A Truthful and Efficient Auction Mechanism for Data Preservation in Base Station-less Sensor Networks

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***Abstract*—We design a truthful and efficient auction mechanism for data preservation in the base station-less sensor networks (BSNs). BSNs refer to many emerging sensing applications that are deployed in challenging environments such as underwater or remote areas. In these environments, as installing a high-power base station near the sensing field is not feasible, sensory data must be preserved inside the network before uploading opportunities arise. We consider that all the sensor nodes are intelligent and selfish and propose an efficient auction mechanism to motivate the sensor nodes to achieve energy-efficient data preservation in the BSN. We investigate the rationality, truthfulness, and energy efficiency of the auction mechanism. Via theoretical and simulation results, we show that our auction mechanism is not only time- and energy-efficient but also guarantees the truthfulness for the selfish sensor nodes.**

Keywords – Auction Mechanism, Base Station-less Sensor Networks, Data Preservation, Truthfulness

I. Introduction

Background. With the strides made in sensor technologies over the past decade, sensor networks have been developed in frontiers that used to be inaccessible or hostile (e.g., deepwater exploration [8], [4] and volcano eruption monitoring [5]). In such challenging environments, as it is infeasible to deploy high-storage and high-power base stations near the sensing field for data collection, autonomous underwater vehicles (AUVs) [4] or robots [25] are usually dispatched into the sensing field to collect the sensory data. We refer to such sensor networks as *base station-less sensor networks* (BSNs).

Our network model is as follows. Some sensor nodes are close to the events of interest and constantly generate sensory data, thus depleting their storage spaces; they are referred to as *source nodes*. Before the arrival of the aforementioned uploading opportunities such as AUVs and robots, source nodes need to offload their *overflow data* to nearby sensor nodes with available storage (referred to as *storage nodes*) to prevent data loss. We call this process *data preservation in BSNs*. The main challenge of data preservation is achieving energy efficiency, as all the sensor nodes are battery-powered.

This paper proposes an auction-based mechanism for energy-efficient data preservation in the BSN. Auction theory [10], [1] is an applied branch of economics that studies how to achieve predictable outcomes in auction markets consisting of sellers and buyers of some objects. Allowing sellers to raise higher revenues and buyers to procure at a lower cost, the auction is a popular incentive scheme that efficiently allocates sellers' resources to buyers at competitive prices. In particular, it has been applied to solve many distributed task and resource allocation problems in engineering and computer science [19].

In recent years, equipped with artificial intelligence and machine learning techniques, the newly developed sensors have become more intelligent [3]. Not only can they sense, compute, and communicate like traditional sensors, but they can perceive, reason, and learn from each other and the environment. Meawhile, although sensor nodes are getting more intelligent, they are generally still resource-constrained with limited processing power, memory and storage capacity, and battery power. As such, they could behave selfishly, only to conserve their own resources and thus have little incentive to participate in the assigned tasks. Take our data preservation problem, for example. In a selfish and distributed environment, storage nodes could be unwilling to spend their limited battery power and storage capacities to help store overflow data packets from source nodes. Incentivizing selfish storage nodes to participate in energy-efficient data preservation in the BSN becomes a critical problem. We refer to it as *selfish data preservation problem*.

Our Contributions. A few works studied selfish data preservation problems [20], [12], [28]. Yu et al. [28] utilize the Vickrey-Clark-Groves (VCG) mechanism [23], a well-known mechanism design methodology, to achieve truthfulness and network efficiency in data preservation. However, it assumes that data packets are of the same sensor type with the same sizes. With this assumption, they show that the data preservation problem is equivalent to the minimum cost flow problem [2], which can be solved optimally and efficiently. It shows that the VCG mechanism is sufficient to motivate the selfish storage nodes in the data preservation of the BSN [28].

