Resource Allocation of Video Streaming over Vehicular Networks: A Survey, Some Research Issues and Challenges

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***Abstract*—In intelligent transportation systems (ITS), the vehicular ad-hoc network (VANET) is an enabling technology that can provide information exchange services among connected and autonomous vehicles (CAVs). Video streaming over VANETs is a potential application to ensure the safety of drivers and passengers and improve infotainment services. However, owing to the dynamic network topology, video transmission in VANETs is very challenging in terms of latency, reliability, and security. Therefore, a comprehensive summary of the state-of-art video streaming over VANETs is surveyed in this work. Firstly, related works and background knowledge are introduced. Then, a systematic survey on resource allocation (RA) scheme for video streaming in VANETs is provided, and some prevailing and feasible optimization tools are elaborated. Furthermore, enabling technologies of video streaming over VANETs are summarized with a special focus on the integration of video communication, caching, and computing. Finally, we give some challenges and future research directions.**

***Index Terms*—Video Streaming, Vehicular Ad-Hoc Network, Resource Allocation, Caching, Reinforcement Learning.**

I. Introduction

The KPMG claimed the connected and autonomous vehicles (CAVs) can deliver substantial social and economic benefits in the UK. Estimates include 2,500 lives saved, 25,000 serious accidents prevented to the economy by 2030 [1]. Vehicular Ad-Hoc Network (VANET) has the potential to enable diverse applications associated with traffic safety, traffic efficiency, and infotainment [2]. In an intelligent transportation system (ITS), connected vehicles integrate on-board unit (OBU), perception systems (camera, LiDAR, Radar), and sensor systems (GPS, IMU, etc), which can be used as nodes to exchange information by using VANET-based applications. VANET supports different communication modes, including vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I) and vehicle-to-roadside (V2R) [3]. The main wireless access technology candidates for vehicular communication consist of dedicated short-range communications (DSRC) and cellular communications. Moreover, a heterogeneous vehicular network that integrates DSRC with cellular networks can meet the communication requirements of the ITS. However, VANETs are characterized by dynamic network topology, a small effective network diameter, a fast time-varying channel, and frequent network disconnection. Therefore, VANETs face great challenges in terms of latency, reliability, and security for vehicular applications.

The network architecture of fifth-generation (5G) vehicular networks is about to transform from connection-centric to content-centric, with the aid of emerging mobile edge computing (MEC) and software-defined networking (SDN) technologies [4]. The integration of MEC, SDN and VANETs can increase the overall network reliability and scalability for video communication under high traffic density conditions [5], [6]. Firstly, driven by the new video applications, such as augmented reality (AR) navigation and virtual reality (VR) and 4K/8K, the vehicular network faces exponential growth in data traffic and connections. Vehicular edge computing (VEC) is used to sink communication and computing resources to close vehicular nodes. Therefore, the video processing tasks can be offloaded to RSUs, and the network latency can be reduced, significantly. Secondly, the software-defined vehicular network (SDVN) is an emerging network architecture with simplify network management and innovation through network programmability. SDVN can provide high throughput, low latency, and scalability for video communication [7]. Therefore, the integration of such heterogeneous vehicular networks has been considered to exploit the unique benefits.

Furthermore, VANETs are a challenging environment for video transmission in terms of quality of service (QoS) and quality of experience (QoE). On one hand, video-enabled safety applications, such as driver assistance, collision avoidance, and emergency management [8], [9], focus on reducing accidents and their impact. Ultra-low latency is required to ensure the exchange of vehicle information. On the other hand, comfort and infotainment applications need to support high-quality video content to meet the users' QoE, where the challenge is how to scale to multiple users with high mobility [10], [11]. In addition, with the growth of emerging multimedia applications, such as AR and VR, The available bandwidth and storage in VANETs is limited for transmitting video streaming [12]. Although there are some existing works

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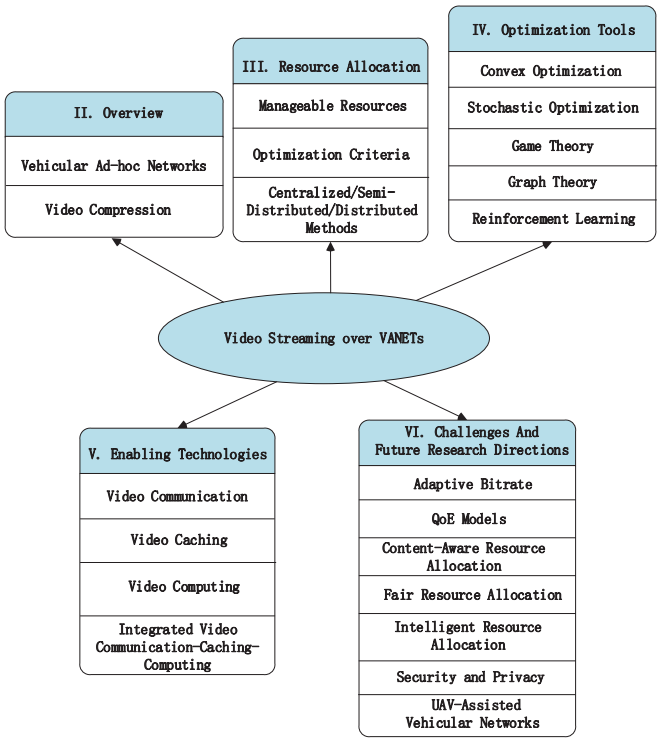


Fig. 1: Road map of video streaming over VANETs.

studying video streaming over VANETs, which is as shown in Table I. However, the resource allocation (RA) issues of video streaming in VANET are largely ignored.

To fill this gap, this overview paper identifies the challenges of utilizing video streaming over VANETs, and a comprehensive survey on applications, enabling technologies, and RA issues is provided. Fig.1 shows a road map of our approach, and the main contribution of this paper are summarized as follows.

- Overviews of vehicular networks and video streaming are described. Moreover, software-defined vehicular networks, information-centric vehicular networks, and vehicular edge computing are highlighted.
- The resource allocation problems for video streaming over VANETs are discussed, where the manageable resources, optimization criteria, and control structure are surveyed.
- The enabling technologies which consider video communication, caching, and computing are reviewed, and the comparison of advantages and shortcoming is summarized.
- Challenges and future research directions of video streaming over VANETs are stated.

The rest of the paper is organized as follows. In Section II, we provide an overview of VANET and video streaming. Then Section III introduces resource allocation for video streaming approaches. In Section IV, some optimization tools for resource allocation are surveyed, including convex optimization, stochastic optimization, game theory, graph theory, and reinforcement learning. In Section V, enabling technologies for video streaming are described. The taxonomy of RA is investigated in Section V. In Section VI, the challenges and future research directions are discussed. The conclusion is depicted in Section VIII.

II. Overview

In this section, the background of the vehicular network, software-defined vehicular network, information-centric vehicular network, vehicular edge computing, and video streaming is introduced. The main abbreviations in this paper are summarized in Table II.

A. Vehicular Ad-hoc Network

1) DSRC Network:

DSRC is one-way or two-way short-range to medium-range wireless communication channels, which is a set of protocols and standards designed for connected vehicles [25]. DSRC is an IEEE 802.11p-based wireless communication technology that enables highly secure, high-speed direct communication. IEEE 802.11p is an approved amendment to the IEEE 802.11 standard to add wireless access in vehicular environments (WAVE), a vehicular communication system. Moreover, DSRC can provide low latency, limited interference information services between vehicles and infrastructures in the 5.9GHz frequency band.

Fig. 2(a) shows a typical DSRC vehicular network framework. DSRC has two communication modes, including V2V and V2I. DSRC can provide secure, high-speed communication even in the presence of obstructions. DSRC is an effective communication technology in supporting both safety and non-safety applications, such as warnings on blind spots, safety inspection, collision warning, In-vehicle display of road signs, and billboards.

2) C-V2X Network:

Cellular vehicle-to-everything (C-V2X) is proposed hereafter to completely integrate ITS services in 4G/5G and beyond networks. C-V2X is an alternative to IEEE 802.11p, which can provide reliable communication and supports short- and long-range transmissions between vehicles and infrastructure [26]. Moreover, C-V2X is a potential technology with complex environmental perception, intelligent decision-making, collaborative control and execution functions, which can realize safe, comfortable, energy-saving and efficient driving.

An overview of C-V2X network is shown in Fig. 2(b) The communication modes of C-V2X are vehicle-to-network (V2N), device-to-device (D2D), and vehicle-to-pedestrian (V2P), where D2D refers to allow two physically close end devices to use a side link without sending the data via the cellular access and core network, including V2V and V2I. The benefits that C-V2X promises are to improve the road capacity and parking infrastructure utilization. The potential applications of C-V2X include forward collision warning, V2V-based emergency vehicle warning, pre-crash sensing warning, V2N traffic flow optimization, and cooperative adaptive cruise control [27].

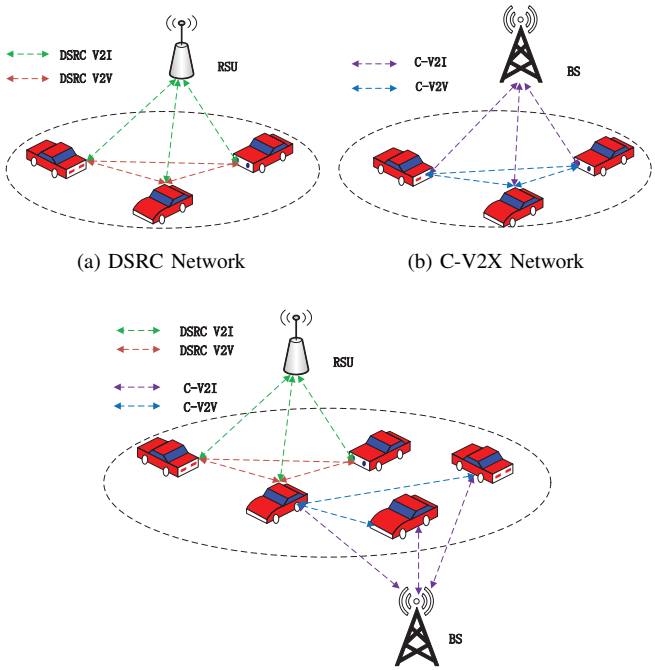
TABLE I: Summary of existing surveys on VANET and video streaming.

