Coalitional Formation-based Group-buying for UAV-enabled Data Collection: an Auction Game Approach

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Abstract—Unmanned aerial vehicles (UAVs) enable promising solutions in assisting data collection in wide-area distributed sensor networks, leveraging their advanced properties of high mobility and line-of-sight communication links. However, existing UAV-assisted data collection methods mainly focus on unilaterally maximizing the utility of UAVs or sensors. Unfortunately, the problem driven by the market economy is ignored, namely the game between buyer and seller, in the process of sensors competing for UAV services. To address this problem, we propose a group-buying coalition auction method that encourages sensors to form coalitions to bid for UAV data collection services. Then, a parallel variable neighborhood ascent search algorithm is designed to quickly search the approximately optimal group-buying coalition structure. We further propose a novel group-buying coalition auction method, named TRUST, which can ensure the economical properties, i.e., truthfulness, individual rationality, and maximization of social welfare. Numerical results show that the sensors' average age of information (AoI) under the proposed method is reduced by 16.7% and 44.5% compared with the coalition formation game (CFG) and joint trajectory design-task scheduling (TDTS) UAV-to-community methods. To our best knowledge, this is the first effort on truthful coalition formation-based group-buying auction.

Index Terms—Unmanned aerial vehicle (UAV), age of information (AoI), double auction, coalition formation game, truthfulness.

1 Introduction

Wireless sensor networks (WSNs) have been widely deployed in various applications, such as environmental monitoring and event detection [1], [2], [3], [4]. In WSNs, sensors usually transmit the status data packets (e.g., perceived environmental parameters) to the destination node in a multi-hop manner. However, sensors with limited transmission power have small wireless communication coverage, so the high quality and low delay of long-distance communication cannot be guaranteed. Recently, unmanned aerial vehicles (UAVs) have been widely integrated into the fifth generation and beyond wireless networks due to high mobility and distributed deployment [5]. They are able to quickly approach the sensors and establish a high-quality air-to-ground communication link to collect data from the sensors [4], [6]. This significantly reduces the transmission energy of sensors and prolongs the life of WSNs.

Timely collected status information is crucial for time-sensitive sensor network applications, while stale status information may yield incorrect decisions. Most existing UAV-aided data collection research focuses on optimizing data transmission energy consumption and throughput while ignoring the valution of information freshness. The notion of the age of information (AoI) was recently proposed to quantify the freshness of the status information [2]. Formally, AoI is defined as the time elapsed since the latest valid status packet generated by the source node is received at the collection node. AoI has been investigated in various WSN-based status update systems [2], [7], [8].

For UAV-enabled large-scale WSNs, it is extremely challenging for UAVs to design the planning of data collection according to the locations and status of all sensors. To address this challenge, sensors can effectively reduce the complexity of data collection planning by forming coalitions to aggregate transmission data [3], [9]. In a coalition, each member delivers packets to the coalition head. Then, UAVs fly to each coalition head for aggregated data collection. As ordinary sensors may have limitations such as limited energy and unstable transmissions, the access points (APs) can be used to cache the aggregated status data packets owing to the advantages of strong storage capacity and low probability of transmission outage. In practice, APs are introduced as coalition heads to assist with the data collection in WSNs [3].

The UAV-enabled wireless communication networks

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also face the challenge of market economy factors. From the perspective of industrial UAV development, there are many recent commercial companies using UAVs for wireless communication transmission, e.g., Qualcomm and AT&T. Qualcomm and AT&T are jointly deploying UAV-assisted information transmission on AT&T's commercial network to pave the way for large-scale wireless communication in the fifth generation of wireless network [1]. Driven by the economic properties, it is necessary to design an incentive-based mechanism to appropriately encourage UAVs to assist in the transmission of wireless communication devices. Auction is a classic allocation mechanism following market rules and is able to ensure the fairness, efficiency, and economy of the whole trading market when participants are rational and competitive. Nowadays, auction has been widely used in communication network resource allocation, such as spectrum resource transactions, communication computing resource transactions, and edge cloud service transactions [10], [11], [12], [13]. Applying auction mechanisms to resource allocation in WSNs introduces the following advantages: 1) Economy driven: The auction mechanism is an economy-driven transaction that can effectively allocate the resources of sellers to the buyers at a competitive price in the wireless communication network market. 2) Fair transaction: An important economic attribute of auction is truthfulness, also known as strategy-proofness. The authentic auction mechanism can ensure that honest bidding is the only dominant strategy of the buyer and guarantee the reasonable and fair allocation of resources. 3) Less information needed: In the auction process, the auctioneer and the seller do not need to know the complete information, but only the buyer's bid to determine the resource matching relationship. Applying resource auctions to wireless communication networks can significantly reduce unnecessary information interaction overhead.

When using auction mechanism in UAV-enabled WSNs, a single sensor may not be competitive enough to attract a UAV to serve its data collection. Instead, the sensors may cooperate with each other to form a group-buying coalition to increase the bid so as to attract the UAV services. The UAV-enabled data collection in WSN can be regarded as a typical distributed multi-agent decision process, in which participants make decisions through information interaction and evaluate their behaviors according to the potential utility. Coincidentally, coalition formation game (CFG) shares the same idea that focuses on how to encourage independent participants to cooperate as an entity [14], [15]. Moreover, coalition formation is a typical combinatorial optimization problem. The existing coalition formation algorithms need large amounts of information interaction and cannot be implemented in parallel. So they are not suitable for the optimization of large-scale sensor networks. Therefore, it is crucial to design a coalition formation algorithm so that sensors can efficiently form a group-buying coalition to improve the data transmission efficiency.

The combination of auction and coalition formation game theories enables analyzing the formation of the economy-driven group-buying coalition. Truthfulness is a key attribute in auction, which can ensure that buyers submit bids for the true valuation of tradable resources. The truthful bid mechanism of auction is particularly important. For example, in the process of buyers competing for sellers' resources, some buyers may dishonestly submit a high or low bid to seek high profits, which may result in additional costs for other buyers. Some works have designed bid mechanisms for non-cooperative auctions, such as the second price auction, monotonic critical bid, and bid fraud punishment measures, to ensure the honesty of the auction process [11], [13], [16]. However, the previous truthful non-cooperative auction mechanisms are no longer suitable for the group-buying coalition auction. Therefore, it is necessary to design an auction mechanism to ensure the truthfulness of group-buying coalition formation.

1.1 Related Work

Due to high mobility and line-of-sight channels, UAVs provide promising solutions to assist in the collection of status data packets in WSNs. Zhan *et al.* [22] studied task offloading in UAV-assisted multi-access edge computing (MEC) systems. A successive convex approximation-based alternating UAV trajectory optimization algorithm was proposed to minimize the tradeoff between the completion time and energy consumption. Considering the Markov property of the time-varying communication channel, Liu *et al*. [23] proposed a deep reinforcement learning-based algorithm to maximize the computation utility in a cooperative UAV-assisted MEC network. In contrast to the previous works, which focused on system transmission throughput, delay, and energy consumption, some researchers considered the time value difference between sensor status data packets and used the sensor AoI as the objective function. Hu *et al*. studied the status packet transmission scenario of UAV-assisted ground sensors [18]. They optimized the non-convex problem to minimize the average AoI of sensors. Zhang *et al*. developed a UAV-assisted communication framework for delay-sensitive internet of thing (IoT) devices in sixth-generation networks, in which AoI was taken as a new metric to measure the quality of services [19].

In the above studies, the UAV serves sensors individually and sequentially. Hence, these methods can hardly be applied to the large-scale WSN. In this regard, the data clustering uploading of sensors has been studied in [18], [19], [24]. Ebrahimi *et al*. proposed a projection-based compressive data gathering method for UAV-assisted dense WSNs [17]. To improve energy efficiency, Liu *et al*. proposed an incremental clustering method in which sensors are clustered based on UAV flight trajectories [9]. As a powerful tool for analyzing user grouping, coalition formation game has been widely used in communication networks. Chen *et al*. proposed a coalition formation game method to realize joint task allocation and spectrum allocation in heterogeneous UAV communication networks [14]. Saad *et al*. proposed a selfish coalition formation method to realize that UAVs cooperatively transmit data to base stations [15].

Truthfulness is an important economic attribute in auction, which can ensure the reasonable allocation of UAV transmission service resources in the market. There have been many designs to ensure the truthfulness of the non-cooperative auction mechanism, such as the famous second-price auction, named Vickrey, which sets the second-highest bid as the buyer's payment to ensure the independence

TABLE 1
A Comparison with Main Related Data Collection Methods.

Existing UAV-enabled data collection works in wireless networks	Economic	Cooperation	Truthfulness	AoI	Distributed
Clustering scheme [3] [17]	×	×	×	×	✓
AOI-based method [2] [18] [19]	×	×	×	✓	×
Auction scheme [6] [11]	✓	×	✓	×	✓
Coalition-auction scheme [20] [21]	✓	✓	×	×	×
Our group-buying coalition auctions scheme	✓	✓	✓	✓	✓

of the buyer's payment and bid. This setting ensures the truthfulness of the buyer's bid. Some works have applied Vickrey to resource auction in communication networks [25], [26], [27]. The authors in [26] adopted Vickrey-Clarke-Groves to ensure the truthfulness of the spectrum auction market. Some works investigate the dynamic and rational characteristics of communication networks in order to ensure the veracity of auctions. For example, Zhang *et al*. studied the distributed real auction mechanism in mobile cloud computing task allocation. They proposed an incentive-compatible online cloud auction method to prevent the seller from making dishonest behaviors, such as manipulating the payment for their own profits [11]. Hyder *et al*. proposed an online auction mechanism for the dynamic spectrum market, which designed penalty rules to avoid manipulating bids [28].

The auction mechanism is an efficient and economics-driven resource allocation approach in wireless communication networks. Ning *et al*. [6] proposed a community-based delay approximation algorithm and a dynamic task allocation auction algorithm to jointly optimize UAV trajectory and task scheduling. Subsequently, to minimize the computation cost, the authors formulated two stochastic games to optimize the UAV trajectory and computation offloading from the potential game-theoretic perspective in their extended work [29]. Apostolopoulos *et al*. [30] studied the data offloading approach in UAV-assisted MEC networks. They proposed a non-cooperative game decision-making framework to maximize satisfaction of users under uncertain computation resource auction. However, the majority of existing investigations focused on maximizing the utility in a non-cooperative auction. There has been limited research combined coalition formation and auction to allocate wireless communication resources. Sun *et al*. proposed a spectrum auction method based on overlapping coalition to optimize the composition of users using the same spectrum [31]. However, the users were divided into the same coalition just depending on whether they shared the same channel, while the cooperative relationship among coalition members was ignored. In effect, coalition members can be formed to improve mutual benefits. Considering the cooperative relationship among buyers or sellers, some studies combined auction with coalition and applied them to the wireless communication network resource allocation [20], [21]. Zhang *et al*. proposed a game framework based on a group-buying coalition to reduce user data download overhead, in which users perceive the data content demands of nearby members and form a group-buying coalition to share the downloaded data according to their preferences [20]. However, in this case, only the benefits from the user's unilateral perspective were considered while the mutual benefits of both auction parties are neglected. Ng *et al*. proposed a joint auction-coalition formation framework to obtain the composition and distribution of UAV coalition with maximum auction profit [21]. However, the preceding works focused solely on how to form a coalition structure to maximize auction profit while ignoring the truthfulness of the group-buying coalition auction.

Table 1 presents the comparison among clustering, auction, and coalition-auction methods from the perspectives of whether it is economy-driven, cooperative, trustful, and in a distributed way or not. If the proposed method considers the corresponding metric, there will be a checkmark "✓"; otherwise, a "×". Compared with other methods, our method considers the cooperation between sensors and guarantees the truthfulness of the group-buying auction. Besides, the AoI performance is also considered, which is critical for WSN nodes.

