Contract-based Incentive Mechanism for AI-Generated Content Services in Vehicle Edge Computing

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***Abstract*—Artificial Intelligence Generated Content (AIGC) is a paradigm that utilizes AI models to automatically generate content. Within the framework of Internet of Vehicles (IoV) networks, mobile AIGC services present numerous advantages over conventional cloud-based solutions, notably enhanced network efficiency and enhanced data security and privacy. However, the implementation of AIGC services often demands significant resources, leading to challenges for Roadside Units (RSUs) in managing information uncertainty and effectively addressing all user service requests without compromising overall system performance. To address these challenges, in this paper, we propose a multi-to-multi contract-based incentive mechanism for AIGC services within vehicle edge computing. This approach leverages contract theory to design an optimal contractual framework between Mobile AIGC Service Providers (MASPs) and vehicles. We present the necessary and sufficient conditions for achieving an optimal contract and explore the simplification of the associated constraints. The simulation results demonstrate that our proposed method effectively provides incentives and outperforms existing benchmark schemes.**

***Index Terms*—Artificial Intelligence Generated Content (AIGC), Internet of Vehicles (IoV), incentive mechanism, contract theory.**

I. Introduction

The rapid development of Artificial Intelligence (AI) has led to the emergence of Artificial Intelligence Generated Content (AIGC), which facilitates the automated production of content through advanced AI models. As these technologies evolve, they are increasingly being integrated into various domains, including the Internet of Vehicles (IoV) [1]. For instance, AIGC can produce dynamic traffic alerts and personalized navigation suggestions based on real-time road conditions and user preferences, thereby enhancing route efficiency and minimizing travel time [2]. Furthermore, it allows for the creation of customized infotainment content that aligns with passenger preferences, thereby enriching the in-vehicle experience [3]. Deploying AIGC services on Roadside Units (RSUs) enables data processing to occur closer to the source compared to traditional cloud-based solutions, effectively reducing latency and bandwidth consumption [4]. Additionally, mobile AIGC services enhance data security and privacy by minimizing data transfers to remote cloud servers, thereby mitigating the risk of potential cyber threats.

Despite these benefits, there are significant challenges to providing AIGC services in a mobile environment. The heterogeneous nature of AIGC services requires RSUs to manage diverse content generation tasks, which can be resource intensive. Furthermore, as the number of connected vehicles increases, RSUs must effectively handle the growing volume of service requests while maintaining overall system performance. It is necessary to propose a service allocation mechanism, which can dynamically respond to user demands without affecting the quality of service. Du $et\ al.$ [5] present the concept of AIGC-as-a-Service (AaaS) and propose a general and effective model to illustrate the relationship between computational resources and user-perceived quality evaluation metrics. To address the challenges of environmental uncertainty and variability, Du $et\ al.$ [6] develop the AI-Generated Optimal Decision (AGOD) framework based on a diffusion model, which is utilized in Deep Reinforcement Learning (DRL) for efficient and optimal AIGC Service Provider (ASP) selection. Fan $et\ al.$ [7] propose a decentralized mechanism for mobile AIGC service allocation within the IoV framework, leveraging multi-agent deep reinforcement learning to enhance user experience while minimizing transmission latency. Xu $et\ al.$ [8] propose a generative AI-empowered autonomous driving architecture for the vehicular Metaverse and introduce a multi-task Digital Twin (DT) offloading model tailored for diverse requirements at RSUs.

In the case of information asymmetry, contract theory [9] is able to design optimal contracts to reduce the risk of the involved parties. Wen $et\ al.$ [10] introduce a user-centric incentive mechanism framework that utilizes contract theory to design contracts for edge AIGC service providers in 6G-IoT networks, effectively addressing information asymmetry and client decision-making. Liu $et\ al.$ [11] propose a diffusion-based contract model aimed at incentivizing ASPs in the realm of mobile AIGC services. Additionally, Wen $et\ al.$ [12] propose a Generative Diffusion Models (GDM)-based contract theory model to motivate users to contribute high-quality sensing data for the fine-tuning of Generative AI models. However, these studies primarily focused on one-to-multi contract designs, involving either a single seller with multiple buyers or a single buyer with multiple sellers. None address the constraints of limited resources and the complexities of multi-to-multi contract structures within the system, where multiple sellers interact with multiple buyers, thereby limiting the efficacy of the incentive mechanisms.

