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Task-Efficiency Oriented V2X Communications: Digital Twin Meets Mobile Edge Computing

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***Abstract*—Digital Twin (DT) has emerged as an enabling technology for the sixth generation (6G) vehicle-to-everything (V2X) communications. However, there are two crucial issues on leveraging DT for 6G V2X communications. First, what kind of DT capabilities can be combined with the 6G V2X networks? Second, how to transform the DT capabilities into the practical V2X network performance gain? Motivated to solve these problems, this article investigates the DT capabilities under a DT and mobile edge computing empowered 6G V2X network architecture. Specifically, three DT capabilities are presented: (1) Strengthening the human-machine interaction via driving behavior analysis; (2) Improving the traffic safety via knowledge-based vehicle fault diagnosis; (3) Analyzing the spatial-temporal traffic characteristics via data aggregation. Furthermore, we investigate two case studies for illustrating how the DT capabilities can be utilized to perform the task-efficiency oriented V2X network scheduling. In the first case study, the driver behavior analysis result is combined with the V2X channel scheduling strategy. In the second case study, a deep reinforcement learning based vehicle merging decision is devised in the DT domain. Then, a coalition based V2X channel scheduling strategy is proposed to help accomplish the vehicle merging decision task. Finally, we evaluate the performance of our proposed task-efficiency oriented V2X channel scheduling schemes and highlight the future research directions.**

I. Introduction

6G vehicle-to-everything (V2X) communications are anticipated to support diverse applications in future intelligent transportation systems, including coordinated platoon, smart routing, and safety driving, etc [1], [2]. The success of these applications relies on flexible and efficient V2X transmission and scheduling strategies to guarantee fast and reliable application task transmission. One main research trend is to leverage Mobile Edge Computing (MEC), a task offloading paradigm, for relieving the vehicular computation burden and improving the task processing reliability. The authors in [3] propose a hybrid energy-powered multi-server MEC system, where a multi-vehicle task offloading scheme is investigated to balance the trade-off between the system energy cost and the task queue length. In [4], 6G V2X virtualization functions are utilized to slice the transportation applications into standard service chains. Then, a multi-winner committee selection model is adopted for solving the service chain embedding and offloading problem. In [5], MEC based spectrum aggregation is investigated to efficiently utilize the licensed and unlicensed spectrum for the joint optimization of the V2X network routing, caching, and computing. In [6], an artificial intelligence based multi-timescale framework is proposed to mitigate the MEC based V2X network optimization complexity.

Another research trend has focused on leveraging Digital Twin (DT) to optimize the MEC based V2X networks. The DT was initially introduced for the maintenance of spacecraft and then further applied to many other fields such as manufacturing, transportation, etc. Through DT, a digital representation of the physical real-world counterparts can be constructed to simulate, analyze and optimize the physical network [7]. Zhang *et al.* [8] utilizes the DT to evaluate the vehicular cooperation gains and distributively schedule the MEC resource allocation via multiagent deep reinforcement learning. Xu *et al.* [9] utilizes the DT to model the computation offloading and service caching for improving the intelligent transportation system efficiency. In [10], the DT is used to store and train the network data via neural networks. The training results can help release the MEC computing pressure and further realize intelligent MEC node collaborations. In [11], the DT is utilized to train offline deep reinforcement learning models to realize ubiquitous control over the heterogeneous vehicular traffic.

Although the aforementioned studies have made significant contributions, the following problems still remain unsolved. *(i) What kind of DT capabilities can be combined with the 6G V2X networks?* The existing studies commonly utilize the DT as a powerful high-fidelity simulator for intelligently analyzing and optimizing the physical networks. However, to fully discover the DT advantages, it is believed that the DT will act as a key component instead of a simple simulator in the future 6G V2X networks. Therefore, there necessitates a deep investigation on what capabilities the DT can bring to the 6G V2X networks. *(ii) How to transform the DT*

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capabilities into the practical V2X network performance gain? The existing studies mainly leverage the DT to optimize the spectrum-efficiency or the computation-efficiency of the V2X networks. Such optimization schemes ignore the 'task-efficiency', i.e., the proportion of the application tasks which can be accomplished per V2X transmission rate unit. In addition, the existing optimization schemes usually suffer from high complexity, making it difficult to find the optimal V2X resource allocation within tolerable delay constraints.

