From the view of auctioneer, it can hold a preference list denoted by $\mathbf{T_A}$ (which contains the indexes of buyer-seller pairs) for any buyer-seller pair in a non-ascending order so as to maximize the overall revenue. Accordingly, the preference list can be established based on the preference relationship as (23),

$$\mathbf{T_A}:(l,m,n)\succ_A(l,i,k)\Leftrightarrow R_{l,m,n}>R_{l,i,k}, \tag{23}$$

where $\succ_A$ means the auctioneer prefers the left than the right.

Similarly, each buyer l can establish a preference list $\mathbf{T_l}$ (indexes of seller pairs) by sorting the preference value $R_{l,m,n}, m\in\mathcal{M}_l, n\in\mathcal{N}_{l,m}$ in a non-ascending order, which can be denoted as,

$$\mathbf{T_l}:(l,(m,n))\succ_l(l,(i,k))\Leftrightarrow R_{l,m,n}>R_{l,i,k}. \tag{24}$$

Finally, we can obtain $\mathbf{T_A}$ and $\mathbf{T_l}$ for both the auctioneer and each buyer l, respectively. To ensure the truthfulness of the sellers, we add a virtual *NULL seller pair* at the end of $\mathbf{T_l}$ with preference value equals 0, which describing that if no real sellers wins the auction for the buyer, the buyer is assigned to a null seller pair. Particularly, if any preference value $R_{l,m,n}<0$, then buyer-seller pair (l,m,n) will not be stored in $\mathbf{T_A}$ and $\mathbf{T_l}$ to prevent non-positive revenue.

Obviously, each buyer tends to select the top sell pairs in its preference list. However, as each seller pair can only trade with one buyer, the auctioneer prefers to assign the seller pair to the buyer with higher preference value. For example, assume seller pair (m,n) is on the top of list of buyer l and l' at the same time, the auctioneer assigns seller pair (m,n) to buyer l if $R_{l,m,n}>R_{l',m,n}$. Considering the preference lists of the auctioneer and buyers, winning buyer-seller pairs are matched accordingly in the one-sided matching process until all buyers are matched.

B. Suboptimal winner determination and payment rule

To facilitate the presentation of our proposed winner determination and payment rule, the definition of *critical value* is given below:

Definition 6. *(Critical value): The critical value of any buyer-seller pair (l,m,n) in one-sided matching is defined as*

$$\widetilde{R_{l,m,n}}=v_{l,\widetilde{(m,n)}}-J_{l,\widetilde{(m,n)}}, \tag{25}$$

where $\widetilde{(m,n)}$ is the first seller pair located behind seller pair (m,n) in the preference list $\mathbf{T_l}$.

The overall one-sided matching-based suboptimal reverse auction mechanism mainly compromises two phases: 1) one-sided one-to-one matching based suboptimal winner determination; 2) and payment calculation. We first give the payment rule based on the one-sided matching result. Specifically, the total payment $P_{i,k}^f$ of the winning seller pair (i,k) from buyer l is calculated as

$$P_{i,k}^f=v_{l,(i,k)}-\widetilde{R_{l,i,k}}. \tag{26}$$

We summarize the one-sided matching based suboptimal reverse auction in **Algorithm 2**. By applying lines 1-4, we calculate the preference value by given the input parameter, then we build the preference list for the auctioneer and buyers by sorting the preference value in non-ascending order in lines 5-6. Lines 8-14 illustrate the one-sided matching process. Finally, the final payment of the winning seller is calculated in lines 15-21.

Algorithm 2 One-Sided Matching-Based Suboptimal Reverse Auction Algorithm

Input: Buyer set $\mathcal{L}$, seller sets $\mathcal{M}$, $\mathcal{N}$, bid information of each seller and buyer B_m^d, $\vec{c}_m$, $\mathbf{E}_n$, B_n^u, d_l, $\mathbf{V}_l$.
Output: Winner determination result $\mathbf{X}$, final payment profile $\vec{P}^d$ of data-sellers and $\vec{P}^u$ of UAV-sellers.
1: Initializes $\mathbf{X}$ with all zeros.Virtualize data-sellers, UAV-sellers, and obtain the joint matrix $\mathbf{J}_l$ for each buyer l.
2: **for** buyer $l\in\mathcal{M}$ and seller pair $(i,k), i\in\mathcal{M}_l, k\in\mathcal{N}_{l,i}$ **do**
3:     Calculate the preference value $R_{l,i,k}$ according to (22).
4: **end for**
5: $\mathbf{T_A}\Leftarrow Sort(l\in\mathcal{L}, i\in\mathcal{M}_l, k\in\mathcal{N}_{l,i}|R_{l,i,k}, ``non-ascending'')$.
6: $\mathbf{T_l}\Leftarrow Sort(i\in\mathcal{M}_l, k\in\mathcal{N}_{l,i}|R_{l,i,k}, ``non-ascending'')$.
7: $\mathcal{W}\Leftarrow\mathcal{M}$.
8: **while** $\mathbf{T_A}\neq\varnothing$ and $\mathcal{W}\neq\varnothing$ **do** *%Phase 1: Winner determination*
9:     **for** each first entry $(l,i,k)\in\mathbf{T_A}$ **do**
10:         $x_{l,i,k}\Leftarrow 1$
11:         $\mathbf{T_A}\Leftarrow\mathbf{T_A}\backslash\{$all elements related to $l,i,k\}$
12:         $\mathcal{W}\Leftarrow\mathcal{W}\setminus\{l\}$
13:     **end for**
14: **end while**
15: **for** $x_{l,i,k}\in\mathbf{X}$ **do** *%Phase 2: Payment calculation*
16:     **if** $x_{l,i,k}=1$ **then**
17:         Calculate the total payment $P_{i,k}^f$ of seller pair (i,k) according to (27).
18:         Calculate the received payment of the winning data-seller i and UAV-seller k as: $p_i^d=\frac{q_{i,l}}{J_{l,(i,k)}}P_{i,k}^f$, $p_k^u=\frac{s_{k,i,l}}{J_{l,(i,k)}}P_{i,k}^f$.
19:     **else**
20:         $p_i^d\Leftarrow 0$, $p_k^u\Leftarrow 0$.
21:     **end if**
22: **end for**