To address the above challenges, in this paper, we propose a contract-based incentive mechanism for AIGC Services in vehicle edge computing. Specifically, we formulate the interaction between various types of Mobile AIGC Service Providers (MASPs) and various types of vehicles as an optimal contracts design problem. We consider a scenario where each MASP has a limited resource capacity, i.e. the total inference steps within a time window is limited. The RSU designs contracts for different types of MASPs and vehicles based on the real-time type distribution. We present the necessary and sufficient conditions for achieving optimal contracts and simplify the associated constraints. Then, we employ the standard interior point method to derive the optimal contract. Comparing with the previous works, the major contributions of this paper can be summarized as follows:

- We propose a multi-to-multi contract-based incentive mechanism to motivate various types of MASPs to provide AIGC services to various types of vehicles, taking into account resource limitations and asymmetric information within the system.
- We present the necessary and sufficient conditions for deriving optimal contracts and simplify the related constraints.
- We validate the effectiveness of proposed incentive mechanism through simulations, demonstrating that our proposed method provides effective incentives and outperforms existing benchmark schemes.

II. System Model

We consider a system comprising of a RSU , multiple Mobile AIGC Service Providers (MASPs), and multiple vehicles, as depicted in Fig. 1. Each MASP maintains an AIGC model, fine-tuning it to align with local preferences. The set of MASPs is represented by $\mathcal{P} = \{1, 2, ., P\}$, where P denotes the total number of the MASPs. All MASPs are categorized into M types based on their model complexity, ranging from low to high, with the set of types denoted by $\Phi = \{\phi_1, \phi_2, ..., \phi_i, ..., \phi_M : 1 \leq i \leq M\}$. Generally, greater complexity in an AIGC model corresponds to enhanced inference capabilities; however, it also results in higher energy consumption for the same number of inference steps. The set of vehicles is denoted by $\mathcal{N} = \{1, 2, ., N\}$, where N represents the total number of the vehicles. Due to inherent limitations in computational and storage resources, vehicles cannot deploy numerous AIGC models locally for inference. To ensure service quality, vehicles can submit multiple AIGC task requests to MASPs at various intervals, with the MASP returning results upon completion of the inference. In order to represent the differing quality of inference required by vehicles, we classify the vehicles into K types, defining $\Psi = \{\psi_1, \psi_2, ..., \psi_k, ..., \psi_K\}$ to indicate the range of vehicle

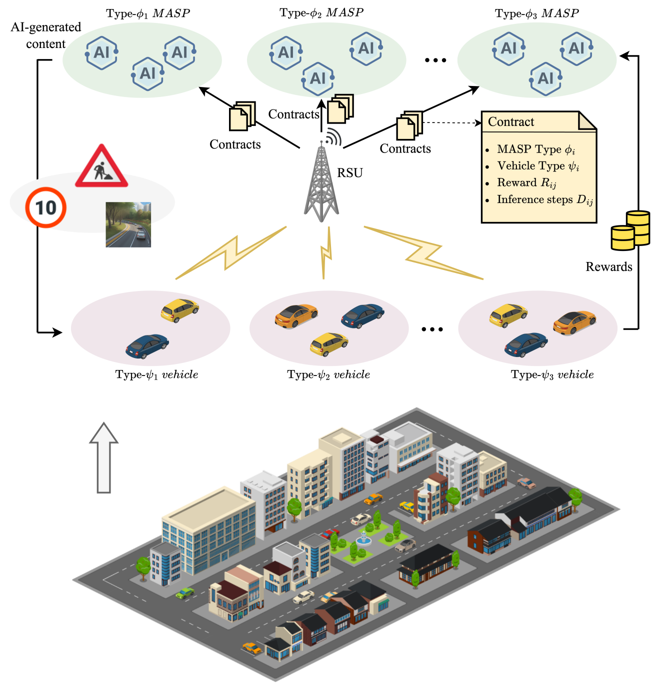


Fig. 1. System model.

types. We define D_k^{min} as the minimum inference step required by type-ψ_k vehicle.

