Digital Twins Enabled On-demand Matching for Multi-task Federated Learning in HetVNets

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***Abstract*—In the heterogeneous vehicular networks (HetVNets), the roadside units (RUs) can exploit the massive amounts of valuable data collected by vehicles to complete federated learning tasks. However, most of the existing studies consider the scenario of one task requester (TR) and ignore the fact that multiple TRs may concurrently request their model training tasks in the HetVNets. In this paper, we consider the scenario of multi-TR and multi-RU and propose a digital twins (DT) enabled on-demand matching scheme for multi-task federated learning to address the two-way selection problem between TRs and RUs. Specifically, by jointly considering the diversified requirements of the TRs and the differentiated training capabilities of the RUs, we first design a DT enabled on-demand matching architecture to facilitate the multi-task federated learning in the HetVNets. Then, based on the personalized requirement of the DT of each TR (DT-TR), a marginal utility based vehicle selection mechanism is proposed to enable the DT of each RU (DT-RU) to determine the customized model training strategy. With the determined strategies, the two-way selection problem between the DT-TRs and the DT-RUs is formulated as an on-demand matching game in DT networks, where a matching algorithm is designed to obtain their optimal strategies. Simulation results demonstrate that the proposed scheme outperforms the conventional schemes in terms of training accuracy, performance-cost ratio (PCR), and task completion rate (TCR).**

***Index Terms*—Digital twins, multi-task federated learning, game theory, heterogeneous vehicular networks.**

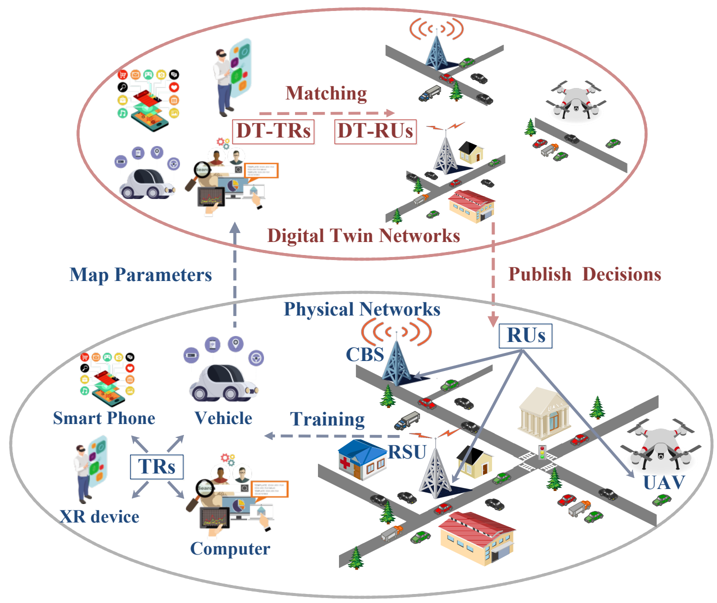

Fig. 1. The system model of the digital twins enabled on-demand matching for multi-task federated learning.

I. Introduction

With the development of space-air-ground integrated networks (SAGINs) [1]–[3], the massive amounts of valuable data can be collected by vehicles in the heterogeneous vehicular networks (HetVNets) to train different machine learning models [4]–[8]. In the traditional task training process, each roadside unit (RU) in the networks collects the data from the vehicles in its coverage to complete the training task after receiving the request of the task requester (TR). However, this approach has the following drawbacks. For one thing, the traditional centralized learning architecture may leak the private information of the vehicles. For another thing, the transmission of massive data between the RU and the vehicles in its communication coverage consumes a lot of resources, resulting in high communication overhead.

The federated learning framework is an efficient solution to solve the above problems [9]–[12]. In the process of federated learning, the vehicles within the coverage of the RU will first obtain the global model of the current round. Then, the vehicles use their local data to train the model and deliver the training results to the RU. After that, the RU performs parameter aggregation to generate a new global model, where the updated global model will be fed back to the vehicles in the next round. Repeat the above process until the model meets the accuracy requirement or the maximum number of the iterations is reached. In this way, the vehicles only need to upload the model to the RU, where the risk of privacy leakage and the overhead of data transmission between the vehicles and the RU can be significantly reduced.

With the above advantages, a large number of federated learning schemes have been studied to facilitate various ve-

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hicular applications [13]–[19]. However, the existing schemes lack the consideration of the fact that different TRs have diversified requirements for the model accuracy and the price paid for the training tasks. In addition, the RUs in the networks have different training capabilities that can be measured by the number of vehicles in the coverage and the cached historical training information. However, the existing studies are used to measure the training ability from the amount of data and the non-independent and identically distributed (non-IID) degree, while ignoring the impact of the historical training information on the model. In general, the RU with storage resources usually caches the trained models. When training a new model, the historical information can be exploited to facilitate the training process of the new model. Besides, the existing research usually considers the scenario where the appropriate trainers in the networks are selected to complete the training model for one TR [20]–[25]. This ignores the fact that multiple TRs may concurrently request their model training tasks in the HetVNets, as shown in Fig. 1. By jointly considering the diversified requirements of TRs and the differentiated capabilities of RUs, a RU may meet the training requirements of multiple TRs, and the personalized training requirement of a TR may also be satisfied by multiple RUs. Therefore, it is necessary to design an efficient scheme to handle the two-way selection problem between the multi-TR and the multi-RU, so as to optimize the performance-cost ratio (PCR) and maximize the task completion rate (TCR) while ensuring the accuracy of the training models.

To address the above challenges, in this paper, we consider the multi-TR and multi-RU scenario and propose a digital twins (DT) enabled on-demand matching scheme for multi-task federated learning in the HetVNets. In the scheme, we first design a DT enabled on-demand matching architecture to facilitate the interactions between the multi-TR and the multi-RU for decision making. Then, by considering the personalized requirement of the DT of each TR (DT-TR), we propose a marginal utility based vehicle selection mechanism for the DT of each RU (DT-RU) to determine the customized model training strategy. With the requirement of each DT-TR and the model training strategy of each DT-RU, the two-way selection problem between the DT-TRs and the DT-RUs is formulated as an on-demand matching game. By obtaining the stable matching pairs of the game, the optimal game strategies of both the DT-TRs and the DT-RUs can be obtained to improve the PCR and the TCR while guaranteeing the model training accuracy. Our main contributions are three-fold.

- **DT enabled matching architecture:** We consider the multi-TR and multi-RU scenario and propose a DT enabled on-demand matching architecture to train federated learning models for the TRs in the HetVNets. With the designed architecture, the DT-TRs and the DT-RUs can interact with each other in the DT networks to efficiently make decisions and complete the federated learning tasks.
- **Marginal utility based vehicle selection mechanism:** To enable each DT-RU to make the optimal model training strategy for each DT-TR, we propose a marginal utility based vehicle selection mechanism by considering the training capability of the DT-RUs. With the proposed mechanism, the model training strategy for each DT-TR can be customized by selecting the optimal set of vehicles to complete the learning task.
- **On-demand matching game:** Based on the personalized requirement of each DT-TR and the customized model training strategy of each DT-RU, the two-way selection problem between the DT-TRs and the DT-RUs is formulated as an on-demand matching game, where the optimal strategies of both the DT-TRs and the DT-RUs are obtained to improve the PCR and the TCR while guaranteeing the model training accuracy.

The remainder of this paper is organized as follows. Section II introduces the related work. Section III describes the system model. Section IV presents the proposed DT enabled on-demand matching scheme for the multi-task federated learning. Section V evaluates the performance of the proposed scheme and Section VI closes the paper with the conclusion.

II. Related Work

The federated learning and matching theory have been widely studied in vehicular networks to support various services and applications.

A. Federated Learning

Pokhrel *et al.* [26] develop a communication efficient federated learning framework to enhance the performance of vehicular networks. In the framework, the learning models are trained by exchanging inputs, outputs and learning parameters to protect the privacy of vehicles. Lu *et al.* [27] propose a new architecture based on federated learning to relieve the transmission load and protect the privacy of vehicles, where the reliability of the shared data is guaranteed by integrating the learned models into blockchain. To achieve the minimum cost in the worst case of federated learning, Xiao *et al.* [28] develop a min-max optimization problem to jointly optimize the computation capability, transmission power, and local model accuracy. Lim *et al.* [29] propose a contract-matching approach to facilitate federated learning in UAV-enabled vehicular networks. The simulation results validate that the designed approach can guarantee the incentive compatibility of the contract and enhance the efficiency of the matching. By using the private training data of vehicles, Yu *et al.* [30] design a mobility-aware proactive edge caching scheme based on federated learning to predict content popularity. The experimental results demonstrate that the cache hit ratio can be improved with the adoption of the caching scheme. By integrating 6G and vehicular networks, Zhou *et al.* [31] propose a two-layer federated learning model that utilizes the heterogeneous data generated at the network edge to achieve efficient and accurate learning.

