QoI-Aware Wireless Sensor Network Management for Dynamic Multi-Task Operations

Chi Harold Liu†, Chatschik Bisdikian‡, Joel W. Branch‡ and Kin K. Leung†
† Imperial College, London, U.K.
‡ IBM T. J. Watson Research Center, Hawthorne, U.S.A.
†{chiliu, kin.leung}@imperial.ac.uk, ‡{bisdik, branchj}@us.ibm.com

***Abstract*—This paper considers the novel area of quality-of-information (QoI)-aware network management of multitasking wireless sensor networks (WSNs). Specifically, it provides an investigation of new task admission and resource utilization mechanisms for controlling the individual QoI provided to new and existing tasks using real-time feedback-based monitoring mechanisms. The paper describes three key design elements in support of the above: (a) the *QoI satisfaction index* of a task, which quantifies the degree to which the required QoI is satisfied by the WSN; (b) the *QoI network capacity*, which expresses the ability of the WSN to host a new task with specific QoI requirements without sacrificing the attained QoI levels of other existing tasks, and (c) an adaptive, negotiation-based admission control mechanism that reconfigures and optimizes the usage of network resources in order to optimally accommodate the QoI requirements of all tasks. Finally, extensive results are presented for assessing the performance of the proposed solution for the case of an intruder detection application scenario.**

I. Introduction

Continuing advances in sensor-related technologies, including those in pervasive computing and communication domains, are opening opportunities for the deployment and operation of smart *autonomous* wireless sensor networks (WSNs) [1]. A significant portion of research in this area of WSN *operation and management* (O&M) focuses primarily on the "internal" aspects of WSNs such as energy-efficiency, coverage, routing topologies for efficient data dissemination, and so on [1]. The complementary area that considers the "external" relationships that WSNs have with the information needs of the sensing tasks (or simply *tasks*) they support have experienced significantly less exposure. The novel study of WSN O&M for the efficient and effective support of the multi-dimensional *quality of information* (QoI) needs of tasks are central to our broader research goals and this paper in particular.

Broadly speaking, QoI relates to the ability to judge if available information is *fit-for-use* for a particular purpose [2], [3]. 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 [4].

This research was sponsored by US Army Research laboratory and the UK Ministry of Defence and was accomplished under Agreement Number W911NF-06-3-0001. The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the official policies, either expressed or implied, of the US Army Research Laboratory, the U.S. Government, the UK Ministry of Defense, or the UK Government. The US and UK Governments are authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation hereon.

Existing research in the O&M area usually uses network utility analysis techniques, striving to achieve desirable network operation by fine tuning both statically and dynamically configurable WSN resources, such as traffic flows, routing paths, transmission power, to maximize a network utility curve that is assumed to be known *a priori* [5], [6]. However, the design requirement of prior knowledge of utility functions is quite challenging, and even more so if the utility comes to represent the entire network's behavior when dealing with the multi-dimensionality of QoI attributes for the varying needs of on-demand tasks. These challenges are further compounded when considering time-varying radio, energy, and other network resource conditions, along with the stochastic nature of the task arrival and departure processes.

Our contributions in addressing these challenges are as follows. One, we employ a *runtime* learning of the QoI benefit provided by the WSN to the tasks it supports. We do so by monitoring the level of QoI satisfaction the tasks attain in relation to the QoI levels they request. This relaxes the requirement for the *a priori* knowledge of utility functions and facilitates the dynamic accommodation of tasks with heterogenous requirements. Two, we introduce the concept of *QoI network capacity* to represent the ability of a WSN to host a new task (with specific QoI requirements) without sacrificing the QoI of existing tasks. Three, we propose an adaptive negotiation process to dynamically configure the usage of network resources to best accommodate the QoI requirements of all tasks. We evaluate the proposed WSN management approach in a dynamic multi-task environment.

The rest of the paper is organized as follows. In Section II, we highlight related research activities. Section III establishes a formal model and the flow of our system. Section IV describes the framework's key design elements. Experimental results and discussions are presented in Section V. Finally, Section VI concludes the paper by describing plans for future research.

II. Related Work

To the best of our knowledge, the proposed QoI-aware O&M framework represents the first such WSN application management solution of its kind. However, there is a related body of work that has motivated our current research path.

Despite endeavors for defining QoI [2], [3], it was not until recently that work in [7] proposed a conceptual framework to enable the dynamic binding of sensor information producers and consumers in a QoI-aware manner. The framework expresses information requirements and capabilities according to the 5WH (who, what, when, where, why) principle and enables information producers to categorize the quality attributes of their information in an application-agnostic manner while permitting information consumers to access QoI in application-specific way. Such principles largely enable the development of a framework such as ours.

The network utility maximization (NUM) framework has been recently extended to consider a major aspect of WSNs: shared consumption of a single sensor data source by multiple tasks with different utility functions [5]. This is further addressed in [6], where NUM is used for jointly adapting source data rates and node transmission powers in a multicast, multi-hop wireless environment. Our proposed framework harbors a more flexible negotiation process bridging between tasks' QoI requirements and network status and we also propose the novel concept of *QoI network capacity*.

Other work has focused on modeling the state of the network with respect to supporting quality-related administrative decisions. This includes characterizing information loss due to network delays and buffer overflows to make task admission decisions [8] and monitoring resource allocations and the status of sensed phenomena to determine available QoI [9] and sustain required QoS [10]. Sensor network management issues were studied in [11], [12], where in [11] information quality (completeness and accuracy) is supported by a dynamic Bayesian network model based constraint optimization problem which takes into account all the levels of information processing, including measurement and data aggregation and delivery with predefined network utility. Similarly, [12] further compared the solution with Bayesian network model.

In closing we also mention here work on WSN middleware designs [13], [14], [15] to support some notion of information quality; the latter work has particularly inspired aspects of our current research. We also note that early thoughts behind the research presented in this paper were reported in [16], but without the technical depth and numerical results included here.

III. System Model

We consider a WSN comprising a set $\mathcal{S}$ of sensor nodes, $\mathcal{S} = \{s_i; i = 1, 2, \ldots, N\}$, and a sink node (with sufficient information processing and energy capabilities). Let $\mathcal{J}$ be the set of tasks the WSN currently services, i.e., tasks that currently are bound to the WSN and retrieve the sensed information from it. Let l_j be the duration of that service for task $j \in \mathcal{J}$, and let $\mathcal{S}_j \subset \mathcal{S}$ be servicing task j. The arrival and service duration processes are in general stochastic in nature and their details will be specified as needed later on.

Task $j \in \mathcal{J}$ requires the monitoring of specific feature(s) of interest such as temperature, event occurrences or locations, density of a hazardous chemical, and so on. Each feature is associated with one or more QoI attributes (members of the vector $\mathbf{z}$), such as accuracy and latency of the received information, whose desired values are declared by the tasks upon their arrival for service. We use the superscript r to denote a QoI attribute value as *required* (and declared) by a task and superscript a for the level of the QoI attribute *attained* by the WSN. For example, α_j^r and α_j^a may denote the required and attained probability of detection of an event, respectively. Finally, tasks belong to one of U priority classes with higher priority tasks enjoying preferential treatment and higher guarantees for receiving satisfactory QoI levels. The set $\mathcal{J}_u \subset \mathcal{J}$ represents all the tasks of priority u, $u = 1, 2, \ldots, U$.