Theme	Reference	Major Contribution
VANET	[13]	A complete review of the heterogeneous vehicular networks, including requirements and cases of safety and non-safety services.
	[14]	A comprehensive overview of the resource allocation approach for VANETs, as well as challenges and opportunities.
	[15]	A review of vehicular edge computing for architecture, applications, technical issues, as well as future research challenges.
	[16]	A comprehensive summary of cooperative vehicular networking, including physical, medium access control, and routing protocols, as well as link scheduling and security.
	[17]	A survey of vehicular cloud computing for architectures, applications, and mobility, as well as research directions.
	[18]	A comprehensive survey on security of VANETs, including attacks and security mechanisms, trust management, as well as open issues.
Video Streaming over VANETs	[19]	An overview of video streaming over mobile ad-hoc networks, including application techniques, network techniques and case studies, as well as ongoing research.
	[20]	A brief overview of context-aware video streaming over VANETs, including characteristics, applications, and current challenges.
	[21]	A review of video streaming over vehicular networks with different QoS/QoE approaches, as well as research challenges.
	[22]	A comprehensive survey on video streaming in IoT environments, including supporting technologies, applications and metrics, as well as open research challenges.
	[23]	A survey on QoE models for video streaming over VANETs, including advantages and disadvantages, as well as research challenges.
	[24]	A systematic review of video streaming over VANETs, including applications and requirements, as well as open issues.

3) Heterogeneous Vehicular Network:

Either DSRC or C-V2X can not satisfy the QoS requirements for safe/non-safety applications. Therefore, the collaboration between DSRC and C-V2X is essentials. Heterogeneous Vehicular NETwork (HetVNET) integrates cellular networks with DSRC, which is a potential solution for meeting the communication requirements of ITS services [28]. HetVNETs are in the process of constituting a fundamental information platform, and will eventually evolve into all vehicles connected [29].

Fig. 2(c) shows an architecture of HetVNET which integrates DSRC and C-V2X communications. Depending on their specific characteristics, different candidate schemes can be selected to support V2I and V2V. For one thing, DSRC is designed to provide robust, low-latency, and high throughput services for ITS, which is very effective in supporting both safety or non-safety services in V2V communications. For another, D2D communication can take advantage of the physical proximity of communicating devices in LTE systems mainly for non-safety services.



(a) DSRC Network (b) C-V2X Network

(c) Heterogeneous Vehicular Network

Fig. 2: Vehicular network architecture.

B. Video Compression

Video streaming is a typical media streaming, which can be continuously transmitted over vehicular networks. Owning to the requirements of QoS/QoE of streaming applications, video streaming over vehicular network faces challenges that include to achieve the high delivery ratio with low latency and support high quality video services. In general, encoding efficiency is strongly related to the ability to provide the maximum compression ratio while conserving good-quality decoded videos, as well as the capability to get real-time video broadcasting and minimum energy consumption [30]. The popular modern video coding standards are H.264/AVC, H.265/HEVC, AVS2, and AV1 [31]–[33]. The latest video coding standard H.265/HEVC was released in April 2013. Compared with the previous generation standard H.264/AVC, H.265/HEVC achieves 50% bitrate gain while keeping the same video quality. In order to meet the increased demand for higher resolution (up to $4K \times 2K$ and $8K \times 4K$), the Joint Video Experts Teams (JEVT) was set up to develop a new standardization known as Versatile Video Coding (VVC) [34]. The new video coding standard VVC will be released around 2020, which is expected to increase the coding efficiency by 50% while keeping the same visual quality of H.265/HEVC. However, modern video coding technologies face great challenges: real-time processing and low power consumption [35]. With the promotion of high-resolution video applications, how to further improve the encoding efficiency is a great challenge for modern encoders [36]. Moreover, the computational complexity of the modern video encoder increases dramatically due to its recursive quad-tree construction [37]. Therefore, the high efficiency video codec can be developed to decrease the load and reduce the bandwidth taken by video streaming over VANETs.

TABLE II: The main abbreviations.

Term	Definition
ABR	Adaptive Bitrate
ADAS	Automotive Driver Assistance Systems
CAV	Connected and Autonomous Vehicle
D2D	Device-to-Device
DASH	Dynamic Adaptive Streaming over HTTP
DSRC	Dedicated Short-Range Communications
HetVNET	Heterogeneous Vehicular Network
HEVC	High Efficiency Video Coding
IoV	Internet of Vehicle
ITS	Intelligent Transportation System
LTE	Long Term Evolution
MAC	Medium Access Control
MDP	Markov Decision Process
MEC	Mobile Edge Computing
OBU	On-Board Unit
QoE	Quality of Experience
RA	Resource Allocation
RL	Reinforcement Learning
RSU	Roadside Unit
SDN	Software-Defined Network
V2V	Vehicle-to-Vehicle
V2I	Vehicle-to-Infrastructure
V2X	Vehicle-to-Everything
VANET	Vehicular Ad-Hoc Network
VR	Virtual Reality
WAVE	Wireless Access in Vehicular Environments

Video communication is of high benefit for driver assistance as well as for providing infotainment services. However, the great challenge of video streaming over VANETs is to achieve a high delivery ratio. Due to the frequent network disconnection, the loss of packet happens tritely, which is strongly related to the video quality. Moreover, a delay is also a challenge for video transmission in VANETs. The network congestion easily leads to packet delay. For real-time video applications, the delay reduces the user's QoE. Previous works in [38]–[42] have been made towards friendly video communication for reducing the packet delay and loss.

C. Others

The information-centric vehicular network (ICVN) is a potential technology for future communication that integrates information centric network (ICN) into vehicular networks, which promise enhancements in the areas of application, mobility, and security [43]. Modesto $et.al.$ [44], [45] propose a service-based system architecture for ICVN that can enable application co-existence and service exchange. The proposed service-exchange vehicular network (SEVeN) architecture consists of the application layer, service sublayer, and access layer. SEVeN enables efficient delivery of content model while ensuring that priority services can maintain functionality with high network load.

III. Resources Allocation

In the following, the categories of resource allocation for video streaming are surveyed. Firstly, the manageable resources in video communication are reviewed. Then, the optimization criteria are described, according to the different objectives. Finally, the control structures of resource allocation are discussed.

A. Manageable Resource

Owing to high mobility and the limited spectrum, video streaming over VANETs is a great challenge task. The popularity of mobile devices and the exponential growth of mobile Internet traffic have been fueling the prosperity of numerous emerging services such as computation-intensive, content-centric, and delay-sensitive services. Then, it is vital to allocate resources of networking, caching and computing resources, which can improve the performance of video streaming over VANETs. Based on vehicular communication, manageable radio resources include spectrum/bandwidth, power, and time slot [46], [47]. The caching resource is evaluated by storage availability [48], and the computing resource is evaluated by computational ability [49]. In addition, the resource allocation problems and the corresponding allocation approaches are faced with difficulties and show a significant difference.

B. Optimization Criteria

Optimization criteria might differ depending on the aim and objective of previous work. Video streaming over VANETs is evaluated by using the following criteria: energy efficiency, throughput, utility, QoS/QoE, and revenue. Firstly, with the demand increasing for video applications, concerns about energy efficiency have been raised, with the objective of reducing vehicular network operational costs. Secondly, the transmission of video streaming in VANETs represents a major challenge due to limited and variable bandwidth. Therefore, the throughput is the import criteria when transmitting video streaming from source to the destination. Finally, utility maximization problems for video streaming over VANETs refer to optimize the communication-caching-computing resources. The utility function has taken the delivery delay, Quality of Services, and storage cost into consideration. Therefore, various optimization criteria are discussed as follows.

1) Energy Efficiency: In vehicular networks, energy efficiency (EE) is defined as the ratio of system throughput to energy consumption. In the previous works, resource allocation approaches of EE focus on minimizing energy consumptions [50]–[53]. In general, the measurement indicators of EE mainly involve three levels: component level, device level, and network level. Component-level EE mainly measures the performance of specific components (such as antennas, power amplifiers, and baseband processors) in wireless devices [54]. Device-level indicators are usually used to measure the EE of specific devices (such as base stations). Network-level EE is not only concerned with the energy consumption of devices, but also with network characteristics such as coverage and capacity.

2) Throughput Maximization: Throughput refers to the aggregated data rate of the radio access network in a certain period time and area, which are typically determined by bandwidth and transmitting power. For video streaming over vehicular network applications, the throughput criteria can be used to maximize the transmission rate [55], the network-wide throughput [56]–[58], the achievable video generating rate [59] and the long-term expected average effective throughput of networks [60].

3) Utility Maximization: During the resource allocation process for video streaming over VANETs, utility maximization is of great importance [61]. Utility is one of the most basic concepts in economics, which refers to a measure by which consumers can satisfy their needs and desires through consumption. In wireless networks, because the user is most concerned about the actual service effect of the network, the user's satisfaction with the service obtained can be used to describe the utility. The total utility of the network can reflect the efficiency of network resource allocation, while the utility function also reflects the fairness of resource allocation. This criterion may broadly refer to maximize the total system utility [62]–[71], the utility of each cloudlet [72] and the mean of the total utility value accumulated [73].

4) QoS/QoE Assurance: The quality of service (QoS) metric is generally represented by a set of variables, which characterize the network performance experienced by end users. QoS variables include bandwidth, packet loss, packet delay, delay jitter, availability of the connection, and reliability [74]. In general, different networks and transmission services are corresponding to different QoS requirements. For video streaming applications under the VANET scenarios, resource allocation schemes that focus on achieving the trade-off between QoS demand and available wireless resources have been widely investigated in [75]–[77]. Depending upon the type of video applications, QoS criteria may refer to minimize the integral content offloading time [78], the delivery time [79], [80], the delay time [81]–[84] and the maximal task completion time [49].

