Unity makes strength: Coalition Formation-based Group-buying for Timely UAV Data Collection

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***Abstract*—With their high mobility, unmanned aerial vehicles (UAVs) become appealing data collectors in hard-to-reach wide-area distributed sensor networks. Different from existing works focusing on the perspective of UAVs for service order optimization and UAV utility maximization, we consider the utilities of both sensors and UAVs, and innovatively model the competition among sensors (buyers) for the service of UAVs (sellers) as an auction game. A "unity makes strength" strategy is exploited. That is, to strengthen the bidding competitiveness, a group-buying coalition auction method that encourages sensors to form coalitions to bid for UAV service is proposed. Besides, we propose a parallel variable neighborhood ascent search algorithm, we can quickly determine the approximately optimal group-buying coalition structure. Numerical results show that the proposed method outperforms the joint trajectory design-task scheduling (TDTS) UAV-to-community method and the single coalition formation game (CFG) method.**

***Index Terms*—Unmanned aerial vehicles (UAVs), age of information (AoI), auction mechanism, coalition formation game.**

I. Introduction

Wireless sensor networks (WSNs) have been applied widely in many fields, such as disease monitoring, environmental monitoring and event detection [1]. In WSNs, sensors typically transmit status messages (e.g., perceived environmental parameters) to static ground access points in a multi-hop manner. However, due to the limited transmission power and small wireless communication coverage of sensors, the quality and delay of long-distance communication cannot be guaranteed. In this case, UAVs have great potential as aerial APs in wireless sensor networks, owing to their high mobility and distributed deployment [2]. In addition, most of the existing UAV-assisted data acquisition schemes focus on optimizing the energy consumption of data transmission [3]. However, timely collected status information is crucial for a time-sensitive sensor network, while stale status information may yield incorrect decisions, which is ignored in [4]. Therefore, the notion of the age of information (AoI) has been recently proposed to quantify the freshness of information [1].

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For UAV-enabled large-scale WSNs, sensors can effectively improve the uploading efficiency by forming coalitions to aggregate transmission data [5]. The UAV-enabled data collection in WSNs can be regarded as a typical distributed multi-agent decision process, in which participants make decisions through information interaction and decide their behaviors rationally (i.e., by evaluating the potential utility). Coincidentally, the coalition formation game (CFG) is a classic cooperative game that encourages independent participants to cooperate as an entity [6]. However, most existing coalition formation algorithms are not suitable for large-scale sensor networks as they aim to optimize the service order of UAVs for different sensors and unilaterally pursue for UAV utility maximization from the perspective of UAVs [5], which requires a large amount of information interactions and cannot be implemented in a timely manner.

Driven by the economic property that marketing transactions are dominated by demand-and-supply and competition, it is necessary to take bilateral (namely both buyers and sellers') utilities into account, on which basis the most competitive users have the highest priority of occupying/utilizing the on-demand market resources. In this way, the best buyer-and-seller match is expected to be achieved. An individual unilateral auction game was used in [7] to improve the dynamic data collection of UAVs, but the information asymmetry between buyers and sellers in the individual unilateral auction was a hinder to the auction fairness. To deal with the consumer market preference in an auction, Lu *et al* proposed an iterative auction mechanism to coordinate auction transactions, but group-buying-based bidding strategy was not considered [8]. Applying the auction mechanism in the form of group purchase to resource allocation can ensure the fairness, efficiency, and utilization of resource allocation when participants are rational and competitive [7], [8].

Motivated by the above-mentioned challenges and to promote UAVs to provide timely data collection service in WSNs, this paper first proposes a group-buying coalition auction method that encourages sensors to form coalitions to raise their bids for UAV service. To reflect the time value of status

