Caching on Vehicles: A Lyapunov Based Online Algorithm

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Abstract. With the explosive increase of mobile data and users, data tsunami seriously challenges the mobile operators worldwide. The vehicular caching, which caches mobile data on widely distributed vehicles, is an efficient method to solve this problem. In this paper, we explore the impact of vehicular caching on cellular networks. Specifically, targeting on network performance in energy efficiency, we first formulate a fractional optimization model by considering the network throughput and energy consumption. We then apply nonlinear programming and Lyapunov technology to relax the nonlinear and nonconvex model. Based on analysis, we propose a novel online task decision algorithm. Based on this algorithm, vehicles determine to act either as servers or task schedulers for the requests of users. The burden of cellular MBS (Macro Base Station) then can be alleviated. Extensive simulations are finally conducted and results verify the effectiveness of our proposal.

Keywords: Caching · Nonlinear programming
Lyapunov optimization

1 Introduction

As indicated in [1], the monthly global mobile data traffic would be 49 exabytes by 2021 under 11.6 billion mobile connected devices, which increases about sevenfold between 2016 and 2021. Mobile users thus can enjoy a large number of new applications and fairly rich network experience. However, the data tsunami also pushes a huge challenge to the mobile operators all over the world for their network capacity in terms of network throughput, and processing delay.

To solve above problem, a variety of techniques focus on the improvement of edge process capacity by applying edge computing technology on network edge, including offloading technologies [2,3], edge caching schemes [4,5]. However, most

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of these researches relay on the deployment of large-scale infrastructure, resulting in huge deployment and maintenance cost. To cope with this problem, we aim to make a full use of the moving vehicles to cache mobile data and then serve mobile users. Compared with traditional SBS (Small Base Station) or AP (Access Point), vehicles as data carriers are widely distributed and cost-effective. Besides, the V2X (Vehicle-to-Everything) technology has been specified in the 5G communication standard, which makes vehicle-to-user communications be efficient and reliable.

In this paper, we aim to explore the impact of caching vehicles on the energy efficiency of cellular network. To this end, we assume that the communications with caching vehicles are default setting in mobile users, and caching vehicles act as task schedulers to determine the requests of users are served by themselves or MBS. Specifically, to obtain the optimal task decision from global perspective, we first formulate a fraction optimization model towards to the minimization of network energy efficiency. Based on the solution for the optimization model, we then develop a new online algorithm, which is used to obtain the real-time task decision for vehicles. Assisted by caching vehicles, the burden of MBS can be alleviated. We proceed in three steps. (1) $ProblemFormulation$: Based on the analysis on network throughput and energy consumption, we formulate the task decision problem as a fraction optimization model. The task decision of all caching vehicles can be obtained by solving this model. (2) $AlgorithmDesign$: We then transform the nonlinear and nonconvex model as a linear and convex model based on the nonlinear programming. To solve the transformed model, a novel online task decision algorithm is developed based on Lyapunov optimization theory. (3) $Simulations$: To evaluate the performance of the proposed algorithm, we conduct extensive simulations. Results show that our algorithm achieve obvious improvement in energy efficiency compared with traditional network paradigm.

The remainder of this paper is structured as follows: Sect. 2 illustrates the system models and formulate the optimization model. Section 3 presents the algorithm design, which is based on the solution of the optimization model. Section 4 evaluate the performance of the algorithm based on simulation results while Sect. 5 concludes our study.

2 System Description and Problem Formulation

In this section, we mainly make a description about the system scenario in our study, and finally formulate a fractional optimization problem.

2.1 System Description

We consider a scenario that includes three types of nodes, MBS, caching vehicles, and mobile users. In this scenario, a part of vehicles caching the popular mobile data act as task schedulers to alleviate the burden of MBS. Mobile users can be served either by cellular MBS or caching vehicles. Specifically, when detecting the caching vehicle within the communication range, mobile users will send requests to it and ask for services. According to the task decision, the caching vehicle determines whether to serve the requests or not. Once the request of the user are declined, it will receive a feedback from the vehicle and then switch to cellular network. It is assumed that networks operate in slotted time, *i.e.*, the time slot t is within the time interval $[t, t+1)$, $t \in \{0, 1, 2, ...\}$. As such, our goal is to determine the task decision $\mathbf{T} = \{T_1(t), T_2(t), T_3(t), ...T_n(t)\}$ on caching vehicles, where $T_n(t) \in [0, 1]$ is a fractional variable and denotes the task decision of the vehicle n. We make some basic assumptions to simplify our analysis as follows.

