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

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***Abstract*—This paper introduces the novel research area of the multi-task-oriented, quality-of-information (QoI)-aware operations and management of wireless sensor networks (WSNs). Primarily, this includes 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 the following 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 QoI of other existing tasks, and (c) an adaptive and negotiation-based admission control mechanism that reconfigures and optimizes the usage of network resources in order to best accommodate all tasks' QoI requirements. 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 *quality of information* (QoI) needs of tasks are central of 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]. QoI has been sparsely studied in sensor networks; however, 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].

An increasing body of research in the O&M area uses network utility analysis techniques that aim to achieve desirable network operation by fine tuning both statically and dynamically configurable WSN parameters (e.g., traffic, routing paths, transmission power, etc.), to maximize a network's utility [5], [6]. Such approaches are anchored on an *a priori* knowledge (in the form of a analytically tractable, closed form expressions) of the benefits provided by the WSN as a function of the managed resources. This, however, is not an adequate approach for establishing desirable QoI for WSN tasks. Describing information-related, as opposed to network-related, tasks in a closed form is extremely challenging, especially when multiple dynamic tasks with different QoI requirements are serviced by the WSN simultaneously at runtime.

We address the aforementioned challenges by proposing a QoI-aware O&M framework for WSNs, a novel research path in its own right. Our general approach is to separate the process of calculating the QoI performance of the network at large from that of calculating utility resulting from allocating network resources to individual tasks. First, we conduct *runtime* learning of the QoI benefit provided by the WSN to the tasks it supports by monitoring the level of QoI satisfaction (or, the *QoI satisfaction index* of a task) they attain in relation to the QoI they request. This relaxes the requirement for the *a priori* knowledge of utility functions and facilitates the dynamic accommodation of tasks with heterogenous requirements. Second, by proposing the concept of *QoI network capacity*, the ability of a WSN to host a new task (with specific QoI requirements) is expressed without sacrificing the QoI of existing tasks. Third, an adaptive, negotiation-based admission control mechanism is proposed to dynamically configures the usage of network resources to best accommodate all tasks' QoI requirements. Finally, an evaluation of the WSN QoI performance at runtime in a dynamic multi-task environment is presented.

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

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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 related work that has motivated our current research path. Despite of 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 principle and enables information producers to categorize the quality attributes of their information in an application-agnostic manner while permitting information consumers to calculate 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 unique 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. 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

This section presents a formal model for describing our system. We consider a WSN comprising a set of sensor nodes, $\mathcal{S} = \{s_i; i = 1, 2, \ldots, N\}$ and a sink node (of sufficient processing and energy capabilities). Tasks arrive at the WSN and request service (i.e., retrieve sensed information) to last some period of time l_j, where $\mathcal{J}$ represents the set of tasks currently serviced by the WSN and sensors in $\mathcal{S}_j \subset \mathcal{S}$ be servicing task j; sensors may potentially serve multiple tasks simultaneously. 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 occurrence or location, density of a hazardous chemical, and so on. Each feature is associated with one or more QoI attributes, 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 *required* (and declared) by a task and a for that value *attained* by the WSN, e.g., α_j^r and α_j^a will denote the probability of detection of an event. Finally, tasks belong to one of U priority classes with higher priority ones experiencing more 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, $u = 1, 2, \ldots, U$. Tasks, upon arrival, inform the sink node of their information needs in terms of (multiple) QoI requirements, and they participate in an admission control process with the sink in order to be serviced by the WSN. The admission control may involve a negotiation phase and a resource reallocation phase if necessary to accommodate the QoI needs of existing and newly arriving tasks (and these will be detailed later in Section IV).

IV. Flow of the Proposed Approach

This section describes the overall flow of the proposed O&M framework, and details of the key concepts of the framework are presented in next Section. 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. Hence, we opt to adopt a "black box" view for the WSN encompassing the sensors and associated network resources, reflecting a universal framework for solving the problem. These sensors include 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 are not limited to, time, buffers, bandwidth, energy, etc.

The I/O behavior of the black box is not known exactly but estimated at runtime. Without loss of generality, let this I/O behavior be represented by the mapping $f(\cdot)$, where $f : \mathbb{R}^M \to \mathbb{R}$ $\big(\underline{x}(t) \to y(t)\big)$[1]. We consider two types of input variables: $\underline{x}(t) = \big(\underline{x}^1(t), \underline{x}^2(t)\big)$, where $\underline{x}^1(t) = \big(x_1^1(t), x_2^1(t), \ldots, x_{M_1}^1(t)\big)$ denotes M_1 system-level parameters, like the number of running tasks, and $\underline{x}^2(t) = (x_1^2(t), x_2^2(t), \ldots, x_{M_2}^2(t))$ denotes M_2 task QoI requirements, like accuracy and latency; $M = M_1 + M_2$. The output $y(t)$ reflects the overall system utilization, denoted as QoI satisfaction index, see Section V-A for more detail. We characterize the potential admission of a new task as an input change $\Delta\underline{x}(t) = \big(\Delta\underline{x}^1(t), \Delta\underline{x}^2(t)\big) = \big(\Delta x_1^1(t), ..., \Delta x_{M_1}^1(t), \Delta x_1^2(t), ..., \Delta x_{M_2}^2(t)\big)$ into the black box, which will result in change of output to:

$$\tilde{y}(t) = f\big(\underline{x}(t) + \Delta\underline{x}(t)\big). \quad (1)$$

[1] The underlined notation signifies a vector quantity.