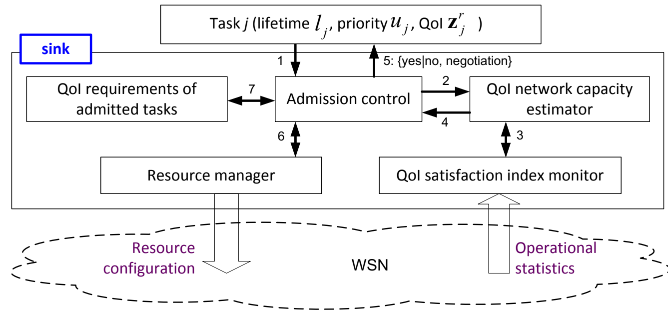

Fig. 1. The overall flow of the proposed approach.

We close this section by highlighting the overall flow of the proposed QoI O&M approach, as shown in Fig. 1. Tasks arrive at the sink for admission (arrow 1), upon which the *QoI network capacity* is measured (arrow 2, see Section IV-B). The capacity value is estimated by monitoring the *QoI satisfaction index* of completed tasks (arrow 3, see Section IV-A). Each of the QoI requirements of the new task is then compared with the QoI network capacity (arrow 4); if there are enough network resources to support the admission of the task (admission decision represented by arrow 5), then optimal resource allocation among all occupying tasks is calculated (arrow 6). Otherwise, a negotiation process may be called upon in an attempt to adjust the QoI requirements of existing tasks so that the new task will be accommodated (arrows 3, 4, 6, and 7; see Section IV-C). When a task completes, the resource allocation function is called again to re-optimize the allocation of limited network resources so that existing ongoing tasks' QoI will be improved.

IV. Key Design Elements

In this section, we will elaborate on the three key design elements of our proposal: (a) the QoI satisfaction index, (b) the QoI network capacity, and (c) the negotiation-based admission control process.

A. QoI Satisfaction Index

The QoI satisfaction index (SI) describes the level of QoI satisfaction the tasks receive from the WSN. It is applicable to each task j and QoI attribute z (member of the vector of

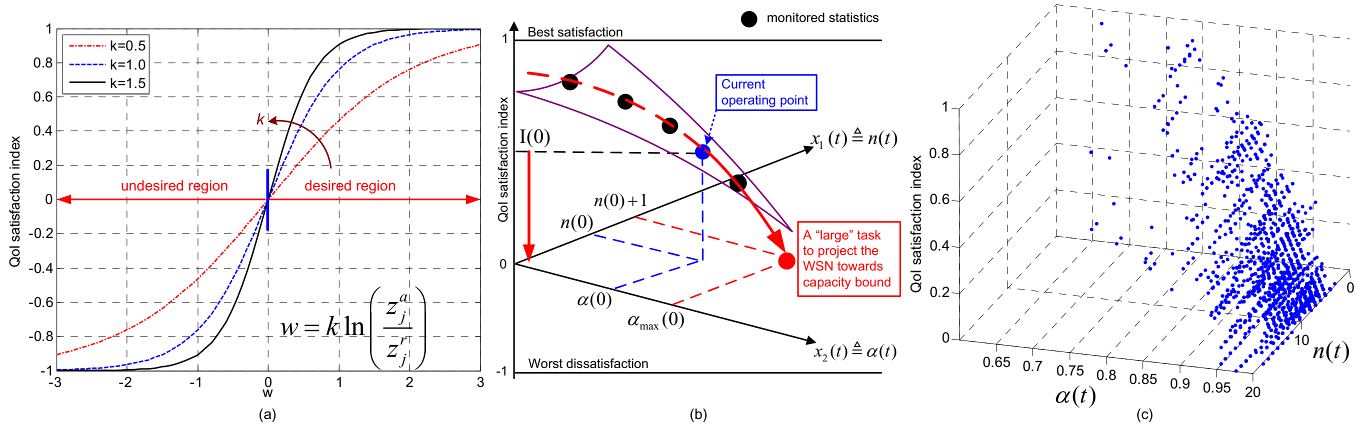

Fig. 2. (a) An illustrative example for the definition of QoI satisfaction index. It is desirable to have $z_j^a \geq z_j^r$ since it is assumed that higher QoI attribute values are more preferable. (b) An example of the shape of the curve produced by mapping f to show how to obtain QoI network capacity $\alpha_{\max}(t)$. (c) 3-D system simulation for the mapping f.

QoI attributes $\mathbf{z}$) and is defined as:

$$\mathrm{I}_j^z \triangleq \tanh\Big(k \cdot \ln \frac{z_j^a}{z_j^r}\Big), \quad \forall j \in \mathcal{J}, \forall z \in \mathbf{z}, \tag{1}$$

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

A per task QoI SI I_j can be defined by combining the per QoI attribute indexes above. In this paper, we opt to use the minimum of these indexes, i.e.,

$$\mathrm{I}_j = \min_{z \in \mathbf{z}} \big(\mathrm{I}_j^z\big) \in (-1, 1), \forall j \in \mathcal{J}. \tag{2}$$

It follows immediately from the definition of the QoI SI that:

Corollary 4.1: For any task $j \in \mathcal{J}$, its QoI requirements are simultaneously satisfied if and only if $\mathrm{I}_j \in [0, 1)$.

Likewise, we can define the instantaneous QoI SI of the network $\mathrm{I}(t)$ as the minimum of indexes of tasks in service at time t, i.e.,

$$\mathrm{I}(t) = \min_{\forall j \in \mathcal{J}} \mathrm{I}_j. \tag{3}$$

B. QoI Network Capacity

Before admitting a new task for service, it is important to identify the potentially limiting resources and estimate the maximum "capacity" the WSN can support at any given time t. Specifically, we define the *QoI network capacity* $\mathbf{C}(t)$ of a WSN as its time-varying capability to satisfy the QoI requirements of all the tasks it serves, i.e., $\mathrm{I}_j \in [0, 1), \forall j \in \mathcal{J}$. The QoI network capacity $\mathbf{C}(t)$ is a collection of elements $\mathbf{C}_p(t)$, $p = 1, 2, \ldots, P$ representing QoI-related parameters such: the maximum probability of detection, the maximum information accuracy, the smallest information gathering delay, etc.

The QoI levels attained are the result of multiple operations spanning several layers (i.e., physical, MAC, network, information processing) where there is no one way to form an optimal interrelation. Thus, we opt to adopt a "black box" view for the WSN encompassing the sensors and associated network resources, including the data sources, relays, and sinks, which are involved in collecting and reporting sensor measurements. Finite resources are shared by multiple tasks within the black box that include, but not limited to, time, bandwidth, energy, etc.

The I/O behavior of the black box is not known a priori but estimated during runtime. Let f represent this I/O behavior:

$$f : \mathbf{x}(t) \in \mathbb{R}^M \rightarrow y(t) \in \mathbb{R}. \tag{4}$$

The input parameters $\mathbf{x}$ comprise the number of running tasks and their QoI requirements. The output $y(t)$ reflects the overall system utilization, as represented by the QoI SI $\mathrm{I}(t)$, hence, $y(t) = \mathrm{I}(t) = f\big(\mathbf{x}(t)\big)$.

