Optimal Auction for Effective Energy Management for UAV-assisted Metaverse Synchronization System

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***Abstract*—In this paper, we investigate an effective energy management in a UAV-assisted Metaverse synchronization system. The UAVs perform the data collection for a virtual service provider (VSP) for the synchronization between the physical objects and digital twins (DTs). The UAVs buy energy resources from an energy service provider (ESP). The key issue is to motivate both the ESP and the UAVs to participate in the energy trading market. For this, we design a deep learning (DL)-based auction scheme that maximizes the revenue of the ESP while guaranteeing individual rationality (IR) and incentive compatibility (IC). We provide numerical results to demonstrate the improvement of the DL-based auction scheme compared to the baseline scheme in terms of revenue, IC, and IR.**

***Index Terms*—Digital twin, energy trading, Metaverse, optimal auction, deep learning**

I. Introduction

To provide Metaverse services to users with high quality of experience (QoE), air-assisted Internet of Vehicles (IoVs) such as unmanned aerial vehicles (UAVs) have been recently proposed for the data synchronization between physical objects in the real world and digital twins (DTS) [1]. UAVs operating in a high altitude is able to provide line-of-sight (LoS) for the data sensing and communication to the physical objects and to ground base stations (GBS) of virtual service providers (VSPs). Therefore, the use of UAVs helps to reduce time of the data sensing and data communication, which allows the VSP to have fresh data and provide the Metaverse services with high QoE. As a result, recent works, e.g., [1] and [2] have investigated the use of UAVs for the Metaverse synchronization.

However, UAVs are constrained by their energy supply, and thus they need to be charged during their long-term operation. In general, they can be replenished from surrounding environments [3] or electrical sources [4] which are deployed by an energy service provider (ESP). In particular for the electrical sources, mobile charging stations (MCSs) can be deployed to serve UAVs conveniently. However, for the ease of mobility, MCS typically has a smaller size and lower energy capacity, and thus only a limited number of UAVs is served by MCS. Therefore, the key issue is how the ESP efficiently and effectively allocates the energy resources to the UAVs. Another key issue is to motivate the ESP to provide the energy resources to the UAVs as well as to motivate the UAVs to participate in the energy trading market.

Auction is known as an appropriate solution which guarantees that the energy resources are allocated to the UAVs that value the resources most. In a classical auction, buyers or bidders compete for items (commodities) by submitting their prices, i.e., bids, to a seller or an auctioneer. The seller then determines the winning bidders and the prices that they need to pay. There are three classical auction mechanisms such as the first price auction, second-price auction (SPA), and Vickrey-Clarke-Groves (VCG) auction [5]. In particular, the first price auction scheme enables the ESP to achieve high revenue, but it does not guarantee desirable economic properties such as incentive compatibility (IC) (truthfulness) and individual rationality (IR). Note that IC and IR are very important properties in resource allocation mechanisms. Specifically, IC motivates the UAVs to reveal their true values on the resource and hence maintains the system stability. Meanwhile, IR guarantees the non-negative utility (payoff) for the UAVs that motivates them to participate in the energy market. To guarantee IC and IR, the SPA and VCG auction schemes are used. However, the SPA and VCG auction schemes do not achieve a high revenue, which discourage the ESP to provide the energy resources. Therefore, the problem of designing an optimal auction to maximize the revenue for the ESP while ensuring both IC and IR is considerably challenging [6].

Deep learning (DL) has been recently shown to find global optimal solutions, and it was proposed for designing the optimal auctions [6]. As presented in [6], the DL-based auction mechanism designed for the multi-item scenario is able to achieve the optimal revenue while guaranteeing IC and IR. In this paper, we thus propose to use the DL-based auction for the energy resource allocation in the UAV-assisted Metaverse synchronization system. Therein, we formulate valuation functions of energy resources for the UAVs. The valuation functions account for Metaverse synchronization parameters apart from the remaining energy and the total energy consumption of the UAVs. We design two feed-forward neural network (FNNs) for the allocation and payment rules. The first FNN is to determine the winning UAVs, and the second FNN is to determine the prices that the winning UAVs need to pay. Based on the dataset including bidding profiles, i.e., valuation profiles, of the UAVs, the two FNNs are simultaneously trained to minimize a common loss function. Since the goal of the designed DL-based auction is to fit the optimal auction that maximizes the revenue of the ESP and guarantee IC and IR constraints, the loss function of the two FNNs is formulated by combining the expected revenue, IR constraints, and IC constraints together via the augmented Lagrangian method. We provide numerical results to demonstrate the improvement of the DL-based auction schemes compared to the classical auctions in terms of revenue, IC, and IR.

