Contract-based Incentive Mechanism for Blockchain-enabled Federated Learning in Vehicle Edge Computing

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***Abstract*—Vehicular edge computing (VEC) has been introduced to bring powerful in-proximity computing solutions to vehicles. VEC is able to boost the development of vehicular networks by handling computing tasks and accommodating artificial intelligence (AI). To fulfill the requirements of low latency and security in realizing AI for vehicular networks, and fully utilize the vehicles' capabilities on sensing and computing, federated learning (FL) in VEC emerges as a potential solution. However, privacy protection, data security and information asymmetry issues pose challenges on efficiently and securely motivating more vehicles to participate in FL. Thus, this paper proposes a contract-based incentive mechanism for blockchain-enabled FL, which employs contract theory to establish an optimal contract design between VEC servers and vehicles. We present the necessary and sufficient conditions to obtain an optimal contract and analyze the simplification of the constraints. The simulation results show that our proposed method is effective in providing incentives and outperforms other benchmark schemes.**

***Index Terms*—Vehicular edge computing, federated learning, privacy protection, blockchain, contract theory.**

I. Introduction

With the rapid development of vehicular networks, various emerging applications are being designed for vehicles. The exponential surge in data has resulted in an increased demand for computing and communication resources. In recent years, Vehicle Edge Computing (VEC) has been introduced to bring powerful computing units closer to the vehicles. VEC is able to boost the development of vehicular networks by handling computing tasks and accommodating artificial intelligence. In order to fulfill the requirements of low latency and security, and fully utilize the vehicles' capabilities of sensing and computing, Federated Learning (FL) has been proposed and gained significant attention. In the VEC, FL enables vehicles to locally train datasets based on a global model while only transmitting the trained model parameters to the mobile edge computing (MEC) server or roadside unit (RSU) to perform global aggregation. In order to fully utilize the benefits of FL, there are certain issues to be addressed. Firstly, a malicious node can recover some of the original data by utilizing gradient information. Secondly, malicious threats can tamper with or steal locally and globally updated information. Thirdly, in the information asymmetry scenario, the MEC server may not have knowledge of privacy information such as the privacy sensitivity and computing power of vehicles. In order to improve the efficacy of FL, MEC server needs to incentivize more vehicles to participate and motivate them to collect more data to train local models.

To further enhance the privacy-preserving capability of FL, blockchain, as a ledger technology, can be utilized to the development of FL. Recently, researchers are interested in exploring the potential of blockchain on improving the design of FL in vehicular networks. The authors of [1] propose an enhanced DPoS consensus scheme that can be applied to blockchain-enabled Internet of Vehicles (IoV). Nguyen *et al.* in [2] present a comprehensive overview of the fundamentals of FL and blockchain, and propose a novel FLchain architecture that can be applied to the MEC system. To address the privacy concerns of user updates, the authors of [3] propose a blockchain-based crowdsourcing FL system that applies differential privacy (DP) noise to perturb the output of normalization layers.

To improve the efficiency and accuracy of FL, Yang *et al.* [4] propose a joint computation and transmission optimization problem for FL within wireless networks, aiming at minimizing the total energy consumption of local computation and wireless transmission. The authors of [5] present a two-stage Stackelberg game model to investigate the challenge of optimizing the individual utility of clients and MECs for constructing a superior FL model. Liu *et al.* [6] design a two-stage Stackelberg game-based incentive mechanism to motivate mobile users to participate in FL. In recent years, contract theory has proven to be a powerful tool in designing incentive schemes for various applications in wireless networks [7]. In the case of information asymmetry, contract theory is able to design optimal contracts to reduce the risk of the involved parties. Gupta *et al.* [8] propose a contract theory-based incentive design mechanism for opportunistic Internet of Thing (IoT) to encourage IoT nodes to cooperate in forwarding messages. Liu *et al.* [9] formulate the interaction between edge devices (ED) and access point (AP) as an optimal contract design problem for a federated cloud-edge learning system. Once the contract is accepted, the ED will provide the AP with a local model update while adhering to a specified privacy budget. Saputra *et al.* [10] propose an energy-efficient framework for an electric vehicle network utilizing a contract theory-based economic model to maximize the utility of charging stations.

