Transmission Control Policy Design for Decentralized Detection in Sensor Networks

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***Abstract*—A Wireless Sensor Network (WSN) deployed for detection applications has the distinguishing feature that sensors cooperate to perform the detection task. Therefore, the decoupled design approach typically used to design communication networks, where each network layer is designed independently, does not lead to the desired optimal detection performance. Recent work on decentralized detection has addressed the design of MAC and routing protocols for detection applications by considering independently the Quality of Information (QoI), Channel State Information (CSI), and Residual Energy Information (REI) for each sensor. However, little attention has been given to integrate the three quality measures (QoI,CSI,REI) in the complete system design. In this work, we pursue a cross-layer approach to design a QoI, CSI, and REI-aware Transmission Control Policy (TCP) that coordinates communication between local sensors and the fusion center, in order to maximize the detection performance. We formulate and solve a constrained nonlinear optimization problem to find the optimal TCP design variables. We compare our design with the decoupled approach, where each layer is designed separately, in terms of the delay for detection and WSN lifetime.**

I. Introduction

The deployment of Wireless Sensor Networks (WSNs) in decentralized detection applications is motivated by the availability of low cost sensors with computational capabilities, combined with the advances in communication network technologies. In Decentralized Detection (DD), multiple sensors collaborate to distinguish between two or more hypotheses. In a typical configuration, sensors are distributed geographically to sample the environment, pre-process the data, and communicate a *summary* of the information to the fusion center for final decision-making.

The classical problem in DD is to find the local sensor detection strategies (quantization rules) to minimize a system-wide cost function using different network topologies and channel models [1]. This classical quantization problem is unlikely to play a major role in modern WSNs. The reason is twofold: 1) performance loss due to quantization decays rapidly with the number of information bits in the packet payload [2], [3], and 2) the payload of a packet could be considered large enough to represent local sensor information with adequate accuracy, as additional bits in the payload are unlikely to affect power or delay, given the relatively large packet overhead [4], [5] (e.g., IEEE 802.15 standard has minimum overhead of 9 bytes, representing the frame control, address information, and the frame check sequence [6]). On the other hand, the deployment of WSNs in detection applications brings new challenges to the field. In addition to the design of signal processing algorithms at the application layer that has been previously addressed [7], protocols for other communication layers have to be designed to optimize the detection performance.

The layered approach commonly adopted to design wireless networks may not be appropriate for detection applications. Although the layered approach provides simplicity in the design due to the decoupling of system layers, it neither provides the optimal resource allocation nor exploits the application domain knowledge. As an example, throughput is a common performance metric used to design media access control protocols. In DD applications, maximizing the throughput is not the prime objective, rather, maximizing the quality of the information received that yields the best detection performance is the prime objective. Accordingly, a cross-layer design approach is desired for efficient implementation of WSNs in decentralized detection applications.

In this work, we integrate the physical layer, MAC layer, and the detection application layer in one unified model, that captures three quality measures, namely the Quality of Information (QoI), Channel State Information (CSI), and Residual Energy Information (REI). Our objective is to design an optimal Transmission Control Policy (TCP) that includes, not only the transmission probabilities, but also the communication rate and the power allocation for each sensor. Our approach is to express the detection performance measure as a function of the parameters and design variables of the integrated system model, and solve a constrained optimization problem to obtain the TCP variables that maximize the detection performance.

In making our modeling choices, we are motivated by the desire to develop a system model that captures the basic features of practical sensor networks, while being amenable to analysis. Specifically, we make the following design assumptions:

- *Digital transmission*. Although uncoded analog transmission is optimal in a sensor network under certain conditions (see,

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e.g., [8]), digital transmission is still the choice for cost-effective, commercial off-the-shelf deployments of sensor network applications. This also takes into account the fact that sensor nodes are designed to work in a variety of environments, network configurations, and to accomplish different tasks. The digital transmission promotes the ON/OFF channel model (akin to the model developed in [5]), where the packet is either received successfully or discarded.

- *Slotted ALOHA MAC*. The traditional assumption of a dedicated orthogonal channel between each sensor node and the fusion center may not be feasible in practice. Slotted ALOHA multiaccess scheme, on the other hand, forms the basis for many standard protocols (e.g., GPRS in 3G GSM networks). Therefore, tuning of the protocol parameters to optimize the detection performance can be done in practice without a need to redesign the system. We use a simplified version of the slotted ALOHA protocol, ignoring the protocol specifics, to keep the analysis tractable.
- *Single hop networks*. We focus on the case where sensor nodes cannot communicate with each other to form a multihop network to the fusion center, e.g., cellular nodes communicating to a base station. Accordingly, the routing problem is beyond the scope of this work.

We summarize the contributions of our work as follows:

- **Integrated model for the detection system**. We model the wireless channel to capture the effect of the physical channel parameters, i.e., communication rate and transmission power, on the packet loss rate. Similarly, we model the multiaccess communication protocol to capture the effect of collisions on the packet loss rate. The sensing model integrates the complete system model by capturing the effect of packet loss, caused by the physical and MAC layers, on the detection performance.
- **Inclusion of QoI, CSI, and REI**. We include the QoI in the sensing model, by defining the detection performance measure (equivalently, the QoI) as our objective function. The CSI is included in the wireless channel model, where the state of the channel defines the fading level that may cause packet loss. The REI is included in the wireless channel model, by linking it to the average transmission power used by each sensor.
- **Design of a complete transmission control policy**. We formulate a constrained optimization problem, with the objective function representing the detection performance measure. The objective function is the outcome of the developed integrated model. The design variables of the objective function are the TCP variables that include the retransmission probability, communication rate, and transmission power for each sensor. These design variables could be determined by solving the optimization problem using a variety of existing algorithms. Using the Karush-Kuhn-Tucker (KKT) necessary conditions for optimality, we provide further results that limit the number of candidate points for a local maximum. The results also provide an educated guess for the initial point for the optimization algorithm. This has the impact of speeding up the convergence process of the algorithm, hence obtaining the solution for the design variables in a more efficient way.
- **Enhanced detection performance**. We solve the formulated optimization problem using the interior point algorithm for an example sensor network. We show that the proposed design approach has a significant detection performance improvement over the classical decoupled design approach, for different values of the delay for detection and network lifetime constraints.

The rest of the paper is organized as follows: Section II is a survey on the related work. Section III presents the problem formulation. Section IV explains the system model. Section V presents the solution of the optimization problem to obtain the optimal TCP design. Section VI presents a numerical example, and the work is concluded in Section VII.

