QoI-aware energy management for wireless sensor networks

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Chi Harold Liu
Beijing Institute of Technology

Joel Branch
IBM

Bo Yang
IBM

QoI-Aware Energy Management for Wireless Sensor Networks

Chi Harold Liu†, Pan Hui§, Joel W. Branch‡ and Bo Yang†
†IBM Research - China, Beijing, China
§Deutsche Telekom Laboratories/TU-Berlin, Berlin, Germany
‡IBM T. J. Watson Research Center, Hawthorne, U.S.A.
†{chiliu, boyang}@cn.ibm.com, §pan.hui@telekom.de, ‡branchj@us.ibm.com

***Abstract*—In this paper, we propose an efficient energy-management framework in wireless sensor networks (WSNs) to address the fundamental research challenge imposed by both the maintenance of the energy supply and the support of the quality-of-information (QoI) requirements. By quantifying the QoI benefit the tasks receive in relation to the level of QoI they request as the *QoI satisfaction index*), we propose a QoI-aware energy-management scheme to distributedly decide the participating state of each sensor. Specifically, by using the mathematical framework of the Gur Game, we propose a novel pay-off structure taking into account the QoI and the energy consumption. We finally evaluate the proposed scheme under an event occurrence detection scenario, where the proposed scheme successfully guarantees less than 7% QoI outage, saves 80% of the energy reserve if compared with the lower bound solution, and achieves the suboptimum with only 4% gap if compared with optimal solution.**

I. Introduction

After more than a decade of contributions from various communities (e.g., academia and the government), wireless sensor network (WSN) technology has reached a reasonably mature state. This is evidenced by, among other things, the growing availability of WSN-based commercial offerings for tracking mobile assets [1], monitoring elderly citizens at home [2], and monitoring the health of physical infrastructures [3]. By many accounts, we have reached a stage where managing sensor *data* is the central focus of building and operating WSN-based systems. This is primarily because many low-level WSN concerns (e.g., security, networking, etc.) are rapidly becoming abstracted away as more users focus on reusability and interoperability to build larger, more dynamic sensor-based systems. Prominent examples include those based on participatory sensing [4] and Internet-of-Things [5] frameworks. As disparate sensor *domains* are used to compose such applications, the *quality-of-information* (QoI) provided by the sensors becomes more important in interpreting higher-level application performance. Supporting QoI in such systems, however, exasperates another long-standing WSN problem: *energy-efficiency*.

This paper addresses the following novel challenge: *balancing QoI with energy-efficiency in WSN-based systems in a manner that is transparent to underlying communication protocols*, to fill the research gap [6] of designing generic energy-management algorithms, irrespective of what underlying communication protocols in use, like MAC scheduling. Broadly speaking, QoI represents a (set of) metric(s) to judge if information is *fit-for-use* for a particular purpose [7], [8]. For the purposes of this paper, we will assume that QoI is characterized by a number of quality attributes, such as accuracy, latency, and spatiotemporal relevancy [9]. Unfortunately, a sensor's energy usage generally increases with the QoI produced; in order to achieve high QoI, sensors will likely participate in more tasks. However, if sensors participate in less tasks, saving more energy, QoI will decrease. This balancing problem is further exasperated in the previously described multi-domain WSN-based systems primarily because both QoI and energy-efficiency are beyond the direct control of the high-level application owner. Only the sensors' owner(s) can control such functions.

We address the aforementioned challenges by proposing a QoI-aware energy-efficient network management scheme for WSNs, a novel research path in its own right. We specifically make the following contributions. First, we formally quantify the QoI benefit that applications (or tasks) receive in relation to the level of QoI they request as the *QoI satisfaction index*). Second, we propose a local QoI-aware energy-management scheme to decide if a sensor will participate in a task. Specifically, we locally guide the balance between QoI and energy-efficiency using the Gur Game framework, which controls a duty-cycling scheme based on notions of reward and punishment, represented here by the received QoI and energy loss, respectively. We finally evaluate the scheme extensively using an event detection scenario. The main advantage of the proposed approach is that it is transparent to underlying communication protocols, but locally uses sensed information to facilitate duty-cycling, so that the overall QoI level attained is satisfactory while activating the minimum number of sensors to preserve the network's energy.