C. Complexity and properties analysis

In this subsection, we analyze the complexity and properties of the proposed one-sided matching-based reverse auction. Moreover, we prove that the one-sided matching-based reverse auction is stable.

Theorem 3. *(Computational efficiency): The proposed one-sided matching-based reverse auction algorithm is computationally efficient.*

Proof. In Algorithm 2, the time complexity of line 1-4 is $\mathcal{O}(LMN)$ and the two sort procedures in line 5 and 6 is $\mathcal{O}(LMNlog(LMN))$ and $\mathcal{O}(MNlog(MN))$, respectively [40]. Similarly, the time complexity of line 8-21 is $\mathcal{O}(2LMN)$. Thus, Algorithm 2 has overall polynomial time complexity. $\square$

Theorem 4. *(Truthfulness of seller pair): The proposed one-sided matching-based reverse auction of FL service market is truthful for each seller pair.*

Proof. First, for any given seller pair (i,k) with truthful bid $J_{l,(i,k)}=c_{i,l}+e_{k,(i,l)}$, according to (12), (25) and (26), the seller pair's revenue can be denoted as,

$$U_{(i,k)}=v_{l,(i,k)}-\widetilde{R_{l,i,k}}-J_{l,(i,k)}. \tag{27}$$

Meanwhile, we assume a virtual seller pair (i',k') who is exactly the same as the seller pair (i,k) except the sell-bid, is considered as the case that seller pair (i,k) bids untruthfully with a different joint bid $J_{l,(i,k)}{}'$, thus its revenue can be denoted as,

$$U'_{(i,k)} = v_{l,(i,k)}{}' - \widetilde{R_{l,i,k}}{}' - J_{l,(i,k)}. \tag{28}$$

Then, $U_{(i,k)} - U'_{(i,k)}$ can be denoted as,

$$\begin{aligned} U_{(i,k)} - U'_{(i,k)} &= v_{l,(i,k)} - \widetilde{R_{l,i,k}} - v_{l,(i,k)}{}' + \widetilde{R_{l,i,k}}{}' \\ &= \widetilde{R_{l,i,k}}{}' - \widetilde{R_{l,i,k}}, \end{aligned} \tag{29}$$

note that $v_{l,(i,k)} = v_{l,(i,k)}{}'$ since they have same properties.

Generally, there are two cases: seller pair (i,k) wins or loses in the original auction. First, we assume that seller pair (i,k) used to be a winner and obtains revenue $U_{(i,k)}$.

1) If $J_{l,(i,k)}{}' < J_{l,(i,k)}$, in this case, seller pair (i',k') always wins as it must be located before (i,k) or at its original position in $\mathbf{T_1}$, which means $\widetilde{R_{l,i,k}}{}' \geq \widetilde{R_{l,i,k}}$, thus we have $U_{(i,k)} - U'_{(i,k)} \geq 0$.
2) If $J_{l,(i,k)}{}' > J_{l,(i,k)}$, it is obvious that seller pair (i',k') will locate at the same position or behind (i,k) in $\mathbf{T_1}$: if (i',k') stays at the original position, then it obtains the revenue $U'_{(i,k)} = U_{(i,k)}$ according to the payment rule; if seller pair (i',k') located behind (i,k) in $\mathbf{T_1}$, then (i',k') definitely loses and gets revenue $U'_{(i,k)} = 0$, as there must be another seller pair can offer higher revenue to be matched with buyer l.

Second, we consider seller pair (i,k) used to be a loser and obtains $U_{(i,k)} = 0$:

1) If $J_{l,(i,k)}{}' < J_{l,(i,k)}$, in this case, there are possibilities that seller pair (i',k') locates at the same position or before (i,k). Specifically, if (i',k') stays at the original location, then it still loses and gets revenue $U'_{(i,k)} = 0$. If (i',k') locates before (i,k) and loses, it still obtains revenue $U'_{(i,k)} = 0$; if (i',k') locates before (i,k) and wins, then it gets revenue $U'_{(i,k)}$, according to (22) and (28), $U'_{(i,k)}$ can be rewrite as follows:
$$U'_{(i,k)} = R_{l,i,k} - \widetilde{R_{l,i,k}}{}', \tag{30}$$
thus if seller pair (i',k') is in front of (i,k), we have $R_{l,i,k} < \widetilde{R_{l,i,k}}{}'$ and $U'_{(i,k)} < U_{(i,k)} = 0$, which means it is not encouraged for an individual rational seller.
2) If $J_{l,(i,k)}{}' > J_{l,(i,k)}$, obviously, seller pair (i',k') always loses and obtains revenue $U'_{(i,k)} = 0$.