1.2 Contributions and Organization

In this paper, we develop a double auction framework based on a group-buying coalition to encourage UAVs to provide reliable, cost-effective, and timely data collection services in sensor networks. Firstly, the sensors form a group-buying coalition to cooperatively raise their bids to ensure that the UAV can be attracted to collect data for all sensors in the coalition. To reflect the time value of sensor status information, the sensor bidding is designed as the weighted average of sensor AoI and energy loss. Secondly, for the coalition formation in large-scale sensor networks, we design a parallel variable neighborhood ascent search coalition formation algorithm to update the coalition structure in parallel and accelerate the division of coalitions. Finally, we proposed a novel group-buying coalition bidding truthful auction mechanism, which is named TRUST (sTrategy-proof auction for VickeRy groUp-buying Sensor coaliTion) to ensure the honest bids of sensors. To the best of our knowledge, this paper is the first to study the truthful coalition formation-based group-buying auction. The main contributions of this paper are threefold: 1) A group-buying coalition-based double auction method is proposed for UAV-enabled data collection in WSNs. Combining double auction and coalition game theory, sensors decide on the formation of group-buying coalition to raise the bid. Specifically, sensors form a coalition to raise the bid for the UAV to encourage it to provide a data collection service, which effectively reduces the AoI of sensors. 2) To obtain the optimal group-buying coalition structure, a parallel variable neighborhood ascent search coalition formation algorithm is proposed. Then, the sensors can change the coalition structure in parallel

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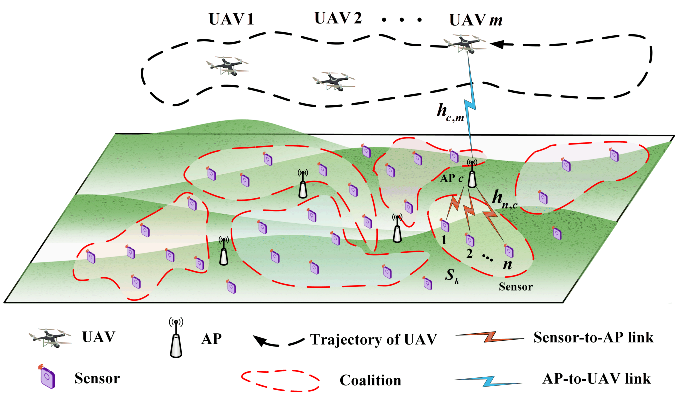

Fig. 1. Multi-UAV system model for WSN data collection

according to the cooperative bidding preference criteria and gradually converge to a stable and satisfactory bidding coalition structure. And 3) A TRUST auction mechanism is proposed to maximize the social welfare. The TRUST modifies the bidding and payment rules of the group-buying coalition, which is proven to meet truthfulness and individual rationality. Our simulation results verify that the proposed scheme can reduce the AoI of sensors as compared with existing task-driven coalition formation schemes on the premise of ensuring truthfulness.

This paper is an extended version of [32] with a detailed literature study, the design of TRUST auction mechanism, improved system model, and extensive experimental results. The remainder of this paper is organized as follows. Section II illustrates the system model. The details of TRUST are presented in Section III. Our proposed group-buying coalition formation-based auction algorithm is discussed in Section IV. Section V proves the economy of the proposed TRUST auction. Section VI presents numerical results and performance analyses, and Section VII concludes this paper.

2 System Model

We consider UAV-enabled status data collection in WSNs. As shown in Fig. 1, there are N geographically distributed ground sensors denoted as $\mathcal{N} = \{1, 2, ..., n, ..., N\}$. In most cases, sensors are deployed in remote and harsh physical areas, and cannot access the data collection center. Suppose there are M UAVs that can collect sensors' status information, represented by a set $\mathcal{M} = \{1, ...m..., M\}$. To reduce the interruption probability caused by long-distance transmission, APs are introduced to assist in the transmission between UAVs and sensors. Suppose there are C distributed APs, represented by a set $\mathcal{C} = \{1, ...c..., C\}$. Similar to cloud-edge data processing mode, APs act as edge servers to cache the status data from sensors. UAVs act as cloud servers to receive and process those aggregated status data from APs. Thus, a dual-layer transmission scheme is designed. As presented in Fig. 2, in the first layer, the sensors transmit the status data packets to the AP; in the second layer, the UAV flies just above the AP and collects the aggregated status data packets from it. For convenience, key variables and their definitions are listed in Table 2.

TABLE 2
List of Notations

Variables	Explanation
$\mathcal{N} = \{1, ...n..., N\}$	Set of sensors
$\mathcal{M} = \{1, ...m..., M\}$	Set of UAVs
$\mathcal{C} = \{1, ...c..., C\}$	Set of APs
$\Upsilon = \{S_1, ...S_k, ...S_K\}$	Coalition structure of sensors
r	The round of auction
$a_n^{(r)}$	The AoI of sensor n in the r^{th} round
$\varepsilon_n^{(r)}$	The amount of status packets by sensor n
$b_n^{(r)}$	The bid of sensor n in the r^{th} round
$\bar{b}_n^{(r)}$	The truthful bid of sensor n
$\Phi_{S_k}^{(r)}$	The bid of coalition S_k
$\Psi_{m,S_k}^{(r)}$	The actual coalition bid of coalition S_k
$E_{m,S_k}^{(r)}$	Energy consumption of UAV m
ω_1	Energy weight coefficients
$Q_{m,S_k}^{(r)}$	The second highest payment of $S_k^{(r)}$
$I_{m,S_k}^{(r)}$	Indicator function of Transaction result
$\mathbf{SW}^{(r)}$	Social welfare in the r^{th} round

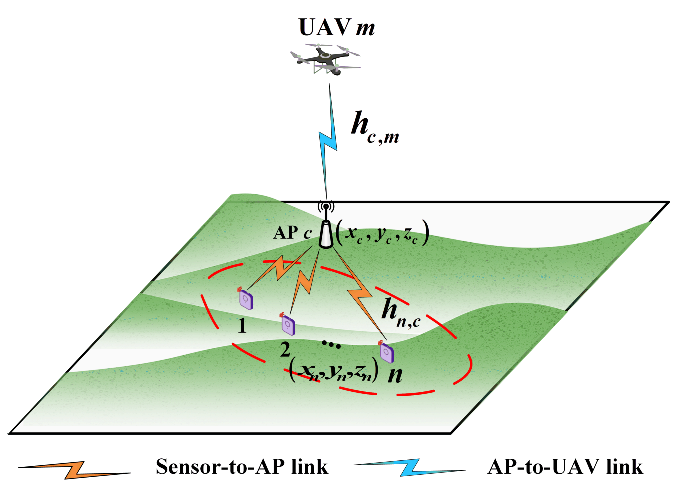

Fig. 2. Dual-layer information transmission processes from sensors to their AP and from the AP to a UAV.

To encourage UAVs to participate in the sensor status data collection, a double auction is leveraged for modeling the transaction process of the UAVs and sensors. The auction participants are composed of three parties, i.e. UAVs (sellers), sensors (buyers), and the auctioneer (who can be acted by APs). Due to the fact that 1) the bid of a single sensor may not be attractive enough to UAVs and 2) the UAV's usefulness in serving a single sensor at a time is relatively low, sensors form multiple group-buying coalitions and bid for the UAV data collection service. A continuous dynamic multi-round auction is proposed so that the UAVs will successively serve different coalitions according to the auction results. Sensors who lost in the previous round of auction can also adjust their bids and participate in the next round of auction. As shown in Fig. 3, our proposed group

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buying coalition auction method can be divided into six stages:

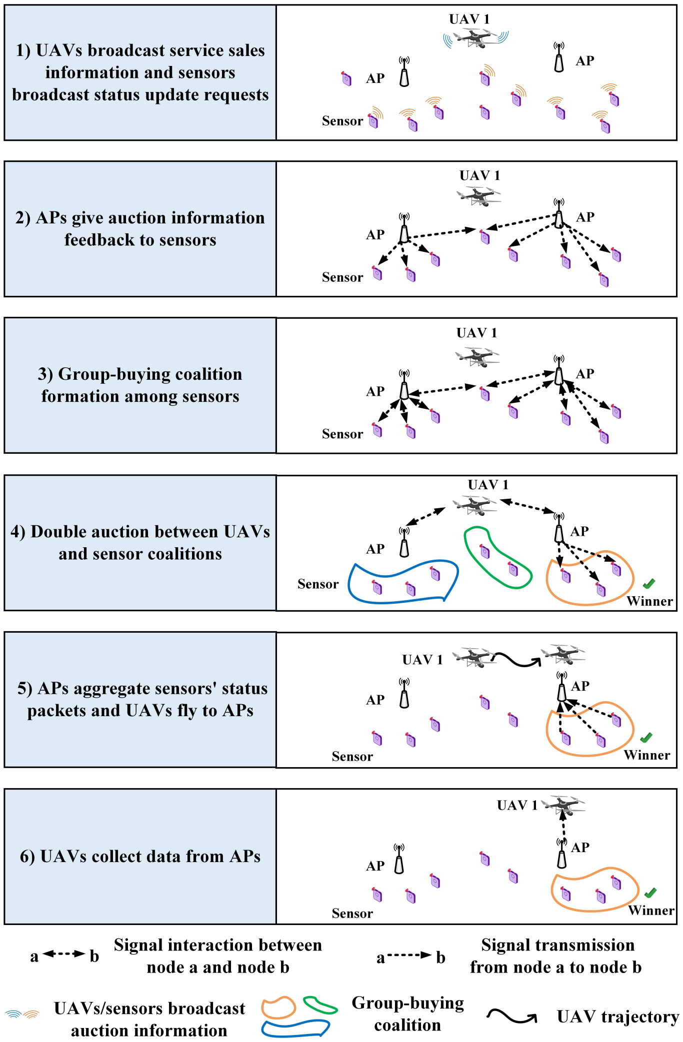

Fig. 3. The signaling of group-buying coalition auction implementation. Note that we only take one UAV as an example to illustrate.

Stage 1 (UAVs broadcast service sales information and sensors broadcast status update requests): the sensors broadcast the status update request information, e.g., AoI status, location. The UAVs broadcast the data collection service sale information, e.g., communication capabilities, location.

Stage 2 (APs give auction information feedback to sensors): after receiving the service sale information from the UAVs, the APs give this auction information feedback to the sensors in need and invite them to participate in group-buying bidding.

Stage 3 (Group-buying coalition formation among sensors): sensors form multiple group-buying coalitions to improve the market competitiveness of their bids.

Stage 4 (Double auction between UAVs and sensor coalitions): the coalitions report their bids and relevant requirements for updating status packets to the APs. The APs decide the winning sensor coalitions and UAVs.

Stage 5 (APs aggregate sensors' status packets and UAVs fly to APs): if the coalitions' bids for UAVs' service is successful, the APs collect the sensors' status packets and the UAVs fly to the APs.

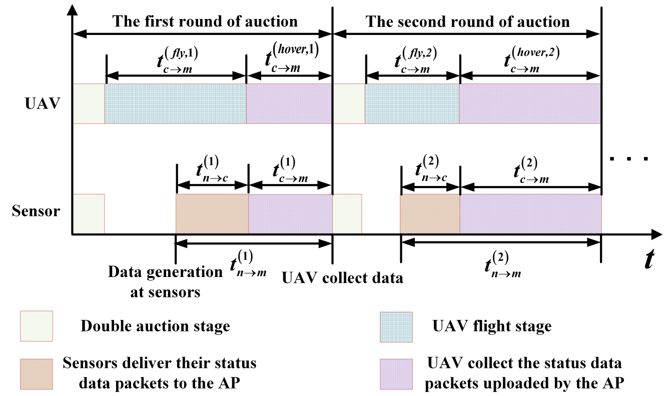

Fig. 4. The time slot division of the group-buying coalition auction.

Stage 6 (UAVs collect data from APs): the UAVs collect the aggregated sensors' status packets from the APs.