The key contributions of our work can be summarized as follows. To solve the aforementioned problems, this article studies the DT capabilities that can be combined with the MEC empowered 6G V2X networks. The first is that the DT can strengthen the human-machine interaction through the driver behavior analysis. Second, the DT can improve the traffic safety by enabling knowledge-based vehicle fault diagnosis. Third, the DT can help to analyze out the spatial-temporal characteristics of the traffic flow via traffic data aggregation. More importantly, we investigate how to leverage the DT capabilities to realize the task-efficiency oriented V2X communications. First, we utilize the DT capability of the driver behavior analysis to improve the performance of the V2X channel scheduling strategy. Afterwards, we utilize the DT aided learning capability to develop a deep reinforcement learning (DRL) based vehicle merging strategy at the ramp area. A coalition based V2X channel scheduling strategy is devised to accomplish the vehicle merging application task. Finally, we validate that our proposed schemes can improve the performance of the task-efficiency with low complexity.

The remainder of this article is organized as follows. The proposed DT capabilities are presented in Section II. The case studies of the DT-assisted task-efficiency orientated V2X communications are presented in Section III. The open research directions are in Section IV. Section V concludes this article.

II. The DT Capabilities Combined with the MEC Empowered V2X Networks

As shown in Fig. 1, we propose a DT empowered MEC architecture for the 6G V2X networks. The proposed architecture can be divided into two domains. The physical domain consists of the physical transportation and V2X network entities including the drivers, vehicles, and roadside MEC nodes. The DT domain resides in a commercial or private cloud, which can communicate with the physical domain through dedicated backhauls. The DT domain performs periodical data sampling from the physical domain. These data will go through the processes of storage, analyzing, learning and predicting in the DT domain. The analyzing and predicting results are fed back to the physical domain for V2X networks to fulfill the task-efficiency oriented V2X communications. The detailed functions of each domain are elaborated as follows.

A. Physical Domain

In a foreseeable future, the road traffic will demonstrate a high level of heterogeneity where vehicles with different automation levels coexist on the road. Therefore, in this article, we consider two vehicle types, i.e., automated vehicles (AVs) and human-driven vehicles (HVs), as shown in Fig. 1. AVs are with level-5 automation defined by Society of Automotive Engineers (SAE) [12] (fully automated), and HVs rely on human driver operations (partially automated). These vehicles are equipped with onboard sensors (e.g., ultrasonic, Lidar and camera, etc), localization modules (e.g., GPS) and V2X communication devices, which are interconnected via vehicle Controller Area Network-Bus (CAN BUS). The AVs can leverage vehicle position, speed, acceleration, and the line-of-sight (LoS) lane environment information for automated decisions. The HVs can leverage V2X information to assist in safe and efficient driver decisions. The MEC node, located at the roadside, is composed of three parts, including the roadside unit (RSU), the MEC server and the RSU sensor. The RSU provides V2X access to the vehicles. The RSU sensor collects Non-Line-of-Sight (NLoS) lane environment data. The MEC server provides enhanced computation resources to the vehicles.

B. DT Domain

The DT domain has two main functions. First, it samples and stores the driver, vehicle and infrastructure data from the physical domain to construct the DT modeling. Then, learning and predicting can be performed to dig the data features. These features are finally fed back to the physical V2X network controller for realizing the task-efficiency oriented V2X communications. Second, the DT's virtualization capability can help evaluate the safety of the traffic control strategy in the virtual DT domain before application. For instance, the safety of the vehicular merging or lane-changing strategy can be evaluated in a SUMO based platform by incorporating the real-world road map data. The virtual evaluation can reduce the experiment cost, realize the flexible strategy deployment and meet the fault-intolerance requirement of the transportation system. In the following part, we divide the DT modeling into three levels according to the different scales of the DT services, i.e., the driver DT and the vehicle DT as the micro-level services, and the traffic DT as the macro-level service.

1) Strengthening the human-machine interaction via driving behavior analysis: Human-machine interaction is a critical issue since how vehicles interact with drivers, passengers or pedestrians determines the driving safety, comfort and efficiency. Therefore, in this part, a driver DT model is proposed to strengthen the human-machine interaction and improve the V2X service efficiency. The driver DT is built based on the driver's data pool which stores the driver data. The data can be sampled from the vehicle sensors or the vehicle operating interface. The data pool includes the driver age, gender, job and health conditions, as well as the driver operation data under different scenarios such as the braking, steering and accelerating, etc. Based on these data, the driver DT can analyze the driver behavior via an offline learning approach.