The mapping f is learned during runtime by monitoring the QoI delivered to tasks serviced by the WSN. Whenever there is a task admission or completion, the inputs $\mathbf{x}(t)$ are updated and the corresponding output $\mathrm{I}(t)$ is recorded. Then, the mapping f is derived by smoothly interpolating across the QoI satisfaction levels delivered by the network thus far to completed tasks. Specifically, we characterize the potential admission of a new task as an input change $\Delta\mathbf{x}(t)$ into the black box, with a corresponding output change:

$$\tilde{\mathrm{I}}(t) = f\big(\mathbf{x}(t) + \Delta\mathbf{x}(t)\big). \tag{5}$$

Assuming that $f(\cdot)$ is sufficiently smooth, we write:

$$\begin{aligned} \tilde{\mathrm{I}}(t) \quad \approx \quad & f(\mathbf{x}(t)) + \sum_{i=1}^{M} \frac{\partial f}{\partial x_i(t)} \Delta x_i(t) + \frac{1}{2} \sum_{i=1}^{M} \frac{\partial^2 f}{\partial x_i^2(t)} \Delta x_i^2(t) \\ & + \frac{1}{2} \sum_{i=1}^{M} \sum_{j \neq i} \frac{\partial^2 f}{\partial x_j(t) \partial x_i(t)} \Delta x_i(t) \Delta x_j(t). \end{aligned} \tag{6}$$

Note that as per Corollary 4.1, the absolute lowest satisfaction level allowed is when $\mathrm{I}(t) = 0$, at which level the corresponding input variables defined the QoI network capacity.

To illustrate the process of estimating the QoI network capacity, we consider a case where event detection tasks request service from the WSN declaring a required probability of detection $\alpha_j^r, \forall j \in \mathcal{J}$. In this case, the QoI network capacity reduces to a scalar representing the maximum probability of detection the WSN can provide to all its tasks, or $\mathbf{C}(t) \triangleq \alpha_{\max}(t)$. We assume that a new task arrives for admission at $t = 0$ when the WSN's state was: $\mathbf{x}(0) = \big(n(0), \alpha(0)\big) \in \mathbb{R}^2$, where $n(0)$ denotes the number of existing tasks, and $\alpha(0) = \max_{\forall j \in \mathcal{J}} \alpha_j^r$ denotes the maximum required probability of detection. Then our black box is represented by the mapping,

$$\mathrm{I}(0) = f\big(n(0), \alpha(0)\big), \tag{7}$$

as shown in Fig 2(b). The admission of a very "demanding" (with regard to requested QoI levels) new task at time $t = 0$ forces the network to reach its capacity, where an input change $\Delta\mathbf{x}(0) = \big(\Delta n(0), \Delta\alpha(0)\big) = \big(1, \alpha_{\max}(0) - \alpha(0)\big)$ results in a change of output to,

$$\tilde{\mathrm{I}}(0) = f\big(n(0) + 1, \alpha_{\max}(0)\big) = 0. \tag{8}$$

Therefore, we rewrite (6) as,

$$\begin{aligned} &\mathrm{I}(0) + \frac{\partial f}{\partial n(0)} + \Delta\alpha(0)\frac{\partial f}{\partial \alpha(0)} + \frac{1}{2}\frac{\partial^2 f}{\partial n^2(0)} \\ &+ \frac{[\Delta\alpha(0)]^2}{2}\frac{\partial^2 f}{\partial \alpha^2(0)} + \Delta\alpha(0)\frac{\partial^2 f}{\partial n(0)\partial\alpha(0)} = 0, \end{aligned} \tag{9}$$

where $\Delta\alpha(0) = \alpha_{\max}(0) - \alpha(0)$ and all partial derivatives are computed at current network state $\mathbf{x}(0) = (n(0), \alpha(0))$ at time $t = 0$. Since, $n(t)$ is discrete, we approximate its "derivatives" by the slopes of adjacent network measurements. For example, assume that at least two adjacent measurements $(n_1, \mathrm{I}_1), (n_2, \mathrm{I}_2)$ around the current state n are obtained; for brevity, we have dropped the time index t. Then the first order partial derivative is computed as the average of two adjacent slopes of measurements,

$$\frac{\partial f}{\partial n}\Big|_1 \approx \frac{\mathrm{I}_1 - \mathrm{I}}{n_1 - n}, \quad \frac{\partial f}{\partial n}\Big|_2 \approx \frac{\mathrm{I} - \mathrm{I}_2}{n - n_2}, \tag{10}$$

and the second order partial derivative is computed as the change of the above two slopes:

$$\frac{\partial^2 f}{\partial n^2} \approx \frac{\frac{\partial f}{\partial n}|_1 - \frac{\partial f}{\partial n}|_2}{(n_1 - n) - (n - n_2)}. \tag{11}$$

Expression (9) is a quadratic function with only decision variable $\alpha_{\max}(0)$. Therefore, since $\alpha_{\max}(0) > \alpha(0)$,

$$\alpha_{\max}(0) = \alpha(0) + \frac{-b + \sqrt{b^2 - 4ac}}{2a}, \text{ where:} \tag{12}$$

$$a = \frac{1}{2}\frac{\partial^2 f}{\partial \alpha^2(0)}, \quad b = \frac{\partial^2 f}{\partial n(0)\partial\alpha(0)} + \frac{\partial f}{\partial \alpha(0)},$$
$$\text{and } c = \mathrm{I}(0) + \frac{\partial f}{\partial n(0)} + \frac{1}{2}\frac{\partial^2 f}{\partial n^2(0)}.$$

If, furthermore, the second order term is negligible around the current system operating point $\mathbf{x}(0) = (n(0), \alpha(0))$, we can further simplify (12):

$$\alpha_{\max}(0) = \alpha(0) - \frac{\mathrm{I}(0) + \partial f/\partial n(0)}{\partial f/\partial \alpha(0)}. \tag{13}$$

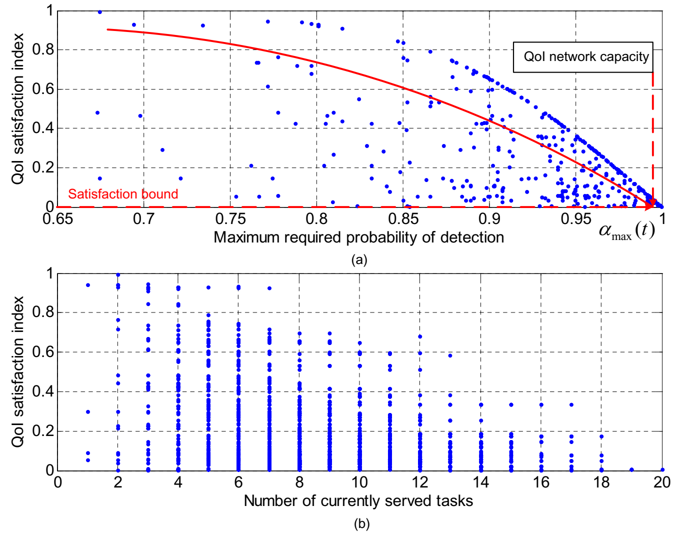

Fig. 3. (a) System simulation to show $\alpha(t)$ dimension of the statistics. (b) System simulation to show $n(t)$ dimension of the statistics.

Fig. 2(b) illustrates how this methodology is used, and Fig. 2(c) depicts a 3-D real-time measurement (from a system simulation) of QoI SIs collected. Each dimension of statistics collected is shown in Fig. 3(a) and Fig. 3(b), where QoI network capacity is estimated.

