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QoS Support in Event Detection in WSN through Optimal *k*-Coverage

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Abstract

Wireless sensor networks promise to guarantee accurate, fault tolerant and timely detection of events in large scale sensor fields. To achieve this the notion of *k*-coverage is widely employed in WSNs where significant redundancy is introduced in deployment as an event is expected to be sensed by at least *k* sensors in the neighborhood. As sensor density increases significantly with *k*, it is imperative to find the optimal *k* for the underlying event detection system. In this work, we consider the detection probability, fault tolerance and latency as the Quality of Service (QoS) metrics of an event detection system employing *k*-coverage and present a probabilistic model to guarantee given QoS support with the minimum degree of coverage taking into account the noise related measurement error, communication interference and sensor fault probability. This work eventually resolves the problem of over or under deployment of sensors, increases scalability and provides a well defined mechanism to tune the degree of coverage according to performance needs.

Keywords: WSN, event detection, *k*-coverage, accuracy

1. Introduction

Features such as random deployment over large inaccessible terrain and decentralized collaborative nature make wireless sensor networks (WSNs) apt for a wide range of applications, ranging from smart home system to space station surveillance [1, 2]. Although earlier WSNs concentrated mostly on data gathering for monitoring purposes, recently however, more attention is shifted towards event detection which is crucial for many applications, such as disaster management, pollution detection, industrial monitoring, fault detection [1] etc.

In most WSN-based applications, sensor nodes are expected to be low cost error prone and deployed in adverse terrain and harsh condition, hence the probability of node malfunction is significantly higher in WSNs compared to traditional networks such as TCP/IP and cellular networks. Usually, communication is more vulnerable to the environmental noise in WSNs due to the relatively low signal strength used by sensors to preserve energy. Many event based services, like fire monitoring, require immediate detection, that is the average time elapsed between event occurrence and its detection by the system is very short, which makes the timeliness very crucial in event detection . Overall, the issues that should be addressed for event detection in WSNs are: i) reliable detection of events with high

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accuracy, ii) robust event detection against sensor fault and environmental noise, and iii) timeliness of detection.

Traditional WSN based event detection models, where each location within the network is covered by only a single sensor, are not reliable due to noise, and sensor faults and/or measurement errors. Therefore, recent studies advocate the introduction of redundant nodes in the network so that every possible event location can be monitored by multiple nodes and the individual detection decisions can be aggregated to rule out inaccuracies. This idea brought the notion of k-coverage in WSNs. A WSN is called k-covered if every point in the network is within the sensing range of at least k nodes, k ($\geq$1) being the degree of coverage. In k-coverage event detection models, the decision on the occurrence of an event is made in collaboration among the k sensors detecting the event. While increasing the degree of coverage k will enhance the detection performance metrics such as detection probability, fault tolerance and latency at the cost of higher network traffic, energy consumption and deployment cost; lowering k would exhibit degraded accuracy and loss of robustness. Therefore, an optimal coverage is of paramount importance to attain a trade-off among the aforementioned opposing factors. To the best of our knowledge no prior work exists in the literature that provides an analytical solution to determine the degree of coverage i.e. value of k in WSN-based event detection. To address this issue in this paper we make following contributions:

- Event detection probability is modelled considering sensing noises, communication interferences and sensor malfunctions.
- An analytical measure is formulated for event detection latency for the k-coverage WSN model.
- Finally, a lower bound on k is obtained that probabilistically guarantees the required performance metrics such as event detection accuracy, fault tolerance and latency.

2. Related Works

There are two types of event detection schemes that have been proposed in the literature: i) centralized scheme that requires a sensor node to send its observation directly to the base station for decision and ii) decentralized scheme where each sensor makes local decision independently and these decisions are combined in a local fusion centre to make the final decision. Since sensor nodes are constrained with low power, the centralized detection schemes requiring each node to transmit its measurement directly to the base station are not suitable. This makes decentralized schemes more popular in event detection paradigm. One of the first works on distributed fault tolerant event detection was presented in [3]. It considered the spatial correlation in event measurement and proposed Bayesian decision fusion to detect an event in collaboration among the neighboring sensors. But this work assumed known constant decision error probability for every node which is not realistic and it provides no indication on determining suitable degree of coverage.