However, the above assumption is no longer valid as nowadays, a sensing application could consist of different types of sensors (e.g., video cameras, voice recorders, and thermometers) collecting data of different physical attributes from the environment. Consequently, the sensory data generated from different types of sensors may have very different formats and sizes. For example, in an underwater acoustic scenario for submarine surveillance and monitoring [4], the audio clips are a few KBs per packet, whereas the high-resolution picture frames are a few MBs. As such, the data preservation problem becomes NP-hard [21]. Nisan and Ronen [17] have shown that when applying VCG mechanisms to NP-hard problems and replacing optimal outcomes with computationally tractable approximation or heuristic algorithms, the VCG-based mechanism is no longer truthful.

In this paper, we consider that data packets in the BSN could have different sizes and propose a new auction mechanism for data preservation in the BSN. It is based on a sealed-bid second-price auction [10]. We model the data preservation process as an auction market, in which the storage and source nodes are the sellers and buyers of sensor resources (i.e., storage spaces and battery power), respectively. In particular, storage nodes submit bids with claimed energy costs of storing the overflow data packets from source nodes, and the source nodes provide payment to the storage nodes following our payment model. We propose an efficient auction mechanism to decide the winning bids and their payments. We investigate the rationality, truthfulness, and energy efficiency of the auction mechanism. Via theoretical and simulation results, we show that our auction mechanism is not only time- and energy-efficient but also guarantees the truthfulness for the selfish sensor nodes. That is, truth-telling of its energy cost is a dominant strategy for the sensor nodes.

Paper Organization. Section II reviews all the related work to give a context to our contribution. Section III formulates the data preservation problem in the BSN. Section IV presents our auction mechanism and proves its truthfulness and other related properties. Section V presents our detailed simulation results and analysis. Section VI concludes the paper with a discussion of future work.

II. Related Work

Auction theory has been applied extensively to solve research problems in several areas including spectrum allocation [31], [30], edge computing [11], social networks [26], mobile phone crowd sensing and sensor networks [27], [24], [13], [15], [16], [7]. As our work is about data preservation in the BSN, we review the literature on mobile crowd sensing and sensor networks to give a context of our contributions in this field. Please refer to [29], [18] for a more extensive review.

Auctions in Mobile Crowd Sensing Research. Mobile phone sensing uses pervasive smartphones to collect and analyze data. Yang et al. [27] designed incentive mechanisms for mobile phone sensing to attract more user participation. They designed an incentive mechanism for a platform-centric model using a Stackelberg game, where the platform is the leader while the users are the followers. For a user-centric model, they designed an auction-based incentive mechanism that is computationally efficient, individually rational, profitable, and truthful. Wen et al. [24] proposed an auction-based incentive mechanism where the phone users are paid off based on the quality of sensed data. They theoretically prove that the mechanism is truthful, individually rational, platform profitable, and social welfare optimal. Mak [13] extended the optimal auction theory to a crowdsourcing application, where the bid for work consists not only of the unit cost but also the maximum amount of work the workers are willing to do, and proved that a dominant strategy exists in this case. However, in the above works on mobile phone sensing auction mechanism design, critical network-related properties such as network topology and the capacity of networked nodes are largely ignored. In this paper, we consider these parameters and study their effect on mechanism design.

Auctions in Sensor Network Research. Auctions have also been applied in sensor network research. Melodia [15] was one of the first to introduce auction theory into sensor networking research. In particular, they designed a localized auction protocol to coordinate between the sensors, which sense information, and the actors, which analyze the data and take action. Their auction mechanism is essentially a single-round sealed-bid auction [14], where each buyer submits its bids in one shot irrespective of the bids from other buyers. Neda [16] formulated the real-time distributed task allocation problem in wireless sensor networks as incomplete information, incentive compatible, and economically robust reverse auction game. The main objective of this scheme is to maximize the overall network lifetime, considering the application's deadline as the constraint. Zheng et al. [7] proposed an auction-based adaptive sensor activation algorithm for target tracking in wireless sensor networks, wherein the cluster heads receive bids from nodes to form clusters. However, all of the above works assume a traditional sensor networking model where a base station is available to collect the data. However, in the data preservation of the BSN, we need to decide where the overflow data packets will be stored. Thus, our auction mechanism is dramatically different from the existing works.