A. The utility of MASP

For a type-ϕ_i MASP, it provides computational resources by conducting AIGC inferences for vehicles. The utility of a type-ϕ_i MASP towards type-ψ_k vehicle can be defined as

$$U_{\phi_i}^{MASP} = R_{k,i}\phi_i - \beta C(D_{k,i}), \tag{1}$$

where β is a cost parameter, and $C(D_{k,i})$ represents the cost incurred by the MASP to complete the task for a type-ϕ_i vehicle, which is related to the number of inference steps.

Typically, an increase in the number of inference steps correlates with higher energy consumption during the inference process. For simplicity, we define the cost for MASP to complete the task for a type-ϕ_i vehicle as follow

$$C(D_i) = \gamma D_{k,i}, \tag{2}$$

where γ is a energy consumption parameter.

In the information asymmetry scenario, the type-ϕ_i MASP lacks complete information about the vehicles, except for the distribution indicating the type of a specific vehicle. The distribution of types among all vehicles can be calculated as follows

$$\theta_k = \frac{1}{N}\sum_{n=1}^{N} \mathbb{1}_{\{\psi_n = \psi_k\}}, \tag{3}$$

where $\mathbb{1}$ is an indicator function which returns 1 if the given condition is true and 0 otherwise.

Given the limited computational resources of the MASP, the optimal contract should satisfy the following conditions

$$\sum_{k=1}^{K} N\theta_k D_{k,i} \le D_i^{max}, D_{k,i} \ge 0, \tag{4}$$

where D_i^{max} denotes the maximum number of inference steps available to the type-ϕ_i MASP within a time slot.

Consequently, the utility function of the type-ϕ_i MASP with respect to the type-ψ_k vehicle is expressed as

$$\begin{aligned} U_i^{MASP} &= R_{k,i}\phi_i - \beta C(D_{k,i}) \\ &= R_{k,i}\phi_i - \beta\gamma D_{k,i}. \end{aligned} \tag{5}$$

B. The Utility of Vehicle

For a type-k vehicle, it submits an AIGC task request to the MASP. The MASP assigns the task to AIGC model for inference and subsequently transmits the generated content to the vehicle. Upon receiving the generated content, the vehicle pays a reward to MASP. Thus, the utility of type-ψ_k vehicle towards type-ϕ_i MASP can be expressed as

$$U_{k,\phi_i}^{ve} = \alpha Q(\phi_i, D_{k,i}) - R_{k,i}\phi_i, \tag{6}$$

where α is a satisfaction parameter, and $Q(\cdot)$ denotes the content satisfaction assessment function, which is related to the number of inference steps and the complexity of AIGC model. According to [5], in general, the more the number of inference steps and the more complex the AIGC model, the more accurate the generated content. Then, the quality assessment function of type-ψ_k vehicle towards type-ϕ_i MASP can be defined as follow

$$Q(\phi_i, D_{k,i}) = \phi_i ln(D_{k,i}), \tag{7}$$

where D_i represents the number of inference steps, and D_k^{min} is the minimum inference step required for a type-k vehicle.

Therefore, the utility function of type-ψ_k vehicle towards type-ϕ_i MASP can be defined as

$$\begin{aligned} U_{k,\phi_i}^{VE} &= \alpha Q(\phi_i, D_{k,i}) - R_{k,i}\phi_i \\ &= \alpha\phi_i ln(D_{k,i}) - R_{k,i}\phi_i, \end{aligned} \tag{8}$$

In the information asymmetry scenario, the type-ψ_k vehicle does not have full information about the MASPs, except for the distribution with which a certain MASP belongs to type-ϕ_i. The distribution of types of all MASPs and can be calculated as follows

$$\rho_i = \frac{1}{N}\sum_{n=1}^{N} \mathbb{1}_{\{\phi_n = \phi_i\}}, \tag{9}$$

where $\mathbb{1}$ is an indicator function which returns 1 if the given condition is true and 0 otherwise.