In [4], Luo *et al.* presented a fault tolerant energy efficient event detection mechanism. To disambiguate events from noise and sensor faults, the authors suggested that the above factors are likely to be spatially uncorrelated while event measurements are correlated spatially. They formulated event detection as a binary hypothesis test problem and individual decisions were fused taking measurements from nodes in a neighborhood. While this work gave an indication of suitable neighborhood size from energy efficiency point of view, it did not deal with introducing redundancy to cope up with faults and noise, rendering this work inapplicable in k-coverage context. The idea of k-watched event detection was formalized in [6] from energy efficiency and bounded delay point of view, though binary decision fusion technique similar to [3], [4] is used. They extended the detection scheme for composite event and considered detection delay. This scheme achieved fault tolerance by having each point in the sensor field being monitored by k nodes and takes an event as detected even when k-1 nodes concurrently fail. This was somewhat unrealistic from the accuracy point of view because occurrence of an event unnoticed by k-1 nodes but reported by only one, may indicate sensor fault. This work lacks in the analysis of achieved accuracy or closed form for delay in their model. Zhu and Zheng [12] studied the event detection delay in WSN and they quantified the detection performance of a distributed event detection WSN by deriving the closed forms of detection delay and detectability.

Wang *et al.* [11] analyzed detection latency using a probabilistic approach for k-sensor detection model and considered latency as a performance metric for detection. Zhu and Ni [13] first formalized the QoS provisioning problem in event detection applications in WSNs. They presented detection latency and detection probability as the two key performance metrics for event detection systems and proposed a probabilistic approach to provisioning QoS. Although their work formalized the concept of provisioning QoS for event detection system, it did not consider the k-coverage detection model. None of the works discussed so far has taken the contention in medium access control (MAC) layer in consideration that may incur additional delay in *k*-coverage event detection. To address that issue, we have explored the sensor specific MAC protocols [9] such as S-MAC, B-MAC, Sift and Z-MAC in detail and incorporated the MAC introduced delay in our model.

3. System Model and Problem Statement

3.1. The Network and Event Detection Model

We consider a WSN consisting of a set of sensor nodes deployed randomly over the network area, where the number of sensors deployed is sufficient enough to achieve *k*-coverage. We assume that the transmission range of each sensor is sufficient enough to maintain the sensor connectivity across the network. Moreover, the sensing area of a sensor follows the disc model i.e. the sensing range is a circle centred at that node.
In our approach, we divide time into a series of periodic sensing cycles where at each cycle, a sensor senses its surrounding environment and the information acquired thereby is used to decide on event occurrence. The event detection model is binary, i.e. each node compares its local measurement with some threshold and takes a one bit decision whether an event has occurred or not, and the decision is sent to a local fusion centre. For example, in Fig. 1 the event is sensed by four sensors (k=4), each node sensing a circular area, and their sensing decision is sent to a node (marked by a dotted circle) which acts as a sensing node as well as a local fusion centre. The local fusion centre may be selected in a round robin fashion. A distributed decision fusion scheme like majority voting in [14] can be employed to take the final decision at the local fusion centre aggregating the decisions sent from the k sensors monitoring the event point. This decision is then sent to a base station (BS). Unlike [14], we consider 'n out of k' rule for decision fusion which is more generic and offers more flexibility. Considering real life incident such as fire, chemical pollution or natural disaster, events are usually persistent and stationary. Then it can be safely assumed that the average event lifetime, denoted by T, is greater than the sensing cycle, denoted by τ, i.e. , $T \gg \tau$.

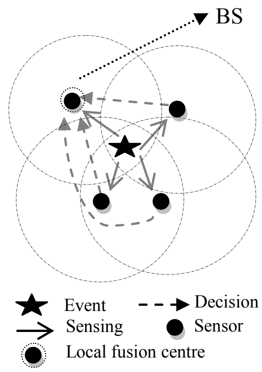


Figure 1: *k*-coverage detection

3.2. The Fault and Noise Model

A decision error in an individual sensor may arise from three different sources: i) noisy measurement by the sensor due to environmental interference referred to as the sensing noise, ii) sensor malfunction or physical damage referred to as fault, and iii) alteration of a sensor decision due to the noise present in the communication channel during transmission to the local fusion centre referred to as the communication noise. In the following, we formally model each of the above impairments:

- **Sensing noise**: Let $S = \{s_1, s_2, ..., s_k\}$ be the set of k sensors monitoring an event and u be the expected measure of the physical data sensed by a sensor in the absence of any sensing noise. But due to the sensing noise, sensed data may not exactly be u. Moreover, sensing noise at different sensors might vary, and consequently their observation data. Such sensing noise can be modelled using Gaussian distribution [5]. Let the sensing noise at the i-th sensor be n_i which follows a Gaussian distribution with μ_s mean and σ_s^2 variance $\aleph(\mu_s, \sigma_s^2)$. Let $\{y_i\}_{i=1}^k$ be the set of observations of the k sensors monitoring the event, where

$$y_i = u + n_i. \tag{1}$$

- **Fault probability**: Sensor fault may arise from many sources, such as manufacturing fault, physical damage during deployment, energy depletion with time, circuit malfunctioning due to environment impact or aging, etc. While some of these factors are dependent on the surrounding conditions where the sensor is located, some are independent of sensor location. For simplicity we take the mean of the fault probability over the entire sensor field to be individual node's fault probability which is denoted by P_f.

- **Communication noise**: Let the binary decision taken by a sensor is sent to the local fusion centre via a communication channel, which is subject to an additive white Gaussian noise (AWGN) with zero mean and σ_c^2 variance. Since we are concerned about sending a binary decision, a communication error event can alter a single bit decision with the probability, P_b, which is the bit error probability of the channel. Given the AWGN model $\aleph(0, \sigma_c^2)$, the approximated bit error probability, as obtained in [8], has the following form,

$$P_b = Pr(\gamma_b) = \frac{\alpha_M}{\log_2 M} Q\left(\sqrt{\frac{\gamma_b \beta_M}{\log_2 M}}\right) \tag{2}$$

where, Q denotes the standard tail probability of the standard Gaussian distribution, M, α_M and β_M depend on the type of approximation and modulation type, and γ_b is called the SNR per bit which can be calculated from σ_c^2. While this is more of a generic form, different other models have also been proposed in literature for channel specific characteristic that calculate the bit error probability as a function of SNR [10].

3.3. Problem Statement

As discussed in Section 1, the performance of an event detection system such as detection probability, fault tolerance and latency are dependent on the degree of coverage k. Our goal is to determine the minimum k so that the QoS requirements are satisfied and can be formulated as the following optimization problem: minimize k,

s.t.,

$$\begin{cases} P_{k,n} \geq \alpha \\ P_f \leq \beta \text{ and,} \\ L_{k,n} \leq \lambda \end{cases} \tag{3}$$

where α, β and λ are the QoS requirements for an application corresponding to the detection accuracy, fault tolerance and latency, respectively. $P_{k,n}$ and $L_{k,n}$ are the event detection probability and latency respectively when an event is monitored by k sensors and 'n out of k' rule is applied for decision fusion.

4. Optimal Degree of Coverage

To derive the optimal degree of coverage, we first estimate the errors due to different types of impairments in the detection environment as presented below.

Decision error due to sensing noise: Due to sensing noise , a sensor $s_i \in S$ generates data y_i instead of actual event measure u. A sensor makes a binary decision, event occurrence (1) or non-event (0), by comparing its generated data y_i with the threshold value γ that characterizes the occurrence of an event. The threshold value is application specific and pre-calculated based on domain knowledge [14]. The noise may deviate the sensed reading in either direction, i.e., it may drive a non-event to an event occurrence resulting in a false detection, or it may drive an event occurrence to a non-event situation missing an actual event. Therefore having knowledge on sensing noise that may exist in the sensor field, it is possible to estimate the tolerable noise margin (n_{max}) without causing any decision error which is given by

$$n_{max} = |\gamma - u|. \tag{4}$$

Then with reference to (1) the probability of decision error (P_s) at a sensor due to the sensing noise can be calculated as follows:

$$\begin{aligned} P_s &= Pr(|n_i| > n_{max}) \\ &= \tfrac{1}{2}\left(1 - \operatorname{erf}\left(\tfrac{n_{max}-\mu_s}{\sigma_s\sqrt{2}}\right)\right). \end{aligned} \tag{5}$$

Decision error due to communication noise: Let $\{x_i\}_{i=1}^k$ be the set of individual binary decisions made by k sensors monitoring the event, where

$$x_i = \begin{cases} 1, \text{if } y_i \geq \gamma, \\ 0, \text{otherwise.} \end{cases} \tag{6}$$

