An Event Detection Framework for Wireless Sensor Networks

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Declaration

This thesis is my own work and has not been submitted in any form for another degree or diploma at any university or other institute of tertiary education. Information derived from the published and unpublished work of others has been acknowledged in the text and a list of references is given.

Kh Mahmudul Alam
23 January, 2013.

Dedicated to my parents for their life long inspirations, sacrifices, love and care.

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Abstract

Wireless Sensor Networks (WSNs) introduce a new paradigm for sensing and disseminating information from various sources in the physical environment around us. WSNs facilitate the detection of various real-world phenomena (e.g. environmental anomaly, natural disasters, structural faults, man-made hazards and so forth) and thereby aim to reduce any economic and human loss. Typically, a WSN consists of a large number of sensor nodes deployed over a geographic area and each sensor is capable of sensing one or more attributes of the surrounding environment. Unlike traditional communication networks, the structure of a WSN is tightly coupled with the target application. Therefore, the design of a WSN based event detection system involves careful consideration of application-specific performance requirements, diversity in real-world sensing fields, impacts and contexts of the types of target events. The research presented in this thesis focuses on the reliability and accuracy of the detection of physical events using WSNs. Studies in the relevant literature suggest the use of node redundancies in the form of k-coverage to ensure robust detection. In this thesis, first, an optimal QoS support framework for k-coverage in an event-centric WSN using static nodes is presented. Then the concept of coverage hole recovery using variable range sensing is introduced that deals with the loss of coverage arising from node faults and ageing in the post deployment scenario. However, the redundant coverage can be cost prohibiting as the number of nodes becomes very high for high degree of coverage requirement. To reduce the deployment cost, a dynamic k-coverage scheme is proposed that ensures 1-coverage during deployment and provides k-coverage on-demand only after an event is sensed by at least one node. Two different solutions - one using the sensing range adjustment technique and another using node mobility are presented and compared for performance and cost analysis.

The proposed detection scheme in this thesis also considers the detection of multiple simultaneous events in a WSN where events may have different priorities depending on their locations and costs of missed-detections. The differentiated treatment for event on a priority basis is evident in many real-world applications. Finally, incorporating the context information in conjunction with the sensed data extends the event detection framework and facilitates the seamless integration of WSNs to the Internet of Things for event detection purpose.

Acronyms

AODV	Ad-hoc On-demand Distance Vector
AWGN	Additive White Gaussian Noise
BELP	Bounded Event Loss Probability
BER	Bit Error Rate
BS	Base Station
CH	Cluster Head
CSR	Complete Spatial Randomness
DAMSEL	Distributed Approach for Mobile Sensor Selection
GPS	Global Positioning System
IoT	Internet of Things
ITU	International Telecommunication Union
MAC	Medium Access Control
MEMS	Microelectromechanical systems
PDF	Probability Distribution Function
PSED	Priority Sensitive Event Detection
QoC	Quality of Coverage
QoS	Quality of Service
RFID	Radio-Frequency Identification
ROC	Receiver Operating Characteristics
ROI	Region of Interest
RSSI	Received Signal Strength Indication

SHM	Structural Health Monitoring
SHT	Statistical Hypothesis Test
SNR	Signal-to-Noise Ratio
VSN	Vehicular Sensor Network
WSAN	Wireless Sensor and Actuator Network
WSN	Wireless Sensor Network
WVG	Weighted Voting Game

List of Symbols

$\bar{r}$	Average sensing radius
γ_b	SNR per bit
E_s	Energy consumed in sensing
E_{in}	Initial energy of a node
E_{rem}	Remaining energy of a node
$E_{tx}(d)$	The energy consumed to transmit a packet to a distance d
H_i	The i-th hypothesis in a hypothesis test model
N	Total number of sensor nodes in a WSN
N_e	Neighbourhood size of any individual node in a WSN
N_m	Number of mobile sensor nodes
N_s	Number of static nodes
P_D	Detection probability of a WSN system
P_F	False alarm probability of a WSN system
P_d	Detection probability of an individual sensor
P_{det}	Probability of detection of an event in one duty cycle
$Q(.)$	The complementary distribution function of standard Gaussian.
R	Communication range of a sensor node
$S(.)$	The survivor function a sensor device
T_e	Event lifetime, i.e., staying time of an event
T_{nd}	Neighbour discovery period
$U(x)$	Signal power measured by sensor at distance x from the event or target
Λ	Given detection delay bound of an event in a WSN
$\Omega_{i,n}$	The set of combinations of i nodes chosen from n nodes
α	Given detection probability bound of an event detection system

β	Given fault tolerance level of an event detection system
$\chi(.)$	Cumulative distribution function of a Chi-square distribution
δ	Scaling parameter of Weibull distribution
η_d	Decision fusion threshold
η_v	Value fusion threshold
γ_l	Path loss exponent in shadow fading
γ_u	Signal attenuation exponent
$\hat{u}_i$	Signal power measurement at sensor s_i in presence of noise
λ	Event arrival rate
$\mathcal{A}$	Area of the target sensing field
$\mathcal{B}$	Banzhaf index, power index in a voting game
$\mathcal{L}$	Network lifetime of a WSN
$\mathcal{S}$	A set of sensors
μ_X	Mean of random variable X
π_i	Priority of event class i
ψ	Network lifetime threshold, i.e., a WSN lifetime ends when more than ψ fraction of nodes die
ρ	Density of sensor nodes in a WSN
σ_X	Variance of random variable X
σ_f	Fading parameter in shadow fading model
τ	Lifetime of a single node
υ_r	Sensing range adjustment ratio
ε	Environmental noise in sensing
ζ	Probability of event occurrence in a region of interest
b_i	Binary decision outcome of the sensor s_i
c_s	Loss co-efficient in sensing energy model
c_t	Loss co-efficient in transmission energy model
c_w	Shape parameter of Weibull distribution
d_i	Distance of i-th sensor or i-th event
$g(.)$	Signal decay function
$h(t)$	The hazard function, i.e., the failure rate of a node at time t
k	Degree of coverage in a WSN
$p(x)$	Probability of detection of an event at distance x
p_b	Probability of alteration of a 1-bit decision in transmission

p_f	Sensor fault probability of an individual sensor
p_s	Probability of decision error due to noise in sensing
r	Sensing range of a sensor node
r_{max}	Maximum possible sensing range of a node
r_{min}	Minimum possible sensing range of a node
s	An individual sensor
s_i	i-th sensor from a set of sensor nodes
t_c	Sensing duty cycle of a sensor
u	Signal power emitted from a target event
u_i	Signal power measurement at sensor s_i without any noise
(x, y)	Location co-ordinate in a 2D sensor field

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Chapter 1

Introduction

"Any sufficiently advanced technology is indistinguishable from magic" [1]
- Arthur C. Clarke

One such magical invention of the twentieth century was the computer which has changed the way of life over the last 60 years. It has greatly extended our capacity to understand the world around us and process the information perceived from the environment. The pervasiveness of the usage of computing devices in almost every aspect of human life has made people look for newer ways to narrow the gap between the computer and the real world and let the computer monitor and interact with the real world directly and freely without human intervention. Sensor technologies augment the computing devices with perception capability and revolutionise the way of collecting information. This has initiated a shift towards human-centred computing where technology is no longer a barrier, but can work for us adapting to our needs and preferences. However, monitoring the world and enriching our knowledge base through this augmented visibility of the real world is not enough. Reactive usage of such knowledge in the welfare of the human race is a necessity. That is why it is crucial to process the data perceived from the environment carefully and determine when to act on it. Imagine a world where such devices with perception capabilities monitor our neighbourhood and raise an alarm whenever there is a fire or other hazards, or, an assisted living facility, sensors in wearable clothes sense and inform in the state of emergency. It is then very crucial to determine an incident at the very moment of its occurrence and activate an actuation system in response. This is why detection of events of interest is an essential part of this new generation technology referred to here.

The research in this thesis focuses on the efficient and reliable detection of events in a real-world scenario via a network of sensors that augment the visibility capabilities of computers.

1.1 Wireless Sensor Networks

A Wireless Sensor Network (WSN) is regarded as an emerging technology that combines the concept of wireless network with sensors. Recent advances in Micro Electro-Mechanical Systems (MEMS) technology have made possible the construction of tiny and low-cost sensor nodes containing on-board sensing, signal processing and wireless communication capabilities [2, 3]. A wireless sensor network is a collection of such sensor nodes spatially deployed in an ad hoc fashion that performs distributed sensing tasks in a collaborative manner without relying on any underlying infrastructure support [3, 4]. Rentala *et al.* [5] regarded nodes in WSNs "as wireless integrated network sensors that combine micro-sensor technology and low power computing and wireless networking in a compact system. The individual nodes have a limited capability, but are capable of achieving a big task through coordinated effort in a network that typically consists of hundreds to thousands of nodes." Nodes in a WSN are generally deployed randomly, and once deployed they organise themselves as a network through radio communication. Sensor nodes generate data from the surrounding environment and send to a higher level computing entity, which then generates a meaningful scenario about the phenomena of interest and responds accordingly. By combining sensing, processing and communication capabilities, WSNs enable the virtual world to bridge with the physical world practically everywhere; from mines to distant forests, from home to hostile battlefields, from ocean beds to Antarctica, places where it is difficult to reach because of dangers, natural obstacles and other humanly limitations.

These vast foreseeable application fields of WSN lead the communication research to take up the challenge of standardising existing communication protocols and make them WSN-compatible. Some major standardisation efforts are Zigbee [6], WirelessHART [7] and 6LoWPAN [8]. The layered architecture has been adopted in the development of WSN systems due to its success with the Internet. However, resource constraints and the application specific nature of the WSN paradigm lead to cross layer solutions that tightly integrate the layered protocol stack. For which, early works in sensor networking include designing efficient routing algorithms suitable for energy constrained nodes [9, 10], developing WSN specific MAC protocols [11, 12] and clock synchronisation in a distributed sensor network [13]. The research trends in WSN are summarised in Fig. 1.1. It is noteworthy that, initial research trends were focused on carrying over the

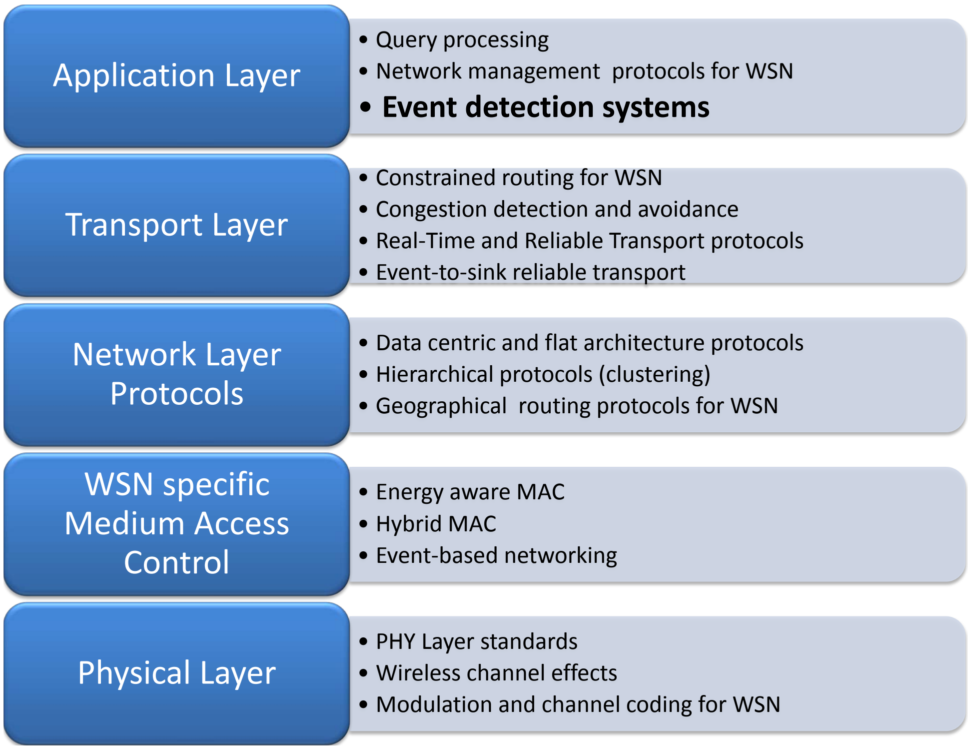


Figure 1.1: A summary of WSN research trends

pre-existing communication protocols to WSN architecture. The evolution of different aspects of communication has been being carried out for over a decade now. However, new research challenges have arisen with the application of WSN in detecting real-world phenomena. Unfortunately, traditional event detection algorithms and designs do not carry over to WSN, since event-centric WSNs encapsulate highly application specific trade-offs in terms of complexity, resource utilisation and communication algorithms. The successful detection of physical events depends on the appropriate consideration of the underlying sensor field and the nature of the events. Since users are interested in collaborative information from multiple sensors, time synchronisation is needed for the correct ordering of sensed events to accurately model the physical environment. Localisation protocols need to be incorporated in the protocol stack to associate the physical phenomena with their surroundings. Event detection in WSNs thereby exhibits higher application dependency than any other traditional distributed applications and calls for closer attention.

The increasing maturity, performance and miniaturisation of sensor devices and their interoperability with external services and objects are enabling the move towards ubiquitous computing. WSN is considered an important technological cornerstone of the next generation Internet of Things (IoT) which views the future of the world wide web as a global network of uniquely identifiable objects, sensors and mobile entities that dynamically connects the physical and virtual world [14, 15]. The IoT allows human and any entities in the environment to be connected anytime, anywhere, with any other similar or heterogeneous objects and build a giant network of smart things. The IoT is already forecast to have huge influence on a wide range of domains, including ambient intelligence and pervasive computing which will weave itself in the environment surrounding us and assist in our everyday life when needed. WSN is deemed as one of the building blocks of IoT as sensors are the only means of observing the physical world. In this project we focus our research on the challenges and issues related to event detection in WSN and study the paradigm shift in event detection technology as sensor networking evolves as a part of the IoT.

1.2 Event Detection using WSN

The ability to sense and identify real-world states and events is essential to the success of WSNs. In an event detection scenario, sensor nodes are deployed in the target field to collect data either continuously or on a periodic basis. Typically, an event is defined as an exceptional change in the sensed parameters such as temperature, pressure, humidity etc. that requires immediate attention and, in some cases a response. However, in reality, an event can occur in many ways such as a dramatic or sudden change of sensed parameters or a gradual and continuous change over time, and the attributes may maintain spatio-temporal correlation [16]. The main idea of the event detection paradigm is to identify the physical attributes of the sensed environment that will exhibit a gradual or sharp variation over time and/or space and define the event accordingly.

In general, an event generates a specific pattern of sensor data distribution on the nodes in a particular region in the network over time. For example, a node can report the presence of an animal or an object when its motion sensor readings match a temporal predefined pattern related to that incident [17, 18]; a gas leakage in a mine can be detected when the gas density sampled by the nodes in a particular region exhibits a certain spatial distribution over a short span of time [19]; a fire event in a forest can be characterised by the temperature value reaching a certain threshold while the smoke sensors show high density supporting the possible occurrence of fire [20, 21]. An overview of basic event detection in sensor networks is shown in Fig. 1.2. The shaded region denotes the spread of the signal emitted by the event. Any node within this region will exhibit a specific pattern of data that characterises the event being monitored. Nodes sensing this event signal transmit the data to a sink or gateway node that is responsible for further processing of the event signal and notifying the users in the system,

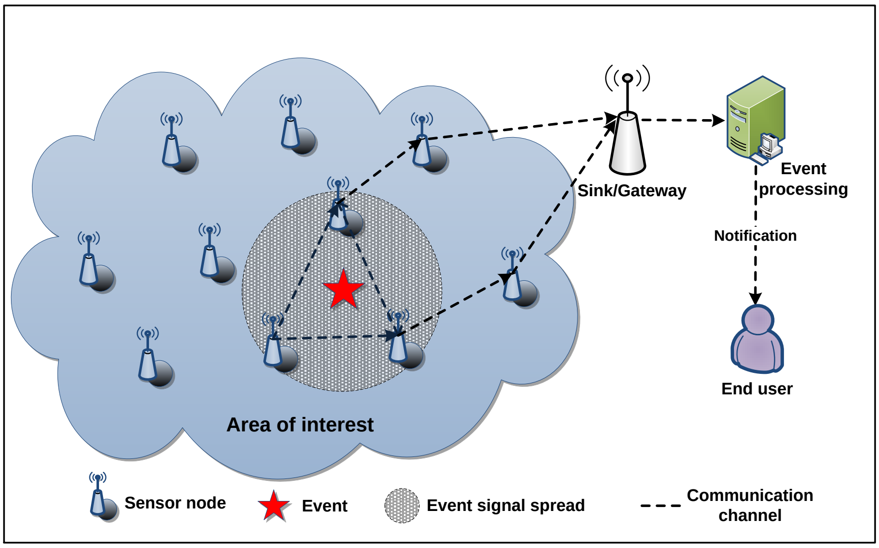


Figure 1.2: Overview of event detection in a WSN

WSNs may consist of many different types of sensors including but not limited to thermal, visual, seismic, magnetic, infrared, acoustic, and radar, which enables them to monitor a wide variety of ambient conditions such as temperature, humidity, pressure, motion, electro magnetic field, radiation, light, noise levels and the presence or absence of certain kind of objects. This makes WSNs increasingly apt for event detection applications. The wide spectrum of WSN applications for detecting events of interest in several domains includes i) habitat monitoring, ii) environment monitoring, iii) intrusion detection, iv) structural monitoring, v) industrial process monitoring, and vi) battlefield surveillance.

1.3 Challenges in Event Detection

In this section we discuss the issues that need to be addressed in event detection in a wireless sensor network.

1. **Resource constraint**: One of the main benefits of WSNs is the fact that they do not require cabling, which is also the main operational constraint [22]. Sensor nodes are typically battery powered which limits the maximum energy usage in the lifetime of the node. Replacement of energy sources is not a feasible option in most cases, as nodes are likely to be deployed in an outdoor environment and left unattended [23]. Apart from this, usually hundreds or even thousands of nodes can be deployed in a large scale sensor network and replacing energy sources regularly can be time consuming and expensive. Energy harvesting techniques such as solar or wind power are also not practical as WSNs are often deployed in concealed environments. All these necessitate energy awareness in the design of event detection techniques using WSNs.

2. **Unbalanced energy consumption**: The energy consumption by nodes in an event-driven sensor network is inherently different from data gathering networks as the usage of energy depends on the distribution of events. In monitoring applications, each individual node continuously collects data and periodically sends sensed data to the base station. In an event-driven network, generally nodes respond to and send data to the base station only when they detect an event. In most real-world applications, events are not uniformly distributed across the sensor field [24]. The frequency of events in some regions may be much higher than others. Consequently, nodes in the neighbourhood of a high frequency event region suffer from faster energy depletion than others. This causes unbalanced consumption of energy across the sensor field and ultimately results in reduced network life. One of the major challenges in designing event detection techniques

is to handle the non-homogeneous spatial distribution of events for the balanced use of node energy [25, 26].

3. **Coverage and connectivity constraint**: Sensing coverage characterises how well the sensor network can monitor an environment and collect data. Different applications require different degrees of sensing coverage. While some applications may require every point in the region of interest to be covered by at least one node, other applications may require higher degree of coverage. For example, event detection based on data or decision fusion usually requires multiple nodes monitoring every location in the sensor field for reliable detection [27]. The coverage requirement also depends on the expected fault resilience property of the system and the dynamic nature of the sensing environment. This requires the capability to adjust the degree of coverage dynamically. For example, in some mission oriented event-centric sensor networks [28, 29], initially a low degree of coverage is maintained. After the occurrence of an event, the region in the vicinity of the event needs to be reconfigured to achieve a higher degree of coverage to detect the event more accurately. However, a higher degree of coverage incurs high energy consumption and increased deployment costs, and it is imperative to minimise the number of nodes to keep the operational overheads at a minimum. Therefore, a fundamental problem in event detection WSNs is to minimise the coverage while still maintaining the expected degree of coverage for event scenarios.

   Apart from efficient and reliable coverage, for successful and reliable operation, a sensor network must also maintain connectivity so that the nodes can communicate between themselves and to the base station. The communication range of the sensor nodes is usually kept low to save energy which necessitates a sophisticated network design to maintain connectivity between nodes. Single connectivity is often not sufficient for many event-centric applications as a single node failure can disconnect the network. Also, redundant connectivity may be required in many cases to avoid communication bottleneck when multiple events occur in one region [30]. Maintaining energy efficient coverage and connectivity for seamless operation of WSNs has been investigated extensively and many near optimal solutions have been proposed based on the global information of the network

[31, 32, 33, 34]. Yet, few address the dynamic reconfiguration and adaptation of the network to meet the specific requirements of event detection systems.

Topology management to maintain connectivity and coverage of the WSN is critical in event detection, especially for hazard detection applications since any coverage hole may result in degraded detection performance and the cost of a missed detection is usually much higher and often involves life threats. Apart from that, the sensor observation data in a WSN are usually spatially correlated across nodes [16, 35]. For example, in many real-world applications (e.g. radiation detection and volcano monitoring), the impact of an event spreads over a region and a number of nodes need to collaborate before the final decision on the event occurrence can be reached. The underlying WSNs need to maintain optimum connectivity and coverage required for such detection.

4. **Node mobility**: Recent progress in distributed robotics and low power embedded systems has encouraged many researchers to propose mobile sensor networks [36] for event detection. Mobile nodes may be useful in many mission critical applications to provide dynamic event coverage as mobility allows sensor nodes to adapt to unpredictable changes in the environment and irregular spatio-temporal distribution of events [28, 29, 37]. In many cases, mobile nodes remain stationary initially but move towards the possible event location and achieve higher detection probability. However, node mobility imposes another unique challenge in maintaining required coverage and connectivity in WSNs. Irregular node movements can create temporary coverage holes and degrade detection performance. Also, the energy consumption is much higher in mobile nodes compared to their static counterpart. In a sensor field with highly irregular spatial distribution of events, a relocation strategy can lead to random node movements and unbalanced energy consumption across the network. It is challenging to design an efficient and reliable event detection technique that reduces node movement, maintains temporal coverage and connectivity and still yields acceptable detection performance.

5. **Heterogeneity**: Many event detection applications require data on a number of different physical attributes of the target environment. This can demand the deployment of multiple classes of sensors which may vary of their physical parameters such as initial energy, deployment density, mobility and so on. Especially,

in the IoT environment, WSNs need to interface with all other devices that are present in the environment and maintain network connectivity. Successful collaboration among diverse types of sensor nodes with different hardware capabilities makes the design of an event detection system more challenging.

6. **Scalability**: Large scale sensor networks with nodes in the order of hundreds to tens of thousands are becoming commonplace especially in environmental monitoring and battlefield surveillance applications [5, 38]. The size of sensor networks is highly application specific and may vary from tiny to very large coverage areas employing small to large numbers of sensors. Therefore, it is required that the event detection protocols used in WSNs be scalable so that they can cope with varying network sizes in terms of the number of nodes and coverage area.

7. **Quality of services**: Wireless sensor networks can be used in many mission critical applications of a diverse nature as stated earlier. In these types of applications, reliable and timely detection of events plays a crucial role in the success of the mission. However, unlike the traditional networks such as TCP/IP and cellular networks, in most WSN based applications, sensor nodes are low cost, error prone and subject to various external noises. As such, observations from individual sensors are often noisy and unreliable which makes it challenging for the event detection techniques to make an accurate detection decision from noisy data. In addition, the environments in which sensor networks are deployed usually vary, largely ranging from cold winter conditions with frost and ice in arctic regions, to heat and humidity in equatorial regions. WSNs are often deployed in adverse terrains such as near an active volcano or battlefields and left unattended during the period of operation, which increases the probability of node failure. Sensors are often air-dropped in otherwise inaccessible terrain which makes them prone to damage during deployment and irreplaceable. In addition to node malfunction, data faults are also common in sensor nodes. Various sensor network measurement studies have established the prevalence of transient faults in sensor readings [39, 40]. Event detection WSNs need to be robust against such node failures. This is a challenging task considering the fact that the *a priori* failure rate modelling is non-trivial because of diverse sources of node faults. Usually, communication among the nodes in a WSN is more vulnerable to environmental noise due to the

relatively low signal strength used by the sensor nodes to preserve energy. This makes it even more challenging to design robust event detection systems.

Many event-based services, such as fire warning or earthquake or lightning detection, require immediate detection i.e. the time elapsed between the occurrence of an event and its detection by the system needs to be bounded. This makes the timeliness of detection very crucial. For example, spread features of forest fires show that, in order to put out a fire without any permanent damage, the fire control centre should be aware of a threat in at most six minutes after the initial ignition [20, 41]. A number of factors, including the spatial and temporal distribution of events and the degree of coverage, affect the timeliness of detection. Current literature advocates the use of node redundancy to allow some nodes to go to sleep without affecting the overall coverage in order to prolong network life [42]. For example, IEEE 802.15.4 slotted carrier-sense multiple access with collision avoidance (CSMA-CA) adopts periodic sleeping for energy efficiency support [43]. In these efforts, both randomised and synchronised sleep schedules are proposed for sensor nodes. This causes an event to be sensed within a finite delay bound rather than immediately all the time. Thereby, an inherent trade-off lies between the network life and coverage, which in turn affects the detection delay.

The overall the performance of an event detection system is measured by the following QoS metrics:

- **Detection probability**: The probability that an event will be captured occurring anywhere in the sensor field. The required probability of detection by the system may vary depending on the application domain. Detection probability should be high for sensitive events, especially in hazard monitoring and detection applications, and moderate in other non-critical applications such as greenhouse monitoring or habitat monitoring.
- **Fault Tolerance**: The event detection system needs to be robust against a certain degree of node failures and sensor data faults. The desired fault tolerance level of the system will depend on the environment in which the network will be deployed and also on the inherent fault probability of sensor nodes.

- **Detection delay**: Event detection delay or latency is defined by the average time elapsing between the event occurrence and its detection by the nearby sensors. Unlike data gathering WSNs, most event detection systems have the real-time requirement, i.e. events need to be detected within a specified delay bound that enables the system or user to react.

1.4 Motivation and Problem Statement

As we move towards realising ubiquitous computing, the role of sensor networks is not limited to collecting information about the surrounding environment, rather it is more desirable for WSNs to understand the physical interpretation of the data and be able to isolate and identify phenomena that need attention in real time. Event detection is an efficient way of mining meaningful information from a huge volume of gathered sensor data. Naturally, event detection is recognised as one of the major functionalities of sensor networks these days and will surely become the key in the foreseeable future. This is why it is important to address the issues of reliable and efficient detection of events in sensor networks .

Numerous event detection techniques have been proposed in the literature to ensure high detection accuracy and low delay while maintaining minimum energy consumption, (see, e.g., various notable studies [25, 26, 27, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54]). Some of these have focused on designing a generic event detection framework [46, 47, 55], while others have proposed domain specific solutions [48, 56, 57, 58]. Some works have focused on threshold based detection (e.g. [59, 60, 61, 62, 63, 64]), while others have handled non-threshold based events [65]. Some addressed the issues in single event detection [47, 66], while others examined multiple events [53, 67] or composite events [68, 69]. Some techniques considered the nodes of the underlying WSNs to be static only [26, 27, 46, 50, 51], while others considered a combination of static and mobile nodes for event detection [28, 29, 37, 70, 71]. Some detection techniques assumed the underlying sensor network to be homogenous [47], while others addressed the scenario where heterogeneous sensors collaborate to detect events [54, 69, 72]. Irrespective of the nature of underlying sensor networks or the target environment, directly or indirectly, all these works aim at attaining optimum detection performance characterised by one or more of the QoS metrics, namely, detection probability, detection delay and fault tolerance, at the same time targeting prolonged network life. Here, the event detection problem is viewed from a totally different angle compared to existing work and the expected values of QoS parameters of an application drive the design method.

Most existing work focuses on developing optimal and energy efficient decision fusion rules or investigating the statistical properties of event observations. For example, the performance of a fault tolerant and energy efficient event detection scheme was studied in [51, 52] for a scenario where noise and sensor faults are likely to be uncorrelated while event signals are likely to be spatially correlated. It was shown that the detection error decreases exponentially with node density and neighbourhood size without considering the unpredictable nature of the environment in which WSNs operate. Several other optimal distributed detection systems were proposed based on statistically dependent observations from the sensor field using a specific signal attenuation model [27, 50] and an optimal local decision fusion rule. P. Vershney [45] and Wang *et al.* [51] studied the problem of binary hypothesis testing using binary decisions from independent and identically distributed sensors and developed an optimal fusion rule. Ould-Ahmed-Vall *et al.* [54] addressed the fault tolerance of such systems in the context of binary detection and assumed spatial correlation among sensor observations to rule out faulty data. Karumbu and Prashanti [73] focused on the timeliness of detection and studied the problem of minimising the mean detection delay imposing bound on the probability of false alarms based on a centralised fusion model. Yingshu *et al.* proposed an energy aware method for monitoring events and delivering warnings in a timely manner for hazard detection domain. On the other hand, energy has always been a key issue in WSN and almost all of these works attempted to optimise the energy usage at different levels of the detection process such as routing algorithms [9, 10], sleep scheduling [74, 75, 76], fusion process, node clustering where energy is usually traded for detection latency [43, 73], accuracy [26] or node density [25].

Considering the application of WSNs in diverse real-world problems, it is increasingly desirable for the underlying sensor network to be aware of the application requirements rather than attempting to maximise performance blindly. The design of the next generation event detection systems should be guided by the expected QoS metrics specific to the application domain. This observation is the motivation behind the idea presented in this thesis to view the detection problem objectively and to develop a QoS aware event detection technique. Studying the nature of physical events occurring in the environment, it is clear that QoS requirements depend on the application nature and type of events. For example, detecting the presence of certain animals in a habitat monitoring WSN is not as critical as detecting a fire hazard in a forest fire monitoring system or detecting radiation leakage in a nuclear reactor monitoring network. Also, the QoS requirement is not the same allover of the target sensor field. In addition to that, QoS parameters may also vary depending on the context of real world phenomena, i.e. the same event can have different sensitivity based on the context characterised by the state of the surrounding environment. Therefore, we need to design an event detection architecture with the following features:

- **QoS Aware**: The design of the underlying WSN of an event detection system should be guided by the QoS requirements of the target application. The WSN should guarantee a set of given performance metrics, namely, bounded detection probability, fault tolerance and detection delay.
- **Adaptive**: The WSN for event detection should be adaptive to the dynamic nature of the target environment such as noise, node faults and irregular event occurrence distribution and should be able to reconfigure the adjustable parameters of the sensor network as needed.
- **Priority Sensitive**: In the case of multiple simultaneous events with variable priority occurring over the target sensor field, the system should be sufficiently flexible to handle a different QoS guarantee for different types of events.
- **Context Aware**: The event detection technique needs to be context aware, that is, the method needs to be able to treat the same events differently depending on the context of the event.

The key functional metric that controls the detection performance of a WSN is the sensing coverage of the target field, which characterises the quality of monitoring. In its simplest form, coverage means that every point in a target area is monitored, i.e. covered within the range of at least one sensor. However, for robust and accurate detection of events, it is important that each point is covered by multiple sensor nodes. This idea is formally characterised as k-coverage, where every point in the network is covered by at least k (≥ 1) nodes, k being the degree of coverage. To guarantee the aforementioned features of an event detection system, the thesis adopts a k-coverage model, where the decision on the occurrence of an event is made in collaboration between the k sensors detecting the event individually. Even though redundant coverage increases the robustness of a network, it entails high deployment cost and energy consumption. These coverage problems have been extensively studied in the existing literature from an energy efficiency and lifetime point of view [30, 33, 34, 77, 78, 79]. However, the problem of QoS aware modelling of event coverage has been ignored to date. The current work is complementary to the existing work since we address the coverage issues specific to event detection rather and focus on the trade-off between the intrinsic properties of WSN coverage and event detection performance.

1.5 Research Objectives

The objective in this thesis is to model efficient event detection architecture in a WSN with guaranteed accuracy and latency bound. It also focuses on how the event detection in a WSN can be integrated to the Internet of Things and be merged with the ubiquitous platform. Outlines are as follows,

i. Determine the optimal degree of coverage in an event detecting WSN to guarantee given detection probability and latency with given fault tolerance at deployment time. A dynamic recovery technique is also developed to maintain this required degree of coverage during operational lifetime.

ii. Devise a strategy to provide dynamic k-coverage to achieve given QoS metrics with a reduced number of nodes and less energy dissipation by ensuring event coverage in an on-demand basis.

iii. Develop a technique to provision QoS of event detection depending on the priority when multiple events with variable priority occur simultaneously in the sensing field.

iv. Devise a technique that facilitates context-aware event detection by exploiting the context information made available through the integration of WSNs into the IoT environment.

1.6 Contributions

In regard to the research objectives formulated in the previous section, Fig. 1.3 illustrates the overall research contributions made in this thesis. Block 1 to Block 4 in the "Contribution Overview" window at the bottom correspond to Objective **i** to Objective **iv**, respectively and the "Underlying Networks" window at the top reveals the type of underlying network in relation to each contribution.

The primary contributions of this thesis are summarised as follows:

i. As the first step towards designing a QoS aware event detection system, the key performance metrics for detection are identified, namely detection probability, fault tolerance and detection latency. The energy-accuracy trade-off is explored from the event coverage point of view and an analytical solution is presented to determine the optimal degree of coverage (k) to satisfy given QoS parameters. To make this model realistic, the environmental noise, communication interferences and node fault probability are also considered. A lower bound on the degree of coverage in a k-coverage detection system is obtained that probabilistically guarantees the required performance metrics. This forms the foundation of a goal-directed solution where performance requirements are used as design parameters. Then this work is extended to exploit the variable range sensing technology to attain robustness considering a time-dependent node fault model. Part of this work has been published in Alam *et al.* [80] and the complete work is currently under first review at the IEEE Transactions of Mobile Computing [81].

ii. To fulfil the next objective, we developed a dynamic event coverage technique where QoS guarantee for event detection is provided on-demand in a specific region of interest after the occurrence of an event. This on-demand detection reduces the required number of nodes to a great extent and also extends the WSN lifetime compared to the complete coverage method. Two different solutions are proposed. First, the variable range sensing technique is utilised to ensure redundant coverage of an event only when necessary by adjusting the sensing range of the nodes in the close vicinity of event location. An energy aware node selection algorithm is devised for efficient event detection and prolonged network life. However, the range adjustment technology is limited to a certain set of the physical attributes of the

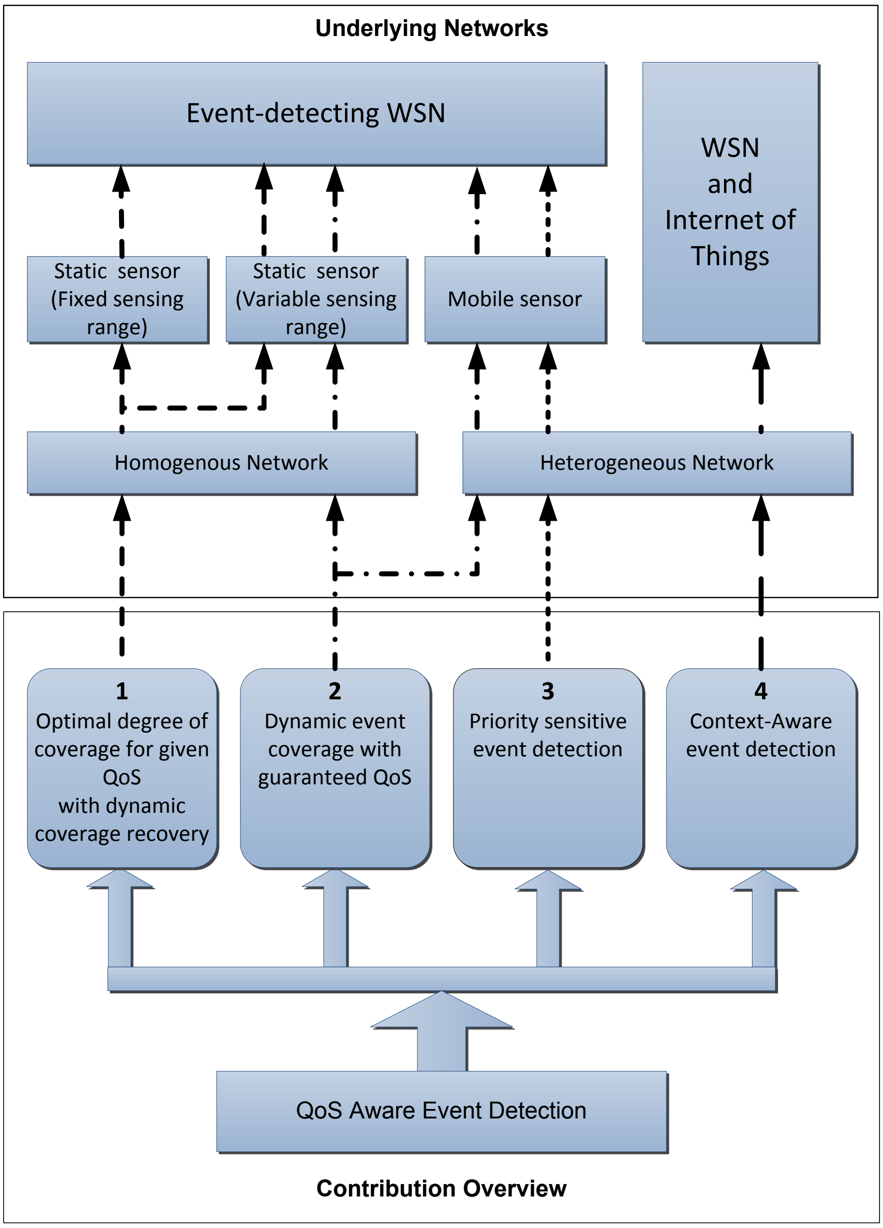


Figure 1.3: A schematic view of the overall research contribution

environment being monitored and irregular event distribution can lead to unbalanced energy consumption in some cases. To handle such a scenario, an alternative dynamic event detection technique is proposed using mobile nodes to ensure on-demand event coverage. The latter method considers the spatial distribution of the occurrence of events in a network and designs a self-organising autonomous node movement strategy to provide dynamic k-coverage in event-centric mobile WSNs. A game-theory based distributed scheme is used to minimise the energy spent due to mobility while taking advantage of the spatial locality tendency of events to enhance detection performance. Part of this work has been published in Alam *et al.* [82] and the extension of this work is currently under first review at the IEEE Transactions on Parallel and Distributed Systems [83].

iii. The third contribution is to propose an event detection system that considers differentiated priority and missed-detection cost of events occurring in the target field to enhance detection performance. A number of real-world examples of events are explored to gain an insight into the necessity of differentiated treatment in detecting multiple simultaneous events. QoS metrics such as accuracy and timeliness in the proposed event detection system are provisioned on a priority basis, which ensures overall detection performance. An analytical model is established for the proposed model. The experimental result shows superior performance of the proposed method compared to traditional flat priority event detection systems in terms of both energy and accuracy. The outcome of this work is published in Alam *et al.* [84].

iv. Finally, focus is given on the evolution of event detection from WSNs to the Internet of Things that connects the physical and virtual world together. We identify the key challenges to fit an event-centric WSN into the IoT architecture. For generic and dynamic detection of real-world phenomena, an ontology based event definition language is proposed which is suitable for the IoT environment where sensors, objects and persons are all individual entities. Unlike existing work, the proposed method is context-aware which makes it perfect for the diverse and composite nature of the events that WSNs are responsible for within the scope of the envisaged Internet of Things.

1.7 Thesis Organisation

The rest of the thesis is organised as follows:

Chapter 2 presents the background of event detection using WSN and reviews a number of existing event detection techniques in different application domains, their merits and demerits and the maturity achieved to date.

Chapter 3 proposes an analytical model for the determination of optimal degree of coverage that ensures given QoS requirements for event detection. It also introduces a variable range event sensing method to recover from any loss of coverage and to maintain fault tolerance and reliability of the detection. An extensive theoretical analysis on the proposed method and experimental results supporting the analytical derivations are presented.

Chapter 4 presents two different techniques for on-demand event coverage. The first part of this chapter outlines a QoS and energy aware algorithm for event detection using variable range sensing. The theoretical foundation of this technique, along with the deployment guideline, lifetime analysis and experimental results supporting the theory are presented. This is followed by a second method for on-demand coverage using both mobile sensor nodes for cases where static sensors are not sufficient and event distribution is unpredictable. A game theory based node movement strategy is outlined along with the experimental results.

Chapter 5 proposes a priority sensitive event detection technique that ensures event coverage according to their priority levels and cost of missed detection. It presents a greedy optimisation algorithm for mobile node selection for event coverage followed by extensive theoretical analysis of the expected event detection performance in relation to event priority.

Chapter 6 outlines the key challenges for the paradigm shift of event detection systems from stand-alone WSNs to the next generation Internet of Things. It introduces the idea of context-aware event detection using WSN, which makes detection possible in a pervasive monitoring environment accompanied by experimental results showing context-dependent events in a testbed implementation.

