# AI-Generated Bidding for Immersive AIGC Services in Mobile Edge-Empowered Metaverse

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***Abstract*—Recent advancements in Artificial Intelligence Generated Content (AIGC) provide personalized and immersive content generation services for applications such as interactive advertisements, virtual tours, and metaverse. With the use of mobile edge computing (MEC), buyers can bid for the AIGC service to enhance their user experience in real-time. However, designing strategies to optimize the quality of the services won can be challenging for budget-constrained buyers. The performance of classical bidding mechanisms is limited by the fixed rules in the strategies. To this end, we propose AI-generated bidding (AIGB) to optimize the bidding strategies for AIGC. AIGB model uses reinforcement learning model to generate bids for the services by learning from the historical data and environment states such as remaining budget, budget consumption rate, and quality of the won services. To obtain quality AIGC service, we propose a semantic aware reward function for the AIGB model. The proposed model is tested with a real-world dataset and experiments show that our model outperforms the classical bidding mechanism in terms of the number of services won and the similarity score.**

***Index Terms*—Artificial intelligence generated content, artificial intelligence generated bid, budget-constraint bidding**

## I. Introduction

Artificial Intelligence Generated Content (AIGC) is a technology that uses artificial intelligence (AI) algorithms to automatically create and customize content [1] such as videos, images, and audio. In the context of the metaverse, AIGC can be used to create immersive and interactive experiences for users. For example, AI-generated video can be used to create personalized and interactive advertisements, virtual tours, or training sessions. By leveraging AI-generated content, the metaverse can provide highly engaging and realistic experiences for users, enhancing the overall user experience. Edge-enabled AIGC generation involves the use of mobile edge computing (MEC) to process data at the edge of the network, reducing latency and improving overall user experience. This approach can be applied to AI-generated content creation, such as videos, images, and audio. By leveraging MEC, AI algorithms can generate content in real-time or near real-time, providing highly engaging and personalized experiences for users [2]. The use of edge computing can also enhance the security and privacy of the users' data, as sensitive information can be processed locally without the need for transmitting it to external servers. Overall, edge-enabled AIGC generation can significantly enhance the capabilities of the metaverse and provide highly engaging and realistic experiences for users.

To obtain AIGC in real-time, we can adopt real-time bidding (RTB) mechanisms in which service buyers bid for the AIGC service in real-time. Budget-constrained bidding is a typical strategy in RTB where the bidders hope to maximize the total value of returns under a budget. This strategy could help AIGC bidders to maximize their returns under budget constraints. The bidding process can be described as follows. During a time period, one day for instance, there are AIGC service opportunities arriving sequentially. The bidder gives a bid according to the AIGC value and competes with other bidders in real-time. The bidder with the highest bid has the privilege to obtain the AIGC service and enjoys the value brought by the AIGC. In the second price auction, the price is determined by the second highest bid in the auction. The bidding process terminates whenever the total cost reaches the bidder's budget limit or all the AIGC services have gone through the auction. The goal of budget-constrained bidding is to maximize the total value of returns under the budget.

Classical bidding mechanisms such as fixed linear bidding (FLB) linearly scales the bid with a fixed scaling factor. Budget Smoothed Linear Bidding [3] combines the fixed linear bidding with the current budget consumption information. When the budget left ratio is lower than the time left ratio, the bid is decreased, otherwise, the bid is increased to consume more budget. Instead of using fixed rules to scale the bids, AI-generated bidding (AIGB) uses deep learning networks to learn from the historical bids and their respective returns to optimize the bidding strategies for future bids. For example, model-free Reinforcement Learning (RL) [4] is proposed to resolve the optimization problem of budget-constrained bidding. Deep neural networks are used to learn the appropriate reward so that the optimal policy can be learned effectively. A unified solution [5] is proposed to formulate various demands as constrained bidding problems and then derive a unified optimal bidding function to achieve the optimum. RL method is adopted to dynamically adjust parameters to achieve the optimum. Most of the AIGB models focus on bidding problems in display advertising. A few works have addressed the formulation of AIGB mechanisms in AIGC service. Moreover, the training process of AIGB for AIGC is challenging because there are limited real-world datasets with AIGC bidding. To