Therefore, the utility function of type-ψ_k vehicle overall MASPs can be expressed as

$$\begin{aligned} U_k^{VE} &= \sum_{i=1}^{M} \rho_i U_{k,\phi_i}^{VE} \\ &= \sum_{i=1}^{M} \rho_i \Big(\alpha\phi_i ln(D_{k,i}) - R_{k,i}\phi_i\Big). \end{aligned} \tag{10}$$

III. Multi-to-Multi Optimal Contract Design

A. Contract Formulation

In this paper, we focus on the discrete-consumer-type mode with a finite number of vehicle types. Denoting $\mathcal{C} = \{(R_{k,i}, D_{k,i}) | \forall\phi_i \in \Phi, \forall k \in \mathcal{K}\}$ as the optimal contracts for all vehicles, which are devised to attract the participation of the vehicles through win-win trading to both the MASP and the vehicles. A type-ϕ_i MASP chooses the appropriate contract according to its type to maximize its utility, while ensuring compliance with the individual rationality (IR) and incentive compatible (IC) constraints.

Definition 1. *Individual Rationality (IR): A MASP only selects to take on its contract if its utility is nonnegative, i.e.,*

$$R_{k,i}\phi_i - \beta\gamma D_{k,i} \ge 0, \forall\phi_i \in \Phi. \tag{11}$$

Definition 2. *Incentive Compatible (IC): MASPs must prefer the contract designed specifically for their own types, i.e.,*

$$\begin{aligned} R_{k,i}\phi_i - \beta\gamma D_{k,i} &\ge R_{k,j}\phi_i - \beta\gamma D_{k,j}, \\ &\forall\phi_i, \phi_j \in \Phi, i \ne j. \end{aligned} \tag{12}$$

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

$$\begin{aligned} \max_{R_{k,i}, D_{k,i}} \quad & \sum_{k=1}^{K}\sum_{i=1}^{M} N\theta_k\rho_i U_{k,\phi_i}^{VE} \\ s.t. \quad & R_{k,i}\phi_i - \beta\gamma D_{k,i} \ge 0, \forall\phi_i \in \Phi, \\ & R_{k,i}\phi_i - \beta\gamma D_{k,i} \ge R_{k,j}\phi_j - \beta\gamma D_{k,i}, \\ & \qquad \forall\phi_i, \phi_j \in \Phi, i \ne j, \\ & \sum_{k=1}^{K} N\theta_k D_{k,i} \le D_i^{max}, \\ & D_{k,i} \ge 0, R_{k,i} \ge 0, \forall\phi_i \in \Phi. \end{aligned} \tag{13}$$

B. Contract Feasibility

Given the complexity of the constraints, directly solving the problem presented in (13) proves challenging. We can first ascertain the essential prerequisites derived from the IR and IC constraints.

Lemma 1. *For any feasible contract, $\phi_i, \phi_j \in \mathcal{K}$, $R_{k,i} > R_{k,j}$ if and only if $D_{k,i} > D_{k,j}$, $R_{k,i} = R_{k,j}$ if and only if $D_{k,i} = D_{k,j}$.*

Proof. From the IC constraints in (12), we have

$$R_{k,i}\phi_i - \beta\gamma D_{k,i} \ge R_{k,j}\phi_i - \beta\gamma D_{k,j}, \tag{14}$$

and it can be reformulated as

$$\phi_i(R_{k,i} - R_{k,j}) \ge \beta\gamma(D_{k,i} - D_{k,j}). \tag{15}$$

It is evident that if $D_{k,i} > D_{k,j}$, then $R_{k,i} > R_{k,j}$. Additionally, from the IC constraints in (12), we can obtain

$$R_{k,j}\phi_j - \beta\gamma D_{k,j} \ge R_{k,i}\phi_j - \beta\gamma D_{k,i}, \tag{16}$$

and it can be reformulated as

$$\beta\gamma(D_{k,i} - D_{k,j}) \geq \phi_j(R_{k,i} - R_{k,j}). \tag{17}$$

Thus, if $R_{k,i} > R_{k,j}$, it follows that $D_{k,i} > D_{k,j}$. Furthermore, $R_{k,i} > R_{k,j}$ if and only if $D_{k,i} > D_{k,j}$. Furthermore, a similar argument can be applied to demonstrate that $R_{k,i} = R_{k,j}$ if and only if $D_{k,i} = D_{k,j}$, this part of the proof is omitted here due to space limitations. □