Let $\underline{\mathcal{R}}(t) = \big(R^1(t), R^2(t), \ldots, R^P(t)\big)^T \in \mathbb{R}^P$ denote a P-dimensional column vector describing the instantaneous remaining network resources (e.g., energy, bandwidth, buffer size, etc.), and $\underline{\xi}_j^*(t) = \big(\xi_j^{1,*}(t), \xi_j^{2,*}(t), \ldots, \xi_j^{P,*}(t)\big)^T \in \mathbb{R}^P$ denote the corresponding optimal resource occupancy of each task $j, \forall j \in \mathcal{J}$, after the resource allocation. Then, column vector $\underline{\eta}(t) = \big(\eta^1(t), \eta^2(t), \ldots, \eta^P(t)\big)^T \in \mathbb{R}^P$ represents the total resource occupancy for all running tasks at time t, i.e., $\underline{\eta}(t) = \sum_{\forall j \in \mathcal{J}} \underline{\xi}_j^*(t)$.

The mapping $f(\cdot)$ is obtained by monitoring the QoI delivered to tasks serviced by the WSN at runtime so that whenever there is a task admission or completion, the current network status $\underline{x}(t)$ (M input variables) is updated along with the corresponding single output $y(t)$. When the new task arrives for network admission, it expresses its QoI requirements to the WSN, which will result in an input change $\Delta\underline{x}(t)$, if admitted. Then, the mapping $f(\cdot)$ is derived by smoothly interpolating across the attained, completed tasks' QoI satisfaction level delivered thus far by the network. The mapping $f(\cdot)$ is used to estimate the *QoI network capacity* (see Section V-B), which is used to decide whether to admit the new task by comparing with the QoI network capacity element-by-element. If there is enough network resources to support, optimal resource allocation then runs to seek for optimal resource occupancy among all tasks, and $\underline{\xi}_j^*(t), \forall j \in \mathcal{J}$, is obtained. Otherwise, a negotiation process is called such that existing tasks' QoI requirements are adapted to release some resources for the new task, see Section V-C. When task completes, the resource allocation function is called again to re-optimize the distribution of limited network resources so that existing running tasks' QoI will be improved.

V. Key Design Elements

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

A. QoI Satisfaction Index

As its name implies, this index is used to describe the level of QoI satisfaction the tasks received from the WSN. It is applicable to each task j and QoI attribute z and is defined as:

$$\mathrm{I}_j^z \triangleq \tanh\Big(k \ln \frac{z_j^a}{z_j^r}\Big), \quad \forall j \in \mathcal{J}, \tag{2}$$

where z, which represents elements of the $\underline{x}^2(t)$ vector, could be the probability of detection of an event, and 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. 1(a). A per task QoI satisfaction index 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.,

$$\mathrm{I}_j = \min\big(\mathrm{I}_j^z\big) \in (-1, 1), \forall j \in \mathcal{J}. \tag{3}$$

It follows immediately from the definition of satisfaction index that:

Lemma 5.1: For any task $j \in \mathcal{J}$, its (multiple) QoI requirements are simultaneously satisfied if and only if $\mathrm{I}_j \in [0, 1)$.

Likewise, we can define the instantaneous QoI satisfaction index $\mathrm{I}(t)$ as the minimum of indexes $\min_{\forall j \in \mathcal{J}} \mathrm{I}_j$ of tasks in service at time t. Note that the QoI satisfaction index not only represents the sensing quality at a selected group of data sources $\mathcal{S}_j$, but also reflects the communications quality of multi-hop WSNs for the reporting route, when the data is measured at the sink side. In other words, information sensing of multiple data sources and information reporting through multi-hop WSNs both contribute to the satisfactory attained QoI level.

B. QoI Network Capacity

Before admitting a new task for service, we would like to identify the potentially limiting resources and estimate the maximum "capacity" $\underline{\mathcal{C}}(t) = \big(\mathcal{C}_1(t), \mathcal{C}_2(t), \ldots, \mathcal{C}_P(t)\big)^T \in \mathbb{R}^P$ a WSN can support at any given time t. Thus, we define:

QoI network capacity indicates the time-varying capability a WSN can provide to any task with satisfactory QoI requirements, such that $\mathrm{I}_j \in [0, 1), \forall j \in \mathcal{J}$. QoI network capacity $\underline{\mathcal{C}}(t)$ is a multi-dimensional column vector with network defined dimension P such that each element $\mathcal{C}_p(t) \in \underline{\mathcal{C}}(t), \forall p = 1, 2, \ldots, P$, can represent any one of the following parameters (not exclusively though): the network-wide maximum cardinality of the task set $\mathcal{J}$, maximum queue length for each node, maximum probability of detection, smallest information gathering delay, etc.

With reference to our black box view of WSN, we set its output $y(t) \triangleq \mathrm{I}(t) = f(\underline{x}(t))$. Assuming $f(\cdot)$ is (at least) doubly differentiable, we write:

$$\begin{aligned}\tilde{y} \;&=\; f\big(\underline{x} + \Delta\underline{x}\big) \approx f\big(\underline{x}\big) + \sum_{i=1}^{M} f'_{x_i} \Delta x_i \\ &\quad + \frac{1}{2}\Big(\sum_{i=1}^{M} f''_{x_i} \Delta x_i^2 + \sum_{i=1}^{M} \sum_{j \neq i} f''_{x_j x_i} \Delta x_i \Delta x_j\Big),\end{aligned} \tag{4}$$

where the time index t is implied and $f'_{x_i} = \partial f / \partial x_i$, $f''_{x_i} = \partial f^2 / \partial x_i^2$, $f''_{x_j x_i} = \partial f^2 / \partial x_j \partial x_i$.

