edge computing with vehicular networks introduces additional challenges related to resource management, particularly in heterogeneous environments. The diversity of edge computing resources and vehicular devices requires sophisticated resource allocation and task scheduling mechanisms to ensure optimal performance [20]. The use of deep reinforcement learning (DRL) algorithms has been proposed as a potential solution to these challenges, enabling VEC systems to learn and adapt to dynamic network conditions and optimize task offloading strategies in real-time [16].

Furthermore, the high mobility and dynamic nature of vehicular networks pose significant challenges to task offloading, as frequent handoffs and varying network conditions can lead to increased latency and reduced service quality [42]. To address these challenges, innovative solutions such as the Handoff-Aware Distributed Computing Scheme (HADCS) have been proposed, which aim to minimize handoff delays and ensure seamless data transmission in VEC systems [42].

The integration of advanced technologies, such as Distributed Massive MIMO (DM-MIMO) systems and High Altitude Platforms (HAPs), offers promising solutions to address the challenges of task offloading in VEC [7]. These technologies enhance the capacity and coverage of vehicular networks, enabling reliable and low-latency data transmission even in dynamic environments [21].

Moreover, the development of efficient task offloading strategies that optimize resource utilization and minimize energy consumption is crucial for the sustainability of VEC systems [22]. The integration of deep reinforcement learning algorithms within VEC systems has been explored as a means to enhance task offloading efficiency and improve the overall performance of vehicular networks [23]. By leveraging real-time data and predictive analytics, VEC systems can make informed decisions regarding task offloading, optimizing resource utilization and reducing latency [2].

4.6 Latency and Energy Efficiency in Task Offloading

Task offloading in Vehicular Edge Computing (VEC) systems is a critical process for optimizing both latency and energy efficiency, which are essential for the effective operation of modern vehicular networks. The dynamic nature of vehicular environments, characterized by high mobility and varying network conditions, presents significant challenges for task offloading strategies [16]. To address these challenges, various strategies have been proposed to improve latency and energy efficiency in task offloading.

One of the primary strategies for enhancing latency and energy efficiency is the implementation of optimized task offloading algorithms. These algorithms consider factors such as network conditions, resource availability, and task requirements to make informed decisions regarding task distribution [23]. By leveraging real-time data and predictive analytics, these algorithms can dynamically adjust task offloading decisions, ensuring efficient resource utilization and minimizing energy consumption [21].

The integration of advanced technologies, such as Distributed Massive MIMO (DM-MIMO) systems and High Altitude Platforms (HAPs), further enhances the performance of VEC systems in terms of latency reduction and energy efficiency [7]. These technologies provide improved signal quality and increased network capacity, enabling more efficient task offloading and data transmission in vehicular networks [23].

Furthermore, the use of age of information (AoI) as a metric for optimizing task offloading strategies has been explored as a means to enhance latency reduction and energy efficiency in VEC systems [21]. By maintaining the freshness of information and minimizing the execution duration of tasks, VEC systems can significantly improve the quality of service and overall network performance .

4.7 Challenges and Solutions in Task Offloading

Task offloading in Vehicular Edge Computing (VEC) systems presents a range of challenges that must be addressed to optimize computational efficiency and reduce latency. One of the primary challenges is the dynamic nature of vehicular networks, characterized by high mobility and varying network conditions, which complicates the decision-making process for task offloading strategies . The dynamic environment of vehicular networks, with frequent network handoffs and interruptions, poses significant challenges for task continuity and resource management [42].

To address these challenges, various solutions have been proposed, including the development of advanced task offloading strategies that leverage real-time data and predictive analytics to optimize resource allocation and reduce latency [22]. The integration of deep reinforcement learning (DRL) techniques in task offloading decisions has shown promise in optimizing resource utilization and enhancing the performance of vehicular edge computing systems .

The adoption of collaborative task offloading strategies, such as the Collaborative Vehicular Edge Computing (CVEC) framework, has also been proposed as a solution to address the challenges of task offloading in VEC environments [16]. By leveraging the computational capabilities of neighboring vehicles and edge servers, CVEC enhances resource utilization and reduces latency, leading to improved service delivery in vehicular networks [19].