The learning result can be delivered to the physical domain and help the MEC node better understand the driver's capabilities and limitations. Thus, finer-grained V2X resource scheduling and service provision can be performed. For instance, some drivers tend to take risky actions such as frequent lane-changing or accelerating, which may affect the surrounding

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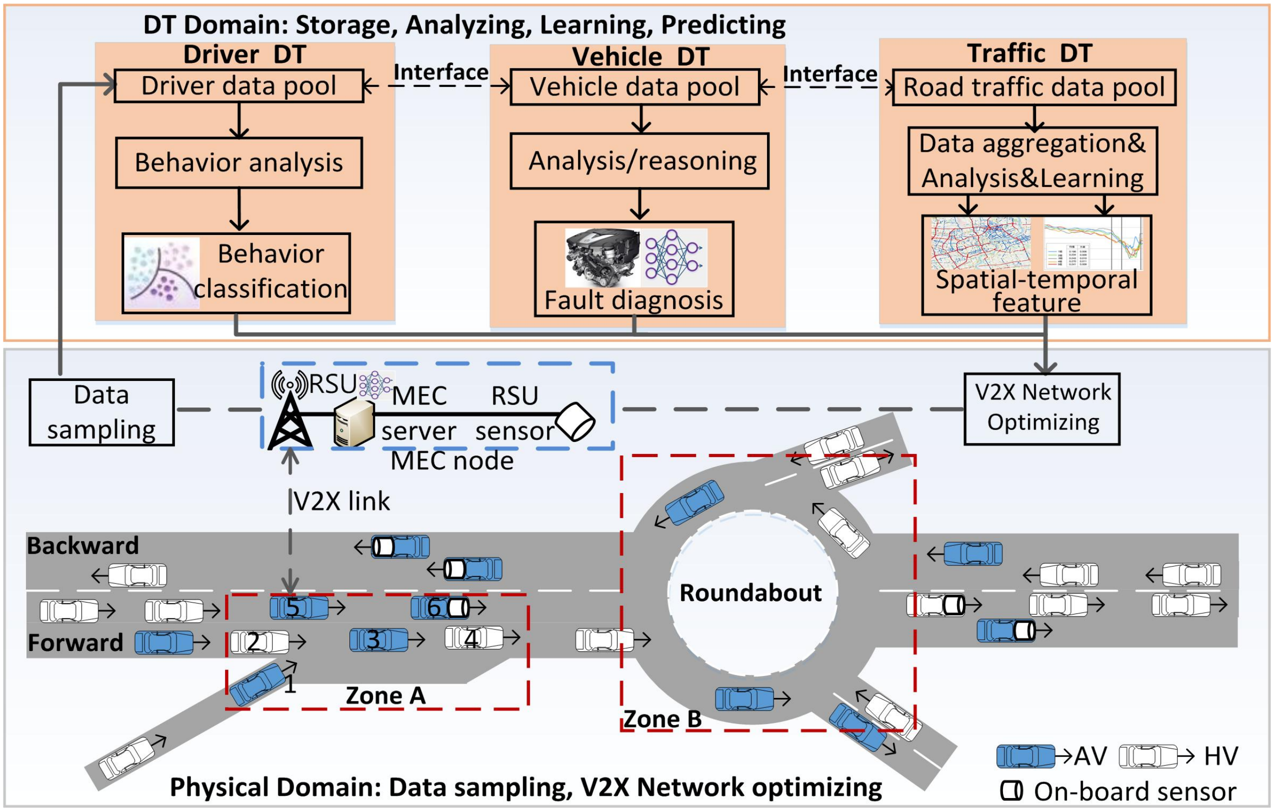

Fig. 1: The DT capabilities combined with the MEC empowered V2X networks

vehicles' speed or safety. Thus, more frequent V2X safety warning or speed limitation messages should be delivered to these drivers with stricter delay constraints. By contrast, less V2X messages or driving assistance are required by the cautious drivers. Therefore, different V2X service priorities can be provided to the drivers with different driving behaviors to improve the V2X service efficiency. In addition, considering that the driver behavior may change after traffic punishment or accidents, the priority of a specific driver can be dynamically adjusted.

2) Improving the traffic safety via knowledge-based vehicle fault diagnosis: Fault diagnosis is of crucial importance to the traffic safety. Conventional fault diagnosis commonly adopts model-based methods, which monitor the consistency between the practical vehicle output and the model output. However, the model adaptability cannot be guaranteed considering the varying vehicle conditions. To overcome this disadvantage, we leverage the DT to carry out knowledge-based fault diagnosis. First, a vehicle DT model is constructed to collect and store the vehicle operation data. Such data includes the vehicle speed, steering angle, engine statement and energy consumption, etc. Second, the data analysis and reasoning process can be performed through intelligent techniques such as deep neural networks or long short-term memory networks, etc. The analysis results can be utilized to predict the fault conditions, for example, the time and probability with which the fault will occur. The major advantages of the knowledge-based methods are two-folded. First, they do not rely on explicit mathematical models; Second, the knowledge can be adaptively expanded according to the updating and learning of the vehicle data.