C. Negotiation-based Admission Control for Sensing Tasks

Following the estimation of the QoI network capacity, suppose a new task j' with priority $u_{j'}$ and QoI requirements $\mathbf{z}_{j'}^r$, arrives at the sink at time t. Before assigning the task to any sensor(s), an admission control decision is made according to the following conditions,

$$\mathbf{C}(t) \succeq \mathbf{z}_{j'}^r \begin{cases} \text{Admit, if true,} \\ \text{Negotiate, otherwise,} \end{cases}$$

where $\succeq$ denotes the element-by-element comparison. An admission control scheme typically will outright ban the new task if some threshold condition is violated. Instead, we opt first for a negotiation between all tasks, new and old, in search of an acceptable (to the tasks) and attainable (by the network) compromise regarding the QoI SI delivered by the network. Resource management in this case includes scheduling, rate and power allocation, sensor selection, integration of data compression, etc.

Under the guidance of the resource optimization, ongoing tasks may internally reconfigure and reallocate network resources among themselves, so that the optimized network status will give the best achievable QoI for the new task. Nevertheless, sometimes the network might be overloaded operating near the capacity bound, in which case no matter how the network resources are optimized and reconfigured, the required QoI will not be satisfied, in which case the negotiation process may also be employed. As a result of the negotiation, the new task may *adapt* its originally requested QoI level in order to meet network capabilities, or existing tasks with lower priority levels may tune their QoI requirements and release resources for the new higher priority one. During the negotiation phase, the following optimization is pursued:

$$\{\boldsymbol{\xi}_j^*(t)\} = \arg \max_{\forall u_j < u_{j'}} \mathcal{F}\left(\mathbf{z}_j^r, \boldsymbol{\xi}_j(t)\right) \tag{14}$$

$$\text{subject to: } \left\{ \begin{array}{l} z_j^a \geq z_j^r, \forall u_j < u_{j'}, j \in \mathcal{J}, z \in \mathbf{z} \\ \sum_{\forall j \in \mathcal{J} \cup j'} \boldsymbol{\xi}_j(t) \preceq \boldsymbol{R}(t). \end{array} \right.$$

Recall that $u_{j'}$ denotes the priority of the new task. The objective function $\mathcal{F}$ is chosen to balance the *fairness* among prioritized tasks. The arguments to this optimization problem are adaptable multiple QoI requirements $\{\mathbf{z}_j^r\}_{\forall u_j < u_{j'}}$ of those tasks with lower priority classes, and the resource occupancy $\{\boldsymbol{\xi}_j(t)\}$. The optimization is first constrained by the need to respect the QoI satisfaction of all tasks of low priority currently serviced. Then it is further constrained by the resource allocation. Let $\boldsymbol{R}(t) = \{\mathcal{R}^p(t)\}|_{p=1}^P \in \mathbb{R}^P$ describe the instantaneous remaining resources like energy, and let $\boldsymbol{\xi}_j^*(t) = \{\xi_j^{p,*}(t)\}|_{p=1}^P \in \mathbb{R}^P$ denote the corresponding optimal resource occupancy of each task $j, \forall j \in \mathcal{J} \cup j'$, after the resource allocation. Then, $\boldsymbol{\eta}(t) = \{\eta^p(t)\}|_{p=1}^P \in \mathbb{R}^P$ represents the total resource occupancy for all ongoing tasks at time t, i.e.,

$$\boldsymbol{\eta}(t) = \sum_{\forall j \in \mathcal{J} \cup j'} \boldsymbol{\xi}_j^*(t). \tag{15}$$

These total resource demands have to be smaller or equal than the remaining resources $\boldsymbol{R}(t)$ element by element.

V. Performance Evaluation

A. The Evaluation Scenario

We evaluate the proposed scheme under an intruder detection user scenario [17], where multiple detection tasks with different QoI requirements arrive at the WSN over time comprising $N = 30$ sensor deployed over an area 200×200 meters, see Fig. 4. Task j requests a given probability of detection α_j^r and this is the only QoI parameter of concern. At deployment time, each sensor has an energy reserve at level $\mathcal{E}$, so that $N\mathcal{E}$ is the overall energy reserve for the entire network. Tasks arrive according to a Poisson process with rate λ and last for a random, exponentially distributed time interval l_j with average duration $1/\mu$. The are two priority levels for tasks, high and low, and $1/5$ of tasks are high priority ones. While high priority tasks have guaranteed QoI requirements that are not negotiable, the QoI requirements of low priority tasks are adaptable between low and high QoI satisfaction levels, $\alpha_j^{r,l}$ and $\alpha_j^{r,h}$, respectively. Sensors are equipped with smart antenna arrays such that at any given time one sensor could form multiple beams to service concurrent tasks and the strength of the beam is controlled by power allocated to each sensor (e.g. sensor 8 shown in Fig. 4).

1) Detection Model: We employ a simple detection model [18] using physical properties of the sensors, where the detection probability p_{ij} for task j from sensor i is achieved

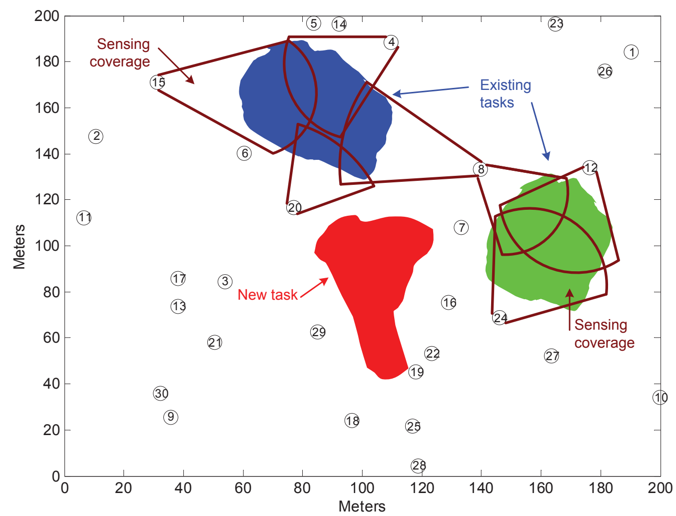

Fig. 4. Simulation scenario for intruder detection scenario. Two existing intruder detection tasks are running in the network (marked as the blue and green regions), while a new task (marked as red region) arrives for admission. Several sensors are selected per task as data sources (sensor 8 executes two tasks simultaneously by adjusting antenna beams).

assuming using a normalized full power level $\gamma_j^*(t) = 1$, i.e.,

$$p_{ij} = \begin{cases} 1, & \text{if } r_{ij} < d_1, \\ e^{-\beta_1 (r_{ij} - d_1)^{\beta_2}}, & \text{if } d_1 < r_{ij} < d_2, \\ 0, & \text{if } r_{ij} > d_2 > d_1, \end{cases} \tag{16}$$

$\forall i \in \mathcal{S}_j$; we use the values $\beta_1 = 0.12$, $\beta_2 = 0.8$, $d_1 = 28$m, and $d_2 = 58$m also used in [18] and r_{ij} denotes the sensor-to-target distance. The optimal resource occupancy vector $\boldsymbol{\xi}_j^*(t)$ reduces to a scalar, representing the power in this case, i.e., $\boldsymbol{\xi}_j^*(t) \triangleq \gamma_j^*(t)$, and the *attained* QoI SI I_j can be explicitly expressed in the following form,

$$\mathrm{I}_j = \tanh\left(k \ln \frac{\gamma_j^*(t) \times \min_{\forall i \in \mathcal{S}_j} p_{ij}}{\alpha_j^r}\right), \forall j \in \mathcal{J}, \tag{17}$$

where attained probability of detection is computed as $\alpha_j^a = \gamma_j^*(t) \min_{\forall i \in \mathcal{S}_j} p_{ij}$. Note that we assume that the probability of detection a task experiences is given by the smallest of all probabilities of detection attained by any of the sensors that service the task ($\min_{\forall i \in \mathcal{S}_j} p_{ij}$). Furthermore, we assume that the QoI level received by task j, α_j^a, increases linearly with the corresponding power $\gamma_j^*(t)$.

