Service-Oriented Edge Collaboration: Digital Twin Enabled Edge Collaboration for Composite Services in AVNs

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***Abstract*— Edge collaboration is expected to effectively relieve the load of base stations and enhance the driving experience of autonomous vehicles (AVs). However, in existing edge collaboration schemes, the frequent information exchange between AVs will consume a significant amount of resources. In addition, the existing schemes ignore the types of services, where services with different types may be combined into a composite service which affects the utility of AVs. To this end, we consider various types of services in autonomous vehicular networks (AVNs) and propose a digital twin (DT)-enabled edge collaboration scheme for composite services. Specifically, we first divide the DTs of service requesters (DT-SRs) into service request groups (SRGs) based on the same basic service requests and propose an architecture to facilitate the edge collaboration between the DTs of the leaders of SRGs (DT-L-SRGs) and the DTs of the service providers (DT-SPs). In this architecture, different service composition forms will result in different resource purchase strategies for DT-L-SRGs and different resource pricing strategies for DT-SPs. Therefore, we model the process of service composition as a coalition game to determine the optimal service composition form for each basic service. In the process of the coalition game, in order to obtain the optimal resource purchase strategy for each DT-L-SRG and the optimal resource pricing strategy for each DT-SP under different coalition structures, the interaction between the DT-L-SRGs and the DT-SPs is formulated as a Stackelberg game. By obtaining the game equilibrium, the optimal strategies of each DT-L-SRG and each DT-SP can be determined to measure the performance of the given coalition structure until a stable and optimal composite service structure is finally formed through multiple rounds of iterations. Compared with traditional schemes, the simulation results demonstrate that our scheme can bring the highest utilities to both the SRs and the SPs.**

***Index Terms*— Edge collaboration, vehicular networks, digital twins, composite services, autonomous vehicles, game theory.**

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I. INTRODUCTION

WITH the widespread applications of artificial intelligence and communication technology, both traditional automobile companies and Internet companies have built autonomous vehicles (AVs) and started actual driving tests to support various applications in intelligent transportation systems (ITS) [1], [2], [3], [4]. Unlike traditional vehicles which are driven by humans, AVs can autonomously perceive the surrounding driving environment and make driving decisions by analyzing the sensed data [5]. Therefore, AVs can avoid traffic problems caused by human driving errors. In addition, with the help of the autonomous vehicular networks (AVNs), AVs are easier to be dispatched than human-driven vehicles, thereby improving the traffic efficiency of the ITS and enhancing the quality of experience (QoE) of passengers.

During the driving process of AVs, the requirements of passengers and the driving decisions of AVs will change dynamically with the environment so that each AV will generate a large number of vehicular services. For example, AVs need to process and analyze environmental data in real time [6]. In addition, passengers may download entertainment content, such as news, videos and pictures, during the trip. In traditional AVNs, diversified vehicular services are completed by cellular base stations (CBS) which are equipped with edge computing devices (ECDs) [7], [8], [9]. However, within the coverage of a CBS, it is difficult to meet the diverse service requests generated by massive AVs [10], [11], [12]. On the other hand, if a single AV requests service from a CBS, it usually has to bear expensive resource costs, which significantly reduces the QoE of passengers [13].

Edge collaboration, as a collaborative driving paradigm in AVNs, can effectively solve the aforementioned problems by allowing the AVs with resources to complete the services released by the AVs with requirements. In this way, as shown in Fig. 1, a large number of vehicular services can be provided

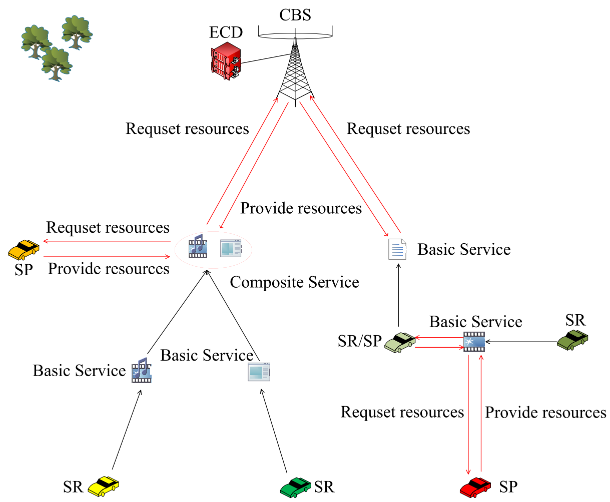

Fig. 1. Edge collaboration between the SRs and the SPs in the AVNs.

by the AVs without the need to frequently request services from the CBSs, where the load of the CBSs can be reduced and the efficiency of services can be improved. Furthermore, the AVs on the same road segment usually have similar or identical service requirements. Therefore, these AVs can collaboratively request services to reduce service costs and improve the QoE.

Driven by the above advantages, a number of scholars have considered AVs to complete services collaboratively and have studied edge collaboration in AVNs from different perspectives [14], [15], [16], [17], [18]. However, in existing edge collaboration schemes, frequent information exchange is required to determine the collaboration strategy for each AV, which undoubtedly consumes a lot of time and resources and reduces the QoE of passengers. Therefore, in the AVNs, how to establish a new architecture to promote efficient edge collaboration between service providers (SPs) and service requesters (SRs) is a challenge. In addition, existing research on edge collaboration lacks the consideration of service types. In general, services of different types may be combined into a composite service which affects the collaboration process and the utility of AVs. Therefore, in the process of edge collaboration between the SRs and the SPs, it becomes a challenge to determine the service composition forms for different types of basic services to request resources. Besides, given the service composition form of each SR, both the SRs and the SPs intend to improve their utilities in the edge collaboration process. Therefore, it is also a challenge to model the interaction between the SRs and the SPs given the determined service composition forms to maximize their utilities. In particular, the maximum utilities of SRs and SPs may vary with the form of each composite service. Therefore, the second and third challenges are actually coupled problems.

To address the aforementioned challenges, we consider the various types of services in the AVNs and propose a digital twin (DT)-enabled edge collaboration scheme for composite services. Specifically, we first divide the DTs of the SRs (DT-SRs) into service request groups (SRGs) based on the same basic service requests and propose an edge collaboration architecture for composite services to facilitate the interaction between the DTs of the leaders of the SRGs (DT-L-SRGs) and the DTs of the service providers (DT-SPs). In the designed architecture, the diversified service composition forms will lead to each DT-L-SRG determining different resource purchase strategies and each DT-SP determining different resource pricing strategies. To this end, we design a coalition game to model the process of service composition to determine the optimal service composition form for each basic service. In the coalition game, in order to obtain the optimal resource purchase strategy for each DT-L-SRG and the optimal resource pricing strategy for each DT-SP under different coalition structures, the interaction between the DT-L-SRGs and the DT-SPs under any given coalition structure is formulated as a Stackelberg game. By obtaining the equilibrium of the game, the optimal strategies of the DT-L-SRGs and DT-SPs can be obtained to maximize their utilities. The contributions of this paper are three-fold.

- **Composite-service-oriented edge collaboration architecture**: By considering different service types in the AVNs, we design a DT-enabled edge collaboration architecture for composite services. With this architecture, the DT-L-SRGs and the DT-SPs in DT networks can replace the AVs in physical networks to make edge collaboration decisions efficiently.
- **Coalition-game-based service composition mechanism**: By considering the different utilities caused by different strategies of DT-L-SRGs and DT-SPs under various service composition forms, we design a service composition mechanism based on a coalition game model to obtain the optimal service composition form for each DT-SR to request service resources.
- **Stackelberg-game-based collaboration mechanism**: Given any service composition form, we model the edge collaboration between the DT-L-SRGs and the DT-SPs as a Stackelberg game by jointly considering the cost of resources and the discount of the composition services. With the designed collaboration mechanism, the optimal resource purchase strategy and optimal resource pricing strategy of each DT-L-SRG and each DT-SP can be obtained under the given service composition form.

The remainder of this paper is organized as follows. Section II reviews the related works. Section III introduces the system model. In Section IV, we present the proposed DT-enabled edge collaboration architecture in detail. In Section V, we introduce the designed coalition-game-based service composition mechanism and the Stackelberg-game-based collaboration mechanism, respectively. Section VI evaluates the proposed scheme by simulations, and Section VII closes this paper with the conclusion.

II. RELATED WORK

A. Services in AVNs

Zhang et al. [19] study a service-oriented cooperation mechanism for AVs at continuous static critical sections. In this mechanism, a priority-based centralized scheduling algorithm is adopted to promote the quality of services. By regarding collaboration as a service, Hui et al. [20] propose a

DT-enabled scheme to support collaborative driving services. In the scheme, two game-based mechanisms are designed to facilitate the collaborative and distributed autonomous driving. Chekired et al. [21] design a SDN-based framework to enhance the quality of service of autonomous driving applications. Their simulation results show that this framework meets the low-latency requirement of the applications. To solve the problem of privacy disclosure when AVs share services, Hadian et al. [22] propose a privacy-preserving task scheduling scheme for time-sharing services. Zhao et al. [23] design a strategy to optimize cache services in AVNs by using a reinforcement learning algorithm. With the designed algorithm, the hit ratio of cache services can be maximized. Su et al. [24] focus on computing services and develop a collaborative computing scheme for AVs to facilitate autonomous driving, where a Markov-based algorithm is designed to enable the centered AV to offload its services to the surrounding AVs. Tian et al. [25] pay attention to the computing and caching services and propose a collaborative computation offloading and content caching method. Their method considers the high mobility and time-varying requests of AVs so that the service quality of AVs can be improved.

Unlike these studies on services in AVNs, our scheme considers the types of services and proposes a DT-enabled edge collaboration scheme for composite services. In this scheme, the diversified basic services in AVNs can form multiple composite services through the designed coalition game. For different service composition forms, a Stackelberg game is designed for the DT-L-SRGs and the DT-SPs to maximize their utilities by obtaining the optimal resource purchase and pricing strategies.

B. Edge Collaboration in AVNs

Chen et al. [26] propose a driving strategy to enhance the cooperation between an AV and the nearby AVs. With this strategy, the AV can efficiently avoid collisions in the overtaking and the lane-changing scenarios. In order to perform different traffic maneuvers, Mohseni et al. [27] develop a cooperative control method for AVs. With this method, a collision-free trajectory can be obtained for each AV. Chen et al. [28] design an intelligent strategy to control the vehicle spacing of cooperative autonomous driving, where a Markov chain-based algorithm is proposed to predict the parameters of the system states. By considering the cooperative perception scenario, Xiong et al. [29] propose a privacy-preserving cooperative object classification framework. The framework allows cooperative AVs to exchange sensor data without leaking private information. To facilitate reliable cooperative tracking, Pi et al. [30] propose a malicious user detection framework to avoid malicious AV users sending false information. Their simulation results show that the framework can ensure the accuracy and reliability of cooperative mobile tracking. Thandavarayan et al. [31] propose an improved algorithm to enhance the reliability of cooperative perception. In the algorithm, the message generation rules are adopted to reduce the number of perception messages per second. Yu et al. [32] formulate the driving topology of AVs as a dynamic coordination graph to model the mobility of AVs. Based on the coordination graph, two basic learning approaches are designed to coordinate the driving maneuvers of a group of AVs.

