Cooperative Packet Forwarding in Multi-Domain Sensor Networks

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Abstract

Sensor networks are large scale networks of low-power devices that collaborate in order to perform a given task. The sensors are limited in battery energy, capacity and computational power. In recent years, researchers have proposed several protocols for such sensor networks assuming that all sensors belong to the same authority. In this paper, we introduce the concept of multi-domain sensor networks *that was, to the best of our knowledge, never considered before. We propose a game-theoretic model to investigate the impact of cooperation and show the conditions for which cooperation is the best strategy.*

1. Introduction

Multi-hop wireless networks provide both new networking environments and extensions of existing network infrastructures. Sensor networks, in particular, emerge as a new paradigm of a large scale wireless network for data gathering purposes. Sensor networks have the potential to extend the current solutions and to open the possibility for more precise environmental monitoring.

In the literature of sensor networks, it is generally assumed that the sensors are under the control of a single authority. In real deployments of sensor networks, it is reasonable to assume, however, that different sensor networks are going to be deployed independently of each other in the same area. Typical examples of future co-located deployments can be found in freight transport (e.g., vehicle, container, and material tracking sensors co-located with control sensors in the warehouse, airport, harbor, or train station), in environmental monitoring (e.g., forest fire, earthquake and flood detection sensors), in intelligent buildings (e.g., material tracking, environmental control, and building state monitoring networks), and in animal monitoring (e.g., where each subset of a herd belongs to a different owner)[1]. Even if the sensors perform different tasks, the communication interface between them is likely to be standardized, making them able to cooperate with each other.

In our paper, we consider sensor networks that are deployed at the same area, but are controlled by different authorities. In such a situation, sensors may reduce transmission energy if their packets are forwarded by sensors that belong to another authority. There is the risk, however, that the sensors belonging to another authority drop the packets (the reason can be denial of service attack, lack of agreement on the common goal, etc.).

Our goal is to determine the best strategy for the authorities that control the sensor networks; for this purpose, we make use of game theory. We do not rely on any cooperation enforcement mechanism, but rather we want to see whether cooperation can exist based solely on the self-interest of the authorities. Our simulation results show that cooperation of co-located sensor networks extends their lifetime, thus authorities are better off if they cooperate with each other.

The paper is organized as follows. In Section 2, we give an overview of related work. In Section 3, we provide a general system model and the corresponding game of multi-domain sensor networks. Section 4 presents our simulation results. Finally, we conclude in Section 5.

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1 For a survey on sensor network applications see [1].

2. Related work

Sensor networks are envisioned to perform distributed sensing in both military and civilian applications. Due to the limited capabilities of the sensors (typically energy limitation), such networks need energy-aware protocols to be deployed. A survey of sensor networks can be found in [1].

Cooperation between several authorities is a new concept in sensor networking. However, the problem of non-cooperation was already addressed for ad hoc networks. An approach that addresses cooperation in the absence of any incentive mechanism is provided by Srinivasan *et al.* [9]. Their work focuses on the energy aspects of cooperation. Felegyhazi, Hubaux and Buttyan [4] establish the connection between the network topology and the possible existence of cooperation. MacKenzie and Wicker [6] study the stability of the slotted Aloha medium access protocol in a game theoretic framework.

Buchegger and Le Boudec [2] define a protocol that is based on a reputation system. In their approach, the nodes observe the behavior of each other and store this knowledge locally in reputation reports. Zhong, Yang and Chen [11] present a solution, where an off-line central authority collects *receipts* from the nodes that relay packets and remunerates them based on these receipts. Another solution, presented by Buttyan and Hubaux [3], is based on a virtual currency, called *nuglet*: If a node wants to send its own packets, it has to pay for it, whereas if the node forwards a packet for the benefit of another node, it is rewarded.

3. Game-theoretic model

In this section, we present our system model and the cooperative game that enables to investigate cooperative packet forwarding in co-located sensor networks.

3.1. System model

We assume a set of small, battery-powered devices called *sensors*. For simplicity, we assume that each battery has the same maximum energy it can store, which we denote by B. We assume that two sensors are able to communicate with each other if they reside within transmission range, even if they belong to different sensor networks; in other words, inter-operability is ensured by the device manufacturers. We assume an ideal channel without packet losses; with other words, we assume that each packet loss is due to the strategic behavior of the sensors.