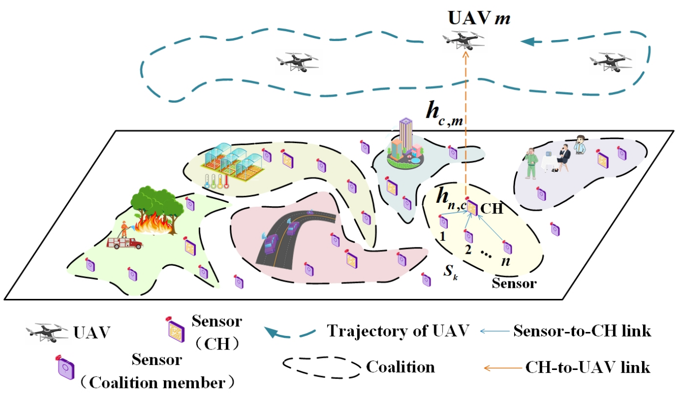

Fig. 1. Multi-UAV system model for WSN data collection

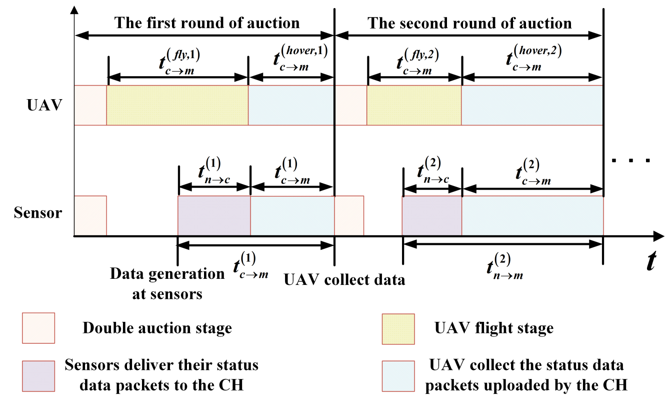

Fig. 2. Auction phase slots.

information, the sensor bidding is designed as the weighted difference of sensor AoI and energy loss [1]. Second, to strengthen the bidding competitiveness, this paper constructs a joint auction-coalition formation game for the group-buying coalition formation. Third, to obtain the optimal group-buying coalition structure, a parallel variable neighborhood ascent search coalition formation algorithm is designed. Finally, the efficiency of the proposed method is demonstrated.

II. System Model

A. Scenario Description

We consider UAV-enabled status data collection applications in WSNs, where UAVs assisted data collection status data packets from sensor cluster head (CH). As shown in Fig. 1, there are N geographically distributed ground sensors, represented by a set $\mathcal{N} = \{1, ..., n, ..., N\}$. Suppose there are M UAVs that can collect status information from sensors, and the UAV index set is denoted as $\mathcal{M} = \{1, ..., m, ..., M\}$.

To encourage UAVs to participate in the collection of sensor status data, an auction mechanism is leveraged for modeling the transaction process between UAVs and sensors. The participants in the auction process include UAVs (sellers) and sensors (buyers). As the bid of a single sensor may not be attractive enough to UAVs, sensors form multiple coalitions to buy the data collection service of UAVs in the form of group buying. For large-scale WSNs, it may not be possible to plan data collection trajectories of UAVs based on locations and status of all sensors. As presented in Fig. 1, in the first layer, the sensor coalition members transmit the status data packets to the sensor CH; in the second layer, the UAV flies just above the CH and collects the aggregated status data packets from it. In the auction process, all information does not need to be known by the UAVs, but only the group-buying coalition's bid to determine the data collection trajectory so as to reduce unnecessary information interaction.

A continuous dynamic multi-round auction is proposed that UAVs successively serve different coalitions according to the auction results. The coalition structure is defined as a partitioned area that contains all sensors, i.e.,

$$\Omega^{(r)} = \left\{S_1^{(r)}, ..., S_k^{(r)}, ..., S_K^{(r)}\right\}, \quad \bigcup_{k=1}^{K} S_k^{(r)} = \mathcal{N}, \tag{1}$$

where S_k is a sensor coalition, r is the index of auction round, and k represents the coalition index. Note that one sensor can only join one coalition, $S_k^{(r)} \cap S_{k'}^{(r)} = \emptyset, \forall k \neq k'$. If the remaining energy of each UAV is sufficient, it can participate in the next round of auction after completing the previous round. Sensors that failed in the previous round of auction can also adjust their bids according to the changes of their own status and participate in the next round of auction. Each round of auction can be divided into three stages: 1) Group-buying coalition formation stage: ground sensors form multiple group-buying coalitions to improve the market competitiveness of their auction bids; 2) Auction stage: coalitions report the bids and relevant requirements for updating status packets to UAVs, and the UAVs decide the winning sensor coalition according to the corresponding benefit and cost; 3) Data collection stage: after the sensor coalition successfully purchases UAVs' service during the auction, the sensors deliver their status data packets to the CH, and then a UAV flies just above the CH to collect the status data packets uploaded by the CH.

