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QoI-Aware Operations & Management in Multi-Task-Oriented Wireless Sensor Networks

Chi Harold Liu[1], Chatschik Bisdikian[2], Joel W. Branch[2], Kin K. Leung[1]

[1]Imperial College
London
UK

[2]IBM Research Division
Thomas J. Watson Research Center
P.O. Box 704
Yorktown Heights, NY 10598
USA

QoI-Aware Operations & Management in Multi-Task-Oriented Wireless Sensor Networks

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

***Abstract*—In this paper, the novel area of the task-oriented, quality-of-information (QoI)-aware operation and management of wireless sensor networks (WSNs) is proposed and investigated. Driven by a runtime monitoring of the QoI levels provided to sensing tasks, the paper proposes a task admission and WSN resource utilization procedures to control the overall QoI levels provided to new and existing tasks. The paper describes the key design elements in support of the proposed approach, namely: (a) the *QoI satisfaction index* of task, which quantifies the degree to which the required QoI is satisfied by the WSN; (b) the QoI-centric *sensor network capacity*, which expresses the ability of the WSN to host a new task (with specific QoI requirements) without sacrificing the QoI of other currently hosted tasks; (c) a negotiation-based admission control process that relies on iteratively reconfiguring and optimizing the usage of network resources and the degree of QoI acceptance of prioritized sensing tasks; and (d) a resource allocation method to optimally allocate network resources for running and new tasks. Finally, extensive performance results are provided for assessing the performance of the proposed approach for the case of an intruder detection use scenario.**

I. Introduction

Continuing advances in sensor-related technologies, including those in pervasive computing and communications, are opening more and more opportunities for the deployment and operation of smart autonomous wireless sensor networks (WSNs) [1]. A significant portion of research in the area of WSN deployment and operation focuses primarily on the “internal” aspects of WSNs such as energy-efficiency, coverage, routing topologies for efficient query and 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 central theme of this paper (and of our research in general) is bridging between the operational characteristics of WSNs with the quality-related information requirements of the tasks they service. Specifically, the paper considers a WSN during its operation in a dynamic environment where multiple sensing tasks share the information-producing, sensing capabilities of the WSN. The tasks have varying *quality of information* (QoI) requirements and arrive at the WSN at random times and request service (i.e., retrieve desired sensed information) of random length. The network is managed (e.g., tasks are admitted and network resources are allocated) in a prioritized, task-centric manner manifested by the QoI the serviced tasks receive from the WSN relative to the QoI they requested. Broadly speaking, QoI relates to the ability to judge available information *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] that sensing tasks request from the network. Addressing this problem gives rise to the novel research direction of QoI-aware operation and management (O&M) of WSNs.

Our approach to coping with the problem is influenced by the increasing body of research for WSNs exploiting utility analysis techniques [5], [6]. These techniques strive to drive WSNs toward a desirable operational point that maximizes some measure of goodness (utility) produced by the network. They do so by fine tuning configurable WSN resources, such as traffic flows, routing paths, transmission power, buffer allocations, etc. This certainly parallels our pursuit for providing QoI-aware O&M. However, and in addition to not dealing with tasks coming and going, utility-based techniques are anchored on an *a priori knowledge* (in the form of a analytically tractable, closed form expressions) of the goodness produced by the network as a function of the managed resources. This goodness is expressed in the form of simple network-level benefits, typically a maximization of *packet* flows. Deriving such an expression for the benefit at the information level (e.g., increased information accuracy) in a closed form is extremely difficult, especially when considering entire WSNs simultaneously supporting multiple sensing tasks with different QoI requirements and priorities; we acknowledge though the existence of benefits of models tying a single sensor to a single task, e.g., detection probability vs. energy, which we will exploit.

Therefore, in building our QoI-aware O&M framework for WSNs, we have opted to decouple (or layer) describing the dynamic QoI performance experienced by all the tasks from the entire network at large from the QoI relationships between sensor resources to individual tasks. For the former, we adopt

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a *runtime learning* of the QoI benefit provided by the WSN as a whole to the sensing tasks it supports by monitoring the level of "QoI satisfaction" they attain in relation to the QoI levels they had requested. This relaxes the requirement for the a priori knowledge of network-wide utility functions and facilitates the dynamic accommodation of sensing tasks with heterogenous requirements. For the latter, we leverage existing models and relationships linking network resources to QoI performance, e.g., relationships between transmit power, sensor location to probability of detection, sensor coverage, etc., [7], [8], [9].