Although edge collaboration in AVNs has received extensive research in recent years, edge collaboration for composite services has not yet been fully considered. To this end, we constructively consider the types of services in the network and design a DT-enabled collaboration scheme for the DT-L-SRGs and the DT-SPs in AVNs under different service composition forms. In the proposed scheme, we model the service composition process and the interaction between the DT-L-SRGs and the DT-SPs as two game models to provide the optimal collaboration strategies and maximize their utilities.

III. System Model

In this section, we introduce the system model of the edge collaboration for composite services in DT-enabled AVNs (DT-AVNs). The notations used in our paper are summarized in Table I.

A. Service Model

Generally, the type of services in the networks can be divided into basic services and composite services.

Basic services: Basic services are the smallest service unit in the AVNs. We use $\mathbb{M} = \{1, \ldots, m, \ldots, M\}$ and $\mathbb{N}_m = \{1, \ldots, n_m, \ldots, N_m\}$ to represent the set of service types and the set of specific services with type m, where N_m is the number of services with service type m. For example, the traffic information of a road section and the parking lot information of this road section can be regarded as a service type and a basic service, respectively.

Composite services: In AVNs, each basic service may be associated with other basic services to form a composite service. For example, federated learning tasks typically require data storage resources and data computing resources [33]. This means that federated learning services consist of two basic services (i.e., a data storage service and a computing service) [34]. For basic service n_m, when it forms a composite service with different basic services, the SPs have different prices for the resources to complete the composite services, which in turn affects the utility of the SR that requests n_m. This is because if multiple basic services in a composite service can be provided by a same SP, it can avoid the additional overhead caused by selling resources to other SRs. For example, if a SP has training data and computing resources that can complete a model training task, the SP no longer needs to sell these resources separately to different SRs and only needs to interact with the SR that requests the task, thereby reducing the communication overhead.

B. Network Model

RUs: The roadside units (RUs) in the networks refer to CBSs, unmanned aerial vehicles (UAVs) and other access points deployed along the roadside [35]. Let $\mathbb{J} = \{1, \ldots, j, \ldots, J\}$ denote the set of RUs in the networks, where each RU $j (j \in \mathbb{J})$ can connect with the AVs within its

TABLE I
SUMMARY OF NOTATIONS

Notations	Description
$\mathbb{M}$	The set of service types.
$\mathbb{N}_m$	The set of specific services with type m.
$\mathbb{J}$	The set of RUs in the networks.
$\mathbb{I}$	The set of AVs in the coverage of RU j.
$\mathbb{I}_r$	The set of SRs.
$\mathbb{I}_p$	The set of SPs.
$\hat{i}$	The DT of AV i.
$\Gamma_{\hat{i}}$	The requirements and resource status of DT $\hat{i}$.
$D_{i_p}^m$	The amount of resources that AV i can provide for services of type m.
$c_{i_p}^{n_m}$	The unit resource cost of services provided by AV i.
$p_{i_r}^{n'_{m'}}$	The expected price per unit resource of AV i to request service $n'_{m'}$.
E_{n_m}	The DTs deployed in RU j that require service n_m.
$\hat{i}_{r^*,n_m}$	The leader DT of SRG E_{n_m}.
$\mathbb{K}$	The set of composite services.
$U_{\hat{i}_p}$	The utility function of DT-SP $\hat{i}_p$.
$p_{\hat{i}_p}^{n_m}$	The optimal resource price of DT-SP $\hat{i}_p$ to provide resources for basic service n_m.
$d_{\hat{i}_p}^{n_m}$	The amount of resources purchased by the DT-L-SRG that requests basic service n_m from DT-SP $\hat{i}_p$.
$\varphi_{\hat{i}_p}^k$	The discount factor of DT-SP $\hat{i}_p$ to provide resources for composite service k.
$S_{\hat{i}_r}^{n_m}$	The satisfaction of DT-SR $\hat{i}_r$.
$\alpha_{\hat{i}_r}^{n_m}$	The utility coefficient of DT-SR $\hat{i}_r$.
$U_{\hat{i}_r}^{n_m}$	The utility of DT-SR $\hat{i}_r$.
$Q_{\hat{i}_p}^{n_m}$	The set of members that intend to purchase resources from DT-SP $\hat{i}_p$ in SRG E_{n_m}.
$U_{\hat{i}_{r^*,n_m}}$	The average utility of all DT-SRs in SRG E_{n_m}.
$\mathbb{H}$	The set of coalitions.
$u_{\hat{i}_{r^*,n_m}}$	The utility of DT-L-SRG $\hat{i}_{r^*,n_m}$.
$\mathbb{H}_{-g}$	The set of all coalitions except for coalition H_g.
$\mathbf{p}_{\hat{i}_p}^*$	The optimal pricing strategy vector of DT-SP $\hat{i}_p$.
$\mathbf{d}_{n_m}^*$	The optimal resource purchase strategy vector of DT-L-SRG $\hat{i}_{r^*,n_m}$.

communication coverage. In addition, each RU is equipped with an ECD which can be used to provide vehicular services such as computing and caching.

AVs: Let $\mathbb{I} = \{1, \ldots, i, \ldots, I\}$ denote the set of AVs in the coverage of RU j. As an intelligent robot with integrated sensing, computing, caching, and publishing functions, each AV is not only a service requester, but also a resource provider of diversified services in the AVNs. In other words, AVs in the networks can act as the SRs by requesting various resources to complete driving services or enjoy entertainment services. On the other hand, AVs with available resources can act as the SPs to provide resources for the SRs to obtain profits. Let $\mathbb{I}_r = \{1, \ldots, i_r, \ldots, I_r\}$ and $\mathbb{I}_p = \left\{1, \ldots, i_p, \ldots, I_p\right\}$ denote the set of SRs and the set of SPs in the AVNs, respectively. Note that some AVs may have both service requests and service resources, we thus have $\mathbb{I}_r \cap \mathbb{I}_p \neq \emptyset$.

C. Digital Twin Model

In DT-AVNs, the DT of AV i is denoted as $\hat{i}$ and deployed in its connected RU. As a digital representation of AV i, DT $\hat{i}$ has the following functions.

Mapping: For AV i, its personal parameters will be uploaded to DT $\hat{i}$ so that DT $\hat{i}$ can map its needs and resource status in the network [36]. The requirements and resource status of DT $\hat{i}$ can be expressed as

$$\Gamma_{\hat{i}} = \Big\{ D_{i_p}^m, c_{i_p}^{n_m}, p_{i_r}^{n'_{m'}}, \forall n_m, \in \mathbb{N}_m, \forall n'_{m'} \in \mathbb{N}'_{m'}, \forall m, m' \in \mathbb{M}, m \neq m' \Big\}, \tag{1}$$

where $D_{i_p}^m$ is the total amount of resources that AV i can provide for services of type m, $c_{i_p}^{n_m}$ is the unit resource cost of services provided by AV i, $\mathbb{N}'_{m'} = \left\{1, \ldots, n'_{m'}, \ldots, N'_{m'}\right\}$ and $N'_{m'}$ are similar to the definition of $\mathbb{N}_m$ and N_m, which represent the set of specific services and the number of services with service type m', $p_{i_r}^{n'_{m'}}$ is the expected price per unit resource of AV i to request service $n'_{m'}$.

Decision: After mapping the parameters of AVs, the DTs of the AVs deployed in the same RU can interact with each other in the virtual network based on different service requirements and resource states. In this way, the optimal collaboration strategies of the DTs can be determined to maximize their utilities [37]. Then, the collaborative decisions determined by the DTs will be transmitted to the AVs in the physical networks to guide the AVs in completing the edge collaboration.

Payment: In DT-AVNs, each DT has a virtual account to complete transactions for edge services. During the cooperation process, each DT-SR will pay the price for the requested service, while each DT-SP will obtain profits based on the provided resources.

Update: After completing an edge collaboration, each AV in the physical networks can selectively update its DT parameters by connecting the RU [38].

Migration: Each DT $\hat{i}$ in the virtual network will migrate from the current RU to a new RU in advance based on the driving path of AV i in the physical network [39]. When AV i enters the coverage of the new RU, it can directly collaborate with other AVs based on the decisions made by DT $\hat{i}$.

IV. DIGITAL TWIN ENABLED EDGE COLLABORATION ARCHITECTURE

In DT-AVNs, the collaboration decisions of the AVs are completed by the DTs deployed in RUs. We divide the time into time slots of equal length, where each slot has a length of ΔT. Given the initial time T, the DTs deployed in each RU can replace the AVs in the physical network to complete collaborative service decisions within time slot $[T+(x-1)\Delta T, T+x\Delta T)$. As shown in Fig. 2, the architecture has the following steps.

Step 1: Map service parameters. After completing the edge collaboration in time slot $[T+(x-2)\Delta T, T+(x-1)\Delta T)$, AV i needs to determine whether to update its service requirements and resource status. If AV i intends to update information, the AV can map the parameters to its DT through the linked RU to facilitate the collaboration in time slot $[T+(x-1)\Delta T, T+x\Delta T)$.

Step 2: Publish service requirements. After the parameters are updated, DT $\hat{i}$ will migrate from the original RU to the next RU j on the path of AV i and share service information $\Gamma_{\hat{i}}$ with other DTs.