The time slot division of the group-buying coalition auction is shown in Fig. 4. The definition of the sensor coalition structure is given as follows:

***Definition* 1** (coalition structure). *For the collection of all sensors, $\mathcal{N}=\{1,...n...,N\}$, the coalition structure $\Upsilon^{(r)}=\left\{S_1^{(r)},...S_k^{(r)}...,S_K^{(r)}\right\}$ is defined as a partition that contains all sensors (namely, $\bigcup_{k=1}^{K} S_k^{(r)}=\mathcal{N}$) in the r^{th} round of auction. S_k is a sensor coalition and k is the coalition index. Due to one sensor can only join in one coalition, $S_k^{(r)}\cap S_{k'}^{(r)}=\emptyset,\forall k\neq k'$.*

2.1 Communication Model

2.1.1 Sensors-AP communication

In the r-th round of the auction, each sensor coalition $S_k^{(r)}$ finds the nearest AP c as the data aggregation point of all coalition sensor members according to

$$g\left(S_k^{(r)}\right)=\arg\min_{c}\sum_{n\in S_k^{(r)}} d_{n,c}, \tag{1}$$

where $d_{n,c}=\sqrt{(x_n-x_c)^2+(y_n-y_c)^2+(z_n-z_c)^2}$ is the distance between sensor n and AP c; x_n, y_n, and z_n are the three-dimensional coordinates of sensor n; x_c, y_c, and z_c are the three-dimensional coordinates of AP c.

The communication channel between the sensor and AP is assumed to be non-line-of-sight (NLoS) [33]. Let $h_{n,c}$ represent the channel gain between sensor n and AP c, which is expressed as

$$|h_{n,c}|^2=(d_{n,c})^{-\alpha_1}, \tag{2}$$

where α_1 is the path loss exponent over the sensor-AP c link. Specifically, orthogonal frequency division multiplexing technology is used to avoid interference between APs. APs in close proximity are assigned different orthogonal channels for data transmission. Hence, the achievable communication transmission rate from sensor n to AP c is

$$R_{n,c}=B_c\log_2\left(1+\frac{|h_{n,c}|^2 p_n}{N_0B_c+\mu_n}\right), \tag{3}$$

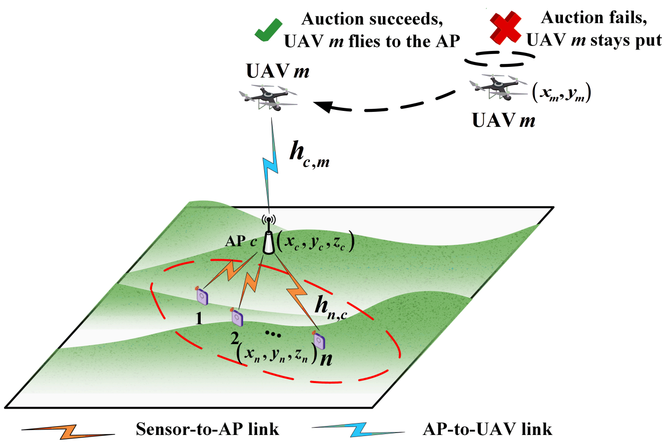

Fig. 5. Illustration of UAV position change before and after each round of auction.

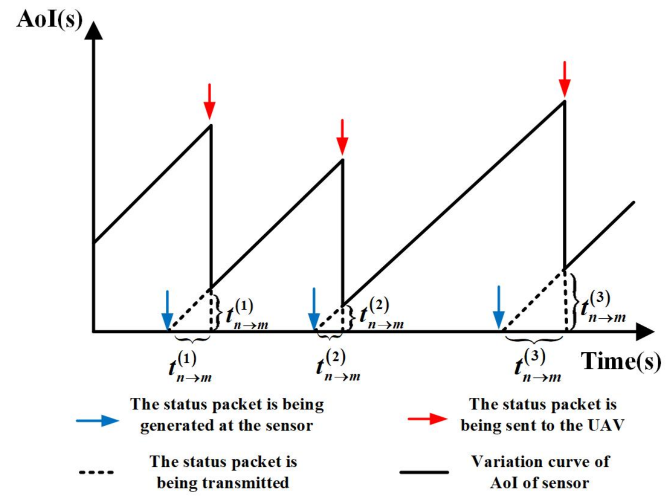

Fig. 6. Illustrative curves of age of information (AoI) versus time.

where B_c is the channel bandwidth occupied by AP c, p_n is the sensor transmission power, N_0 is the one-sided power spectral density of white Gaussian noise. Sensors communicating with the same AP occupy the same channel and experience co-channel interference μ_n, i.e.,

$$\mu_n = \sum_{n' \in S_k^{(r)}, n' \neq n} \left| h_{j,n'} \right|^2 p_{n'} \tag{4}$$

Hence, the expected communication time from sensor n to AP c is

$$t_{n \to c}^{(r)} = \mathbb{E}\left\{ \frac{\varepsilon_n^{(r)}}{R_{n,c}} \right\}, n \in S_k^{(r)}, c = g\left(S_k^{(r)}\right), \tag{5}$$

where $\mathbb{E}\{\cdot\}$ is the expectation operator. $\varepsilon_n^{(r)}$ is the bit number of status packets (bits) generated by sensor n in the r^{th} round of auction.

2.1.2 AP-UAV communication

After collecting the status information packets of all coalition sensor members, AP c will transmit the aggregated data packets to UAV m. The channel between the UAV and sensor is modeled as a probabilistic line-of-sight (LoS) and non-line-of sight (NLoS) link [33]. The probability calculation formula of the LoS channel between AP c and UAV m is

$$\Pr_{c,m}(\text{LOS}) = \frac{1}{1 + \vartheta_l \exp\left(-\zeta_l \left[\theta_{c,m} - \vartheta_l\right]\right)}, \tag{6}$$

where ζ_l and ϑ_l are constants that depend on the environment (rural areas, compact cities, or others), and $\theta_{c,m}$ is the elevation. Besides, $\Pr_{c,m}(\text{NLOS}) = 1 - \Pr_{c,m}(\text{LOS})$. Let $h_{c,m}$ represent the channel gain between c and m, that is

$$\left| h_{c,m} \right|^2 = \begin{cases} (d_{c,m})^{-\alpha_2}, \text{LoS}; \\ \eta (d_{c,m})^{-\alpha_2}, \text{NLoS}, \end{cases} \tag{7}$$

where η is an additional loss coefficient due to the NLoS connection. α_2 is the path loss exponent over the AP-UAV link. $d_{c,m}$ is the distance between the UAV and the AP. We assume that different UAVs fly at different fixed altitudes. If the auction is successful, the UAV will fly to the position just above the AP to communicate with it. Thus, $d_{c,m} = H_m - z_c$, in which H_m is the fixed flight altitude of UAV m and is strictly greater than the UAV's minimum flight clearance in [34]. The achievable communication transmission rate between AP c and UAV m is

$$R_{c,m} = B_c \log_2 \left(1 + \frac{\left| h_{c,m} \right|^2 p_c}{N_0 B_c} \right), \tag{8}$$

where B_c is the channel bandwidth used by AP c. p_c is the transmission power of AP c. The expected transmission time duration from c to m is defined as $t_{c \to m}^{(r)}$, of which the expression is the total amount of information required to be transmitted divided by the transmission rate, that is

$$t_{c \to m}^{(r)} = \sum_{n \in S_k^{(r)}} \mathbb{E}\left\{ \varepsilon_n^{(r)} / R_{c,m} \right\}, c = g\left(S_k^{(r)}\right). \tag{9}$$

2.2 Energy consumption model

As shown in Fig. 5, the position changes of UAV m before and after r^{th} round of auction are as follows

$$x_m^{(r+1)} = \begin{cases} x_c, & \text{if UAV } m \text{ serves coalition } S_k^{(r)} \\ & \text{and } c = g\left(S_k^{(r)}\right); \\ x_m^{(r)}, & \text{else.} \end{cases}$$
$$y_m^{(r+1)} = \begin{cases} y_c, & \text{if UAV } m \text{ serves coalition } S_k^{(r)} \\ & \text{and } c = g\left(S_k^{(r)}\right); \\ y_m^{(r)}, & \text{else.} \end{cases} \tag{10}$$

If the transaction is successful, UAV m will fly to the spot just above the AP c that the coalition chose. The position of UAV m will be updated to the abscissa and ordinate of AP c. Otherwise, the position of UAV m will remain unchanged. Since the propulsion power of a UAV is dominant compared to the communication power [35], the propulsion loss of the UAV is mainly considered. Then, $E_{m,S_k}^{(r)}$ is defined as the overall energy loss caused by UAV m completing data collection service for coalition $S_k^{(r)}$, which is the sum of energy loss in the flight and hover states, that is

$$E_{m,S_k}^{(r)} = P(v_m) t_{c \to m}^{(fly,r)} + P(0) t_{c \to m}^{(hover,r)}, c = g\left(S_k^{(r)}\right), \tag{11}$$

where v_m is the flight speed of UAV m. $P(v_m)$ and $P(0)$ are the flight and hover propulsion power, respectively. $t_{c\to m}^{(fly,r)} = \sqrt{\left(x_m^{(r)} - x_c\right)^2 + \left(y_m^{(r)} - y_c\right)^2}/v_m$ is the time of UAV m flying to AP c. $t_{c\to m}^{(hover,r)}$ is the hover time of UAV m at sensor c. The hover time of the UAV is equal to the time required for data transmission, i.e., $t_{c\to m}^{(hover,r)} = t_{c\to m}^{(r)}$. Thus, the time spent by the UAV in the r^{th} round of auction is the sum of the flight time and hovering time, i.e.,

$$t_{c\to m}^{(cost,r)} = t_{c\to m}^{(fly,r)} + t_{c\to m}^{(hover,r)}. \tag{12}$$

2.3 AoI model

Age of information (AoI) is introduced to quantify the freshness of information, which is defined as follows.

***Definition* 2** (Age of Information)**.** *The age of information of a source node is the time elapsed since the latest valid status packet is received at the collection node.*

The time interval of each round of auction is defined as t_{auc}. In the r^{th} round of auction, for a sensor n, its AoI before the auction is defined as $a_n^{(r)}$ and that after the auction is updated to $a_n^{(r+1)}$ as below

$$a_n^{(r+1)} = \begin{cases} t_{n\to m}^{(r)}, & \text{update;} \\ a_n^{(r)} + t_{auc}, & \text{otherwise.} \end{cases} \tag{13}$$

As illustrated in Fig. 6, (13) indicates that if UAV m collects data packets from sensor n, its AoI changes as the time interval starting from the status packets generation at sensor n to the arrival at UAV m, i.e., $t_{n\to m}^{(r)} = t_{n\to c}^{(r)} + t_{c\to m}^{(r)}$. Otherwise, its AoI increases by the period of one auction round. Assuming that a sensor coalition successfully purchases a UAV for data collection, we define $f\left(a_n^{(r)}\right)$ as the valuation function of updating status information based on AoI reduction, that is

$$f\left(a_n^{(r)}\right) = \frac{1}{1 + \exp^{-\delta_n\left(a_n^{(r)} - t_{n\to m}^{(r)} - \varsigma_n\right)}}, \tag{14}$$

where δ_n and ς_n are the sensitivity and tolerance threshold of sensor n to the AoI, respectively. Different types of sensors may have different requirements for information freshness. A smaller ς_n means a smaller inflection point of valuation function and a lower tolerance to the AoI; similarly, a smaller δ_n implies a smaller slope at the inflection point of valuation function and a lower sensitivity to the change of information freshness.

3 TRUST Formulation

It is considered that sensors have certain rational and independent decision-making abilities, they can evaluate their behaviors according to their utilities. As stated in the introduction part, if there is no mechanism to ensure the truthfulness of the coalition group-buying auction, sensors can obtain more utility by dishonestly reporting their bid. For example, as shown in Fig. 7, there are three sensor members in the coalition, among which sensor 1 reports a dishonest bid that is smaller than the true valuation. Compared to an honest bid, sensor 1 pays a lower payment. However, it still obtains the true valuation after the successful auction and the UAV data collection service. In this case, sensor 1 obtains a higher utility by dishonestly reporting the bid. To ensure the truthfulness of the coalition group-buying auction, this Section introduces the auction mechanism of the lowest coalition bidding based on Vickery. Hereinafter, it will be referred to as a sTrategy-proof VickeRy groUp-buying Sensor coaliTion auction (TRUST).