B. Communication Model

1) Sensor to CH communication: The communication between sensors is assumed to be non-line-of-sight (NLoS) connections [9]. Let $h_{n,c}$ represent the channel gain between sensor n and CH c, that is,

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

where α_1 is the path loss exponent over the sensor-sensor link, and $d_{n,c}$ is the distance between n and c. Therefore, the achievable communication transmission rate from n to c is

$$R_{n,c} = B_n \log_2\left(1 + \frac{|h_{n,c}|^2 p_n}{N_0 B_n}\right), \tag{3}$$

where B_n is the channel bandwidth used by sensor n, p_n is the transmitting power, and N_0 is the one-sided power spectral density of white Gaussian noise. Hence, the expected communication time from sensor n to CH c is

$$t^{(r)}_{n\to c} = \mathbb{E}\left\{\varepsilon^{(r)}_n / R_{n,c}\right\}, \tag{4}$$

where $\mathbb{E}\{\cdot\}$ is the expectation operator and $\varepsilon^{(r)}_n$ is the amount of status packets (bits) generated by sensor n in the r-th round of auction.

2) CH to UAV communication: After collecting the status information packets of all coalition sensor members, CH c transmits the aggregated data packets to UAV m. The channel between UAV and sensor is modeled as probabilistic lineof-sight (LoS) and non-line-of-sight (NLoS) links [9]. The probability calculation formula of the LoS channel is

$$\Pr_{c,m}(\mathrm{LOS}) = \frac{1}{1+\vartheta_l \exp\left(-\eta_l\left[\theta_{c,m}-\vartheta_l\right]\right)}, \tag{5}$$

where η_l and ϑ_l are constant values that depend on environment (rural areas, compact cities or others), and $\theta_{c,m}$ is the elevation. Besides, $\Pr_{c,m}(\mathrm{NLOS}) = 1 - \Pr_{c,m}(\mathrm{LOS})$. The channel gain between c and m is denoted by $h_{c,m}$, that is,

$$|h_{c,m}|^2 = \begin{cases} (d_{c,m})^{-\alpha}, & \mathrm{LoS} \\ \mu (d_{c,m})^{-\alpha}, & \mathrm{NLoS} \end{cases} \tag{6}$$

where μ is the additional loss coefficient due to the NLoS connection, $\alpha \geq 2$ is the path loss exponent over the sensor-UAV link, and $d_{c,m}$ is the distance between CH c and UAV m. We assume that if the auction is successful, the UAV will fly to the position just above the CH to communicate with it. Thus, $d_{c,m}=H$, where H is the fixed flight altitude of the UAV. The achievable communication transmission rate between c and m is

$$R_{c,m} = B_c \log_2\left(1 + \frac{|h_{c,m}|^2 p_c}{N_0 B_c}\right), \tag{7}$$

where B_c is the channel bandwidth used by CH c, and p_c is the transmitting power. The expected transmission time from CH c to UAV m is defined as $t^{(r)}_{c\to m}$, of which the expression is the total amount of information required to be transmitted divided by the communication capacity, that is,

$$t^{(r)}_{c\to m} = \sum_{n\in S_k^{(r)}} \mathbb{E}\left\{\varepsilon^{(r)}_n / R_{c,m}\right\}. \tag{8}$$

C. Energy consumption model

Since the propulsion power of a UAV is dominant as compared with its communication power [10], the propulsion loss of the UAV is mainly considered. Then, $E^{(r)}_{m,S_k}$ 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 flight and hover states, that is,

$$E^{(r)}_{m,S_k} = P(v_m) t^{(fly,r)}_{c\to m} + P(0) t^{(hover,r)}_{c\to m}, \tag{9}$$

where v_m is the flight speed of UAV m, $P(v_m)$ is the flight propulsion power, and $P(0)$ the hover propulsion power; $t^{(fly,r)}_{c\to m} = \tilde{d}^{(r)}_{c,m}/v_m$ is the time of UAV m flying to sensor c, $\tilde{d}_{c,m}$ is the horizontal distance between c and m, and $t^{(hover,r)}_{c\to m}$ 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., $t^{(hover,r)}_{c\to m} = t^{(r)}_{c\to m}$. Thus, the time spent by the UAV in the rth round of auction is the sum of the flight time and hovering time, i.e.,

$$t^{(cost,r)}_{c\to m} = t^{(fly,r)}_{c\to m} + t^{(hover,r)}_{c\to m}. \tag{10}$$