Step 3: Form the SRGs. In our paper, let $\mathbb{E}_{N_m} = \{1, \ldots, E_{n_m}, \ldots, E_{N_m}\}$ denote the set of SRGs. For each basic

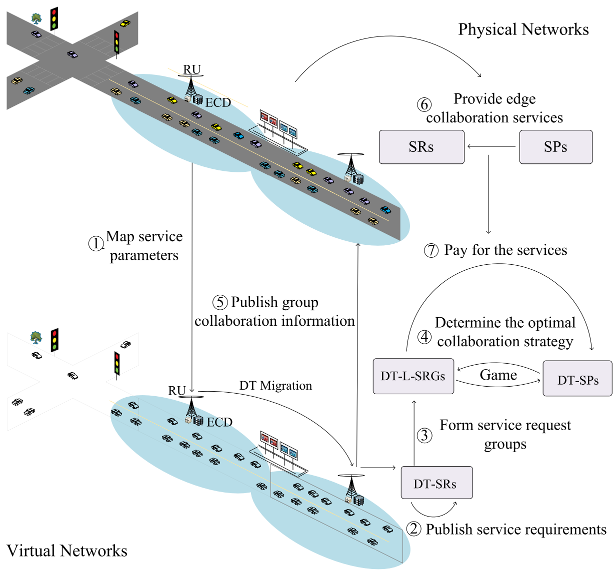

Fig. 2. Edge collaboration process for composite services in DT-AVNs.

service n_m, all the DTs deployed in RU $j(j \in \mathbb{J})$ that require this service form a SRG $E_{n_m} = \{1, \ldots, \hat{i}_{r,n_m}, \ldots, \hat{I}_{r,n_m}\}$, where $E_{n_m} \in \mathbb{E}_{N_m}$ and the number of the members in group E_{n_m} is denoted as $|E_{n_m}|$. The leader DT of the SRG (DT-L-SRG) will replace all members of the group in making resource purchase decision. In addition, the members of the same group will share service results and service costs. For SRG E_{n_m}, the DT with the highest expected price per unit resource in the group will be selected as the DT-L-SRG $\hat{i}_{r^*,n_m}$. We have

$$\hat{i}_{r^*,n_m} = \arg\max \left\{ p_{i_r}^{n_m}, \forall \hat{i}_{r,n_m} \in E_{n_m} \right\}. \tag{2}$$

Step 4: Determine optimal collaboration strategies. DT-L-SRG $\hat{i}_{r^*,n_m}$ can choose to combine basic service n_m with one or more other basic services to form a composite service, and purchase resources from DT-SPs in the form of the composite service. For basic service n_m, when it is in different composite services, the DT-SPs have different prices for their resources, which in turn affects the utility of the DT-L-SRG. Therefore, for each DT-L-SRG $\hat{i}_{r^*,n_m}$, how to determine the optimal service composition form is an important issue. To solve this problem, we design the coalition-game-based service composition mechanism to determine the optimal service composition form for each basic service. The details of the mechanism will be introduced in Section V-B.

In the coalition game, given any coalition structure (i.e., the service composition forms of all the basic services), each DT-SP needs to price its resources based on the service composition forms in this structure, while each DT-L-SRG needs to determine the optimal resource purchase strategy based on the resource price and the service composition form. In this process, on one hand, multiple DT-L-SRGs that require the same resources can simultaneously purchase service resources from one DT-SP. On the other hand, a DT-L-SRG can purchase the same service resources from multiple DT-SPs. Therefore, we model the resource trading process between multiple DT-L-SRGs and multiple DT-SPs as a Stackelberg game. By obtaining the equilibrium solution of the game, the optimal resource purchase strategy of each DT-L-SRG and the optimal resource pricing strategy of each DT-SP under the given coalition structure can be obtained. According to the optimal strategies obtained from the Stackelberg game for each DT-L-SRG and each DT-SP, DT-L-SRGs can calculate their maximum utilities and compare their maximum utilities under the current coalition structure with the maximum utilities under the previous coalition structure to make coalition decisions. After multiple rounds of coalition iterations, a stable optimal combination service structure can be formed. The specific Stackelberg-game-based collaboration mechanism will be detailed in Section V-C.

Step 5: Publish collaboration information. In Step 4, the optimal coalition structure (i.e., composition form of each basic service) can be determined. In addition, we can obtain the optimal resource purchase strategy of each DT-L-SRG and the optimal resource pricing strategy of each DT-SP based on the formed coalition structure. Then, RU $j(j \in \mathbb{J})$ broadcasts the coalition structure and the optimal strategies to the physical networks.

Step 6: Provide edge collaboration services. The SPs in the physical networks provide resources for the corresponding SRGs based on the strategies published by the RU. In addition, the members in each SRG share the service results.

Step 7: Pay for the services. All the SRs that have obtained the service result send service completion information to their DTs. The DTs deployed in RU $j(j \in \mathbb{J})$ receive service confirmation information and pay for the services through their virtual accounts.

V. Game Analysis

In this section, as shown in Fig. 3, we introduce the edge collaboration process which integrates two game-based mechanisms. We first introduce the utility functions for the DT-SPs and the DT-L-SRGs in the edge collaboration process. Then, we design the coalition-game-based service composition mechanism to help DT-L-SRGs obtain the optimal form of each composition service. After that, we design the Stackelberg-game-based collaboration mechanism that nests within the coalition-game-based service composition mechanism to obtain the optimal resource purchase strategies and the optimal resource pricing strategies for the DT-L-SRGs and the DT-SPs under a given coalition structure. With the designed Stackelberg game, the utility of each DT-L-SRG after forming a coalition can be calculated, thereby evaluating the performance of the formed coalition structure.

A. Utilities of the DT-SPs and the DT-L-SRGs

Before introducing the coalition-game-based service composition mechanism and the Stackelberg-game-based collaboration mechanism, we first introduce the utility functions for the DT-SPs and the DT-L-SRGs.

1) The Utility of the DT-SPs: The DT-SPs can provide resources for DT-L-SRGs to obtain profits. Therefore, the utility function of the DT-SPs needs to consider both profits and costs. For the cost of a composite service, the more resources that a DT-L-SRG purchases from DT-SP $\hat{i}_p$ for each

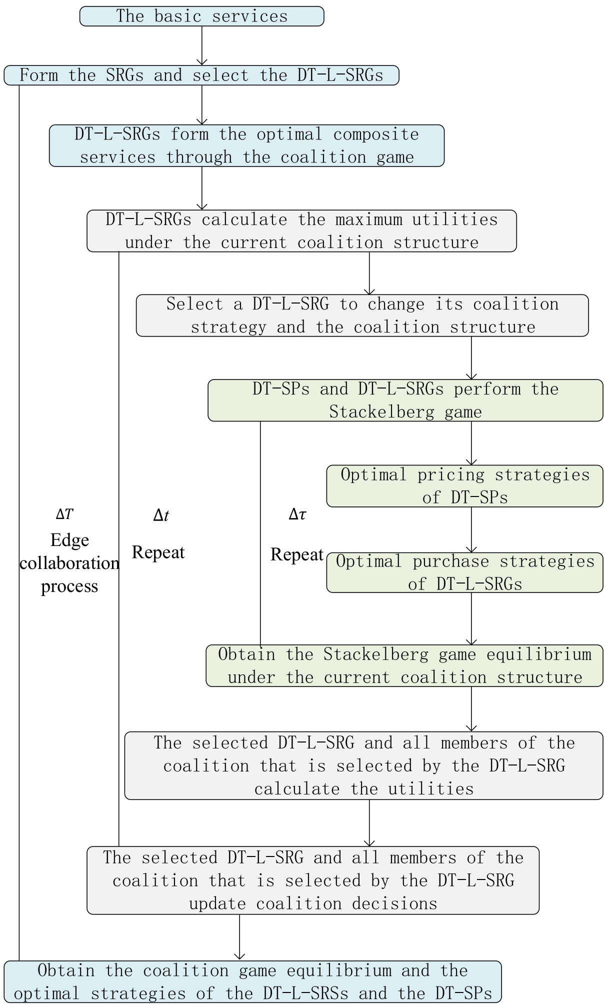

Fig. 3. The flowchart of the edge collaboration process, where the Stackelberg-game-based collaboration mechanism is nested within the coalition-game-based service composition mechanism to obtain the optimal strategies.

basic service within the composite service, the lower the cost per unit resource of DT-SP $\hat{i}_p$ to provide resources for the basic service. Let $\mathbb{K} = \{1, \ldots, k, \ldots, K\}$ denote the set of the composite services. Then, the utility function of DT-SP $\hat{i}_p$ can be expressed as

$$U_{\hat{i}_p} = \sum_{k \in \mathbb{K}} \sum_{n_m \in k} \left(p_{i_p}^{n_m} - \left(c_{i_p}^{n_m} - \varphi_{i_p}^{k} \frac{\sum_{n'_m \in k} d_{i_p}^{n'_m}}{|k|} \right) \right) d_{i_p}^{n_m}, \tag{3}$$

where $p_{i_p}^{n_m}$ is determined by the Stackelberg game. It represents the optimal resource price of DT-SP $\hat{i}_p$ to provide resources for basic service n_m. $d_{i_p}^{n_m}$ is the amount of resources purchased by the DT-L-SRG that requests basic service n_m from DT-SP $\hat{i}_p$. $\sum_{n'_m \in k} d_{i_p}^{n'_m}$ represents the total amount of resources purchased from DT-SP $\hat{i}_p$ by the DT-L-SRGs except for DT-L-SRG $\hat{i}_{r*,n_m}$ in composite service k. $\varphi_{i_p}^{k}$ is a coefficient which represents the discount factor of DT-SP $\hat{i}_p$ to provide resources for composite service k, and $|k|$ is the number of basic services in the composite service.

2) The Utility of the DT-L-SRGs: We first analyze the utility of each DT-SR in SRG E_{n_m}. The utility function of each DT-SR is related to two factors, namely service satisfaction and service price paid to the DT-SPs. We use a logarithmic function to describe the satisfaction of DT-SR $\hat{i}_r$ [40], [41], [42], which can be expressed as

$$S_{i_r}^{n_m} = \alpha_{i_r}^{n_m} \log \left(1 + \sum_{i_p=1}^{I_p} d_{i_p}^{n_m} \right), \tag{4}$$

where $\alpha_{i_r}^{n_m}$ $\left(\alpha_{i_r}^{n_m} > 0\right)$ denotes the utility coefficient of DT-SR $\hat{i}_r$ towards service n_m. It represents the relationship between basic service n_m requested by DT-SR $\hat{i}_r$ and the service satisfaction experienced by DT-SR $\hat{i}_r$.

According to (4), the utility of DT-SR $\hat{i}_r$ can be defined as the satisfaction of purchasing resources minus the cost of purchasing resources, shown as

$$U_{i_r}^{n_m} = \alpha_{i_r}^{n_m} \log\left(1 + \sum_{i_p=1}^{I_p} d_{i_p}^{n_m} \right) - \sum_{i_p=1}^{I_p} \frac{p_{i_p}^{n_m} d_{i_p}^{n_m}}{\left| Q_{i_p}^{n_m} \right|}, \tag{5}$$

where $Q_{i_p}^{n_m}$ represents the set of members that intend to purchase resources from DT-SP $\hat{i}_p$ in SRG E_{n_m}, $|Q_{i_p}^{n_m}|$ is the number of members in the set.