However, QoS metrics take into account system components' characteristics, not human perception. From the user's point of view, the quality of experience (QoE) analyzes the user's experience quality of the video streaming service, which aspects not only to subjective perception, but also usability, human factors and context [85]. Therefore, for video streaming services in vehicular networks, QoE-enabled schemes may refer to maximize the video perceived quality [46], [52], [86]–[92], the average video quality received by users [93], the end-to-end total video distortion [94], [95] and the total mean opinion score (MOS) [96]. Moreover, QoS and QoE performance-enhancing approaches have been considered in [97].

5) Revenue Maximization: Profit, which can be defined as the difference between revenue and cost, can be used to reflect the effectiveness of VANET-enabled video streaming systems. In order to support the video streaming applications, the integrated framework jointly considering networking, caching and computing can be used to improve the performance of vehicular networks. Therefore, these criteria may refer to maximize the total acquired profits [98], [99], the expected revenue [100], [101] and the system reward [48], [102]–[108].

C. Centralized/Semi-Distributed/Distributed Methods

1) Centralized: Based on the centralized approach, a centralized entity, including base stations (eNodeB/gNodeB), is responsible for the resource allocation. There are some advantages for centralized-based RA method: (1) It is easy to implement and the stability of the network is well [91]. (2) Centralized control refers to the use of a single controller that makes decisions on the computations, networks, or communication of the resources. The central entity collects information, such as the file's popularity, user requests, and relevant channel information. Based on this information, the central entity decides which file should be placed in which BS or UE, and where should the files be transmitted from. Therefore, the centralized approach can provide the optimal solution for the entire network [82]. However, the centralized approach relies on the joint coordination of all APs and all users, which requires the gathering of the channel state information of the whole network at a central node and inevitably induces a heavy computational burden at this node. Therefore, the disadvantages lie in the high computational complexity and large signaling overhead [109]. Goudarzi $et.al.$ [110] provide a new SDN edge (SDNE) framework for resource assignment in vehicular networks by the integration of edge computing and SDN. This proposed framework consists of the cloud computation layer, EC layer, and device layer. Moreover, the optimization problem is formulated to minimize the total delay. Then, a reinforcement learning-based approach is adopted to solve this problem.

2) Distributed: Compared with the centralized approach, the distributed approach is a low-complexity solution the flexibility and robustness. With the distributed-based approach, each node/user can make the decision individually, and the optimization problem can be divided into some subproblems [87], [89]. Several distributed approaches are adopted to solve the resource optimization problem, such as the alternating direction method of multipliers (ADMM) [84] and a multiuser game model [73]. Wang $et.al.$ [111] propose a fog-based distributed network architecture toward real-time control applications. In this context, a case study of connected cruise control (CCC) is introduced to demonstrate the efficiency of the proposed system. Moreover, a linear quadratic optimization problem is formulated to minimize the deviations of CAV's headway. Finally, a two-step control scheme is proposed to solve this problem in a distributed control manner.

3) Semi-Distributed: Moreover, the semi-distributed scheme converges the advantages of centralized and distributed approaches. In general, the stable clusters can be built in VANET, which are a sort of virtual groups that have been formed by a clustering algorithm [112]. The semi-distributed scheme can divide the entities into some clusters, and each cluster has at least one cluster head for inter-cluster distributed and intra-cluster centralized execution. Therefore, the resource allocation problem can be modeled by jointly considering intra-cluster and inter-cluster [113]–[115]. Eksert $et.al.$ [116] propose a novel intra- and inter-cluster link scheduling mechanism over the control and user plane separation (CUPS) architecture in VANETs. Moreover, a two-phase scheduling optimization problem is formulated to maximize the utilization of available resource blocks. Then, an iterative history-based solution is adopted to solve this problem.

IV. Optimization Tools

In this section, several optimization tools including convex optimization, stochastic optimization, game theory, graph theory, and reinforcement learning are highlighted. Moreover, we present the state-of-the-art solutions with their special advantages. Finally, we give a summary of these techniques.

A. Convex Optimization

Convex optimization is a subfield of mathematical optimization that involves the problem of minimizing convex functions over convex sets. Convex optimization technology has been applied to various fields, including communications and networks, signal processing, automatic control, data analysis, and modeling, etc. A convex optimization problem is in standard form if it is written as [117]:

$$\begin{aligned} \underset{\mathbf{x}}{\text{minimize}} \quad & f(\mathbf{x}) \\ \text{subject to} \quad & g_i(\mathbf{x}) \leq 0, \quad i = 1, \ldots, m \\ & h_i(\mathbf{x}) = 0, \quad i = 1, \ldots, p, \end{aligned} \tag{1}$$

where $\mathbf{x} \in \mathbb{R}^n$ is the optimization variable, the function $f : \mathcal{D} \subseteq \mathbb{R}^n \to \mathbb{R}$ is convex, $g_i : \mathbb{R}^n \to \mathbb{R}, i = 1, \ldots, m$, are convex, and $h_i : \mathbb{R}^n \to \mathbb{R}, i = 1, \ldots, p$, are affine.

In resource allocation of video streaming over VANETs, the optimization problems may be convex/non-convex, linear/non-linear, or continuous/combination. The typical convex optimization problems consist of linear programming (LP) [69], [71], [82], [91], second-order cone programming (SOCP) and semidefinite programming (SDP), etc. Moreover, contemporary methods, such as the bundle method, interior-point method, sub-gradient method, Lagrange duality method, etc. can be used to solve these convex optimization problems. For the non-convex problem, it can be transformed into a convex or heuristic algorithm to obtain a feasible solution.

Convex optimization technology can achieve the optimal scheme for resource allocation problems [56], [109]. However, many RA problems are non-convex in VANETs, which are hard to solve. Moreover, the complexity of RA is high to find the optimal solution for a number of vehicles. Therefore, some suboptimal approaches are proposed to solve the optimization problems [59], [87], [89], [118], and the ADMM method is adopted to handle the large-scale optimization problem [84]. Table III shows a brief summary of the RA solution by using convex optimization in VANETs.

B. Stochastic Optimization

Whereas deterministic optimization problems are formulated with known parameters, VANET-based resource problems almost invariably include some unknown parameters. Stochastic optimization methods are optimization methods that generate and use random variables. Some stochastic optimization methods use random iterates to solve stochastic problems. For video streaming applications in VANETs, several typical stochastic optimization methods are introduced.

1) Queuing Theory:

Queuing optimization model is to minimize the total cost of waiting cost and service cost. The queuing systems consist of input processes, queuing and queuing rules, service agencies, and service rules. In the queuing model based RA problem, the main optimization objectives include: (1) to determine the optimum service level to minimize the total cost; (2) to maximize the difference between service income and service cost. The most important aspect of queuing optimization is how you value your customers compare to how you value the cost of your servers.

Therefore, for video streaming applications under VANET environments, some RA problems are formulated based on the queuing model [119]. In [52], a joint optimization problem is modeled to maximize the user's QoE by using queuing theory. The authors of [120] propose the multimedia streaming transmission framework in vehicular information-centric networking, and a lightweight multi-path selection approach is formulated to optimize the system utilization by using queuing theory. As the reference in [121], the buffer dynamics are formulated based on the queuing model, and the RA problem is modeled to minimize the total load on the cellular infrastructure.

2) Lyapunov Optimization:

Lyapunov optimization refers to the use of a Lyapunov function to optimally control a dynamic system. The Lyapunov function is used extensively in control theory to ensure different forms of system stability, which is a non-negative scalar measure of this multidimensional state. In general, the Lyapunov function is defined to become larger when the system enters an undesired state [122]. By taking control measures to make the Lyapunov function drift to zero in the negative direction, the stability of the system is achieved. Suppose there are N queues in the network, and define the vector of queue backlogs at time t by:

$$Q(t) = (Q_1(t), \ldots, Q_N(t)) \tag{2}$$

The function $L(t)$ is defined as the sum of the squares of all queue sizes at time t, and is called a Lyapunov function:

$$L(t) = \frac{1}{2} \sum_{i=1}^{N} Q_i(t)^2 \tag{3}$$

Then, the Lyapunov drift is defined:

$$\Delta L(t) = L(t+1) - L(t) \tag{4}$$

Every slot t, the current queue state is observed and control actions are taken to greedily minimize a bound on the following drift-plus-penalty expression:

$$\Delta L(t) + V p(t) \tag{5}$$

where $p(t)$ is the penalty function and V is a non-negative weight.

For some RA problems under VANET scenarios, the Lyapunov function can be used to handle the long-term control problem by minimizing the system stability and penalty [92]. In [48], the dynamic cache resource allocation is formulated to maximize the time-average network reward by using Lyapunov

TABLE III: A Summary of convex optimization based RA solutions.

Ref.	Problem type	Objective	Solution approach
[56]	Non-convex	Maximizing network-wide throughput	Formulating the generalized multi-radio and channel-power joint optimization. -Adopting the decentralized Markov approximation to solve the RA problem.
[109]	Non-convex	Maximizing the expected utility	Propsing Lagrangian Multiplier to obtain the optimal solution.
[89]	Non-convex	Maximizing average QoE evaluation	The generalized-reduced gradient method to solve the nonlinear optimization problem.
[87]	Non-convex	Maximizing the average QoE evaluation	The RA problem is transformed into a constrained optimization problem. - Presenting Lagrange Multiplier method to obtain the optimal solution.
[118]	Non-convex	Minimizing the infrastructure load	Proposing Lagrangian multipliers to solve the RA problem.
[69]	Convex	Maximizing the total utility	Applying the max slope-based to solve the optimization problem.
[71]	Non-convex	Maximizing their revenue	Proposing Linear Programming approach to solve the RA problem.
[91]	Non-convex	Achieving a trade-off between the service latency and quality loss	Proposing dynamic task allocation framework. - Applying linear programming-based optimization and binary particle swarm optimization to solve the RA problem.
[82]	Non-convex	Minimizing the delivery time	Formulating the placement problem of the coded pieces as an ILP model.
[84]	Non-convex	Minimizing delay	The RA problem is transformed into a linear optimization problem. -Adopting ADMM technique to solve the RA problem.
[59]	Non-convex	Maximizing the achievable video generating rate	Proposing successive convex optimization technique to solve the RA problem.

optimization method. The authors of [123] propose a computation offloading and resource allocation approach to minimize the own costs, and Lyapunov optimization technique is used to solve this problem.

