Resource Coordination in Wireless Sensor Networks by Combinatorial Auction Based Method

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Abstract— Wireless Sensor Networks (WSN) consists of small sensor devices with sensing, processing and communication capabilities. Sensor nodes are operated by batteries. As the replacement of these batteries are not practical, this network is very much energy sensitive. Resource coordination is an important issue to make this system energy efficient. Sensor nodes can be applied in various applications. Object tracking, routing, event detection are some common applications in WSN. These application needs to perform some tasks like sensing, transmitting, sleeping, receiving etc. At each time step, the sensor nodes need to perform one task based on its application demand. Scheduling of these tasks is very important aspect for WSN in order to coordinate the resources. In this paper, an effective market based method is proposed for resource coordination in WSN. At first the description of the problem is presented then the combinatorial auction based method is proposed. The simulation results show the efficiency of the proposed method comparing with other existing methods.

Keywords- Resource Coordination; Wireless Sensor Networks; Market Based Methods and Combinatorial Auction.

I. INTRODUCTION

The effective coordination of the available resources is a very important aspect in resource limited systems such as wireless sensor networks (WSN). In general resource coordination means to regulate or manage the resources in such a way that the planned tasks can be achieved effectively. There are various resources of interest in wireless sensor networks such as energy, computing performance, memory, available information or data, communication capabilities and processing functionality [4].

As WSNs are resource constrained networks, resource coordination can be performed at individual nodes but also at part of network. There are several reasons for dynamically maintaining the resources: for example to increase the lifetime of a network, to overcome the problem of resource deficit especially when sensors exhibit failures, to maintain the runtime adaptation of resources and to determine the best allocation of tasks to resources.

This paper proposes a market based method for resource coordination in WSN. We apply combinatorial auction based method for the resource coordination. Our simulation results show better performance. We also model a sensor network with this combinatorial auction based method and prove its efficiency comparing with existing techniques.

The rest of this paper is organized as follows. In section 2, the description of the problem and design challenges on resource coordination in WSNs are discussed. Related works are discussed in section 3. The model applied with combinatorial auction based method is described in section 4. Object tracking application is discussed in section 5. Simulation results and evaluation are described in section 6. We conclude with final remarks in section 7.

II. PROBLEM DESCRIPTION AND DESIGN CHALLENGES

A Wireless Sensor Network (WSN) consists of many untethered sensor nodes with sensing, processing and communication capabilities. As a WSN is very much application specific and resource constrained, careful consideration should be given to resource coordination.

Object tracking, area monitoring, coverage, clustering, routing and in-network data aggregation are some of the common applications in sensor networks. For these applications sensor nodes need to perform some tasks like sensing, transmitting, receiving, sampling, sleeping etc. For resource scarcity it is very much needed to coordinate the resources. It is also necessary to perform a specific application by applying some tasks with effective usage of resources.

Generally a WSN node can perform one of the following four tasks at each time step: transmit, receive, sleep and sense. Each task corresponds to a specific power consumption level. Energy consumption in sense task is relevant to a specific application, while energy consumptions in other tasks are related to work process of a node. In addition, energy consumption for the radio component in a node is much greater than that of other components in the majority of WSN applications [2]. Therefore, the energy consumption per time unit, the transmit task usually consumes the most energy, receive consumes second to transmission, then sense and sleep task consumes the least among these tasks.

Resource coordination allows sensor nodes to self schedule its tasks with only local information. It helps to find out the best allocation of tasks to resources for the specific application by performing some triggering activities. It also assists to learn usefulness of tasks in any given state to maximize the total amount of reward over time. This triggering can be performed by several ways such as offline, periodic, on demand or can be issued by changes in network [3].

For example, if some sensor nodes are scattered in a particular area for object tracking application, it needs to model the network in such a way that it can efficiently allocate its tasks to resources. For object tracking the tasks needed for the sensor nodes are sampling, transmitting, receiving, aggregating and sleeping. If we apply resource coordination in this system for object tracking, it needs to model this in such a way that it can maximize the network lifetime over time. That means resource coordination maintains the quality of service by best allocation of self scheduled tasks to resources with adaptive support in dynamic environment.