II. Related Work

The cross-layer design approach has been recently explored for the design of MAC and routing protocols for detection applications. Cooperative MAC, where individual sensor transmissions are superimposed in a way that allows the fusion center to extract the relevant detection information is considered in [9]. The communication channel under this scheme is sometimes referred to as single-slot multiaccess communication channel. This approach leads to significant gains in performance when compared to conventional architectures allocating different orthogonal channels for each sensor. However, work proposed in the literature for cooperative MAC protocols provides more of a theoretical study rather than a practical scheme, due to certain technical issues such as symbol and phase synchronization [4], [10].

Data-centric MAC, where existing protocols are tuned and/or modified for optimal performance, by exploiting the properties of the collected data, represents a viable alternative to cooperative MAC, and therefore, has gained considerable attention recently. Decision fusion over slotted ALOHA MAC employing a collision resolution algorithm is studied in [11]. Identical sensors are considered, and the objective is to analyze the performance, rather than design the MAC layer to optimize the detection performance. A more thorough investigation of the design of MAC transmission policies to minimize the error probability has been considered in [12]. The system model includes the MAC layer and the detection application layer, excluding the physical channel model. Sensors are assumed non-identical, and the MAC policy is assumed stochastic, being dependent on the instantaneous observation values. Although stochastic transmission policy results in performance gains compared to deterministic policies, the extension of this framework to include the channel state information is not straightforward.

The integration of the channel model and the MAC layer in the context of distributed estimation has been considered in [13], where analog transmission of sensor data is assumed. The cross-layer approach is also considered in [5] where an integrated model for the physical channel and the queuing behavior for sensors is developed. The design problem is to choose the code rate and the number of sensors to minimize the error probability for an FDMA system, where orthogonal channels are used between sensors and the fusion center.

Routing for decentralized detection has been considered separately from the MAC design problem. Energy-efficient routing for signal detection in WSNs is considered in [14], where the objective is to find the optimal route for local data from a target location to the fusion center, to maximize the detection performance or to minimize the energy consumption. Cooperative routing for distributed detection in large sensor networks is studied in [15] using a link metric that characterizes the detection error exponent. For a survey on the interplay between signal processing and networking in sensor networks, see [16] and the references therein.

Our work differentiates from previous work in the following main aspects: 1) We consider the three sensor quality measures, QoI, CSI, and REI, in the design, 2) We design the complete TCP including retransmission probabilities, communication rates, and power allocation, and 3) We consider the delay for detection and network lifetime as additional constraints for the detection problem.

III. Problem Formulation

Figure 1 illustrates the detection system architecture, where a set of N wireless sensors denoted by the set $\mathcal{S} = \{S_1, S_2, \ldots, S_N\}$, and a fusion center denoted by FC, collaborate to detect the phenomenon of interest. Initially, the fusion center broadcasts a message containing the location of the phenomenon (target, smoke,...etc) to be detected, to solicit information from different sensors. Each sensor responds with the following information: 1) sensor location, 2) the average signal to noise ratio of the measured phenomenon at the sensor location, and 3) the energy the sensor will devote to the detection process. This information could be achieved in practice as follows: 1) the sensor location could be estimated by different localization methods [17], and is used by the fusion center, along with channel measurement techniques, to estimate the CSI for the sensor. 2) The average signal to noise ratio of the measured phenomenon, representing the QoI, could be estimated by the sensor using the distance between the sensor and the phenomenon location, prior information about the phenomenon measured, and the information of the channel state between the sensor and the phenomenon location. 3) Finally, the energy devoted for the detection process, representing the REI, is estimated by the sensor from the battery charging state and the desired remaining useful life of the sensor.

The fusion center receives the information from different sensors, calculates the optimal transmission control policy for each sensor by solving a constrained nonlinear optimization problem, and transmits the values of the TCP variables back to the relevant sensors. Some sensors may not contribute to the detection process, due to either low quality of information (e.g. phenomenon is too far), low channel state (e.g. high noise or long distance to the fusion center), or not enough energy to transmit to the fusion center (e.g. not enough battery power or long distance to the fusion center combined with bad channel quality). The fusion center transmits the TCP variables only to the sensors which are specified by the optimization algorithm to be reliable to contribute to the detection task. The resulting values of the TCP variables remain valid for the given location as long as the quality measures for each sensor did not change from the last run of the optimization algorithm.

After each sensor receives the optimal values of the TCP variables, the detection process proceeds as follows: the fusion center broadcasts a message to initiate a detection cycle at the local wireless sensors. Each local sensor samples the environment by collecting a number of observations x_i, and then forms a data packet and communicates its message directly to the fusion center over a shared wireless link using the slotted ALOHA multiaccess control scheme. Finally, the fusion center makes a final decision after a fixed amount of time representing the maximum allowed delay for detection.

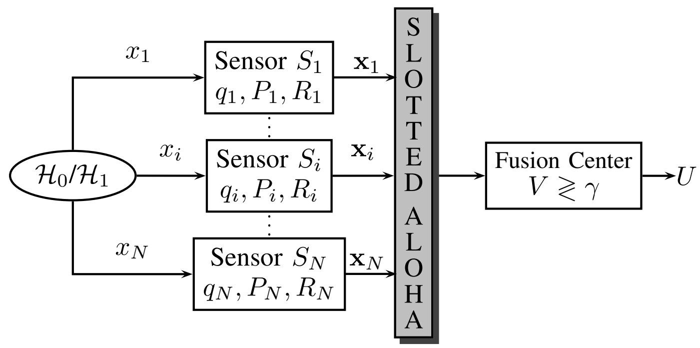

Fig. 1. System model for detection in one-hop sensor networks. Sensors communicate periodically their observations to the fusion center over MAC. At the end of the detection window, the fusion center makes a global final decision regarding the true state of nature.

IV. System Model

The detection scheme described above suggests a layered approach to system modeling, as depicted in Figure 2. The physical layer represents the wireless channel model, and defines system parameters such as the communication bit rate and the energy consumed in communicating sensor information to the fusion center. The MAC layer represents the slotted ALOHA protocol model, and defines the protocol-specific parameters such as the transmission probability. Finally, the application layer represents the sensing model, and defines the model of the observations obtained by local sensors. We seek a cross-layered design approach, where the parameters of system layers are the decision variables that need to be selected to optimize the detection performance.

A. Wireless Channel Model

We focus on the case where the sensor nodes and the fusion center have minimal movement and the environment changes slowly. Since detection applications typically have low communication rate requirements, the coherence time of the wireless channel could be considered much larger than the transmission frame length. Accordingly, only the slow fading component of the wireless channel is considered.