The rest of the paper is organized as follows. In Section II, we highlight related research activities. Section III establishes a formal model of our system, and Section IV presents the concept of the QoI satisfaction index. Then, Section V introduces the distributed energy management scheme through the mathematical model of the Gur Game. Section VI presents simulation results and finally, Section VII concludes the paper

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and presents the future work.

II. Related Work

Various techniques have been proposed for controlling sensor energy usage. [10] describes a distributed low power scheduling algorithm for sensors to determine their active time slots in a TDMA scheme operating on top of a slotted CSMA network. [11] describes a distributed topology control technique to schedule nodes' active time slots, which is then used by a MAC protocol to improve energy-efficiency and delay. [12] describes a system for collaborative energy management, in which sensor nodes can evaluate the impact of their actions on other nodes' energy usage. Catnap [13] describes a system that allows sensor to sleep during data transfers. EEMSS [14] has a keener focus on information quality, as it aims at detecting users' current states (e.g., walking in the street, talking in a meeting) and state transitions using the minimum number of mobile device sensors. [15] describes the use of the Gur Game framework [16], [17] to dynamically and iteratively adjust the optimal number of sensors to operate in a distributed manner. The Gur Game was extended in [18] to more explicitly focus on balancing sensor coverage with energy usage.

Finally, our previous work describes a framework for managing the QoI offered by a shared WSN using negotiation techniques between application tasks and network resources and real-time estimates of the network's total QoI capacity [19]. However, energy-efficient network operation was not considered. Overall, most energy-efficient duty-cycling schemes lack a clear notion of QoI, transparency to underlying communication protocols, and distributed local operation.

III. System Model

This section presents a formal model for describing our QoI-aware energy management system. Let $\mathcal{N} = \{i = 1, 2, \dots, N\}$ denotes the set of sensing sources in the WSN, and a sink node with sufficient information processing and energy capabilities is available coordinating the task queries from the application and collecting the data from the sensing sources. Sensing task $q \in \mathcal{Q}$, where set $\mathcal{Q}$ denotes the tasks arrive for service during the lifetime of the WSN, is generated from the sink node and requests service (i.e., retrieve sensed information at some specified location within the WSN); and later it broadcasts its associated one or more QoI attributes to all sensors. These attributes include, but are not limited to, the probability of detection and latency, etc. We use the superscript r to denote a QoI attribute value *required* (and declared) by a task upon their arrival for service, and a for that value *attained* after the sensing from each sensing source and information fusion at the sink, e.g., let z_q^r and z_q^a denote the required probability of detection for task q, respectively.

Fig. 1 shows the flow of the propose iterative energy-management approach, where the upper box represents the sink node who coordinate the tasks, and the lower boxes represent the sensor nodes in a WSN, who report the retrieved information to the sink node. Upon task arrival, the sink node is informed about the required QoI level and propagates

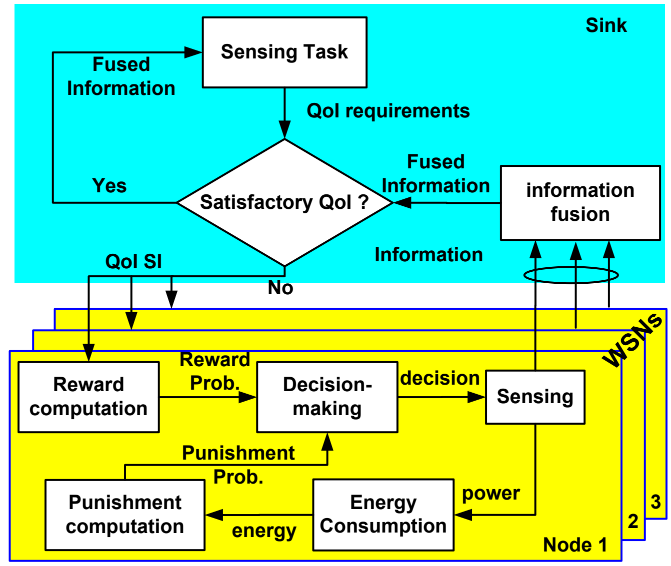

Fig. 1. The flow chart of the proposed energy-efficient management framework for the support of QoI.

