Optimizing AIGC Services Using Learning-Based Stackelberg Game in Vehicular Metaverses

Bingkun Lai, Xiaofeng Luo, Jiawen Kang, *Senior Member, IEEE*, Xiaozheng Gao, *Member, IEEE*, Zuyuan Yang, Dusit Niyato, *Fellow, IEEE*, and Shiwen Mao, *Fellow, IEEE*

***Abstract*—The emerging vehicular metaverse embodies the next-generation vehicular networking paradigm. In the vehicular metaverses, Artificial Intelligence-Generated Content (AIGC) technology as a powerful content generation tool, is capable of providing an immersive experience for Vehicular Metaverse Users (VMUs). Due to limited computational resources within vehicles, VMUs rely on AIGC Service Providers (ASPs) to execute resource-intensive AIGC tasks within vehicular metaverses. However, large-scale AIGC service requests can lead to resource scarcity within the ASP, ultimately leading to declining service quality for VMUs. To tackle this challenge, we introduce a novel Stackelberg game framework utilizing the Generative Diffusion Model (GDM) for AIGC services, in which we experimentally reveal a relationship between image quality and diffusion steps. A Transformer-based Deep Reinforcement Learning (TDRL) algorithm is employed to find the optimal Stackelberg equilibrium under incomplete information. Numerical results indicate that our method converges to equilibrium efficiently, with superior utilities compared to baseline approaches.**

***Index Terms*—Vehicular metaverse, AIGC, stackelberg game, transformer-based DRL.**

I. Introduction

The rapid advancement of the vehicular metaverse has ignited people's widespread imagination regarding future transportation paradigms [1], [2]. As a key enabling technology, Artificial Intelligence-Generated Content (AIGC) significantly accelerates the creation of metaverse elements like buildings, plants, and Non-Player Characters (NPCs), which are essential for metaverse environment rendering. Beyond this, AIGC technology allows drivers and passengers in vehicular metaverses (known as Vehicular Metaverse Users (VMUs) [1]) to request customized AIGC services, such as Augmented Reality (AR) navigation and online Virtual Reality (VR) games.

Received 29 August 2024; revised 1 January 2025; accepted 12 February 2025. Date of publication 21 February 2025; date of current version 18 July 2025. This work was supported in part by the National Natural Science Foundation of China (NSFC) under Grant U22A2054 and Grant 62201054, in part by Guangzhou Basic Research Program under Grant 2023A04J1699, in part by Guangdong Basic and Applied Basic Research Foundation under Grant 2023A1515140137, in part by National Research Foundation, Singapore and Infocomm Media Development Authority through Future Communications Research and Development Programme under Grant FCP-NTU-RG-2022-010 and Grant FCP-ASTAR-TG-2022-003, and in part by the Singapore Ministry of Education (MOE) Tier 1 under Grant RG87/22 and Grant RG24/24. The review of this article was coordinated by Dr. Xuanyu Cao. *(Corresponding author: Jiawen Kang.)*

Bingkun Lai, Xiaofeng Luo, Jiawen Kang, and Zuyuan Yang are with the School of Automation, Guangdong University of Technology, Guangzhou 510006, China (e-mail: bingkunlai@163.com; gdutxiaofengluo@163.com; kavinkang@gdut.edu.cn; zuyuangdut@aliyun.com).

Xiaozheng Gao is with the School of Information and Electronics, Beijing Institute of Technology, Beijing 10081, China (e-mail: gaoxiaozheng@bit.edu.cn).

Dusit Niyato is with the College of Computing and Data Science, Nanyang Technological University, Singapore 639798 (e-mail: dniyato@ntu.edu.sg).

Shiwen Mao is with the Department of Electrical and Computer Engineering, Auburn University, Auburn, AL 36849 USA (e-mail: smao@ieee.org).