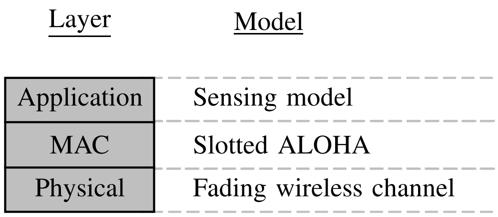

Fig. 2. A layered approach to detection system modeling. The design variables are coupled through the system-wide objective function and the energy and delay constraints.

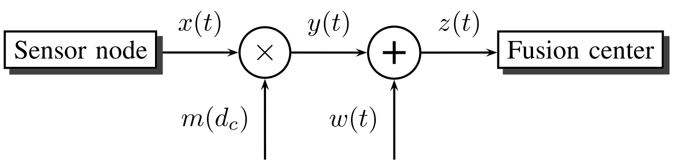

Fig. 3. Block diagram for the wireless communication channel. The transmitted signal is subject to large-scale fading and additive white Gaussian noise.

Figure 3 shows the fading channel model, where $w(t)$ is an additive white Gaussian noise with power spectral density $N_0/2$. The term $m(d_c)$ represents the mean path attenuation for a sensor node at a distance d_c from the fusion center, where the dependence on time t is dropped since slow fading is considered. We use the Hata path-loss model for the mean path attenuation, where the total dB power loss is given by [18]:

$$P_L = \underbrace{20\log\left(\frac{4\pi d_0}{\lambda_p}\right) + 10\rho_c \log(d_c/d_0)}_{\mu_c} + X_{\sigma_c} \quad \text{dB} \tag{1}$$

where d_0 is a reference distance corresponding to a point located in the far field of the transmit antenna, λ_p is the wavelength of the propagating signal, ρ_c is the path loss exponent, and X_{σ_c} is a zero-mean Gaussian random variable with variance σ_c^2. The power loss (in dB) is therefore a Gaussian random variable with mean μ_c and variance σ_c^2, i.e. $P_L \sim \mathcal{N}(\mu_c, \sigma_c^2)$.

The given wireless channel represents an unreliable bit pipe for the data link layer, with instantaneous Shannon capacity given by:

$$C = W \log_2\left(1 + \frac{P_r}{N_0 W}\right) \quad \text{bps} \tag{2}$$

where W is the channel bandwidth, and P_r is the signal power received by the fusion center. Using Shannon coding theorem, the data link layer could achieve arbitrary communication rates R up to the channel capacity using appropriate coding schemes. Given the state of the art coding schemes that approach the Shannon capacity, we can approximately assume that the fusion center can perform error-free decoding for any transmission with bit rate $R < C$. Therefore, the channel is considered "ON" when $R < C$ and "OFF" otherwise, giving rise to the two-state channel model akin to the one presented in [5]. Using (1), this condition is equivalent to:

$$P_r \underset{\text{OFF}}{\overset{\text{ON}}{\gtrless}} N_0 W \left(2^{\frac{R}{W}} - 1\right) \tag{3}$$

and noting that $P_r = P_t 10^{-P_L/10}$, where P_t is the average signal power transmitted by the local sensor, we get:

$$P_L \underset{\text{ON}}{\overset{\text{OFF}}{\gtrless}} 10\log\left(\frac{P_t}{N_0 W \left(2^{\frac{R}{W}} - 1\right)}\right) \tag{4}$$

Using the result that $P_L \sim \mathcal{N}(\mu_c, \sigma_c^2)$, we get the probability of the channel being "ON" during a transmission:

$$P[\text{ON}] = \lambda_c = \Phi\left[\frac{1}{\sigma_c}\left(10\log\frac{P_t}{N_0 W (2^{\frac{R}{W}} - 1)} - \mu_c\right)\right] \tag{5}$$

where $\Phi(.)$ is the cumulative distribution function for the standard normal PDF.

The equation in (5) represents the probability of a successful packet transmission from the sensor node to the fusion center, provided that the local sensor node successfully gained the channel access. In Section IV-B, we show that this probability is further reduced due to the collisions resulting from the random access to the channel.

B. Media Access Control Protocol Model

We assume a slotted ALOHA multiaccess communication protocol, where each packet requires one time slot for the transmission, all time slots have the same length, and all transmitters are synchronized. When it is desired to detect the phenomenon of interest, the fusion center broadcasts a message to all sensors, triggering the detection cycle. The detection cycle, demonstrated in Figure 4, has length τ, which defines the *delay for detection*, and is composed of L transmission slots, each of time τ/L. Each local sensor i collects a number of observations n_i and forms an information packet for transmission over the wireless channel. The sensor i then attempts to transmit to the fusion center with probability q_i and communication rate R_i, given by:

$$R_i = \frac{bLn_i}{\tau} \tag{6}$$

where b is the number of encoding bits for each observation. Sensors attempt transmission in every slot during the detection cycle, despite the state of their last transmission. The decision takes place at the end of the detection cycle, using the information received during that detection cycle. The process repeats for every detection request initiated by the fusion center. We note that in the above description for the MAC protocol, we ignored the packet overhead, which is a reasonable approximation for practical WSN protocols with large packet payload. Now, we calculate the overall probability of a successful packet transmission. At any given time slot, the probability of a single packet transmission by sensor i is given by $q_i \prod_{j\neq i}(1 - q_j)$. Further, this packet will be successfully received by the fusion center if the state of the physical

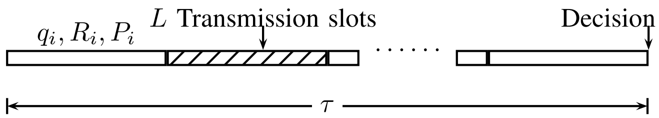

Fig. 4. Detection cycle is composed of L slots, where each sensor attempts transmission with proability q_i and bit rate R_i. A final decision is taken by the fusion center at the end of the detection cycle.

channel between the sensor and the fusion center is “ON” during this time slot. Therefore, from (5), the total probability of a successful packet transmission by sensor i is given by:

$$\lambda_i = q_i \prod_{j \neq i} (1 - q_j) \Phi \left[\frac{1}{\sigma_c^i} \left(10 \log \frac{P_t^i}{N_0 W (2^{\frac{R_i}{W}} - 1)} - \mu_c^i \right) \right] \tag{7}$$

C. Energy Model

To formulate the energy model for each sensor, we first introduce the following definition for the network lifetime. The network lifetime $\mathcal{L}$ could be defined as the average time span from the deployment to the instant when the network can no longer perform the task, which could be expressed as [16]:

$$\mathcal{L} = \frac{\mathcal{E}^0 - \mathcal{E}^w}{f_r \mathcal{E}^r} \tag{8}$$

where $\mathcal{E}^0 = \sum_{i=1}^N e_i^0$ is the total initial energy in all sensors at the time of deployment, $\mathcal{E}^w = \sum_{i=1}^N e_i^w$ is the total wasted energy remaining in sensor nodes when the network cannot perform the assigned task, f_r is the average sensor reporting rate defined here as the number of detection cycles per unit time, and $\mathcal{E}^r = \sum_{i=1}^N e_i^r$ is the expected reporting energy consumed by all sensors in one detection cycle. The total wasted energy could be defined for our detection problem as the energy required to achieve a minimum pre-specified value for the adopted detection measure. If the total energy remaining in the sensor nodes is below the total wasted energy value, the obtained detection performance is less than the minimum acceptable level, and the sensor network is no longer able to perform the detection task.