Given more stringent QoI requirements for the input variables, a lower QoI satisfaction index is expected. At the same time, Lemma 5.1 indicates that the shape of curve will reach a lowest satisfaction level when QoI satisfaction index $\mathrm{I}(t) = 0$, at which level the QoI network capacity is also defined. This lowest point is estimated based on the curve for $f(\cdot)$ derived along each dimension of the mapping, see Fig. 1(b) and (c). The procedure is to *project* a "large" task with stringent enough QoI requirement into the network, so that it pushes the system to the capacity bound: the minimum supportable QoI satisfaction index $\mathrm{I}(t) = 0$.

To illustrate this, consider a use case where event detection tasks ask service from the WSN declaring a required detection probability $\alpha_j^r, \forall j \in \mathcal{J}$. In this case, the QoI network capacity

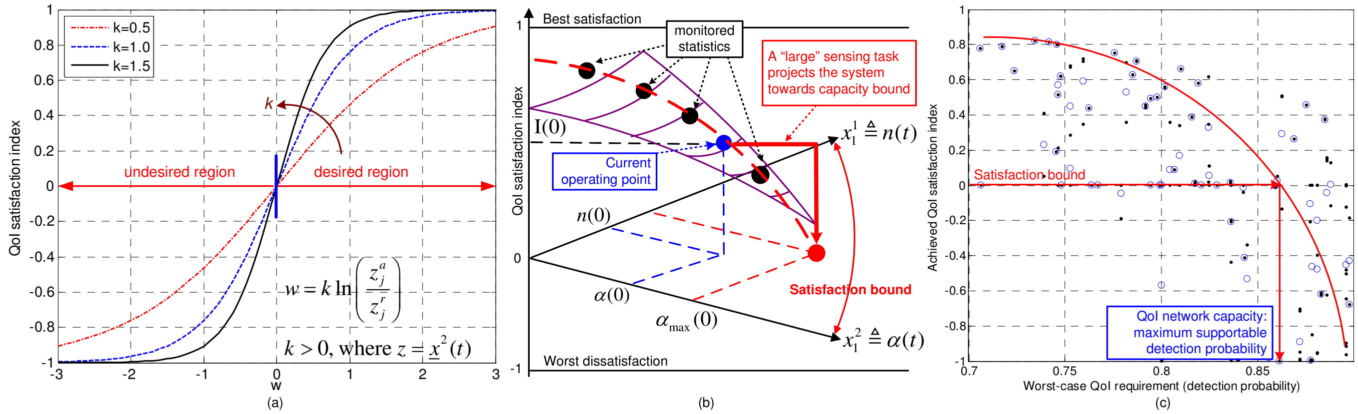

Fig. 1. (a) The illustrative example for the definition of QoI satisfaction index. It is desirable to have $z_j^a \geq z_j^r$ since it is assumed that the QoI attribute values are such that the bigger the better. (b) An example of the shape of curve produced by mapping f to show how to obtain QoI network capacity $\alpha_{\max}(t)$. (c) Real-time statistics for QoI network capacity estimation.

reduces to a scalar representing the maximum probability of detection the WSN can provide to its tasks, $\underline{\mathcal{C}}(t) \triangleq \alpha_{\max}(t)$. We assume that a new task arrives at $t = 0$ when the WSN's state was: $\underline{x}(0) = \left(\underline{x}^1(0), \underline{x}^2(0)\right) = \left(n(0), \alpha(0)\right) \in \mathbb{R}^2$, where $n(0)$ denotes the number of existing tasks as the system parameter, and $\alpha(0)$ denotes the worst-case guaranteed detection probability as the QoI parameter. Then our black box is represented by mapping,

$$y(0) \triangleq \mathrm{I}(0) = f\left(n(0), \alpha(0)\right), \tag{5}$$

as shown in Fig 1(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 $\Delta\underline{x}(0) = \left(\Delta n(0), \Delta\alpha(0)\right) = \left(1, \alpha_{\max}(0) - \alpha(0)\right)$ results a change of output to,

$$\tilde{y}(0) = f\left(n_{\max}(0), \alpha_{\max}(0)\right) = 0. \tag{6}$$

For brevity we show the time index only when necessary; and therefore, we rewrite (4) as,

$$\mathrm{I} + \Delta n f_n' + \Delta\alpha f_\alpha' + \frac{\Delta n^2}{2} f_n'' + \frac{\Delta\alpha^2}{2} f_\alpha'' + \Delta n \Delta\alpha f_{n\alpha}'' = 0, \tag{7}$$

or,

$$f_n' + (\alpha_{\max} - \alpha)\left(f_\alpha' + f_{n\alpha}''\right) + \frac{1}{2} f_n'' + \frac{(\alpha_{\max} - \alpha)^2}{2} f_\alpha'' = -\mathrm{I}, \tag{8}$$

where all partial derivatives are computed at current system state $\underline{x} = (n, \alpha)$ at time $t = 0$. It is not difficult to observe that (8) is a quadratic function with only decision variable $\alpha_{\max}$. Therefore, we derive its closed-form expression as:

$$\alpha_{\max} = \alpha - \frac{f_{n\alpha}'' + f_\alpha' - \sqrt{\left(f_{n\alpha}'' + f_\alpha'\right)^2 - 2 f_\alpha'' \left(2 f_n' + f_n'' - 2\mathrm{I}\right)}}{f_\alpha''}. \tag{9}$$

Furthermore, if the shape of curve f is smooth enough around current system operating point $\underline{x} = (n, \alpha)$ so that the second order derivatives are negligible, we simplify (9) as:

$$\alpha_{\max} = \alpha - \frac{\mathrm{I} + f_n'}{f_\alpha'}. \tag{10}$$

Fig. 1(b) illustrates how this methodology is used, and Fig. 1(c) depicts real-time measurement (from a system simulation) of QoI satisfaction indexes collected and interpolated to estimate the current shape of the $f(\cdot)$ curve.