Several novelties are central to the design of our QoI-aware O&M framework whose descriptions form the basis of this paper. First is the metric *QoI satisfaction index*, which quantifies the degree to which a WSN (and its current operational configuration) satisfies the QoI requirements of a task it serves. Second is the the concept of QoI-centric *sensor network capacity*, which expresses the ability of a WSN to host a new sensing task (with specific QoI requirements) without sacrificing the QoI of other currently hosted ones. Third is a priority and negotiation-based admission control process which, when a new task is to be admitted to the network, uses the aforementioned items to iteratively adjust network resources and QoI levels in an effort to maintain desirable and predictable QoI satisfactions for all serviced tasks. Last is an optimal resource allocation framework to achieve certain network objectives (e.g., fairness) given QoI and network resource constraints.

The rest of the paper is organized as follows. In Section II, we highlight related research activities. Section III presents the system model. Section IV describes four key design elements for such QoI-aware O&M framework. An exemplar of our O&M framework for a specific use case and numerical results are presented in Section V. Finally, we conclude in Section VI with a summary and concluding remarks.

II. Related Work

To the best of our knowledge, the proposed QoI-aware O&M framework for WSNs represents the first management solution of its kind (including: QoI, arriving and departing tasks, priority treatment); we note that early thoughts on the subject were verbalized by the authors in [10] without any of the technical detail and extend covered in this paper. There is, of course, related work that has motivated and influenced our current research path. Despite the study of QoI in enterprise systems [2], [3], it was not until recently that work in [11] proposed a conceptual framework to enable the dynamic binding of sensor information producers and consumers in QoI-aware manner, a principle that is a cornerstone behind our framework; this has been further extended on to a formal definition of QoI in sensor networks in [4].

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 sensing 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.

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 [12] and monitoring network resource allocations and the status of sensed phenomena to determine available QoI [13] and sustain required QoS [14]. Sensor network management issues were studied in [15], [16], where in [16] 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, from measurement to aggregation to data delivery with predefined network utility. Similarly, [15] further compared the solution with Bayesian network model.

Finally, we refer to WSN middleware designs [17] to support some notion of information quality [18], [19], [20]; the latter work has inspired aspects of our research in the area.

III. System Model

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). Sensing tasks arrive at the WSN and request service (i.e., retrieve sensed information) to last some period of time. The arrival and service duration processes are in general stochastic in nature and their details will be specified as needed later on. Let $\mathcal{J}$ represent the set of tasks currently serviced by the WSN and let sensors in $\mathcal{S}_j \subset \mathcal{S}$ be servicing task j; sensors may potentially serve multiple tasks simultaneously.

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 in 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 the level of of the QoI attribute *attained* by the WSN, e.g., τ_j^r and τ_j^a will denote the probability of detection of an event (an accuracy attribute) or likewise d_j^r and d_j^a for the latency. Finally, tasks belong to one of U priority classes with higher priority sensing tasks enjoy 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, $u = 1, 2, \ldots, U$. Task admission control is performed at the sink node before being assigned to any sensor node.

The QoI levels attained are the result of multiple operations spanning several layers (physical, MAC, network, information processing) whose interrelation is too complex to describe effectively in any meaningful way. Therefore, we have opted to go around this issue by adopting a "black box" view for the WSN encompassing the sensor nodes and associated network resources. These sensors include data sources, relays, and sinks, which are involved in collecting and reporting sensor