Different from the above works, we consider a scenario where multiple TRs request federated learning tasks concurrently in the HetVNets, where a TR needs to compete with other TRs to select the appropriate RU to complete the training task. In addition, we design a DT enabled on-demand matching scheme for multi-task federated learning in the HetVNets.

With the designed scheme, the diversified requirements of the DT-TRs and the differentiated training capabilities of the DT-RUs can be jointly considered to address the two-way selection problem in the DT networks.

B. Matching Theory

Zeng *et al.* [32] develop a cooperative electric vehicle charging and discharging scheme using the proposed optimal matching algorithm. The simulation results show that the designed scheme can improve the quality of experience of the electric vehicle users and enhance the reliability of the power grid. By jointly considering vehicle mobility and energy consumption constraints, Gu *et al.* [33] propose a vehicular task offloading scheme to minimize the average delay. In the scheme, a matching game is formulated to model the interactions between tasks and vehicles. Zhou *et al.* [34] propose a contract-matching scheme to minimize the delay of vehicular edge computing. In this scheme, the task assignment problem is formulated as a two-way matching problem between vehicles and user equipment. Considering the resource management and sharing problem, Yu *et al.* [35] propose a coalition game model based on two-way matching theory to allocate bandwidth and computing resources in vehicular networks. With the designed model, the cloud service providers are incentived to share their idle resources. Dai *et al.* [36] design a vehicle-assisted computing offloading scheme for UAVs in smart city. In the scheme, based on the preference lists of UAVs and vehicles, a matching mechanism is proposed to derive the optimal matching between UAVs and vehicles. By measuring the service abilities of parked vehicles, Huang *et al.* [37] design a matching game approach to model the associations between tasks and parked vehicles. The simulation results demonstrate that the designed scheme can improve the TCR and the utility of computation offloading.

Unlike the above studies, we design a DT enabled on-demand matching scheme for multi-task federated learning in HetVNets. Specifically, we design a DT enabled on-demand matching architecture that integrates the marginal utility based vehicle selection mechanism and the on-demand matching game. With the designed game, the personalized requirement of each DT-TR and the customized model training strategy of each DT-RU in the HetVNets can be jointly considered to form the stable matching pairs.

III. System Model

In this section, we introduce the system model of the DT enabled on-demand matching scheme for multi-task federated learning. The notations used in our paper are summarized in Table I.

A. Task Requesters

As shown in Fig. 1, the TRs in the networks are the task requesters such as vehicles, smart phones, and extended reality (XR) devices. They plan to use the data of the vehicles within the coverage of the RUs to complete model training tasks. In general, different TRs in the networks have different training tasks. In addition, different TRs have different requirements for the training tasks such as training accuracy and training price. Let $\mathbb{I} = \{1, ..., i, ..., I\}$ and $\mathbb{N} = \{1, ..., n, ..., N\}$ denote the sets of the TRs and the model types in the HetVNets. For TR i that intends to complete learning task n, it can select the optimal RU to train the learning model based on its training requirement and the differentiated capabilities of the RUs.

B. Roadside Units

As shown in Fig. 1, the RUs in the HetVNets refer to cellular base stations (CBSs), roadside units (RSUs), and unmanned aerial vehicles (UAVs) [38]. Each RU can use the data cached by the vehicles in its coverage to provide model training services. Let $\mathbb{J} = \{1, ..., j, ..., J\}$ denote the set of the RUs in the networks. In general, the RUs in the HetVNets have different training capabilities. This is because the number of vehicles within the coverage of different RUs is different from each other. Accordingly, the available data cached in the vehicles and the non-IID degree of the cached data have diverse features. In addition, the RUs have different model training experiences. We use the training models that the RU has completed to describe its training experience. Specifically, each RU j maintains two sets, i.e., a historical model set $j_{\mathbb{N}} = \{j_1, ..., j_n, ..., j_N\}$ and a historical model accuracy set $A_{j_{\mathbb{N}}} = \{A_{j_1}, ..., A_{j_n}, ..., A_{j_N}\}$. The minimum value and the maximum value of A_{j_n} are denoted as $A_{j_n}^{\min}$ and $A_{j_n}^{\max}$, respectively. Based on the historical model accuracy A_{j_n}, we can measure the historical experience of RU j. For example, $A_{j_n} > 0$ means that RU j has trained model n in the past. Consequently, RU j can use the historical model j_n as the global model to complete the training process.

C. Vehicles

The vehicles are the trainers of the learning models in the networks. When a vehicle enters or parks in the coverage of a RU, it can connect to the RU through the wireless link to upload its data information [39]–[42]. With the cached data, the vehicle then has a chance to be selected by the RU to join the model training process and obtain profits. Let $\mathbb{K}_j = \{1_j, ..., k_j, ..., K_j\}$ denote the set of vehicles in the coverage of RU j. For vehicle k_j, its data information for model n can be expressed as $\{n, D_{k_j}^n, \sigma_{k_j}^n, C_{k_j}^n\}$, where $D_{k_j}^n$ is the amount of data that can be provided by vehicle k_j, $\sigma_{k_j}^n$ is the average earth mover's distance (EMD) which is used to measure the non-IID degree of data [22], $C_{k_j}^n$ is the price declared by vehicle k_j to train the model, we have

$$C_{k_j}^n = a_{k_j} D_{k_j}^n, \tag{1}$$

where a_{k_j} is the price per unit data.

D. Digital Twins

Digital twin is a technology that can be used to map the states of the entities in the physical networks to the DT networks [43]–[48]. With this technology, the complex decisions can be made in the DT networks to reduce the interaction delay of the physical entities [49]–[51]. In our scheme, the DTs of

TABLE I
SUMMARY OF NOTATIONS

Notations	Description
$\mathbb{I}, \mathbb{J}, \mathbb{I}', \mathbb{J}', \mathbb{N}$	The sets of TRs, RUs, DT-TRs, DT-RUs, and model types.
$\mathbb{K}_j, \mathbb{K}_{j'}$	The sets of vehicles in the coverage of RU j and DT-RU j'.
$j_{\mathbb{N}}, A_{j_{\mathbb{N}}}, j'_{\mathbb{N}}, A_{j'_{\mathbb{N}}}$	The historical model set and the model accuracy set of RU j and DT-RU j'.
$D^n_{k_j}, \sigma^n_{k_j}, C^n_{k_j}, D^n_{k_{j'}}, \sigma^n_{k_{j'}}, C^n_{k_{j'}}$	The amount of data, the average EMD, and the declared price of vehicle k_j and $k_{j'}$.
a_{k_j}	The price per unit data of vehicle k_j.
$C_{i'_n}, A_{i'_n}, R_{i'_n}$	The training price, the minimum model accuracy, and the minimum PCR of DT-TR i'.
$A_{j',i'_n}, R_{j',i'_n}, C_{j',i'_n}$	The training accuracy, the PCR, and the training price declared by DT-RU j' for DT-TR i'.
$A_{j',i'_n}\|_m, A_{j',i'_n}(k_{j'})\|_m$	The training accuracy if the m^{th} vehicle is selected and the training accuracy if the selected m^{th} vehicle is $k_{j'}$.
$R_{j',i'_n}\|_m, R_{j',i'_n}(k_{j'})\|_m$	The PCR if the m^{th} vehicle is selected and the PCR if the selected m^{th} vehicle is $k_{j'}$.
$C_{j',i'_n}\|_m, C_{j',i'_n}(k_{j'})\|_m$	The training price if the m^{th} vehicle is selected and the training price if the selected m^{th} vehicle is $k_{j'}$.
$D_{j',i'_n}, \sigma_{j',i'_n}$	The amount and the average EMD of the training data provided by DT-RU j'.
$\sigma_{j',i'_n}\|_m, \sigma_{j',i'_n}(k_{j'})\|_m$	The average EMD of the training data if the m^{th} vehicle is selected and the average EMD of the training data if the selected m^{th} vehicle is $k_{j'}$.
$D_{j',i'_n}\|_m, D_{j',i'_n}(k_{j'})\|_m$	The amount of the training data if the m^{th} vehicle is selected and the amount of the training data if the selected m^{th} vehicle is $k_{j'}$.
$\mathbb{M}_{j',i'_n}$	The set of the training vehicles selected by DT-RU j' for DT-TR i'.
$\sigma_{j'_n}, D_{j'_n}$	The average EMD and the amount of the data used to quantify historical model j'_n.
$b_{j'}, g_{j'}, h_{j'}$	The price parameters of DT-RU j'.
U_{j',i'_n}	The utility of DT-RU j' to undertake the task requested by DT-TR i'.
$U_{j',i'_n}\|_m, U_{j',i'_n}(k_{j'})\|_m$	The utility of DT-RU j' if the m^{th} vehicle is selected and the utility of DT-RU j' if the selected m^{th} vehicle is $k_{j'}$.
$\Delta U_{j',i'_n}\|_m, \Delta U_{j',i'_n}(k_{j'})\|_m$	The marginal utility if the m^{th} vehicle is selected and the marginal utility if the selected m^{th} vehicle is $k_{j'}$.
$\mathbb{J}'_{i'}, L(\mathbb{J}'_{i'})$	The set of the admissible DT-RUs and the DT-RU preference list of DT-TR i'.
$\mathbb{I}'_{j'}, L(\mathbb{I}'_{j'})$	The set of the admissible DT-TRs and the DT-TR preference list of DT-RU j'.
$\mathbb{E}_{j'}$	The set of the DT-TRs which send matching requests to DT-RU j'.
$\tilde{i}'$	The DT-TR which has the highest ranking in set $\mathbb{E}_{j'}$.
Γ	The set of the optimal TR-RU matching pairs.