Based on the utility of DT-SR $\hat{i}_r$, we define the utility of DT-L-SRG $\hat{i}_{r*,n_m}$ as the average utility of all DT-SRs in SRG E_{n_m}. We have

$$U_{\hat{i}_{r*,n_m}} = \frac{\sum_{i_r=1}^{|Q_{i_p}^{n_m}|} \left(\alpha_{i_r}^{n_m} \log\left(1 + \sum_{i_p=1}^{I_p} d_{i_p}^{n_m} \right) - \sum_{i_p=1}^{I_p} \frac{p_{i_p}^{n_m} d_{i_p}^{n_m}}{\left| Q_{i_p}^{n_m} \right|} \right)}{\left| E_{n_m} \right|}. \tag{6}$$

B. Coalition-Game-Based Service Composition Mechanism

For basic service n_m, when it forms composite services with different basic services, the DT-SPs have different prices for their resources. Therefore, for DT-L-SRG $\hat{i}_{r*,n_m}$, how to determine the optimal service composition form is an important issue. To this end, we model the interaction between all the DT-L-SRGs as a coalition game. In this game, the members in each coalition are the DT-L-SRGs. When multiple DT-L-SRGs form a coalition, it means that the corresponding multiple basic services form a composite service. Let $\mathbb{H} = \left\{H_1, \ldots H_g, \ldots H_G\right\}$ represent the set of coalitions. In the coalition game, each DT-L-SRG tends to join an optimal coalition to maximize its utility. For DT-L-SRG $\hat{i}_{r*,n_m}$ in coalition H_g, we define the utility of $\hat{i}_{r*,n_m}$ as the added utility of joining a new coalition $H_{g'}$. In this way, if the following two conditions are satisfied, $\hat{i}_{r*,n_m}$ will leave coalition H_g and join coalition $H_{g'}$ [43]. First, the utility of DT-L-SRG $\hat{i}_{r*,n_m}$ after joining $H_{g'}$ is larger than zero. We have

$$u_{\hat{i}_{r*,n_m}} = U_{\hat{i}_{r*,n_m}} \left(H_{g'} \cup \left\{ \hat{i}_{r*,n_m} \right\} \right) - U_{\hat{i}_{r*,n_m}} \left(H_g \right) > 0, \tag{7}$$

where $U_{\hat{i}_{r*,n_m}} \left(H_g \right)$ is the utility of DT-L-SRG $\hat{i}_{r*,n_m}$ in the original coalition. $H_{g'} \cup \left\{ \hat{i}_{r*,n_m} \right\}$ represents the new coalition after DT-L-SRG $\hat{i}_{r^*,n_m}$ joins coalition $H_{g'}$. Second, after DT-L-SRG $\hat{i}_{r^*,n_m}$ joins coalition $H_{g'}$, the utility of any DT-L-SRG $\hat{i}'_{r^*,n'_{m'}}$ that requests service $n'_{m'}$ in coalition $H_{g'}$ should not be lower than the original utility. We have

$$u_{\hat{i}'_{r^*,n'_{m'}}} = U_{\hat{i}'_{r^*,n'_{m'}}}\left(H_{g'} \cup \left\{\hat{i}_{r^*,n_m}\right\}\right) - U_{\hat{i}'_{r^*,n'_{m'}}}\left(H_{g'}\right) \geq 0, \forall \hat{i}'_{r^*,n'_{m'}} \in H_{g'}. \quad (8)$$

Based on the above conditions, we then introduce the designed coalition game. As shown in Algorithm 1, let the time interval from t to $t + \Delta t$ be the iteration cycle of DT-L-SRGs. Then, the steps of the coalition game are as follows.

Step 1: At the initialization time t of the game, each coalition in the coalition set has only one DT-L-SRG, which means that all DT-L-SRGs purchase resources separately.

Step 2: Select a DT-L-SRG $\hat{i}_{r^*,n_m}$ that is in coalition H_g and let the DT-L-SRG submit an application to one coalition $H_{g'}$ in set $\mathbb{H}_{-g}$, where $\mathbb{H}_{-g}$ is the set of all coalitions except for coalition H_g. Subsequently, coalition $H_{g'}$ tentatively agrees to form a new coalition with DT-L-SRG $\hat{i}_{r^*,n_m}$. By doing so, the set of coalitions (i.e., the coalition structure) can be represented as

$$\mathbb{H} = \left\{H_1, \ldots, H_g / \left\{\hat{i}_{r^*,n_m}\right\}, H_{g'} \cup \left\{\hat{i}_{r^*,n_m}\right\}, \ldots, H_G\right\}. \quad (9)$$

Step 3: Based on the above coalition set, we can obtain the service composition form for DT-L-SRG $\hat{i}_{r^*,n_m}$ under this coalition structure. Then, the DT-SPs and the DT-L-SRGs need to obtain the optimal resource pricing strategies and optimal resource purchase strategies under the current coalition structure to calculate the utility of DT-L-SRG $\hat{i}_{r^*,n_m}$ after joining the new coalition $H_{g'}$. The above strategies will be obtained through the designed Stackelberg-game-based collaboration mechanism in Section V-C. After obtaining the optimal strategies, DT-L-SRG $\hat{i}_{r^*,n_m}$ then can calculate its added utility $u_{\hat{i}_{r^*,n_m}}$ based on equation (7).

Step 4: If $u_{\hat{i}_{r^*,n_m}} \leq 0$, the optimal strategy of DT-L-SRG $\hat{i}_{r^*,n_m}$ is to stay in the original coalition H_g. On the contrary, if $u_{\hat{i}_{r^*,n_m}} > 0$ which means that the utility of DT-L-SRG $\hat{i}_{r^*,n_m}$ after joining coalition $H_{g'}$ is higher than its utility in the original coalition H_g, then DT-L-SRG chooses to join coalition $H_{g'}$. In addition, each DT-L-SRG $\hat{i}'_{r^*,n'_{m'}}$ in coalition $H_{g'}$ calculates the utility that DT-L-SRG $\hat{i}_{r^*,n_m}$ brings to coalition $H_{g'}$ through equation (8) based on the optimal resource pricing strategies and optimal resource purchase strategies obtained in Step 3. If $u_{\hat{i}'_{r^*,n'_{m'}}} \geq 0, \forall \hat{i}'_{r^*,n'_{m'}} \in H_{g'}$, the utility of each DT-L-SRG $\hat{i}'_{r^*,n'_{m'}}$ in coalition $H_{g'}$ will not decrease, then coalition $H_{g'}$ agrees to accept DT-L-SRG $\hat{i}_{r^*,n_m}$. We have

$$\left\{H_g, H_{g'}\right\} \to \left\{H_g / \left\{\hat{i}_{r^*,n_m}\right\}, H_{g'} \cup \left\{\hat{i}_{r^*,n_m}\right\}\right\}. \quad (10)$$

Subsequently, the coalition structure can be updated by

$$\mathbb{H} = \mathbb{H} / \left\{H_g, H_{g'}\right\} \cup \left\{H_g / \left\{\hat{i}_{r^*,n_m}\right\}, H_{g'} \cup \left\{\hat{i}_{r^*,n_m}\right\}\right\}. \quad (11)$$

Algorithm 1 **Coalition-game-based service composition algorithm**

```
Input: Γ_î, i ∈ 𝕀, t
The DT-L-SRGs work alone and have no cooperation
ℍ' = ∅, ℍ = {H_1, ..., H_g, ..., H_G}
while ℍ' ≠ ℍ do
  ℍ' ← ℍ
  for each DT-L-SRG î_{r*,n_m} do
    for H_{g'} = 1, H_{g'} ≤ H_G do
      if H_{g'} ≠ H_g then
        î_{r*,n_m} submits a coalition application to H_{g'}.
        DT-SPs and DT-L-SRGs obtain the equilibrium
        of the Stackelberg game under the current coali-
        tion structure using Algorithm 2.
        î_{r*,n_m} calculates u_{î_{r*,n_m}} using (7).
        if u_{î_{r*,n_m}} > 0 then
          Each î'_{r*,n'_{m'}} calculates u_{î'_{r*,n'_{m'}}} using (8).
          if u_{î'_{r*,n'_{m'}}} ≥ 0, ∀î'_{r*,n'_{m'}} ∈ H_{g'} then
            Update the coalition structure using (11).
          end if
        end if
      end if
    end for
  end for
  t = t + Δt
end while
Output: The stable coalition structure ℍ*
```

On the contrary, if $u_{\hat{i}'_{r^*,n'_{m'}}} < 0, \exists \hat{i}'_{r^*,n'_{m'}} \in H_{g'}$, the utility of at least one DT-L-SRG in coalition $H_{g'}$ will decrease after DT-L-SRG $\hat{i}_{r^*,n_m}$ joins the coalition. Then, the coalition rejects DT-L-SRG $\hat{i}_{r^*,n_m}$ from joining the coalition and the original coalition structure remains unchanged.

Step 5: After all DT-L-SRGs go through the above process in sequence, the coalition structure $\mathbb{H}$ after the first iteration is formed. Afterwards, the above process will be repeated until the optimal coalition structure $\mathbb{H}^*$ is obtained.

Definition 1: A coalition structure $\mathbb{H}$ is stable if no DT-L-SRG can improve its utility by changing its coalition strategy unilaterally [44], [45], [46].

Theorem 1: The coalition game can ultimately converge to a stable coalition structure within a limited number of iterations.

Proof: In the coalition game, if there is no DT-L-SRG that can unilaterally change the coalition structure to increase its utility, then the coalition structure $\mathbb{H}$ is stable. That is to say, in the case of stable coalition structure, no DT-L-SRG has the motivation to leave the current coalition and form a new coalition with other DT-L-SRGs. To prove Theorem 1, we denote the initial set of coalitions as $\mathbb{H}^0$. When conducting coalition operations, the existing coalition structure may be transformed into a new coalition structure. Therefore, there is a series of coalition structures, namely $\mathbb{H}^0 \to \mathbb{H}^1 \to \mathbb{H}^2 \ldots$. In the above process, given the number of DT-L-SRGs, the total number of possible coalition structures is limited. Therefore, starting from any initial coalition structure $\mathbb{H}^0$, the sequence always terminates to a stable structure $\mathbb{H}^*$ after finite number of iterations. On the other hand, if $\mathbb{H}^*$ is unstable, it means that there is at least one DT-L-SRG that can increase its utility by performing coalition operations. Therefore, $\mathbb{H}^*$ is not the final stable structure, which contradicts the previous assumption. The theorem is proved [47], [48], [49].

C. Stackelberg-Game-Based Collaboration Mechanism

In the process of the service composition, as discussed in Section V-B, we need to obtain the optimal resource pricing strategies and optimal resource purchase strategies for the DT-SPs and the DT-L-SRGs under the current coalition structure to calculate the utility of DT-L-SRG $\hat{i}_{r*,n_m}$. Therefore, in this subsection, we analyze the interaction between multiple DT-L-SRGs and multiple DT-SPs given any coalition structure based on the utility functions of DT-SPs and DT-L-SRGs established in Section V-A.