2) Lower Bound QoI Parameter: The maximum achieved probability of detection is, of course, bounded by $\alpha_{\max}^a = 1, \forall j \in \mathcal{J}$, while the required probability of detection is pre-specified by different tasks. Therefore, the selection of parameter k in (1) should be such that the highest QoI SI is achieved, i.e., $\mathrm{I}_j^{\max} \approx 1$, when $\alpha_{\max}^a = 1$. In other words, $\mathrm{I}_j^{\max} = \tanh\left(k \ln \frac{1}{\alpha_j^r}\right) \approx 1, \forall j \in \mathcal{J}_1 \bigcup \mathcal{J}_2$. Setting the maximum achievable QoI SI at $\mathrm{I}_j^{\max} = 0.999$, we derive the lower bounds of parameter k for high and low priority tasks respectively, as:

$$k_h \geq \tanh^{-1}\left(\mathrm{I}_j^{\max}\right) / \ln \frac{1}{\alpha_j^{r,h}}, \forall j \in \mathcal{J}_1,$$
$$k_l \geq \tanh^{-1}\left(\mathrm{I}_j^{\max}\right) / \ln \frac{1}{\alpha_j^{r,l}}, \forall j \in \mathcal{J}_2. \tag{18}$$

For tasks with different QoI requirements α_j^r, the lower bounds k_h, k_l will change accordingly, e.g., if $\alpha_j^{r,h} = 0.8$ and $\alpha_j^{r,l} = 0.5$, we are able to compute QoI parameters $k_h \geq 17, k_l \geq 5.5$, which enforce that when the optimal detection is achieved, the maximum QoI SI $\mathrm{I}_j^{\max}$ is received.

3) Optimal Power Allocation: Optimal power allocation is performed among all existing and new tasks such that the QoI requirements of all tasks are successfully guaranteed and certain network objective (e.g., fairness) is achieved. We have:

$$\{\gamma_j^*(t)\}_{\forall j \in \mathcal{J}} = \arg\max \min_{\forall j \in \mathcal{J}} \mathrm{I}_j \tag{19}$$

$$\text{subject to: } \begin{cases} \alpha_j^a \geq \alpha_j^r, \forall j \in \mathcal{J}, \\ \sum_{\forall j \text{ on } i} \gamma_j(t) l_j \leq \zeta_i(t), \forall i \in \mathcal{S}_j, \end{cases}$$

where the design objective is chosen to balance the QoI SIs achieved by all tasks. I_j is defined in (17) as a function of resource occupancy $\gamma_j(t)$. The first constraint represents the QoI satisfaction condition among all tasks, while the second constraint represents the energy reserve, and $\zeta_i(t)$ denotes the remaining energy constraint for each sensor. Assuming equal power is allocated for every sensor source of a particular task, the decision variable for this optimization problem is a set of power levels $\{\gamma_j^*(t)\}_{\forall j \in \mathcal{J}}$.

4) Negotiation Process: When the network does not have enough network resources (energy in this scenario) to support the new task, existing lower priority tasks have to adapt/degrade their QoI levels to release resources for the new task. The optimization objective for this process is to minimize the maximum percentage of QoI loss among negotiated tasks, as:

$$\{\gamma_j^*(t)\}_{\forall j \in \mathcal{J}_2} = \arg\min \max_{\forall j \in \mathcal{J}_2} \frac{\mathrm{I}_j^{\text{before}} - \mathrm{I}_j^{\text{after}}}{\mathrm{I}_j^{\text{before}}} \tag{20}$$

$$\text{subject to: } \begin{cases} \alpha_j^a \geq \alpha_j^{r,l}, \forall j \in \mathcal{J}_2, \\ \sum_{\forall j \text{ on } i} \gamma_j(t) l_j \leq \zeta_i, \forall i \in \mathcal{S}_j, \end{cases}$$

where the $\mathrm{I}_j^{\text{after}}$ denotes the attained QoI level *after* negotiation by using power $\widetilde{\gamma}_j^*(t)$ in (20). While the first constraint denotes the QoI requirement constraint for high and low priority users, the second constraint represents the per-sensor energy reserve for the sum of allocated energy among tasks. The solution of this optimization problem gives the best achievable QoI level for the new task by adapting the QoI requirements of existing tasks.

B. System Dynamic Behaviors

Next, we take a look at the detailed system behaviors due to dynamic task arrivals and departures, heterogeneous QoI requirements, resource optimizations and negotiations. Fig. 5(a) illustrates the simulated traffic pattern (i.e., the number of tasks, task arrival and departure processes, QoI requirements), and Fig. 5(b) and Fig. 5(c) show dynamic QoI changes experienced by 70 tasks, with respect to (w.r.t.) two different QoI SI parameters k_h, k_l.

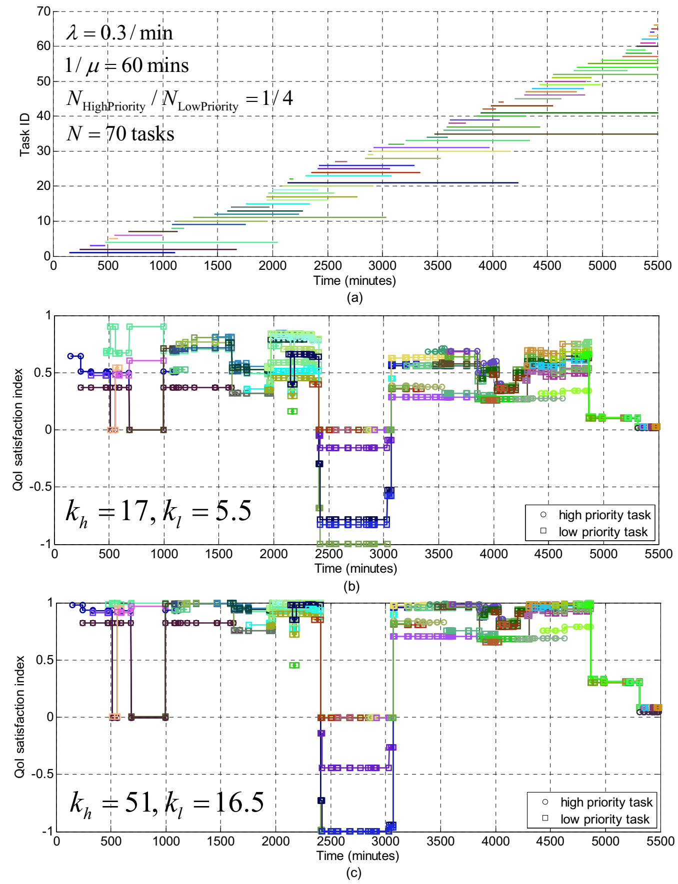

Fig. 5. Simulation results for system behavior. (a) Task arrival and departure time line. (b) QoI SI change vs. time for $k_h = 17, k_l = 5.5$. (c) QoI SI change vs. time for $k_h = 51, k_l = 16.5$.

