Multiagent Co-ordination of Wireless Sensor Networks

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Abstract. Wireless Sensor Networks (WSNs) are generally composed of a large number of battery operated nodes with limited capacities. Therefore, a main challenge in the management of a WSN is how to reduce the energy consumption while maintaining a good quality of the sensed data. Artificial intelligence techniques like multiagent coalition formation can help on this. In this paper we propose an algorithm called *Coalition Oriented Sensing Algorithm* and test it in a realistic scenario. We experimentally show how this new algorithm allows nodes to self-organise: nodes perform a good monitoring of the environment while maximising the life span of the overall sensor network.

Keywords: Wireless Sensor Networks, Sensor Coalitions, Resourse Saving Strategies.

1 Introduction

Wireless Sensor Networks (WSNs) are networks formed by a large number of battery-operated sensing nodes to develop monitoring tasks in different environments. Each node is a low-cost, low-consumption device of limited capabilities, yet able to sense its environment and communicate wirelessly. As the nodes are cheap and easy to deploy, this technology allows to perform surveillance tasks in very large physical spaces. Moreover, the large numbers of nodes make these networks very robust to individual node failures, enabling them to operate in remote, hazardous environments. These characteristics, plus their non invasive nature, make WSNs appropriate for a great range of monitoring applications. As a result, WSNs have been applied to a number of different domains, such as environment monitoring, security control, military surveillance, and traffic control.

Depending on the application environment and its accessibility, the challenges posed by these systems can be more or less acute, especially those referred to the limited energy availability. Multiagent System (MAS) technologies can help in alleviating such constraints by introducing coordination mechanisms between sensors.

In MAS approaches, the nodes are understood as agents that can coordinate among themselves to improve their efficiency. This paper exploits that multiagent

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viewpoint to develop energy-saving data treatment strategies for WSNs. This is, nodes will coordinate to extend the life span of the network while maintaining a certain quality of the information transmitted (the main purpose of the network). In a generic scenario, the task of a sensor is to sense the environment and relay the collected data to a server node, the *sink*, where this information is further processed.

The main contribution of this paper is the Coalition Oriented Sensing Algorithm (COSA). COSA aims at exploiting the periods of invariance in (parts of) the environment. It implements a strategy for (not necessarily optimal) coalition formation in WSNs. Thereafter, only coalition leaders have to sense and transmit information, allowing the rest of the nodes to save energy. This is, COSA implements a mechanism that provides a trade-off between *information accuracy* and *energy consumption*.

As a result, the network's life span is increased at the expense of reporting less data to the sink. However, coalitions are made in such a way that the non-transmitted data do not cause a deterioration in the system performance. COSA is fully distributed in the network and robust to failures in individual nodes. Also, it assumes that the nodes are fully cooperative, as WSNs are built to serve the owner's goal.

Thereafter, we demonstrate the benefits of COSA by means of an empirical evaluation. Since deploying a full sensor network requires big investments, the experiments have been carried out in a simulation environment. Therefore, we modelled a scenario where the sensors are deployed along the course of a river, with the objective of monitoring it to detect sources of pollution. The simulation has been implemented using RepastSNS, a simulator especially designed to test sensor networks from a multiagent perspective. Further, we also run simulations where the sensors do not cooperate, sensing and transmitting data independently. The obtained results show that COSA is able to significantly extend the network's lifetime, without losing accuracy of the information received at the sink.

The rest of the paper is organised as follows. In Section 2, we revise some important contributions in the area of WSN and coalition formation in MAS. Section 3 is dedicated to the presentation and characterisation of COSA. The simulation model that we have used to test it is described in Section 4. Section 5 presents the experimental results obtained and finally, conclusions and future work are discussed in Section 6.

2 Related Work

From a MAS perspective, coalitions represent a fundamental form of organisation, as it allows the agents to organise themselves in coalitions. Agents then cooperate within the coalition in order to share resources or reach shared goals that cannot be achieved individually. Agents' association to perform a task has been considered almost from the initial conception of the MAS paradigm. The approach taken for the design of these coalition or groupal strategies have evolved as the MAS application environments diversified. Therefore, a whole range of different coalition formation (CF) mechanisms exist depending on the conditions and characteristics of the application scenario and the nodes composing the network.