Another promising solution is the use of reconfigurable intelligent surfaces (RIS) to enhance communication quality and mitigate interruptions caused by physical obstructions in vehicular networks [24]. By dynamically adjusting the reflection coefficients of RIS elements, VEC systems can optimize task offloading and ensure reliable data transmission, even in challenging network conditions [7].

4.8 Task Offloading in Heterogeneous Environments

The task offloading process in Vehicular Edge Computing (VEC) systems, particularly within heterogeneous environments characterized by varying network conditions and vehicle mobility, introduces a complex array of challenges—including latency, resource allocation, and congestion prediction—while simultaneously offering opportunities for improved computational efficiency and reduced energy consumption through innovative algorithms and adaptive strategies. [34, 28, 39, 36, 37]. These environments are characterized by diverse network technologies, variable computational resources, and high user mobility, all of which necessitate sophisticated strategies for efficient task distribution and resource management .

One of the primary challenges in these environments is the difficulty in efficiently mapping multiple computational tasks to multiple helper nodes, especially under dynamic channel conditions [55]. The dynamic nature of vehicular networks, with frequent changes in network topology and varying resource availability, further complicates task offloading processes [23]. To address these challenges, advanced task offloading strategies have been developed, such as the VeSoNet method, which focuses on traffic-aware content caching and task offloading to ensure effective computational task distribution among vehicles [46].

Moreover, the integration of multi-tier computing architectures has been proposed as a solution to enhance task offloading efficiency in heterogeneous vehicular environments [55]. These architectures leverage the strengths of different network tiers, such as edge servers, cloud servers, and high altitude platforms (HAPs), to optimize task offloading decisions and improve overall network performance [7]. By dynamically allocating resources and optimizing task offloading rates, multi-tier computing environments can effectively address the challenges posed by high user mobility and varying network conditions [55].

In addition, the implementation of energy-efficient offloading strategies is crucial for minimizing energy consumption in green vehicular edge computing environments [16]. These strategies focus on optimizing task distribution and resource allocation to ensure sustainable and efficient operation of VEC systems. The integration of advanced algorithms, such as deep reinforcement learning (DRL), has been proposed as a means to enhance task offloading efficiency by dynamically adapting to changing network conditions and optimizing resource utilization [23].

The VeSoNet method, as explored by [46], exemplifies an approach that integrates task offloading with traffic-aware content caching to optimize computational task distribution among vehicles. This method highlights the importance of considering vehicular mobility patterns and network conditions in the development of effective task offloading strategies for VEC systems.

4.9 Latency and Energy Efficiency in Task Offloading

In the realm of Vehicular Edge Computing (VEC), the dual objectives of minimizing latency and enhancing energy efficiency in task offloading are critical to the performance and sustainability of vehicular networks. The high mobility of vehicles and the rapidly changing network conditions typical of vehicular environments create significant challenges for effective communication and content delivery, necessitating the development of advanced strategies such as Mobile Edge Computing (MEC) and task offloading techniques that optimize resource allocation and enhance performance under stringent delay constraints. [56, 38, 46, 1]

One of the promising strategies to achieve these goals is the implementation of deep reinforcement learning (DRL)-based task offloading algorithms. The proposed algorithms leverage advanced techniques such as multi-agent reinforcement learning to dynamically adapt to real-time network conditions, enabling efficient task distribution and optimized resource utilization. Specifically, these algorithms facilitate the offloading of computation-intensive tasks from user devices to edge servers, addressing challenges like limited bandwidth and high latency. By employing a unified quality of experience (QoE) criterion, the algorithms ensure improved task execution speed and enhanced overall system performance, particularly in multi-user scenarios within edge computing environments. [57, 58]. By leveraging local observations and predictive analytics, DRL-based strategies can significantly reduce latency and energy consumption, enhancing the overall efficiency and performance of VEC systems .

