On the MAC Protocols of Co-Existing Time-Slotted Sensor Networks

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Abstract

We consider a joint scheduling approach for clustered sensor networks, where clusters use a time-slotted mechanism to access a shared medium. It is shown that a significant increase in packet delivery probability can be achieved if the transmission schedules at neighboring clusters are considered jointly. In our consideration of the problem, we include realistic propagation effects, such as Rayleigh fading, something that is often neglected in the literature. For networks with more than two clusters, the scheduling problem is NP-hard, and we therefore approach the problem using Lagrangian relaxation methods. A numerical evaluation of the proposed algorithm show that gains in packet delivery probability up to thirty percent can be achieved over a random scheduling.
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1 Introduction

Over the last few years, interest in sensor networks has been steadily on the rise, both from industry and academia. One of the many reasons for this large (and still growing) interest are the many diverse application areas where sensor networks may be employed, see, e.g., [1, chap. 1] and references cited therein. What is encompassed by the term sensor network varies widely in the literature. However, a few common traits can be found: (a) The purpose of the network is to gather information, e.g., to sense its surrounding environment (b) the sensed information is often funnelled from the sensors to a data-sink, and (c) communication between network nodes often takes place over wireless links. Although recent advances in both hardware and software technology has made large sensor networks a feasibility today, some obstacles still need to be overcome before many of the envisioned applications can be realized. One of the main problems is energy consumption, stemming from the fact that most network nodes are battery powered, hence energy is a scarce resource that must be conserved. Node complexity is another limiting factor, since, for many of the envisioned applications to be feasible the size and cost of individual sensor nodes must be kept at a minimum.

In order to conserve energy, the number of packet retransmissions in the network should be kept as low as possible. Strong interference among network nodes is therefore undesirable, since it can potentially cause high packet-loss rates. Interference suppressing mechanisms based on, e.g., coding, are often not applicable in sensor networks due to their inherent complexity. Thus, an important component in sensor network design is the medium-access-control (MAC) layer, that controls access to a shared wireless medium. Another important factor in preserving energy is the duty cycle of individual sensor nodes. Recent work on energy consumption has shown that most wireless sensor devices consume almost as much energy when listening to the wireless channel, or even being in idle mode, as they do when actively transmitting a packet [1, chap. 2]. From this perspective, a synchronized time-slotted MAC-scheme (TDMA) where sensors can sleep for extended periods of time seems preferable both from interference and duty-cycle points of view. However, even in a perfectly synchronized TDMA system, interference will still be present if two or more networks, or ”clusters” of sensors, are co-located in close vicinity of each other, perhaps unaware and scheduled independently of each other using the same shared communication resource. In order to minimize interference from a global network perspective, we would like to schedule trans-
missions of neighboring clusters in such a way as to minimize this inter-cluster interference.

Such a joint assignment of time slots to nodes in separate clusters is not an easy task. Similar assignment problems arise in more general communication systems based on TDMA, frequency division multiple access (FDMA), and code division multiple access (CDMA) which are all known to be NP-hard. In [2], these assignment problems are classified into a unified framework, and a centralized graph coloring heuristic is applied in order to arrive at a sub-optimal solution. Similar but distributed algorithms are proposed in [3–5]. One problem with the work listed above, and other work in the area, is the assumption that only nodes one hop away from the receiver can generate significant interference. This assumption is equivalent to assuming equal transmission and interference ranges, which was recently shown by Xu et. al. to be an unrealistic assumption [6]. Moreover, important aspects of propagation, such as fading, is often ignored. In the presence of fading, in theory, no distance separation guarantees a collision free transmission. One paper that does consider fading in conjunction with interference is [7]. In this work, the effect of co-channel interference on simultaneous connections within a single piconet of an IEEE 802.15.3 wireless personal area network (WPAN) is investigated. In the proposed scheme, the piconet coordinator allows multiple simultaneous communication links over a shared medium if the communicating nodes are located such that no significant interference is generated.