D. AoI model

Age of information (AoI) is introduced to quantify the freshness of information, which is defined as the time elapsed since the latest valid status packet is received at the collection node. The period of each round of auction is defined as t_{auc}. For sensor n, its AoI before the r-th round of auction is defined as $a_n^{(r)}$ and updated as below.

$$a_n^{(r+1)} = \begin{cases} t^{(r)}_{n\to m}, & \text{update}; \\ a_n^{(r)} + t_{auc}, & \text{otherwise}. \end{cases} \tag{11}$$

This formula indicates that when UAV m collects data packets from sensor n, its AoI changes as the period from the generation of status packets at sensor n to the arrival at UAV m, i.e., $t^{(r)}_{n\to m} = t^{(r)}_{n\to c} + t^{(r)}_{c\to m}$. 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,

$$f\left(a_n^{(r)}\right) = \frac{1}{1+\exp\left(-\lambda_n\left(a_n^{(r)} - t^{(r)}_{n\to m} - \varsigma_n\right)\right)}, \tag{12}$$

where λ_n and ς_n are sensitivity and tolerance thresholds 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 λ_n implies a lower sensitivity to the change of information freshness.

III. Problem Formulation

A. Auction Design

Under a given coalition structure $\Pi^{(r)} = \left\{S_1^{(r)},\ldots,S_k^{(r)},\ldots,S_K^{(r)}\right\}$, sensors form a coalition and bid according to their own AoI status to the UAV data transmission service. For each coalition $S_k^{(r)}$, in the r-th round of auction, the bid of the coalition as a whole is defined as the lowest bid among the coalition members being multiplied by the number of coalition members, i.e.,

$$\beta^{(r)}_{S_k} = \min_{n\in S_k^{(r)}} b_n^{(r)} \cdot \left|S_k^{(r)}\right|, \tag{13}$$

where symbol $|\cdot|$ means the cardinality of a set, and $\min\limits_{n\in S_k^{(r)}} b_n^{(r)}$ refers to the lowest bid among the coalition members. The design idea of (13) is similar to [11], where the coalition bid is independent of the winning sensors to ensure the truthful bidding of sensors. For sensor n, the strategy for each round of bidding is defined as $b_n^{(r)}$. Specially, $b_n^{(r)}$ is the truthful bidding strategy, which is the true valuation that the sensor thinks it can bring to itself, i.e.,

$$b_n^{(r)} = f\left(a_n^{(r)}\right). \tag{14}$$

In truthful auctions, UAVs organize the auction process and rational sensors can maintain a honest bidding strategy, i.e., $b_n^{(r)} = b_n^{(r)}$. Costs of different UAVs for serving different sensor coalitions vary with positions and capabilities. The attraction of a coalition's same bid to different UAVs is distinct. Therefore, the actual bid of a 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 the flight energy consumption, that is,

$${}^{(r)}_{m,S_k} = {}^{(r)}_{S_k} - w_1 E^{(r)}_{m,S_k}, \tag{15}$$

where w_1 is the parameter for balancing value. To determine the price to be paid by the final winning coalition, every winning coalition should have its critical payment. According to the Vickery auction mechanism, the sensor coalition with the highest real bid successfully obtains the UAV service, and its critical payment is the second-highest real bid among sensor coalitions. In the rth round of auction, $I^{(r)}_{m,S_k}$ is defined to indicate whether there is a successful transaction between coalition $S_k^{(r)}$ and UAV m, of which the expression is

$$I^{(r)}_{m,S_k} = \begin{cases} 1, & \text{if coalition } S_k^{(r)} \text{ is a winner}, \\ 0, & \text{otherwise}. \end{cases} \tag{16}$$