To represent the spatial distribution of mobile users, we refer to [6] and use the Poisson point process (PPP) to calculate the distribution probability with mean rate λ_u. The exponential distribution is commonly used to model the distribution of vehicles on roads. In our analysis, the contact time between a user and vehicles is assumed to follow the exponential distribution [7]. To simplify the analysis, we assume the data catalogue consists of N_f files with same size, *i.e.*, $\mathbf{F}$=$\{F_1, F_2, ...F_{N_f}\}$. This assumption is reasonable in the analysis of edge caching since files can be divided into multiple fragments with same size [8]. To model the request probability of different files, we apply the widely used Zipf-like distribution [9]. Specifically, let p_n denote the request probability of the file n, it can be calculated as $p_n = \frac{1}{\left(\sum_{n=1}^{N_f} 1/n^{\phi}\right) n^{\phi}}$, where ϕ is the Zipf exponent.

2.2 Problem Formulation

Communication Model. There are two communication modes in our network, *i.e.*, vehicle-to-user communications and cellular communications. As many existing communication protocols, such as DSRC, LTE-A, and upcoming 5G for vehicular communicaions, rate adaptation mechanism is adopted to characterize the diversity of data rates. Note that, the communication mode of V2P (Vehicle-to-Pedestrian) is similar with V2V excepted the limited power consumption on the mobile devices of pedestrian users [10]. In this paper, we make a simplified assumption that data rates between users and vehicles are determined by Euclidean distance, and the mean rate is $R_v = 5$ Mbps [11]. The mean data rate in cellular network, due to the large-power MBS, is assumed as $R_m = R_v + \xi$, where $\xi \geq 0$. It means the data rate of cellular network is larger than that from vehicle to user.

The total network throughput in our network is

$$R_{tot}(t) = \sum_{m=1}^{N_m} R_m\{\mathbf{T}(t)\} + \sum_{v=1}^{N_v} R_v\{\mathbf{T}(t)\}, \tag{1}$$

where N_m and N_b are the number of requests served by caching vehicles and MBS, respectively.

Energy Consumption. Energy consumption is considered an important metric. On the one hand, green communications in wireless cellular networks have been an important task for a long time [2]. On the other hand, with the development of battery electric vehicles, the energy consumption management in vehicular networks becomes an major challenge [12]. As such, we explore the vehicular caching algorithm targeting at the full use of energy consumption. Since we assume that $R_m \geq R_v$, MBS may result in large throughput with a more transmission power due to the large-power transmitter. By contrast, caching more data on vehicles saves total energy consumption with a cost of the decrease of throughput. For simplicity, we only consider the energy consumption that can be impacted by the caching policy, *i.e.*, transport energy from MBS, transport energy and caching energy from caching vehicles. Therefore, we aim to find a trade-off between the energy consumption and network throughout. A series of energy consumption models are given below.

By referring to [13], we use the linear energy consumption model to calculate the transport energy consumed by MBS. At each time slot, the transport energy is

$$P_m(t) = \sum_{m=1}^{N_m} R_m\{\mathbf{T}(t)\}\omega_t^m, \tag{2}$$

where ω_t^m denotes the energy consumption rate of transmission from MBS (in Watt/bit).

The energy consumption at caching vehicles consists of two parts [4], transport energy and caching energy, *i.e.*, $P_{cv}(t) = P_t^v(t) + P_{ca}(t)$. Specifically, P_t^v is a function of the transmit power of caching vehicles

$$P_t^v(t) = \zeta_v P_{tx}^v(t), \tag{3}$$

where ζ_v is a simplified impact parameter for power amplifier cooling, and power supply. The energy-proportional model is used to represent the caching energy

$$P_{ca}(t) = R_v(t)\omega_c, \tag{4}$$

where ω_c is the caching factor (in Watt/bit).

Based on the analysis above, the total energy consumed at time slot t is

$$P_{tot}(t) = P_{cv}(t) + P_m(t) \tag{5}$$

Fraction Optimization. The problem of task decision at vehicles can be formulated as a fraction optimization model. Specifically, from the perspective of long-term optimization, the network energy efficiency model is

$$\begin{aligned} \min \eta_{EE} = \lim_{K\to\infty} \frac{\frac{1}{K}\sum_{t=0}^{K-1} P_{tot}(t)}{\frac{1}{K}\sum_{t\to 0}^{K-1} R_{tot}(t)} = \frac{\overline{P}_{tot}}{\overline{R}_{tot}} \\ \text{s.t. C1: } Q_n(t) \text{ are mean rate stable, } \forall n \in \{1, ..., N_u\} \\ \text{C2: } 0 \leq T_n(t) \leq 1,\ \forall j \in \{1, ..., N_v\}, \end{aligned} \tag{6}$$

where C1 is the constraint that guarantees the stability of user queue. $T_n(t)$ is the task decision of vehicle n at time slot t.