In this work, we propose a MAC-layer that schedules sensor transmissions of one or several clusters with the objective to maximize the packet delivery ratio in a Rayleigh fading environment. The maximization is done either for a single cluster in the presence of other “alien” clusters that cannot be controlled, or jointly among several cooperating clusters. We assume estimates of the distance between nodes are available [1, chap. 9], and formulate the problem as an integer programming problem. Due to the above mentioned NP-hardness, the assignment problem is approached using Lagrangian relaxation and the auction algorithm, coupled with an iterative dual method. Lagrangian relaxation methods have been used in similar contexts before. For instance in [8], a Lagrangian relaxation method is used to solve a load balancing problem for WLAN access points in the multi-channel multi-sector directional antenna (MCMSDA) protocol. However, the assignment problem we solve here is of higher dimension and therefore more complex than the problems considered in [7] and [8]. To the best of our knowledge, our approach to modelling and solving the sensor
scheduling problem has not been applied in this context before.

The remainder of this work is organized as follows. In Sec. 2 we define the network and interference model and state additional assumptions on the system. The interference model is later used in the proposed MAC algorithm, that is derived in Sec. 3. The proposed algorithm is analyzed and evaluated through computer simulation in Sec. 4, and we conclude the paper in Sec. 5.

2 System model

Let $M$ sensor nodes be located in a confined area. The nodes are assumed to be clustered into $K$ sets $\{C_i\}_{i=1}^K$. Let a frame be an interval of time divided into $W$ of slots, indexed by $w \in \{1, \ldots, W\}$, and let $S_w$ be the set of sensors, one from each cluster, scheduled for transmission in slot $w$. There can be no more than one sensor from each cluster scheduled in a given slot $w$. Denote the distance (assumed known) between node $i$ and sink $k$ by $d_{i,k}$. Each cluster is assumed to have a dedicated sink node, and this node receives all packets in its cluster. Here, we assume all sink nodes are coarsely synchronized on a packet level, so that transmissions in a given slot takes place at approximately the same time in all clusters. Synchronization errors on a cluster level would of course affect the performance of the proposed system, but this aspect of the system is left for future work. It is also assumed a central entity exist that control the scheduling of all or a subset of clusters.

The average received signal power at reference distance $d_0$ is denoted $P_0$. The signal power is assumed to decline exponentially with distance, and the path-loss exponent $\alpha$ is assumed known. Each transmission link is also affected by Rayleigh fading of unit gain. Hence, the received power from node $i$ at sink $k$ is modelled by

$$P_{i,k} = \kappa_{i,k}P_0 \left( \frac{d_0}{d_{i,k}} \right)^\alpha$$

where $\kappa_{i,k}$ is a unit mean exponentially distributed random variable that models the effect of Rayleigh fading on instantaneous received signal power. Any other fading is assumed insignificant in comparison to the Rayleigh fading. We assume a packet capture effect, i.e., if the instantaneous signal to interference and noise ratio (SINR) at the receiving node is above a given threshold, then the packet is received correctly with high probability, and lost otherwise [9].

In each cluster, if there are more sensors than available slots, it is assumed that the transmissions of surplus sensors are deferred to future frames. If, on the other hand, there are fewer sensors than slots in a cluster, ”dummy” sensors at infinite distance from
all sinks are added to the cluster. Thus, in each frame, $W$ sensors from each cluster are always to be scheduled.

### 2.1 Interference and reliability model

Under the packet capture assumption, a packet is lost with high probability if the instantaneous SINR at the receiving sink goes below a given threshold $\Theta$. In order to quantify and measure the reliability on a given link, we derive the probability of this event occurring, conditioned on the current network scenario, that is assumed known by the central entity.

The instantaneous SINR at sink $k$ when a message from node $i$ is received in slot $w$ is given by

$$
\Gamma(i, k, w) = \frac{\kappa_{i,k} P_0 \left( \frac{d_0}{d_{i,k}} \right)^\alpha}{P_{N_k} + \sum_{j \in S_w, j \neq i} \kappa_{j,k} P_0 \left( \frac{d_0}{d_{j,k}} \right)^\alpha},
$$

where $P_{N_k}$ denotes the (known) noise power at sink $k$. Therefore, the packet-loss probability can be modelled by

$$
P_{\text{loss}}(i, k, w) = P(\Gamma(i, k, w) < \Theta | S_w)
$$

$$
= P \left( \kappa_{i,k} \gamma(i,j,k) + \Theta \frac{P_{N_k}}{P_0} \left( \frac{d_{i,k}}{d_0} \right)^\alpha \right)
$$

where $\gamma(i,j,k) = \Theta \left( \frac{d_{i,k}}{d_{j,k}} \right)^\alpha$. Since all fading coefficients are assumed independent, exponentially distributed, and of unit mean, we have