Finally, Chapter 7 presents some concluding remarks on the impact of the research undertaken and outlines a number of possible research directions based on the findings in this thesis.

Chapter 2

Event Detection using WSN - An Overview

The detection of real world phenomena using WSN has attracted major research efforts in recent years. It is gaining more importance as the physical world around us is getting closer to virtual world and moving towards automation. Researchers have continued investigating innovative ideas to realise practical, inexpensive, flexible and robust detection of events using wireless sensor networks. However, any promising common ground is yet to be reached to guarantee QoS aware detection. In the following, first we briefly present the background of WSN and its envisaged extension to Internet of Things in Section 2.1 and a survey of WSN applications for event detection in several domains in Section 2.2. Then we investigate the fundamental theories used in event detection research in Section 2.3, classification of the common event detection techniques in Section 2.4, comprehensive study of the factors affecting the QoS metrics in event detection systems in Section 2.5 & 2.6 and Section 2.7 presents event detection in the IoT scenario. Having described the state of the art techniques in these sections, research directions are summarised in Section 2.8.

2.1 WSN Architecture

The concept of WSNs was first proposed by the US military in 1970's [5]. Since then, many research projects, applications and theories have come forth till date. During the last decade of twentieth century, processing and communication technologies of computing devices have undergone rapid development. With the continuous development in microelctromechanical systems (MEMS), WSNs have become commonplace in our life within the last decade. Wireless sensor network typically refers to a ad-hoc network of large number of tiny devices equipped with sensing and communication capability that are deployed in a target field to monitor the surrounding environment [22, 38]. The basic elements of a WSN are described in Fig. 2.1.

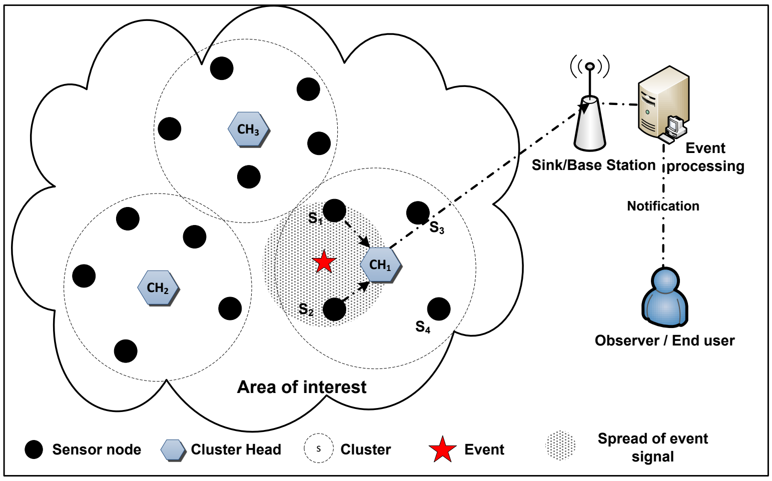


Figure 2.1: A generic cluster based WSN architecture

1. **Sensor node**: A sensor node is the lowest level entity in a WSN that collects the raw data from the surrounding environment. A sensor mainly consists of sensing, transmission, storage and power units. Nodes communicate with each other in an Ad-hoc manner. A node can act as a data collection unit as well as a router. Each node can dynamically search, locate and restore connections.

2. **Cluster head**: To minimise the energy consumption, sensors nodes in a WSN usually forms multiple clusters and only one node from each cluster communicates with the sink node. This special nodes are called cluster heads. Clustering results in a hierarchical architecture in a WSN and cluster heads are higher level entity than the basic sensors. In a heterogeneous WSN, cluster heads are usually more powerful than lower level nodes and they tend to distribute the data aggregation and network reconfiguration task of a WSN.

3. **Sink / Base station**: A sink node is a high level entity located near the sensing filed to collect the data from multiple sensor nodes, cluster heads and even directly from individual nodes. It is the sink node's responsibility to aggregate the collected data and transmit the information to end users. Any central coordination of the low level sensor nodes are supervised by the sink node. A sink is also called a gateway node or a a base station.

4. **End users/ Observers**: End users are the actual users of WSN applications who generates query and utilise the sensed information directly or indirectly. It can also be another system that collects data from other WSN(s).

In essence, a WSN is basically a multi hop self-organising network of diversified nodes communicating with each other wirelessly. However, there are certain distinctive features of WSNs compared to traditional ad-hoc networks, that make them the object of special research attention. We outline the major features below:

1. **Application-specific**: WSNs can be deployed in diversified target field to sense the attributes of physical worlds. The confluence of this close coupling to the physical world that is subject to change, the nodes forming the network will experience wide variations in connectivity and operational factors. It causes the hardware platform, software systems and communication protocols to be application specific, which is a significant shift from the traditional networks.

2. **In-network processing**: In-network processing, involving operations such as filtering, data compression and data or decision fusion, is a technique widely used in wireless sensor networks (WSN) for reducing the communication overhead [85], [86]. In-network processing improves the versatility and scalability of WSNs.

3. **Large-scale distribution**: WSNs are usually deployed in large stretch of areas intensively. In most cases, nodes are inexpensive compared to traditional TCP/IP network, which makes large-scale deployment and distribution of sensor nodes feasible. In case of large outdoor terrains, nodes can often be airdropped to form distributed sensor networks. The areas monitored are often complex and harsh, so it is usually very difficult to conduct operational maintenance. Therefore, the software and hardware of the sensor network should have high robustness and strong fault-tolerance.

4. **Dynamic topology**: Many reasons can change the topologies of WSNs dynamically. For example, there are often new nodes joining or leaving the networks; in some cases, sensor nodes might be mobile; some nodes are set to switch between work and sleep status discretionarily for power saving; some nodes may break down at any time due to various unpredictable reasons. With the dynamic changes of topological structures of the networks, WSNs should have the abilities of self-adjusting and reconstructing [5], [2].

5. **Mobility and flexibility**: Recent advancement in distributed robotics and low power embedded systems has led to the creation of mobile sensor networks [36]. Mobile nodes can capture more area than their static counterpart since the coverage capability is not limited to specific region of sensor field [87], [28]. Mobile nodes allow a network to reconfigure topology and change node density at different part of sensing field. This makes it attractive for WSNs with dynamically changing nature.

6. **Self-organising:** There are many unpredictable factors in the physical environments of networks. For example, the locations of the nodes can not be established in advance precisely; some nodes die due to energy depletion or other reason; wireless communication quality subjected to environmental impacts can not be forecasted accurately. All these require that nodes should have the ability of self-organisation. Without human intervention and any other pre-network facilities, the nodes can make their self-configuration and self-management automatically and quickly.

Such features open the frontier of endless potentialities in WSN based real world applications such as environmental monitoring [88], [89], disaster management and warning system [90], [91], [92], [21], target detection and tracking [46], [47], health care systems, emergency navigation and traffic management [93], [94], etc. Thus event detection is potentially a prominent application for emerging sensor network technologies [95]. Even though, in its early age, WSNs were primarily used in data gathering applications where efficient and reliable data delivery were the main research focus. Majority research is now being devoted to ensure accurate and reliable detection of physical events using sensor network [43, 46, 47, 48, 73, 96, 97, 98, 99, 100, 101].

Wireless sensor networks are increasingly becoming an integral part of our everyday life. No wonder it is a strong candidate to be integrated with the future Internet of Things. The future Internet, designed as an "Internet of Things (IoT)", is foreseen to be a world-wide network of interconnected objects uniquely addressable, based on standard communication protocols [14, 15, 102]. Identified by a unique address, any object including computers, sensors, RFID tags or mobile phones will be able to dynamically join the network, collaborate and cooperate efficiently to achieve different tasks.

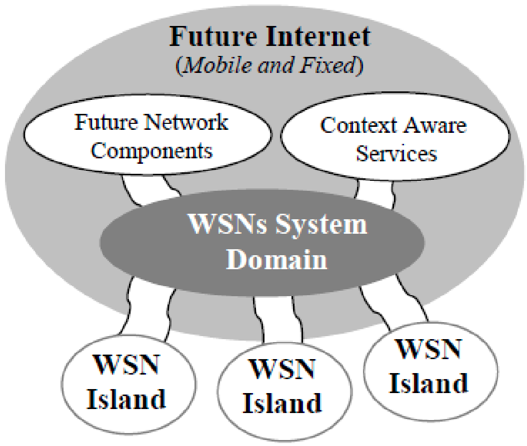


Figure 2.2: WSN integration with IoT

The future Internet and integration with WSN is illustrated in Fig. 2.2. Integrating sensor networks to this ubiquitous IoT platform opens a new horizon in the field of detection and monitoring [103, 104, 105]. Though IoT is still in its infancy, research interest is gradually moving towards it and WSN based event detection is envisaged to go through a paradigm shift in near future. Therefore, it is worth studying the trends in such field.

2.2 WSN Based Event Detection Applications

Applications of WSNs in the event detection domain can be categorised into five major categories. They are : i) Military applications, ii) Environmental monitoring and hazard detection, iii) Structural integrity and condition monitoring, iv) Home and Industry automation, and v) Emergency healthcare. We explore few representative applications from each domain in this section as outlined in Fig. 2.3.

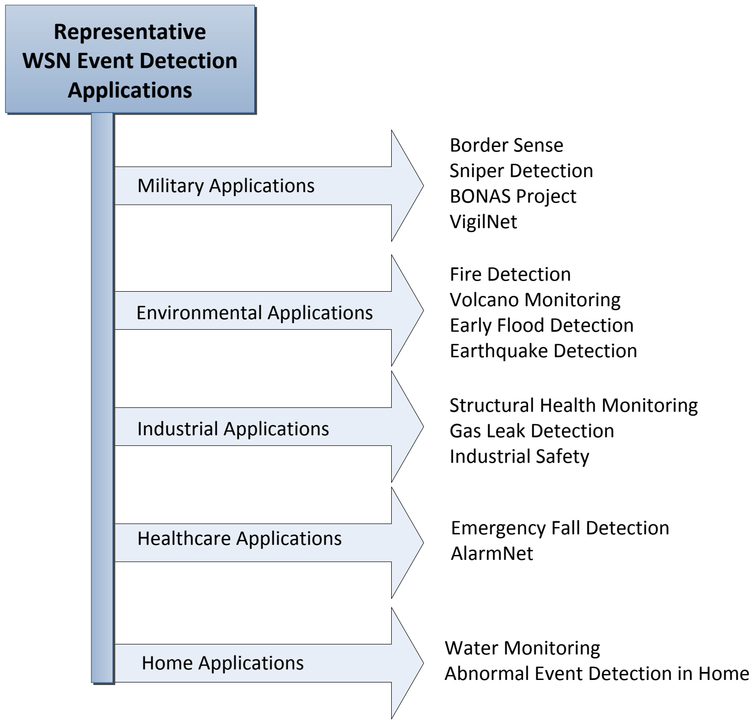


Figure 2.3: Outline of major application domains in event detection using WSN

2.2.1 Military Applications

WSNs produced revolutionary effect on military defence and battlefield surveillance since its early age. In fact, the maturity of the today's sensor technology originated from the result of military research as WSNs can be an integral part of military command, control, communication, computing, intelligence, surveillance, reconnaissance and target (C4ISRT) systems [106]. The rapid deployment, self organisation and fault tolerance characteristics make them apt for promising sensing techniques in such fields. For example, battlefields are generally hostile environment for expensive equipment as they can be exposed to enemy attacks anytime. WSNs can comprise of a large number of inexpensive and disposable nodes building a distributed architecture and maintain dense deployment offering a degree of fault tolerance. As such the destruction of a number of nodes in enemy attacks does not render the complete network non-operational. In addition to this, WSNs can be deployed randomly from an aircraft which makes it feasible to deploy specific purpose sensor network in battlefields where land access may be too risky [107, 108]. Sensor nodes can be closely positioned to the target for improved information accuracy. Information is one of the crucial keys to winning in

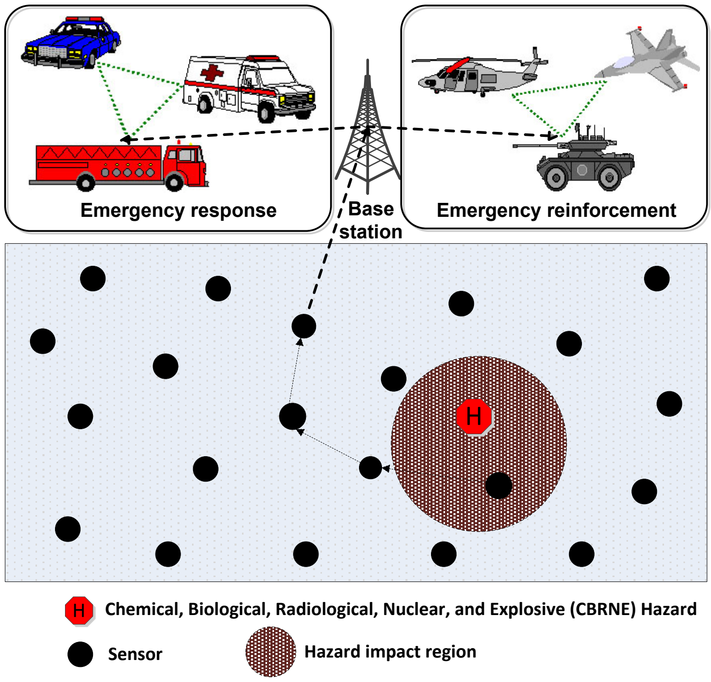


Figure 2.4: WSN application in Battlefield surveillance

modern warfare. WSNs revolutionise this field by keeping an eye on every corner of the battlefield via intelligent sensors [109]. The typical application is to scatter a number of smart nodes across the combatant area usually from unmanned air vehicles. By self organising themselves, sensor nodes collect and fused the sensed data for the purpose of gaining clear idea of the target field and anticipating attacks. A typical sensor network based surveillance system is illustrated in Fig. 2.4. It shows a WSN collecting relevant information from a battle field and the base station can initiate reinforcement or emergency response based on the collected information. WSNs are used to detect and characterise Chemical, Biological, Radiological, Nuclear, and Explosive (CBRNE) attacks and materials [110, 111, 112], battlefield surveillance and reconnaissance of opposing forces [110], target detection, intrusion detection [113], and border security [17, 107]. There representative applications are discussed below.

2.2.1.1 BorderSense

Conventional border patrol has extensively been based on fixed checkpoints and human involvement. However, the relative cost for the increasing number of personnel as well as the diminishing accuracy through human-only surveillance demand the involvement of high-tech devices in border patrol and distributed WSNs proved to be a suitable option for this. BorderSense [17] is a border patrol system framework based on hybrid wireless sensor networks, which can accurately detect and track border intrusions with minimum human involvement. It utilises multiple sensor network technologies, including the wireless multimedia sensor networks and the wireless underground sensor networks that can collaborate to provide real-time detection with high accuracy.

The underlying WSN in BorderSense consists of three types of sensor nodes: multimedia sensor nodes equipped with video cameras or night vision scopes, scalar sensor nodes that are equipped with vibration/seismic sensor, and mobile sensor nodes. It uses a three-layered hierarchical system architecture. The unattended ground sensors and the underground sensors constitute the lower layer of the architecture, which provide higher granularity for monitoring. At the second layer, multimedia sensors mounted on surveillance towers provide visual information. Finally, mobile ground robots and unmanned aerial vehicles constitute the higher layer that provides additional coverage and flexibility. Features of BorderSense are that the multimedia sensors complement the information acquired by the ground sensors and improve detection accuracy. The underground sensors increase the stealthiness of network and guarantee the proper system functionalities where aboveground visible devices are not preferred for concealment purposes. Aside from detection, mobile sensors provide intrusion tracking capability after any intrusion is detected. Cooperative intrusion detection is performed through in-network processing of the sensor data and the result is reported to a remote base station.

2.2.1.2 Sniper Detection System

Sensor networks can use the acoustic signal and small-arms fire to detect shooting event and localise the shooter in both battlefields and urban areas [114, 115, 116]. The Boomerang sniper detection system [114] can monitor a shooting incident and pinpoint the sniper location by detecting arms fire from the shooter. It has been used by the military, law-enforcement agencies, and municipalities. The countersniper system [116] uses passive acoustic sensors to detect incoming fire using sensors mounted on wearable clothes of the soldiers. The detected audio from the microphones enables the system to estimate the relative position of the shooter as well. The network consists of Mica2 nodes equipped with a sensor board with a high-power DSP to provide real-time detection, classification, and correlation of acoustic events. This system is suitable for law-enforcement agencies and municipalities to provide protection during events such as public speeches.

2.2.1.3 BONAS Project

BONAS (BOmb factory detection by Networks of Advanced Sensors) is a collaborative project financed by the European Commission [117]. The aim of this project was to design, develop and test a novel wireless sensor network to detect bomb threats. The proposed model relies on the WSN based detection of improvised explosive device (IED) in urban area [112]. The proposed system serves the security and safety needs for the citizens to counter terrorist attacks, in particular against the threat posed by IED devices. The proposed sensor network focuses on the detection of traces of precursors used in IED production (particulates, gases and/or waterborne) in the environment surrounding the vicinity of a bomb source. The sensors are specifically designed to be deployed in sensitive locations and easily camouflaged.

2.2.1.4 VigilNet

VigilNet [118, 119] is a large-scale battlefield surveillance sensor network for energy-efficient and stealthy event detection and target tracking in harsh environments. The underlying WSN implementation consists of 70 Mica2 nodes equipped with magnetic sensors that detect the magnetic field generated from vehicles and magnetic objects. The main goal of this application is to provide energy-efficient surveillance support through distributed sensor nodes. VigilNet focuses on achieving prolonged network life through a hierarchical architecture of nodes in the network. Few nodes are denoted as sentries that coordinate the event detection by lower level nodes termed as non-sentry node. Sentry nodes remain in low power state until any event occurs in the sensor field. Once an event occurs, the network is reorganised into clusters and collaborative detection takes place. VigilNet sets an example of application of WSN based event detection and tracking system that minimise the exposure of military personnel to hazardous materials and enemy attack.

2.2.2 Environmental Applications

The cost effective large-scale deployment and autonomous coordination capabilities of WSNs have produced a wide variety environmental monitoring and disaster management applications. In fact, sensor network studies over the last decade indicate the most extensive use of WSN in this domain. The reactive nature of WSN systems made event detection the most attractive functionality these days, especially in environmental hazard detection. There are basically two different types of environmental applications. Some environmental applications are non-critical but deployed over any specific terrain or forest to collect information for long period of time and detect changes in the monitored condition. These applications include habitat monitoring [120, 121], bird species detection [122], small animals or insects detection, biodiversity and ecosystem monitoring [88, 123], detecting changes in environmental condition that affect crops and irrigation [89], chemical spill on soil or air pollution monitoring [19, 124], condition monitoring in marine, soil and atmospheric contexts [125], greenhouse monitoring system [126, 127], flood monitoring [92, 128]. However, the use of WSNs in critical environmental hazard detection and disaster warning system attracted more attention in recent years as it promises safety of human lives and properties. Typical applications in such fields include forest fire detection [20, 21, 57, 129], volcano monitoring [130, 131, 132], seismic event detection and earthquake warning system [90, 91, 133, 134], lightning detection [135, 136], tsunami alarm [137], flood detection, hazardous material detection in mines [138], radiation detection [139, 140], chemical and biological hazard detection in urban areas [124, 141, 142] or any other meteorological hazard characterised by some ambient physical attributes of the corresponding environments [143]. Recent research focuses on these mission critical applications of WSNs considering their impacts on human life. We discuss a few environmental event detection WSNs below.

2.2.2.1 Fire Detection

Wireless sensor networks constitute a powerful technology to monitor large-scale environment and has been proved effective in detecting fire hazards in forest, underground mines and city areas. Forest fire is a fatal threat in many countries in the world. Table

Fire season	Location	Area burnt (hectares)
1993-94	Sydney/Blue Mountains/North coast NSW	800,000+
1995	Southeast Qld	333,000
1997-98	Hunter/Blue Mountains/Shoalhaven, NSW	500,000+
1997-98	Caledonia River, Gippsland, Vic.	32,000
2001-02	Greater Sydney, NSW	744,000
2002	Stanthorpe/Toowoomba, Qld	40,000
2002-03	Eastern Highlands, Vic.	1.1 million
2002-03	Brindabella Ranges/Canberra, ACT/NSW	157,000+
2002-03	NSW east coast including greater Sydney	1.46 million
2002-03	Arthur-Pieman, Tas.	100,000
2005	Eyre Peninsula, SA	145,000
2006-07	Eastern Highlands, Vic.	1.05 million

Table 2.1: Major forest fires in Australia from 1993 to 2007

2.1 gives an overview of wildfire occurrences and the atrocity caused in different regions of Australia since 1993 [144]. Despite all the preventive measures that sometimes include satellite imaging, the risk is still high and the main reason behind such loss is the lack of sufficiently early warning of the hazard. Over the last decade more than 100,000 forest fire incidents have been reported all over the world and significant research effort is directed to mitigate the risk of such fire [20]. Cutting edge technologies such as satellite imaging are being employed in large-scale fire detection. However, satellite monitoring can take up to 1-2 days to capture a complete image of any big forest and this large scan period is not acceptable in many cases. The smallest fire size that can be detected using satellite is 0.1 hectare, which makes the early detection almost impossible. Studies show that, in order to prevent any permanent damage in wild fire, the fire control centre needs to be notified at most 6 minutes after the fire starts [41]. Human based monitoring by the forest rangers is also subject to significant delay. WSNs came as a promising alternative for detection of forest fire and have been successfully implemented in several countries. WSN deployed in a forest can locally detect occurrence of fire by monitoring temperature, humidity, barometric pressure and smoke in the atmosphere, and send alarm to the control centre in a remote location and necessary measures can be taken.

Extensive research works have been performed in fire detection using WSN during the last decade [20, 21, 57, 129, 145, 146, 147, 148]. Some of them focused on protocol level optimisation for fire detection systems such as routing or MAC protocol suitable for emergency event reporting in case of fire. Some focused on application level framework development considering single or multiple ambient attributes characterising such fire. Hafeeda and Bagheri [148] developed a WSN for forest fire detection that improves the accuracy of detection by considering fire weather index (FWI) which is a fire danger rating system used in the USA. The detection system adopts a centralised architecture where sensors collect weather data and send to the control centre and the final decision is taken at that control centre. Garcia and Serna [146] designed a simulation environment that can create model for a fire by analysing collected data from sensor and considering any additional geographic information available. The fire hazard reports and spread of fire are sent to the hand-held devices of the fire fighters. Aslan *et al.* [20] developed a framework that facilitates the use of sensor networks for fire detection and forecast, and also provides accurate localisation of the fire hazard. Most recently, advanced sensing such as camera based sensors or active infrared (IR) sensors are being used in fire detection [129, 145]. Jorge *et al.* [129] proposed a vision-enabled wireless sensor network for reliable and early on-site detection of forest fires. They devised a robust vision algorithm for smoke detection and implemented power-efficient smart imager designed for such algorithm. Their implemented testbed yielded high degree of reliability in terms of both successful detection and low false-alarm rate. The significant role of event-centric WSN in fire detection systems is evident from the research trends witnessed in recent years.

2.2.2.2 Volcano Monitoring

WSNs greatly assist the geo-spatial event detection through their realistic deployment in extreme environments that are generally inaccessible or risky for humans. In volcano monitoring, a sensor network is deployed near active volcanoes and continuously monitor for events such as eruptions, earthquake, or tremor activity [130, 131, 132] . In 2004-2005, two test beds for such monitoring were implemented in two volcanoes in Ecuador as a proof of concept [131]. In 2004, a small wireless sensor network on Volcan Tungurahua was deployed. Nodes were equipped with microphone and continuous data were collected for three days. Later a larger and more capable network of 16 nodes equipped with seismoacoustic sensors was deployed over 3km area on Volcan Reventador in Northern Ecuador. Over three weeks of continuo monitoring, the network was able to capture 230 volcanic events. Werner-Allen [131] studied the nature of the corresponding data stream and documented the high data rate and high fidelity requirement for such network. The underlying event detection system uses a short term and long term average threshold detector. Because of high bandwidth requirement, each node collects and samples data locally and only sends a report to sink when an event is detected. When the sink receives a number of reports in a certain time window, it starts data collection from the entire network. The main goal of this application is to detect the small earthquakes that occur near the active volcanoes. Since these events usually last for less than 60 seconds, a high sampling rate (100Hz) is employed which limits the locally stored information and energy consumption is high. This made the trade-off between reliable detection and false alarm very critical.

In July 2009, Huang *et al.* designed and deployed a sensor network on Mount St. Helens for long term volcano hazard monitoring as a part of Optimised Autonomous Space In-situ Sensorweb (OASIS) [132]. OASIS station is a sensor unit capable of multimodal sensing equipped with seismic, infrasonic, lightning sensors and GPS unit for localisation. The seismometer detects earthquakes, infrasonic sensors detect volcanic explosions, and lightning sensors detect eruption clouds. Combining all three data streams, the observatory centre takes further decision. They developed a auto-recovery feature which is very crucial as nodes are deployed in rugged terrain and only reachable by helicopter. The study suggested that fault tolerance and robustness are the most important features for normal operation of such event-centric WSNs. The successful design and deployment of this volcano monitoring system greatly promoted the confident use of WSN for real-time monitoring and hazard detection in harsh environment.

2.2.2.3 Early Flood Detection

Flood is an annual threat in many countries, especially in low lying regions, and early warning can mitigate the loss caused by flood to a great extent. In this regard, WSNs are now being used for early flood detection in many developing countries [92, 128, 149]. The main drawback in the existing systems is the dependency on human personnel for continuous monitoring of river beds. Instead, model-based prediction systems can be used by exploiting the statistical properties of data collected by a network of sensor nodes. Such a system has been developed at MIT and tested in Honduras, where frequent floods significantly affect urban life [149]. Flood monitoring requires a large-scale sensor network as large area needs to be monitored for effective early detection. Basha *et al.* [149] designed a two-tier network architecture. Three different type sensors are used in the lower level for measuring rainfall, air temperature, and water flow data. Each closely deployed sensor forms a group and is connected to the second-tier computation nodes. Data collection and information processing are performed at the computation nodes, which inform the control centres, in case of a potential flood. Since flood events usually do not occur frequently, long term energy efficient monitoring is a critical requirement. Several other research efforts are directed to timely detection of floods recently [92, 95].

2.2.2.4 Earthquake Detection

Earthquake is another geo-physical event that can be monitored using the sensor technology. Studies show that the major earthquakes are often preceded by a series of small seismic events and capturing them correctly makes it possible to provide early warning of earthquakes [143]. Recent advancement in sensor networks attracted significant research interest in WSN based earthquake disaster protection systems [90, 91, 133, 134, 150, 151]. Wang *et al.* [133] presented a a dynamic real-time wireless earthquake disaster monitoring system which has great significance to the earthquake hazard prediction.

2.2.3 Industrial Applications

Event-driven WSNs are now becoming commonplace in industrial fields for monitoring the performance and operational faults, and to detect safety issues in large industrial plants [56, 152, 153], building automation [154, 155], structural integrity monitoring [156, 157, 158, 159], sensitive plant monitoring (e.g. nuclear reactor) [160]. Typical monitored parameters include temperature, vibration, pressure, fluid flow, humidity, valve positions, gas leak, radio activity. Major motivational factors for using WSNs instead of their wired counterparts are the flexibility and self-organisation capability resulted from the elimination of extensive cabling. In this way, the monitoring performance can be improved anytime by adding additional sensors in suitable positions without having to worry about cabling. In addition to this, sensors can be placed in the moving parts of machineries and otherwise inaccessible areas for remote monitoring, where wired sensors and maintenance may not be viable solution. Unlike many non-critical monitoring such as habitat monitoring or bird species detection mentioned earlier, the detection of faults or anomaly in industry is very sensitive from both cost of damage and personnel safety point of view. Consequently, high reliability of detection is the fundamental requirement of industrial applications. It is possible to achieve high reliability in WSNs even in adverse condition by employing redundant sensors and self healing algorithm as well as fault resilient decision making algorithm. We discuss few commercial applications in the following.

2.2.3.1 Structural Health Monitoring (SHM)

Distributed WSNs can track the spatio-temporal patterns of vibrations induced throughout the structure and intra-structure vacuum. This enables the detection of cracks and potential damages almost in real time. Existing structural health monitoring techniques rely on periodic inspection or expensive wired data acquisition technique, which are not viable for large structures such as skyscrapers or bridges. D. Roach [156] explored the potentials of comparative vacuum monitoring (CVM) sensors to monitor structural health and prevent unexpected flaw growth by detecting any crack in real-time. Becker *et al.* [161] designed an aircraft structural health monitoring system to track fatigue, detect damage or stress of structural parts using a network of autonomous sensors. The proposed system is self-powered employing power harvesting capabilities such as thermoelectric power, vibration generator and solar cells. This ensures detection of any flaws during operation and facilitates sufficient maintenance free operation. BriMon [162] is a railway bridge monitoring sensor network system that monitors the structural health of a railway bridge by sensing vibrations and reporting damages as soon as they occur in the bridge structure. Chebrolu *et al.* [162] designed this system which triggers an event in response to an oncoming train and starts collecting vibration data. Collected data are then transferred to a central location whereupon decision on the current health is made and necessary measures are taken.

2.2.3.2 Gas Leak Detection

High pressure gas distribution channels are commonly used in many industrial processes such as chemical, electricity and cement industry, and any leaks in the pipeline may cause economic losses and environmental pollution. WSNs are gradually replacing the traditional systems for instant detection and localisation of such leaks of hazardous material [56, 153]. Chengjun *et al.* [56] developed a gas leak detection and localisation system based on WSN. There are two application modes in the proposed system : fixed-point monitoring and dynamic deployment. In fixed point monitoring mode, sensor nodes are deployed on some fixed locations near the potential risk areas such as pipe joints, reaction points and places that are subject to erosion. In dynamic deployment, some wireless nodes are thrown through ejection and all the information of the distribution of temperature and gas density is collected. Using the location-aware sensor nodes, this system provides nearly accurate location of the leaks, which facilitates quick recovery.

2.2.3.3 Industrial Safety

Many event driven WSNs are being used in hazardous industrial environment such as coal mines [138], oil refinery [163], nuclear power plants [164] etc. The sensors attached with workers' clothes identify the persons and environmental hazard, and monitors their security situation by collaborating with other fixed nodes in the factory [165]. This detects any hazard toxic gas emission or lack of oxygen at the early stage and warns the workers and lead them to safety.

2.2.4 Emergency Health Applications

Wireless sensor technologies provide a ubiquitous and cost effective way to continuously and autonomously monitor a person's physiological conditions as well as activities of daily living. Recent developments in implanted biomedical devices and smart integrated sensors make the use of WSNs for medical applications possible. This enables WSNs based applications to detect emergency health condition and inform corresponding medical centre instantly. While these systems may not replace every aspect of the conventional wellness monitoring approach, they provide a supplementary service for data collection and greatly improve the emergency response through instant detection of any anomaly in patients' bodily functions and activities. Some of the emergency health applications include accident management in assisted living [166, 167], fall detection in elderly care [168], dangerous activity recognition [169], continuous health monitoring and alarm system [170, 171, 172].

2.2.4.1 Emergency Fall Detection

Dokas *et al.* in [168] designed and developed a patient status monitoring system that monitors the human activity and detects any threats on personal health such as elderly falls or patient collapses. The system uses motion sensors attached to patient's body together with microphone array and vision-enabled sensors installed in the environment to capture audio, video and motion data. The audio directionality analysis in conjunction with the motion information from body sensors and subject's visual location information are used to detect emergence fall incidents. The post fall visual and motion information is also processed to determine the severity of fall. The system utilises the context awareness concept for severity analysis in case of fall events, which makes it suitable for complex real world living environment. The severity analysis is performed via a rule based ontological representation of patient's context awareness. Such systems can replace the existing human based monitoring in elderly facilities and provides a solution for the less invasive patient monitoring, which is getting more and more desirable considering the privacy concern.

2.2.4.2 AlarmNet

AlarmNet is a context-aware residential monitoring network for pervasive healthcare in assisted living communities with residents or patients regarding diverse needs [166]. It accommodates heterogeneous devices in a common architecture as shown in Fig. 2.5 that spans wearable body networks, emplaced wireless sensors, user interfaces, and back-end processing elements. Body network in AlarmNet is a network of wireless sensor devices worn by residents that enables activity classification or physiological sensing, such as an ECG, pulse oximeter, or accelerometers. A middleware gateway system disseminates data from the body network and mediates interaction with the surrounding WSN. Emplaced sensors are deployed in living spaces to sense ambient properties of the environmental such as temperature, dust, and light, or resident activities. Motion and tripwire sensors, in particular, provide a spatial context for activities and enable location tracking. The central gateway serves as a communication backbone and application-level gateway between the WSN and backend system. The flexible user interface allow doctors, nurses, residents, family, and others to query sensor data, subject to enforced privacy policies. One of the striking features is that, this real time patient tracking system makes it possible to generate emergency situation alert to PDA or hand-held devices carried by the doctors and attendants.

2.2.5 Home Applications

WSNs are a part of our everyday life with the advancement in sensor technology and continuing standardisation efforts that bring heterogeneous devices under a common platform. A multitude of sensors and actuators can be embedded in our everyday appliances like vacuum cleaners, microwave ovens, stoves, dvd layers, water and electricity monitoring system of our home. This paves the way to pervasive sensing environment where WSNs can monitor our everyday life and determine real world phenomena that needs to be taken care of automatically for smart home system [104, 173, 174, 175].

2.2.5.1 Water Monitoring

The Nonintrusive Autonomous Water Monitoring System (NAWMS) [175] is a recent addition to home applications of WSNs. The main goal of NAWMS is to detection and localise the wastage in water usage and inform tenants almost in real-time. Using

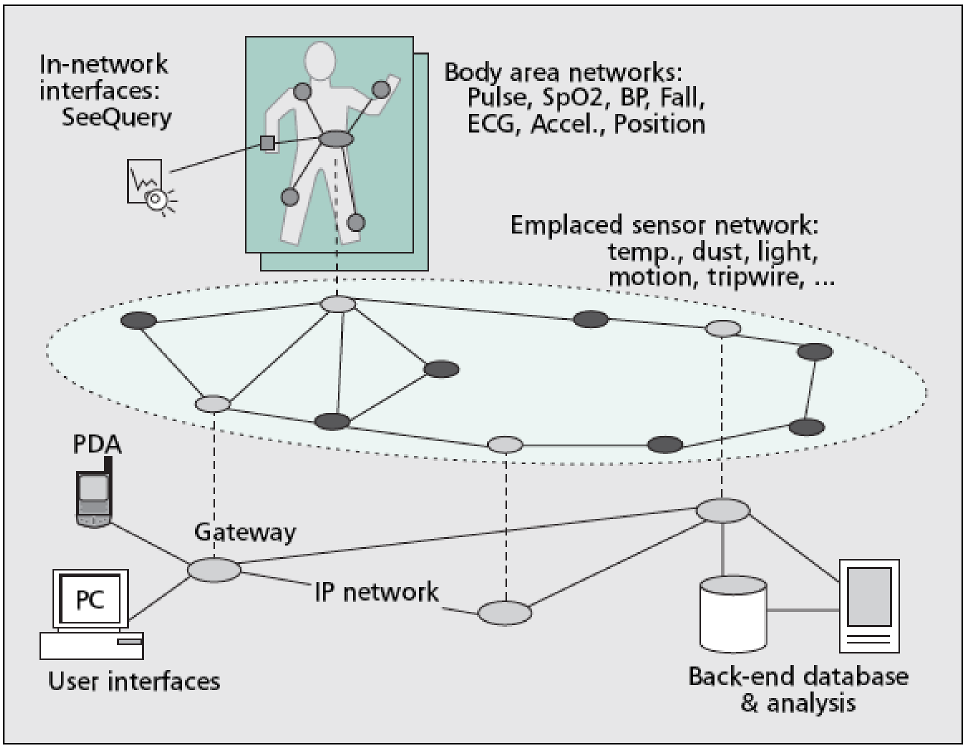


Figure 2.5: Heterogenous WSN architecture for AlarmNET [166]

a distributed WSN of sensor nodes attached to the water pipes, the water usage and any potential leak in house plumbing system can be tracked at a low cost. NAWMS estimates the water flow in a particular pipe by measuring the vibrations of that pipe because of the proportional relationship between the two. Accordingly, wireless sensor nodes are attached to the water pipes to measure the vibrations through accelerometers. Because of the nonlinear relationship between vibration and water flow, however, each sensor node needs to be calibrated to determine the optimal set of parameters that relate acceleration information to water flow. Instead of manual calibration that can be performed by individually installing water flow sensors at each pipe, in NAWMS this calibration is performed automatically with the help of the main water meter. The system provides real-time water usage information at different location in the house which can be connected to the Internet in future and generate alarms to users via mobile phones.

2.2.5.2 Abnormal Event Detection in Home WSN

Lee *et al.* [174] proposed a sensor network based anomaly detection mechanism for rapidly identifying abnormal home events such as high temperature or unnoticed flow of water or irregular airflow. To capture the real world phenomena occurring in our everyday life, it requires careful consideration of the context of the event characterised by the state of the surrounding environment. The study in [174] shows that home sensor networks usually consist of diverse types of sensor nodes, and correlating these nodes is quite important for understanding the context of events. The proposed system analyzes sensor network data for a set of related sensor data rather than for individual one and generates a correlation graph based on long term dependency analysis. Features corresponding to the events of interest such as high temperature in a room or unsupervised water flow are extracted to construct the long-term dependency relationship among correlation graphs for identifying abnormal events in home network. Sensor nodes inside a home can interact with each other and also with the external network via the Internet which enables such home event detection to act as a part of next generation Internet of Things. Such research effort makes event-centric sensor network an integral part of the IoT.

The potential application fields for WSN are expanding aggressively everyday and we could only cover a few representative ones here due to time and space constraints. Some more real world examples are listed in Table 2.2.

2.3 Event Detection Preliminaries

Event detection using WSN has received growing research interest over the recent years due to its extensive real world applications in numerous domains as described earlier this chapter. Typically event in WSN corresponds to a real world phenomena occurring in the environment being monitored by the sensor network. The nature of such phenomena has been extensively studied in the existing literature. Related research generally characterises event as an exceptional change in the monitored attribute or any specific distribution of the sensed data over space or time [27, 50, 63, 67, 100, 178]. In the following, we describe some of the fundamental concepts related to event detection using WSN in the light of existing literature.

2.3.1 Signal Model

Physical phenomena usually emit or radiate energy signals and sensors perform detection by measuring the energy of the signals emitted by the target event. Such energy is subject to attenuation with distance from the event location. Suppose a sensor s_i is at a distance d_i from the event location and the energy emitted by the target event is u_0. Considering a signal decay function $g(.)$, the measured signal power at sensor s_i is given by,

$$u_i = u_0.g(d_i) \tag{2.1}$$

Typically signal power decays isotropically as a function of distance. The most commonly used power decay model in literature [50, 63, 179] is,

$$g(x) = \begin{cases} 1 & \text{, if } 0 < x \leq d_0 \\ \frac{d_0^{\gamma_u}}{x^{\gamma_u}} & \text{, if } x \geq d_0. \end{cases} \tag{2.2}$$

Zhu *et al.* [63] described a three dimensional unobstructed region monitored by a set of sensors detecting the signal emitted from a target within the monitoring area. They used a power attenuation model given by,

$$u_i = \frac{u_0}{\sqrt{1 + cd_i^{\gamma_u}}} \tag{2.3}$$

Application	**Type**	**Sensed Attributes**	**Goal**
BorderSense [17]	Border Security	Audio, Video, Vibration	Detection and tracking of border intrusions
Forest Fire Detection [20]	Hazard Detection	Temperature, Humidity and Smoke	Detect & Predict forest fire, provide early warning
Volcano Monitoring [132]	Environmental Monitoring	Seismic Wave	Detection of seismic events
Earthquake Warning [90]	Disaster Management	Seismic Wave, GPS location	Early warning of earthquake
Fire Alarm in Coal Mines [57]	Underground Mine Monitoring	Temperature, Carbon Monoxide and Oxygen concentration	Early detection of fire hazard in coal mines
Smart Building Monitoring [156]	Structural Health Monitoring	Vibration and Vacuum	Real time crack detection
Radioactive Source Detection [176]	Nuclear Radiation Monitoring	Gamma emission	Detection and localization of radioactive sources
Emergency Fall Incident Detection	Assisted Living Facility [168]	Motion, Sound and Visual perceptual components	Fall detection of patients in assisted living facility
Gas leak detection [56]	Environmental Monitoring	Sulfur dioxide, Sulfurated hydrogen, Carbon monoxide and oxygen sensor	Detection and localisation of gas leak
Great Duck Island [177]	Habitat Monitoring	Video	Bio diversity monitoring
Greenhouse Monitoring [126]	Agricultural Automation	Temperature, Air & Soil Humidity	Monitoring environment inside greenhouse
Big awareness [109]	Military	Ambient Temperature, Light, Vibration, Acoustic waves, Image	Situational awareness and actuation

Table 2.2: WSN Event Detection Applications

where, c is a system constant and γ_u is a signal attenuation exponent typically ranging from 2 to 3. The attenuation model in (2.2) is quite general and can be used in most of the event detection systems. For example, for a spherical acoustic wave radiated by a simple source, the signal decays at a rate inversely proportional to the square of the distance [179]. Most physical events can be characterised by the sensed signal following such power decay model either employing some threshold value for detection or any specific spatio-temporal pattern observed in the signal values.