The rest of this paper is organized as follows. Section II presents the UAV-assisted Metaverse synchronization system, the energy consumption of the UAVs, and the valuation function. Section III introduces the energy trading market and problem formulation. Section IV provides and discusses simulation results. Section V concludes this paper.

II. System Model

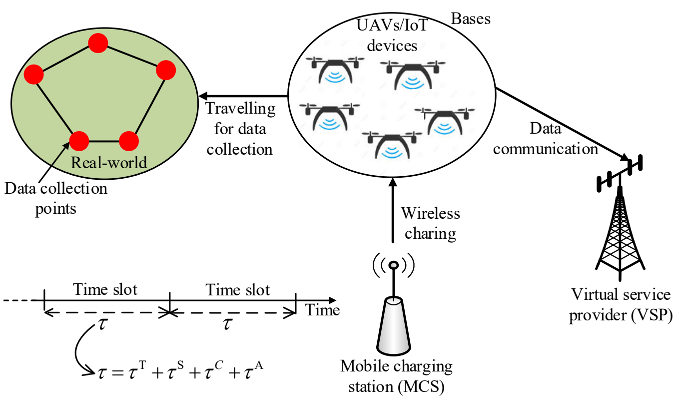


Fig. 1. a) UAV-assisted Metaverse synchronization system and b) DL-based auction scheme.

We consider a UAV-assisted Metaverse synchronization system as shown Fig. 1. The system consists of a set $\mathcal{N}$ of N UAVs that perform sensing tasks for a virtual service provider (VSP). The VSP has D digital twins (DTs) that are critical to its virtual business profit. The sensing task of each UAV can be implemented in multiple time slots. In each time slot, the UAVs do travelling, data sensing, and data communication. In particular, the UAVs first travel from their bases to a sensing region. After performing sensing the physical objects in the region, the UAVs come back to their bases and transmit the collected data to the VSP via a ground base station (GBS) for the DT synchronization. At their bases, the UAVs perform the wireless charging from a mobile charging station (MCS), which is owned by an energy service provider (ESP). Each UAV requests energy units for their battery charging. Due to the limited energy resources, the auction is adopted to determine the winners of energy units and the corresponding payments. Note that as the auction is used, all the UAVs need to submit their bids to the ESP simultaneously. This means that the auction does not accept any bid that arrive late. To avoid this issue and to guarantee the QoS of the DT service, the time duration of the travelling, data sensing, data communication, and auction is fixed in every time slot. We denote τ as the duration of the time slot. Then, τ is expressed as follows:

$$\tau = \tau^{\mathrm{T}} + \tau^{\mathrm{S}} + \tau^{\mathrm{C}} + \tau^{\mathrm{A}}, \tag{1}$$

where τ^{T}, τ^{S}, τ^{C}, and τ^{A} are the travelling duration, sensing duration, data transmission duration, and auction duration, respectively. That means all the UAVs need to finish their travelling, sensing, and data transmission in τ^{T}, τ^{S}, and τ^{C}, respectively.

A. Energy Modeling

We denote E_i^{Tot} as the total energy consumption of UAV i in the time slot. In particular, E_i^{Tot} is determined as follows [7]:

$$E_i^{\mathrm{Tot}} = E_i^{\mathrm{T}} + E_i^{\mathrm{S}} + E_i^{\mathrm{C}}, \tag{2}$$

where E_i^{T}, E_i^{S}, and E_i^{C} are the travelling energy, sensing energy, and communication energy, respectively. They are defined as follows.