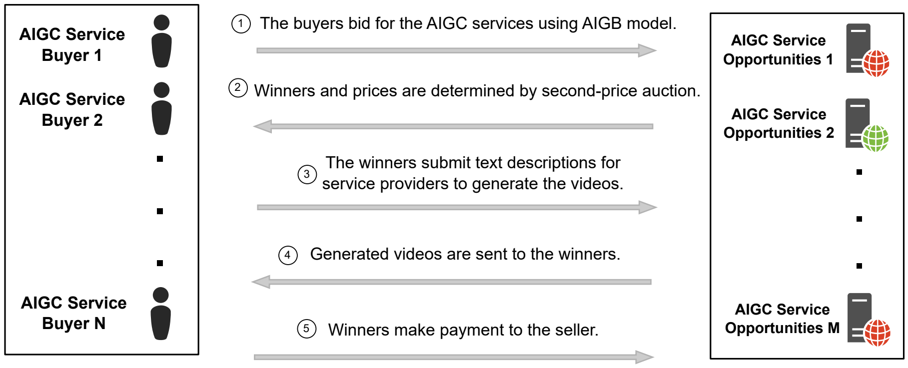


Fig. 1: System Model.

this end, we propose a budget-constrained AIGB model for AIGC service with AIGC-related metrics considered in the problem formulation. A bidding dataset for AIGC is generated to train and evaluate the proposed AIGB model. The main contributions of our paper are as follows:

- We propose a budget-constrained AIGB for AIGC. Different from the previous works where bid values are decided by fixed rules, AIGB model learns from the historical data and generates dynamic bid value in real-time to maximize the return of the service buyers.
- We propose a semantically aware AIGC-related reward function to optimize the value of the AIGC service. In contrast to the existing AIGB models where the semantic value of the service is not considered in the reward function, we proposed to measure the semantic value of the AIGC based on text-video similarity extracted by cross-modal language-video attention.
- We propose a dataset generation method to simulate the bidding process with real-world data. Text descriptions from real-world video captioning dataset are randomly sampled. Then, videos are generated using the text descriptions of the auction winner in our simulation. Finally, the text-video similarity score is extracted as the reward of the winner in our model.

## II. System Model

In our model, there are $M$ AIGC service opportunities offered by the service providers to the service buyers. Each service opportunity offers to generate a video from a text description sent by the winner. Due to resource constraints, e.g., bandwidth, energy, and computing resources, the service providers might offer video generation services with different video lengths. The service buyers bid for the service opportunities according to their valuations of the services. Our model uses second price auction (SPA) to decide the winner and price of the service opportunities. In SPA, the highest bidder wins the auction and pays the price of the second-highest bid. To realize RTB for AIGC service, we consider a service buyer

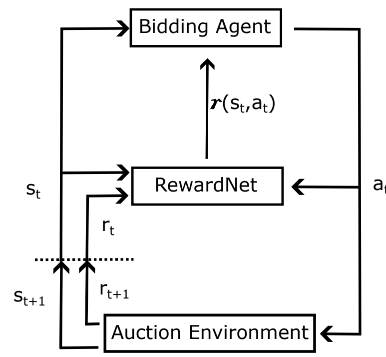


Fig. 2: AI-generated bidding model.

has a fixed budget, $B$, and target to maximize the value of the AIGC service won:

$$\begin{aligned} &\max \sum_{m=1}^{M} y_m v_m \\ &s.t. \sum_{m=1}^{M} y_m c_m \leq B \end{aligned} \tag{1}$$

where $M$ is the total number of service opportunities, $y_m$ is the binary value to indicate whether the service opportunity $m$-th service opportunity is won, and $v_m$ is the value of the service. The optimal bidding strategy is hard to derive due to the complexity and volatility of the auction environment. As such, we propose a model-free reinforcement learning framework as the AIGB model to help service buyers optimize their bidding strategy (Fig. 1).