If DT-SRs need to purchase resources, they first form SRGs based on the same service requests and then select DT-L-SRGs. In time slot Δt, DT-L-SRGs send the information of the requested services to the DT-SPs. Then, the DT-SPs check the type of the available resources based on the information of the DT-L-SRGs and consider the cost of providing each service. Afterwards, each DT-SP can calculate the optimal resource pricing strategy and send its strategy to the DT-L-SRGs. Finally, each DT-L-SRG determines its optimal strategy for purchasing resources based on the price of each DT-SP. The above process has the characteristics of a Stackelberg game. Therefore, we formulate the resource purchase strategy of each DT-L-SRG and the resource pricing strategy of each DT-SP as a Stackelberg game to maximize their utilities. In the Stackelberg game, according to (3), the optimization problem of DT-SP $\hat{i}_p$ can be expressed as

$$\begin{aligned} \text{P1}: &\max U_{\hat{i}_p} \qquad (12)\\ &=\sum_{k\in\mathbb{K}}\sum_{n_m\in k}\left(p_{i_p}^{n_m}-\left(c_{i_p}^{n_m}-\varphi_{i_p}^{k}\frac{\sum_{n'_m\in k} d_{i_p}^{n'_m}}{|k|}\right)\right)d_{i_p}^{n_m},\\ \text{s.t.}\quad &\sum_{n_m=1}^{N_m} d_{i_p}^{n_m}\leq D_{i_p}^{m}\end{aligned}$$

Similarly, for DT-L-SRG $\hat{i}_{r*,n_m}$ that requests basic service n_m, the optimization problem can be expressed as

$$\begin{aligned} \text{P2}: &\max U_{\hat{i}_{r*,n_m}} \qquad (13)\\ &=\frac{\sum_{i_r=1}^{|Q_{i_p}^{n_m}|}\left(\alpha_{i_r}^{n_m}\log\left(1+\sum_{i_p=1}^{I_p} d_{i_p}^{n_m}\right)-\sum_{i_p=1}^{I_p}\frac{p_{i_p}^{n_m}d_{i_p}^{n_m}}{\left|Q_{i_p}^{n_m}\right|}\right)}{\left|E_{n_m}\right|},\\ \text{s.t.}\quad &\sum_{n_m=1}^{N_m} d_{i_p}^{n_m}\leq D_{i_p}^{m}\end{aligned}$$

Definition 2: Let $\mathbf{p}_{i_p}^*$ and $\mathbf{d}_{n_m}^*$ denote the optimal pricing strategy vector of DT-SP $\hat{i}_p$ and the optimal resource purchase strategy vector of DT-L-SRG $\hat{i}_{r*,n_m}$. Then, if condition (14) is satisfied, $(\mathbf{P}^*,\mathbf{D}^*)$ is the Nash equilibrium of the Stackelberg game [50].

$$\begin{cases} U_{\hat{i}_{r*,n_m}}\left(\mathbf{P}^*,\mathbf{d}_{n_m}^*,\mathbf{D}_{-n_m}^*\right)\geq U_{\hat{i}_{r*,n_m}}\left(\mathbf{P}^*,\mathbf{d}_{n_m},\mathbf{D}_{-n_m}^*\right),\\ U_{\hat{i}_p}\left(\mathbf{D}^*,\mathbf{p}_{i_p}^*,\mathbf{P}_{-i_p}^*\right)\geq U_{\hat{i}_p}\left(\mathbf{D}^*,\mathbf{p}_{i_p},\mathbf{P}_{-i_p}^*\right),\end{cases} \qquad (14)$$

where $\mathbf{P}^*=\{1,\ldots,\mathbf{p}_{i_p}^*,\ldots,\mathbf{p}_{I_p}^*\}$ and $\mathbf{D}^*=\{1,\ldots,\mathbf{d}_{n_m}^*,\ldots,\mathbf{d}_{N_M}^*\}$ are the optimal resource pricing strategies of the DT-SPs and the optimal resource purchase strategies of the DT-L-SRGs.

Theorem 2: For DT-L-SRG $\hat{i}_{r*,n_m}$, there exists a unique Nash equilibrium for its resource purchase strategy [51].

Proof: In the Stackelberg game, the resource purchase strategy space for any DT-L-SRG is a nonempty, convex, and compact subset of Euclidean space. In addition, the utility function $U_{\hat{i}_{r*,n_m}}$ of DT-L-SRG $\hat{i}_{r*,n_m}$ is continuous in its strategy space. Therefore, we only need to prove that the utility function is a concave function to prove Theorem 2 [52]. Specifically, we take the first derivative of $U_{\hat{i}_{r*,n_m}}$ with respect to $d_{i_p}^{n_m}$, shown as

$$\frac{\partial U_{\hat{i}_{r*,n_m}}}{\partial d_{i_p}^{n_m}}=\frac{1}{\left|E_{n_m}\right|}\left(\frac{\alpha_{i_r}^{n_m}}{1+\sum_{i_p=1}^{I_p} d_{i_p}^{n_m}}-\frac{p_{i_p}^{n_m}}{\left|Q_{i_p}^{n_m}\right|}\right). \qquad (15)$$

Then, the second derivative of $U_{\hat{i}_{r*,n_m}}$ with respect to $d_{i_p}^{n_m}$ can be expressed as

$$\frac{\partial^2 U_{\hat{i}_{r*,n_m}}}{\partial d_{i_p}^{n_m\,2}}=-\frac{\alpha_{i_r}^{n_m}}{\left|E_{n_m}\right|}\left(\frac{1}{1+\sum_{i_p=1}^{I_p} d_{i_p}^{n_m}}\right)^2<0. \qquad (16)$$

From (16), we can see that $U_{\hat{i}_{r*,n_m}}$ is a strictly concave function, which ensures the existence and uniqueness of the Nash equilibrium. The theorem is proved.

Theorem 3: For DT-SP $\hat{i}_p$, there exists a unique Nash equilibrium for its resource pricing strategy [51].

Proof: In the Stackelberg game, the resource pricing strategy space for any DT-SP is a nonempty, convex, and compact subset of Euclidean space. In addition, the utility function $U_{\hat{i}_p}$ of DT-SP $\hat{i}_p$ is continuous in its strategy space. Therefore, similar to Theorem 2, we only need to prove that the utility function is a concave function to prove Theorem 3. We first substitute the optimal resource purchase strategy of each DT-L-SRG into P1. Then, P1 can be rewritten as

$$\begin{aligned}&\text{P3}:\\ &\max U_{\hat{i}_p}=\sum_{k\in\mathbb{K}}\sum_{n_m\in k}\left(p_{i_p}^{n_m}-\left(c_{i_p}^{n_m}-\varphi_{i_p}^{k}\frac{\sum_{n'_m\in k} d_{i_p}^{n'_m}}{|k|}\right)\right)\end{aligned}$$

$$\left(\frac{\alpha_{i_r}^{n_m} * |Q_{i_p}^{n_m}|}{p_{i_p}^{n_m}} - 1 - \sum_{i'_p=1, i'_p \neq i_p}^{I_p} d_{i'_p}^{n_m}\right), \tag{17}$$

$$\text{s.t.} \quad \sum_{n_m=1}^{N_m} d_{i_p}^{n_m} \leq D_{i_p}^{m}$$

We take the first derivative of $U_{\hat{i}_p}$ with respect to $p_{i_p}^{n_m}$, shown as

$$\frac{\partial U_{\hat{i}_p}}{\partial p_{i_p}^{n_m}} = -1 - \sum_{i'_p=1, i'_p \neq i_p}^{I_p} d_{i'_p}^{n_m} + \frac{\alpha_{i_r}^{n_m *} \left|Q_{i_p}^{n_m}\right| * c_{i_p}^{n_m}}{p_{i_p}^{n_m\,2}} - \varphi_{i_p}^{k} \frac{\alpha_{i_r}^{n_m *} \left|Q_{i_p}^{n_m}\right| * \sum_{n'_m \in k} .d_{i_p}^{n'_m}}{|k| * p_{i_p}^{n_m\,2}}. \tag{18}$$

Then, the second derivative of $U_{\hat{i}_p}$ with respect to $p_{i_p}^{n_m}$ can be expressed as

$$\frac{\partial^2 U_{\hat{i}_p}}{\partial p_{i_p}^{n_m\,2}} = -\frac{2 * \alpha_{i_r}^{n_m} * \left|Q_{i_p}^{n_m}\right|}{p_{i_p}^{n_m\,3}} \left(c_{i_p}^{n_m} - \varphi_{i_p}^{k} \frac{\sum_{n'_m \in k} d_{i_p}^{n'_m}}{|k|}\right) < 0. \tag{19}$$

From (19), it can be known that $U_{\hat{i}_p}$ is a strictly concave function, which ensures the existence and uniqueness of the Nash equilibrium. The theorem is proved.

Based on Theorem 2 and Theorem 3, we can conclude that the Nash equilibrium in the Stackelberg game exists and is unique. Next, we use a dynamic iterative algorithm to obtain the equilibrium of the Stackelberg game. Due to the mutual influence of the strategies between the DT-SPs and the DT-L-SRGs, the DT-SPs and the DT-L-SRGs require several iterations in the game to achieve the Nash equilibrium. Let time interval from τ to $\tau + \Delta\tau$ denote an iteration cycle of the resource pricing strategies and the resource purchase strategies for the DT-SPs and the DT-L-SRGs. In an iteration cycle, after obtaining the resource pricing strategies for all DT-SPs, each DT-L-SRG can obtain its resource purchase strategy by setting the first derivative of $U_{i_{r^*,n_m}}$ to 0. We have

$$d_{i_p}^{n_m} = \frac{\alpha_{i_r}^{n_m} * \left|Q_{n_m}\right|}{p_{i_p}^{n_m}} - 1 - \sum_{i'_p=1, i'_p \neq i_p}^{I_p} d_{i'_p}^{n_m}. \tag{20}$$

Based on (20), the resource purchase strategy of DT-L-SRG $\hat{i}_{r^*,n_m}$ can be updated by

$$d_{i_p}^{n_m}(\tau + \Delta\tau) = \max\left\{\frac{\alpha_{i_r}^{n_m} * \left|Q_{n_m}\right|}{p_{i_p}^{n_m}(\tau)} - 1 - \sum_{i'_p=1, i'_p \neq i_p}^{I_p} d_{i'_p}^{n_m}(\tau), 0\right\}. \tag{21}$$

After obtaining the resource purchase strategies for all DT-L-SRGs, each DT-SP iteratively updates its resource pricing strategy. Specifically, if $\sum_{n_m=1}^{N_m} d_{i_p}^{n_m} \leq D_{i_p}^{m}$, the price iteration equation of DT-SP $\hat{i}_p$ is

$$p_{i_p}^{n_m}(\tau + \Delta\tau) = p_{i_p}^{n_m}(\tau) + \psi_{i_{p,n_m}} \frac{\partial U_{\hat{i}_p}}{\partial p_{i_p}^{n_m}}, \tag{22}$$