1) Traversal energy: E_i^{T} is determined as follows:

$$E_i^{\mathrm{T}} = \tau^{\mathrm{T}} P(V_i), \tag{3}$$

where V_i is the flying speed of UAV i and $P(V_i)$ is the propulsion power consumption at speed of V_i. In general, $P(V_i)$ is a function of the speed of the UAV, the tip speed of the rotor blade, the mean rotor induced velocity in hover, the fuselage drag ratio and rotor solidity, and the air density and rotor disc area. The formulation of $P(V_i)$ can be found in the literature, e.g., [8]. Without loss of generality, the UAVs have the same types and the same speed. Thus, the propulsion power consumption is the same for all the UAVs. As we focus on energy trading, to minimize $P(V_i)$ by optimizing V_i is hence out of this paper's scope.

2) Sensing energy: Each UAV collects the sensing data from one physical object in the region. As performing sensing, the UAV typically hovers a collection point, i.e., $V_i = 0$. Thus, the energy consumption during the sensing stage includes the hovering energy, i.e., $P(V_i = 0)$, and the data aggregation energy. We denote ϵ as the energy consumed to collect a data bit, which is assumed to be the same for all the UAVs. We further denote λ_i as the sensing rate of UAV i. Here, λ_i is measured in packets per second, and each packet consists of L bits. Given the sensing duration of τ^{S}, the sensing energy consumption of UVA i is given by [7]

$$E_i^{\mathrm{S}} = \left(\epsilon^{\mathrm{S}} \lambda_i L + P(V_i = 0)\right) \tau^{\mathrm{S}}. \tag{4}$$

3) Communication energy: In the communication stage, the UAVs transmit their sensing data to the VSP for the synchronization during τ^{C}. Thus, the communication energy, i.e., E_i^{C}, is determined as follows.

First, we calculate the data rate achieved by UAV i given by

$$R_i = B \log_2 \left(1 + \frac{p_i^{\mathrm{C}} h_i}{\sigma^2 \Gamma}\right), \tag{5}$$

where B is the bandwidth assigned to UAV i, p_i^{C} is the transmit power of UAV i, σ^2 is the variance of noise, and $\Gamma > 1$ accounts for the gap from the channel capacity due to the practical modulation and coding scheme employed [7], and h_i is the channel gain between UAV i and the GBS deployed by the VSP. In general, the UAVs can communicate with the GBS by both LoS and NLoS links. However, due to the high altitude of UAVs, the LoS communication between the UAV and GBS dominates the NLoS communication. Thus, we assume that there exists only the LoS communication between the UAVs and the GBS. In particular, the channel gains between the UAVs and the GBS depend only on the distances between the UAVs and the GBS. Furthermore, there is no Doppler effect caused by the UAVs' mobility due to their hovering. Thus, the channel gain, denoted by h_i, from UAV i to the GBS follows the free-space path loss model and is given by [9]:

$$h_i = \beta_0 d_i^{-2}, \tag{6}$$

where β_0 denotes the channel power at the reference distance of $d_0 = 1$ m, and d_i is the distance between UAV i to the GBS. Note that the UAV already collects $\lambda_i L \tau^{\mathrm{S}}$ bits during the sensing stage. To transmit these bits during τ^{C}, the UAV needs to consume the amount of energy determined by

$$E_i^{\mathrm{C}} = \left(\frac{\sigma^2 \Gamma}{h_i} \left(2^{\lambda_i L \tau^{\mathrm{S}} / B \tau^{\mathrm{C}}} - 1 \right) + P(V_i = 0) \right) \tau^{\mathrm{C}}. \tag{7}$$

As mentioned earlier, the UAVs have the same propulsion power, and thus the hovering energy consumption of the UAVs are the same. Therefore, the difference in the total energy consumption among the UAVs is from the sensing energy and the data transmission energy [7]. Therefore, we do not include the travelling energy consumption as well as the hovering energy consumption in the total energy consumption since they does not impact the performance evaluation of the proposed algorithms. Thus, the total energy consumption of UAV i is

$$E_i^{\mathrm{Tot}} = \epsilon^{\mathrm{S}} \lambda_i L \tau^{\mathrm{S}} + \frac{\sigma^2 \Gamma}{h_i} \left(2^{\lambda_i L \tau^{\mathrm{S}} / B \tau^{\mathrm{C}}} - 1 \right) \tau^{\mathrm{C}}. \tag{8}$$