We also assume that the sensors perform a given task and that they periodically report their measurements to one or several base station nodes in the network. We refer to the base stations as *sinks*. We further assume that the measurement data can be included in a single message that we call a *packet*. We assume that packets have the same size. Hence, we express the *transmission cost* C for a single packet as a function of the transmission distance, in particular we assume $C = c \cdot d^{\alpha}$, where c is a constant that includes antennae characteristics, d is the distance of the transmission and $2 \leq \alpha \leq 5$ is the *path loss exponent* [8]. Without loss of generality, we assume that $c = 1$. We assume that a fixed energy for computation is included in the transmission cost. We introduce the *unit* of energy as the transmission cost to the distance of one meter. We also assume that the energy consumed by receiving and processing a packet is fixed and we denote the *reception cost* by R.

We assume that P sensor networks, each controlled by a different *authority*, are co-located on the same area. We investigate two scenarios:

- *Separate sinks:* The sinks belong to different authorities (e.g., each sensor network has its own sinks).
- *Common sinks:* The sinks are common resources used by all authorities.

We call the set of networking elements controlled by authority i, a *domain* D_i. In the case of the common sink scenario only the sensors belong to D_i, while in the case of the separate sink scenario the sinks controlled by i are also part of D_i. We define the *inactivity* of a domain as the time when the battery of the first sensor in the domain is depleted.

We assume that there exists an energy efficient routing algorithm that enables sensors to send packets to the sinks via several hops. The design of energy efficient routing algorithms is a focus of on-going research efforts. Throughout this paper, we assume that the routing protocol establishes a minimum energy path from each sensor to the sink, as it is presented by Ye *et al.* in [10]. Note that we assume that routing is performed properly; we postpone the investigation of selfish behavior in routing as a separate problem to our future work. In our model, two routes are established for each sensor: one route in the own network (non-cooperative routing) and one route in the common network of all authorities (cooperative routing). If a sensor runs out of battery, then its domain is excluded from the game and routes are recalculated. We also assume that the communication from the sinks to the sensors is performed via a single-hop, (i.e., the sinks have sufficient energy to reach their sensors directly).

3.2. Game

Game theory [5] provides an appropriate tool to model strategic decision situations. In our system, the authorities have to decide, whether they help each other to increase the lifetime of their network or they ignore the possible help from other sensor networks and rely on their own network to achieve their goal. We model this cooperative packet forwarding situation, as a multi-stage game $G = (\mathcal{P}, \mathcal{S}, \mathcal{U})$, where $\mathcal{P}$ denotes the set of *players*[2], $\mathcal{S}$ the set of strategies and $\mathcal{U}$ is the set of utility functions. We assume that if a domain becomes inactive (as defined in Section 3.1), it is excluded from the game. The game ends when the last domain becomes inactive. Note that in the last phase of the game there is only one domain.

We assume that the time is divided into time units called *time slots*. Once per time slot t the sensors of each domain send measurement packets towards the sinks. The length of a time slot is defined by the frequency of the packet sending and it has no effect on the game. Correspondingly, we assume that the sensors wake up almost synchronously to report to the sinks. We will consider the effect of asynchronous wake-up in our future work.

In each time slot, each of the players i has to define two actions for its domain (a) whether its sensors and sinks should forward the packets of sensors in domain D_j, where $j \neq i$, or not (in case they are asked to forward), and (b) whether to request the sensors and sinks belonging to other domains to forward the packets of sensors in D_i or to send the packets only within D_i[3]. We refer to the decision of any player i in time slot t as a *move* $m_i(t)$. Note that the players apply the same move for each packet of each other domain in a given time slot t. We use the following short notation for the possible moves of the players:

- *DD (don't ask/drop)*: *do not ask* others to forward and *drop* all packets from others if asked for help
- *DF (don't ask/forward)*: *do not ask* others to forward and *forward* all packets from others if asked for help
- *AD (ask/drop)*: *ask* others to forward and *drop* all packets from others if asked for help
- *AF (ask/forward)*: *ask* others to forward and *forward* all packets from others if asked for help

We further assume that each player has to perform a move exactly once in each time slot. We denote the vector of the moves of all players in time slot t by $\bar{m}(t)$. Note that the decision does not affect the reception. We assume that if a sensor is active, it will always receive packets.

We define $\xi_i(t) \in \{true,false\}$, the *success* of the measurement in time slot t as follows. In each time slot t, player i evaluates the proportion of its sensors from which it has received measurement data denoted by $\rho_i(t)$. If $\rho_i(t) \geq SR_i$, where SR_i is a required number of measurement data defined by the application, then the measurement is successful (meaning that $\xi_i(t) =$ *true*); otherwise $\xi_i(t) =$ *false*.