In general, we can include the energy allocation problem in our formulation, i.e. finding optimal e_i^r values for all sensors that maximize the detection performance while guaranteeing a minimum network lifetime. In this work, however, we focus on the optimal TCP problem, and therefore we resort to a simpler energy formulation. First, we assume that e_i^w is the energy remaining in the sensor battery when the sensor is not capable of operating its electronic circuits for computations and communication, which is fixed and known for each sensor. Second, we assume that the reporting energy for each sensor e_i^r is a fixed percentage of the net useful energy at the time of sensor deployment, i.e.:

$$e_i^r = \alpha (e_i^0 - e_i^w) \qquad 0 < \alpha < 1 \tag{9}$$

where α is the same for all sensors. Accordingly, from (8) we obtain:

$$\mathcal{L} = \frac{\sum_{i=1}^N (e_i^0 - e_i^w)}{f_r \sum_{i=1}^N e_i^r} = \frac{\sum_{i=1}^N (e_i^0 - e_i^w)}{f_r \alpha \sum_{i=1}^N (e_i^0 - e_i^w)} = \frac{1}{f_r \alpha} \tag{10}$$

From (9) and (10), we get:

$$e_i^r = \frac{e_i^0 - e_i^w}{f_r \mathcal{L}} \qquad \forall i \tag{11}$$

which could be calculated for each sensor and for any desired network lifetime $\mathcal{L}$. Finally, using this reporting energy value, and by noting that the expected number of transmissions by sensor i during a detection cycle is Lq_i, we get:

$$P_t^i = \frac{(e_i^r / \tau)}{q_i} = \frac{(e_i^0 - e_i^w)}{\tau \mathcal{L} f_r q_i} \tag{12}$$

where e_i^r/τ is the average power over the detection cycle, which summarizes the Residual Energy Information (REI) for each sensor. Therefore, the problem here is to optimally allocate the power across sensors. Using (12) in (7), we get:

$$\lambda_i = q_i \prod_{j \neq i} (1 - q_j) \Phi \left[a_i - \left(\frac{10}{\sigma_c^i} \right) \log q_i \left(2^{\frac{R_i}{W}} - 1 \right) \right] \tag{13}$$

where

$$a_i = \frac{1}{\sigma_c^i} \left(10 \log \frac{e_i^r}{N_0 W} - 10 \log \tau - \mu_c^i \right) \tag{14}$$

$$= \frac{1}{\sigma_c^i} \left(10 \log \frac{(e_i^0 - e_i^w)}{f_r N_0 W} - 10 \log \mathcal{L} \tau - \mu_c^i \right) \tag{15}$$

where (14) is used in delay for detection performance comparisons, and (15) is used in network lifetime performance comparisons. We note that in the above discussion, we neglected the energy consumed by each sensor to report its quality measures to the fusion center. This energy component could be included in the analysis by subtracting it from the initial sensor energy in (9). However, for slowly-varying environments, where the sensor characteristics need to be updated less frequently, this energy component could be neglected compared to the periodic sensor reporting energy.

D. Sensing Model

We consider a detection application where a set of sensors are randomly placed in a surveillance area to detect the presence of an object. Sensors have fixed positions, which could be estimated using different localization algorithms. The surveillance area is divided into a number of range resolution cells that are probed by local sensors upon receiving a command from the fusion center. The fusion center determines the subset of sensors that contribute to the detection process in each resolution cell, such that the detection performance is maximized. The determination of sensors and their design variables is accomplished by the fusion center by solving a nonlinear constrained optimization problem involving the QoI, CSI, and REI for each sensor, as explained in section V.

We focus our work on detection using signal amplitude measurements. Therefore, when there is an object at a specific resolution cell, the observation at sensor i, located at d_i distance from the object, could be expressed as:

$$x_i = \frac{\epsilon}{d_i^{\eta/2}} + w_i \tag{16}$$

where ϵ is the amplitude of the emitted signal at the object, η is a known attenuation coefficient, typically between 2 and 4, and w_i is an additive white Gaussian noise with zero mean and variance $\sigma_s^{i^2}$. We note that the above observation model considers passive sensing. In the active sensing case, the observation model is given by:

$$x_i = \zeta \frac{\epsilon_{tr}}{(2d_i)^{\eta/2}} + w_i \tag{17}$$

where ζ is a known reflection coefficient at the object, ϵ_{tr} is the amplitude of the signal transmitted by the active sensor (illuminating signal), and $2d_i$ is the round trip distance travelled by the signal. We note that the two observation models differ only in the scaling factor $\zeta/2^{\eta/2}$. Therefore, without loss of generality, we assume the passive sensing model in the following discussion.

The detection problem could be defined as the following binary hypothesis testing problem, for each time slot k:

$$\begin{aligned} &\mathcal{H}_0 : x_i[j,k] = w_i[j,k] && j = 1, 2, \dots, n_i \\ &\mathcal{H}_1 : x_i[j,k] = \mu^i + w_i[j,k] && j = 1, 2, \dots, n_i \end{aligned} \tag{18}$$

where $\mu^i = \epsilon/d_i^{\eta/2}$, and n_i is the number of observations obtained by sensor i at each time slot. We note that noise samples are independent across sensors, i.e., the observations at local sensors are independent across time and space, but not necessarily identically distributed since some sensors may be closer to the measured phenomenon, and noise variances are assumed unequal. In the following, we designate the vector of sensor observations at time slot k by $\boldsymbol{x}_i[k] = \begin{bmatrix} x_i[1,k] & x_i[2,k] & \dots & x_i[n_i,k] \end{bmatrix}$. We note that $\boldsymbol{x}_i$ has the multivariate Gaussian distribution $\mathcal{N}(\mathbf{0}, \mathbf{C})$ under hypothesis $\mathcal{H}_0$ and $\mathcal{N}(\boldsymbol{\mu}, \mathbf{C})$ under hypothesis $\mathcal{H}_1$, where $\boldsymbol{\mu} = \begin{bmatrix} \mu^1 & \mu^2 & \dots & \mu^N \end{bmatrix}^T$, and $\mathbf{C} = \sigma_s^{i^2} \boldsymbol{I}$.