Digital Object Identifier 10.1109/TVT.2025.3544227

As a widely used generative AI model, the Generative Diffusion Model (GDM) [3] is distinguished for its superiority in high-quality image generation. VMUs can utilize GDMs to generate various types of content, fulfilling their individualized requirements such as crafting their unique avatar profiles within vehicular metaverses. However, due to the computational constraints of in-vehicle devices, VMUs typically rely on AIGC Service Providers (ASPs), e.g. RSUs, with robust computational capabilities to execute AIGC tasks like image generation, obtaining high-quality AIGC services [4], [5]. In this way, VMUs should pay ASPs for access to the required services, and in return, the ASP allocates computational resources commensurate with the payments. Nevertheless, a surge in AIGC service requests from VMUs within a short period can strain the resources of the ASP, leading to a sharp decline on quality of experience for VMUs in vehicular metaverses. Consequently, investigating the computational resource trading problem between the ASP and VMUs becomes imperative to ensure sustainable AIGC service provisioning. In a monopolistic market, where the leader (i.e., ASP) sets the prices first and the follower (i.e., VMUs) determine their computational resource requirements, a Stackelberg game [2] is appropriate to address this situation. However, few existing works study the AIGC services from a Stackelberg game perspective. Furthermore, a more efficient Stackelberg game solution is needed in vehicular metaverses due to the large-scale user network. Expanding upon the above challenges, we delve into the computational resource allocation problem for GDM-based AIGC services in vehicular metaverses, in which diffusion steps are used to quantify the computational resource usage. The main contributions are as follows:

- Through empirical experiments, we establish the correlation between image generation quality and diffusion steps in image repainting tasks using parameter fitting techniques for diffusion-based AIGC services.
- We introduce a novel Stackelberg game-based framework for AIGC services in vehicular metaverses, in which we reveal the interplay between the pricing strategy of ASP and computational resource requirements of VMUs related to the diffusion steps.
- Considering the sequential decision-making characteristic of Stackelberg game under incomplete information, we employ a Transformer-based DRL algorithm to solve the formulated game. Numerical results indicate that the proposed solution closely approximates Stackelberg equilibrium, which demonstrates its effectiveness.

II. Related Work

A. Vehicular Metaverse

Metaverse technology combines advanced technologies such as AI, Internet of Things (IoT), and Extended Reality (XR) to create a splendid physical-virtual hybrid environment to improve people's lives [1], [6]. Building on this, the vehicular metaverse is an emerging concept that integrates intelligent transportation systems with metaverse technology, enabling users within vehicles to interact with both physical entities and virtual worlds seamlessly and improve driving and riding experiences [1], [2], [6], [7]. Several studies have explored the vehicular metaverse from different perspectives. For example, Luo et al. [1] delved into the privacy and security challenges in vehicular metaverses, in which they comprehensively sorted out four types of privacy attacks

0018-9545 © 2025 IEEE. All rights reserved, including rights for text and data mining, and training of artificial intelligence and similar technologies. Personal use is permitted, but republication/redistribution requires IEEE permission. See https://www.ieee.org/publications/rights/index.html for more information.

Authorized licensed use limited to: Auburn University. Downloaded on January 29,2026 at 21:33:15 UTC from IEEE Xplore. Restrictions apply.

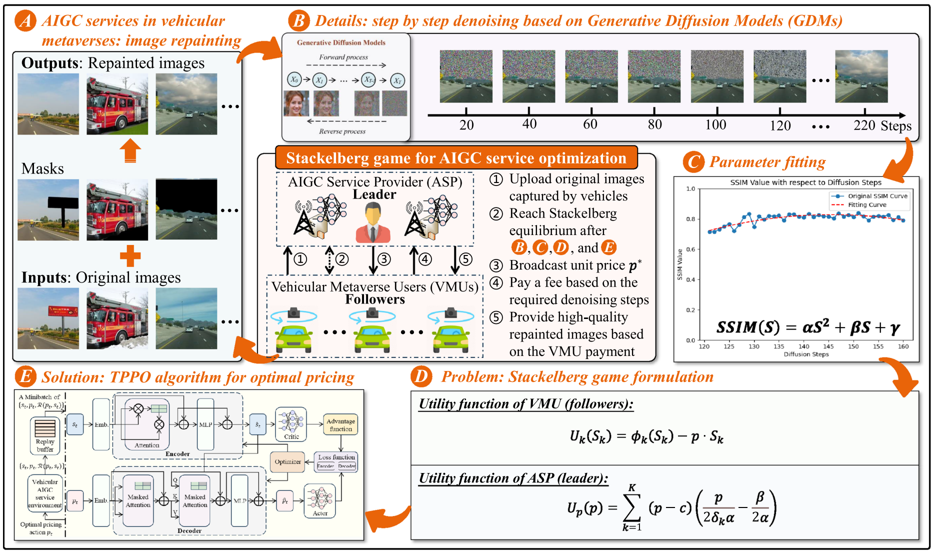


Fig. 1. Schematic diagram of the proposed Stackelberg game framework for GDM-based AIGC services in vehicular metaverses.

targeting VMUs and their digital counterparts while offering a feasible dual pseudonym change solution to protect user privacy. Liu et al. [7] introduced an efficient vehicular reputation management and resource allocation scheme for the PBFT consensus, which reduces latency and energy consumption to facilitate user collaboration within vehicular metaverses. Other research works have addressed issues such as resource optimization [2] and dynamic service migration [6] in vehicular metaverses. However, limited research has explored the potential of AIGC in accelerating real-world applications of vehicular metaverses.