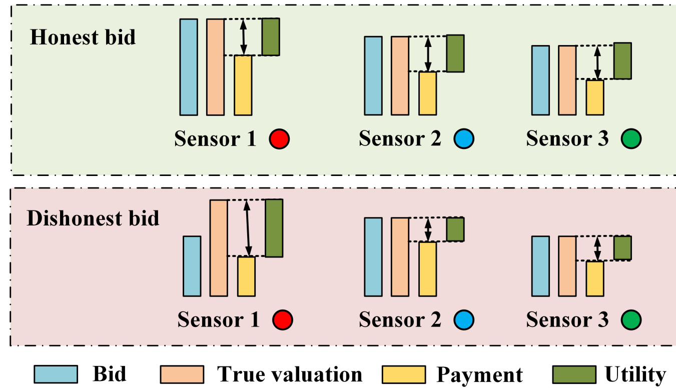

Fig. 7. Honest versus dishonest bids. The utility is the difference between true valuation and payment, i.e., utility = true valuation − payment.

The main idea of TRUST is as follows. Firstly, the lowest bid coalition is defined to ensure that the bid of the whole coalition is decided by the coalition member with the lowest bid, and will not change due to other members' dishonest bids. Furthermore, the utility will not be increased regardless of whether the coalition members submit dishonest bids that are higher or lower than the true valuation. Secondly, considering the Vickery auction mechanism together, the coalition payment is defined as the second-highest coalition bid to ensure the truthfulness of the coalition bid. Finally, the truthfulness of the whole auction process is ensured through the design of the lowest bid coalition and Vickery-based coalition payment. Specific proof of truthfulness is given in section V.

3.1 The lowest bid coalition

Under a given coalition structure $\Upsilon^{(r)} = \left\{S_1^{(r)}, \ldots, S_k^{(r)}, \ldots, S_K^{(r)}\right\}$. The bid of the coalition $S_k^{(r)}$ in the r^{th} round of auction is defined as the lowest bid among the coalition members being multiplied by the number of coalition members, and can be formulated as

$$\Phi_{S_k}^{(r)} = \min_{n\in S_k^{(r)}} b_n^{(r)} \cdot \left|S_k^{(r)}\right|, \tag{15}$$

where symbol $|\cdot|$ means the cardinality of a set. $b_n^{(r)}$ is defined as the bidding strategy of sensor n in the r^{th} round. $\min\limits_{n\in S_k^{(r)}} b_n^{(r)}$ is the lowest bid among the coalition members. Specially, the honest bidding strategy is denoted as $\bar{b}_n^{(r)}$, which is the true valuation that the sensor thinks it can bring to itself, i.e.,

$$\bar{b}_n^{(r)} = f\left(a_n^{(r)}\right) \triangleq (13). \tag{16}$$

Different UAVs have different costs to serve different sensor coalitions due to differences in positions and capabilities. The attraction of a coalition's same bid to different

UAVs is distinct. Therefore, the actual bid of coalition is introduced to represent the actual bid attraction to UAVs. The actual bid of coalition $S_k^{(r)}$ for UAV m is defined as the weighted difference between the coalition bid and flight energy consumption, that is

$$\Psi_{m,S_k}^{(r)} = \Phi_{S_k}^{(r)} - w_1 \cdot E_{m,S_k}^{(r)}, \tag{17}$$

where w_1 is the parameter for balancing coalition bid and UAV flight energy consumption. If $\Psi_{m,S_k}^{(r)} < 0$, coalition $S_k^{(r)}$ will lose the bidding qualification towards UAV m in the r^{th} round.

3.2 Vickery-based coalition payment

In auction mechanism, critical pricing is defined to determine the winning coalition's payment [25]. Combined with Vickery auction for ensuring truthfulness, the highest bid coalition wins the UAV service and its critical pricing is the second-highest bid of coalitions.

In the r^{th} round of auction, $I_{m,S_k}^{(r)}$ is defined to indicate whether there is a successful transaction between coalition $S_k^{(r)}$ and UAV m, that is

$$I_{m,S_k}^{(r)} = \begin{cases} 1, & \text{if coalition } S_k^{(r)} \text{ is a winner;} \\ 0, & \text{otherwise.} \end{cases} \tag{18}$$

For sensor coalition $S_k^{(r)}$, the payment charged by the auctioneer is the second-highest actual bid plus the flight energy consumption of UAV m, that is

$$Q_{m,S_k}^{(r)} = \begin{cases} \max\left\{\Psi_{m,S_{-k}}^{(r)}\right\} + w_1 \cdot E_{m,S_k}^{(r)}, & \text{if } I_{m,S_k}^{(r)} = 1; \\ 0, & \text{otherwise,} \end{cases} \tag{19}$$

where S_{-k} represent another sensor coalitions except coalition S_k and $\max\left\{\Psi_{m,S_{-k}}^{(r)}\right\}$ is the second-highest actual bid. Every sensor member in a coalition should equally share the purchase payment of the UAV service. Therefore, $q_n^{(r)}$ is defined as the payment of coalition member sensor n, that is

$$q_n^{(r)} = Q_{m,S_k}^{(r)} / \left|S_k^{(r)}\right|, n \in S_k^{(r)}. \tag{20}$$

The utility of sensor n in the r^{th} round auction is defined as the true valuation minus its payment, that is

$$u_n^{(r)} = \begin{cases} \underbrace{\bar{b}_n^{(r)}}_{\text{true valuation}} - \underbrace{q_n^{(r)}}_{\text{payment}}, & \text{if } I_{m,S_k}^{(r)} = 1, n \in S_k^{(r)}; \\ 0, & \text{otherwise.} \end{cases} \tag{21}$$

After receiving payment $Q_{m,S_k}^{(r)}$ from coalition $S_k^{(r)}$, the auctioneer draws a proportion of κ from the second-highest actual bid as its utility. Hence, the utility of the auctioneer is $\sum\limits_{m\in\mathcal{M}} \sum\limits_{S_k^{(r)}\in\Upsilon^{(r)}} I_{m,S_k}^{(r)} \kappa \max\left\{\Psi_{m,S_{-k}}^{(r)}\right\}$.

Then, the auctioneer gives the remaining payment to UAV m. Hence, the utility of UAV m is $\sum\limits_{S_k^{(r)}\in\Upsilon^{(r)}} I_{m,S_k}^{(r)} (1-\kappa) \max\left\{\Psi_{m,S_{-k}}^{(r)}\right\}$.

3.3 Social welfare maximization problem formulation

We expect our group-buying coalition auction method to improve not only the utility of data collection, but also economic indicators. *Social welfare* is an important performance indicator in auction, which is defined as the sum of winning coalitions' bids, i.e.,

$$\mathbf{SW}^{(r)} = \sum_{m\in\mathcal{M}} \sum_{S_k^{(r)}\in\Upsilon^{(r)}} I_{m,S_k}^{(r)} \max\left\{\Psi_{m,S_{-k}}^{(r)}\right\}. \tag{22}$$

In this paper, the optimization goal is to find an optimal group-buying coalition structure $\Upsilon^{(r)}$ in each round of auction to maximize the social welfare, i.e.,

$$\begin{aligned} &(\mathrm{OP1}): \Upsilon^{(r)} = \arg\max \mathbf{SW}^{(r)}, && (23)\\ &\text{s.t.} \quad t_{c\to m}^{(cost,r)} \le t_{\mathrm{auc}}, && (24)\\ &\qquad \sum_{S_k^{(r)}\in\Upsilon(r)} I_{m,S_k}^{(r)} = \{0,1\}, \forall m \in \mathcal{M}, && (25)\\ &\qquad R_{n,c} \ge R^{(th)}, c = \mathrm{g}\left(S_k^{(r)}\right), \forall n \in S_k^{(r)}. && (26) \end{aligned}$$

Constraint (24) indicates that the total time cost of UAV m must be smaller than the period of each round of auction, which ensures that UAV m can complete data collection service within an effective time. Constraint (25) ensures that one UAV can only be matched with one coalition in one round of auction. Constraint (26) indicates that the achievable communication transmission rate from sensor n to AP c must be higher than the signal to interference plus noise ratio (SINR) demodulation threshold $R^{(th)}$. Obtaining the optimal coalition structure solution by exhaustive search is NP-hard. Thus, we leverage the coalition formation game (CFG) to design a relatively low computational complexity method, which approximates the optimal solution.

4 Design of Group-buying Auction Algorithms

This section proposes a group-buying coalition formation-based auction algorithm (GB-CFA) to solve OP 1 and the algorithm is illustrated in Fig. 8. The proposed GB-CFA algorithm is mainly composed of two sub-algorithms. Firstly, a parallel variable neighborhood ascent search-based coalition formation algorithm is proposed. The sensors make the decision of coalition formation to obtain the coalition structure that maximizes the whole coalition bid. Then, a TRUST auction algorithm is designed to determine the successfully-matched coalition and UAV, and the bid, while maximizing the social welfare on the premise of ensuring truthfulness. After succeeding in a round of auction, the UAV provides data collection service for its matched coalition. After data collection, the AoI of sensors will update and the next round of auction will start. The details are illustrated in **Algorithm 1**.

4.1 Parallel variable neighborhood ascent search-based Coalition formation algorithm

The sensor group-buying coalitions bid for UAV services can be regarded as a typical distributed multi-agent decision

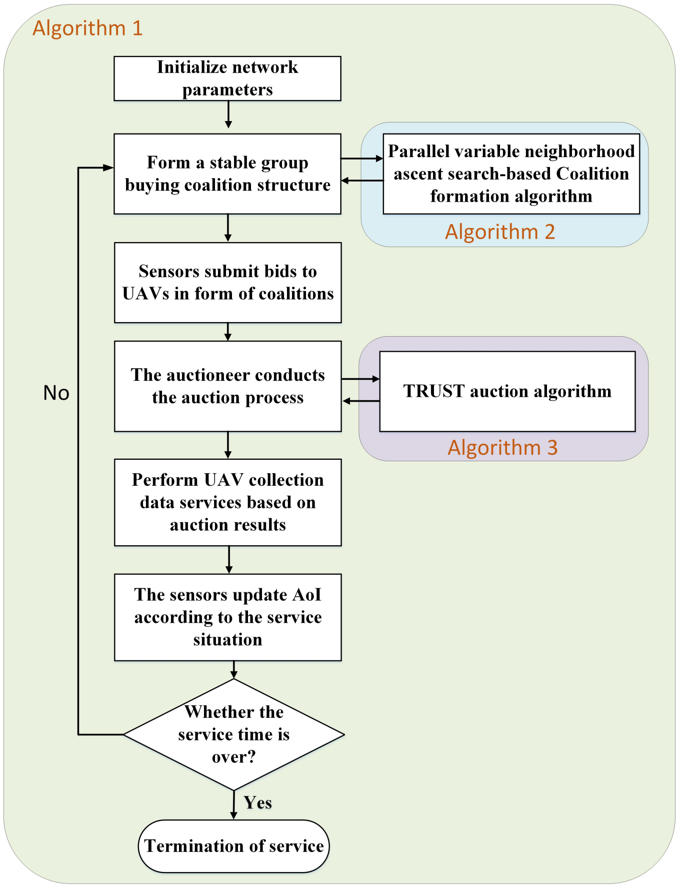

Fig. 8. Illustration of group-buying coalition formation-based auction algorithm determination process.

process, in which sensors make cooperative coalition formation decisions based on their status information. In the coalition formation game, participants continuously optimize the coalition structure according to the preference criteria to improve the utility [36]. To avoid falling into a local optimum coalition structure solution, a parallel variable neighborhood ascent search coalition formation algorithm is proposed to find the optimal solution with relatively low computational complexity. Specifically, the sensors make the operation of coalition structure change to explore possible coalition bids. Then, the sensor performs comparisons and updates to continuously improve the coalition bid based on the collaborative bid preference criteria. Finally, the coalition structure is continuously improved until a stable sensor group-buying coalition structure is obtained. The details are illustrated in **Algorithm 2**.