Lemma 2. *For any feasible contract, $\phi_i, \phi_j \in K$, $R_{k,i} > R_{k,j}$ if and only if $\phi_i > \phi_j$.*

Proof. We employ a counterfactual method to prove this lemma. Assume there exist i, j such that $R_{k,i} < R_{k,j}$ when $\phi_i > \phi_j$ or $R_{k,i} > R_{k,j}$ when $\phi_i < \phi_j$. Then, we have

$$(R_{k,i} - R_{k,j})(\phi_i - \phi_j) < 0. \tag{18}$$

According to the IC constraint given in (12), we obtain

$$R_{k,i}\phi_i - \beta\gamma D_{k,i} \geq R_{k,j}\phi_i - \beta\gamma D_{k,j}, \tag{19}$$
$$R_{k,j}\phi_j - \beta\gamma D_{k,j} \geq R_{k,i}\phi_j - \beta\gamma D_{k,i}. \tag{20}$$

By adding constraints (19) and (20), we derive

$$R_{k,i}\phi_i + R_{k,j}\phi_j \geq R_{k,j}\phi_i + R_{k,i}\phi_j. \tag{21}$$

By further derivation, we can derive

$$(R_{k,i} - R_{k,j})(\phi_i - \phi_j) \geq 0, \tag{22}$$

which contradicts (18). Therefore, $R_i > R_j$ if and only if $\phi_i > \phi_j$. From (22), if $\phi_i > \phi_j$, to balance the two sides, $R_i > R_j$ must also hold. □

Definition 3. *(Monotonicity): For any feasible contract, $\phi_i, \phi_j \in \mathcal{K}$, if $\phi_i > \phi_j$, then $R_{k,i} > R_{k,j}$, which can be expressed as $0 \leq R_{k,1} < R_{k,2} < ... < R_{k,M}$.*

Lemma 3. *For any feasible contract, the utility of each type ϕ of MASP must satisfy*

$$0 \leq U_1^{MASP} < U_2^{MASP} < ... < U_M^{MASP}.$$

Proof. We have proved that if $\phi_i > \phi_j$, then $R_{k,i} > R_{k,j}$ and $D_{k,i} > D_{k,j}$. Consequently, we have

$$\begin{aligned} U_i^{MASP} =& R_{k,i}\phi_i - \beta\gamma D_{k,i} > R_{k,j}\phi_i - \beta\gamma D_{k,j} \\ &> R_{k,j}\phi_j - \beta\gamma D_{k,j} = U_j^{MASP}. \end{aligned}$$

□

IV. Optimal Contract Solution

In this section, we investigate the optimal contract solution by simplifying the IC and IR constraints. We derive the local downward (LDIC) and local upward incentive compatibility (LUIC) incentive compatibility conditions, thereby ensuring optimal utility for each vehicle type.

Lemma 4. *Under the IC condition, the IR constraints can be expressed as*

$$R_{k,1}\phi_1 - \beta\gamma\phi_1 D_{k,1} = 0. \tag{23}$$

Proof. Given the IC condition and $0 < \phi_1 < \phi_2 < ... < \phi_M$, $\forall\phi_i \in \mathcal{K}$, we have

$$R_{k,i}\phi_i - \beta\gamma D_{k,i} > R_{k,1}\phi_1 - \beta\gamma D_{k,1}.$$

To enhance the optimization objective function U^{VE}, the vehicle will decrease the value of $R_{k,1}$ until the utility for the vehicle of type ϕ_1 drops to 0. Thus, the IR constraints can be reformulated as $R_{k,1}\phi_1 - \beta\gamma\phi_1 D_{k,1} = 0$. □

Lemma 5. *Considering monotonicity, the IC condition can be represented as local downward incentive compatibility (LDIC)*

$$R_{k,i}\phi_i - \beta\gamma D_{k,i} \geq R_{k,i-1}\phi_i - \beta\gamma D_{k,i-1}, \forall\phi_i \in \mathcal{K}. \tag{24}$$

and the local upward incentive compatibility (LUIC) given by

$$R_{k,i}\phi_i - \beta\gamma D_{k,i} \geq R_{k,i+1}\phi_i - \beta\gamma D_{k,i+1}, \forall i \in \mathcal{K}. \tag{25}$$