B. AIGC Service Optimization

AIGC technology plays a pivotal role in the functionality of vehicular metaverses [4]. It can be employed to generate personalized content, enhancing the on-board experiences for drivers and passengers, while also enabling adaptive decision-making for autonomous vehicles in the face of complex traffic scenarios. Existing research has focused on enhancing user experience in metaverses by optimizing AIGC services. For example, Lin et al. [8] innovatively integrated blockchain with semantic communication to establish decentralized and trustworthy AIGC services in metaverses. In [5], Du et al. introduced an AI-generated optimal decision algorithm to generate optimal ASP selection decisions. However, the above works did not address the optimization of AIGC for dynamic vehicular networks, especially for vehicular metaverses. Furthermore, efficient methods for solving the resource optimization problem of GDM-based AIGC services are still lacking.

III. System Model

A. Network Model

The GDMs have been widely used across various generation tasks recently [5], [9]. These tasks include text-to-image generation, image super-resolution, and image repainting [10]. By leveraging powerful GDMs, the vehicular metaverse can provide immersive and high-quality experiences for VMUs. However, the widespread application of AIGC is still in its infancy due to the limited resources of VMUs. For instance, the inability to support mobile GPUs with high computing power requirements and the substantial bandwidth consumption of transmitting AI-generated high-resolution images can seriously restrict the deployment of AIGC on mobile devices. Therefore, to improve AIGC service quality in vehicular metaverses, a feasible and efficient solution is urgently needed. In recent years, the Stackelberg game has gained widespread adoption in resource allocation, in which the theoretical model can effectively describe the interactive actions between users and service providers [2], [11]. To better address the resource allocation problem of AIGC services, we propose a novel Stackelberg game framework for GDM-based AIGC services in vehicular metaverses as shown in Fig. 1. The detailed network model, i.e., the two parties involved in the Stackelberg game and the workflow are as follows:

- *ASP (Leader):* The ASP is the owner of computing resources at the network edge (e.g., RSUs), and provides AIGC service for VMUs by selling diffusion steps.
- *VMUs (Followers):* VMUs are the drivers and passengers within vehicles with resource constraints. They can pay the ASP according to their needs for the required number of diffusion steps to access AIGC services.

Step 1. Send AIGC service requests to the ASP: In the vehicular metaverse, due to the limited computational resources, VMUs send their service requests to the ASP so that the ASP can perform difficult AIGC tasks for them. The set of VMUs is represented as $\mathcal{K} \triangleq \{1, 2, \ldots, k, \ldots, K\}$, among which each VMU k has its unique satisfaction function, denoted as $\phi_k(\cdot)$.

Step 2. Formulate a Stackelberg game for AIGC services: After receiving the requests from all the VMUs, the ASP, as a leader with monopoly power, can strategically set the price of diffusion steps denoted as p to maximize its profit. Based on the the published price p, the VMUs, as followers, can decide how many diffusion steps the ASP performs. Hence, a Stackelberg game between the ASP and the VMUs is formulated.

Step 3. Utilize the TDRL algorithm to find the optimal game solutions: Furthermore, to provide efficient and stable resource allocation solutions for the AIGC services network, we utilize the TDRL approach to generate optimal Stackelberg game strategies.

Step 4. Adopt the optimal game solutions to perform AIGC tasks: Finally, with the optimal Stackelberg game solutions obtained by the TDRL algorithm, the ASP can provide AIGC services for VMUs, employing GDMs to generate personalized content according to users' demands.

Authorized licensed use limited to: Auburn University. Downloaded on January 29,2026 at 21:33:15 UTC from IEEE Xplore. Restrictions apply.

B. Trade-Off Between the Quality of AIGC Services and the Diffusion Steps

As GDM emerges as one of the main generative AI models, there arises a need to further explore the trade-off between diffusion denoising steps and content generation quality. Generally speaking, a higher number of diffusion denoising steps can generate higher-quality content, but it can result in a higher computational overhead [5]. In this subsection, we explore the quantitative trade-off relationship between the diffusion step and the content generation quality.