Proposition 1: The optimal test statistic at the fusion center for the given system description is given by:

$$V = \sum_{k=1}^{L} \sum_{i=1}^{N} \sum_{j=1}^{n_i} \left(\frac{\mu^i}{\sigma_s^{i^2}} \right) r_i[k] x_i[j,k] \tag{19}$$

where $r_i[k]$ is a Bernoulli random process representing the success ($r_i = 1$) or failure ($r_i = 0$) of receiving a packet from sensor i in communication slot k. The sample space and probability measure of r_i are defined as $\Omega_{r_i} = \{0, 1\}$ and $P[r_i = 1] = \lambda_i$, respectively.

Proof: See Appendix A. ■

We adopt the deflection coefficient as a detection performance measure, defined as [19]:

$$D^2 = \frac{(E[V; \mathcal{H}_1] - E[V; \mathcal{H}_0])^2}{\text{var}[V; \mathcal{H}_0]} \tag{20}$$

which provides more tractable results in our study. The deflection coefficient is also closely related to other performance measures, e.g., Receiver Operating Characteristics (ROC) curve. In general, the detection performance monotonically increases with increasing the deflection coefficient.

Proposition 2: The deflection coefficient for the detector in (19) is given by:

$$D^2 = L \sum_{i=1}^{N} n_i \underbrace{\left(\frac{\mu^i}{\sigma_s^i} \right)^2}_{c_i} \lambda_i \tag{21}$$

Proof: See Appendix B ■

We note that the quantity $D_i = n_i \left(\frac{\mu^i}{\sigma_s^i} \right)^2$ represents the signal to noise ratio at sensor i, and we adopt it as a measure of the sensor Quality of Information (QoI). From (21), we note that the overall deflection coefficient at the fusion center is simply a weighted sum of the individual deflection coefficients for each sensor, where the weights are the probabilities of successful packet transmission for each sensor, and the deflection coefficient in case of a collision is set to 0.

Combining (6), (13), and (21) we obtain the objective function:

$$\begin{aligned} D^2 = \frac{\tau}{b} \sum_{i=1}^{N} c_i R_i q_i \prod_{j \neq i} (1 - q_j) \\ \times \Phi \left[a_i - \left(\frac{10}{\sigma_c^i} \right) \log q_i \left(2^{\frac{R_i}{W}} - 1 \right) \right] \end{aligned} \tag{22}$$

The trade-off in selecting the communication rate for each sensor is reflected in (22). Increasing the communication rate R results in higher QoI while reducing the probability of successful packet transmission.

One note about the effect of the amplitude of the emitted signal by the object is in order. We note that $c_i = \epsilon^2/\sigma_s^{i^2} d_i^{\eta}$, therefore the signal amplitude at the object to be detected appears as a scaling factor only in the objective function. This means that the signal amplitude does not affect the optimal operating point for the system. However, the amplitude does affect the detection performance, as intuitively expected. We further note that the objective function does not depend directly on L and n_i. Rather, from the optimal communication rates and (6), L and n_i could be arbitrarily chosen such that:

$$L n_i = \frac{\tau R_i}{b} \tag{23}$$

We note that for any nonzero communication rate, i.e. $R_i > 0$, $n_i \geq 1$, and consequently $L \leq \frac{\tau R_i}{b}$.

Table I lists the model parameters and their description. The third column classifies each parameter according to its method of calculation as either given from the application knowledge, estimated online, calculated, or as a design parameter. The fourth column highlights the parameters that are a measure of the REI, CSI, or QoI for each sensor. The last column classifies each parameter according to its relevant layer in the system model. A complete nomenclature for the system model is included in Appendix C.

TABLE I
MODEL PARAMETERS

Parameter	Description	Calc.	Notes	Layer
W	Channel bandwidth	G		
N_0	Noise PSD	E	CSI	
μ_c	Mean path loss	C (1)	CSI	Physical Layer
σ_c^2	Path loss variance	E	CSI	
P_t	Transmission power	D		
R	Communication bit rate	D		
L	Num. of comm. slots	C (6)		
b	Num. of encoding bits/obs.	G		MAC Layer
q	Retransmission probability	D		
τ	Delay for detection	G		
n	Number of observations	C (6)		APP. Layer
$c = (\frac{\mu}{\sigma_s})^2$	Signal to noise ratio	G	QoI	
e^r	Energy/detection cycle	G	REI	

E: Estimated, G: Given, C (): Calculated (eq. number), D: Design

V. TCP DESIGN FOR OPTIMAL DETECTION

The optimization problem could be summarized as follows:

$$\begin{aligned} \max \quad & \frac{\tau}{b}\sum_{i=1}^{N} c_i R_i q_i \prod_{j\neq i}(1-q_j) \\ & \times \Phi\left[a_i - \left(\frac{10}{\sigma_c^i}\right)\log q_i \left(2^{\frac{R_i}{W}}-1\right)\right] \\ \text{s.t.} \quad & 0 \le q_i \le 1, \quad R_i \ge 0 \qquad i = 1,2,\ldots,N \end{aligned} \tag{24}$$

By denoting the decision variables by $\boldsymbol{x} = \begin{bmatrix} q_1 & q_2 & \ldots & q_N & R_1 & R_2 & \ldots & R_N \end{bmatrix}$, where $\boldsymbol{x} \in \mathbb{R}^{2N}$, and the objective function by $J(\boldsymbol{x})$, the optimization problem could be rewritten on the form:

$$\begin{aligned} \min_{\boldsymbol{x}} \quad & -J(\boldsymbol{x}) \\ \text{subject to} \quad & A\boldsymbol{x} \ge \boldsymbol{b} \end{aligned} \tag{25}$$

where

$$A = \begin{bmatrix} I & \mathbf{0} \\ -I & \mathbf{0} \\ \mathbf{0} & I \end{bmatrix}, \qquad \boldsymbol{b} = -\begin{bmatrix} \mathbf{0} \\ \mathbf{1} \\ \mathbf{0} \end{bmatrix} \tag{26}$$

