This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

Digital Twin Empowered Content Caching in Social-Aware Vehicular Edge Networks

Ke Zhang, *Member, IEEE*, Jiayu Cao, Sabita Maharjan, *Senior Member, IEEE*, and Yan Zhang, *Fellow, IEEE*

***Abstract*—The rapid proliferation of smart vehicles along with the advent of powerful applications bring stringent requirements on massive content delivery. Although vehicular edge caching can facilitate delay-bounded content transmission, constrained storage capacity and limited serving range of an individual cache server as well as highly dynamic topology of vehicular networks may degrade the efficiency of content delivery. To address the problem, in this article, we propose a social-aware vehicular edge caching mechanism that dynamically orchestrates the cache capability of roadside units (RSUs) and smart vehicles according to user preference similarity and service availability. Furthermore, catering to the complexity and variability of vehicular social characteristics, we leverage the digital twin technology to map the edge caching system into virtual space, which facilitates constructing the social relation model. Based on the social model, a new concept of vehicular cache cloud is developed to incorporate the correlation of content storing between multiple cache-enabled vehicles in diverse traffic environments. Then, we propose deep learning empowered optimal caching schemes, jointly considering the social model construction, cache cloud formation, and cache resource allocation. We evaluate the proposed schemes based on real traffic data. Numerical results demonstrate that our edge caching schemes have great advantages in optimizing caching utility.**

***Index Terms*—Digital twin network, social-aware, vehicular edge caching.**

I. Introduction

POWERED by sensing, computing, and communication capabilities, smart vehicles are not simply means of transport, but active entities for providing various infotainment services, for facilitating automated driving, and for realizing intelligent transportation in modern cities [1]. To enable these smart vehicular applications, a huge amount and high diversity of content need to be disseminated and shared between interactive vehicles under stringent delay constraints. However, due to limited spectrum resources, it may be challenging for current wireless systems to deliver content ensuring that such requirements are met, especially during peak-traffic times with high vehicle density.

Mobile edge caching has emerged as a promising paradigm, where popular contents are brought closer to end-users via distributed storage servers at the network edge. The cache data empower local communication and considerably accelerate the responsiveness of content acquisition from the edge, compared to fetching them from remote content providers.

Although edge caching is an appealing technique to efficiently improve QoS for time-sensitive content transmissions over vehicular networks, unstable communications, and highly dynamic topology introduce new challenges in designing optimal caching schemes for vehicular edge networks. In practice, an individual edge cache server always has constrained storage space, which makes it impossible for a single server to hold multiple large files at the same time. Moreover, when the cache servers are equipped on several RSUs, a limited coverage range of an individual RSU may lead to short communication duration and a small amount of data delivery. The caching approach with the separate content assignment and independent server operation may fail to provide large-size content delivery and stable data transmission.

In order to effectively utilize the constrained cache and communication resources with dynamic topology, cooperative caching needs to be leveraged, where content subscribers can be served by multiple caching servers. Furthermore, the cooperative caching includes not only the servers equipped on RSUs but also those on smart vehicles. Equipped with onboard caching units and communication modules, smart vehicles are envisioned as new units of mobile data storage, which can deliver cached data to interconnected content subscribers. In this regard, the content serving range can be considerably expanded by the mobility of caching vehicles, thus relieving the traffic burden on cellular networks caused by data-hungry and delay-sensitive applications.

In the use of onboard caching servers, social interactions among the vehicles have been leveraged to improve the contend dispatch efficiency [2]. Social characteristics of vehicles are basically related to the drivers, who determine a content preference, daily driving routines, and affect the other vehicles that may be encountered on the road or in the parking lot. These characteristics have led to the introduction of the concept of social-aware vehicular networks and sparked considerable related research. However, previous works have

Manuscript received November 29, 2020; revised February 7, 2021; accepted March 14, 2021. This work was supported in part by the National Natural Science Foundation of China under Grant 61941102 and Grant 62071092; in part by the Key Research and Development Project of Sichuan Province under Grant 2019YFG0520; and in part by the National Key Research and Development Program of China under Grant 2018YFE0117500. *(Corresponding author: Yan Zhang.)*

Ke Zhang and Jiayu Cao are with the School of Information and Communication Engineering, University of Electronic Science and Technology of China, Chengdu 611731, China (e-mail: zhangke@uestc.edu.cn; liuda945@163.com).

Sabita Maharjan is with the Department of Informatics, University of Oslo, 0373 Oslo, Norway, and also with Simula Metropolitan Center for Digital Engineering, 0167 Oslo, Norway (e-mail: sabita@ifi.uio.no).

Yan Zhang is with the Department of Informatics, University of Oslo, 0316 Oslo, Norway (e-mail: yanzhang@ieee.org).

Digital Object Identifier 10.1109/TCSS.2021.3068369

mainly treated vehicular social features as fixed and in terms of being independent. The relationship between vehicular social features and vehicle mobility patterns, communication capacity, and onboard storage space in scheduling edge caching service is largely unexplored.

Moreover, integrating social-aware smart vehicles and the mobile edge computing framework also requires addressing challenges that the social-aware smart vehicles bring in. For instance, the vehicular social characteristics are time-varying, they may change dynamically according to the content popularity, traffic density, and vehicle speed. Furthermore, due to the rapid movement of vehicles, high intermittent connectivity between vehicular content providers and subscribers may seriously undermine the efficiency of social-aware content transmission. In addition, since vehicular caching capacity is limited, multiple cache-enabled vehicles need to cooperate to provide sufficient storage for large-size contents. To this end, realizing the cooperative approach requires addressing several unique issues. For instance, the cooperation between vehicular cache resources needs to cater to the road traffic distribution, channel quality, and content popularity. Moreover, collisions may occur between vehicular communication pairs due to spectrum reuse. Multiple vehicles that collaborate on storage capabilities also require coordination in utilizing communication resources. Thus, supporting delay-bounded content delivery over the vehicular social networks with multiple cache-enabled smart vehicles is a challenging problem.

To address the above challenges, we resort to digital twin technology, which maps physical system presentations into virtual space, and consequently helps managers to get comprehensive insights of the investigated systems and improves managing efficiency [3]. More specifically, in the social-aware vehicular edge caching networks, the digital twin approach can enable cache controllers to grasp the social relations between vehicles, understand the vehicle flow distribution, and effectively allocate communication and storage resources for content delivery. However, incorporating digital twin with vehicular caching is an unexplored problem.

In this article, we propose a digital twin empowered content caching mechanism for social-aware vehicular edge networks. Different from the previous studies, we leverage digital twin to capture the social characteristics of the smart vehicles and improve the effectiveness of cache management. Furthermore, the social correlation of contents stored in various types of cache servers and road traffic features are incorporated into cache arrangement. Catering for the dynamic vehicular social networks, we design learning-based edge caching schemes, which maximize edge service utilities under content latency constraints. The main contributions of this article are summarized as follows.

1) We present a digital twin empowered vehicular edge caching framework that comprehensively captures vehicular social features and improves caching scheduling in highly dynamic vehicular networks.
2) By analyzing data delivery performance, we design a vehicular caching cloud, in which the correlation between segmented contents as well as the vehicular social characteristics is incorporated.
3) By applying a deep deterministic policy gradient (DDPG) learning approach, we propose optimal vehicular caching cloud formulation and edge caching arrangement schemes, which maximize the system utility in diverse traffic environments.

The remainder of the article is organized as follows. In Section II, we review related works. In Section III, we present the system model. We design digital twin empowered social model construction and discuss vehicular caching cloud formation in Section IV. DDPG learning-based edge cache scheduling schemes for vehicular social networks are described in Section V. Performance evaluation is presented in Section VI. Finally, we conclude our work in Section VII.

II. Related Work

We first review some recent studies that focus on vehicular edge caching networks. In [4], the authors took vehicular caching as a double time-scale Markov decision process and designed a cooperative edge caching scheme for joint content placement and data delivery. In [5], the authors investigated the performance of edge caching systems for smart industry and internet of vehicles applications, and introduced a mathematical framework to reveal the impact of content catalog on the caching efficiency. In [6], the authors developed intent-based control schemes, which orchestrate vehicular edge caching and computing using a deep reinforcement learning approach, to improve the utility of network operators. Catering for the content demands of connected vehicles, Mahmood *et al.* [7] presented a roadside cache scheme that ensures in-order content chunks delivery to end-users. To secure sensitive information in edge caching, Dai *et al.* [8] integrated permissioned blockchain into vehicular networks, and established a decentralized peer-to-peer content transaction environment. In [9], the authors proposed a novel and adaptive task scheduling scheme for 5G-enabled vehicular network, which significantly improves the overall system-wide profit.

Being a promising paradigm to enhance the cognition and intelligence of vehicular networks, the learning approach has been leveraged in vehicular edge caching management. In [10], the authors took deep reinforcement learning to design an integrated framework that jointly orchestrates vehicular networking, caching, and computing. In [11], the authors developed a caching and computing resource management scheme by exploiting deep reinforcement learning, which efficiently improves vehicular system utility. Ning *et al.* [12] brought artificial intelligence empowered caching and computing to the proximity of smart vehicles, and utilized Lyapunov optimization and imitation learning approaches to minimize vehicular application processing delay. In [13], the authors leveraged federated learning to obtain content popularity in dynamic vehicular networks, and proposed a mobility-aware edge caching scheme with a high cache hit ratio.