Selfish Data Preservation in the BSN. A few works studied data preservation problems with selfish sensor nodes [20], [12], [28]. Rivera et al. [20] analyzed the performance of the Nash Equilibria of data preservation in terms of the price of anarchy and the price of stability [9], two main concepts in economics and game theory that measure the system degradation due to selfishness. Yu et al. designed a computationally efficient and truthful data preservation game based on the Vickrey-Clark-Groves (VCG) mechanism [23], a well-known mechanism design methodology to achieve truthfulness and efficiency. Ly al. [28] further considered that data packets could have different values and designed a data preservation game with a performance guarantee. However, one common assumption of all the work is that the data packets to be preserved have the same sizes. The data preservation problem can then be solved optimally and efficiently, and an efficient VCG mechanism can be utilized to motivate the selfish nodes.

In contrast, in this paper, we assume that data packets could have different sizes, wherein the data preservation problem becomes NP-hard [21]. As the VCG-based mechanism is no longer necessarily truthful for NP-hard problems [17], we propose a new auction mechanism based on sealed-bid second-price auction [10], wherein bidders submit bids without knowing others' bids and the highest bidder wins, but the price paid is the second-highest bid.

Other Related Works. Our work is inspired by [22], which stimulates mobile devices to execute tasks for others in the mobile device cloud environment. In particular, they studied two task models, heterogeneous and homogeneous task models, which assume the different and the same resource requirements of the tasks, respectively. For the heterogeneous task model, they propose an efficient heuristic winning-bids determination algorithm to allocate the tasks and decide the payment of each seller for its winning bids. For a homogeneous task model, they designed a VCG-based auction mechanism to determine the payment of each bid. They show that both mechanisms achieve several desirable properties, such as individual rationality, truthfulness, and computational efficiency.

III. Data Preservation Problem

System Model. We model a BSN as an undirected graph $G(V, E)$, where $V = \{1, 2, ..., n\}$ is the set of n sensor nodes, and E is the set of edges. There are $k < n$ source nodes $V_s = \{1, 2, ..., k\}$ and $n-k$ storage nodes $V_r = \{k+1, k+2, ..., n\}$. The sensory data are modeled as a sequence of data packets, each of which could have different sizes. In particular, we assume that the overflow data packets from the same source node have the same sizes, while packets from different source nodes could have different sizes. Let $g_i > 0$ be the size of each overflow data packet (in bits) at source node $i \in V_s$.

Let d_i denote the number of overflow data packets source node $i \in V_s$ generates, which must be offloaded to some storage nodes to avoid being lost. Let $d = \sum_{i=1}^{k} d_i$ be the total number of overflow data, and let $D = \{1, 2, ..., d\}$ denote the set of these d data packets. Let $s(j) \in V_s$, $1 \leq j \leq d$ denote data packet j's source node and D_i be the set of data packets at source node i; that is, $D_i = \{j \in D | s(j) = i\}$ and $|D_i| = d_i$. Let m_i be the available free storage space (in bits) at sensor node $i \in V$. Note that $m_i = 0$ for $i \in V_s$ while $m_i > 0$ for $i \in V_r$. We assume that $\sum_{i=k+1}^{n} m_i > \sum_{i=1}^{k} (d_i \cdot g_i)$; otherwise, data preservation is not feasible.