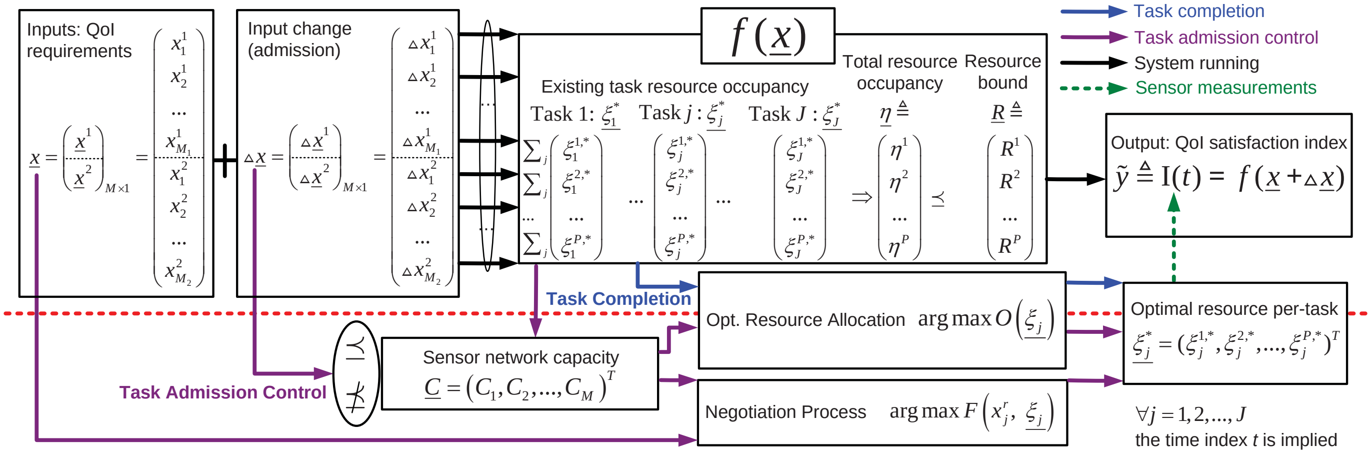

Fig. 1. The flow of QoI-aware O&M framework for any WSN. The system continuously measures the degree of resource occupancy and updates its knowledge of the state of system. When the new sensing task arrives for admission, QoI-aware sensor network capacity is obtained that aids admission decision. Then, optimal resource allocation, or negotiation process if necessary, seeks for optimal resource occupancy for all sensing tasks. When any task completes, the resource allocation function is called again to re-optimize the distribution of limited network resources so that running tasks' QoI are improved.

measurements. Finite resources are shared by multiple sensing tasks within the black box that include, but are not limited to, devices, time, buffers, bandwidth, energy, etc. The inputs to the black box are the sensing tasks' QoI requirements and system/network-level parameters. The output of the black box is a task's degree of QoI satisfaction.

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 dimension system-level parameters, like the number of running tasks and the buffer size of each sensor, and $\underline{x}^2(t) = (x_1^2(t), x_2^2(t), \ldots, x_{M_2}^2(t))$ denotes M_2 dimension sensing tasks' 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 next section. We characterize the potential new task admission 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:

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

Next, we describe the overall flow of the proposed O&M framework, see Fig. 1; detail of the key concepts introduced are presented in the next section. The region above the dashed red line pertains to the external QoI (task-oriented) black-box behavior of WSN, while below the line relates to the internal operation of the WSN. Let $\underline{R}(t) = \big(R^1(t), R^2(t), \ldots, R^P(t)\big)^T \in \mathbb{R}^P$ denote a P dimension column vector describing the instantaneous remaining resources, like energy, bandwidth, 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 sensing 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 sensing tasks serviced by the WSN so that whenever there is a task admission or completion, the current network status (M input variables) is updated along with the corresponding single output. When the new sensing task arrives for network admission, it expresses its QoI requirements to the WSN, which will results in a input change $\Delta\underline{x}(t)$ (if the task is actually admitted). The mapping $f(\cdot)$ is derived by smoothly interpolating across the levels of QoI level delivered so far by the network to various tasks it has serviced and this is used to estimate the QoI-centric *sensor network capacity*, see Section IV-B, that is used to decide whether to admit the new task. The new task's QoI requirements are then compared with the sensor network capacity element-by-element such that if there is enough network resources to support, optimal resource allocation, see Section IV-D, runs to seek for optimal resource occupancy among all sensing 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 IV-C. When sensing 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.

In the next section, we will elaborate on the four key design elements of our proposal, namely, (1) QoI satisfaction index, (2) sensor network capacity, (3) negotiation-based admission control process, and (4) optimal resource allocation.

IV. Key Design Elements

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

[1]The underlined notation signifies a vector quantity.