2.3.2 Sensing model

In WSN based event detection system, the probability of detection by an individual sensor depends on the signal strength of the event, environment around it and the hardware of the node. These factors are characterised by the sensing model of a node. Sensing models used in the existing literature can be broadly categorised into two different types: i) Deterministic model and ii) Probabilistic model. We briefly discuss these sensing models below.

2.3.2.1 Deterministic model

In majority event detection literature [30, 34, 180, 181, 182], the sensing range is assumed to be a uniform disk of radius r. The disk model assumes that the occurrence of an event within a distance r of a node will be detected deterministically. r is referred to as the sensing range. On the other hand, an event occurring at a distance $r + \epsilon$ can not be detected at all. Such model is also called the boolean sensing disk model as it supports only two states in a detection process, i.e. an event will either be detected or completely missed out based on the distance, there is no possibility of partial detection as shown in Fig. 2.6(a).

Such model is simplistic and does not consider the dependency on external factors such as environmental condition (obstacles, buildings, foilage) and the strength of the emitted signal on sensing capability. The disk sensing model is widely accepted as it supports geometric treatment of the detection problem and simplifies the design of coverage protocols for WSN. It also makes the analytical and asymptotic modelling feasible. The key shortcoming of disk sensing model is that it doesn't capture the stochastic nature of sensing. Tan *et al.* [50] demonstrated the limitation of the disk model in real time detection problem by studying the sensing performance of an acoustic sensor where real time performance of boolean sensing proved to be worse than probabilistic model. Nonetheless, deterministic sensing still plays major role in the literature as it ensures optimal solutions in many coverage problems for event detection.

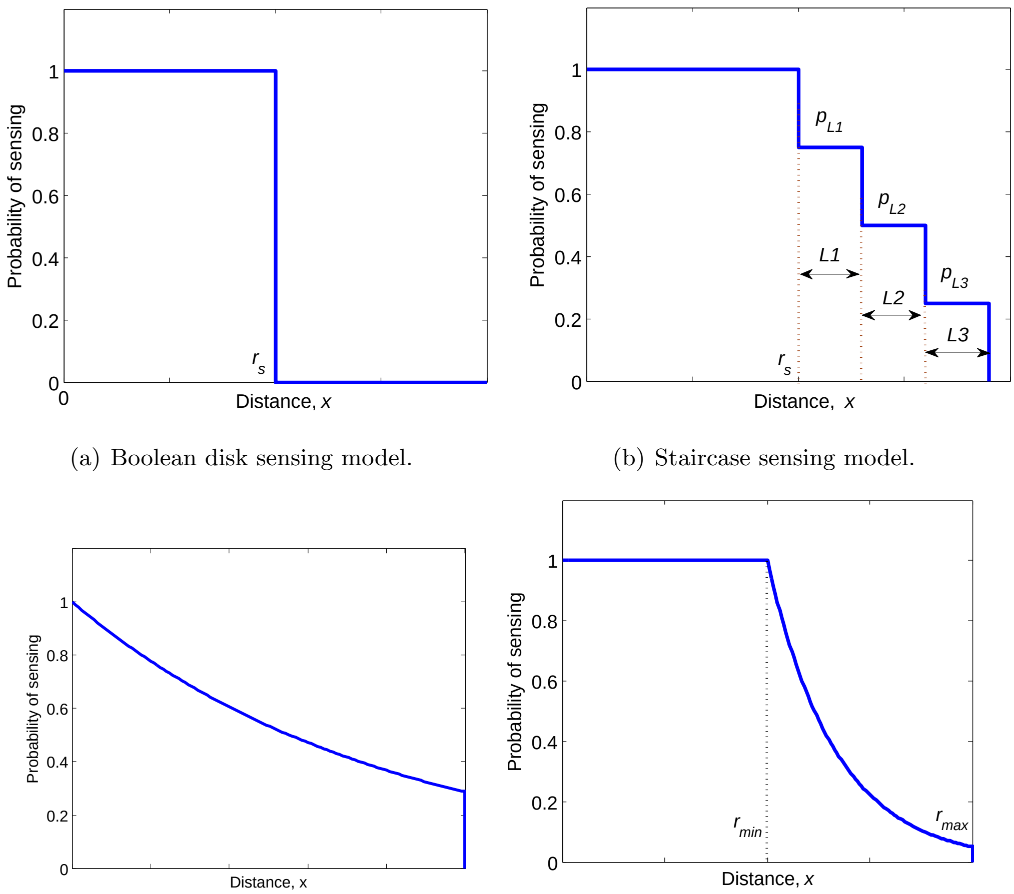
2.3.2.2 Probabilistic model

Probabilistic sensing model assumes that the physical signal denoting an event does not drop abruptly from high strength to zero beyond the sensing range r. For example, Cao *et al.* in [183] analysed the experimental study of passive infrared (PIR) sensors and showed that the sensing range is better modelled by a continuous probability distribution, which is a normal distribution for PIR sensors. Several other works such as [31, 32, 77, 184, 185] investigated the probabilistic nature of sensing to provide a more realistic sensing model. We present here three variations of probabilistic sensing models established in the existing literature.

- **Staircase model**: The authors in [77] proposed a staircase model for probabilistic sensing. According to this, sensing range can be modelled as layers of concentric circles with increasing diameters and each layer has a fixed probability of sensing as shown in Fig. 2.6(b). The probabilities decrease in steps with every layer. Although the authors claimed that their coverage evaluation protocol can be extended to a dynamic event coverage protocol, no specific details of such protocol exists yet. Use of this model is limited in WSN as such layered model representing real world phenomena is not available *a priori* in most cases.

- **Shadow fading model**: This model considered the dependency of sensing probability on external factors that cause irregular and nonuniform sensing patterns at different sensor nodes and in different directions. Such behaviour is similar to the shadowing effect in radio wave propagation. Tsai in [186] examined the impact of the shadowing effects, as well as that of the asymmetric property in the sensing capability and presented an analytical model for shadow fading sensing. Assuming a lognormal shadowing path loss model, the probability of detection (P_{det}) for an event at distance x from sensor node is given by,

$$P_{det} = Q\left(\frac{10\gamma_l log_{10}(x/r)}{\sigma}\right), \tag{2.4}$$



(a) Boolean disk sensing model.

(b) Staircase sensing model.

(c) Shadow fading sensing model.

(d) Exponential model.

Figure 2.6: Different sensing models in the literature

where,

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{\infty} e^{-y^2/2} dy, \tag{2.5}$$

γ_l is the path loss exponent $(2 \leq \gamma_l \leq 4)$,

r is the ideal sensing radius without fading,

and σ_f is the fading parameter.

While shadow-fading model captures the environmental factors in some real world deployments, it is hard to capture the exact model parameters in diverse WSN deployment scenario. This is not suitable for generic design of event detection system and makes analytical models intractable.

- **Exponential model**: Exponential models dominate the probabilistic sensing literature because of the advantages it brings to the analytical modelling of event detection [31, 32, 77, 179]. According to exponential sensing model, the sensing probability degrades exponentially beyond a certain threshold distance as shown in Fig. 2.6(d) . In this model, the probability that a sensor detects an event at a distance x is given by,

$$p(x) = \begin{cases} 1 & \text{, if } x \leq r_{min} \\ e^{-\gamma_1 (x - r_{min})^{\gamma_2}} & \text{, if } r_{min} < x < r_{max} \\ 0 & \text{, if } x \geq r_{max}. \end{cases} \tag{2.6}$$

  where, r_{min} is the starting point of uncertainty in sensing, and γ_1 and γ_2 are sensing device specific parameters that are adjusted according to the physical properties of sensor. r_{max} is the maximum sensing range of the node. This model is more general as this can be applied to most sensing scenario adjusting the tuneable parameters properly. It also capture the stochastic properties of the device hardware.

In addition to these, few other recent research efforts [187] in the sensing model attempted to capture the sensing irregularities present in physical event detection cases considering further granular properties of sensing environment. The authors in [187] investigated the sensing irregularities and its impact on real world applications and introduced *Physical Sensing Area Modelling (P-SAM)*, which provides accurate physical sensing area for individual nodes. P-SAM uses training events in a controlled manner to identify accurate nonparametric sensing patterns (areas), which are close to the on-the-ground truth. This can be applicable when diverse event related data are available and detailed architecture (obstacles, inaccurate hardware calibration) of WSN is known at the design phase. However, such modes are unsuitable for analytical design. In this thesis, we used Boolean model and exponential model whichever was appropriate in the context.

2.3.3 Spatio-temporal correlation

Efficient design and development of event detection systems largely depend on exploiting the correlation among sensor observations. Due to the high density in the network topology compared to traditional ad-hoc networks, sensor observations are likely to be correlated in the space domain. For example, a fire event in a forest will generally affect multiple sensor nodes as nodes are typically few meters or tens of meters apart. In addition to this, physical phenomena constitute temporal correlation between consecutive observations by a node. Usually the monitored attributes such as temperature or humidity do not abruptly change to a high value in one moment and drops to normal value in the next instant, rather they observe gradual change over time. There has been significant research effort to study such correlation in WSN data [16, 188, 189, 190, 191]. The extensive study [16] by Vuran *et al.* on spatio-temporal correlation among sensor observations in a WSN summarises the characteristics of such correlation as follows:

- **Spatial correlation**: Typical WSN applications require spatially dense sensor deployment in order to achieve satisfactory coverage. As a result, multiple sensors record information about a single event in the sensor field. Due to high node density in the network topology, spatially proximal sensor observations are highly correlated with the degree of correlation increasing with decreasing internode separation.

- **Temporal correlation**: Some of the WSN applications such as event tracking may require sensor nodes to periodically perform observation and transmission of the sensed event features. The nature of the energy-radiating physical phenomenon constitutes the temporal correlation between each consecutive observation of a sensor node. The degree of correlation between consecutive sensor measurements may vary according to the temporal variation characteristics of the phenomenon.

The existence of such correlation in space and time among sensor observations enables the design and development of efficient event detection and communication protocols for sensor network. Dereszynski *et al.* [191] exploited the spatio-temporal correlation to detect and correct faulty observations in an environmental monitoring sensor network. Their proposed model is adaptive to specific WSN deployment through Bayesian learning [47, 192] that captures spatial relationships among sensor data, and it extends the structure to a dynamic Bayesian network to incorporate temporal correlations as well. Performance evaluation of their method on the dataset from SensorScope [88] project shows the ability to flag faulty observations and predict the correct values of the missing or corrupt readings. Jindal *et al.* [190] investigated the impact of correlation in designing monitoring algorithms and attempted to obtain a simple and accurate model of spatially correlated sensor network data. They proposed Markov model that captures correlation in sensor data irrespective of the node density, the number of source nodes, or the topology. Vuran et al. [189] exploited such correlation to design a collaborative medium access control for WSN. Apart form these communication protocols many collaborative event detection techniques take advantage of the spatial correlation to increase the reliability/fidelity of detection via data fusion [52, 54, 174]. However, the spatial correlation among the locations of the events and the temporal correlation among consecutive occurrences are not well explored yet. We exploited such correlation in our dynamic event coverage technique in Chapter 4.

2.3.4 Noise in sensed data

Sensor measurements of any signal are subject to an additive random noise from the surrounding environment or sensor hardware flaws. Under such assumptions, for an original signal value u_i, the measurement at sensor i denoted as $\hat{u}_i$ is given by,

$$\hat{u}_i = u_i + \varepsilon_i,$$

where ε_i is the energy of noise at sensor i. Such noise is usually modelled by a Gaussian distribution of mean μ_ε and variance $\sigma_w \varepsilon^2$, i.e., $n_i \sim \mathcal{N}(\mu_w \varepsilon, \sigma_\varepsilon^2)$ in the literature [27, 50, 193].

2.3.5 Fault model

A generalised fault model was presented in [192] which is used in most event detection techniques because of its generic nature. Without loss of generality, a particularly large value can be considered as event, while the normal reading is typically a low value. Let the event decision at the sensor node, s_i be modelled by a binary variable b_i. Each sensor decides between two hypothesis, event (H_1) or normal situation (H_0). $b = 0$ if sensor measurement indicates normal reading and $b_i = 1$ if the sensor measurement indicates an event. Now there are two different cases where an error is observed,

1. *False positive:* a sensor can report a normal reading as event with probability, $P(b_i = 1|H_0)$

2. *False negative:* a sensor may fail to report an event when it occurs with probability, $P(b_i = 0|H_1)$.

Assuming symmetric and uncorrelated sensor fault probability, the fault probability, p_f is given by,

$$p = P(b_i = 0|H_1) = p(b_i = 1|H_0)$$

Let u_n be the mean normal reading and u_e be the mean event reading for a sensor. The authors [192] showed that, if the errors due to sensor faults and the fluctuations in the environment can be modelled by Gaussian distributions with mean 0 and standard deviation σ_e, and the threshold is taken to be $0.5(u_n + u_e)$, the fault probability p_f would indeed be symmetric. This fault probability can be evaluated using the tail probability of a Gaussian, the Q-function, as follows [192]:

$$p_f = Q\left(\frac{0.5(u_n + u_e) - u_n}{\sigma}\right) = Q\left(\frac{u_e - u_n}{2\sigma}\right) \tag{2.7}$$

As the Q-function is a monotonically decreasing function, it is evident from (2.7) that the fault probability is higher when the mean normal and event readings are not sufficiently distinguishable, or when the standard deviation of the sensor measurement errors is low. While this model lays the foundation for fault probability modelling, sensors faults are often correlated and asymmetric. More on this will be discussed on Section 2.5.2.

2.3.6 Accuracy analysis

Accuracy of an event detection system is measured by both the detection probability and false alarm rate. Receiver operating characteristics (ROC) curves are useful for organising such classifiers and visualising their performance. ROC graphs are commonly used in decision making and classification tasks especially in machine learning and data mining research [194]. ROC graphs are two-dimensional graphs in which successful detection probability (also called hit rate) is plotted on the Y-axis and false alarm (false positive) rate is plotted on the X-axis. Conceptually, an ROC graph depicts relative tradeoffs between benefits (true positives) and costs (false positives). A basic ROC curve is shown in Fig. 2.7. The area under the curve indicates the accuracy of the system.

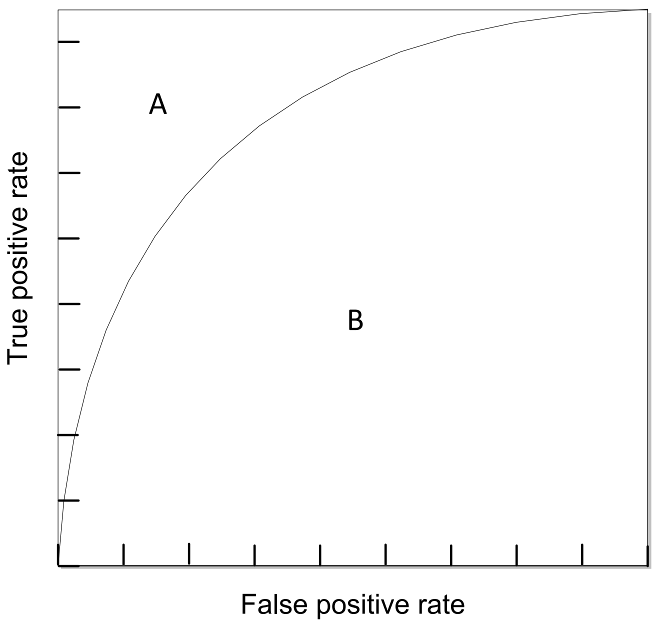


Figure 2.7: A basic ROC curve

Event detection using WSN is a decision making process in essence that distinguishes event situations from normal sensor readings. This is why it is increasingly used in the study of event detection to illustrate the detection performance. We also used ROC curves for performance evaluation in this thesis.

2.4 Overview of Event Detection Techniques

Theoretically, event detection using WSN is a descendant of the classical decision making problem in the large-scale sensor network. Based on the decision system architecture and how much information is sent to the base station, event detection systems can be broadly categorised into two classes: i) Centralised detection, and ii) Distributed detection. The decision making process for each of these techniques can be further categorised into two categories namely, threshold based and non-threshold based option. In WSN, event signals are usually correlated as explained earlier, which makes the collaboration among neighbouring sensors necessary to successfully detect and localise any physical event being monitored. Based on such collaboration, threshold based events are again divided into two subclasses which are value fusion and decision fusion. A high level classification of the existing event detection techniques is presented in Fig. 2.8.

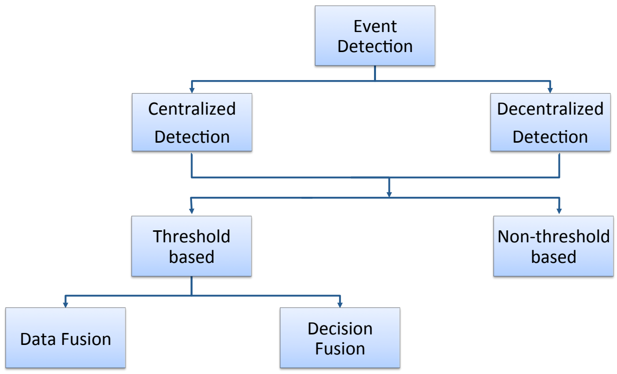


Figure 2.8: Classification of event detection techniques.

2.4.1 Centralised detection

In a centralised detection system, each censor node transmits its observation directly to a central base station without any loss of information. It is the responsibility of the control centre to aggregate the data and decide whether an event of interest has occurred or not. The main idea is to put the processing burden on the sink node which is generally equipped with higher processing power. Fig. 2.10 shows a generic centralised detection framework.

Typically Bayesian decision fusion and Neyman-Pearson detection are used to make a detection decision at the sink node or base station [45]. Since the energy consumption for sensing and data processing is generally less than that for data transmissions, one of the major challenges in the centralised detection scheme is to reduce the average number of data transmissions for preserving the available energy in resources constrained WSN. In addition to the energy, sensor networks are usually deployed in outdoor environment and the communication channel to the control centre is subject to non-uniform noise over the sensor field. The observation data from different sensors may arrive at the central receiver at different instants of time, each being subject to different time delay. In order to properly aggregate the streams of data arriving from different sensors, these streams need to be synchronised [13]. Stringent requirements

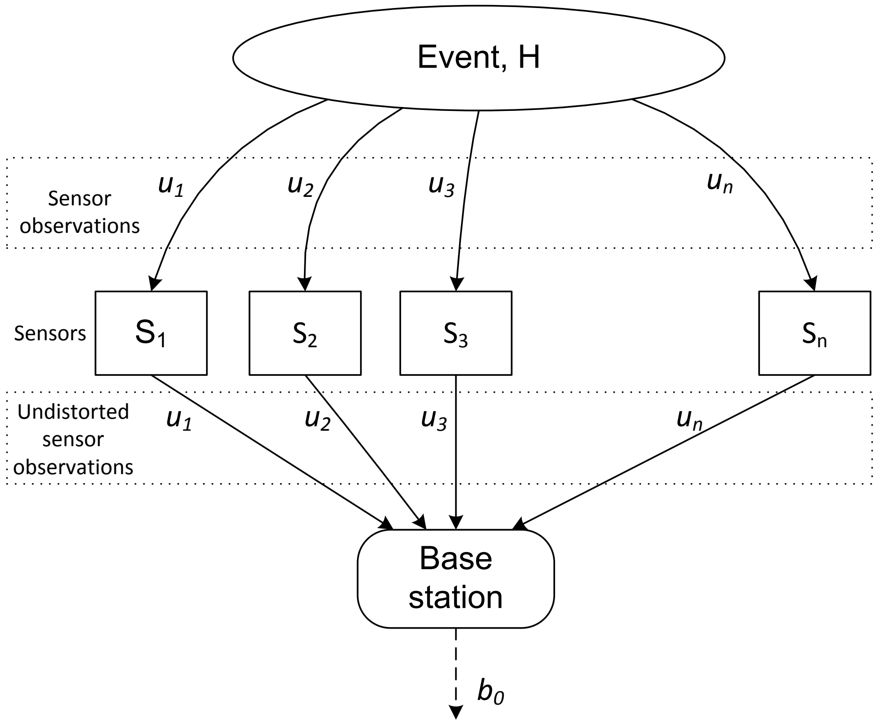


Figure 2.9: Centralised detection framework.

such as high volume data transmission, increased energy consumption, and synchronisation make centralised detection architecture practically unattractive. However, in certain applications the lossless transmission of sensor observation to the base station may be a strict requirement for successful detection such as wireless camera sensor network [195] or sensitive surveillance system consisting of smart sensors [196]. In addition to this, the performance of centralised detection serves as a performance benchmark for decentralised detection strategy.

2.4.2 Decentralised detection

Large scale sensor networks are increasingly being deployed in real world applications [27, 110, 197, 198, 199, 200] and the transmission of large amount of data to base station is becoming more costly. This also incurs significant delay in event detection. Since sensor nodes are constrained by low power and low bandwidth communication, the centralised detection schemes that require each node to transmit their measurements directly to a central fusion centre are not suitable for WSN, especially for large network.

Naturally, the decentralised detection has paved its way over the centralised scheme in event-centric WSNs in recent years. In decentralised detection architecture, each sensor node decides on the occurrence of an event based on its own sensed data and only the detection decision is sent to the local or central fusion centre. Often the neighbouring sensors collaborate to make local decision on the occurrence of an event and only the final detection decision is sent to the fusion centre. A generic decentralised detection model is presented in Fig. 2.10.

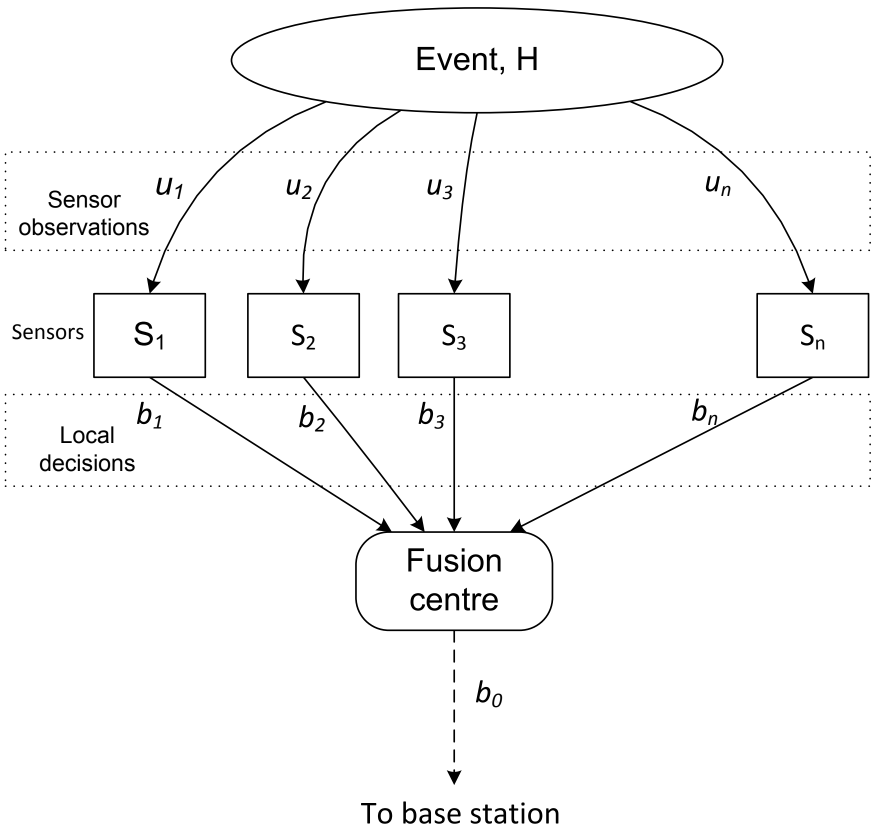


Figure 2.10: Decentralised detection framework.

Evidently, in decentralised detection systems, nodes only send partial information to the fusion centre. As a result, the overall detection performance under such architecture is suboptimal compared to a centralised system in which the fusion centre receives the observations from all sensors without any loss [201]. The availability of undistorted data in fusion centre makes value fusion the most commonly used technique in centralised detection while decision fusion dominates the decentralised detection domain. This trade-off between value fusion and decision fusion was explored elaborately by Costa and Sayeed in [201] which showed the sub-optimality of decision fusion.

Nevertheless, such as energy constraint, transmission bandwidth limitation and complexity make decentralised detection with fusion the most popular technique in the event detection research [25, 46, 47, 64, 98, 198, 202]. The key challenges in decentralised detection have been investigated by a number of researchers over the years [27, 45, 47, 201]. The crux of a standard decentralised detection is to determine what type of information each sensor should send to the fusion centre. It has been shown that once the structure of the data being sent by each node is fixed, the fusion centre faces a standard problem of statistical inference. So a likelihood-ratio test on the received data will minimise the probability of error at the fusion centre for a binary hypothesis testing problem, and a minimum mean square error for an estimation problem. In our work we considered the decentralised detection and distributed architecture of sensor network for its advantage and tried to determine the optimum setting for event detection satisfying the requirements set by applications. Designing efficient decision rules for event detection in sensor network has been another major research issue.

2.4.3 Threshold Based Detection

An event occurrence is reported when any monitored attribute exceeds a predetermined threshold value for that. The detection condition persists as long as the parameter value is above the threshold set point. The threshold values may be determined based upon historical parameter values, analogy to similar sensors and systems, engineering estimates, or parametric analysis. A generic threshold based detection rule is presented in [59]. It assumes that every sensor node in the network employs same threshold value η_d and the signal strength ε_i for a sensor i can be given by (2.3) according to the distance from the event location. The portability of detection, p_{d_i} and probability of false alarm p_{f_i} is then derived as [59],

$$p_{d_i} = \int_{\eta_d}^{\infty} \frac{1}{\sqrt{2\pi}} e^{\frac{-(x-\varepsilon_i)^2}{2}} dx,$$

and

$$p_{f_i} = \int_{\eta_d}^{\infty} \frac{1}{\sqrt{2\pi}} e^{\frac{-x^2}{2}} dx = Q(\eta_d),$$

where $Q(.)$ is the complementary distribution function of standard Gaussian as defined in (2.5).

Different threshold based methods are studied in the literature [47, 51, 54, 59, 60, 61, 183, 203]. Chamberland *et al.* in [47] showed that if the structure of the information supplied by each sensor is predetermined, the fusion centre faces a classical hypothesis testing problem in event detection scenario. The probability of estimation error is then minimised by the maximum *a posteriori* detector. This work considers the scenario where the sensor network is constrained by the capacity of the wireless channel over which the sensors are transmitting, and they studied the structure of an optimal sensor configuration. In [183], Cao *et al.* proposed two novel algorithms based on statistical hypothesis test (SHT). They considered the spatial and temporal correlation among the sensor observation. They applied hypothesis test about temporal correlation on sensor measurement series to locally disambiguate the event from faults accurately and efficiently.

Among other works on statistical methods, Niu *et al.* in [179] derived the exact analytical expression for the distributed detection performance, and proposed some approximations via Binomial distributions and Demoivre-Laplace approximation, which require much less computation load and yet yield fairly accurate results. Furthermore, they investigated the detection performance for a more realistic scenario where the total number of sensors is random and the wireless channels between sensors and the fusion centre are noisy. Their work is largely motivated by [204] which shows that in case of binary hypothesis testing in decentralised detection, likelihood-ratio tests at the sensor nodes are optimal when the observations are conditionally independent given each hypothesis. However, if the observations are stochastic in nature or if the sensors are subject to external noise, these assumptions may not be valid.

Most of the existing event detection methods rely on a static threshold for all the nodes. The static threshold method exhibits a memory less property from one observation to the next, assuming that the current observation and detection condition are independent of all prior observations. However, in practice, observed values are dependent upon prior observed values, and one would not reasonably expect the observed values to radically change in the short period of time between successive observations. Ray *et al.* in [60] proposed a dynamic local sensor threshold scheme. The intuition behind their approach is that, as the nodes may be at different distances from the event and the external factors may not be the same for every node, different sensors have unequal signal-to-noise (SNR) ratios. This indicates that improved performance may be achieved by using non-identical thresholds for different sensors. They proposed a false discovery rate (FDR) based local sensor threshold selection method to dynamically update the threshold for better performance. A similar approach was proposed by Chen *et al.* in [61] where the authors exploited event dynamics to devise *Hidden Markov Model (HMM)* based approach for adaptive threshold value. While adjusting threshold brings certain enhancement to detection performance according to their experiments, it is not always feasible to capture the realistic model of diverse sensing environments, and local storage in sensor nodes limit the amount of history that can be maintained. This limits the use of adaptive thresholds in event detection literature and static threshold makes the analytical modelling of generic detection algorithm easier.

2.4.3.1 Data fusion

The distributed detection using data fusion or value fusion systems was studied in [45, 193, 205]. In data fusion method, each node sends its own measurement of event signal to the fusion centre without any loss of information. The fusion centre combines the raw values obtained from collaborating sensors and compares the average value to a threshold for final decision. Due to limited transmission capacity of sensor nodes, value fusion is not suitable for WSN.

2.4.3.2 Decision Fusion

Existing literature uses a two layer detection system: i) a local decision rule at individual sensor node, and ii) a final decision fusion rule at the fusion centre where collaborative detection is accomplished [45]. The occurrence of event is usually modelled as a binary hypothesis testing problem with two hypothesis "event" and "no-event". Each sensor node within the sensing range of an event makes a binary decision independently based on its own observation and sends binary decision to a local fusion centre. On receiving the decisions from all the neighbouring sensors, the local fusion centre employs a decision rule to make the final decision. Let H_i, $i = 0, 1$ indicate whether an event occurs or not, and n sensor nodes $s_1, s_2, \cdots, s_n$ in the neighbourhood participate in the local decision fusion. Let the binary variable b_j, $j = 1$ to n denotes the local decision of a sensor.

$$b_j = \begin{cases} 1, \text{ if } H_1 \\ 0, \text{ if } H_0 \end{cases}$$

The fusion centre takes the final decision, $\hat{H}$ by applying appropriate fusion rule on the n binary values of b_j. The design of the final decision fusion rule under such assumption depends on the choice of the threshold value at the decision centre.

Decision fusion is a well investigated area in the distributed detection domain [45]. Several decision fusion techniques from this domain have been employed in event detection systems in the existing literature, such as Bayesian fusion [27, 45, 63], Neyman-Pearson fusion [45, 206], AND-fusion [47], OR-Fusion [63], Majority voting [64, 178] and *'k out of n'* rule [52].

- **'k out of n' rule**: According to this rule, the fusion centre detects an event ($\hat{H} = H_1$) if the number of "1"s received from n participating sensors is greater than or equal to k. Letting $\hat{b} = 1$ if the fusion centre decides H_1 (event) and $\hat{b} = 0$ if the fusion centre decides H_0, it gives,

  $$u_j = \begin{cases} 1, \, b_1 + b_2 + \cdots + b_n \geq k \\ 0, \, b_1 + b_2 + \cdots + b_n < k \end{cases}$$

  where k is an integer between 1 to n. In this thesis, we employed 'k out of n' rule for decision fusion since it is the most general case of count based rules. Setting $k = n$ turns it into the AND rule, setting $k = 1$ makes it the OR rule and setting $k = n/2 + 1$ gives the majority voting rule.

2.4.4 Non-threshold Based Detection

Threshold based techniques described above are only applicable for detecting events that can be characterised by a cutoff threshold on some attribute of the monitored environment. However, complex events that are characterised by a particular type of sensor data distribution over space and time can hardly be captured by a simple cutoff method. It is necessary to consider the exact state of the environment and the context of the collected data to identify such events. For example, a gas leak hazard in underground coal mine [56], chemical or bio-nuclear hazard [124, 139] or complex context-sensitive event in home environment [174, 207] can not be accurately captured by filtering simple sensed attributes using some thresholds. To detect such complex events, non-threshold based techniques has received significant attention in the event detection research [35, 46, 48, 65, 100, 173, 174, 195, 207]. In such approach, complex events are usually described through a certain spatio-temporal data pattern and capturing the pattern from the variety sensor data using appropriate application specific and context-aware technique.

Xue *et al.* [100] recently proposed a generic model for detecting non-threshold based events in a distributed WSN. They identified the two main issues in complex event detection as:

1. *Event modelling*: How to represent an event based on the sensor network deployment and a set of user inputs? The event model must be expressive in specification in order to capture the subtle semantics of different events in the physical world.

2. *Data matching*: How to detect an event by developing algorithms to match the event model with the real-time data collected from the sensor network? The matching algorithms must be resilient against data faults in sensors [39, 40] and rely on the light-weight computation to ensure the timeliness of detection.

Due to the stringent resource constraint in sensor network, it is also challenging to design energy-efficient data delivery method to the base station. 3D monitoring field also raises non-trivial issues in abstracting the environment in case of non-threshold based events. Li *et al.* [65] explored these issues in a non-threshold based event detection for 3D environmental monitoring. They proposed a multi path routing architecture to provide robust data delivery to generate a representative environmental data map and evaluated the effectiveness of the proposed approach using datasets from a real coal-mine environment. Few non-threshold based detection schemes in the literature are presented below.

2.4.4.1 Pattern based detection

In this method complex non-threshold based events are considered as patterns and lightweight pattern recognition techniques are used to detect event. These patterns can be predefined by domain experts provided that history data on target event are available. In case of unspecified events that may dynamically evolve throughout the network lifetime, on-line learning of pattern was proposed [208, 209]. Diverse types of pattern based event detection schemes in distributed sensor network have been proposed by a number of researchers over the last few years [46, 101, 208, 210, 211]. Contour map matching proposed in [210] is an event detection technique with predefined event patterns. Contour map for a physical attribute is a topographic map that displays the distribution of the attribute value over the network. The proposed method abstracts the event in the target WSN into spatio-temporal data pattern and matching is done through contour map matching. A similar approach for complex event detection using predefined event pattern is proposed in [65] which extends the detection into 3D environment.

However, sufficient history data or perfect knowledge on the contour map of event related data may not always be available *a priori* for the above schemes to work. Zhang *et al.* [209] proposed a pattern based detection for unspecified events in WSNs. The basic idea behind their approach is to distinguish the infrequent events from frequently occurring patterns, as the rare patterns are more likely to represent an event from information theoretic point of view. The proposed method first learns the frequently occurring patterns from the initial measurement, which is called the learning phase. After the learning phase, it creates new patterns from incoming sensor data and decides whether it is a frequent or infrequent pattern. Infrequent patterns are reported as events. Similar learning based technique is discussed in [208] which converts real valued sensor data into symbolic representation to handle non-linear and complex data patterns efficiently. However, given the diversity of the application scenarios and user requirements, no single pattern based technique is sufficient. This problem becomes more challenging in the emerging IoT domains where sensors in a network need to exchange information with a variety of heterogeneous devices.

2.4.4.2 Probabilistic detection

Probabilistic event detection methods consist of those methods in which the probability distribution of event related data for different parameters are either known or can be inferred or learned. For example, Ihler *et al.* in [212], developed a probabilistic framework for unsupervised event detection and learning based upon a time-varying Poisson process model that can also account for anomalous events. Their experimental results indicate that the proposed time-varying Poisson model provides a robust and accurate framework to adaptively separate unusual event from normal activity. This model also performs significantly better than a non-probabilistic, threshold-based event detection technique.

Sauvageon *et al.* [213] investigated the Distributed Gaussian Method (DGM) for detecting surface temperature changes. In this technique, Gaussian curves are generated such that they are centred on each node. Then, these curves are normalised and summed in order to reduce the geometric effect of node placement. The maximum predicted temperature value is then easily located in order to detect the temperature peak. Abadi *et al.* presented a probabilistic detection approach in [200]. This work considered the spatial correlation in event measurement and proposed Bayesian decision fusion to detect an event in collaboration among the neighbouring sensors. Geyik *et al.* [214] employed a probabilistic context free grammar to recognise events from raw sensor measurements. The proposed algorithm uses an evaluation metric based on Bayesian formula for maximising grammar a posteriori probability given the training data. The hypothetical system was evaluated using simulation on a real-world scenario for monitoring a parking lot. Although there are several works on probabilistic event detection, none of them assumes any distribution of the event occurrences in the sensor field. We believe if the event distribution in the corresponding application domain can be taken into consideration, the detection can be made far more efficient and accuracy can be increased.

2.4.4.3 Fuzzy systems in detection

Few researchers attempted to exploit the advantages of fuzzy logic over crisp logic based systems for improved event detection in WSNs [215, 216, 217]. Krasimira *et al.* [216] indentified a number of properties of fuzzy logic that make it suitable for event detection in WSN: i) it can tolerate unreliable and imprecise sensor readings, ii) it is much closer to the natural way of thinking. For example, rather than defining a fire event by a threshold (e.g. $temperature > 80^oC$), we can think of fire as an event described by high temperature; and iii) compared to other probability theory based methods, fuzzy logic is much intuitive. In [216], Marin *et al.* developed a fuzzy logic engine for rule-based detection in sensor network. The mote fuzzy validation and fusion (Mote-FVF) algorithm was developed for wireless sensors network. This algorithm can distinguish between sensor failures and abnormal environmental behaviours by using network redundancy to compensate for sensor reliability. Fuzzy logic based methods for sensor validation and fusion are unique in that they do not require or rely upon a mathematical model of the system. Despite sparse research efforts fuzzy logic is yet to pave its way in the field of distributed event detection in WSN because the rule base for fuzzy logic grows exponentially to the number of attributes that might require significant amount of local storage in sensors.

Despite different practical limitations, non-threshold based detection is envisaged to be of paramount importance in the pervasive environment and environmental intelligence in the emerging IoT paradigm. Capturing the true context of the collected data is becoming the key issue event-centric WSNs that act as a building block of IoT. Both threshold based and non-threshold based event detection systems have their respective strengths and weakness. It needs careful consideration of the application requirements and the environmental factors to adopt the appropriate method. In our research, we primarily focused on threshold based events as they dominate the event detection domain. However, considering the foreseeable application of event detection in heterogeneous sensor network and pervasive environment, we also designed a non-threshold based detection technique that incorporates context of event in a complex real world environment. Event detection in pervasive environment employs non-threshold based techniques [105, 208, 209, 214]. However, majority of the existing literature do not consider the context of physical environment. Table 2.3 summarises a number of non-threshold based techniques and their strengths and weaknesses.

2.5 QoS Consideration in Detection

Performance parameters of event detection systems are the detection probability, false alarm rate, fault tolerance, detection delay and energy consumption. Majority of the event detection research are devoted to designing energy efficient mechanisms to yield high accuracy and low detection delay. There is an inherent trade-off between detection performance and energy consumption. In addition to that, in many critical applications achieving low detection delay often requires compromising false alarm probability. In the following, we present the research efforts attempted to handle such trade-offs in event detection using WSNs.

Detection Scheme	Strengths/Features	Weakness/Limitations	Context-Awareness
Predefined event patten based [65, 210]	No training required, Capture complex spatio-temporal event pattern	Event patterns should be specified in advance. Can not be adjusted once deployed.	No
On-line learned event pattern [208, 209]	Traning process is on-line and accomplished during operation. Prior domain knowledge is not important and adaptive.	Only applicable for finding infrequent event patterns.	No
Regression model based detection [100]	Capture the complex event data distribution and improves performance with time.	Selecting suitable regression parameters require extensive domain knowledge. Accuracy of detection is largely affected in case of wrong selection.	No
Fuzzy systems [215, 216]	Tolerant against imprecise sensor reading. Easy to describe events intutitively.	Not suitable for in-network processing. Increased delay in detection.	No
Grammatical inference using PCFGs [214]	High level event definition is possible. Light-weight processing.	Events should be predefined, can not be adapted or modified easily.	No
Automata based [105]	Easy to develop, handles dynamic environment	Number of states grows exponentially with the complexity of the environment	Partially
Rule based sensor network	Suitable for high level event definition	Rules are static, does not adapt to changes in dynamic environment	Partially

Table 2.3: Comparison among some non-threshold based event detection techniques

2.5.1 Detection probability

Accurate detection of an event is the ultimate goal of any detection system. Hence, most of the event detection approach in the literature attempts to maximise the detection probability. However, false alarm rate of a system tends to increase along with the detection probability. This requires careful consideration in designing event detection techniques. It has been described in Section 2.3.5 that false alarm becomes higher as the difference between event readings and normal readings decreases. Under such circumstances, it is challenging to maintain high detection probability keeping the false alarm minimal. Furthermore, there is an intrinsic trade-off between energy consumption and detection accuracy in WSNs because continuous high quality monitoring and transmitting undistorted data in detection requires higher energy. Energy-aware accurate detection has been the primary focus in event detection in WSN [26, 27, 37, 48, 100, 179, 213, 214, 218, 219].

