Massive Opportunistic Sensing with Limited Collaboration for Age of Information

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***Abstract*—We consider an Internet of thing scenario, where a set of sensors collect data and exchange them with a common receiver. We analyze their interaction, considering a shared goal to minimize Age of information at the receiver's side. We argue that a fully collaborative setup, albeit generally succeeding in this task at first, often leads to resource wastage in the long run. We try to achieve a similar level of cooperation through a purely opportunistic mechanism, in which nodes are driven by selfish objectives, but still aware of the ultimate goal of maximizing information freshness. We show how our proposed approach, allowing fewer nodes to participate in the task (up to one order of magnitude), results in a better resource management, still improving the long-term average age of information. At the same time, a target number of participating nodes can be set, e.g., to a given fraction of the network, by properly tuning the individual objectives and the communication costs.**

***Index Terms*—Age of Information, Collaborative Sensing, Game Theory, Internet of Things**

I. Introduction

The Internet of Things is currently experiencing a convergence between massive connectivity by a multitude of devices and the increased integration between their computation and sensing capabilities. This, in turn, reflects on the option to implement strategic sensing operations, where nodes interact with each other during the acquisition, computation, and communication phases [1], [2].

This has led to various applications that can leverage the availability of real-time information to improve their quality of service, such as smart and cooperative driving applications, where knowing the location and status of surrounding vehicles is crucial to devise proper choices in rushed traffic [3]–[5]. At the same time, automated industrial monitoring systems for intelligent control and actuation, as well as smart city management, can achieved improved accuracy and reliability, and enable the implementation of digital twins [6].

The aforementioned application goals are grounded in obtaining fresh status reporting, as measured by age of information (AoI). The latter metric has been proposed by multiple researchers as a quantitative way to assess the reliability and timeliness of the data stream [7]–[9].

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However, the perspective of AoI studies is often on a single transmitter-receiver pair, and even when multiple information sources are present, they do not directly interact with each other, if not in terms of resource sharing. We argue that the previously discussed sensing tasks better rely on collaborative sensing, requiring collaboration of multiple nodes in the sensing task [10], [11]. However, this requirement may result in energy and communication resources wastage as many times data coming from sensors that monitor the same physical process has some inherited correlation [12].

In this work, we analyze the opportunistic interaction between a set of sensors with transmission capabilities and a receiver, whose task is to collect the data from the sensors and combine them into a coherent measurement. This extra step is needed to align the distribution of the data as different sensors may have different calibrations or collect measurements that represent different aspects of the underlying process, e.g., temperature and light intensity in a room [13]–[15].

Our contribution stands out from the literature in that we consider each node as having its own interest the AoI as seen by the receiver, and it can decide to participate in the sensing task with its own probability [16]. Furthermore, it is aware of the fact that there is an optimal number of simultaneously participating nodes that ensures the success of the sensing task. Finally, it considers the brevity of information collection phase as well as the energy expenditure as side objectives [17], [18].

As a result, we design a static game of complete information to model the opportunistic interaction between the nodes in optimizing the information freshness [19]. The analytical solution of this game gives the Nash equilibrium (NE) strategy that the selfish nodes will autonomously compute and play.

The analytical derivation of the NE, as well as its quantification through sample numerical results, highlight important structural properties of the NE that may be used for inferring distributed system management strategies. In particular, we show how the system manager can set and disseminate proper parameters (such as a virtual cost for transmission) that achieve an efficient setup, in terms of both expected AoI as well as overall sensing duration and energy consumption, through a fully distributed control, without the need for additional information exchange [20], [21].

The remainder of this paper is as follows: in Sec. II we compare this work to the current state of the art; in Sec. III we describe our model and we perform the game theoretic analysis; in Sec. IV we report the numerical results we obtained by solving the equations we formulated, finally in Sec. V we draw the final conclusions and future work.

II. Related Work

Collaborative sensing has become steadily more important in recent years [2]. Many works focus on distributed optimization solutions for sensing scheduling with nodes unable to move in space. The authors in [21] study a distributed optimization problem aimed at finding optimal periodic policies for sensing scheduling, showing that there are sensible advantages instead of sampling nodes at random. There is also a branch of research that focuses on sensors able to move independently in the environment. In [5], the authors analyze a mobile tracking scenario with an architecture resembling the ones of edge computing and they develop a dynamic resource allocation method for real time tracking. Besides, in [22] the authors solve a constrained optimization problem for UAV sensing considering their flight range and the request of sensed data.