To improve the content caching efficiency and delivery hit ratio, some studies have incorporated the social characteristics into the edge caching management framework. E.g., in [14], the authors took social interactions between devices into account and introduced proactive caching and

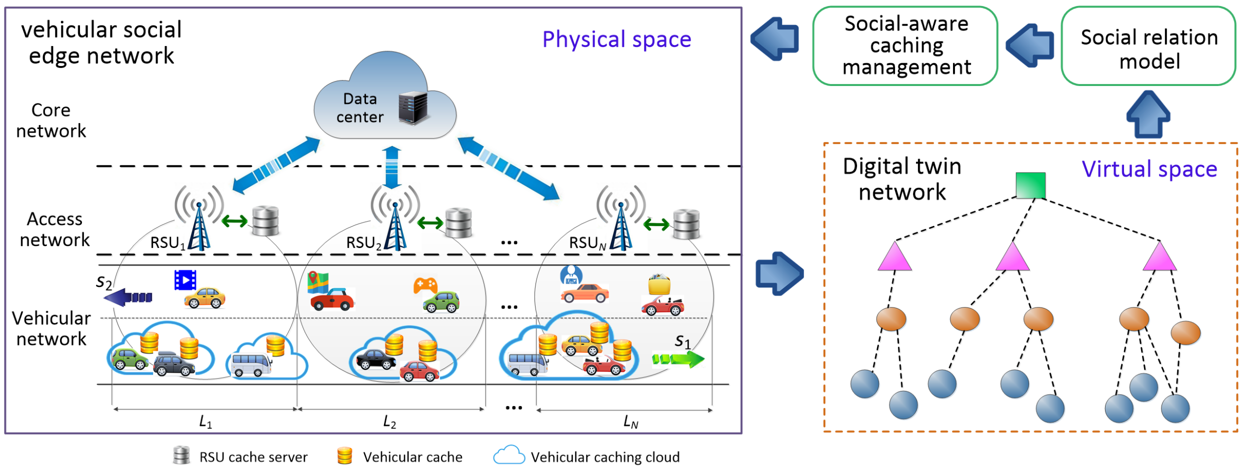


Fig. 1. Digital twin empowered vehicular social edge network.

content-sharing strategies to minimize communication costs. In [15], the authors proposed a cognitive caching mechanism for the mobile edge social networks, which used a multi-agent deep reinforcement learning approach to adjust content placement and for collaboration with neighbor nodes. In [16], the authors exploited the trust relationships among users, and designed a social-aware deep reinforcement learning-based caching resource allocation scheme. In [17], the authors leveraged the auction theoretic approach to improve the live video streaming service in the cellular edge system, and developed a dynamic programming algorithm to maximize social-related utilities.

Few studies have investigated social relations between smart vehicles and applied them to vehicular edge caching scheduling. In [18], the authors formulated a hidden Markov model to exploit vehicle moving behaviors and then introduced a cooperative caching scheme based on the social-aware moving predictions. Bitaghsir *et al.* [19] focused on a vehicular social network overlies with a cellular network, and designed an optimal content distribution algorithm based on users' social degree. Considering the social interests of vehicles, Vegni *et al.* [20] proposed a probabilistic-based broadcasting scheme and assessed its performance in a realistic traffic scenario. In [21], the authors incorporated content delivery with data processing and developed a deep learning-based vehicular social edge computing and caching mechanism. Although these works have provided some insights about cache-enabled vehicular networks and social-related content arrangement, the social-aware collaboration of capacity-limited smart vehicles for serving large contents in diverse traffic environments has not been thoroughly studied.

The digital twin technology is an emerging research field and led to many important related works recently. In [22], the authors exploited federated learning to build digital twin models of industrial IoT devices based on their running data, and proposed an asynchronous model update scheme. In [23], the authors aimed to alleviate the estimation deviations of digital twin modeling, and designed a trust-based aggregation strategy in a federated learning approach. Lu *et al.* [24] integrated digital twin into 6G wireless networks and presented a blockchain empowered federated learning framework to migrate real-time data processing burden and privacy threats on the edge plane. Gehrmann and Gunnarsson *et al.* [25] investigated how to apply the digital twin model and corresponding trusted architecture to improve data sharing and control security in industrial applications. In [26], the authors applied digital twin to build IoT network topology and model stochastic task arrival and presented energy-efficient computation offloading and resource allocation schemes. Being a promising technical tool, the digital twin has been leveraged to tackle diverse types of problems in previous studies. However, it has not been put forth for applying in vehicular edge caching systems.

To fill this gap, in this article, we propose a digital twin empowered content caching framework in social-aware vehicular edge networks. Moreover, we leverage digital twin network to construct the vehicular social relation model, which helps to make full use of the distributed vehicle cache resources to deliver large-size contents in highly dynamic traffic environments.

III. System Model

Fig. 1 shows the digital twin empowered vehicular social edge network. We consider an intelligent transport system in urban areas, where smart vehicles provide various powerful applications, such as smart navigation, online video, and interactive gaming. The implementation of these applications always requires content generated by the data center that locates in the core network. The required contents are classified into G types. Each type of content is described in three terms as $T_g = \{f_g, t_g^{\max}, \mu_g\}$, $g \in \mathcal{G}$, where f_g is the size of content type g, and $t_g^{\max}$ is its maximum delay tolerance. μ_g is the delay sensitivity coefficient that can be taken as the utility gained from unit time reduction compared to $t_g^{\max}$ during the content delivery process. In some practical edge caching applications, content subscribers may gain more utility from the reduction of content acquisition delay. For instance, for e-sports players, faster access to game data will help them make a more agile reaction in game control, thereby increasing the winning probability. Another example is virtual reality (VR) applications. The faster the interactive environment data is delivered to the user, the more real the user can perceive as.

To form access networks and provide data to the vehicular content subscribers, N roadside units (RSUs) are located along bidirectional roads, which can receive contents from the data center and then relay them to the vehicles. The diameter of the regions covered by these RSUs are $\{L_1, L_2, \ldots, L_N\}$, respectively. Each RSU is equipped with an edge caching server. The caching capability of these servers is $\{C_1, C_2, \ldots, C_N\}$, respectively. To avoid long transmission latency between the data center and the vehicles, the servers can retrieve popular contents from the center previously and store them in their cache.

Besides being cached in RSUs, contents can also be pre-stored in smart vehicles. The cache-enabled smart vehicles running on the road act as content carriers and forward cached data to encountered vehicles through vehicle-to-vehicle (V2V) communication. To fully exploit V2V content delivery, vehicular social relation is leveraged in edge cache management. When the supply and demand content between vehicles is consistent and communication link for data delivery can be established, we say that the vehicles are socially related. Following this viewpoint, the vehicular social relation is characterized by two elements. One element is the content matching between the supply and demand sides, and the other is the communication contact rate of the vehicles. We consider that vehicles in this system demand G types of contents with probability $\beta = \{\beta_1, \beta_2, \ldots, \beta_G\}$, respectively, where $\sum_{g \in \mathcal{G}} \beta_g \leq 1$. When a vehicle with type g content in its cache is driving on the roads, the probability of encountering a vehicle, which exactly needs this type of content, is β_g. Thus, the content matching element can be described by probability β. The communication contact rate is defined as the number of vehicles that a given vehicle can be associated within a unit of time during its driving.

Due to the constrained caching capacity of an individual vehicle, which is given as C_v, a content with a large amount of data needs to be segmented and stored in several cache-enabled vehicles. In order to efficiently carry and forward large contents to vehicular content subscribers, the concept of vehicular caching cloud is introduced, which consists of a group of smart vehicles providing a given type of content. In real road traffic scenario, the vehicles moving in the same direction always remain relatively stationary, and a cache-enabled vehicle can only serve contents to few adjacent vehicles, which fails to fully utilize the vehicular caching capability. However, in a two-way road, a vehicle may encounter multiple vehicles in the opposite lane during its running and can deliver contents to them. Motivated by this consideration, the design and scheduling of the vehicular caching cloud should be optimized based on the social relations between oncoming vehicles. Without loss of generality, for a given area of this vehicular network, the speed of content subscriber vehicles running in one direction is denoted as s_2, while the speed of the provider vehicles running in the opposite direction is s_1.

The vehicular social relation depends not only on the content preference of the vehicle users, but also on the traffic states, such as the vehicle speed and distribution density. These factors may vary in different areas at different time periods. For instance, in industrial areas during rush hours, traffic density is high and users focus on finding the least congested roads for travel. In contrast, in residential areas on weekends, traffic density is reduced and users are more concerned with shopping or entertainment information. To capture these dynamic factors and to obtain accurate social relation of current traffic scenarios, we incorporate digital twin into the edge caching system. The digital twins are constructed in the RSUs with the help of smart vehicles, where the vehicles running on the roads send their content preference and traffic states to nearby RSUs, while the RSUs analyze the collected state data and construct the social models. These RSUs interact with the vehicles to keep state consistency and make the model accurate.

IV. Social Model Construction and Vehicular Caching Cloud Formation

In this section, we first propose the digital twin empowered social model construction approach. Then, we present vehicular caching cloud framework, and derive some parameter selection criteria in the cloud formation, in terms of the size of cached contents and the distance between consecutive vehicular content providers.

A. Digital Twin Empowered Social Model Construction

Fig. 2 illustrates the main framework of the proposed digital twin and long short-term memory (LSTM)-based social model construction approach. The digital twin network consists of five modules, where the information collection module gets vehicular network states from smart vehicles through Vehicle-to-RSU (V2R) communication. These states include vehicles' location coordinates, service capacity, driving status, and data requirements. As the digital twin network is built on the RSUs located in an area, the inter-RSU collaboration module is responsible for exchanging data between the RSUs and maintaining their digital twin model consistency. The model is built and stored in the digital twin formation module, and periodically updated based on the collected information. The control module determines the update cycle and adjusts the data type and interactive frequency in the information collection. The adjustment will be issued to the smart vehicles through the instruction output module, thereby changing the vehicles' state sampling and reporting mode.