the entities (i.e., TRs and RUs) are deployed in the cloud. Let $\mathbb{I}' = \{1', ..., i', ..., I'\}$ and $\mathbb{J}' = \{1', ..., j', ..., J'\}$ denote the sets of the DT-TRs and the DT-RUs, where the DT of TR i and the DT of RU j are denoted as i' and j', respectively. For DT-TR i', it maps the model training requirement of the TR. Similarly, the training capability of RU j is uploaded to its DT-RU j'. If TR i intends to complete a learning task, its DT-TR i' will interact with the DT-RUs in the DT networks based on the requirement of the learning task and the capabilities of the DT-RUs. After that, the optimal DT-RU can be selected by DT-TR i' in the DT networks to facilitate the model training process in the physical networks.

IV. Digital Twin Enabled On-demand Matching Scheme for Multi-task Federated Learning

In this section, we first introduce the DT enabled on-demand matching architecture for multi-task federated learning. Then, based on the personalized requirements of the DT-TRs, we design a marginal utility based vehicle selection mechanism to enable each DT-RU to select the optimal vehicles to customize the task training strategy. After that, we model the interactions between the DT-TRs and the DT-RUs as a two-way selection problem and propose an on-demand matching game to obtain the optimal TR-RU matching pairs.

A. Digital Twins Enabled On-demand Matching Architecture

As shown in Fig. 2, the DT enabled on-demand matching architecture has the following steps.

a) Determine Personalized Requirement: Considering different vehicular applications in the HetVNets, the diversified training requirements of the DT-TRs can be reflected by the following aspects: the type of the model, the accuracy of the requested model, and the price paid for completing the learning task. First, due to the differences in applications, the DT-TRs usually request different training models which means that the DT-TRs have different preferences for the DT-RUs. For example, if DT-TR i' intends to obtain a high accuracy for model type n, the DT-RU with higher historical model accuracy is more likely to be selected. Second, each DT-TR can set its PCR to reflect the minimum accuracy requirement and the maximum acceptable price for its task, where the PCR refers to the ratio of the price to the accuracy. If the PCR provided by DT-RU j' is less than the requirement of DT-TR i', the DT-TR will reject DT-RU j' even though the accuracy requirement of the DT-TR is satisfied. In a nutshell, the personalized requirement of DT-TR i' can be expressed as

$$O_{i'_n} = \{n, A_{i'_n}, R_{i'_n}\}, \tag{2}$$

where $A_{i'_n}$ is the minimum model accuracy requirement of DT-TR i'. $R_{i'_n}$ is the minimum PCR requirement. It can be calculated by

$$R_{i'_n} = \frac{r_{i'_n} A_{i'_n}}{C_{i'_n}}, \tag{3}$$

where $C_{i'_n}$ is the training price that DT-TR i' plans to pay to the selected DT-RU. $r_{i'_n}$ is a factor that varies according to

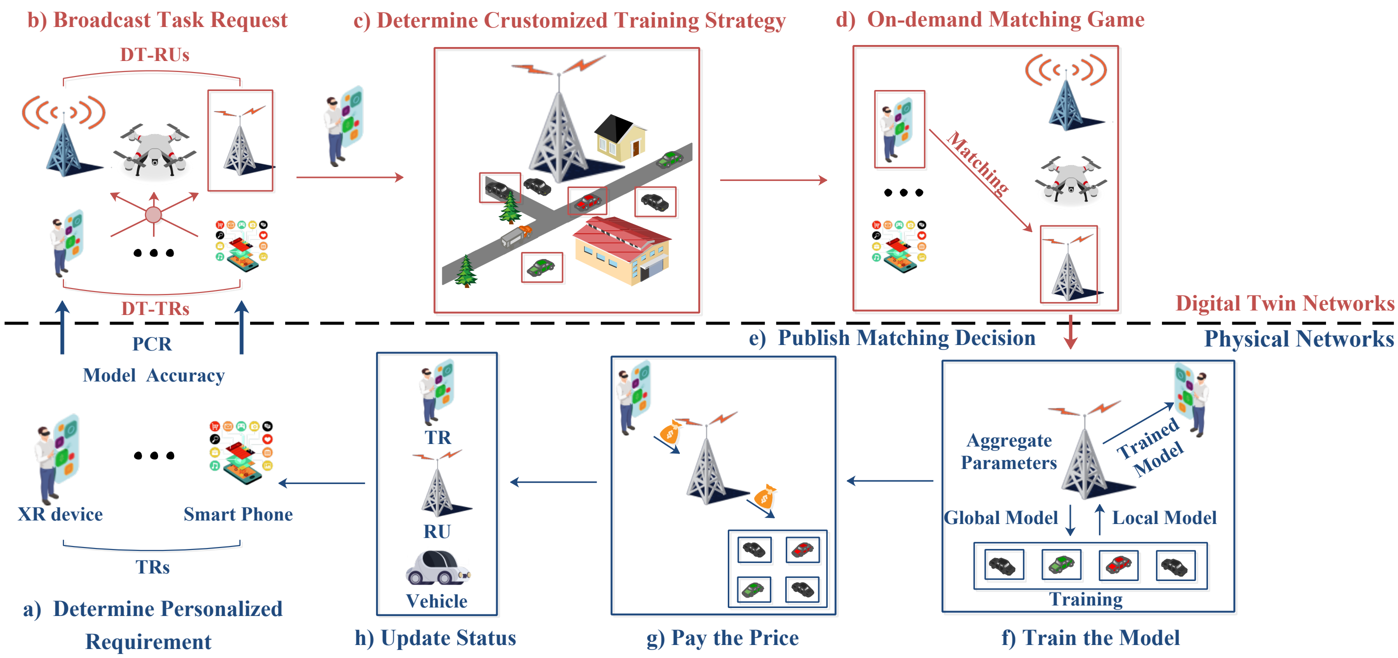

Fig. 2. The digital twins enabled on-demand matching architecture.

the preference of DT-TR i'.

b) Broadcast Task Request: After determining the task requirement, each DT-TR $i'\,(i' \in \mathbb{I}')$ in the DT networks broadcasts its task information $O_{i'_n}$ to all the DT-RUs.

c) Determine Customized Training Strategy: By considering the requirement of DT-TR i', DT-RU j' generates its training strategy S_{j',i'_n} for DT-TR i' based on its training capability. In the HetVNets, the training capability of each DT-RU is related to a number of factors. On the one hand, the differences in the coverage size and geographic location result in different numbers of vehicles and various data available to the DT-RUs. On the other hand, the training experiences of the DT-RUs are different, which means that the historical model parameters are different for different types of learning models. Therefore, based on the above factors, we can model the training capability of DT-RU j' for the learning task requested by DT-TR i'. Specifically, based on the task information $O_{i'_n}$, DT-RU j' retrieves the historical model j'_n and the corresponding accuracy $A_{j'_n}$. Meanwhile, DT-RU j' analyzes the available data information $\{n, D^n_{k_{j'}}, \sigma^n_{k_{j'}}, C^n_{k_{j'}}\}$ of each vehicle $k_{j'}\,(k_{j'} \in \mathbb{K}_{j'})$ within its coverage. Based on the training experience of the DT-RU and the data information of the vehicles, the DT-RU then selects a set of vehicles to execute the learning task. The details of the vehicle selection mechanism will be discussed in Section IV-B. With the designed mechanism, a customized training strategy S_{j',i'_n} for DT-TR i' can be obtained. Specifically, if DT-RU j' does not meet $O_{i'_n}$, we have $S_{j',i'_n} = \{0, 0\}$. Otherwise, we have