If the measurement is successful, then player i receives a *gain* $g_i(t) = G_i$; otherwise it receives $g_i(t) = 0$. The player has a *cost* in time slot t denoted by $c_i(t)$ that represents the total transmission and reception cost of all sensors that belong to i for all packets (both for own packets and packets for the opponents). In general, we can assume that $G_i >> c_i(t)$ in any time slot t, meaning that the possible benefit received from successful information sending is higher than the value of the total cost (i.e., it is worth to send packets towards the sinks). We assign a *payoff* $\pi_i(t) = g_i(t) - c_i(t)$ to each player i for each time slot of the game.

A *strategy* $s_i \in \mathcal{S}$ is a function that defines the move of player i for a time slot $t+1$ given the success of player i in the previous time slot. Here $\mathcal{S}$ stands for the set of all possible strategies. We can write the strategy of player i as:

$$m_i(t+1) = s_i[\xi_i(t)] \tag{1}$$

In order to reduce the complexity of the sensors, it is reasonable to assume that there is a pre-programmed packet forwarding strategy stored at each sensor. Each sink informs its own sensors about the success of gathering the last measurement, as an input of this strategy[4], hence the feedback can be included in a single bit. Our solution is beneficial, because it minimizes the reception energy of the feedback.

In our analysis, we define the *utility* as the cumulative payoff for the nodes in the packet forwarding game (hence $U_i = \sum_{t=0}^{T} \pi_i(t)$), where T denotes the lifetime of the domain controlled by player i. The goal of the players is to maximize their utility in the game. Intuitively, this goal means to report measurement successfully as many times as possible, while minimizing their energy consumption (maximizing their lifetime).

We assume that players are rational and that rationality is a common knowledge (meaning that they know that the others are rational as well). We also assume that the constitution of the game is known to every player, thus they are able to analyze it and act according to the analysis.

4. Simulation results

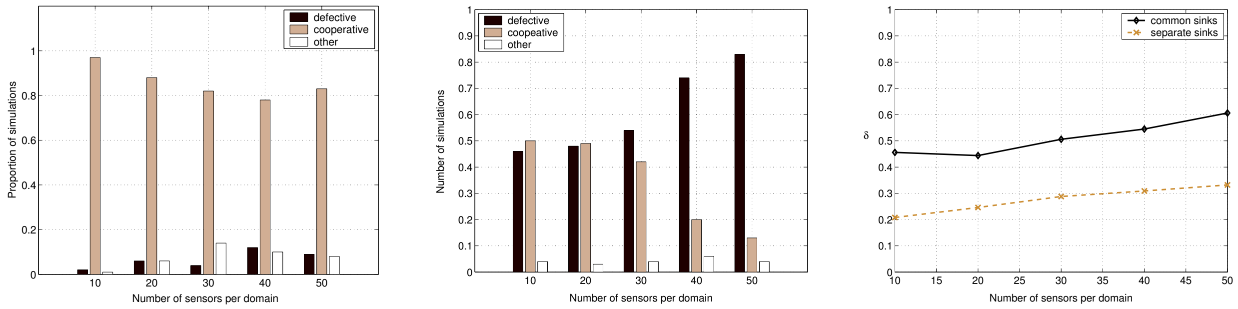
In this section, we present our simulation results in which we have identified the best packet transmission strategies in randomly generated scenarios. We also quantify the difference between equilibrium strategies.

We assume two authorities that deploy their sensor network in the same area, in such a way that they are initially connected. In our simulations, we investigate both the separate sink and the common sink scenario: In the separate sink scenario, we put one sink per domain in two different positions; and in the common sink scenario, we put a single sink in the middle of the simulation area.

2 We model authorities as players in the game, meaning that $|\mathcal{P}| = P$.

3 Note that in the separate sink scenario, the decision of player i applies also to the sinks in D_i.

4 In the common sink scenario, the common sinks inform the sensors in each domain.



(a) (b) (c)

Figure 1. Effect of the network size on cooperation; (a) in the separate sink scenario and (b) in the common sink scenario. (c) Ratio of the utility achieved by defection with respect to the utility achieved by cooperation (δ) as a function of the network size.

Table 1 presents our simulation parameters[5].