After establishing the digital twin, which offers a virtual representation of the physical vehicular network, we need to extract some key features of the vehicular social relations and construct a social model. LSTM is an improved version of recurrent neural networks, which is capable of learning long-term dependences. Considering vehicle driving states and content demands are time-varying, we use LSTM recurrent network to dig the social features from the received data sets.

The LSTM module consists of three layers, where the input layer obtains vehicle traffic and content demand information of different areas from the established digital twin and then puts the information to neurons in the hidden layer to obtain social model elements. The parameters of the neurons have

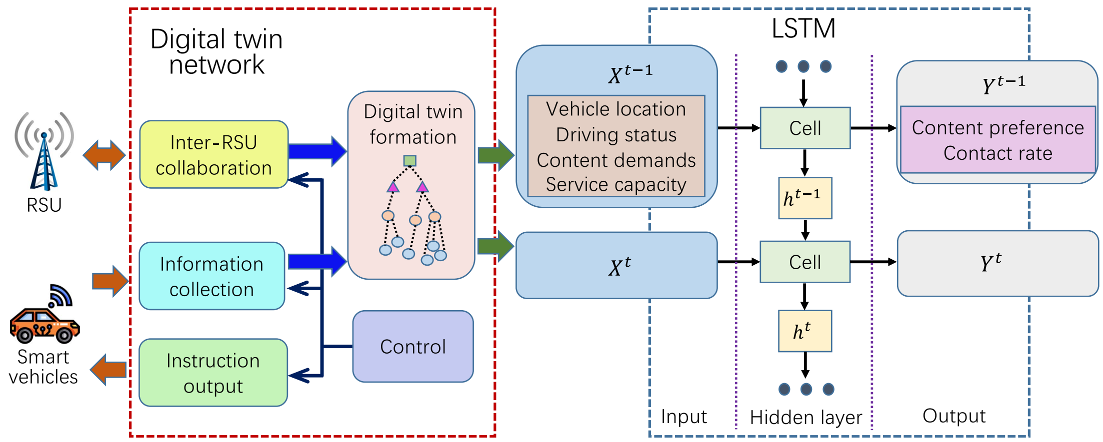


Fig. 2. Digital twin and LSTM-based social model construction.

been trained by some historical collected input and output data pairs. The social model construction system operates in time steps. Along its operation, the neuron parameters are updated periodically.

Recall that the elements of social model consist of content probability and vehicle communication contact rate. Given the vehicular wireless transmit power and antenna gain, the contact rate is mainly determined by vehicles' distribution density and their driving speed. Moreover, we find that for steady traffic running at speed s, the average distance between two consecutive vehicles can be presented as

$$\bar{d}_s = d_0 + sT_0\big[1-(s/s_0)^{\delta}\big]^{-\frac{1}{2}} \tag{1}$$

where s_0 is the desired velocity of the road. d_0 is safe distance, T_0 is reaction time, and δ is vehicular acceleration exponent [27]. According to (1), vehicles' distribution density in an area can be calculated based on the vehicle speed. Thus, the output social model of an area is formally expressed as $\{\beta, s_1, s_2\}$.

We take $\psi_g(\xi_g)$ to denote the accuracy of the social model that reflects the relations between the supply and demand vehicles for type g content, where ξ_g is the amount of the system information gathered by digital twin for training the LSTM network and obtaining social model $\{\beta, s_1, s_2\}$. The value of $\psi_g(\xi_g)$ is the ratio modulus of the estimated social model parameters to these of the true model, and $0 \le \psi_g(\xi_g) \le 1$. As more information would help improve the model accuracy, $\psi_g(\xi_g)$ is a monotonically increasing function in terms of ξ_g. Furthermore, as ξ_g continues to grow, the magnitude of the partial derivative of $\left|\partial\psi_g(\xi_g)/\partial\xi_g\right|$ keeps decreasing and comes to zero when ξ_g is sufficiently large, which indicates that simply increasing the size of information will not continue to improve the accuracy of the social model [28].

B. Maximum Amount of Contents in Vehicular Cache

Fig. 3 shows the proposed vehicular caching cloud. Each cloud consisting of multiple vehicles running in the same direction is responsible for carrying a type of content.

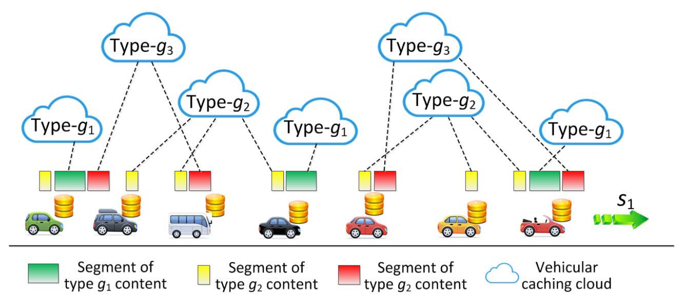


Fig. 3. Framework of vehicular edge caching cloud.

As a vehicle may simultaneously cache segments of different types of contents, there exists multidimensional mapping relationship between the cache-enabled vehicles and the clouds, i.e., a cloud may consist of multiple vehicles, and a vehicle can belong to multiple clouds at the same time. To make full utilization of vehicular cache resources while providing content service covering the entire road, the clouds that cache a given type of content are consecutively arranged along the road.

When contents are delivered through V2V communication, the amount of content transmitted from a cache-enabled vehicle to a subscriber depends on two factors. One is the size of the content cached on the vehicle, and the other is the transmission rate between these two vehicles.

Let $\gamma^{\min}$ be the minimum SINR at a receiver under the premise that the received data can be decoded. In an ideal environment without co-channel interference, the maximum distance between V2V communication pairs is given as

$$d^{\max}_{v,v'} = (P_v/L_0 P_w \gamma^{\min})^{\frac{1}{\alpha}}. \tag{2}$$

Based on distance $\bar{d}_s$ given in (1), the average number of cache-enabled vehicles, which may interfere the content transmission between vehicles v and v', can be calculated as $\bar{N}_{int} = 2\ d^{\max}_{v,v'}/\bar{d}_s$. Then, for content provider vehicle v and subscriber vehicle v', the average amount of data transmitted from v to v' during these vehicles within their communicable range is

$$\bar{\chi}_{\upsilon,\upsilon'} = 2\int_0^{\frac{d^{\max}_{\upsilon,\upsilon'}}{s_1+s_2}} B_\upsilon \log\left(1+\frac{P_\upsilon/L_0\left[{d^{\min}_{\upsilon,\upsilon'}}^2+((s_1+s_2)t)\right]^{\frac{\alpha}{2}}}{P_w+\bar{N}_{int}P_\upsilon/L_0\bar{d}^{\alpha}_{z,\upsilon'}}\right)\mathrm{d}t \tag{3}$$

where $\bar{d}_{z,\upsilon'}$ is the average distance between vehicle z and υ', which can be calculated as

$$\bar{d}_{z,\upsilon'} = \int_0^{d^{\max}_{z,\upsilon'}} \sqrt{{d^{\min}_{z,\upsilon'}}^2 + \hat{l}^2}\,\mathrm{d}\,\hat{l}/d^{\max}_{z,\upsilon'}. \tag{4}$$

Constrained by the V2V transmission capacity between two encountered vehicles as well as the limited storage space of a vehicle, the maximum amount of data pre-stored in a cache-enabled vehicle for a subscriber can be written as

$$Q^{\max}_\upsilon = \min\{\bar{\chi}_{\upsilon,\upsilon'}, C_\upsilon\}. \tag{5}$$

C. Distance Between Vehicular Content Providers

The proposed vehicular caching cloud is a promising approach to enable large content caching in resource-constrained smart vehicles. However, when the content is pre-stored in densely-distributed vehicles, part of the cached data may not be delivered to a subscriber due to the non-concurrence of communications at one receiver. Thus, one subscriber cannot get contents from multiple cache-enabled vehicles at the same time.

In order to efficiently utilize vehicular cache resources while providing consecutive content delivery service, the formulation of a vehicular caching cloud, which stores the segments of a large size content cooperatively should follow a certain position distribution. For two adjacent vehicles belonging to the same cloud serving content subscriber υ', the effective distance between them is

$$d^{\mathrm{adj}}_g = Q_g s_1/\bar{\chi}_{\upsilon,\upsilon'} \tag{6}$$

where Q_g is the amount of type-g content segment cached in a vehicle.

V. Learning-Based Optimal Edge Caching Schemes

In this section, we formulate an optimal caching problem for the digital twin empowered vehicular edge networks. By exploiting the DDPG learning technique and sub-gradient approach, we design joint strategies for social-aware vehicular caching cloud arrangement and edge resource scheduling.

A. Problem Formulation

In the proposed vehicular edge caching network, to alleviate the traffic burden of cellular networks and to fully utilize V2V communication resources, we consider that unit data transmission cost ς_r for V2R mode is higher than the cost ς_υ for V2V mode. Thus, vehicles prefer to get contents from cache-enabled vehicles through V2V communication than to obtain them from RSUs through V2R. However, when encountered cache-enabled vehicles cannot provide the required contents, subscriber vehicles turn to obtain the contents from the RSU caching servers. Compared to the storage space of an individual smart vehicle, the caching capacity of an RSU server is much larger. Some complete contents can be stored in an RSU server. In the case that the demanded contents have not been pre-stored in an RSU server, they should be fetched from the data center, which incurs extra transmission cost ς_c for transmitting a unit data. Due to delay sensitivity of the application contents, the vehicular subscriber gets utility if the duration of content delivery is less than the maximum delay tolerance threshold $t^{\max}_g$. To improve the delivery time efficiency while reducing transmission costs, the contents need to be efficiently pre-stored in appropriate cache nodes. Moreover, the caching arrangement depends on the vehicular social model obtained from the digital twin empowered LSTM system. The more information gathered by the digital twin network, the higher the accuracy of the model. However, the information collection process incurs V2R communication costs. Thus, the trade-off between V2R communication cost and model accuracy, as well as its impact on caching system utility also needs to be considered in the cache scheduling.