$$S_{j',i'_n} = \{A_{j',i'_n}, R_{j',i'_n}\}, \tag{4}$$

where R_{j',i'_n} is the PCR that can be provided by DT-RU j'. A_{j',i'_n} is the expected training accuracy of the learning task that is requested by DT-TR i' and completed by DT-RU j'. It is determined by the amount of training data, the average EMD and the type of the model, we have

$$A_{j',i'_n} = A\left(D_{j',i'_n}, \sigma_{j',i'_n}\right), \tag{5}$$

where D_{j',i'_n} and σ_{j',i'_n} are the amount of data and the average EMD of the training data provided by DT-RU j', respectively. Based on [22], we have

$$A(D_{j',i'_n}, \sigma_{j',i'_n}) = \alpha\left(\sigma_{j',i'_n}\right) - \kappa^n_1 e^{-\kappa^n_2\left(\kappa^n_3 D_{j',i'_n}\right)^{\alpha\left(\sigma_{j',i'_n}\right)}}, \tag{6}$$

where $\alpha\left(\sigma_{j',i'_n}\right) = \kappa^n_4 e^{-\left(\frac{\sigma_{j',i'_n} + \kappa^n_5}{\kappa^n_6}\right)^2} < 1$. $\alpha\left(\sigma_{j',i'_n}\right)$ means that an increase in the average EMD leads to a decrease in the upper limit of the accuracy. $-\kappa^n_1 e^{-\kappa^n_2\left(\kappa^n_3 D_{j',i'_n}\right)^{\alpha\left(\sigma_{j',i'_n}\right)}}$ indicates that the marginal benefit decreases with the increase of the amount of training data. $\kappa^n_1 - \kappa^n_6$ are the parameters that are related to model type n. It means that different learning models have different parameters. These parameters are used to reflect the fact that different learning models may obtain different training accuracies even with the same amount of training data and EMD. Therefore, given each model type n, we can analyze the historical training experiences and calculate the accuracy by substituting the parameters $\kappa^n_1 - \kappa^n_6$ into Equations (5) and (6).

d) On-demand Matching Game: After each DT-RU $j'\,(j' \in \mathbb{J}')$ that meets $O_{i'_n}$ sends its training strategy S_{j',i'_n} to TR $i'\,(i' \in \mathbb{I}')$, the DT-TR needs to select the optimal DT-RU to train the requested model by jointly considering $O_{i'_n}$ and S_{j',i'_n}. At the same time, each DT-RU needs to select the optimal DT-TR to maximize its profits. Therefore, we model the two-way selection process between the DT-TRs and the DT-RUs in the DT networks as an on-demand matching game to obtain the set of the optimal TR-RU matching pairs Γ. The details of the matching game will be discussed in Section IV-C.

e) Publish Matching Decision: The matching result Γ will be delivered from the DT networks to the corresponding TRs and RUs in the physical networks to enable them to execute the learning tasks.

f) Train the Model: If DT-TR i' and DT-RU j' are a matching pair in Γ, RU j will extract the model j_n requested by TR i from the historical model set $j_{\mathbb{N}}$ and distribute j_n as the global model to the selected training vehicles. The set of the selected training vehicles is denoted as $\mathbb{M}_{j',i'_n}$, we have $\mathbb{M}_{j',i'_n} \in \mathbb{K}_{j'}$. After the vehicles in set $\mathbb{M}_{j',i'_n}$ complete a round of training, RU j collects the trained local models and aggregates them to generate a new global model. When the requirement of DT-TR i' is satisfied, the model training result will be delivered from RU j to TR i.

g) Pay the Price: After obtaining the task result, each TR i pays the price C_{j',i'_n} to the matched RU j, where C_{j',i'_n} is the price declared by DT-RU j' in the DT networks. In addition, RU j pays the price $C^n_{k_{j'}}$ to each vehicle $k_{j'}$ $\left(k_{j'} \in \mathbb{M}_{j',i'_n}\right)$.

h) Update Status: Each RU j updates the information (i.e., the training set $j_{\mathbb{N}}$ and the data information owned by the vehicles in its coverage) cached in its DT-RU j', waiting to participate in the next round of matching process.

B. Marginal Utility Based Vehicle Selection Mechanism

1) The Utility of DT-RU: Before introducing the vehicle selection mechanism, we first define the utility of each DT-RU. For each DT-RU j' $(j' \in \mathbb{J}')$, the training price increases with the increase of the training accuracy A_{j',i'_n} and decreases with the increase of the historical training accuracy $A_{j'_n}$. Therefore, the price declared by DT-RU j' for DT-TR i' can be given by

$$C_{j',i'_n} = b_{j'}\left(e^{-g_{j'}A_{j'_n}+h_{j'}A_{j',i'_n}} - 1\right), \tag{7}$$

where $b_{j'}$, $g_{j'}$, and $h_{j'}$ are the price parameters. Based on (7), the utility of DT-RU j' can be given by

$$\begin{aligned} U_{j',i'_n} &= C_{j',i'_n} - \sum_{k_{j'} \in \mathbb{M}_{j',i'_n}} C^n_{k_{j'}} \\ &= b_{j'}\left(e^{-g_{j'}A_{j'_n}+h_{j'}A_{j',i'_n}} - 1\right) - \sum_{k_{j'} \in \mathbb{M}_{j',i'_n}} C^n_{k_{j'}}, \end{aligned} \tag{8}$$

where $\sum_{k_{j'} \in \mathbb{M}_{j',i'_n}} C^n_{k_{j'}}$ is the price paid by DT-RU j' to the selected training vehicles.

2) Marginal Utility based Vehicle Selection: According to $O_{i'_n}$, each DT-RU j' needs to select a set of vehicles $\mathbb{M}_{j',i'_n}$ within its coverage to complete the learning task with the target of maximizing its utility. To this end, we design the marginal utility based vehicle selection mechanism to enable DT-RU j' to select the optimal vehicles. We first discuss the case where DT-RU j' selects the $m^{th}\,(m=1)$ vehicle and then describes the case where DT-RU j' selects the $m^{th}\,(1 < m \le K_{j'})$ vehicle. After that, we present the termination conditions of the designed mechanism. Based on the designed mechanism, a marginal utility based vehicle selection algorithm is proposed to obtain the customized training strategy S_{j',i'_n} for DT-TR i'.

a) Select the $m^{th}\,(m=1)$ Vehicle: When DT-RU j' does not select any vehicle, we have $A_{j',i'_n}|_0 = A_{j'_n}$ and $\mathbb{M}_{j',i'_n} = \emptyset$. Based on (8), the initial utility of DT-RU j' can be expressed as

$$\begin{aligned} U_{j',i'_n}|_0 &= C_{j',i'_n}|_0 - 0 \\ &= b_{j'}\left(e^{\left(-g_{j'}+h_{j'}\right)A_{j'_n}} - 1\right). \end{aligned} \tag{9}$$

Then DT-RU j' considers $O_{i'_n}$ to select the first vehicle for DT-TR i' from set $\mathbb{K}_{j'}$. If vehicle $k_{j'}$ with training data of model n is selected by DT-RU j', the marginal utility obtained by DT-RU j' in the first round can be expressed as

$$\begin{aligned} \Delta U_{j',i'_n}\left(k_{j'}\right)|_1 &= U_{j',i'_n}\left(k_{j'}\right)|_1 - U_{j',i'_n}|_0 \\ &= b_{j'}e^{-g_{j'}A_{j'_n}+h_{j'}A_{j',i'_n}\left(k_{j'}\right)|_1} - C^n_{k_{j'}} \\ &\quad - b_{j'}e^{\left(-g_{j'}+h_{j'}\right)A_{j'_n}}, \end{aligned} \tag{10}$$

where $A_{j',i'_n}\left(k_{j'}\right)|_1$ is the accuracy of the model which is trained by vehicle $k_{j'}$. For ease of calculation, we quantify the impact of the historical model j'_n as training data. Based on (6), the average EMD of the data and the amount of the data can be given by

$$\begin{cases} \sigma_{j'_n} = \kappa^n_7 / A_{j'_n}, \\ D_{j'_n} = \dfrac{e^{\ln\left(-\ln\frac{\alpha\left(\sigma_{j'_n}\right)-A_{j'_n}}{k^n_1}/k^n_2\right)/\alpha\left(\sigma_{j'_n}\right)}}{k^n_3}, \end{cases} \tag{11}$$

where κ^n_7 is a control parameter.