Thus, we can conclude that any seller pair (i,k) cannot obtain higher revenue by bidding untruthfully. □

Theorem 5. *(Individual rationality of seller pair): The proposed one-sided matching-based reverse auction of FL service market is individually rational for each seller pair.*

Proof. As denoted in (27), the revenue of any winning seller pair (i,k) can be further denoted as,

$$\begin{aligned} U_{(i,k)} &= v_{l,(i,k)} - \widetilde{R_{l,i,k}} - J_{l,(i,k)} \\ &= (v_{l,(i,k)} - J_{l,(i,k)}) - \widetilde{R_{l,i,k}} \\ &= R_{l,i,k} - \widetilde{R_{l,i,k}}. \end{aligned} \tag{31}$$

Since $\widetilde{R_{l,i,k}}$ is the preference value of seller pair located behind (i,k) in $\mathbf{T_1}$, thus $R_{l,i,k} - \widetilde{R_{l,i,k}} \geq 0$ always holds, thus each seller pair can obtain non-negative revenue when it wins the auction. □

Similarly, based on the truthfulness and individual rationality of seller pair, we can also have the following corollary.

Corollary 3. *In the one-sided matching-based reverse auction of FL service market, each data-seller and UAV-seller is individual rational and truthful.*

Proof. The proof is the same as the proof in Section IV and is omitted here. □

Although the truthfulness and individual rationality of the proposed one-sided matching-based reverse auction have been proved, considering the selfishness of buyers and sellers, matching stability is critical to ensure the stability and efficiency of reverse auction. We first present the definition of stability of reverse auction in Definition 7.

Definition 7. *(Stability of reverse auction): The proposed one-sided matching-based reverse auction is said to be stable if no buyer or sellers have incentives to deviate from the auction result.*

Theorem 6. *The proposed one-sided matching-based reverse auction of FL service market is stable.*

Proof. First, for sellers, based on the mechanism of reverse auction, once a seller wins the auction, it can obtain non-negative revenue and this seller cannot refuse to deliver services. Besides, if any buyer l is matched to the seller pair (i,k), each buyer has two choices. If buyer l quits, then its service requirement cannot be fulfilled and thus get zero revenue, which clearly is not a dominant strategy. When the buyer intends to replace its auction result to obtain higher revenue, however, which is not possible, since the matching result is determined by the preference list of $\mathbf{T_A}$ which maximizes the overall revenue. Thus, both buyers and sellers are stable in the proposed one-sided matching-based reverse auction. □

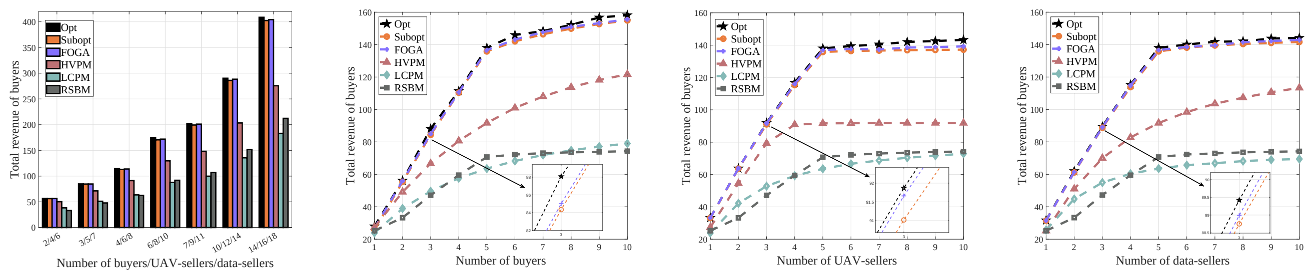
Remark 1. *The winning buyers are generally truthful and individually rational in the proposed reverse auction.*

Proof. Since buyers cannot determine the final trading prices in the proposed reverse auction, the corresponding truthfulness and individual rationality of buyers are often overlooked, e.g., in [32] and [42]. This part briefly discusses these two properties of winning buyers. First, submits a service requirement bid lower than a buyer's true need, will definitely fail to meet its requirement. Besides, if a buyer reports a service requirement bid higher than its true need, the corresponding payment may increase since the payment relies heavily on the corresponding service requirements. Apparently, each buyer has no incentive to be untruthful in our proposed reverse auction model.

Individual rationality of winning buyers can be analyzed from the following two views. First, in the VCG-based reverse auction, since $F(x^*_{l,m,n}) - F_{\setminus(i,k)}(y^*_{l,m,n}) \geq 0$ always holds (see Theorem 2), we can conclude that if a buyer wins the auction, it can obtain non-negative revenue. More intuitively, a buyer can be selected as a winner iff it will not decrease the overall revenue. Then, in the proposed one-sided matching-based reverse auction, we build the preference list based on

TABLE II
RUNNING TIME (SECONDS) OF DIFFERENT METHODS CONSIDERING VARIOUS NUMBER OF BUYERS/UAV-SELLERS/DATA-SELLERS

Methods \ Problem size	1/5/5	3/5/5	5/5/5	7/5/5	9/5/5	1/3/5	2/4/6	3/5/7	4/6/8
Opt	10097	11384	13771	27799	2213192	7478	11901	25048	151866
Subopt	0.358	0.558	1.304	1.097	1.303	0.266	0.432	0.743	1.093
FOGA	3.94	5.43	15.50	81.01	1137.99	0.73	5.25	192.16	17870.20
HVPM	0.305	0.321	0.388	0.414	0.421	0.250	0.309	0.321	0.364
LCPM	0.277	0.331	0.350	0.411	0.424	0.279	0.310	0.329	0.382
RSBM	0.305	0.400	0.407	0.427	0.434	0.292	0.336	0.342	0.354