The application of CF techniques to distributed sensor networks has been investigated by numerous researchers, as it is the case of [1]. In this work, a negotiation process and individual utility calculations lead the agents to discover their organizational relationships and, according to them, to group establishment for tracking tasks.

As typically deployed in dynamic scenarios, sensor networks should be inherently adaptive. Based on this idea, the Dynamic Regions Theory was proposed in [2]. According to this theory, the network partionates itself into several regions based on the individual nodes' current circumstances and the system global policy.

The influence of the network topology structure in a MAS perfomance for task solving has also been considered in different approaches, [3,4,5]. In these cases, the system divides itself into disjoint groups in order to accomplish the demanded tasks.

In the work of [3], agents can rewire their connections to their neighbours to form better coalitions. This can be done according to their degree of connectivity or a performance-based policy. The decision factor for rewiring in [4] is the similarity among neighbours and some task and group success indicators. Finally, the work of [5] enriched the previous one by considering a more realistic coalition model. However, none of these three approaches takes into account the energy consumption and the cost derived from the rewiring pocilies.

Saving energy is one of the main objectives pursued by clustering algorithms proposed for WSNs, such as LEACH [6], EEHC [7] and HEED [8]. All these algorithms divide the sensor network distributedly into a set of non-overlapping clusters, each of them with a cluster head which is in charge of sending the collected data in the group to the sink. Our approach differs from these works in the way the cluster head is chosen, as the characteristics of the own node, its state and the perception their neighbouring nodes have of it are taken into account. A more recent approach to this problem is presented in [9], where a cluster based routing algorithm is introduced. In this case, the base station determines which the cluster heads are and implements also a centralised predictive filtering algorithm to decrement the amount of transmitted data. In contrast, we propose an approach in which the nodes make autonomous decisions without any centralised control.

In the same vein of reducing the number of transmissions, but far from the coalition/group perspective presented above,the work in [10] proposes an algorithm for individual node adaptive sampling that tries to extend the network lifetime of a glacial sensor network. This same goal is also pursued in the work of [11], in which a real deployment of an automated wildlife monitoring system is presented. In contrast to these previous works, we propose a CF strategy for homogeneous nodes in a sensor network scenario that allows to extend the useful life time of the network by avoiding redundant sensing and transmission. This group formation strategy is based on the nodes' state and the conditions of the environment. There is no intervention of any central authority and the algorithm is fully distributed and embedded in the nodes' behaviour. The main objective of the algorithm is achieved by allowing nodes in a coalition to delegate their sensing tasks to other neighbouring nodes, while restricting the maximum information loss, therefore the initial purpose of the system —faithfully monitoring the environment— is not missed.

3 Algorithm Description

The *Coalition Oriented Sensing Algorithm* (COSA) has been designed considering an scenario composed of a set $A = \{a_1, \ldots, a_N\}$ of cooperative and homogeneous agents (the network's nodes). We do not consider that agents can be competitive or selfish as in this kind of problems there are neither resources to fight for nor rewards to be won by the agents.

The basic behaviour of an agent a_i is to sense the environment and relay the observed measures to a server or *sink*.

As explained above, COSA's objective is to save system resources by allowing agents to form coalitions of agents that are perceiving very similar measures. Thereafter, a single agent can act as a representative for the whole coalition, avoiding redundant sensing and saving resources. To find an appropriate distribution of the agents in coalitions, we take into account the similarity of the individual measurements and the topology of the neighbourhood structure, which determines the neighbourhood relationships to be established among agents.

A *coalition structure* $c = \{g_k\}_{k:1..K}$ is defined as a partition of A in K groups. The criterion that guides the formation of the different coalition structures is to find (in a distributed manner) the best partition so that the energy consumption of the system is somehow minimised, while the accuracy of the information sent to the sink is constrained to a certain range. COSA appears as a tuneable algorithm thanks to the definition of a set of parameters p (to be explained later) whose values drive the agents' behaviour. Depending on p, agents take different kinds of sampling and *transmission actions*, represented as $m^j \in M_p$, where M_p is the set of existing actions available for that p configuration.