B. Reward Function

After performing the data communication, each UAV receives an incentive cost, i.e., a reward, from the VSP for its contribution. The reward should be proportional to the quality of sensing data that the UAV collects. Furthermore, the reward should be proportional to the number of DTs of the VSP. We denote r_i as the reward obtained by UAV i. Then, r_i can be defined as follows:

$$r_i = \frac{D \eta (1 + \theta) \lambda_i}{\sum_k \lambda_k}, \tag{9}$$

where θ denotes the value decay rate, e.g., reliability, of the DTs to the VSP, and η denotes the intensity or rate at which the synchronization activities are performed. In particular, if $\eta = 0$, meaning that the VSP decides not to synchronize all the DTs, then the value of DTs deteriorates a the rate θ. Otherwise, if $\eta > 0$, the VSP can slow down the process of deterioration of its DTs.

C. Valuation Function

In this section, we formulate valuation functions of energy resources to the UAVs. The valuation of each UAV to an energy unit represents how much the UAV is willing to buy the energy unit. The valuation of each energy unit to the UAV is proportional to its total energy consumed in the time slot and inversely proportional to its remaining energy. In particular, as the remaining energy of the UAV is low, it is more willing to buy the energy resource. Moreover, the UAV has a higher valuation to the energy unit if the reward paid by the VSP for the sensing data collection is higher. We denote v_i as the valuation of the energy unit to UAV i and E_i^{R} as the remaining energy of UAV i. Then, to represent the valuation function of UAV i, we use the α-fair function as follows [10]:

$$v_i = \frac{\left(1 + r_i \frac{E_i^{\mathrm{Tot}}}{E_i^{\mathrm{R}}} \right)^{1-\alpha}}{1 - \alpha}, \tag{10}$$

where $\alpha \in [0, 1)$ is the scaling factor.

III. Deep Learning (DL)-based Auction for Energy Trading Markets

In this section, we consider a general scenario in which the ESP has multiple energy units to serve the UAVs. The objective is to achieve the revenue optimality while guaranteeing IR and IC. We first introduce concepts of expected utility, expected revenue, IR violation and IC violation as follows:

- *Expected utility:* We denote $\mathcal{M}$ as a set of M energy units. We denote v_{ij} as the valuation of energy unit j to UAV i. In this work, we assume the additive users, meaning that the valuation to M energy units of each user is the sum of individual valuations of the energy units to the user. Also, each user can wins more energy units to serve its long-term operation. We denote b_{ij} as the bid that UAV i submits to the ESP for energy unit j, where $b_{ij} = 0$ means that the UAV does not want to buy energy unit j. After receiving the bids from the UAVs, the ESP performs the allocation rule and the payment rule. The allocation rule is denoted by $\mathbf{g} = (g_{1,1}, \ldots, g_{N,M})$, where $g_{i,j}$ represents the allocation probability of energy unit j to UAV i. We have $\sum_{i=1}^{n} g_{i,j} \leq 1$. The payment rule is denoted by $\mathbf{p} = (p_1, \ldots, p_N)$, where p_i represents the (total) price that UAV i needs to pay the ESP for winning the energy units. The utility of each UAV i is defined as follows:

$$u_i = \sum_{j}^{M} g_{i,j} v_{i,j} - p_i. \tag{11}$$

- *Expected revenue:* The expected revenue is the total price that the ESP receives from the UAVs and determined as $R = \sum_{i=1}^{N} p_i$.
- *IR violation:* IR guarantees that the utility of each UAV is non-negative, i.e., $u_i \geq 0$, as participating in the auction. The IR violation happens if the auction results in negative utility for any UAV. We want to design the auction that guarantees IR, meaning that the IR violation

is the smallest and preferably zero. We denote IR_i as the violation constraint to UAV i, and then IR is guaranteed if $IR_i \leq 0$ with $IR_i \triangleq \max\{0, -u_i\}$.

