

A Mobility-Aware Vehicular Caching Scheme in Content Centric Networks: Model and Optimization

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Abstract—Edge caching is being explored as a promising technology to alleviate the network burden of cellular networks by separating the computing functionalities away from cellular base stations. However, the service capability of existing caching scheme is limited by fixed edge infrastructure when facing the uncertainties of users' requests and locations. The vehicular caching, which uses the moving vehicles as cache carriers, is regard as an efficient method to solve the problem above. This paper studies the effectiveness of vehicular caching scheme in content centric networks by developing optimization model towards the minimization of network energy consumption. Particularly, we model the interactions between caching vehicles and mobile users as a 2-D Markov process, in order to characterize the network availability of mobile users. Based on the developed model, we propose an online vehicular caching design by optimizing network energy efficiency. Specifically, the problem of caching decision making is firstly formulated as a fractional optimization model, towards the optimal energy efficiency. Using nonlinear fractional programming technology and Lyapunov optimization theory, we derive the theoretical solution for the optimization model. An online caching algorithm to enable the optimal vehicular caching is developed based on the solution. Finally, extensive simulations are conducted to examine the performance of our proposal. By comparison, our online caching scheme outperforms the existing scheme in terms of energy efficiency, hit ratio, cache utilization, and system gain.

Index Terms—Vehicular caching, convex optimization, nonlinear fractional programming, Lyapunov optimization, energy efficiency

I. INTRODUCTION

The explosive growth of mobile data [1] is driving a myriad of novel services and applications, such as augmented/virtual reality, ultra-high definition video, which make mobile users enjoy a fairly rich network experience. However, the resulting data tsunami seriously challenges mobile operators worldwide

in their network performance [2], *e.g.*, network capacity, Quality of Service (QoS), and energy consumption. Particularly, a predication report from Cisco shows that there are about 49 exabytes of monthly global mobile data with 11.6 billion of mobile devices in 2021, increasing about sevenfold between 2016 and 2021 [1]. The large-scale deployment of infrastructure is the simplest method to accommodate titanic data requests in the future, which however incurs huge monetary costs.

A variety of novel and exciting techniques have been studied to tackle the problem. By deploying large-scale small cells, UDN (Ultra-Dense Network) has been stressed upon as a promising technology for the next generation of mobile communication, aiming to reduce the burden at MBSs (Macro Base Stations) [3]. A new computing paradigm called edge computing has been proposed with the push from cloud services and pull from the voluminous and complex data, in order to provide the reliable data processing at the network edge [4], [5]. Data offloading is an efficient method to improve the network experience of mobile users by using the complementary technologies in 5G systems, such as Wi-Fi, to offload the mobile data originally targeted toward cellular networks [2]. By offering storage resource to the edge of network, the edge caching is recently proposed to deal with the increasing data demand of mobile users and balance the overload in cellular networks, in order to satisfy the ultra-low latency requirement of next generation mobile networks [6].

All above technologies focus on scheduling computation and communication resources to achieve a better system utilization, targeting on the improvement of network capacity. Nevertheless, they fail to consider the uncertainties of mobile users, including locations and requests, which will degrade the QoE (Quality of Experience) perceived by users due to the fixed service range and low utilization of mobile data. Besides, the strong dependence on fixed infrastructure also limit the extension of service coverage. The vehicular caching, which caches mobile data in vehicles (*e.g.*, taxis and buses) and uses the mobility of vehicles to improve the service range and capacity of caching, is a potential method.

In this work, we explore the energy-efficient caching services provided by vehicular caching scheme in content-centric networks [7] for mobile users. The content-centric networking (CCN) is a communication architecture built on named data [7]. Compared with traditional networks that built on named hosts, CCN requires less backhaul energy at the cost of caching energy in wireless caching networks, which thus contributes to the construction of energy-efficient wireless networks. On

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the other hand, as a key component of 5G network, the vehicular communication techniques enabled by IEEE 802.11p or LTE (Long Term Evolution) have been widely studied in recent years, including communication protocols [8]–[10], multi-hop backbone communications [11], big data driven vehicular social networks [12], [13], and traffic safety [14]. Most of these researches aim to deal with the highly-dynamic network topology caused by the mobility of vehicles. The extensive interactions between moving vehicles and mobile users provide a positive condition to improve the service range of vehicular caching scheme. However, this natural feature has not yet attracted wide attention. Therefore, using the mobility of vehicles to provide mobile users with fast and reliable data access in CCN becomes our motivation.

Different from the existing works above, three advantages is achieved by the mobility-aware vehicular caching scheme in CCN. 1) *Cost-saving deployments*: By caching the mobile data in moving vehicles, the large-scale deployment of infrastructure is reduced. The cost input in both operators and users thus would be significantly decreased. 2) *Enhanced service capacity*: Using the mobility of caching vehicles, the service capacity of caching is enhanced, including the service range and cache utilization. This is because that users will encounter multiple caching vehicles in a short time, thus the caching vehicles may perform multiple times services after caching data one time. 3) *Energy-efficient updating*: Based on CCN, the cached mobile data is managed by naming information, the overhead of cache updating thus can be reduced. Besides, real-time V2V communications can be used to share the caching data, which also decreases the overhead of backhaul. To achieve above goals, the optimal caching decision in caching vehicles becomes the major object. In this paper, we first explore the relationship of caching vehicles and mobile users. Based on the interactions between moving vehicles and mobile users, a vehicular caching design in CCN is proposed to improve the network energy efficiency. We proceed in three steps:

- *Modeling*: We formulate the interactions between caching vehicles and mobile users as a 2-D Markov process, in order to characterize the network availability of mobile users. This is the first step to incorporate the mobility of vehicles, and to provide more flexible and wider caching services for mobile users. Based on this model, the service probability of mobile users can be obtained.
- *Designing*: Based on the developed model above, we propose a vehicular caching scheme by caching mobile data in vehicles. To make the optimal caching decision, we first formulate the network energy efficiency in vehicular caching as a fractional optimization problem, and then explore the solution by incorporating fractional programming technology and Lyapunov optimization theory. Based on the solution, a novel online algorithm is proposed to ensure the energy efficiency oriented vehicular caching.
- *Validations*: Finally, our proposal is evaluated by extensive simulations. Simulation results show that our scheme achieves a better performance in terms of energy

TABLE I

Notations	Descriptions
F	Set of files
B	Fragment size
W	System bandwidth
q_j	Cache decision of F_j
p_j	Request probability of F_j
ϕ	Zipf exponent
N_f	Number of fragments
N_v	Number of vehicles
N_u	Number of users
R	Radius of cellular cell
μ	Mean service rate of cellular network
ν	Mean service rate of caching vehicles
λ	Mean arrival rate of users' requests
ξ	Mean inter-meeting rate between users and caching vehicles
ω	Tolerant time of requests
σ^2	Noise power

efficiency, hit ratio, cache utilization and system gain.

The remainder of this paper is structured as follows: Section II presents a briefly survey about the existing works related to our study. Section III illustrates the system model of our research. Section IV firstly formulates the vehicular caching as an optimization problem and then introduces the designed online vehicular caching scheme. Section V conducts the performance evaluation about our proposal while Section VI closes our paper with conclusion.

II. RELATED WORKS

Edge caching has been extensively studied in recent years. In this section, we briefly survey existing literature in edge caching from the perspective of access networks [15], coding [16], [17], prediction [18], [19], and vehicular communications [20], [21].