The objective of minimising the system's energy consumption is formally expressed in Equation 1. According to this equation, we try to find an optimal set of parameters $p*$, where m_i^j is the action j taken by agent i and E_j represents the energy consumption associated to that action. Measurements' accuracy is guaranteed through an adequate p parameters election.

$$p* = \operatorname*{arg\,min}_{p \in P} \Delta E = \operatorname*{arg\,min}_{p \in P} \sum_{m^j \in M_p} \sum_{a_i \in A} \# m_i^j E_j \tag{1}$$

Group formation among agents is based on a peer-to-peer negotiation protocol by means of which agents exchange information about their measurements and their adequacy to represent their neighbours. As a consequence of this negotiation, agents assume one of two possible roles : *leader*, if it is the representative of its coalition (where it may be the only member); or *follower*, if it joined a coalition lead by another agent. The main concepts that drive this negotiation are *adherence degree* and *leadership attitude*.

The *adherence degree* of an agent i to an agent j is a measure that indicates how much agent i intends to form part of a group led by agent j. The higher the degree, the higher the intention. The *adherence degree* is defined as the product of two factors. To evaluate those factors, we assume that the variable under observation follows a Normal distribution, $\mathcal{N}$. On the one hand, the first factor in the adherence equation (2) captures the similarity between the measurements of agents i and j. To avoid unproductive calculation, this factor is only defined for neighbour agents whose measurements verify that $\|x_j - x_i\| \leq d_{max}\sigma_j$, where d_{max} is a parameter and x_i, σ_j are the corresponding sample and deviation of agents i and j. On the other hand, the second factor captures the *goodness* of the neighbour's distribution and avoids obtaining high adherence values to neighbours with wide distributions. To achieve that, this factor restricts the evaluation to those neighbours whose σ belongs to the interval $(\sigma_{min}, \sigma_{max})$, through the evaluation of the distribution's entropy normalized on that range.

As a result, the evaluation of the degree to which an agent a_i may be interested in being led by one of its neighbours a_j is calculated as follows:

$$adh(a_i, a_j) = \frac{p(x_i, \mathcal{N}_j(\bar{x}_j, \sigma_j))}{p(\bar{x}_j, \mathcal{N}_j(\bar{x}_j, \sigma_j))} \cdot (1 - \frac{e^{H_j} - e^{H_{min}}}{e^{H_{max}} - e^{H_{min}}}) \qquad (2)$$

Note that the set of p parameters, as presented previously, can be identified now as $p = \langle d_{max}, \sigma_{min}, \sigma_{max} \rangle$ defined over the space $p \in \Re^3$. As previously stated, the set of values to which these parameters are set influences the actions that a node can take.

When an agent receives an adherence value from a neighbour, it has to decide whether it is interested in becoming the leader of this agent or not. Let us call $P(a_i)$ (potential group) the group formed by a_i and the agents willing to become part of a group led by a_i. The attitude of a_i as a leader of this group depends on different factors that can be identified in (3). The first factor is called *prestige* and it is an average of the adherence level of the group's members. The *capacity* factor indicates the available energy of the node to act as a leader. This value is derived from the current energy level of the node minus the security energy level (E_{sl}) divided by the maximum energy level available E_{max}. E_{sl} defines the minimum energy that the node has to keep to ensure sending one last message before completely depleting its battery.

Finally, the last factor in (3), *representativeness*, indicates how well the potential leader's measurement fits as a representative of the potential group agents' measurements. So, a_i characterizes the set of data received together with its own data, that is, the set $\{x\}_{P(a_i)}$, with their mean and standard deviation, noted as $(\bar{x}_{P(a_i)}, \sigma_{P(a_i)})$. To encourage the formation of groups with very similar measurements, an exponential function establishes the divergence growing ratio.

Those potential groups whose measurement distribution is very disperse are also penalized through the inclusion of the Pearson's coefficient in the equation.

A good group leader is an agent who has enough energy and whose measurements are similar enough to the measurements of the other group members. In summary, the leadership capacity of an agent a_i for its potential group $P(a_i)$ is calculated as follows:

$$\frac{\sum_{a_j \in P(a_i)} adh(a_j, a_i)}{N} \cdot \frac{E(a_i) - E_{sl}}{E_{max}} \cdot \frac{1}{e^{|x_i - \bar{x}_{P(a_i)}| CV_{P(a_i)}}} \tag{3}$$

This information exchange takes place following a certain operational protocol according to which, every agent involved in a negotiation with a neighbour goes through these phases:

- *Sample information exchange*. This process corresponds to the variable sampling and measurements broadcast.
- *Adherence graph construction*. Once the agent has calculated the adherence degrees to its neighbours, it communicates the maximum adherence value to the corresponding most preferred neighbour.
- *Leadership information exchange*. Based on the current adherence relationships, the agent calculates and communicates its attitude as a leader towards the agents willing to adhere to it.
- *Group definition*. Depending on the information available for an agent at a certain moment, it decides wether to stay in its current group (as a leader or dependant of a leader node), to leave this group to join a different one or to constitute its own group.