Since the vehicular metaverse requires a large amount of data for real-time rendering, the AIGC technology emerges as a perfect tool to provide generated data [1], [6]. As illustrated in Fig. 1, we study the image repainting problem as an example of the AIGC services in vehicular metaverses. We utilize the pre-trained image repainting model, *RePaint* [10], for our experiments. The *RePaint* model is a widely used diffusion-based model that has demonstrated its effectiveness in various image repainting tasks. Note that we take a series of original images as inputs to the *RePaint* model, which then generates repainted images according to VMUs' demands through the denoising process. For example, the ASP can repaint a snowy road with grass or change the weather of the road. By this way, the VMUs can use geneated images for vehicular metaverse rendering. Here, we adopt the widely used Structural Similarity Measure (SSIM) as the image performance metric [12], which is calculated by

$$SSIM(x,y) = g(C(x,y), L(x,y), u(x,y)), \tag{1}$$

where $C(x,y)$, $L(x,y)$, and $u(x,y)$ denote the contrast comparison, luminance comparison, and structure comparison between the image x and y, respectively. Moreover, $g(\cdot)$ represents the combination function of the three functions. Notably, we conducted the experiment multiple times to obtain the average SSIM value of the diffusion steps. Following that, we apply a parameter fitting method to obtain the relationship between the SSIM value and the diffusion steps [13]. As observed in Fig. 1, the SSIM value can be approximately fitted as a quadratic function of diffusion steps. Hence, the SSIM function of diffusion steps is expressed as

$$SSIM(S) = \alpha S^2 + \beta S + \gamma, \tag{2}$$

where S denotes the diffusion steps, while $\alpha < 0$, $\beta > 0$ and $\gamma < 0$ represent the experimentally fitting parameters. In our model, the number of diffusion steps is proportional to the time cost. For the diffusion model, each additional step is equivalent to one more inference of the diffusion model, so the higher the number of steps, the longer the AIGC service time. Moreover, considering the personalized satisfaction degree for the randomly generated images, we formulate the satisfaction function of VMU k by

$$\phi_k(S_k) = \delta_k SSIM(S_k). \tag{3}$$

Here, a higher satisfaction coefficient δ_k means that the VMU k is more satisfied with the generated images. Particularly, our method can be easily applied to various AIGC service analyses through efficient parameter fitting techniques.

IV. Stackelberg Game Problem Formulation

Game theory serves as a powerful mathematical tool for analyzing interactions among multiple players, each pursuing their own interests. This theoretical model ensures that there is no unilateral motivation for the players to deviate from their strategies [13]. In the AIGC service network, VMUs rely on computing power provided by the ASP to execute AIGC tasks. Consequently, as the primary holder of computing resources, the ASP plays the role of a monopolist in a monopolistic market, possessing the sole pricing power over computing resources. To be specific, when the price of the diffusion steps is relatively low, VMUs are more willing to increase the number of diffusion steps to attain higher-quality generated images. Conversely, VMUs are reluctant to purchase adequate diffusion steps if the price is too high, potentially leading to poor AIGC service experiences for VMUs. Moreover, the incentive mechanism between the ASP and the VMUs is modeled as a two-stage Stackelberg game. In the first stage, the ASP publishes the selling price of diffusion steps. Following that, the VMUs determine their diffusion step strategies based on the price in the second stage. Note that these interactions will iterate until reaching the Stackelberg equilibrium, and the second stage can be considered as a competitive game [13].

1) Utility of the VMUs: The utility of VMU k is the difference between the satisfaction function and the payment for the ASP to perform AIGC tasks. Hence, the utility function of VMU k is expressed by

$$U_k(S_k) = \phi_k(S_k) - p \cdot S_k, \tag{4}$$

where p represents the unit price of the diffusion steps. For simplicity, the diffusion step S_k is considered as a continuous variable. In the follower stage of the Stackelberg game, the VMUs determine their diffusion step strategies according to the current price p. To maximize the utility, the objective problem of the VMU k is denoted by

$$\begin{aligned} \textbf{Problem1}: & \max_{S_k} U_k(S_k) \\ & \text{s.t. } S_{\min} \le S_k \le S_{\max}. \end{aligned} \tag{5}$$

Here, $S_{\min}$ and $S_{\max}$ denote the lower bound and the upper bound of diffusion steps, respectively. Since diffusion generates images by progressive denoising from Gaussian noise, images exhibit higher levels of noise when the number of steps is low [5]. Conversely, the image quality will not increase when reaching a high level of diffusion steps. To maintain a satisfactory image quality, we set a minimum and maximum diffusion step limit for image generation.