Once each individual sensor makes its decision, each sends its decision to the local fusion centre through a communication channel whose noise model is given by (2). Due to channel noise the fusion centre may receive an altered decision. Let $\{\hat{x}_i\}_{i=1}^{k}$ be the set of decisions received at the fusion centre corresponding to the set $\{x_i\}_{i=1}^{k}$. Since each decision is a 1-bit binary value, the probability of error being introduced during transmission from a sensor to the fusion centre can be expressed as

$$Pr(x_i \neq \hat{x}_i) = P_b.$$

Probability of detection: We assume that the observations are independent and identically distributed, and sensor faults and communication noise are also independent of the observations. Also a sensor will cause sensing error only if it is not faulty, otherwise a sensor generating erroneous data is faulty with probability P_f. Then considering error probabilities from all types of error, the probability that a sensor would correctly detect an event and its decision would reach error free at the fusion centre is given by,

$$P_d = (1 - P_b)(1 - P_f)(1 - P_s). \tag{7}$$

Now, the decisions $\{\hat{x}_i\}_{i=1}^{k}$ from k sensors at the fusion centre can be considered as a series of independent Bernoulli random variables with success probability P_d. The fusion centre employing the 'n out of k' rule will decide the hypothesis as correct provided that at least n nodes successfully detect the true event situation. The individual decision from each of k sensors at the fusion centre can be given by k conditionally independent and identically distributed Bernoulli random variables. The probability for successful detection of an event at the fusion centre employing 'n out of k' rule is then given by,

$$P_{k,n} = \sum_{i=n}^{k} \binom{k}{i} {P_d}^i (1 - P_d)^{k-i}. \tag{8}$$

For a given detection probability P_d and fixed n, $P_{k,n}$ is an increasing function of k. As argued in Section 1, in addition to detection accuracy, latency is also a crucial QoS parameter. So an important WSN design issue would be to determine the value k to satisfy a given latency constraint.

The delay incurred has two components - the time required to detect the event by at least n different sensors and the time required to transmit the results to the fusion centre considering MAC layer contention. Let $L_{det}(k, n)$ be the time required for the event to be successfully detected by n or more sensors and $L_{mac}(n, k)$ be the delay incurred due to contention in the transmission medium. In this regard we have the following proposition:

Proposition 1. *The expected latency $L_{det}(k, n)$ for successful detection of an event for 'n out of k' rule is,*

$$L_{det}(k, n) = \left(\frac{\left(2 + P_{rep}\right) - \sqrt{\left(2 + P_{rep}\right)^2 - \frac{8nP_{rep}}{kP_{det}}}}{2P_{rep}} \right) \tau. \tag{9}$$

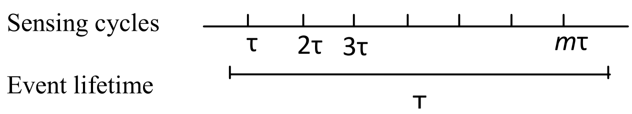


Figure 2: Timing illustration of sensing cycles and event lifetime.

Proof. Let us consider an event occurring in the sensor field. Let T be the lifetime for which the effect of an event persists and remains detectable as shown in Fig. 2 and τ be the point in time when the first sensing cycle starts after the event begins. It is assumed that the sensors are time synchronized.

In 'n out of k' rule the fusion centre can declare the event as detected once at least n sensors send positive result. Let m be the expected number of sensing cycles required to detect the event by more than n sensors. The detection probability at individual sensor in a given cycle is $P_{det} = (1 - P_f)(1 - P_s)$ and the detection of the event by the sensors is independent in each cycle. The expected number of sensors detecting the event in a given cycle is then kP_d. But a portion of this kP_d sensors may already have detected the event in any previous cycle, so it is counted only once towards the calculation of n. Let the probability that a node detects the event repeatedly in two or more cycles be P_{rep}. Then the number of distinct nodes v_i detecting the event upto i-th cycle can be given by,

$$\begin{aligned} v_i &= kP_{det} + kP_{det}(1 - P_{rep}) + ... + kP_{det}\left(1 - (i-1)P_{rep}\right) \\ &= kP_{det}\left(i - \left(\tfrac{i(i-1)}{2}\right)P_{rep}\right). \end{aligned}$$