3 Algorithm Design

3.1 Problem Transformation

In this part, we refer to [14] and transform the fractional and nonconvex model (6) to a linear and convex one.

To make the transformation, we have the following theorem.

Theorem 1. *The problem (6) equals to minimizing* $\overline{P}tot - \eta_{EE}^{opt}\overline{R}_{tot}$ *subject to the same constraints.*

Proof. To prove Theorem 1, we assume that $\mathbf{T}^*(t)$ is the optimal task decision at time slot t. The proof is divided into two parts, *i.e.*, necessity proof and sufficiency proof.

The necessity proof is to prove that $\mathbf{T}^*$ is the solution of $\min \overline{P}tot - \eta_{EE}\overline{R}_{tot}$ because it is the solution of (6).

Specifically, since $\mathbf{T}^*$ is the optimal solution of optimization problem (6), we have

$$\eta_{EE}^{opt} = \frac{\overline{P}_{tot}(\mathbf{T}^*)}{\overline{R}_{tot}(\mathbf{T}^*)} \leq \frac{\overline{P}_{tot}(\mathbf{T})}{\overline{R}_{tot}(\mathbf{T})}. \tag{7}$$

We further transform (7) to

$$\overline{P}_{tot}(\mathbf{T}^*) - \eta_{EE}^{opt}\overline{R}_{tot}(\mathbf{T}^*) = 0, \tag{8}$$

$$\overline{P}_{tot}(\mathbf{T}) - \eta_{EE}^{opt}\overline{R}_{tot}(\mathbf{T}) \geq 0, \tag{9}$$

Therefore, we can obtain the following equation.

$$\begin{aligned} &\min \overline{P}_{tot}(\mathbf{T}) - \eta_{EE}^{opt}\overline{R}_{tot}(\mathbf{T}) \\ &= \overline{P}_{tot}(\mathbf{T}^*) - \eta_{EE}^{opt}\overline{R}_{tot}(\mathbf{T}^*) \\ &= 0. \end{aligned} \tag{10}$$

The proof for the necessity of Theorem 1 is completed.

For sufficiency proof, we aim to prove that $\mathbf{T}^*$ is the solution of problem (7) with the assumption below that it is the solution of $\min \overline{P}tot - \eta_{EE}\overline{R}_{tot}$. Firstly, we assume the following equation hold

$$\begin{aligned} &\min \overline{P}_{tot}(\mathbf{T}) - \eta_{EE}^{opt}\overline{R}_{tot}(\mathbf{T}) \\ &= \overline{P}_{tot}(\mathbf{T}^*) - \eta_{EE}^{opt}\overline{R}_{tot}(\mathbf{T}^*) \\ &= 0, \end{aligned} \tag{11}$$

where $\mathbf{T}^*$ is the optimal task decision. By rearranging above equation, we obtain

$$0 = \overline{P}_{tot}(\mathbf{T}^*) - \eta_{EE}^{opt}\overline{R}_{tot}(\mathbf{T}^*) \leq \overline{P}_{tot}(\mathbf{T}) - \eta_{EE}^{opt}\overline{R}_{tot}(\mathbf{T}). \tag{12}$$

Furthermore, we obtain

$$\eta_{EE}^{opt} = \frac{\overline{P}_{tot}(\mathbf{T}^*)}{\overline{R}_{tot}(\mathbf{T}^*)} \leq \frac{\overline{P}_{tot}(\mathbf{T})}{\overline{R}_{tot}(\mathbf{T})}. \tag{13}$$

It can seen that $\mathbf{T}^*$ is also the solution of (7). The proof of Theorem 1 is completed.

Hence, the fractional optimization problem (6) is transformed to

$$\begin{aligned} &\min \overline{P}_{tot} - \eta_{EE}\overline{R}_{tot} \\ &\text{s.t. C1, C2.} \end{aligned} \tag{14}$$

The original problem now becomes a linear and convex one [14].