this information to the WSN; and this is when the proposed iterative process starts. The iteration happens among the sink and the sensing sources, where for each sensing source at each iteration step, the QoI satisfaction index (which is computed at the sink side, see Section IV, and inform to each sensor periodically), and the energy usage according to the participation decision of the previous iteration, are used as the inputs to the automaton embedded at each sensor to compute the parameters for the Gur Game [15], [16], [17]. These parameters are the reward and punishment probabilities, or the pay-off structure (see Section V), which helps make the decision on participation at the current iteration step. The decision of each sensor either corresponds to the state `idle` or `participation`; and later all these collected participating information from all sensing sources would result in a different degree of QoI satisfaction if compared with that of the previous iteration. This new QoI satisfaction index will be used as the input to the new round of iteration, and then the new round of iteration starts. The whole process repeats, where the key design parameters, the attained QoI level and the energy usage, are both satisfactory and minimized.

Finally, to conclude this section we also claim that the proposed Gur Game model is a distributed energy-management framework embedded at each sensor with the only input of the attained QoI satisfaction index coordinated at the sink; and this framework help achieve the long-term balance between the maintenance of the energy and the support of QoI.

IV. QoI Satisfaction Index

As its name implies, this index is used to describe the level of QoI satisfaction the tasks received from the WSNs. It is applicable to each task $q \in \mathcal{Q}$ and for a specific QoI attribute z, the attained measurement is computed as:

$$z_q^a = f(z_q^{i,a}), \quad \forall q \in \mathcal{Q}, z \in \underline{z}, \tag{1}$$

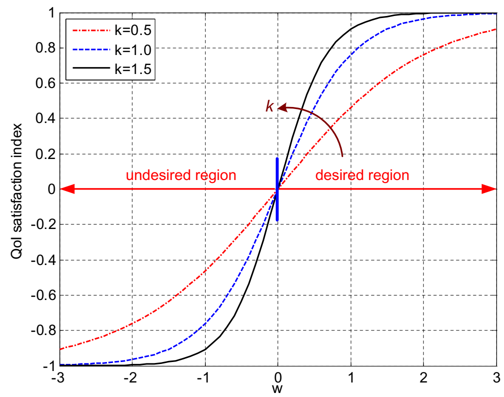

Fig. 2. The illustrative example for the definition of QoI satisfaction index, where $w = k\ln(z_q^a/z_q^r)$. It is desirable to have $z_q^a \geq z_q^r, \forall q \in \mathcal{Q}$ since it is assumed that the QoI attribute values should be at least as big as the required value to guarantee the QoI.

where $\underline{z}$ represents multi-dimensional QoI requirements, one of which z could be the image resolution requirement. f denotes the information fusion algorithm. Then, the network-wide QoI satisfaction index for QoI attribute z is denoted as:

$$\theta_q^z \triangleq \tanh\Big(k \ln \frac{z_q^a}{z_q^r}\Big), \quad \forall q \in \mathcal{Q}, z \in \underline{z}, \tag{2}$$

where k denotes a scaling factor. The selection of the functions $\ln(\cdot)$ and $\tanh(\cdot)$ is rather arbitrary but result in the intuitively appealing and desirable behavior for satisfaction as shown in Fig. 2.

Therefore, the overall QoI satisfaction index I_q for any task with multiple-QoI requirements during the service of the participatory sensing can be defined by taking the minimum of all QoI satisfaction indexes for each QoI attribute $z \in \underline{z}$, i.e.,

$$\mathrm{I}_q = \min_{z \in \underline{z}} \theta_q^z \in (-1, 1), \quad \forall q \in \mathcal{Q}. \tag{3}$$

It follows immediately from the definition of the QoI satisfaction index that for any participatory sensing task, its (multiple) QoI requirements are simultaneously satisfied if and only if $\mathrm{I}_q \in [0, 1), \forall q \in \mathcal{Q}$. We show in the next section how this QoI satisfaction index is used to facilitate both the energy and quality-aware network management.