By substituting $\sigma_{j'_n}$, $D_{j'_n}$ and the data information $\{n, D^n_{k_{j'}}, \sigma^n_{k_{j'}}, C^n_{k_{j'}}\}$ of vehicle $k_{j'}$ into (5), $A_{j',i'_n}\left(k_{j'}\right)|_1$ in (10) can be given by

$$A_{j',i'_n}\left(k_{j'}\right)|_1 = A\left(D_{j',i'_n}\left(k_{j'}\right)|_1, \sigma_{j',i'_n}\left(k_{j'}\right)|_1\right), \tag{12}$$

where

$$\begin{cases} D_{j',i'_n}\left(k_{j'}\right)|_1 = D^n_{k_{j'}} + D_{j'_n}, \\ \sigma_{j',i'_n}\left(k_{j'}\right)|_1 = \dfrac{\sigma^n_{k_{j'}}D^n_{k_{j'}} + \sigma_{j'_n}D_{j'_n}}{D_{j',i'_n}\left(k_{j'}\right)|_1}. \end{cases} \tag{13}$$

After obtaining $\Delta U_{j',i'_n}\left(k_{j'}\right)|_1$ of each $k_{j'}$ $(k_{j'} \in \mathbb{K}_{j'})$, the first vehicle $k^*_{j'}|_1$ for DT-RU j' can be selected by

$$k^*_{j'}|_1 = \arg\max_{k_{j'}}\{\Delta U_{j',i'_n}\left(k_{j'}\right)|_1 > 0, \forall\ k_{j'} \in \mathbb{K}_{j'}\}. \tag{14}$$

Here, $\Delta U_{j',i'_n}\left(k_{j'}\right)|_1 > 0$ means that DT-RU j' will obtain positive profits by selecting vehicle $k_{j'}$ as the first training vehicle. In contrast, the case where $\Delta U_{j',i'_n}\left(k_{j'}\right)|_1 = 0$ or $\Delta U_{j',i'_n}\left(k_{j'}\right)|_1 < 0$ is discussed as a termination condition in Section IV-B, which means that DT-RU j' will not obtain positive profits when vehicle $k_{j'}$ is selected as the first training vehicle. In this case, DT-RU j' will terminate the vehicle selection process.

After selecting the first vehicle, the selected vehicle $k^*_{j'}|_1$ will be removed from set $\mathbb{K}_{j'}$ and added to set $\mathbb{M}_{j',i'_n}$. Based on the selected vehicle in the first round, the model accuracy and the utility of DT-RU j' then can be updated. We have

$$\begin{cases} A_{j',i'_n}|_1 = A\left(D_{j',i'_n}|_1, \sigma_{j',i'_n}|_1\right), \\ U_{j',i'_n}|_1 = b_{j'}\left(e^{-g_{j'}A_{j'_n}+h_{j'}A_{j',i'_n}|_1} - 1\right) - C^n_{k^*_{j'}|_1}, \end{cases} \tag{15}$$

where

$$\begin{cases} D_{j',i'_n}|_1 = D^n_{k^*_{j'}|_1} + D_{j'_n}, \\ \sigma_{j',i'_n}|_1 = \dfrac{\sigma^n_{k^*_{j'}|_1} D^n_{k^*_{j'}|_1} + \sigma_{j'_n} D_{j'_n}}{D_{j',i'_n}|_1}. \end{cases} \tag{16}$$

b) Select the $m^{th}\,(1 < m \le K_{j'})$ Vehicle: When selecting the $m^{th}\,(1 < m \le K_{j'})$ vehicle, DT-RU j' has determined the parameters including $\mathbb{M}_{j',i'_n}$, $\sigma_{j',i'_n}|_{m-1}$, $D_{j',i'_n}|_{m-1}$ and $A_{j',i'_n}|_{m-1}$. Thus, the marginal utility offered by $k_{j'}\,(k_{j'} \in \mathbb{K}_{j'})$ in the $m^{th}\,(1 < m \le K_{j'})$ round can be given by

$$\begin{aligned} \Delta U_{j',i'_n}(k_{j'})|_m &= U_{j',i'_n}(k_{j'})|_m - U_{j',i'_n}|_{m-1} \\ &= b_{j'} e^{-g_{j'} A_{j'_n} + h_{j'} A_{j',i'_n}(k_{j'})|_m} - C^n_{k_{j'}} \\ &\quad - b_{j'} e^{-g_{j'} A_{j'_n} + h_{j'} A_{j',i'_n}|_{m-1}}. \end{aligned} \tag{17}$$

Similar to (12), we have

$$A_{j',i'_n}(k_{j'})|_m = A\left(D_{j',i'_n}(k_{j'})|_m, \sigma_{j',i'_n}(k_{j'})|_m\right), \tag{18}$$

where

$$\begin{cases} D_{j',i'_n}(k_{j'})|_m = D^n_{k_{j'}} + D_{j',i'_n}|_{m-1}, \\ \sigma_{j',i'_n}(k_{j'})|_m = \dfrac{\sigma^n_{k_{j'}} D^n_{k_{j'}} + \sigma_{j',i'_n}|_{m-1} D_{j',i'_n}|_{m-1}}{D_{j',i'_n}(k_{j'})|_m}. \end{cases} \tag{19}$$

Thus, based on (14), the $m^{th}(1 < m \le K_{j'})$ vehicle $k^*_{j'}|_m$ for DT-RU j' can be selected by

$$k^*_{j'}|_m = \arg\max_{k_{j'}} \{\Delta U_{j',i'_n}(k_{j'})|_m > 0, \forall\, k_{j'} \in \mathbb{K}_{j'}\}. \tag{20}$$

In addition, the selected vehicle $k^*_{j'}|_m$ will be added to $\mathbb{M}_{j',i'_n}$ and removed from $\mathbb{K}_{j'}$. After selecting the $m^{th}(1 < m \le K_{j'})$ vehicle, the parameters can be updated by

$$\begin{cases} A_{j',i'_n}|_m = A\left(D_{j',i'_n}|_m, \sigma_{j',i'_n}|_m\right), \\ U_{j',i'_n}|_m = b_{j'}\left(e^{-g_{j'} A_{j'_n} + h_{j'} A_{j',i'_n}|_m} - 1\right) \\ \qquad - \displaystyle\sum_{k_{j'} \in \mathbb{M}_{j',i'_n}} C^n_{k_{j'}}, \end{cases} \tag{21}$$

where

$$\begin{cases} D_{j',i'_n}|_m = D^n_{k^*_{j'}|_m} + D_{j',i'_n}|_{m-1}, \\ \sigma_{j',i'_n}|_m \\ = \dfrac{\sigma^n_{k^*_{j'}|_m} D^n_{k^*_{j'}|_m} + \sigma_{j',i'_n}|_{m-1} D_{j',i'_n}|_{m-1}}{D_{j',i'_n}|_m}. \end{cases} \tag{22}$$

c) Termination Conditions: Once the $m^{th}(1 \le m \le K_{j'})$ vehicle is selected, DT-RU j' needs to calculate $R_{j',i'_n}|_m$, shown as

$$R_{j',i'_n}|_m = r_{i'_n} \frac{A_{j',i'_n}|_m}{C_{j',i'_n}|_m}, \tag{23}$$

where

$$C_{j',i'_n}|_m = b_{j'}\left(e^{-g_{j'} A_{j'_n} + h_{j'} A_{j',i'_n}|_m} - 1\right). \tag{24}$$

Considering the marginal utility of DT-RU j' and the task requirement $O_{i'_n} = \{n, A_{i'_n}, R_{i'_n}\}$ of DT-TR i', the termination conditions can be set as follows.