Liu *et al.* [15] study the performance analysis of typical BS-assisted caching networks. The factors that impact caching performance in cache-enabled wireless access networks, including interference, backhaul capacity, BS density, and cache capacity, are investigated to efficiently deploy BS cache. To improve the utilization of cache storage, coding based edge caching is a potential research direction in recent years. Gabry *et al.* [16] explore the impact of MDS (Maximum-Distance Separable) coding on the energy efficiency performance of edge caching, in order to minimize the backhaul rate and the total energy consumption. Ji *et al.* [17] propose a coded distributed caching system for the canonical shared link caching network based on linear index coding. They conclude that caching file fragments rather than full files will obtain a better performance. Another important problem in caching is the uncertainty of users' requests, which poses a serious impact on hit ratio edge caching. Song *et al.* [18] propose a MAB (multi-armed bandit) based content caching and sharing scheme, in order to profile the unknown content popularity and make the caching more efficient. Focusing on the scenario of vehicular communications, Zhao *et al.* [19] design a multi-tier caching mechanism based on a novel hybrid Markov model to predict the connection of vehicles and RSUs. As such, the content offloading in RSU can be optimized.

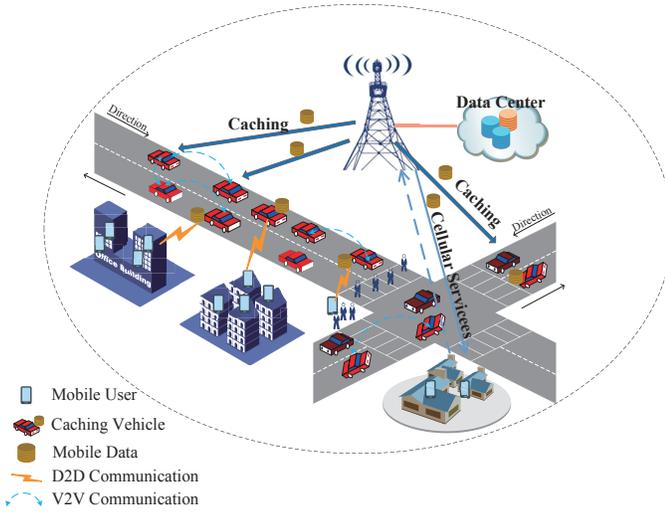


Fig. 1: Network Scenario

All above researches focus on improving the performance of the edge caching scheme/algorithm. However, they fail to consider the limited service range and cache utilization due to the strong dependence on fixed infrastructure. Different from these works, we use the moving vehicles as cache carriers, called vehicular caching. We shift vehicles from service consumers to service providers, in order to achieve a higher flexibility to provide caching services. On the other hand, mobile users in traditional caching schemes have to move to encounter different cache carriers, resulting in the degradation of QoE and also causing low hit ratio. This drawback can also be overcome by vehicular caching because caching vehicles can encounter and serve multiple mobile users continuously after updating the cache one times.

In recent years, Vigneri *et al.* are devoted to the studies of vehicular caching [20], [21]. They highlight the strength of vehicular communications based on the comparison between the caching in vehicular networks and cellular networks. In this work, we further develop an online vehicular caching scheme and explore the improved performance in hit ratio, energy efficiency, cache utilization and system gain. Particularly, we explore the performance enhancement by adopting named data information and D2D communications in vehicular caching scheme, which is the first work to do this research to the best of our knowledge.

III. SYSTEM MODEL

This section elaborates on the system model of our study. We first describe the network scenario, and then introduce the communication model based on D2D communications. Before modeling the interactions of caching vehicles and mobile users, we present the energy consumption models to evaluate the impact of vehicular vehicles on the total energy consumption. The notations in our analysis are listed in TABLE I.

A. Network Scenario

In our study, we consider an urban scenario within the coverage of a cellular MBS, as shown in Fig. 1. Different from

traditional cellular networks, we focus on an edge caching CCN where the requests of users are served by either MBS or caching vehicles, in order to avoid the system performance degradation incurred by the rapid increasing of mobile users and data demands. Nowadays, the complex and large-scale road systems make the meetings between mobile users and moving vehicles frequent. As such, the real-time communications between mobile users and moving vehicles can directly take place with the support of IEEE 802.11p or LTE protocol as long as their distance is within the valid communication range. We apply D2D (Device-to-Device) communication technology to support data transmissions between caching vehicles and mobile users because of its strength in resource utilization and network throughput [22]. The communication modes of mobile users are determined by network environments. Since this work focuses on the solution when or before the network burden takes place, we assume that in this case the communications with caching vehicles act as the preference setting of mobile users. Two types of data packets are involved in CCNs, *i.e.*, Interest packets and Data packets [7]. The same content is identified by matching the names in both Interest packets and Data packets. Note that the name of each packet is an opaque and binary object to networks. As such, the sources of packets (in public naming conventions) even packet names (in private naming conventions) cannot be obtained by other network members, such as routers, in order to protect the privacy of users and transmission security [7]. Therefore, multiple users interested the same content can share the transmissions from caching vehicles. Specifically, each user sends Interest packets involving the naming information of requested content to nearby vehicles by broadcasting. Any vehicle that receives the Interest packets and has the requested content in the cache storage directly delivers the Data packets to the user. Otherwise, the vehicle sends these pending Interests to surrounding vehicles and informs the user about the pending time. The pending time is determined by the distance between the vehicle caching requested content and the user. If the pending time exceeds the user's tolerance time, the request will be switched to MBS. Therefore, there are three types of communication nodes in our scenario, *i.e.*, MBS, mobile users, and caching vehicles. Mobile users can access network services either from the always-on MBS by cellular communications or from the opportunistic caching vehicles by D2D communications. It should be noted that the network throughput is improved by caching mobile data in vehicles while the energy consumed by caching is accordingly increased. Since the network performance varies over time, we start our analysis by assuming networks operate in slotted time, *i.e.*, time slot t represents the time interval $[t, t + 1)$, $t \in \{0, 1, 2, \dots\}$. Other assumptions in analysis, which are simple but can capture the basic elements, are shown as follows.

- *Mobile users*: We incorporate all the users that request cellular services within the service range of MBS, *i.e.*, mobile users. To characterize the spatial distribution of mobile users is the first step to analyze the connections among mobile users, MBS, and moving vehicles.

The Poisson point process (PPP), which is a classical and reliable method to model spatial distribution, has been widely used in the analysis of cellular networks. Many existing prediction methods, such as Markov based mobility prediction algorithm [19], cannot be directly applied in our scenario since it is difficult to get specific mobility traces of mobile users in the two-dimensional plane. Therefore, by referring to [15], [23], we use the homogeneous Poisson point process (PPP) to characterize the specific distribution of mobile users in a given range. For instance, assuming the mean rate of PPP is λ_u , the probability that there are N_u users in the cell is obtained as $\frac{\lambda_u^{N_u}}{N_u!} e^{-\lambda_u}$.

- *Caching vehicles*: We assume the contact times between a user and the vehicles caching the requested data follow the exponential distribution with mean rate λ_v [20] [24].
- *Data catalogue*: We denote the requested mobile data catalogue by a set of file fragments with same size, *i.e.*, $F = \{F_1, F_2, \dots, F_{N_f}\}$. It should be noted that the assumption is reasonable since files can be divided into multiple fragments with same size [20], [25]. Besides, the approach that caches the complete file or none of it may not achieve the optimal network performance [20]. All file fragments have different requested probabilities, denoted by the vector $\mathbf{p} = \{p_1, \dots, p_{N_f}\}$. We apply the widely used Zipf distribution model to compute the popularity of fragments, *i.e.*, the request probability of the fragment F_j is

$$p_j = \frac{1}{\left(\sum_{j=1}^{N_f} 1/j^\phi\right) j^\phi}, \quad (1)$$

where ϕ is the Zipf exponent and its specification can be referred to [16], [26]. Let q_j , $j \in \{1, 2, \dots, N_f\}$ denote the probability that fragment j is cached in vehicles. The caching probability vector $\mathbf{q} = \{q_1, q_2, \dots, q_{N_f}\}$ then can be formed.