Algorithm 2 **Stackelberg-game-based collaboration algorithm**

Input: $\Gamma_{\hat{i}}$, $i \in \mathbb{I}$, $\mathbb{H}$, τ
Initialize: $d_{i_p}^{n_m}$, $p_{i_p}^{n_m}$, $\forall p_{i_p}^{n_m} \in \mathbf{P}$, $i_p \in \mathbb{I}_p$
Repeat
for each DT-SP $\hat{i}_p$ **do**
  if $\sum_{n_m=1}^{N_m} d_{i_p}^{n_m} \leq D_{i_p}^{m}$ **then**
    Update the strategy of DT-SP $\hat{i}_p$ using (22).
  else
    Update the strategy of DT-SP $\hat{i}_p$ using (23).
  end if
end for
for each DT-L-SRG $\hat{i}_{r^*,n_m}$ **do**
  Update the strategy of DT-L-SRG $\hat{i}_{r^*,n_m}$ using (21).
end for
$\tau = \tau + \Delta\tau$
Until $|p_{i_p}^{n_m}(\tau + \Delta\tau) - |p_{i_p}^{n_m}(\tau)| \leq \varepsilon$, $\forall p_{i_p}^{n_m} \in \mathbf{P}$, where ε is a small value.
Output: $\mathbf{P}^*$, $\mathbf{D}^*$

where $\psi_{i_{p,n_m}}$ is the iteration step size. On the contrary, if $\sum_{n_m=1}^{N_m} d_{i_p}^{n_m} > D_{i_p}^{m}$, the strategy of DT-SP $\hat{i}_p$ is to increase its resource price, we have

$$p_{i_p}^{n_m}(\tau + \Delta\tau) = p_{i_p}^{n_m}(\tau) + \psi_{i_p,n_m}\lambda, \tag{23}$$

where λ is a small positive value.

Based on (22) and (23), as shown in Algorithm 2, the DT-SPs can dynamically adjust resource pricing strategies by considering the resource purchase strategies of the DT-L-SRGs. In contrast, the DT-L-SRGs dynamically adjust resource purchase strategies based on the resource pricing strategy of each DT-SP. The final result of the iteration is that all the DT-SPs and the DT-L-SRGs reach the Nash equilibrium ($\mathbf{P}^*$, $\mathbf{D}^*$). In this equilibrium state, no participant in the game can achieve a higher utility by privately changing its strategy.

VI. Performance Evaluation

In this section, we evaluate the performance of the proposed scheme. We first introduce the simulation scenario, and then discuss the simulation results.

A. Simulation Scenario

In the simulation, we consider the AVs in the coverage of a CBS, where the number of SPs participating in the edge collaboration varies from 10 to 50. The number of SRs that request the same basic service lies in [0, 10], where the number of basic service types requested by these SRs changes from 1 to 9. For the same service type, the number of basic services varies from 4 to 12. The range of the satisfaction parameter of each SR is [1500, 2500]. For each SP, the cost per unit resource and the total amount of each type of resources are selected from [0.4, 0.8] and [100, 500], respectively. The lowest value and the highest value of the discount factor are set to 0.005 and 0.045.

With this simulation scenario, we evaluate the utilities of the SRs and the SPs by changing different parameters (i.e., the resources owned by the SPs, the number of SPs, the number of the resource types requested by the SRs, the number of basic services with the same type, and the value of the discount factor). The conventional schemes used to compare with our proposal in the simulation are as follows.

- **Optimal Pricing and Optimal Purchase Scheme (OPOP)**: In this scheme, basic services do not form composite services. In other words, the DT-L-SRGs and the DT-SPs directly obtain the optimal resource purchase strategies and the optimal resource pricing strategies using the Stackelberg-game-based collaboration mechanism.
- **Random Pricing and Optimal Purchase Scheme (RPOP)**: In this scheme, basic services do not form composite services. In addition, the DT-L-SRGs obtain the optimal resource purchase strategies through the Stackelberg game, while the DT-SPs randomly provide resource pricing strategies.
- **Optimal Pricing and Random Purchase Scheme (OPRP)**: In this scheme, basic services do not form composite services. The DT-SPs obtain the optimal resource pricing strategies through the Stackelberg game, while the DT-L-SRGs randomly provide resource purchase strategies.
- **Coalition + Random Pricing and Optimal Purchase Scheme (C+RPOP)**: In this scheme, the basic services are formed into composite services through the coalition-game-based service composition mechanism. In addition, the DT-L-SRGs obtain the optimal resource purchase strategies through the Stackelberg game, while all DT-SPs randomly provide resource pricing strategies.
- **Coalition + Optimal Pricing and Random Purchase Scheme (C+OPRP)**: In this scheme, the basic services are formed into composite services through the coalition-game-based service composition mechanism. Furthermore, the DT-SPs obtain the optimal resource pricing strategies through the Stackelberg game, while the DT-L-SRGs randomly provide resource purchase strategies.

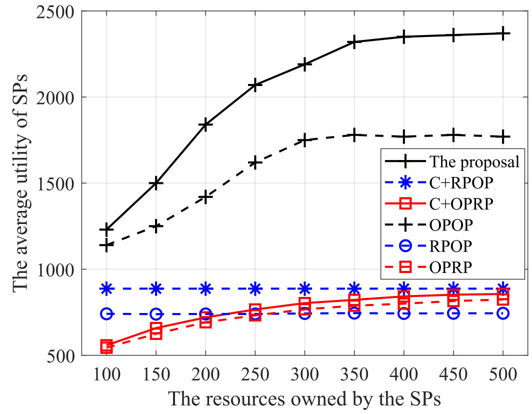

Fig. 4. The average utility of SPs by changing the resources owned by the SPs.

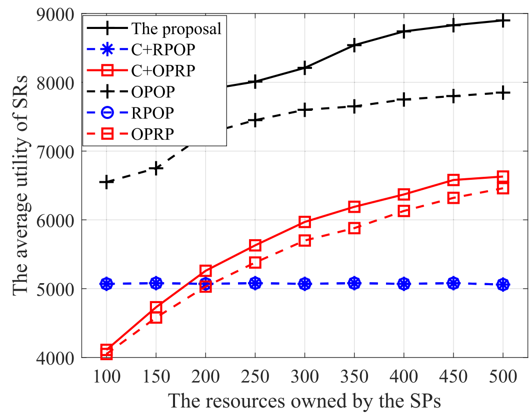

Fig. 5. The average utility of SRs by changing the resources owned by the SPs.

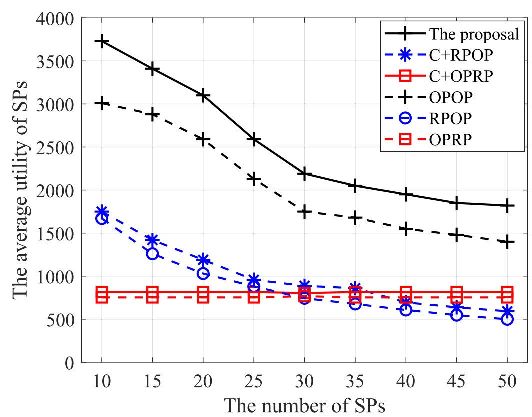

Fig. 6. The average utility of SPs by changing the number of SPs.

B. Simulation Results

Fig. 4 and Fig. 5 show the average utilities of the SPs and the SRs by changing the resources owned by the SPs. From Fig. 4, it can be seen that as the amount of the resources owned by the SPs increases, the average utility of the SPs in OPOP, OPRP, C+OPRP, and our proposal first increases and then gradually becomes stable. When the initial amount of resources increases, the SRs will purchase more resources to increase their utilities. As the amount of resources further increases, the competition between the SPs intensifies. In order to sell more resources, the SPs will further decrease their prices, but the effect of increasing sales will become weaker, which will prevent a significant increase in the utilities of the SPs. In RPOP and C+RPOP, there is no change in the average utility of the SPs. This is because in these two schemes, the resource price of each SP is randomly selected and remains unchanged, resulting in a fixed amount of resources purchased by the SRs from the SPs. In Fig. 5, it can be seen that as the amount of resources owned by the SPs increases, the average utility of the SRs in OPOP, OPRP, C+OPRP, and our proposal continues to increase. The reason is that the resource price of each SP decreases with the increase of the amount of resources provided by the SPs. In addition, we can see from the two figures that the average utilities of the SPs and the SRs in the proposed scheme are higher than those in the comparative schemes.

Fig. 6 and Fig. 7 depict the average utilities of the SPs and the SRs by changing the number of SPs. From Fig. 6, it can be seen that as the number of SPs increases, the average utility of the SPs in RPOP, C+OPOP, OPOP, and our proposal shows a downward trend. This is because with the number of

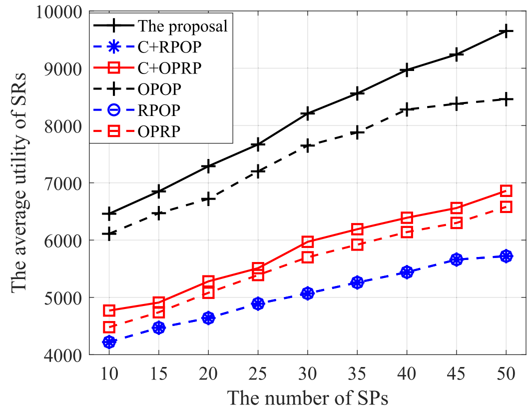

Fig. 7. The average utility of SRs by changing the number of SPs.

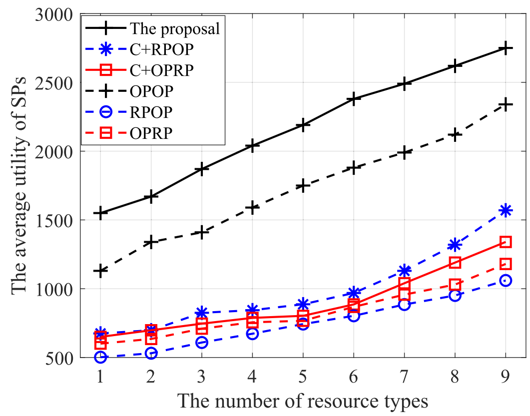

Fig. 8. The average utility of SPs by changing the number of resource types.

the SPs increases, the amount of resources purchased by the SRs from each SP decreases, which reduces the unit resource price of each SP. Therefore, the average utility of the SPs decreases with the increase of the number of SPs. In the OPRP and C+OPRP schemes, the average utility of the SPs does not change with the increase in the number of the SPs. The reason is that in these two schemes, the amount of resources purchased by the SRs from each SP does not change. From Fig. 7, we can see that as the number of SPs increases, the utility of the SRs shows an upward trend. As the competition among the SPs intensifies, the SRs can obtain service resources from multiple SPs at lower prices, thereby increasing the average utility of the SRs. From Fig. 6 and Fig. 7, it can be seen that the average utilities of the SPs and the SRs in the proposed scheme are higher than OPRP, RPOP, and OPOP. The reason for this is that these schemes do not consider the service discount in the coalition state. In addition, the higher service costs may exceed the expected purchase price of a portion of the SRs. Therefore, in these schemes, the average utility of the SRs will decrease.