2) Utility of the ASP: The utility of the ASP is equal to the total payment received from all VMUs minus the cost of performing AIGC tasks for VMUs. Thus, the utility function of the ASP is represented by

$$U_p(p) = \sum_{k=1}^{K} (p \cdot S_k - c \cdot S_k), \tag{6}$$

where $c > 0$ is the unit cost of diffusion steps. In the leader stage, when the ASP executes AIGC tasks for VMUs, there exists a maximum total amount of computing resources available. Consequently, the optimization problem in the leader stage can be formulated as

$$\begin{aligned} \textbf{Problem 2}: & \max_{p} U_p(p) \\ & \text{s.t. } S_{\min} \le S_k \le S_{\max}, \forall k, \\ & \sum_{k=1}^{K} S_k \le R, \\ & c \le p \le p_{\max}. \end{aligned} \tag{7}$$

3) Stackelberg equilibrium analysis: Through the combination of the **Problem 1** and **Problem 2**, we can formulate the Stackelberg game for AIGC services. At a Stackelberg equilibrium, neither the ASP nor any VMU can increase their profits by individually altering their strategies. The formal definition of Stackelberg equilibrium is as follows:

Authorized licensed use limited to: Auburn University. Downloaded on January 29,2026 at 21:33:15 UTC from IEEE Xplore. Restrictions apply.

Definition 1. (Stackelberg equilibrium): The optimal diffusion step strategy set is denoted as $\mathbf{S}^* = \{S_k^*\}_{k=1}^K$, while the optimal unit price of the diffusion steps is represented as p^*. Therefore, we denote $(\mathbf{S}^*, p^*)$ as the Stackelberg equilibrium involving the ASP and VMUs if the following conditions are strictly satisfied:

$$\begin{cases} U_p(\mathbf{S}^*, p^*) \geq U_p(\mathbf{S}^*, p), \\ U_k(S_k^*, \mathbf{S}_{-k}^*, p^*) \geq U_k(S_k, \mathbf{S}_{-k}^*, p^*), \forall k \in \mathcal{K}. \end{cases} \tag{8}$$

According to the study in [2], we utilize the backward induction method to prove the Stackelberg equilibrium.

Theorem 1: There exists a unique sub-game perfect equilibrium in the VMUs' subgame.

Proof: The first-order derivative and the second-order derivative of $U_k(S_k)$ with respect to S_k are calculated as follows:

$$\frac{\partial U_k}{\partial S_k} = \delta_k(2\alpha S_k + \beta) - p, \tag{9}$$

$$\frac{\partial^2 U_k}{\partial S_k^2} = 2\delta_k \alpha < 0. \tag{10}$$

Since the second-order derivative of $U_k(S_k)$ is negative, and the first-order derivative of $U_k(S_k)$ has a unique zero point, the utility function U_k of VMU k is strictly concave. Following that, we can obtain the best response function of VMU k based on the first-order optimal condition, i.e., $\frac{\partial U_k}{\partial S_k} = 0$, which is

$$S_k^* = \frac{p}{2\delta_k \alpha} - \frac{\beta}{2\alpha}. \tag{11}$$

Therefore, there is a unique sub-game perfect equilibrium in the VMUs' subgame. □

Theorem 2: The Stackelberg equilibrium $(\mathbf{S}^*, p^*)$ in the formulated game is unique.

Proof: Based on Theorem 1, there is a unique Nash equilibrium among the VMUs given any price strategy p. Hence, the ASP can maximize its utility by determining the optimal price. Substituting (11) into (6), we have

$$U_p(p) = \sum_{k=1}^{K} (p - c) \left(\frac{p}{2\delta_k \alpha} - \frac{\beta}{2\alpha} \right), \tag{12}$$

Following that, we calculate the first-order derivative and the second-order derivative of $U_p(p)$ with respect to p as follows

$$\frac{\partial U_p}{\partial p} = \sum_{k=1}^{K} \left(\frac{p}{\delta_k \alpha} - \frac{c}{2\delta_k \alpha} - \frac{\beta}{2\alpha} \right), \tag{13}$$

$$\frac{\partial^2 U_p}{\partial p^2} = \sum_{k=1}^{K} \frac{1}{\delta_k \alpha} < 0. \tag{14}$$

It can be deduced that the first-order derivative of U_p has a unique zero point, while the second-order derivative of U_p is negative, so the utility function of ASP is strictly concave [11]. Therefore, the Stackelberg equilibrium in the formulated game exists uniquely. □

V. TDRL-Based Incentive Mechanism Solution for AIGC Services

In this section, we introduce how to utilize the TDRL algorithm to solve the Stackelberg game for AIGC services under incomplete information. Traditional algorithms rely on precise network information when solving optimization problems. However, VMUs within AIGC service networks are often unwilling to share their complete information with the ASP. Fortunately, the DRL algorithm, as a reinforcement learning algorithm based on deep learning technology, can effectively learn to select the optimal solution based on the current state [14]. To further improve the training efficiency, we propose employing Transformer-based Deep Reinforcement Learning (TDRL) to solve the Stackelberg game.