- *IC violation:* IC guarantees that each UAV achieves the highest utility by only submitting its truthful value as its bid. Then, the IC violation is defined as the maximum gain in utility that the UAV can receive if it submits an untruthful value knowing the bids of others [6]. We denote IC_i as the IC violation to UAV i, then we have $IC_i = \sum_{j=1}^{M} IC_{i,j}$, where $IC_{i,j} = (\max_{v'_{i,j} \neq v_{i,j}} u_i(v'_{i,j})) - u_i(v_{i,j})$. As IC_i is small, the utility gain that the UAV receives when it submits a non-truthful bid is small. Ideally, IC_i is zero, meaning that the UAV has no incentive to submit its untruthful value.

1) DL-based auction architecture and training: The auction scheme needs to determine the allocation probabilities of the UAVs and the prices that the UAVs need to pay. Thus, we use two FNNs for the allocation rule and payment rule. We denote $\mathbf{w}$ as the matrix containing the weights of the FNN for the allocation rule and $\mathbf{w}'$ as the matrix containing the weights of the FNN for the payment rule. The FFNs are used since they map the input, i.e., the UAVs' valuations, to the outputs, i.e., the allocation rules and payment decisions. The two FNNs (and their weight parameters) are independent with each other, but they use the same UAVs' bidding profile as their inputs. The dataset consists of the UAVs' bidding profile. As explained earlier, it is hard to obtain a dataset of historical bids of the UAVs. However, the ESP can generate and leverage the valuations of the UAVs according to (10). We denote $v_{i,j}$ as the valuation of UAV i on the energy unit j. Then, we can express $\mathbf{v}^{(q)} = (v_{1,1}^{(q)}, \ldots, v_{N,M}^{(q)})$ as the q-th bidding profile in the dataset, where $q = 1, \ldots, Q$ with Q being the size of the dataset. The FNNs designed for the allocation and

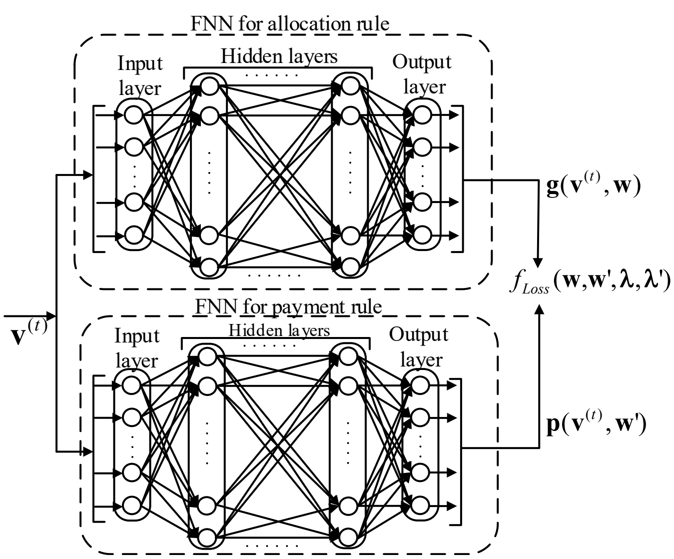


Fig. 2. FNNs for allocation and payment rules.

payment rules are shown in Fig. 2. In particular, the FNN for the allocation rule consists of an input layer, multiple hidden layers, and an output layer. The hidden layers use $sigmoid$ activation functions to transform each bidding profile of the UAVs to the allocation vector $\mathbf{g} = (g_{1,1}, \ldots, g_{N,M})$, where $g_{i,j}$ refers to the probability that UAV i wins the energy unit j. Since there may be multiple UAVs competing for the energy unit, we use the $softmax$ functions at the output layer to determine the allocation probability of the energy units for the UAVs. The FNN structure for the payment rule is similar to that for the allocation rule. However, the output of FNN is the payment vector of $\mathbf{p} = (p_1, \ldots, p_N)$, where p_i is the price that the UAV needs to pay the ESP for winning energy energy units. Since the prices are not negative, the output layer uses the $ReLU$ functions to generate the prices. As such, the outputs of both the FNNs are functions of the bidding profile and FNNs' weights, and thus we can express $\mathbf{g}(\mathbf{v}^{(b)}, \mathbf{w})$ and $\mathbf{p}(\mathbf{v}^{(b)}, \mathbf{w}')$.