It is established in the literature that to improve detection performance, a certain degree of redundancy is introduced in the sensor field through dense deployment so that more than one node is guaranteed to capture an event. The final detection decision is taken via collaborative decision fusion or value fusion [26, 51, 52, 54, 193]. The general expression for detection probability in multi sensor value fusion in presence of noise is derived in [193, 205] as,

$$P_D = 1 - \chi\left(n\eta_v - \sum_{i=1}^{n} U(x_i).T\right), \tag{2.8}$$

where, $\chi(.)$ is the cumulative distribution function of a Chi-square distribution modelling the combined noise value. Here, n is the number of nodes sensing the event, x_i is the distance of node s_i from the target and η_v is the threshold for multi-sensor value fusion model.

An analytical expression for detection probability in a 'k out of n' based detection scheme is derived in [193] as follows. For n sensors detecting an event the collaborative detection probability using 'k out of n' rule is given by,

$$P_D = \sum_{i=k}^{n} \sum_{\varsigma \in \Omega_{i,n}} \left[\Pi_j = 1^i p_{\varsigma(j)} \Pi_{j=i+1}^{n} \left(1 - p_{\varsigma(j)}\right)\right], \tag{2.9}$$

where $\Omega_{i,n}$ is the set of combinations of i nodes from n detecting sensors, ς is any specific combination and the set $\{\varsigma(j), 1 \leq j \leq i\}$ are the indices of the sensors. This model is the basis for performance analysis in fault free collaboration among sensors. Later works [26, 51, 52] augment such analysis considering the application specific properties of the system such as noise, random deployment and known fault probability. Niu *et al.* [179] derived an exact system level probability for lossy communication channel and random deployment scenario. For N sensors deployed randomly in a $L \times L$ square region of interest, the probability mass function of exactly k sensors detecting an event correctly is derived as [179] ,

$$P(n = k|H_1) = \frac{1}{L^2} \binom{N}{k} \int_{-\frac{L}{2}}^{\frac{L}{2}} \int_{-\frac{L}{2}}^{\frac{L}{2}} (p_d(x, y))^k (1 - p_d(x, y))^{N-k} \, dxdy,$$

where, H_1 denotes the hypothesis indicating an event occurring at (x, y) and $p_d(x, y)$ is the probability of individual detection. The threshold selection for event characterisation is also very important as the difference between normal reading and threshold value affects the sensitivity of the detection system. A rigid threshold selection may reduce the detection probability while keeping the false alarm rate very low. On the other hand, setting the threshold for guaranteed detection in a noisy environment makes the system subject to increased possibility of false alarm [193]. Diverse environment and sensing characteristics require careful analysis to guarantee desired detection probability.

2.5.2 Fault tolerance

In most WSN-based applications, sensor nodes are expected to be low cost but error prone and deployed in inaccessible terrain, hence the probability of node malfunction is significantly higher in WSNs compared to the traditional networks such as TCP/IP and cellular networks. Owing to random deployment, sensor nodes are significantly more prone to damage. In addition, placing sensor nodes in a harsh or inaccessible area makes the replacement costly and infeasible in some cases. This intrinsic unreliability of sensor nodes make fault tolerance the most challenging QoS metric. Significant research works have been conducted to achieve fault tolerant event detection in harsh and adverse WSN environment [37, 40, 51, 52, 53, 54, 72, 192, 197, 200, 219, 220, 221, 222]. These works mostly attempt to model the distribution of faults in sensor readings and design preventive measures to deal with them.

As mentioned above, spatio-temporal correlation is a unique characteristic of sensor observations in a WSN [16]. This has been one of the keys to designing distributed fault-tolerant mechanisms for event detection. One of the early works on fault tolerance in event detection using the assumption of spatial correlation is presented in [192]. It presents a generalised fault recognition and correction algorithm in a binary detection system under the assumptions presented in Section 2.3.5. The method exploits the spatial correlation among sensor readings to correct the decision of individual sensors. Each sensor collects information about its neighbours' observations to verify its own reading. For a sensor s_i with neighbourhood size, N_e (excluding) among which n nodes reports the same observation, the probability of its own observation being correct is given by,

$$P_{in} = \frac{(1-p)n}{(1-p)n + N_e(N_e - n)}$$

While this algorithm commends itself a robust fault detection and correction method, it assumes that all nodes in the network have the same detection error probability and this rate is known prior to deployment, which renders it unrealistic in many cases. Ould-Ahmed-Vall *et al.* [54] used the collaboration among neighbouring nodes to increase the reliability of the detection decisions without depending on the fault distribution to be known *a priori*. This work is based on the assumptions that sensor observations are correlated spatially but the sensor faults are not. Although this work is an improvement over previous models, the idea that the failure at node is independent from failure of any of its neighbours is highly unlikely, especially in case of physical damage, environmental noise or energy depletion. Wang *et al.* [51] proposed a collaborative sensor fault detection method where the local fusion centre is responsible to identify the faulty sensors and discard their observations from the final decision fusion. The proposed method uses Kullback-Leiblar distance (KL) to characterise the deviation of faulty readings from normal values and devise a likelihood estimation to isolate faulty nodes in real time during operation. The possibility of spatial correlation among sensor faults is not considered and no analytical model is suggested to determine the required neighbourhood size to minimise fault.

While these fault tolerant methods are suitable for threshold based binary detection, they fail to capture the events where decision fusion is not sufficient. Banaerjee *et al.* [53] presented a fault tolerant detection scheme for non-threshold based events which takes into consideration both the spatial and temporal correlation among the nodes in close proximity to disambiguate faults and events. Due to spatial-correlation, neighbouring sensors sense similar data values. In addition to that, in most cases a sensor's own reported reading will not be significantly different from the reading it reported in the previous instant due to the property of temporal correlation. Therefore, identification of sudden, irregular readings deviating from its readings at the previous instants or highly different from its neighbours' readings beyond a pre-specified threshold helps to detect faulty sensors. Such deviations may occur due to several reasons. For example, a sensor may have hardware failure. These are permanent faults that could cause a node to die because of the communication hardware failure [39, 40]. Permanent failures can also occur due to being accidentally damaged or by turning malicious. A sensor can also give wrong, transient reading due to a temporary impact of environment. Since the sensor undergoing permanent failure needs to be replaced or repaired, this work reports the location of the faulty sensor. The work devised a tree based aggregation approach that uses spatio-temporal characteristics of sensors in detecting multiple simultaneously occurring events after identifying faulty sensors in the network and quick conveying of this information to the base station.

Hong *et al.* in [223] proposed a fault tolerant event region detection based on distributed weight system for sensor node. They also used the spatial correlation between the neighbouring nodes but their algorithm assigns weight with sensor node that controls its degree of participation in the fusion technique. The fault-event disambiguation depends on the suitable weight assignment to neighbouring sensors. It is evident from the above discussion that robustness against sensor faults can be achieved by introducing significant redundancy in the network; however, the existing literature lacks in analytical modelling of proper neighbourhood size to realise the required fault tolerance.

2.5.3 Detection delay

One of the most important performance metrics for event monitoring WSNs is the *detection delay* which indicates the delay between the occurrence of an event and its detection. This is a crucial success parameter for an event detection system. Event detection systems promise to reduce the damage and threat by natural or man-made disasters [90, 92, 115, 116, 132, 143, 148, 156]. In such mission-critical applications, immediate detection of event is more important to the users than detailed information to reduce the impact of the disaster. Real time detection is a requirement in many applications [116, 143, 148, 156]. A real world deployment of long term volcano monitoring WSN described in [132] observes that the seismic events around an active volcano lasts about 30 seconds. This indicates the detection task should be accomplished and control centre should be notified within this short period of time. The studies on forest fire detection [148] shows that the fire control centre needs to be notified of the fire within 6 minutes after the start of a fire incident to avoid any permanent damage. Number of research works in recent years focused on minimising the detection delay in WSN based event detection [42, 43, 72, 73, 75, 96, 182, 224]. The factors affecting delay as identified in the literature includes communication architecture (transmission bandwidth, mac and routing protocols), event dynamics (duration of event, frequency and spread of occurrence), sensor collaboration method, and node density and duty cycles of nodes [12, 43, 72, 74, 99, 205, 225, 226]. Delay aware methods emphasise on one or more of these factors to minimise the detection delay. Unpredictable environment and diverse energy optimisation methods complicate the exact analysis of detection delay and only few works (e.g. [72], [73], [226]) have been done in this regard so far.

Li *et al.* in [72] presents a delay bounded detection method in WSN where the system attempts to guarantee an user specified delay. The authors explored the trade-off between delay and energy consumption in this work and proved the energy efficient bounded delay problem to be NP-hard. An approximation algorithm was proposed that ensures given delay constraint, α and maintains the energy consumption to $\Delta\left(1 + \frac{\eta_{max}}{\eta_{min}} n^{\gamma-1} (\frac{2}{\alpha-1})^{\gamma}\right)$, where η_{max}, η_{min} are the minimum and maximum detection thresholds among the sensors and n is the number of nodes and $\gamma \in [2, 4]$. The duty cycle and density of the nodes were not considered in this model, which leaves it incomplete for robust event detection employing node redundancy. A more comprehensive analysis of delay in collaborative event detection was presented by Wang *et al.* in [99]. The assumptions considered were: i) the event detection delay consists of two parts, namely, *the discovery delay* for individual nodes to sense and detect the event, and *the delivery delay* for the network to relay reports to the sink; ii) an event is generally considered to be detected only when a given number, k, of reports are received by the sink. The authors modelled the overall delay using a non-homogeneous Poisson distribution, which was then used to estimate the mean event delay. However, the delay guarantee may not always be possible due to the randomness in the network topology and unpredictable factors of the environment. To address this, a soft delay bound was proposed [99] which is called (n, p)-delay bound. The (n, p)-delay indicates the time required for n nodes to detect and report an event with probability p. Such analysis brings the delay estimation closer to the ground truth. However, the duty cycles of the nodes and event characteristics were not considered. The detection delay for periodic monitoring

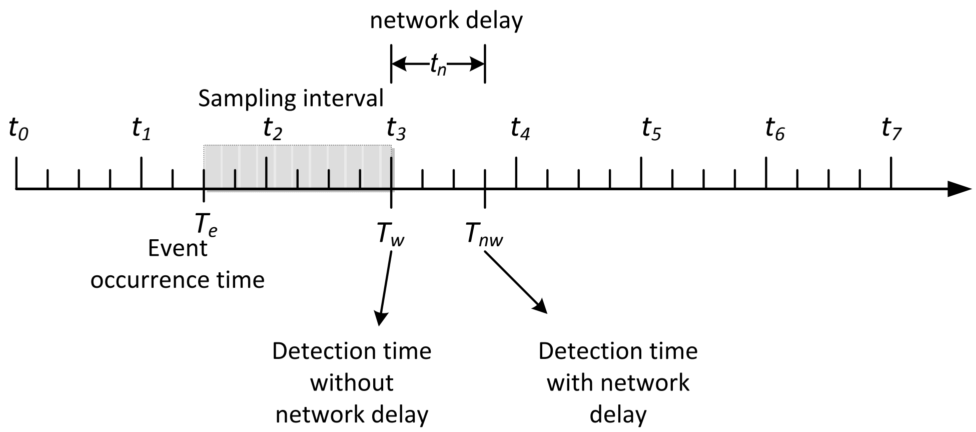


Figure 2.11: Event detection time considering network delay. t_is denote the sampling period. An event occurs at time T_e and the sampling delay for this event is shown by the shaded portion. The sampling period is given by, $T_w = t_3 - T_e$. The node gets a time slot to send the decision to fusion centre after a successful contention. $T_{nw} = T_w + t_n$ denotes the detection time with network delay.

case in a WSN is investigated by Karumbu *et al.* in [73]. Their work focuses on the trade-off between decision delay and network-introduced delay. Under periodic sampling, higher sampling rate reduces the detection delay but increases the random access delay due to higher packet rate. The impact of sampling periods and network delay on the overall detection delay is illustrated in Fig. 2.11. The authors presented a network delay model and two different methods based on this : i) network oblivious processing - that do not consider the network introduced delay, and ii) network aware processing - that incorporates the network delay into event detection delay. Both of them attempts to minimise the detection delay. However, closed form analytical expression could not be derived.

The delay models discussed so far are based on the implicit assumption that the underlying WSN consists of static nodes only. However, event detection using mobile nodes have become commonplace in many event detection applications [28, 29, 37, 70, 71]. The delay analysis becomes more complicated in the presence of mobile nodes and this issue is not well explored in literature to date. Xu and Wang [226] investigated the event reporting delay in a large-scale WSN taking node mobility and transmission power into consideration. They assumed that any node detecting or relaying an event report to sink may not always have a persistent communication link with the neighbouring nodes. Each sensor meets a neighbour periodically when travelling around the region of interest. This requires holding time at each node when an event report is travelling from source to sink. Under such assumption, the event reporting speed ν is bounded as,

$$\frac{(R-2\sqrt{2})^3}{4\sqrt{2}L^2T_{nd}} \leq \nu \leq \frac{(R+1)(R+2)(2R+3)}{2L^2T_{nd}},$$

where, R is the communication range, L is the side length of the square region of interest and T_{nd} is the neighbour discovery period, i.e., each node attempts to discover link availability to a neighbour once in every T_{nd} interval. This gives the reporting delay after an event has occurred. From this model, it appears that mobility introduces significant delay in detection and the delivery time dominates the detection and processing time. Very large detection delay can render the use of mobile nodes in event detection application infeasible. Therefore, more sophisticated node mobility model that takes the spatial distribution of event occurrence and moves on-demand basis may be developed to minimise this delay.

2.5.4 Energy Consumption

Energy constraint is a fundamental issue in any WSN based system as sensor nodes typically rely on limited battery power. The goal of event detection makes it more challenging, as there is a trade-off between the information accuracy and energy consumption. An energy efficient detection scheme will extend the system's lifetime while maintaining the desired detection performance throughout the lifetime. This issue has been addressed by many researchers under different contexts in event-centric WSNs over the years [9, 10, 11, 25, 26, 42, 49, 74, 75, 76, 198, 199, 202, 227, 228, 229, 230, 231, 232, 233]. However, the design of energy-efficient techniques specific to event detection are still far from perfection [26, 42, 74, 75, 76, 230, 232]. Research works on energy conservation techniques include design and development of energy efficient routing protocols

[9, 10, 228, 229], sensor specific MAC protocols [11, 225, 234], energy aware sleep scheduling [76, 233, 235], node clustering [236, 237], and energy harvesting techniques in WSN [76, 233, 235, 238].

Typically, sensor nodes are equipped with limited power source (current rating $< 0.5\ Ah$ and voltage rating from $1.2V - 1.5V$) [38]. Sources of energy consumption of a sensor node can be divided into three categories, namely, *sensing*, *communication* and *data processing*. For example, a breakdown of power consumption of a MicaZ sensor node is shown in Fig. 2.12. It is assumed that a sensor node can either be in active mode or sleep mode [76, 233] and switching from sleep mode to active state consumes some power to wake up which is included in the communication energy.

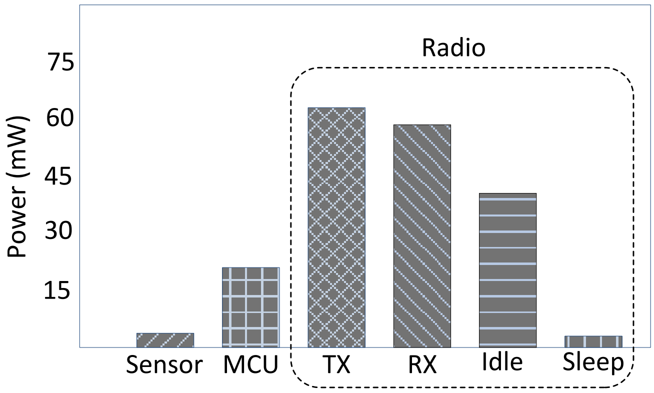


Figure 2.12: Breakdown of energy consumption of a MicaZ mote [38]

Communication is considered as the primary source of energy consumption in WSNs and most of the existing works focus on designing energy efficient communication among nodes. According to the literature, the energy consumed by the transceiver in a sensor node consists of energy spent in transmission and receiption. The transmission energy depends on the packet size and the distance of the destination node from the source node. The energy consumed to transmit a packet to a distance d is given by [44],

$$E_{tx}(d) = l_p(e_t d^{\gamma_l} + e_o) = c_t d^{\gamma_l} + o_t,$$

where, l_p represents the packet length in bits, γ_l represents the path loss component, e_t denotes the loss co-efficient related to 1 bit transmission and e_o is the overhead energy due to the processing of the same amount of data. This energy model is widely adopted in most event detection WSN systems. The increased energy consumption for large packet size motivates most of the existing works to employ decision fusion that sends only 1-bit decision instead of data fusion at the fusion centre [25, 26, 27, 51, 52, 198, 202]. Yu *et al.* [26] investigated the energy-accuracy trade-off in event detection and showed that the reduced energy consumption in the decision fusion based systems comes at the cost of increased processing energy and reduced detection accuracy. They proposed a hybrid detection scheme where each sensor sends its one bit decision if the expected detection accuracy exceeds a predefined threshold; otherwise sends out undistorted information. The energy-accuracy trade-off is also exploited by a number of other researchers in designing energy efficient protocols [239] and detection algorithms [55].

Sleep scheduling or duty cycling is a commonly used technique in continuous monitoring sensor network applications to achieve the goal of energy efficiency [75, 76, 233]. Such techniques affect the detection delay as an event may occur when the nearby nodes are in sleep mode. Similarly, a sufficiently long sleep period may cause missed detection of transient events that disappears within the sleep duration [240]. Qing Cao *et al.* in [42] investigated the trade-off between event detection delay and the duty cycle of a sensor node. The authors developed a rotating sleep scheduling protocol to minimise the detection delay subject to a constraint on energy consumption expressed as duty-cycle constraint. Xiao *et al.* [74] further analysed the problem of energy aware sleep scheduling under the quality of service constraints such as bounded detection delay, detection probability, and network coverage intensity. However, none of these works considered the event dynamics such as event occurrence probability and the distribution of inter-arrival delay, which renders the analysis incomplete. Among the recent works, Shibo *et al.* in [240] and Yau *et al.* [241] attempted to optimise the sleep schedules by exploiting the event dynamics and achieved significant improvement in event detection compared to the traditional sleep schedule. The authors primarily considered the temporal distribution of stochastic events, which leaves the correlation of spatial distribution and energy consumption in such networks yet to be explored.

While communication energy remains the main bottleneck in static sensor nodes, in mobile WSNs, bulk energy is consumed due to mobility. Designing energy-efficient node movement has become a major research challenge in mobile sensor networks performing long term surveillance [28, 29, 37, 70]. Tan *et al.* [29] presented a reactive mobility scheme where nodes remain stationary until an event occurs and moves only on-demand basis. Ammari in his work [37] proposed a distributed movement strategy that considers a node's closeness to the target region to minimise mobility energy. However, comprehensive studies of spatio-temporal correlation in sensor observations [16] and event distribution [24] indicate that only distance based sensor relocation scheme is not adequate. We studied these shortcomings in Chapter 4 and achieved improved energy efficiency in node movement strategy considering spatial distribution of event occurrences.

2.6 WSN Coverage for Event Detection

Sensing coverage characterises the monitoring quality provided by WSN. From the discussion above, it is evident that the performance of event detection techniques rely on the effective collaboration among sensor nodes. Therefore, how many sensors cover an event at any instant determines the accuracy and reliability of detection. This effectively controls the above-mentioned QoS metrics in a WSN based event detection system. This brings the notion of k-coverage in WSN [31, 180, 242]. A sensor network is called k-covered if any point in the sensor field is within the sensing range of at least $k(\geq 1)$ nodes, k being the degree of coverage. An example k coverage is illustrated in Fig 2.13. While some applications may require that every location in a region be

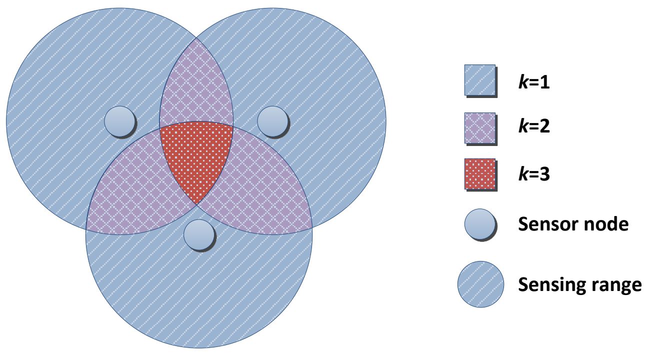


Figure 2.13: Concept of k cover.

monitored by one sensor only, other applications require higher degree of coverage. For example, the counter sniper [116] system or shooter detection [114] sensor network requires at least three nodes ($k = 3$) to detect the impact of shooting event to identify and locate the event. Even though, higher degree of coverage ensures better detection performance, the added redundancy introduces increased deployment cost, complex topology control and higher energy consumption. It is non-trivial to design a WSN that would minimise cost, reduce computation and communication overhead, provide a high degree of coverage and maintain network wide connectivity. The problem of coverage has been extensively investigated over the last decade in different contexts [30, 31, 32, 33, 34, 77, 78, 79, 87, 107, 180, 181, 182, 184, 185, 240, 243, 244]. However, its impact on event detection system and the trade-off between detection performance and degree of coverage yet remains inadequately explored. We present some general coverage optimisation techniques here and discuss their shortcomings in regard to event detection.

Once the nodes are deployed in a sensor field they form a communication network and continue to monitor the region. Depending on whether they can dynamically change the network configuration with time, the coverage techniques are divided into two classes : static coverage and dynamic coverage.

2.6.1 Static coverage

Majority of the research works on coverage consider the nodes to remain stationary after the initial deployment [30, 33, 77, 78, 79, 181]. Once they are deployed, they do not change their locations. Coverage for such networks should be designed before the deployment. Hafeez *et al.* [180] presented an analytical solution to determine the minimum number of nodes to provide full coverage in an arbitrary shaped region. The authors provided two different formulations for minimum cost coverage under deterministic deployment and random deployment. According to their analysis, the minimum number of nodes to k-cover an arbitrary shaped region under deterministic deployment, is given by [180],

$$N_{min}^{det} = \left\lceil \frac{k[\sum_{i=1}^{n}(x_i y_{i+1} - x_{i+1} y_i) + (x_n y_1 - x_1 y_n)]}{2r^2\{\pi - 2(\theta - sin\theta)\}} \right\rceil , \tag{2.10}$$

where, (x_i, y_i) is the location of sensor i, r is the sensing range, θ is the angle subtended by the chord of intersection between two neighbouring sensors to the centre of one and k is the degree of coverage. For random deployment, they showed that the number of required nodes becomes almost seven times higher than that of deterministic deployment. This work gives a indicative idea how quickly the number of nodes grows with higher degree of coverage.

The Voronoi diagram is the basis for many research works in coverage [31, 243, 245, 246]. A Voronoi diagram for sensor network is a diagram of boundaries around each sensor such that every point within a sensor's own polygon is closer to that sensor than any other sensor in the network. Fig. 2.14 illustrates the idea of Voronoi diagram in a sensor network. Carbunar *et al.* [243] employed Voronoi diagrams as a means of detecting and reducing coverage redundancy during deployment. They also proposed a method to determine the boundary of each node's individual coverage area. Their algorithm can recompute the Voronoi diagram during the operation when the network topology is affected by a sensor failure or addition of new nodes. However, such static coverage algorithm is not suitable for handling the trade-off between the detection performance and degree of coverage, as no event related parameters are taken into consideration. Also, their algorithm does not effectively guarantee k-connectivity with k-coverage.

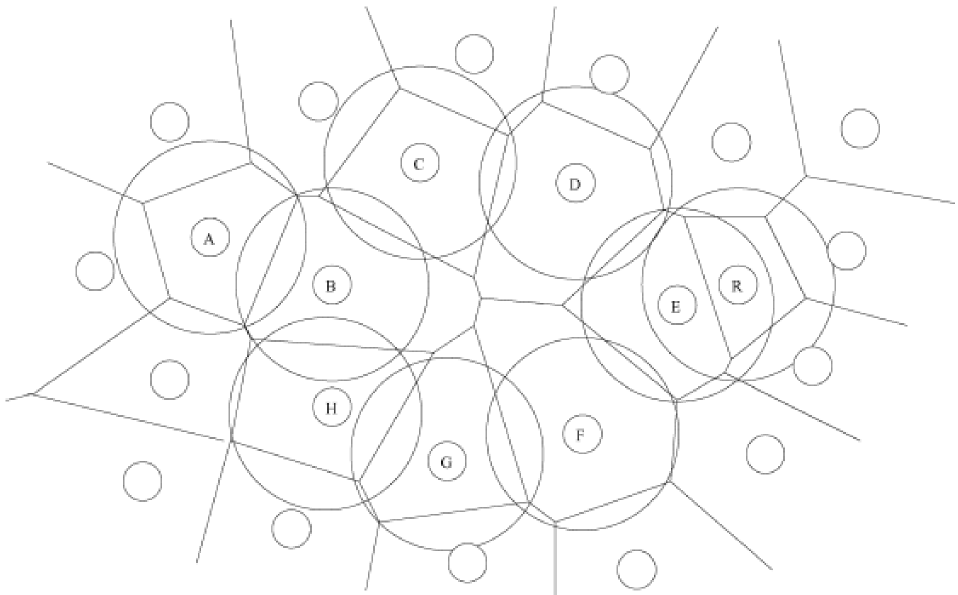


Figure 2.14: Voronoi diagram for 9 sensors. The sensing disk is shown by the concentric lager circle around each node and the polygon within which each node stays in denotes their Voronoi polygon or cell.

Ahmed *et al.* [77] explored the coverage in case of probabilistic sensing range mentioned in Section 2.3. They used the path loss to determine the probability of event detection within the sensing range of a node. However, the actual spatio-temporal distribution of event and the nature of sensing was not considered. In addition to this, the proposed method solves the coverage optimisation problem in general but it is not specific to k-coverage. Their algorithm can not be easily extended to incorporate k coverage. The k coverage issue was further explored in [242] where the authors present an approximation algorithm to solve the k-coverage problem as set cover problem. The effectiveness of their algorithm depends on dense deployment and hence it does not scale well with the increase of network size. Xing *et al.* [30] presented a coverage and connectivity configuration protocol (CCP) that integrates the coverage and connectivity requirement together and determines the optimum coverage strategy for a required degree of coverage, k. This work formally states the sufficient condition for guaranteed connectivity in a 1-covered sensor network using the theorem below.

Theorem 1. *For a set of nodes that at least 1-cover a convex region, the communication graph is connected if $R_c \geq 2R_s$, where R_c and R_s are the communication radius and sensing range, respectively.*

The general k-coverage optimisation approaches discussed above do not fit directly to the event-centric WSN as they do not consider the event dynamics such as spatial distribution of event occurrence, duration of events and arrival rate into consideration. A number of recent works [34, 240, 247] addressed this issue and proposed optimum temporal coverage where a number of sensor nodes are periodically put to sleep to reduce energy consumption and while still ensuring sufficient coverage for events. Yau *et al.* [247] analysed the quality of event monitoring in a sensor network where nodes are periodically put to sleep. Each individual node was assumed to be active only for t_a amount of time in every $t_c, (t_c \geq t_a)$ time and the stochastic processes of the event arrivals/departures are pre known. The distribution of event duration (referred to as *staying time*) was used to optimise the sleep schedule of a single sensor for event capture. Two types of event staying time distribution is used in [247] ,

- Exponential distribution ($\lambda_1 > 0$) :

$$f(x) = \lambda_1 e^{-\lambda_1 x} \text{ , } x > 0, \text{ mean } = \frac{1}{\lambda_1}.$$

- Pareto distribution ($\gamma_\alpha, \gamma_\beta > 0$):

$$f(x) = \frac{\gamma_\alpha \gamma_\beta^{\gamma_\alpha}}{x^{\gamma_\alpha + 1}} \text{ , } x > \beta, \text{ mean } = \frac{\gamma_\alpha \gamma_\beta}{\gamma_\alpha - 1} \text{ , } \gamma_\alpha > 1.$$

Methods	Sensing Model	Coverage Type	Hole Detection Algorithm	Analytical Model	Tradeoffs Handled	Scalability
Carbunar *et al.* [243]	Deterministic disk model	Spatial	Yes	Voronoi Tessellation based redundancy analysis	Delay vs Coverage	Scalable
Ahmed *et al.* [77]	Probabilistic model	Spatial	No	Not provided	Accuracy vs Coverage	Scalable
Liu *et al.*	Deterministic disk model	Spatio-temporal	No	Not provided	Network life vs Coverage	Scalable
Hafeeda *et al.* [242]	Deterministic disk model	Spatial	No	Approximation algorithm provided	Coverage vs Cost, Coverage vs. Network life	Not scalable
Yau *et al.* [247]	Deterministic disk model	Spatio-temporal	No	Analysis of event distribution	Energy vs. Coverage	Scalable
Li *et al.* [248]	Deterministic disk model	Spatial	Yes	No analytical model	Coverage vs Cost	Not scalable
Yigal [33]	Deterministic disk model	Spatial	Yes	No analytical model	Accuracy vs. Coverage	Scalable

Table 2.4: Comparison among some static coverage based monitoring in WSN

Based on such distributions of event known *a priori*, [247] presents a simulated annealing algorithm to find the sensor sleep schedule that maximises the overall fraction of events captured. This method relies on centralised synchronisation of nodes for sleep scheduling. Shibo *et al.* [240] extended this method by incorporating both synchronous and asynchronous sleep. In addition to that, they proposed a regional synchronisation method that can maintain synchronisation in a specifiable region. However, none of these works provided any analysis of the unavoidable delay introduced in detection due to periodic node sleep. In many applications, prior knowledge on the distribution of event duration is not available [90, 124, 249] which limits the use of works [240, 247]. Apart from this, in case of sensitive event detection applications such as radiation leak detection in a nuclear reactor monitoring system, the possibility of missing an event during node sleep state may cause huge damage. To handle this issue, different priority in different region needs to be considered and ensure coverage accordingly. Table 2.4 presents a summary of the strengths and weaknesses of some static coverage based methods.

Static sensor nodes complicate the deployment process for a desired coverage. It is not always possible to deploy the nodes in a strictly deterministic fashion because of the diverse nature of the terrain in the target sensor field. Random deployment is more common in large-scale sensor network and nodes are often deployed from an aircraft [31, 33, 78, 107]. In such cases, ensuring uniform degree of coverage all over the sensor field involves significant redundancy, almost seven times higher than the deterministic placement of nodes [180]. Therefore, it is very crucial from both economic and energy consumption point of view to determine the optimum degree of coverage that guarantees the required detection performance. QoS directed event coverage has not yet been addressed thoroughly in the literature. Zhu and Ni [250] first formally approached the QoS provisioning problem in event detection applications in WSNs. They suggested detection latency and detection probability as the two key performance metrics for event detection systems and proposed a probabilistic approach to QoS provisioning for distributed event detection applications. Although their work formalised the concept of provisioning QoS for event detection system, it does not consider the k-coverage detection model. Wang *et al.* [182] presented an analysis of detection delay in the context of probabilistic k-coverage detection model and considered latency as a performance metric for detection. None of these works have taken the contention in medium access control (MAC) layer in consideration that may incur additional delay in k-coverage event detection. To address this issue, we studied the sensor specific MAC protocols [11, 12, 225, 234] such as S-MAC, B-MAC, Sift and Z-MAC in detail and incorporated the MAC introduced delay in our detection model presented in Chapter 3.

2.6.2 Coverage hole recovery

Coverage hole recovery is another challenging issue in static coverage scenario. As we have mentioned earlier, degree of coverage is not always uniform across the sensing field due to random aerial deployment, node failures caused by power depletion or manufacturing faults. In the post deployment scenario, nodes in a specific region can be destroyed due to environmental factors like excessive heat or vibration, malicious intrusion or explosion which creates a coverage hole [181]. In case of strict coverage constraint, even a single coverage hole can disrupt required coverage and connectivity of the network, which may reduce detection performance. Due to the intrinsic unreliability of sensor nodes, holes are unavoidable in a WSN. It is important to incorporate hole detection and recovery techniques to meet expected performance goals in WSNs.

Several authors have proposed different strategies to detect coverage holes and recover from them [181, 244, 248, 251]. Most of them utilise computational geometry approaches to discover the presence of coverage holes. In [252, 253], the authors proposed various hole detection techniques using Voronoi diagram and Delaunay triangulation approach. However, the proposed algorithms primarily depend on centralised co-ordination and require exact location information which may not always be easily obtained centrally. H.-C. Ma *et al.* [181] designed a distributed coverage hole detection protocol based on local information in self-organised WSNs. The proposed computational geometry based approach also depends on the precise location information exchange among sensors. Yigal Bejerano in his work [33] addressed the coverage verification without location information. The author defined the k-coverage hole as a continuous area of target field comprised of point locations that are covered by at most $k-1$ sensors. Each node is capable of measuring the distance from its neighbours and the proposed algorithm can verify if k-coverage exists based on this localised information. While this is an improvement over the previous works none of these methods except [248] provides a recovery technique when coverage holes are detected. Li *et al.* [248] proposed a hole detection and recovery scheme which depends on the connectivity information only to discover holes. The proposed algorithm recovers from a coverage hole by turning on minimum number of redundant nodes present in the network for such recovery. Evidently, recovery from coverage holes is not a trivial problem in static WSN and having redundant nodes all over the network is not always a cost efficient idea as holes may not occur uniformly over the sensing field. Without proper hole recovery measures, it is not possible to provide guaranteed QoS in an event detection systems throughout the network lifetime. We have addressed this issue in our self-healing QoS aware detection scheme presented in Chapter 3.

2.6.3 Dynamic coverage

A major limitation of the afore-mentioned coverage schemes is that they can only provide a fixed degree of coverage designed during the deployment time. They cannot reconfigure themselves during operation to provide application specific coverage or adjust to the dynamic environment, sensor faults or spatio-temporal distribution of physical phenomena. To address these issues and to make the WSN coverage more scalable and adaptive to real world environments, recently attention is shifted towards dynamic coverage in WSN. Major works in this domain are discussed here.

2.6.3.1 Dynamic coverage using node mobility

There have been fairly large amount of research efforts in dynamic coverage lately using mobile sensor nodes that can patrol the target region of interest in order to provide better quality of coverage and detection capability [28, 29, 37, 70, 71, 87, 205, 244, 251, 254, 255, 256, 257]. The quality of coverage using mobile sensor nodes depends on the velocity, mobility patterns, surface condition of the terrain and the dynamics of the event being monitored. Efficient design of dynamic coverage using mobile nodes is not trivial mainly due to a number of practical limitations identified in the literature as,

- *Energy consumption:* Mobility consumes relatively high energy compared to communication or sensing. For example, a Robomote [36] sensor depletes of energy in 20 minutes if constantly moving. WSNs are typically deployed in harsh environment and inaccessible terrain where replenishing energy is difficult and sometimes impossible.

- *Relocation time*: Dynamic reconfiguration of coverage using mobile nodes requires significant amount of time especially when the velocity is limited and the target WSN is large. Typical velocity ranges from 0.2 m/s to 2 m/s (Packbot [258], Robomote [36]).

- *Limited mobility*: Node mobility can also be fully or partially limited by the obstacles in terrain [251, 256].

One of the early works on this field was by Cortes *et al.* [255], that focused on adaptive coverage control technique for autonomous vehicles performing sensing. The authors addressed the inherent spatial distribution of events and communication constraints of a mobile network and designed a distributed coverage control algorithm that can adapt to changes in sensing environment. Even though, the proposed scheme specifically focused on multi-vehicle networks, the concept of coverage control using mobility subsequently lead to a series of works in the domain of mobile sensor network.

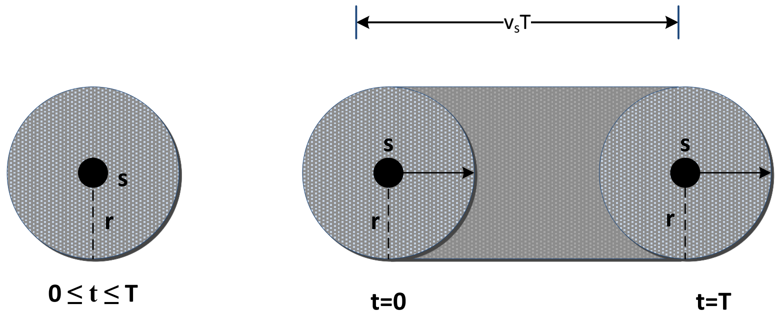


Figure 2.15: Spatio-temporal coverage by a mobile node. If a sensor node s with sensing range r remains static, it covers an area of πr^2 within an interval T. If the node is kept moving at a velocity v_s, the same node can cover $\pi r^2 + 2rTv_s$ area throughout the interval T.

It is evident that, a mobile node covers more area than a static node within a given interval of time as shown in Fig. 2.15, which ensures better temporal coverage. Liu *et al.* [251] described how the coverage aspects of a WSN evolve from spatial to temporal domain with the introduction of node mobility. Considering static distribution of node according to a Poisson point process over a two-dimensional plane with a node density ρ and sensing range r, the fraction of the region of interest (ROI) covered by at least one sensor at time t is given by [251],

$$A_{static}(t) = 1 - e^{-\rho\pi r^2}.$$

However, if nodes move around in the sensing field according to a random mobility model and with velocity v_s, then the fraction of area covered by a mobile node during a time interval $[0, t)$ is given by [251],

$$A_{mobile}(t) = 1 - e^{-\rho(\pi r^2 + 2rE[v_s]t)},$$

where $E[v_s]$ is the expected velocity of the mobile nodes. The authors proposed a random initial sensor placement and random mobility model to improve coverage and derived analytical expressions for the detection time for both static and mobile targets. However, their contribution is limited to fixed velocity mobile nodes and the model is not adaptive to dynamic network parameters. It does not dynamically reconfigure the spatial coverage according to the event specific QoS requirements. The proposed random mobility model also does not attempt to minimise the energy consumption due to mobility. Similar mobility model was proposed by Lambrou *et al.* in [259] which presents a distributed architecture for collaboration among static and mobile nodes to detect and locate event. They characterised the node movement strategy as a path-planning problem that would minimise the coverage hole. Nonetheless their analysis was based on the coverage hole detection and dynamic path selection for mobile nodes, thereby the issue of balancing the energy consumption due to mobility and spatial event clustering were deemed to be beyond the scope of their work.

Bisnik *et al.* [28] considered the fraction of events captured by mobile nodes as a coverage quality metric and analysed the quality of coverage (QoC) in mobile sensor network considering the event dynamics, node velocity and number of mobile sensors. First, they modelled the coverage quality in terms of event loss probability. For a given arrival rate of event around any point of interest (PoI), the method generates a motion plan for the mobile sensors such that the missed detection probability is bounded by some $\epsilon > 0$. Two versions of this bounded event loss probability (BELP) model is presented: i) minimum velocity BELP, and ii) minimum sensors BELP. In the minimum velocity model, given a set of PoIs and event arrival rate around them, the goal is to find the minimum velocity required for a mobile sensor to satisfy the missed-detection probability constraint. In minimum sensor model, for mobile nodes with a fixed velocity v, the goal is to find the minimum number of sensor nodes required to ensure the minimum miss probability. Both of these problems were proved to be NP-hard and heuristic based approximate solutions were provided. These results can be applied to a wide range of surveillance and detection problems where given detection probability needs to be ensured. However, for long term event monitoring, which is the most common scenario in environmental sensing and hazard detection, it is not feasible from energy efficiency point of view to keep the nodes mobile throughout the network lifetime. It is always efficient to move the nodes only on demand basis.

Based on such observation, Ammari and Das in [37] proposed a mission oriented sensor mobility model that ensures k-coverage to a region whenever necessary by introducing the idea of on-demand k-coverage. They proposed a pseudo-random sensor placement technique and distributed movement strategy that considers a node's closeness to the target region to minimise mobility energy. Thereby, target distance is the dominating factor in their node selection method. Another significant property is that, their model is based on the assumption of homogeneous mobile sensor networks and the network topology and connectivity are vulnerable to node movement. That is why an additional type of node called dMULE or data mule was introduced to maintain connectivity and carry the data to sink. The node collaboration and energy minimisation were maintained per mission basis, but that may not always guarantee the best and balanced usage of energy. If the sensing field observes event clustering as discussed in the previous section, some nodes may die at the early stage in the network lifetime causing overall reduction in the fraction of events captured. Based on this observation, we have tried to make the energy consumption due to mobility balanced, prioritising nodes that are farther from the event location but much healthier in remaining energy over a almost dying nearby node. A similar idea is explored by Tan *et al.* in [29] where the authors proposed a reactive mobility technique to improve detection performance in WSNs. In their approach, mobile sensors remain stationary until any target event is detected and move toward the possible target location to increase the accuracy of the final detection. Such scheme results in significant increase in delay because of the limited physical movement speed. This limits the use of such scheme in case of high frequency events. Table 2.5 gives a comparison of major mobility strategy in WSN for event detection.