Fig. 8 and Fig. 9 show the average utilities of the SPs and the SRs by changing the number of resource types requested by the SRs. From Fig. 8, we can see that as the types of resources required by the SRs increase, the average utility of the SPs in all schemes shows an upward trend. This is because as the types of resources required by the SRs increase, each SP can sell more types of resources to increase its utility. In Fig. 9, the average utility of the SRs in our scheme and C+OPRP increases with the increase of the number of resource types

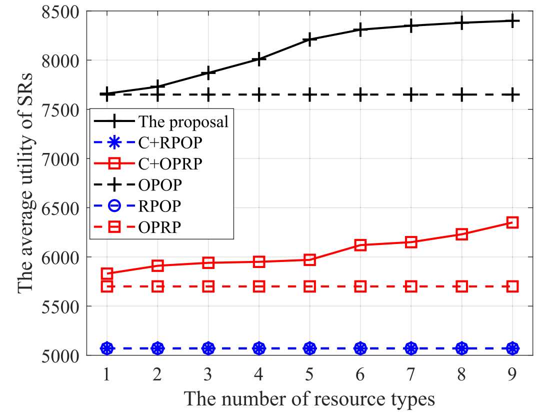

Fig. 9. The average utility of SRs by changing the number of resource types.

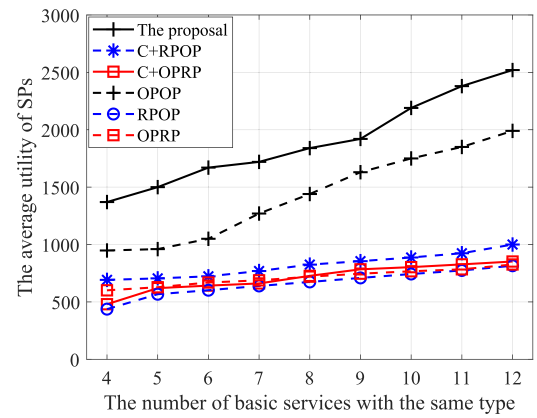

Fig. 10. The average utility of SPs by changing the number of basic services with the same type.

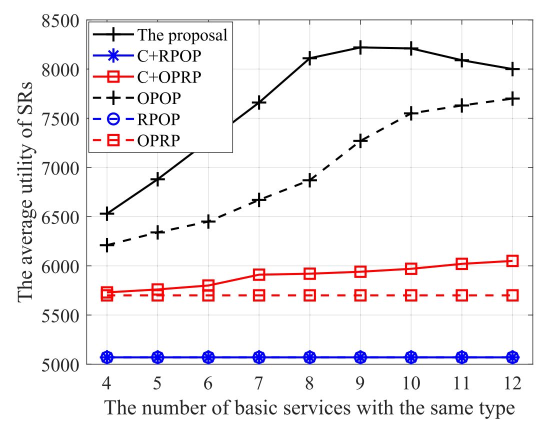

Fig. 11. The average utility of SRs by changing the number of basic services with the same type.

required by the SRs. As the number of resource types increase, more basic services appear in the network, and better service composition forms can be generated to obtain larger price discounts. Therefore, the average utility of the SRs in our scheme and C+OPRP increases.

Fig. 10 and Fig. 11 illustrate the average utilities of the SPs and the SRs by changing the number of basic services with the same type. With the increase of the number of basic services requiring the same resources, we can see from Fig. 10 that the average utility of the SPs in our scheme and the conventional schemes shows an upward trend. This is because as the number of basic services requesting the same type of resources increases, the amount of resources purchased by SRs

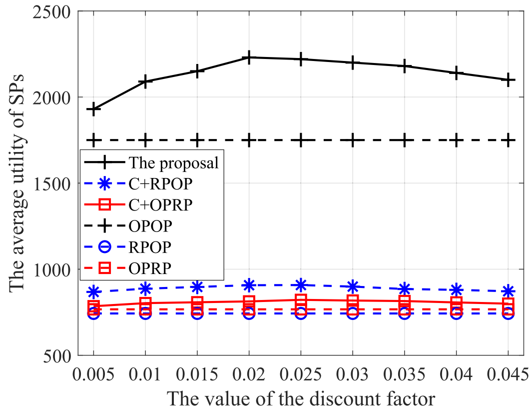

Fig. 12. The average utility of SPs by changing the value of the discount factor.

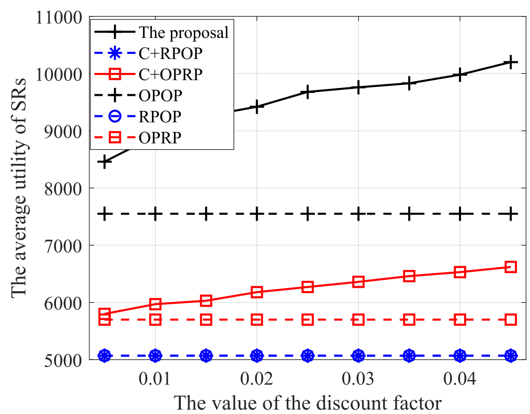

Fig. 13. The average utility of SRs by changing the value of the discount factor.

from SPs will increase. In Fig. 11, it can be seen that the average utility of the SRs in our scheme first increases and then decreases with the increase in the number of basic services with the same type. When the number of basic services that require the same type of resources initially increases, the basic services can obtain larger price discounts to increase the utility. However, due to the limited amount of resources owned by each SP, as the demand for basic services of the same type of resources further increases, the competition for purchasing resources between the basic services intensifies, leading to an increase in resource prices and a decrease in the average utility of the SRs.

Fig. 12 and Fig. 13 show the average utilities of the SPs and the SRs by changing the value of the discount factor. From Fig. 12, we can see that as the discount factor of each SP increases, the average utility of the SPs in our scheme, C+OPRP, and C+RPOP shows a trend of first increasing and then decreasing. When the discount factor initially increases, it can motivate the SRs to purchase more service resources, and the utility of the SPs increases accordingly. However, as the discount factor further increases, the increase in the amount of resources sold by the SPs is insufficient to compensate for the decrease in their unit resource profit. As a result, we can see that the utility of the SPs is decreased accordingly. In OPOP, RPOP, and OPRP schemes, the basic services do not form any composite services, so these schemes will not obtain price discounts. Therefore, the discount factor has no impact on the average utilities of the SPs and the SRs in these schemes. From Fig. 13, it can be seen that the average utility of the SRs in C+OPRP and our scheme increases with the increase of discount factor. In addition, the average utility of the SRs in our scheme is higher than that in the conventional schemes. The reason for this is that our proposal can obtain the optimal service composition forms for the basic services and the optimal strategies for the SPs and the SRs simultaneously.

VII. Conclusion

In this paper, we have proposed a DT-enabled edge collaboration scheme for composite services by considering the types of services in the DT-AVNs. Specifically, we have grouped the SRs based on the same basic service requests and proposed an architecture for the composite services to facilitate the edge collaboration between the DT-L-SRGs and the DT-SPs. In this architecture, we have formulated the process of service composition as a coalition game to determine the optimal service composition form for each basic service. In the process of the coalition game, in order to obtain the optimal resource purchase strategy for each DT-L-SRG and the optimal resource pricing strategy for each DT-SP under different coalition structures, we have modeled the interaction between the DT-L-SRGs and the DT-SPs under a given coalition structure as a Stackelberg game. The simulation results have demonstrated that our scheme can bring the highest utilities to the participants than the conventional schemes.

For future work, the composite services in 6G space-air-ground integrated vehicular networks will be studied to further enhance the edge collaboration in the DT-AVNs. Furthermore, we will integrate the research results on composite services with the technologies such as artificial intelligence (AI) and extended reality (XR) to facilitate the vehicular applications in the Metaverse.

References

[1] H. Zhang, M. Jiang, X. Liu, X. Wen, N. Wang, and K. Long, “PPO-based PDACB traffic control scheme for massive IoV communications,” *IEEE Trans. Intell. Transp. Syst.*, vol. 24, no. 1, pp. 1116–1125, Jan. 2023.

[2] J. Wang, Y. Huang, Z. Feng, C. Jiang, H. Zhang, and V. C. M. Leung, “Reliable traffic density estimation in vehicular network,” *IEEE Trans. Veh. Technol.*, vol. 67, no. 7, pp. 6424–6437, Jul. 2018.

[3] H. Peng, Q. Ye, and X. S. Shen, “SDN-based resource management for autonomous vehicular networks: A multi-access edge computing approach,” *IEEE Wireless Commun.*, vol. 26, no. 4, pp. 156–162, Aug. 2019.

[4] R. Valiente, B. Toghi, R. Pedarsani, and Y. P. Fallah, “Robustness and adaptability of reinforcement learning-based cooperative autonomous driving in mixed-autonomy traffic,” *IEEE Open J. Intell. Transp. Syst.*, vol. 3, pp. 397–410, 2022.

[5] H. Li, C. Chen, H. Shan, P. Li, Y. C. Chang, and H. Song, “Deep deterministic policy gradient-based algorithm for computation offloading in IoV,” *IEEE Trans. Intell. Transp. Syst.*, vol. 25, no. 3, pp. 2522–2533, Mar. 2024.

[6] Q. Wu, Y. Zhao, and Q. Fan, “Time-dependent performance modeling for platooning communications at intersection,” *IEEE Internet Things J.*, vol. 9, no. 19, pp. 18500–18513, Oct. 2022.

[7] N. Cheng et al., “Air-ground integrated mobile edge networks: Architecture, challenges, and opportunities,” *IEEE Commun. Mag.*, vol. 56, no. 8, pp. 26–32, Aug. 2018.

[8] K. Wang, L. Wang, C. Pan, and H. Ren, “Deep reinforcement learning-based resource management for flexible mobile edge computing: Architectures, applications, and research issues,” *IEEE Veh. Technol. Mag.*, vol. 17, no. 2, pp. 85–93, Jun. 2022.

[9] Y. Yang, K. Wang, G. Zhang, X. Chen, X. Luo, and M. Zhou, "MEETS: Maximal energy efficient task scheduling in homogeneous fog networks," *IEEE Internet Things J.*, vol. 5, no. 5, pp. 4076–4087, Oct. 2018.

[10] Y. Hui, Z. Su, T. H. Luan, C. Li, G. Mao, and W. Wu, "A game theoretic scheme for collaborative vehicular task offloading in 5G HetNets," *IEEE Trans. Veh. Technol.*, vol. 69, no. 12, pp. 16044–16056, Dec. 2020.