For fixed QoI parameters k_h, k_l, abrupt QoI changes can be seen for relatively high traffic load conditions. When a new task arrives, the negotiation process will attempt to accommodate it while reasonably degrading the QoI SIs of existing tasks, though still maintaining the minimum required levels for them. When completed tasks are removed from the network, network resources are released and, hence, the QoI SIs of ongoing tasks are improved. Our framework is able to adjust resource utilizations (power in this use case) in a way that maximizes the QoI satisfaction whenever there is an opportunity. Meanwhile, when there is a sudden surge in task arrivals and very stringent QoI requirements during a short period of time or the tasks require very stringent QoI requirements (as, for example, from time 2500mins to 3000mins), some tasks would experience QoI failures as their QoI satisfaction levels cannot be satisfied in any meaningful way; nonetheless there are still tasks successfully maintaining the minimum level, i.e., $\mathrm{I}_j = 0$, to utilize the limited network resources.

On the other hand, when we increase QoI parameters k_h and

k_l proportionally, we improve the attained QoI SI compared with the one calculated using the lower k_h and k_l. From Fig. 5(c), it can be seen that this helps the system ease the resource competition among tasks and increase their satisfaction level (due to higher estimated QoI network capacity).

C. Optimal Network Design Analysis

In this subsection, we explore the performance limits for constrained sensor network resources and varying QoI requirements for the different tasks, focusing on higher QoI network capacity, longer system lifetime, and increased admission rate, while satisfying the required QoI of admitted tasks. To do so, we parallel the entire WSN system as a service or queuing system with servicing resources including the bandwidth, the radio conditions, the energy reserves of the network, etc. In this queuing system, the service capacity is not fixed or known a priori. It is represented by the QoI network capacity, which, as previously discussed, is learned at runtime from the QoI levels that the WSN delivered to tasks in the past. Given an average arrival rate of tasks λ and an average task service duration $1/\mu$, questions of interest for such a queueing system include:

(1) Given network load $\rho = \lambda/\mu$, what is the WSN lifetime $T_{\max}$ given that all accepted tasks experience satisfactory QoI levels, i.e., $\mathrm{I}_j \geq 0$?
(2) Given a minimum required WSN lifetime $T_{\min}$ and satisfactory QoI levels for all tasks, what is the region of admission rates $\lambda \leq \lambda_{\max}$ that the WSN can sustain as a function of task duration $1/\mu$?

Note that for the purpose of the intruder detection case considered here, we define the WSN lifetime $T_{\max}$ as the useful length of time for the WSN beyond which the amount of remaining energy reserve cannot guarantee a minimum probability of detection $\alpha^r_{\min} = \min_{\forall j \in \mathcal{J}} \alpha^r_j$ for any task arriving at the WSN requesting service at this time.

The following Theorem relates to the above questions.

Theorem 5.1: The task arrival rate λ vs. WSN lifetime T trade-off is of the form $\frac{\lambda T}{\mu} \leq \frac{N\mathcal{E}}{\beta \alpha^r_{\min}}$, where $\beta \triangleq \min_{\forall i \in \mathcal{S}_1} p_{i1}$ denotes a constant given geographic locations of sensors and tasks. Furthermore, the WSN lifetime and the maximum admission rate can be expressed as $T_{\max} = \frac{N\mathcal{E}}{\beta \alpha^r_{\min} \rho}$, and $\lambda_{\max} = \beta \frac{N\mathcal{E}\mu}{\beta \alpha^r_{\min} T_{\min}}$, respectively.

Proof: Recall that for the intruder detection case, the resource occupancy for each task j is reduced to the scalar power $\gamma^*_j(t)$, and the relationship between $\gamma^*_j(t)$ and QoI SI I_j is described by (17), which can be rewritten as:

$$\gamma^*_j(t) = \alpha^r_j \frac{\exp\left(\frac{1}{k}\tan \mathrm{I}_j\right)}{\min_{\forall i \in \mathcal{S}_j} p_{ij}}. \tag{21}$$

According to Corollary 4.1, the lower bound resource condition for satisfactory QoI is taken when $\mathrm{I}_j = 0$, which produces the minimum required power assumption $\gamma^*_{j,\min}(t)$, as:

$$\gamma^*_j(t) = \frac{\alpha^r_j}{\min_{\forall i \in \mathcal{S}_j} p_{ij}} \geq \frac{\alpha^r_{\min}}{\min_{\forall i \in \mathcal{S}_j} p_{ij}} = \gamma^*_{j,\min}(t), \tag{22}$$

where the inequality condition uses the notation $\alpha^r_j \geq \alpha^r_{\min}, \forall j \in \mathcal{J}$.

At the same time though, given the constraint on the total energy reserves in the network, $N\mathcal{E}$, it follows that:

$$\sum_{\forall j \in \mathcal{J}^T} \gamma^*_j(t) l_j \leq N\mathcal{E}, \tag{23}$$

where N denotes the total number of sensor sources in the field, $\mathcal{J}^T$ denotes the set of tasks that have been serviced during the WSN lifetime T, and l_j denotes the duration of task j. Taking expectations on both sides of (23), recall that l_j is exponentially distributed with parameter μ, yields:

$$\begin{aligned} N\mathcal{E} &\geq \mathbb{E}\Big(\sum_{\forall j \in \mathcal{J}^T} \gamma^*_j(t) l_j\Big) = \mathbb{E}\Big(\mathbb{E}\Big(\sum_{\forall j \in \mathcal{J}^T} \gamma^*_j(t) l_j \Big| \mathcal{J}^T\Big)\Big) \\ &= \mathbb{E}\Big(\sum_{\forall j \in \mathcal{J}^T} \mathbb{E}\Big(\gamma^*_j(t) l_j\Big)\Big) = \mathbb{E}\Big(\mathcal{J}^T \mathbb{E}\Big(\gamma^*_1(t) l_1\Big)\Big) \\ &= \mathbb{E}\Big(\mathcal{J}^T\Big)\mathbb{E}\Big(\gamma^*_1(t) l_1\Big) = \lambda T \mathbb{E}\Big(\gamma^*_1(t)\Big)\mathbb{E}\Big(l_1\Big) \\ &= \frac{\lambda T}{\mu}\mathbb{E}\Big(\gamma^*_1(t)\Big), \end{aligned} \tag{24}$$

where we use the fact that the arrival and departure processes of tasks, and the task optimal resource occupancies $\gamma^*_j(t), \forall j \in \mathcal{J}^T$, are independent random variables. Furthermore, the average number of tasks $\mathbb{E}\left(\mathcal{J}^T\right)$ admitted during WSN lifetime T can be approximated by the Little's theorem [19] as $\mathbb{E}\left(\mathcal{J}^T\right) = \lambda T$, and average duration of task can be represented by $\mathbb{E}\left(l_1\right) = 1/\mu$. Therefore, we further simplify (24) by using condition (22), as:

$$\begin{aligned} N\mathcal{E} &\geq \frac{\lambda T}{\mu}\mathbb{E}\Big(\gamma^*_1(t)\Big) \geq \frac{\lambda T}{\mu}\mathbb{E}\Big(\gamma^*_{1,\min}(t)\Big) \\ &\geq \frac{\lambda T}{\mu}\mathbb{E}\left(\frac{\alpha^r_{\min}}{\min_{\forall i \in \mathcal{S}_1} p_{i1}}\right) \\ &= \frac{\alpha^r_{\min}\lambda T}{\beta\mu}, \end{aligned} \tag{25}$$

where $\beta \triangleq \min_{\forall i \in \mathcal{S}_1} p_{i1}$ denotes a constant given the geographic location of sensors and tasks. Hence, we rewrite (25) as,

$$\frac{\lambda T}{\mu} \leq \frac{N\mathcal{E}}{\beta \alpha^r_{\min}} \tag{26}$$