4.1.1 *Variable neighborhood ascent search*

As shown in Fig. 9, we propose three neighborhood-based coalition operations to change the coalition structure $\Upsilon = \{S_1, \ldots, S_k, \ldots, S_K\}$, including:

1) Joining operation: sensor n join coalition S_j from coalition S_k. $N_1(n)$ is denoted as the neighborhood of current coalition structure solution Υ through sensor n joining operation, that is

$$N_1(n) = \left\{ \tilde{\Upsilon} \left| \Upsilon \backslash \{S_k, S_j\} \cup \left\{ \tilde{S}_k, \tilde{S}_j \right\} \right. \right\}, \tag{27}$$

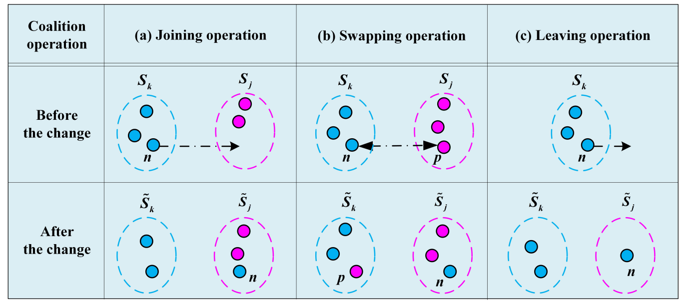

Fig. 9. Three types of coalition operations.

Algorithm 1. Group-buying Coalition Formation-based Auction (GB-CFA)

Input: t_{auc}, $a_n^{(1)}$;
Initialization: $r = 1$, $t = 0$;
while $t \leq T$ **do**
  Compute the optimal coalition structure $\Upsilon^{(r)}$ from **Algorithm 2**;
  Input $\Upsilon^{(r)}$ to **Algorithm 3** for auction results $I_{m,S_k}^{(r)}$ and payment $\max\left\{\Psi_{m,S_{-k}}^{(r)}\right\}$;
  Calculate social welfare $\mathbf{SW}^{(r)}$ by equation (22);
  Update Sensor n's AoI $a_n^{(r+1)}$ by equation (13);
  $t = t + t_{auc}$;
  $r = r + 1$;
end while
Return $\left\{\mathbf{SW}^{(1)}, \ldots, \mathbf{SW}^{(r)}\right\}$;

---

where the original coalitions S_k and S_j are updated as $\tilde{S}_k = S_k \backslash n, \tilde{S}_j = S_j \cup n$.

2) Swapping operation: sensor n in coalition S_k is swapped with sensor p in the coalition S_j. $N_2(n)$ is denoted as the neighborhood of the current coalition structure solution Υ through sensor n swapping operation, that is

$$N_2(n) = \left\{ \tilde{\Upsilon} \left| \Upsilon \backslash \{S_k, S_j\} \cup \left\{ \tilde{S}_k, \tilde{S}_j \right\} \right. \right\}, \tag{28}$$

where the original coalitions S_k and S_j are updated as $\tilde{S}_k = S_k \backslash n \cup p, \tilde{S}_j = S_j \backslash p \cup n$.

3) Leaving operation: sensor n leaves coalition S_k to form a separate coalition. $N_3(n)$ is denoted as the neighborhood of the current coalition structure solution Υ through sensor n leaving operation, that is

$$N_3(n) = \left\{ \tilde{\Upsilon} \left| \Upsilon \backslash \{S_k, S_j\} \cup \left\{ \tilde{S}_k, \tilde{S}_j \right\} \right. \right\}, \tag{29}$$

where the original coalitions S_k and S_j are updated as $\tilde{S}_k = S_k \backslash n, S_j = \emptyset, \tilde{S}_j = \{n\}$.

The search is performed in a variable neighborhood ascent way. If a better coalition structure solution is not found, the algorithm will skip to the next neighborhood to continue the search; Otherwise, the algorithm will go back to the first neighborhood and start the search again. The search neighborhood varies with the coalition operations, preventing the search from falling into a local optimum solution.

Algorithm 2. Parallel Variable Neighborhood Ascent Search-based Coalition Formation

Input: $\mathcal{N}$, T_{max}
Output: $\Upsilon^{(r)}$
Initialization: $\Upsilon^{(r)} = \left\{S_1^{(r)}, \ldots, S_k^{(r)}, \ldots, S_K^{(r)}\right\}$, $K = N$, $S_k^{(r)} = \{k\}$, $T_{stable} = 0$;
loop $\forall n \in \mathcal{N}$
  Broadcast requests to search for a possible coalition structure updates;
  Sensor $n \in S_k^{(r)}$ makes the i-th coalition operation to search the
  optimal coalition structure solution.
    1) Joining operation: Sensor n leaves the current coalition $S_k^{(r)}$ and joins another coalition $S_j^{(r)}$.
    2) Swapping operation: Sensor $n \in S_k^{(r)}$ and $p \in S_j^{(r)}$ swap coalitions;
    3) Leaving operation: Sensor n leaves the current coalition $S_k^{(r)}$ and forms a singleton coalition;
  Calculate the bids $\Phi_{S_k}^{(r)}$ and $\Phi_{S_j}^{(r)}$ according to the original coalition structure $\Upsilon^{(r)}$;
  Calculate the bids $\Phi_{\tilde{S}_k}^{(r)}$ and $\Phi_{\tilde{S}_j}^{(r)}$ according to the changed coalition structure $\tilde{\Upsilon}^{(r)}$;
  Search the optimal coalition structure solution $\tilde{\Upsilon}^{(r)}$ from neighborhood $N_i(n)$;
  if $\tilde{\Upsilon}^{(r)} \succ_n \Upsilon^{(r)}$ **then**
    $\Upsilon^{(r)} = \tilde{\Upsilon}^{(r)}$;
    $T_{stable} = 0$;
    /∗ Move to the first neighborhood operation ∗/
    $i = 1$;
  else
    $T_{stable} = T_{stable} + 1$;
    /∗ Move to the next neighborhood operation ∗/
    $i = i + 1$;
    if $i > 3$ **then**
      $i = 1$;
    end if;
  end if;
end loop if $T_{stable} > T_{max}$, which is, all sensors remain the coalition formation strategies;
Return $\Upsilon^{(r)}$;

4.1.2 Parallel mode updating

For the sensor group-buying coalition game model proposed in this section, we define:

***Definition* 3** (Preference relationship [15])**.** *The symbol $\succ_n$ represents a complete, relaxed, and transitive binary relationship. Given any two coalition structures Υ and $\tilde{\Upsilon}$, for sensor n, $\tilde{\Upsilon} \succ_n \Upsilon$ represents that the coalition structure $\tilde{\Upsilon}$ is preferred by n as compared with the structure Υ.*

In the coalition formation game, the preference criterion is the basis for game participants to choose to leave the original coalition or join a new coalition. The authors in [31] proposed the social welfare criterion of coalition auction, which ensures that the coalition operation can improve the auction revenue of the whole network. However, it is not suitable for large-scale communication network as the information interaction required to calculate the whole network auction revenue is very large. The authors in [15] proposed a selfish coalition criterion, that is, coalition members tend to choose the coalition with a higher revenue. Though the information interaction is greatly reduced under this criterion, focusing on individual utility can weaken the cooperation among coalition members. To address these problems, we formulate the criterion from the perspective of coalition cooperative bid promotion, which is called the cooperative bid preference criterion.

Algorithm 3. Social Welfare Maximization-based TRUST Auction

Input: $\Upsilon^{(r)}$, $\mathcal{M}$;
Output: $I_{m,S_k}^{(r)}, \max\left\{\Phi_{m,S_{-k}}^{(r)}\right\}$;
Initialization: $I_{m,S_k}^{(r)} = 0, \forall m \in \mathcal{M}, S_k^{(r)} \in \Upsilon^{(r)}$
while $\Upsilon^{(r)}$, $\mathcal{M} \neq \emptyset$ **do**
  Calculate $E_{m,S_k}^{(r)}$ based on equation (11);
  Calculate $\Phi_{S_k}^{(r)}$ based on equation (15);
  Calculate $\Psi_{m,S_k}^{(r)} = \Phi_{S_k}^{(r)} - E_{m,S_k}^{(r)}$;
  Calculate $\max \Psi_{m,S_k}^{(r)}$;
  if $\max \Psi_{m,S_k}^{(r)} \geq 0$ **then**
    Determine winning coalition $S_{k^*}^{(r)}$ and UAV
$$m^* = \arg\max_{m,S_k}\left(\Psi_{m,S_k}^{(r)} + w_2 \sum_{n\in S_k^{(r)}} Fair_n(r)\right);$$
    $I_{m^*,S_{k^*}}^{(r)} = 1$;
    Calculate $\max\left\{\Psi_{m,S_{-k}}^{(r)}\right\}$;
    $\Upsilon^{(r)} = \Upsilon^{(r)} \backslash S_k^{(r)}, \mathcal{M} = \mathcal{M} \backslash m$;
  else
    break;
  end if
end while
Return $I_{m,S_k}^{(r)}, \max\left\{\Phi_{m,S_{-k}}^{(r)}\right\}$;

***Definition* 4** (Cooperative bid preference criterion)**.** *For sensor n, the two coalition structures obtained before and after the coalition operation Υ and $\tilde{\Upsilon}$ must satisfy*

$$\tilde{\Upsilon} \succ_n \Upsilon \Leftrightarrow \Phi_{\tilde{S}_k} + \Phi_{\tilde{S}_j} > \Phi_{S_k} + \Phi_{S_j}. \quad (30)$$

This criterion means that each sensor n prefers the coalition operations that can improve the sum of two involved coalition bids.

Remark 1. *Unlike the designs of criterion that directly maximize the social welfare of the whole auction, the advantage of our design is that each operation only needs to calculate the bid change of two coalitions and the communication cost only lies in the currently changing coalitions. Besides, only the sensors that select the same coalition in the neighborhood for coalition operation will affect each other. Therefore, multiple sensors can perform coalition operations in parallel to change multiple coalitions, which further accelerates the convergence process of the coalition structure.*

TABLE 3
Complexity of the Proposed Algorithm

Operations	Complexity
Step 1 of **Algorithm 1**: sensors estimate the information of the channel state	$\mathcal{O}(C_1)$
Step 2 of **Algorithm 1**: sensors compute the coalition bids for comparison	$\mathcal{O}(C_2N)$
Step 3 of **Algorithm 1**: sensors make requests and respond to feedback	$\mathcal{O}(C_3)$
Step 1 of **Algorithm 2**: auctioneer decides the winning coalitions and their payments	$\mathcal{O}(C_4M)$

4.2 TRUST auction algorithm

A TRUST auction algorithm is proposed to maximize the social welfare of the auction results on the premise of ensuring truthfulness, i.e., the sensor's bid can reflect the real value of UAV data transmission service.

The details are illustrated in **Algorithm 3**. Firstly, the actual bid of each coalition is calculated according to equation (17). Secondly, the highest bid coalition and matching UAV are found. On this basis, the second-highest coalition bid is determined and set as the senor coalition payment for UAV service according to the Vickrey auction. Then, the winning sensor coalition and UAV are deleted from the buyer and seller sets, respectively. The above process is repeated until one of the sensor or UAV sets is empty, or the remaining coalition bids are all smaller than 0. Finally, the social welfare maximization is realized and the current round of auction process is over.

4.3 Complexity analyses

The algorithm complexity of coalition group-buying UAV service is mainly determined by **Algorithms 2** and **3**:

1) For **Algorithm 2**, the algorithm complexity of estimating channel status parameters is $\mathcal{O}(C_1)$, where C_1 is a small constant related to channel estimation time [9]. In the worst case, each sensor may try all possible coalition combinations with other sensors that it can communicate with. Thus, the complexity is $\mathcal{O}(C_2N)$, in which C_2 depends on the time spent on utility calculation and coalition comparison based on preference criterion in **Definition 4** . The complexity of coalition structure updating is $\mathcal{O}(C_3)$, where C_3 is a constant that depends on the period of the sensor's request and responds to feedback.
2) For **Algorithm 3**, in the worst case (i.e., the most complex case) each UAV has to execute a transaction in one round of auction. As there is a total of M UAVs, the complexity is $\mathcal{O}(C_4M)$, where C_4 depends on the interaction period of transaction.