A. Transformer-Based Deep Reinforcement Learning

The Transformer model, as a highly effective tool for processing sequential data, has recently gained widespread application in fields such as Natural Language Processing (NLP). It demonstrates superior performance compared to models based on traditional neural network architectures like convolutional neural networks. This advantage arises from its unique attention mechanism, which can fully capture the relationships between data sequences, thereby facilitating a more comprehensive understanding of the data [6]. Let d_k represent the dimension of $\mathbf{K}$. The attention function is expressed as

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{QK}{\sqrt{d_k}} \right) \mathbf{V}. \tag{15}$$

Here, $\mathbf{Q}$, $\mathbf{K}$, and $\mathbf{V}$ denote the vectors of queries, keywords, and values, respectively [6]. They share the same set of parameters, which is the principle of self-attention mechanism. The architecture of TDRL is illustrated in Fig. 1. The advantage of this architecture is its superior ability to learn the relationships between the sequence data of the environment state.

B. TDRL-Based Stackelberg Game Solution

The details of the DRL algorithm to solve the Stackelberg game is illustrated in *Part E* of Fig. 1. Firstly, the encoder encodes the state of the environment, which is the pricing strategy of the ASP and the diffusion steps of VMU in the past n rounds, and then the encoded state is utilized as the input to the critic network. Subsequently, the decoder observes the encoded states and the past pricing action p_t to output the current pricing strategy of the ASP to the actor network. The model parameters are updated according to the loss function, and this process is repeated until convergence. Below are more details about the Transformer-based DRL algorithm.

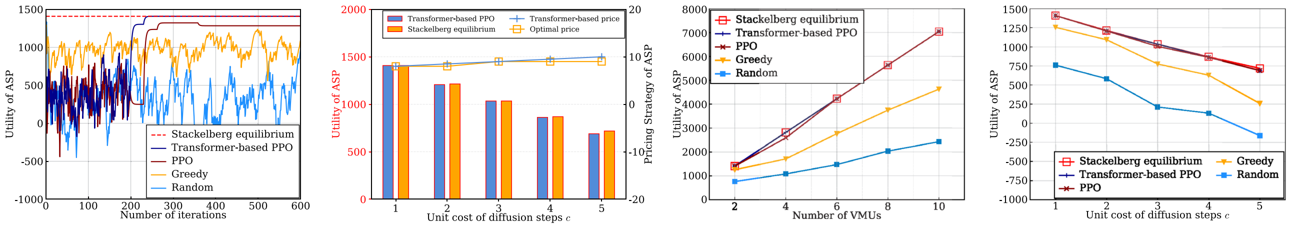
1) State space: When employing the TDRL algorithm to solve Stackelberg game problems, the state space normally comprises previous strategies information [13]. In the context of providing AIGC services, we consider that the ASP only possesses incomplete network information in real scenarios. The ASP can solely observe decision actions of the preceding n rounds [2]. Hence, in the current game round $t \in \mathcal{T} = \{1, \ldots, t, \ldots, T\}$, the state space consists of two parts, the pricing strategy of the ASP and the diffusion steps of VMU in the past n rounds [13], which is denoted as

$$s_t = \{p_{t-n}, \mathbf{S}_{t-n}, p_{t-n+1}, \mathbf{S}_{t-n+1}, \ldots, p_{t-1}, \mathbf{S}_{t-1}\}. \tag{16}$$

2) Action space: After receiving the previous strategies as inputs, the ASP, acting as an intelligent agent for network optimization, will make an optimal pricing decision $p_t \in [c, p_{\max}]$ to maximize its own benefit [13]. Therefore, the policy of ASP is represented by a neural network π_θ, which can be expressed as $\pi_\theta(p_t|s_t) \to [c, p_{\max}]$, where θ denotes the neural network parameters. *3) Reward:* When the ASP takes action p_t based on the current state s_t, the intelligent agent receives a reward [2], [13]. We define the reward function of ASP as

$$\mathcal{R}(p_t, s_t) = U_p^t, \tag{17}$$

Authorized licensed use limited to: Auburn University. Downloaded on January 29,2026 at 21:33:15 UTC from IEEE Xplore. Restrictions apply.