As a WSN is resource constrained network, there are challenges for performing resource coordination. Some of the challenges and design issues are as follows:

Autonomous coordination: Autonomous coordination is an important and challenging issue for resource coordination. As a static or human controlled approach is not feasible in such dynamic networks, it is necessary to consider this issue.

Adaptation of resources: As WSN is resource constrained, we need to think about the proper adaptation of resources to the distributed nodes.

Best allocation of tasks to resources: To find out the best allocation of tasks to resources is another challenging issue. The tasks should be performed in such a way that always it maintains the best allocation of resources to nodes.

Emergent coordination: The coordination should be emergent over time which helps to maximize the collective reward over time.

Scalability: The coordination should be scalable. Added new nodes in the system should not affect the performance of the coordination mechanism.

Robustness: It should be robust in case of failure of nodes. Coordination should be performed in such a way that the failure of links or nodes does not affect the coordination mechanism.

III. RELATED WORKS

In distributed networks, the goal is to build a collaborative environment for facilitating the effective usage of resources [11]. Resource coordination research addresses this issue and aims at creating an environment where nodes are able to manage the different resources. They can cooperate to provide value-added services such as to increase the lifetime of the network, which could not be provided if the nodes were to operate individually. To find out the best scheduling of tasks in a collaborative environment is a challenging issue for resource coordination. Only a few related works are available which considers tasks scheduling for resource coordination. Most of the existing methods do not provide online scheduling of tasks. There is no work which considers the cooperation of nodes for resource coordination. Combinatorial auction is a method that can be applied online to the system and helps to coordinate the resources.

N. Edalat et al. [1] proposed a combinatorial auction based method for resource management in wireless sensor networks. In their approach, the total system is centralized. They have considered application manager and centralized auctioneer for their work which is not suitable for distributed wireless sensor networks. They have considered the tasks sharing among multiple applications. They have not considered the tasks scheduling for individual nodes which can maximize the total utility of the network. In [8], a predefined static action scheduling approach is proposed. T. Liu et al. [9] proposed random selection of tasks for scheduling. We have compared our approach with these existing approaches. It results in a better performance comparing to these in terms of cumulative reward over time and also in residual energy of the network. To our knowledge this is the first work which considered the tasks scheduling of nodes to coordinate the resources by combinatorial auction based method.

IV. COMBINATORIAL AUCTION BASED METHOD FOR RESOURCE COORDINATION

A market based approach for task scheduling in WSN for resource coordination is considered. Object tracking is considered as application here. This object tracking responsibility of sensor node *i* for an object can be expressed when its field of view, FOV=1 and data to transmit, DTT= 1. Here FOV is one variable which means the field of view of a sensor node and DTT is a variable which represents the data to transmit. When an object enters in the field of view of a sensor node then the variable FOV becomes one. That sensor node owns that object for tracking it and it may sell it to the other sensor nodes. So the sensor node who owns the object acts as an auctioneer and tries to sell the object to other node. It initiates an auction. The neighboring nodes calculate the objective function to win the object as its own. Objective function is as follows:

$$Objective(j) = \alpha.S^{j} + \frac{\beta}{\eta^{j}} + \frac{\gamma}{D^{j}}$$

Where the node j has the signal strength S^{j}, the node with higher signal strength carries more information about the target.The resource price η^{j}, the node with lower resource price should be given priority as the node can perform a task with lower resource price can maintain the resource efficiency in the system and the term D^{j} defines the distance between the target and the node. α , β and γ are equilibrium constant. The term η^{j} can be calculated by the following parameters. Required CPU cycle (R_{CPU}): It refers to the expected CPU cycle required for accomplishing the task.

Available CPU: It is sensor node's CPU clock frequency.

Computation Cost: It can be calculated by the following equation that is used in [5].

$$CompCost(R_{CPU}, f) = NCV_{dd}^2 + V_{dd}(I_0 e^{\frac{V_{dd}}{nV_T}})(\frac{R_{CPU}}{f})$$

$$f \cong K(V_{dd} - c)$$

Where v_T is the thermal voltage and C, I_0, n, K and c are processor dependent parameters.
Remaining Energy (*E*): It refers to the remaining energy of the sensor node.
Ideal gap (T_{IG}): It is a gap between the time that sensor nodes accomplish the task and the time that sensor nodes communicate the task's output to its neighbor. If the ideal gap is very large, the incentive for the task would rather decrease.