Therefore, the total complexity of the algorithm is $\mathcal{O}(C_1)+\mathcal{O}(C_2N)+\mathcal{O}(C_3)+\mathcal{O}(C_4M)$, as shown in Table 3. In practice, due to the limitations of communication distance and delay, more coalition members produce more cooperation costs. So the large-scale coalitions may not be formed. Moreover, once a larger sensor coalition is formed, the possible attempts of each coalition will be reduced due to the reduction of possible operation space. Therefore, the complexity of coalition structure change operation is tolerable.

5 Proof of Auction Economy

Since the TRUST auction combines the coalition formation process with double auction, it is crucial to ensure that it retains economic robustness. In this section, we first introduce two basic definitions related to the economic robustness in double auction, then we prove that the proposed TRUST method satisfies economic robustness.

***Definition* 5** (Individual rationality [31])**.** *if no winning seller obtains the revenue smaller than its cost and no winning buyer pays more than the real value it obtains from the transaction, the double auction is individually rational.*

This definition guarantees the utilities of both the seller and buyer are not smaller than 0, which provides incentives for them to participate in the auction.

***Definition* 6** (Truthfulness [31])**.** *If no buyer can improve its utility by misreporting its bid to the auctioneer, the double auction is truthful or strategy-proof.*

In our proposed method, truthfulness requires that each buyer cannot improve its utility by bidding higher or lower than the true valuation of UAV data collection service.

***Proposition* 1.** *The TRUST auction is individually rational.*

Proof: The utility of honest winning sensor n is $\bar{b}_n - Q_{m,S_k}/|S_k|$ according to equations (20), (16), and (21). Because the Vickery auction mechanism (namely second-highest bid method) is adopted, $Q_{m,S_k} \leq \min_{n\in S_k}\bar{b}_n \cdot |S_k|$. So we can obtain that $\bar{b}_n - Q_{m,S_k}/|S_k| \geq 0$, which ensures that sensor n can obtain a non-negative utility. On the other hand, the winning UAV's utility satisfies $\sum\limits_{S_k\in\Upsilon} I_{m,S_k}(1-\kappa)\max\left\{\Psi_{m,S_{-k}}\right\} \geq 0$. Therefore, the proposed TRUST auction is individually rational.

***Proposition* 2.** *The proposed TRUST auction is truthful. If the bidding strategies of other sensors remain unchanged, a sensor cannot improve its utility through a dishonest bid $b_n \neq \bar{b}_n$, i.e., $u_n(\bar{b}_n) \geq u_n(b_n)$.*

Proof: Consider a sensor n that belongs to coalition S_k, its dishonest bid is unequal to the true valuation of UAV data collection service, i.e., $b_n \neq \bar{b}_n$. Then, all four possible auction results of coalition S_k are listed in Table 4 when sensor n bids honestly and dishonestly. To prove the truthfulness of our proposed TRUST auction, we need to illustrate that no sensor in all four scenarios can improve its utility through a dishonest bid.

For scenario 1: Coalition S_k wins the auction with sensor n's honest bid b_n but loses with a dishonest bid $\bar{b}_n$. Since **Proposition 1** has proved that the utility of a successful auction is non-negative while a failed auction is 0. In this scenario, sensor n has no incentive to submit a dishonest bid that reduces its utility.

For scenario 2: For both sensor n's honest and dishonest bids, coalition S_k wins the auction. Winning the auction implies that whether sensor n bids honestly or dishonestly,

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TABLE 4
Scenarios of Auction Result

Scenarios	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Sensor n in coalition S_k bids honestly	Win	Win	Lose	Lose
Sensor n in coalition S_k bids dishonestly	Lose	Win	Lose	Win

coalition S_k's bid is higher than the second-highest coalition bid. However, the payment of the winning coalition takes the value of the second-highest coalition bid. Hence, the utility of each winning coalition member remains unchanged. In this scenario, sensor n cannot increase its utility by submitting a dishonest bid $b_n \neq \bar{b}_n$.

For scenario 3: For both sensor n's honest and dishonest bids, coalition S_k loses the auction. The utility of sensor n is 0, i.e., $u_n\left(\bar{b}_n\right) = u_n\left(b_n\right) = 0$. In this scenario, sensor n cannot submit a dishonest bid $b_n \neq \bar{b}_n$ to increase its utility.

For scenario 4: Coalition S_k loses the auction with sensor n's honest bid b_n but wins with a dishonest bid $\bar{b}_n$. The premise of failure in the auction is that coalition S_k's bid is not the highest, i.e.,

$$\max\left\{\Psi_{m,S_{-k}}\right\} \geq \bar{\Psi}_{m,S_k} = \min_{n\in S_k} \bar{b}_n \cdot |S_k| - w_1 \cdot E_{m,S_k}. \quad (31)$$

Obviously, sensors can only win the auction if they dishonestly increase bids. The coalition bid is decided by the sensor member with the lowest bid. To win the auction, only the lowest bid sensor n provides a dishonest bid that is higher than its true valuation and satisfies

$$\begin{aligned}&\Phi_{m,S_k} - \min_{n\in S_k} b_n \cdot |S_k| - w_1 \cdot E_{m,S_k} \geq \max\left\{\Psi_{m,S_{-k}}\right\}\\ &\geq \bar{\Phi}_{m,S_k} - \min_{n\in S_k} \bar{b}_n \cdot |S_k| - w_1 \cdot E_{m,S_k},\end{aligned} \quad (32)$$

which means increasing dishonest bid b_n above the current maximum bid. Then, sensor n's utility satisfies

$$\begin{aligned}&u_n\left(b_n\right) = \bar{b}_n - \left(w_1 \cdot E_{m,S_k} + \max\left\{\Psi_{m,S_{-k}}\right\}\right)/|S_k| \leq\\ &\bar{b}_n - \left(w_1 \cdot E_{m,S_k} + \min_{n\in S_k} \bar{b}_n \cdot |S_k| - w_1 \cdot E_{m,S_k}\right)/|S_k| = 0.\end{aligned} \quad (33)$$

According to the principle of individual rationality, the sensor has no incentive to submit a dishonest bid $b_n \neq \bar{b}_n$ that makes its utility smaller than 0 in this scenario.

In conclusion, no sensor can improve its utility through a dishonest bid. Hence, submitting an honest bid is a dominant strategy for each sensor. The proof is thereby completed.

6 Numerical Results and Analyses

In this section, extensive simulations are conducted to evaluate the performance of our proposed group-buying coalition formation-based auction (GB-CFA) method. We start with presenting the auction results. Then, we compare the proposed algorithm against existing methods to verify the effectiveness and superiority of our algorithm. Finally, the truthfulness of the auction is verified. The sensors are randomly distributed in an area of 2×2 km^2 area. All simulation parameters are listed in Table 5.

TABLE 5
Parameter settings

Parameter	Value
Number of sensors, N	20 - 60
Number of UAV, M	1 - 7
Sensor transmit power p_n [3]	100 mW
AP transmit power p_c [3]	5 W
Flight altitude H [34]	100 - 150 m
Maximum speed of UAV v_m [34]	12 - 24 m/s
One-sided power spectral density of white Gaussian noise N_0 [33]	-120 dBm
Bandwidth B_n, B_c [33]	1 MHz, 5 MHz
Path loss exponent for sensor-AP link α_1 [33]	3
Path loss exponent for AP-UAV link α_2 [33]	2
Excessive attenuation factor for NLoS η [33]	20 dB
Environment parameters ζ_l, ϑ_l [33]	0.136, 11.95

TABLE 6
AoI Model Parameter

Parameter	S_1-S_5	S_6-S_{10}	S_{11}-S_{15}	S_{16}-S_{20}
AoI tolerated threshold ς_n (s)	15	15	25,15,15 15, 15	15
AoI sensitivity δ_n	0.7	0.7	0.9	0.5
Initial AoI $a_n^{(0)}$ (s)	10-15	20-30	10-15	5

6.1 Auction results and analyses

To illustrate the impacts of the sensor parameters, including sensor AoI tolerance threshold, AoI sensitivity, and amount of information, the values of the relevant sensor parameters are designed and presented in Table 6. It is designed so that the initial ages of the sensor S_{16}-S_{20} are relatively lower than AoI sensitivity; S_{11}-S_{15} are relatively higher than AoI sensitivity; the AoI tolerance threshold of S_{11} is larger than those of other sensors.

Fig. 10 presents the three dimentional formation and distribution of the group-buying coalition. The arrow points to the corresponding AP of the winning coalition in the current round, to which the UAV flies from the current position. The following can be observed:

1) The winning coalition will be served by the UAV and the AoI of sensors in the winning coalition decreases after the data collection service. As a contrast, sensors in a losing coalition will experience a substantially increasing AoI. For example, it can be seen that $\{S_{12}, S_{13}, \cdots, S_{15}\}$ as a coalition wins the first-round auction. UAV 1 flies to their data aggregation AP 3 to provide data collection service (as

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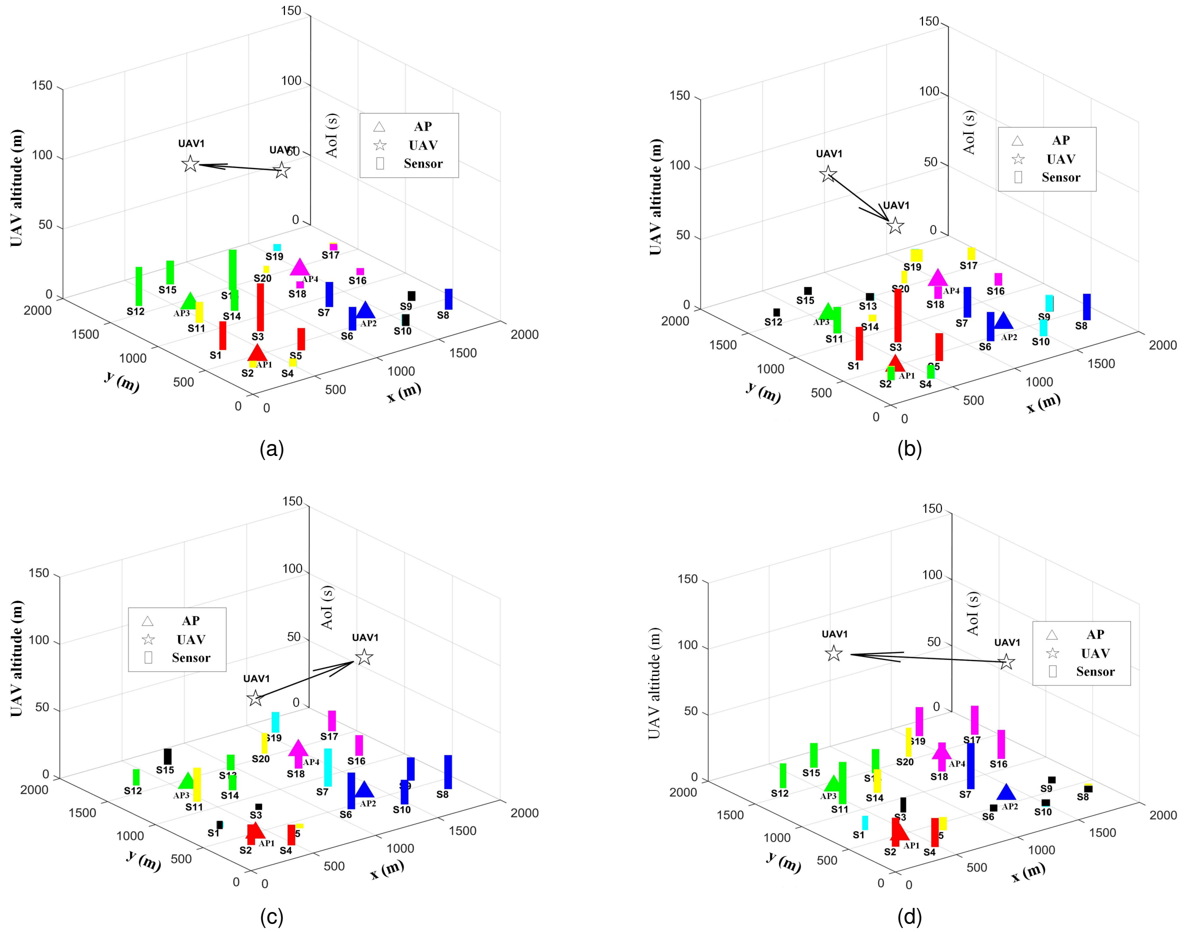

Fig. 10. UAV auction results. (a) Results of the first round of auction. (b) Results of the second round of auction. (c) Results of the third round of auction. (d) Results of the fourth round of auction. The triangles represent the APs, the rectangles represent the sensors, and the height of rectangles represent the AoI value of the sensors. Besides, the sensors with the same color are in the same group-buying coalition, and the APs with the same color are selected by this coalition as the status information aggregation point. The number of UAVs is set as $M = 1$.

can be seen in Fig. 10 (a)). Correspondingly, the AoIs of S_{12}-S_{15} all decrease to close 0, while other sensors' AoIs increase (as can be seen by comparing the heights of rectangle in Figs. 10 (a) and (b)).