Algorithm 1 The Vehicle Selection Algorithm

1: **Input:** $\mathbb{K}_{j'}, O_{i'_n}, A_{j'_n}, \mathbb{M}_{j',i'_n} = \emptyset$, $m = 1$
2: $A_{j',i'_n}|_0 = A_{j'_n}$
3: Calculate $R_{j',i'_n}|_0$ using (23)
4: Calculate $U_{j',i'_n}|_0$ using (9)
5: **for** $\forall\, k_{j'} \in \mathbb{K}_{j'}$ **do**
6:   **if** $D^n_{k_{j'}} = 0$ **then**
7:     $\mathbb{K}_{j'} \leftarrow \mathbb{K}_{j'}/k_{j'}$
8:   **end if**
9: **end for**
10: **while** $m \le K_{j'}$ **do**
11:   **if** $m = 1$ **then**
12:     **if** $\Delta U_{j',i'_n}(k_{j'})|_m \le 0, \forall\, k_{j'} \in \mathbb{K}_{j'}$ **then**
13:       Jump to line 43
14:     **else**
15:       Determine $k^*_{j'}|_m$ using (14)
16:       Calculate $A_{j',i'_n}|_m$ using (15)
17:       Calculate $R_{j',i'_n}|_m$ using (23)
18:       $\mathbb{M}_{j',i'_n} \leftarrow k^*_{j'}|_m$, $\mathbb{K}_{j'} \leftarrow \mathbb{K}_{j'}/k^*_{j'}|_m$
19:     **end if**
20:   **else**
21:     **if** $\Delta U_{j',i'_n}(k_{j'})|_m \le 0, \forall\, k_{j'} \in \mathbb{K}_{j'}$ **then**
22:       Jump to line 43
23:     **else**
24:       Determine $k^*_{j'}|_m$ using (20)
25:       Calculate $A_{j',i'_n}|_m$ using (21)
26:       Calculate $R_{j',i'_n}|_m$ using (23)
27:       $\mathbb{M}_{j',i'_n} \leftarrow k^*_{j'}|_m$, $\mathbb{K}_{j'} \leftarrow \mathbb{K}_{j'}/k^*_{j'}|_m$
28:     **end if**
29:   **end if**
30:   **if** $R_{j',i'_n}|_m \ge R_{i'_n}$ **then**
31:     **if** $m < K_{j'}$ **then**
32:       $m = m + 1$
33:       Jump to line 11
34:     **else**
35:       **if** $A_{j',i'_n}|_m \ge A_{i'_n}$ **then**
36:         $S_{j',i'_n} = \{A_{j',i'_n}|_m, R_{j',i'_n}|_m\}$
37:       **else**
38:         $S_{j',i'_n} = \{0, 0\}$, $\mathbb{M}_{j',i'_n} = \emptyset$
39:       **end if**
40:       break
41:     **end if**
42:   **else**
43:     **if** $A_{j',i'_n}|_{m-1} \ge A_{i'_n}$ **then**
44:       $S_{j',i'_n} = \{A_{j',i'_n}|_{m-1}, R_{j',i'_n}|_{m-1}\}$
45:     **else**
46:       $S_{j',i'_n} = \{0, 0\}$, $\mathbb{M}_{j',i'_n} = \emptyset$
47:     **end if**
48:     break
49:   **end if**
50: **end while**
51: **Output:** The customized training strategy S_{j',i'_n} and the optimal set of training vehicles $\mathbb{M}_{j',i'_n}$

- PCR: If $R_{j',i'_n}|_m < R_{i'_n}$, DT-RU j' will terminate the vehicle selection process. In this case, if $A_{j',i'_n}|_{m-1} \ge A_{i'_n}$, DT-RU j' will output $S_{j',i'_n} = \{A_{j',i'_n}|_{m-1}, R_{j',i'_n}|_{m-1}\}$ and $\mathbb{M}_{j',i'_n}$. Otherwise, the strategy of DT-RU j' is $S_{j',i'_n} = \{0, 0\}$ and we have $\mathbb{M}_{j',i'_n} = \emptyset$.

- Marginal Utility: If $\Delta U_{j',i'_n}(k_{j'})|_m \leq 0$, $\forall\ k_{j'} \in \mathbb{K}_{j'}$, DT-RU j' will terminate the vehicle selection process. Futhermore, if $A_{j',i'_n}|_{m-1} \geq A_{i'_n}$, DT-RU j' will output $S_{j',i'_n} = \{A_{j',i'_n}|_{m-1}, R_{j',i'_n}|_{m-1}\}$ and $\mathbb{M}_{j',i'_n}$. Otherwise, the strategy of DT-RU j' is $S_{j',i'_n} = \{0, 0\}$ and we have $\mathbb{M}_{j',i'_n} = \emptyset$.
- Number of Vehicles: If all the vehicles in set $\mathbb{K}_{j'}$ are selected, the vehicle selection process will end. In this case, we need to further check the accuracy condition. Namely, if $A_{j',i'_n}|_m \geq A_{i'_n}$, DT-RU j' will output $S_{j',i'_n} = \{A_{j',i'_n}|_m, R_{j',i'_n}|_m\}$ and $\mathbb{M}_{j',i'_n}$. Otherwise, we have $S_{j',i'_n} = \{0, 0\}$ and $\mathbb{M}_{j',i'_n} = \emptyset$.

d) Vehicle Selection Algorithm: Based on the above steps, we design the vehicle selection algorithm as shown in Algorithm 1. In the algorithm, lines 5-9 delete the vehicles that do not have the requested data, lines 11-29 aim to select the optimal vehicles and update the parameters, and lines 30-49 illustrate the termination conditions.

C. On-demand Matching Game

In the DT networks, each DT-TR needs to select a DT-RU to complete the learning task. For each DT-TR i', its admissible DT-RUs in set $\mathbb{J}'$ can be given by

$$\mathbb{J}'_{i'} = \{j' : j' \in \mathbb{J}', S_{j',i'_n} \neq \{0, 0\}\}. \tag{25}$$

Similarly, the set of the admissible DT-TRs in set $\mathbb{I}'$ of each DT-RU j' can be expressed as

$$\mathbb{I}'_{j'} = \{i' : i' \in \mathbb{I}', S_{j',i'_n} \neq \{0, 0\}\}. \tag{26}$$

Based on (25) and (26), the DT-TRs and DT-RUs then can determine their matching preference lists. Specifically, each DT-TR i' generates its DT-RU preference list $L(\mathbb{J}'_{i'})$ based on the descending order of R_{j',i'_n}. Meanwhile, each DT-RU j' generates its DT-TR preference list $L(\mathbb{I}'_{j'})$ based on the descending order of U_{j',i'_n}. After establishing the preference lists, the DT-TRs and DT-RUs start matching to generate the set of the optimal TR-RU pairs Γ.

Definition 1(Stable Matching): Given the set of the optimal TR-RU pairs Γ, if DT-TR i' and DT-RU j' in Γ are not a matching pair and they do not satisfy

$$\begin{cases} R_{j',i'_n} > R_{j'^*,i'_n}, \\ U_{j',i'_n} > U_{j',i'^*_n}, \end{cases} \tag{27}$$

Γ is considered to be stable. In (27), DT-TR i' and DT-RU j'^*, DT-TR i'^* and DT-RU j' are two TR-RU pairs in Γ.

Based on the definition of stable matching, we then detail the steps of the on-demand matching game. *a) Decide Training Strategy:* After receiving $O_{i'_n}$ from each DT-TR $i'(i' \in \mathbb{I}')$, each DT-RU $j'(j' \in \mathbb{J}')$ that meets the requirement decides the training strategy $S_{j',i'_n} = \{A_{j',i'_n}, R_{j',i'_n}\}$ and sends it to DT-TR i'.

b) Generate DT-RU Preference List: Each DT-TR $i'(i' \in \mathbb{I}')$ determines $\mathbb{J}'_{i'}$ based on (25). With the determined $\mathbb{J}'_{i'}$, DT-TR i' generates the DT-RU preference list $L(\mathbb{J}'_{i'})$ based on the descending order of R_{j',i'_n}.

Algorithm 2 **The On-demand Matching Algorithm**

Input: $\mathbb{I}' = \{1', ..., i', ..., I'\}, \mathbb{J}' = \{1', ..., j', ..., J'\}$
//The DT-TR $i'(i' \in \mathbb{I}')$ generates DT-RU preference list
for $\forall$ DT-TR $i'(i' \in \mathbb{I}')$ **do**
  Calculate $\mathbb{J}'_{i'}$ using (25)
  Generate DT-RU preference list $L(\mathbb{J}'_{i'})$ in descending order of R_{j',i'_n}
end for
//The DT-RU $j'(j' \in \mathbb{J}')$ generates DT-TR preference list
for $\forall$ DT-TR $j'(j' \in \mathbb{J}')$ **do**
  Calculate $\mathbb{I}'_{j'}$ using (26)
  Generate DT-TR preference list $L(\mathbb{I}'_{j'})$ in descending order of U_{j',i'_n}
end for
//On-demand matching process
$\Gamma = \emptyset$
while $\exists$ unmatched DT-TR $i'(i' \in \mathbb{I}')$ and $L(\mathbb{J}'_{i'}) \neq \emptyset$ **do**
  for unmatched DT-TR $i'(i' \in \mathbb{I}')$ **do**
    Send matching request to the first DT-RU in $L(\mathbb{J}'_{i'})$
    Remove the first DT-RU in $L(\mathbb{J}'_{i'})$
  end for
  for $\forall$ DT-TR $j'(j' \in \mathbb{J}')$ **do**
    Determine DT-TR $\widetilde{i'}$ using (28)
    if DT-RU j' has matched DT-TR i' **then**
      Compare the ranking of DT-TR $\widetilde{i'}$ and DT-TR i' in $L(\mathbb{I}'_{j'})$
      Select the DT-TR with the higher ranking to form a TR-RU matching pair
      Add the matching pair to Γ
    else
      DT-TR j' matches DT-TR $\widetilde{i'}$
      Add the matching pair to Γ
    end if
  end for
end while
Output: The set of the optimal matching pairs Γ

c) Generate DT-TR Preference List: Each DT-RU $j'(j' \in \mathbb{J}')$ determines $\mathbb{I}'_{j'}$ based on (26). With the determined $\mathbb{I}'_{j'}$, DT-RU j' generates the DT-TR preference list $L(\mathbb{I}'_{j'})$ based on the descending order of U_{j',i'_n}.