The resource price is calculated by the following equation:

$$\eta^j = (\frac{CompCost}{E}) \times \exp(T_{IG})$$

Where *CompCost* refers to Computation cost, *E* refers to remaining energy and T_{IG} means ideal gap [5]. After calculating the resource price, the sensor nodes will bid for the object to track it. Now we need an algorithm that will find out the winner and the bids that will maximize the revenue of each agent as we consider the sensor nodes here as agents in a multi agent environment.

We use Combinatorial Auction named Progressive Adaptive User Selection Environment (PAUSE) auction method [7].

A PAUSE auction for m items has m stages. Stage 1 consists of having simultaneous ascending price open-cry auctions for each individual item. During this stage the bidders can only place individual bids on items. At the end of this state we will know what the highest bid for each individual good is and who placed that bid.

In each successive stage k = 2, 3, . . . ,m we hold an ascending price auction where the bidders must submit sets of bids that cover all goods but each one of the bids must be for k goods or less. The bidders are allowed to use bids that other agents have placed in previous rounds when placing their bid, thus allowing them to find better solutions. Also, any new bid set has to have a sum of bid prices which is bigger than the currently winning bid set.

At the end of each stage k all agents know the best bid for every subset of size k or less. Also, at any point in time after stage 1 has ended there is a standing bid set whose value increases monotonically as new bid sets are submitted. Since in the final round all agents consider all possible bid sets, we know that the final winning bid set will be one such that no agent can propose a better bid set. Note, however, that this bid set is not guaranteed to be the one that maximizes revenue since we are using an ascending price auction so the winning bid for each set will be only slightly bigger than the second highest bid for the particular set of goods.

The agents maintain a set B of the current best bids, one for each set of items of size $\leq$ k where k is the current stage. As our bid is composed of some items or parameters, we use combinatorial auction. Combinatorial auction is useful to deal with the bids combined of some items [8].

At any point in the auction, after the first round, there will also be a set W $\subseteq$ B of currently winning bids. This is the set of bids that currently maximizes the revenue, where the revenue of W is given by-

$$r(W) = \sum_{b \in W} b^{value}$$

Agent i's value function is given by where S is a set of the items. Given an agent's value function and the current set of winning bids W we can calculate the agent's utility from W as

$$u_i(W) = \sum_{b \in W / b^{agent}=i} v_i(b^{items} - b^{value})$$

That is, the agent's utility for a bid set W is the value it receives for the items it wins in W minus the price it must pay for those items. If the agent is not winning any items then its utility is zero. The goal of the bidding agents in the PAUSE auction is to maximize their utility.
Formally, given that W is the current set of winning bids, agent i must find a g^* such that $r(g^*) >= r(w) + \in$

Algorithm PAUSEBID:
PAUSEBID (i,k)
Initialize:
    my-bids $\leftarrow \phi$
    their-bids $\leftarrow \phi$
for b $\in$ B **do**
  if b^{agent} = i or $v_i(b^{items}) > b^{value}$ **then**
   Set my-bids $\leftarrow$ my-bids + new Bid (i, b^{items}, $v_i(b^{items})$)
   else their-bids $\leftarrow$ their-bids+b
   end else
  end if
 for S $\in$ subsets of fewer items such that
      v_i (S) > 0
 Set my-bids $\leftarrow$ my-bids + new Bid (i, S, $v_i(S)$)
   bids $\leftarrow$ my-bids+their-bids
   $g^* \leftarrow \phi$
   $u^* \leftarrow u_i(W)$
MAXIMUM(bids, φ)
surplus $\leftarrow \sum_{b \in g^* / b^{agent}=i} b^{value} - W(b^{items})$
 if surplus=0 **then**
   return g^*
 end if
my-payment $\leftarrow v_i(g^*) - u^*$

for $b \in g^{*} / b^{agent} = i$
if my-payment $\le$ 0
$b^{value} \leftarrow 0$

else

$b^{value} \leftarrow W(b^{items})$ + my-payment. $\dfrac{b^{value} - W(b^{items})}{surplus}$

end else
end if
end for
end for
end for

return g^{*}
MAXIMUM (bids, g)
for each iteration **do**
sort the bids in increasing order
N= {bid_1, bid_2,….bid_n }
for i=1 to n
Set $T_n \leftarrow$ the task for which the bidder bids.
Set g $\leftarrow$ the list of bids in increasing order.
end for
end for