Solving $v_i \geq n$ will give the expected number of cycles required for n detections, leading to

$$kP_{det}\left(i - \left(\frac{i(i-1)}{2}\right)P_{rep}\right) \geq n$$

$$\Rightarrow i \geq \frac{\left(2 + P_{rep}\right) - \sqrt{\left(2 + P_{rep}\right)^2 - \frac{8nP_{rep}}{kP_{det}}}}{2P_{rep}}$$

According to our definition,

$$m = \frac{\left(2 + P_{rep}\right) - \sqrt{\left(2 + P_{rep}\right)^2 - \frac{8nP_{rep}}{kP_{det}}}}{2P_{rep}}. \tag{10}$$

Therefore, $L_{det}(k, n) = \left(\frac{(2+P_{rep}) - \sqrt{(2+P_{rep})^2 - \frac{8nP_{rep}}{kP_{det}}}}{2P_{rep}}\right)\tau$, which completes the proof.

Now, all nodes detecting the event within m cycles may not be able to transmit the data to the fusion centre due to contention in Medium Access Control layer. Let P_{mac} denotes the probability of successful transmission of a node in one time slot in the contention window. The duration of a slot is given by t_d and one sensing cycle consists of c slots, that is, $\tau = ct_d$. Let π_i be the expected number of unique nodes that detect and transmit successfully upto i-th cycle.

$$\begin{aligned} \pi_1 &= cv_1P_{mac} \\ \pi_2 &= \pi_1 + c(v_2 - \pi_1)P_{mac} \\ &= cv_1P_{mac}\left(1 - cP_{mac}\right) + cv_2P_{mac}. \end{aligned}$$

Proceeding this way, we get,

$$\pi_m = cP_{mac}\sum_{i=1}^{m} v_i \left(1 - cP_{mac}\right)^{m-i}. \tag{11}$$

Even after n detections among k sensors, we still may have $(v_m - \pi_m)$ nodes still waiting to send their detection decisions due to contention. Let ρ be the additional number of transmission slots that will be required to transmit these outstanding decisions. Then,

$$L_{mac}(k, n) = \rho t_d = \left(\frac{v_m - \pi_m}{P_{mac}}\right)t_d.$$

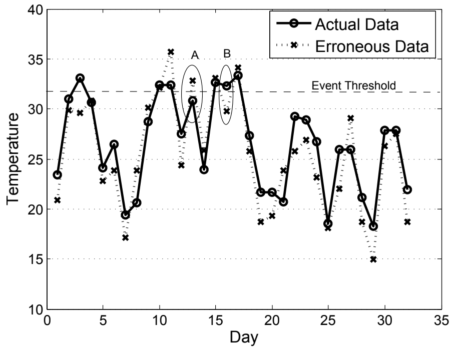
The overall expected delay before at least n distinct nodes can detect and transmit their results to the fusion centre is given by,

$$L_{k,n} = L_{det}(k, n) + L_{mac}(k, n). \tag{12}$$

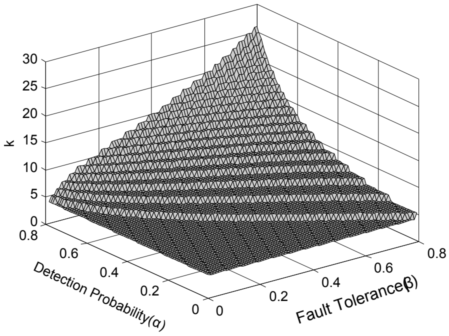
The term P_{mac} depends on the sensor specific MAC protocol and the number of competing stations. It is practical to assume that a sensor detecting the event more than once will send the result only once in the current cycle even if the result from any previous cycle is still unsent, i.e. it will send the most recent data only. For simplicity, the average number of competing stations can be assumed to be kP_d.

Finding the Optimal Degree of Coverage: We are interested in finding the minimum value of k that satisfies the given performance metrics. (7) indicates that P_d decreases with increasing sensor fault probability P_f. According to the given constraint in (3) the maximum allowable fault tolerance limit is β, so to satisfy this we can replace P_f by β in (7). This yields following expression for the probability of successful detection of an event by an individual sensor at the fusion centre that satisfies a given fault tolerance,