The integration of reconfigurable intelligent surfaces (RIS) within VEC systems has been proposed as another innovative approach to enhance communication quality and reduce latency in vehicular networks [24]. RIS technology enables VEC systems to dynamically optimize wireless communication channels, improving signal quality and reducing interference, which is crucial for maintaining reliable and low-latency data transmission in vehicular networks .

Moreover, the integration of digital twin technology with deep reinforcement learning (DRL) has been explored as a means to further enhance task offloading efficiency in VEC systems . This approach leverages real-time data and predictive analytics to optimize task offloading decisions, ensuring efficient resource utilization and minimizing energy consumption [23]. By creating a virtual representation of the physical vehicular environment, digital twin technology enables VEC systems to simulate and optimize task offloading strategies, further reducing latency and improving energy efficiency .

The development of novel task offloading frameworks, such as the Joint D2D Collaboration and Task Offloading (JD2C-TO) method, offers a promising approach to optimizing latency and energy efficiency in VEC systems [59]. This method effectively adapts to user dynamics and optimizes task offloading decisions, ensuring efficient resource utilization and minimizing energy consumption in vehicular networks .

Furthermore, the implementation of reconfigurable intelligent surfaces (RIS) within VEC systems, as proposed by [24], offers a novel approach to enhancing communication and processing capabilities. By adaptively adjusting the RIS phase-shift and power allocation based on real-time conditions, VEC systems can optimize communication channels and reduce latency, ensuring reliable and efficient data transmission [24].

In addition, the use of multi-tier computing architectures has been explored as a means to enhance task offloading efficiency and reduce latency in heterogeneous vehicular environments [55]. These architectures leverage the strengths of different network tiers, such as edge servers, cloud servers, and high altitude platforms (HAPs), to optimize task offloading decisions and improve overall network performance . By dynamically allocating resources and optimizing task offloading rates, multi-tier computing environments can effectively address the challenges posed by high user mobility and varying network conditions [55].

4.10 Challenges and Solutions in Task Offloading

Task offloading within Vehicular Edge Computing (VEC) systems is a multifaceted process that presents numerous challenges and requires innovative solutions to optimize computational efficiency and reduce latency. The inherent characteristics of vehicular networks, such as high mobility, dynamic network conditions, and resource constraints, exacerbate these challenges . The dynamic nature of vehicular networks, marked by frequent changes in network topology and fluctuating resource availability due to high vehicle mobility and the increased demand for communication and computational resources, significantly complicates the decision-making processes involved in efficient resource allocation and task scheduling. This complexity arises from various challenges, including unreliable wireless channels, fragmented spectrum, and the need to maintain Quality of Service (QoS) for diverse applications such as road safety, traffic efficiency, and infotainment. Consequently, optimizing resource utilization in these networks is critical for supporting the evolving landscape of Intelligent Transportation Systems (ITS) and vehicular edge computing. [38, 60, 61, 1]

One of the primary challenges is the highly coupled nature of optimization variables, which necessitates simultaneous optimization of multiple factors, such as transmit power and computational resources, to ensure efficient task offloading and resource management [62]. This complexity is further exacerbated by the NP-hard nature of the task offloading problem, which can restrict the applicability of certain optimization algorithms in large-scale vehicular networks with diverse service demands [20].

To address these challenges, various solutions have been proposed, including the use of deep reinforcement learning (DRL) algorithms. These algorithms enable VEC systems to learn and adapt to dynamic network conditions, optimizing task offloading decisions in real-time . DRL-based strategies have shown promise in managing the joint allocation of transmit power and computational resources, effectively addressing the complexities of task offloading in dynamic vehicular environments [62].

Another challenge in task offloading is the reliance on accurate predictions of task arrivals and channel conditions, as inaccuracies can lead to suboptimal task allocation and increased latency [63]. To address this, learning-based task offloading strategies have been proposed, which utilize real-time data and predictive analytics to improve the accuracy of task offloading decisions .