C. Game Theory

Game theory is the study of mathematical models of strategic interaction among rational decision-makers, which has applications in various fields, including logic, system science, and computer science. Three elements of game theory consist of player, strategy, and payoff. Game theory can be divided into cooperative/non-cooperative, symmetric/asymmetric or static/dynamic games. Game theory, a theoretical framework designed for strategic interactions among rational decision-makers who faces with scarce resources, can be used to model and analyze individual or group behaviors of communication entities in VANETs. Stochastic game and Bayesian game models can be used to model and analyze different conflicting situations in a vehicular network.

- Stochastic game refers to capture repeated interactions among a number of players whose environment changes stochastically, and the environment change is affected by the decision of players. A stochastic game is a 5-tuple: $(N, A, S, q(s|s', a), u_i,)$, where N is a set of players, A is a finite set of action, S is a finite set of state, $q(s|s', a)$ is the transition probability that action a in state s at time t will lead to state s' at time $t+1$, and u_i is a utility function for each player $i \in N$. Therefore, at each stage t with a corresponding state s_t, each player $i \in N$ chooses an action $a_{i,t} \in A_i(s_t)$ and receives a payoff $u_i(s_t, a_t)$, in which a_t is the vector of actions of all player at game stage t. Then, the game moves to a new state s_{t+1} with the transition probability $q(s_{t+1}|s_t, a_t)$. In a stochastic game, the players are characterized by their states. The state transitions are random and may possess the Markov property. To describe the characteristics of vehicles' drive-through and video playback, a stochastic game is adopted to model the states and state transition probabilities of the vehicles [73].
- Bayesian game is a game in which players have incomplete information about the other players, where it has to specify type spaces, strategy spaces, payoff functions, and prior beliefs. A Bayesian game is a tuple (N, A, Θ, p, u_i), where N is the set of players i, A is the set of actions for each player $a_i \in A_i$, Θ is a finite type set for each player $\theta_i \in \Theta_i$, p is the common prior over Θ, and u_i is a utility function for each player $i \in N$. In general, if play i uses the pure strategy s_i, other players use the strategies s_{-i} and the play i's type is θ_i, the expected utility can be calculated as [124]:

$$E[u_i(s_i|s_{-i}, \theta_i)] = \sum_{\theta_{-i} \in \Theta_{-i}} u_i(s_i, s_{-i}(\theta_{-i}), \theta_i, \theta_{-i}) p(\theta_{-i}|\theta_i) \tag{6}$$

In a vehicular network, complete information to select a strategy or action may not be available to a vehicular node. Therefore, to achieve the optimal strategy in such an environment, Bayesian game models based on incomplete information need to be formulated and solved. The learning automata are assumed to be the players in a game and are deployed on vehicles, and dynamic coalition using the concepts of Bayesian theory is formulated among the players of the game [55].

D. Graph Theory

Graph theory is the study of graphs, which are mathematical structures used to model pairwise relations between objects. Therefore, graphs can be used to formulate many types of relations and processes in mathematics, computer science, physics, and social sciences. The graph $G = (V, E)$ comprises a set of vertexes V and edges E. In general, the vertex represents the entity in the network, and the edge represents the "relationship" between two related vertexes. Graph theory is among the most widely used tools for modeling and analyzing the many types of interactions, relations and dynamics in vehicular networks [81], [83]. According to the optimization approaches, the RA problem can be modeled by graph theory with different types such as maximum flow problem, multi-commodity flow problem, and maximum weight matching problem.

- Maximum flow problem refers to find a feasible flow through a flow network that obtains the maximum possible flow rate. An s-t flow network $G = (V, E, s, t, C)$ is

a directed graph, where s is the source, t is the sink, and C is a nonnegative capacity function $c_{ij} \in C$. A feasible flow $f_{i,j}$ usually meets the following two constraints [125]:

$$\text{s.t.} \quad 0 \leq f_{ij} \leq c_{ij}, \quad \forall (v_i, v_j) \in E,$$
$$\sum_{(v_i,v_j)\in E} f_{ij} = \sum_{(v_j,v_i)\in E} f_{ji}, \quad \forall (i,j) \in V - \{s,t\}.$$

Therefore, the maximum flow problem is to maximize the value of flow $val(f)$ which is defined by

$$\max \ val(f) = \sum_{(v_s,v_j)\in E} f_{sj} - \sum_{(v_j,v_s)} f_{js}. \tag{7}$$

In order to process a road layout and an associated vehicular mobility trace, a max-flow problem is formulated to optimize the system throughput by using a time expanded graph [126] .

- Multi-commodity flow problem is a network flow problem with multiple commodities between different sources and sink nodes. We can assume it is a directed network $G = (V, E)$ and let A denote the node-arc incidence matrix. The multi-commodity flow problem can be formulated as [127]:

$$\min \sum_{1\leq k\leq K} c^k x^k \tag{8}$$

where the corresponding constraints are

$$\text{s.t.} \quad \sum_{1\leq k\leq K} x^k \leq u_{ij}, \quad \forall (v_i, v_j) \in E,$$
$$Ax^k = b^k, \quad k = 1, 2, ..., K,$$
$$0 \leq x^k_{ij} \leq u^k_{ij}, \quad \forall (v_i, v_j) \in E, k = 1, 2, ...K.$$

where x^k_{ij} is the flow of commodity k on arc (i, j), x^k is the flow vector for commodity k, c^k is the per unit cost vector for commodity k, and u_{ij} is the capacity for each arc. The multi-commodity flow model has been adopted in the ad-hoc network routing and optimization [67]. Quang $et.al.$ [96] use the multi-commodity network flow model to describe flows in ad-hoc networks, and the QoE-based routing problem is described as an optimization problem of maximizing the total mean opinion score.

- Maximum weight matching problem is the problem of finding, in a weighted graph, a matching in which the sum of weights is maximized. The maximum weight matching problem is solved using the primal dual framework, it is useful to think in terms of upper bounds on the weight of a matching. To select the relay vehicular users to assist the video users in VANETs, the relay assignment problem is transformed to the maximum weighted bipartite matching problem [65].

E. Reinforcement Learning

A Markov decision process (MDP) is a 4-tuple: (S, A, P_a, R_a), where S is a finite set of states, A is a finite set of actions, $P_a(s, s')$ is the probability that action a in state s at time t will lead to state s' at time $t + 1$, $R_a(s, s')$ is the immediate reward received after transitioning from state s to state s', due to action a. The core problem of MDPs is to find a "policy" for the decision-maker: a function π that specifies the action $\pi(s)$ that the decision-maker will choose when in state s. The goal is to choose a policy π that will maximize some cumulative function of the random rewards, typically the expected discounted sum over a potentially infinite horizon [128]:

$$E[\sum_{t=0}^{+\infty} \gamma^t R_{a_t}(s, s_{t+1})] \tag{9}$$

where a_t=$\pi(s_t)$, and γ is the discount factor satisfying $0\leq \gamma \leq 1$. The solution for an MDP is a policy that describes the best action for each state in the MDP, known as the optimal policy. The algorithm includes two steps: (1) a value update and (2) a policy update, which are repeated in some order for all the states until no further changes take place. Moreover, the variants of MDP include the continuous-time Markov decision process (CTMDP) [106], stochastic semi-Markov decision process (SMDP) [94], [102], and partially observable Markov decision process (POMDP) [129]. For RA problems of VANET-based video streaming applications, plenty of previous works focus on modeling the RA problem as the stochastic optimization problem and further solving it through MDP methods [46], [60], [68].

Reinforcement learning (RL) is an area of machine learning concerned with how software agents ought to take actions in an environment to maximize some notion of cumulative reward. The general RL problem is formalized as a discrete-time stochastic control process, such as MDP. In general, there are two main types of RL methods, including value-based and policy-based. The value-based RL method tries to find or approximate the optimal value function, which is a mapping between an action and a value, and the most famous algorithm is Q-learning. The policy-based RL method tries to find the optimal policy directly without the Q-value as a middleman. Deep reinforcement learning (DRL) uses deep learning and reinforcement learning principles to create efficient algorithms, and previously some unsolvable problems can be solved by using the powerful DRL model [130]. Taking advantage of the general-purpose framework in decision-making, reinforcement learning is widely used in solving RA problems in VANETs [103]. Moreover, some typical RL-based approaches are proposed to optimize the resources, including Q-learning, actor-critic, and proximal policy optimization algorithms.

- Q-learning is a value-based reinforcement learning algorithm, which can solve problems with stochastic transitions and rewards. Moreover, Q-learning can identify an optimal action-selection for a given Markov decision process. Q-learning algorithm has a function that calculates the quality of a state-action combination:

$$Q : S \times A \rightarrow \mathbb{R} \tag{10}$$

The core of Q-learning algorithm as a Bellman equation as a simple value iteration update, using the weighted average of the old value and the new information [131]:

$$Q_{t+1}(s_t, a_t) = Q_t(s_t, a_t) + \alpha[r_{t+1} + \gamma \max_a Q_t(s_{t+1}, a) - Q(s_t, a_t)] \tag{11}$$

where r is the reward received when moving from the state s_t to the state s_{t+1}, and α is the learning rate ($0 \leq \alpha \leq 1$). The enhancements of Q-learning include deep Q network (DQN) and double dueling Q network (DDQN). As studied in [107], the proactive caching schedule problem is formulated as a Markov decision processes problem, and a heuristic Q-learning method is used to solve this problem. In [100], the Markov decision process based adaptive video streaming approach is proposed to reduce the playback deadline miss, and a Q-learning method is used to learn the optimal decisions. Moreover, the authors of [104], [105] propose an integrated framework to optimize networking, caching, and computing resources in VANETs, and a DQN-based reinforcement learning method is used to solve the RA problem.