Energy Model [6]. When node i sends a data packet to its neighbor i' over their distance $l_{i,i'}$, the amount of *transmitting energy* spent by i is $E_i^t(i') = a \cdot \epsilon_i^a \cdot l_{i,i'}^2 + a \cdot \epsilon_i^e$. Here, $\epsilon_i^a = 100pJ/bit/m^2$ and $\epsilon_i^e = 100nJ/bit$ are the energy consumption of transmitting one bit on the transmit amplifier and circuit of node i, respectively. When node i' receives a data packet, the amount of *receiving energy* it spends is $E_{i'}^r = a \cdot \epsilon_{i'}^e$. Given an edge $(i, i') \in E$, its weight $w(i, i')$ is the total energy consumption of sending and receiving one packet from i to i'; that is, $w(i, i') = E_i^t(i') + E_{i'}^r$.

Problem Formulation. We define a *preservation function* as $f : D \rightarrow V_r$, showing $j \in D$ is offloaded from its source node $s(j) \in V_s$ to a storage node $f(j) \in V_r$ along the shortest path between them (referred to as *data preservation path*). Let $c(i, i')$ be the cost of the data preservation path between source node i and storage node i'. The goal of the data preservation problem is to find an f to offload all the overflow packet D, such that the *total preservation cost* $C = \sum_{j=1}^{d} c\big(s(j), f(j)\big)$ is minimized under the storage constraint of storage nodes: $\forall i \in V_r$, $\sum_{1 \leq j \leq d} x_{i,j} \cdot g_{s(j)} \leq m_i$, where $x_{i,j} = 1$ if $f(j) = i$ and 0 otherwise. Table I shows all the notations.

TABLE I
NOTATION SUMMARY

Notation	Description
$G(V, E)$	BSN graph, $V = V_s \cup V_r$, $\lvert V \rvert = n$
V_s	Set of k source nodes
V_r	Set of $n-k$ storage nodes
d_i	Number of overflow data packets at source node $i \in V_s$
g_i	Value of overflow data packets at source node $i \in V_s$
d	Total number of overflow data packets
D	The set of d overflow data packets
D_i	The set of overflow data packets at source node i
i, i'	Index for sensor nodes, $1 \leq i, i' \leq n$
j	Index for overflow data packets, $1 \leq j \leq d$
$s(j)$	The source node of data j, $1 \leq j \leq d$
m_i	Storage capacity of storage node $i \in V_r$
$E_i^t(i')$	Transmission energy spent by i to transmit one packet to i'
E_i^r	Receiving energy spent by i to receive one data packet
f	Data offloading function
$b_{i,j}$	the bid (i.e., claimed energy cost) of storage node i to store data packet j
$c_{i,j}$	the true cost of storage node i to store data packet j
$p_{i,j}$	the payment to storage node i for storing data packet j
$\pi_{i,j}$	$\pi_{i,j} = p_{i,j} - c_{i,j}$, node i's utility of storing data packet j
b_{i^*,j^*}	The winning bid of storage node i storing packet j

Unlike the uniform data size case (i.e., all the data packets have equal sizes), the data preservation problem for arbitrary data sizes is APX-hard [21]. It is not only NP-hard, but also, a polynomial time approximation algorithm is unlikely. Below, we present a truthful and efficient auction mechanism for the data preservation problem of arbitrary data sizes, considering that sensor nodes are selfish.

IV. An Auction Mechanism for Data Preservation

Auction Model. We consider all the source nodes as buyers and all the storage nodes as sellers. This is because source nodes want their overflow packets preserved by the storage nodes. To begin with the auction, each storage node i submits its bids for all the d data packets: $B_i = \{b_{i,1}, ..., b_{i,j}, ..., b_{i,d}\}$, where $b_{i,j}$ denotes the energy cost spent in storing data packet j. Here, we assume each storage node i claims on behalf of all other nodes involved in preserving the data packet finally stored at i and compensates their cost accordingly. To assist the communication between the buyers and sellers, a central authority (i.e., *auctioneer*) collects the bids and computes the winning bids and their corresponding payments following our designed auction mechanism below.