$$
P(\Gamma(i,k,w) < \Theta | S_w) = \int_{\kappa_{S_w,k} \in \mathcal{A}} \int_{\kappa_{i,k} = 0} \cdots \int_{\kappa_{i,k} = 0} e^{-\sum_{l \in S_w} \kappa_{i,k}} d\kappa_{S_w,k}
$$

$$
= 1 - e^{-\frac{P_{N_k}}{P_0} \left( \frac{d_{i,k}}{d_0} \right)^\alpha} \prod_{j \neq i} \left( 1 + \gamma(i,j,k) \right)
$$

where $\kappa_{S_w,k} = \left[ \kappa_{C_1 \cap S_w,k}, \ldots, \kappa_{C_{p} \cap S_w,k} \right]$, i.e., all fading coefficients to sink $k$ in slot $w$, and $\mathcal{A} = \{ \kappa_{S_w,k} \in (\mathbb{R}^+)^{S_w} : \kappa_{i,k} = 0 \}$.

The reliability of a link to sink $k$, using slot $w$, from the $i$th nodes’ point of view can now be measured by $1 - P_{\text{loss}}(i, k, w)$. This can also be said to be the ”value”, or ”utility”, that the parent cluster $C_p$ associates with scheduling node $i$ in slot $w$, knowing what nodes from other clusters that will generate interference in this slot.

We denote this utility at cluster $p$ of a certain slot $w$ assignment $S_w$.
by $U_p(w, S_w)$. However, this utility is only for a single cluster, and says little about the reliability and expected packet delivery ratio of the entire network. To quantify the total reliability in the network at slot $w$, all cluster utilities must be considered jointly. The global utility of an assignment $S_w$ in slot $w$ is therefore defined by

$$U(w, S_w) = \sum_{p=1}^{K} U_p(w, S_w).$$

$$\text{(1)}$$

3 MAC

The aim of the proposed MAC layer is to schedule sensor transmissions such that the average probability of a successful packet delivery in the network is maximized. Using the reliability measure derived in the previous section, and constraints on sensor transmissions, this problem is equivalent to the multi-dimensional assignment problem from the research area of integer programming, see, e.g., [10, chap. 5]. Thus, the MAC problem for the $K$ clusters $\{C_i\}_{i=1}^{K}$, and $W$ time-slots is

$$\max \sum_{w=1}^{W} \sum_{c_1 \in C_1}^{C_K} \cdots \sum_{c_K \in C_K} U(w, \{c_1, \ldots, c_K\}) I_{w c_1 \cdots c_K}$$

subject to

$$\sum_{c_1 \in C_1} \cdots \sum_{c_K \in C_K} I_{w c_1 \cdots c_K} = 1, \forall w \in \{1, \ldots, W\}$$

$$\sum_{w=1}^{W} \sum_{c_2 \in C_1} \sum_{c_3 \in C_3} \cdots \sum_{c_K \in C_K} I_{w c_1 \cdots c_K} = 1, \forall c_1 \in C_1$$

$$\vdots$$

$$\sum_{w=1}^{W} \sum_{c_1 \in C_1} \cdots \sum_{c_{K-1} \in C_{K-1}} I_{w c_1 \cdots c_K} = 1, \forall c_K \in C_K.$$

$$\text{(2)}$$

Here, $I_{w c_1 \cdots c_K}$ is an indicator function that is unity when nodes $c_1, \ldots, c_K$ has been assigned to slot $w$, and zero otherwise. As the number of sensors and clusters in the network grows, the complexity of a brute-force solution to this problem quickly becomes prohibitive (in fact, for $K > 2$ the problem is NP-hard). We therefore approach the problem using a Lagrangian dual method, adopted from [11] with modifications.

It is noted that the utility function $U(w, S_w)$ in (2) does not necessarily need to encompass all clusters. The reliability and subsequent optimization from a single cluster’s, or from a subset of
clusters’ point of view is obtained simply by removing adequate terms from the sum in (1). The implications of this are analyzed in Sec. 4.