V. OBJECT TRACKING APPLICATION USING OUR APPROACH

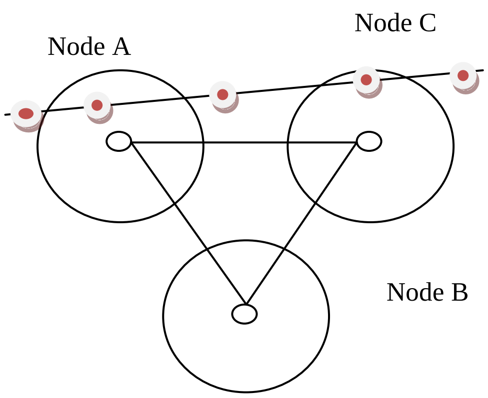

Figure 1. Object tracking example.

We consider the movement of the object as simple random walk. After certain time period, the object moves in to the field of view of a particular sensor node.

Figure 1 shows the one walk of a single object, ie. the "red dotted circles" represents the object's position at different time points. Consider three nodes, which are fully connected. Each node has no information of what actions are better for them in terms of energy consumption. They will learn by performing some actions over time based on their utility.

Nodes A, B and C have no idea about what tasks are better for them. Node A, B and C are only aware about the application oriented tasks. Here we consider the tasks needed for object tracking. These are transmit, receive, sleep and sense.

Stage 1 consists of having simultaneous ascending price open-cry auctions for each individual task. During this stage the bidders (the sensor nodes) can only place individual bids on items. At the end of this state we will know what the highest bid for each individual task. Every node maintains a set B of the current best bids, one for each set of items of size $\le$k where k is the current stage. At any point in the auction, after the first round, there will also be a set W $\subseteq$ B of currently winning bids. All bids are broadcasted and when a node receives a bid from another node it updates the set of best bids and determine if the new bid is indeed better than the currently winning bid.

After performing the PUASEBID algorithm node A will aware that it gets maximum utility for the sensing first, then transmit, after that receive and finally for sleep at this scenario. In this way, Node B will aware the scheduling order is sleep, receive, sense and transmit according to this scenario. Node C will aware that it will be sleep, sense, transmit and receive.

VI. SIMULATION RESULTS AND EVALUATION

In our simulation we have considered four tasks or items. These are transmit, receive, sleep and sense. It consists of three agents or sensor nodes. Each of the sensor nodes are equipped with microprocessor with the CPU frequency randomly selected between 100 MHz and 300 MHz and initial energy level of each node is 2.8 Joule. The other parameters for computational and communication energy consumption are V_T =26 mV, C=0.67 nF, I_0=1.196 mA, n=21.26, K=239.28 M Hz/V, c=0.5, α =0.5, β =0.5 and γ =0.5 used for calculating the computational cost communication energy in [5]. The signal strength and the distance from the target are randomly chosen from the values between 1 to 10.

To calculate the resource price we need the following information for performing the tasks:

Required CPU cycle:
Sensing: 10 M Hz
Transmit: 26 M Hz
Receive: 26 M Hz
Sleeping: 0
Energy requirement:
Sensing: 0.0000841 J
Transmit: 0.00233 J
Receive: 0.00231 J
Sleeping: 0.000012 J
Ideal time gap:
Sensing: 25 msec
Transmit: 10 msec
Receive: 10 msec
Sleeping: 0

We have calculated the variance of the available energy as Var= $\frac{1}{n}\sum_{i=1}^{n}(E_i - \overline{E})^2$, where n is number of sensor nodes, E is the remaining energy level of sensor nodes and $\overline{E}$ is the mean which is calculated as $\overline{E} = \frac{1}{n}\sum_{i=1}^{n} E_i$. The higher variance value corresponds to the unbalanced available energy among the sensor nodes and also not energy efficient [6]. According to our simulation, we have found the better performance than static and random scheduling. So, it can be used for online scheduling of tasks.