Proof. The total number of IC constraints in (12) is $M(M-1)$, which can be divided into $M(M-1)/2$ downward incentive compatibility (DIC) and $M(M-1)/2$ upward incentive compatibility (UIC), expressed as

$$R_{k,i}\phi_i - \beta\gamma D_{k,i} \geq R_{k,j}\phi_i - \beta\gamma D_{k,j} \quad \forall\phi_i > \phi_j \tag{26}$$
$$R_{k,i}\phi_i - \beta\gamma D_{k,i} \geq R_{k,j}\phi_i - \beta\gamma D_{k,j} \quad \forall\phi_i < \phi_j \tag{27}$$

This proof consists of two parts. First, we demonstrate that the DIC can be expressed as the LDIC. By applying the LDIC to three continuous types, $\phi_{i-1} < \phi_i < \phi_{i+1}$, $\forall i \in 2, ..., M-1$, we have

$$R_{k,i+1}\phi_{i+1} - \beta\gamma D_{k,i+1} \geq R_{k,i}\phi_{i+1} - \beta\gamma D_{k,i}, \tag{28}$$
$$R_{k,i}\phi_i - \beta\gamma D_{k,i} \geq R_{k,i-1}\phi_i - \beta\gamma D_{k,i-1}. \tag{29}$$

By applying monotonicity, we obtain

$$(\phi_{i+1} - \phi_i)(R_{k,i} - R_{k,i-1}) \geq 0, \tag{30}$$
$$\phi_{i+1}(R_{k,i} - R_{k,i-1}) \geq \phi_i(R_{k,i} - R_{k,i-1}). \tag{31}$$

Combining (28), (29), (31), we have

$$\begin{aligned} \phi_{i+1}(R_{k,i} - R_{k,i-1}) &\geq \phi_i(R_{k,i} - R_{k,i-1}) \\ &\geq \beta\gamma D_{k,i} - \beta\gamma D_{k,i-1}. \end{aligned} \tag{32}$$

Equally, the above equation becomes

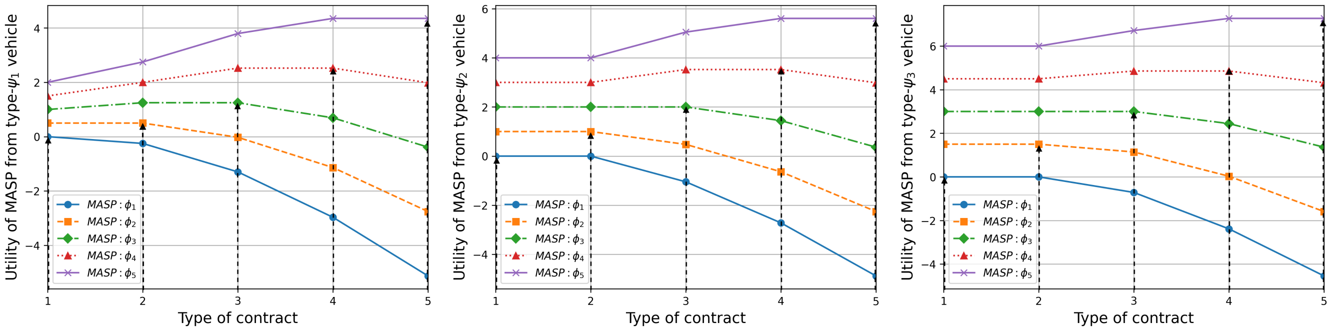
$$R_{k,i}\phi_{i+1} - \beta\gamma D_{k,i} \geq R_{k,i-1}\phi_{i+1} - \beta\gamma D_{k,i-1}, \tag{33}$$
$$R_{k,i}\phi_i - \beta\gamma D_{k,i} \geq R_{k,i-1}\phi_i - \beta\gamma D_{k,i-1}. \tag{34}$$

Similarly, we can demonstrate that the UIC can be expressed as the LUIC. □

Lemma 6. *Assuming that each MASP receives the optimal contract to maximize its utility, the IC condition can be further simplified as*

$$R_{k,i}\phi_i - \beta\gamma D_{k,i} = R_{k,i-1}\phi_i - \beta\gamma\phi_i D_{k,i-1}, \forall\phi_i \in \mathcal{K}. \tag{35}$$