The predicted results can be further utilized by the V2X networks to improve the traffic safety. For instance, when the fault of the vehicle engine or automated controller is predicted to occur, the communication resources can be reserved or pre-allocated to guarantee emergency message transmission in the predicted time slot. Meanwhile, the onboard vehicular computation tasks, especially the safety related tasks such as lane-changing decision and distance keeping, can be temporarily offloaded to the roadside computation units for temporary management.

3) Analyzing out the spatial-temporal traffic characteristics via data aggregation: Traffic characteristics such as throughput, speed and density are critical to traffic management. For example, the traffic density can be utilized to optimize the traffic routing and traffic signal phasing schemes. However, it is ignored that how the traffic characteristics can be utilized to optimize the MEC based V2X networks for accomplishing the intelligent transportation application tasks. Therefore, we first propose a traffic DT model for the traffic characteristic analysis. More importantly, we demonstrate how the traffic characteristics can be utilized to improve the performance of the MEC empowered V2X networks. The proposed traffic DT serves as a data fusion node which aggregates the LoS traffic data with the NLoS traffic data. The data aggregation can help to gain more centralized and in-depth analysis into the traffic characteristics. For instance, the NLoS traffic condition data of the roadside sensors can be aggregated with the LoS vehicular sensor data to help the vehicle to sense the overall traffic conditions and take actions more efficiently. Note that the LoS and NLoS data refers the aggregated data of multiple

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vehicles collected by the DT to reflect the overall traffic state.

The spatial-temporal characteristics mainly include the dynamic traffic parameters such as the density and speed, as well as the static road structure parameters such as the ramp and roundabout, etc. Consider the ramp area in zone A of Fig. 1 as an example. The branch-lane vehicle (i.e., vehicle 1) merges into the main-road, which interferes with the main-lane vehicles (i.e., vehicles 2, 3, 4, 5, 6), thus leading to traffic deceleration or collision. To improve the vehicle merging safety and efficiency, the vehicles within zone A can form a temporary coalition to make cooperative decisions. Specifically, the MEC node should be responsible for deciding which vehicles (whether the branch-lane or the main-lane vehicles) to move forward. Furthermore, dedicated V2X/computation resources should be allocated to the coalition. The MEC node can leverage these resources to transmit the control message to the coalition members. In the next part, we will validate the performance of the coalition based V2X network management through detailed case studies.

III. Case Studies of the DT-Assisted Task-Efficiency Orientated V2X Communications

In this section, we provide two case studies of leveraging the DT capabilities to accomplish the task-efficiency oriented V2X communications. In the first case study, we simulate the DT capability of driver behavior analysis based on the simulated driving data. Then, we combine the driver behavior analysis result with the V2X channel scheduling. In the second case study, we investigate the DRL based vehicle merging strategy in the DT domain. Then, a coalition based V2X channel scheduling scheme is devised to help accomplish the vehicle merging task.

A. Driver behavior based V2X channel scheduling for the safety message task

1) Driver behavior analysis in the DT domain: To simulate the driver behavior analysis process of the driver DT, we first conduct a simulated driving experiment through a UC-win/Road [13] platform. The UC-win/Road is a virtual reality based driving testbed, where multiple driving scenarios can be constructed via built-in 3D modeling software. In addition, the human-machine interfaces are provided to link the driver with the simulated 3D driving scenarios through the vision and operation equipment. Fig. 2 (a) demonstrates a snapshot of the conducted driving experiment, where the participant (driver) interacts with the UC-win/Road through a 130° field of vision in the forward direction, and a left/right field of vision in the backward mirror direction. The driver operates the vehicle through a set of Logitech steering wheel and pedals.

We recruit 208 participants, including 124 males and 84 females, whose ages range from 22 to 48 years old, averaging 33. The participants are in good health conditions and with at least one year driving experience. We collect the data of throttle, brake and vehicle speed at the period of 0.1 second during the experiment. The throttle and brake are measured by the degree that the driver slam on throttle and brake pedals, which reflect the driver's evaluation and reaction to the traffic environment. The values of throttle and brake can be normalized to $[0, 1]$, and the larger number means the higher degree. The experiment city road is bidirectional four lane of 3.5 meters lane-width and 1.5 kilometers lane-length.