As mentioned in the previous section, the existence of coverage holes is an indicative measure of the health of a WSN and it may affect detection performance severely. Detection of coverage holes in a WSN is as important as the presence of proper recovery measures. Mobile nodes can play an important role to this end as they can relocate to recover holes when necessary. Several works in the recent literature [87, 244, 255, 260, 261] attempts to minimise coverage hole using mobile nodes. Due to high energy consumption in mobility, most of these hole recovery techniques deteriorate network lifetime. Wu *et al.* addressed the energy issue in coverage hole self repair using mobile nodes. However, energy can still be a bottleneck in large-scale sensor network and limited node mobility. We have investigated this issue in Chapter 4 in case of event detection systems and minimised node mobility significantly by incorporating the event dynamics in mobile node selection process for hole recovery.

2.6.3.2 Dynamic coverage using variable range sensing

Energy and accuracy aware detection has been the primary focus of the research on event centric WSN systems for the last decade. Most works discussed earlier proposed redundant nodes using k-coverage. This could be an appealing solution when the nodes are very inexpensive so that a large area can be covered with redundant node deployment. However, unfortunately, that is not the case in general and especially for sensors with active sensing technology, self localisation capability (equipped with GPS) and multi-modal sensing capability [262, 263]. In such cases, full k-coverage all over the target sensor field throughout network lifetime turns out to be an impractical solution due to the prohibiting cost. To settle for an acceptable solution with sparse node distribution, dynamic coverage using mobile nodes promised to reduce redundancy while providing reasonable degree of robustness dynamically as discussed in the previous section. However mobility comes with its own limitations such as energy consumption, limited physical movement and delay, which limits the real world applications of mobile sensor nodes. Such limitations demand an alternative approach to the dynamic coverage schemes in WSN and an elegant solution would be to vary the sensing range of nodes to reconfigure the degree of coverage dynamically.

Traditionally, event detection in WSN assumes a hard-limit sensing model of nodes, i.e., the sensing radius is fixed and within this radius the probability of detection by individual node remains the same. In practice sensing can be active or passive.

Detection technique	Architecture	Node type	Goal	Event dynamics	QoS consideration	Energy balanced?	Consider Event Priority?
CAMSEL [37]	Centralised	Mobile	On-demand k coverage for event	Not considered	Minimise delay	No	No
DAMSEL [37]	Distributed	Mobile	on-demand k coverage for event	Not considered	Minimise delay	No	No
Sensor Relocation based on Cascaded Movement [261]	Distributed	Mobile	Cascaded sensor relocation to recover fault	Not considered	Minimise delay	Yes	No
Stochastic event capture subject to Quality of Coverage (QoC) [28]	Distributed	Mobile	Maximise the fraction of events captured	Considers event dynamics	Bounded missed detection	No	No
Mobility-assisted Detection with Decision Fusion [29]	Distributed	Mobile	Near optimal movement scheduling to reduce movement distance	Not considered	Bounded delay, detection probability, false alarm rate		
Mobility-assisted Spatiotemporal Detection (MSD) [205]	Distributed	Static and mobile	Dynamic coverage Minimise movement distance	Not considered	Bounded delay, detection probability, false alarm rate	No	No

Table 2.5: Comparison among some dynamic event coverage techniques

Passive sensors detect radiation emitted or reflected by the object or surrounding areas, examples of which include heat radiation, humidity, infrared, radiometer, etc. On the other hand, in active sensing technique, sensors emit energy often in the form of a beacon in order to scan presence of certain signals or objects and can control sensing range through power adjustment. Many sensor devices in WSN are based on active sensing technologies, such as those equipped with radars and sonars, thermocouple based temperature sensors [264], underwater sensors relying on acoustic signals [262] or piezoelectric transducers for structural health monitoring [263]. A number of sensors with adjustable sensing radii are already commercially available [265, 266, 267].

The idea of adjustable range is known in the communication domain for almost over a decade (e.g. [268]). However, the technique is employed primarily to vary the communication radius of network entities to optimise communication power. Recently, the increasing maturity in sensor technology enabled a number of sensor types with variable sensing radius capability [266, 267]. One good example is the commercially available adjustable range photoelectric sensor, EQ-501 by panasonic electronics [267]. The EQ-500 series of photoelectric sensors provide a long-range diffuse reflective solution that is suitable for applications where it is not feasible to get close to the sensing object. The sensing range is conveniently adjustable within a range of 3.94 to 98.43 inches. Existence of such technology allows the WSN design to take a new step in designing dynamic coverage and deployment strategies. A number of research efforts already attempted to exploit this variable range sensing technology [268, 269, 270, 271].

Zhou *et al*. [269] addressed the minimum energy k-coverage problem by exploiting the variable sensing and transmission range. Their work takes advantage of the energy conservation in smaller sensing or transmission radius by providing an optimum connected k-cover but the number of sensors can still be large since k-coverage is maintained persistently from deployment time. Similar approach was presented in [270]where Bartolini *et al*. employed the sensing range adaptation technique in heterogeneous sensor network to achieve prolonged lifetime of WSN. While these two works conceptually establish the viability of adjustable sensing range in WSN operation, their primary focus was on guaranteeing complete redundant coverage all the time. The proposed algorithms optimise the sensing range during the deployment time to achieve the required complete coverage, but do not dynamically adjust sensing radius locally according to system behaviours such as event occurrence. The authors focused only on the generic coverage problem rather than event-specific properties of WSN.

In case of event centric WSN, it is more efficient to dynamically achieve the required degree of coverage for any event by adjusting the sensing range of nearby sensors as needed. Such an approach is more cost effective and energy-efficient while maintaining desired level of event detection performance. We introduce the idea of dynamic on-demand coverage using adjustable sensing range for event detection in our thesis in Chapter 4. Adjustable sensing range can also be employed in coverage hole recovery as an alternative approach to mobile nodes.

2.7 Event Detection in IoT

In 1991 Mark Weiser stated 'the most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it' [272]. Such vision, supported by the advancement of Microelctromechanical Systems (MEMS), paved the way to the Internet of Things. The notion of IoT promises to revolutionise the idea of our current understanding of communication and connectivity between the physical and virtual world. It views the future of the world wide web as a global network of uniquely identifiable objects, sensors and mobile entities that can dynamically join the network to collaborate and accomplish tasks collectively. The International Telecommunication Union (ITU) introduced a new communication paradigm, i.e., the IoT in early 2005 [14], stating - *A new dimension has been added to the world of information and communication technologies (ICTs): from anytime, anyplace connectivity for anyone, we will now have connectivity for anything.* Conceptually, IoT allows humans and any entities in the environment to be connected anytime, anywhere with any other similar or heterogeneous objects and build a giant world wide web of smart *'Things'*. IoT is already forecasted to have huge influence on a wide range of domains including ambient intelligence, pervasive computing, environmental monitoring, telecommunication, and intelligent healthcare. This adds a new dimension in the corresponding research domains and necessitates the revision of several existing networking concepts and application architectures.

Information sources are mostly homogenous in traditional event centric WSN. But this is no longer the case when the WSN works as a part of the IoT. Recent years have seen an explosion of the IoT research which is anticipated as the next generation Internet . While most of works focuses on services and architecture, some works in recent times focus on detecting events using IoT platform. One popular example of such effort is the fall detection method in the assisted living applications [273]. Alemdar *et al.* in [273] designed a multi-modal fall detection mechanism in an ambient intelligent environment using accelerometers together with a video sensor. The accelerometer attached to the wearable clothes triggers a video processing of the target that detects the fall. A major portion of the research in IoT focuses on the context awareness that address the issues related to the integration of different devices, systems and services [274, 275, 276]. The term context awareness refers to the capability of capturing the state of physical environment and widely studied in literature within the scope of various domains. Henricksen *et al.* [276] identified the challenges introduced by context and attempted to address them by proposing a set of conceptual models designed to support context consideration. Even though, their contribution is solely limited to software engineering domain, it provides an indication of how important it is to combine the contextual information from several heterogeneous sources for enhancing system performance.

Detection of real world phenomena is one of the most important functionalities required by the IoT applications as envisioned by many researchers [104, 105]. One of the popular IoT applications that requires user activity recognition and event detection is the ambient assisted living (AAL) by Dohr *et al.* [103]. They outlined an AAL environment that is capable of processing relevant data and establishing communication channels among elderly people and their environment and different groups of caregivers (physicians, relatives, mobile care providers). However, in their work, context is considered to collect relevant information on specific situations rather than early detection of context sensitive events. Event detection requires a closer look at the sensor data while considering the object-state interaction at the same time.

Jin *et al.* identified the composite nature of events in the IoT in their work [104]. They investigated the spatial and temporal relationship of events in the IoT environment and proposed a middleware architecture for identifying events of interest. However, their work does not consider the issues resulting from the integration of sensor network with the IoT. As the contextual information in the IoT originates from heterogeneous sources, a common standard for data interpretation and enhancement is a mandatory requirement for information exchange. To this end, Eno *et al*. [277] outlined the importance of ontologies for semantic representation of data harvested from real and virtual worlds. Strang *et al*. [278] presented the ontology based and object-oriented based models as the two core models suitable for describing context for pervasive computing. Even though, these studies do not focus on event-centric systems in general, they suggest that, ontologies provide a powerful means for capturing the generic nature of composite event patterns in the IoT. Based on such observations, we resort to ontology based reasoning approach in designing our context-sensitive detection architecture that contains information from heterogeneous sources and expressed in normalised forms. We present our context-aware detection framework in Chapter 6.

2.8 Research direction in Event Detection using WSN

1. **Designing QoS guaranteed detection**: It is evident from the above discussion that most of the works on event detection using sensor networks attempt to maximise performance regardless of the specific need of the applications. With the growing use of event detection systems in our everyday life, WSN designs needs to more application specific and QoS aware. Soheterogeneous me applications may require high detection probability while tolerate the detection delay. Accuracy should be the primary design factor in such applications. Again, some applications may have stringent delay requirement while accuracy may be sacrificed up to a certain level. For example, the non-critical environmental event detection applications such as bird detection [122] or fence monitoring [18]. The performance of an event detection system such as detection probability, tolerance against node faults and detection latency depends on the degree of coverage k. While increasing the k will enhance the detection performance 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 between the aforementioned opposing factors. It raises the question, *"What should be the appropriate value of k to guarantee given detection probability and latency within certain tolerance level as directed by the application need?"*. Therefore, given the application specific values of the QoS metrics such as detection probability, α, fault tolerance, β and detection latency

Λ, the required degree of coverage, k for detection should be a function of them as given by,

$$k = F(\alpha, \beta, \Lambda).$$

2. **Dynamic fault recovery**: Sensor faults lead to coverage holes in a WSN which results in degraded detection performance. While existing literature focuses on fault finding techniques, it doesn't provide sufficiently robust recovery techniques. The issue of dynamic recovery considering the characteristics of the physical events such as the occurrence probability in specific region or the duration of an event is still unexplored. For example, an event detection system can estimate the event occurrence probability in certain region based on historical data and prioritise the recovery of coverage holes in the region with high frequency of occurrence in case of resource constraint, such as limited number of mobile nodes. The system may predict the presence of holes by estimating spatio-temporal distribution of faults which helps in energy efficient recovery. Such dynamic fault recovery techniques for event detection are still not present in literature.

3. **Dynamic coverage with variable range sensing**: As mentioned earlier in Section 2.6.3.2, variable range sensing technique enables a WSN to dynamically reconfigure the coverage in the post deployment scenario. This can be used in robust event detection algorithms to increase the degree of coverage of an event on-demand basis dynamically. The limitations of mobile node based systems can be overcomes by careful design of sensing range adjustment during operation. Existing event detection systems in WSN do not take advantage of this sensing range adjustment capability to improve the QoS of event detection.

4. **Mobility strategy adaptive to event dynamics**: Event detection systems using mobile nodes are becoming commonplace in many event detection applications. Most of the existing techniques attempt to optimise the travelling distance of mobile nodes for the sake of energy efficiency. However, in an event detection system, desired QoS should be the guiding parameters of the movement strategy. The detection scheme should incorporate the distribution of events to design energy-efficient node movement strategy that guarantees the given user specified values of QoS metrics $\langle \alpha, \beta, \Lambda \rangle$ rather than a general optimisation.

5. **Priority sensitive detection**: Event centric WSN applications may exhibit simultaneous events occurring in close proximity, especially in disaster monitoring, sensitive structure/plant monitoring or in military applications. In such case of multiple events, it is natural that different types of events will have different severity levels depending on the consequences of missing that event, and thereby, will have different performance requirements. It is not possible for resource limited sensor network to provide the same QoS guarantee for all the events at the same time. For example, a nuclear hazard detection and parking lot event monitoring do not demand the same level of attention. In many cases, missing some high priority sensitive events can lead to enormous loss or damage, while missing some low priority events can be tolerable. Treating all the events similarly may yield an apparent acceptable system performance but the huge damage possible by the few sensitive missed events will render the detection system useless. Such event detection system should consider the overall accuracy weighted by the priority to reflect actual system performance. We have addressed these issues in Chapter 5.

6. **Context-aware detection**: As WSN are gradually becoming parts of the IoT, the context of sensing environment is an important factor that will yield more meaningful detection by the system. A particular distribution of sensor observation can lead to event in one context, while may be ignored in another context. Therefore, the event detection systems in the IoT need to be context aware to guarantee given performance metrics.

2.9 Conclusion

In this chapter, we have explored the major application domains in WSN and that established the significance of reliable detection of real world events. After thoroughly investigating the existing literature in WSN and event detection, we have conclusively pointed out the shortcomings of the existing schemes and identified a number of pressing research challenges that need to be resolved. In the following chapters, these research problems are addressed.

Chapter 3

QoS Aware Event Coverage

Studies in the previous chapter evidence that in most WSN-based applications, sensor nodes are expected to be low cost error prone and deployed in adverse terrains and harsh condition. Therefore, the probability of node malfunction is significantly higher in WSNs compared to traditional networks such as TCP/IP and cellular networks. In addition to that, 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 accuracy, ii) robust event detection against sensor fault and environmental noise, and iii) timeliness of detection. To overcome the intrinsic unreliability in detection, we resort to the notion of k-coverage where every point in the network is within the sensing range of at least k nodes, k ($\geq$1) being the degree of coverage. 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. As the first step of our QoS aware event detection, we derive an analytical framework to determine the optimal degree of coverage to ensure given performance metrics.

It is also important for a WSN to deal with the post deployment degradation of degree of coverage to continue to maintain the expected detection performance. In most mission-critical event based WSN systems, a small unmonitored area can render the system useless if crucial events go undetected. Event detection performance largely depends on how the WSN can adjust itself to sensor faults and resultant coverage holes after the initial deployment. Sensor networks are usually deployed for long term monitoring and detection over the area of interest and prevalence of sensor faults can never be completely avoided. Sharma *et al.* in [40], demonstrated that it is impossible to deploy a perfectly calibrated WSN studying sensor faults in real world deployments. To recover coverage holes generated during network life and ensure energy-efficient QoS guaranteed operation for prolonged period, we introduce variable range sensing in event detection later in this chapter.

3.1 Optimal QoS support through k-coverage

As WSN applications are commonplace in our everyday life now, it is worthwhile to formalise the design parameters based on the specific requirements of the target applications. This motivates us to provide analytical solution to determine the degree of coverage i.e. value of k in WSN-based event detection to guarantee given performance metrics. Zhu and Ni [250] first formalised 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 formalised the concept of provisioning QoS for event detection system, it did not consider the k-coverage detection model. We consider the detection probability, fault tolerance and detection delay as the primary QoS metrics of a WSN system and propose a design guideline to probabilistically guarantee the required QoS. To make the model realistic, we incorporate the environmental noise, communication impairments and sensor fault probability in our model. To address this issue 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.

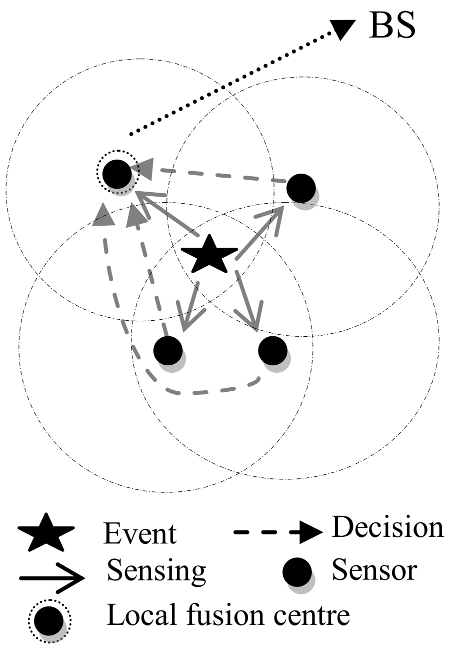


Figure 3.1: k-coverage detection

- Finally, a lower bound on k is obtained that probabilistically guarantees the required performance metrics such as event detection accuracy, fault tolerance and latency.

3.2 System Model and Problem Statement

3.2.1 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. 3.1 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 [51] is 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 [51], 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_e, is greater than the sensing cycle, denoted by t_c, i.e. , $T_e \gg t_c$.

3.2.2 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 $\mathcal{S} = \{s_1, s_2, ..., s_k\}$ 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. Let the sensed data after imposing noise be denoted by $\hat{u}$. Sensing noises at different sensors might vary, and consequently their observation data. Such sensing noise can be modelled using Gaussian distribution [279]. Let the sensing noise at the i-th sensor be ε_i which follows a Gaussian distribution with μ_ε mean and σ_ε^2 variance $\aleph(\mu_\varepsilon, \sigma_\varepsilon^2)$. Let $\{\hat{u}_i\}_{i=1}^{k}$ be the set of observations of the k sensors monitoring the event, where,

$$\hat{u}_i = u + \varepsilon_i. \tag{3.1}$$

- **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 ageing, 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 [280], has the following form,

$$p_b = Pr\left(\gamma_b\right) = \frac{\Upsilon_{1M}}{\log_2 M} Q\left(\sqrt{\frac{\gamma_b \Upsilon_{2M}}{\log_2 M}}\right) \tag{3.2}$$

  where, Q denotes the standard tail probability of the standard Gaussian distribution, M, Υ_{1M} and Υ_{2M} 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 a more 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 [281].

3.2.3 Problem Statement

As discussed in Section 3.1, 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 optimisation problem:

$$minimise\ k,$$

$$s.t.,$$

$$\begin{cases} P_{k,n} \geq \alpha \\ P_f \leq \beta \text{ and,} \\ D_{k,n} \leq \Lambda \end{cases} \tag{3.3}$$

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 $D_{k,n}$ are the event detection probability and delay, respectively when an event is covered by k sensors and 'n out of k' rule is applied for decision fusion.

3.3 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.

3.3.1 Decision error due to sensing noise

Due to sensing noise , a sensor $s_i \in \mathcal{S}$ generates data $\hat{u}_i$ instead of actual event measure u_i. A sensor makes a binary decision, event occurrence (1) or non-event (0), by comparing its generated data $\hat{u}_i$ with the threshold value η_d that characterises the occurrence of an event. The threshold value is application specific and pre-calculated based on domain knowledge [51]. 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 (ε_{max}) without causing any decision error which is given by,

$$\varepsilon_{max} = |\eta_d - u|. \tag{3.4}$$

Then with reference to (3.1) the probability of decision error (P_s) at a sensor due to the sensing noise can be calculated as follows:

$$\begin{aligned} p_s &= Pr(|\varepsilon_i| > \varepsilon_{max}) \\ &= \frac{1}{2}\left(1 - \text{erf}\left(\frac{\varepsilon_{max} - \mu_\varepsilon}{\sigma_\varepsilon\sqrt{2}}\right)\right). \end{aligned} \tag{3.5}$$

3.3.2 Decision error due to communication noise

Let $\{b_i\}_{i=1}^k$ be the set of individual binary decisions made by k sensors monitoring the event, where

$$b_i = \begin{cases} 1, \text{if } \hat{u}_i \geq \eta_d, \\ 0, \text{otherwise.} \end{cases} \tag{3.6}$$

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 (3.2). Due to channel noise the fusion centre may receive an altered decision. Let $\{\hat{b}_i\}_{i=1}^k$ be the set of decisions received at the fusion centre corresponding to the set $\{b_i\}_{i=1}^k$. 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

$$Pr(b_i \neq \hat{b_i}) = p_b.$$

3.3.3 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. 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,

$$P_d = (1 - p_b)(1 - p_f)(1 - p_s). \tag{3.7}$$

Now, the decisions $\{\hat{b}_i\}_{i=1}^k$ 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,

$$P_{k,n} = \sum_{i=n}^{k} \binom{k}{i} {P_d}^i (1 - P_d)^{k-i}. \tag{3.8}$$

For a given detection probability P_d and fixed n, $P_{k,n}$ is an increasing function of k. As argued in Section 3.1, 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.

3.3.4 Detection Delay

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 $D_{det}(k,n)$ be the time required for the event to be successfully detected by n or more sensors and $D_{mac}(n,k)$ be the delay incurred due to contention in the transmission medium. In this regard we have the following proposition:

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

$$D_{det}(k,n) = \left(\frac{(2+P_{rep}) - \sqrt{(2+P_{rep})^2 - \frac{8nP_{rep}}{kP_{det}}}}{2P_{rep}} \right) \tau. \tag{3.9}$$

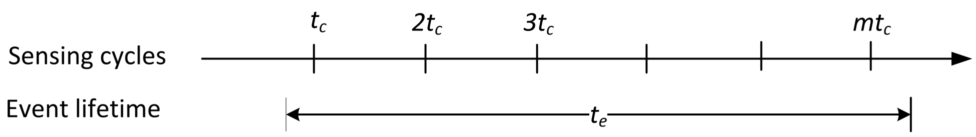


Figure 3.2: Timing illustration of sensing cycles and event lifetime.

Proof. Let us consider an event occurring in the sensor field. Let t_e be the lifetime for which the effect of an event persists and remains detectable as shown in Fig. 3.2 and t_c be the point in time when the first sensing cycle starts after the event begins. It is assumed that the sensors are time synchronised.

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 outcomes of the event by the sensor are independent in each cycle. The expected number of sensors detecting the event in a given cycle is then kP_{det}. But a portion of this kP_{det} 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 ν_i detecting the event up to i-th cycle can be given by,

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

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

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

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

According to our definition,

$$m = \frac{(2+P_{rep}) - \sqrt{(2+P_{rep})^2 - \frac{8nP_{rep}}{kP_{det}}}}{2P_{rep}}. \tag{3.10}$$

Therefore, $D_{det}(k,n) = \left(\frac{(2+P_{rep}) - \sqrt{(2+P_{rep})^2 - \frac{8nP_{rep}}{kP_{det}}}}{2P_{rep}}\right) t_c$, 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 (MAC) 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 n_{slot} slots, that is, $t_c = n_{slot}t_d$. Let ϱ_i be the expected number of unique nodes that detect and transmit successfully upto i-th cycle.

$$\begin{aligned}\varrho_1 &= n_{slot}\nu_1 P_{mac} \\ \varrho_2 &= \varrho_1 + n_{slot}(\nu_2 - \varrho_1)P_{mac} \\ &= n_{slot}\nu_1 P_{mac}\left(1 - n_{slot}P_{mac}\right) + n_{slot}\nu_2 P_{mac}.\end{aligned}$$

Proceeding this way, we get,

$$\varrho_m = n_{slot}P_{mac}\sum_{i=1}^{m} \nu_i \left(1 - n_{slot}P_{mac}\right)^{m-i}. \tag{3.11}$$

Even after n detections among k sensors, we still may have $(\nu_m - \varrho_m)$ nodes waiting to send their detection decisions due to contention. The additional number of transmission slots that will be required to transmit these outstanding decisions is given by, $\left(\frac{\nu_m - \varrho_m}{P_{mac}}\right)$. Therefore,

$$D_{mac}(k,n) = \left(\frac{\nu_m - \varrho_m}{P_{mac}}\right) t_d.$$

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

$$D_{k,n} \quad = \quad D_{det}(k,n) + D_{mac}(k,n). \tag{3.12}$$

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_{det}.

3.3.5 Finding the Optimal Degree of Coverage:

We are interested in finding the minimum value of k that satisfies the given performance metrics. (3.7) indicates that P_d decreases with increasing sensor fault probability p_f. According to the given constraint in (3.3) the maximum allowable fault tolerance limit is β, so to satisfy this we can replace p_f by β in (3.7). 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,

$$P_d = (1 - p_b)(1 - \beta)(1 - p_s). \tag{3.13}$$

Using the above expression in (3.8) 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,

$$k_{\alpha,\beta} = \arg\min_k \left(\sum_{i=n}^{k} \binom{k}{i} {P_d}^i (1 - P_d)^{k-i} > \alpha \right). \tag{3.14}$$

The above $k_{\alpha,\beta}$ can be calculated in a simple iterative fashion. From (3.12) latency $D_{k,n}$ 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,

$$\left(\frac{(2 + P_{rep}) - \sqrt{(2 + P_{rep})^2 - \frac{8nP_{rep}}{kP_{det}}}}{2P_{rep}} \right) n_{slot} t_d + \left(\frac{\nu_i - \varrho_i}{P_{mac}}\right) t_d \le \Lambda. \tag{3.15}$$

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 (3.14) and (3.15), 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 optimisation defined in (3.3) as, $k_{min} = \min(k_{\alpha,\beta}, k_\Lambda)$.

Finally, we pose one validation check on the result to ensure minimising 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.

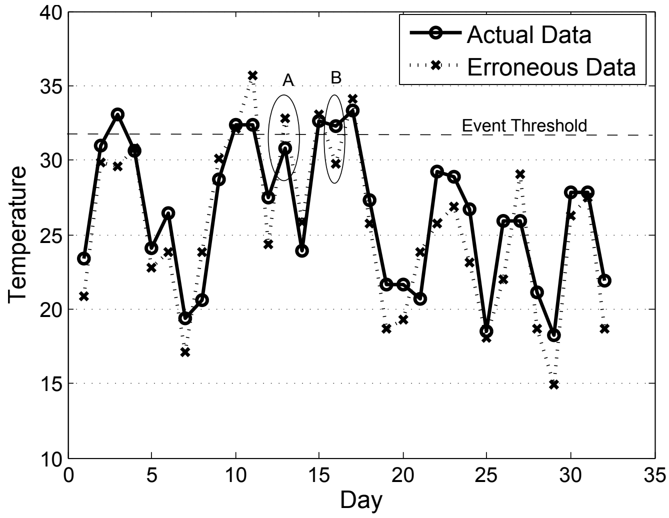


Figure 3.3: Impact of sensing noise on sensed temperature

3.4 Simulation and Results

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 2.10, 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 temperature data were taken from [282] 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 B-MAC [11] for simulation. '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 the figure.

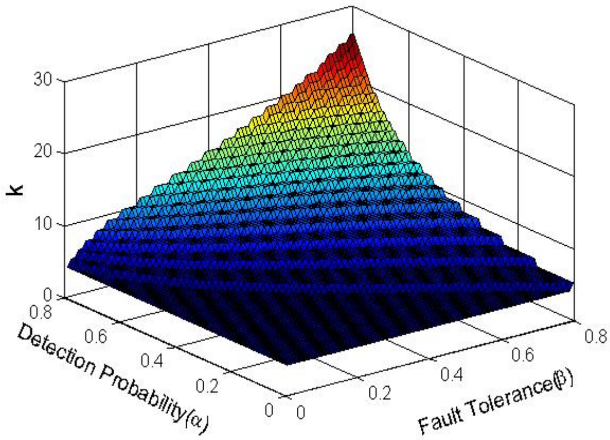


Figure 3.4: k vs. fault tolerance and detection probability

Figure 3.3 shows how the simulated noise affects real data causing missed detection, B and a false alarm, A. Fig. 3.4 represents the combined effect of given detection probability and fault tolerance on the degree of coverage k, in a surface plot. This helps to visualise 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. 3.5 the experimental value of k is compared with the one obtained from (3.14). 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. 3.6 plots the relation between optimal k and fault tolerance for a fixed detection probability. This also shows a closer match between theory and

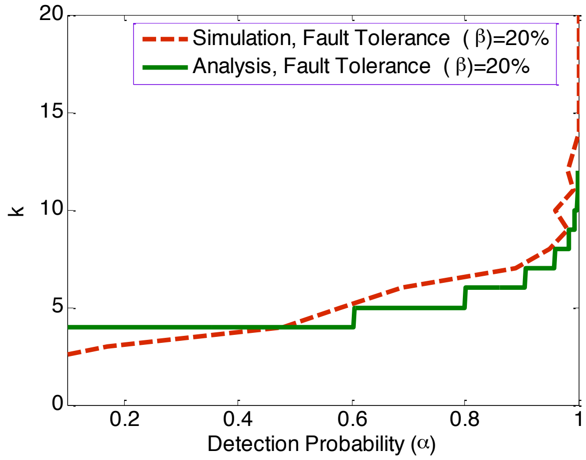


Figure 3.5: k vs. detection probability

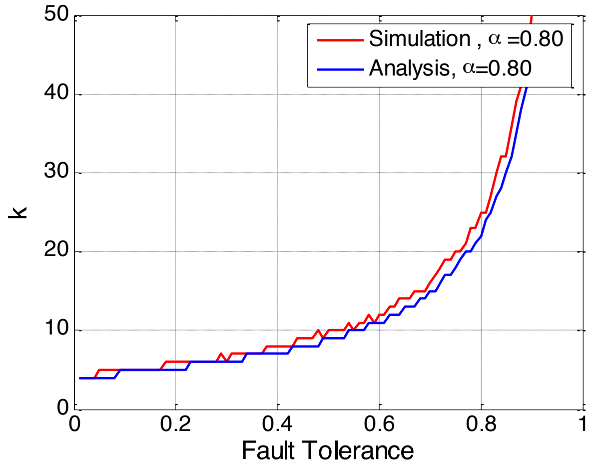


Figure 3.6: k vs. fault tolerance.

simulation. This is because, while observing the effect of k on fault tolerance (Fig. 3.6), 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. 3.5 that the theoretical 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. 3.7 illustrates the trade-off between fault tolerance and detection probability. It shows that one has to be sacrificed to achieve more of the other. Therefore, 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.

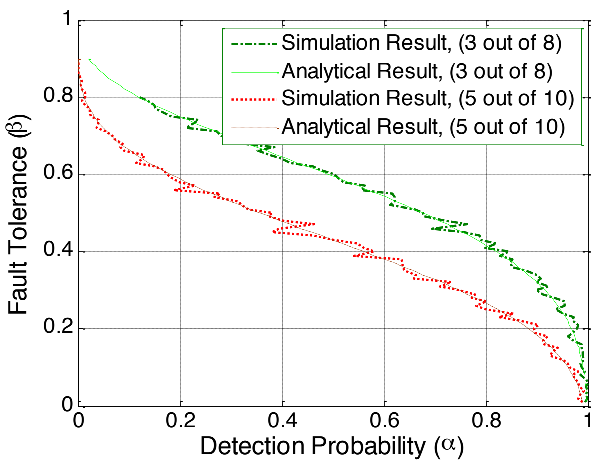


Figure 3.7: Detection probability vs. fault Tolerance.

Figure 3.8 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 theoretical result as k gets higher

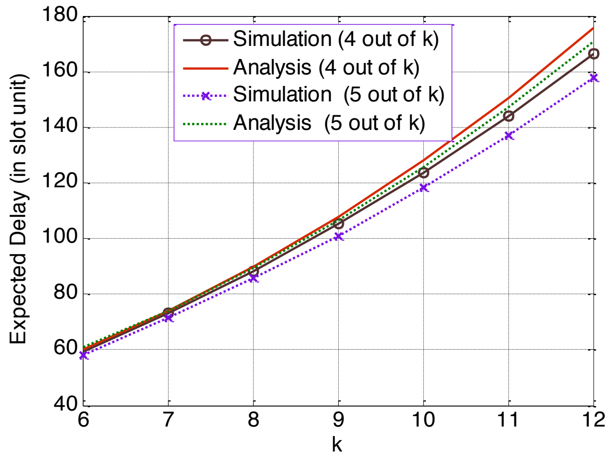


Figure 3.8: Expected delay vs. k (for B-MAC)

(especially for $k \geq 10$). This is because our simulation setup is dependent on the probabilistic model presented in [180] 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 theoretical value as k is increased. This deviation is not significant though, because in most real case scenarios, more than 10-coverage is not practical.

3.5 Discussions

The model presented above analytically determines 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 indicated a close match between our theoretical 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. However, this is a deployment time method and changes in environment may necessitate changes in the required degree of coverage with time. Therefore, this k-coverage model needs to be extended to facilitate the post deployment performance guarantee.

3.6 Self-Recovery for Event Coverage

One of the major problems is the inherent inability of static k-coverage schemes to dynamically recover from the loss of coverage as the network coverage degrades with time due to environmental impacts, sensor faults or any other external reasons. Node faults prevail in real world deployment due to calibration error, battery depletion, physical wearing and/or manufacturing fault [39, 40]. The physical impacts resulting from the event may also cause node malfunction and create coverage holes. For example, unusual high temperature or chemical reaction/erosion may render nodes non-operating after the occurrence of an event. This necessitates an effective coverage recovery technique sufficiently resilient against node failures to continue reliable detection. Some recent works (e.g. [248]), rely on the presence of a set of reserved redundant nodes in addition to the number of nodes required for k coverage and activate those nodes when a coverage hole is discovered. This increases the actual required degree of coverage, and thereby, deploys more nodes than required.

Some other works in event coverage and target detection (e.g. [29, 257]) attempt to exploit reactive mobility to improve event coverage performance and adjust with the random nature of spatio-temporal distribution of faults. From the discussions in Section 2.6.3.1, it is evident that relocation of mobile nodes in event-centric WSN is not unarguably a viable alternative to the dense deployment of static nodes. On the other hand, static fixed-range nodes inherently lack the flexibility to adapt to dynamic degradation of coverage during operation. To face these challenges, we exploit the idea of variable sensing range to ensure reliable detection and dynamic adaptation to network changes. In the case of node failures in a k-covered WSN or coverage hole, neighbouring sensors can increase their sensing range to regain k-coverage. In the proposed approach, we take advantage of variable sensing range technology as discussed in Section 2.6.3.2 to design a self-healing WSN that maintains desired detection performance by ensuring stable k-coverage through dynamic recovery of coverage holes.

There are several challenges to overcome before the above idea of self-healing sensor network with variable radii sensors can be made to work. Noting that detection accuracy and energy consumption (i.e., network lifetime) remain the key aspects to ensure, the challenges are:

- Since the capability to adjust the sensing range is limited, the network topology and sensor density should be maintained in such a way as to make the hole recovery feasible.

- Enhancing sensing radius involves increased energy consumption according to the sensing model described in Section 3.7.3. Hence the sensor selection process needs to ensure balanced energy consumption among sensors to yield a better network life.

- To make such system scalable, the self-recovery of k-coverage scheme needs to be distributed. This involves a local collaboration and decision making among sensors to dynamically detect coverage holes and recover from it.

To the best of our knowledge, this is the first work to exploit the benefits of variable sensing range technology to provide dynamic coverage recovery in event-centric WSNs with only static sensors. This adds the following contributions-

- Low cost and fault tolerant event coverage by introducing the variable sensing radius for coverage hole detection and recovery.

- Selection of nodes participating in hole recovery in a way so that energy consumption is minimised and detection probability is maximised. This will lead to enhanced network life.

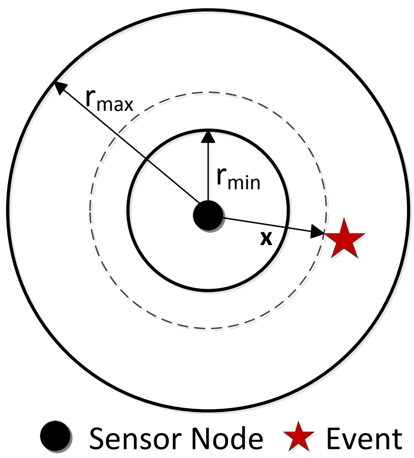
- Optimisation of sensing radius for hole recovery to reduce any unnecessary redundancy in coverage.

3.7 System Model for Self-Healing

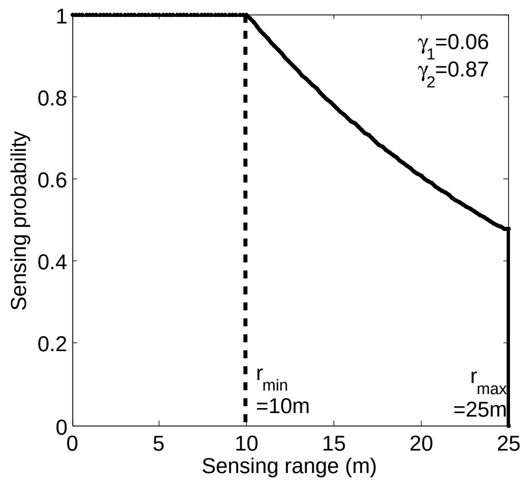
In this section, we extend the basic model in Section 3.2. The main components of the system model for variable range sensing such as variable sensing and transmission, dynamic sensor failure model, probabilistic sensing model, energy consumption model, network coverage model and WSN lifetime definition are presented.

3.7.1 Sensing Model

The WSN in this scheme comprises of static sensors equipped with a sensing and a communication unit capable of range adjustment. In case of variable sensing radii, the nodes can adjust their sensing ranges from r_{min} to r_{max}, i.e. $r \in [r_{min}, r_{max}]$. The transmission radii are adjusted accordingly so that any two sensors with intersecting or tangential sensing circles can communicate with each other. This condition is implied by the constraint $R \geq 2r$. The transmission range can vary from R_{min} to R_{max}, i.e., $R \in [R_{min}, R_{max}]$ along with the adjustment of sensing radius as needed. Variable



(a) Variable sensing model.



(b) Sensing probability vs. variable sensing range.

Figure 3.9: Probabilistic sensing model

range sensing are inherently probabilistic. Probabilistic sensing models assume that the sensing probability is dependent on the distance of the event from the sensor node. To make the model realistic, we adopt the Elfes probabilistic sensing model from robot perception literature [283], that is suitable for the adjustable sensing range. According to this model, the probability that a sensor senses an event at a distance x is,

$$p(x) = \begin{cases} 1 & \text{, if } x \leq r_{min} \\ e^{-\gamma_1 (x - r_{min})^{\gamma_2}} & \text{, if } r_{min} < x < r_{max} \\ 0, & \text{, if } x \geq r_{max}. \end{cases} \quad (3.16)$$

where, r_{min} is the starting of uncertainty in sensing and γ_1 and γ_2 are sensing device specific parameters that are determined from the physical properties of the sensor.

γ_1 and γ_2 determine how fast the sensing probability decays beyond the minimum sensing range. These parameters can be determined from manufacture's specification or experimental data. Fig. 3.9 illustrates the probabilistic sensing model adopted in this work.

3.7.2 Dynamic Fault Model

The fault model used in Section 3.2, was not dynamic and can not capture the time dependent failure characteristic. With ageing and the dynamic nature of environmental impact, the failure rates in nodes can vary and become time-dependent. The analysis of reliability requires real-time consideration of fault models. In this extended model, we address this dynamic nature of faults and adopt a parametric time-dependent fault model that captures the real-life nature of nodes in WSN systems.

Faults in sensor nodes can be categorised in several types such as -

- Crash faults - node fails completely due to mechanical malfunction.
- Omission faults - the sensed values are not delivered properly to the fusion node.
- Transient faults - faults referring to temporary malfunction or glitches.