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 $\{z_{j'}^r\}$, arrives at the sink for the admission decision at time t; the z's scan the elements of vector $\underline{x}^2(t)$ in Fig. 1(b). Before assigning the task to any sensor(s), an admission control decision is made according to the following conditions,

$$\underline{\mathcal{C}}(t) \succeq \{z_{j'}^r\} \begin{cases} \text{Admit, if true,} \\ \text{Negotiate, otherwise,} \end{cases}$$

where the notation $\succeq$ denotes the element-by-element comparison. Typically, an admission control scheme will outright ban the new task if some threshold condition was violated. However, we assume that negotiation is possible between all tasks, new and old, and the admission control functionality, in search of an acceptable (to the tasks) and attainable (by the network) compromise regarding the QoI satisfaction index delivered. Resource management in this case includes scheduling, rate and power control allocation, sensor selection, integration of data compression, etc. Note that the implementation of the negotiation operation is a choice left to the designer that design a particular sensor-enabled system.

Under the guidance of the resource optimization, ongoing tasks may internally reconfigure and reallocate network resource usages 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, i.e., however the network resources are optimized and reconfigured, the required QoI will not be satisfied. Hence, the negotiation process is employed, i.e., the new task may gradually adapt its 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. The negotiation may iterate if necessary until a satisfactory levels of QoI delivered to all the tasks is reached or the new task is blocked from admission.

Mathematically, during the negotiation phase, the following optimization is pursued:

$$\left\{\underline{\xi}_j^*(t)\right\}_{\forall j\in\mathcal{J}} = \arg\max \mathcal{F}\left(\left\{z_j^r\right\}_{\forall u_j<u_{j'}}^{z\in\underline{x}^2(t)}, \underline{\xi}_j(t)\big|_{\forall j\in\mathcal{J}}\right) \quad (11)$$

$$\text{subject to: } \left\{\begin{array}{l} z_j^a \geq z_j^r, \forall j\in\mathcal{J}, z\in\underline{x}^2(t) \\ \underline{\eta}(t) \triangleq \sum_{\forall j\in\mathcal{J}} \underline{\xi}_j(t) \preceq \underline{\mathcal{R}}(t), \end{array}\right.$$

recall that $u_{j'}$ denotes the priority of the new task. The objective function *Fairness* $\mathcal{F}$ is chosen as the optimization target since service degradation and adaptation for lower priority tasks may violate the QoI requirements of ongoing tasks. The arguments to this optimization problem are adaptable multiple QoI requirements $\left\{z_j^r\right\}_{\forall u_j<u_{j'}}^{z\in\underline{x}^2(t)}$ of those tasks with lower priority classes, and resource occupancy vector $\underline{\xi}_j(t)\big|_{\forall j\in\mathcal{J}}$. Note that the optimization is further constrained by the need to respect the QoI satisfaction for the tasks of different priority groups and resource constraints under current network status. A specific example of the objective functions $\mathcal{F}$ for the negotiation will be used in the numerical example later on.

VI. Numerical Results

A. The Scenario

We access the proposed scheme under an intruder detection user scenario [17], where multiple detection tasks arrive dynamically into a WSN with different QoI constraints (see Fig. 2). Detection probability α_j^r for task j is the only parameter that is considered in the multi-dimensional QoI requirements, and 30 sensors are deployed randomly in a 2-D square 200×200 meters. Suppose that a total energy amount E is equally distributed among all sensors. Tasks arrive according to Poisson process with rate λ and last for a random exponential time interval l_j with average duration $1/\mu$. All tasks are categorized randomly into a high priority task set $\mathcal{J}_1$ and a low priority task set $\mathcal{J}_2$, or $\mathcal{J}=\mathcal{J}_1\cup\mathcal{J}_2$. While high priority tasks have guaranteed QoI requirements that are not negotiable, the QoI requirements of low priority tasks are adaptable between least-satisfactory and most-satisfactory QoI 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 (as sensor 8 shown in Fig. 2).

1) Detection Model: We employ a simple detection model [18] using physical properties of the sensors, where the detection probability p_{ij}^d for task j from sensor i is achieved assuming using normalized full power level $\gamma_j^*(t)=1$, i.e.,

$$p_{ij}^d = \left\{\begin{array}{ll} 1, & \text{if } r_{ij}<d_t^1, \\ e^{-\beta_1(r_{ij}-d_t^1)^{\beta_2}}, & \text{if } d_t^1<r_{ij}<d_t^2, \\ 0, & \text{elseif } r_{ij}>d_t^2>d_t^1, \end{array}\right. \quad (12)$$

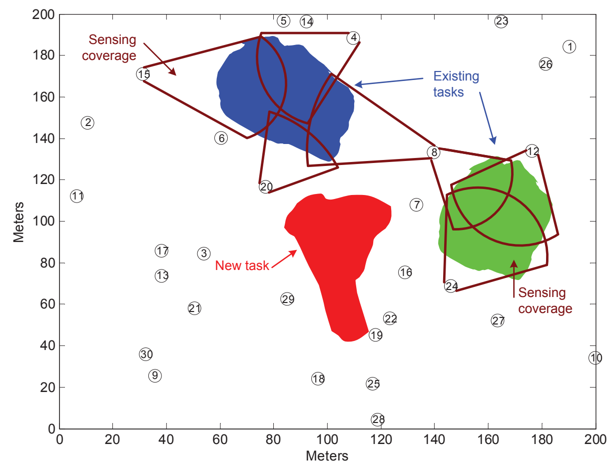

Fig. 2. Simulation scenario for intruder detection application. Two existing intruder detection tasks are running in the network (marked as the blue and green regions), while a new task (marked as red region) arrives for admission. Several sensors are selected per task as data sources (sensor 8 executes two tasks simultaneously by adjusting antenna beams).