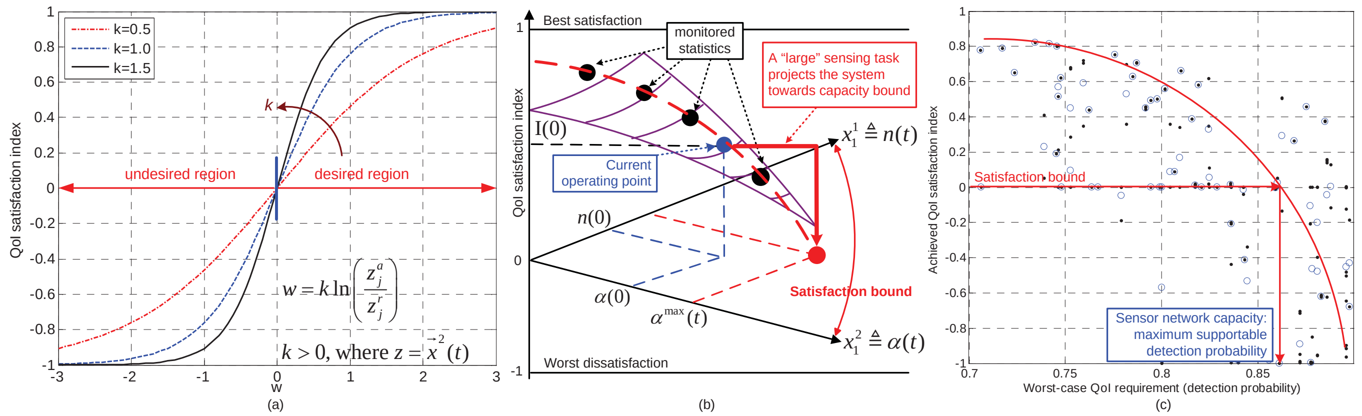

Fig. 2. (a) The illustrative example for the definition of QoI satisfaction index. It is desirable to have $z_j^a \ge z_j^r$ since it is assumed that the QoI attribute values are such that the bigger the better. (b) An example of the shape of curve produced by mapping f to show how to obtain sensor network capacity $\alpha^{\max}(t)$. (c) Real-time statistics for sensor network capacity estimation.

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 τ or d for accuracy or latency, respectively, 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. 2(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.,

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

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. It follows immediately from the definition of satisfaction index that:

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

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. This is important because QoI relies on two parts: information sensing of multiple data sources, and information reporting through multi-hop WSNs that may incur further packet loss, delay, or damage.

B. Sensor 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:

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

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

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, Corollary 4.1 indicates that the shape of curve will reach a lowest satisfaction level when QoI satisfaction index $\mathrm{I}(t) = 0$, at which level the sensor 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. IV(b) and (c). The procedure is to *project* a “large” sensing 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 sensor network capacity 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: $\underline{x}(0) = \big(\underline{x}^1(0), \underline{x}^2(0)\big) = \big(n(0), \alpha(0)\big) \in \mathbb{R}^2$, 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,

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

A large new sensing task admission corresponds to an input change $\Delta \underline{x}(0) = \big(\Delta \underline{x}^1(0), \Delta \underline{x}^2(0)\big) = \big(\alpha(0), n(0)\big) = \big(\alpha^{\max}(t) - \alpha(0), 1\big)$, and for the expected output change,

$$\tilde{y}(0) = \mathrm{I}(t) = f\big(n^{\max}(t), \alpha^{\max}(t)\big) = 0. \tag{6}$$

Therefore, we rewrite (4) as,

$$\begin{aligned} \mathrm{I}(t) \quad = \quad & \mathrm{I}(0) + \Delta n f'_{n(t)} + \Delta\alpha f'_{\alpha(t)} \\ & + \frac{\Delta n^2}{2} f''_{n(t)} + \frac{\Delta\alpha^2}{2} f''_{\alpha(t)} + \Delta n \Delta\alpha f''_{n(t)\alpha(t)}, \end{aligned} \tag{7}$$

or,

$$\mathrm{I}(0) + f'_{n(t)} + \big[\alpha^{\max}(t) - \alpha(0)\big] f'_{\alpha(t)} + \frac{1}{2} f''_{n(t)} + \frac{\big[\alpha^{\max}(t) - \alpha(0)\big]^2}{2} f''_{\alpha(t)} + \big[\alpha^{\max}(t) - \alpha(0)\big] f''_{n(t)\alpha(t)} = 0, \tag{8}$$

where all partial derivatives are computed at current system state $\underline{x}(0) = \big(n(0), \alpha(0)\big)$ at time $t = 0$. It is not difficult to observe that (8) is a quadratic function with only decision variable $\alpha^{\max}(t)$, hence, we can write:

$$\underline{\mathcal{C}}(t) \triangleq \alpha^{\max}(t) = \alpha(0) - \frac{f''_{n(t)\alpha(t)} + f'_{\alpha(t)}}{f''_{\alpha(t)}} + \frac{\sqrt{\big[f''_{n(t)\alpha(t)} + f'_{\alpha(t)}\big]^2 - 2 f''_{\alpha(t)} \big[2 f'_{n(t)} + f''_{n(t)} - 2\mathrm{I}(0)\big]}}{f''_{\alpha(t)}}. \tag{9}$$

Furthermore, if the shape of curve f is smooth enough around current system operating point $\underline{x}(0) = \big(n(0), \alpha(0)\big)$ so that the second order derivatives are negligible, we simplify (9) as:

$$\underline{\mathcal{C}}(t) \triangleq \alpha^{\max}(t) = \alpha(0) - \frac{\mathrm{I}(0) + f'_{n(t)}}{f'_{\alpha(t)}}. \tag{10}$$

Fig. 2(b) illustrates of how this methodology is used, and Fig. 2(c) provides illustrates real-time statistics (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