Reliability analysis involves the study of survivor and hazard functions [284]. The survivor function $S(t)$ is defined as the probability that the lifetime (T) of an object is at least as much as t, that is,

$$S(t) = P(T \geq t), 0 < t < \infty \tag{3.17}$$

The probability density function of T is ,

$$f(t) = \lim_{\Delta t \to 0^+} \frac{P(t \leq T < t + \Delta t)}{\Delta t} = -\frac{dS(t)}{dt}$$

The hazard function, specifies the instantaneous rate of failure at $t = T$, conditional upon survival up to time t. It is defined as:

$$h(t) = \lim_{\Delta t \to 0^+} \frac{P(t \leq T < t + \Delta t | T \geq t)}{\Delta t}$$

We propose a parametric distribution for the hazard model to make the system adaptive to the dynamic nature of the environment where WSNs are usually deployed in. The most common and robust model in reliability literature is the Weibull distribution as it fits the device reliability models closely [284]. The Weibull distribution for lifetime analysis for a sensor node is given by,

$$h(t) = \frac{1}{c_w}\delta(\frac{t}{c_w})^{\delta-1} \tag{3.18}$$

where c_w and δ are the shape and scaling parameters respectively. The hazard function of Weibull distribution is monotonically increasing if $\delta > 1$ and decreasing if $\delta < 1$. A typical Weibull curve for hazard rate is shown in Fig. 3.10. For $\delta = 1$ the Weibull distribution becomes exponential distribution and for $\delta = 2$ it assumes the Rayleigh distribution. This way, the Weibull distribution is generic in nature and can be adjusted to use in various WSNs by adjusting the parameters. We use these definitions for analysing the overall network lifetime and detection performance of our event detection system. It is assumed that each sensor node in the proposed WSN system is aware of

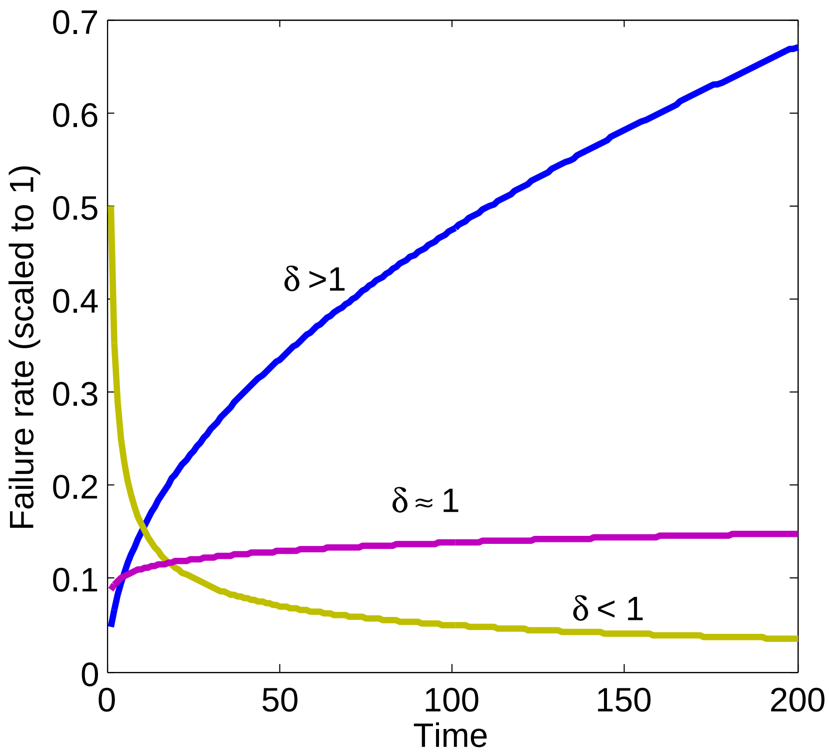


Figure 3.10: Hazard frequency using Weibull distribution

its failure model parameters. Thereby, in the post deployment scenario, nodes may have different failure rates depending on their individual lifetimes and device specific parameters. The hazard rate of a node s_i at time t_i after its deployment is denoted by $h_i(t_i)$ hereafter. This parameter will be used to discard high error-prone nodes in the dynamic recovery method described in Section 3.8.3.2.

3.7.3 Energy consumption

A sensor node consumes energy mainly for sensing, data transmission and reception. In the proposed approach, to achieve the goal of efficient and reliable event detection, data transmission and sensing are done in both fixed and adjustable range mode. For the purpose of this work, we consider the sensing energy model introduced in [269]. If a sensor s has sensing radius r, the energy consumption in sensing is given by,

$$E_s\left(r\right) = c_s r^{\gamma_s} + o_s. \tag{3.19}$$

The parameters c_s and o_s are device specific constants, and γ_s is related to the sensing technology in use and typically varies in the range of 2 to 4 in case of sensors adopting an active sensing technology [269].

When sensor nodes increase their sensing radii to cover for a neighbouring node failure, their transmission radii may also need to be adjusted accordingly for establishing communication among all the detecting nodes to accomplish local fusion. This is accomplished by varying the transmission power. It indicates that the adjustable sensing technique affects both sensing and transmission energy and thereby the overall total energy. For transmission power consumption in such scenario, we adopt the model for adjustable transmission power used in [285]. In this model, the energy consumption for transmitting one packet to any node or sink at d distance is given by,

$$E_{tx}(d) = c_t d^{\gamma_t} + o_t, \tag{3.20}$$

where, c_t denotes the path loss component, γ_t stands for the loss coefficient and o_t is the overhead energy required for transmitting one packet. Usually in existing literature [285], commonly used values of c_t lies between 2 to 4.

Total communication energy consumption in a communication between two nodes is given by,

$$E_c(d) = E_{tx}(d) + E_r, \tag{3.21}$$

where E_r is the receive energy required per node.

3.7.4 Network Lifetime Definition

Conceptually, the lifetime of a sensor network is defined as the duration of time for which the network provides guaranteed coverage and can be deemed as operational. But in reality, the lifetime definition depends on the application requirement and a number of different definitions exist in literature. In many studies (e.g. [285]), the lifetime is defined as the time when the first node dies. An alternative definition based on the duration as long as the network remains fully connected is adopted in [286, 287]. Another widely accepted definition is the moment when a certain portion of node dies [288]. According to this, the network lifetime is the period before the number of live nodes drops below $(1 - \psi)N$, where $\psi < 1$ and N denotes the total number of nodes in the network. ψ is referred to as the lifetime threshold. In this chapter, we adopt the definition based on the ratio of dead nodes, since it is more generic and includes the definition using first node die, half node die or last node die.

3.7.5 Network Coverage Model

In this model, we consider a WSN consisting of a set of N sensor nodes deployed randomly over the area of interest to achieve full k-coverage. Each sensor senses any event occurring within its sensing range and reports the sensed event to a local fusion node, as described in Section 3.2.1. In a full coverage scenario, the connectivity requirement is that any node should be within the communication range of one or more active nodes so that all nodes can form a connected communication backbone. As established in [30], for a set of nodes that at least 1-cover a convex region, the connectivity in communication is guaranteed if, $R \geq 2r$. Our coverage recovery method maintains this relationship while enhancing the sensing radius by adjusting the communication radius accordingly.

3.8 Variable sensing range k-cover

Primarily, our goal is to make the event detection method fault tolerant by adjusting sensing radius to recover from the coverage hole caused by node faults described in Section 3.7.2. The method consists of two phases. In the first phase, any coverage hole is detected as soon as it occurs. In the second phase, the newly generated hole is recovered by extending the sensing range of one of the neighbouring sensors using our energy-aware recovery technique.

3.8.1 Preliminary concepts

In order to address the problem of coverage in the presence of heterogeneous devices, namely devices with different sensing ranges and different capabilities of adjusting their settings, we employ the notion of Voronoi diagrams in Laguerre geometry. Our target is to exploit such geometric properties to decrease coverage redundancy (and thus the energy consumption due to sensing and transmission) while preserving network coverage and connectivity. In a Voronoi diagram, the *Vor line* is defined as the axis generated by two sensors which is equidistant from them and perpendicular to the line segment connecting their centres. This line divides the plane into two halves as shown by the dashed line in Fig. 3.11. In the case of sensors with the same sensing radius, the Voronoi line properly delimits the responsibility regions of the two sensors as it is the symmetry axis between the two. However, if the sensors have heterogeneous radii (e.g. operational sensing range in our scheme), the Voronoi line fails to determine the responsibility region correctly, as demonstrated in Fig. 3.11. On the other hand

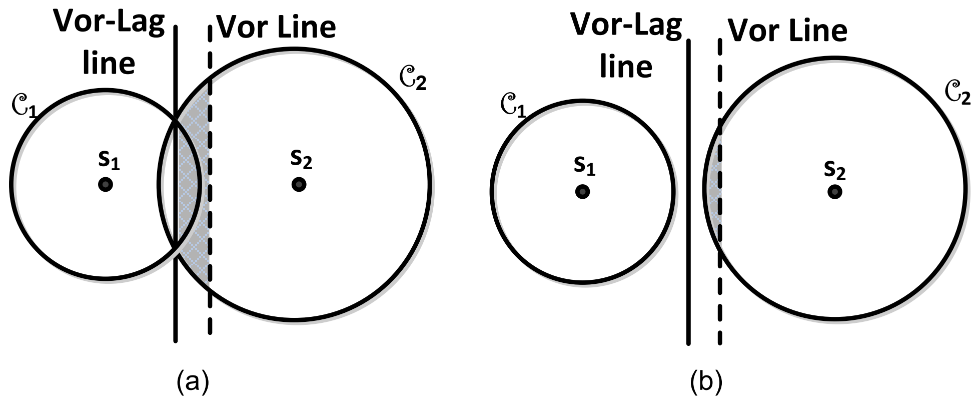


Figure 3.11: Voronoi-Laguerre geometry demonstrating the responsibility regions of sensors for - (a) overlapping sensing circle, and (b) non-overlapping sensing circle. The shaded regions are wrongly assigned to s_1 by Voronoi line, while they are closer to s_2 and should be s_2's responsibility. Vor-Lag line correctly assigns these regions to s_2

a Vor-Lag line between two circles is the locus of the points equi-distant from them and it is perpendicular to the line segment connecting the centres (shown by the solid line in Fig. 3.11). The Vor-Lag line between two intersection circles is the chord connecting their intersection points. Computing the pairwise Vor-Lag lines among a set of circles will generate the Voronoi-Laguerre diagram. Let us consider we have N sensors, $s_1, s_2, ..., s_N$ in a sensor field and the sensing disk of sensor s_i having the radius r_i, is denoted by circle $\mathcal{C}_i$. The Voronoi-Laguerre polygon of circle $\mathcal{C}_i$ comprises of all the points that are closer to $\mathcal{C}_i$ than $\mathcal{C}_j$, $\forall j \neq i$. Such a polygon is always convex and a tessellation of the plane of system of circles is called a Vorono-Laguerre diagram. We denote the Voronoi Laguerre polygon of circle $\mathcal{C}_i$ as $V_L(\mathcal{C}_i)$, e.g. $V_L(\mathcal{C}_1)$ for $\mathcal{C}_1$ shown in Fig. 3.12. By definition, every point in such a polygon is closer to the sensor that generates the circle, than any other sensor. Thereby, Voronoi-Laguerre diagrams are the appropriate tool for event coverage in heterogenous case. It can partition the area of interest into regions of respective responsibility of the sensors proportional to their sensing ranges. Two sensors are Voronoi-Laguerre neighbours if their polygons have one edge in common. For a sensor s_i, the set of its Voronoi-Laguerre neighbours is hereafter referred to as $\mathcal{N}_{VL}(s_i)$. We assume that each sensor is aware of its own location via GPS or any other localisation method available [289]. This facilitates the distributed computation of Voronoi-Laguerre polygon of each node. We employ Voronoi-Laguerre polygons first to detect a coverage hole, second to determine the appropriate node(s) and their enhanced range(s) to cover the hole, and third to lower ranges of other nodes, whenever possible, to reduce unnecessary coverage redundancy.

3.8.2 Hole Detection

We emphasise on the local detection of coverage hole because a node failure can occur anytime in the network and continuous centralised monitoring is infeasible due to energy constraint in WSNs. Every sensor node performs a periodic coverage verification scheme and inform the higher level entity (usually a cluster head or base station) for further recovery measures. The complete Voronoi-Laguerre tessellation of a WSN may be costly. However, we adopt a simpler method where each sensor can estimate its own polygon and use this information to determine if there is any coverage hole around it. This process starts by a sensor sending a *hello* message to its one hop neighbours and each neighbour receiving this message acknowledges its presence with a *hello acknowledgement* that includes its current radius and position. The sensor sending the *hello* message can now estimate the Vor-Lag axis between itself and each of its neighbours

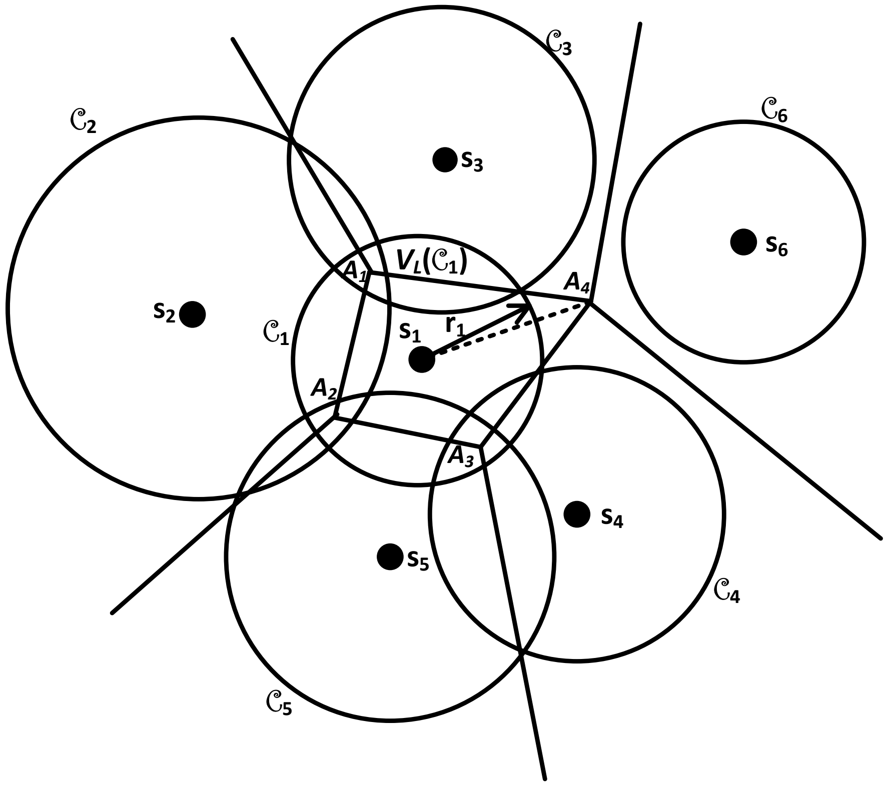
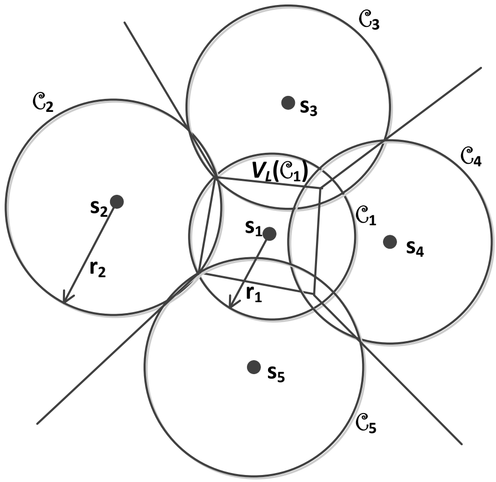
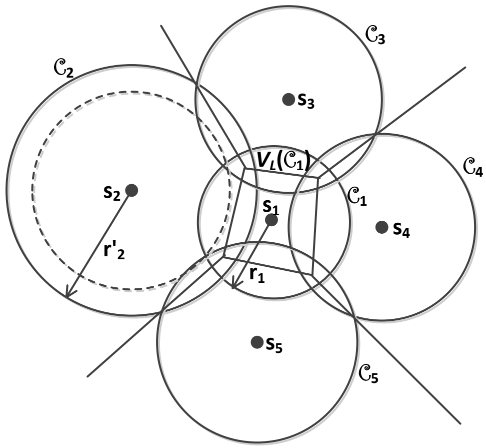


Figure 3.12: Detection of coverage hole by s_1 using Vor-Lag geometry and example of irreducible sensing radius case for s_1.

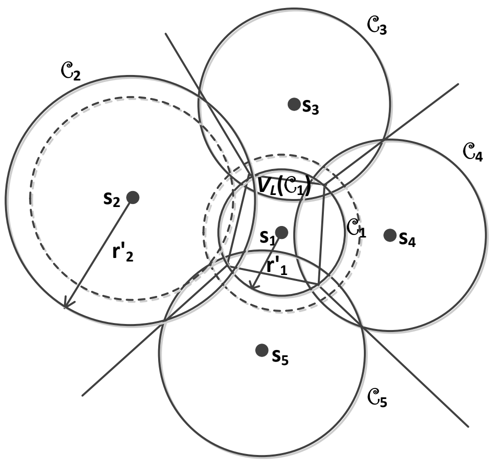
individually and thereby calculates its own Voronoi-Laguerre polygon. To determine if a coverage hole exists, a node checks whether its distance to the farthest vertex of its polygon is longer than the sensing range. If yes, then some coverage hole exists and this sensor is a candidate to heal this. For example, in Fig. 3.12, s_1 calculates its Voronoi Lageurre polygon, $A_1A_2A_3A_4$, denoted by $V_L(\mathfrak{C}_1)$, after receiving the location and range information from s_2, s_3, s_4, s_5. The distance of the furthest vertex, A_4 from s_1 is longer than r_1, which indicates a coverage hole around A_4. Following the similar method, s_3, s_4 and s_6 also find that they border a coverage hole around the common vertex A_4. Note that, this coverage hole can be healed by either increasing the sensing ranges of s_3, s_4 and s_6 up to A_4 or enhancing the range of each of the four bordering sensors individually. Our self-healing recovery algorithm described in Section 3.8.3.2 will select which subset of the s_1, s_3, s_4, s_6 should increase their sensing ranges to heal the coverage hole.



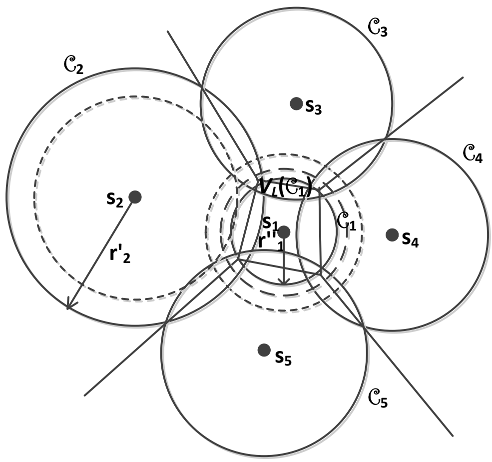
(a) Initial state



(b) s_2 increases its radius



(c) Radius reduction by s_1.



(d) Further radius reduction by s_1.

Figure 3.13: Radius adjustments and re-computation of Voronoi-Laguerre polygon

3.8.3 Dynamic Hole Recovery

3.8.3.1 Coverage redundancy and radius adjustment

Upon deployment, the Voronoi-Laguerre diagram for the whole WSN is calculated. During the operation nodes are subject to dynamic reduction or enhancement of sensing range to remedy the holes generated from the failure of neighbouring nodes. This adjustment of sensing radius requires the Voronoi-Laguerre polygon of certain nodes to be recomputed. In this section, we characterise the radius adjustments in such cases, which forms the basis of our recovery algorithm. In our method, upon detection of a coverage hole, one or more sensors with sensing circle bordering the hole will enhance their sensing ranges to cover the hole. The selection of such nodes is described in the next section. As a result of radius enhancement by one node, the Vor-Lag polygons of its neighbouring nodes are affected and may be eligible for radius reduction. We characterise such reduction of sensing radius in three different cases.

(i) **Null polygon**: It may happen that the Voronoi-Laguerre polygon $V_L(\mathcal{C}_i)$ of a sensor s_i does not contain any point of the plane. This happens when the half-planes generated by the Vor-Lag axes formed by $\mathcal{C}_i$ and its neighbouring sensors' sensing circles have no overlap. In this case, $V_L(\mathcal{C}_i)$ is called a null polygon. The newly computed polygon can subsume the responsibility region of another node completely.

(ii) **Partially covered polygon**: If the newly computed Vor-Lag polygon for a sensor is partially covered by the generating sensor, its sensing range can not be further reduced without affecting the coverage. This case occurs when at least one vertex of the generated polygon is on or outside the sensing circle. In Fig. 3.12, assume $V_L(\mathcal{C}_1)$ is the new Vor-Lag polygon of s_1. It is evident from the figure that its sensing range can not be further reduced as such reduction will increase the coverage hole.

(iii) **Reducible sensing range**: If a sensor covers its generated polygon completely and the vertices of the polygon are not necessarily on the sensing border (as shown in Fig. 3.13(b)), it may reduce its sensing radius to certain extent determined by the position of the vertices of the polygon. Fig. 3.13(a)-3.13(c) illustrates such cases.

We now address the third situation in detail as it has more complex impact on the recovery algorithm and it can lead to cascaded range reduction. Let us consider an initial configuration of 5 sensors s_1, s_2, s_3, s_4 and s_5 operating with sensing radii r_1, r_2, r_3, r_4 and r_5 respectively as shown in Fig. 3.13(a). Let us assume that node s_2 increases its sensing radius up to r_2' to account for any neighbouring sensor fault. This makes the Vor-Lag polygons of s_1, s_3 and s_5 to be recomputed as shown in Fig. 3.13(b). It is evident from the figure and sensor s_1 falls under case (iii) mentioned above and can reduce its sensing radius up to the furthest vertex of its Vor-Lag polygon. Let the new radius to be r'_1. This causes its Vor-Lag polygon to be further recomputed as shown in Fig. 3.13(c) which makes it possible to reduce the radius to r''_1 (Fig. 3.13(d)). This iterative process continues until the newly computed polygon falls under case (ii) which completes the reduction process. The proof of convergence of such process is established in [270] using Voronoi-Laguerre geometry.

Let the initial sensing radius of sensor s_i be r_i^{ini} and the final radius of the sensor s_i upon convergence be r_i^{fin}. If the adjustment is radius enhancement, this will increase the energy consumption and the amount of additional energy required is,

$$\Delta E_s^-(s_i) = a\left((r_i^{fin})^{\gamma_s} - (r_i^{ini})^{\gamma_s}\right). \tag{3.22}$$

At the same time, increasing the radius may decrease event sensing probability according to the probabilistic model described in (3.16). The loss in sensing probability is given as,

$$\Delta P^-(s_i) = p(r_i^{ini}) - p(r_i^{fin}). \tag{3.23}$$

On the other hand if the adjustment is radius reduction, the gain in energy consumption is,

$$\Delta E_s^+(s_i) = a\left((r_i^{ini})^{\gamma_s} - (r_i^{fin})^{\gamma_s}\right). \tag{3.24}$$

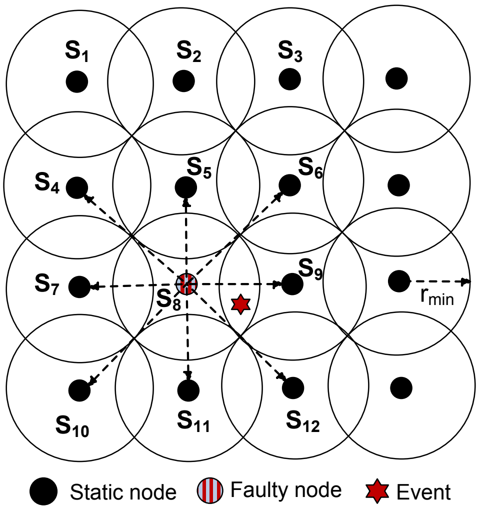
Similarly, the gain in sensing probability of sensor s_i is,

$$\Delta P^+(s_i) = p(r_i^{fin}) - p(r_i^{ini}). \tag{3.25}$$

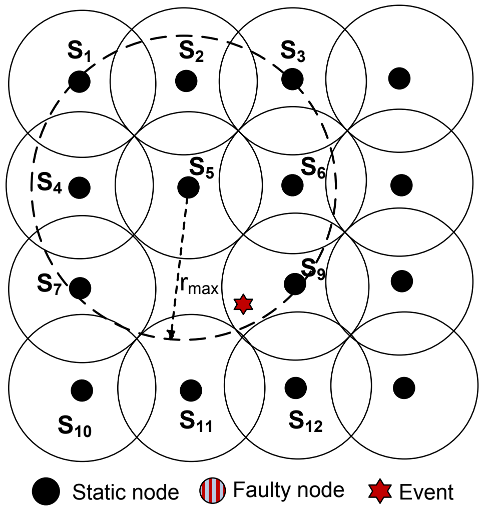
Our self-healing coverage process considers these two factors of each neighbouring node of a hole in selecting the suitable nodes whose sensing range needs to be enhanced to heal the coverage hole. The node selection scheme is described in the next section.

3.8.3.2 Self-Healing Algorithm

Upon detection of a node fault and uncovered region, our method selects one or more neighbouring nodes to enhance their sensing radii to cover the uncovered region. First, the nodes bordering a coverage hole are identified using the method described in Section 3.8.2. We call this set S_c, *the candidate set*, since one or more nodes from this set will be chosen for range enhancement. For example, $\{s_4, s_5, s_6, s_7, s_9, s_{10}, s_{11}, s_{12}\}$ is the candidate set for the hole shown in Fig. 3.14(a). Upon selection of the candidate



(a) Node failure and creation of a coverage hole



(b) Hole recovery

Figure 3.14: Self-healing algorithm for coverage hole recovery

set, a local cluster head collects the current sensing radius, lifetime and fault model parameters of each node in S_c. Using the fault model parameters and individual lifetime, the instantaneous hazard rate, $h_i(t_i)$ of node s_i, for each $s_i \in S_c$ is computed. Then the range adjustment procedure is simulated by a local cluster head by virtually selecting each subset of node as the candidate set for enhancement. The overall energy cost of adjustments in each case and the overall loss (gain) in sensing accuracy in the changed condition are computed using the probabilistic sensing model.

Let us consider $S_e \subset S_c$ is the set of nodes selected to enhance their radii in the coverage healing process. As a result of this, a set of nodes may reduce their sensing range as described earlier in Section 3.8.3.1 and let this set be S_r. Then following (3.22)-(3.25), the total gain (loss) in sensing energy consumption, TG_E and total loss (gain) in sensing probability, TL_S in such process with S_e as the selected set, is given by,

$$TG_E(S_e) = \sum_{s_j \in S_r} \Delta E_s^+(s_j) - \sum_{s_i \in S_e} \Delta E_s^-(s_i), \tag{3.26}$$

and,

$$TL_S(S_e) = \sum_{s_i \in S_e} \Delta P_s^-(s_i) - \sum_{s_j \in S_r} \Delta P_s^+(s_j). \tag{3.27}$$

The problem can be formulated as an optimisation problem expressed as:

$$\begin{aligned}
&\text{Select } S_e \subset S_c \text{ as to,}\\
&minimise\ \frac{TL_S(S_e)}{TG_E(S_e)}\\
&s.t.,\ h_i(t_i) \leq h_{th}, \forall s_i \in S_e
\end{aligned} \tag{3.28}$$

Here, h_{th} is the maximum tolerable hazard rate for a node to be selected and $h_i(t_i)$ is the hazard rate of node s_i having individual life time t_i. This constraint ensures the exclusion of highly error prone or nearly dying nodes from the range adjustment process.

The selection algorithm for our self-healing coverage is outlined in Algorithm 3.8.3.2. Steps 3-7 of this algorithm enforces the hazard rate constraint and steps 9-15 are executed for each subset of the candidate set. Step 9 simulates the range enhancement for current subset and step 10 computes all the other nodes that are affected by this range adjustment. Steps 11-14 estimates the energy-accuracy trade-off and the current best selection is saved in step 13-15. Finally, the best selected set of nodes is returned in step 17. The computational complexity of the proposed algorithm is exponential in the size of candidate set, $O(|S_c| \times 2^{|S_c|})$. However, the number of nodes in the candidate set is usually very small (typically less than seven) [30], the computation time is negligible.

At the end of this selection phase, the selected nodes are informed by the cluster head to adjust their sensing ranges. After the radius adjustment, the selected nodes and all the Voronoi-Laguerre neighbours recompute their Vor-Lag polygons and apply iterative radius reduction as explained in Section 3.8.3.1.

3.9 Performance Analysis

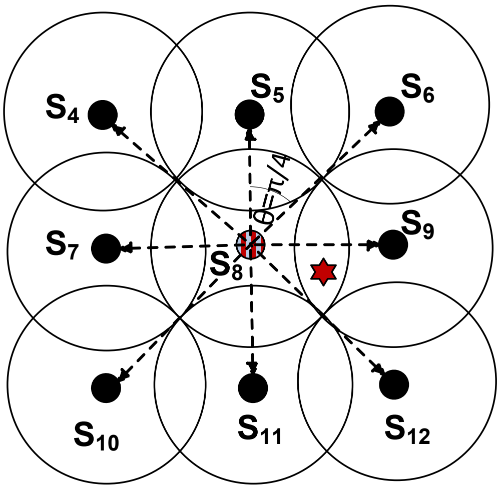
In this section we analyse the performance of the proposed method in terms of detection performance and network lifetime. It is noteworthy that both the energy consumption and detection probability depend on the sensing range of the sensors covering an event and sensing range is variable in the proposed method. To facilitate further analysis we first estimate the expected radius that a sensor maintains in its lifetime.

Algorithm 3.1: Node Selection For Hole Recovery

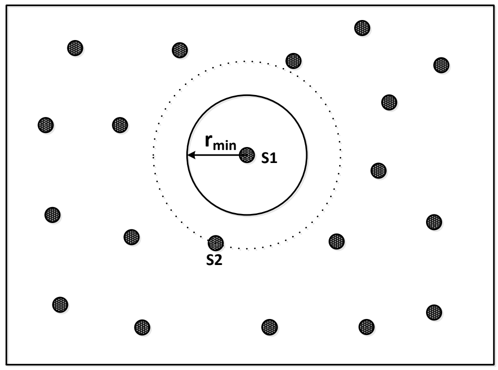
Require: S_c: set of candidate nodes
Ensure: S_e : set of selected nodes
$temp \leftarrow \infty$
$S_e \leftarrow \emptyset$
for each $s_j \in S_c$ **do**
  if $h_j(t_j) > h_{th}$ **then**
    $S_c \leftarrow S_c \backslash s_j$
  end if
end for
for each $S' \in 2^{S_c}$ **do**
  simulate radius enhancement for each $s_i \in S'$
  $S_r \leftarrow \cup_{s_i \in S'} \mathcal{N}_{VL}(s_i)$
  $TG_E(S') = \sum_{s_j \in S_r} \Delta E_s^{+}(s_j) - \sum_{s_j \in S'} \Delta E_s^{-}(s_j)$
  $TL_S(S') = \sum_{s_j \in S'} \Delta P_s^{-}(s_j) - \sum_{s_j \in S_r} \Delta P_s^{+}(s_j)$
  if $\frac{TL_S(S')}{TG_E(S')} \leq temp$ **then**
    $S_e \leftarrow S'$
    $temp \leftarrow \frac{TL_S(S')}{TG_E(S')}$
  end if
end for
return S_e

3.9.1 Average Sensing Radius

Sensing radius adjustment of a sensor is affected by two factors - the number of neighbours of a node within its R radius and the probability of one or more of those neighbours to fail. Let, the average failure rate and the number of neighbours of a node within R radius are $\bar{h}$ and n_e respectively. In case of deterministic deployment, the number of neighbour of a sensor within its communication radius can be easily calculated using the angle subtended by two consecutive neighbours to its centre. For a rectangular grid deployment shown in Fig. 3.15(a), the angle created by s_5 and s_6 to the centre of s_8 is $\theta = \frac{\pi}{4}$. For a grid deployment any two consecutive neighbours of a node maintain equal angular distance, θ in reference to its centre which gives the



(a) Neighbours placement in grid deployment.



(b) Neighbours placement in random deployment. The dotted line shows the increased sensing range of s_1

Figure 3.15: Number of neighbours, n_e of a faulty node

number of neighbours as,

$$n_e = \frac{2\pi}{\theta}. \tag{3.29}$$

However, random deployment is more common in sensor networks (Fig. 3.15(b)). To calculate the number of neighbours in such case, we consider the complete spatial randomness (CSR) as a generalised node distribution model which is a point process controlled by a density (ρ) parameter [290]. In such case, the number of neighbours within certain radius of a node depends on the deployment density. According to this distribution, the probability of finding exactly κ nodes within an area A with deployment density ρ is given by,

$$P(\kappa, \rho, A) = \frac{(A\rho)^{\kappa} e^{-(A\rho)}}{\kappa!} \tag{3.30}$$

The number of neighbours of a node can be estimated by the expected number of nodes within an area $A = \pi R^2$ centred around itself. Therefore, for random deployment, the number of neighbours of a node is estimated as,

$$n_e = \sum_{\kappa=0}^{\infty} \frac{(\pi\rho R^2)^{\kappa} e^{-(\pi\rho R^2)}}{(\kappa-1)!} - 1. \tag{3.31}$$

Lemma 1. *Given that a sensor can vary its sensing range from* r_{min} *to* r_{max}*, i.e.* $r \in [r_{min}, r_{max}]$*, and has* n_e *number of neighbours, the expected sensing radius of a node in the self-healingproof network model is given by,*

$$\begin{aligned}\bar{r} = \quad & r_{min}\left((1-\bar{h})^{n_e} \right. \\ & \left. +1-\textstyle\sum_{i=1}^{n_e}\left[1-(1-\frac{1}{n_e})^i\right]\bar{h}^i(1-\bar{h})^{n_e-i}\right) \\ & +r_{max}\textstyle\sum_{i=1}^{n_e}\left[1-(1-\frac{1}{n_e})^i\right]\bar{h}^i(1-\bar{h})^{n_e-i}.\end{aligned} \tag{3.32}$$

Proof. In the proposed method, a sensor will increase its sensing radius only when one or more of its neighbours fail and create a coverage hole, and it is selected to recover the hole. In case of one node failure, n_e nodes are eligible to repair the hole. From Fig. 3.14(a), when the node, s_8 fails, the set of eight nodes, $\{s_4, s_5, s_6, s_7, s_9, s_{10}, s_{11}, s_{12}\}$ are eligible for radius increment and recovery. In ideal case, probability of any one of them to be selected is $\frac{1}{n_e}$. Let us consider a node participating in the recovery process and the average failure rate of a node is given by $\bar{h}$. The probability of exactly one neighbour of this node to fail is $\bar{h}(1-\bar{h})^{n_e-1}$ and in consequence, the probability of this node to get selected is $\frac{1}{n_e}$. In the same way, the probability of two neighbouring node failures is $\bar{h}^2(1-\bar{h})^{n_e-2}$ and in such case, this node will be selected with a probability of $1-(1-\frac{1}{n_e})^2$. Therefore, in case of one or more failures among the neighbours, a node will be selected for range enhancement with a probability, p_h given by,

$$\begin{aligned}p_h =& \frac{1}{n_e}\bar{h}(1-\bar{h})^{n_e-1} + \left[1-(1-\frac{1}{n_e})^2\right]\bar{h}^2(1-\bar{h})^{n_e-2} + \cdots + \bar{h}^{n_e} \\ =& \sum_{i=1}^{n_e}\left[1-(1-\frac{1}{n_e})^i\right]\bar{h}^i(1-\bar{h})^{n_e-i}.\end{aligned}$$

Otherwise, not being selected in the healing process means that it will continue to operate in its normal sensing range. Similarly, in case of no node failure occurring in its neighbourhood, it will continue to operate in its normal sensing range, the probability of which is $(1-\bar{h})^{n_e}$. Therefore, the expected radius of a node is given by,

$$\begin{aligned}\bar{r} =& r_{min}(1-\bar{h})^{n_e} + r_{max}p_h + r_{min}(1-p_h) \\ =& r_{min}\left((1-\bar{h})^{n_e} + 1 - \sum_{i=1}^{n_e}\left[1-(1-\frac{1}{n_e})^i\right]\bar{h}^i(1-\bar{h})^{n_e-i}\right) \\ & + r_{max}\sum_{i=1}^{n_e}\left[1-(1-\frac{1}{n_e})^i\right]\bar{h}^i(1-\bar{h})^{n_e-i}.\end{aligned}$$

□

Considering the network coverage and connectivity model described in Section 4.2, the expected communication radius, $\bar{R}$ throughout the network lifetime will be bounded by, $\bar{R} \geq 2\bar{r}$.

3.9.2 Detection Performance Analysis

In this section, we derive the false alarm probability and detection probability of our system. According to the coverage model described in Section 4.2, k sensors collaborate in detecting an event via decision fusion. In practice, the measurement of each sensor is susceptible to an environmental noise. Since the distance from the sensed event is not same for every participating node, the effect of noise will be different on each node and so will be its individual detection capability as per (3.16). Such sensing noise can be modelled using a Gaussian distribution with 0 mean and unit variance, $\aleph_s(0,1)$. Let the event signal measured at sensor s_i be u_i and the threshold for event detection be η_d, that is a sensor considers an event as detected if the measured signal value is greater than or equal to η_d. The probability of detection, P_{d_i} for sensor s_i is then given by,

$$P_{d_i} = p(d_i) \int_{\eta_d}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-u_i)^2}{2}} dx, \tag{3.33}$$

where d_i is the estimated distance of sensor s_i from the event location and $p(d_i)$ as defined per (3.16). The false alarm probability, i.e. the probability of noise being greater than or equal to the threshold, η_d, is given by,

$$P_f = \int_{\eta_d}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx. \tag{3.34}$$

We assume the decision fusion threshold as k_1, which means at least k_1 or more sensors among the k collaborating sensors must have measured signal above the threshold before making a final decision. Similarly, false alarm in decision fusion occurs when k_1 or more sensors generate a false detection. So the overall false alarm probability is given by,

$$P_F = \sum_{i=k_1}^{k} \binom{k}{i} P_f^i (1-P_f)^{k-i}. \tag{3.35}$$

Now collaborative detection takes place when k_1 or more sensors individually detects an event after its occurrence. According to the variable range sensing model used here, the sensing probability of each node is a function of the distance from the event as shown in (3.16). Hence, the aggregated detection probability will depend on which combination of at least k_1 nodes are selected. Let $\Omega_{k,i}$ denotes the set of combinations of i sensors selected from k detecting sensors and $\vartheta \in \Omega_{k,i}$ denotes a specific combination of detecting sensors where $\vartheta(.)$ denotes the indices of the sensors. For any set of detecting sensors, ϑ, the probability of detection will be $\Pi_{j=1}^{i} P_{d_{\vartheta(j)}} \Pi_{j=i+1}^{k}(1 - P_{d_{\vartheta(j)}})$. Considering different combinations, $\vartheta \in \Omega_{k,i}$ and different number of sensors, i, (where $k_1 \leq i \leq k$), the overall detection probability after decision fusion is given by,

$$\begin{aligned} P_D = & \frac{1}{(k - k_1 + 1)} \sum_{i=k_1}^{k} \frac{1}{\binom{k}{i}} \times \\ & \left[\sum_{\vartheta \in \Omega_{k,i}} \left(\Pi_{j=1}^{i} P_{d_{\vartheta(j)}} \Pi_{j=i+1}^{k} (1 - P_{d_{\vartheta(j)}}) \right) \right]. \end{aligned} \tag{3.36}$$

Next, we determine the expected lifetime of an event detection system with self-recovery scheme. For this, we need the average sensing and communication radius of nodes modelled above as the energy consumed in sensing depends on these range.

3.9.3 Network Lifetime Analysis

As demonstrated in the energy model for variable sensing, energy consumption increases with the increased sensing and communication range. The self-healing coverage recovery technique select one or more nodes to increase their sensing radius to cover a hole created in the neighbourhood. This results into consumption of additional energy by that node from this point forward and affects the network lifetime. Therefore, the lifetime of such WSN depends primarily on three factors: i) node failure rate, ii) spatiotemporal event distribution, and iii) average sensing radius. In this section, we present an analytical model for the network lifetime considering these key factors.

1. *Event distribution*: We assume that events occur randomly and independently over the sensor field following a spatio-temporal Poisson distribution with mean λ' per unit area. Such distribution is commonly used in literature to model random and independent events [291, 292]. We assume a cluster based WSN model as demonstrated in Fig. 2.1. In this model, when an event occurs, each sensor sensing the event reports it to the local cluster head. Since each sensor

reports all events occurring within its sensing range, r, the number of events processed between 0 and T time units, follows the distribution,

$$P(M = q) = \frac{e^{-\lambda'\pi r^2 T}(\lambda'\pi r^2 T)^q}{q!} = \frac{e^{-\lambda T}(\lambda T)^q}{q!}, \tag{3.37}$$

where, $\lambda = \lambda'\pi r^2$ stands for the mean of event occurrence rate for any sensor node. In the k-coverage event detection technique, a node will always process an event which occurs within its current sensing range, r. Since a node may maintain different sensing ranges over the time, it can be assumed that a node responds to any event within its average sensing range, $\bar{r}$. The effective rate of event occurrence within the responsibility region of a sensor is then given by,

$$\lambda_k = \pi\bar{r}^2\lambda'.$$

Assuming a sensor generates a fixed number of packets to process an event, the number of packets generated by a sensor within the time interval $[0, T]$ follows the distribution,

$$P(M = m) = \frac{e^{-\lambda_k T}(\lambda_k T)^m}{m!}.$$

2. *Individual node survival time*: As mentioned earlier, we adopt the Weibull distribution as a generalised reliability model. Using (3.17) and (3.18), the survivor function becomes,

$$S(t) = exp\left[-(\frac{t}{c_w})^\delta\right],\ t > 0.$$

Therefore, $S(\tau)$ indicates the probability that a node will achieve a lifetime, τ for a given hazard model.