d) Match the DT-TRs and the DT-RUs: DT-TR $i'(i' \in \mathbb{I}')$ and DT-RU $j'(j' \in \mathbb{J}')$ start to match with each other based on their preference lists. Specifically, for each unmatched DT-TR $i'(i' \in \mathbb{I}')$, it will keep selecting the first DT-RU in $L(\mathbb{J}'_{i'})$ to send matching request and remove the DT-RU in $L(\mathbb{J}'_{i'})$. If the match fails, DT-TR i' will continue to match the new first DT-RU in its preference list. When the preference list is empty, DT-TR i' will stop matching. Let $\mathbb{E}_{j'}$ denote the set of the DT-TRs which send matching requests to DT-RU $j'(j' \in \mathbb{J}')$. In set $\mathbb{E}_{j'}$, the DT-TR $\widetilde{i'}$ which has the highest

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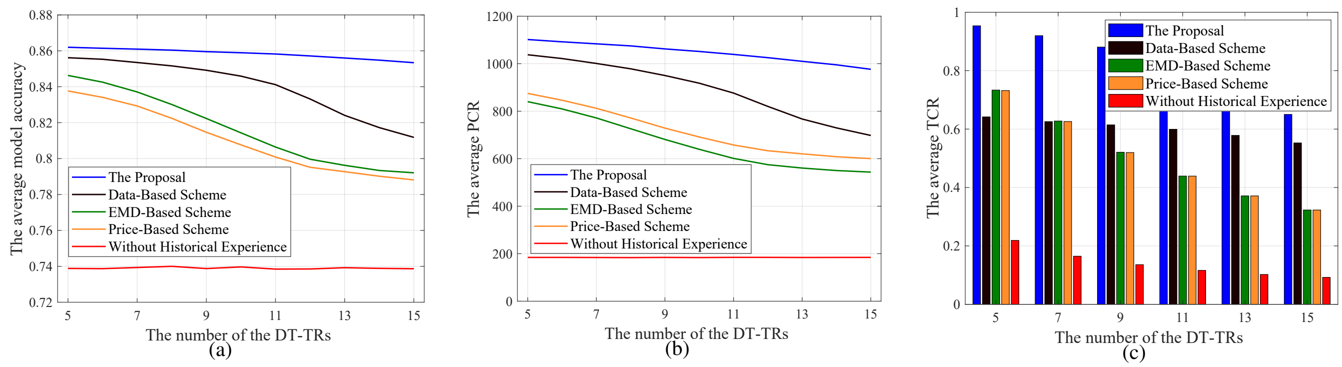

Fig. 3. (a) The average model accuracy by changing the number of the DT-TRs; (b) The average PCR by changing the number of the DT-TRs; (c) The average TCR by changing the number of the DT-TRs.

ranking in $L\left(\mathbb{I}'_{j'}\right)$ can be selected by

$$\widetilde{i'} = \arg\max_{i'} \{U_{j',i'_n}, \forall\ i' \in \mathbb{E}_{j'}\}. \tag{28}$$

For DT-RU j', if it is unmatched, it will match with DT-TR $\widetilde{i'}$. In contrast, if it has already matched with DT-TR i', it will compare the ranking of DT-TR $\widetilde{i'}$ and DT-TR i' and select the one with the higher ranking to form the matching pair.

Based on the above discussion, we summarize the on-demand matching process in Algorithm 2. By using this algorithm, the set of the optimal matching pairs Γ will be determined to enable as many DT-TRs as possible to select their optimal DT-RUs.

Theorem 1: For the on-demand matching game, the set Γ constitutes a stable matching.

Proof: To prove this theorem, we assume that DT-TR i' in Γ prefers DT-RU j', but matches DT-RU j'^{*}, i.e., $R_{j',i'_n} > R_{j'^{*},i'_n}$. This result means that DT-RU j' rejects DT-TR i' in the matching process. This rejection indicates that DT-RU j' has matched DT-TR i'^{*} which brings more utility to DT-RU j' than DT-TR i', i.e. $U_{j',i'_n} \leq U_{j',i'^{*}_n}$. However, as mentioned in Definition 1, the unstable conditions are $R_{j',i'_n} > R_{j'^{*},i'_n}$ and $U_{j',i'_n} > U_{j',i'^{*}_n}$. Therefore, there is no instability in Γ and Γ is considered to be a stable matching. The theorem is proved.

V. Performance Evaluation

In this section, we evaluate the performance of the proposed DT enabled on-demand matching scheme for multi-task federated learning in HetVNets. We first introduce the simulation scenario, followed by the simulation results.

A. Simulation Scenario

In the simulation, we consider a multi-TR and multi-RU scenario, where the DT-TRs have the model training requests and the DT-RUs have the training resources. Specifically, the number of both the DT-TRs and the DT-RUs in the networks ranges from 5 to 15. For each DT-TR, the required minimum model accuracy and PCR are randomly selected from [0.7, 1] and [100, 500], respectively. The number of the task types that can be requested by the DT-TRs is set to 10. In the coverage of each DT-RU, the number of vehicles is randomly selected from [10, 20]. The value of $A_{j_n}^{\min}$ is 0.3. In cantrast, $A_{j_n}^{\max}$ varies from 0.5 to 0.95 for simulation. For each vehicle, the amount of available training data for each task type lies in [0, 15]. The values of κ_1^n-κ_6^n are the same as [22].

With this scenario, we evaluate the average model accuracy, the PCR, and the TCR by changing different parameters (i.e., the number of the DT-TRs, the number of the DT-RUs, and the maximum historical model accuracy owned by each DT-RU). The schemes used in the simulations are detailed as follows.

- The Proposal: In our proposal, each DT-RU uses Algorithm 1 to select the training vehicles to customize the training strategy for each DT-TR. In addition, the DT-TRs and the DT-RUs are matched by using Algorithm 2.
- Data-based Scheme: Each DT-RU selects the training vehicles to determine the training strategy for each DT-TR by considering the amount of data and the historical training experience.
- EMD-based Scheme: Each DT-RU selects the training vehicles to determine the training strategy for each DT-TR by considering the non-IID degree of data (i.e., EMD) and the historical training experience.
- Price-based Scheme: Each DT-RU selects the training vehicles to determine the training strategy for each DT-TR by considering the training price and the historical training experience.
- Without Historical Experience: Each DT-RU selects the training vehicles to determine the training strategy for each DT-TR by considering the amount of data, the non-IID degree of data (i.e., EMD) and the training price.

B. Simulation Results

Fig. 3(a) illustrates the average model accuracy of the DT-TRs by changing the number of the DT-TRs in the networks. From Fig. 3(a), it can be seen that the average model accuracy of the DT-TRs decreases with the increase of the number of the DT-TRs in the schemes that consider the historical training experience. This is because an increase in the number of the DT-TRs will intensify the competition among the DT-TRs. As a result, some DT-TRs can not be matched to the DT-RUs with the most historical training experience, thus reducing the average model accuracy of the DT-TRs. In addition, we can see that the proposal can lead to the highest model accuracy

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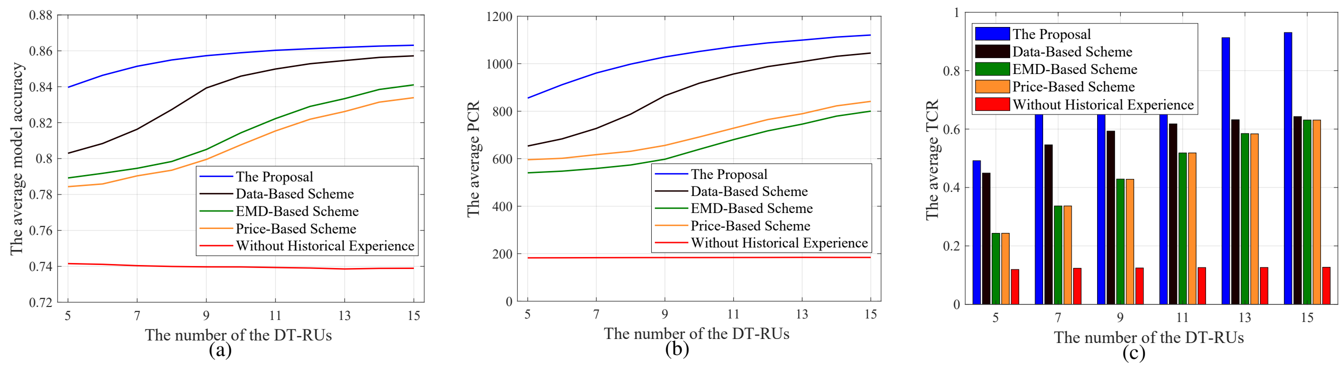

Fig. 4. (a) The average model accuracy by changing the number of the DT-RUs; (b) The average PCR by changing the number of the DT-RUs; (c) The average TCR by changing the number of the DT-RUs.