- Actor-critics (AC) method is a temporal-difference method that has a separate memory structure to explicitly represent the policy independent of the value function [132]. Actor-Critics aims to take advantage of all the good stuff from both value-based and policy-based while eliminating all their drawbacks. There are two popular improvements of AC models, including advantage actor-critic (A2C) and asynchronous advantage actor-critic (A3C) [133], [134]. As studied in [108], the proactive caching schedule problem is modeled as a Markov decision process problem for multi-view 3D video applications, and an AC-based method is adopted to solve this problem. In [135], a joint optimization problem is formulated to maximize the video bitrate and decrease time-delays and bitrate variations, where a soft actor-critic DRL algorithm is adopted to solve this problem.
- Proximal policy optimization (PPO) algorithm involves collecting a small batch of experiences interacting with the environment and using that batch to update its decision-making policy [136]. Once the policy is updated with this batch, the experiences are thrown away and a newer batch is collected with the newly updated policy. The key contribution of PPO is ensuring that a new update of the policy does not change it too much from the previous policy. PPO is the current state of the art and used widely to solve for environment with uncertainties. Guan $et.al.$ [137] propose an RL training algorithm, model accelerated proximal policy optimization(MA-PPO), which incorporates a prior model into PPO algorithm to enhance sample efficiency. Zhan $et.al.$ [138] model the offloading scheduling process by MDP, and the training method is designed based on the PPO algorithm.

F. Other Algorithms

1) Heuristic algorithm:

Heuristic algorithm is to solve problems faster and more efficiently than traditional methods by sacrificing optimality, accuracy, precision, or completeness in exchange for speed. Heuristic algorithm can solve a wide range of RA problem for video applications [70], [93], [139], [140]. Some RA problems can be modeled as integer programming (IP) problems, and these IP problems can be solved by efficient approximate algorithms. Hu $et.al.$ [78] formulate an integrity-oriented content offloading (ICO) problem on minimizing the integral content offloading time. Then, the authors split the formulated ICO problem into two subproblems, and heuristically solve them to achieve a near-optimal ICO scheme. Moreover, Hu $et.al.$ [99] study the multimedia multicast scheduling problem, and a heuristic scheduling algorithm is adopted to solve this problem. With the simulation, the performance of the proposed heuristic algorithm approaches the optimal result. Some other RA problems can be formulated as mixed integer programming (MIP) problems which can be solved by the low-complexity heuristic algorithms. Huang $et.al$ [90] propose an adaptive heuristic mechanism to achieve a cost-efficient video delivery in VANETs. With the simulation, the proposed approach is close to the optimal solution in solving efficiency.

2) Approximation Algorithm:

For video streaming applications in VANETs, several RA problems are non-convex and hard to solve. The approximation algorithms are efficient algorithms that find approximate solutions to NP-hard optimization problems with provable guarantees on the distance of the returned solution to the optimal one [49], [64], [141], [142]. Some RA problems can be modeled as a knapsack problem, the dynamic programming method is used to solve the problem. Xu $et.al$ [62] propose a dynamic programming based algorithm for the resource allocation problem of scalable video streaming in VANETs. With the simulation, the proposed algorithm outperforms the greedy algorithms.

It is noted that approximation algorithms provide a worst-case performance guarantee in both computational time and solution quality in dynamic environments, while heuristic algorithms provide a feasible solution without guarantee on its optimality, or even quality, or algorithm running time. The design and analysis of approximation algorithms crucially involve mathematical proof certifying the quality of the returned solutions in the worst case, which distinguishes them from heuristics.

G. Summary

In this section, we focus on the typical technical methods in VANETs. To conclude, we give a summary of the above solutions in Table IV.

V. Enabling Technologies

In this section, enabling technologies of video streaming over VANETs are summarized, which taking account of video communication, caching, and computing.

A. Video Communication

In the following, the state-of-the-art video communication modes based on VANETs are described, including V2V, V2I, and V2X. Therefore, some typical video communication schemes are discussed here. Finally, the summary of video communication in vehicular networks according to their communication modes is listed in Table V.

TABLE IV: Resource optimization technologies.

Technique	Features	Advantages	Disadvantages	Complexity
Convex optimization	These RA problems can be formulated into maximization/minimization problems with constraints.	The solving method can obtain the optimal solution.	It is hard to solve dynamic, time-varying optimization problems.	With the combination of other distributed algorithms, the complexity can be reduced.
Stochastic optimization	Dealing with RA problems under uncertain operating conditions as well as uncertain models.	It suitable for the RA problem with the uncertain environment, and the optimization approach is hard to solve.	No guarantee for a global optimization solution.	Stochastic optimization algorithms are designed to deal with highly complex optimization problems.
Game theory	The RA optimization models include a set of decision-makers to choose the optimal strategy.	The computational complexity and signaling overhead of RA problem can be reduced, significantly.	The assumption that players have the knowledge about their own pay-offs and pay-offs of others is not practical.	Many problems about Nash equilibrium are known to be NP-hard.
Graph theory	Graph theory can model an algorithm for the RA problem by analyzing the interactions in the networks.	The RA problem can be solved by studying the structure of graph.	Adjacency matrix consumes huge amount of memory for storing big graphs.	Low-complexity sub-optimal solutions are obtained through a global scheduler or distributed optimization.
Reinforcement learning	The RA problems are formalized as a discrete time stochastic control process.	RL can address the RA problem by maximizing a numerical reward signal while interacting with the unknown environment.	RL is not preferable to use for solving simple problems.	In RL setting, the equivalence with the model complexity of the learning method may be seen in the policy class complexity.

TABLE V: The summary of video communications in vehicular networks.

Ref.	Communication Mode	Purpose	Evaluation
[143]	V2V	Improving users' QoE	SUMO
[144]		Evaluating video quality	EXata
[145]		Improving the performance of video delivery	EvalVid, SUMO, and NS-3
[146]		Reducing the frame loss as well as increasing the packet delivery ratio	QualNet
[113]		Enhancing PSNR	Simulation
[147]	V2I	Enhancing QoS and QoE performance	Simulation
[148]		Improving visual quality	Simulation
[149]		Mitigating the impact of interference	Monte Carlo simulation
[150]		Evaluating video quality	A real testbed
[151]		Maximizing the utility	Simulation
[152]		Maximizing the effective transmission rate.	NS-2
[92]	V2X	Maximizing QoE	LTE-A simulator
[153]		Helping to reduce stress as well as improving traffic flow	Simulation
[154]		Achieving continuous video delivery	Simulation
[155]		Enhancing the performance of multimedia service	Simulation
[97]		Maximizing the transmission rate	Simulation

1) V2V Communication:

In the VANET environment, the nodes move very fast. Therefore, video streaming applications are supposed to be a difficult task. Quadros $et.al.$ [143] propose a QoE-driven and link-quality receiver-based routing protocol to enhance video quality in V2V scenarios. The proposed protocol combines location information, current link quality conditions, and QoE-indicators to establish multi-hop backbones for video streaming. Moreover, the proposed approach can react well to node failures and enhance the user's experience. Simulation results show that the proposed method can improve users' QoE and reduce network delay.

Video quality measurements for three competitive networks, including IEEE 802.11p, LTE, and LTE direct, have been studied well in previous work. Roy $et.al.$ [144] model and emulate the performance of three networks. The video codec is based on H.264/AVC, and video quality assessment is based on PSNR and structural similarity (SSIM). Moreover, two road scenarios have been considered, including highways and urban. Based on EXata emulator [156], simulation results demonstrate the suitability of these networks for real-time communications in terms of bitrate, inter-vehicle relative speeds and distances. However, the cooperative communication approach needs to be investigated in future work.

By using cooperative V2V communications, Abdi $et.al.$ [145] propose an adaptive video streaming approach for a highway scenario. In the proposed system, video streaming is augmented, compressed, broadcasted, and displayed in surrounding vehicles, which can enhance the driver's visibility and supports the driver's overtaking decision. The simulators are based on EvalVid [157], SUMO [158], and NS-3 [159]. Simulation experiment results confirm that the proposed method can improve the performance of video delivery in terms of the packet delivery ratio and delay.

Moreover, platooning technology is ignored in previous work. The authors of [146] focus on improving real-time video quality in the platoon. Firstly, the performance of video streaming is evaluated in V2V communications environments. Then, a pseudo-broadcast approach is adopted to mitigate the frame loss. Finally, the request-to-send/clear-to-send (RTS/CTS) enabled approach is designed to solve the hidden terminal problem. Based on QualNet simulator [1], the results show that the proposed approach can reduce frame loss and increase the packet delivery ratio.

Clustering for V2V communications and video transmission has not been considered in previous work. Yaacoub $et.al.$ [113] propose a collaborative SVC video streaming approach by using V2V communications. In the proposed system, moving vehicles are grouped into cooperative clusters to enhance video quality. Moreover, LTE is adapted to transmit the video to cluster heads and vehicle communication is based on IEEE 802.11p. The experiments are implemented in Matlab, and simulation results show that the proposed approach can lead to significant enhancements in PSNR. However, future research

[1] http://web.scalable-networks.com/qualnetnetwork-simulator-software

needs to extend the proposed approach to maximize QoE.

2) V2I Communication:

Unlike the work in [113], the authors of [147] propose a collaborative technique for real-time video streaming by using V2I communications. Firstly, the QoE metric is customized for video transmission. Then, different approaches are investigated to improve QoS/QoE performance. Finally, based on 802.11p and LTE communications, a joint collaborative approach is adopted to enhance the performance of video quality. Simulation results show the best performance for different video sequences. However, topics for future work include the joint V2I and V2V communications for video transmission.