As $b_{i,j}$ is storage node i's private information unknown to others, i may manipulate its claimed cost to gain higher utility. Let $x_{i,j}$ denote if storage node i wins the bid to data packet j (thus j is eventually stored at i following the shortest path between them); $x_{i,j} = 1$ if so and zero otherwise. Thus to minimize the total preservation cost, the auctioneer needs to determine the winning bids to minimize the total claimed bids $\sum_{i \in V_r} \sum_{j=1}^{d} b_{i,j}$ under the storage constraint: $\sum_{j=1}^{d} x_{i,j} \cdot g_{s(j)} \leq m_i$, $\forall i \in V_r$ while all the packets must be offloaded for preservation: $\sum_{i \in V_r} x_{i,j} = 1$, $\forall j \in D$.

Auction Mechanism. The auction mechanism includes Algo. 1, which determines the winning bids, and Algo. 2, which is the payment model for the winning bids.

Determining Winning bids. Algo. 1 works as follows. It first sorts all the bids $b_{i,j}$ in non-decreasing order of $\frac{b_{i,j}}{g_{s(j)}}$ (line 1), as the bid with smaller cost per unit packet size should have higher chance to win the bid. It then sorts all the data packets in non-decreasing order of their sizes (line 2). Then, it works in iterations. In each iteration, it first selects the bid with the smallest cost per unit packet size as the winning bid and updates related information (lines 4 and 5). Let this storage node and data packet pair be (i^*, j^*). It then removes all the bids from B, where $B = \cup_{i=k+1}^{n} B_i$, that claim data packet j^* (lines 6-10). Finally, it updates the available storage capacity of storage node i^* and checks if it still has enough capacity to store at least one data packet (lines 11-13). If not, it removes all the bids of storage node i^* from B (lines 14-18). The above takes place until all the data packets receive a winning bid, at which point the final set of winning bids is returned (line 21). Algo. 1 takes $|B| \cdot \log(|B|) + d \cdot \log(d) + d \cdot |B|$, where $|B|$ is the total number of bids and $d = |D|$ is the total number of data packets. As $|B| = |V_r| \cdot |D| = O(n \cdot d)$, where n is the total number of sensor nodes, the time complexity of Algo. 1 is $O\big(n \cdot d \cdot (\log(n \cdot d) + d)\big)$.

Algorithm 1: Determining Winning Bids.
Input: A BSN graph $G(V, E)$, $B = \{b_{i,j}\}$, $i \in V_r$, $j \in D$;
Output: A set of winning bids $W \subset B$.
Notations:
B: $B = \cup_{i=k+1}^{n} B_i$ is the entire set of bids;
D: set of data packets to be preserved;
W: final set of winning bids, initially empty;
$x_{i,j}$: 1 if $b_{i,j} \in B$ is a winning bid, initially 0;
b_{i^*,j^*}: the winning bid in the current iteration;
1. Sort $b_{i,j} \in B$ in non-increasing order of $\frac{b_{i,j}}{g_{s(j)}}$;
2. Sort $j \in D$ in non-decreasing order of their sizes $g_{s(j)}$;
3. **while** (D is not empty)
4. Select the first available bid in B, denoted as b_{i^*,j^*}, as the winning bid; i.e., $x_{i^*,j^*} = 1$;
5. $W = W \cup \{x_{i^*,j^*}\}$, $D = D - \{j^*\}$, $B = B - \{b_{i^*,j^*}\}$;
6. **for** (each bid $b_{i,j} \in B$)
7. **if** ($j == j^*$)
8. $B = B - \{b_{i,j}\}$; // Remove bids b_{i,j^*} from B
9. **end if;**
10. **end for;**
11. $m_{i^*} = m_{i^*} - g_{s(j^*)}$;
12. Let the first data packet in D be j_1;
14. **for** (each bid $b_{i,j} \in B$)
15. **if** ($i == i^*$)
16. $B = B - \{b_{i,j}\}$; // Remove bids $b_{i^*,j}$ from B
17. **end if;**
18. **end for;**
19. **end if;**
20. **end while;**
21. **RETURN** Set of winning bids W.