As shown in Fig. 1, following the estimation of the sensor network capacity, suppose a new sensing task j' with priority $u_{j'}$ and QoI requirements $\{z^r_{j'}\}$, arrives at the sink for the admission decision at time t; the z's scan the elements of vector $\underline{x}^2(t)$ in the figure, in abuse of notation, we will right $z = \underline{x}^2$ for it. Before assigning the task to any sensor(s), an admission control decision is made according to the following conditions (see Fig. 1),

$$\underline{\mathcal{C}}(t) \succeq \{z^r_{j'}\} \begin{cases} \textit{admit}, \text{ if true}, \\ \textit{negotiate}, \text{ otherwise}, \end{cases}$$

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

Under the guidance of the resource optimization, ongoing sensing 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 sensing 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 sensing 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. This information would feed to the admission control module for admission; if still unsuccessful, WSN will trigger the resource optimization module to further reconfigure the limited resources based on updated QoI levels. This is an *iterative* process, where sensing task QoI, admission control, and resource optimization collaborate until satisfactory QoIs for all tasks are reached, or otherwise the new sensing task is eventually rejected.

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

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

$$\text{subject to:} \quad \begin{cases} z^a_j \geq z^r_j, \forall j \in \mathcal{J}, z \in \underline{x}^2(t) \\ \underline{\eta}(t) \triangleq \sum_{\forall j \in \mathcal{J}} \underline{\xi}_j(t) \preceq \underline{\mathcal{R}}(t), \end{cases}$$

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 ongoing sensing tasks' QoI satisfactions. The arguments to this optimization problem are adaptable multiple QoI requirements $\big\{z^r_j\big\}^{z \in \underline{x}^2(t)}_{\forall u_j < u_{j'}}$ 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 task of different priority groups and resource constraints under current network status.

D. Optimal Resource Allocation

After the admission decision is made for the new sensing task, network resources will be allocated given that all running tasks' QoI levels cannot be violated, which is guaranteed by an optimization problem as shown in Fig. 1. Suppose a generic mathematical function $\mathcal{O}(\cdot)$ is used to represent the network design objective, where inputs are resource allocation vector $\underline{\xi}_j(t)$ for all running and new task $j \in \mathcal{J}$. The optimization

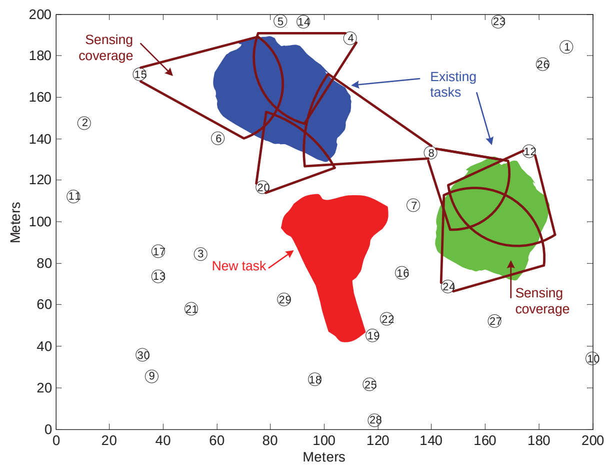

Fig. 3. A runtime simulation snapshot, where two detection tasks are running in the network (who declared a region of interest for detection upon its arrival), while a new sensing task (with new declared region of interest) arrives for admission. Several sensors are selected per sensing task as data sources (sensor 8 executes two tasks simultaneously by adjusting antenna beams).

problem is constrained with QoI satisfaction for all tasks and resource availabilities under limited resource bound, as:

$$\left\{\underline{\xi}_j^*(t)\right\}_{\forall j\in\mathcal{J}} = \arg\max \mathcal{O}\left(\underline{\xi}_j(t)\big|_{\forall j\in\mathcal{J}}\right) \tag{12}$$

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

A specific example of the objective functions $\mathcal{F}$ (for the negotiation) and $\mathcal{O}$ (for the resource allocation) will be used in the numerical example later on.

V. Numerical Results

We exercise our framework for an event (such as intruder) detection use-case [7], where multiple detection tasks arrive dynamically into a WSN (see Fig. 3). There are 30 sensors deployed randomly in a 200m $\times$ 200m square region. Tasks arrive according to Poisson process with rate λ and have a duration l (or l_j for the j-th task) that is exponentially distributed with mean $1/\mu$; the arrival and service processes are assumed i.i.d. Sensing tasks are defined by declaring regions of random shape over which they are interested in detecting intruders. We use detection probability as the QoI requirement with the probability α_j^r denoting task j's requirement. All tasks are categorized randomly into a high priority task set $\mathcal{J}_1$ and a low priority task set $\mathcal{J}_2$, or $\mathcal{J} = \mathcal{J}_1 \cup \mathcal{J}_2$. High priority tasks have guaranteed QoI requirements that are not negotiable. Low priority tasks's QoI requirements are negotiable between least-satisfactory ($\alpha_j^{r,w}$) and most-satisfactory ($\alpha_j^{r,h}$) QoI levels. Sensors cover regions (i.e., are able to detect events in the region) using smart antenna arrays forming beans that sweep the regions. A sensor may service multiple tasks by forming multiple such beams (as sensor 8 in Fig. 3). The strength of a beam is controlled is power controlled and we assume that at deployment time, there is a total energy reserve $\mathcal{E}$.