The set of performatives that the agents use to complete these stages are:

- *inform*: to indicate the transmission of data (measurements, maximum adherence and leadership values).
- *firmAdherence*: to express the desire of the sending node to adhere to the addressee node.
- *ackAdherence:* to express the acknowledgment to a previously received firmAdherence message.
- *break*: for a leader node to break a leadership relationship.
- *withdraw*: for a dependant node to break a leadership relationship.

The CF protocol is embedded in the agent generic behaviour. Agents behave in a proactive and reactive way. Proactive because the core behaviour of an agent is the continuous process of looking for the best group of neighbours that matches with its measurement and its state. To achieve this objective, an agent exchanges messages asynchronously with its neighbours. Reactive because their acts and decisions are triggered by the observation of the environment and the information they receive.

4 Simulation Model

Our experiments run over RepastSNS [12], an event-based simulator especially designed to model sensor networks as multi-agent systems. In RepastSNS, all the environment objects are modelled as agents that communicate via message passing. The platform is open source and developed in Java over Repast. It is designed as a two-layered structure with an object layer and a network layer. The object layer defines the behaviour of the individual sensors and the network layer defines the topology and the relationships among the sensors. The simulation platform is an extension of Repast classes, so the program structure of RepastSNS fits into this known MAS simulation engine.

All these characteristics make RepastSNS a general purpose simulation environment, that allows different application domains for WSN to be tested over it. This can be done without too much effort, as the environment provides a scalable and extensible infrastructure to build up networks of basic WSN components. The main task that a programmer has to do over this environment is just to configure and adapt its pre-defined elements (observable phenomena, sensors, agents, communication mechanisms) to the specific domain being modelled.

The advantage of using RepastSNS instead of any other network simulator such as ns2, OMNeT or J-SIM is twofold: (i) it provides for a more abstract level description than these other simulators, allowing the programmer to concentrate on the actual agent behaviour instead of dealing with hardware details; and (ii) it brings with it a convenient basic implementation of all the components needed to model wireless sensor networks.

To avoid confusions, from now on we will use the term *node* when we refer to a wireless sensor device and the term *sensor* when we refer to the specific physical device that measures a parameter of environment.

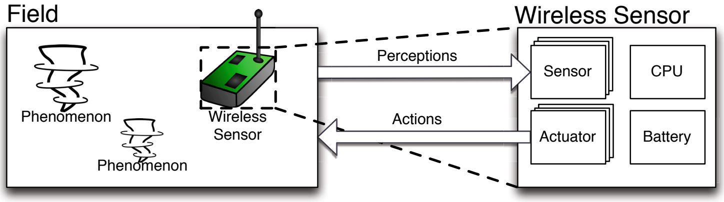

Fig. 1. RepastSNS simulation architecture

Figure 1 outlines the architecture of a sensor network simulation on RepastSNS. In RepastSNS all the observable phenomena are contained inside a *field* that includes the nodes themselves. Furthermore, the nodes are composed of multiple modules: a cpu, a battery, and any number of sensors and actuators. Sensors are those devices that allow the node to perceive the field's phenomena and their properties. Analogously, actuators allow the cpu agent to modify existing phenomena or produce new ones. This very simple model is surprisingly sound, as any phenomena or agent behaviour needed in a system can be easily modelled and incorporated. For instance, wireless radio interfaces can be modelled as an actuator that generates wireless waves (a phenomenon), plus a sensor that detects them.

5 Experimental Results

To demonstrate the proposed MAS algorithm, the experimental evaluation compares a WSN performance when it implements COSA and when it behaves according to a random sampling policy. Our main aim is to compare the energy usage of both approaches, as well as the accuracy of the data reported in each case. The two approaches deliver different data as the random sampling scheme implies that measurements taken from the environment are directly send to the general server, while the characteristic grouping imposed by COSA translates in association data sending.