However, the above work does not consider the impact of local training dataset size on system energy consumption and local model generalization capability in VEC. In this paper, the interaction between the MEC servers and the vehicles is established as an optimal contract design problem, thereby allowing the MEC to motivate vehicles to participate in the FL task without requiring any foreknowledge of the privacy information of the individual vehicles. We present the necessary and sufficient conditions to obtain optimal contracts and simplify the constraints. The simulation results demonstrate that the proposed scheme outperforms other benchmark schemes concerning the evaluated performance parameters.

The remainder of this paper is organized as follows. We present the system model in Section II and formulate the utility functions for vehicles and MECs. In Section III, the optimal contract design is discussed. Simulation results are presented in Section IV. Finally, Section V concludes the paper.

II. System model

The system model is shown in Fig. 1. We consider a system with multiple Roadside Units (RSUs) and vehicles, wherein each RSU is equipped with a MEC server. The set of all MECs is denote by $\mathcal{J} = \{1, 2, ..., J\}$. In this system, the task publisher first uploads the initialized global model to the blockchain for each MEC to download. Then the MEC distributes the models to the vehicles. During an iteration of FL, Vehicles train local models using their own local datasets and transmit local model parameters to the MEC. Each MEC aggregates these local parameters and gives vehicles rewards as a result. In this paper, we consider a blockchain based on the consensus algorithm of Delegated Proof of Stake (DPoS), where MECs serve as miners and vehicles function as light nodes to assist in verification [11]. In the DPoS consensus algorithm, MECs take turns acting as block producers for aggregating the global model and uploading it to the blockchain network. To represent the willingness of a vehicle to accept a FL task and the private information, such as the residual battery, transmission power, and privacy budget, we define $\phi = \{\phi_{min}, ..., \phi, ..., \phi_{max}\}$ to denote the range of vehicle types.

A. Federated Learning Model

In FL, vehicle i utilizes a specific number of local samples D_i for local training. The data samples are denoted as the input-output pair (x_i, y_i), where x_i indicates the input vector of the FL with a variable size depending on the specific FL task, and y_i denotes an output scalar of the FL. Let ω_i be the local model parameter. An example of the loss function is

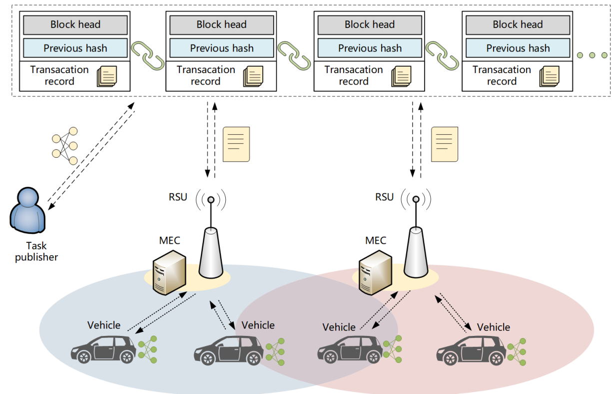


Fig. 1. System model.

$f_i(\omega_i) = \frac{1}{2}(x_i^T - y_i)^2$. Then the loss function on the data set of vehicle i is defined as

$$J_i(\omega_i) = \frac{1}{D_i} \sum\nolimits_{n \in D_i} f_n(\omega_i). \tag{1}$$

For partial aggregation, the goal is to minimize the following loss function

$$min \;\; J(\omega) = \sum\nolimits_{i=1}^{N} \frac{D_i}{|D|} J_i(\omega_i), \tag{2}$$

where $|D| = \sum_{i=1}^{N} D_n$ represents the sum of the number of data samples of all vehicles.

B. The utility of Vehicle

For vehicle i, there are four processes it is mainly involved in, which are training the local model, transferring model parameters, and assisting miners in validating transactions. Once the vehicle i has completed its task, the MEC will give it a reward R_i, which can be a monetary payment.

Let f_i denote the computing capability of vehicle i in CPU cycles per second, θ_i is the number of local epochs and s_i is the number of CPU cycles required to execute a sample. Then the computing time for local computation can be expressed as follows

$$\mathrm{t}_i^{loc}(D_i) = \frac{\theta_i s_i D_i}{f_i}. \tag{3}$$

Let the energy consumption coefficient of vehicle i denoted by δ_i, and it depends on the vehicle's chip. The computing power of vehicle i for local training is $P_i^{loc} = \delta_i f_i^3$. Then the energy consumption of vehicle i for local training can be given by