3. *Average sensing radius*: Both of the energy consumption and the effective event occurrence rate depend on the average sensing radius which was derived in Section 3.9.1.

Now, we first consider the lifetime of an individual sensor node based on these factors and then extend the analysis to derive the expected network lifetime. Let the idle-time sensing energy for a node is e_{idle} per unit time. The total number of events that can be processed by one sensor in its lifetime, τ is given by,

$$\phi_i = \frac{E_{in} - \tau e_{idle}}{E_s(\bar{r}_{s_i}) + E_c(\bar{R}_{c_i})}. \tag{3.38}$$

Here, E_{in} is the initial energy of a sensor node, and $\bar{r}$ and $\bar{R}$ denote the expected sensing and communication radius, respectively. We assume that all nodes have the same initial energy. The average sensing radius, $\bar{r}$ is derived in (4.11) and average communication radius, $\bar{R}$ is bounded by $\bar{R} \geq 2\bar{r}$. Now the total number of events that can be detected by a node in its lifetime eventually indicates the lifetime of a single sensor.

Theorem 1. *For an initial energy E_{in}, the conditional probability of a sensor node to achieve lifetime exceeding τ is given by,*

$$P(t_i \geq \tau | \phi_i) = S(\tau)\left(1 - \frac{\gamma(\phi_i, \lambda_k \tau)}{\Gamma(\phi_i)}\right) \tag{3.39}$$

where $\gamma(.,.)$ and $\Gamma(.)$ represent the lower incomplete gamma function and the gamma function, respectively , and are given by,

$$\gamma(a, x) = \int_0^x t^{a-1} e^{-t} dt$$

$$\Gamma(x) = \int_0^\infty t^{x-1} e^{-t} dt$$

Proof. A node can die either from energy depletion or it can incur node fault. If we consider node failure probability, the lifetime would be $S(\tau)$ as derived earlier. On the other hand, assuming node faults do not occur, the total lifetime, t_i of a sensor s_i can be computed by summing the inter-arrival delays of all the events it detects in its lifetime. Let $t_{i,j}$ be the interval between event $j-1$ and j within the range of sensor s_i. Then,

$$t_{i|\phi_i} = \sum_{j=1}^{\phi_i} t_{i,j}.$$

Since event occurrences follow a Poisson process, the inter-arrival times between consecutive events, i.e. $t_{i,j}$s are independent random variables that take an exponential distribution with mean $\frac{1}{\lambda_k}$. and expressed as,

$$f_{int}(x) = \lambda_k e^{-x\lambda_k} \tag{3.40}$$

The sum of independent and identically distributed (i.i.d.) random variables follows a gamma distribution [293]. Therefore, for a given ϕ_i, the probability density function of lifetime, t_i of a node, i can be expressed as,

$$f_{t_i|\phi_i}(x) = \lambda_k^{\phi_i} \frac{x^{\phi_i - 1} e^{-\lambda_k x}}{\Gamma(\phi_i)}, \tag{3.41}$$

Now, considering both node faults and energy depletion leads to,

$$\begin{aligned} P(t_i \geq \tau|\phi_i) &= S(\tau)\,(1 - P(t_i < \tau|\phi_i)) \\ &= S(\tau)\left(1 - \int_0^{\tau} \lambda_k^{\phi_i} \frac{x^{\phi_i-1} e^{-\lambda_k x}}{\Gamma(\phi_i)} dx\right) \\ &= S(\tau)\left(1 - \frac{\gamma(\phi_i, \lambda_k \tau)}{\Gamma(\phi_i)}\right) \end{aligned}$$

□

To estimate the network lifetime as defined in Section 3.7.4, we have to consider the individual lifetime of all the nodes deployed in the network. For random deployment over an area, ϕ_i is a random variable with pdf $f_\phi(x)$. This distribution depends on the shape of the area and energy dissipation model. Such distribution for some common shape of networks and random deployment scenario is derived in [294].

Theorem 2. *For a WSN with total N number of nodes deployed uniformly over an area of interest, $\mathcal{A}$ and all nodes having same initial energy, the probability of achieving network lifetime, $\mathcal{L}$ to be at least τ is,*

$$P(\mathcal{L} \geq \tau) = Q(\frac{\sqrt{N}(1 - \psi - \mu_l)}{\sqrt{\mu_l(1 - \mu_l)}}) \tag{3.42}$$

where,

$$\begin{aligned} \mu_l &= \textstyle\int_{\mathcal{A}} S(\tau)\left(1 - \frac{\gamma(x, \lambda_k \tau)}{\Gamma(x)}\right) f_\phi(x) dx, \\ Q(x) &= \textstyle\frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-\frac{u^2}{2}} du. \end{aligned}$$

and ψ is the lifetime threshold.

Proof. From the definition of network lifetime based on the ratio of dead nodes as stated in Section 3.7.4, the network will achieve a lifetime of at least τ if the number of individual nodes that live up to τ period of time is at least ψN. To compute the number of such nodes, let us define a Bernoulli random variable, l_i for each sensor s_i in the following manner,

$$l_i = \begin{cases} 1, & \text{if sensor } s_i \text{ achieves lifetime more than } \tau. \\ 0, & \text{otherwise.} \end{cases} \tag{3.43}$$

The success probability of l_i given ϕ_i, denoted by $p_{s|\phi_i}$ follows from (4.16),

$$p_{s|\phi_i} = P(t_i \geq \tau|\phi_i) = S(\tau)\left(1 - \frac{\gamma(\phi_i, \lambda_k \tau)}{\Gamma(\phi_i)}\right).$$

Since l_is are Bernoulli random variable, the conditional mean and variance of l_i are given by, $E[l_i|\phi_i] = p_{s|\phi_i}$ and $Var[l_i|\phi_i] = p_{s|\phi_i}(1 - p_{s|\phi_i})$, respectively. Let us define a new random variable ω to denote the number of sensor nodes that live till at least τ period of time. From the definition of l_i, ω is the sum of successes of N Bernoulli trials as described above, that is, $\omega = \sum_{i=1}^{N} l_i$. Since the event occurrences are i.i.d. according to the event model described above, l_is are also independent and identically distributed random variables. Therefore, by definition, ω follows a Binomial distribution, $B(N, p_s)$. The number of sensor nodes is usually large in a typical WSN. According to Central Limit Theorem [293], the Binomial distribution can be approximated with a Gaussian distribution for large N. This leads to the following probability distribution function of ω,

$$f_\omega(x) = \frac{1}{\sqrt{2\pi}\sigma_\omega} e^{-\frac{(x-\mu_\omega)^2}{2\sigma_\omega^2}} \tag{3.44}$$

where μ_ω and σ_ω are the mean and variance of ω, respectively. From the definition of ω, its mean and variance can be calculated from unconditional mean and variance of l_i. The unconditional mean and variance of l_i, denoted as μ_l and σ_l^2 can be calculated using its conditional mean and variance [293] as follows,

$$\begin{aligned} \mu_l = E[l_i] &= E[E[l_i|\phi_i]] = E[p_{s|\phi_i}] \\ &= \textstyle\int_{\mathcal{A}} p_{s|x} f_\phi(x) dx, \end{aligned}$$

which leads to,

$$\mu_l = \int_{\mathcal{A}} S(\tau) \left(1 - \frac{\gamma(x, \lambda_k \tau)}{\Gamma(x)}\right) f_\phi(x) dx, \tag{3.45}$$

and,

$$\begin{aligned} \sigma_l^2 = Var[l_i] &= E[Var[l_i|\phi_i]] + Var[E[l_i|\phi_i]] \\ &= E[p_{s|\phi_i}(1 - p_{s|\phi_i})] + Var[p_{s|\phi_i}] \\ &= E[p_{s|\phi_i}] - (E[p_{s|\phi_i}])^2, \end{aligned}$$

which follows from the fact that, $E[x + y] = E[x] + E[y]$ and $Var[x] = E[x^2] - (E[x])^2$. Therefore,

$$\sigma_l = \sqrt{\mu_{l_i} - \mu_{l_i}^2}. \tag{3.46}$$

Since, ω is a sum of l_is and l_is are i.i.d. random variables, $\mu_\omega = N\mu_l$ and $\sigma_\omega^2 = N\sigma_l^2$. Now,

$$\begin{aligned} P(\mathcal{L} \geq \tau) &= P(\omega \geq (1 - \psi)N) \\ &= \int_{(1-\psi)N}^{\infty} \frac{1}{\sqrt{2\pi}\sigma_\omega} e^{-\frac{(x-\mu_\omega)^2}{2\sigma_\omega^2}} dx \end{aligned}$$

Network Parameters	
Number of sensor	[200, 500]
Minimum sensing radius, r_{min}	10m
Maximum Sensing radius, r_{max}	25m
Area of Interest	200x200 m^2
Sensing prob. decay factor,	γ_1=0.09, γ_2=0.81
Dead node ratio for network life, ψ	0.4
Energy Parameter	
Initial Energy, E_{in}	$2J$
Energy consumption model	cubic law

Table 3.1: System parameters for simulation

Substituting $\frac{(x-\mu_\omega)}{\sigma_\omega} = u$, the above can be written as,

$$\begin{aligned} P(\mathcal{L} \geq \tau) &= \frac{1}{\sqrt{2\pi}} \int_{\frac{\sqrt{N}(1-\psi-\mu_l)}{\sqrt{\mu_l(1-\mu_l)}}}^{\infty} e^{-\frac{u^2}{2}} du \\ &= Q(\frac{\sqrt{N}(1-\psi-\mu_l)}{\sqrt{\mu_l(1-\mu_l)}}) \end{aligned}$$

□

Having analysed the characteristics of our proposed approach, in the following section, we evaluate its performance both theoretically and through simulation.

3.10 Performance Evaluation

The performance gain of dynamic fault recovery technique using variable sensing radius is two-fold. First, it provides the performance guarantee of full k-coverage for longer period of time during the operation. It does not require an additional set of sensors to activate on hole detection which is desirable from economic and deployment perspective. At the same time it achieves better network lifetime compared to other models where all the nodes operates in fixed sensing range all the time. In this section, we analyse the theoretical results and compare those with the simulation results.

We designed our simulation using the network simulator $ns-3$ and derived the theoretical results using MATLAB. We developed and incorporated the variable radius model described in this Section 3.16 to ns-3 platform and conducted a series of event detection tasks by varying the sensing range of sensors dynamically to recover from coverage holes as per Algorithm 1. The events are generated using a Poisson process of rate $\lambda = 1/hour$. Each simulation was run 100 times and averaged results are presented in this section. Simulation parameters are formally listed in Table 4.1.

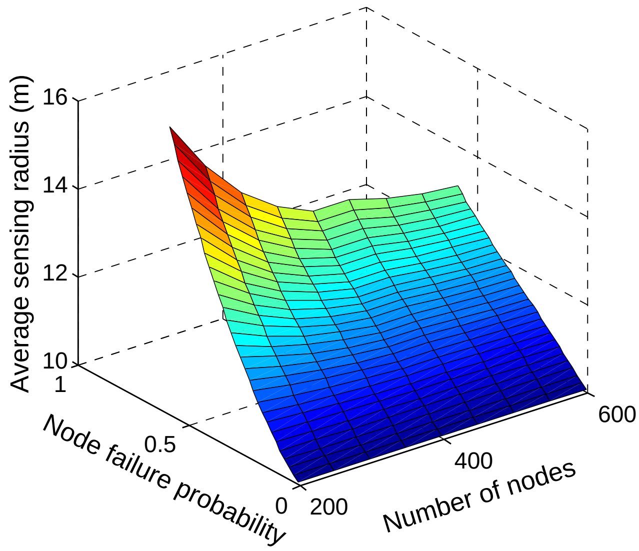


Figure 3.16: Theoretical values for average sensing radius ($\bar{r}$) vs. node fault probability (k) and number of nodes deployed (N).

First, to verify our theoretical findings, we compare the analytical values of average sensing radii and lifetime derived in Section 3.9.3 with our simulation results. Fig. 3.16 plots the analytically derived average sensing radius for different values of average node fault probability and number of nodes. It shows that average sensing range remains close to the minimum sensing range for moderate node fault probability ($< 40\%$). Even at 40% node failure rate, our method will ensure successful recovery by extending the sensing range by only $2m$ on an average. The left hand side corner corresponds to the scenario of high node fault probability to be recovered with low number of nodes. The plot indicates that, in such case, nodes need to operate at more than half of the maximum sensing range ($\sim 16m$). However, even in such case, certain energy saving will be ensured as the average sensing range is still much lower than the maximum range. Fig. 3.17, shows how the average sensing radius increases with higher node failure rates. It is interesting to note that the average radius is much lower in case of higher degree of coverage, $k = 4$ than in the case with $k = 3$. This is a significant characteristic of

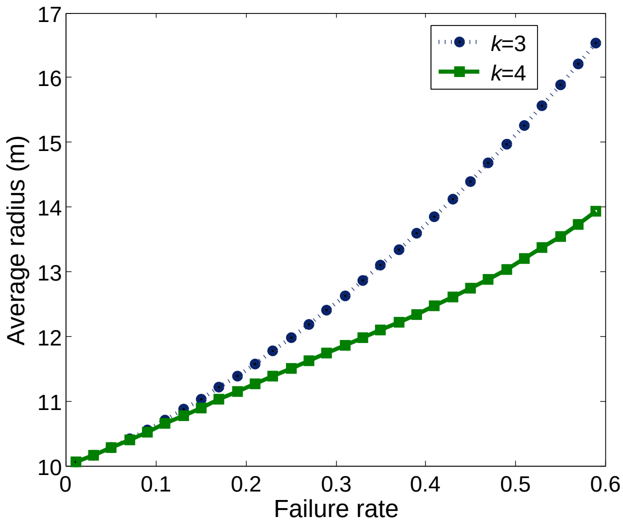


Figure 3.17: Theoretical values for average sensing radius ($\bar{r}$) for different k and different node failure rates.

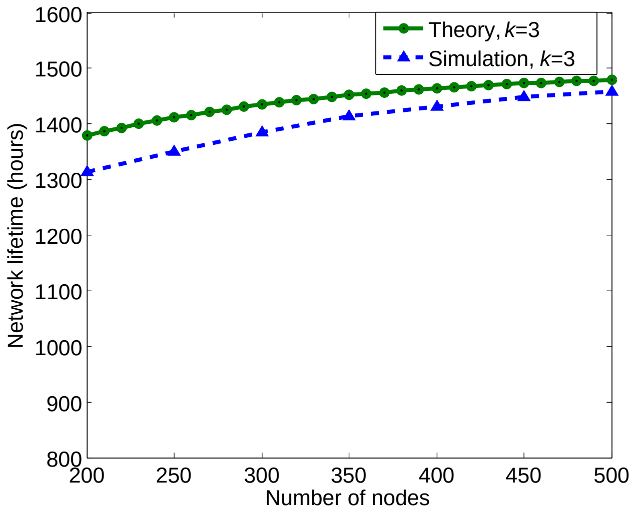


Figure 3.18: Lifetime comparison between theoretical value vs simulation result at 20% node failure rate.

our method as it ensures better performance with respect to sensing energy in higher node density. Since, sensing range of a node is usually characterised by isotropic sensing around the node, when a node increase its range to recover from one hole, it also creates unnecessary overlapping in other sides. It is evident from the Fig. 3.17 that our scheme exploits this overlapping and the cascading range reduction described in Section 3.8.3 results in reduced sensing range increment in high node density. Fig. 3.18 plots the analytical value for expected lifetime along with the average lifetime achieved in the simulation for a certain degree of coverage ($k = 3$). The simulation result shows close match with the theoretical values, especially in high node density.

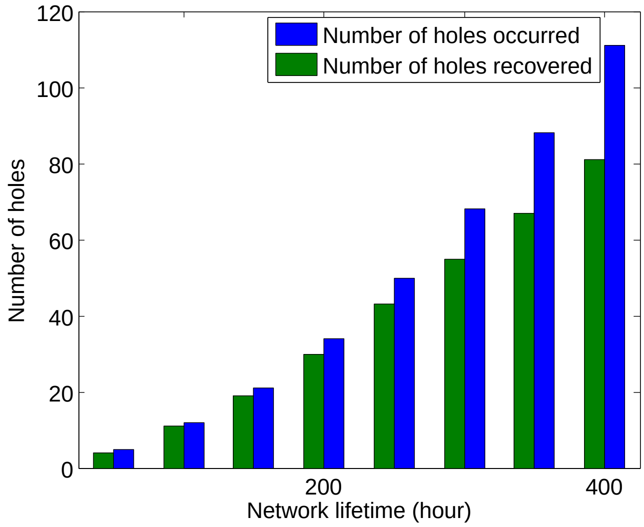


Figure 3.19: Hole recovery performance

Figure 3.19-3.22 provides the simulation results. The dynamic hole detection and recovery performance of the proposed scheme is shown in Fig 3.19. It plots the total number of holes created in the whole sensor field against the number of holes dynamically recovered by our scheme. The figure shows that majority of the holes are recovered. The fact that some holes are left uncovered is because of the random deployment. Some holes exist that can not be triangulated by the neighbouring nodes and can not be detected without central coordination and location aware services. The number of such unrecoverable holes increases with time as node failure rate increases with time according to our Weibull fault model with $\beta > 1$ and more unrecoverable holes are created. However, the overall percentage of recovery is still above 90% in almost all cases. The

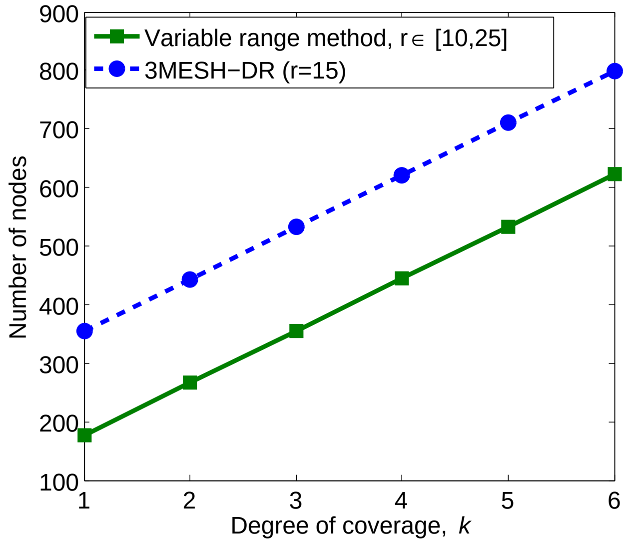


Figure 3.20: Comparison of the required number of nodes to enable coverage hole recovery in our method and 3MESH-DR method [248]

economic perspective of our scheme is established by comparing the number of nodes required in our method and in the *triangular mesh distributed hole recovery (3MESH-DR)* method proposed in [248] in Fig. 3.20. 3MESH-DR scheme assumes the presence of redundant nodes all over the network and activates them to recover holes during the operation. This requires the number of nodes for one additional degree of coverage to be in reserve. Fig. 3.20 evidences that our method requires lower number of nodes for same degree of coverage as it eliminates the need for additional redundant number of nodes in reserve. This results in much lower deployment cost in fault recovery scheme.

The overhead cost of fault recovery techniques using mobile nodes is presented in Fig. 3.21 and 3.22 in terms of recovery time and energy. We compared the time to recover from a detected node fault in our method and the mobility assisted coverage optimisation method described in [295]. In [295], holes are detected and healed in the post deployment scenario by relocating nodes to the coverage holes. The energy and mobility parameters are taken from [295] for fair comparison. Fig. 3.21 shows that the time required to recover from holes is much higher in the mobility based method due to limited movement speed. Although, the time decreases with high node density, it still is not suitable for event detection method. On the other hand, our variable range scheme maintains a constant recovery time which is nearly zero as enhancing sensing

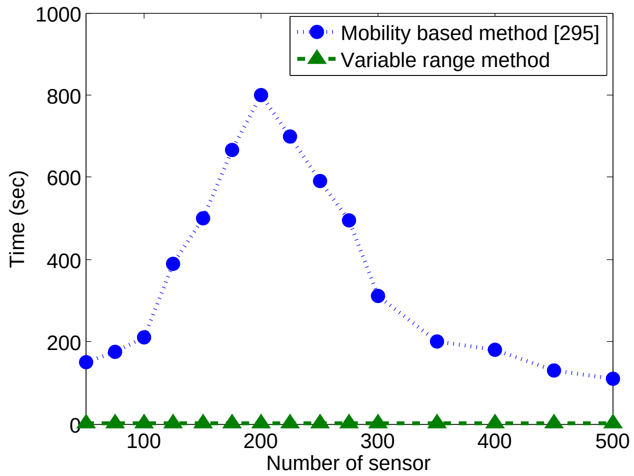


Figure 3.21: Comparison of the time required for successful hole recovery using node mobility [295] and the proposed range adjustment method

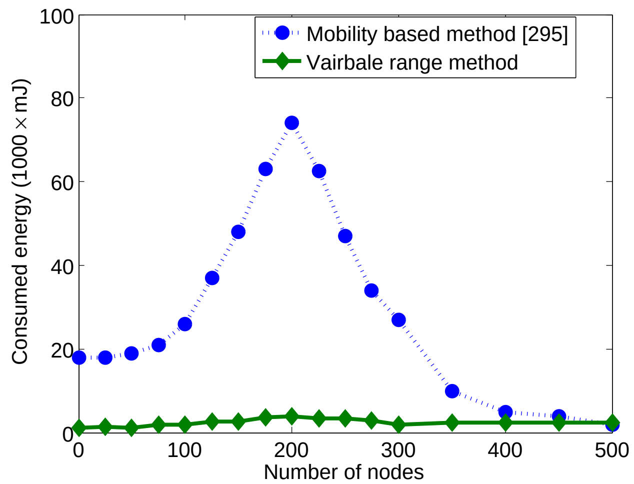


Figure 3.22: Comparison of energy consumption between variable range recovery and mobile node recovery [295]. Combined energy spent in sensing, communication and mobility.

range does not take up any significant time. Fig. 3.22 plots the energy requirement in the coverage healing process in two methods. Our method consumes much less energy than the method in [295] as the energy spent for sensing with enhanced range is much less than the energy spent for node relocation.

3.11 Conclusion

In this chapter, first we presented an analytical model to determine the appropriate degree of coverage that ensures a given set of QoS metrics at the deployment time. Then we extended the scheme by introducing the idea of distributed fault recovery technique employing variable range sensing in WSNs. We developed a geometry based scheme to make such technique applicable considering the key issues in fault-tolerant event-centric WSNs such as detection performance, instantaneous failure rate and energy consumption. Simulation results show the effectiveness of our approach yielding enhanced network lifetime and improved fault recovery technique compared to traditional fixed range sensing used in static coverage or dynamic coverage using mobile nodes. The scheme is easily implementable due to its distributed nature. However, the k-coverage schemes discussed in this chapter still require a large number of nodes to be deployed to ensure redundant coverage and required detection performance. In the following chapters, we will overcome this by introducing dynamic event coverage techniques.

Chapter 4

Dynamic Event Coverage

In the previous chapter, we introduced redundant degree of coverage in WSN to ensure robust detection from unreliable sensor readings while conserving energy using distributed detection. However, increased deployment cost and energy limitation make such approach unrealistic as the number of required static sensor nodes grows prohibitively large to maintain desired level of fault tolerance and accuracy. In this chapter, we explore two potential solutions to overcome such limitation - one using the variable range sensing and the other employing mobile nodes.

4.1 Dynamic Coverage Using Variable Range Sensing

The trade-off between detection performance and energy consumption is still a fundamental challenge in event centric WSNs. Though traditional cheap tiny sensors consume most energy for communication purpose only, new generation sensors are multimodal equipped with camera, radar, sonars or infrared which consume significant amount of energy for sensing as well. These new generation sensors, being increasingly smarter and sophisticated, are also costly. The higher cost and energy consumption makes redundant (i.e, static k) coverage cost prohibiting and environmentally unfavourable due to increasing carbon footprint. This motivates the research community towards providing redundant coverage not by maintaining a permanent k-coverage all the time but, only to provide redundancy in an on-demand basis. On-demand coverage refers to the technique of providing instantaneous k-coverage only after an event is detected by at least one sensor. Here, we exploit the concept of adjustable sensing radius to handle this trade-off between deployment cost, energy requirement and event coverage.

Exploiting variable range sensing technology, we propose the idea of on-demand k-coverage for event detection using static nodes with adjustable sensing range. The main idea is to guarantee redundant coverage for event dynamically while ensuring 1-coverage at the time of the deployment. In such setting, each sensor works in its lower end of sensing limit leaving the provision for increasing the sensing range later when necessary. During the operation, as soon as a node detects an event, it requests its neighbours to collaborate. A selected set of neighbour nodes then increase their sensing ranges temporarily to ensure redundant coverage for that event. Event detection is then accomplished via local decision fusion among these selected nodes. The proposed on-demand k-coverage scheme ensures instantaneous k-coverage without having to deploy a large number of nodes. It saves sensing energy operating at the minimum range during normal operation.

There are several challenges to overcome before the above idea of event detection system with variable range sensor technology can be made workable. Noting that detection accuracy and energy consumption (i.e., network lifetime) remain the key aspects to ensure, the challenges are:

- For an specific event location, determination of the set of sensors that need to adjust sensing range and the extent of adjustment required to yield expected detection performance with minimum energy consumption.
- Since the capability to adjust the sensing range is limited, the network topology and sensor density should be maintained in such a way as to make the on-demand coverage feasible.
- Increasing sensing radius involves increased energy consumption according to the sensing model described in Section 3.7.3. Hence, the sensor selection process needs to ensure balanced energy consumption among sensors to yield a improved network lifetime.
- To make such system scalable, the on-demand k-coverage scheme needs to be distributed. This involves a local collaboration and decision making among the sensors.

In this work, we deal with these challenges using a greedy approach for distributed sensor selection and an analytical model to outline sensor deployment. To the best of our knowledge, this is the first work to exploit the benefits of variable sensing range technology to provide on-demand k-coverage in event-centric WSNs with only static sensors. Our contributions are-

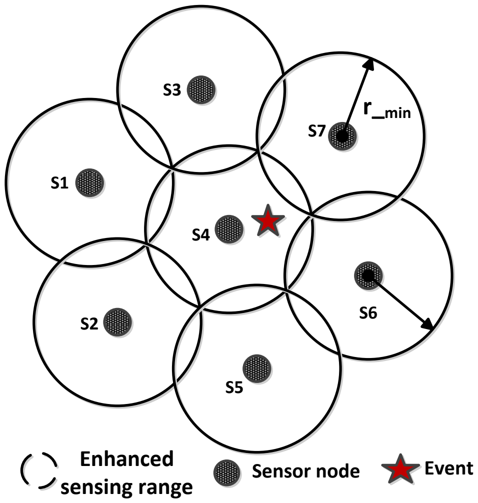
- Mission oriented on-demand k-coverage for event detection by adjusting the sensing range of static nodes.
- Decentralised sensor selection algorithm to ensure joint optimisation of energy consumption and detection performance.
- Analytical model to guide the sensor deployment strategy to facilitate the effective implementation of variable sensing radii technique in real world applications.
- Lifetime analysis of the proposed detection scheme considering the variable sensing range.

4.2 System Model

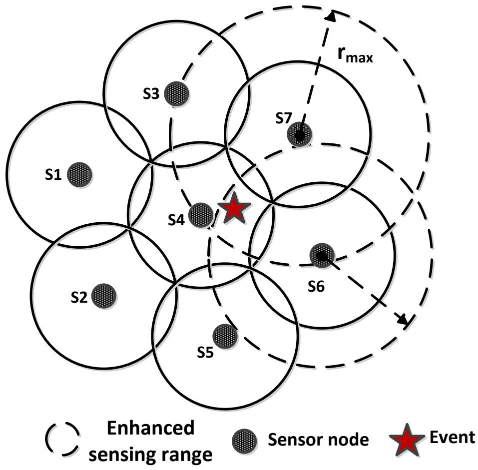
The main components of the system model for this scheme, namely variable sensing and transmission, probabilistic detection model, energy consumption model, and WSN lifetime definition were introduced in Section 4.2. The event coverage model for on-demand k-coverage using variable range sensing and the event occurrence model to facilitate the performance analysis are described in the following.

4.2.1 Event Occurrence Model

In an event driven network, sensors sense the environment for event and transmit the information to sink when an event of interest occurs. We assume that events occur randomly and independently over the sensor field following a spatio-temporal Poisson distribution with mean λ' per unit area. Such distribution is commonly used in literature to model random and independent events [291, 294, 296]. We adopt a local decision fusion based detection model. In this model, after an event has occurred, each sensor detecting the event participates in the local decision fusion. Since each sensor



(a) 1-coverage (Normal scenario)



(b) k-coverage (Event occurred)

Figure 4.1: On demand event coverage for enhanced detection performance

reports all events occurring within its sensing range, r, the number of events processed between 0 and T time units, follows the distribution,

$$P(M = m) = \frac{e^{-\lambda'\pi r^2 T}(\lambda'\pi r^2 T)^m}{m!} = \frac{e^{-\lambda T}(\lambda T)^m}{m!}, \tag{4.1}$$

where, $\lambda = \lambda'\pi r^2$ stands for the mean of event distribution within the sensing disk of a sensor node.

4.2.2 Event Coverage Model

Let us consider a WSN consisting of a set of N sensor nodes deployed over the area of interest to provide 1-coverage in the sensor field. In our approach, full k-coverage is not assumed all the time. Rather, the number of nodes deployed over the sensor field is sufficient enough to provide static 1-coverage. To ensure such goal, the number of sensors, N is determined according to (2.10). This means the network will be at least 1-covered throughout its lifetime. Deployment guideline for this 1-coverage is presented in Section 4.3.3. After an event has occurred, at least one sensor detects the event and broadcasts the occurrence of the event to all its neighbouring nodes. If more than one node sense the same event, they are within each other's communication range and it can be locally decided which sensor senses the strongest signal. The node with the strongest signal initiates collaborative detection phase and here after referred as the *initiating node*. Additional $(k-1)$ number of nodes then adjust their sensing range (if necessary) to provide dynamic k-coverage.

Consider the scenario presented in Fig. 4.1(a) which shows an area 1-covered by sensors and each sensor operating in its normal sensing range (r_{min}) indicated by the solid circle around it. Suppose, an event occurs within the sensing range of $s4$. According to (3.16), the event will be detected by s_4. Now to increase the reliability of detection, additional sensor nodes are required to cover the event. Let us consider 3-coverage is required in this case. Based on the sensor selection technique demonstrated in Section 4.3, sensors s_6 and s_7 are selected and they increase their sensing ranges to provide dynamic 3-coverage for the event as shown in Fig. 4.1(b). The extended sensing ranges are shown by the large concentric dashed circles around s_6 and s_7. Now each of the three sensors (s_4, s_6, s_7) measures the event signal and the final detection decision is taken via decision fusion. In this scenario, node s_4 is the *initiating node*. The set of nodes that can extend their sensing ranges up to r_{max} to cover an event is called the *candidate set*. In Fig. 4.1, the set of nodes $\{s_1, s_2, s_3, s_5, s_6, s_7\}$ comprises the candidate set.

Since our WSN is 1-covered during the normal time, it is important to facilitate decision fusion among nodes that will make dynamic k-coverage possible for events. To ensure on-demand k-coverage using variable sensing radii, we need to maintain a certain ratio between sensing radius, r and communication radius, R to ensure network connectivity. In 1-coverage scenario, the connectivity requirement is that any node should be within the communication range of one or more active nodes so that all nodes can form a connected communication backbone, while any point in the coverage region to be within the sensing range of at least one node. As established in [30, 33], for a set of nodes that at least 1-cover a convex region, the connectivity in communication is guaranteed if, $R \geq 2r$. Our on-demand coverage model maintains this relationship by adjusting the communication radius according to the enhancement the sensing radius.

4.2.3 QoS Aware Degree of Coverage (k)

The focus of this work is not determining the required degree of coverage to attain certain performance goal. In the previous chapter we derived an analytical model that suggests an optimal value of k satisfying the requirement of an event detection application. Here we assume that, the required degree of coverage (k) is known *a priori* depending on the type and purpose of the event detection application. Our proposed method achieves the detection performance by ensuring the same required degree of coverage on-demand through adjusting the sensing range.

4.3 On Demand k-coverage Model

As described in Section 4.2.2, on-demand k-coverage technique does not maintain a full k-coverage ($k > 1$) all the time. It exploits the variable sensing range capabilities of a sensor to provide dynamic k-coverage after an event has occurred. The key idea is to reduce cost and achieve energy efficiency while at the same time maintain reliable and accurate detection. From the discussions in the previous chapters, we know that the contribution of each additional node in improving detection accuracy diminishes gradually with the increment of spatial redundancy. From Fig. 4.1(b), it is evident that there can be more than k nodes in the *candidate set*. The actual number of sensors in the candidate set depends on the deployment strategy, network topology and communication radius. The problem of on-demand k-coverage with variable sensing radius is to determine the sensor set that yields the maximum detection performance with minimum energy consumption for an specific event.

4.3.1 Problem Formulation

Let us consider s_j^* is the initiating node for an event and $S_c = \{s_1, s_2, ..., s_n\}$ is a set of n candidate sensors as defined in the previous section. To achieve on demand k-coverage, a set $S_e' \subseteq S_c$ with $(k-1)$ nodes needs to be selected in such a way that the set of nodes, $S_e = S_e' \cup \{s_j^*\}$ minimises the energy consumption and maximises the aggregated detection probability. Let us define the cost function,

$$\digamma(S_e) = \frac{\sum_{s_i \in S_e} [E_s(r_{s_i}) + E_c(d(s_i, s_j^*))]}{\zeta(S_e)}, \tag{4.2}$$

where,

$d(s_i, s_j^*)$ is the distance from node s_i to node s_j^*

$E_s(r_{s_i})$ denotes the sensing energy consumption with increased sensing radius r_{s_i} of node s_i,

$E_c(d(s_i, s_j^*))$ is the energy required for communication between node s_i and s_j^*, and

$\zeta(S_e)$ is the estimated detection probability achievable by the subset of nodes, S_e. This value is estimated by the initiating node by considering the potential participating nodes in S_e. This can be done by estimating the expected probability of detection of the event by individual nodes and predicting the outcome of fusion of those individual detections. A number of fusion rules were discussed in Chapter 2. In Section 4.3.4, we present a theoretical analysis for estimating detection probability by individual nodes as well as 'n out of k' decision fusion technique, which is used to calculate $\zeta(S_e)$.

$\digamma$ gives the normalised cost of accuracy in terms of energy, i.e., hypothetically, $\digamma(S_e)$ stands for the average energy consumption per unit accuracy achieved by the collaboration of the set of nodes in S_e.

Let $E_{rem}(s_i)$ denotes the remaining energy of a node s_i at a given time. The problem can now be formulated as the selection of subset of nodes from the possible candidate nodes around an event. For a set of candidates S_c, select $S_e \subseteq S_c$ such as to,

$$\begin{aligned}
&minimise\ \digamma(S_e)\\
&s.t.,\ E_s(r_{s_i}) + E_t(d(s_i, s_j^*)) < E_{rem}(s_i), \forall i \in S_e\\
&\zeta(S_e \setminus s_i) < \zeta(S_e) \text{ and } \zeta(S_e) > 0, \forall s_i \in S_e
\end{aligned}$$

The first constraint enforces that the selected sensors has adequate remaining energy to carry out the detection task and the second constraint ensures that no redundant sensor is added to the set S_e.

4.3.2 On Demand k-Coverage Algorithm

In this section we present the energy-accuracy aware node selection for on demand k-coverage using variable sensing radii. From our network model described in Section 4.2.2, it is evident that an event will always lie within the minimum sensing range (r_{min}) of at least one sensor first and then additional neighbouring sensors may increase their radius to cover the event as needed. The initiating node co-ordinates the whole process of on demand event coverage. All the nodes within its communication range are the possible candidates to adjust their radius. A two way message passing between the initiating node and neighbours takes place to determine the sensors in such a way as to minimise the energy consumption and maximise the collaborative detection performance as per (4.2).

First, the node detecting the event estimates the approximate event distance relative to its own location information available via GPS or any other localisation method available [289]. Then it sends a reinforce request to all the neighbouring sensors within its communication range. Each node receiving the request replies acknowledging its availability along with its current remaining energy level and location information. The initiating node then estimates the amount of energy to be consumed for each node if that corresponding node is included in the detection process.

The node selection task is accomplished in an iterative and incremental manner employing greedy approach. In each pass, our algorithm selects one node from the set of the candidate nodes. Initially, the initiating node is the only member in the target set, S_e (steps 1-2 of Algorithm 4.2). The algorithm runs for $(k-1)$ iterations to select a new node at each pass greedily (steps 3-7). At $i-$th iteration, the node, $\nu^{(i)}$ that contributes the most in minimising the cost function in (4.2), is selected as follows,

$$\nu^{(i)} = \arg_{s_j \in S_c}\{\min \mathcal{F}(S_e \cup \{s_j\})\}.$$

The process in Algorithm 4.2 returns the sensor set, S_e that participates in dynamic event coverage and collaborative detection by adjusting the sensing range of its members. After this selection phase, the initiating node notifies the selected nodes. Upon receiving this notification, each selected node starts increasing its sensing radius and stops when it can sense the specific event. After the sensing range adjustment, those nodes also increase their communication ranges to maintain the relationship, $R \geq 2r$, that is, the connectivity requirement. The collaborative detection of event is accomplished by the decision fusion among these participating sensor nodes (Section 4.3.4). Once the detection task is completed, participating nodes return back to their normal range.

The computational complexity of the proposed algorithm is $O(|S_c|^2)$. Since the number of nodes in the candidate sets is usually very small (typically around seven) [31, 243], the computation time is negligible.

Before moving on to the detection performance and network lifetime analysis, we provide a deployment guideline for variable range on-demand event coverage in the next section for both deterministic and random deployment scenario.

Algorithm 4.1: Greedy On Demand Node Selection

Input: S_c: set of candidate nodes
Output: S_e : set of selected nodes

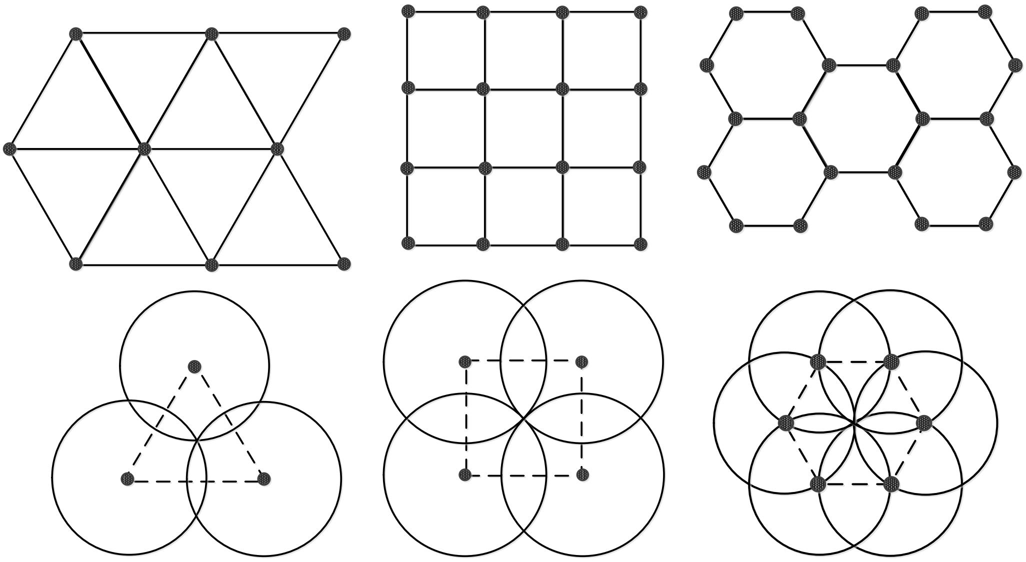
$S_e \leftarrow \emptyset$
$S_e \leftarrow S_e \cup \{initiating\ node\}$
for $i = 1$ to $k - 1$ **do**
  $\nu^{(i)} = \arg_{s_j \in S_c}\{\min \mathcal{F}(S_e \cup \{s_j\})\}$
  if $\mathcal{F}(S_e \cup \{\nu^{(i)}\}) > \mathcal{F}(S_e)$ **then**
    $S_c \leftarrow S_c \setminus \{\nu^{(i)}\}$
    $S_e \leftarrow S_e \cup \{\nu^{(i)}\}$
  end if
end for
return S_e

4.3.3 Node Placement for Variable Range Sensing

The deployment strategy and topology of the sensor network play an important role in the practical implementation of our proposed technique. In reality, the possible enhancement in sensing radius is limited by device capability and energy. In most cases, any node can extend its range to mostly cover the area monitored by its immediate neighbours. Fig. 4.2 illustrates that the overlapping area between the neighbouring nodes are different in different node arrangements. It is evident that larger overlapping during initial deployment will require smaller increment in sensing radius to cover the immediate neighbours when necessary. As such, the probability of providing effective coverage depends on the network topology. The relationship between the maximum sensing range and such overlapping needs to be known before deployment to make on-demand k-coverage technique applicable. The amount of overlapping required for effective on-demand coverage depends on the maximum achievable sensing range of the device. To express the capability of sensing range adjustment of a sensor, we define the sensing radius *Adjustment ratio*, υ_r,

Definition 1. *The sensing radius adjustment ratio of any node is the ratio of its maximum and minimum sensing radius which, in turn, determines the percentage of the additional area that can be covered by radius adjustment.*

$$Adjustment\ ratio, \upsilon_r = \frac{r_{max}}{r_{min}}. \tag{4.3}$$



(a) Triangle lattice (b) Square lattice (c) Hexagonal lattice

Figure 4.2: Different type of grid deployment

Now, we derive the relationship between the adjustment ratio and network topology for both deterministic and random deployment scenario that will guide the deployment process.