For the sensor coalition $S_k^{(r)}$, the payment charged by the auctioneer is the second-highest real bid among sensor coalitions and the energy loss of UAV, i.e.,

$$Q^{(r)}_{m,S_k} = \begin{cases} E^{(r)}_{m,S_k} + \max\left\{ {}^{(r)}_{m,S_{-k}} \right\}, & \text{if } I^{(r)}_{m,S_k} = 1, \\ 0, & \text{otherwise}, \end{cases} \tag{17}$$

where S_{-k} represents another sensor coalition other than the coalition S_k and $\max\left\{ {}^{(r)}_{m,S_{-k}} \right\}$ is the second largest real bid. Each coalition sensor member n should pay equally for the purchase of UAV service. Therefore, $q_n^{(r)}$ is defined as the payment to be paid by coalition member sensor n, and can be expressed as

$$q_n^{(r)} = Q^{(r)}_{m,S_k} / \left|S_k^{(r)}\right|, n \in S_k^{(r)}. \tag{18}$$

The utility of sensor n in the rth round of auction is defined as the true valuation minus its payment, which is expressed as

$$u_n^{(r)} = \begin{cases} \underbrace{b_n^{(r)}}_{\text{true valuation}} - \underbrace{q_n^{(r)}}_{\text{payment}}, & \text{if } I^{(r)}_{m,S_k} = 1, n \in S_k^{(r)}, \\ 0, & \text{otherwise}. \end{cases} \tag{19}$$

In this paper, the maximization of social welfare is pursued, which is defined as the sum of bids of the winning coalitions, i.e.,

$${}^{(r)} = \sum_{m \in M} \sum_{S_k^{(r)} \in {}^{(r)}} I^{(r)}_{m,S_k} \max\left\{ {}^{(r)}_{m,S_{-k}} \right\}. \tag{20}$$

B. 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. In this paper, the social welfare maximization is defined as the sum of bids of the winning coalitions. The system optimization goal is to find an optimal sensor group-buying coalition structure ${}^{(r)} = \left\{S_1^{(r)}, \ldots, S_k^{(r)}, \ldots, S_K^{(r)}\right\}$ in each round of auction to maximize the social welfare, i.e.,

$$(\text{OP1}): {}^{(r)} = \arg\max {}^{(r)}, \tag{21}$$

$$\text{s.t.} \quad t^{(cost,r)}_{c \to m} \le t_{\text{auc}}, \tag{22}$$

$$d_{n,c} \le d^{(th)}, \forall n, c \in S_k^{(r)}. \tag{23}$$

Constraint (22) indicates that the total cost time of a UAV needs to be less than the duration of each round of auction to ensure that the UAV can complete data collection service within an effective time; constraint (23) indicates that the distance between the sensor and the CH in the coalition must be less than the maximum communication distance $d^{(th)}$ to ensure that the status data information of coalition members can be transmitted to the CH. Obtaining the optimal coalition structure by exhaustive search is NP-hard. Thus, we leverage the CF game to design a scheme with relatively low computational complexity to approximate the optimal solution.

IV. Design of Algorithms

This section proposes a group-buying coalition formation-based auction algorithm (GB-CFA) to solve the Problem 1 (OP1). First, data collection is designed, and coalition structure change is decided by following the preference criteria of coalition bid maximization to obtain the coalition structure that maximizes the whole coalition bid. Then, based on the bid of the current coalition, an auction algorithm is designed to maximize the social welfare and determine the successfully-matched coalition and UAV.

The group-buying sensor coalitions bidding for UAV service can be regarded as a typical distributed multi-agent decision 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 [12]. 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, sensors first change the coalition structure to explore possible coalition bids, and then perform comparisons and updates to continuously improve the coalition bid based on the collaborative bid preference criteria until a stable group-buying coalition structure is obtained.

We propose three neighborhood-based coalition operations and realize the parallel optimization of coalition structure by designing the cooperative bid preference criteria.