B. Communication model

In this part, we describe D2D-enabled communication models in vehicular caching scenario. Many works has been on applying D2D communications in vehicular networks, in order to enhance the network performance of traditional ad-hoc vehicular networks [27], [28]. Besides, V2P (Vehicle-to-Pedestrian) communications are considered as a similar communication mode with V2V excepted the limited power consumption of pedestrian user according to [29]. We denote by $h_{i,j}$ as the channel gain from the transmitter i to the receiver j , and assume a case that caching vehicles reuse the downlink channel. According to [22], [30], the instantaneous SINR (signal-to-interference-plus-noise ratio) for the user k served by MBS is

$$\gamma_k^B = \frac{P_B^t h_{B,k}}{\sigma^2 + \sum_{n=1}^{N_v} \varepsilon_{n,k} P_{v,k}^t h_{n,k}}, \quad (2)$$

where P_B^t is the transmit power of MBS, and $h_{B,k}$ denotes the channel gain of the wireless propagation channel between

MBS and the user k . The part of $\sum_{n=1}^{N_v} \varepsilon_{n,k} P_{v,k}^t h_{n,k}$ shows the interference from the vehicles reusing the same channel with the downlink of MBS. N_v is the number of vehicles. $\varepsilon_{n,k} = 1$ denotes that the vehicle n reuses the link of the user k . Similarly, the SINR for the communication link between the caching vehicle and the user k is

$$\gamma_k^v = \frac{P_{v,k}^t h_{v,k}}{\sigma^2 + P_{B,k}^t h_{B,k} + \sum_{n=1, n \neq v}^{N_v} \varepsilon_{n,m} P_{v,k}^t h_{n,k}}, \quad (3)$$

where $P_{v,k}^t$ is the transmit power of the caching vehicle, and $P_{B,k}^t h_{B,k}$ is the interference at user k caused by the MBS. Similarly with (2), the part of $\sum_{n=1, n \neq v}^{N_v} \varepsilon_{n,k} P_{v,k}^t h_{n,k}$ shows the interference from the vehicles reusing the same channel with the transmitting vehicle.

Following [27] and [31], we only consider the large-scale fading phenomenon when computing γ_k^v . Note that, the methods of resource allocation and channel reuse to alleviate the interference of D2D-enabled vehicular communications have been widely studied, so that we assume the ideal interference management.

For V2V communications, the unit disk model is used to grossly capture the fact that communication performance depends on the transmission range of two vehicles. According to this model, the communication can directly take place when the Euclidean distance of a pair of vehicles is within the valid communication range [32].

C. Energy Consumption Model

Constructing green wireless networks is a long-term target not only for traditional mobile communication networks but for next generation vehicular networks, which makes the energy efficiency in vehicular communications concerned, especially with the popularization of electric vehicles [33]. It should be noted that, using the caching scheme may reduce the transport energy consumption from MBS at the expense of the increase of caching energy. Therefore, our goal is to find the optimal caching solution by taking account of the increased throughput and energy consumption. To develop the energy consumption model in vehicular caching scheme, we only consider the energy consumption that can be impacted by the caching policy, *i.e.*, transport energy consumed by MBS, transport energy and caching energy consumed by caching vehicles by simplifying the energy consumption model in traditional cellular networks [34].

- *Energy consumption for MBS*. Let S denote the coverage area of a MBS. To denote the transport energy consumed by MBS, we apply the linear energy consumption model [16], [35] as

$$P_m(t) = R_m(t) \omega_t^m, \quad (4)$$

where $\omega_t^m = 0.5 * 10^{-8}$ J/bit denotes the rate of energy consumption for the transmissions from MBS [16], and $R_m(t)$ is the total data served by MBS in time slot t .

- *Energy consumption for caching vehicles*. The energy consumed by caching vehicles consists of two parts, *i.e.*, transport energy and caching energy. Considering the

A. Problem Formulation

Based on the analysis in III-B, the total network throughput in time slot t based on Shannon's formula can be obtained as

$$\begin{aligned} R_{tot}(t) &= R_m(t) + R_v(t) \\ &= W \sum_{k=1}^{N_u} [k P_{s,m,k}(t) \sum_{j=1}^{N_f} (q_j(t) |p_j(t)) \log_2(1 + \gamma_k^m(t)) \\ &\quad + k P_{s,v,k}(t) \sum_{j=1}^{N_f} ((1 - q_j(t)) |p_j(t)) \log_2(1 + \gamma_k^v(t))], \end{aligned} \quad (18)$$

where $R_m(t)$ and $R_v(t)$ are the throughput served by MBS and caching vehicles, respectively. Besides, $P_{s,m,k}(t)$ and $P_{s,v,k}(t)$ denote $P_{s,v}\{k\}$ and $P_{s,v}\{k\}$ at time slot t , respectively. $q_j(t)$ denotes the caching probability of fragment j at time slot t . We adopt the same system bandwidth for both vehicle-user links and cellular links. This is typical in existing researches related with the coexistence of two kinds of links, such as in D2D-enabled vehicular communications [28], LTE-based V2X communications [38], and D2D relay networks [39].

To obtain the optimal caching policy, we focus on the energy efficiency of networks and formulate a fractional optimization problem. From a long-term perspective, the optimization model of network energy efficiency is

$$\begin{aligned} \min \eta_{EE} &= \lim_{t \rightarrow \infty} \frac{\frac{1}{t} \sum_{\tau=0}^{t-1} P_{tot}(\tau)}{\frac{1}{t} \sum_{\tau=0}^{t-1} R_{tot}(\tau)} = \frac{\bar{P}_{tot}}{\bar{R}_{tot}} \quad (19) \\ \text{s.t. C1: } &\bar{D}_n \leq D_{av}, \forall n \in \{1, \dots, N_u\}, \\ \text{C2: } &\sum_{j=1}^{N_j} q_j(t) B \leq S_{cv}, \\ \text{C3: } &0 \leq q_j(t) \leq 1, \forall j \in \{1, \dots, N_f\}, \end{aligned}$$

where \bar{D}_n is the time average expectation of response time that users experience, and the constraint C1 is to guarantee the stability of user queue with data arrival. Considering users' requirements in QoE, we assume $D_{av} = \omega$, where ω is the mean delay tolerance of users. S_{cv} is the maximum storage capacity of each caching vehicle. The vector $\mathbf{q} = \{q_1(t), q_2(t), q_3(t), \dots, q_j(t)\}$ denotes the caching decisions for mobile data. C2 is to limit the total caching capacity of caching vehicles.

B. Problem Solution

1) *Transformation*: It is obvious that the above optimization problem is nonconvex. As such, we first transform the above fractional and tough nonconvex problem into a linear and convex one based on the nonlinear fractional programming technology [40].

To make the transformation, we have the following theorem.

Theorem 1: The problem of $\min \eta_{EE}$ can be equivalently transformed to $\min \bar{P}_{tot} - \eta_{EE}^{opt}(t) \bar{R}_{tot}$

Proof: To prove Theorem 1, we assume that $\mathbf{q}^*(t)$ is the optimal caching decision vector at time slot t . We now prove that at any time slot, when \mathbf{q}^* is the solution of one of the

two minimization problems, it must be the solution of the other one. Specifically, we divide the proof into two parts, *i.e.*, necessity proof and sufficiency proof.