2) Sensors are less willing to group with those of which the AoI tolerance thresholds are high. For example, S_{11} does not join a nearby group-buying coalition in Fig. 10 (a). As can be seen in Table 5, S_{11} has a higher AoI tolerance threshold than its nearby sensors. Hence, S_{11}'s bid is low and not attractive enough for UAV's information update service (as can be seen from equation (15)). Hence, nearby sensors $\{S_{12}, S_{13}, \cdots, S_{15}\}$ form a coalition without it.

Fig. 11 presents the UAV traveling process among different APs in 6 auction rounds. We observe that a higher AoI sensitivity of sensor results in a higher bid (as can be seen from equation (14)), which further leads to a stronger auction competitiveness (equivalently, a higher coalition bid in equation (14)). As an example, we compare AP 3 and AP 4, and observe that, during 6 rounds of auction, the UAV first flies to AP 3 and later re-visits AP 3, whereas AP 4 is served later and only once. In other words, the UAV frequently flies to AP 3 and serves the coalition formed by its nearby sensors $\{S_{11}, S_{12}, \cdots, S_{15}\}$, compared to AP 4 and its nearby sensors $\{S_{16}, S_{17}, \cdots, S_{20}\}$. The reasons are analyzed as below. As can be seen in Table 6, sensors $\{S_{11}, S_{12}, \cdots, S_{15}\}$ close to AP 3 have relatively higher AoI sensitivity ($\delta_n = 0.9$) and hence a larger bid. Sensors $\{S_{16}, S_{17}, \cdots, S_{20}\}$ close to AP 4 have relatively lower AoI sensitivity ($\delta_n = 0.5$) than other sensors.

6.2 Performance comparison

To illustrate the advantages of the proposed GB-CFA method, comparisons with the following three methods are carried out:

1) Joint trajectory design and task scheduling (TDTS) UAV-to-community algorithm [6]: users automatically form communities based on geographical location and the UAV compares throughput and flight delay to determine the flight sequence and the update of sensors.
2) Coalition formation game (CFG) algorithm [9]: the sensors use a merge-split framework to form coalitions. After that, the UAV receives the data upload request of the ground sensor coalitions and given with priority to serve the nearest sensor coalition.
3) Maximum throughput first (MTF) [37]: the UAV aims to maximize system throughput by collecting as much sensor data information as possible.

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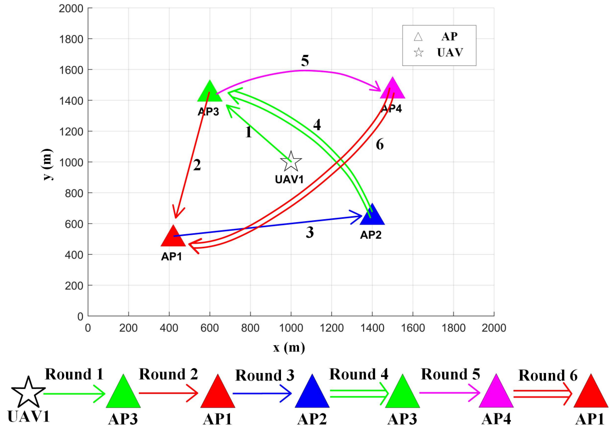

Fig. 11. UAV traveling process among different APs. The number of UAVs $M = 1$.

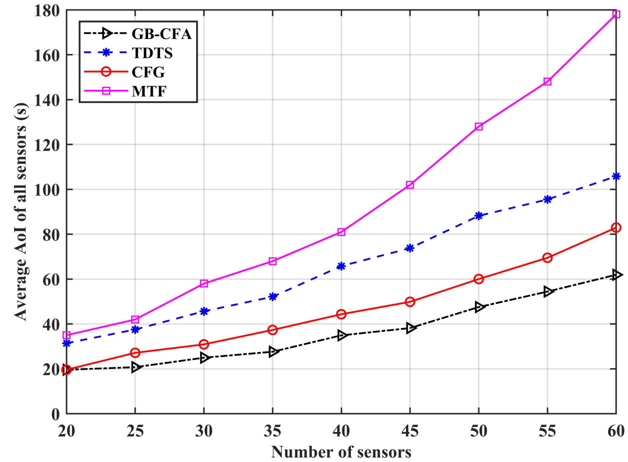

Fig. 12. Average AoI versus the number of sensors. The number of UAVs $M = 3$.

In the following, we present the performance in terms of three indicators: the average AoI of all sensors, the total amount of data collected by all UAVs (referred to as "total amount of collected data" for short), and the social welfare of auction. Without loss of generality, all AoI model parameters are randomly generated within reasonable limits. All simulations results are obtained by averaging over 1000 independent trials.

6.2.1 *Impact of the sensor number*

Fig. 12 shows the curve of the average AoI for all sensors versus the number of sensors. It can be observed that: 1) The average AoI of the sensor increases with the number of sensors. This is because as the demand for UAV data collection increases, sensors status updates become more difficult due to the intense competition for UAV services. 2) Our UAV service scheduling is more advantageous, which can effectively reduce the average AoI of all sensors, especially in the case of high-density sensor deployment. Compared with CFG, TDTS, and MTF methods, our proposed GB-CFA method decreases the average AoI of all sensors by 16.7%, 44.5%, and 65.3%, respectively. This benefits from the fact that: our proposed joint coalition-auction framework can achieve ground-air collaborative optimization. On the one hand, ground sensors can continuously optimize the group-buying coalition structure based on their own conditions. On the other hand, UAVs can determine their service based on the trade-off between coalition bid and cost.

Fig. 13 presents the curves of total amount of collected data versus the number of sensors. The following observations can be obtained. 1) With the increase in the number of sensors, the total amount of collected data of the system increases. When the number of sensors increases to a certain value, the total amount of collected data stops increasing due to communication constraints. 2) Our proposed GB-CFA method increases the total amount of collected data by 14% compared with the TDTS method. The reason is that our method encourages more members to form a better bidding group-buying coalition. In addition, the MTF method only focuses on maximizing the total amount of collected data and increases by 13.3% than that of our scheme.

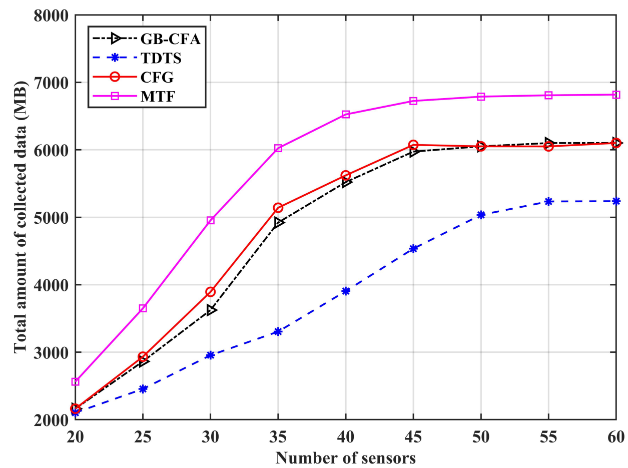

Fig. 13. The total amount of collected data versus the number of sensors. The number of UAVs $M = 3$.

6.2.2 *Impact of the UAV number*

Fig. 14 shows the curves of the average AoI of all sensors versus the number of UAVs. Compared with CFG, TDTS, and MTF methods, our proposed GB-CFA method can decrease the average AoI of all sensors by 24.1%, 40.3%, and 66.7%, respectively. Besides, it can be seen that the average AoI of the sensor decreases with the number of UAVs. The reason is that the increase in the number of UAVs leads to a reduced bid threshold of a successful auction. Hence, more sensors can obtain the UAV service for status information updates.

6.2.3 *Impact of UAV speed on performance*

Fig. 15 presents the curves of average AoI with UAV flying speed. The average AoI of the sensor decreases with the flight speed of UAVs. The reason is that UAVs with higher speeds have higher mobility so that they can better schedule their flight trajectories and update the status of sensors in a more timely fashion. Besides, compared with CFG, TDTS, and MTF methods, our proposed GB-CFA method can decrease the average AoI of all sensors by 17.5%, 32.2%, and 57.5%, respectively.

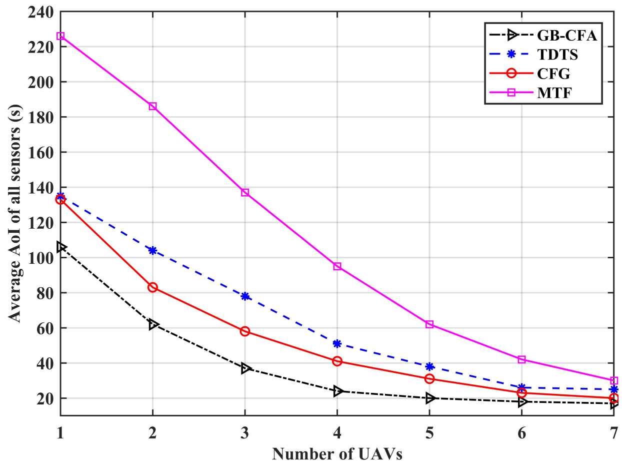

Fig. 14. Average AoI versus the number of UAVs. The number of sensors $N = 40$.

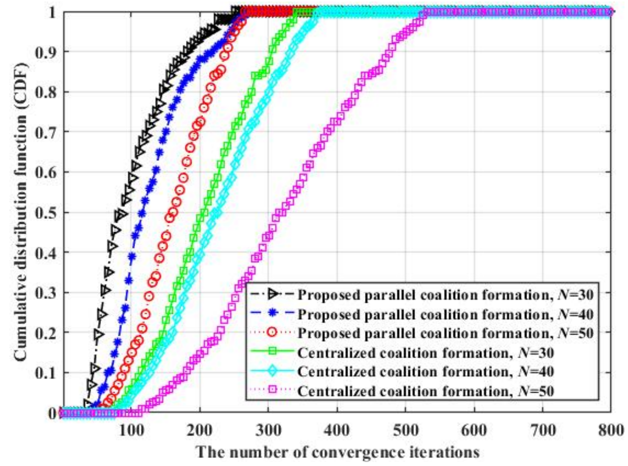

Fig. 16. Convergence performance of the proposed GB-CFA algorithm with various sensors.