After obtaining the driver data, we utilize the K-means algorithm [14] for the data analysis. The K-means is a classical machine learning method, which can be utilized to efficiently classify the unlabeled driver data into different categories according to the inherent data characteristics. The analysis result shows that the driver characteristics can be categorized into three types, i.e., the aggressive driver, the normal driver and the conservative driver. As shown in Fig. 2 (b), the data marked in red corresponds to the aggressive driver, who tends to have large throttle and brake degree with high driving speed. The data marked in green corresponds to the normal driver, who tends to have small throttle degree and medium brake degree with high driving speed. The data marked in yellow corresponds to the conservative driver, who tends to have small throttle degree and high brake degree with low driving speed.

2) Driver behavior based V2X channel scheduling in the physical domain: The V2X channel scheduling priority can be divided according to the driver characteristics. The aggressive drivers are allocated with the highest V2X channel scheduling priority. Thus, the traffic safety messages (e.g., speed limit, accident warning, etc) can be timely delivered to prevent the aggressive drivers from radical actions such as high acceleration and frequent lane-changing actions. The normal drivers and the conservative drivers are allocated with lower V2X channel scheduling priority, since they tend to drive more carefully with lower acceleration and fewer lane-changing actions. And the traffic safety can still be guaranteed.

We evaluate our proposed V2X scheduling scheme by comparing with the conventional scheme, which only maximizes the throughput without considering the driver characteristics. Furthermore, we evaluate the performance of the task-efficiency, which is defined as the proportion of the safety message tasks which can be accomplished per V2X transmission rate unit. The simulated V2X channel number is 150 and the channel bandwidth is 0.18 MHz. The results are demonstrated in the CDF (Cumulative Distribution Function) curve of Fig 2 (c). We can observe that the conservative drivers have the highest task-efficiency. The reason is that the low V2X channel allocation priority leads to decreased channel allocation diversity gain. Thus, the application tasks are accomplished via comparatively low V2X transmission rate. In contrast, the aggressive drivers have low task-efficiency owing to the high channel allocation diversity gain. The task-efficiency of the conventional scheme lies between the conservative driver and the aggressive/normal driver, since it does not differentiate between the driver characteristics.

B. Coalition based V2X channel scheduling for the vehicle merging task

1) Vehicle merging decision in the DT domain: We utilize the DRL for the vehicle merging decision at the ramp. The DRL framework can help improve the decision adaptability by iteratively updating the training data. And the cumulative

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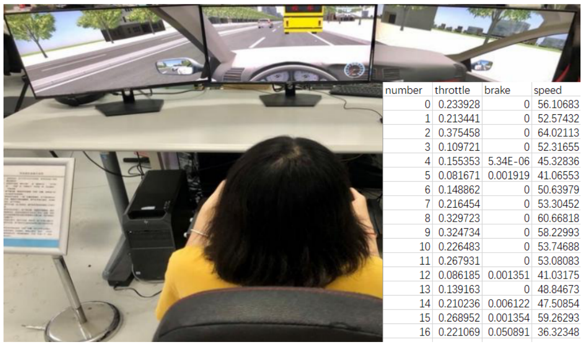
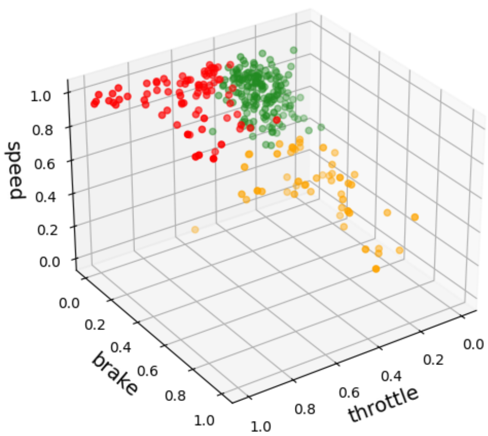
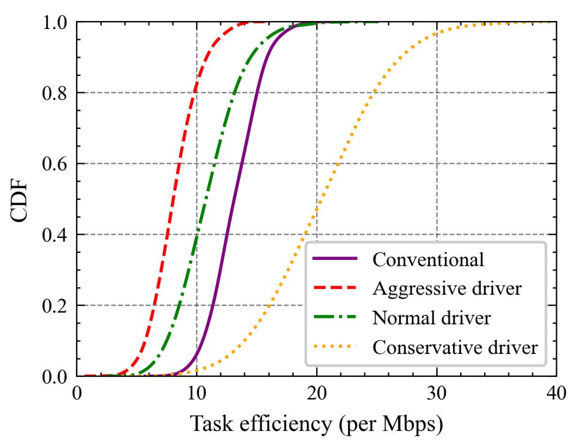