$\forall i\in\mathcal{S}_j$, where $\beta_1=0.12, \beta_2=0.8$ are scaling parameters, $d_t^1=28$m, $d_t^2=58$m, and r_{ij} denotes the sensor-to-target distance. Note in this use case the optimal resource occupancy vector $\underline{\xi}_j^*(t)$ is reduced to a scalar. The QoI satisfaction index I_j is given by:

$$\mathrm{I}_j = \tanh\left(k\ln\frac{\gamma_j^*(t)\times\min_{\forall i\in\mathcal{S}_j} p_{ij}^d}{\alpha_j^r}\right), \forall j\in\mathcal{J}, \quad (13)$$

where attained probability of detection is computed as $\alpha_j^a=\gamma_j^*(t)\min_{\forall i\in\mathcal{S}_j} p_{ij}^d$, where we assume that the probability of detection it experiences is given by the smallest of all probabilities of detection attained by any of the the sensors that service the task ($\min_{\forall i\in\mathcal{S}_j} p_{ij}^d$). 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: Interestingly, under the considered intruder detection use case, the maximum achieved detection probability is bounded to 1, while the required detection probability is pre-specified by different tasks. Therefore, the selection of k parameter should enforce the highest QoI satisfaction index is achieved, i.e., $\mathrm{I}_j^{\max}\approx1$. In other words, $\mathrm{I}_j^{\max}=\tanh\left(k\ln\frac{1}{\alpha_j^r}\right)\approx1, \forall j\in\mathcal{J}_1\bigcup\mathcal{J}_2$, from which we could derive the lower bounds of k parameters for high and low priority tasks as:

$$\left\{\begin{array}{l} k_h \geq \tanh^{-1}(\approx1)\ln\alpha_j^{r,h}, \forall j\in\mathcal{J}_1, \\ k_l \geq \tanh^{-1}(\approx1)\ln\alpha_j^{r,l}, \forall j\in\mathcal{J}_2. \end{array}\right. \quad (14)$$

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 parameter $k_h\geq17, k_l\geq5.5$, which enforce that when optimal detection is achieved, maximum QoI satisfaction index $\mathrm{I}_j^{\max}\approx1$ is received.

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

$$\{\gamma_j^*(t)\}_{\forall j\in\mathcal{J}} \triangleq \arg\max \min_{\forall j\in\mathcal{J}} \mathrm{I}_j \tag{15}$$

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

where the design objective is chosen to balance the QoI satisfaction indexes achieved by all tasks. I_j is defined in (13) 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 user scenario) supporting 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 all existing tasks negotiated, as:

$$\begin{aligned} \{\gamma_j^*(t)\}_{\forall j\in\mathcal{J}} &= \arg\max \mathcal{F}\Big(\alpha_j^r|_{\forall j\in\mathcal{J}_2}, \gamma_j(t)|_{\forall j\in\mathcal{J}}\Big) \\ &\triangleq \arg\min \max_{\forall j\in\mathcal{J}_2} \frac{\widetilde{\mathrm{I}}_j - \mathrm{I}_j}{\widetilde{\mathrm{I}}_j} \end{aligned} \tag{16}$$

$$\text{subject to: } \begin{cases} \alpha_j^a \geq \alpha_j^{r,h}, \forall j \in \mathcal{J}_1, \\ \alpha_j^a \geq \alpha_j^{r,l}, \forall j \in \mathcal{J}_2, \\ \sum_{\forall j \text{ on } i} \gamma_j(t) l_j \leq \zeta_i, \forall i \in \mathcal{S}_j, \end{cases}$$

where $\widetilde{\mathrm{I}}_j$ denotes the attained QoI level *before* negotiation by using power levels $\widetilde{\gamma}_j^*(t)$ in (13). While the first two constraints denote QoI requirement constraints for high and low priority tasks, the third 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 existing ones' QoI requirements.

B. System Dynamic Behaviors

This section aims to understand the detailed system behaviors due to dynamic task arrivals and departures, heterogeneous QoI requirements, resource optimizations and negotiations, as key design elements for such O&M framework. Fig. 3(a) illustrates the simulated traffic pattern (i.e., the number of tasks, task arrival and departure processes, QoI requirements), and Fig. 3(b) and (c) shows dynamic QoI changes experienced by 70 tasks, with respect to (w.r.t.) two different QoI satisfaction index parameter k_h, k_l.

For fixed QoI parameters k_h, k_l, abrupt QoI changes can be seen under the relatively high traffic load conditions. When new task arrives, the negotiation process will attempt to accommodate it while reasonably degrading existing tasks' level of QoI satisfactions, but still maintaining the minimum required levels for them. Meanwhile, when completed tasks are removed, pre-allocated network resources are released by the resource optimizer so that the QoI levels of ongoing tasks are improved. However, our framework shows its capability to always optimize the resource utilization (power in this use case) in a way to maximize the QoI satisfaction whenever there is an opportunity. Meanwhile, when there is a sudden surge task arrival during a short period of time or the tasks require very stringent QoI requirements (as shown from time 2500mins to 3000mins), some tasks would experience QoI failures as their QoI satisfaction levels cannot be satisfied in any meaningful anyway; but nevertheless there are still portions of tasks successfully maintain the minimum level, i.e., $\mathrm{I}_j \geq 0$, to utilize the limited network resource[2].