Multi-hop transmission of real-time video in vehicular networks has not been studied well. Pokhrel $et.al.$ [148] evaluate the video quality of three-dimensional discrete wavelet transform (3-D DWT) and H.264 video coding standard for multi-hop video transmission by using V2I communications. With the system, a reversible Markov network (RMN) based analytical model is designed to estimate packet loss ratio and throughput. Moreover, field based routing (FBR) method is used to improve visual quality. Simulation results demonstrate that the adaptive video rate has a strong relationship with vehicles' number, locations, and velocities.

Moreover, the impact of interference on real-time high-definition video streaming has not been investigated well in previous work. Kim $et.al.$ [149] study the impact of interference on 60 GHz wireless HD real-time 1080p video streaming in infrastructure-to-vehicle (I2V) telematics platforms. Firstly, the received signal strength has been computed. Secondly, the modulation and coding scheme and achievable rate can be selected. Finally, the video quality can be evaluated. Based on Monte Carlo simulation, the results have the potential to be utilized for the system design. In future work, additional video quality metrics, including QoS and QoE need to be considered for video quality.

Vehicular mobility is ignored in previous work. Belyaev $et.al.$ [150] focus on V2I-enabled multimedia applications, and the performance of multiuser Skype video streaming is evaluated. At first, video sequences can be inputted to Skype in a loop, video transmission is based on UDP protocol. When the Internet is disconnected, the measurement of video bitrate can be processed in terms of PSNR. Simulation results demonstrate that the fairness of bandwidth allocation and users' QoE is important for multiuser Skype call.

Furthermore, maximizing user satisfaction level is a significant issue of concern. Pan $et.al.$ [151] propose a multi-vehicle video dissemination approach by using V2I communications. With the system model, the throughput is a map to the level of the user's satisfaction. Moreover, the scheduling problem is formulated to maximize the utility, which is NP-hard, and can be transferred into the finite-state decision problem. In this context, the admission control and scheduling (ACS) algorithm is adopted to solve this problem. Based on Matlab, simulation results show that the proposed method can achieve better performance than the state of the art.

Kumar $et.al.$ [152] propose a mobile video surveillance system in vehicular sensor networks (VSNs). In this context, game players are mapped on vehicles by using the learning automata theory, where a coalition is formed by using Bayesian game theory. A novel heuristic algorithm is used to solve the data gathering problem. Furthermore, the resource allocation of video dissemination is formulated to maximize the effective transmission rate. In this context, the Nash equilibrium (NE) is used to solve this problem. Based on NS-2, simulation results show the proposed approach is better than the state of the art.

3) V2X Communication:

V2X communication is a key enabler that connects vehicles to neighboring vehicles. khan $et.al.$ [92] propose a joint video quality selection and resource allocation to enhance QoE for vehicular devices. With the system model, a network slicing based clustering algorithm is adopted to partition the vehicles into multiple networks. Moreover, the joint optimization problem is formulated to maximize QoE under constraints of queue stability and QoE. In this context, Lyapunov optimization is used to solve this problem. Based on LTE-A simulator, the results show that the proposed approach achieves low latency and high-reliability communication.

In previous work, approaches combining V2V with V2I communications to improve traffic safety and make driving have not been studied well. Torres $et.al.$ [153] propose a V2X-based video collection approach to reduce stress and improve traffic flow. In this context, different traffic flooding approaches are studied, including the counter-based scheme, distance-based scheme, density-aware reliable broadcast protocol, and backfire scheme. With the different low, medium and high vehicle densities, simulation results show these approaches can achieve acceptable performance in terms of packet arrival ratio and delay.

The performance evaluation in terms of bandwidth, latency, and communication reliability is ignored for video streaming over VANETs. Brahim $et.al.$ [154] propose a dual-interface enabled platform to provide V2X communication. The proposed system framework consists of video processing module, video transmission module and QoS monitoring module. Moreover, QoS-aware radio access selection and vertical handover algorithms are designed to provide continuous video transmission. Simulation results show the proposed approach can balance the usage of the interface and QoS. In addition, a link quality estimator that could predict the link reliability needs to be developed in future work.

However, solutions integrating networking slicing into vehicular networks have not been studied well in previous work. In [155], 5G network slicing enabled V2X framework is proposed to support safety and non-safety applications. The set of 5G slices include autonomous driving, Tele-operated driving, vehicular infotainment and vehicle remote diagnostics/management. The slice for autonomous driving can provide efficient and safe services by using video exchange. The slice for tele-operated driving can provide low latency and highly reliable services by video transmission. Moreover, the slice for vehicular infotainment can ensure passenger comfort service by media consumption. The slice for vehicle remote diagnostics and management can provide vehicle tracking and remote diagnostic services.

Further work on [113], [147], the authors of [97] study the SVC-based video streaming transmission technology under

TABLE VI: The summary of video caching in vehicular networks.

Ref.	Caching Strategy	Purpose	Optimization Tool	Evaluation
[160]	Placement	Optimizing the caching operations	N/A	Tested
[161]		Minimizing the mean waiting time for frames to be cached	N/A	SUMO
[162]		Reducing content retrieval time as well as enhancing the users' QoE	N/A	NS3
[71]		Maximizing the utility	Linear programming	NS-3
[89]		Maximizing the average QoE evaluation	Generalized-reduced gradient	Simulation
[142]		Minimizing the expected amount of offloaded traffic	Approximation algorithm	Simulation
[140]		Minimizing the number of bytes downloaded	Heuristic algorithm	Simulation
[48]		Maximizing the time-averaged network reward	Lyapunov optimization	Simulation
[163]	Delivery	Maximizing the cache hit ratio and delivery cost	Alternating least squares	Simulation
[80]		Minimizing the average time of data downloading	Greedy methods	Simulation
[107]		Maximizing the reward	Deep Q-learning	Simulation
[108]		Maximizing the reward	DRL	Simulation
[164]		Finding the optimal policy	Q-learning	Simulation
[131]	Joint placement and delivery	Maximizing long-term expected reward	Q-learning	SUMO
[165]		Minimizing the communication cost and cache cost	LSTM	NS-3 and SUMO

VANETs, and the cooperative approach is proposed to enhance the video quality. Firstly, the QoE metric of video transmission is customized. Then, the different approaches are investigated to enhance QoS/QoE performance based on V2V and V2I communications. Moreover, a resource allocation problem is formulated to maximize the transmission rate. Simulation results show the proposed approach can lead to significant enhancements in PSNR and QoE.

B. Video Caching

In the following, the state-of-the-art video caching in VANETs categories include placement and delivery. The content placement focuses on studying methods for optimally storing videos in which BS or UE, and the content delivery studies to decide how to send the files, by determining transmission parameters. Therefore, some typical video caching approaches are introduced here. Finally, the summary of video caching according to their categories is listed in Table VI.

1) Placement:

Zhao $et.al$ [160] propose a hierarchical VANET architecture to support caching at different layers, including RSUs, regional servers, and origin servers. With the proposed framework, a content prefetching mechanism assisted by vehicle mobility prediction is developed to optimize the caching operations. Moreover, a real-world VANET testbed is adopted to verify the performance of the proposed scheme.

Due to the high mobility of VANETs, QoS assurance is a challenging task. Kumar $et.al$. [161] propose a QoS-aware video caching scheme in Internet-based vehicular ad hoc networks (IVANETs). The load utilization ratio (LUR) and the query to connectivity ratio (QCR) are adopted to evaluate the QoS. Moreover, the resource allocation problem is formulated to minimize the mean waiting time for frames to be cached. Based on VanetMobiSim [166] and NS-2 [1] with SUMO simulator, the results show the proposed approach is more efficient than the state-of-the-art approaches, including dynamic service, weighted segment, and machine learning based approach.

[1]http://www.isi.edu/nsnam/ns/

In previous work, integrating content-centric networks into vehicular networks has not been studied well. Wei $et.al$. [162] propose a layered cooperative cache management approach for adaptive scalable video streaming in vehicular content-centric networks (VCCNs). With the system, the different layer content can be selected for neighbor nodes, which can reduce content retrieval time and prevent stalls of the video playback. Simulation results show the proposed method can reduce content retrieval time and enhance the users' QoE.

The above solution in [162] lacks an accurate evaluation of caching placement in ICVNs. Therefore, Cao $et.al$. [71] propose a family-aware pricing strategy (FAPS) to improve the performance of video streaming. Firstly, cooperative routing is designed to support near-end video fetching by considering vehicular movement direction, user playback preference, and video popularity. Then, the unicast-based approach is utilized to reduces bandwidth consumption and delay. Finally, a pricing-based video caching strategy is formulated to maximize the utility. In this context, linear programming is used to solve this problem. Based on NS-3, simulation results show the proposed approach can achieve better performance in terms of caching hit ratio and searching delay.

A distributed caching strategy has been ignored in previous work. Sun $et.al$. [89] propose a QoE centric distributed caching approach to enhance users' QoE. Firstly, the QoE evaluation model can be developed. Then, the relationship between bitrate and caching resources is established. Finally, the distributed caching resource allocation is modeled to maximize the average QoE evaluation. In this context, the generalized–reduced gradient (GRG) algorithm is used to solve this problem [167]. Based on Matlab, simulation results indicate that the proposed scheme can increase the users' satisfaction ratio.

Previous works focus on caching at RSUs, while caching at vehicles has not been studied well. Vigneri $et.al$. [142] propose a per chunk allocation policy for video streaming from a vehicular cloud. Firstly, a cache allocation problem is formulated to minimize the expected amount of offloaded traffic, which is NP-hard problem. In this context, two approximation algorithms are adopted to solve this problem. Simulation results show the proposed approach can offload much more

traffic than the state of the art. However, the proper modeling of the per chunk download success probability should be investigated in future work.