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

Fig. 3. The obtained total revenue of buyers of different methods versus the number of buyers/UAV-sellers/data-sellers.

the preference value as defined in (22), and delete the buyer-seller pair associated with any negative preference value. Thus, the final winning buyers can always get non-negative revenues. □

VI. SIMULATION AND PERFORMANCE EVALUATION

This section conducts comprehensive simulations to evaluate the feasibility of our proposed reverse auction mechanisms. Notably, this paper mainly focuses on the trading in the multiple FL services trading market based on general evaluation functions (e.g., cost function, valuation function). Besides, the proposed algorithms are executed before the specific FL training starts, which means they are irrelevant to specific FL algorithms and ML models (as also supported by existing works [15]–[17], [32]) and can be applied in any distributed learning schemes. To this end, numerical simulations based on general assumptions of properties of participants are sufficient to verify our proposed Algorithms. Specifically, the proposed Algorithm 1 and Algorithm 2 are abbreviated as "Opt" and "Subopt" for notational simplicity. Moreover, to better evaluate performance gains achieved by the proposed algorithms, while considering the characteristics of problem given in (10), four heuristic methods are considered as baselines [50]:

- **Fragmental Optimization Genetic Algorithm (FOGA)**: FOGA [51] is a heuristic algorithm that can be used to solve tripartite matching problems, e.g., problem (10), which is a combination of fragmental optimization and genetic algorithm.
- **High Valuation Preferred Method (HVPM)**: In HVPM, a seller pair is matched to a buyer is of the highest value, based on (5), under constraints (10b)-(10e), until all the buyers are assigned to feasible seller pairs.
- **Low Cost Preferred Method (LCPM)**: Similar to HVPM, in LCPM, a seller pair is matched to a buyer is of the lowest cost, under constraints (10b)-(10e), until all the buyers are assigned to feasible seller pairs.
- **Random Sampling-Based Method (RSBM)**: In RSBM, a seller pair is randomly selected for each buyer, under constraints (10b)-(10e), until all the buyers are assigned to feasible seller pairs.

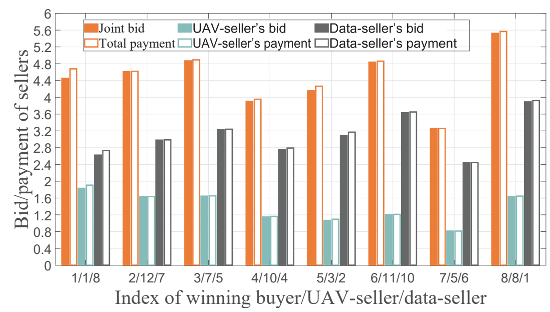


Fig. 4. Individual rationality of seller-pairs and individual sellers upon considering 8 buyers, 10 UAV-sellers and 12 data-sellers.

Notably, buyers may fail to be matched to feasible seller pairs due to factors such as the conflicts among buyers, and insufficient number of sellers.

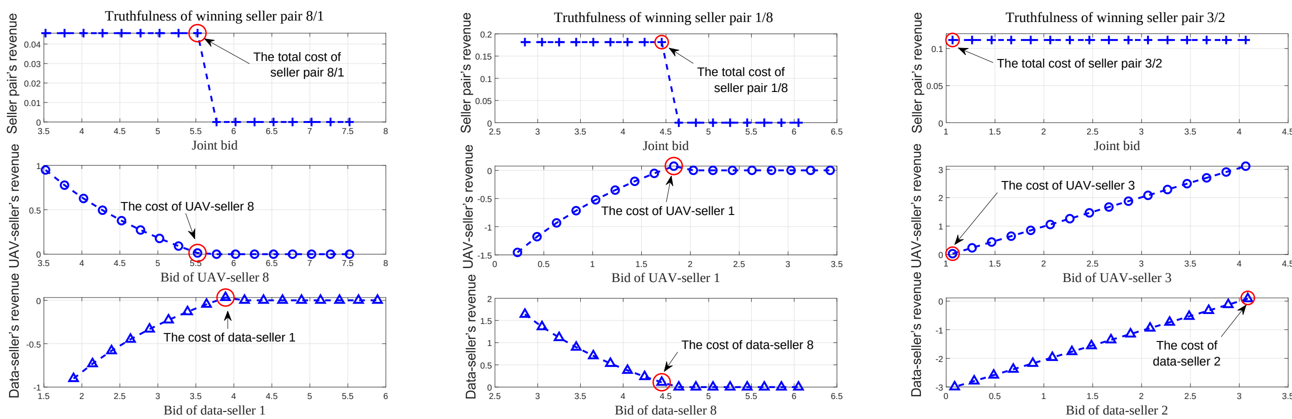
A. Simulation settings

For data-sellers, we assume that the normalized data size (normalized by 500 units[6]) $d_{m,l}$ of each data-seller m follows a uniform distribution $[10, 30]$, and the unit data cost $\sigma_{m,l}$ can be randomly selected from a uniform distribution $[0.0002, 0.0004]$. For UAV-sellers, we assume the fly distance t_n follows the distribution $[10, 100]$ meters, while the unit

[6]One unit could be 1 KB, 1 MB or 1 GB data.

TABLE III
DETAILED PERFORMANCE OF THE PROPOSED ONE-SIDED MATCHING-BASED REVERSE AUCTION UPON CONSIDERING 8 BUYERS, 10 UAV-SELLERS AND 12 DATA-SELLERS.