5.1 Experimental Setting

COSA algorithm aims at faithfully monitoring the state of a dynamic environment and extending the life time of the network as much as possible. To test this, the scenario considered is that of a river, whose state is to be monitored. Different state variables and phenomena that could be sensed in this domain are water temperature, salinity or hydrocarbon presence. The deployment of the sensor network in such an environment can rely on the buoys and signalling elements deployed along the course of the waterway.

To correctly fit this application domain into the simulation platform, we start by defining a river phenomenon. This phenomenon represents a river section of 50 kilometers long by 2 kilometers wide, and it is composed of a grid of water cells. In order to mimic the effects of water flowing through the river, we define a simple river movement schedule that will cause that any phenomenon appearing in the river will be displaced by the current of the water. The model used to implement this functioning considers a drift component, a sedimentation component and a solvent component, i.e. the general intensity of the phenomenon reduces in time and a part of it remains in its origin, while the rest flows according to the strength of the current. Therefore if any contaminant is poured in a water cell, it will spread to its downward cells through time according to the following model $River(x,y) = (1-\rho)River(x,y) + \rho(\alpha(River(x-1,y-1)) + \beta(River(x,y-1)) + \gamma(River(x+1,y-1)))$. During each simulation run, three different contamination sources appear at random locations, but at specific times and keep spewing contaminant between 30 and 60 weeks.

The surveillance nodes are the ones responsible of monitoring the river's condition and informing the sink about their observations. As explained before, they are formed by a CPU, battery, sensor and radio. These components are modeled after Waspmote ones, real wireless sensor devices whose specifications are summarized in Table 1.

Two different kinds of surveillance nodes are considered according to the two sampling approaches proposed. Regardless the sampling policy nodes implement,

Table 1. Node components specifications

Component	Specification
Battery capacity	13000mAh@3.7V
CPU active consumption	9000uAh@3.3V
CPU sleep consumption	62uAh@3.3V
CPU hibernate consumption	1uAh@3.3V
Radio transmission consumption	210000uAh@3.3V
Radio reception consumption	80000uAh@3.3V
Radio bandwidth	156Kbps
Radio Sensing radius	1.5km
Radio sleep consumption	60uAh@3.3V
Sensor consumption	6uAh@3.3V
Sensor sampling time	1.63s

both kind of nodes have to send the collected data to a sink node. This sink node represents the central monitoring station to which the nodes deployed along the river are reporting to. In our setting, this agent has the ability to obtain the actual contamination values at any time at every point in the river, and can therefore determine the differences between node-reported values and the real ones. Differently from sensing nodes, the sink node does not take samples from the environment, neither is it constrained to low power or low processing capacity, as it acts as a server in the system, being part of the network control unit.

As previously explained, the system basic functioning consists of monitoring the environment through periodical samples collection. The way nodes deployed in the scenario behave to satisfy this purpose is what defines the applied sampling policy. The base case considered for the experimentation set is that of a random policy. The random setting presents a set of nodes (called random nodes) that take a sample from the environment at a random moment within the sampling period specified for the network.

The so called cf nodes (coalition formation) act according to the COSA algorithm presented in previous sections. Therefore, these nodes sample the environment periodically as expected, but instead of directly sending every individual measurement to the sink, these measurements are used to establish peer to peer negotiations with neighbourghs so that sensing groups can be formed. Consequently, only one node for each group (the leader) senses and sends information to the sink on behalf of the others, which delegate their tasks on it for a certain period of time.

The sink node in both scenarios receives the information collected by active nodes. In the random scenario, this information corresponds to every single measurement periodically collected by all the random nodes. The sensing task delegation among cf nodes may cause the sink to receive a group measurement representing the information associated to a set of nodes in a group. Assuming a common sample for a set of nodes may cause the loss of some pieces of information and consequently, some noise is added to the reported data.