In collaborative sensing scenarios, it is also important to aggregate data effectively as the distributions of the samples collected by the single sensors may not be aligned [13]. Furthermore, if these concepts are applied to Federated Learning, the local models may not be aligned with the centralized one either [15]. We argue that in massive scenarios it is beneficial to limit the participation of the nodes to reduce energy consumption and network utilization.

This view is also shared by [12], where the authors design an heuristic algorithm to optimize the number of nodes participating in the communication task to maximize battery lifetime of the single nodes and network coverage. Similarly, [23] defines an heuristic algorithm for finding multiple cover sets that can be activated at different time instants to guarantee full area coverage while saving energy.

All these solutions focus on a centralized optimization phase for communication scheduling that has to be performed globally for the whole network. This approach is unfeasible when considering a massive collaborative sensing scenario as the number of tunable variables makes computation very demanding. For this reason, we propose a decentralized solution where the single nodes act opportunistically optimizing a common goal [20], [24].

The analysis of the opportunistic behavior of nodes with distributed control can benefit from the use of a game theoretic approach [19], [25], [26]. This is especially true when the objective is to optimize the AoI metric as it allows to obtain closed form solutions. Many papers consider adversarial scenarios where an attacker has the objective of increasing the other nodes' AoI [27]. Only a handful of works consider a common AoI to optimize. In [16], the author analyzes the strategic interaction between two nodes and the AoI resets when at least one of the two communicates, which is extremely simplified.

Finally, we take inspiration from [11], where multiple sources are considered and the condition to reset the AoI depends on a concave function that controls the success rate when a certain number of nodes collaborate. In this work, we focus on a similar scenario, but we argue that asking many nodes to collaborate in a sensing task is inefficient from an energy standpoint. For this reason, we design a tunable concave increasing function and an exponential decreasing function to control the success rate of the sensing procedure thus allowing a control on the number of collaborating nodes.

III. System Model

We consider a discrete time axis divided into slots. In our transmission model we analize the interaction of N transmitting nodes and a receiver R. The transmitting nodes are equipped with sensors that monitor different aspects of an underlying process. For instance, a group keeps track of temperature, another one light intensity, another one magnetometer readings and so on [14]. The receiver is interested in keeping the information fresh for each one of these aspects as analyzed by the transmitting nodes. For this reason we adopt the AoI metric (δ), formally defined as the current time minus the time instant of the last successful update. The transmitting nodes can choose independently from each other their transmission probability p_i. We further state that the sources have always data to transmit (generate-at-will model) and we neglect the transmission delay, as commonly done in the literature [20].

In each slot, the nodes independently access the channel. We look at the transmission process from the perspective of upper layers, thus we neglect any collision due to simultaneous transmission. This is not a restrictive assumption as it can be relaxed by following, for instance, the procedure presented in [7]. However, for the present contribution such an investigation would be out of scope because we are more interested in describing the strategic interaction of the players when making the crowd-sensing decision.

Instead of considering a success probability related to the medium access, i.e. we have a successful transmission if there is an attempt, we want to capture that, in our system, if the number of participants in a given round falls below a specified threshold, denoted as m, the receiver may not fully comprehend the phenomenon being measured by the transmitting nodes. Conversely, it becomes inefficient and resource-wasteful if the collaboration of nodes exceeds the designated threshold, m. We further define a concave function that serves the purpose of reducing the success probability if there are some nodes that decide not to transmit while less than m of them are collaborating. This is to account the fact that there might be some noisy data collected by the single nodes or some characteristics of the underlying analyzed phenomenon can be better characterized only if a certain amount of the nodes collaborate on the update. Similarly we define an exponential decreasing function that penalizes the collaboration of a number of nodes which is bigger than the optimal amount.