number	throttle	brake	speed
0	0.233928	0	56.10683
1	0.213441	0	52.57432
2	0.375458	0	64.02113
3	0.109721	0	52.31655
4	0.155353	5.34E-06	45.32836
5	0.081671	0.001919	41.06553
6	0.148862	0	50.63979
7	0.216454	0	53.30452
8	0.329723	0	60.66818
9	0.324734	0	58.22993
10	0.226483	0	53.74688
11	0.267931	0	53.08083
12	0.086185	0.001351	41.03175
13	0.139163	0	48.84673
14	0.210236	0.006122	47.50854
15	0.268952	0.001354	59.26293
16	0.221069	0.050891	36.32348

(a) Driving simulation platform and dataset example training



(b) Driver classification result, red: aggressive driver, green: normal driver, bisque: conservative driver



(c) The CDF curve of task-efficiency under our proposed and the conventional V2X channel scheduling schemes

Fig. 2: The UC-win/Road platform and driver classification result, and V2X scheduling performance comparison

DRL reward function can help improve the decision efficiency by learning from the aggregated LoS and NLoS traffic data. As shown in Fig. 3, we model the branch-lane vehicle as the DRL learning agent. The agent obtains a reward from the environment (i.e., the aggregated environment data) to evaluate its action under a specific state. In our case study, we obtain the environment data through a sumo simulator. The state, action and reward of the proposed DRL are as defined follows.

State: The state represents the traffic flow characteristics at the ramp area, which is defined as $\mathcal{S} = \{S_{i,j}\} = \{S_{3,0}, S_{3,1}, S_{2,1}\}$. $i \in 1, 2, 3$ is the lane number index and $j \in 0, 1$ is the lane sector index. $j = 0$ corresponds to the upstream lane and $j = 1$ corresponds to the downstream lane. $S_{i,j}$ is the traffic column (vehicle per minute) of lane i on sector j.

Action: The action corresponds to the binary vehicle merging decision variable $A \in \{0, 1\}$. $A = 0$ represents stopping and waiting to merge, $A = 1$ represents performing the vehicle merging.

Reward: The reward is defined as the weighted sum of the average traffic speed, which can be written as $R = \sum_i \sum_j w_{i.j} \overline{v}_{i.j}$. $\overline{v}_{i.j}$ is the average traffic flow speed of lane i on sector j. $w_{i.j}$ denotes the sum weight which can be utilized to adjust the relative importance of different lane sectors.

The objective of the DRL is to maximize the expected cumulative agent rewards through the iterative learning from the environment data. To obtain the optimal policy, we adopt the classical training process as shown in Fig. 3. The training includes three parts, i,e., the experience replay memory, the target DRL network and the evaluated DRL network. The experience replay memory is utilized to store the history environment data, and a small part of samples is randomly selected from the memory to train the DRL network (mini-batch sampling). The objective is to eliminate the correlation of data samples and to guarantee fast convergence of the DRL network training. The parameters of the evaluated DRL are updated in every training epoch. The target network can be defined as an old version of the primary network and its parameters are only updated every several training epochs by replacing it with the evaluated DRL.

2) Coalition based V2X channel scheduling in the physical domain: The DRL based strategy needs to be offline trained, evaluated and verified in the DT domain. For realization, the DT continuously samples the environment data from physical domain for the offline DRL training. The well-trained DRL decision network is delivered, stored and updated in the MEC node with large time cycles, for instance, every several days. To support the vehicle merging decision task, we propose a coalition based V2X channel scheduling as follows.

The branch-lane vehicle sends the merging decision requirement message to the MEC node through the uplink V2X communications. Then, a coalition is formed under the assistance of the MEC node, which includes the vehicles in the ramp area. Then, the MEC node allocates the dedicated communication and computation resources to the coalition. Meanwhile, the MEC node accesses the DRL decision network in its local memory, and utilizes the aggregated environment data as the network input. Finally, the ouput, i.e., the optimal merging policy A^*, can be transmitted to the coalition through a broadcast V2X channel. If $A^* = 0$, the branch-lane vehicle decelerates and waits to merge, and the main-lane vehicles can preferentially pass through the ramp. If $A^* = 1$, the branch-lane vehicle can merge into the road, and the main-lane vehicles need to decelerate and wait. Our proposed scheme needs to schedule $1 + |\mathcal{V}|$ channels for each merging decision