In our framework, the buyers bid for the service according bid value generated by the AIGB model. Each buyer starts with an initial scaling parameter, $\lambda_0$. Then, the agent of our reinforcement learning framework regulates the scaling parameter sequentially with a fixed number of steps until the episode ends. At each time step, the agent observes the states and adjusts the scaling parameter, $\lambda_t$. The bid for the AIGC service is decided by dividing the valuation of the service by the scaling parameter:

$$b_m = v_m / \lambda_t \tag{2}$$

**Algorithm 1** AIGB Model

Initialize replay memory $D_1$ to capacity $N_1$
Initialize the weights $\theta$ of $Q$ randomly
Initialize the weights $\theta^-$ of $Q$ $target$ as $\theta$
**for** each episode **do**
  Initialize $\lambda_0$
  Bid according to Equation (2)
  **for** each timestep **do**
    Update RewardNet
    Get state $s_t$
    Obtain action $a_t$ from adaptive $\epsilon$-greedy policy
    Adjust scaling parameter $\lambda_{t-1}$ to $\lambda_t$
    Bid according to Equation (2) with $\lambda_t$
    Get $r_t$ from RewardNet
    Get next state $s_{t+1}$
    Store $(s_t, s_{t+1}, a_t, r_t)$ in $D_1$
    Sample mini batch of $(s_j, s_{j+1}, a_j, r_j)$ from $D_1$
    **if** $s_{j+1}$ is the terminal state **then**
      Set $y_j = r_j$
    **else**
      Set $y_j = r_j + \gamma \max_{a'} Q(s_{j+1}, a'; \theta^-)$
    **end if**
    Update $\theta$ with loss $(y_j - Q(s_j, a_j; \theta))^2$
    Reset $Q$ $target = Q$ every C steps
  **end for**
  Store data for RewardNet
**end for**

The agent's goal is to learn an optimal scaling parameter control policy to maximize the cumulative reward as long as the total cost is less than the budget. The total value of the similarity constitutes the immediate reward, associated with the cost to obtain the service.

More specifically, the core elements of the framework are further explained as follows:

- State $\mathcal{S}$ consists of the following parameters: 1) the current time step, $t$, 2) the remaining budget at the current time step, $B_t$, 3) the number of scaling parameter regulation opportunities left at the current time step, $R_t$, 4) the budget consumption rate, $U_t$, 5) the cost per similarity score of the won services between time step $t-1$ and $t$, 6) the auction win rate reflecting the ratio of winning services versus total services available, $W_t$, and 7) the total value of similarity as the quality of the won services, $S_{t-1}$.
- Action $\mathcal{A}$: a number of adjustment rates to be multiplied with the scaling parameter. Specifically, an action $a \in \mathcal{A}$ returns an adjustment rates $\beta_a$. Scaling parameter can be expressed as $\lambda_t = \lambda_{t-1} * (1 + \beta_a)$.
- Reward: We use the similarity between the description and the video generated as the immediate reward. The similarity is extracted by using the cross-modal attention between the language (text) and visual (video) features.
- Cost: the price paid by the winner, decided by second-price auction (SPA).

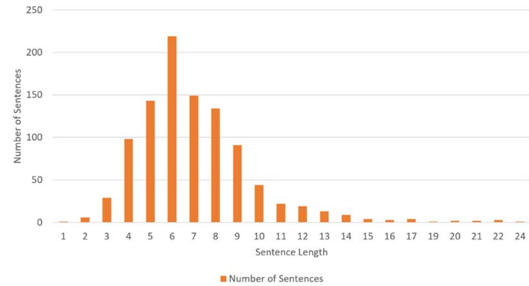

Fig. 3: Sentence Length Distribution.

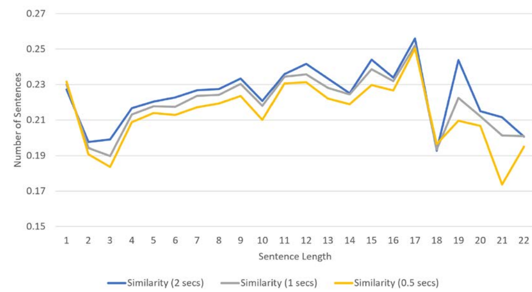

Fig. 4: Text-Video Similarity Score.