On the other hand, when we increase QoI parameters k_h, k_l proportionally, which means the improved QoI satisfaction level even with the same attained detection probability, it 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

Given the proposed QoI-aware framework, we would like to explore the system limits under the conditions of constrained network resources and varying QoI requirements for different tasks, aiming at higher QoI network capacity, longer system lifetime, and increased admission rate, while satisfying the required QoI of admitted tasks. Particularly, for the considered intruder detection use case, WSN lifetime $T_{\max}$ is defined in a QoI-friendly fashion, as:

WSN lifetime is defined as the useful length of time for the WSN so that the amount of remaining energy reserves can always guarantee a minimum probability of detection $\alpha_{\min}$ for any task appearing at this time, located anywhere within the sensing field.

For this, we view the entire WSN system as a service or "queuing" system where resources are not just the server and buffer capacities, but bandwidth, radio conditions, energy reserves of the system, etc. In this queuing system, the service capacity is not fixed or known *a priori*. It is represented by *QoI network capacity*, which, is as previously discussed, is learned at runtime from the QoI levels that the WSN delivered in the past and relates to network resource availability, energy consumption rate, etc. Given an average arrival rate of task λ, and an average task service duration $1/\mu$, questions of interest for such a system include:

(1) Given network load $\rho = \lambda/\mu$, what is the maximum WSN lifetime $T_{\max}$ provided that all tasks accepted experience satisfactory QoI levels, i.e., $\mathrm{I}_j \geq 0$? Or,

[2]This is more like a game, where tasks compete for limited network resources according to the relative compatibility of their priority and requested QoI requirements with dynamic network status. In other words, not necessarily in the extreme case all tasks give up execution, but some low priority tasks with low QoI requirements may successfully survive.

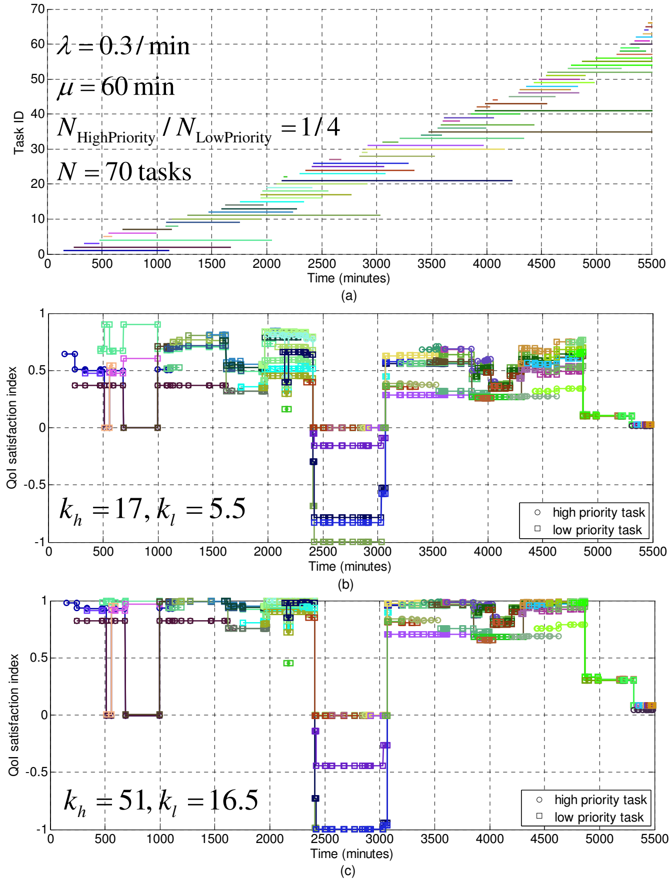

Fig. 3. Simulation results for system behavior, (a) task arrival and departure time line; real-time QoI satisfaction index change with chosen parameter (b) $k_h = 17, k_l = 5.5$, and (c) $k_h = 51, k_l = 16.5$. All figures are plotted with the same set of traffic and their QoI requirements.

(2) Given minimum WSN lifetime $T_{\min}$ and satisfactory QoI levels for all tasks, what is the region of admissible rates $\lambda \leq \lambda_{\max}$ that the system can sustain as a function of μ?

In the following Lemma we broadly derive some expression regarding the above questions under the intruder detection scenario considered. Recall that in this use case, the resource occupancy for each task j is reduced to a scalar as power levels, $\underline{\xi}_j^* = \gamma_j^*$, and thus the relationship between γ_j^* and QoI satisfaction index I_j can be analytically represented by (13).

Lemma 6.1: The task arrival rate λ vs. WSN lifetime T trade off is of the form $\frac{\lambda T}{\mu} \leq \frac{\mathcal{E}}{\beta \overline{\alpha}}$, where $\overline{\alpha} \triangleq \mathbb{E}\left(\alpha_1^r\right)$ denotes the average detection probability given its distributions, $\beta \triangleq \min_{\forall i \in \mathcal{S}_1} p_{i1}^d$ denotes a constant given geographic locations of sensor sources and tasks. Furthermore, the maximum WSN lifetime and the maximum admissible rate can be expressed as $T_{\max} = \beta \frac{\mathcal{E}}{\overline{\alpha}\rho}$, and $\lambda_{\max} = \beta \frac{\mathcal{E}\mu}{\overline{\alpha} T_{\min}}$, respectively.