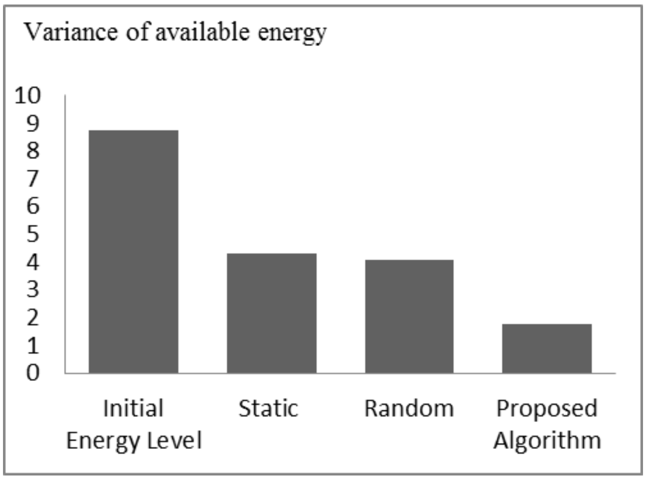

Figure 2. Variance of the available energy for different methods.

The simulation results in figure 2 shows that our proposed algortihm gives better performance in terms of energy efficiency comparing with static and random scheduling of tasks.

Figure 3 shows the residual energy of the network at each time step. We can observe that our proposed algorithm gives better performance comparing with other existing techniques.

In figure 4, we show the task scheduling of node A, B and C considering the case of figure 1 with combinatorial auction based method. Each node has no information of what tasks are better for them and try to learn over time based on the utility of their tasks.

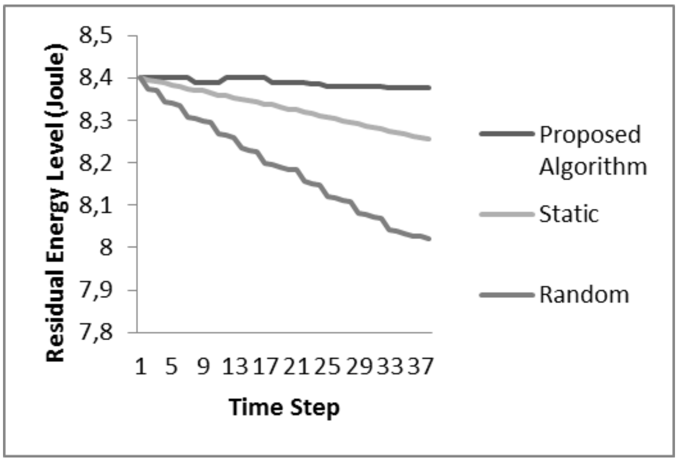

Figure 3. Residual energy of the network.

For example, node A does not know that it needs to sense as object is in its field of view. Here each bar represents a task executed at each time step. We represent “Receive”, “Transmit”, ”Sense” and “Sleep” tasks in descending order of height of the bars. We can observe that node A immediately learns that it is getting paid to sense as object is in its field of view. In the middle of the simulation time, as the target is out of reach of all sensor nodes, all nodes will be rewarded for sleeping. Similarly, we can observe that for node C, it will be rewarded for sensing after some times when the object is in its field of view. After that when the object is out of reach of all sensor nodes, all the nodes will be rewarded for sleeping.