The necessity proof is to prove that \mathbf{q}^* is the solution of $\min \bar{P}_{tot} - \eta_{EE}^{opt} \bar{R}_{tot}$ because it is the solution of $\min \eta_{EE}$.

Specifically, since \mathbf{q}^* is the optimal solution of optimization problem (19), we have

$$\eta_{EE}^{opt} = \frac{\bar{P}_{tot}(\mathbf{q}^*)}{\bar{R}_{tot}(\mathbf{q}^*)} \leq \eta_{EE} = \frac{\bar{P}_{tot}(\mathbf{q})}{\bar{R}_{tot}(\mathbf{q})}, \quad (20)$$

where $\mathbf{q}^* \in \mathbf{q}$. We further transform (20) to

$$\bar{P}_{tot}(\mathbf{q}^*) - \eta_{EE}^{opt} \bar{R}_{tot}(\mathbf{q}^*) = 0, \quad (21)$$

$$\bar{P}_{tot}(\mathbf{q}) - \eta_{EE}^{opt} \bar{R}_{tot}(\mathbf{q}) \geq 0, \quad (22)$$

$$\bar{P}_{tot}(\mathbf{q}) - \eta_{EE} \bar{R}_{tot}(\mathbf{q}) = 0. \quad (23)$$

Therefore, we can obtain the following equation.

$$\begin{aligned} \min \bar{P}_{tot}(\mathbf{q}) - \eta_{EE}^{opt} \bar{R}_{tot}(\mathbf{q}) \quad (24) \\ = \bar{P}_{tot}(\mathbf{q}^*) - \eta_{EE}^{opt} \bar{R}_{tot}(\mathbf{q}^*) \\ = 0. \end{aligned}$$

The proof for the necessity of Theorem 1 is completed.

For sufficiency proof, we aim to prove that \mathbf{q}^* is the solution of problem (19) with the premise that \mathbf{q}^* is the solution of $\min \bar{P}_{tot} - \eta_{EE}^{opt} \bar{R}_{tot}$.

Assuming \mathbf{q}^* is the solution of (24), we have

$$\begin{aligned} \min \bar{P}_{tot}(\mathbf{q}) - \eta_{EE}^{opt} \bar{R}_{tot}(\mathbf{q}) \quad (25) \\ = \bar{P}_{tot}(\mathbf{q}^*) - \eta_{EE}^{opt} \bar{R}_{tot}(\mathbf{q}^*) \\ = 0. \end{aligned}$$

By rearranging above equation, we obtain

$$0 = \bar{P}_{tot}(\mathbf{q}^*) - \eta_{EE}^{opt} \bar{R}_{tot}(\mathbf{q}^*) \leq \bar{P}_{tot}(\mathbf{q}) - \eta_{EE}^{opt} \bar{R}_{tot}(\mathbf{q}). \quad (26)$$

So that, we have

$$\eta_{EE}^{opt} = \frac{\bar{P}_{tot}(\mathbf{q}^*)}{\bar{R}_{tot}(\mathbf{q}^*)}, \quad (27)$$

and

$$\eta_{EE}^{opt} \leq \frac{\bar{P}_{tot}(\mathbf{q})}{\bar{R}_{tot}(\mathbf{q})}. \quad (28)$$

It can be seen that \mathbf{q}^* is also the solution of (19). The sufficiency proof of Theorem 1 is completed.

Therefore, the proof of Theorem 1 is completed. ■

Hence, the original fractional optimization problem (19) is transformed to

$$\begin{aligned} \min \bar{P}_{tot} - \eta_{EE}^{opt}(t) \bar{R}_{tot} \quad (29) \\ \text{s.t. C1, C2, C3.} \end{aligned}$$

In the time slot t , since $\eta_{EE}^{opt}(t)$ is unknown, we relax the minimization (29) as

$$\begin{aligned} \min \bar{P}_{tot} - \eta_{EE}(t) \bar{R}_{tot} \quad (30) \\ \text{s.t. C1, C2, C3.} \end{aligned}$$

According to [40], [41], this model is a linear and convex optimization model.

2) *Virtual Queue*: Although the original fractional optimization model is transformed to a linear and convex one, it is still difficult to directly solve it due to the existence of time-related variables. Besides, using the traditional heuristic or iterative algorithm easily incur large computing overhead and delay, which is intolerant in highly dynamic communication environments. As such, we explore the application of Lyapunov optimization theory in this study to solve the optimization problem [41]. Before that, the primary question is to tackle the time-related inequality constraint C1. To this end, the virtual queue technology is used to transform the time-related variable into a problem of queue stability [42], [43]. Specifically, for constraint C1, the virtual queue $H_n(t)$ for the user n is defined as

$$H_n(t+1) = \max[H_n(t) + e_n(t), 0], \quad (31)$$

where $e_n(t) = D_n(t) - D_{av}$. Based on the definition, we give Theorem 2 below.

Theorem 2: The constraint C1 can be satisfied by guaranteeing that the virtual queue is mean rate stable.

Proof: The equation (31) can be recast as

$$H_n(t+1) \geq H_n(t) + e_n(t). \quad (32)$$

By summing over $t \in \{0, \dots, K-1\}$ at both sides of above inequality and rearranging terms, we have

$$H_n(K) \geq H_n(0) + \sum_{t=0}^{K-1} e_n(t). \quad (33)$$

If we divide both sides of (33) by K , and take the value of K going to infinity, we obtain

$$\lim_{K \rightarrow \infty} \frac{1}{K} H_n(K) \geq \lim_{K \rightarrow \infty} \frac{1}{K} H_n(0) + \lim_{K \rightarrow \infty} \frac{1}{K} \sum_{t=0}^{K-1} e_n(t). \quad (34)$$

Taking an expectation for (34), the equation becomes

$$\lim_{K \rightarrow \infty} \frac{1}{K} E[H_n(K)] \geq \lim_{K \rightarrow \infty} \frac{1}{K} E\left[\sum_{t=0}^{K-1} D_n(t)\right] - D_{av}. \quad (35)$$

According to Jeasen's theory, the following inequality can be obtained

$$0 \leq |E\{H_n(t)\}| \leq E\{|H_n(t)|\}. \quad (36)$$

Because $H_n(t)$ is mean rate stable, we have

$$\lim_{K \rightarrow \infty} \frac{E\{|H_n(K)|\}}{K} = 0. \quad (37)$$

Therefore, due to $H_n(K) \geq 0$, it is obvious that $|E\{H_n(t)\}| = E\{H_n(t)\}$. Hence, the left side of (35) should be

$$D_{av} \geq \bar{D}_n, \quad (38)$$

where $\bar{D}_n = \lim_{K \rightarrow \infty} \frac{1}{K} E\left[\sum_{t=0}^{K-1} D_n(t)\right]$.

The proof of Theorem 2 is completed. ■

3) *Lyapunov Optimization*: In this part, we aim to apply the Lyapunov optimization theory to solve the optimization problem (30). Firstly, we need to define the Lyapunov function as follows.

Let $\Theta(t) \triangleq \mathbf{H}(t)$ denote the combined queue backlog vector where $\Theta(t) = (\theta_1(t), \theta_2(t), \theta_3(t), \dots, \theta_N(t))$, the quadratic polynomial of Lyapunov function is defined as [41]

$$L(\Theta(t)) \triangleq \frac{1}{2} \sum_{n=1}^{N_u} H_n(t)^2. \quad (39)$$

After that, the one-slot conditional Lyapunov drift can be obtained as

$$\Delta(\Theta(t)) \triangleq E\{L(\Theta(t+1)) - L(\Theta(t)) | \Theta(t)\}. \quad (40)$$

Further, we use the drift-plus-penalty to guarantee the stability of the virtual queue and solve the optimization problem. By the drift-plus-penalty, the problem (30) can be solved as

$$\min \Delta(\Theta(t)) + VE\{P_{tot}(t) - \eta_{EE}(t)R_{tot}(t) | \Theta(t)\}. \quad (41)$$

To solve the minimization problem (41), we give Theorem 3 as follows.