I is the identity matrix, and $\mathbf{0}(\mathbf{1})$ is the vector/matrix of all zeros (ones) with appropriate dimensions. Although the objective function is not, in general, convex, the inequality constraints are linear. Therefore, the KKT conditions represent a necessary condition for a local maximizer of the objective function [20]. We first form the Lagrangian:

$$L(\boldsymbol{x},\boldsymbol{\nu}) = -J(\boldsymbol{x}) - \boldsymbol{\nu}^T(A\boldsymbol{x}-\boldsymbol{b}) \tag{27}$$

where $\boldsymbol{\nu}$ is the vector of Lagrange multipliers, defined as:

$$\boldsymbol{\nu}^T = \begin{bmatrix} \nu_{q_1^0} & \nu_{q_1^1} & \ldots & \nu_{q_N^0} & \nu_{q_N^1} & \nu_{R_1} & \ldots & \nu_{R_N} \end{bmatrix}$$

where $\nu_{q_i^0}$ is the Lagrange multiplier for the constraint $q_i \ge 0$, $\nu_{q_i^1}$ is the Lagrange multiplier for the constraint $q_i \le 1$, and ν_{R_i} is the Lagrange multiplier for the constraint $R_i \ge 0$. We denote the primal and dual optimal points by $\boldsymbol{x}^*$ and $\boldsymbol{\nu}^*$, respectively. The KKT conditions are thus given by:

$$-\nabla J(\boldsymbol{x}^*) - A^T\boldsymbol{\nu}^* = \mathbf{0} \qquad \text{(Stationarity)} \tag{28}$$

$$\boldsymbol{\nu^*}^T(A\boldsymbol{x}^* - \boldsymbol{b}) = 0 \qquad \text{(Comp. slackness)} \tag{29}$$

$$(A\boldsymbol{x}^* - \boldsymbol{b}) \succeq \mathbf{0} \qquad \text{(Primal feasibility)} \tag{30}$$

$$\boldsymbol{\nu}^* \succeq \mathbf{0} \qquad \text{(Dual feasibility)} \tag{31}$$

$$-Z^T\nabla^2 J(x^*)Z \succeq 0 \tag{32}$$

where Z is a null-space matrix for the matrix of active constraints at x^*, and $\succeq$ represents componentwise inequality for vectors and positive-semidefiniteness for matrices. Further, the KKT conditions are sufficient for a strict local maximizer if the following condition holds:

$$-Z_+^T\nabla^2 J(x^*)Z_+ \succ 0 \tag{33}$$

where Z_+ is a null-space matrix for the matrix of *nondegenerate* active constraints at x^*, i.e. constraints with Lagrange multipliers $\neq 0$.

This optimization problem could be solved efficiently using a variety of existing algorithms, e.g. interior-point method. However, the result may be a local maximum. To guarantee a global maxima over the function domain, we need to enumerate all possible combinations of the active and inactive constraints, which becomes infeasible for large number of sensors. However, by exploiting the problem nature, the number of combinations can be reduced considerably. The following proposition limits the number of candidate points for a local maximum.

Proposition 3: The maximum value of the objective function in (24) occurs either when one sensor transmits with probability one and all other sensors remain silent, or at a stationary point of the objective function, i.e. at $\boldsymbol{x}^*$ where $\nabla J(\boldsymbol{x}^*) = 0$.

Proof: The formal proof is omitted for space limitation. However, the result could be derived directly from the KKT conditions. We give here an informal argument justified by intuition about the problem. We divide the problem into two cases:

- $q_i = 1$ for one sensor. If $q_j \neq 0$ where $j \neq i$ for any other sensor, then a collision is guaranteed when sensor j attempts transmission. Therefore, the fusion center will not receive any information from sensor j. Clearly, q_j should be set to $0 \quad \forall j \neq i$, i.e. all other sensors have to be silent. Therefore, the set of N points $(q_i = 1, q_j = 0, j \neq i)$ are candidates for a local maximum.
- $0 \le q_i < 1 \quad \forall i$. if $q_i > 0 \quad \forall i$, then all sensors participate in the detection process, and the point is a candidate for a local maximum. Since all constraints are inactive in this case, the candidate point is a stationary point for the objective function, i.e. $\boldsymbol{x}^*$ where $\nabla J(\boldsymbol{x}^*) = 0$. If $q_i = 0$ for some number of sensors k, then this is essentially the same original problem with k sensors eliminated, i.e. with $N-k$ sensors. This point could also be shown to satisfy the stationarity condition for the original problem. Therefore all candidate points in this case are stationary points.

∎

Since we may have multiple stationary points in the interior of the objective function domain, the proposition does not guarantee obtaining the global maximum. However, the proposition is still useful for the following reasons: 1) it avoids the case where the optimization algorithm may terminate at the local maximum $q_i = 1, q_j = 0$, while a better local maximum maybe at one of the stationary points, and 2) it provides some information about the choice of the initial point for the optimization algorithm, where initial points near the corner points $q_i = 1, q_j = 0$ have to be avoided.

We note that the result obtained in proposition 3 is due to the problem nature, i.e., the sharing of the communication channel between multiple sensors. Therefore, the result carries out to similar problem structures, e.g., tree wireless networks with shared channels between sibling nodes.

VI. Numerical Example

We consider the problem of 10 wireless sensors deployed for detection. The small-scale network is chosen for demonstration-purposes only. Large-scale sensor networks could be used as well, due to the scalability of the optimization algorithm. The system parameters are shown in Table II, which replicates the structure of Table I for easy reference. We use the interior-point algorithm to calculate the optimal solution. For the given problem data, the optimal point is always at the stationary point, i.e. $q_i, R_i \neq 0 \quad \forall i$.

We compare our design approach with the decoupled approach, where each layer is designed separately. In the conventional slotted ALOHA, The MAC sublayer is designed to minimize the probability of collision, without regard to the QoI or CSI of each node. Minimum probability of collision occurs at $q_i = 1/N$, and consequently $P_t^i = e_i^r N/\tau$. The physical layer is designed to guarantee a minimum probability of successful packet transmission, λ. Using (5), we obtain:

$$R_i = W \log_2 \left(1 + 10^{\left[0.1\sigma_c^i (a_i - \Phi^{-1}[\lambda]) + \log N\right]}\right) \qquad (34)$$

and using (22), the deflection coefficient is given by:

$$D^2 = \frac{\tau \lambda W}{bN} \left(1 - \frac{1}{N}\right)^{N-1} \times \sum_{i=1}^{N} c_i \log_2 \left(1 + 10^{\left[0.1\sigma_c^i (a_i - \Phi^{-1}[\lambda]) + \log N\right]}\right) \qquad (35)$$

In practice, λ is pre-specified independent from the application. However, to make a fair comparison, we use the value of λ that maximizes the deflection coefficient in (35), i.e.:

$$\lambda = \arg\max_{\lambda} D^2 \qquad 0 \leq \lambda \leq 1 \qquad (36)$$

We note that the deflection coefficient is smaller for both small and large values of λ. For small λ values, not enough observations are transmitted, while for large values of λ, more collisions occur, hence less observations are received at the fusion center.