$$e_i^{loc}(D_i) = \theta_i s_i D_i \delta_i f_i^2. \tag{4}$$

We consider a time-sharing multi-access protocol, such as Orthogonal Frequency-Division Multiple Access (OFDMA), for the transmission of vehicles. For the uplink, the data transmission rate of vehicle i is given by

$$r_i = B_i \log_2(1 + \frac{P_i h_i}{N_0}), \tag{5}$$

where B_i is the bandwidth, P_i is the transmission power, N_0 is the background noise, and $h_i = o_i d_i^{-2}$ is the channel gain of the vehicle i with o_i being the Rayleigh fading parameter and d_i being the distance between vehicle and MEC. Denote the data size of vehicle i by $G(\omega_i)$. Then the transmission time between vehicle i and MEC is given by

$$t_i^{com} = G(\omega_i)/r_i = \frac{G(\omega_i)}{B_i \log_2(1+\frac{P_i h_i}{N_0})}. \tag{6}$$

Therefore, the energy consumption of vehicle i for transmitting the local FL model is denoted by

$$e_i^{com} = t_i^{com} P_i = \frac{P_i G(\omega_i)}{B_i \log_2(1+\frac{P_i h_i}{N_0})}. \tag{7}$$

Assuming that the vehicle is traversing a two-lane straight road. The duration of a vehicle's stay within the communication range of RSU j can be expressed as $t_{ij}^d = \widehat{d}_{ij}/\overline{v}_i$, where $\overline{v}_i$ is the average velocity of vehicle, $\widehat{d}_{ij}$ represents the distance between the location of v_i and endpoint of the circle in the direction of the vehicle. When $t_{ij}^d < t_i^{loc} + t_i^{com}$, the vehicle will be unable to accomplish the FL task on time, leading to the rejection of the task request.

In order to mitigate the deleterious effects of malevolent attacks on FL participants, we consider applying DP-based method to FL. DP is defined follows:

Definition 1. *A randomized mechanism* $\mathrm{M}:\mathrm{X} \rightarrow \mathrm{R}$ *with domain X and range R satisfies* (ϵ, δ) *- Differential Privacy [12], if for all neighboring datasets D, D′ ∈ X and for all measurable sets* $S \in R$, $Pr[M(D) \in S] \leq e^{\epsilon} Pr[M(D') \in S] + \delta$, *where* ϵ *is the privacy budget and* δ *is the probability that D, D′ cannot be bounded.*

In our system, different vehicles have different privacy budgets, which represent the degree of privacy protection. When the local model training is finished, Gaussian noise is added to the model parameters $\omega_i = \omega_i + \mathcal{N}(0, \sigma^2 I_z)$, where z is the parameter dimension. Similar to [9], the Gaussian noise standard deviation is denoted as

$$\sigma = \frac{2L\sqrt{T\log(1.25/\delta)}}{D\epsilon}, \tag{8}$$

where L is the clipping parameter and T is the number of model aggregations.

A reputation parameter $\mathcal{Q}$ is introduced for every vehicle, which indicates the ability of the vehicles to successfully complete the FL task. We define the binary variables $\eta \in \{0, 1\}$ to denote the completion of a task, respectively, where η = 1 if the vehicle successfully completes the FL task and η = 0 in other cases. Let $\mathcal{Q}^k$ be the reputation of vehicle's k_{th} federated learning task, it is calculated as follows:

$$\mathcal{Q}^k = (\eta \mathcal{Q}_{max} - \mathcal{Q}^{k-1}) * \lambda + \mathcal{Q}^{k-1}, \tag{9}$$

where the $\mathcal{Q}_{max}$ is the maximum value of reputation, and $\lambda \in [0, 1]$ is the decay factor. A vehicle's reputation increases every time it successfully completes a federated learning task, and its reputation decreases conversely.

Definition 2. *(Vehicle Type). The type of the vehicle* i *is determined by various factors, including its reputation* $\mathcal{Q}_i$, *Signal-to-noise ratio (SNR), distance* d_i, *privacy budget* ϵ_i *and residual battery* A_i. *It can be expressed as:*

$$\phi_i = w_1 \mathcal{Q}_i + w_2 \frac{P_i h_i}{N_0} + w_3 A_i - w_4 d_i + w_5 \epsilon_i, \tag{10}$$

where each weight value w_i, $i \in \{1, ...5\}$, *is in* $[0, 1]$, *and* $\sum_{i=1}^{5} w_i = 1$.

For MEC, it wants to attract more vehicles with high types to participate in FL. Because a higher type means a vehicle with a higher reputation, power, and privacy cost, which makes local model training more efficient.