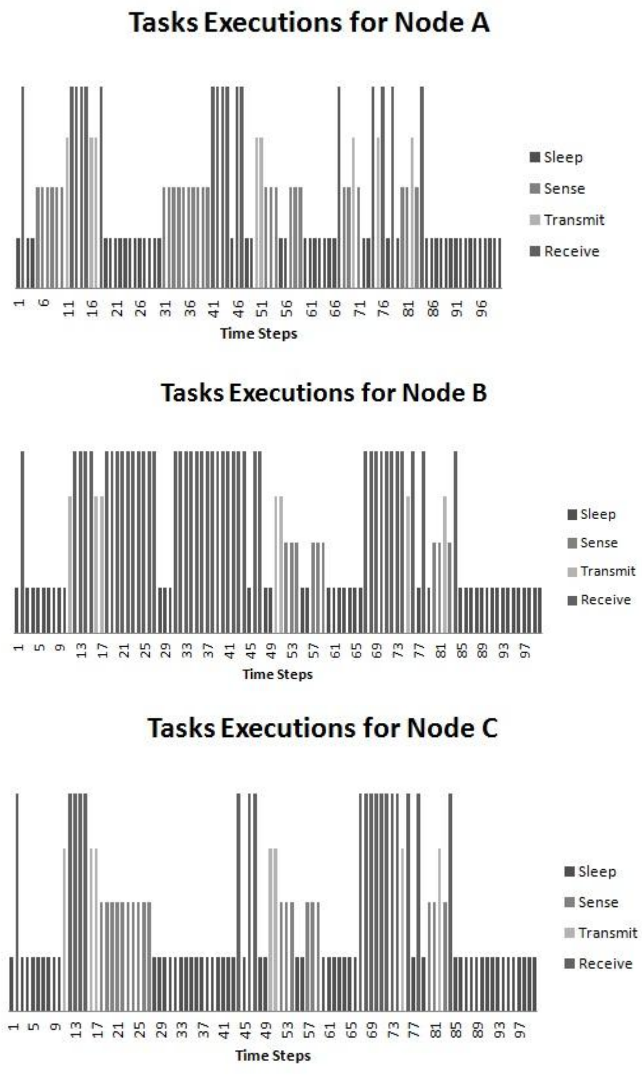

Figure 4. Task executions for Node A, B and C

We also calculated the revenue of the network by NetLogo simulator. Three agents are considered for this simulation. On each agent, the porposed algorithm is implemented. Figure 5 shows the cumulative revenue for the network with three agents. We can observe the cumulative revenue of the network converges after certain time periods.

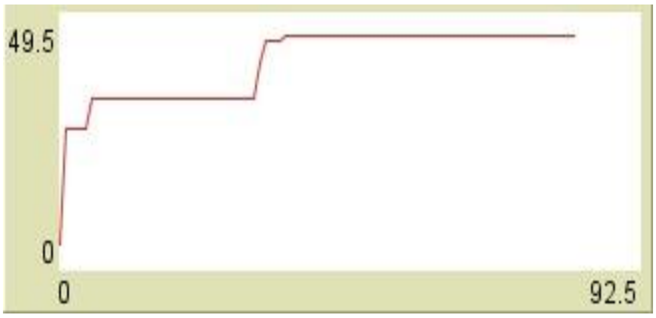

Figure 5. Cumulative reveneue of the network with three agents.

From the simulation result and evaluation, we can say that by applying combintorial auction based method it is possible to learn the usefulness of actions to perform in different states. Our proposed method scheduled the tasks in such a way that the energy consumption is reduced. It also receives better cumulative revenue over time comparing with other approaches. The resudual energy of the network also remains more in our proposed approach comapring with other approaches.

VII. CONCLUSION

Effective resource coordination is an important issue in WSN. To increase the lifetime of the network and to overcome the problem of resource deficit, resource coordination is very necessary. Tasks scheduling is an effective way for resource coordination [4]. We have used a combinatorial auction based approach for tasks scheduling. Our simulation results show that our approach gives better scheduling comparing with other methods. It also improves the cumulative revenue over time. It also gives better performance for residual energy of the network which helps to increase the lifetime of the network.

The paper is based on our initial work to apply auction based algorithm for action scheduling in sensor networks. We have not considered so many states and tasks for our work. To design our state space with more dynamic variables of the environment, to take the consideration of processing as an action is one aspect of our future work. We have performed our experiments on a fully connected topology. To apply our algorithm in random deployment of nodes with different topologies can be another future work. To apply other market based algorithms and to find out the efficiency comparing with our proposed approach can extend our future work.

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