Each source has the objective of reducing the AoI at the receiver and just lacks coordination with others. We introduce

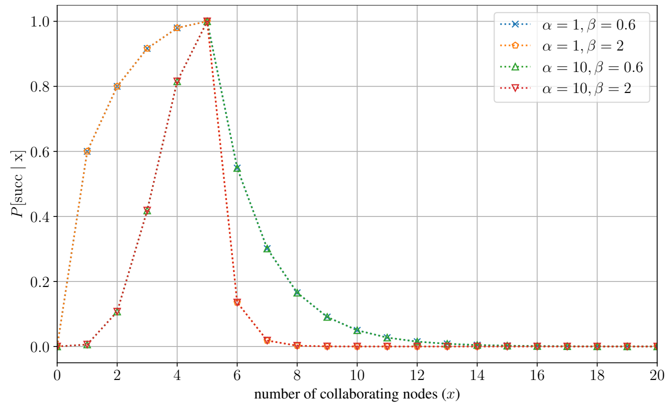

Fig. 1. Success probability conditioned on the number of collaborating nodes for different values of parameters α and β. $N = 20$ for readability.

a cost term c which models the burden of an update on the single source. To correctly reduce the probability of an update from a source we need to consider $c \geq 1$ otherwise this would be insufficient in making the nodes refrain from transmitting at every slot.

We define the expected AoI for the receiver as

$$\mathbb{E}[\delta] = \frac{1}{P_{\text{succ}}} - 1 \;, \tag{1}$$

where P_{succ} is the probability of a successful update to occur. We can model the transmission of independent sources with different transmission probabilities as a Poisson-Binomial distribution. This success probability can be defined as the survival rate of this distribution

$$P_{\text{succ}} = Q(m) = \sum_{t=m}^{N} P[x=t] \;. \tag{2}$$

In our analysis, we will concentrate on a specific scenario where the probability of task success is less than 1 and steadily increases when fewer than m nodes participate simultaneously. The probability becomes precisely 1 when m nodes collaborate, but it diminishes exponentially if more than m nodes attempt to communicate. This models the fact that we want to encourage the collaboration between the nodes up to the required value. If more nodes try to collaborate, then there is a waste of resources thus we strongly penalize the success rate. This leads us to define a piecewise function where the first part up to m is a concave function and the second one is a decaying exponential as

$$P[\text{succ}|x] = \begin{cases} \left(\sqrt{1-\frac{(x-m)^2}{m^2}}\right)^{\alpha} & \text{if } 0 \leq x \leq m \\ e^{-\beta(x-m)} & \text{otherwise} \end{cases} \tag{3}$$

where the exponent $\alpha \geq 0$ is to tune the steepness of the growth of the success rate in the concave function and $\beta \geq 0$ controls the exponential decay of the conditional success probability. See Fig. 1 for a graphical display of the resulting function, under various choices of α and β. This means that the summation in (2) starts from 1 as we consider that the case when none of the nodes participate, always ends up in a failure.

With this definition we can now write the success probability in a more general form by applying the definition of conditional probability

$$\begin{aligned} P_{\text{succ}} &= \sum_{t=1}^{N} P[\text{succ} \wedge x=t] \\ &= \sum_{t=1}^{N} P[x=t] \cdot P[\text{succ} \mid x=t] \;. \end{aligned} \tag{4}$$

Note that $\alpha \to \infty$ and $\beta \to \infty$ mean that we require exactly m nodes to participate in the task. Expanding further this expression, we can leverage the results of [28] in having an equation for the probability mass function of the Poisson-Binomial distribution to achieve a closed-form expression for P_{succ} and consequently for the expected AoI

$$\begin{aligned} P_{\text{succ}} = \sum_{n=0}^{N} \Bigg\{ \left[\sum_{t=1}^{N} P[\text{succ} \mid x=t] \cdot \exp\left(-\frac{2\pi jnt}{N+1}\right) \right] \cdot \\ \cdot \prod_{l=1}^{N} \left(p_l \left(\exp\left(\frac{2\pi jn}{N+1}\right) - 1 \right) + 1 \right) \Bigg\} \Bigg/ (N+1) \end{aligned} \tag{5}$$

where j is the imaginary unit.

Consequently, each node has its own utility that is dependent not only on the transmission probability of the node itself, but also all the other nodes' transmission probabilities. More specifically, the utility of a generic node i is set as [7]

$$u_i = -\mathbb{E}[\delta] - cp_i = -\frac{1}{P_{\text{succ}}} + 1 - cp_i, \tag{6}$$

where we consider the linear combination of two terms, the AoI of the source and the individual cost paid [16], weighted with coefficient c. Also, note the negative sign to both terms, since the players in the game will seek for minimizing both of these terms.