The algorithm of the AIGB model is shown in Algorithm 1. The overall structure of the AIGB model is illustrated in Fig. 2. Instead of using the immediate reward, RewardNet [4] is used to predict the reward by learning from the data in mini-batches. This is to avoid high consumption of the budget at the beginning to obtain high immediate rewards. The state-action value function, $Q$ uses a multilayer perceptron with 3 hidden layers. Each hidden layer has 100 nodes. The RewardNet is built with a similar neural network structure.

## III. Numerical Results

To obtain the train and test dataset, we generate videos based on 1000 descriptions randomly selected from the video captioning dataset [6]. The sentence length distribution of the descriptions is shown in Fig. 3. For each description, we generate three videos with lengths of 0.5s, 1s, and 2s. To evaluate the quality of the generated videos, we obtain the text-video similarity of each video and description pair using cross-modal language-video attention [7]. The analysis of the video generated is shown in Fig. 4. We can observe that the similarity is higher when the video is longer. The trend is consistent across different sentence lengths. Hence the video length offered by the service provider should be considered by the buyers when bidding for the service. Samples of the videos generated are shown in Fig. 5. With initial scaling parameter $\lambda_0 = 1$, the loss of deep Q-network is recorded in Fig. 7. We can observe that the network converges quickly to increase the reward (similarity score) of the bidding results. In Fig. 8, we show that our model performs consistently with different numbers of bidders. We obtain the number of services won

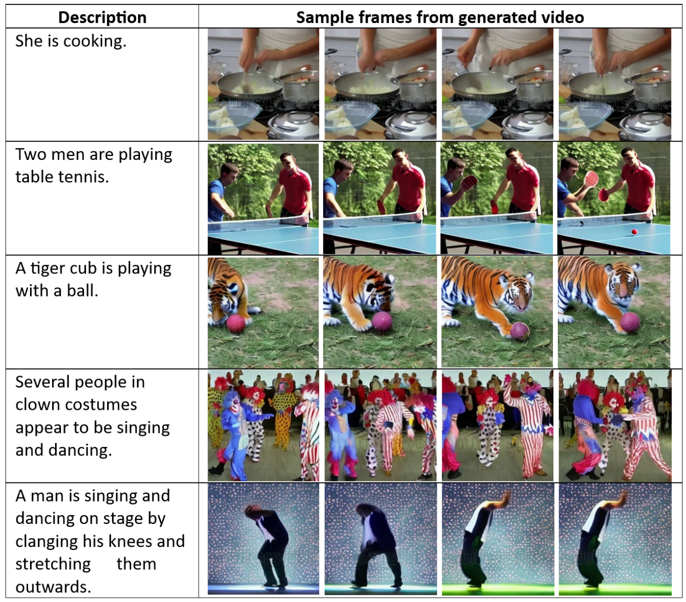


Fig. 5: Samples of videos generated with text descriptions.

TABLE I: Relationship between the action size (under different adjustment ranges and step sizes) and the performance of the model. Bold values indicate the best results in our experiment.

| Adjustment Range | Service Won (step size = 2%) | Action Size (step size = 2%) | Service Won (step size = 1%) | Action Size (step size = 1%) |
|---|---|---|---|---|
| [-5%,5%] | 572.60 | 6 | 524.11 | 11 |
| [-10%,10%] | 571.33 | 11 | **625.33** | **21** |
| [-15%,15%] | 614.64 | 16 | 528.89 | 31 |
| [-20%,20%] | 613.80 | 21 | 590.88 | 41 |
| [-25%,25%] | 515.22 | 26 | 547.89 | 51 |

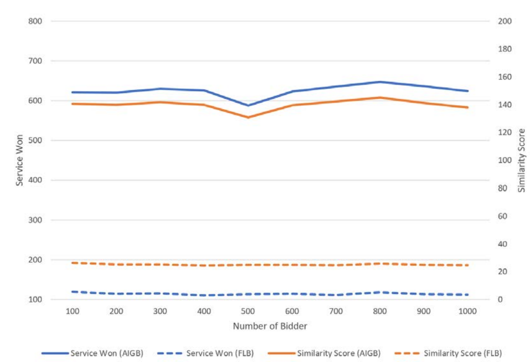


Fig. 6: Comparison of the AI-generated Biddng (AIGB) and Fixed Linear Bidding (FLB).