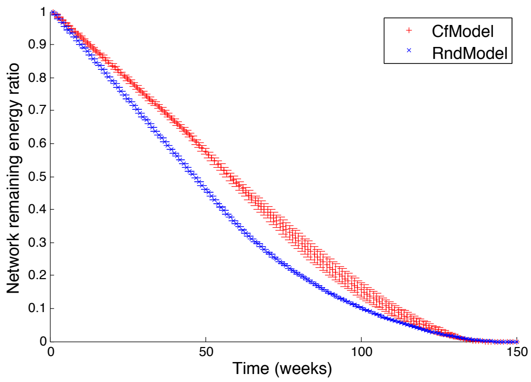

Fig. 2. Network remaining energy ratio

Finally, to completely define the experimental setup, Table 2 presents the values assigned to the COSA algorithm parameters as well as the sampling frequency demanded to the system. The number of nodes considered is set to 50 and their deployment along the river course is assumed to follow a regular chain distribution. Every node is situated in the middle of the river section considered and evenly spaced.

Table 2. Parameters' values

Parameter	Value
Sampling frequency	10min
d_{max}	1.75
σ_{min}	0.0005
σ_{max}	6
Node asleep time	1day

5.2 Results

To test if COSA achieves the objectives that inspired its definition, we study its performance in terms of the energy consumption and the quality of the reported information. The reference base for these two gauges are supplied by the random nodes' behaviour, as they follow a dummy sampling policy.

All the experiments have been run until every node in the network has completely depleted its battery, that is, for our experimental setting, 140 weeks. Figure 2 shows the ratio of network remaining energy for both kind of nodes, cf nodes and random nodes.

In this figure, as initially expected, we can observe how the COSA algorithm allows the network to keep a higher level of global energy than the random policy during most of its life time; however, both sampling policies lead to a very similar network death time.

The energy consumption curve obtained for the random nodes follows a stable pattern, whereas cf nodes present more variability, especially by the end of the experiments. This phenomenon is because COSA causes different group configurations to appear in the network over time. The influence of the group configuration reached in the network grows as the global energy in the system decreases. At these middle-end stages, the leader node situation and the available energy of the set of nodes still alive have a severe impact on the global energy level.

In contrast, the results obtained for random nodes clearly show the effect of their independent sampling behaviour. This is neither affected by their neighbours' state, nor by the dynamics of the environment. The decreasing energy curve, therefore, shows the effect of nodes dying, dependent on their distance to the sink. The extension of the useful life span of the network can be better identified in Figure 3.

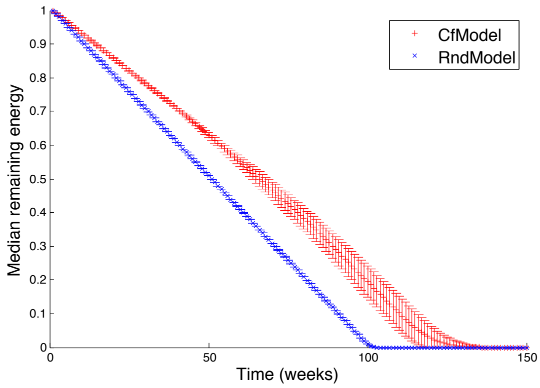

Fig. 3. Network median remaining energy

This figure shows the median of the nodes' energy values per week. We observe that half of the random nodes are already disabled by week 101, whereas this same value is reached over 30 weeks later for cf nodes (specifically by week 134). This result translates directly into better system performance during the network lifetime. COSA causes nodes' death to be evenly distributed, which guarantees that the network is going to get a fairly good representation of the whole environment, for most of its life time.

This result relates to the previous figure, as the nodes that deplete their battery first are the more distant ones to the sink. This means that the sink is blind to this area. Random nodes situated there are the first to die, while the ones situated near the sink keep most of their battery power and are the last to die, but are only able to sample the sink's surroundings. The even battery depletion in cf nodes causes a more simultaneous node death phenomenon, but in terms of global energy in the system, both policies reach zero level at the same time.