Payment Model. Next, we compute p_{i^*,j^*}, the payment to storage node i^* for its winning bid b_{i^*,j^*}. Our payment model specified in Algo. 2 accomplishes this. It starts by removing b_{i^*,j^*} from the entire bid set $B = \cup_{i=k+1}^{n} B_i$ and sorting all the bids $b_{i,j}$ in non-decreasing order of $\frac{b_{i,j}}{g_{s(j)}}$ and all the data packets in non-decreasing order of their sizes (lines 1-3). It then chooses one winning bid from $B - \{b_{i^*,j^*}\}$, which is b_{i^+,j^+}, and updates all the related information (lines 6-21). This continues until data packet j^* appears in another winning bid, say b_{i',j^*}; that is, storage node i' wins its bid to packet j^* without the presence of the bid b_{i^*,j^*}. Finally, we set p_{i^*,j^*}, the payment to winning bid b_{i^*,j^*}, as b_{i',j^*} and return it (lines 23-24). The time complexity of Algo. 2 is also $O\big(n \cdot d \cdot (\log(n \cdot d) + d)\big)$.

Algorithm 2: Payment model of computing p_{i^*,j^*}.
Input: A BSN graph $G(V, E)$, winning bids $W = \{b_{i^*,j^*}\}$;
Output: Payment p_{i^*,j^*} for b_{i^*,j^*}.
Notations:
p_{i^*,j^*}: the payment to node i^* for its winning bid b_{i^*,j^*};
1. $B = B - \{b_{i^*,j^*}\}$;
2. Sort $b_{i,j} \in B$ in non-increasing order of $\frac{b_{i,j}}{g_{s(j)}}$;
3. Sort $j \in D$ in non-decreasing order of their sizes $g_{s(j)}$;
4. $x_{i,j} = 0$, $\forall b_{i,j} \in B$;
5. **while** ($\sum_{b_{i,j^*} \in B} x_{i,j^*} == 0$)
6. Let the first available bid in B be b_{i^+,j^+}, choose it as the winning bid; i.e., $x_{i^+,j^+} = 1$;
7. $B = B - \{b_{i^+,j^+}\}$, $D = D - \{j^+\}$;
8. **for** (each bid $b_{i,j} \in B$)
9. **if** ($j == j^+$)
10. $B = B - \{b_{i,j}\}$; // Remove bids b_{i,j^+} from B
11. **end if;**
12. **end for;**
13. $m_{i^+} = m_{i^+} - g_{s(j^+)}$;
14. Let the first data packet in D be j_1;
15. **if** ($m_{i^+} < g_{s(j_1)}$)
16. **for** (each bid $b_{i,j} \in B$)
17. **if** ($i == i^+$)
18. $B = B - \{b_{i,j}\}$; // Remove bids $b_{i^+,j}$ from B
19. **end if;**
20. **end for;**
21. **end if;**
22. **end while;**
23. Assume $x_{i',j^*} = 1$, then set $p_{i^*,j^*} = b_{i',j^*}$;
24. **RETURN** p_{i^*,j^*}.

Theoretical Analyses. Define the utility of storage node $i \in V_r$ for preserving data $j \in D$ as $\pi_{i,j}$. $\pi_{i,j} = 0$ if

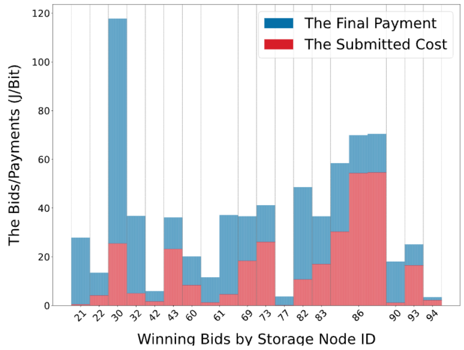

Fig. 1. The bids and payments of winning bids.