3.1 Two clusters

Since we assume no time-dependence, the utility function $U(w, S_w)$ in fact only depends on $S_w$ and not on $w$. Therefore, if there are only two clusters in the network, we can randomly assign sensors from cluster $C_1$ to slots without loss in maximum achievable utility. For convenience, we denote the node from $C_1$ already assigned in slot $w$ as $\{S_w \setminus C_2\}$. The MAC problem now reduces to the two-dimensional assignment problem

$$\max_{I_{wc}} \sum_{w=1}^{W} \sum_{c_2 \in C_2} U(w, \{S_w \setminus C_2 \cup \{c_2\}\}) I_{wc_2}$$

subject to

$$\sum_{c_2 \in C_2} I_{wc_2} = 1, \forall w \in \{1, \ldots, W\}$$

$$\sum_{w=1}^{W} I_{wc_2} = 1, \forall c_2 \in C_2.$$ (3)

Unlike the case of the multi-dimensional assignment problem in (2), efficient algorithms exist that solve (3) in polynomial time. We use the auction algorithm, due to Bertsekas [10, chap. 6], briefly described in App. 6.

3.2 Arbitrary number of clusters

Even though the problem in (2) is NP-hard for $K > 2$, an optimal solution may often be found using a primal-dual method similar to the two-cluster case. We successively relax constraints on cluster nodes in (2), adding an unconstrained Lagrangian multiplier for each relaxed constraint, down to a point where we only have constraints on slots, $C_1$ and $C_2$ left,

$$\max_{I_{wc_1 \cdots c_K}} \sum_{w=1}^{W} \sum_{c_1 \in C_1} \cdots \sum_{c_K \in C_K} (U(w, \{c_1, \ldots, c_K\}) - \mu_{c_3} \cdots - \mu_{c_K}) I_{wc_1 \cdots c_K}$$

$$+ \sum_{c_3 \in C_3} \mu_{c_3} \cdots + \sum_{c_K \in C_K} \mu_{c_K}$$

subject to constraints on slots, $C_1$ and $C_2$. 

where we denote the multiplier associated with node $c_p$ of cluster $p$ by $\mu_{c_p}$. After relaxing constraints on all nodes in cluster $C_{r+1}$, we compute a set of modified utilities

$$
\tilde{U}^{(r)}(w, \{c_1, \ldots, c_r\})
= \max_{c_{r+1}, \ldots, c_K} \left( U(w, \{c_1, \ldots, c_K\}) - \mu_{c_{r+1}} \cdots - \mu_{c_K} \right).
$$

Now, after relaxation of all but two clusters, and for a given set of multipliers (one multiplier for each relaxed node constraint), using the modified utilities $\tilde{U}^{(2)}$ instead of $U$, the relaxed problem in (4) is equivalent to a two-dimensional assignment problem, which we solve using the auction algorithm. We then successively enforce the relaxed constraints cluster by cluster, again using the auction algorithm but with modified costs $\tilde{U}^{(r)}$ when assigning sensors in $C_r$.

This will most likely lead to a sub-optimal assignment with respect to the primal objective in (2), but from duality theory [10, chap. 5], we know that, for all multiplier vectors, we have

$$
q(\mu) \geq f \geq f^*,
$$

where $q(\mu)$ is the dual objective function value in (4) (in fact relaxed to arbitrary number of clusters [11]), $f$ is any primal feasible objective function value, and $f^*$ is the (unknown) optimal primal objective function value. We therefore iteratively minimize $q(\mu)$ over $\mu$, while at each iteration successively enforcing constraints on $\{C_i\}_{i=2}^K$ to get a primal feasible (sub-optimal) solution. As the algorithm proceeds, we compute the "duality-gap" between our best primal objective value found so far, and its upper bound, i.e., the smallest value of $q(\mu)$ found so far.

To minimize $q(\mu)$, we employ a sub-gradient method [10]. After enforcing constraints on clusters $\{C_k\}_{k=1}$, we update multipliers for each node in $C_{i+1}$ according to:

if $\exists(w_1, w_2, n)$ such that

$$
n = \arg \max_{c_{i+1} \in C_{i+1}} \tilde{U}^{(i+1)}(w_1, \{S_{w_1} \cup_{j=i+1}^K C_j\}, c_{i+1})
= \arg \max_{c_{i+1} \in C_{i+1}} \tilde{U}^{(i+1)}(w_2, \{S_{w_2} \cup_{j=i+1}^K C_j\}, c_{i+1}),
$$

then $\mu_n = \mu_n + \Delta$

if $\nexists(w, n)$ such that

$$
n = \arg \max_{c_{i+1} \in C_{i+1}} \tilde{U}^{(i+1)}(w, \{S_w \cup_{j=i+1}^K C_j\}, c_{i+1}),
$$

then $\mu_n = \mu_n - \Delta$.