Theorem 3: The bound of the drift-plus-penalty can be written as

$$\begin{aligned} \Delta(\Theta(t)) + VE\{P_{tot}(t) - \eta_{EE}(t)R_{tot}(t) | \Theta(t)\} &\leq B \\ &+ \sum_{n=1}^{N_u} H_n(t) E\{e_n(t) | \Theta(t)\} \\ &+ VE\{P_{tot}(t) - \eta_{EE}(t)R_{tot}(t) | \Theta(t)\}, \end{aligned} \quad (42)$$

where

$$B \geq \frac{1}{2} \sum_{n=1}^{N_u} E\{e_n(t)^2 | \Theta(t)\}. \quad (43)$$

Proof: By squaring both sides of equation (31) and rearranging terms, we have

$$\frac{1}{2} [H_n(t+1)^2 - H_n(t)^2] \leq \frac{1}{2} e_n(t)^2 + H_n(t)e_n(t). \quad (44)$$

Summing over $n \in \{1, \dots, N_u\}$ for (44) and taking a conditional expectation, we have

$$\begin{aligned} \frac{1}{2} \sum_{n=1}^{N_u} E\{H_n(t+1)^2 - H_n(t)^2 | \Theta(t)\} &\leq \\ \sum_{n=1}^{N_u} \frac{1}{2} E\{e_n(t)^2 | \Theta(t)\} &+ \sum_{n=1}^{N_u} H_n(t) E\{e_n(t) | \Theta(t)\}. \end{aligned} \quad (45)$$

According to (40), the above equation equals to

$$\Delta(\Theta(t)) \leq \frac{1}{2} \sum_{j=1}^J E\{e_j(t)^2 | \Theta(t)\} + \sum_{j=1}^J H_j(t) E\{e_j(t) | \Theta(t)\}. \quad (46)$$

Adding $VE\{P_{tot}(t) - \eta_{EE}(t)R_{tot}(t)|\Theta(t)\}$ on both sides of (46), it becomes

$$\begin{aligned} \Delta(\Theta(t)) + VE\{P_{tot}(t) - \eta_{EE}(t)R_{tot}(t)|\Theta(t)\} &\leq B \\ &+ VE\{P_{tot}(t) - \eta_{EE}(t)R_{tot}(t)|\Theta(t)\} \\ &+ \sum_{j=1}^J H_j(t)E\{e_j(t)|\Theta(t)\}. \end{aligned} \quad (47)$$

Therefore, the equation (42) can be proved, where

$$B \geq \frac{1}{2} \sum_{j=1}^J E\{e_j(t)^2|\Theta(t)\}. \quad (48)$$

The proof of Theorem 3 is completed. \blacksquare

Based on above analysis, the optimization problem of (30) can be solved by minimizing the right-hand-side of inequality (47) rather than directly minimizing $\Delta(\Theta(t)) + VE\{P_{tot}(t) - \eta_{EE}(t)R_{tot}(t)|\Theta(t)\}$.

4) *Performance of Lyapunov Optimization*: In this part, we further conduct a theoretical performance analysis about the Lyapunov optimization based the solution above.

Boundedness Assumptions

Before the anlysis, we first give general assumptions as follows.

$$E\{R_{tot}(t)\} \in [R_{\min}, R_{\max}], \quad (49)$$

$$E\{P_{tot}(t)\} \in [P_{\min}, P_{\max}], \quad (50)$$

$$0 \leq q(t) \leq 1, \quad (51)$$

$$E\{P_{tot}^*(t)\} \leq E\{R_{tot}^*(t)\}(\eta_{EE}^{opt} + \delta^2), \quad (52)$$

$$E\{e_n(t)|\Theta(t)\} = E\{e_n(t)\} \leq \delta^2. \quad (53)$$

Apparently, the assumptions (49)-(51) are reasonable since the three variables must be limited in specified ranges. The assumption (52) is reasonable according to (21). For the assumption (53), since $e_n(t)$ may take positive or negative value, we thus assume that its expectation is less than a finite constant δ^2 .

Performance Analysis

In Theorem 3, we successfully prove that the problem (30) is equivalent to minimizing the right-hand-side of (42) based on the Lyapunov optimization theory. As such, we further explore the performance of the right-hand-side minimization. Specifically, assuming that the optimal caching decision \mathbf{q}^* is obtained by the right-hand-side minimization, there are several properties we aim to discuss.

It should be noted that the virtual queue is mean rate stable, since the inequality (42) satisfies the basic form of drift-plus-penalty in [41]. Therefore, the constraint C1 is satisfied according to Theorem 2.

By substituting the boundedness assumptions into (42) and taking $\delta \rightarrow 0$, we have

$$\begin{aligned} \Delta(\Theta(t)) + VE\{P_{tot}(t) - \eta_{EE}(t)R_{tot}(t)|\Theta(t)\} &\leq B \\ &+ VE\{P_{tot}^*(t) - \eta_{EE}(t)R_{tot}^*(t)|\Theta(t)\}. \end{aligned} \quad (54)$$

Due to $E[E[X_2|X_1]] = E[X_2]$, we then take an expectation on both sides of inequality (54), it thus becomes

$$\begin{aligned} E\{L(\Theta(t+1))\} - E\{L(\Theta(t))\} + VE\{P_{tot}(t) \\ - \eta_{EE}(t)R_{tot}(t)\} &\leq B + VE\{P_{tot}^*(t) - \eta_{EE}(t)R_{tot}^*(t)\}. \end{aligned} \quad (55)$$

Summing over from $t \in \{0, \dots, K-1\}$, we get

$$\begin{aligned} E\{L(\Theta(K))\} - E\{L(\Theta(0))\} + V \sum_{t=0}^{K-1} E\{P_{tot}(t) \\ - \eta_{EE}(t)R_{tot}(t)\} &\leq KB + KVE\{P_{tot}^*(t)\} \\ &- VE\{R_{tot}^*(t)\} \sum_{t=0}^{K-1} \eta_{EE}(t). \end{aligned} \quad (56)$$

Plugging assumption (52) into (56), we then divide (56) by VK and take $K \rightarrow \infty$, it becomes

$$\begin{aligned} \lim_{K \rightarrow \infty} \frac{1}{K} \sum_{t=0}^{K-1} E\{P_{tot}(t) - \eta_{EE}(t)R_{tot}(t)\} &\leq \frac{B}{V} \\ &+ \eta_{EE}^{opt} E\{R_{tot}^*(t)\} - E\{R_{tot}^*(t)\} \lim_{K \rightarrow \infty} \frac{1}{K} E\left\{ \sum_{t=0}^{K-1} \eta_{EE}(t) \right\}, \end{aligned} \quad (57)$$

where

$$\lim_{K \rightarrow \infty} \frac{1}{K} \sum_{t=0}^{K-1} E\{L(\Theta(K))\} - E\{L(\Theta(0))\} = 0. \quad (58)$$

According to the Lebesgue dominated convergence theorem, we obtain

$$\lim_{K \rightarrow \infty} \frac{1}{K} E\left\{ \sum_{t=0}^{K-1} \eta_{EE}(t) \right\} = \eta_{EE}, \quad (59)$$

where we assume $\lim_{K \rightarrow \infty} \frac{1}{K} \sum_{t=0}^{K-1} \eta_{EE}(t)$ is convergent. Rearranging (57) we have

$$\frac{B}{V} + \eta_{EE}^{opt} E\{R_{tot}^*(t)\} \geq E\{R_{tot}^*(t)\} \eta_{EE}. \quad (60)$$

Finally, we obtain the upper bound of η_{EE} as

$$\eta_{EE} \leq \frac{B}{VE\{R_{tot}^*(t)\}} + \eta_{EE}^{opt}. \quad (61)$$

From (61) we can see, η_{EE} will approach to η_{EE}^{opt} by increasing the parameter V .