Winning pair	UAV's bid	DO' bid	Joint bid	Total payment	Seller pair's revenue	UAV's payment	UAV's revenue	DO's payment	DO's revenue
1/1/8	1.8304	2.6219	4.4523	4.6337	0.1814	1.9066	0.0762	2.7271	0.1052
2/12/7	1.6292	2.9789	4.0681	4.6187	0.0106	1.6329	0.0037	2.9858	0.0069
3/7/5	1.6438	3.2232	4.8670	4.8910	0.0240	1.6519	0.0081	3.2391	0.0159
4/10/4	1.1473	2.7552	3.9025	3.9537	0.0502	1.1624	0.0151	2.7913	0.0361
5/3/2	1.0655	3.0868	4.1523	4.2638	0.1115	1.0941	0.0286	3.1697	0.0829
6/11/10	1.2048	3.6317	4.8365	4.8609	0.0244	1.2109	0.0061	3.6500	0.0183
7/5/6	0.8124	2.4433	3.2557	3.2562	0.0005	0.8125	0.0001	2.4437	0.004
8/8/1	1.6318	3.8899	5.5217	5.5673	0.0456	1.6453	0.0135	3.9220	0.0321



(a) (b) (c)

Fig. 5. Truthfulness of seller-pairs and individual sellers: a) UAV-seller bids truthfully and data-seller bids untruthfully; b) UAV-seller bids untruthfully and data-seller bids truthfully; c) both sellers bid untruthfully when the joint bid remains truthful.

flying cost λ_n follows the distribution $[0.02, 0.05]$. For simplicity, we mainly consider the UAV communication delay during the model transmission as the estimation of UAV-service cost function [32][7]. Specifically, we assume the model size of each buyer follows a uniform distribution $[100, 500]$ KB, while the communication rate between UAV-seller n and data-seller m follows a uniform distribution $[100, 300]$ KB/s [16], so that the model transmission delay (namely, service cost of UAV) can be calculated. For buyers, the valuation function of each buyer is supposed to be calculated by a log function $\alpha_1 * log(1 + \alpha_2 * d)$ according to [15], where $\alpha_2 = 1$ and α_1 follows a uniform distribution $[8, 12]$, which can be different from various buyers. We set $d_l = 5000$ for all the buyers. We conduct the simulation with MATLAB 2021b on Intel(R) Core(M) i7-11700F@2.5 GHz, and the simulation results demonstrated in the following sections are the results averaged over 1000 simulations (auctions), unless otherwise stated.

B. Performance of running time

The running time performance comparison is detailed by Table II, upon considering different number of buyers, UAV-sellers, and data-sellers. For example, let 2/4/6 denote the problem of 2 buyers, 4 UAV-sellers and 6 data-sellers. Notably, the running time of the proposed Opt algorithm is about 10^2 to 10^6 times that of the other five methods. Since a large number of enumeration and permutation calculations are required during the execution process of Opt algorithm, which thus causes huge memory pressure and makes it computationally intractable and unpractical in implementation. Moreover, it can be observed that the proposed Subopt algorithm has the same or lower level regarding running time in comparison with baseline methods, which proves the corresponding computational efficiency, and thus can achieve acceptable running time for various problem sizes.

C. Performance of total revenue of buyers

The comparisons on the total revenue of buyers, i.e., the value of $F(x_{l,m,n})$ defined in (9), among six methods upon considering various problem sizes, are demonstrated in Fig. 3. Firstly, Fig. 3 indicates that the proposed Subopt algorithm achieves similar or approaches to the total revenue of FOGA and the Opt algorithm, and greatly outperforms the other three baseline methods. For example, compared with Opt, the obtained total revenue is only decreased by 2.25% via applying the proposed Subopt algorithm and decreased by 1.5%, 25.64%, 49.70%, and 47.30% when considering FOGA, HVPM, LCPM, and RSBM, respectively, under problem size 6/8/10. Although FOGA achieves slightly larger revenue than the Subopt algorithm under the cost of longer running time, it fails to guarantee the properties of truthfulness, individual rationality, and computational efficiency. Revisit the above-

[7]More complicated service costs can be replaced by considering specific scenario or communication protocols as future work.

mentioned running time performance, the proposed Subopt algorithm can achieve a satisfying trade-off between running time and total revenue, in comparison with FOGA. Then, Fig. 3(b), Fig. 3(c), and Fig. 3(d) illustrate the performance of the total revenue versus the number of buyers, UAV-sellers, and data-sellers, respectively, when keeping the number of other two (of the three) parties fixed at 5. Obviously, the total revenue of different methods increases with the increasing number of participants, at different growth rates. Interestingly, the growth rates of Opt, Subopt and FOGA slowed down significantly after 5 (the value of x-axis), while other methods can still maintain a slow growth. This is because as the number of participants increases, other methods can obtain better suboptimal solutions thanks to a larger searching space.

D. Performance of economical properties

Since the properties of the VCG-based reverse auction have been extensively verified in existing works, we thus focus on the properties (truthfulness and individual rationality) of the proposed Subopt algorithm. Specifically, we conduct the simulations under 8 buyers, 10 UAV-sellers, and 12 data-sellers. Performance on individual rationality is shown in Fig. 4, with the joint bid and the total payment of winning seller pairs (8 in this figure), as well as individual bids and the corresponding payment of each UAV/data seller. For example, 2/12/7 means buyer 2 is matched to the winning UAV-seller 12 and data-seller 7. Notably, each winning seller can obtain a final payment no less than its bid, which proves the individual rationality of both seller pairs and individual sellers as given in **Theorem 5** and **Corollary 3**. To achieve better analysis, detailed performance of each winning seller pair is shown by Table III.