To stabilize the learning algorithm, we use the batch of samples, each of which is the bidding profile, to train the FNNs. In particular, we shuffle the whole dataset and take randomly a batch of B samples. We denote the set of the batch as $\mathcal{B}$. We calculate the average IC violation to each UAV i over B samples of the training batch as follows:

$$\overline{IC}_i(\mathbf{g}, \mathbf{p}) = -u_i(v_{i,j}^{(b)}, \mathbf{v}_{-i,-j}^{(b)}, \mathbf{g}, \mathbf{p}) + \frac{1}{B} \sum_{l=1}^{B} \sum_{j=1}^{M} \left(\max_{v'_{i,j}{}^{(b)} \in \mathcal{B}, v'_{i,j}{}^{(b)} \neq v_{i,j}^{(b)}} u_i(v'_{i,j}{}^{(b)}, \mathbf{v}_{-i,-j}^{(b)}, \mathbf{g}, \mathbf{p}) \right), \tag{12}$$

where $\mathbf{v}_{-i,-j}^{(b)}$ is the bidding profile excluding the valuation of energy unit j to UAV i. The average IR violation is

$$\overline{IR}_i(\mathbf{g}, \mathbf{p}) = \frac{1}{B} \sum_{b=1}^{B} \max\{0, -u_i(\mathbf{v}^{(b)}, \mathbf{g}, \mathbf{p})\}. \tag{13}$$

The objective is to maximize the revenue of the ESP, and thus we define an expected negative revenue of the ESP as

$$\overline{R}(\mathbf{g}, \mathbf{p}) = -\frac{1}{B} \sum_{t=1}^{B} \sum_{i=1}^{N} p_i(\mathbf{v}^{(b)}, \mathbf{g}, \mathbf{p}). \tag{14}$$

Then, the training problem over the dataset is as follows:

$$\arg \min_{\mathbf{w}, \mathbf{w}'} \overline{R}\left(\mathbf{g}(\mathbf{w}), \mathbf{p}(\mathbf{w}')\right) \tag{15a}$$

$$\text{s.t. } \overline{IC}_i(g(\mathbf{w}), p(\mathbf{w}')) = 0, \forall i \in \{1, \ldots, N\}, \tag{15b}$$

$$\overline{IR}_i(g(\mathbf{w}), p(\mathbf{w}')) = 0, \forall i \in \{1, \ldots, N\}. \tag{15c}$$

The constraints in (15b) are to guarantee the IR properties, and the constraints in (15c) are to guarantee the IC properties. The problem given in (15a) still includes the constraints, which is not in the form of the loss function of the training. In other words, it needs to be equivalently transferred to an unscontrained optimization that consists of the expected negative revenue, N IR constraints, and N IC constraints. This can be implemented by using the augmented Lagrangian optimization. We denote $\mathcal{L}$ as the loss function, which can be formulated as follows [6]:

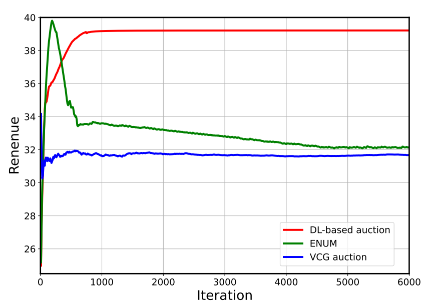
$$f_{Loss}(\mathbf{w},\mathbf{w}',\omega,\omega') = \overline{R}\left(\mathbf{g}(\mathbf{w}),\mathbf{p}(\mathbf{w}')\right) + \sum_{i=1}^{N}\omega_i\overline{IC}_i(g(\mathbf{w}),p(\mathbf{w}')) + \sum_{i=1}^{N}\omega_i'\overline{IR}_i(g(\mathbf{w}),p(\mathbf{w}')) + \frac{\mu}{2}\Big(\sum_{i=1}^{N}\overline{IC}_i^2(g(\mathbf{w}),p(\mathbf{w}')) + \sum_{i=1}^{N}\overline{IR}_i^2(g(\mathbf{w}),p(\mathbf{w}'))\Big), \tag{16}$$