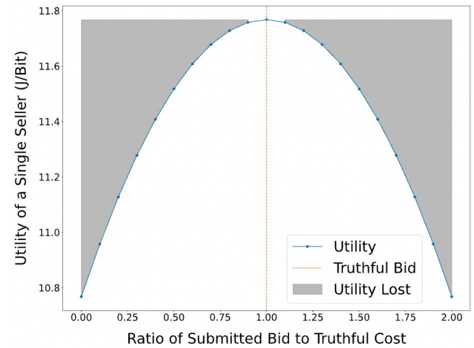

Fig. 2. Demonstrating Truthfulness.

$x_{i,j} = 0$, and $\pi_{i,j} = p_{i,j} - c_{i,j}$ if $x_{i,j} = 1$. Our goal is to design an auction mechanism so that each storage node is willing to participate in the auction and tell the truth about its data preservation cost. In other words, in the equilibrium of the auction, each storage node bids its true cost of data preservation, and its corresponding utility is non-negative. We define these two conditions below:

(1). Truthfulness: The bid submitted by each storage node for each data reflects the true cost of node $i \in V_r$ for preserving data $j \in D$. I.e., $b_{i,j} = c_{i,j}$.

(2). Individual Rationality: The utility of storage node i for its data preservation is non-negative, i.e., $\pi_{i,j} \geq 0$, $\forall i \in V_r$ and $\forall j \in D$.

Theorem 1: The auction mechanism given by Algos. 1 and 2 satisfies truthfulness for each storage node $i \in V_r$. I.e., $b_{i,j} = c_{i,j}$ is a weakly dominant strategy of node $i \in V_r$.

Proof: For storage node i, we need to prove that $b_{i,j} = c_{i,j}$ weakly dominates any other bid $b'_{i,j} \neq c_{i,j}$.

First, consider $b'_{i,j} > c_{i,j}$. If node i wins or loses the bid for preserving data j with either $b_{i,j}$ or $b'_{i,j}$, its utility is $b_{i',j} - c_{i,j}$ under Algorithm 2 with either bid when it wins, and its utility is zero with either bid when it loses. Thus node i is indifferent between $b_{i,j}$ and $b'_{i,j}$. Instead, consider when i wins the bid under $b_{i,j}$ but loses the bid under $b'_{i,j}$. By Algo. 2, when it wins under $b_{i,j}$, its utility is $b_{i',j} - c_{i,j} \geq 0$ since $b_{i',j} \geq b_{i,j}$; while when it loses under $b'_{i,j}$, its utility is zero. Thus bidding $b_{i,j}$ weakly dominates bidding $b'_{i,j}$.

Second, consider $b'_{i,j} < c_{i,j}$. Similarly, when node i wins or loses the bid under either $b_{i,j}$ or $b'_{i,j}$, its utility is the same either way, and i is indifferent between $b_{i,j}$ and $b'_{i,j}$. Instead, consider when i wins the bid under $b'_{i,j}$ but loses the bid under $b_{i,j}$. By Algo. 2, when it wins under $b'_{i,j}$, its utility is $b_{i',j} - c_{i,j} < 0$ since $b_{i',j} < b_{i,j}$ because bidding $b_{i,j}$ loses the bid; while when it loses under $b_{i,j}$, its utility is zero. Thus bidding $b_{i,j}$ weakly dominates bidding $b'_{i,j}$. We conclude that $b_{i,j} = c_{i,j}$ is a weakly dominant strategy of node i, $\forall i \in V_r$. ∎

Theorem 2: The auction mechanism given by Algos. 1 and 2 satisfies individual rationality for each storage node $i \in V_r$.