Fig. 5 illustrates the truthfulness of seller pairs and individual sellers. As discussed in subsection C of Section IV, three seller pairs (seller pair 8/1, 1/8, and 3/2) in Table III are taken as examples. In Fig. 5(a), UAV-seller 8 bids truthfully at 1.6318 while data-seller 1 bids untruthfully from 1.8899 to 5.8899. Notably, if data-seller 1 bids smaller than its cost, the revenue of seller pair remains the same at 0.0456 and becomes zero when data-seller 1 overbids, while data-seller 1 only obtains positive revenue 0.0321 when the bid equals its cost 3.8899 (marked by a red circle), which indicates that any individual seller or seller pair cannot obtain higher revenue by bidding untruthfully, similar conclusion can also be concluded from Fig. 3(b). In Fig. 3(c), UAV-seller 3 overbids from 1.0655 to 4.0655, and data-seller 2 underbids from 3.0688 to 0.0868, and the joint bid remains truthful. It can be observed that the seller pair's revenue remains unchanged, and the UAV-seller's revenue increases with the increase of its bid, while data-seller 2 only obtains negative revenue by underbidding, which is consistent with the analysis in **Corollary 2**. Finally, we can conclude from Fig. 5 that the proposed Subopt algorithm greatly holds the property of truthfulness.

VII. Conclusion

In this paper, we study a novel multiple FL services trading problem among buyers, data-sellers and UAV-sellers, in a UAV-aided network based on a well-designed reverse auction. A 0-1 integer programming problem is formulated to maximize the overall revenue of buyers. An interesting concept of seller pair and joint bid is proposed to facilitate the trading among these three parties. We first propose a VCG-based reverse auction mechanism to obtain the optimal solutions which, however, is computationally intractable. We then propose a computation-efficient one-sided matching-based reverse auction mechanism to obtain suboptimal solutions that approach to optimal ones, upon considering a large number of participants. Significant properties such as truthfulness and individual rationality are comprehensively analyzed for both mechanisms. Finally, extensive simulation results demonstrate the effectiveness of our proposed algorithms as compared with four baseline methods.

Acknowledgment

This work is supported in part by the National Natural Science Foundation of China (grant nos. 61971365, 61871339, 62171392), Digital Fujian Province Key Laboratory of IoT Communication, Architecture and Safety Technology (grant no. 2010499), the State Key Program of the National Natural Science Foundation of China (grant no. 61731012), the Natural Science Foundation of Fujian Province of China No. 2021J01004.

References

[1] W. Saad, M. Bennis and M. Chen, "A Vision of 6G Wireless Systems: Applications, Trends, Technologies, and Open Research Problems," *IEEE Netw.*, vol. 34, no. 3, pp. 134-142, Jun. 2020.

[2] S. Zhang, H. Zhang, and L. Song,"Beyond D2D: Full Dimension UAV-to-Everything Communications in 6G," *IEEE Trans. Veh. Technol.*, vol. 69, no. 6, pp. 6592-6602, Jun. 2020.

[3] W. -C. Chien et al., "Intelligent Architecture for Mobile HetNet in B5G," *IEEE Netw.*, vol. 33, no. 3, pp. 34-41, Jun. 2019.

[4] S. Hosseinalipour, C. G. Brinton, V. Aggarwal, H. Dai and M. Chiang, "From Federated to Fog Learning: Distributed Machine Learning over Heterogeneous Wireless Networks," *IEEE Commun. Mag.*, vol. 58, no. 12, pp. 41-47, Dec. 2020.

[5] J. Konecny, H. B. McMahan, F. X. Yu, P. Richtarik, A. T. Suresh, and D. Bacon, "Federated learning: Strategies for improving communication efficiency," arXiv preprint arXiv:1610.05492, 2016.

[6] Y. Deng et al., "AUCTION: Automated and Quality-Aware Client Selection Framework for Efficient Federated Learning," *IEEE Trans. Parallel Distrib. Syst.*, vol. 33, no. 8, pp. 1996-2009, Aug. 2022.

[7] Y. Zhan, P. Li, S. Guo and Z. Qu, "Incentive Mechanism Design for Federated Learning: Challenges and Opportunities," *IEEE Netw.*, vol. 35, no. 4, pp. 310-317, July/August 2021.

[8] M. Ribeiro, K. Grolinger and M. A. M. Capretz, "MLaaS: Machine Learning as a Service," in *Proc. 2015 IEEE 14th International Conference on Machine Learning and Applications (ICMLA)*, Miami, FL, USA, Dec. 2015.

[9] H. B. McMahan et al., "Communication-Efficient Learning of Deep Networks from Decentralized Data," in *Proc. Int'l. Conf. Artificial Intelligence and Statistics*, Apr. 2017

[10] T. Huang, W. Lin, W. Wu, L. He, K. Li and A. Y. Zomaya, "An Efficiency-Boosting Client Selection Scheme for Federated Learning With Fairness Guarantee," *IEEE Trans. Parallel Distrib. Syst.*, vol. 32, no. 7, pp. 1552-1564, Jul. 2021.

[11] Q. Zeng, Y. Du, K. Huang and K. K. Leung, "Energy-Efficient Resource Management for Federated Edge Learning with CPU-GPU Heterogeneous Computing," *IEEE Trans. Wireless Commun.*, vol. 20, no. 12, pp. 7947-7962, Dec. 2021.