In addition, after the vehicle is hired by the MEC, it also acts as a light node to assist the miner in verifying the transactions. Let c_i is the cost of the vehicle i as a cooperative verifier.

Therefore, the utility of the i_{th} vehicle is given by

$$\begin{aligned} U_i^{ve} &= R_i \phi_i - e_i^{loc}(D_i) - e_i^{com} - c_i \\ &= R_i \phi_i - C_i^{ve}(D_i), \end{aligned} \tag{11}$$

where

$$C_i^{ve}(D_i) = e_i^{loc}(D_i) + e_i^{com} + c_i. \tag{12}$$

C. The utility of MEC

For MEC, it receives a reward I from the task publisher and then hires vehicles to participate in FL. There are three processes it is mainly involved in, partial aggregation, global aggregation, and validation of transactions.

Generalization ability is the ability of the learned model to predict unknown data and can be measured by generalization error. The generalization error is the error in the model's prediction of the unknown data, which can be expressed as

$$J_i^{ge}(\omega) = \mathrm{E}[J_i(\omega)] = \int_{X \times Y} J_i(\omega) P(x, y) dx dy. \tag{13}$$

A generalization error is an expectation error. Since it exists only in a theoretical sense, we can only find the upper bound on the probability of generalization error theoretically. Mathematically, according to [13], the generalization error bound can be expressed as

$$J_i^{ge}(\omega) \leq J_i(\omega) + \frac{a}{\sqrt{D_i}}, \tag{14}$$

where a is a constant that depends on the complexity of the model and the distribution of the data. It is obvious that the generalization upper bound decreases with increasing D_i. Therefore, we define the generalization level as

$$l(D_i) = \xi_i(\gamma_{max} - \frac{a}{\sqrt{D_i}}), \tag{15}$$

where γ_{max} is the maximum value of $\frac{a}{\sqrt{D_i}}$ which is acceptable to the FL task, and the ξ_i is the positive coefficient, which represents the weight about the generalization ability.

In the FL process, it is essential for vehicles to guarantee the low-latency requirements of MEC. Let the maximum delay tolerated of MEC to vehicle i is T_{max}. According to [14], the saved time is denoted by $T_i(D_i)$, which is

$$T_i(D_i) = T_{max} - t_i^{loc}(D_i) - t_i^{com}. \tag{16}$$

We consider a blockchain network with a consensus algorithm based on DPOS. Miners receive transaction fees based on their verification contribution (the number of verifiers recruited for block verification is N_j). The verification revenue of the MEC can be expressed as

$$\Pi_j = \frac{N_j h}{\sum_{x\in J} N_x}, \tag{17}$$

where $\sum_{x\in J} n_x$ is the total number of cooperative verifiers and h is the total blockchain verification transaction cost.

Therefore, the utility function of the MEC is expressed as

$$U_j^{MEC} = I + \frac{N_j h}{\sum_{x\in J} N_x} + \sum_{i=1}^{N_j} \Big(\xi_i l(D_i) + \beta_i T_i(D_i) - R_i\phi_i\Big). \tag{18}$$

III. Information Asymmetry-Based Optimal Contract

A. Contract Formulation

In this paper, we only consider the discrete-consumer-type mode with a finite number of vehicle types. The set of type ϕ is denoted as $\mathcal{K} = \{1, 2, ..., K\}$. Without loss of generality, we assume that $0 < \phi_1 < \phi_2 < ... < \phi_K$.

Denoting $\mathcal{C} = \{(R_i, D_i)|\forall i \in \mathcal{K}\}$ as the optimal contracts for all vehicles, which are devised to attract the participation of the vehicles through win-win trading to both the MEC and the vehicles. The vehicle i chooses the appropriate contract according to its type to maximize its utility. In this case, it needs to satisfy individual rationality (IR) constraint and incentive compatible (IC) constraint.