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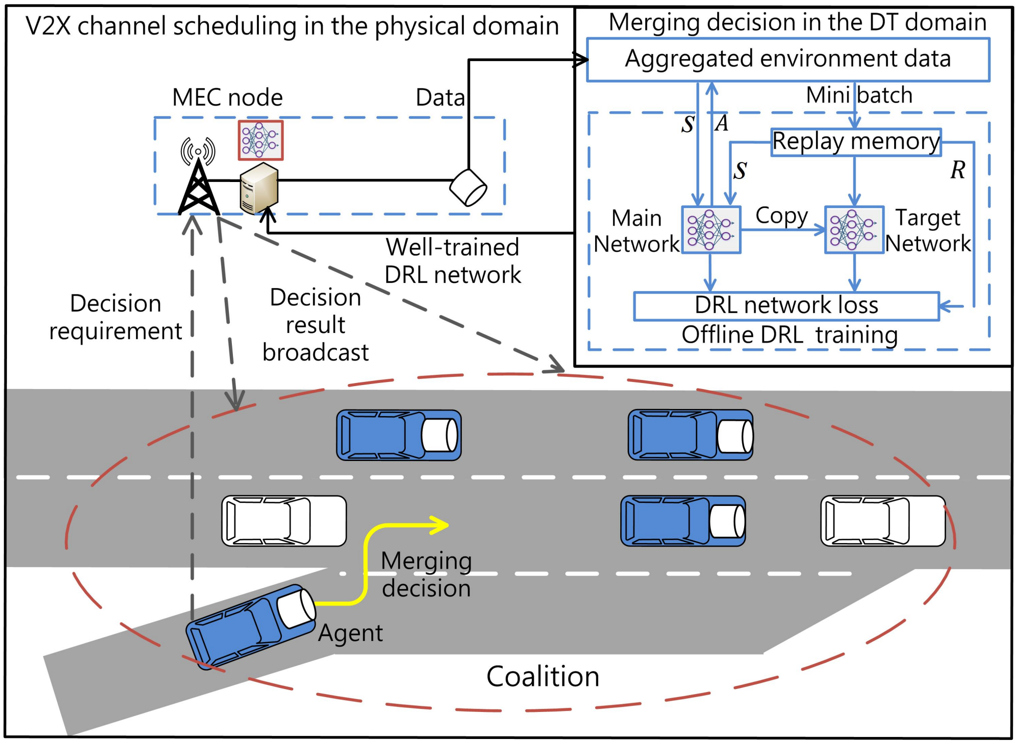

Fig. 3: The DT Assisted vehicle merging and V2X channel scheduling

task. $|\mathcal{V}|$ is the channel number of the data sampling and 1 is the broadcast channel number. In comparison, a conventional scheme need to schedule a number of $C^2_{|\mathcal{V}|}$ Vehicle-to-Vehicle (V2V) channel links, where $|\mathcal{V}|$ denotes the cardinality of $\mathcal{V}$. The reason is that arbitrary two vehicles in the vehicle set $\mathcal{V}$ need to transmit the vehicle merging related messages to guarantee the real-time safety distance between the vehicles.

In this part, we evaluate the performance of our proposed DRL based vehicle merging scheme and the coalition based V2X channel scheduling scheme.

The DRL is trained in a SUMO based traffic simulator with the maximum acceleration of $4.5m/s^2$ (meters per second squared) and the maximum speed of $35m/s$ (meters per second). Fig. 4 (a) shows the convergence of the proposed DRL. It can be observed that proposed DRL can converge within around 80 training episodes. Fig. 4 (b) compares the task-efficiency of the coalition based V2X channel scheduling with the conventional scheme. It can be observed that the task-efficiency keeps decreasing as the vehicle number increases. The reason is that more V2X or V2V links are required for the vehicle merging task accomplishment, leading to a heavier utilization of the channel resources. In comparison, our proposed channel scheduling scheme consumes less channel resources than the conventional one, while achieving an increased task-efficiency. In conclusion, our proposed traffic DT assisted V2X network scheduling can achieve the average task-efficiency improvement of 1.00 per Mbps compared with the conventional scheme.