The integration of advanced technologies, such as Distributed Massive MIMO (DM-MIMO) systems and High Altitude Platforms (HAPs), offers promising solutions to address the challenges of task offloading in VEC [7]. These technologies enhance the capacity and coverage of vehicular networks, enabling reliable and low-latency data transmission even in dynamic environments [21].

Moreover, the development of efficient task offloading frameworks, such as the Joint D2D Collaboration and Task Offloading (JD2C-TO) method, has shown promise in optimizing latency and energy efficiency in VEC systems [59]. By considering vehicle-road interactions and optimizing resource allocation, this method ensures efficient resource utilization and minimizes energy consumption, addressing the challenges of high mobility and dynamic network conditions.

However, some limitations persist in the current task offloading methods. For instance, the learning-based task offloading approach, as discussed by [64], may not always accurately reflect current network conditions, particularly during rapid changes, due to its reliance on historical data. Similarly, the optimal task offloading policy proposed by [65] relies on accurate modeling of task arrival probabilities and server availability, which may not always align with real-world scenarios.

5 Resource Allocation in Vehicular Edge Computing

5.1 Challenges in Resource Allocation

Resource allocation in Vehicular Edge Computing (VEC) systems involves complex challenges due to the integration of diverse communication technologies and the dynamic nature of vehicular networks. The rising demand for computation, storage, and communication resources to support these networks is compounded by high mobility, variable network conditions, and heterogeneous edge nodes (ENs), making resource management strategies crucial for optimizing computational and network resources, ultimately enhancing system performance and reducing latency [39, 1]. The NP-hard nature of resource allocation problems, especially in multi-user MEC systems, adds to these challenges, requiring adaptive strategies to handle rapid mobility and fluctuating network conditions [7].

Constraints such as bandwidth and energy consumption further complicate resource allocation, as high mobility and dynamic environments can lead to increased energy usage and latency, threatening VEC systems' sustainability and performance [22]. To address these issues, innovative strategies like energy-efficient task offloading and caching mechanisms are being developed to optimize resource utilization [16]. The heterogeneous nature of edge nodes and the lack of collaboration among various edge computing solutions necessitate sophisticated resource allocation and task scheduling mechanisms that can adapt to dynamic conditions [23, 19].

Emerging technologies such as Distributed Massive MIMO (DM-MIMO) systems and High Altitude Platforms (HAPs) offer potential solutions to enhance resource allocation in vehicular networks by improving capacity and coverage [7]. Additionally, Reconfigurable Intelligent Surfaces (RIS) can optimize wireless communication channels, improving communication quality and reducing latency through dynamically adjusted reflection coefficients [24].

As illustrated in Figure 6, the key challenges and solutions in resource allocation for VEC systems are highlighted, showcasing the critical resource management issues, optimization techniques, and emerging technologies that are pivotal in addressing these challenges.

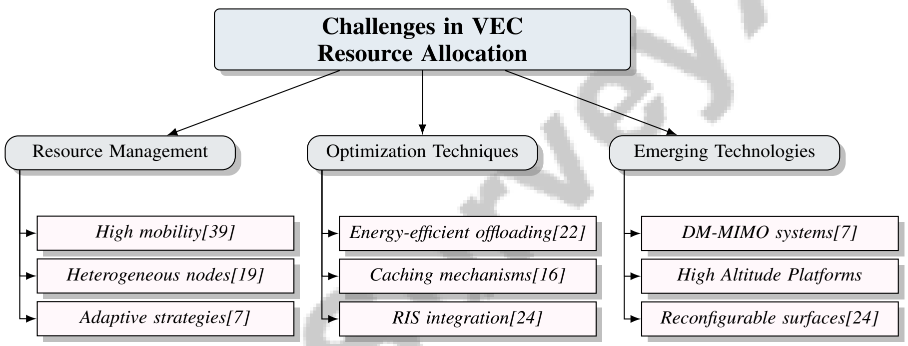

Figure 6: This figure illustrates the key challenges and solutions in resource allocation for Vehicular Edge Computing (VEC) systems, highlighting resource management issues, optimization techniques, and emerging technologies.