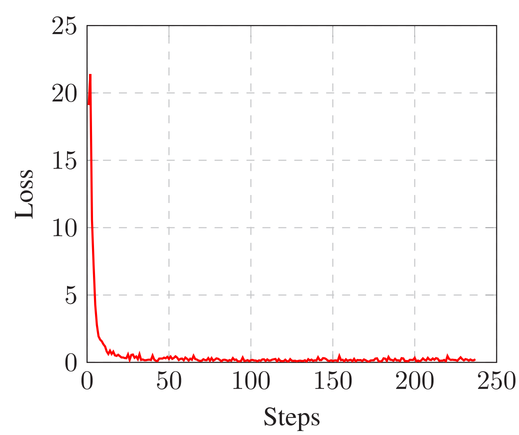


Fig. 7: Deep Q-Network Loss.

and the total similarity score with an adjustment range of [-10%,10%] and step size of 1% in 10 days with 96-time steps.

To investigate the effect of adjustment range on the number of services won, the model is tested with different adjustment ranges. The results are shown in Fig. 9. It can be observed that the adjustment range of [-10%,10%] has the best overall results. This is because a smaller adjustment range ([-5%,5%]) limits the maximum bid that the model can generate, reducing the chances of winning the auction. On the other hand, higher adjustment ranges ([-15%,15%],[-20%,20%],[-25%,25%]) increase the action size of the model, and it is more challenging for reinforcement learning models to learn the optimal action with action redundancy [8]. A better view of the relationship between the action size and adjustment range is shown in TABLE I. Note that the action size is also related to the step size of the adjustment rate, i.e., a smaller step size has a larger action space. From TABLE I, we can observe that the model

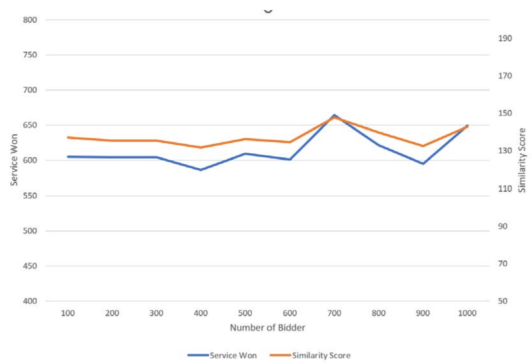


Fig. 8: Service won and similarity score under different numbers of bidders.

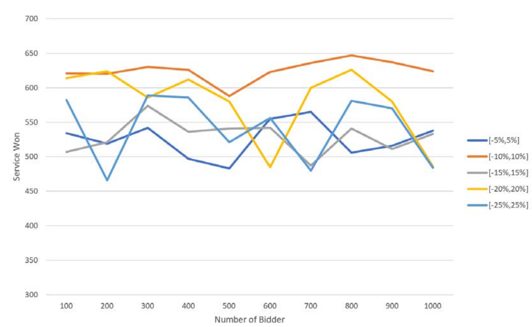


Fig. 9: Performance of the model with different adjustment ranges.

operates better with an action size around 16 to 21, and with an adjustment range equal to or larger than [-10%,10%]. The results recorded are the average number of services won under different numbers of bidders (100-1000).

Finally, in Fig. 6, we compare our model with the fixed linear bidding (FLB) model where the adjustment rate is fixed. The FLB performance is obtained by averaging the results of a fixed adjustment rate in the range of [-10%,10%] with a step size of 1%. Our model with the same adjustment range wins more services and achieves a higher similarity score than the FLB model. This is because the AIGB model adjusts the bid according to the video length and historical auction results to win more services.

## IV. Conclusion

In this paper, we developed a budget-constrained AIGB model for AIGC service bidding. By learning from the historical data to generate dynamic bid values, our model outperforms the classical bidding mechanism in terms of the number of services won. To simulate real-world bidding process for AIGC, we generated videos from text descriptions sampled from real-world data. Experiments show that the quality of services won is optimized by the semantic aware reward function which considers the text-video similarity extracted by cross-modal attention mechanism. For future work, we can study the AIGB models for different AIGC services such as audio, 3-dimensional visual data, and multi-modal data generations.

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