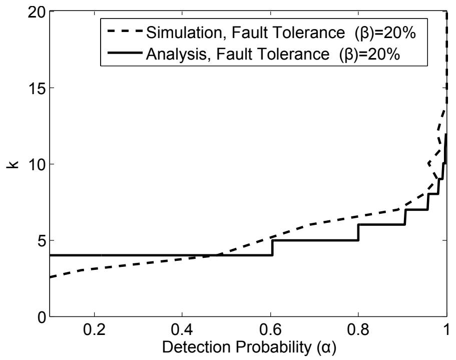
$$P_d = (1 - P_b)(1 - \beta)(1 - P_s). \tag{13}$$



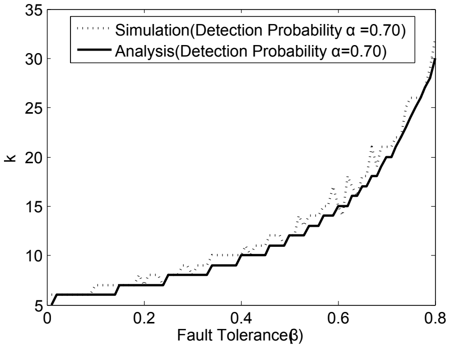
(a) Impact of sensing noise on sensed temparature



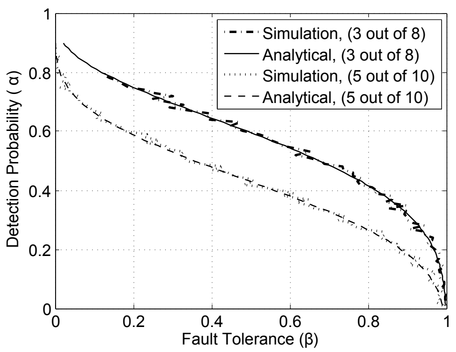
(b) k vs. fault tolerance and detection probability



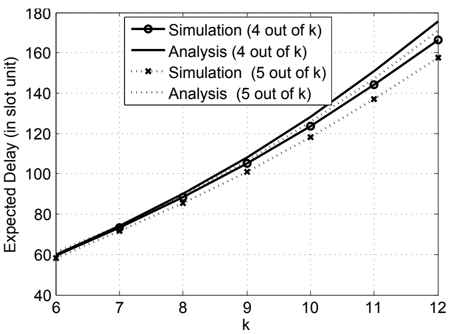
(c) k vs. detection probability



(d) k vs. fault tolerance



(e) Detection probability vs. fault Tolerance.



(f) Expected delay vs. k (for B-MAC)

Figure 3: Comparison of analytical and simulation results depicting the relationship among k, detection probability, fault tolerance and detection delay.

Using the above expression in (8) gives an estimate of the detection probability $P_{k,n}$, that satisfies a given fault tolerance β. Therefore, the minimum value of k that satisfies required fault tolerance and detection probability can be expressed as,

$$k_{\alpha,\beta} = \arg\min_{k} \left(\sum_{i=n}^{k} \binom{k}{i} {P_d}^{i} (1 - P_d)^{k-i} > \alpha \right). \tag{14}$$

The above $k_{\alpha,\beta}$ can be calculated in a simple iterative fashion. From (12) latency $L_{k,n}$ is an increasing function of k for a given n. Let k_λ be the maximum number of node coverage that satisfies the given latency constraint λ. k_λ can be determined by solving,

$$\left(\frac{\left(2 + P_{rep}\right) - \sqrt{\left(2 + P_{rep}\right)^2 - \frac{8nP_{rep}}{kP_{det}}}}{2P_{rep}} \right) ct_d + \left(\frac{\nu_i - \pi_i}{P_{mac}} \right) t_d \leq \lambda. \tag{15}$$

Now, two different cases are possible - i) $k_{\alpha,\beta} > k_\lambda$ and ii) $k_{\alpha,\beta} \leq k_\lambda$. In the first case, it is not possible to satisfy all three performance metric concommitantly, because setting $k_{min} = k_\lambda$ will not meet the degree of coverage requirement for accuracy and fault tolerance. Therefore, either latency ($k_{min} = k_\lambda$) or the other two ($k_{min} = k_{\alpha,\beta}$) can be met. In the latter case, the solution is feasible. Combining the results from (14) and (15), the expression for the minimum degree of coverage k with a 'n out of k' fusion rule satisfying all three QoS related constraints leads to the solution of the optimization defined in (3) as, $k_{min} = \min(k_{\alpha,\beta}, k_\lambda)$.