We compare the detection performance against two system design parameters; delay for detection and network lifetime.

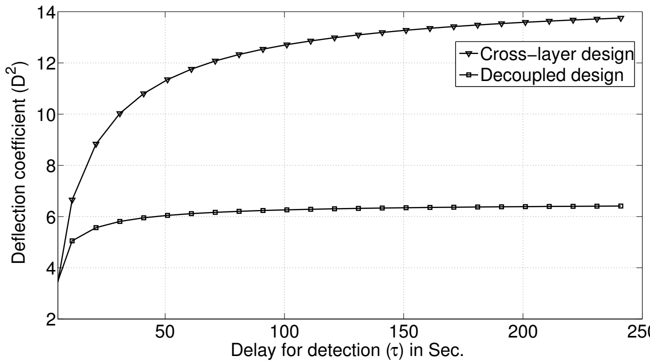

Fig. 5. Deflection coefficient as it varies with the delay for detection.

1) Delay for detection: In this case, we vary the delay for detection τ, and calculate numerically the optimal deflection coefficient for each design approach. We assume a fixed network lifetime $\mathcal{L}$, or equivalently a fixed reporting energy e_i^r for each sensor. We use (14) along with the objective function in (22).

Figure (5) shows the deflection coefficient versus the delay for detection. The cross-layer design approach clearly outperforms the decoupled design even when using the optimal success probability λ for each delay for detection value. We also note that the deflection coefficient saturates much faster in the decoupled design case. The saturation value is given by $\lim_{\tau \to \infty} D^2$, where D^2 is given by (35). From the problem constraints, the deflection coefficient saturates also in the case of the cross-layer design. This is true since the energy allocated by each sensor for a single detection cycle is finite. Therefore, increasing the delay for detection over a certain value would not contribute to the detection performance. The saturation value in the cross-layer design case, however, cannot be obtained in a closed form.

2) Network Lifetime: In this case, we vary the network lifetime $\mathcal{L}$, and calculate numerically the optimal deflection coefficient for each design approach. We assume a fixed delay for detection $\tau = 100$ sec. We use (15) along with the objective function in (22).

Figure (6) shows this relationship for the given example network, with average sensor reporting rate $r = 200$ times per day. The cross-layer design approach outperforms the decoupled approach for all given network lifetimes. The horizontal line represents the minimum acceptable detection performance, which subsequently defines the maximum effective network lifetime.

VII. Conclusion

We presented a cross-layer design approach for the TCP of wireless sensors deployed for detection applications. The TCP includes the transmission probabilities, communication rate, and power allocation for each sensor. The approach outperforms the decoupled approach ,where each layer is designed independently, for arbitrary delay for detection and network lifetimes. The extension of this approach to multihop

TABLE II
MODEL PARAMETERS FOR THE NUMERICAL EXAMPLE. DESIGN VARIABLES ARE SHOWN IN BOLD.

Parameter	Description	Value
W	Channel bandwidth	2×10^3 Hz
N_0	Noise power spectral density	10^{-10} W/Hz
μ_c	Mean path loss	$\begin{bmatrix} 42 & 44 & 37 & 40 & 45 & 42 & 44 & 39 & 43 & 45 \end{bmatrix}$ dB
σ_c	Path loss std. dev.	$\begin{bmatrix} 4 & 6.5 & 5 & 4.5 & 7 & 4 & 6.5 & 5 & 4.5 & 7 \end{bmatrix}$ dB
P_t	**Transmission power**	$e_i^r/\tau q_i$
R	**Communication bit rate**	Design variable
L	**Number of comm. slots**	$Ln_i = \tau R_i/b$
b	Number of bits/observation	16 bits
q	**Retransmission probability**	Design variable
τ	Delay for detection	0:250 sec.
n	**Number of observations**	$Ln_i = \tau R_i/b$
$c_i = (\mu^i/\sigma_s^i)^2$	Signal to noise ratio	$\begin{bmatrix} 0.05 & 0.071 & 0.04 & 0.03 & 0.075 & 0.05 & 0.07 & 0.04 & 0.03 & 0.075 \end{bmatrix}$
e^r	Energy/detection cycle	$\begin{bmatrix} 1 & 1.1 & 0.9 & 1.15 & 0.8 & 1 & 1.1 & 0.8 & 1.15 & 0.8 \end{bmatrix} \times 10^{-3}$ J

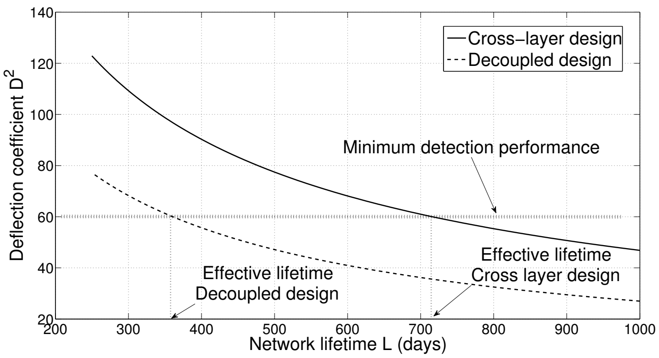

Fig. 6. Deflection coefficient as it varies with the network lifetime. The cross-layer design approach outperforms the decoupled approach for all values of the network lifetime.

sensor networks is currently under research. In addition, the application of the proposed approach on the correlated observations case, and the study of the dependency of the system design on the degree of correlation between sensors represent one of the future research directions.