Further work on [142], the authors of [140] study on caching multimedia content in VANETs scenario. Firstly, a resource allocation problem is modeled to maximize the number of chunks offloaded. Then, a two-phase per-chunk allocation policy problem is formulated to minimize the number of bytes downloaded. Finally, a heuristic algorithm is used to solve this problem. Based on Matlab, simulation results show the proposed method can lead to considerable gains.

However, cache-enabled ABR streaming over vehicular networks has not been studied well in previous work. Guo $et.al.$ [48] propose a two time-scale dynamic caching algorithm (DCA) for ABR streaming in VANETs. Moreover, a joint video quality adaptation, cache placement, and radio resource allocation problem is formulated to maximize the time-averaged network reward. In this context, the optimization problem is divided into two sub-problems, and Lyapunov optimization is used to solve this problem. Simulation results indicate the effectiveness of the proposed approach. In future work, the effect of BS caching and computing on the performance of ABR streaming should be studied.

2) Delivery:

Due to the high delay, traditional reactive caching approaches are inefficient. Zhang $et.al.$ [163] propose a hierarchical proactive caching approach to reduce network load and improve users' QoE in the self-driving system. In the proposed system, and mobility is considered with the integration of ICN and vehicular networks. The nonnegative matrix factorization (NMF) technique is adopted to predict user's preferences. Moreover, the caching decision problem is formulated to maximize the cache hit ratio and delivery cost. Then, the alternating least squares method is adopted to solve this problem. Simulation results indicate that the proposed approach is significantly more efficient than the state of the art.

RSUs are the significant infrastructures to be deployed for enhancing the network capacity. Ding $et.al.$ [80] propose a RSU caching approach by caching popular files in the RSUs with large storage capacity. Therefore, a resource allocation problem is formulated to minimize the average time of data downloading from on-board units (OBUs). In this context, three algorithms are designed to solve this problem, including optimal, sub-optimal, and greedy methods. Simulation results show the proposed method can reduce the downloading time and improve delivery efficiency.

The existing works mainly focus on caching on RSUs and vehicles, while artificial intelligence (AI)-enabled caching is not considered. Hou $et.al.$ [107] propose a proactive caching strategy in vehicular networks. Firstly, a long short-term memory (LSTM) network is adopted to predict the moving direction of vehicles [168]. Then, based on Markov decision processes, the optimal caching resource allocation problem is formulated to maximize the reward. Finally, a deep Q-learning based algorithm is used to solve this problem. Simulation results show the proposed scheme can receive the highest long-term system rewards than the state of the art.

Furthermore, the proactive caching approach for multi-view 3D videos has been ignored in previous work. Zhang $et.al.$ [108] propose the proactive caching approach for multi-view 3D videos in VANETs. Based on Markov decision processes, the reward function is defined as a combination of cache cost and quality of video streaming. Then, the caching resource allocation problem is formulated to maximize the reward. Finally, a DRL-based algorithm with dynamic k-nearest neighbor is used to solve this problem. Simulation results show the QoE improvement of the proposed scheme. However, more prior information needs to be considered in future research.

The impact of dynamic popularity in VANETs is ignored in previous works. Sadeghi $et.al.$ [164] propose the approach to account for space-time popularity of user requests by casting the caching task. The Markov model is used for the popularity dynamics, and a Q-learning caching algorithm is used to learn the optimal policy. Moreover, the proposed approach entails estimation of the popularity profiles both at the local as well as at the global scale. Finally, an approximation algorithm is adopted to offer faster convergence.

3) Joint Placement and Delivery:

Dai $et.al.$ [131] propose an ABR streaming approach in MEC-based vehicular networks. A joint cache placement, bandwidth allocation, and chunk quality adaptation problem is formulated to optimize average service quality and average freezing delay. In this context, a Q-learning-based chunk placement algorithm is to maximize long-term expected rewards. Moreover, an adaptive-quality-based chunk selection algorithm is to maximize the summation of benefit. Based on SUMO, simulation results show the effectiveness and scalability of the proposed algorithm.

Most of the existing works focus on reinforcement learning-based caching resource optimization, while deep learning-based approaches have been ignored. Khelifi $et.al.$ [165] propose a proactive caching scheme in vehicular networks. The caching resource allocation is formulated to minimize the communication cost and cache cost. Moreover, an LSTM-based algorithm is adopted to predict the moving direction of vehicles. Based on NS-3 and SUMO simulators, and results show the performance improvement in terms of the cache utilization and network delay. In future work, integrating different V2X communication needs to be investigated.

C. Video Computing

In this subsection, video computing focuses on the task of computation offloading with the partial offloading or full offloading. A part of the computation is processed locally and the rest is offloaded to the RSU in the partial offloading manner, while the whole computation is offloaded and processed by the RSU in the full offloading manner. The research on partial offloading focuses on the minimization of the energy consumption while predefined delay constraint is satisfied, or to find a trade-off between the energy consumption and the execution delay. The main objective of the full offloading decision is to minimize an execution delay, or finding a proper trade-off between both the energy consumption and the execution delay. Table VII summarizes the characteristics of the existing video offloading schemes in VANETs.

TABLE VII: The summary of video computation offloading in vehicular networks.

Ref.	Offloading Type	Purpose	Optimization Tool
[169]	Partial offloading	Minimize the cost of transmission computing and task execution	Game theory
[170]		Minimizing the total energy consumption of the vehicles	Convex optimization
[49]		Minimizing the maximal task completion time	Approximation algorithms
[78]	Full offloading	Minimizing the integral content offloading time	Heuristic algorithms
[171]		Minimizing video stalling time	Greedy algorithm
[91]		Minimizing the maximum service latency	Linear programming
[135]		Maximizing video qualities of all vehicles	DRL

1) Partial offloading:

The goal to minimize the total cost of the off-loading process under the delay tolerance of each computation task is pursued by Zhang $et.al.$ [169]. The authors propose an optimal predictive combination-mode MEC off-loading mechanism for various types of computation tasks in VANETs. Moreover, the optimal offloading problem is formulated to minimize the cost of transmission computing and task execution. In this context, the Nash equilibrium (NE) game based method is used to solve this problem. Simulation results indicate the proposed scheme greatly reduces the off-loading cost.

The minimization of the energy consumption while satisfying the delay constraints is also the main objective of [170]. The authors propose an energy-efficient task offloading approach for vehicular edge computing. Moreover, the offloading proportion and uplink/computation/downlink bit allocation of multiple vehicles are formulated to optimize the system performance. In this context, convex optimization is used to solve this problem. Numerical results indicate that the proposed approach can achieve significant energy savings.

VR applications are computation sensitive and delay-sensitive. Current vehicular networks can not satisfy the latency and throughput requirements of wireless VR applications. Since vehicular entertainments have extremely high requirements of delay and computation, it drives the development of a new vehicular networks framework. The authors of [49] propose a cooperative approach for parallel computing and transmission for VR. With the system, VR tasks can be offloaded into the vehicles and MEC servers. Moreover, a joint computation offloading and communication resource allocation problem is formulated to minimize the maximal task completion time, which is NP-hard problem. In this context, a joint offloading proportion and resource allocation optimization (JOPRAO) algorithm is adopted to solve this problem. Simulation results show that the proposed approach can reduce the VR task completion time, significantly.

2) Full offloading:

In order to minimize the integral content offloading time, Hu $et.al.$ [78] propose an integrity-oriented content offloading (ICO) policy approach in vehicular networks. Based on a finite-state Markov chain-based model, a resource allocation problem is formulated to optimize the system performance, which is NP-hard problem. Therefore, the optimization problem is transferred into two sub-problems. In this context, heuristic algorithms are used to solve these problems. Simulation results show that the proposed approach can reduce the integral content offloading time than baseline algorithms.

The traffic offloading for online video service by a cooperative approach has not been studied well. Sun $et.al.$ [171] present a cooperative traffic offloading approach for online video service in heterogeneous vehicular networks. In the proposed framework, RSUs can download video streaming from the Internet and then share it with nearby vehicles. Moreover, a graph-based schedule transmission problem is formulated to minimize stalling time as well as maximize the received amount. In this context, a greed-based algorithm is adopted to solve this problem. Simulation results show that the proposed scheme can outperform the baseline algorithm.

The goal to recognize potential obstacles from a video clip and require to offload this service instance to fog nodes is pursued by Zhu $et.al.$ [91]. The authors propose a solution for latency and quality optimized task allocation in vehicular fog computing. Moreover, a joint optimization problem is formulated to minimize video stalling time. In this context, a linear programming algorithm and binary particle swarm optimization algorithm are adopted to solve this problem. Simulation results show the proposed framework can achieve a better trad-off between the latency and quality.

In order to provide a high quality, low latency, and low bitrate variance live streaming service for vehicles, Fu $et.al.$ [135] propose a live video transcoding approach in fog-enabled vehicular networks. By considering vehicle scheduling, bitrate selection, and computational resource allocation, a joint optimization problem is formulated to maximize the video qualities of all vehicles. Based on a Markov decision process, a soft actor-critic DRL algorithm is adopted to solve this problem. Simulation results indicate that the proposed approach can effectively improve video quality while decreasing latency and bitrate variations, and access excellent performance.

D. Integrated Video Communication, Caching and Computing

For computation-intensive and time-consuming video streaming applications, the integration framework of communication, caching, and computing can provide rich computing and storage resources in VANETs. The related approaches applying the integration framework to video streaming are summarized in Table VIII.

Jiau $et.al.$ [172] propose a multimedia cloud computing framework to improve performance by integrating cloud computing and caching with vehicular networks. The cloud-based vehicular networks (CBVNs) model consists of the perception layer, physical layer, and clustering layer. Based on traffic monitoring and traffic data mining technologies. Moreover,

TABLE VIII: The summary of integrated video communication, caching, and computing in vehicular networks.