(a) (b) (c) (d)

Fig. 2. Performance of the proposed TPPO-based Stackelberg game framework for AIGC services in vehicular metaverses. (a) Convergence analysis. (b) The pricing strategy of ASP vs. unit cost of diffusion steps. (c) The utility of ASP vs. number of VMUs. (d) The utility of ASP vs. unit cost of diffusion steps.

where U_p^t is the utility function of the ASP in the current round, calculated by (6). Next, we introduce the computation complexity of the transformer-based DRL solution. Given the input sequence length h, and the hidden vector dimension d, the computation complexity of attention mechanism is denoted as $O(h^2 d)$, while the computation complexity of linear transformation is represented as $O(hd^2)$ [15]. Therefore, the total computation complexity of the transformer-based DRL solution is calculated as $O(L(hd^2 + h^2 d + hdd_{ff}))$, where L is the number of transformer layers, and d_{ff} refers to the hidden layer dimension of the feed-forward network.

VI. Numerical Results

In this section, we present the performance of the proposed framework for AIGC services. Firstly, we provide the important simulation parameters. Following that, we evaluate the proposed framework through simulation experiments.

A. Experiment Settings

We conduct the simulations on a high-performance server with 2 Intel Xeon 6133 CPUs and 2 Nvidia RTX A6000 GPUs. For image repainting tasks, we conduct real experiments to model the relationship between the SSIM value and diffusion steps. We generate the repainted images with an amount of 10 samples and get the average results, with the diffusion steps ranging from 120 to 160. In this way, we obtain the fitting parameters of $SSIM(S)$ in (2), which are $\alpha = -0.000174$, $\beta = 0.075$, and $\gamma = 4891.89$. In the formulated Stackelberg game for AIGC services. Moreover, the k is set to 2 and the average satisfaction coefficient is set as 200 by default. The unit cost c and maximum price p are 1 and 20, respectively. For the learning-based algorithm execution, the TDRL algorithm is designed based on the famous DRL algorithm, Proximal Policy Optimization (PPO) [16].

B. Simulation Results

We evaluate the performance of the proposed TPPO algorithm with another DRL algorithm, the PPO, along with two conventional baselines, Greedy and Random [2]. As shown in Fig. 2(a), in the Stackelberg game for AIGC services, the TPPO algorithm achieves faster convergence and greater utility compared to other baselines, demonstrating its higher performance and efficiency. Moreover, we observe that the utility of the proposed algorithm is initially lower and more fluctuating than that of the traditional algorithm like greedy. The reason is that the DRL algorithms usually generate their strategies by a randomly initialized neural network. Therefore, the initial neural network is still in the exploration stage. As the training proceeds, the DRL agent gradually gains a deeper understanding of the environment, enabling it to make more accurate predictions and achieve higher rewards. It should be noted that we conducted the experiment 3 times and took the average utility as the result.

Fig. 2(b) and (d) demonstrate the impact of the unit cost of diffusion steps. To be specific, we change the unit cost from 1 to 5 while keeping other parameters unchanged. As observed, even though the cost is changing, both the utilities and pricing actions of the ASP are still close to the Stackelberg equilibrium, demonstrating the effectiveness of the proposed TPPO-based game solutions under incomplete information. Furthermore, as the cost increases, we can find that the price of diffusion steps also increases. This is because as the cost increases, the ASP would have to set a higher price to maintain the profit. Meanwhile, the rise in cost results in a notable decrease in the utility of the ASP. This occurs because the increase in cost drives up prices, eventually leading to a decline in VMUs' pursuit of diffusion steps, thereby diminishing the ASP's utility. Furthermore, both TPPO and PPO algorithms achieve higher utility than traditional algorithms like greedy and random. The reason is that, unlike traditional algorithms, DRL algorithms can interact with an environment to generate near-optimal actions through continuous learning [14].

Fig. 2(c) shows the utility variations of the ASP with respect to different numbers of VMUs. As the number of VMUs increases, the utility of the ASP increases correspondingly. With more VMUs joining the vehicular AIGC services, the AIGC network becomes larger, resulting in the growth of the utility of the ASP. The TPPO algorithm can still reach the optimal Stackelberg game solutions when more VMUs join the network, further demonstrating the superiority of the TPPO method in the Stackelberg game under incomplete information.

VII. Conclusion

In this correspondence, we propose a Stackelberg game framework to optimize diffusion-based AIGC services in vehicular metaverses. To optimize AIGC services, we first study the relationship between AIGC service quality and diffusion steps through parameter fitting techniques. Building on this, we formulate a Stackelberg game between the ASP and the VMUs. Subsequently, the TPPO-based algorithm is employed to find the optimal game solution under incomplete information. Numerical results show that the proposed TPPO algorithm converges to the Stackelberg equilibrium and outperforms other baseline methods. The current framework only considers a single server as the ASP, which limits its large-scale deployment in vehicular metaverses. Future work will extend this framework to a multi-leader multi-follower Stackelberg game to further improve practicality.