APPENDIX

A. Proof of Proposition 1

Proof: At the fusion center, the LLR ratio is the sum of the individual LLR's received at each time slot. Therefore, the test could be expressed as:

$$\sum_{k=1}^{L}\sum_{i=1}^{N} r_i[k] l(\mathbf{x}_i[k]) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \ln\gamma \tag{37}$$

where:

$$\begin{aligned} l(\mathbf{x}_i[k]) &= \ln\frac{p_{\mathbf{x}_i}(\mathbf{x}_i[k];\mathcal{H}_1)}{p_{\mathbf{x}_i}(\mathbf{x}_i[k];\mathcal{H}_0)} \\ &= \ln\frac{\exp\left[-\frac{1}{2}(\mathbf{x}_i[k]-\mu^i\mathbf{1})^T\mathbf{C}^{-1}(\mathbf{x}_i[k]-\mu^i\mathbf{1})\right]}{\exp\left[-\frac{1}{2}\mathbf{x}_i^T[k]\mathbf{C}^{-1}\mathbf{x}_i[k]\right]} \\ &= \frac{\mu^i}{\sigma_s^{i2}}\mathbf{1}^T\mathbf{x}_i[k] - \frac{1}{2}\left(\frac{\mu^i}{\sigma_s^i}\right)^2\mathbf{1}^T\mathbf{1} \\ &= \frac{\mu^i}{\sigma_s^{i2}}\sum_{j=1}^{n_i} x_i[j,k] - \frac{n_i}{2}\left(\frac{\mu^i}{\sigma_s^i}\right)^2 \end{aligned} \tag{38}$$

The LR test then reduces to:

$$\begin{aligned} V = \sum_{k=1}^{L}\sum_{i=1}^{N}\sum_{j=1}^{n_i}\left(\frac{\mu^i}{\sigma_s^{i2}}\right) r_i[k]x_i[j,k] \quad &\underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \\ \frac{1}{2}\sum_{k=1}^{L}\sum_{i=1}^{N} n_i r_i[k]\left(\frac{\mu^i}{\sigma_s^i}\right)^2 + \ln\gamma = \gamma\prime \end{aligned} \tag{39}$$

■

B. Proof of Proposition 2

Proof: To calculate the deflection coefficient for the detector in (19), we use the fact that both $r_i[k]$ and $x_i[j,k]$ are strict-sense stationary random processes (being IID) and independent of each other. Therefore:

$$E[V;\mathcal{H}_0] = L\sum_{i=1}^{N} n_i E[r_i]E[x_i]\left(\frac{\mu^i}{\sigma_s^{i2}}\right) = 0 \tag{40}$$

$$E[V;\mathcal{H}_1] = L\sum_{i=1}^{N} n_i\lambda_i\left(\frac{\mu^i}{\sigma_s^i}\right)^2 \tag{41}$$

$$\begin{aligned} \mathrm{var}[V;\mathcal{H}_0] &= L\mathrm{var}\left[\sum_{i=1}^{N}\sum_{j=1}^{n_i} r_i x_i[j]\left(\frac{\mu^i}{\sigma_s^{i2}}\right)\right] \\ &= LE\left[\left(\sum_{i=1}^{N}\sum_{j=1}^{n_i}\left(\frac{\mu^i}{\sigma_s^{i2}}\right) r_i x_i[j]\right)^2\right] \\ &- L\left(E\left[\sum_{i=1}^{N}\sum_{j=1}^{n_i}\left(\frac{\mu^i}{\sigma_s^{i2}}\right) r_i x_i[j]\right]\right)^2 \\ &= L\sum_{i_1=1}^{N}\sum_{i_2=1}^{N}\sum_{j_1=1}^{n_{i_1}}\sum_{j_2=1}^{n_{i_2}} E\left[\left(\frac{\mu^{i_1}\mu^{i_2}}{{\sigma_s^{i_1}}^2{\sigma_s^{i_2}}^2}\right) r_{i_1}r_{i_2}x_{i_1}[j_1]x_{i_2}[j_2]\right] \\ &- L\left(\sum_{i=1}^{N}\sum_{j=1}^{n_i}\left(\frac{\mu^i}{\sigma_s^i}\right) E\left[r_i x_i[j]\right]\right)^2 \end{aligned}$$

TABLE III
NOMENCLATURE

Param.	Description
λ_p	Wavelength of the propagating signal
d_c	Distance between sensor and fusion center
ρ_c	Channel path loss exponent
μ_c^i	Mean path loss for sensor i
σ_c^i	Path loss std. deviation for sensor i
W	Communication channel bandwidth
P_t^i	Transmission power for sensor i
P_r^i	Signal power received at the fusion center from sensor i
N_0	Noise power spectral density
R_i	Communication rate for sensor i
b	Number of encoding bits/observation
L	Number of transmission slots
n_i	Number of observations sampled by sensor i
τ	Delay for detection
λ_i	Successful packet transmission probability for sensor i
q_i	Retransmission probability for sensor i
$\mathcal{L}$	Sensor network lifetime
e_i^0	Initial energy in sensor i battery
e_i^w	Wasted energy remaining in sensor i battery
e_i^r	Reporting energy for sensor i
f_r	Reporting frequency for the sensor network
α	Percentage of net useful energy used in reporting
ϵ	Amplitude of emitted signal at detected object
d_i	Distance between sensor i and the object
η	Attenuation coefficient for object signal
ζ	Reflection coefficient at the object
$x_i[j,k]$	Observation number j at time slot k for sensor i
$c^i = (\frac{\mu^i}{\sigma_s^i})^2$	Detected object signal to noise ratio at sensor i
V	Test statistic at the fusion center
N	Total number of wireless sensors
$r_i[k]$	Success or failure of sensor i transmission in slot k
D^2	Deflection coefficient

and noting that $E[r_{i_1} r_{i_2}] = 0$ for $i_1 \neq i_2$, and $E[r_i^2] = \lambda_i$, we get:

$$\begin{aligned}
\text{var}[V; \mathcal{H}_0] &= L \sum_{i=1}^{N} \sum_{j_1=1}^{n_{i_1}} \sum_{j_2=1}^{n_{i_2}} \left(\frac{\mu^i}{\sigma_s^{i^2}}\right)^2 \lambda_i E\left[x_i[j_1] x_i[j_2]\right] \\
&= L \sum_{i=1}^{N} \sum_{j=1}^{n_i} \left(\frac{\mu^i}{\sigma_s^{i^2}}\right)^2 \lambda_i E[x_i^2[j]] \\
&+ L \sum_{i=1}^{N} \sum_{j_1=1}^{n_{i_1}} \sum_{\substack{j_2=1 \\ j_2 \neq j_1}}^{n_{i_2}} \left(\frac{\mu^i}{\sigma_s^{i^2}}\right)^2 \lambda_i E[x_i[j_1]] E[x_i[j_2]] \\
&= L \sum_{i=1}^{N} n_i \lambda_i \left(\frac{\mu^i}{\sigma_s^i}\right)^2 \qquad (42)
\end{aligned}$$

From (40), (41), and (42), we get:

$$D^2 = L \sum_{i=1}^{N} n_i \left(\frac{\mu^i}{\sigma_s^i}\right)^2 \lambda_i \qquad (43)$$

■

C. Nomenclature

Nomenclature for the complete system model is shown in Table III

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