5.2 Strategies for Efficient Resource Management

Efficient resource management is vital for optimizing VEC system performance and reducing latency. Advanced strategies that adapt to fluctuating network conditions and varying resource demands are essential, especially in next-generation wireless networks and intelligent Internet of Vehicles (IoV) scenarios [55, 49, 66]. Decentralized deep reinforcement learning (DRL) enables Vehicular Users (VUs) to optimize power usage and task processing efficiency based on local states, facilitating real-time decision-making [4]. The Intent-Based Resource Orchestration (IBRO) framework further enhances resource management by dynamically aligning system resources with user requirements, maintaining optimal performance [26].

Economic models offer a novel perspective on optimizing VEC performance. Pricing-driven strategies and the Market-based Resource Allocation Framework (MRA) allocate resources effectively among competing services by assigning prices to Edge Nodes (ENs) resources and computing a market equilibrium solution [67]. Cognitive Software-Defined Networking (SDN) architectures further enhance resource allocation efficiency by adapting dynamically to varying traffic conditions [20].

5.3 Existing Resource Allocation Frameworks

Resource allocation is fundamental in VEC systems for optimizing computational and network resources to enhance performance. Various frameworks and algorithms address VEC resource allocation complexities. The Mobile Edge Computing (MEC) paradigm, while effective in providing

AI-generated, for reference only.

Benchmark	Size	Domain	Task Format	Metric
UAV-5G[15]	12,000	Drone Computing	Latency Measurement	Service Delay, Latency

Table 4: Table illustrating a representative benchmark in the domain of drone computing, focusing on the UAV-5G benchmark. This benchmark comprises 12,000 data points and evaluates performance based on latency measurement, specifically service delay and latency metrics.

localized computing resources and reducing latency, often faces scalability and flexibility limitations [11]. The Joint Optimization of Application Offloading and Resource Allocation (JOAoDR) approach integrates multiple optimization objectives to enhance MEC system performance [11]. The Parkingchain framework enhances trustworthiness and addresses security concerns through a permissioned blockchain, ensuring transparent resource allocation [68].

The Adaptive Resource Allocation Algorithm (ARAA) employs machine learning to optimize resource distribution in real-time, emphasizing adaptability in resource management strategies [57]. In DSRC and C-V2X networks, resource allocation strategies focus on MAC parameter allocation, channel allocation, and rate allocation techniques [38]. The Federated Serverless Edge Computing (FSEC) method optimizes for low latency and high reliability, leveraging serverless computing paradigms to enhance resource utilization [40].

The OJTORA (Online Joint Task Offloading and Resource Allocation) algorithm uses Lyapunov optimization techniques to convert stochastic optimization problems into deterministic ones for each time slot, enhancing resource allocation efficiency [49]. Additionally, blockchain technology integration enhances security and fairness, ensuring transparent resource allocation and minimizing unauthorized data access [68, 17]. Table 4 provides an overview of a representative benchmark used in the evaluation of resource allocation frameworks within drone computing environments.

5.4 Innovative Approaches and Algorithms

Innovative approaches and algorithms for resource allocation in VEC are crucial for enhancing system performance and efficiency in dynamic vehicular networks. These methodologies address complexities like rapid mobility and fluctuating traffic loads, supporting the stringent performance requirements of Intelligent Transportation Systems (ITS) and emerging vehicular applications [46, 28, 36, 1]. The Improved Branch and Bound Algorithm (IBBA) effectively optimizes task offloading and UAV trajectory, minimizing energy consumption through digital twin technology for real-time simulation and optimization of resource allocation strategies [69, 41].

Deep learning techniques, such as a CNN-based method, have also been explored to enhance task offloading efficiency, achieving performance comparable to exhaustive search methods with reduced CPU runtime [13]. Cognitive SDN architectures dynamically adapt to varying traffic conditions, enhancing resource allocation efficiency [26].