[11] L. Jiao, J. Zhao, Y. Xu, T. Zhang, H. Zhou, and D. Zhao, "Performance analysis for downlink transmission in multiconnectivity cellular V2X networks," *IEEE Internet Things J.*, vol. 11, no. 7, pp. 11812–11824, Apr. 2024.

[12] H. Zhou, J. Li, K. Yang, H. Zhou, J. An, and Z. Han, "Handover analysis in ultra-dense LEO satellite networks with beamforming methods," *IEEE Trans. Veh. Technol.*, vol. 72, no. 3, pp. 3676–3690, Mar. 2023.

[13] L. Wang, X. Deng, J. Gui, X. Chen, and S. Wan, "Microservice-oriented service placement for mobile edge computing in sustainable Internet of Vehicles," *IEEE Trans. Intell. Transp. Syst.*, vol. 24, no. 9, pp. 10012–10026, Sep. 2023.

[14] F. Zeng, K. Zhang, L. Wu, and J. Wu, "Efficient caching in vehicular edge computing based on edge-cloud collaboration," *IEEE Trans. Veh. Technol.*, vol. 72, no. 2, pp. 2468–2481, Feb. 2023.

[15] D. Wu, T. Liu, Z. Li, T. Tang, and R. Wang, "Delay-aware edge-terminal collaboration in green Internet of Vehicles: A multiagent soft actor-critic approach," *IEEE Trans. Green Commun. Netw.*, vol. 7, no. 2, pp. 1090–1102, Jun. 2023.

[16] T. Deng, Y. Chen, G. Chen, M. Yang, and L. Du, "Task offloading based on edge collaboration in MEC-enabled IoV networks," *J. Commun. Netw.*, vol. 25, no. 2, pp. 197–207, Apr. 2023.

[17] Y. Hui, Z. Su, T. H. Luan, and C. Li, "Reservation service: Trusted relay selection for edge computing services in vehicular networks," *IEEE J. Sel. Areas Commun.*, vol. 38, no. 12, pp. 2734–2746, Dec. 2020.

[18] H. Peng et al., "Resource allocation for cellular-based inter-vehicle communications in autonomous multiplatoons," *IEEE Trans. Veh. Technol.*, vol. 66, no. 12, pp. 11249–11263, Dec. 2017.

[19] K. Zhang, A. Yang, H. Su, A. de La Fortelle, K. Miao, and Y. Yao, "Service-oriented cooperation models and mechanisms for heterogeneous driverless vehicles at continuous static critical sections," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 7, pp. 1867–1881, Jul. 2017.

[20] Y. Hui, Z. Su, and T. H. Luan, "Unmanned era: A service response framework in smart city," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 6, pp. 5791–5805, Jun. 2022.

[21] D. A. Chekired, M. A. Togou, L. Khoukhi, and A. Ksentini, "5G-slicing-enabled scalable SDN core network: Toward an ultra-low latency of autonomous driving service," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 8, pp. 1769–1782, Aug. 2019.

[22] M. Hadian, T. Altuwaiyan, X. Liang, and H. Zhu, "Privacy-preserving task scheduling for time-sharing services of autonomous vehicles," *IEEE Trans. Veh. Technol.*, vol. 68, no. 6, pp. 5260–5270, Jun. 2019.

[23] L. Zhao, H. Li, N. Lin, M. Lin, C. Fan, and J. Shi, "Intelligent content caching strategy in autonomous driving toward 6G," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 7, pp. 9786–9796, Jul. 2022.

[24] Z. Su, Y. Hui, and T. H. Luan, "Distributed task allocation to enable collaborative autonomous driving with network softwarization," *IEEE J. Sel. Areas Commun.*, vol. 36, no. 10, pp. 2175–2189, Oct. 2018.

[25] H. Tian et al., "CoPace: Edge computation offloading and caching for self-driving with deep reinforcement learning," *IEEE Trans. Veh. Technol.*, vol. 70, no. 12, pp. 13281–13293, Dec. 2021.

[26] X. Chen, S. Leng, J. He, and L. Zhou, "Deep-learning-based intelligent intervehicle distance control for 6G-enabled cooperative autonomous driving," *IEEE Internet Things J.*, vol. 8, no. 20, pp. 15180–15190, Oct. 2021.

[27] F. Mohseni, E. Frisk, and L. Nielsen, "Distributed cooperative MPC for autonomous driving in different traffic scenarios," *IEEE Trans. Intell. Vehicles*, vol. 6, no. 2, pp. 299–309, Jun. 2021.

[28] Y. Chen, C. Lu, and W. Chu, "A cooperative driving strategy based on velocity prediction for connected vehicles with robust path-following control," *IEEE Internet Things J.*, vol. 7, no. 5, pp. 3822–3832, May 2020.

[29] J. Xiong, R. Bi, Y. Tian, X. Liu, and D. Wu, "Toward lightweight, privacy-preserving cooperative object classification for connected autonomous vehicles," *IEEE Internet Things J.*, vol. 9, no. 4, pp. 2787–2801, Feb. 2022.

[30] W. Pi et al., "Malicious user detection for cooperative mobility tracking in autonomous driving," *IEEE Internet Things J.*, vol. 7, no. 6, pp. 4922–4936, Jun. 2020.

[31] G. Thandavarayan, M. Sepulcre, and J. Gozalvez, "Generation of cooperative perception messages for connected and automated vehicles," *IEEE Trans. Veh. Technol.*, vol. 69, no. 12, pp. 16336–16341, Dec. 2020.

[32] C. Yu et al., "Distributed multiagent coordinated learning for autonomous driving in highways based on dynamic coordination graphs," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 2, pp. 735–748, Feb. 2020.

[33] J. Shen et al., "RingSFL: An adaptive split federated learning towards taming client heterogeneity," *IEEE Trans. Mobile Comput.*, vol. 23, no. 5, pp. 5462–5478, May 2024.

[34] Y. Hui et al., "RCFL: Redundancy-aware collaborative federated learning in vehicular networks," *IEEE Trans. Intell. Transp. Syst.*, vol. 25, no. 6, pp. 5539–5553, Jun. 2024.

[35] J. He et al., "Service-oriented network resource orchestration in space-air-ground integrated network," *IEEE Trans. Veh. Technol.*, vol. 73, no. 1, pp. 1162–1174, Jan. 2024.

[36] L. U. Khan, Z. Han, W. Saad, E. Hossain, M. Guizani, and C. S. Hong, "Digital twin of wireless systems: Overview, taxonomy, challenges, and opportunities," *IEEE Commun. Surveys Tuts.*, vol. 24, no. 4, pp. 2230–2254, 4th Quart., 2022.

[37] Z. Liu, H. Sun, G. Marine, and H. Wu, "6G IoV networks driven by RF digital twin modeling," *IEEE Trans. Intell. Transp. Syst.*, vol. 25, no. 3, pp. 2976–2986, Mar. 2024.

[38] X. Shen, J. Gao, W. Wu, M. Li, C. Zhou, and W. Zhuang, "Holistic network virtualization and pervasive network intelligence for 6G," *IEEE Commun. Surveys Tuts.*, vol. 24, no. 1, pp. 1–30, 1st Quart., 2022.

[39] Y. Hui, Y. Qiu, Z. Su, Z. Yin, T. H. Luan, and K. Aldubaikhy, "Digital twins for intelligent space-air-ground integrated vehicular network: Challenges and solutions," *IEEE Internet Things Mag.*, vol. 6, no. 3, pp. 70–76, Sep. 2023.

[40] H. Zhou, Z. Wang, G. Min, and H. Zhang, "UAV-aided computation offloading in mobile-edge computing networks: A Stackelberg game approach," *IEEE Internet Things J.*, vol. 10, no. 8, pp. 6622–6633, Apr. 2023.

[41] Y. Jiang, Y. Zhong, and X. Ge, "IIoT data sharing based on blockchain: A multileader multifollower Stackelberg game approach," *IEEE Internet Things J.*, vol. 9, no. 6, pp. 4396–4410, Mar. 2022.

[42] Y. Chen, H. Zhou, T. Li, J. Li, and H. Zhou, "Multifactor incentive mechanism for federated learning in IoT: A Stackelberg game approach," *IEEE Internet Things J.*, vol. 10, no. 24, pp. 21595–21606, Dec. 2023.

[43] J. S. Ng et al., "Joint auction-coalition formation framework for communication-efficient federated learning in UAV-enabled Internet of Vehicles," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 4, pp. 2326–2344, Apr. 2021.

[44] S. Maiti, S. Misra, and A. Mondal, "CBP: Coalitional game-based broadcast proxy re-encryption in IoT," *IEEE Internet Things J.*, vol. 10, no. 17, pp. 15642–15651, Sep. 2023.

[45] K. Xiong, T. Zhang, G. Cui, S. Wang, and L. Kong, "Coalition game of radar network for multitarget tracking via model-based multiagent reinforcement learning," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 59, no. 3, pp. 2123–2140, Jun. 2023.

[46] A. Hammoud et al., "Dynamic fog federation scheme for Internet of Vehicles," *IEEE Trans. Netw. Service Manag.*, vol. 20, no. 2, pp. 1913–1923, Jun. 2023.

[47] Y. Hui et al., "Collaboration as a service: Digital-twin-enabled collaborative and distributed autonomous driving," *IEEE Internet Things J.*, vol. 9, no. 19, pp. 18607–18619, Oct. 2022.

[48] J. Chen et al., "Joint task assignment and spectrum allocation in heterogeneous UAV communication networks: A coalition formation game-theoretic approach," *IEEE Trans. Wireless Commun.*, vol. 20, no. 1, pp. 440–452, Jan. 2021.

[49] Z. Zhou, H. Yu, C. Xu, Y. Zhang, S. Mumtaz, and J. Rodriguez, "Dependable content distribution in D2D-based cooperative vehicular networks: A big data-integrated coalition game approach," *IEEE Trans. Intell. Transp. Syst.*, vol. 19, no. 3, pp. 953–964, Mar. 2018.

[50] Z. Liu, J. Su, Y.-A. Xie, K. Ma, Y. Yang, and X. Guan, "Resource allocation in D2D enabled vehicular communications: A robust Stackelberg game approach based on price-penalty mechanism," *IEEE Trans. Veh. Technol.*, vol. 70, no. 8, pp. 8186–8200, Aug. 2021.

[51] F. Li, H. Yao, J. Du, C. Jiang, and Y. Qian, "Stackelberg game-based computation offloading in social and cognitive industrial Internet of Things," *IEEE Trans. Ind. Inf.*, vol. 16, no. 8, pp. 5444–5455, Aug. 2020.

[52] Z. Su, Q. Xu, Y. Hui, M. Wen, and S. Guo, "A game theoretic approach to parked vehicle assisted content delivery in vehicular ad hoc networks," *IEEE Trans. Veh. Technol.*, vol. 66, no. 7, pp. 6461–6474, Jul. 2017.

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