where $\boldsymbol{\omega} = (\omega_1,\ldots,\omega_N)$ and $\boldsymbol{\omega}' = (\omega_1',\ldots,\omega_N')$ are the vectors of Lagrange multipliers associated with the IC and IR constraints, respectively, and μ is the weight associated with the constraints.

IV. Performance evaluation

In this section, we present experimental results to demonstrate the effectiveness of the proposed DL-based auction mechanisms. Simulation parameters for the network model are listed in TableI. The DL-based auction algorithm is implemented by using the TensorFlow deep learning library.

The FNNs for the allocation and payment rules both have 2 hidden layers, and the number of neural nodes in each hidden layer is 20. To ensure that the training phase does not miss local minima, the learning rate is set low, i.e., 0.001. However, this may slows down the training process. To achieve the fast and smooth convergence, we use the Adam optimizer in the training. For ease of presenting the findings, the number of UAVs is set to 5 and the number of energy energy units is 3. The training data consists of 10^4 valuation profiles of the UAVs. Each valuation profile consists of $\{v_{i,j}\}_{i\in\{1,2,3,4,5\},j\in\{1,2,3\}}$, where $v_{i,j}$ is randomly generated according to (10). For the comparison performance,



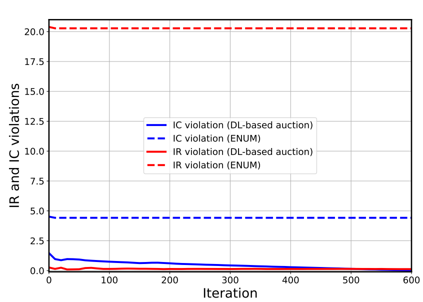


Fig. 3. (a) Convergence of the algorithms and (b) IR and IC violations comparison.

we use VCG-auction [5] scheme and the ENUM scheme [11]. The VCG-auction and ENUM schemes are used as baselines since they are typically applicable in multi-item markets. With the VCG-auction, the ESP selects the UAVs with highest bids as winners and then charges each of them so as to maximize the social welfare. With the aim of maximizing the social welfare, the VCG-auction scheme as a general scheme of SPA guarantees the truthfulness, i.e., IC, but the revenue obtained by this mechanism is not high. With the ENUM scheme, the ESP (i) lists the UAVs in a descending order of their bids and (ii) iteratively selects the UAVs with the highest bids as the winners. Each winner then pays the ESP a price equal to the bid that it submits. As such, the ENUM scheme is expected to obtain high revenue.

Figure 3(a) illustrates the convergence of schemes. As seen, all the schemes are able to converge to stable revenue values. The revenue obtained by the DL-based auction is much higher than those obtained by the ENUM and VCG auction schemes. These results validate the efficiency of the use of DL in solving the auction problem. Moreover, as expected, the revenue obtained by the VCG auction scheme is the lowest. The reason is that the VCG auction scheme aims to maximize the social welfare, which sacrifices the revenue of the ESP.

Next, we evaluate the performance of the schemes in terms of IC violation as shown in Fig. 3(b). Note that the VCG auction scheme is not shown in Fig. 3(b) since it has been theoretically proved in the literature to guarantee IC [5]. As seen, the IC violation obtained by the ENUM scheme is around 4.41, while that obtained by the DL-based auction is close to zero. Clearly, the IC violation of the DL- based auction is much lower than that of the ENUM scheme. Recall that the IC violation is close to zero meaning that the truthfulness is guaranteed, i.e., the UAVs have no incentive to submit their bids that deviate from their true values.