V. Distributed Energy Management for QoI

In this section, we describe the proposed distributed energy management scheme for each sensing source, through the mathematical model of the Gur Game. Followed by the introduction of the Gur Game, we propose our pay-off structure and present how the decision is made distributedly.

A. The Gur Game

The mathematical model of the Gur Game [15], [16], [17] was first used to power on the desired number of wireless sensors in a region distributedly through a few steps of iterations. We now briefly introduce the fundamental concept and how our proposed system behaves.

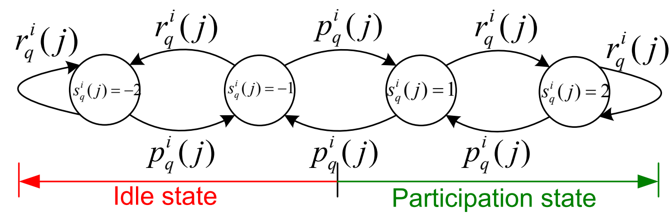

Fig. 3. An example of the Gur Game with associated memory size $M = 2$, where positive number states give the corresponding output of "participation" and negative numbers state represent "idle" decision.

Assuming every sensor $i \in \mathcal{N}$ within the proximity of the site of interest is associated with a finite discrete-time automaton with the same length of memory $M, \forall i \in \mathcal{N}$ (however this limitation can be relaxed to different length of memory, left for future work), as shown in Fig. 3. This automaton is a single nearest-neighbor chain of consecutive states where the total size of the memory is $2M$. Starting from the left-most state, the states are numbered from $-M$ to -1, then followed by numbering 1 to M to the right-most state. We denote these $2M$ energy consumption states as $\mathcal{S} = \{-s, s | s = 1, 2, \ldots, M\}$. This partitions the overall Markov chain into negative numbered states, which represent the "`idle`" state of the sensor (or no participation), and positive numbered states, which represent the "`participation`" state of the sensor.

The transition among energy-consumption states for each sensor i is driven by the pay-off function and works in a greedy fashion. Let $r_q^i(j)$ and $p_q^i(j)$ denote the reward and penalty sensor i received from interaction step $j-1$ to j for task q, before making the decision, respectively. After the current iteration j, the current state of the sensor would transit probabilistically according to the received pay-off function to the next state, i.e., $s_q^i(j) = s_q^i(j)+1$ or $s_q^i(j) = s_q^i(j)-1$. Higher values of performance pay-off function drive the finite state automaton to move towards two edge states $-M$ and M. However if $s_q^i(j-1)$ happens to be the left-most or right-most state $-M$ or M, then the next energy-consumption state $s_q^i(j)$ is only allowed to be in its own state or the adjacent state. In a summary, it is interesting to see that the punishment behavior will make the energy consumption state of the sensor shift the chain towards middle while a rewarding behavior will shift it outward.

B. The Pay-off Structure

It is desired that the goal of our proposed energy management approach is to prolong the lifetime of all sensors by reducing the energy consumption rate, to provide the satisfactory QoI experience to all tasks. Since the proposed scheme is an iterative process, we denote the step count as $j = 1, 2, ..., J$ if total J steps are allowed for convergence.