From the analysis above, the original optimization problem (19) now can be solved by minimizing the right-hand-side of (42). The minimization of the right-hand-side of (42) equals to

$$\begin{aligned} \min \sum_{n=1}^{N_u} H_n(t)D_n(t) + VE\{P_{tot}(t) - \eta_{EE}(t)R_{tot}(t)|\Theta(t)\} \\ \text{s.t. C2, C3.} \end{aligned} \quad (62)$$

The new optimization model (62) obtains a trade-off between the minimization of energy efficiency and the stability of the virtual queue. In this case, the large V will achieve a

Algorithm 1 Online Caching Algorithm.

Input: $H_n(t), \eta_{EE}(t)$;

Output: $H_n(t+1), \eta_{EE}(t+1), \mathbf{q}^*(t+1)$;

- 1: At the time slot t , get the current variables and obtain the optimal caching decision $\mathbf{q}^*(t+1)$ by solving (62);
- 2: Update $H_n(t+1)$ according to (31);
- 3: Update $\eta_{EE}(t+1)$ according to;

$$\eta_{EE}(t) = \frac{\sum_{t=0}^{K-1} P_{tot}(\mathbf{q}^*(t+1))}{\sum_{t=0}^{K-1} R_{tot}(\mathbf{q}^*(t+1))},$$

- 4: $t = t + 1$;
-

good energy efficiency performance with the cost of the performance degradation of virtual queue stability. Therefore, to select an appropriate value for V that balances the performance of energy efficiency and virtual queue stability is critical.

C. Online Caching

Based on the conclusion above, we develop an online caching scheme in Algorithm 1. Specifically, at each time slot, the cache decision for next time slot is determined in MBS by optimizing the network energy efficiency. Once the caching decision is received by a caching vehicle, it will compare the decision from MBS with their own caching data and in case of similarity, it does not need to update the current cache, otherwise, it should renew the cache based on the received decision from MBS. There are two methods to update caching data based on CCNs, *i.e.*, caching vehicles can get the updating data based on the naming formation from nearby vehicles or from MBS. In the next time slot, mobile users will enjoy the services under the cooperation of caching vehicles and MBS. Algorithm 1 shows the detailed decision-making process. Firstly, using the variables $H_n(t)$ and $\eta_{EE}(t)$, the decision $\mathbf{q}^*(t+1)$ can be calculated by (62) and then be broadcasted to caching vehicles. Secondly, $H_n(t)$ and $\eta_{EE}(t+1)$ are updated according to their renewal processes, respectively. Finally, MBS switches to next time slot and prepare to a new process.

Remark 1: In the online caching scheme, the decision at next time slot is made by the current network state. However, due to the highly dynamic network environments and the uncertainty of mobile users, the hit ratio of caching vehicles may be influenced with different slot lengths. In Section V, we do not evaluate the impact of different slot lengths on the performance of the online vehicular caching. This is because that the problem above can be easily solved by existing predication algorithms, such as deep learning [44]. The prediction based caching decision is also our next work.

V. PERFORMANCE EVALUATION

In this section, the performance of our proposal is evaluated by extensive simulations on Matlab.

A. Simulation Settings

We consider a simple but practical urban simulation scenario. In the cell served by a MBS with a disk of radius

TABLE II: Simulation Parameters

Parameters	Value	Parameters	Value
$P_{v,k}^t$	23dBm	σ^2	-110dBm
P_B^t	46dBm	W	10MHz
ζ_v	15.13	ϕ	0.7
B	1000	F_n	10Mb

$R = 350$ meters, we select a road segment that has four-lane bidirectional traffic flow. The system bandwidth is set as 10 MHz, which is a typical setting in D2D/LTE related researches, as shown in [28], [38], [39]. The performance under the joint service of caching vehicles and MBS is simulated. Specifically, to simulate the behavior of vehicles, we use the real-world mobility traces of taxi cabs, collected from the GPS coordinates of approximately 320 taxis over 30 days in Rome, Italy [45]. According to the data set, we extrapolate the statistics of vehicle distribution, which then is assumed as the Poisson distribution in our simulation. We model the spatial distribution of mobile users as homogeneous Poisson point process (PPP) [15]. The probability that there are n mobile users in a given region thus can be obtained. The parameter V , which is used to control the trade-off between queue stability and energy efficiency, has been widely studied in existing literature [41]–[43]. We therefore opt for $V = 50$ that guarantees the convergence according to their results, in order to fully focus on evaluating the performance with the variations of request arrival rate, cache proportion and cache capacity. Other parameters in our simulations are shown in TABLE II.

B. Simulation Results

Fig. 3 shows the relationship between energy efficiency and request arrival rate. In this experiment, we assume that the normalized caching capacity is 0.01, *i.e.*, each caching vehicle caches at most 1% of total data due to the storage limitation. Besides, the cache proportion is set to 0.5, which means that half of vehicles act as cache carriers. Fig. 3 compares the energy efficiency (η_{EE}) of online vehicular caching (Online VC) with that of offline vehicular caching (Offline VC) and no vehicular caching (No VC). The lower η_{EE} means that the lower energy is consumed by data transmissions, which demonstrates the better performance in energy consumption. With different λ , the results of No VC remain at a steady level. The Offline VC means that the cache decision is updated at a relatively long time interval, *e.g.*, one day, as illustrated in [21]. This approach may reduce the backhaul energy consumption but the real-time and optimal hit ratio cannot be obtained. For Offline VC, the energy efficiency increases gradually when λ is small. When $\lambda \geq 0.6$, the η_{EE} of Offline VC also remains at a steady level. For Online VC, the η_{EE} is apparently increased with the increase of λ though the increment gradually decreases. The large λ also makes the η_{EE} of Online VC steady gradually. This is because that too many requests of mobile users exceed the service capacity of caching vehicles. In this case, much more users will be served by MBS. Therefore, the strength of energy performance incurred by caching vehicles is gradually reduced. Averagely,

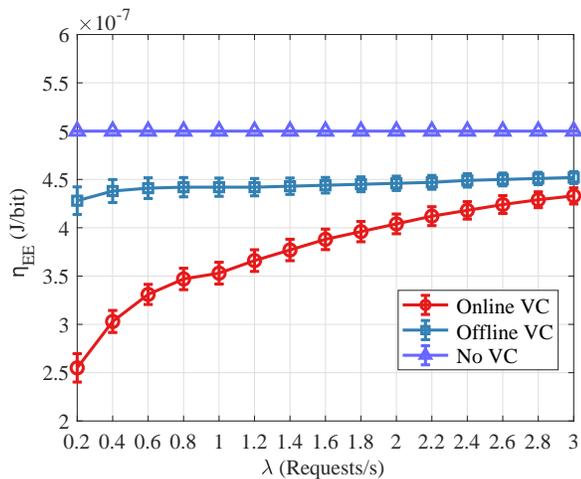


Fig. 3: Comparison for the energy efficiency of three schemes

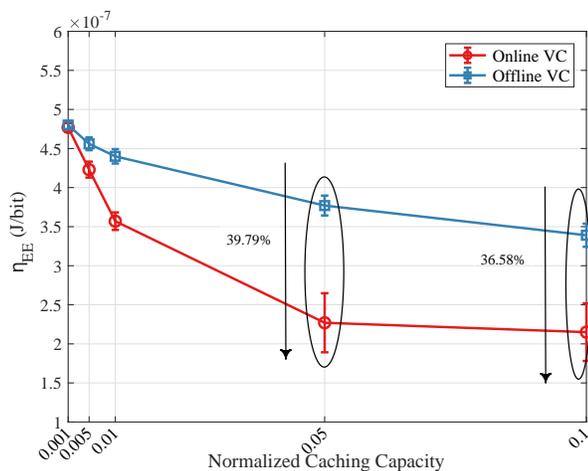


Fig. 4: Impact of normalized caching capacity on energy efficiency

the energy efficiency of Online VC improves about 35.8% compared with No VC, and about 12.63% compared with Offline VC. The reason that Online VC outperforms Offline VC is that Online VC covers the changing needs of mobile users by making caching decisions in a small slot time based on the newly proposed algorithm.