Proof: We only need to show $\pi_{i,j} = p_{i,j} - c_{i,j} \geq 0$ for $x_{i,j} = 1$. According to Algo. 2, $p_{i,j} = b_{i',j}$. Suppose $b_{i',j} < b_{i,j}$, then it holds that $b_{i',j}/g_{s(j)} < b_{i,j}/g_{s(j)}$. By Algo. 1, it should be node i' winning the auction for data j, not node i, a contradiction to $x_{i,j} = 1$. Thus $b_{i',j} \geq b_{i,j}$ and $\pi_{i,j} = b_{i',j} - c_{i,j} = b_{i',j} - c_{i,j} \geq 0$. ∎

V. Simulation Results

Simulation Setup. We write our simulator in Python on a Mac Mini (M1, 2020) with an Apple M1 Processor and 8GB of memory. We randomly place 100 sensor nodes in an area of 2000m $\times$ 2000m. Two nodes are connected if their distance is less than or equal to 250m, the transmission range of sensor nodes. Each source node has 100 data packets. We assume packets from the same source node have the same sizes, while packets from different source nodes are a random number in [4KB, 8KB]. The storage capacity of each storage node is 25KB. The storage node is the seller and the bidder, and the source node is the buyer. The storage node bids for each source node using the shortest path energy consumption of one bit between the source node and the storage node, while it can lie about this cost. Each data point in the plots has an average of 20 runs; a BSN instance is randomly generated in each. The confidence interval is 95%. Below, we investigate our auction mechanism's rationality, truthfulness, and energy efficiency.

Investigating the individual rationality. Fig. 1 evaluates the mechanism's performance concerning rationality, where there are 20 source nodes and 80 storage nodes. The depicted figure reveals that all final payments for winners surpass their respective submitted bids. Consequently, it can be inferred that individual rationality is preserved within this mechanism.

Investigating the truthfulness. Fig. 2 investigates the mechanism's performance on truthfulness, where bids are generated through the random selection of one seller. The x-axis is the ratio of the submitted bid to the truthful valuation. It shows that maximum utility is attained when the ratio equals 1, representing a truthful bid. Conversely, any deviation from this truthful cost results in a proportional loss of utility, as evidenced by the respective ratio.

Investigating the energy efficiency. Fig. 3 compares the total data preservation costs of three distinct data packet allocation schemes viz. First Price, Second Price, and Exhaustive by varying the number of source nodes. Here, the First Price is Algo. 1, which finds the winning bids in one round; the Second

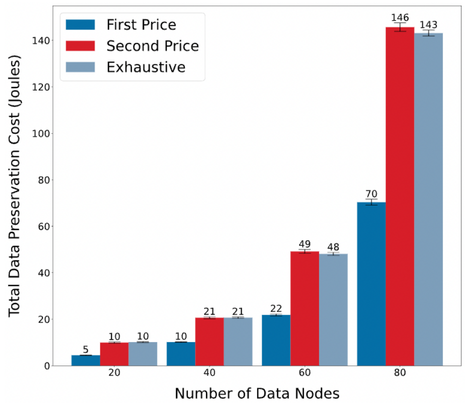

Fig. 3. Comparing three algorithms.

Price refers to our auction mechanism, including Algo. 1 and Algo. 2; and the Exhaustive refers to an optimal algorithm that enumerates all the allocation routes and finds the one with minimum cost. A close alignment in total energy cost is observed between the second price and exhaustive methods, suggesting our mechanism approximates optimality. The first price emerges as the most cost-efficient, albeit at the expense of forgoing assurances of truthfulness and rationality.

VI. Conclusions

We designed a truthful auction mechanism for data preservation in the base station-less sensor networks operated in many emerging sensing applications such as underwater exploration and climate monitoring. Via theoretical and simulation results, we showed that our auction mechanism is not only time- and energy-efficient but also guarantees the truthfulness of the selfish sensor nodes. In future work, we will study if our greedy bid-selection algorithm achieves any performance guarantees, that is, if the achieved total data preservation cost is within a constant ratio of the optimal solution. We assume all the sensor nodes have enough energy to participate in the data preservation. When nodes have minimal battery power, some could deplete their power and cause network partition and interruption, drastically obstructing data preservation. As an ongoing work, we are investigating how to augment our auction mechanism to incorporate this challenging scenario.

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