Here $\Delta$ is a positive quantity similar to a step-size, see [10,11] for discussions on this step-size and its selection. Intuitively, the sub-gradient update approach can be interpreted as follows: If, after
fixing the assignment up to and including cluster $C_i$, two or more slots have a given sensor in $C_{i+1}$ as their preferred choice in terms of interference conditions, then the ”price” of this sensor is increased. If there exist a sensor that no slot has as its preferred choice, then the price of this sensor is reduced.

The method may not converge in a finite number of iterations. However, we do obtain a duality gap at each iteration which bounds the distance to the optimal solution. This gap may indicate an acceptable solution quality and allow a premature termination of the algorithm.

4 Numerical analysis and discussion

In order to verify that the proposed method results in SINR improvements, we evaluate the algorithm by computer simulation. For all considered scenarios, we let $\Theta = 10$ dB, $d_0 = 1$ m, and $P_0/P_{N_k} = 10$ dB, for all nodes. With these system parameters, the transmission range, defined as the range at which receiver SNR (in absence of interference and fading) goes below $\Theta$, is

$$R_{tx} = d_0 \sqrt{\frac{P_0}{P_{N_k} \Theta}} = 1 \text{ m}.$$ 

To emulate a network where a clustering procedure has been executed, we randomly deploy $KW + \delta$ nodes over a square area with side $4R_{tx}$, and its lower left corner at $0_2 = \left[0, 0\right]^T$. A very simple clustering algorithm is then executed: (a) The node closest to $0_2$ is chosen, together with the $W$ nodes closest to the chosen node. (b) One of the chosen nodes is randomly selected as sink. (c) The resulting cluster is removed from the deployed nodes, and the process is repeated until $K$ clusters has been formed. The extra $\delta = 2 \max\{W, K\}$ deployed nodes has the effect of making the last formed clusters have co-located nodes. The proposed algorithm was then run until the duality gap was less than 0.1 % of the best found objective function value, or until a maximum of 100 iterations.

After running the proposed algorithm, we evaluate the utility $U_p(w, S_w)$ for each cluster and slot. This utility is then compared to the average utility obtained over $A = 10$ random assignments in the generated topology. As a performance metric, we define the
gain $G_p$ at cluster $p$ and total network gain $G$ as

$$G_p = \frac{\sum_{w=1}^{W} U_p(w, S_w)}{\frac{1}{A} \sum_{a=1}^{A} \sum_{w=1}^{W} U_p(w, R_{w,a})},$$

(6)

$$G = \frac{\sum_{p=1}^{K} \sum_{w=1}^{W} U_p(w, S_w)}{\frac{1}{A} \sum_{a=1}^{A} \sum_{p=1}^{K} \sum_{w=1}^{W} U_p(w, R_{w,a})},$$

(7)

respectively, where $S_w$ is the assignment for slot $w$ generated by the proposed algorithm, and $R_{w,a}$ is the $a$th randomly generated assignment for slot $w$. The expected gain of a random assignment is zero, while a positive gain means we have improved on SINR conditions.

### 4.1 Two clusters

We first investigate a scenario where there are only two clusters. In this case, as mentioned in Sec. 3.1, the auction algorithm of App. 6 yields an $\epsilon$-optimal assignment with respect to the defined objective function.

Two clusters, each with eight nodes were generated according to the procedure described above. The simulations were repeated 500 times, each with a new node layout and fading coefficient realization.

The results, in terms of the cumulative density function (CDF) of the gains in (6) and (7) are plotted in Fig. 1. Here, we first optimized the utility function for cluster one, and then for the sum of utilities of both clusters. As expected, the single cluster gain is higher when we disregard SINR at the other cluster, compared to the total network gain where both clusters are considered. Also, the total network gain when optimizing for only the first cluster is reduced as compared to the joint optimization case. Somewhat surprising is the fact that the utility of the second cluster, when optimizing only for the first, remains at approximately the level obtained using a random assignment for both clusters (not shown). Thus, the second cluster does not suffer from the greedy scheduling performed at its neighboring cluster. This has some interesting implications in scenarios where we cannot control the scheduling of neighboring clusters.