Proof: Recall that for each task j, the amount of resource allocated is sufficiently reflected in (13). Or, we rewrite it as,

$$\gamma_j^*(t) = \alpha_j^r \frac{\exp\left(\frac{1}{k}\tan \mathrm{I}_j\right)}{\min_{\forall i \in \mathcal{S}_j} p_{ij}^d}. \tag{17}$$

According to Lemma 5.1, the the lower bound resource condition for satisfactory QoI is taken $\mathrm{I}_j = 0$ as the input that produces $\gamma_{j,\min}^*(t) = \gamma_j^*(t)|_{\mathrm{I}_j=0}$, or,

$$\gamma_j^*(t) \geq \gamma_{j,\min}^*(t) = \frac{\alpha_j^r}{\min_{\forall i \in \mathcal{S}_j} p_{ij}^d}. \tag{18}$$

At the same time though, resource constraints enforce the total amount of allocated network resource to no more than total energy reserve level $\mathcal{E}$, i.e.,

$$\sum_{\forall j \in \mathcal{J}^T} \gamma_j^*(t) l_j \leq \mathcal{E}. \tag{19}$$

where $\mathcal{J}^T$ denotes the task set has been serviced during WSN lifetime T, and l_j denotes the duration of certain task j that conforms to exponential distribution with parameter μ. Due to the stochastic nature of task arrivals and departures, we use the conditions of expectation to approximate the LHS random variables, as:

$$\begin{aligned}
\mathcal{E} &\geq \mathbb{E}\Big(\sum_{\forall j \in \mathcal{J}^T} \gamma_j^*(t) l_j\Big) = \mathbb{E}\Big(\mathbb{E}\Big(\sum_{\forall j \in \mathcal{J}^T} \gamma_j^*(t) l_j \Big| \mathcal{J}^T\Big)\Big) \\
&= \mathbb{E}\Big(\sum_{\forall j \in \mathcal{J}^T} \mathbb{E}\Big(\gamma_j^*(t) l_j\Big)\Big) = \mathbb{E}\Big(\mathcal{J}^T \mathbb{E}\Big(\gamma_1^*(t) l_1\Big)\Big) \\
&= \mathbb{E}\Big(\mathcal{J}^T\Big)\mathbb{E}\Big(\gamma_1^*(t) l_1\Big) = \lambda T \mathbb{E}\Big(\gamma_1^*(t)\Big)\mathbb{E}\Big(l_1\Big) \\
&= \frac{\lambda T}{\mu}\mathbb{E}\Big(\gamma_1^*(t)\Big),
\end{aligned} \tag{20}$$

where we use the fact that the task's arrival process, departure process, and 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 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 (20) by using condition (18), as:

$$\begin{aligned}
\mathcal{E} &\geq \frac{\lambda T}{\mu}\mathbb{E}\Big(\gamma_1^*(t)\Big) \geq \frac{\lambda T}{\mu}\mathbb{E}\Big(\gamma_{1,\min}^*(t)\Big) \\
&= \frac{\lambda T}{\mu}\mathbb{E}\left(\frac{\alpha_1^r}{\min_{\forall i \in \mathcal{S}_1} p_{i1}^d}\right) = \frac{\overline{\alpha}\lambda T}{\beta\mu},
\end{aligned} \tag{21}$$

where the last equality condition uses the notation $\overline{\alpha} \triangleq \mathbb{E}\left(\alpha_1^r\right)$ that denotes the average detection probability given its distributions, $\beta \triangleq \min_{\forall i \in \mathcal{S}_1} p_{i1}^d$ that denotes a constant given geographic locations of sensor sources and task. Hence, we rewrite (21) as,

$$\frac{\lambda T}{\mu} \leq \frac{\mathcal{E}}{\beta \overline{\alpha}} \tag{22}$$

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

$$T_{\max} = \beta \frac{\mathcal{E}}{\overline{\alpha}\rho}, \quad \lambda_{\max} = \beta \frac{\mathcal{E}\mu}{\overline{\alpha} T_{\min}}. \tag{23}$$

■

Lemma 6.1 proves that (22) serves as the principle system design criterion for this use case, where it shows the fundamental trade-offs among maximum network lifetime,

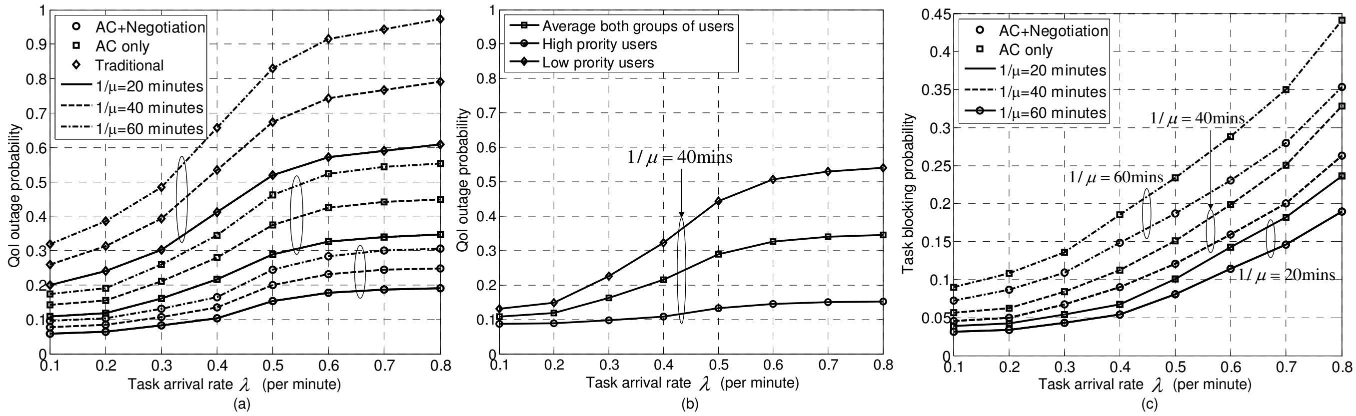

Fig. 4. Simulation results on (a)-(b) average QoI outage probability among all completed tasks, of two different priority classes, and (c) average task blocking probability. All are plotted w.r.t different task arrival rates λ and average task lifetime $1/\mu$.

task duration, arrival rate, and QoI requirement. For instance, higher QoI requirement would constrain the energy usage for multiple tasks which in turn has impact on admissible arrival rate and WSN lifetime.