Definition 3. *Individual Rationality (IR): A vehicle only selects to take on its contract if its utility is nonnegative, i.e.,*

$$R_i\phi_i - C_i^{ve}(D_i) \geq 0, \forall i \in \mathcal{K}. \tag{19}$$

Definition 4. *Incentive Compatible (IC): vehicles must prefer the contract designed specifically for their own types, i.e.,*

$$R_i\phi_i - C_i^{ve}(D_i) \geq R_j\phi_i - C_i^{ve}(D_i), \forall i, j \in \mathcal{K}, i \neq j.$$

Therefore, the optimal contract formulation strategy for MEC can be obtained by

$$\begin{aligned}
\max_{R_i, D_i} \quad & I + \frac{N_j h}{\sum_{x\in J} N_x} + \sum_{i=1}^{N_j} \Big(\xi_i l(D_i) + \beta_i T_i(D_i) - R_i\phi_i\Big) \\
s.t. \quad & R_i\phi_i - C_i^{ve}(D_i) \geq 0, \forall i \in \mathcal{K}, \\
& R_i\phi_i - C_i^{ve}(D_i) \geq R_j\phi_i - C_j^{ve}(D_j), \forall i, j \in \mathcal{K}, i \neq j, \\
& \sum_{i=1}^{N} R_i\phi_i \leq I, D_i \geq 0, \forall i \in \mathcal{K}.
\end{aligned} \tag{20}$$

B. Constraint Reduction

Due to the complex constraints, it is hard to directly solve the problem in (20). We can first determine the essential prerequisites that can be deduced from the IR and IC constraints.

Lemma 1. *For any feasible contract, $i, j \in \mathcal{K}$, $R_i > R_j$ if and only if $D_i > D_j$, $R_i = R_j$ if and only if $D_i = D_j$, $R_i > R_j$ if and only if $\phi_i > \phi_j$, and the utility of each type ϕ of vehicle should fulfill $0 \leq U_1^{ve} < U_2^{ve} < ... < U_K^{ve}$.*

Proof. A similar proof can be seen in [7] and [15]. Due to space limitations, we omit it here. □

Definition 5. *(Monotonicity): For any feasible contract, $i, j \in \mathcal{K}$, if $\phi_i > \phi_j$ and then $R_i > R_j$, which can be expressed as $0 \leq R_1 < R_2 < ... < R_K$.*

Lemma 2. *With the IC condition, the IR constraints can be reduced as*

$$R_1\phi_1 - C_1^{ve}(D_1) = 0. \tag{21}$$

Proof. A similar proof can be seen in [15]. Due to space limitations, we omit it here. □

Lemma 3. *With monotonicity, the IC condition can be reduced as the local downward incentive compatibility (LDIC), given by*

$$R_i\phi_i - e^l(D_i) \geq R_{i-1}\phi_i - C_{i-1}^{ve}(D_{i-1}), \forall i \in \mathcal{K}. \tag{22}$$

and the local upward incentive compatibility (LUIC) given by

$$R_i\phi_i - C_i^{ve}(D_i) \geq R_{i+1}\phi_i - C_{i+1}^{ve}(D_{i+1}), \forall i \in \mathcal{K}. \tag{23}$$

Proof. A similar proof can be seen in [15]. Due to space limitations, we omit it here. □

Lemma 4. *Assuming that each vehicle receives the optimal contract in order to maximize its own utility, the IC condition can be further simplified as*

$$R_i\phi_i - C_i^{ve}(D_i) = R_{i-1}\phi_i - C_{i-1}^{ve}(D_{i-1}), \forall i \in \mathcal{K}. \tag{24}$$

Proof. A similar proof can be seen in [15]. Due to space limitations, we omit it here. □

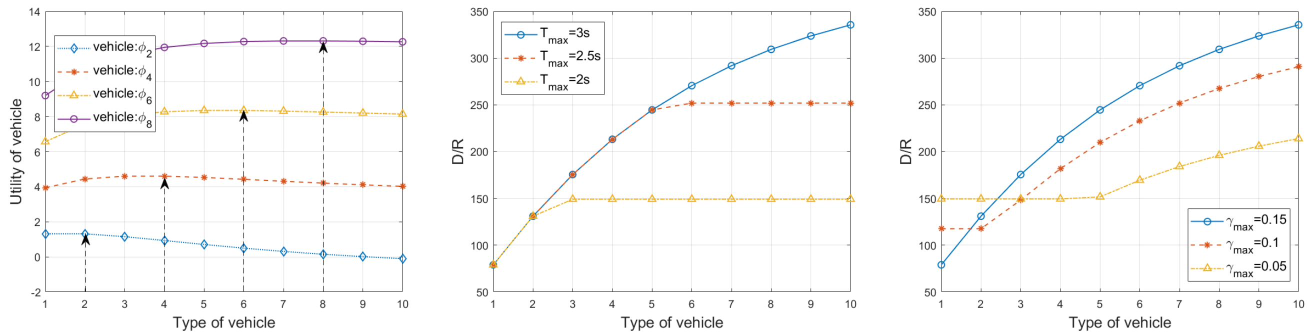
Consequently, the optimal contract formulation strategy for MEC can be simplified as