Parameter	*Value*
Number of sensors per domain	10–50 (25)
Distribution of the sensors	uniformly random
Area size	40x20m
Reception energy (R)	100 units
Path loss exponent	2–5 (4)
Success requirement (SR_i)	1.0
Positions of the sinks (separate sinks)	[10,10] and [30,10]
Positions of the sink (common sink)	[20,10]
Route selection	minimum energy path

Table 1. Parameter values of the simulations

For a given set of parameters, we performed 100 simulation runs, each corresponding to a different topology of the sensors. For each simulation run, we performed an exhaustive search on the available strategy space to identify possible Nash equilibria[6] [7]. For each player, we determined the Nash equilibrium (or several Nash equilibria) that results (or result) in the highest utility. We observed that in each of the selected Nash equilibria, the game stabilizes in the following pair (or pairs) of moves:

- **Defective equilibrium:** The players end up in playing the moves DD-DD.
- **Cooperative equilibrium:** The players end up in playing the moves AF-AF.
- **Other equilibria:** The equilibrium is different from the ones above.

5 We present the default values of variables in parenthesis.

6 Recall that in a *Nash equilibrium*, none of the players can increase its utility by unilaterally changing its strategy.

Defective equilibria always exist in the network, which is not always true for cooperative and other equilibria. Consequently, if several types of equilibria exist in the network (typically both defective and cooperative equilibria), we define δ as the ratio of the utility achieved by defection with respect to the utility achieved by cooperation:

$$\delta = \sum_{i \in \mathcal{P}} \frac{U_i(\textit{defective})}{U_i(\textit{cooperative})} \qquad (2)$$

Figure 1a presents the number of different equilibria in the separate sink scenario as a function of the network size. We can observe that the number of cooperative equilibria is much higher than the number of other types of equilibria. Furthermore, as we increase the number of sensors in the domains, the number of simulation runs with cooperation as the best equilibrium decreases.

It is important to emphasize that in the separate sink scenario, the players control their sinks as well. Thus, the dominance of cooperation might be the result of the presence of the sink of the other domain (which enables shorter routes) and not the result of cooperation between the sensor networks. To investigate the effect of cooperation in the sensor networks, we present results in the common sink scenario. Our results show that this effect decreases as network size increases.

Figure 1b presents the number of different equilibria in the common sink scenario as a function of the network size. We can see that the number of defective equilibria is approximately the same than the number of cooperative equilibria. As we increase the network size, however, the number of defective equilibria increases and the number of cooperative equilibria decreases. The reason is that with the increasing density of sensors, the reception power dominates the energy consumption.

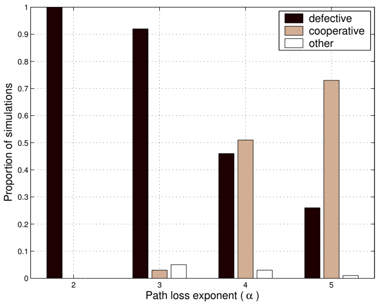


Figure 2. The effect of α on cooperation in the common sink scenario.

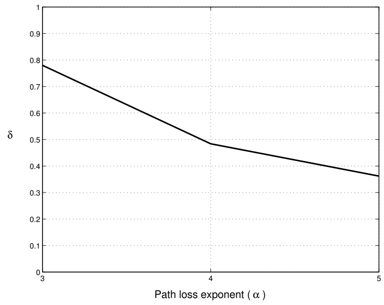


Figure 3. Ratio of the utility achieved by defection with respect to the utility achieved by cooperation δ as a function of α.

Figure 1c presents δ as a function of the network size. We see that in the separate sink scenario, δ is much less than in the common sink scenario, thus choosing cooperation is more beneficial with respect to defection. In both scenarios, δ increases with the network size.

Figure 2 presents the number of different equilibria in the common sink scenario as a function of α. The figure shows that as the path loss exponent increases (which represents a more hostile environment) the number of defective equilibria drops significantly; at the same time the number of cooperative equilibria increases significantly. This shows that the more hostile the environment is, the more beneficial the cooperation is.

Figure 3 presents δ as a function of the path loss exponent. as no cooperative equilibria exist for $\alpha = 2$, we can present the results only for $\alpha > 2$. We can observe that the more hostile the environment is, the better cooperation is with respect to defection.

5. Conclusion

In this paper, we have presented a game-theoretic model to study cooperation in multi-domain sensor networks. The limited computation and energy resources of the sensors motivated us to investigate cooperation in the absence of incentive mechanisms. Our results show that the energy saving by cooperation provides a "natural incentive" for the authorities. The benefit of cooperation is twofold: (a) the authorities can have a significant benefit by providing service of their sinks for other's sensor networks and (b) if sinks are common resources, then cooperative packet forwarding is beneficial for sparse networks or if the environment is hostile.

In terms of future work, we will investigate the effect of different lifetime definitions. We will also take the effect of asynchronous wakeup of the sensors into account.

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