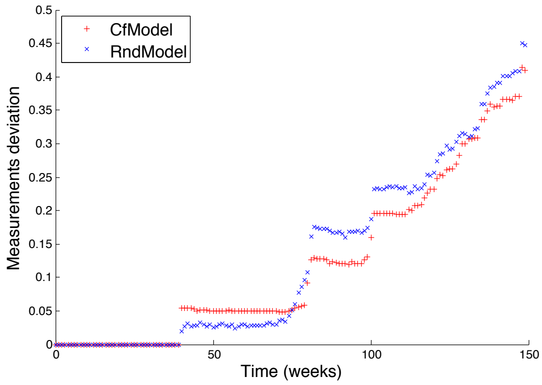

Fig. 4. Reported information deviation

Figures 4 and 5 represent the deviation of the information reported to the sink by random and cf nodes. When no pollution phenomenon has appeared yet, there is no deviation from the real environment state, but as a first pollution phenomenon appears (at week 40), the deviation value of the reported information changes. As both models have all their nodes fully operational by this time, we see that the resulting deviation of both models' reported samples is quite low (in fact, the lowest deviation from real phenomenon values is reached during this period).

Between weeks 40 and 80, the deviation corresponding to the data reported by cf nodes is slightly higher than the corresponding to the random nodes in the same period, with the maximum difference between them of only 0.035. Although both models provide really good representations of the phenomenon, cf nodes data is a little more deviated from reality due to the characteristic group sampling of COSA, which allows a leader node to send a sample on behalf of its dependent nodes. However, as random nodes begin depleting their batteries and becoming unable to sense, the deviation of the information they report quickly deteriorates. Therefore, by the time the second pollution event takes place (week 80) the deviation of random nodes' information suffers a bigger increase than the corresponding leap that cf nodes' deviation takes.

The same behaviour repeats for the third pollution stain, appearing in week 100. Again, the deviation of the data reported by cf nodes is lower than that offered by random nodes. Moreover, the smaller leaps in the deviation resulting from cf nodes' data indicates that they are also more stable, and therefore, more robust to nodes' failure or exhaustion.

This property can also be observed in Figure 5, which shows mean and dispersion values corresponding to the deviation reported by both kinds of nodes. The fact that the standard deviation associated to this gauge increases as the number of nodes decreases supports the hypothesis of robustness for cf nodes for different environmental conditions and lower number of nodes.

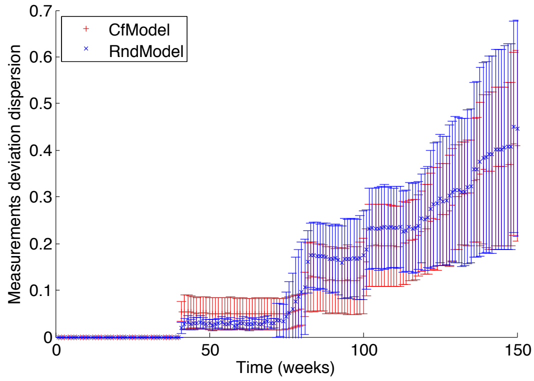

Fig. 5. Mean and standard deviation information accuracy

6 Conclusions

In this paper we have presented the COSA algorithm and have given experimental evidence of its computing properties. This algorithm is aimed at extending the life span of WSNs while guaranteeing their good performance. In contrast to previous approaches that tried to save energy using adaptive sampling schemes, COSA innovates by reaching this objective via a peer to peer negotiation protocol. This negotiation protocol enables nodes to interact and generate groups that produce a network-wide benefit. To attain a good group configuration the algorithm relies on the node local information about its environment state and neighbouring nodes. This local information together with the appropriate COSA algorithm parameter configuration leads to the formation of groups of nodes that act as a single entity, avoiding redundant sensing and transmissions efforts.

The improvements obtained by this algorithm have been shown in a simple scenario representing the section of a river where different pollutant phenomena appear in random positions. Simulating the scenario required the development of the simulation platform RepastSNS, which represents a powerful tool for WSN simulation from a MAS perspective.

The results obtained for the experimentation showed how a sensor network whose nodes implement COSA guarantees a better use of the network energy and a more homogeneous system energy depletion than the ones offered by a sensor network whose nodes follow a simple random sampling policy. Achieving this more regular system exhaustion reverts in the extension of the useful life of the network, as the whole monitoring area can be sampled for longer periods, therefore, getting a more accurate view of the environment.

As future work, we plan to test the behaviour of COSA in different scenarios and for different network topologies. We believe that the COSA parameter configuration highly depends on the dynamics of the phenomena being observed and the distribution of the nodes in the environment. Getting to know the impact of these two factors in the algorithm performance will allow us to fully characterise it and to be able to identify the set of cases for which its use would result beneficial. Even more, being able to assess the improvement expected, which would result in better WSN deployment planning.

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