Fig. 4 shows the energy efficiency performance with the variations of normalized caching capacity. In this experiment, the cache size of each caching vehicle, referred as normalized caching capacity, is set in the range of 0.1 – 10% of the total data catalogue. Besides, λ is set to 1 and the cache proportion is set to 0.5. The comparison of η_{EE} between Online VC and Offline VC is conducted. In Fig. 4, it can be seen that Online VC always outperforms Offline VC in different normalized caching capacity, which verifies the efficiency of the newly proposed algorithm. The gap between these two schemes reaches a maximum value when the normalized cache capacity is 0.05, *i.e.*, Online VC improves about 37.79% compared with Offline VC. Specifically, the gap between two schemes is small when the caching capacity is small. This is because that only a small part of mobile users can be served by caching

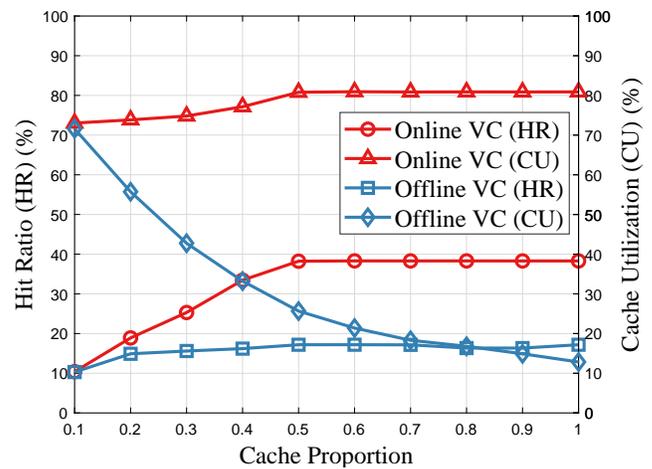


Fig. 5: Impact of cache proportion on hit ratio and cache utilization

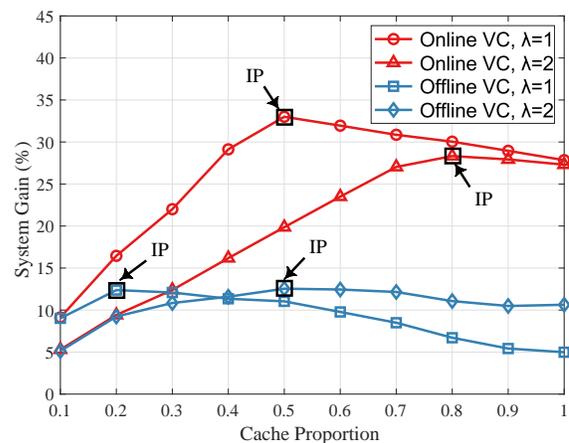


Fig. 6: Comparison of system gain in different scenarios

vehicles, resulting in the minor gain. With the increase of cache capacity, the gap between two schemes increases, which is because more users are served by caching vehicles. In this case, the advantage of our proposal is obvious. When the cache capacity reaches 0.05, the gap is gradually reduced and tends to be steady. This is because that the vehicular cache reaches a saturated condition, *i.e.*, the cache capacity of caching vehicles is enough to provide caching services to mobile users. In this case, the increase of cache capacity will result in extra cache energy on both schemes.

Fig. 5 is to explore the impact of cache proportion on hit ratio and cache utilization. In this experiment, we still set $\lambda = 1$, and assume the normalized cache capacity is 1%. The hit ratio refers to the proportion of users served by caching vehicles when they send requests to vehicles. If the requests cannot be responded by caching vehicles in tolerance time, mobile users will switch to communicate with MBS. As such, the higher hit ratio demonstrates that the vehicular caching has more powerful service capability. The cache utilization denotes the utilization of mobile data cached by vehicles, *i.e.*, the proportion that mobile data in caching

vehicles is accessed by mobile users. The ultimate value of cache utilization (100%) means that the mobile data updated in caching vehicles one times can serve mobile users all the time. In this case, there is no need to update vehicular cache, which will significantly reduce the network overhead. Specifically, when the cache proportion is small, there is a rising tendency in hit ratio for both online and offline caching schemes. The Online VC firstly achieves a major increase and then remains a steady level, which always outperforms the Offline VC. Averagely, the Online VC improves about 10.4% in hit ratio compared with the Offline VC. However, when the hit ratio reaches a steady state, to increase cache proportion will incur extra backhaul energy and caching energy, resulting in the performance degradation of energy efficiency. This conclusion can be a guidance to determine the cache proportion that achieves the optimal energy efficiency. On the other hand, with the increase of cache proportion, the cache utilization obtained by Online VC always remains a relatively stable range, *i.e.*, [73%, 81%]. This stability is achieved by the real-time optimization based on the newly proposed algorithm. However, Offline VC, which updates the cache content at a long time interval, obtains a declining cache utilization with the increase of cache proportion. For cache utilization, Online VC achieves at most 80.63% performance improvement compared with the Offline VC.

Fig. 6 presents the system gain caused by the two caching schemes with the variations of cache proportion. The system gain represents the extra system throughput produced by the vehicular cache, whose increase is because that multiple times services may be performed by a caching vehicle after caching data. Actually, the reason behind the increase of system gain is correspondence with cache utilization in Fig. 5. In this experiment, the normalized cache capacity is also 1%. We opt for two values for λ , *i.e.*, $\lambda = 1$ or $\lambda = 2$, to make a comparison. It can be seen that four curves in Fig. 6 have different Inflection Points (IPs). The existence of IP is because that when the system gain reaches a maximum value, the service of vehicular caching is saturated, which means the increase of cache proportion no longer contributes to the improvement of system throughput. Specifically, when $\lambda = 1$, the IP is reached by Online VC at the point where the cache proportion is 0.5, and by Offline VC when the cache proportion is 0.2. These results show that caching vehicles play a stronger role in Online VC compared with Offline VC. Therefore, the Online VC makes the network accommodate more users compared with Offline VC, accordingly resulting in more system gain. In Fig. 6, the maximum system gain is about 33%, obtained by Online VC. The similar conclusion can also be obtained under $\lambda = 2$ while the maximum system gain is about 28%. Besides, the figure shows that the Online VC achieves a better system gain compared with Offline VC in a given cache proportion, which also verifies the effectiveness of our proposal.