D. Network Performances

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

Traditional WSN research is an one-off deployment configuration assuming “static” behaviors of system parameters, where sensors are positioned on 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, independent of application needs. In contrast, with the proposed QoI-aware management, system parameters will be adjusted judiciously, so that WSN lifetime will be longer given satisfactory QoI requirements. In this simulation, for both “static” and the “dynamic” scenarios, we assume that tasks arrive and last stochastically with the same statistics, and we choose that the probability of detection for which the system is designed to operate in the static case is the average of the probability of detections the various missions request in the dynamic case.

Fig. 4(a) illustrates the average QoI outage probability of all completed tasks as a function of both task arrival rate λ and average task lifetime $1/\mu$. QoI outage is defined as the portion of all completed tasks whose QoI requirements fail, i.e., tasks for which the satisfaction index was less than 0 at least once during their lifetime. For fixed average task lifetime, it is interesting to observe saturation of QoI outage probability for all three schemes when we increase the arrival rate since rejections to new tasks help maintain running ones’ QoI satisfaction. However, levels at which the three schemes saturate vary significantly: the proposed algorithm can even guarantee 81% of QoI satisfaction for any underlying application, as compared to 74% for “AC only” scheme, and 40% for “Traditional”. This is because the impact of newly admitted tasks on existing ones has been estimated and accurately reflected in the parameter of QoI network capacity in terms of maximum detection probability which controls the QoI-aware network status, and the negotiation process helps optimize resource utilization to release some resources for higher priority tasks. On the other hand, when the average task lifetime is increased, QoI outage increases by 20%. This is because the increasing network load $\rho(= \lambda/\mu)$ at any time in the network may jeopardize the 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 behavior of average QoI outage probability for different priority user groups is shown in Fig. 4(b), where only the “AC+Negotiation” scheme is plotted with fixed average task lifetime $1/\mu = 40$mins. Interestingly, although similar behaviors for high and low priority user groups can be seen, the saturation speed of their QoI outage probability differs significantly. This is primarily because our proposed negotiation process successfully guarantees non-negotiable QoI levels for high priority tasks, however, 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. 4(c) shows the behavior of average task blocking probability w.r.t. both task arrival rate and lifetime. While “Traditional” is not plotted in this figure since no rejections are made, 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 shown in Fig. 4(a). On the other hand, when network load ρ is increased by enlarging task lifetime, resource availability decreases as being occupied by higher number of concurrent tasks serviced. Last, for reasonably loaded system, our scheme “AC+Negotiation” can successfully guarantee as low as 5% blocking probability as compared with 8% when negotiation process is not used.

Table. I demonstrates the average jitter of QoI satisfaction index among completed and satisfactory tasks, which is defined as the variance of satisfaction indexes, i.e., $\sigma_{\forall j \in \mathcal{J}}(\mathrm{I}_j)$.

TABLE I
AVERAGE JITTER OF QOI SATISFACTION INDEX, 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

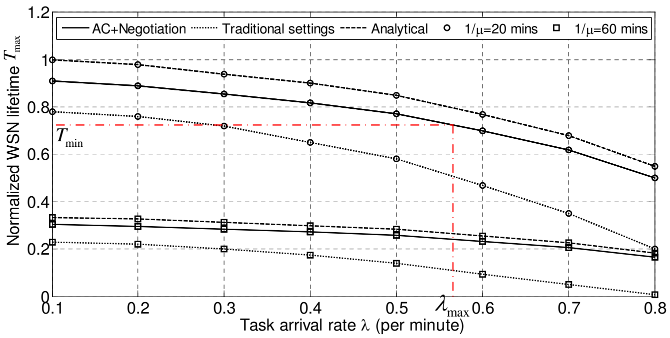

Fig. 5. Simulations on the normalized WSN lifetime w.r.t. different task arrival rate λ and task departure rate μ.

Unlike QoI outage and blocking probability, this performance metric directly reflects the human aspect of experiences when interfacing the system that indicates the performance stability (or fairness) for the proposed O&M framework to provide QoI experiences for all tasks. For fixed average task lifetime $1/\mu$, a 31% jitter increase can been seen if full scheme is compared with the other two schemes.

Fig. 5 shows the normalized WSN lifetime w.r.t. different task arrival rate and departure rates. It can be seen a significant WSN lifetime improvement compared with traditional settings, and this improvement increases when tasks arrive more frequently (due to more efficient resource allocation among all tasks). Furthermore, proposed approach successfully approximate the analytical results given in (23) while traditional settings perform far away behind. Meanwhile, given desired WSN lifetime, this figure also shows the way to obtain the maximum admissible rate $\lambda_{\max}$ the network can support given minimum probability of detection $\alpha_{\min}$.

VII. CONCLUSIONS AND FUTURE WORK

QoI-aware WSN O&M represents a broader area of research challenges that this paper only begins to address. Different from other works focusing on network utility maximization problem with predefined utility functions, this paper employs a unique and 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 satisfaction index, QoI network capacity, and an adaptive and 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 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. First is to extend 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. Second is to include sensor network duty-cycling algorithms as well as the inclusion of networked actuators, which would most likely change the nature of tasks admitted to the framework. Finally, in an effort to make the O&M framework easily *reusable* in real-world sensor network applications, we plan to investigate how to embody the framework in a formalized middleware instantiation.

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