Let x_g and $\mathcal{Y}_g = \{y_{g,1}, y_{g,2}, \ldots, y_{g,N}\}$ denote the probability of pre-storing type g contents in the vehicular caching cloud and in the caching severs equipped on RSUs, respectively. Q_g is the size of the content segment cached in a vehicle. The proposed optimal edge caching problem, which maximizes utility of the caching system under the constraints of node cache capacity and content delivery delay, can therefore be formulated as

$$\begin{aligned}
\max_{\{x_g,\mathcal{Y}_g,Q_g,\xi_g\}} U = \sum_{g\in\mathcal{G}} \Bigg\{ &\sum_{\upsilon'\in\mathcal{V}_2}\sum_{n\in\mathcal{N}} \Psi_g(\xi_g)\beta_g \\
&\times\Big[x_g\big(\mu_g\big(t^{\max}_g - t^{V}_{g,\upsilon'}\big) - f_g\varsigma_\upsilon\big) \\
&+(1-x_g)w_{g,\upsilon',n}\big(\mu_g\big(t^{\max}_g - t^{R}_{g,\upsilon',n}\big) \\
&-f_g\big(\varsigma_r + (1-y_{g,n})\varsigma_c\big)\big)\Big] - \xi_g\varsigma_r\Bigg\}
\end{aligned}$$

$$\begin{aligned}
\text{s.t. } &\mathrm{C1}: 0 \leqslant x_g \leqslant 1, \quad g\in\mathcal{G}\\
&\mathrm{C2}: 0 \leqslant \mathcal{Y}_g \leqslant 1, \quad g\in\mathcal{G}\\
&\mathrm{C3}: e_\upsilon \leqslant C_\upsilon, \quad \upsilon\in\mathcal{V}_1\\
&\mathrm{C4}: \sum_{g\in\mathcal{G}} y_{g,n} f_g \leqslant C_n, \quad n\in\mathcal{N}\\
&\mathrm{C5}: \mathbf{1}\{x_g > 0\}t^{V}_{g,\upsilon'} \leqslant t^{\max}_g, g\in\mathcal{G}, \upsilon'\in\mathcal{V}_2, n\in\mathcal{N}\\
&\mathrm{C6}: \mathbf{1}\{y_{g,n} > 0\}t^{R}_{g,\upsilon',n} \leqslant t^{\max}_g, g\in\mathcal{G}, \upsilon'\in\mathcal{V}_2, n\in\mathcal{N}\\
&\mathrm{C7}: Q_g \leqslant Q^{\max}_\upsilon, \quad g\in\mathcal{G}\\
&\mathrm{C8}: \sum_{g\in G}\xi_g \le \xi^{\max}, \quad \xi_g > 0, \ g\in\mathcal{G}
\end{aligned} \tag{7}$$

where $\mathcal{V}_1$ and $\mathcal{V}_2$ denote the sets of content provider and subscriber vehicles in an area, respectively. $\Psi_g(\xi_g)$ is an influence function, which presents the impact of social model deviation caused by different amounts of gathered information on the system utility. $w_{g,\upsilon',n}$ is the probability that vehicle υ' is located within the coverage of RSU n, and get type g content from cache server equipped on this RSU in V2R mode. This probability can be calculated as $w_{g,\upsilon',n} = L_n/\sum_{i=1}^{N} L_i$.

In (7), $t^V_{g,v'}$ is the time cost for vehicle v' to get type g content from a vehicular caching cloud. A subscriber vehicle obtains segmented type g content from multiple encountered vehicles during its running. As driving and data transmission occur simultaneously, $t^V_{g,v'}$ can be presented as the time cost for the subscriber vehicle arriving at the communication range of the farthest vehicle of the cloud that caches the last segment of type g content

$$t^V_{g,v'} = \frac{\lceil f_g/Q_g \rceil d_g^{\text{adj}}}{s_1 + s_2}. \tag{8}$$

e_v is the amount of content cached in vehicle v, and can be written as

$$e_v = \sum_{g=1}^{G} x_g Q_g \mathbf{1}\left\{\phi_v / \left\lceil d_g^{\text{adj}}/\bar{d}_s \right\rceil = 0\right\} \tag{9}$$

where ϕ_v is the index number of vehicle v, and $\mathbf{1}\{\hat{z}\}$ is an indicator function that equals 1 if $\hat{z}$ is true and 0 otherwise. $t^R_{g,v',n}$ is the time cost for vehicle v' getting type g content from RSU caching server n, and can be calculated as

$$t^R_{g,v',n} = f_v L_n / \bar{\chi}_{n,v'} s_2. \tag{10}$$

Similar to (3), here $\bar{\chi}_{n,v'}$ is the average amount of data transmitted from RSU n to vehicle v', when v' is running within the coverage of this RSU. $\bar{\chi}_{n,v'}$ is given as

$$\bar{\chi}_{n,v'} = \int_0^{L_n/2s_2} B_n \log\left(1 + \frac{P_n}{P_w L_0 \left[{d^{\min}_{n,v'}}^2 + s_2 t)\right]^{\frac{\alpha}{2}}}\right) \mathrm{d}t \tag{11}$$

where $d^{\min}_{n,v'}$ is the shortest distance between vehicle v' and RSU n.

In (7), the first two constraints show the range of caching probability. Constraints C3 and C4 guarantee that the amount of contents on a vehicle and an RSU server should not exceed the maximum storage capacity of the caching node, respectively. Constraints C5 and C6 ensure the time cost for type g content under its delay constraint. Constraint C7 indicates that the size of the content segment cached in a vehicle should not exceed the upper limit given in (5). The last constraint ensures that the amount of information related to type g content is positive, and the total amount of gathered information shall not exceed the maximum threshold $\xi^{\max}$.

In the proposed optimal caching problem, the edge cache scheduling relies on the built social model, while in the model construction, the adjustment of information collection depends on its effect on the system utility. Moreover, due to possible content segmentation and cache resource sharing, there exists a strong correlation between the various types of contents cached in heterogeneous edge caching nodes. These features make solving problem (7) a critical challenge. To address this issue, we propose a learning-based iterative approach. In each iteration, we first obtain the cache scheduling strategies according to a given social model, and then modify the amount of information gathered in model construction based on the determined caching strategies. The iteration continues until the system utility converges. The details of the proposed iterative approach are described as follows.

B. DDPG-Based Edge Cache Scheduling Scheme

Given an established social model and influence function set $\{\Psi_g(\xi_g), g \in \mathcal{G}\}$, we explore the optimal caching strategies that adapt to the vehicular social network. Let

$$\begin{aligned} U' = \sum_{g\in\mathcal{G}} U'_g = \sum_{g\in\mathcal{G}} \sum_{v'\in\mathcal{V}_2} \sum_{n\in\mathcal{N}} \beta_g \\ \times \big[x_g\big(\mu_g\big(t_g^{\max} - t^V_{g,v'}\big) - f_g\varsigma_v\big) + (1 - x_g) w_{g,v',n} \\ \times \big(\mu_g\big(t_g^{\max} - t^R_{g,v',n}\big) - f_g(\varsigma_r + (1 - y_{g,n})\varsigma_c)\big)\big]. \end{aligned} \tag{12}$$

We formulate (12) as a Markov decision process and consider that the content delivery from edge caching nodes to subscribers operates in a discrete time model with fixed length time frames. The length of a frame is denoted as τ. When a subscriber vehicle generates a content demand, the data that is needed but has not been obtained yet, constructs a queue. If part of the required data has been received, the corresponding queue part will be removed. A vehicle does not generate a new content requirement until its previous content demand is satisfied. As the queue length of the demand data in a vehicle at the current time frame is affected by that in the previous frame, each subscriber vehicle can be modeled as a queuing system.

Let $S^l_{v'}$ be the state of the demand data queuing in vehicle v' at time frame l, and $t^l_{v',g}$ denote the remaining time for vehicle v' to obtain type g content under its delay constraint. Thus, the state of the edge caching system is defined as $\mathcal{S}^l = \{S^l_1, S^l_2, \ldots, S^l_{V_2}, t^l_{1,g}, t^l_{2,g}, \ldots, t^l_{V_2,g}\}$. To efficiently pre-store the demanded contents in heterogeneous cache nodes, the caching strategies depend on the characteristics of the edge caching system as well as the system states at current time frame. The caching actions taken at time frame l is denoted as $A^l = \{x^l_g, \mathcal{Y}^l_g, Q^l_g\}$.