Detection Model: In [21], a simple detection model is used where the detection probability p_{ij}^d for sensing task j is described such that the physical properties of the sensors are accommodated by generic model parameters, i.e.,

$$p_{ij}^d = \left\{ \begin{array}{ll} 1, & \text{if } r_{ij} < d_t^1, \\ e^{-\beta_1 (r_{ij}-d_t^1)^{\beta_2}}, & \text{if } d_t^1 < r_{ij} < d_t^2, \\ 0, & \text{elseif } r_{ij} > d_t^2 > d_t^1, \end{array}\right. \tag{13}$$

$\forall i \in \mathcal{S}_j$, where $\beta_1 = 0.12, \beta_2 = 0.8$ are typical scaling parameters used, $d_t^1 = 28$m, $d_t^2 = 58$m, and r_{ij} denotes the sensor-to-target distance. The optimal resource occupancy vector $\underline{\xi}_j^*(t)$ is reduced to the beam-forming power used to service the task, $\underline{\xi}_j^*(t) \triangleq \gamma_j^*(t)$ and the QoI *attained* in this case is described by:

$$\mathrm{I}_j = \tanh\left(k \ln \frac{\gamma_j^*(t) \times \min_{\forall i\in\mathcal{S}_j} p_{ij}^d}{\alpha_j^r}\right), \forall j \in \mathcal{J}, \tag{14}$$

where sensor measurement $\alpha_j^a = \gamma_j^*(t) \min_{\forall i\in\mathcal{S}_j} p_{ij}^d$. For task $j \in \mathcal{J}$, the minimum detection probability attained by multiple sensor sources is considered as the actual received information, i.e., $\min_{\forall i\in\mathcal{S}_j} p_{ij}^d$, and we assume α_j^a is linear to the power $\gamma_j^*(t)$ (alternative relationships are also possible).

Optimal Power Allocation: As discussed in Section IV-D, resources are allocated among all existing and new sensing tasks to satisfy all tasks' QoI requirements and also certain design objective is satisfied. For this use case, we select as network objective achieving a level of fairness among the sensing tasks. Specifically, corresponding to (12), we set:

$$\begin{aligned} \{\gamma_j^*(t)\}_{\forall j\in\mathcal{J}} &= \arg\max \mathcal{O}\left(\gamma_j(t)\big|_{\forall j\in\mathcal{J}}\right) \\ &\triangleq \arg\max \min_{\forall j\in\mathcal{J}} \mathrm{I}_j \end{aligned} \tag{15}$$

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

where the design objective $\mathcal{O}(\cdot)$ in (12) is chosen to balance the QoI satisfaction indexes achieved among all running and new tasks (for their corresponding priority level). I_j is defined in (14) as a function of resource occupancy (i.e., power used) $\gamma_j(t)$. 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; l_j is the duration of the j-th task. Assuming equal power is allocated for every sensor source of a particular sensing task, the decision variable for this optimization problem is a set of power allocations $\{\gamma_j^*(t)\}_{\forall j\in\mathcal{J}}$.

Negotiation Process: When the network does not have enough resources (i.e., enough power) to support the new sensing task, existing lower priority ones have to adapt/degrade their QoI levels to release resources for the new task. Corresponding to (11), the design objective we select here is to minimize the maximum percentage of QoI loss among all tasks participating in negotiation, i.e., the low priority tasks in $\mathcal{J}_2$:

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

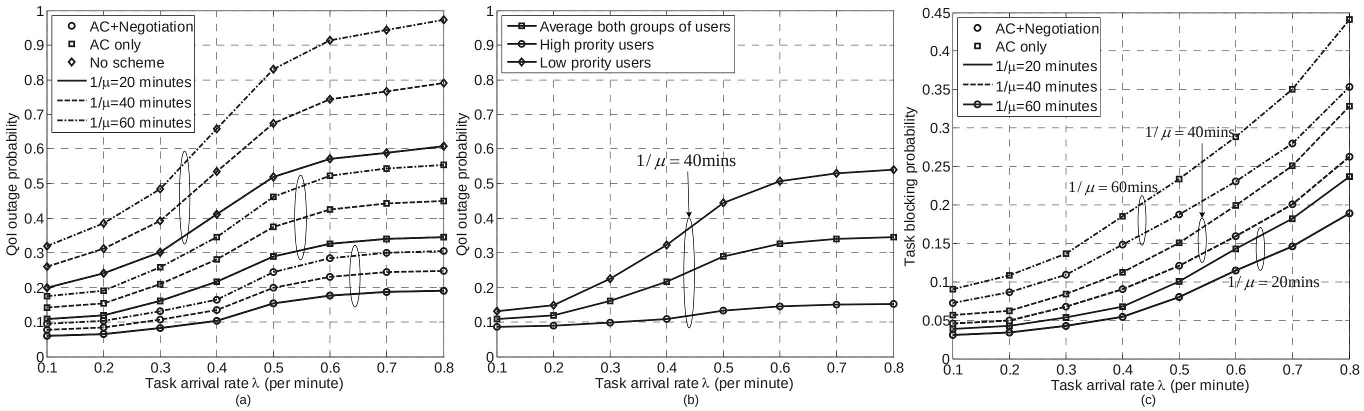

Fig. 4. Simulation results on (a)-(b) QoI outage probability among all completed sensing tasks, of two different priority user groups, and (c) sensing task blocking probability. All are plotted with respect to different sensing task arrival rates λ and average sensing task lifetime $1/\mu$.

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

where $\widetilde{\mathrm{I}}_j$ denotes the attained QoI level *before* negotiation by using power $\widetilde{\gamma}_j^*(t)$ in (14). While the first two constraints denote QoI requirement constraints for high and low priority users, the third constraint represents the per-sensor energy reserve for the sum of allocated energy among sensing tasks. The solution of this optimization problem gives the best achievable QoI level for the new task by adapting existing ones' QoI requirements.

A. Simulations

The proposed algorithm, referred as "AC+Negotiation," is compared with the scheme without negotiation process "AC only" and one with none of the schemes called "No scheme." The overall network performances are investigated in terms of the QoI outage probability among all completed sensing tasks in Fig. 4(a) and Fig. 4(b), blocking probability in Fig. 4(c), and average jitter of QoI satisfaction index in Table I.

Fig. 4(a) illustrates the QoI outage probability of all completed sensing 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 tasks completed whose QoI attained was below required (or negotiated) during some time in their lifetime. For given average task lifetime, we observe the QoI outage probability saturating with the task arrival rate for all three schemes which results from the rejection of new tasks which helps maintain running ones' QoI satisfaction. However, the saturation level of the three schemes vary significantly: with satisfaction levels reaching approximately 80% for AC+Negotiation, compared with 65%, and 40% for AC only, and no scheme, when $1/\mu = 20$min. This is because the impact of newly admitted sensing tasks on existing ones has been estimated and reflected accurately enough in the sensor network capacity in terms of the detection probability which controls the QoI-aware network status. Furthermore, the negotiation process helps optimize resource utilization to release some resources for higher priority users. As expected, the QoI outage probability increases with increasing task lifetime or task arrival rate, as a result of the increased workload $\rho = \lambda\ \mu$ at any time in the network that may jeopardize ongoing sensing tasks' QoI satisfaction, since finite network resources are shared by more sensing tasks than before, which in turn may violate the sensor network capacity bound.

The behavior of 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 sensing 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 sensing tasks in the network.

Fig. 4(c) shows the behavior of sensing task blocking probability with respect to both task arrival rate and lifetime. While "No scheme" is not plotted in this figure since no rejections are made, sensing 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 the task lifetime increases, the resource availability decreases due to usage by a larger number of concurrent tasks that are 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 the satisfactorily completed tasks. The average jitter is defined as the variance of satisfaction indexes, i.e., $\sigma_{\forall j \in \mathcal{J}}(\mathrm{I}_j)$. It is indicative of the "stability" in the QoI levels delivered by the sensing system (implementing our O&M framework) to the tasks it support and, thus, a reflection of a task's *quality of experience* (QoE!) by the sensor-information service. The smaller the value of the jitter the better, and Table I shown moderate to significant decrease of jitter of

TABLE I
AVERAGE JITTER OF QOI SATISFACTION INDEX, WITH FIXED SENSING TASK ARRIVAL RATE $\lambda = 0.5$ PER MINUTE

	AC+Negotiation	**AC only**	**No scheme**
$1/\mu = 20$ 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

the AC only and AC+Negotiation schemes when compared to no scheme.