Finally, we derive the WSN lifetime $T_{\max}$ and the maximum task admission rate $\lambda_{\max}$ as:

$$T_{\max} = \frac{N\mathcal{E}}{\beta \alpha^r_{\min} \rho}, \quad \lambda_{\max} = \frac{N\mathcal{E}\mu}{\beta \alpha^r_{\min} T_{\min}}. \tag{27}$$

■

Theorem 5.1 shows that (26) serves as the principle worst-case (in terms of guaranteeing the minimum QoI requirement) WSN design criterion for this scenario. Furthermore, it shows the fundamental trade-off among the WSN lifetime, the task arrival and departure rates, and the QoI requirement. For instance, a higher QoI requirement ($\alpha^r_{\min}$) would constrain the energy usage for multiple tasks which in turn has impacts

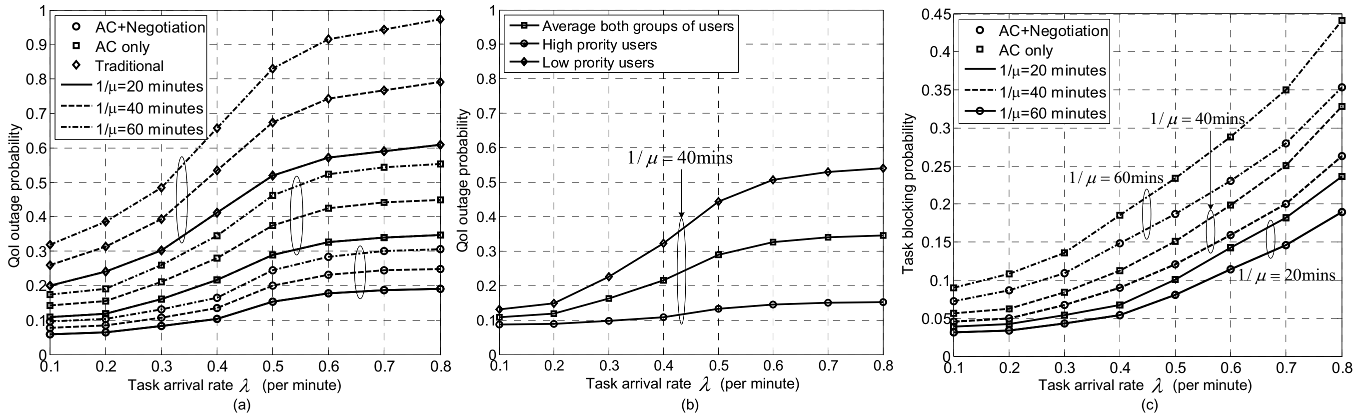

Fig. 6. (a) Average QoI outage probability among all completed tasks. (b) A detailed view of average QoI outage probability of two priority classes. (c) Average task blocking probability. All figures are plotted w.r.t different task arrival rates λ and/or average task lifetime $1/\mu$.

on the maximum admission rate $\lambda_{\max}$ and the WSN lifetime $T_{\max}$.

D. Network Performance

The proposed algorithm, referred as "AC+Negotiation", is compared with the scheme without negotiation process "AC only" and the traditional WSN management approach.

The traditional WSN management approach is an one-off deployment process assuming "static" behaviors of system parameters, where sensors are positioned in the field of interests and set up their power consumptions in order to attain a particular level of probability of detection (e.g. $\alpha_j^r = 90\%$). Furthermore, the WSN does not adjust any of its operational parameters throughout its lifetime, no matter a task's needs. In contrast, the proposed negotiation-based network management approach allows parameters to be adjusted judiciously according to the task needs. In this simulation, we set the probability of detection in the traditional approach as the average of the probabilities of detection that the various tasks request in the proposed approach.

Fig. 6(a) illustrates the average QoI outage probability of all completed tasks as a function of both task arrival rate λ and average task duration $1/\mu$. We define QoI outage as the portion of tasks (among all completed tasks) whose QoI requirements have failed. A QoI failure occurs for task j if $\mathrm{I}_j < 0$ occurs at least once during the task's lifetime l_j. For fixed average task lifetime, it is interesting to observe the saturation feature of QoI outage probability for both "AC only" and "AC+Negotiation" schemes when we increase the arrival rate since admission controlling the new tasks helps maintain the QoI satisfaction of ongoing tasks. However, the saturation bounds of the two schemes vary significantly: for example, when $\lambda = 0.8$/min and $1/\mu = 20$ mins, the proposed algorithm can guarantee 81% of QoI satisfaction for all tasks, as compared to 65% for "AC only" scheme. This is because the negotiation process helps optimize resource utilization to release some resources for higher priority tasks. On the other hand, when the average task duration is increased, the QoI outage probabilities of the three schemes increase by 20% proportionally. This is because the increasing network load $\rho = \frac{\lambda}{\mu}$ at any time in the network may jeopardize the QoI satisfaction of ongoing tasks, since finite network resources are shared by more tasks than before, which in turn may violate the QoI network capacity bound.

The more detailed view of the average QoI outage probability for different priority user groups is shown in Fig. 6(b), where only the "AC+Negotiation" scheme is plotted with a fixed average task lifetime $1/\mu = 40$ mins. Interestingly, although similar behaviors for high and low priority user groups can be seen, the saturation speeds of their QoI outage probability differ significantly. This is primarily because our proposed negotiation process successfully guarantees non-negotiable QoI levels for high priority tasks, and adaptable QoI levels for low priority ones. On the other hand, successful task rejections help maintain low QoI outage probability and high QoI satisfaction for existing tasks in the network.

Fig. 6(c) shows the behavior of the average task blocking probability w.r.t. both task arrival rate and duration (the traditional case is not shown because rejection to new tasks is not applied). We see that the task blocking probability increases significantly when more tasks are offered (higher λ). However, these successful task rejections help maintain low QoI outage probability and high QoI satisfaction for existing ones in the network, as seen consistent with Fig. 6(a). On the other hand, when network load ρ is increased by increasing task duration, the per-task resource availability decreases since the overall network resources are shared by higher number of concurrent tasks serviced.

Table I shows the average jitter of QoI SI among completed and satisfactory tasks, which is defined as the variance of attained QoI SIs. Unlike QoI outage and blocking probability, this performance metric directly reflects the performance stability (or fairness) to provide QoI to all tasks when interfacing the system. For fixed average task lifetime $1/\mu$, we see 5% and 11% jitter decrease if the proposed "AC+Negotiation" scheme is compared with the "AC only" scheme and the "Traditional" scheme, respectively.