Since data pre-storage and vehicle mobility may affect the content delivery process, the state transitions between time frame l and $l+1$ is shown as

$$\begin{aligned} S^{l+1}_{v'} = \mathbf{1}\big\{S^l_{v'} > 0\big\}\Big[x_g\big(S^l_{v'} - \tau\bar{\chi}_{v,v'}(s_1+s_2)/2d^{\max}_{v,v'}\big) \\ +(1-x_g)\sum_{n\in\mathcal{N}} w_{g,v',n}\big(S^l_{v'} - \tau\bar{\chi}_{n,v'}s_2/L_n\big)\Big] \\ +\mathbf{1}\big\{S^l_{v'} = 0\big\}\sum_{g\in\mathcal{G}}\beta_g f_g \end{aligned} \tag{13}$$

and $t^{l+1}_{2,g} = t^l_{2,g} - 1$. At time frame l, the obtained system utility from edge caching action A^l taken on state $\mathcal{S}^l$, is calculated as

$$\begin{aligned} U'^l = \sum_{v\in\mathcal{V}_2}\sum_{g\in\mathcal{G}} \mu_g\Big[t^l_{v,g}\mathbf{1}\big\{S^l_{v'} = 0\big\} - x_g\varsigma_v\tau\bar{\chi}_{v,v'}(s_1+s_2) \\ /2d^{\max}_{v,v'} - (1-x_g)\sum_{n\in N} w_{g,v',n} \\ \cdot\tau\bar{\chi}_{n,v'}s_2(\varsigma_r + (1-y_{g,n})\varsigma_c)/L_n\Big]. \end{aligned} \tag{14}$$

To maximize the utility of this edge caching system, optimal caching strategy π^*, which consists of caching actions for

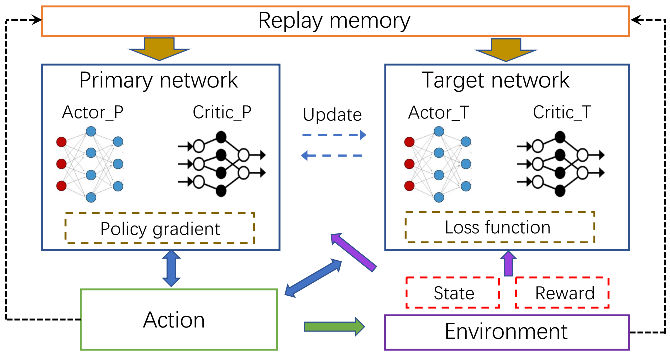


Fig. 4. Architecture of DDPG.

pre-storing various types of contents in heterogeneous cache nodes at different time frames, need to be obtained. Here, π^* is expressed as

$$\pi^* = \arg\max_{\pi} \mathrm{E}\left(\sum_{l=1}^{\infty} \eta^l U'^l\right) \tag{15}$$

where $\eta \in (0, 1)$ is a discounting factor that trades off the immediate utility and the later ones.

To derive the optimal caching strategy π^*, we turn to the artificial intelligence approach. More specifically, we propose a DDPG-based vehicular caching cloud formulation and content edge caching scheme. DDPG is an extension of the deep Q-learning technique, which incorporates an actor-critic approach into the learning process of deep Q-network [29]. More specifically, a DDPG agent learns directly from unprocessed observation spaces in a policy gradient way for estimating the weights of policy, while it uses the actor-critic model to learn value function and update the actor model. As DDPG leverages a stochastic behavior policy for strategy exploration, it significantly saves learning complexity. Moreover, unlike Q-learning that can only handle discrete action spaces, DDPG is able to support the problem with high-dimensional, continuous action spaces. Being a powerful intelligent approach, DDPG has been widely used in diverse applications, such as wireless power control, spectrum scheduling, and task offloading management. Considering that the action taken in the proposed Markov decision process consists of continuous variables, DDPG is able to learn the optimal caching strategy.

Fig. 4 shows the architecture of DDPG. A DDPG learning system consists of two main parts, namely primary network and target network. These two networks have similar compositions, and each of them has an actor and a critic. Here, the actor and critic are two deep neural networks. In the DDPG learning process, the actor of the primary network explores edge caching policy, while the critic network helps the actor to get a better policy in a gradient approach. The target network can be taken as an old version of the primary one, and it generates the target value for training the primary network, where the policy is updated by calculating the loss function. The replay memory stores the learning experience of action reward and state transition, which are used for training the actor and critic parameters.

In applying DDPG to the edge cache management scenario, the Markov decision process takes the form of a reinforcement learning problem. Under a given caching strategy π, the gained average system utility from taking action A^l in state S^l can be expressed as a Q-function, which is shown as

$$Q_\pi(S^l, A^l) = \mathrm{E}_{S^{l+1}}\left[U'^l + \eta Q_\pi(S^{l+1}, A^{l+1}) | S^l, A^l\right]. \tag{16}$$

Catering for the caching system with a large scale of state-action combinations and corresponding Q-values, a non-linear function approximator is introduced to approximate the Q-function, that facilitates the optimal action acquisition process. Here, we choose a multi-layered neural network as the approximator capturing complex interactions among various states and actions. Let θ^l denote the parameters of the neural network at time frame l. Then, Q-function in (16) can be estimated as $Q_\pi(S^l, A^l) \approx Q'_\pi(S^l, A^l, \theta^l)$.

In order to make Q'_π converge to real Q_π value over iterations, experience replay technique is utilized in the learning process, where the learned experience stored in a replay memory is randomly drawn out and used as samples in training θ. The goal of this training is to minimize the difference between $Q_\pi(S^l, A^l)$ and $Q'_\pi(S^l, A^l; \theta)$, which is presented as

$$\Delta(\theta^l) = \mathrm{E}\left[\frac{1}{2}\left(Q^l_{\pi,\mathrm{tar}} - Q'_\pi(S^l, A^l; \theta^l)\right)^2\right] \tag{17}$$

where $Q^l_{\pi,\mathrm{tar}}$ is the target function, which denotes the optimal value of the Q-function in frame l and can be calculated using replay memory data sets $\{S^l, A^l, U'^l, S^{l+1}\}$ as

$$Q^l_{\pi,\mathrm{tar}} = U'^l + \eta Q'_\pi(S^{l+1}, A^*(S^{l+1}); \theta^l_{\mathrm{tar}}). \tag{18}$$

To further improve the efficiency of the learning process, critic function $Q'(S, A; \theta)$ and actor function $A^*(S; \theta')$ based on different approximators are introduced. The critic function is taken to estimate the performance of the proposed caching policy using the Bellman equation, while the actor function is used to explore policy. Then, the target function can be rewritten as

$$Q^l_{\mathrm{tar}} = U'^l + \eta Q'_\pi\left(S^{l+1}, A^*\left(S^{l+1}; \theta'^l_{\mathrm{tar}}\right); \theta^l_{\mathrm{tar}}\right). \tag{19}$$

$A^*(S; \theta')$ is updated by applying chain rule to the expected utility with respect to θ', which can be given as

$$\nabla_{\theta'} J^l = \mathrm{E}\left[\nabla_{A^*} Q'\left(S^l, A^*(S^l; \theta^l)\right) \nabla_{\theta'} A^*\left(S^l; \theta'^l\right)\right]. \tag{20}$$

Then, based on the actor policy obtained from (20), the parameters of the approximators are updated. The main steps of the proposed DDPG-based edge caching scheme are summarized as Algorithm 1.

C. Vehicular Social-Aware Iterative Caching Scheme

Based on the obtained optimal caching strategies, we modify the social model construction process in terms of information collection. Let $U_g^{\prime,\mathrm{opt}}$ denote the value of U'_g when the optimal caching strategies are adopted. In this step, problem (7) can be rewritten as

$$\begin{aligned} &\max_{\{\xi_g\}} U = \sum_{g\in\mathcal{G}} \left\{\Psi_g(\xi_g) U'_{\mathrm{opt}} - \xi_g \varsigma_r\right\} \\ &\text{s.t. C8}: \sum_{g\in G} \xi_g \le \varsigma^{\max}, \quad \xi_g > 0, \ g \in \mathcal{G}. \end{aligned} \tag{21}$$

Algorithm 1 DDPG-Based Vehicular Edge Caching Scheme

Initialization: Initialize critic function $Q(S, A; \theta)$ and actor function $A^*(S; \theta^A)$ with randomly chosen parameters θ and θ', respectively;
Initialize target critic function $Q_{\text{tar}}(S, A; \theta_{\text{tar}})$ and target actor function $A^*_{\text{tar}}(S; \theta'_{\text{tar}})$, where $\theta_{\text{tar}} = \theta$ and $\theta'_{\text{tar}} = \theta'$;
Initialize experience replay buffer.

For a given steady vehicular traffic flow **Do**
  Observe the initial state S^1;
  For time frames $l = 1, \ldots, L_{\max}$ **Do**
    Select a random action A^l with greedy probability ε under the constraints of (7), otherwise choose action $A^l = A^*(S^l; \theta^A)$;
    Execute action A^l, derive the next state S^{l+1} and obtain caching utility U^l according to (13) and (14);
    Store the experience (S^l, A^l, U^l, S^{l+1}) into the experience replay buffer;
    Get a batch of samples from the replay memory, and calculate target critic function according to (19);
    Update critic function through minimizing difference $\Delta(\theta^l)$ according to (17);
    Update actor policy through calculating the gradient of J^l with respect to θ'^l according to (20);
    Update the parameters of target functions as $\theta^{l+1}_{\text{tar}} = \varpi\theta^l + (1-\varpi)\theta^l_{\text{tar}}$ and $\theta'^{l+1}_{\text{tar}} = \varpi\theta'^l + (1-\varpi)\theta'^l_{\text{tar}}$, where $0 < \varpi \ll 1$.
  End For
End For

To obtain the optimal amount of information, we transform (21) to a Lagrangian multiplier problem, and solve it using a sub-gradient approach. The Lagrangian relaxation function of (21) is

$$L(\xi, \lambda) = \sum_{g\in G}\left[\Psi_g(\xi_g)U_g^{\prime,\text{opt}} - \xi_g\varsigma_r\right] + \sum_{g\in G}\lambda_{1,g}\xi_g - \lambda_2\left(\sum_{g\in G}\xi_g - \xi^{\max}\right) \tag{22}$$

where $\xi = \{\xi_1, \xi_2, \ldots, \xi_G\}$, $\lambda = \{\lambda_{1,g}, \lambda_2\}$, $\lambda_{1,g} \in \mathscr{R}^{1\times G}$, $\lambda_2 \in \mathscr{R}$, and $\lambda_{1,g}, \lambda_2 \geq 0$. Then we have the dual problem of (21), which is expressed as

$$\begin{aligned} &\min_{\lambda} L'(\lambda) = \min_{\lambda}\sup_{\xi} L(\xi, \lambda) \\ &\text{s.t. C1}: \ \lambda_{1,g} \in \mathscr{R}^{1\times G}, \quad \lambda_2 \in \mathscr{R} \\ &\quad\ \ \text{C2}: \ \lambda_{1,g}, \lambda_2 \geq 0. \end{aligned} \tag{23}$$

For (23), given Lagrangian multiplier λ, the feasible solutions of its internal maximization problem $\sup_\xi L(\xi, \lambda)$ can be obtained by solving equations $\partial L(\xi, \lambda)/\partial\xi_g = 0$, $g \in \mathcal{G}$, where the solutions should meet the constraints in (21).