B. Optimal Network Design Analysis

Given the WSN O&M framework, we would like to explore the system limits under the conditions of constrained network resources and varying QoI requirements for different sensing tasks, aiming at higher sensor network capacity, prolonging the system lifetime, increasing the admission rate, while satisfying the QoI required of admitted tasks. 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 the sensor network capacity, which, is as previously discussed, is learned at runtime from the QoI levels that the WSN delivered in the past and, of course, 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 sensing tasks accepted experience satisfactory QoI levels, i.e., $\mathrm{I}_j \geq 0$? Or,
(2) Given minimum WSN lifetime $T_{\min}$ and satisfactory QoI levels for all sensing tasks, what is the region of admissible rates $\lambda \leq \lambda_{\max}$ that the system can sustain as a function of μ?

For the use case under consideration, the following Lemma summarizes expressions regarding the above questions considering a single priority system. Recall, the resource occupancy for each task j is the scalar power, i.e., $\underline{\xi}_j^* = \gamma_j^*$, and the relationship between γ_j^* and QoI satisfaction index I_j is represented by (14), see also the RHS of Fig. 1.

Lemma 5.1: The task arrival rate λ vs. WSN lifetime T trade off is of the form $\big(\lambda T/\mu\big) \leq \big(\mathcal{E}/\beta\overline{\alpha}\big)$, where $\overline{\alpha} \triangleq \mathbb{E}(\alpha_1^r)$ denotes the detection probability, $\beta \triangleq \min_{\forall i \in \mathcal{S}_1} p_{i1}^d$ 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 $T_{\max} = \big(\beta\mathcal{E}/\overline{\alpha}\rho\big)$, and $\lambda_{\max} = \big(\beta\mathcal{E}\mu/\overline{\alpha}T_{\min}\big)$, respectively.

Proof: For task j, we rewrite (14) as follows:

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

According to Corollary 4.1, 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 the a task. Taking expectations above, and using the i.i.d. property of the arrival and service processes:

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

where λT denotes the average number of tasks that arrived during the lifetime of the WSN. The RHS of the above inequality simply expresses the average energy consumed servicing tasks during period T, which of course cannot be larger than the lifetime $\mathcal{E}$. Hence, it follows:

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

where the last equality condition uses the notation $\overline{\alpha} \triangleq \mathbb{E}\left(\alpha_1^r\right)$ that denotes the detection probability, $\beta \triangleq \min_{\forall i \in \mathcal{S}_1} p_{i1}^d$ 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 sensing task admissible rate $\lambda_{\max}$ as:

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

■

It follows from the Lemma that Eqn. (22) serves as the principle worst-case (in terms of QoI satisfaction) system design criterion for this use case. It shows the fundamental tradeoffs among maximum network lifetime, sensing task duration, arrival rate, and QoI requirement. For instance, higher QoI requirement would constrain the energy usage for multiple sensing tasks which in turn has impact on admissible arrival rate and WSN lifetime.

VI. Discussions and Conclusions

In this paper, we introduced a framework for the novel area of QoI-aware O&M design of WSNs dealing with sensing tasks that arrive for service to the WSN requiring varying levels of QoI. The framework divides the problem by two: one addressing the task-oriented QoI performance behavior of the entire network at large and one describing the QoI relationships between an individual sensor and a task. We use a runtime learning process for the former, while exploiting existing techniques, such as models describing utility of sensors and network utility analysis techniques for the latter. Four key design elements were introduced including a novel concept of QoI satisfaction index, a QoI-centric sensor network capacity, a negotiation-based admission control process, and the optimal resource allocation. Finally, an intruder detection use case served as an example for the framework and extensive numerical results show how the proposed framework can successfully guarantee satisfactory QoI while maintaining low blocking probability and jitter.

The QoI-aware sensor network operations and management represents a broader area of research challenges that this paper only begins to address. In the course of this work, we have identified several important directions for ongoing research activities, mainly motivated by the requirements of deploying an O&M solution in a broader space of application scenarios.

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. We previously developed a conceptual sensor network middleware framework called Sentire, [20]. While details of the logic for factoring QoI into the design and operation of the middleware was implied, the components were never fully developed. In the Sentire architecture, several components were considered that could map to the elements needed in supporting our framework such as: a *resource manager* that is responsible for facilitating task admission and network resource optimization; a *data manager* that can calculate and provide QoI satisfaction index values for the resource manager to aid the task admission process; and an *interface manager* that brokers all data exchanges between external sensing tasks and the middleware. While this sample architecture shows how an initial middleware solution might be crafted, we expect that other directions of future research will require alterations to this configuration.

Other future research directions 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. The first activity will require distributing the functionality for performing negotiation and calculating sensor network capacity and will affect the design of the middleware architecture. The second pursuit will involve researching how additional network and application behaviors will affect capacity and negotiation. Examples include sensor network duty-cycling algorithms as well as the inclusion of networked actuators, which will most likely change the nature of tasks admitted to the framework.

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