IV. Future Research Trends

- *Low-complexity machine learning algorithms and advanced computation structure:* The DT modeling relies on massive data generated from the real-world transportation system. These data often has different structures and storage modes, which requires large-scale machine learning algorithms to convert these original data into consistent and usable information. These algorithms consume excessive computation resources which may cause large delay, high infrastructure cost, and severe DT synchronization problems. Therefore, lightweight machine learning algorithms, such as transfer learning and meta learning, can be adopted to improve the data processing efficiency. Meanwhile, advanced computation framework such as Ray and MapReduce [15], can provide distributed and parallel computing to help reduce the DT modeling complexity.
- *High-precise sensor deployment and multi-source data fusion:* The accurate and efficient work of DT depends on the data quality of the sensors broadly embedded in the physical domain. To satisfy the DT data requirements, high-precise and multi-source sensors, such as cameras, lidars or mmWave radars, need to be deployed on vehicles, pedestrians and roadside in the physical domain. The heterogeneous data structures require efficient and intelligent data fusion algorithms for removing the redundant data and extracting the useful information containing inside.
- *Data privacy and DT security:* The security is an essential requirement in the transportation system since it is closely related to the traffic safety. Under the DT

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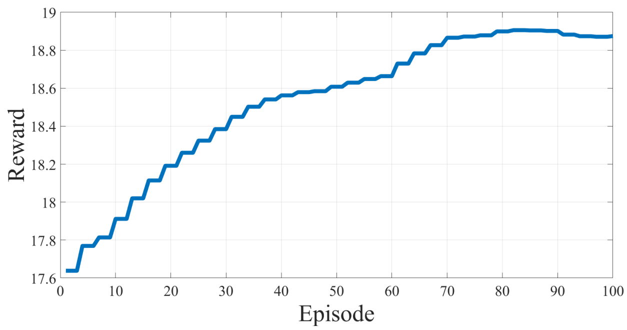

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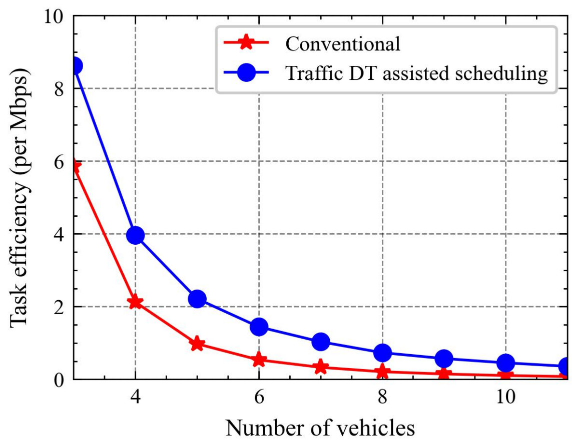

(b) The CDF curve of task-efficiency under our proposed and the conventional V2X channel scheduling schemes

Fig. 4: Performance comparison of the conventional and traffic DT assisted V2X scheduling strategiesn

framework, the sensitive data such as the driver's age and gender, the vehicle speed and position, as well as the traffic infrastructure operation state need to be sampled and transmitted from the physical domain to the DT domain. To protect user's information privacy, encryption algorithms need to be embedded in the DT framework. In addition, security based vehicle and V2X network management mechanisms, such as blockchain and federated learning, need to be devised to protect the vehicle from malicious attack.

- *Holographic communication and remote driving:* The development of holographic communication and augmented reality technologies has provided the DT empowered transportation system with seamless and integrated sensing and control environment. Thus, the remote driving applications can be developed through which the driver is able to determine vehicular control policies (routing, steering and lane-changing, etc) from the cloud end. In addition, the holographic information mapping from the real-world roads, vehicles and traffic infrastructures can help the DT to make more precise analysis and provide more fine-grained services according to different transportation scenarios.
- *DT migration:* The DT modeling requires dedicated communication and computation resources for the data collecting and processing. Thus, to reduce the resource consumption and improve the DT modeling efficiency, DT migration becomes an important research trend. For instance, the common features of the physical domain can be abstracted such as the similar vehicle trajectory or the similar driver behavior. By combining these features with the transfer learning, the experience of the DT modeling can be migrated among different DT entities. The migration process can help reduce the DT complexity with improved resource efficiency.

V. Conclusions

This article investigates the DT capabilities under a DT empowered MEC framework for 6G V2X networks. The novel capabilities provided by the DT include: strengthening the human-machine interaction via driving behavior analysis, improving the traffic safety via knowledge-based vehicle fault diagnosis, and analyzing the spatial-temporal traffic characteristics via data aggregation. Furthermore, we demonstrate how the DT capabilities can be leveraged to accomplish the task-efficiency oriented V2X communications and provide two detailed case studies. Finally, important challenges are highlighted to encourage the future researches.

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