Based on the obtained feasible solution set ξ_g, Lagrangian multiplier set λ is updated in a sub-gradient approach. The iteration process continuous, until the change of λ in two adjacent iterations is lower than a preset threshold υ. Here, the sub-gradients of $L'(\lambda)$ in terms of $\lambda_{1,g}$ and λ_2 are shown as

$$\begin{aligned} \lambda_{1,g}(h+1) &= \left[\lambda_{1,g}(h) + \sigma_{1,g}\xi_g\right]^+ \\ \lambda_2(h+1) &= \left[\lambda_2(h) - \sigma_{2,g}\left(\sum_{g\in G}\xi_g - \xi^{\max}\right)\right]^+ \end{aligned} \tag{24}$$

where $\sigma_{1,g}$ and σ_2 are step sizes in iterative update, and $[\hat{z}]^+ = \max(0, \hat{z})$.

Algorithm 2 Vehicular Social-Aware Edge Caching Scheme

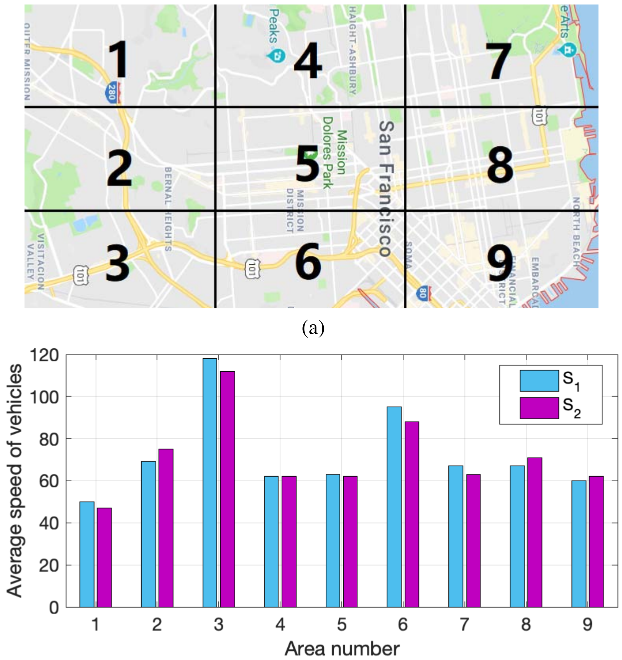
Initialization:
Initialize amount of information ξ and Lagrangian multiplier set λ.

For Index of iterations $T = 1, 2, \ldots, T_{\max}$ **Do**
  Based on ξ_{T-1}, obtain caching strategies $\{x_g, \mathcal{Y}_g, Q_g\}_T$ according to Algorithm 1, and calculate $U'_{\text{opt},T}$;
  For Index of inner iterations $h = 1, 2, \ldots, h_{\max}$ **Do**
    Get the feasible solutions $\{\xi'_g\}$ of (23) by solving $\partial L(\xi, \lambda)/\partial\xi_g = 0$;
    Calculate $\lambda(h)$ according to (24);
    if $\left|\lambda_{1,g}(h) - \lambda_{1,g}(h-1)\right| \leq \varepsilon$ and $|\lambda_2(h) - \lambda_2(h-1)| \leq \varepsilon$; **then**
      Break and $\xi_T = \{\xi'_g\}$;
    else
      $\lambda_j(h) = \lambda_j(h-1))$, $j = \{1, g\}$ or 2;
    end if
  End For
  Calculate system utility U according to (7);
  if $U(T) - U(T-1) \leq \varphi$; **then**
    Break and return $\{\xi_T, \{x_g, \mathcal{Y}_g, Q_g\}_T\}$;
  end if
End For

The main steps of the whole vehicular social-aware edge caching scheme, which includes the cache scheduling and social model construction, are presented in algorithm 2. Given $O(l)$ as the complexity of the DDPG-based vehicular edge caching scheme, which is given in algorithm 1, the complexity of algorithm 2 can be presented as $O(T_{\max}(l + \bar{\omega}))$. $\bar{\omega}$ is the lower band of the step number when the obtained optimal λ in the subgradient approach and satisfies the following inequality

$$\bar{\omega} > \left(\sum_{g\in\mathcal{G}}\frac{\left\|\lambda_{1,g}(0) - \lambda_{1,g}^{\text{opt}}\right\|^2}{{\sigma_{1,g}}^2} + \frac{\left\|\lambda_2(0) - \lambda_{2,g}^{\text{opt}}\right\|^2}{{\sigma_2}^2}\right)/\kappa^2 \tag{25}$$

where κ is a Lipschitz constant [30]. It is noteworthy that the proposed vehicular social-aware edge caching scheme can be easily implemented in the scenario where the content requester and server vehicles are running in both two-way lanes. Since vehicles in one lane only serve the vehicles in the opposite lane, the system with mixed server and subscriber vehicles can be split into two logical systems from the perspective of content services. In each logical system, the server vehicles are driving on one lane, while all the subscriber vehicles running on the other lane. Then the proposed scheme can be independently applied to these two systems to schedule the vehicles' caching service.



(a)

(b)

Fig. 5. Urban areas with different vehicular social characteristics. (a) Area division of the urban district. (b) Average speed of vehicles in different areas.

VI. Numerical Results

In this section, we evaluate the performance of the proposed digital twin empowered and social-aware edge caching schemes based on vehicular traffic data sets in the real world. These sets consist of the mobility traces of approximately 500 taxi cabs in the San Francisco Bay area [31]. In order to distinguish the difference of the vehicular social relations in various traffic environments, we divide the Bay area into nine square areas, which are shown in Fig. 5(a). Moreover, we exploit the vehicular social characteristics through the digital twin network and LSTM approach. Fig. 5(b) gives a snapshot of the obtained average speed of vehicles in different areas at a certain moment to illustrate there are various vehicle contact rates.

We consider a scenario where 1–3 RSUs are randomly located in each area. The data storage capacity of a cache server equipped on each RSU is randomly set within the interval (300, 700) MB. There are ten types of content requirements, of which the content size, maximum delay tolerance, and delay sensitivity coefficient are randomly chosen from (10,100) MB, (0.5, 3) s, and (0.1, 0.3), respectively [21]. For the transmission costs, we set ς_v to 1, ς_r to 5 and ς_c to 8.

Fig. 6 shows the convergence of the proposed digital twin empowered and social-aware edge caching scheme implemented in areas 1, 4, and 6, respectively. These areas have different vehicle running speeds and distinct vehicle contact rates. Despite the difference in the vehicular social characteristics of the areas, all the caching utilities obtained by our scheme converge around 15 iterations.

Fig. 7 compares the utilities of multiple areas with different edge caching scheduling schemes. Our proposed digital twin empowered learning approach gains the highest utilities in all the urban areas compared to the others. Here, the greedy approach, which gets the lowest utility, arranges the content storage in the edge cache nodes only according to the content popularity but ignores the social relations between smart vehicles and fails to make full use of the communication contacts between vehicles to implement V2V data delivery. In contrast to this approach, the social-aware learning scheme takes the content directly delivery among vehicles into account, and dynamically allocates cache and communication resources based on content requirements and known environmental characteristics, thus achieving higher utility. However, its social feature perception mode is fixed, which may increase detection cost or reduce perception accuracy. Unlike the two previous schemes, our proposed one leverages digital twin to reflect the vehicular network states, while adaptively adjusting social model construction strategies with balanced accuracy and costs, thus resulting in the highest caching utility.

Fig. 8 shows the comparison of the content acquisition delay with different schemes in multiple areas. Since the acquisition delay is a key part of the caching utility, the result in Fig. 8 is similar to Fig. 7. That is to say, our proposed

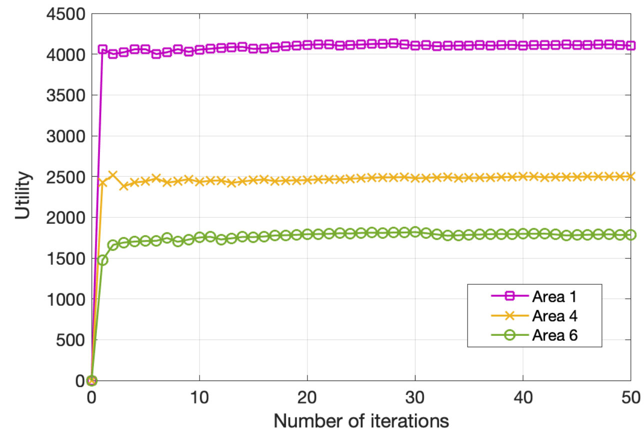


Fig. 6. Convergence of the digital twin empowered and social-aware edge caching scheme.