$$\begin{aligned}
\max_{R_i, D_i} \quad & I + \frac{N_j h}{\sum_{x\in J} N_x} + \sum_{i=1}^{N_j} \Big(\xi_i l(D_i) + \beta_i T_i(D_i) - R_i\phi_i\Big) \\
s.t. \quad & R_1\phi_1 - C_1^{ve}(D_1) = 0, \\
& R_i\phi_i - C_i^{ve}(D_i) = R_{i-1}\phi_i - C_{i-1}^{ve}(D_{i-1}), \forall i \in \mathcal{K}, \\
& R_K > R_{K-1} > ... > R_1 \geq 0, \\
& \sum_{i=1}^{N} R_i\phi_i \leq I, D_i \geq 0, \forall i \in \mathcal{K}.
\end{aligned} \tag{25}$$

C. Proposed Solution

We proceed to solve the optimization problem (25). By performing iterations on (21) and (24), we have

$$\begin{aligned}
C_i^{ve}(D_i) &= \sum_{n=1}^{k} R_n\phi_n - \sum_{i=2}^{k} R_{n-1}\phi_n \\
&= R_1\phi_1 + \sum_{n=1}^{k} (R_n - R_{n-1})\phi_i, \forall i \in \mathcal{K}.
\end{aligned} \tag{26}$$



(a) (b) (c)

Fig. 2. The validity of IR and IC, the impact of T_{max} and γ_{max}. (a) Utility of vehicle versus type of vehicle. (b) D/R versus type of vehicle for different value of T_{max} (γ_{max} = 0.15). (c) D/R versus type of vehicle for different value of γ_{max} (T_{max} = 3s).

Table I
PARAMETER SETTING IN THE SIMULATION

Parameters	Values
Number of MEC J	3
Number of vehicle types K	10
Transmission power of vehicle P_i	1W
Bandwidth of vehicle B_i	1MHz
Number of local training samples D_i	[100,700]
Noise power spectral density N_0	-110dBm/Hz
Rayleigh fading parameter o_i	1
Distance between vehicle and RSU d_i	[200,500]m
The average velocity of vehicle $\overline{v}_i$	20m/s
Number of local epochs θ	5

Substitute (26) into the utility of MEC, and all D_i are removed from the optimization problem (25), which becomes

$$\begin{aligned}
&\max_{R_i} \quad I + \frac{N_j h}{\sum_{x\in J} N_x} \\
&+ \sum_{i=1}^{N_j} \pi_i \Bigg[\xi_i l\Big(R_1\phi_1 + \sum_{i=1}^{k}(R_i - R_{i-1})\phi_i\Big) \\
&+ \beta_i T_i \Big(R_1\phi_1 + \sum_{i=1}^{k}(R_i - R_{i-1})\phi_i\Big) - R_i\phi_i \Bigg] \\
&s.t. \quad R_i \geq 0, \forall i \in \mathcal{K}.
\end{aligned}$$

Note that the optimization function is a concave function on R_i and the constraint set is a convex set. To solve this optimization problem, we can employ the Karush-Kunhn-Tucker (KKT) condition to find the optimal value of R_i^*. Subsequently, we can compute the optimal value of D_i^* by applying (26). Consequently, we have obtained the optimal contract $\mathcal{C} = \{(R_i, D_i)|\forall i \in \mathcal{K}\}$.

IV. NUMERICAL EVALUATION

In this section, we perform numerical experiments utilizing the aforementioned theoretical analysis to evaluate the effectiveness of the proposed scheme. Our simulations are conducted using the MNIST handwritten image dataset, while the training dataset for the vehicles is Non-IID. First, we verify the validity of the IR and IC constraints and conduct the simulations to investigate the impact of T_{max} and γ_{max}. Then the performance of the proposed optimal contract (OC) is compared with those of the incomplete information contract (IIC), fix contract (FC) and Stackelberg game scheme (SG) [6] in terms of the MEC utility and FL loss.