VI. CONCLUSION

This paper focuses on enabling the efficient and reliable vehicular caching in cellular networks. Specifically, we first

develop a 2-D Markov process to model the communications of caching vehicles and mobile users. The probability that mobile users served by caching vehicles or MBS can be calculated. Further, The D2D communication technology is used to evaluate the network throughput in our scenario. By incorporating the D2D communications and a series of energy consumption models, the caching decision problem then be formulated as a fractional optimization model, targeting on the optimization of energy efficiency. To the best of our knowledge, this is the first study that takes the energy efficiency as an optimization goal in vehicular caching, which is because that the energy management is a promising and crucial problem with the popularization of electric vehicles in the future. We then use the nonlinear fractional programming technology and Lyapunov optimization theory to explore the solution of the above optimization problem. The problem thus can be transformed into a linear and convex one. Based on the solution, we develop an online caching algorithm for vehicular caching scheme. This, to the best of our knowledge, is also the first literature to apply the Lyapunov in the research of vehicular caching, which can provide an important reference to other related studies. By extensive simulations based on Matlab, the performance of the online vehicular caching is evaluated in terms of energy efficiency, hit ratio, cache utilization and system gain. The comparison results with other schemes also verify the effectiveness of our proposal.

APPENDIX A

PROOF FOR THE DERIVATION OF $E[L_0]$ AND $E[L_1]$

For simplicity, we assume $M = \xi P_{00} + v P_{11}$. The equation (12) becomes

$$G'_0(z) + \frac{(-\lambda z + \lambda + \xi)}{\omega z - \omega} G_0(z) = \frac{M}{\omega z - \omega}. \quad (63)$$

Assuming that $f(x) = \frac{-\lambda z + \lambda + \xi}{\omega z - \omega}$, we have

$$e^{\int f(x) dx} = e^{-\frac{\lambda}{\omega} z + \frac{\xi}{\omega} \ln(z-1)} = e^{-\frac{\lambda}{\omega} z} (z-1)^{\frac{\xi}{\omega}}. \quad (64)$$

Dividing the terms of (63) by $e^{-\frac{\lambda}{\omega} z} (z-1)^{\frac{\xi}{\omega}}$, we obtain

$$\begin{aligned} G'_0(z) e^{-\frac{\lambda}{\omega} z} (z-1)^{\frac{\xi}{\omega}} + e^{-\frac{\lambda}{\omega} z} (z-1)^{\frac{\xi}{\omega}} \frac{(-\lambda z + \lambda + \xi)}{\omega z - \omega} G_0(z) \\ = \frac{M}{\omega z - \omega} e^{-\frac{\lambda}{\omega} z} (z-1)^{\frac{\xi}{\omega}}. \end{aligned} \quad (65)$$

Then we obtain

$$\frac{d}{dz} [G_0(z) e^{-\frac{\lambda}{\omega} z} (z-1)^{\frac{\xi}{\omega}}] = \frac{M}{\omega z - \omega} e^{-\frac{\lambda}{\omega} z} (z-1)^{\frac{\xi}{\omega}}. \quad (66)$$

Integrating from 0 to z , we get

$$\begin{aligned} G_0(z) e^{-\frac{\lambda}{\omega} z} (z-1)^{\frac{\xi}{\omega}} - G_0(0) = \\ \frac{M}{\omega} \int_0^z e^{-\frac{\lambda}{\omega} x} (x-1)^{\frac{\xi}{\omega}-1} dx. \end{aligned} \quad (67)$$

Further, we have

$$\begin{aligned} G_0(1) &= \lim_{z \rightarrow 1} G_0(z) \\ &= \lim_{z \rightarrow 1} \frac{G_0(0) + \frac{M}{\omega} \int_0^z e^{-\frac{\lambda}{\omega} x} (x-1)^{\frac{\xi}{\omega}-1} dx}{e^{-\frac{\lambda}{\omega} z} (z-1)^{\frac{\xi}{\omega}}}. \end{aligned} \quad (68)$$

Due to $G_0(1)$ is a infinite value, we obtain that

$$G_0(0) = -\frac{M}{\omega} \int_0^z e^{-\frac{\lambda}{\omega}x} (x-1)^{\frac{\xi}{\omega}-1} dx. \quad (69)$$

For simplicity, we rewrite the equation as $G_0(0) = -\frac{M}{\omega}K$. So that, $G_0(1)$ is obtained as

$$\begin{aligned} G_0(1) &= \lim_{z \rightarrow 1} \frac{\frac{M}{\omega}K + \frac{M}{\omega} \int_0^z e^{-\frac{\lambda}{\omega}x} (x-1)^{\frac{\xi}{\omega}-1} dx}{e^{-\frac{\lambda}{\omega}z} (z-1)^{\frac{\xi}{\omega}}} \\ &= \lim_{z \rightarrow 1} \frac{\frac{M}{\omega}K \left(1 - \frac{\int_0^z e^{-\frac{\lambda}{\omega}x} (x-1)^{\frac{\xi}{\omega}-1} dx}{\int_0^1 e^{-\frac{\lambda}{\omega}x} (x-1)^{\frac{\xi}{\omega}-1} dx}\right)}{e^{-\frac{\lambda}{\omega}z} (z-1)^{\frac{\xi}{\omega}}}. \end{aligned} \quad (70)$$

By L'Hopital rule, we have

$$\begin{aligned} G_0(1) &= \frac{\frac{M}{\omega}K}{\frac{\xi}{\omega} \int_0^1 e^{-\frac{\lambda}{\omega}x} (x-1)^{\frac{\xi}{\omega}-1} dx} \\ &= \frac{\frac{M}{\omega}K}{\frac{\xi}{\omega}K} = \frac{M}{\xi}. \end{aligned} \quad (71)$$

According to the equation of $G_1(z)$ and L'Hopital rule, we have

$$\begin{aligned} G_1(1) &= \lim_{z \rightarrow 1} \frac{\xi z G_0(z) - z\nu P_{11} - \xi z P_{00}}{\lambda z + \nu z - \nu - \lambda z^2} \\ &= \frac{\xi G_0(1) + \xi G'_0(1) - \nu P_{11} - \xi P_{00}}{\nu - \lambda}. \end{aligned} \quad (72)$$

Therefore, we have

$$E[L_0] = G'_0(1) = \frac{\nu - \lambda}{\xi} \sum_{n=1}^{\infty} P_{1n}. \quad (73)$$

According to $G'_0(z)$, we obtain

$$E[L_0] = \lim_{z \rightarrow 1} G'_0(z) = \frac{\lambda G_0(1) - \xi G'_0(1)}{\omega}. \quad (74)$$

Due to $\sum_{n=1}^{\infty} P_{1n} + \sum_{n=0}^{\infty} P_{0n} = 1$, we obtain

$$E[L_0] = \frac{\lambda\nu - \lambda^2}{\nu\omega + \nu\xi - \lambda\omega}. \quad (75)$$

Similarly, according to $G_1(z)$, we have

$$\begin{aligned} E[L_1] &= \lim_{z \rightarrow 1} G'_1(z) \\ &= \lim_{z \rightarrow 1} \frac{\xi z G_0(z) - z\nu P_{11} - \xi z P_{00}}{\lambda z + \nu z - \nu - \lambda z^2}. \end{aligned} \quad (76)$$

By L'Hopital rule, it becomes

$$E[L_1] = \frac{\xi G_0(1) + \xi G'_0(1) - \nu P_{11} - \xi P_{00}}{\nu - \lambda} \quad (77)$$

$$\begin{aligned} &= \frac{\xi(\lambda\nu - \lambda^2)}{(\nu\omega + \nu\xi - \lambda\omega)(\nu - \lambda)} \\ &= \frac{\xi\lambda}{\nu\omega + \nu\xi - \lambda\omega}. \end{aligned} \quad (78)$$

The derivation for $E[L_0]$ and $E[L_1]$ is proved.

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