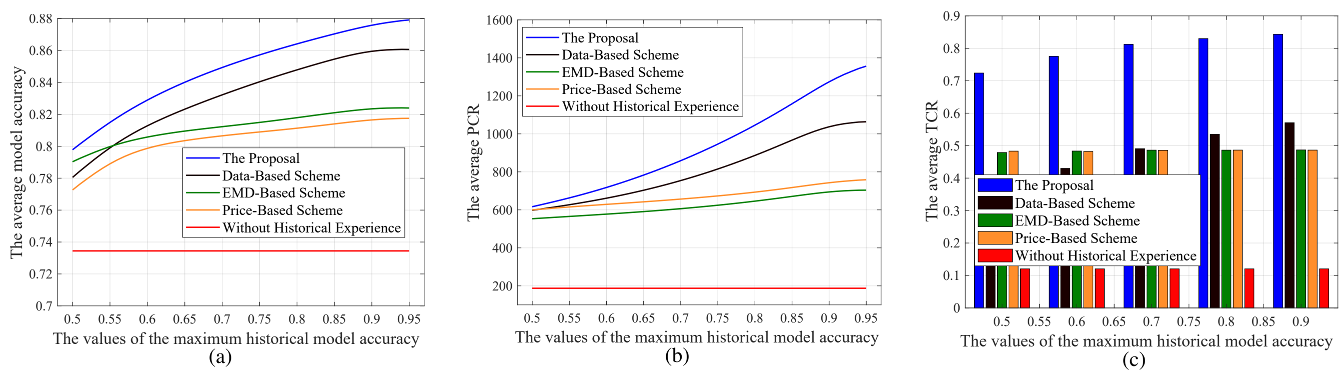

Fig. 5. (a) The average model accuracy by changing the values of the maximum historical model accuracy; (b) The average PCR by changing the values of the maximum historical model accuracy; (c) The average TCR by changing the values of the maximum historical model accuracy.

compared to the conventional schemes. The reasons are as follows. First, the proposal jointly considers the historical training experience of each DT-RU and the non-IID degree of the data owned by the vehicles. Second, in our scheme, the efficient vehicle selection algorithm allows each DT-RU to select the optimal vehicles to train the learning model.

Fig. 3(b) shows the average PCR of the DT-TRs by changing the number of the DT-TRs in the networks. Similar to Fig. 3(a), the average PCR of the DT-TRs decreases with the increase of the number of the DT-TRs in the schemes that consider the historical experience. This is mainly due to the proportional relationship between the PCR and the model training accuracy. By comparing Fig. 3(a) and Fig. 3(b), we can see that the model accuracy in the EMD-based scheme is higher than that of the price-based scheme while the PCR in the EMD-based scheme is lower than that of the price-based scheme. This is because in the price-based scheme, the DT-RUs with low bids will be selected to complete model training tasks at the cost of reducing accuracy.

Fig. 3(c) depicts the average TCR by changing the number of the DT-TRs in the networks. Form this figure, we can see that the average TCR decreases with the increase of the number of the DT-TRs. The reason for this is that the number of the DT-RUs remains constant in this simulation. Therefore, the increase in the number of the DT-TRs in the networks will make some DT-TRs unable to match the DT-RUs, thereby reducing the TCR between the DT-TRs and the DT-RUs. In addition, compared to the conventional schemes, it can be seen from this figure that the proposal can lead to the highest TCR to facilitate the federated learning tasks in the HetVNets.

Fig. 4(a) shows the average model accuracy of the DT-TRs by changing the number of the DT-RUs in the networks. From this figure, we can see that the average model accuracy of the DT-TRs increases with the increase of the number of the DT-RUs. The reasons are as follows. First, with the increase of the number of the DT-RUs, the number of the candidate DT-RUs that can be selected by each DT-TR to complete the training task is increased. Second, the probability that there are the DT-RUs with more training experience increases with the increase of the number of the DT-RUs. Furthermore, it can be seen from this figure that the proposal can obtain a higher model accuracy than the conventional schemes.

Fig. 4(b) depicts the average PCR of the DT-TRs by changing the number of the DT-RUs in the networks. It can be seen that the change trend of the curves in Fig. 4(b) is basically the same as that in Fig. 4(a), where the proposal can lead to the highest PCR for the DT-TRs. In addition, we can see from this figure that the increase in the number of the DT-RUs hardly affects the scheme without historical experience. In addition, the scheme without historical experience obtains the lowest average PCR. This is because the fact that the bids of the DT-RUs for new training model will be high if they do not have model training experience.

Fig. 4(c) illustrates the average TCR by changing the number of the DT-RUs in the networks. As can be seen from the figure, our scheme can bring the highest TCR to facilitate the transactions between the DT-TRs and the DT-RUs. Furthermore, the number of the matched pairs between the DT-TRs and the DT-RUs gradually increases with the increase of the number of the DT-RUs. In comparison, the scheme without historical experience leads to the lowest TCR. This is mainly because the model accuracy and the PCR provided by this scheme may not meet the personalized requirements of the DT-TRs.

Fig. 5(a) depicts the average model accuracy of the DT-TRs by changing the values of the maximum historical model accuracy. Compared with the scheme without training experience, we can see from this figure that the average training accuracy of other schemes increases with the increase of the maximum historical model accuracy. Furthermore, our scheme can bring the highest model training accuracy for the DT-TRs in the networks. This is because the personalized training requirements of the DT-TRs and the customized training strategies of the DT-RUs are comprehensively considered in our scheme to provide them with the optimal matching pairs.

Fig. 5(b) illustrates the average PCR by changing the values of the maximum historical model accuracy. Similar to Fig. 5(a), it can be seen from Fig. 5(b) that the proposal can lead to the highest PCR compared with the conventional schemes. This is due to the fact that the PCR is affected by many factors, such as the amount and the EMD of the data, the historical training experience, and the price paid for the training services. By jointly considering these factors, our scheme designs the personalized requirements of the DT-TRs to obtain the customized training strategies of the DT-RUs, where the optimal matching pairs can be determined to optimize the PCR.

Fig. 5(c) shows the average TCR by changing the values of the maximum historical model accuracy. From this figure, we can see that the TCR obtained by our scheme is consistently higher than 0.7. Furthermore, the TCR in our scheme gradually increases with the increase of the value of the maximum historical model accuracy. The reasons are as follows. First, it can be seen from Fig. 5(a) and Fig. 5(b) that our scheme can obtain the highest model training accuracy and the highest PCR, respectively. Second, with the increase of the value of the maximum historical model accuracy, the number of the DT-RUs that meet the personalized requirements of the DT-TRs increases so that the TCR can be significantly improved.

VI. Conclusion

In this paper, by considering the scenario of multi-TR and multi-RU, we have proposed a DT enabled on-demand matching scheme for multi-task federated learning in HetVNets. Specifically, we have designed a DT enabled on-demand matching architecture, where the DT-TRs and the DT-RUs can interact with each other to complete the model training tasks in the DT networks. Based on the designed architecture, we have proposed the marginal utility based vehicle selection mechanism to enable each DT-RU to select the optimal vehicles and customize the model training strategy for each DT-TR. After that, we have jointly considered the personalized requirements of the DT-TRs and the customized training strategies of the DT-RUs and formulated the two-way selection problem between them as the on-demand matching game, where the matching algorithm has been designed to obtain their optimal strategies. The simulation results have demonstrated that the proposed scheme can obtain the highest training accuracy, PCR, and TCR.

For future work, we plan to integrate the proposed scheme with blockchain, where the transactions between the DT-TRs and the DT-RUs can be recorded on the blockchain to guarantee the utilities of the participants. In addition, based on the various requirements of the DT-TRs, the case where a DT-RU can simultaneously provide training services for multiple DT-TRs will be considered to improve the performance of the proposed scheme.

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