1) Variable neighborhood ascent search: We propose three neighborhood-based coalition operations to change the coalition structure $\Pi = \{S_1, \ldots, S_k, \ldots, S_K\}$, including:

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

$$N_1(n) = \left\{ \tilde{\Pi} \mid \Pi \backslash \{S_k, S_j\} \cup \left\{ S_k, S_j \right\} \right\}, \tag{24}$$

where the original coalitions S_k and S_j are updated as $S_k = S_k \backslash n, S_j = S_j \cup n$.

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

$$N_2(n) = \left\{ \tilde{\Pi} \mid \Pi \backslash \{S_k, S_j\} \cup \left\{ S_k, S_j \right\} \right\}, \tag{25}$$

where the original coalitions S_k and S_j are updated as $S_k = S_k \backslash n \cup p, S_j = S_j \backslash p \cup n$.

3) Leaving: 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 Π through the leaving of sensor n, that is,

$$N_3(n) = \left\{ \tilde{\Pi} \mid \Pi \backslash \{S_k, S_j\} \cup \left\{ S_k, S_j \right\} \right\}, \tag{26}$$

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

Specifically, a sensor selects an operation of coalition structure change in a neighborhood; if there is no better coalition structure solution can be 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 variable neighborhood search strategy can use the neighborhood structure composed of different actions to perform alternate search. The area searched by the solution changes as the neighborhood varies, preventing the search from falling into a local optimum solution.

2) Parallel mode updating: For the group-buying sensor coalition game model proposed in this section, we define:

In the coalition formation game, the preference criteria based on the preference relationship is the basis for game participants to choose to leave the original coalition or join a new one. The social group welfare criterion of coalition auction ensures that the coalition operation can improve the auction revenue of the whole network [11]. However, it is not suitable for large-scale communication network scenarios as the information interaction required to calculate the whole network auction revenue is very large. In view of the above-mentioned problems, we formulate the cooperative bid preference criterion from the perspective of coalition cooperative bid promotion, i.e.,

***Definition** 1 (Cooperative bid preference criterion):* For sensor n and the two coalition structures obtained before and after the coalition operation Π and $\tilde{\Pi}$, there is,

$$\tilde{\Pi} \succ_n \Pi \Leftrightarrow \mathcal{B}_{S_k} + \mathcal{B}_{S_j} > \mathcal{B}_{S_k} + \mathcal{B}_{S_j}, \tag{27}$$

TABLE I

SYSTEM MODEL PARAMETER

Parameters	Value	Parameters	Value
N	20 - 60	M	1 - 5
H	100m	p_n [1]	100 mW
$P(v_m)$ [10]	1 kW	$P(0)$ [10]	2 kW
$\varepsilon_n^{(r)}$	50 - 200 bits	η [9]	20 dB
B_n [9]	1 MHz	B_c	5 MHz
α_1, α_2 [9]	3, 2	γ_l, ϑ_l [9]	0.136, 11.95

Given any two coalition structures Π and $\tilde{\Pi}$, for sensor n, $\tilde{\Pi} \succ_n \Pi$ represents that the coalition structure $\tilde{\Pi}$ is preferred by n as compared with the structure Π. 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 coalition. Besides, during each coalition structure operation, only the sensors that select the same coalition in the neighborhood for coalition operation will affect each other while the rest will not be affected. Therefore, based on the designed cooperative bid preference criterion, multiple sensors can perform coalition operations simultaneously to change multiple coalitions without affecting each other, and further accelerate the coalition convergence process to save the convergence time of the algorithm.

The auction process is as follows. First, the real bid of each coalition is calculated according to equation (15). Second, the coalition with the highest bid and the 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. Third, 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.

V. Numerical Results and Analyses

In this section, we evaluate the performance of our proposed GB-CFA. The sensors are randomly distributed in an area of 2×2 km^2. All simulation parameters are listed in Table I. In the following, we compare the proposed GB-CFA method with the joint trajectory design task scheduling (TDTS) UAV-to-community [13], coalition formation game (CFG) [5], and maximum throughput first (MTF) [14] methods to verify the superiority of our method. All simulation results are obtained by averaging over 1000 independent trials.

Fig. 3 shows the curve of the average AoI for all sensors versus the number of sensors. As can be seen, compared with CFG, TDTS, and MTF methods, the proposed GB-CFA method decreases the average AoI of all sensors by 16.7%, 44.5%, and 65.3%, respectively. The reason for this improvement is that the 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