Proof. From the local downward incentive compatibility (24), it follows that LDIC remains satisfied if both $R_{k,i}$ and $R_{k,i-1}$ are diminished by the same amount. It is possible to enhance



(a) (b) (c)

Fig. 2. The utility of MASP from vehicle vs. the type of contract under various types of vehicles. (a) Utility of MASP from type-ψ_1 vehicle. (b) Utility of MASP from type-ψ_2 vehicle. (c) Utility of MASP from type-ψ_3 vehicle.

the MASP's utility by minimizing the equality constraint. Thus, the LDIC can be reformulated as

$$R_{k,i}\phi_i - \beta\gamma D_{k,i} = R_{k,i-1}\phi_i - \beta\gamma D_{k,i-1}, \forall \phi_i \in \mathcal{K}.$$

Referring to the above equation, we derive

$$\begin{aligned}\phi_i(R_{k,i} - R_{k,i-1}) &= \beta\gamma D_{k,i} - \beta\gamma D_{k,i-1} \\ &\geq \phi_{i-1}(R_{k,i} - R_{k,i-1}).\end{aligned}$$

Consequently, we obtain the LUIC as follows

$$R_{k,i-1}\phi_{i-1} - \beta\gamma D_{k,i-1} \geq R_{k,i}\phi_{i-1} - \beta\gamma D_{k,i}, \forall \phi_i \in \mathcal{K}.$$

Thus, we conclude that the LUIC can be replaced by the LDIC along with the monotonicity condition. □

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

$$\begin{aligned}\max_{R_{k,i},D_{k,i}} \quad & \sum_{k=1}^{K}\sum_{i=1}^{M} N\theta_k\rho_i U_{k,\phi_i}^{VE} \\ s.t. \quad & R_{k,1}\phi_1 - \beta\gamma D_{k,1} = 0, \\ & R_{k,i}\phi_i - \beta\gamma D_{k,i} = R_{k,i-1}\phi_i - \beta\gamma D_{k,i-1}, \\ & R_{k,M} > R_{k,M-1} > ... > R_{k,1} \geq 0, \\ & \sum_{k=1}^{K} N\theta_k D_{k,i} \leq D_i^{max}, \\ & D_{k,i} \geq 0, \forall \phi_i \in \Phi. \end{aligned} \tag{36}$$

It is noteworthy that the optimization function is concave with respect to $R_{k,i}$ and $D_{k,i}$, while the constraint set forms a convex set. To solve this optimization problem, we can utilize the standard interior point method [13] to determine the optimal values of $R_{k,i}^*$ and $D_{k,i}^*$. Consequently, we can derive the optimal contract $\mathcal{C} = \{(R_{k,i}, D_{k,i})|\forall\phi_i \in \Phi, \forall k \in \mathcal{K}\}$.

V. Simulation and Numerical Results

We present the evaluation of the proposed method in this section. We consider a system with 5 types of models and 3 types of vehicles. Each type of MASP provides vehicles with maximal computing resource capacity, i.e., total diffusion steps within a time window. By default, the capacities of MASPs are set to $D^{max} = [500, 600, 700, 1100, 1500]$, the number of vehicles is set to 40, and the number of models is set to 10. The distribution of vehicle types is represented as $\boldsymbol{\theta} = [\theta_1, \theta_2, \theta_3] = [1/3, 1/3, 1/3]$, while the distribution of types of all MASPs is denoted by $\boldsymbol{\rho} = [\rho_1, \rho_2, \rho_3, \rho_4, \rho_5] = [1/5, 1/5, 1/5, 1/5, 1/5]$, unless otherwise specified. In addition, we set the minimum inference step D^{min} to $[5, 10, 15]$, the satisfaction parameter α to 1.5, the cost parameter β to 1, and the energy consumption parameter γ to 0.1.