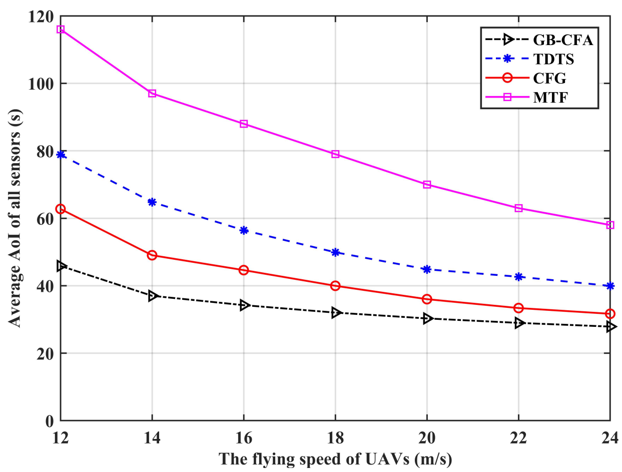

Fig. 15. Average AoI versus the UAV speed. The number of UAVs $M = 3$.

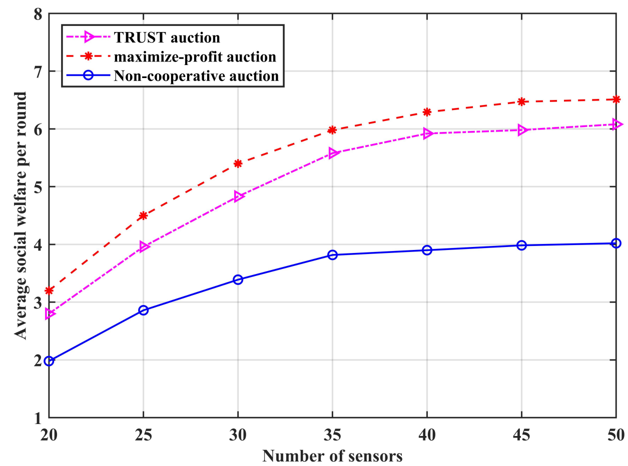

Fig. 17. Average social welfare versus the number of sensors

6.2.4 Convergence performance

We compare the convergence performance of the proposed coalition formation algorithm when varying the number of sensors. Fig. 16 depicts the cumulative distribution function of the convergence iterations, which are obtained by 1000 independent trials in each network scale. It can be observed that the largest convergence iterations of the proposed parallel coalition formation do not exceed 250 with 50 sensors in the WSN. As the number of sensors increase from 30 to 50, the average convergence iterations of the proposed parallel coalition formation algorithm increase from 100 to 175, and the centralized coalition formation algorithm increase from 200 to 350. By comparison, the increased convergence iterations of our proposed parallel coalition formation algorithm is still within an acceptable range. It shows the effectiveness of the proposed parallel coalition formation algorithm in terms of convergence speed.

6.3 Auction truthfulness verification

Fig. 17 presents the curves of average social welfare versus the number of sensors. We have the following observations. 1) The average social welfare from auction transactions increases with the number of sensors. The proposed group-buying coalition formation based TRUST auction can increase the social welfare 145% than non-cooperative auction. The reason is that a bidding improvement group-buying coalition structure is formed as members make decisions of joining the coalition under the proposed preference criterion. 2) However, the increase in social welfare slows down as the coalition scale and the auction bid of each group-buying coalition are limited due to coordination delay and cost. 3) Compared with the optimal result of the maximize-profit auction, the social welfare of our TRUST auction slightly decreases by 8.3% due to our coalition bid setting. But, our proposed TRUST auction can guarantee the truthfulness of the sensor's bid. We prove the truthfulness of the proposed TRUST auction by setting up sensors that bid dishonestly. The following 3 cases are considered.

Case 1: Sensor 4 is set to be a dishonest node and reports a bid that is smaller than its true valuation for UAV services. Assuming that the auction transaction is still successful in this case. As can be seen from Fig. 18, dishonest bids will have no effect on the utilities of other coalition sensor members under our proposed TRUST auction. As a comparison, under the maximize-profit auction, sensor

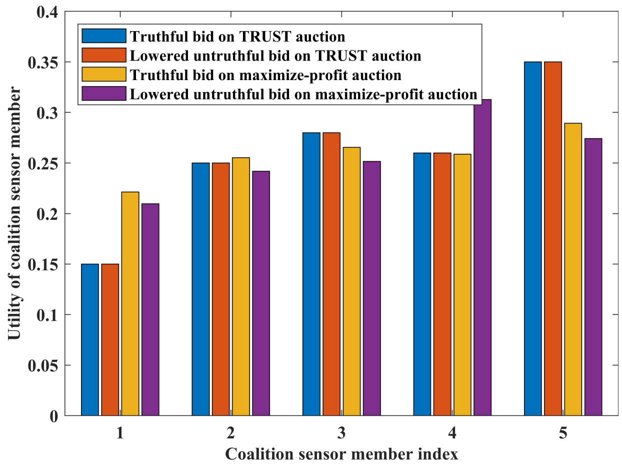

Fig. 18. Utility of the winning sensors under different auction modes (the bid smaller than the actual bid wins).

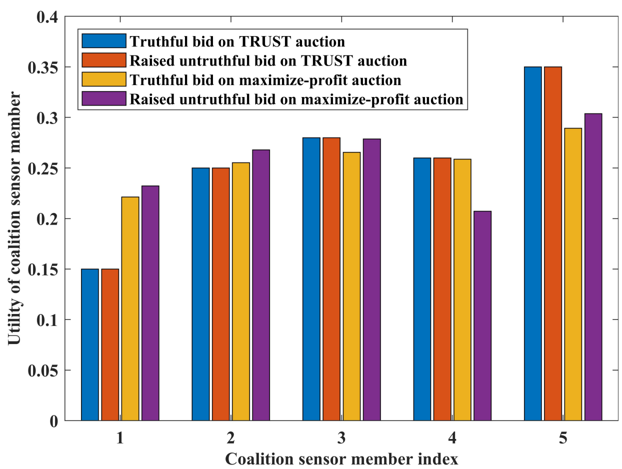

Fig. 19. Utilities of the winning member under different auction modes (the bid higher than the actual bid wins).

4 increases its own utility by the dishonest bid while the utility of other coalition sensor members is reduced.

Case 2: Sensor 4 reports a dishonest bid that is higher than its true valuation for UAV services. Assuming that the auction transaction is still successful in this case. As can be seen from Fig. 19, dishonest bidding has no effect on the utilities of other coalition sensor members under our proposed TRUST auction. As a comparison, the utility of sensor 4 is reduced under the maximize-profit auction.

Case 3: Sensor 4 is set to be a dishonest node and reports a bid that is smaller than its true valuation for UAV services. Assuming that the coalition loses the auction due to the dishonest bid. As can be seen from Fig. 20, the utility of all sensor members will be 0 if the auction is lost. It shows clearly that a dishonest bid will reduce the utilities of the sensors. In this case, each sensor has no incentive to report a dishonest bid.

Based on the above analyses, we conclude that the proposed TRUST method can ensure the truthfulness of the auction. In the proposed TRUST auction, the sensors cannot improve their own utilities by dishonest bidding. However, the sensors can increase their own utilities while harming

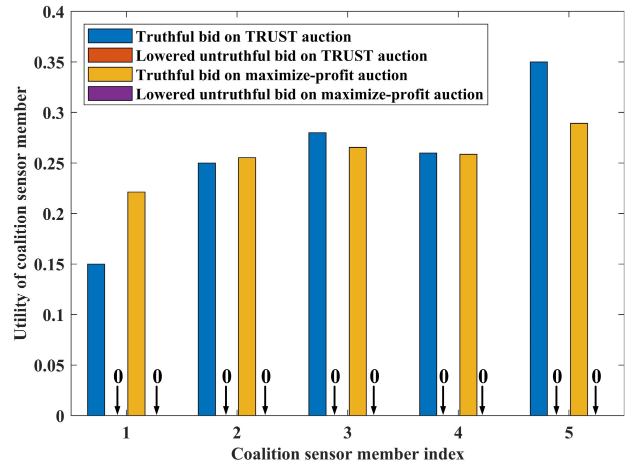

Fig. 20. Utilities of the winning sensors under different auction modes (Sensors whose bids are lower than the actual bid will lose the bid).

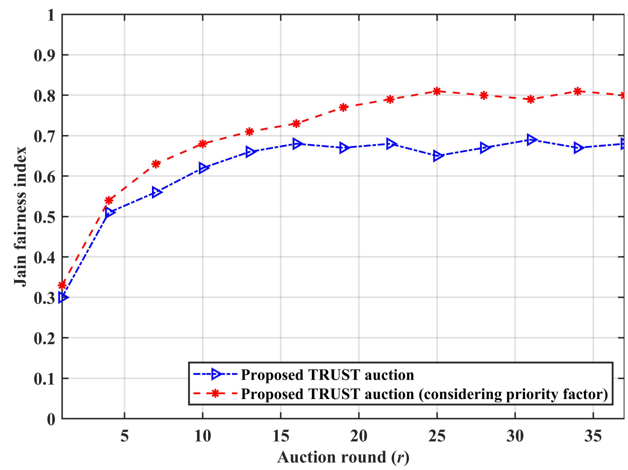

Fig. 21. The Jain fairness index versus the round of auction.

the utilities of other coalition members by dishonestly reporting their bids in the maximize-profit auction.

6.4 Auction fairness verification

The sensors can no longer decide whether they win the auction by raising their bids to satisfy their urgent data collection requests due to the lowest bid coalition rule. Hence, it is not fair for the sensors with urgent needs. Motivated by [38] and [39], a priority-based fair mechanism is designed to guarantee the fairness attribute. Each sensor is given a priority factor based on its bid and auction results in each auction round. In our auction, sensor n's priority factor in r^{th} round is designed as

$$pr_n\left(r+1\right)=\begin{cases}0, & \text{if coalition } S_k^{(r)} \text{wins the auction;}\\ b_n^{(r)}-\min\limits_{n\in S_k^{(r)}} b_n^{(r)} \\ +\gamma pr_n\left(r\right), & \text{if coalition } S_k^{(r)} \text{loses the auction.}\end{cases} \tag{34}$$

where $b_n^{(r)}-\min\limits_{n\in S_k^{(r)}} b_n^{(r)}$ is the amount by which the sensor is dragged down by the lowest bid in the coalition; γ is

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the discount factor and is set at less 1. If the buyers have higher bids but failed in previous rounds, they are given a better chance of winning in the next round. In addition, once the sensor wins the auction, its priority factor is reset to be 0. This design is to prevent malicious sensors from deliberately raising bids to preempt resources in consecutive rounds of auctions. The auctioneer needs to consider the coalition bid and the priority factor to determine the winner comprehensively.

The Jain fairness index is used to measure the fairness of the auction [40], and its expression is

$$Fair_n(r) = \frac{\left(\sum\limits_{n\in\mathcal{N}} \Gamma_n(r)\right)^2}{N \sum\limits_{n\in\mathcal{N}} \left(\Gamma_n(r)\right)^2}, \tag{35}$$

where Γ_n is the average utility of sensor n in auction rounds, i.e.,

$$\Gamma_n(r) = \frac{\sum\limits_{i=1}^{r} u_n^{(i)}}{r}. \tag{36}$$

Fig. 21 presents the curves of the Jain fairness index versus the round of auction. After many rounds of auctions, it can be seen that the Jain fairness index of auctions with the priority-based fair mechanism is increased by 12.4% than those without it.

7 Conclusion

This paper studies the group-buying coalition formation-based method for UAV-enabled data collection in WSNs. To improve the efficiency of data collection by UAVs and the competitiveness of sensors' bids, sensors form multiple group-buying coalitions to bid for UAV data collection services. Then, the coalition formation game is leveraged to design a bid maximization-based problem, which is solved by our proposed parallel variable neighborhood ascent search algorithm. To ensure truthfulness and individual rationality, a sTrategy-proof VickeRy groUp-buying Sensor coaliTion (TRUST) auction is designed. Numerical results show that the sensors' average age of information (AoI) under the proposed method is reduced by 16.7% and 44.5% compared with the coalition formation game (CFG) and joint trajectory design task scheduling (TDTS) UAV-to-community methods. Besides, the social welfare of the proposed TRUST auction increases by 41.3% compared with the non-cooperative auction schemes.

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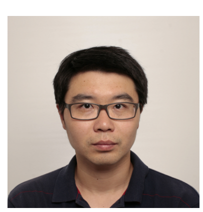

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