[12] V. -D. Nguyen, S. K. Sharma, T. X. Vu, S. Chatzinotas and B. Ottersten, "Efficient Federated Learning Algorithm for Resource Allocation in Wireless IoT Networks," *IEEE Internet Things J.*, vol. 8, no. 5, pp. 3394-3409, Mar. 2021.

[13] L. Liu, J. Zhang, S. H. Song and K. B. Letaief, "Client-Edge-Cloud Hierarchical Federated Learning," in *Proc. 2020 IEEE International Conference on Communications (ICC)*, Dublin, Ireland, Jun. 2020.

[14] A. Hashemi, A. Acharya, R. Das, H. Vikalo, S. Sanghavi and I. S. Dhillon, "On the Benefits of Multiple Gossip Steps in Communication-Constrained Decentralized Federated Learning," *IEEE Trans. Parallel Distrib. Syst.*, in press, doi: 10.1109/TPDS.2021.3138977.

[15] 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.

[16] D. Chen et al., “Matching-Theory-Based Low-Latency Scheme for Multitask Federated Learning in MEC Networks,” *IEEE Internet Things J.*, vol. 8, no. 14, pp. 11415-11426, Jul. 2021.

[17] J. Xu, H. Wang and L. Chen, “Bandwidth Allocation for Multiple Federated Learning Services in Wireless Edge Networks,” *IEEE Trans. Wireless Commun.*, vol. 21, no. 4, pp. 2534-2546, Apr. 2022.

[18] M. N. H. Nguyen, N. H. Tran, Y. K. Tun, Z. Han and C. S. Hong, “Toward Multiple Federated Learning Services Resource Sharing in Mobile Edge Networks,” *IEEE Trans. Mobile Comput.*, in press, doi: 10.1109/TMC.2021.3085979.

[19] W. Dai, C. Dai, K. -K. R. Choo, C. Cui, D. Zou and H. Jin, “SDTE: A Secure Blockchain-Based Data Trading Ecosystem,” *IEEE Trans. Inf. Forensics Security.*, vol. 15, pp. 725-737, Jul. 2020.

[20] Z. Zhou, F. Liu, S. Chen and Z. Li, “A Truthful and Efficient Incentive Mechanism for Demand Response in Green Datacenters,” *IEEE Trans. Parallel Distrib. Syst.*, vol. 31, no. 1, pp. 1-15, Jan. 2020.

[21] Y. Jiao, P. Wang, D. Niyato and K. Suankaewmanee, “Auction Mechanisms in Cloud/Fog Computing Resource Allocation for Public Blockchain Networks,” *IEEE Trans. Parallel Distrib. Syst.*, vol. 30, no. 9, pp. 1975-1989, Sept. 2019.

[22] T. Bahreini, H. Badri and D. Grosu, “Mechanisms for Resource Allocation and Pricing in Mobile Edge Computing Systems,” *IEEE Trans. Parallel Distrib. Syst.*, vol. 33, no. 3, pp. 667-682, Mar. 2022.

[23] X. Gao, P. Wang, D. Niyato, K. Yang and J. An, “Auction-Based Time Scheduling for Backscatter-Aided RF-Powered Cognitive Radio Networks,” *IEEE Trans. Wireless Commun.*, vol. 18, no. 3, pp. 1684-1697, Mar. 2019.

[24] T. H. Thi Le et al., “An Incentive Mechanism for Federated Learning in Wireless Cellular Networks: An Auction Approach,” *IEEE Trans. Wireless Commun.*, vol. 20, no. 8, pp. 4874-4887, Aug. 2021.

[25] H. Zhang, L. Song, and Z. Han, “Unmanned Aerial Vehicle Applications over Cellular Networks for 5G and Beyond,” New York, NY, USA: Springer, 2020.

[26] W. Y. B. Lim et al., “UAV-assisted Communication Efficient Federated Learning in the Era of the Artificial Intelligence of Things,” *IEEE Netw.*, vol. 35, no. 5, pp. 188-195, Sept./Oct. 2021.

[27] W. Y. B. Lim et al., “Towards Federated Learning in UAV-Enabled Internet of Vehicles: A Multi-Dimensional Contract-Matching Approach,” *IEEE Trans. Intell. Transport. Syst.*, vol. 22, no. 8, pp. 5140-5154, Aug. 2021.

[28] J. S. Ng et al., “Joint Auction-Coalition Formation Framework for Communication-Efficient Federated Learning in UAV-Enabled Internet of Vehicles,” *IEEE Trans. Intell. Transport. Syst.*, vol. 22, no. 4, pp. 2326-2344, Apr. 2021.

[29] W. Y. B. Lim et al., “Federated Learning in Mobile Edge Networks: A Comprehensive Survey,” *IEEE Commun. Surveys Tuts.*, vol. 22, no. 3, pp. 2031-2063, thirdquarter 2020.

[30] S. Abdulrahman, H. Tout, H. Ould-Slimane, A. Mourad, C. Talhi and M. Guizani, “A Survey on Federated Learning: The Journey From Centralized to Distributed On-Site Learning and Beyond,” *IEEE Internet Things J.*, vol. 8, no. 7, pp. 5476-5497, Apr. 2021.

[31] D. C. Nguyen, M. Ding, P. N. Pathirana, A. Seneviratne, J. Li and H. Vincent Poor, “Federated Learning for Internet of Things: A Comprehensive Survey,” *IEEE Commun. Surveys Tuts.*, vol. 23, no. 3, pp. 1622-1658, thirdquarter 2021.