3.2 Lyapunov Optimization Based Online Algorithm

In this part, we develop a Lyapunov optimization based online task decision algorithm. The Lyapunov optimization theory is an effective method to deal with the problems of resource allocation in wireless networks [15]. The application of Lyapunov optimization in our paper is due to that the traditional heuristic or iterative algorithm may incur large overhead and latency, which are not tolerant in the delay-sensitive vehicular environments. We first define the Lyapunov function as follows.

Let $\mathbf{\Theta}(t) \triangleq \mathbf{Q}(t)$ denote the combined queue backlog vector. The quadratic Lyapunov function is defined as

$$L(\mathbf{\Theta}(t)) \triangleq \frac{1}{2}\sum_{n=1}^{N_u} Q_n(t)^2 \tag{15}$$

Then, the one-slot Lyapunov drift can be obtained as

$$\Delta(\mathbf{\Theta}(t)) = L(\mathbf{\Theta}(t+1)) - L(\mathbf{\Theta}(t)) \tag{16}$$

We further use the drift-plus-penalty method to guarantee the stability of queues and solve the optimizaiton problem. The drift-plus-penalty is defined as

$$\min \Delta(\mathbf{\Theta}(t)) + VE\{P_{tot}(t) - \eta_{EE}(t)R_{tot}(t)\} \tag{17}$$

The bound of drift-plus-penalty is defined as

$$\begin{aligned} \Delta(\mathbf{\Theta}(t)) + VE\{P_{tot}(t) - \eta_{EE}(t)R_{tot}(t)|\mathbf{\Theta}(t)\} &\le B \\ &+ \sum_{n=1}^{N_u} Q_n(t)E\{A_n(t) - R_n(t)|\mathbf{\Theta}(t)\} \\ &+ VE\{P_{tot}(t) - \eta_{EE}(t)R_{tot}(t)|\mathbf{\Theta}(t)\}, \end{aligned} \tag{18}$$

where

$$B \ge \frac{1}{2}\sum_{n=1}^{N_u} E\{A_n(t)^2 + R_n(t)^2|\mathbf{\Theta}(t)\} \tag{19}$$

Proof. Assuming that the queue $Q_n(t)$ is updated as

$$Q_n(t+1) = max[Q_n(t) - R_n(t), 0] + A_n(t), \tag{20}$$

where $A_n(t)$ is the data arrival at time slot t, and $R_n(t)$ is the service rate of user n.

By squaring two sides of Eq. (20) and rearranging terms, we have

$$\frac{1}{2}[Q_n(t+1)^2 - Q_n(t)^2] \leq \frac{1}{2}[R_n(t)^2 + A_n(t)^2] + Q_n(t)(A_n(t) - R_n(t)) \tag{21}$$

Summing over $n \in \{1, ...N_u\}$ for (21) and taking a conditional expectation, we have

$$\Delta(\mathbf{\Theta}(t)) \leq \sum_{n=1}^{N_u} \frac{1}{2}[R_n(t)^2 + A_n(t)^2|\mathbf{\Theta}(t)] + \sum_{n=1}^{N_u}[Q_n(t)E\{A_n(t) - R_n(t)\}|\mathbf{\Theta}(t)] \tag{22}$$

By adding the term of $VE\{P_{tot}(t) - \eta_{EE}(t)R_{tot}(t)|\mathbf{\Theta}(t)\}$ on both sides of (22), it becomes

$$\begin{aligned} \Delta(\mathbf{\Theta}(t)) + VE\{P_{tot}(t) - \eta_{EE}(t)R_{tot}(t)|\mathbf{\Theta}(t)\} &\leq B \\ &+ VE\{P_{tot}(t) - \eta_{EE}(t)R_{tot}(t)|\mathbf{\Theta}(t)\} \\ &+ \sum_{n=1}^{N_u} Q_n(t)E\{A_n(t) - R_n(t)|\mathbf{\Theta}(t)\} \end{aligned} \tag{23}$$

Therefore, the Eq. (18) is proved, where

$$B \geq \sum_{n=1}^{N_u} \frac{1}{2}[R_n(t)^2 + A_n(t)^2|\mathbf{\Theta}(t)] \tag{24}$$

The proof of (18)–(19) is completed.