References

[1] X. Luo et al., "Privacy attacks and defenses for digital twin migrations in vehicular metaverses," *IEEE Netw.*, vol. 37, no. 6, pp. 82–91, Nov. 2023.

Authorized licensed use limited to: Auburn University. Downloaded on January 29,2026 at 21:33:15 UTC from IEEE Xplore. Restrictions apply.

[2] J. Zhang et al., “Learning-based incentive mechanism for task freshness-aware vehicular twin migration,” in *Proc. IEEE 43rd Int. Conf. Distrib. Comput. Syst. Workshops*, 2023, pp. 103–108.

[3] R. Rombach, A. Blattmann, D. Lorenz, P. Esser, and B. Ommer, “High-resolution image synthesis with latent diffusion models,” in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, 2022, pp. 10684–10695.

[4] B. Lai et al., “Resource-efficient generative mobile edge networks in 6G era: Fundamentals, framework and case study,” *IEEE Wireless Commun.*, vol. 31, no. 4, pp. 66–74, Aug. 2024.

[5] H. Du et al., “Diffusion-based reinforcement learning for edge-enabled AI-generated content services,” *IEEE Trans. Mobile Comput.*, vol. 23, no. 9, pp. 8902–8918, Sep. 2024.

[6] J. Kang et al., “UAV-assisted dynamic avatar task migration for vehicular metaverse services: A multi-agent deep reinforcement learning approach,” *IEEE/CAA J. Automatica Sinica*, vol. 11, no. 2, pp. 430–445, Feb. 2024.

[7] L. Liu, J. Feng, C. Wu, C. Chen, and Q. Pei, “Reputation management for consensus mechanism in vehicular edge metaverse,” *IEEE J. Sel. Areas Commun.*, vol. 42, no. 4, pp. 919–932, Apr. 2024.

[8] Y. Lin et al., “Blockchain-based efficient and trustworthy AIGC services in metaverse,” *IEEE Trans. Serv. Comput.*, vol. 17, no. 5, pp. 2067–2079, Sep./Oct. 2024.

[9] Z. Liu et al., “DNN partitioning, task offloading, and resource allocation in dynamic vehicular networks: A Lyapunov-guided diffusion-based reinforcement learning approach,” *IEEE Trans. Mobile Comput.*, vol. 24, no. 3, pp. 1945–1962, Mar. 2025.

[10] A. Lugmayr, M. Danelljan, A. Romero, F. Yu, R. Timofte, and L. Van Gool, “Repaint: Inpainting using denoising diffusion probabilistic models,” in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, 2022, pp. 11461–11471.

[11] W. Sun, P. Wang, N. Xu, G. Wang, and Y. Zhang, “Dynamic digital twin and distributed incentives for resource allocation in aerial-assisted internet of vehicles,” *IEEE Internet Things J.*, vol. 9, no. 8, pp. 5839–5852, Apr. 2022.

[12] Z. Wang, A. Bovik, H. Sheikh, and E. Simoncelli, “Image quality assessment: From error visibility to structural similarity,” *IEEE Trans. Image Process.*, vol. 13, no. 4, pp. 600–612, Apr. 2004.

[13] Y. Zhan, P. Li, Z. Qu, D. Zeng, and S. Guo, “A learning-based incentive mechanism for federated learning,” *IEEE Internet Things J.*, vol. 7, no. 7, pp. 6360–6368, Jul. 2020.

[14] Z. Liu, L. Huang, Z. Gao, M. Luo, S. Hosseinalipour, and H. Dai, “GA-DRL: Graph neural network-augmented deep reinforcement learning for dag task scheduling over dynamic vehicular clouds,” *IEEE Trans. Netw. Service Manag.*, vol. 21, no. 4, pp. 4226–4242, Aug. 2024.

[15] K. Han, A. Xiao, E. Wu, J. Guo, C. Xu, and Y. Wang, “Transformer in transformer,” in *Proc. Adv. Neural Inf. Process. Syst.*, 2021, pp. 15908–15919.

[16] M. Wen et al., “Multi-agent reinforcement learning is a sequence modeling problem,” in *Proc. Adv. Neural Inf. Process. Syst.*, 2022, pp. 16509–16521.

Authorized licensed use limited to: Auburn University. Downloaded on January 29,2026 at 21:33:15 UTC from IEEE Xplore. Restrictions apply.