A. Game Theoretic Analysis

We model the interaction between the players as a static game of complete information $\mathcal{G} = (\mathcal{S}, \mathcal{A}, \mathcal{U})$, where $\mathcal{S} = \{S_1, \ldots, S_N\}$ is the set of all the players and therefore has cardinality N as the receiver R is just an external entity from the game's perspective; $\mathcal{A}$ is the set of all the possible actions, namely the participation probabilities $p_i \in [0,1]$ for each player i and $\mathcal{U}$ is the set of the utilities u_i for each player as defined in (6).

The NE of game G is obtained through a one-sided optimization of the utility, in other words, each player looks for a *best response* to the unchanged actions of the others. Mathematically, a NE must satisfy the condition

$$\frac{\partial u_i}{\partial p_i} = \frac{\partial P_{\text{succ}}}{\partial p_i} \cdot \frac{1}{(P_{\text{succ}})^2} - c = 0, \tag{7}$$

which is a system of N differential equations obtained through the chain rule applied to (6). The derivative of P_{succ} with

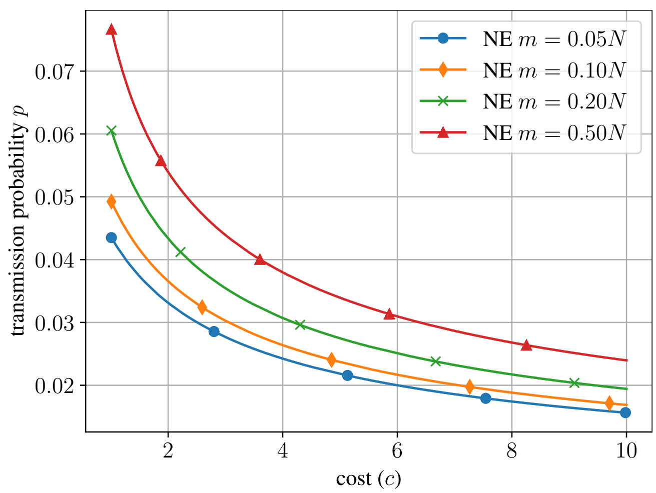

Fig. 2. Transmission probability p for different values of m. $\alpha = 1$, $\beta = 0.6$.

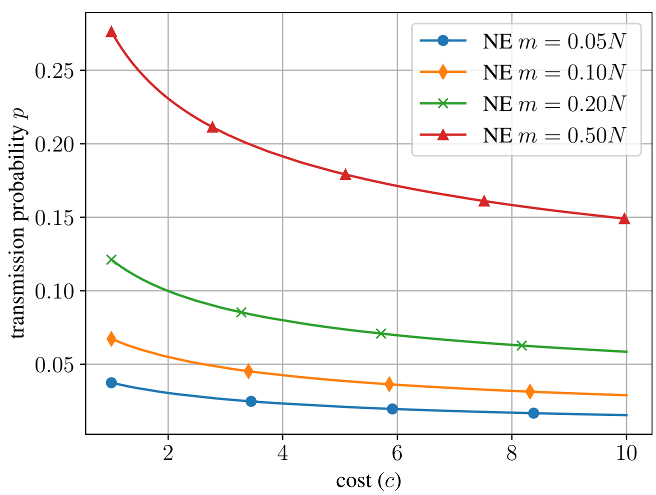

Fig. 3. Transmission probability p for different values of m. $\alpha = 10$, $\beta = 10$.

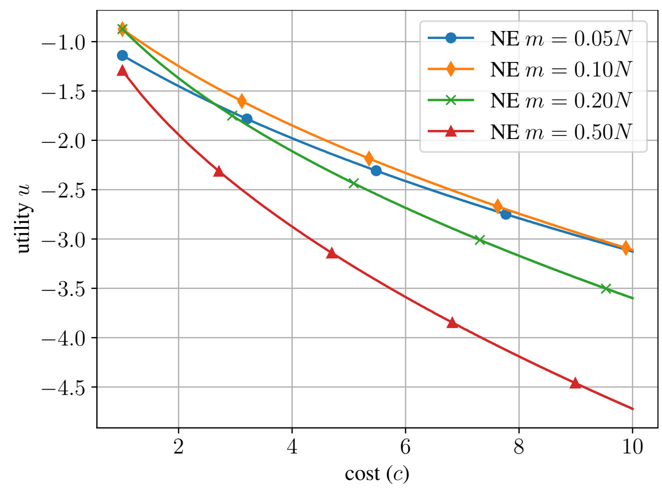

Fig. 4. Expected utility for different values of m. $\alpha = 1$, $\beta = 0.6$.