Fig. 7 shows the normalized WSN lifetime w.r.t. different

TABLE I
AVERAGE JITTER OF THE RECEIVED QOI SI, WITH FIXED TASK ARRIVAL RATE $\lambda = 0.5$ PER MINUTE

	AC+Negotiation	AC only	Traditional
$1/\mu = 20$ mins	0.16	0.21	0.27
$1/\mu = 40$ mins	0.17	0.22	0.28
$1/\mu = 60$ mins	0.18	0.24	0.29

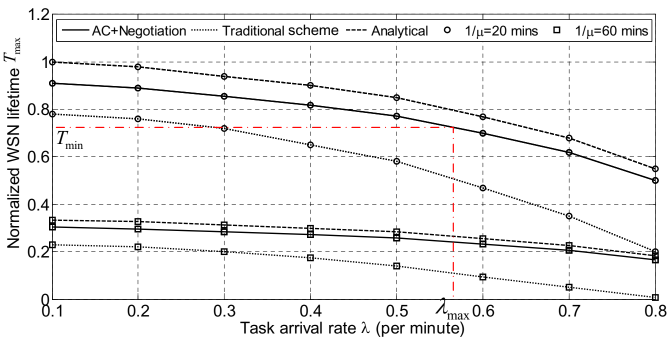

Fig. 7. Normalized WSN lifetime w.r.t. different task arrival rate λ and average task duration $1/\mu$.

task arrival and departure rates. The minimum probability of detection is set to $\alpha^r_{\min} = 90\%$ to compute the analytical bound in (27), and in the simulation of the proposed "AC+Negotiation" scheme, the required probability of detection is set as $\alpha^r_j \in [\alpha^r_{\min}, 1], \forall j \in \mathcal{J}$. For "Traditional" scheme, this QoI requirement is set as the average of that for "AC+Negotiation" scheme. We see significant improvement in the WSN lifetime when compared with the traditional scheme, and this improvement increases when tasks arrive more frequently (due to more efficient resource allocation among all tasks). Furthermore, the proposed approach successfully approximates the analytical results given in (27) while traditional settings perform far away behind. Meanwhile, given the desired WSN lifetime, this figure also shows the way to obtain the maximum admission rate $\lambda_{\max}$ the network can support given a minimum probability of detection $\alpha^r_{\min}$.

VI. CONCLUSIONS AND FUTURE WORK

QoI-aware WSN O&M represents a broad area of research challenges that this paper only begins to address. Contrary to other research focusing on the network utility maximization problem with predefined utility functions, this paper employs a novel runtime design perspective where the WSN learns and optimizes the network utility by probing the satisfaction levels of completed tasks. Three key design elements were proposed, including a novel concept of QoI SI, QoI network capacity, and an adaptive, negotiation-based admission control process. Finally, extensive numerical results on a complete intruder detection user scenario show the proposed framework can successfully guarantee satisfactory QoI, prolong the WSN lifetime while maintaining low blocking probability and jitter.

In the course of this work, we have identified several important future research directions motivated by the deployment issues in a broader space of application scenarios. These include: extending the overall O&M solution to a distributed configuration for large-scale ad hoc networked environments as well as investigating extensions to the definitions of capacity and negotiation; investigating the impact of sensor network duty-cycling; augmenting the network with networked actuators, and their impact on the types of tasks admitted; and investigating making the O&M framework adaptable to different sensor network deployment set-ups, potentially as part of a sensor-oriented middleware such as in [15].

REFERENCES

[1] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "A survey on sensor networks," *IEEE Comm. Mag.*, vol. 40, no. 8, pp. 102–114, Aug. 2002.

[2] R. Y. Wang and D. M. Strong, "Beyond accuracy: what data quality means to data consumers," *J. Manage. Inf. Syst.*, vol. 12, no. 4, pp. 5–33, 1996.

[3] M. E. Johnson and K. C. Chang, "Quality of information for data fusion in net centric publish and subscribe architectures," in *FUSION'05*, vol. 2, July 2005, p. 8.

[4] C. Bisdikian, L. M. Kaplan, M. B. Srivastava, D. J. Thornley, D. Verma, and R. I. Young, "Building principles for a quality of information specification for sensor information," in *FUSION'09*, July 2009, pp. 1370–1377.

[5] S. Eswaran, A. Misra, and T. La Porta, "Utility-based adaptation in mission-oriented wireless sensor networks," in *IEEE SECON'08*, June 2008, pp. 278–286.

[6] Y. Hou, K. K. Leung, and A. Misra, "Enhancing congestion control with adaptive per-node airtime allocation for wireless sensor networks," in *IEEE PIMRC'09*, Sept. 2009.

[7] C. Bisdikian, J. Branch, K. K. Leung, and R. I. Young, "A letter soup for the quality of information in sensor networks," in *IEEE Inf. Quality and Quality of Service (IQ2S) Workshop (in IEEE PerCom'09)*, March 2009, pp. 1–6.

[8] A. Tolstikov, J. Biswas, and C.-K. Tham, "Data loss regulation to ensure information quality in sensor networks," in *IEEE ISSNIP'05*, Dec. 2005, pp. 133–138.

[9] A. Tolstikov, C.-K. Tham, and J. Biswas, "Quality of information assurance using phenomena-aware resource management in sensor networks," in *IEEE Int'l Conf. on Networks'06*, vol. 1, Sept. 2006, pp. 1–7.

[10] Y. Zhang and Q. Ji, "Active and dynamic information fusion for multisensor systems with dynamic bayesian networks," *IEEE Trans. on Systems, Man, and Cybernetics, Part B*, vol. 36, no. 2, pp. 467–472, Apr. 2006.

[11] A. Tolstikov, C.-K. Tham, W. Xiao, and J. Biswas, "Information quality mapping in resource-constrained multi-modal data fusion system over wireless sensor network with losses," in *Int'l Conf. on Information, Comm. & Signal Processing'07*, Dec. 2007, pp. 1–5.

[12] A. Tolstikov, W. Xiao, J. Biswas, S. Zhang, and C.-K. Tham, "Information quality management in sensor networks based on the dynamic bayesian network model," in *IEEE ISSNIP'07*, Dec. 2007, pp. 751–756.

[13] S. Hadim and N. Mohamed, "Middleware for wireless sensor networks: A survey," in *IEEE COMSWARE'06*, Jan. 2006, pp. 1–7.

[14] W. Heinzelman, A. Murphy, H. Carvalho, and M. Perillo, "Middleware to support sensor network applications," *IEEE Network*, vol. 18, no. 1, pp. 6–14, Jan./Feb. 2004.

[15] J. W. Branch, J. S. DavisII, D. M. Sow, and C. Bisdikian, "Sentire: A framework for building middleware for sensor and actuator networks," in *IEEE PerSeNS'05 Workshop*, March 2005, pp. 396–400.

[16] C. H. Liu, K. K. Leung, C. Bisdikian, and J. Branch, "A new approach to architecture of sensor networks for mission-oriented applications," in *SPIE Defense, Security, and Sensing'09*, Apr. 2009.

[17] E. Onur, C. Ersoy, H. Delic, and L. Akarun, "Surveillance wireless sensor networks: Deployment quality analysis," *IEEE Network*, vol. 21, no. 6, pp. 48–53, 2007.

[18] S. S. Iyengar and A. Elfes, "Occupancy grids: a stochastic spatial representation for actie robot perception," *Autonomous Mobile robots: Perception, Mapping, and Navigation*, vol. 1, pp. 60–70, 1991.

[19] L. Kleinrock, *Queueing Systems: Volume* I - *Theory*. New York: Wiley Interscience, 1975.