First, we verify the validity of the IR and IC constraints and conduct the simulations to investigate the impact of the number of vehicles and computing resources of MASPs. Subsequently, we compare the performance of proposed multi-to-multi optimal contract (MOC) with that of optimal contract(OC) [10], [14]. Within the framework of OC, we model the relationship between a type of vehicle and multiple types of MASPs as a one-to-multi optimal contract design problem, where each MASP allocates computational resources equally among vehicle types.

As illustrated in Fig. 2, the utility of a MASP varies with the type of contract corresponding to different vehicle types. Fig. 2(a), Fig. 2(b), and Fig. 2(c) demonstrate that a MASP with type-ϕ_i consistently achieves the highest positive utility when it accepts the contract $(R_{k,i}, D_{k,i})$ specifically designed for its type-ϕ_i. This outcome aligns with the constraints expressed in (11) and (12). Furthermore, these figures indicate that the maximum utility for a MASP increases monotonically with the MASP's type. This trend can be attributed to the fact that higher types are associated with a greater willingness and enhanced capability of the MASP to deliver AIGC services. Based on above analysis, we can confidently conclude that the IR and IC conditions are satisfied, ensuring the efficiency and effectiveness of the contractual agreements.

Fig. 3 illustrates the average utility of vehicles as the number of vehicles increases, under various computing resource constraints of MASPs. The figure shows that the average utility of vehicles decreases as the number of vehicles increases. Furthermore, the rate of decrease in utility varies depending on

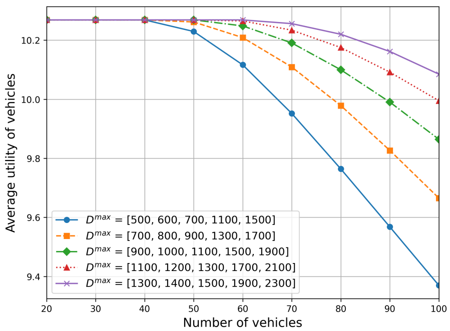


Fig. 3. Average utility of vehicles vs. Number of vehicles.

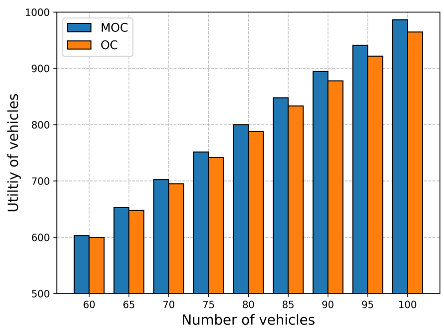


Fig. 4. Average utility of vehicles vs. Number of vehicles.

the D_{max} value. This is because with the growth in the number of vehicles, the computing resources available to the MASPs become relatively scarce, leading to a decrease in the utility of vehicles. Specifically, when the available computing resources are more limited (e.g., D^{max} set to [500, 600, 700, 1100, 1500]), the rate of decline in average vehicle utility is faster. In contrast, when the computing resources are more abundant (e.g., D^{max} set to [1300, 1400, 1500, 1900, 2300]), the decline in average vehicle utility is more slowly. It indicates that by increasing the available computing resources of the MASPs, the average utility of vehicles can be better maintained, even as the number of vehicles increases.

The Fig. 4 demonstrates the utility of vehicles under two optimization methods, the MOC and the OC, as the number of vehicles increases. We set the distribution of vehicles types as $\boldsymbol{\theta} = [1/6, 1/3, 1/2]$. Under both methods, the utility of vehicles rises with the growing number of vehicles involved in AIGC services. Importantly, the MOC method consistently outperforms the OC approach, as it more effectively optimizes the allocation of MASP computational resources more efficiently across different vehicle types. This performance gap becomes more pronounced as vehicle count increases, with MOC exhibiting substantially higher utility.

VI. Conclusion

In this paper, we present a multi-to-multi contract-based incentive mechanism for AIGC services in vehicle edge computing, addressing the challenges faced by RSU in managing user requests under information uncertainty. By applying contract theory, we developed an optimal contract design between various types of MASPs and various types of vehicles, identifying the necessary and sufficient conditions for optimality and simplifying the related constraints. Our simulation results demonstrate that the proposed mechanism effectively provides incentives and outperforms existing benchmark scheme. This work advances the understanding of AIGC services in IoV networks and highlights future research opportunities for refining contract designs and real-world scenarios.

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