1) Reward Structure: Given the defined QoI satisfaction index $\mathrm{I}_q(j)$ for iteration step j, we next show how the reward structure for the Gur Game automaton is formulated. We first compute the reward probability given the received QoI satisfaction index as:

$$r_q^i(j) = \phi_r\{\mathrm{I}_q(j)\}, \quad \forall q \in \mathcal{Q}, i \in \mathcal{N}, j, \tag{4}$$

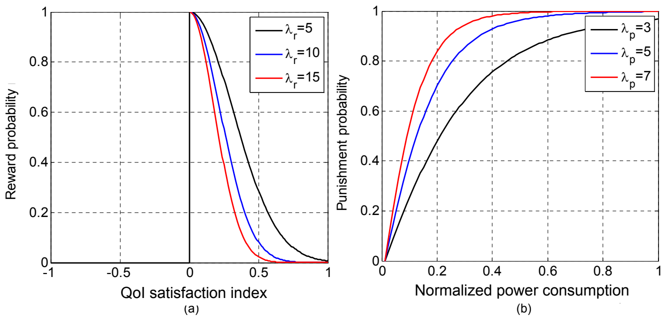

Fig. 4. An example of the probability mappings for (a) the reward and (b) the punishment, respectively.

where let $\phi_r : \mathbb{R} \rightarrow [0, 1]$ denote the mapping from the attained QoI satisfaction index to the reward probability. Fig. 4(a) shows an example of the realization of ϕ_r, where parameters are chosen as $\lambda_r = 5, 10, 15$. Mathematically, we have:

$$r_q^i(j) = \begin{cases} \exp\{-\lambda_r \mathrm{I}_q(j)^2\}, & \text{if } \mathrm{I}_q \in [0, 1), \\ 0, & \text{otherwise}, \end{cases} \tag{5}$$

$\forall q \in \mathcal{Q}, i \in \mathcal{N}, j$. We can see that instead of favoring the highest QoI experience with $\mathrm{I}_q \approx 1$, we aim to provide the satisfactory level $\mathrm{I}_q = 0$, to maintain the energy for future services. Theoretically, the sensors participating in the Gur Game will collaboratively achieve the highest pay-off probability (both the reward and the punishment) through iterations. We introduce the penalty structure capturing the energy consumption upon information contribution in the next section.

2) Penalty Structure: Since the amount of power consumption for each task q varies over time due to the geographically random positions of the tasks, we penalize the energy consumption $\gamma_q^i(j)$ for task q at iteration step j, where the more energy spent at each task, the more penalty the sensor node would receive. In other words, the whole WSN system favors the nodes who are most near to the location of the task for less energy spent for detection, while preserving the energy of sensors far apart. Using $\gamma_q^i(j)$ as the input to the penalty probability mapping $\phi_p : \mathbb{R} \rightarrow [0, 1]$ yields:

$$p_q^i(j) = \phi_p\{\gamma_q^i(j)\}, \quad \forall q \in \mathcal{Q}, i \in \mathcal{N}, j. \tag{6}$$

Fig. 4(b) shows an example of the realization of ϕ_p, where parameters are chosen as $\lambda_p = 3, 5, 7$. Mathematically, we have:

$$p_q^i(j) = \tanh\left(\lambda_p \ln \gamma_q^i(j)\right), \quad \forall q \in \mathcal{Q}, i \in \mathcal{N}, j, \tag{7}$$

where it penalizes the higher energy usage while favoring the minimum energy consumption for any task service.

C. The Decision-Making Process

Given the pay-off structure proposed in Section V-B, we next show the distributed decision-making process for each sensor i, where Fig. 5 shows the event timeline for every sensor. We denote $s_q^i(j), \forall j = 1, 2, 3, \ldots, J$ as the state after the iteration step j. At the beginning of each step, we first compute $\mathrm{I}_q^i(j), \gamma_q^i(j), \forall j = 1, 2, 3, \ldots, J$, and the state stays

Algorithm 1 : Distributed Gur Game

Initialize: J
for all $j = 1, 2, 3, \ldots J$ **do**
  for all Each sensor $i, \forall i \in \mathcal{N}$ **do**
    compute $\mathrm{I}_q(j)$ in (3) and $\gamma_q^i(j)$;
    compute $r_q^i(j)$ and $p_q^i(j)$ in (4) and (6);
    uniformly generate a random number `seed`$\in [0, 1]$;
    state transition condition:

$$\begin{cases} s_q^i(j) = s_q^i(j) + 1, & \text{if seed} \geq \frac{r_q^i(j)}{r_q^i(j) + p_q^i(j)}, \\ s_q^i(j) = s_q^i(j) - 1, & \text{otherwise}, \end{cases} \tag{8}$$

    where if $s_q^i(j) = \pm M$, then $s_q^i(j)$ is only allowed to be in its own state or the adjacent state.
    output action;
  end for
end for
Return: participation: $s_q^i(J) > 0$; idle: $s_q^i(J) < 0$.