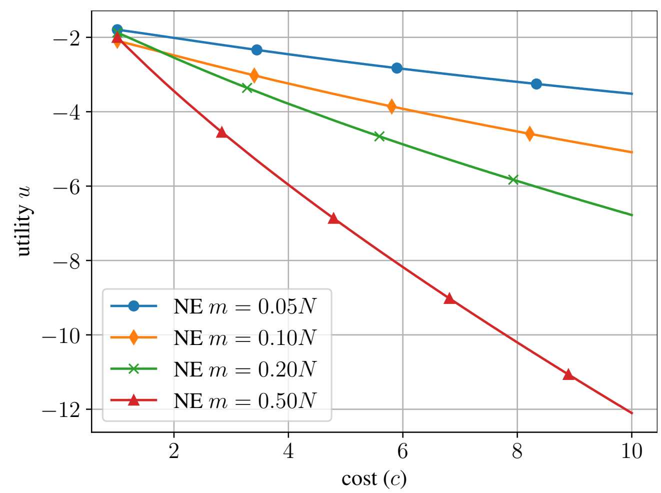

Fig. 5. Expected utility for different values of m. $\alpha = 10$, $\beta = 10$.

respect to p_i is obtained in closed form from (5) with simple derivation rules. The constraint on the probabilities $p_i \in [0, 1]$ leads to a single feasible non-catastrophic NE where the nodes choose transmission probabilities $p_1 = p_2 = \ldots = p_N \doteq p$ due to the symmetries shown previously.

IV. Numerical Results

In this section, we discuss numerical results obtained by solving (7) for a generic p_i and total number of nodes $N = 20$. The following plots do not change for specific values of N as long as we define m as fractions of the number of nodes in the system.

In Fig. 2, we report the curves we obtained for the NE of the transmission probability p chosen by every node in the network with $\alpha = 1$ and $\beta = 0.6$. As expected, for increasing values of m the nodes' participation also increases. Besides, the probability of participation of the nodes is quite low, less than 10%, even in the case where $m = 0.5N$. This was expected due to the shape of (3) for the given choice of parameters. In fact, if fewer than m nodes participate simultaneously in the task, there is still a considerably high probability of success and if more than m participate, the decay of the success probability is not too abrupt, therefore defining a wider participation area where the transmission can be reliably successful. This reduction in transmission probability is considerably reduced by making the requirement of participating nodes more strict. In Fig. 3 we set $\alpha = \beta = 10$. In this scenario the NE values for p and $m = 0.5N$ are three times higher than the ones shown previously in Fig. 2. More interestingly, the curves in this figure are well separated from each other signaling that there is a sensible difference in the required participation probability when a specific amount of nodes need to collaborate. Nonetheless the curves keep the logarithmic decrease for growing cost values.

Fig. 4 presents the utility received by each player that participates in the game with $\alpha = 1$ and $\beta = 0.6$. In this scenario it is interesting to observe that for $m = 0.05N$ the NE solution obtains worse values for the utility than the cases with $m = 0.1N$ where the slope of the curves is similar but for

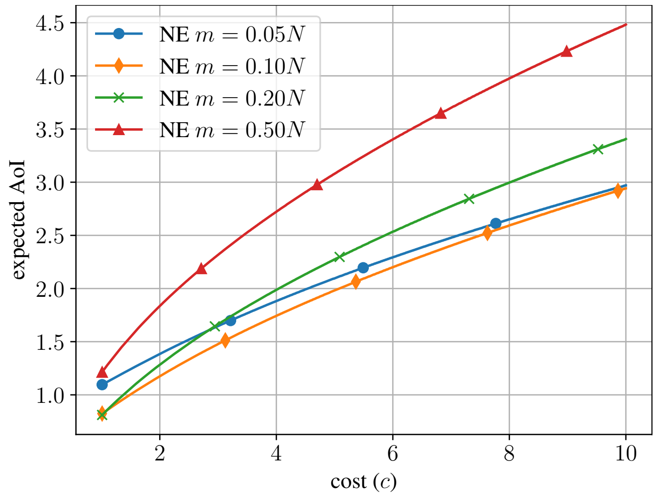

Fig. 6. Expected Age of Information for different values of m. $\alpha = 1$, $\beta = 0.6$.