In the context of 6G networks, the Channel-Constrained Model (CCM) employs GA-based strategies to enhance resource allocation in MEC environments, ensuring efficient resource utilization even in dynamic and heterogeneous vehicular settings [70]. Additionally, DRL algorithms in task offloading and resource allocation dynamically adjust to fluctuating network conditions, minimizing latency and energy consumption while improving overall efficiency in computation offloading [52, 23].

6 Challenges and Future Directions

6.1 High Mobility and Dynamic Environments

Vehicular Edge Computing (VEC) systems face significant challenges due to the high mobility and frequent topology changes inherent in vehicular networks, complicating task offloading and resource allocation processes, which adversely impact system performance and reliability [7, 20]. The unpredictable vehicle movements and constrained communication bandwidth demand robust strategies for efficient resource management [26, 23]. A primary challenge lies in optimizing Reconfigurable Intelligent Surface (RIS) phase-shift and power allocation amidst hardware constraints. The volatility in vehicle participation and task completion times complicates predictions, affecting resource stability during network handoffs [26]. Moreover, inadequate coordination among edge servers can lead to load imbalances, causing server overloads and inefficient resource use [23]. Existing methods often struggle with real-time dynamic resource orchestration due to the NP-hard nature of optimization problems, which complicates simultaneous offloading and resource allocation [71, 36]. Communication delays or errors further limit the effectiveness of these methods [3, 24]. Integrating satellite-terrestrial systems has shown potential in reducing delays and energy consumption [7]. Future research should focus on adaptive resource management strategies and enhancing security protocols to navigate high mobility complexities in VEC systems, improving service delivery and resource utilization to support intelligent transportation systems and smart mobility initiatives [20].

6.2 Security and Privacy Concerns

Security and privacy are critical challenges in deploying VEC systems due to their distributed nature, which introduces risks such as unauthorized access, data breaches, and malicious attacks, necessitating robust measures to protect sensitive user data during task offloading and service delivery [28, 1]. Statistical attacks, which allow attackers to infer sensitive information from cached data patterns, pose a significant threat [46]. The VeSoNet architecture highlights the need for advanced privacy-preserving mechanisms to safeguard user data [46]. Differential privacy techniques have emerged as effective solutions, adding noise to user data to maintain confidentiality even in the presence of statistical attacks [72]. Byzantine attacks, particularly in asynchronous federated learning (AFL), can degrade data quality and threaten global model integrity. Deep reinforcement learning (DRL) can help identify and exclude poorly performing vehicles, enhancing AFL robustness [73, 5, 68]. The dynamic environment reliance on quality training data necessitates adaptive learning techniques to manage variable conditions effectively [51, 58].

6.3 Resource Constraints and Allocation

Resource allocation in VEC systems is constrained by dynamic vehicular environments and diverse computational task requirements. Challenges include fluctuating task arrival rates, network congestion, and the complexity of optimizing resource allocation for varying task types [30]. High vehicle mobility exacerbates these challenges by introducing variability in network conditions and resource availability. Balancing computation and communication needs is crucial, requiring VEC systems to adapt in real-time to environmental changes to meet ultra-reliable low-latency communication (URLLC) demands [32]. Sophisticated algorithms capable of dynamic adaptation to fluctuations in task demands and network conditions are necessary. The inherent limitations of edge nodes, including constrained computational power and bandwidth, highlight the need for innovative strategies to optimize resource utilization while minimizing latency and energy consumption. Integrating advanced technologies such as DRL and cognitive Software-Defined Networking (SDN) can enhance resource allocation efficiency through real-time decision-making [23]. The complexity of resource allocation is compounded by the heterogeneous nature of vehicular networks, necessitating a holistic approach that considers the unique characteristics of each network tier and node for optimal resource allocation across the network [30].