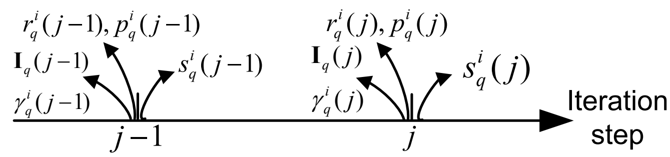

Fig. 5. An illustrative example for the change of the energy-consumption states of any sensor i from step $j-1$ to step j.

at the previous state $s_q^i(j-1)$. The outcome of the decision-making for step j would transit the state to $s_q^i(j)$, which also corresponds to a recommended action. The pseudocode in Algorithm 1 illustrates the steps of iterations.

It is worth noting that the proposed Gur Game approach is fully distributed that sensing sources $\mathcal{N}$ neither need to forecast the energy-consumption states of its own nor exchange any information from other participants. Instead, they use the trial-and-error method to produce the best result at each step and iteratively achieve the overall suboptimum.

VI. Simulation Results

We access the proposed QoI-aware energy-management scheme under an event detection scenario, where the required QoI is denoted as the probability of detection $z_q^r, \forall q \in \mathcal{Q}$. Tasks $q \in \mathcal{Q}$ is generated at the sink attached with the randomly generated QoI metric $z_q^r \in (0, 1]$, and requires for service randomly at a 2-D geographic location (x_q, y_q). We set up our simulator by randomly deploying $N = 30$ identical sensors in a 200×200 meter square, and each sensor has an equal energy reserve initially at level $\mathcal{E}$, so that $N\mathcal{E}$ is the overall energy reserve for the entire network. Finally, we employ a simple event detection model [20] using physical properties of the sensors, where individual attained probability of detection $z_q^{i,a}$ at the Euclidian distance d_q^i is achieved by:

$$z_q^{i,a} = \exp\left\{-\frac{0.5}{\gamma_q^i}\left(d_q^i\right)^{1.2}\right\}, \quad \forall q \in \mathcal{Q}, i \in \mathcal{N}, \tag{9}$$

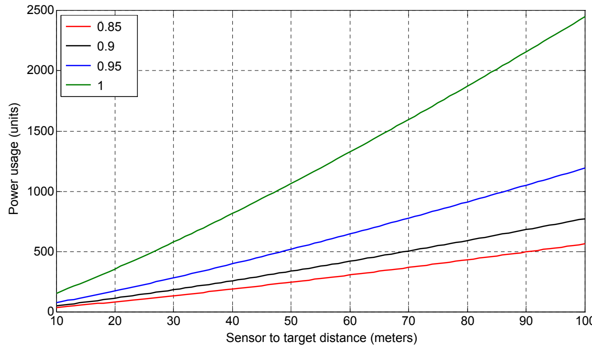

Fig. 6. An example of minimum power usage to achieve different probability of detection requirements, w.r.t. different distances from the senor to the target.

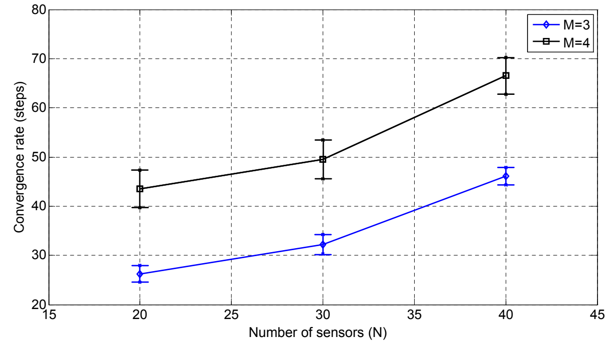

Fig. 8. The impact of memory size and network size on the convergence rate, with 95% confidence interval.