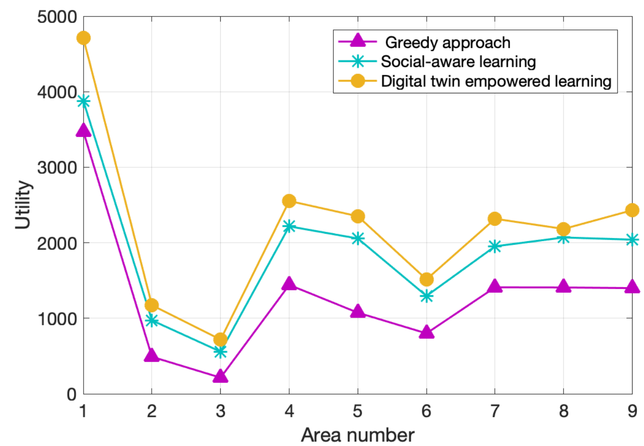


Fig. 7. Comparison of the caching utilities of multiple areas with different schemes.

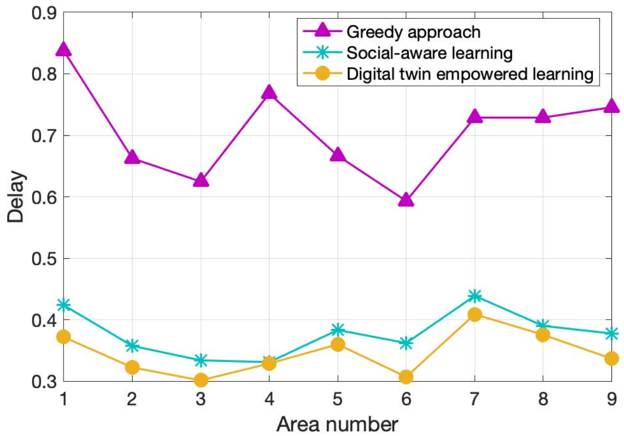


Fig. 8. Comparison of the content acquisition delay of multiple areas with different schemes.

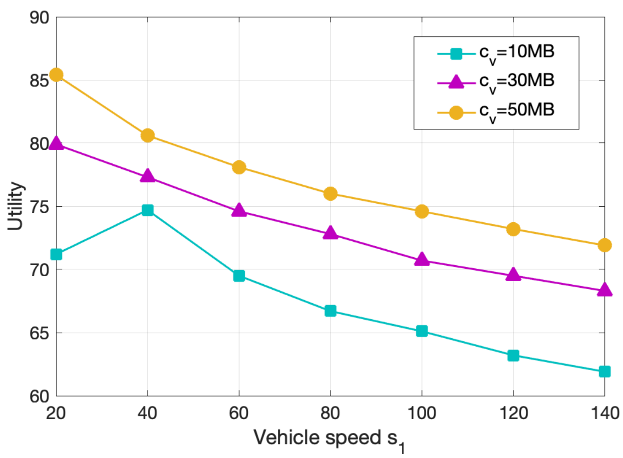


Fig. 9. Caching utility per vehicle with different running speed.

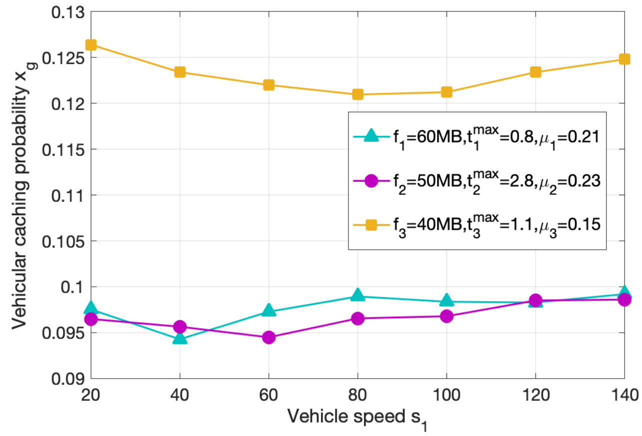


Fig. 10. Vehicular caching cloud arrangement with different vehicle running speed.

digital twin empowered learning scheme outperforms the other two approaches. As this scheme smartly utilizes the vehicular social relations and caching capacity in enabling data direct delivery between vehicles, the content acquisition delay is reduced. It is noteworthy that although in few areas such as area 3 in Fig. 7 and area 4 in Fig. 8, the performance of the digital twin empowered learning scheme is close to that of the social-aware learning approach, in all areas as a whole, the utility(delay) of the digital twin empowered scheme is increased(decreased) by 17%(10%) on average over the simple social-aware scheme. Since both these two schemes leverage vehicular social relations to schedule cache resources, the difference in their performance is smaller than the performance gap between the social-aware schemes and the greedy approach that ignores the vehicular social relation effects. Moreover, the performance gain brought by the digital twin mechanism is affected by the different vehicle distribution, driving states, and caching capacity in various areas. Therefore, there are differences in the gain effects of the digital twin in these areas.

Fig. 9 presents the caching utility gained by a single vehicular content subscriber with the aid of vehicular caching servers with different storage capabilities and running speeds. The figure indicates that larger vehicle cache space brings higher utility to the subscriber, since more contents can be stored in the vehicles and delivered directly in V2V mode with low costs. Moreover, we notice that the general trend of the utilities with different vehicle caching capacity c_v decreases as the speed of the vehicle servers increases. In vehicle traffic, the speed increase may lead to longer inter-vehicle distance, thereby reducing the number of vehicle servers that a subscriber can contact under content delay constraints, and undermining V2V service capability. It is noteworthy that when c_v is 10 MB, there is an increase in the utility at a speed of 40 km/h. When the vehicle speed is 20 km/h, although the inter-vehicle distance is low, the V2V content delivery is mainly restricted by the vehicular cache capacity. When the speed reaches 40 km/h, the enhancement of traffic speed on the vehicle contact rate is higher than the weakening caused by the longer distance. Therefore, a subscriber can get contents from more vehicle servers, thus yielding higher caching utility.

Fig. 10 shows the arrangement strategies of vehicular caching cloud in terms of various types of contents with different vehicle speeds. Here, the caching capacity of a vehicle server is set to 45 MB. For the content type with a size of 40 MB, it can be completely stored in a single vehicle server. Thus, with various traffic speed, the probability of it being stored in the vehicular caching cloud is much higher than that of the other two content types. As both the types of contents with 50 and 60 MB data size need to be stored in multiple vehicle servers in the form of divided segments, they have similar caching probabilities. Moreover, there are caching probability decrease of these two types at traffic speeds of 40 and 60 km/h, respectively. The reason is similar to that of the inflection point of the caching utility shown in Fig. 8, which is caused by the contact rate change as speed increases. In addition, by comparing the delay constraints of the two types of contents, it can be found that the greater the $t_g^{\max}$, the higher the vehicle speed corresponding to the x_g inflection point.

VII. Conclusion

In this article, we investigated social-aware vehicular edge networks and presented a digital twin empowered content caching framework. By mapping physical edge networks into a virtual space in the digital twin approach, the social relation model between vehicles was obtained. We further leveraged the model to exploit the cooperation among resource-constrained vehicles in delivering large-scale contents and proposed learning empowered social relation construction and cache resource scheduling schemes. We evaluated the performance of the proposed schemes based on real-world data sets. The analytic results illustrated that the edge system utility gained from the proposed schemes outperformed the other two benchmark approaches in diverse traffic environments. Although the proposed social-aware edge caching scheme efficiently improves content delivery utility in vehicular networks, there are still some technical issues worthy of future studies. For instance, how to incentivize smart vehicles that are individual rationality oriented to form vehicular edge caching cloud is an unexplored question. Moreover, in complex traffic environments with highly dynamic changes in vehicle topology, the composition update and service maintenance of the cache cloud require further discussion.

References

[1] Z. Ning *et al.*, "Distributed and dynamic service placement in pervasive edge computing networks," *IEEE Trans. Parallel Distrib. Syst.*, vol. 32, no. 6, pp. 1277–1292, Jun. 2021.

[2] X. Wang *et al.*, "Privacy-preserving content dissemination for vehicular social networks: Challenges and solutions," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 2, pp. 1314–1345, 2nd Quart., 2019.

[3] Y. Lu, X. Huang, K. Zhang, S. Maharjan, and Y. Zhang, "Communication-efficient federated learning and permissioned blockchain for digital twin edge networks," *IEEE Internet Things J.*, vol. 8, no. 4, pp. 2276–2288, Feb. 2021.

[4] G. Qiao, S. Leng, S. Maharjan, Y. Zhang, and N. Ansari, "Deep reinforcement learning for cooperative content caching in vehicular edge computing and networks," *IEEE Internet Things J.*, vol. 7, no. 1, pp. 247–257, Jan. 2020.

[5] R. W. L. Coutinho and A. Boukerche, "Modeling and analysis of a shared edge caching system for connected cars and industrial IoT-based applications," *IEEE Trans. Ind. Informat.*, vol. 16, no. 3, pp. 2003–2012, Mar. 2020.

[6] Z. Ning *et al.*, "Joint computing and caching in 5G-envisioned Internet of vehicles: A deep reinforcement learning-based traffic control system," *IEEE Trans. Intell. Transp. Syst.*, early access, Feb. 5, 2020, doi: 10.1109/TITS.2020.2970276.

[7] A. Mahmood, C. E. Casetti, C. F. Chiasserini, P. Giaccone, and J. Harri, "The RICH prefetching in edge caches for in-order delivery to connected cars," *IEEE Trans. Veh. Technol.*, vol. 68, no. 1, pp. 4–18, Jan. 2019.

[8] Y. Dai, D. Xu, K. Zhang, S. Maharjan, and Y. Zhang, "Deep reinforcement learning and permissioned blockchain for content caching in vehicular edge computing and networks," *IEEE Trans. Veh. Technol.*, vol. 69, no. 4, pp. 4312–4324, Apr. 2020.

[9] Z. Ning *et al.*, "Partial computation offloading and adaptive task scheduling for 5G-enabled vehicular networks," *IEEE Trans. Mobile Comput.*, early access, Sep. 18, 2020, doi: 10.1109/TMC.2020.3025116.