6.4 Scalability and Network Performance

Scalability significantly influences VEC systems' performance, especially in high-density vehicular environments. As the number of connected vehicles grows, the demand for computational resources and efficient data processing increases, presenting substantial challenges [50]. While hierarchical reinforcement learning shows promise in optimizing resource allocation and task offloading, its effectiveness may be compromised in rapidly changing environments, affecting prediction accuracy and scalability [50]. Limited computational resources at edge nodes hinder scalability, necessitating advanced algorithms and frameworks for efficient resource allocation and task scheduling to meet growing demands without sacrificing performance [50]. The dynamic nature of vehicular environments, characterized by frequent changes in network topology and resource availability, complicates scalability efforts. VEC systems must be highly adaptable, capable of dynamically adjusting resource allocation and task offloading strategies in real-time to maintain optimal performance [50]. Efficient communication protocols that can handle high data throughput and low-latency requirements are essential for maintaining network performance in scalable VEC systems. Integrating advanced technologies such as Distributed Massive MIMO (DM-MIMO) systems and Reconfigurable Intelligent

Surfaces (RIS) can enhance network capacity and performance, enabling effective scaling in dynamic vehicular environments [50].

6.5 Future Directions and Technological Advancements

The future of VEC is poised for significant advancements through the integration of innovative technologies like Mobile Edge Computing (MEC) and Software-Defined Networking (SDN), addressing increasing demands for low latency, high bandwidth, and efficient resource allocation in Intelligent Transportation Systems (ITS) and autonomous vehicle applications [12, 19, 28, 39, 1]. Overcoming challenges such as high mobility and dynamic network conditions requires a multifaceted approach leveraging emerging technologies and methodologies. Enhancing model adaptability to fluctuating vehicular patterns by integrating sophisticated machine learning techniques for content prediction is a promising research avenue [21]. Exploring adaptive mechanisms for dynamic environments and scaling caching and task offloading solutions is crucial for VEC development [22]. Refining the FGNN-MADRL model to accommodate complex vehicular scenarios and investigating further applications of Graph Neural Networks (GNNs) in edge computing are valuable directions [21]. Future research should focus on extending frameworks to integrate fully with SDN controllers, considering periodic mobility patterns for enhanced intent management [26]. Integrating advanced technologies like blockchain and AI to address scalability challenges is another suggested direction [19]. Enhancing models to incorporate global network information and improve scalability for larger vehicular networks is critical [27]. Developing adaptive strategies that dynamically respond to varying network conditions is essential for VEC's future [25]. Future research could emphasize enhancing methods' adaptability to environmental variations and exploring more efficient algorithms for real-time applications [24].

7 Conclusion

Vehicular Edge Computing (VEC) marks a pivotal development in enhancing the capabilities of vehicular networks by bringing computational power closer to the edge, thereby addressing the demands for low-latency and high-efficiency service delivery. This survey has delved into the critical components of VEC, including service caching, task offloading, and resource allocation, which collectively optimize network performance and operational efficiency. Service caching, through innovative architectures, minimizes latency by positioning frequently accessed data near users, thereby streamlining service delivery. Task offloading enhances processing efficiency by distributing computational loads from vehicles to edge servers, which is essential for supporting real-time vehicular applications.

Resource allocation remains a cornerstone of VEC, with strategies like decentralized deep reinforcement learning and cognitive Software-Defined Networking playing crucial roles in optimizing resource utilization and boosting network performance. Advanced algorithms, such as the Improved Branch and Bound Algorithm and the FlexEdge framework, further refine resource allocation, ensuring robust performance and reliability in the face of dynamic vehicular conditions.

The capability of VEC to significantly uplift vehicular network performance and minimize latency is evident in its facilitation of real-time applications and enhancement of service quality within intelligent transportation systems. By refining service caching, task offloading, and resource allocation, VEC systems not only bolster network performance and reduce latency but also promote energy efficiency, thereby supporting the seamless integration of modern vehicular applications and advancing the paradigm of smart mobility.

The BARGAIN-MATCH framework exemplifies VEC's superiority over traditional methods by demonstrating enhanced system, vehicle, and server utility, even under substantial workloads. This highlights VEC's transformative potential in optimizing resource utilization and elevating network performance, underscoring its critical role in the evolution of vehicular networks.

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