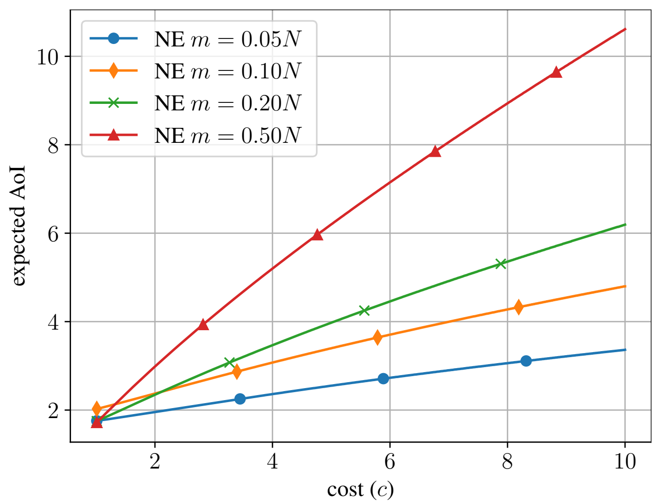

Fig. 7. Expected Age of Information for different values of m. $\alpha = 10$, $\beta = 10$.

cost values large enough the two curves become comparable and $m = 0.2N$ where the decrease of the utility with respect to the cost is much more noticeable but there are values for the weighting coefficient c where the higher m obtains a better utility. This may be due to the stronger penalty introduced by the coefficient β in the success probability as requiring that just one nodes participates does not consider the effect of α in allowing a success even if less than m nodes collaborate, thus penalizing this choice. By increasing both α and β to 10, in Fig. 5 we see that this effect vanishes as the cost of the transmission c takes a bigger part in the results. This is a foreseeable consequence of Fig. 3 as the transmission probability is considerably higher than the previous set of parameters α and β thus increasing the importance of the cost element cp in (6).

In Fig. 6 we report the expected AoI experienced by the receiver when the NE strategy is played in the case of $\alpha = 1$ and $\beta = 0.6$. The curves show a trend similar to that of the utility where $m = 0.05N$ yields higher expected AoI values than bigger values for m. These curves hint that there might be an incentive for the system designer to carefully tune the required optimal number of participating nodes m and the cost factor c, to obtain the best value for the mean information freshness. This result also shows that it is possible to obtain low expected AoI values also when the transmission probability has relatively high values making the cost of the transmission more impactful on the computation. This advantage is less noticeable for big values of α and β and $c \approx 1$ as can be noted in Fig 7 where all the curves are really close to each other, except the one for $m = 0.1N$. Similarly to the utility, low communication cost values incentivize the use of higher values for m as the Expected AoI is also reduced. This effect quickly fades when c is increased. This is a direct consequence of the higher transmission probabilities that was not very noticeable in Fig. 6 as in that figure the configuration of α and β in that case leads to a smaller transmission probability. For this reason, when the situation specific characteristics of the environment make communication attempts very costly, it is convenient to set the target number of participating nodes to smaller values in order to obtain lower values for the expected AoI ensuring better freshness of information.

V. Conclusions

In this work we analyzed a collaborative sensing scenario in the IoT domain. We argued that a fully collaborative setup leads to wastage of resources, we therefore designed an opportunistic mechanism based on game theory, where the nodes driven by selfish objectives interact to minimize the expected AoI at the receiver side [11].

We obtained closed form expressions for the expected AoI at the receiver side as a function of the total number of nodes in the environment and the customized function designed to model the success of the sensing process as a function of the target number of participating terminals.

Furthermore, we showed that there exists only a non-catastrophic NE in the domain of probabilities and it is to set all nodes' participation probabilities to the same value [7]. We showed that our approach is capable of reducing the number of participating nodes while maintaining good information freshness when we consider environments with big communication costs. Otherwise, if the communication attempt is very cheap, it is more convenient to set the optimal number of participating nodes to larger values.

We denote that our approach does not make any assumption on the type of sensors employed in the sensing task. One possible future extension may consider not only the target total number of nodes that need to participate, but also subdivide the sensors in thematic categories and ask for a specific contribution to the task by each of them depending on the current system requirements [8], [13].

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