Finally, we pose one validation check on the result to ensure minimizing false alarm. When no event occurs, the number of nodes that will erroneously detect an event is $k_{min}(1 - P_d)$. So, the condition $\frac{n}{k_{min}} > (1 - P_d)$ needs to be satisfied to reduce the number of false alarms.

5. Simulation Result and discussion

We designed and developed a custom simulator in Matlab and conducted extensive experiments to validate our analytical model. For experiments, we randomly deployed sensors in a 400m×400m square sensor field and the number of nodes, N required for k-coverage was determined according to [7], for different values of k. Each sensor is assumed to have a sensing range of 10m and a communication range twice the sensing range. A set of temparature data were taken from [15] to generate events after imposing noise and events were uniformly distributed over the sensor field. We measured the accuracy of detection for different values of fault tolerance, β and k. We used Z-MAC, S-MAC and B-MAC [9] for simulation and all of them showed similar trends. Due to space limitation we only presented the results generated using B-MAC. '4 out of k' rule is employed in all cases unless otherwise specified in legend. In each case 1000 trials were repeated and their average was reported. The findings are presented in Fig. 3.

Fig. 3(a) shows how the simulated noise affects real data causing missed detection, B and a false alarm, A. Fig. 3(b) represents the combined effect of given detection probability and fault tolerance on the degree of coverage k, in a surface plot. This helps to visualize the inherent relation of k with detection probability and fault tolerance. The figure illustrates that higher degree of coverage is required if either required detection probability (α) or fault tolerance (β) is increased. In Fig. 3(c) the experimental value of k is compared with the one obtained from Eqn. (14). The graph represents close match with the theoretical solution and validates our analytically calculated k being the minimum. It shows that at lower value of α, increasing k increases detection accuracy sharply, however, when accuracy approaches very high value, increasing k does not bring any added advantage. Similarly Fig. 3(d) plots the relation between optimal k and fault tolerance for a fixed detection probability. This also shows a closer match between theory and simulation. This is because, while observing the effect of k on fault tolerance (Fig. 3(d)), the detection probability (α) is kept constant and the noises are drawn from the same distribution, i.e., the average noise components are constant. But in case of k vs. detection probability with fixed fault tolerance, we let the noise components (sensing and communication noise) vary that makes it more sensitive to noise hence exhibits more change. It is also interesting to note from Fig. 3(c) that the theoritical result matches simulation results more closely as k attains higher value. This means very high accuracy at higher k ruling out inaccuracies and noise spikes in a more robust way.

Fig. 3(e) illustrates the trade-off between fault tolerance and detection probability. It shows that one has to be sacrificed to achieve more of the other. Thus in case of coverage constraint, our model gives a clear assessment of the trade-off between QoS parameters which will be useful to applications for deployment purpose. The figure also shows that '3 out of 8' rule has a better tolerance against fault than '5 out of 8' rule. That is as the rule gets stricter , the robustness comes at the cost of compromising fault tolerance. Fig. 3(f) shows the effect of degree of coverage k

on latency. Increasing k yields higher latency. The reason is that, not all the sensors are able to send the data as soon as they detect the event due to the contention condition. So the delay incurred due to the contention in MAC layer is increased as k increases because of more competing nodes. The simulation shows slight deviation from theoritical result as k gets higher (specially for $k \geq 10$). This is because our simulation setup is dependent on the probabilistic model presented in [7] that determines the required number of nodes to provide k-coverage and in that model the probability of full coverage drops as k goes higher. So in simulation it can not guarantee full k coverage as k increases and that is why the experimental latency deviates from the theoritical value as k is increased. This deviation is not significant though, because in most real case scenarios, more than 10-coverage is not practical.

6. Conclusion

In this paper, we have presented a model for event detection WSNs to analytically determine the minimum k-coverage required to probabilistically guarantee a given set of QoS metrics, namely detection accuracy, fault tolerance and latency taking the environmental noise, sensor faults, communication impairments and MAC induced delay into consideration. Simulation results have revealed a close match between our theoritical model and the experimental results. Adoption of this model will be useful in designing WSNs by determining appropriate deployment strategy that satisfies QoS requirement of the application.

Since this is a deployment time method and changes in environment may necessitate changes in the required degree of coverage with time, our model may not provide adaptability which remains the focus of our future work. On the other hand, being a design phase algorithm allows the flexibility of using high power offline processing method for modelling the deployment strategy.

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