Ref.	Purpose	Optimization Tool	Evaluation
[172]	Maximizing the system utility	N/A	NS-2
[52]	Maximizing the QoE of multimedia signals while minimizing energy consumptions	Heuristic algorithm	NS-3
[84]	Minimizing the delay while enhancing the users' QoE.	ADMM	Simulation
[105]	Maximizing the long-term revenue	DRL	Simulation
[173]	Minimizing the system cost	DRL	Simulation
[174]	Minimizing the content downloading delay	Majorization-minimization algorithm	Simulation

a long-term encoding rate assignment problem is formulated to maximize the system utility, and a real-time scheduling problem is designed to achieve each DRV's target utility and bit rate obtained. Based on NS-2, simulation results indicate that the proposed approach

Little specific ICN-based research has looked into energy-efficient multimedia delivery in previous works. Xu $et.al.$ [52] propose a green information-centric multimedia streaming (GrIMS) framework guarantee QoE and energy efficiency (EnE) in heterogeneous VANETs. The proposed GrIMS architecture is developed with the V2V and V2I communication modes. Moreover, based on queuing theory, a joint optimization problem is formulated to maximize the QoE of multimedia signals while minimizing energy consumptions. In this context, three heuristic algorithms are used to solve this problem. Based on NS-3, simulation results the proposed approach outperforms other baseline solutions.

Kazmi $et.al.$ [84] propose an integrated framework to reduce the network delay for infotainment services under VANET scenario by considering communication, caching and computation (3C). Firstly, a joint optimization problem is modeled to minimize the delay while enhancing the users' QoE. Secondly, the problem is transferred into a linear optimization problem. Then, the ADMM approach is used to solve this problem. Simulation results indicate that the proposed approach can reduce the delay compared to the benchmarks. In future work, interference management should be studied.

Jointly considering SDN, NFV, ICN, and MEC technologies for connected vehicles have been largely ignored in the existing research. He $et.al.$ [105] propose an MEC-based integrated framework to improve the performance of video streaming services over vehicular networks by considering networking, computing and caching. Firstly, a joint optimization problem is formulated to maximize the long-term revenue of mobile virtual network operators (MVNO). In this context, the DRL-based approach is adopted to solve this problem. Simulation results show the effectiveness of the proposed approach. In future work, energy efficiency issues need to be considered.

Optimizing the cooperative coded caching placement and computing allocation at both the vehicle level and the RSU level has not been studied well in previous works. The authors of [173] propose a mobility-aware integrated framework in VANETs by considering 3C. Firstly, a joint optimal allocation problem is formulated to minimize system cost. Then, a DRL-based algorithm is used to solve this problem. Simulation results indicate the significant performance gains achieved for the proposed scheme.

Ndikumana $et.al.$ [174] propose a deep learning based caching for self-driving cars in MEC-based VANETs, where the convolutional neural network (CNN) model is adopted to make caching decisions. Firstly, a multi-layer perceptron (MLP) framework is designed to predict the probability of infotainment contents. Then, a joint optimization problem is formulated to minimize the content downloading delay by considering 3C resources, which is non-convex problem. Finally, the block successive Majorization-minimization technique is used to solve this problem. Simulation results show the proposed approach can minimize the delay.

E. Summary

V2V communication enables vehicle video streaming to exchange from one vehicle to another, which enables a significant increase in the visual awareness of each driver. V2I captures video streaming, and then transmits it to inform drivers of conditions they need to be aware of which aids in safety. V2X combines both V2V and V2I technology, which makes every automobile on the road smarter and safer. Moreover, V2X-based video streaming applications can help to alleviate infrastructure deployment costs.

RSUs and vehicles are seen as significant infrastructures to be adopted to improve the network capacity. The existing works related to video caching focus on caching at RSUs and vehicles. Moreover, multi-layer caching approaches have been studied in previous works.

The existing video computation offloading approaches focus on MEC and fog computing (FC) solutions for vehicular networks. Their architectures of MEC and FC have overlapping characteristics but also differences in approach. Moreover, vehicular networks with MEC/FC is a promising approach to address explosive computation demands and restrict delay constraints.

Enabling technologies, including communication, caching, and computing can improve the performance of multimedia services in vehicular networks. With the integrated framework, video contents can be cached on RSUs and vehicles, and video computation offloading tasks can execute on the cloud, MEC, and FC servers. Moreover, the integrated framework with vehicles is a way to increase accessibility to video applications.

VI. Challenges and Future Research Directions

Despite current works being done for video streaming applications over VANETs, with the development of Internet of vehicle and artificial intelligence, some significant research challenges need to be addressed. In this section, we discuss some challenges and present some future research directions.

A. Adaptive Bitrate

Recently, adaptive bitrate (ABR) is a potential technology to enhance the performance of video streaming over VANETs. Firstly, by using ABR technology, BSs can cache video content in better granularity, where the network delay can be reduced and the efficiency of cache resources can be improved. Secondly, the users can consume scalable video content with QoE guarantee. However, enabling ABR to VANET faces challenges. For one thing, the joint video caching and transmission problem can be formulated to optimize the communication and caching resources. For another, video caching scheduling should be optimized at a layered chunk level to enhance the QoE. Finally, distributed caching management for vehicular video streaming should be studied to improve the users' satisfaction ratio.

B. QoE Models

In VANETs, video streaming applications can be used for road safety, traffic coordination, and infotainment applications. Therefore, the video streaming transmission over VANETs remains a challenge on QoS and QoE issues. The QoS is an objective criterion, which focuses on service requirements that need to be met by the network. Moreover, QoE is a subjective criterion, which emphasizes the degree of satisfaction of users. Influence factors, including human, system, and context-aware factors have a great correlation with QoE models. Because the relationship between QoE model and influence factors is complex and nonlinear, it is hard to formulate the QoE model of video streaming over VANETs. Therefore, choosing differently the leading component of influence factors to formate QoE models in different environments and scenarios is a great challenge. In addition, addressing research to standardize QoE models over VANET is a future issue.

C. Content-Aware Resource Allocation

The content-aware resource allocation (CARA) refers to take into account the load and popularity distribution of content to decide the required resources. In the CARA problem, the available resources and their cost should be considered, where the available resources consist of the processing power, storage, and bandwidth. For different video streaming applications over VANETs, users have different content requirements. Therefore, developing content-aware optimized scheduling schemes for video streaming over VANET is an important area of future research.

D. Fair Resource Allocation

During RA for video streaming over VANETs, fairness is an important property. Fairness in RA can ensure the entity provides services to users fairly, when the resources are insufficient to satisfy the requirement. There are two types of fairness, including effort fairness and outcome fairness. In vehicular networks, the frequent network disconnection, unlimited battery power and storage can exhaust the communication, computing, and storage resources. Therefore, RA faces a challenge to achieve the trade-off between fairness and resource utilization. In general, fairness-based RA problems can be modeled by using $max\text{-}min$ fairness and $proportional$ fairness methods. The $max\text{-}min$ fairness refers to allocate available resources to the maximum extent possible to the disadvantaged users. The $proportional$ fairness is achieved when the objective function of RA is maximized. Then, addressing different approaches to the fairness concept in vehicular networks is an open issue.

E. Intelligent Resource Allocation

Recently, artificial intelligence (AI) based methods, especially deep learning (DL), provide new solutions to solve the RA problems with low-complexity [130], [175]. In VANETs, some important features of APs/users, including user requirements, network conditions, resource utilization, can be predicted and modeled conveniently by using DL methods. Moreover, the extracted features can be adopted to make resource optimization decisions. Therefore, how to efficiently predict and model the RA problem to maximize the revenue is an open issue. In addition, when each APs/users can make decisions individually, the distributed DL approaches can be exploited to optimize resources efficiently.

F. Security and Privacy

In VANETs, the communication between vehicles and infrastructure is an open-access environment which causes vehicular networks more vulnerable to attacks [176], [177]. In this case, the attacker can modify, intercept, and delete the data information. For video streaming applications over VANETs, the security threat refers to the network level, including content transport security, identity authentication, and network intrusion [178]. Therefore, different types of security mechanisms of VANETs need to develop for identity and authentication, access control systems, trust management, and intrusion detection systems.

G. UAV-Assisted Vehicular Networks

Unmanned Aerial Vehicles (UAVs) can be used as flying base stations to dynamically cache the popular contents, track the mobility pattern of the corresponding users and, then, effectively serve them. The UAVs-assisted vehicular networks can be exploited to dynamically increase the storage and transmission capacities, and boost coverage, spectral efficiency, and user QoE [179]. However, major challenges for UAV-assisted caching include location optimization of UAVs, user-UAV association, and the contents to cache at UAVs.

H. Others

Federated learning (FL) is a machine learning technique that trains an algorithm across multiple decentralized edge devices or servers holding local data samples, without exchanging them. The FL framework allows vehicles to participate in the training process, train their local models, and upload the model parameters to the RSU. FL applications in vehicular networks aim to address critical issues such as data privacy, data security, data access rights and access to heterogeneous

data [180], which can bring the benefits: better efficiency, better privacy, and better utility.

Age of Information (AoI) refers to quantify the freshness of the knowledge we have about the status of a remote system, which is a novel metric of timeliness, significantly different, to existing ones such as delay and latency. Autonomous vehicles need to exchange critical safety information with other vehicles in their vicinity, and this requirement will grow with the advent of autonomous cars. it is essential to keep the information fresh [181], as outdated information has diminished value.

VII. Conclusion

In this paper, a systematic survey and outlook of video streaming over VANETs were presented. We began a discussion with background knowledge of vehicular networks and video streaming. Then, the categories of RA schemes were presented. Moreover, this survey laid emphasis on some useful and efficient technologies during the RA process, including convex optimization, stochastic optimization, game theory, graph theory, and reinforcement learning. Next, enabling technologies of video streaming over VANETs were provided. Finally, some significant research challenges and future directions were identified.

In summary, research on video streaming over VANETs is quite broad, and some challenges lay ahead. Nevertheless, it is favorable for the network community to address the challenges and go forward. This paper is trying to briefly summarize video streaming applications over VANETs, which may open a new avenue for the development of video streaming applications.

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