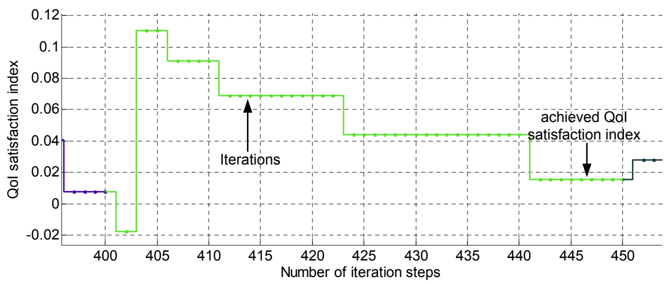

Fig. 7. The convergence rate for a specific task.

where the model assumes that the power usage is proportional to the sensor-to-target distance d_q^i. Fig. 6 shows an example of the power usage. Due to the distributed nature of the decision-making process of each sensor, we set $z_q^{i,a} = z_q^r, \forall i \in \mathcal{N}$ to compute the actual energy usage of all sensors. The proposed energy-management approach embedded on each sensor will recommend the participation action for task q, where $\mathcal{N}_q$ denotes the sensor set. Next, we use a simple information fusion model to fuse the attained information from multiple sources $z_q^{i,a}, \forall i \in \mathcal{N}_q$, achieving a network-wide and potentially higher probability of detection, as:

$$z_q^a = z_q^r + \tanh\left(0.8 \ln |\mathcal{N}_q|\right), \forall q \in \mathcal{Q}, \tag{10}$$

where the higher probability of detection is achieved if more sensors, or information, are received from the sensing sources. Finally, the QoI satisfaction index is computed as in (3).

We first show the convergence of the propose distributed Gur Game approach by showing the change of the received QoI satisfaction index, where a detailed look at one task is demonstrated in Fig. 7. We observe that for the fixed M, the received QoI satisfaction index iteratively converges to the worst-case satisfaction, or: $\mathrm{I}_q = 0, \forall q \in \mathcal{Q}$ within a small number of steps (in this example 32 steps). Achieving $\mathrm{I}_q = 0$ requires the minimum number of sensors involved into participation while preserving much energy for the following tasks; however although the proposed scheme could not guarantee this "optimum", we still achieve the suboptimum (in terms of QoI) with very fast convergence. If considering the possible combinations of the Markov states for N sensors, i.e., M^N, we conclude that the convergence rate in our approach is quite efficient.

Next, we explore the impacts of both the memory size and the network size on the convergence rate, in Fig. 8. It is observed that for the fixed network size, the larger the memory size of the Gur Game is, the more the required number of steps. Meanwhile, for the fixed memory size, the convergence rate increases with the increase of the number of sensors deployed in a fixed geographic region. To cope with this scalability issue, we may reduce the set of participating sensors to the maximum size of $N = 30$ (through restricting the range of query information broadcasting), since sensors far apart would consume more energy in participating the task. In the following simulations, we fix $M = 3$ and $N = 30$.

We compare our algorithm with the optimal sensing scenario, and the worst-case sensing scenario. For the former, it achieves the lower-bound energy usage and QoI satisfactions, by selecting the nearest and minimum number of neighbors with regards to the site of event to help with the sensing according to the sensor locations. And thus it is guaranteed that the sensors chosen would use the minimum power consumption. For the latter, all sensors are forced to participate in any task so that best QoI is achieved with the compromise of the larger energy usage.

Fig. 9(a) shows the histogram of the attained QoI satisfaction index by simulating 800 tasks, and its trend w.r.t different required QoI levels $z_q^r, \forall q \in \mathcal{Q}$ is demonstrated in Fig. 9(b). It can be seen that more than 93% of the tasks receive the satisfactory QoI experience, or the proposed approach successfully guarantees very low QoI outage probability as the suboptimal solution. It is also seen from Fig. 9(b) that the higher level of required QoI decreases the degree of attained QoI satisfactions since more network resources (in our case the number sensing sources) are required for collaborative event detection, and thus although the achieved QoI levels could be the same, but the smaller degree of the satisfaction, or the ratio, will be received as in (3). We also plot 95% of the confidence band where this decrease trend could be more clearly observed; this band of confidence can also serve as the network design criteria, or admission control decisions, for the new tasks before their service.