### 4.2 Multiple clusters

Next, the network density was increased, i.e., the deployment area was kept the same, but four clusters of eight nodes each were
formed. The results, again in terms of the CDF of network gains generated by 500 simulation runs, are shown in Fig. 2. When performing a joint optimization considering all clusters, gains in excess of 18 percent occurred in more than half of simulation runs. The upper bound on gain which is obtained by replacing $U_p(w, S_w)$ in (7) by the smallest found dual function value, $q(\mu)$, is also plotted in this figure. We note that the gain after 500 iterations is very close to the upper bound. We also plot the total network gain achieved with only one iteration of our algorithm. The results show that a large part of the gain can be obtained with only one iteration. A greedy algorithm that only executes $K$ consecutive auction algorithms (similar to the two cluster case) may therefore be employed, at least in the scenario considered here, without significant performance degradation. This conclusion is of importance in networks where complexity is a limiting factor, although we emphasize that there are no guarantees that this behavior occurs for all network layouts and scenarios. It should be noted that in the case of multiple clusters, our algorithm is not guaranteed to converge to an optimal assignment, as was the case for the two-cluster case. However, for the simulations shown in Fig. 2, our algorithm converged to within 0.1 percent of the optimal objective function value in 40% of all cases. A duality gap below 4% of the best found objective function value was attained in 85% of cases, while the worst case duality gap was approximately 7%. Thus, for all practical purposes, the algorithm performed well in terms of convergence.

Figure 1: CDF of cluster and network gains, two cluster scenario
5 Conclusions and future work

In this paper we have shown that a significant increase in packet delivery probability is achievable in TDMA-type clustered sensor networks if the scheduling at neighboring clusters are considered jointly. In our consideration of the problem, we include realistic effects, such as Rayleigh fading, something that is often neglected in the literature. Numerical evaluation of the proposed scheme show performance improvements in the range 10 – 30 % in the packet delivery probability as compared to random assignments, in a majority of simulated scenarios.

Many interesting aspects of this problem has been left for future work. For instance, additional improvements could be achieved if sensors were not required to transmit in each frame, instead deferring their transmissions if overall conditions are not favorable. Also, the impact of synchronization errors among clusters should be investigated. This will surely be an impairing factor on performance, and must perhaps be countered in some way. An even more realistic model of the communication system and packet-loss causing effects would also be of interest.

6 Appendix: Auction algorithm

Consider the problem (3). By relaxing the constraints on sensors in cluster two, and stacking multipliers in vector $\mu$, we obtain the
Lagrangian

\[ \mathcal{L}(I_{w,c_2}, \mu) \]

\[ = \sum_{w=1}^{W} \sum_{c_2 \in C_2} (U(w, c_2) - \mu_{c_2}) I_{w,c_2} + \sum_{c_2 \in C_2} \mu_{c_2} \]

subject to

\[ \sum_{c_2 \in C_2} I_{w,c_2} = 1, \forall w \in \{1, \ldots, W\}. \]

where \( U(w, c_2) = U(w, \{S_w \setminus C_2\}, c_2) \). Thus, the dual problem is

\[ \min_{\mu} \sum_{w=1}^{W} \max_{c_2} (U(w, c_2) - \mu_{c_2}) + \sum_{c_2 \in C_2} \mu_{c_2} \]

subject to

\[ \sum_{c_2 \in C_2} I_{w,c_2} = 1, \forall w \in \{1, \ldots, W\}. \]

This problem can be solved (to within any \( \epsilon > 0 \) of the optimal solution) by the following algorithm: (a) Let each slot \( w \) successively "make a bid" for the sensor \( i = \arg \max_{c_2} U(w, c_2) - \mu_{c_2} \) that yields the highest net value \( v_i = U(w, i) - \mu_i \). (b) After purchasing the sensor, its "price" \( \mu_i \) is raised by \( v_i - z_i + \epsilon \), where \( z_i = \max_{j \neq i} U(w, j) - \mu_j \), i.e., the second best net value. (c) The slot, if any, that owned the recently purchased sensor is set to discontent, and the process is repeated until all slots are content with their purchase. For additional details and results on the auction algorithm, the reader is referred to [10, chap. 6], and references cited therein.

References