In the incomplete information contract, MEC does not have any information about the vehicle, except for the probability with which a certain vehicle belongs to type ϕ_i. As a result, MEC sets a vector of probabilities, denoted by $\pi = [\pi_1, ..., \pi_j, ..., \pi_K]$, where $0 \leq \pi_i \leq 1$ and $\sum_{k=1}^{K} \pi_k = 1$. Then MEC maximizes its expected utility E_j^{MEC}.

$$E_j^{MEC} = I + \Pi_j + \sum_{i=1}^{N_j}\sum_{k=1}^{K} \pi_k \Big(\xi_i l(D_i) + \beta_i T_i(D_i) - R_i\phi_k\Big).$$

In the fixed contract, the MEC sends average contract $(\overline{\mathrm{R}}, \overline{\mathrm{D}})$ to the vehicles, which guarantees a non-negative utility for MEC. The system parameters are listed in Table I. As illustrated in Fig. 2(a), the utility of a vehicle increases monotonically with regard to its type. This is because of the fact that higher types are associated with greater willingness and efficiency of the vehicle to perform federated learning tasks. The MEC is inclined to allocate more funds to hire vehicles with higher types to improve the effectiveness of FL. Furthermore, a vehicle with type ϕ_i always attains the highest positive utility when it accepts the contract (R_i, D_i) designed for its type. From the aforementioned analysis, we can deduce that the IR and IC constraints are guaranteed.

Fig. 2(b) and Fig. 2(c) show the size of local training dataset per unit reward (D/R) for vehicles with different types when the optimal contractors are selected. When time delay and error requirements are not demanding, such as $T_{max} = 3s$ and $\gamma_{max} = 0.15$, D/R increases as the type of vehicle increases. As demonstrated in Fig. 2(b), D/R decreases for high-type vehicles as T_{max} decreases. This is because high-type vehicles need to reduce the training dataset size to satisfy the latency requirements. In Fig. 2(c), a decrease in γ_{max} results in an

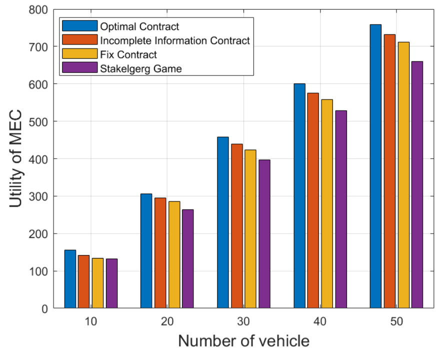


Fig. 3. Utility of MEC versus number of vehicle.

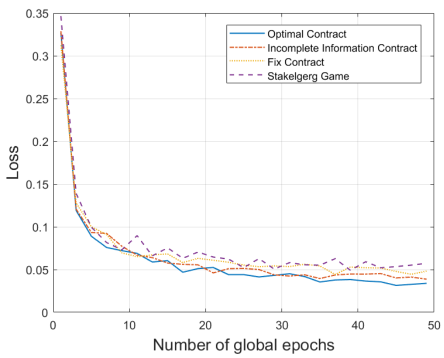


Fig. 4. Federated Learning loss.

improvement in D/R for lower-type vehicles and a decrease for higher-type vehicles. The result is due to lower type vehicles must use a larger dataset for training the model to meet a smaller tolerated generalization error. Concurrently, the MEC needs to pay more to vehicles to devise a feasible contract.

Fig. 3 shows the utility of MEC as the number of vehicles increases. It can be observed that the utility of MEC increase with the number of vehicles under all four methods. This is because as the total number of vehicles increases, the number of vehicles involved in the FL task also increases. In addition, the optimal contract method achieves the highest performance in terms of MEC utility. This is because the optimal contract method is resolved in a scenario of complete information, where the MECs possess complete knowledge of the vehicle's type and try to extract maximal utility from the vehicles.

We also evaluate the loss in FL under four different methods. Our experimentation involved training FL with a cohort of 100 vehicles and 3 MECs. In Fig. 4, it is evident that the optimal contract results in the least amount of loss at the final convergence as the number of global epochs increases.

V. Conclusion

In this paper, a contract-based incentive mechanism is proposed for blockchain-enabled federated learning in vehicle edge computing. We formulate the interaction between MEC and vehicles as an optimal contract design problem. For MECs, they develop appropriate contracts with different rewards and local dataset requirements for different vehicle types. Vehicles select the contract that maximizes their benefits and receives rewards for completing the federated learning task. The numerical evaluation shows that our proposed optimal contract incentive mechanism is effective in providing incentives and outperforms other benchmark schemes.

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