[32] Y. Jiao, P. Wang, D. Niyato, B. Lin and D. I. Kim, “Toward an Automated Auction Framework for Wireless Federated Learning Services Market,” *IEEE Trans. Mobile Comput.*, vol. 20, no. 10, pp. 3034-3048, Oct. 2021.

[33] H. Zhang and L. Hanzo, “Federated Learning Assisted Multi-UAV Networks,” *IEEE Trans. Veh. Technol.*, vol. 69, no. 11, pp. 14104-14109, Nov. 2020.

[34] C. Dai, X. Wang, K. Liu, D. Qi, W. Lin and P. Zhou, “Stable Task Assignment for Mobile Crowdsensing with Budget Constraint,” *IEEE Trans. Mobile Comput.*, vol. 20, no. 12, pp. 3439-3452, Dec. 2021.

[35] M. Liwang, S. Dai, Z. Gao, Y. Tang and H. Dai, “A Truthful Reverse-Auction Mechanism for Computation Offloading in Cloud-Enabled Vehicular Network,” *IEEE Internet Things J.*, vol. 6, no. 3, pp. 4214-4227, Jun. 2019.

[36] Y. Luo, X. Huang, J. Yang, F. Wu and S. Leng, “Auction Mechanism-based Multi-type Task Planning for Heterogeneous UAVs Swarm,” in *Proc. 2020 IEEE 20th International Conference on Communication Technology (ICCT)*, Oct. 2020.

[37] H. Khdr, M. Shafique, S. Pagani, A. Herkersdorf and J. Henkel, “Combinatorial Auctions for Temperature-Constrained Resource Management in Manycores,” *IEEE Trans. Parallel Distrib. Syst.*, vol. 31, no. 7, pp. 1605-1620, Jul. 2020.

[38] M. Liwang, R. Chen, X. Wang, and X. Shen, “Unifying Futures and Spot Market: Overbooking-Enabled Resource Trading in Mobile Edge Networks,” *IEEE Trans. Wireless Commun.*, in press, doi: 10.1109/TWC.2022.3141094.

[39] S. Zhong, J. Chen and Y. R. Yang, ”Sprite: A Simple, Cheat-Proof, Credit-Based System for Mobile Ad-Hoc Networks,” in *Proc. 22nd Annu. Joint Conf. IEEE Comput. Commun. Soc.*, San Francisco, CA, USA, Apr. 2003.

[40] Z. Zheng, Y. Gui, F. Wu and G. Chen, “STAR: Strategy-Proof Double Auctions for Multi-Cloud, Multi-Tenant Bandwidth Reservation,” *IEEE Trans. Comput.*, vol. 64, no. 7, pp. 2071-2083, Jul. 2015.

[41] W. Borjigin, K. Ota and M. Dong, “In Broker We Trust: A Double-Auction Approach for Resource Allocation in NFV Markets,” *IEEE Trans. Netw. Service Manag.*, vol. 15, no. 4, pp. 1322-1333, Dec. 2018.

[42] A. R. Khamesi and S. Silvestri, “Reverse Auction-based Demand Response Program: A Truthful Mutually Beneficial Mechanism,” in *Proc. 2020 IEEE 17th International Conference on Mobile Ad Hoc and Sensor Systems (MASS)*, Delhi, India, Dec. 2020.

[43] Patel, Y.S., Malwi, Z., Nighojkar, A. et al. “Truthful Online Double Auction Based Dynamic Resource Provisioning for Multi-Objective Trade-Offs in IaaS Clouds”. *Cluster Comput.*,vol.24, pp.1855–1879, Jan. 2021.

[44] Q. Wei, W. Sun, B. Bai, L. Wang, E. G. Ström and M. Song, “Resource Allocation for V2X Communications: A Local Search Based 3D Matching Approach,” in *Proc. 2017 IEEE International Conference on Communications (ICC)*, May 2017.

[45] W. Tang and R. Jain, “Hierarchical Auction Mechanisms for Network Resource Allocation,” *IEEE J. Select. Areas Commun.*, vol. 30, no. 11, pp. 2117-2125, Dec. 2012.

[46] M. Stübs, W. Posdorfer and S. Momeni, “Blockchain-Based Multi-Tier Double Auctions for Smart Energy Distribution Grids,” in *Proc. 2020 IEEE International Conference on Communications Workshops (ICC Workshops)*, May 2020.

[47] R. McAfee, “A Dominant Strategy Double Auction”, *J. Econ. Theory*, vol. 56, no. 2, pp. 434-450, 1992.

[48] Segal-Halevi, E., Hassidim, A., and Aumann, Y. “Double Auctions in Markets for Multiple Kinds of Goods”, in *Proc. 2018 IJCAI*, Stockholm, Sweden. Jul. 2018.

[49] Segal-Halevi, E., Hassidim, A., and Aumann, Y. “ MUDA: A Truthful Multi-Uint Double Auction Mechanism”, in *Proc. Thirty-Second AAAI Conference on Artificial Intelligence (AAAI)*, New Orleans, USA. Feb. 2018.

[50] Z. Gao, M. Liwang, S. Hosseinalipour, H. Dai and X. Wang, “A Truthful Auction for Graph Job Allocation in Vehicular Cloud-assisted Networks,” *IEEE Trans. Mobile Comput.*, in press, doi: 10.1109/TMC.2021.3059803.

[51] G. Huang and Andrew L., “A Hybrid Genetic Algorithm for Three-Index Assignment Problem,” in *Proc. CEC ’03.*, Canberra, ACT, Australia, Dec. 2003.