[10] Y. He, N. Zhao, and H. Yin, "Integrated networking, caching, and computing for connected vehicles: A deep reinforcement learning approach," *IEEE Trans. Veh. Technol.*, vol. 67, no. 1, pp. 44–55, Jan. 2018.

[11] Y. Dai, D. Xu, S. Maharjan, G. Qiao, and Y. Zhang, "Artificial intelligence empowered edge computing and caching for Internet of vehicles," *IEEE Wireless Commun.*, vol. 26, no. 3, pp. 12–18, Jun. 2019.

[12] Z. Ning *et al.*, "Intelligent edge computing in Internet of vehicles: A joint computation offloading and caching solution," *IEEE Trans. Intell. Transp. Syst.*, early access, Jun. 5, 2020, doi: 10.1109/TITS.2020.2997832.

[13] Z. Yu, J. Hu, G. Min, Z. Zhao, W. Miao, and M. S. Hossain, "Mobility-aware proactive edge caching for connected vehicles using federated learning," *IEEE Trans. Intell. Transp. Syst.*, early access, Aug. 31, 2020, doi: 10.1109/TITS.2020.3017474.

[14] J. Zhou, X. Zhang, and W. Wang, "Social-aware proactive content caching and sharing in multi-access edge networks," *IEEE Trans. Cognit. Commun. Netw.*, vol. 6, no. 4, pp. 1308–1319, Dec. 2020.

[15] M. Radenkovic and V. S. H. Huynh, "Cognitive caching at the edges for mobile social community networks: A multi-agent deep reinforcement learning approach," *IEEE Access*, vol. 8, pp. 179561–179574, 2020.

[16] Y. He, C. Liang, F. R. Yu, and Z. Han, "Trust-based social networks with computing, caching and communications: A deep reinforcement learning approach," *IEEE Trans. Netw. Sci. Eng.*, vol. 7, no. 1, pp. 66–79, Jan. 2020.

[17] Y.-H. Hung, C.-Y. Wang, and R.-H. Hwang, "Optimizing social welfare of live video streaming services in mobile edge computing," *IEEE Trans. Mobile Comput.*, vol. 19, no. 4, pp. 922–934, Apr. 2020.

[18] L. Yao, Y. Wang, X. Wang, and G. Wu, "Cooperative caching in vehicular content centric network based on social attributes and mobility," *IEEE Trans. Mobile Comput.*, vol. 20, no. 2, pp. 391–402, Feb. 2021.

[19] S. A. Bitaghsir, A. Dadlani, M. Borhani, and A. Khonsari, "Multi-armed bandit learning for cache content placement in vehicular social networks," *IEEE Commun. Lett.*, vol. 23, no. 12, pp. 2321–2324, Dec. 2019.

[20] A. M. Vegni, C. Souza, V. Loscri, E. Hernandez-Orallo, and P. Manzoni, "Data transmissions using hub nodes in vehicular social networks," *IEEE Trans. Mobile Comput.*, vol. 19, no. 7, pp. 1570–1585, Jul. 2020.

[21] K. Zhang, J. Cao, H. Liu, S. Maharjan, and Y. Zhang, "Deep reinforcement learning for social-aware edge computing and caching in urban informatics," *IEEE Trans. Ind. Informat.*, vol. 16, no. 8, pp. 5467–5477, Aug. 2020.

[22] Y. Lu, X. Huang, K. Zhang, S. Maharjan, and Y. Zhang, "Communication-efficient federated learning for digital twin edge networks in industrial IoT," *IEEE Trans. Ind. Informat.*, early access, Jul. 21, 2020, doi: 10.1109/TII.2020.3010798.

[23] W. Sun, S. Lei, L. Wang, Z. Liu, and Y. Zhang, "Adaptive federated learning and digital twin for industrial Internet of Things," *IEEE Trans. Ind. Informat.*, early access, Oct. 29, 2020, doi: 10.1109/TII.2020.3034674.

[24] Y. Lu, X. Huang, K. Zhang, S. Maharjan, and Y. Zhang, "Low-latency federated learning and blockchain for edge association in digital twin empowered 6G networks," *IEEE Trans. Ind. Informat.*, early access, Aug. 18, 2020, doi: 10.1109/TII.2020.3017668.

[25] C. Gehrmann and M. Gunnarsson, "A digital twin based industrial automation and control system security architecture," *IEEE Trans. Ind. Informat.*, vol. 16, no. 1, pp. 669–680, Jan. 2020.

[26] Y. Dai, K. Zhang, S. Maharjan, and Y. Zhang, "Deep reinforcement learning for stochastic computation offloading in digital twin networks," *IEEE Trans. Ind. Informat.*, early access, Aug. 13, 2020, doi: 10.1109/TII.2020.3016320.

[27] M. Treiber, A. Hennecke, and D. Helbing, "Congested traffic states in empirical observations and microscopic simulations," *Phys. Rev. E, Stat. Phys. Plasmas Fluids Relat. Interdiscip. Top.*, vol. 62, no. 2, pp. 1805–1824, Aug. 2000.

[28] S. Wang, Y.-C. Wu, M. Xia, R. Wang, and H. V. Poor, "Machine intelligence at the edge with learning centric power allocation," *IEEE Trans. Wireless Commun.*, vol. 19, no. 11, pp. 7293–7308, Nov. 2020.

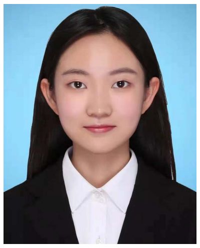
[29] Y. Al-Eryani, M. Akrout, and E. Hossain, "Multiple access in cell-free networks: Outage performance, dynamic clustering, and deep reinforcement learning-based design," *IEEE J. Sel. Areas Commun.*, vol. 39, no. 4, pp. 1028–1042, Apr. 2021.

[30] B. S. Mordukhovich and N. M. Nam, *An Easy Path to Convex Analysis and Applications*. San Rafael, CA, USA: Morgan & Claypool, 2013.

[31] *Dataset of Mobility Traces of Taxi Cabs in San Francisco, USA*. Accessed: Nov. 2020. [Online]. Available: http://crawdad.org/epfl/mobility/20090224

Ke Zhang (Member, IEEE) received the Ph.D. degree from the University of Electronic Science and Technology of China, Chengdu, China, in 2017.

He is currently a Lecturer with the School of Information and Communication Engineering, University of Electronic Science and Technology of China. His research interests include the scheduling of mobile edge computing, design and optimization of next-generation wireless networks, smart grid, and the Internet of Things.



Jiayu Cao received the B.S. degree from the University of Electronic Science and Technology of China, Chengdu, China, in 2018, where she is currently pursuing the Ph.D. degree with the School of Information and Communication Engineering.

Her research interests include the vehicular networks, mobile edge computing, and multi-agent systems.

Sabita Maharjan (Senior Member, IEEE) received the Ph.D. degree in networks and distributed systems from the University of Oslo, Oslo, Norway, and Simula Research Laboratory, Oslo, in 2013.

She is currently an Associate Professor with the Department of Informatics, University of Oslo, and a Senior Research Scientist at Simula Metropolitan Center for Digital Engineering, Oslo. Her current research interests include vehicular networks and 5G, network security, smart grid communications, the Internet of Things, and computational intelligence.

Dr. Maharjan is currently the Vice Chair of the IEEE Communications Society Technical Committee on Green Communications and Computing (TCGCC) SIG on Green AI. She is an Associate Editor for IEEE INTERNET OF THINGS JOURNAL (IoT-J), and she has served as a guest editor for journals, such as IEEE ACCESS, and in the technical program committee of conferences, including top conferences like IEEE INFOCOM and IEEE IWQoS.

Yan Zhang (Fellow, IEEE) received the B.S. degree from Beihang University, Beijing, China, the M.S. degree from the Nanjing University of Post and Telecommunications, Nanjing, China, and the Ph.D. degree from the School of Electrical and Electronics Engineering, Nanyang Technological University, Singapore.

He is currently a Full Professor with the Department of Informatics, University of Oslo, Oslo, Norway. His research interests include next-generation wireless networks leading to 6G and green and secure cyber-physical systems (e.g., smart grid and transport).

Dr. Zhang is a Fellow of the IET, a Senior Member of CCF, and an Elected Member of Academia Europaea (MAE), the Royal Norwegian Society of Sciences and Letters (DKNVS), the Norwegian Academy of Technological Sciences (NTVA), the CCF Technical Committee of Blockchain, and 2019 CCF Distinguished Speaker. In 2018, he was a recipient of the global "Highly Cited Researcher" Award (Web of Science top 1% most cited worldwide). He is the symposium/track chair of a number of conferences, including IEEE ICC 2021, IEEE SmartGridComm 2021, and IEEE GLOBECOM 2017. He is the Chair of IEEE Communications Society Technical Committee on Green Communications and Computing (TCGCC). He is an Editor (or Area Editor, Senior Editor, an Associate Editor) for several IEEE TRANSACTIONS/magazine, including *IEEE Network Magazine*, IEEE TRANSACTIONS ON NETWORK SCIENCE AND ENGINEERING, IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, IEEE TRANSACTIONS ON GREEN COMMUNICATIONS AND NETWORKING, IEEE COMMUNICATIONS SURVEY & TUTORIALS, IEEE INTERNET OF THINGS JOURNAL, IEEE SYSTEMS JOURNAL, *IEEE Vehicular Technology Magazine*, and IEEE BLOCKCHAIN TECHNICAL BRIEFS. He is a Distinguished Lecturer of IEEE Communications Society and a Distinguished Speaker of IEEE Vehicular Technology Society. He was also an Distinguished Lecturer of IEEE Vehicular Technology Society from 2016 to 2020.