Figure 3(b) also shows the IR violation obtained by the ENUM and DL-based auction schemes. As seen, IR violation obtained by the ENUM scheme is very large, i.e., around 20.2, while that obtained by the DL-based auction is almost zero. Note that the IR violation is small, the probability that the utility of each UAV is negative is small, and thus the UAVs have a high incentive to participate in the energy trading market.

Figure 4(a) shows the revenue of the ESP as the number of UAV N varies. As the number of UAV increases, the revenue obtained by all the schemes increases. This is due to fact that as the number of UAVs increases, the ESP has a higher opportunity to receive the high payments from the UAVs. Thus, the expected revenue of the ESP increases. We can explain in a different way that the competition among the UAVs increases as the number of UAV increases. Thus, to win the energy units, the UAVs need to submit higher bids, and thus the ESP receives the high revenue. Moreover, the DL-based auction scheme always outperforms the ENUM and VCG auction schemes in terms of revenue regardless of N. Figure 4(b) shows the impact of the remaining energy status of the UAVs on the revenue of the ESP. As seen, as the remaining

TABLE I
SIMULATION PARAMETERS

Parameter	Value	Parameter	Value
Travelling time (τ^{T})	10 s	Bandwidth (B)	10^6 Hz
Sensing time (τ^{S})	10 s	Number of DTs (D)	5
Transmission time (τ^{C})	10 s	Sensing rate (λ_i)	$\mathcal{U}[960 \times 540, 1280 \times 720,$ $1920{\times}1080, 2560 \times 1440]$ bits/packet
β_0	10^{-6}		
Sensing energy per data bit (ϵ^{S})	50 nJ/bit	Synchronization rate (η)	$[3, 7]$
Length of packet (L)	5 packets per second	Value decay rate (θ)	$\mathcal{U}[0.5, 1]$
Remaining energy (E_i^{R})	$\mathcal{U}[2, 6]$ Watt	α	$[0.3, 0.7]$
Noise variance (σ^2)	10^{-11} Watt	Γ	1.2
		Distance between UAV i to the GBS (d_i)	200 m

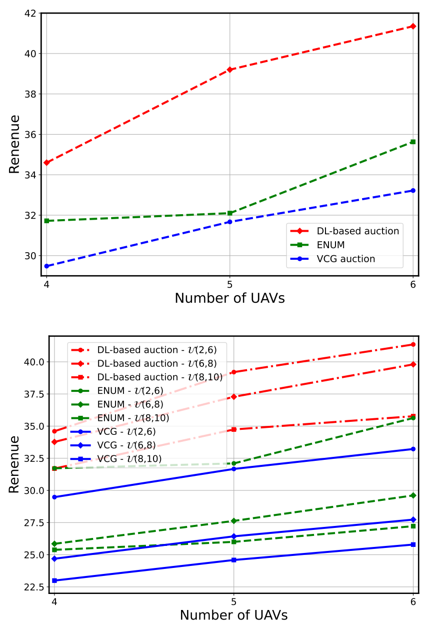


Fig. 4. Revenue versus (a) the number of UAVs and (b) the remaining energy.

energy ranges of the UAVs are low, the revenue of the ESP is high. This is because of that as the remaining energy of the UAVs decreases, the UAVs are more willing to buy the energy units, and they submit higher bids.

V. CONCLUSIONS

In this paper, we have investigated the effective energy resource allocation in the UAV-assisted Metaverse synchronization system. We have considered a system in which multiple UAVs perform the synchronization between physical objects and DTs for a VSP. For the long lifetime operation, the UAVs buy energy resources from an ESP for their wireless charging. To motivate both the ESP and the UAVs to participate in the energy trading market, we have proposed a DL-based auction in which two FNNs are designed for the allocation and payment rules. The FNNs are trained by using valuation profiles. We have formulated the valuations of energy energy units that accounts for Metaverse synchronization parameters. We have provided simulation results to demonstrate the improvement of the DL-based auction compared to the baseline schemes in terms of revenue, IC, and IR.

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