In this case, the optimization problem of (14) can be solved by minimizing the right-side of inequality (23). Specifically, we finally obtain $\mathbf{T}^*$ according to

$$\begin{aligned} &\min V\{P_{tot}(t) - \eta_{EE}(t)R_{tot}(t)\} - \sum_{n=1}^{N_u} Q_n(t)R_n(t) \\ &\text{s.t. C1, C2.} \end{aligned} \tag{25}$$

3.3 Online Algorithm

By the analysis in Subsects. 3.1–3.2, we successfully transfer the original optimization model (6) into the minimization of the right side of the drifty-plus-penalty (18). We hence define a novel online task decision algorithm to schedule the requests of users, as shown in Algorithm 1. At the beginning of time slot, the user requests are predicted by carrying out the Zipf-like model. Due to the limitation of vehicular storage, only a part of requests can be served by vehicles. After selecting the requests served by caching vehicles, the optimal task decision is determined by solving (25). Finally, the queue $Q_n(t)$ and $\eta_{EE}(t)$ are updated.

Algorithm 1. Online task decision.

Input: t, $Q_n(t)$,$\eta_{EE}(t)$
Output: $\mathbf{T}^*$
1: For time slot $[t, t+1)$
2: **while** At the beginning of time slot t **do**
3: **Step 1:**Obtain the number of requests at time slot t based on Zipf-like model
4: **Step 2:**Determine the numbers of requests that can be served by caching vehicles
5: **Step 3:**Calculate the $\mathbf{T}^*$ by solve (25)
6: **Step 4:**Update $Q_n(t)$ according to (20) and update $\eta_{EE}(t)$ according to

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

7: **end while**

4 Simulations

To evaluate the performance of the newly proposed algorithm, we conduct extensive simulations using Matlab.

In all simulations, we consider a hexagonal cellular region with radius 350 m. Considering a four-lane bidirectional road within the coverage of cellular network, the density of vehicles is assumed as 0.086 vehicle/m. Vehicles adapt their velocity at each time slot following Normal distribution with the mean value is within $[20, 60]$ km/h and the standard deviation is 10 km/h. It is assumed that 50% vehicles cache the mobile data. The normalized cache capacity is denoted by η, which is an important parameter in following performance evaluation. Mobile users can get real-time communication with MBS, while the communication with vehicles has a maximum distance of 300 m. The mean rate of user distribution PPP is assumed as $\lambda_u = 1/10$ user/m^2. For Zipf-like model, we assume that $\phi = 0.7$. For energy model, we assume $\omega_t^m = 0.5 * 10^{-8}$ J/bit, $\zeta_v = 15.13$, and $\omega_c = 6.25 * 10^{-12}$W/bit according to [13]. The energy efficiency performance is shown in Figs. 1 and 2.

In Fig. 1, we assume that the arrival of the requests of users follows Poisson distribution with mean rate is $\lambda_r = 1$ request/s. We evaluate the impact of parameter V on the energy efficiency η_{EE}. The parameter V, as shown in (25), is used to control the trade-off between network performance and queue stability. We plot three data sets, determined by $\eta = 0.001$, $\eta = 0.01$, and $\eta = 0.1$. From Fig. 1 we can see, the energy efficiency decreases with V increasing. It means that the larger the V, the better energy efficiency can be achieved by Algorithm 1. However, the high-efficiency energy consumption is achieved with the cost of the stability of user queue. Therefore, Fig. 1 gives a reference for the application of Algorithm 1. Besides, the large η means that vehicles can cache more mobile data. It can be seen that large caching capacity achieves the lower

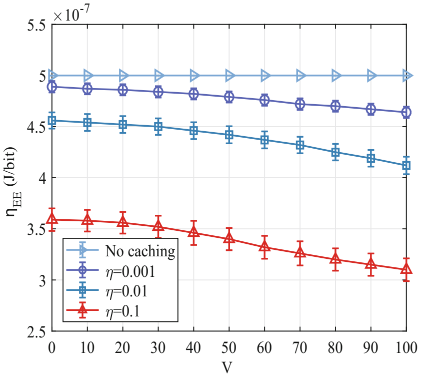

Fig. 1. Relationship between energy efficiency and V

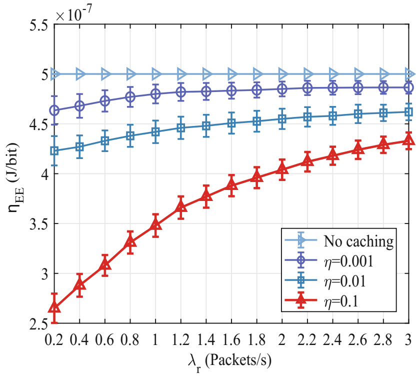

Fig. 2. Relationship between energy efficiency and packet arrival rate

energy efficiency, which however results in large cost. Therefore, there should be a trade-off between energy efficiency performance and storage cost.