Finally, Fig. 10 illustrates the change of the percentage of the remaining energy for three scenarios, where we observe that the proposed energy-management scheme successfully

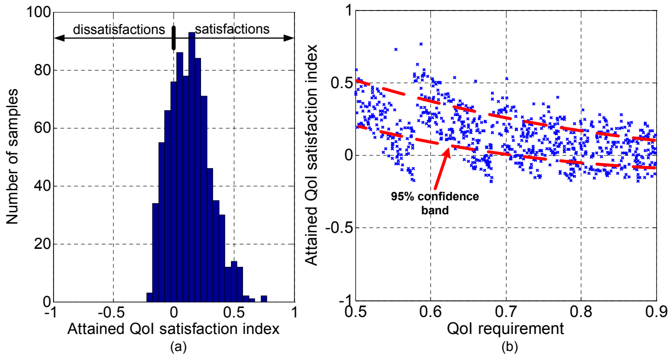

Fig. 9. The received QoI satisfaction index: (a) the histogram and (b) w.r.t. different required QoI levels.

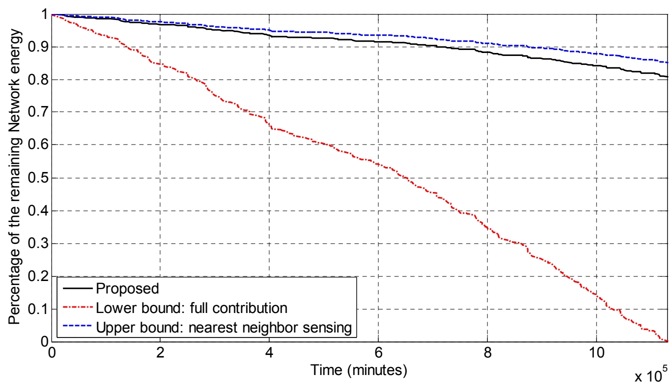

Fig. 10. The remaining energy of the three schemes.

achieve the suboptimal solution with significant gains if compared with the full participation case, i.e., when the worst-case full participation solution drain out the energy preserve of the WSN, the proposed scheme has still 82% of the overall energy left for the future tasks. Even compared with the optimal sensing, the gap is relatively very small, i.e. only 4% higher than our scheme. The suboptimum is achieved primarily due to distributed selection of the set of sensors into participation which may not be the optimal set of sensors who are nearest to the event; and thus the power consumption per-task could be sometimes higher.

VII. Conclusions and Future Work

In this paper, we proposed an efficient energy-management framework for the successful support of QoI in WSNs. We address the fundamental design challenge of bridging QoI satisfactions with energy issues in a distributed approach to provide the degree of transparency to the underlying communication protocols in use. We first quantified the QoI benefit as the concept of the QoI satisfaction index, received from the sensing sources after the information fusion. We next enhanced the mathematical framework of the Gur Game to propose a distributed QoI-aware energy-management scheme for WSNs, where the fundamental trade-off between the maintenance of the WSN energy and the support of the QoI is exploited and fully addressed. Finally, extensive numerical results on a complete event detection scenario are investigated to show the proposed framework can successfully guarantee satisfactory QoI with only less than 7% QoI outage, saves 80% of the energy reserve if compared with the lower bound solution, and achieves the suboptimum with only 4% gap compared with optimal solution.

In the future, we plan to investigate its applicability to the participatory sensing scenario, where the embedded sensors in smartphones, like cameras, could potentially help understanding the event occurrence of a location. Under this context, the fundamental challenge comes from the trade-off between the support of QoI, the maintenance of energy supply of each device, and the incentive-based system to encourage the user's participation.

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