In Fig. 2, we set V to be 50 to evaluate the impact of user requests on energy efficiency performance. From Fig. 2 we can see, when λ_r is small, the Algorithm 1 based vehicular task schedule achieves significant performance improvement compared with no caching, especially when $\eta = 0.1$. However, with the increase of λ_r, the advantage of energy efficiency in vehicular caching is gradually reduced and approached that of no caching. In this time, the number of requests is too large so that most of them must be served by MBS. The vehicular caching now has a little influence on the energy efficiency performance. Besides, the similar conclusion about different η with Fig. 1 can also be obtained.

5 Conclusion

This paper explores the performance of vehicular caching when alleviating the burden of MBS. We first analyze the system model in the cellular network incorporating vehicular caching. The problem of energy efficiency is then formulated as a fractional optimization model. However, this model is non-linear and non-convex, which is difficult to solve directly. We further transform this model into a linear and convex model based on the nonlinear programming. To relax the time-related variable in the transformed model, we then explore the application of the Lyapunov optimization theory on our optimization model. After detailed derivation, the original problem is solved in a simple method. Based on this solution, an online task decision algorithm is developed to schedule the requests of users for vehicles. Extensive simulations are conducted to evaluate the performance of the proposed algorithm. Results show that our algorithm achieves good performance in energy efficiency and gives a reference of application of vehicular caching.

References

1. Index: Global mobile data traffic forecast update. 2016–2021 white paper, Cisco Visual Networking. Accessed 2 May 2017
2. Yu, H., Cheung, M.-H., Iosifidis, G., Gao, L., Tassiulas, L., Huang, J.: Mobile data offloading for green wireless networks. IEEE Wirel. Commun. **24**(4), 31–37 (2017)
3. Xu, J., Chen, L., Ren, S.: Online learning for offloading and autoscaling in energy harvesting mobile edge computing. IEEE Trans. Cogn. Commun. Netw. **3**(3), 361–373 (2017)
4. Liu, D., Yang, C.: Energy efficiency of downlink networks with caching at base stations. IEEE J. Sel. Areas. Commun. **34**(4), 907–922 (2016)
5. Chen, M., Qian, Y., Hao, Y., Li, Y., Song, J.: Data-driven computing and caching in 5G networks: architecture and delay analysis. IEEE Wirel. Commun. **25**(1), 2–8 (2018)
6. Li, C., Zhang, J., Letaief, K.-B.: Throughput and energy efficiency analysis of small cell networks with multi-antenna base stations. IEEE Trans. Wirel. Commun. **13**(5), 2505–2517 (2014)
7. Karagiannis, T., Le Boudec, J.-Y., Vojnovic, M.: Power law and exponential decay of intercontact times between mobile devices. IEEE Trans. Mob. Comput. **9**(10), 1377–1390 (2010)
8. Vigneri, L., Pecoraro, S., Spyropoulos, T., Barakat, C.: Per chunk caching for video streaming from a vehicular cloud. In: ACM MobiCom Workshop on Challenged Networks (CHANTS) (2017)
9. Breslau, L., Cao, P., Fan, L., Phillips, G., Shenker, S.: Web caching and zipf-like distributions: evidence and implications. In: Proceedings IEEE Eighteenth Annual Joint Conference of the IEEE Computer and Communications Societies, vol. 1, pp. 126–134. IEEE (1999)
10. Yang, H., Zheng, K., Zhao, L., Zhang, K., Chatzimisios, P., Teng, Y.: High reliability and low latency for vehicular networks: Challenges and solutions. arXiv preprint arXiv:1712.00537 (2017)
11. Vigneri, L., Spyropoulos, T., Barakat, C.: Quality of experience-aware mobile edge caching through a vehicular cloud. In: 20th ACM International Conference on Modelling, Analysis and Simulation of Wireless and Mobile Systems, pp. 91–98 (2017)
12. Zhang, S., Luo, Y., Li, K., Li, V.: Real-time energy-efficient control for fully electric vehicles based on explicit model predictive control method. IEEE Trans. Veh. Technol. **67**(6), 4693–4701 (2018)
13. Gabry, F., Bioglio, V., Land, I.: On energy-efficient edge caching in heterogeneous networks. IEEE J. Sel. Areas Commun. **34**(12), 3288–3298 (2016)
14. Dinkelbach, W.: On nonlinear fractional programming. Manag. Sci. **13**(7), 492–498 (1967)
15. Neely, M.J.: Stochastic network optimization with application to communication and queueing systems. Synth. Lect. Commun. Netw. **3**(1), 1–211 (2010)