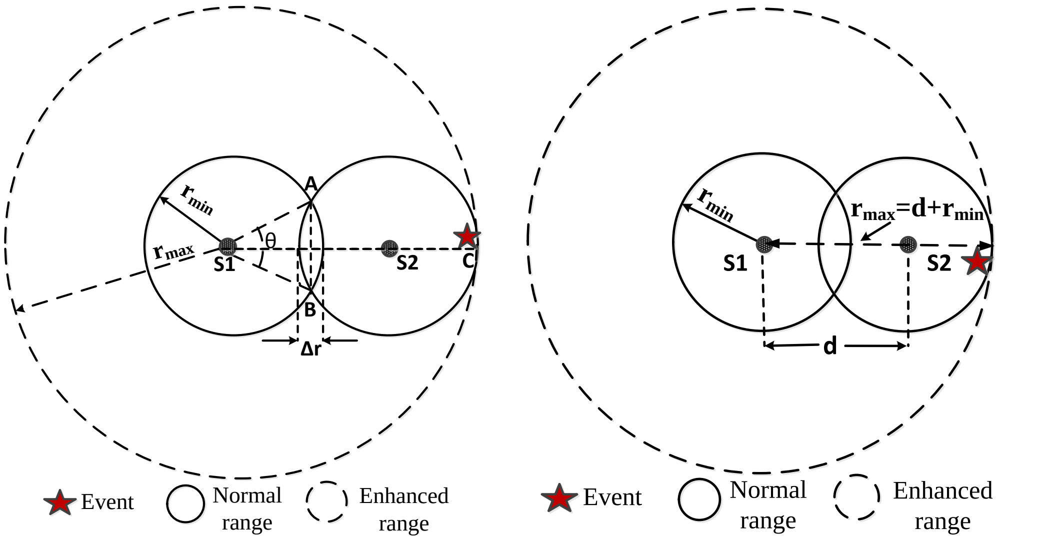
4.3.3.1 Deterministic deployment

From Fig. 4.2, we see that the triangular grid yields the least overlapping area while the hexagonal grid results in the most overlapping among the given three scenarios. The overlapping among the immediate neighbours can be characterised by the angle subtended by the chord of intersection between two sensing disks to the centre of the disk. Consider the two sensors with intersecting sensing disk in Fig. 4.3(a). Clearly, the percentage of overlapping is determined by the angle, θ. For such deterministic deployment the required adjustment ratio is given by the following lemma.

Lemma 1. *Assuming a deterministic grid deployment and known adjustment ratio, υ_r, the deployment should be such that the angle subtended by the intersecting chord of overlapping sensing disks is bounded as,*

$$\theta \geq 2\cos^{-1}\left(\frac{\upsilon_r - 1}{2}\right).$$

Proof. Without loss of generality, we consider the triangle lattice for grid deployment here. Let us consider two sensors $s1$ and $s2$ operating in their normal sensing range (r_{min}) and sharing an overlapped region as shown in Fig. 4.3(a). θ is the angle subtended by the intersecting chord AB to the centre of $s1$. Now, to provide on-demand



(a) Intersecting sensing disks and sensing range increment of s_1 to cover event detected by s_2

(b) Sensing range increment for the worst case location

Figure 4.3: Probabilistic sensing model

coverage to an event primarily sensed by $s2$, $s1$ needs to extend its sensing radius to the point when it can sense the same event within $s2$'s disk. In the worst case scenario, this enhancement may extend up to the farthest point, C on $s2$'s perimeter from the centre of $s1$. This maximum sensing radius, r_{max} of $s1$ depends on the width of the intersection lens between these two disks as denoted by Δr in Fig. 4.3(a).

From figure, it is obvious that,

$$\Delta r = 2r_{min}(1 - \cos\frac{\theta}{2}).$$

Therefore, maximum sensing radius required will be,

$$r_{max} \geq 3r_{min} - \Delta r = r_{min}(1 + 2\cos\frac{\theta}{2}), \tag{4.4}$$

leading to,

$$\frac{r_{max}}{r_{min}} \geq (1 + 2\cos\frac{\theta}{2}).$$

Rearranging,

$$\theta \geq 2\cos^{-1}\left(\frac{\upsilon_r - 1}{2}\right).$$

□

The relationship holds for any other grid deployment strategy. Now the maximum and minimum sensing ranges are supposed to be known for any specific type of device. Therefore, the appropriate deployment strategy can be guided by the adjustment ratio using its relationship with θ.

4.3.3.2 Random deployment

For random deployment, we consider the complete spatial randomness (CSR) which is a point process modelled by the density (ρ) parameter [290]. In such case, the overlapping region among the sensors and consequently the required adjustment ratio depends on this density. Since the accurate estimation of overlapping in case of complete spatial randomness is not possible, we propose an probabilistic approximation of the actual measure.

Lemma 2. *Assuming complete spatial randomness during deployment and known adjustment ratio, the required deployment density is bounded by,*

$$\rho \geq \frac{1}{r_{min}^2 \left(\upsilon_r - 1\right)^2}.$$

Proof. As explained before, the maximum required sensing radius for a node depends on the distance of any event occurred on its neighbour nodes sensing disk. Consider a node s_1 and its nearest neighbour s_2 (Fig. 4.3(b)). To cover an event that occurs within the sensing disk of s_2, s_1 has to increase its radius up to the point when it can sense the same event too. In the worst case, the maximum sensing range required to cover an event detected by a neighbouring sensor requires extending the radius to completely cover the neighbour's sensing disk as shown in Fig. 4.3(b). So we need to determine the average distance from a sensor to its nearest neighbour. From the definition of complete spatial randomness [290], the probability of presence of $l - th$ neighbour of any node at a radial distance, d is given by,

$$P_l(d) = \frac{2\pi^l \rho^l d^{2l-1} e^{-\pi\rho d^2}}{(l-1)!} \tag{4.5}$$

The expected distance from the centre of s_1 to the centre of its immediate nearest neighbour, s_2 can be found by putting $l = 1$ in 4.5 as,

$$E[d] = \int_0^\infty x P_l(x) = \int_0^\infty 2\pi\rho x^2 e^{-\pi\rho x^2} dx \tag{4.6}$$

Using the result of the Gaussian integral of the following form,

$$\int_0^\infty x^n e^{-ax^2} dx = \frac{(n-1)!!}{2^{n/2+1} a^{n/2}} \sqrt{\frac{\pi}{a}}, \text{ for } n \text{ even,} \tag{4.7}$$

the integral in (4.6), evaluates to

$$E[d] = \frac{1}{2}\sqrt{\frac{1}{\rho}}.$$

This means, in case of random deployment, a node may have to increase its range up to $E[d] + r_{min}$ distance. Therefore, the required maximum radius is given by,

$$r_{max} \geq \frac{1}{2}\sqrt{\frac{1}{\rho}} + r_{min},$$

leading to,

$$\upsilon_r \geq \frac{1}{2r_{min}}\sqrt{\frac{1}{\rho}} + 1.$$

Rearranging this,

$$\rho \geq \frac{1}{r_{min}^2 (\upsilon_r - 1)^2}.$$

□

Therefore, having known the maximum and minimum sensing radius *a priori*, the appropriate node density for random deployment can be determined in Lemma 2.

The above-mentioned deployment guidelines provide the minimum required overlapping of sensor coverage (in case of deterministic deployment) and minimum required density (in case of random deployment case). These guidelines can be used in conjunction with any popular hole-aware deployment time coverage optimisation algorithm such as [31, 33, 79, 180] to ensure 1-coverage which is required for our on-demand coverage algorithm.

4.3.4 Detection Performance Analysis

In this section, we derive the false alarm probability and detection probability of our system. According to the on-demand k-coverage technique described in Section 4.3.2, k sensors collaborate in detecting an event via decision fusion. In practice, the measurement of each sensor is susceptible to an environmental noise. Since the distance from the sensed event is not same for every participating node, the effect of noise will be different on each node and so will be its individual detection capability as per (3.16). Such sensing noise can be modelled using a Gaussian distribution with 0 mean and unit variance, $\aleph_s(0,1)$. Let the event signal measured at sensor s_i be u_i and the threshold for event detection be η_d, that is a sensor considers an event as detected if the measured signal value is greater than or equal to η_d. The probability of detection, P_{d_i} for sensor s_i is given by,

$$P_{d_i} = p(d_i)\int_{\eta_d}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-u_i)^2}{2}} dx, \tag{4.8}$$

where d_i is the estimated distance of sensor s_i from the event location and $p(d_i)$ as defined per (3.16). The false alarm probability, i.e. the probability of noise being greater than or equal to the threshold, η_d, is given by,

$$P_f = \int_{\eta_d}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx. \tag{4.9}$$

We assume the decision fusion threshold as k_1, which means at least k_1 or more sensors must have measured signal above the threshold before making a final decision. Similarly, false alarm in decision fusion occurs when k_1 or more sensors among the k collaborating sensor generates a false detection. So the overall false alarm probability is given by,

$$P_F = \sum_{i=k_1}^{k} \binom{k}{i} P_f^i (1-P_f)^{k-i},$$

where P_f is as defined in (4.9).

Now collaborative detection takes place when k_1 or more sensors individually detects an event in the presence of an event. According to the variable range sensing model, the sensing probability of each node is a function of the distance from the event as shown in (3.16). Hence, the aggregated detection probability will depend on which combination of at least k_1 nodes are selected. Let $\Omega_{k,i}$ denotes the set of combinations of i sensors selected from k detecting sensors and $\varsigma \in \Omega_{k,i}$ denotes a specific combination of detecting sensors where $\varsigma(.)$ denotes the indices of the sensors. For any set of detecting sensors, ς, the probability of detection will be $\Pi_{j=1}^{i} P_{d_{\varsigma(j)}} \Pi_{j=i+1}^{k} (1 - P_{d_{\varsigma(j)}})$. Considering different combinations, $\varsigma \in \Omega_{k,i}$ and different number of sensors, i, (where $k_1 \leq i \leq k$), the overall detection probability after decision fusion is given by,

$$\begin{aligned} P_D = & \frac{1}{(k - k_1 + 1)} \sum_{i=k_1}^{k} \frac{1}{\binom{k}{i}} \times \\ & \left[\sum_{\varsigma \in \Omega_{k,i}} \left(\Pi_{j=1}^{i} P_{d_{\varsigma(j)}} \Pi_{j=i+1}^{k} (1 - P_{d_{\varsigma(j)}}) \right) \right]. \end{aligned} \tag{4.10}$$

Next, we determine the expected lifetime of a event detection system employing our proposed technique. For this, we need to estimate the average sensing radius of nodes over the network lifetime as the energy consumed in sensing depends on the sensing range.

4.3.5 Average Sensing Radius

Lemma 3. *Given that a sensor can vary its sensing range from r_{min} to r_{max}, i.e. $r \in [r_{min}, r_{max}]$, the expected sensing radius in the on-demand event coverage model for k degree of coverage is given by,*

$$\bar{r} = \frac{\binom{n_c - 1}{k-2}}{\binom{n_c}{k-1}} \left(\frac{2r_{max}^3 - r_{min}^3 - r_{min} r_{max}^2}{3r_{max}^2} \right) + r_{min}, \tag{4.11}$$

where,

$$n_c = \sum_{\kappa=0}^{\infty} \frac{(\pi \rho R^2)^{\kappa} e^{-(\pi \rho R^2)}}{(\kappa - 1)!} - 1.$$

Proof. The expected sensing range of a node depends on how frequently a node is selected for enhancing its sensing range. This can be estimated using i) the expected number of candidates around an event, ii) the desired degree of coverage, k, and iii) spatial distribution of events. The expected number of candidates in case of an event occurrence depends on the average number of neighbour nodes within the communication radius of the initiating node. Consider a complete spatial randomness with density ρ for node distribution as described in Section 4.3.3.2. In such case, the number of neighbours within certain radius of the initiating node depends on the deployment density.

According to this distribution, the probability of finding exactly κ nodes within an area A with deployment density ρ is given by,

$$P(\kappa, \rho, A) = \frac{(A\rho)^{\kappa} e^{-(A\rho)}}{\kappa!}$$

The number of neighbours of an initiating node can be estimated by the expected number of nodes within an area $A = \pi R^2$ centred around it. Therefore, for random deployment, the expected number of nodes, n_c in a candidate set S_c for an event is given by,

$$n_c = \sum_{\kappa=0}^{\infty} \kappa \frac{(\pi\rho R^2)^{\kappa} e^{-(\pi\rho R^2)}}{\kappa!} - 1. \tag{4.12}$$

Considering uniform probability of getting selected in the detection process, such probability is given by,

$$p_{c,k} = \frac{\binom{n_c-1}{k-2}}{\binom{n_c}{k-1}}. \tag{4.13}$$

Now, we need the probability that a node requires range enhancement. In our method, a sensor needs to increase its sensing radius when an event occurs between the distance r_{min} to r_{max} from the node. Considering the uniform spatial distribution of events, the probability density function of the distance of an event from the sensor is given by,

$$f_r(x) = \frac{2x}{r_{max}^2}. \tag{4.14}$$

We consider three possible cases for a node: i) an event occurs between the distance r_{min} to r_{max} and the node is selected for range adjustment. In this case range is increased up to event location, i) an event occurs between the distance r_{min} to r_{max} but the node is not selected in which case sensing range remains unchanged. and iii) an event anywhere else in the sensor field, in which case sensing range remains unchanged. The expected sensing radius can be found by,

$$\begin{aligned}
\bar{r} &= \textstyle\int_{r_{min}}^{r_{max}} p_{c,k} x f_r(x)dx + \int_{r_{min}}^{r_{max}} (1-p_{c,k}) r_{min} f_r(x)dx + r_{min}[1 - \int_{r_{min}}^{r_{max}} f_r(x)dx] \\
&= \textstyle\int_{r_{min}}^{r_{max}} p_{c,k} x f_r(x)dx - p_{c,k} r_{min} \int_{r_{min}}^{r_{max}} f_r(x)dx + r_{min} \\
&= p_{c,k} \int_{r_{min}}^{r_{max}} \frac{x^2}{2r_{max}^2} dx - p_{c,k} r_{min} \int_{r_{min}}^{r_{max}} \frac{x}{2r_{max}^2} dx \\
&= p_{c,k} \left(\frac{2r_{max}^3 - r_{min}^3 - r_{min} r_{max}^2}{3r_{max}^2} \right) + r_{min}
\end{aligned}$$

Substituting the values of $p_{c,k}$ from (4.13), we get,

$$\bar{r} = \frac{\binom{n_c-1}{k-2}}{\binom{n_c}{k-1}} \left(\frac{2r_{max}^3 - r_{min}^3 - r_{min} r_{max}^2}{3r_{max}^2} \right) + r_{min},$$

□

Considering the network coverage and connectivity model described in Section 4.2.2, the expected communication radius, $\bar{R}$ throughout the network lifetime will be bounded by, $\bar{R} \geq 2\bar{r}$.

4.3.6 Expected Lifetime Analysis

As demonstrated in the energy model for variable sensing, energy consumption increases with the increased sensing and communication range. On-demand k-coverage technique requires at most $(k-1)$ nodes to increase their ranges to k-cover an event. This results into consumption of additional energy beyond the normal sensing mode. In this section, we model the relationship between the maximum sensing radius and the lifetime of WSN for a given spatiotemporal distribution of events. According to the model described in Section 4.2.1, the occurrence of events follows a Poisson distribution with an average rate of λ' per unit area. A node will always process an event which occurs within its minimum range, r_{min}. In addition to that, any event occurring at a distance from r_{min} to r_{max} from a node will be processed by it with a probability $p_{c,k}$ as per (4.13). Considering a uniform spatial distribution of events and required degree of coverage k, the effective rate of event occurrence within the responsibility region of a sensor is given by,

$$\lambda_k = \pi r_{min}^2 \lambda' + p_{c,k}(\pi r_{max}^2 - \pi r_{min}^2)\lambda'.$$

Assuming a sensor generates a fixed number of packets to process an event, the number of packets generated by a sensor within the time interval $[0, T]$ follows the distribution,

$$P(M = q) = \frac{e^{-\lambda_k T}(\lambda_k T)^q}{q!}.$$

First, let us consider the lifetime of one sensor. Let the idle-time sensing energy for a node is e_{idle} per unit time. The total number of events that can be processed by one sensor in its lifetime, τ is given by,

$$\phi_i = \frac{E_{in} - \tau e_{idle}}{E_s(\bar{r}_{s_i}) + E_c(\bar{R}_{c_i})}. \tag{4.15}$$

Here, E_{in} is the initial energy of a sensor node. $\bar{r}$ and $\bar{R}$ denote the expected sensing and communication radius, respectively. We assume that all nodes have the same initial energy. The average sensing radius, $\bar{r}$ is derived in (4.11) and average communication radius, $\bar{R}$ is bounded by $\bar{R} \geq 2\bar{r}$. Now the total number of events that can be detected by a node in its lifetime eventually indicates the lifetime of a single sensor.

Lemma 4. *For an initial energy E_{in}, the conditional probability of a sensor node to achieve lifetime exceeding τ is given by,*

$$P(t_i \geq \tau|\phi_i) = 1 - \frac{\gamma(\phi_i, \lambda_k \tau)}{\Gamma(\phi_i)} \tag{4.16}$$

where $\gamma(.,.)$ and $\Gamma(.)$ represent the lower incomplete gamma function and the gamma function, respectively and ϕ_i is defined by (4.15).

Proof. The total lifetime, t_i of a sensor s_i can be computed by summing the inter-arrival delays of all the events it detects in its lifetime. Let $t_{i,j}$ be the interval between event $j-1$ and j within the range of sensor s_i. Then,

$$t_{i|\phi_i} = \sum_{j=1}^{\phi_i} t_{i,j}.$$

Since event occurrences follow a Poisson process, the inter-arrival times between consecutive events, i.e. $t_{i,j}$s are independent random variables that take an exponential distribution with mean $\frac{1}{\lambda_k}$. The sum of independent and identically distributed (i.i.d.) random variables follows a gamma distribution [293]. Therefore, for a given ϕ_i, probability density function of lifetime, t_i of a node, i can be expressed as,

$$f_{t_i|\phi_i}(x) = \lambda_k^{\phi_i} \frac{x^{\phi_i - 1} e^{-\lambda_k x}}{\Gamma(\phi_i)}, \tag{4.17}$$

which leads to,

$$\begin{aligned} P(t_i \geq \tau|\phi_i) &= 1 - P(t_i < \tau|\phi_i) \\ &= 1 - \int_0^{\tau} \lambda_k^{\phi_i} \frac{x^{\phi_i - 1} e^{-\lambda_k x}}{\Gamma(\phi_i)} dx \\ &= 1 - \frac{\gamma(\phi_i, \lambda_k \tau)}{\Gamma(\phi_i)} \end{aligned}$$

□

To estimate the network lifetime as defined in Section 3.7.4, we have to consider the individual lifetime of all the nodes deployed in the network. For random deployment over an area, ϕ_i is a random variable with pdf $f_\phi(x)$. This distribution depends on the shape of the area and energy dissipation model. Such distribution for some common shape of networks and random deployment scenario is derived in [294, 296].

Theorem 1. *For a WSN with total N number of nodes deployed uniformly over an area of interest, $\mathcal{A}$ and all nodes having same initial energy, the probability of achieving* *network lifetime, $\mathcal{L}$ to be at least τ is,*

$$P(\mathcal{L} \geq \tau) = Q(\frac{\sqrt{N}(1-\psi-\mu_l)}{\sqrt{\mu_l(1-\mu_l)}}) \tag{4.18}$$

where,

$$\mu_l = \int_{\mathcal{A}} \left(1 - \frac{\gamma(x, \lambda_k \tau)}{\Gamma(x)}\right) f_\phi(x) dx,$$

and

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-\frac{u^2}{2}} du.$$

Proof. From the definition of network lifetime based on the ratio of dead nodes as stated in Section 3.7.4, the network will achieve a lifetime of at least τ if the number of individual nodes that live up to τ period of time is at least ψN. To compute the number of such nodes, let us define a Bernoulli random variable, l_i for each sensor s_i in the following manner,

$$l_i = \begin{cases} 1, & \text{if sensor } s_i \text{ achieves lifetime more than } \tau. \\ 0, & \text{otherwise.} \end{cases} \tag{4.19}$$

The success probability of l_i given ϕ_i, denoted by $p_{s|\phi_i}$ follows from (4.16),

$$p_{s|\phi_i} = P(t_i \geq \tau | \phi_i) = 1 - \frac{\gamma(\phi_i, \lambda_k \tau)}{\Gamma(\phi_i)}.$$

Since l_is are Bernoulli random variable, the conditional mean and variance of l_i are given by, $E[l_i|\phi_i] = p_{s|\phi_i}$ and $Var[l_i|\phi_i] = p_{s|\phi_i}(1 - p_{s|\phi_i})$, respectively. Let us define a new random variable ω to denote the number of sensor nodes that live till at least τ period of time. From the definition of l_i, ω is the sum of successes of N Bernoulli trials as described above, that is, $\omega = \sum_{i=1}^N l_i$. Since the event occurrences are i.i.d. according to the event model described in Section 4.2.1, l_i's are also independent and identically distributed random variables. Therefore, by definition, ω follows a Binomial distribution, $B(N, p_s)$. The number of sensor nodes is usually large in a typical WSN. According to Central Limit Theorem [293], the Binomial distribution can be approximated with a Gaussian distribution for large N. This leads to the following probability distribution function of ω,

$$f_\omega(x) = \frac{1}{\sqrt{2\pi}\sigma_\omega} e^{-\frac{(x-\mu_\omega)^2}{2\sigma_\omega^2}} \tag{4.20}$$

where μ_ω and σ_ω are the mean and variance of ω, respectively. From the definition of ω, its mean and variance can be calculated from unconditional mean and variance of

l_i. The unconditional mean and variance of l_i, denoted as μ_l and σ_l^2 can be calculated using its conditional mean and variance [293] as follows,

$$\begin{aligned}\mu_l = E[l_i] &= E[E[l_i|\phi_i]] = E[p_{s|\phi_i}] \\ &= \int_{\mathcal{A}} p_{s|x} f_\phi(x)dx,\end{aligned}$$

which leads to,

$$\mu_l = \int_{\mathcal{A}} \left(1 - \frac{\gamma(x, \lambda_k \tau)}{\Gamma(x)}\right) f_\phi(x)dx, \tag{4.21}$$

and,

$$\begin{aligned}\sigma_l^2 = Var[l_i] &= E[Var[l_i|\phi_i]] + Var[E[l_i|\phi_i]] \\ &= E[p_{s|\phi_i}(1 - p_{s|\phi_i})] + Var[p_{s|\phi_i}] \\ &= E[p_{s|\phi_i}] - (E[p_{s|\phi_i}])^2,\end{aligned}$$

which follows from the fact that, $E[x+y] = E[x] + E[y]$ and $Var[x] = E[x^2] - (E[x])^2$. Therefore,

$$\sigma_l = \sqrt{\mu_{l_i} - \mu_{l_i}^2}. \tag{4.22}$$

Since, ω is a sum of l_is and l_is are i.i.d. random variables, $\mu_\omega = N\mu_l$ and $\sigma_\omega^2 = N\sigma_l^2$. Now,

$$\begin{aligned}P(\mathcal{L} \geq \tau) &= P(\omega \geq (1-\psi)N) \\ &= \int_{(1-\psi)N}^{\infty} \frac{1}{\sqrt{2\pi}\sigma_\omega} e^{-\frac{(x-\mu_\omega)^2}{2\sigma_\omega^2}} dx\end{aligned}$$

Substituting $\frac{(x-\mu_\omega)}{\sigma_\omega} = u$, the above can be written as,

$$P(\mathcal{L} \geq \tau) = \frac{1}{\sqrt{2\pi}} \int_{\frac{\sqrt{N}(1-\psi-\mu_l)}{\sqrt{\mu_l(1-\mu_l)}}}^{\infty} e^{-\frac{u^2}{2}} du$$

Therefore,

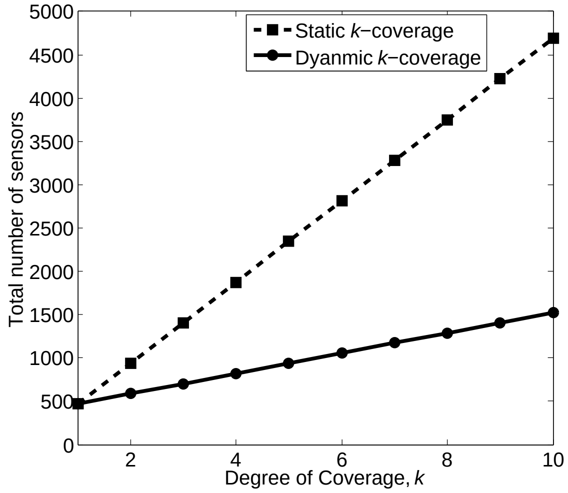
$$P(\mathcal{L} \geq \tau) = Q\left(\frac{\sqrt{N}(1-\psi-\mu_l)}{\sqrt{\mu_l(1-\mu_l)}}\right)$$

□

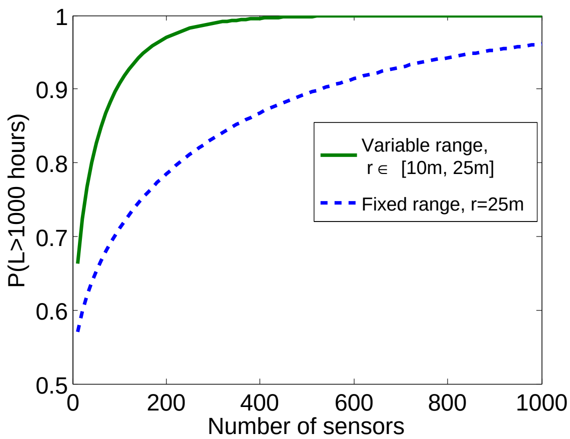
Having analysed the characteristics of our proposed approach, in the following section, we evaluate its performance both theoretically and through simulation.

4.4 Performance Evaluation

The performance gain of on-demand dynamic k-coverage using variable sensing radius is two-fold. First of all, it provides the similar performance guarantee of full k-coverage



(a) Number of sensor nodes required to provide certain degree of coverage



(b) Probability of achieving more than 1000 hours of life-time vs. the number of sensors.

Figure 4.4: Performance gain in terms of number of nodes and network life in our method compared to static coverage

with significantly low number of nodes, which is desirable from economic perspective. At the same time it achieves better network lifetime compared to other models where all the nodes operates in full sensing range all the time.

Network Parameters	
Number of sensor	[200, 600]
Minimum sensing radius, r_{min}	10m
Maximum Sensing radius, r_{max}	25m
Area of Interest	400x400 m^2
Sensing prob. decay factor,	γ_1=0.29, γ_2=0.71
Dead node ratio for network life, ψ	0.4
Energy Parameter	
Initial Energy, E_{in}	$2J$
Energy consumption model	square law

Table 4.1: System parameters for simulation

4.4.1 Cost Effectiveness

From the study of k-coverage [180], it is evident that for higher value of k, the required node density is significantly high and so is the number of nodes during deployment time. But in many cases, nodes are not cheap and such dense deployment is unrealistic due to the huge cost. Our on-demand dynamic k-coverage with variable sensing range requires only 1-coverage during deployment time which makes it extremely cost effective. Using the model described in [180] for full static k-coverage, the numerical values of the required number of nodes for static and dynamic k coverage is shown in Fig. 4.4(a). This shows the benefit of our method in terms of deployment cost.

4.4.2 Lifetime Enhancement

In our model, nodes maintain the minimum sensing range (r_{min}) for majority portion of the time which consumes less energy and extend the sensing radius only on demand and return back to the normal range once the detection task is completed. In fixed static k-coverage, sensors consume much more energy as they operate at the maximum sensing range all the time. The theoretical lifetime of these two methods are compared in Fig. 4.4(b) where the event rate is taken, $\lambda = 1/hour$. The probability of a WSN achieving a lifetime of more than 1000 hours is shown which establishes the performance gain in lifetime in our scheme.

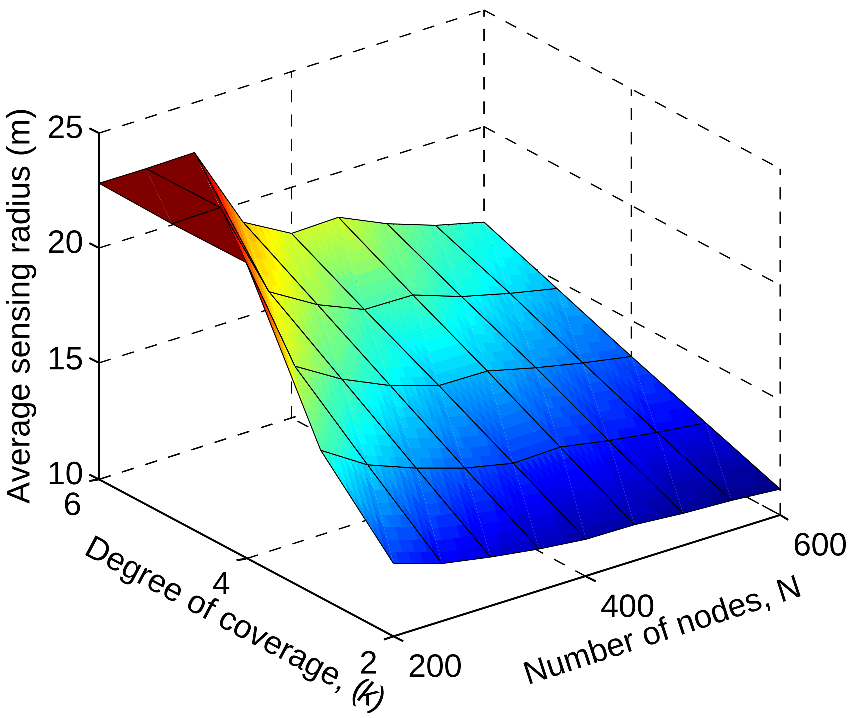


Figure 4.5: Theoretical values for average sensing radius ($\bar{r}$) vs. degree of coverage (k) and number of nodes deployed (N).

4.4.3 Simulations and Results

We designed our simulation using the network simulator $ns-3$. We developed and incorporated the variable radius model to this platform and conducted a series of event detection tasks by varying the sensing range of sensors dynamically on demand. The events are generated using a Poisson process of rate $\lambda = 1/hour$. Each simulation was run 100 times and averaged results are presented in this section. Simulation parameters are formally listed in Table 4.1.

First, to verify our theoretical findings, we compare the analytical values of average sensing radii and lifetime with simulation results. Fig. 4.5 plots the analytically derived average sensing radius for different degrees of coverage and number of nodes. It shows that average radius sensing range is usually much less than the maximum sensing range. The corner at the left hand side corresponds to the scenario of high degree of coverage requirement with low number of nodes. This indicates that, in such case, nodes need to operate at near-maximum sensing range most of the time. However, even in the worst

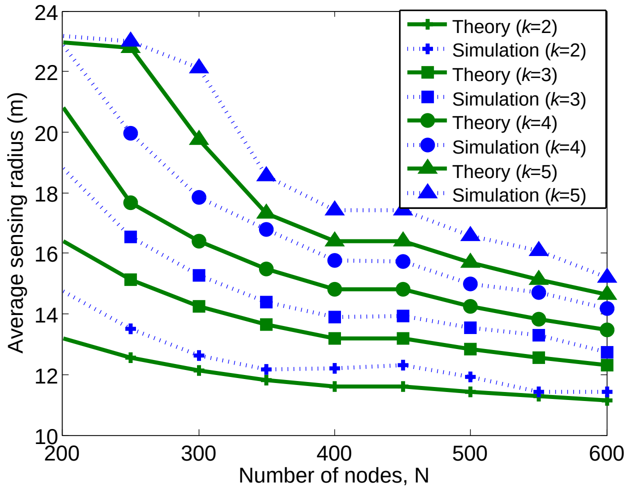


Figure 4.6: Validation of theoretical result for average sensing radius ($\bar{r}$) for different k and number of nodes.

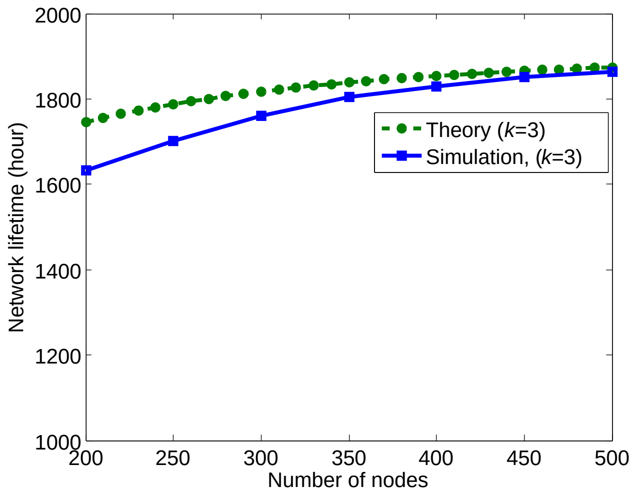


Figure 4.7: Lifetime comparison between theoretical value vs simulation result.

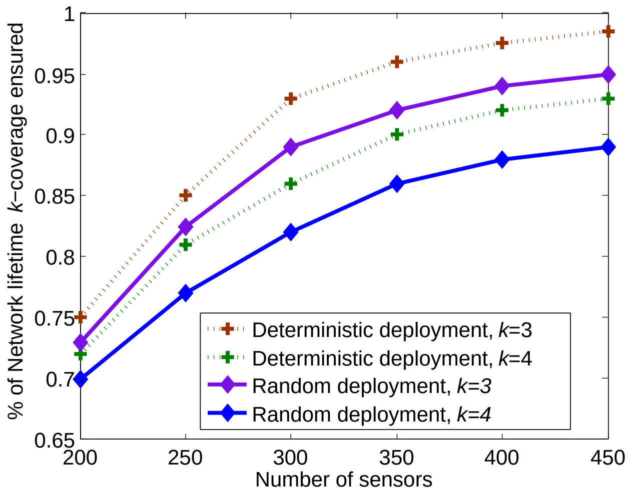


Figure 4.8: Fraction of time desired k-coverage ensured for deterministic and random deployment for different values of k.

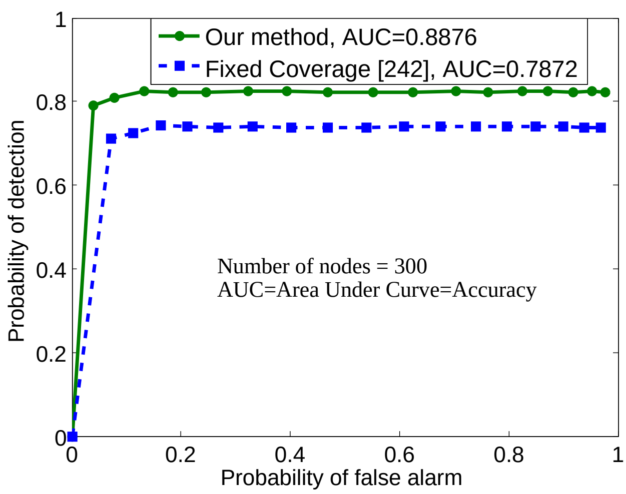


Figure 4.9: Accuracy comparison between fixed range sensing [242] and variable range sensing.

case, certain energy saving will be ensured as the average sensing range is still lower than the maximum range. Fig. 4.6, shows the comparison between analytical values of average sensing radii and the simulation results. The figure shows fairly close match between theory and simulation validating our analysis. Fig. 4.7 plots the analytical value for expected lifetime along with the average lifetime achieved in the simulation for a certain degree of coverage ($k = 3$). The simulation result shows close match with the theoretical values, especially in high node density.

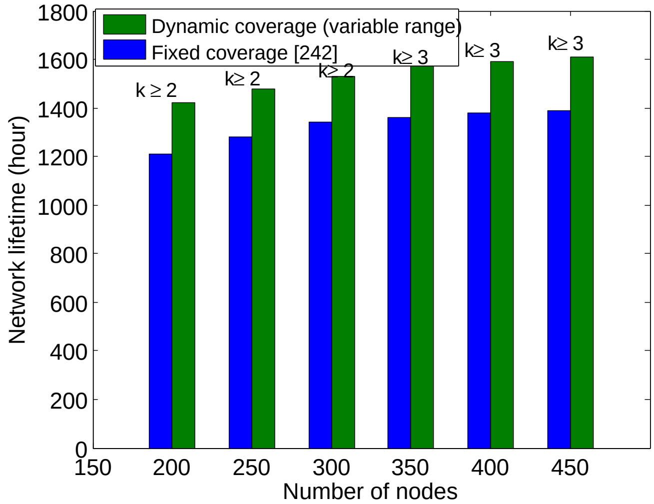


Figure 4.10: Network life comparison between fixed range sensing [242] and our method for different number of nodes.

Figure 4.8 illustrates how well the events are covered by adjusting sensing range over network life even with 1-covered initial deployment. Results for desired degree of coverage $k = 3$ and $k = 4$ are presented for both random and deterministic deployment cases. Results for the deterministic case show that, for the simulation scenario with number of nodes greater than 300, more than 95% of the time 3-coverage and more than 85% of the time 4-coverage is ensured at any event location. The random deployment scenario exhibits a lower value for dynamic coverage. This is because, due to random deployment, 1-coverage was not ensured in some event locations, which, in turn reduced coverage performance compared to deterministic deployment. However, the overall performance of on-demand coverage still ensures 3-coverage for more than 90% of the time and 4-coverage for more than 80% of time. Application of coverage verification algorithms (such as [33]) to ensure 1-coverage at deployment time as mentioned in

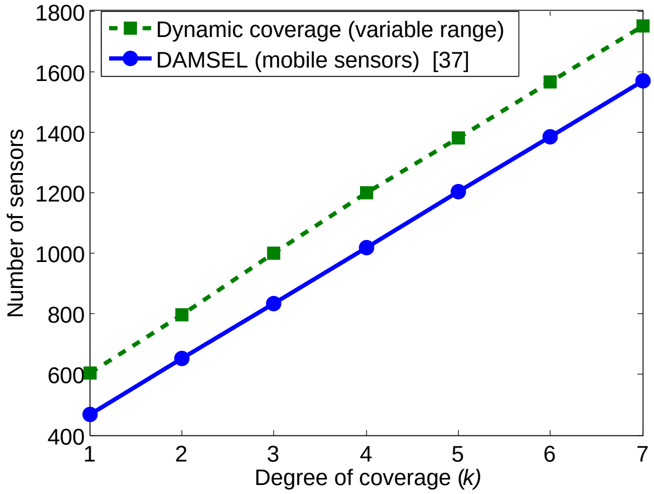


Figure 4.11: Required number of nodes for different degrees of coverage using variable range static sensor and mobile sensor.

Section 4.3.3.2 will certainly improve coverage performance in random deployment to a level comparable to the deterministic scenario.

To compare the detection performance of our variable range method with a fixed range sensing method as described in [242], we considered a simulation scenario using equal number of nodes (300 in this case) in both methods. Sensing range in our method was varied from $10m$ to $25m$, while the fixed range sensors operated in the mean range ($17.5\ m$) for fair comparison. For equal number of nodes, the static event coverage method [242] with no range adjustment only ensures $k = 2$, while our on-demand k-coverage can yield dynamic degree of coverage exceeding three ($k \geq 3$). This results in more than 14% improvement in the overall accuracy as shown in Fig. 4.9. We have used the ROC curve here as illustrated in 2.3.6. From the results showing average sensing radius in Fig. 4.5 & 4.6, it is clear that a fixed range sensor providing k-coverage spends more energy than our variable range method. This energy efficiency results in longer network lifetime in our method as shown in Fig. 4.10.

The cost effectiveness of our method becomes more vivid when we compare the cost of deployment to its mobile counterpart. We choose the method called Distributed Approach for Mobile Sensor Selection (DAMSEL) proposed by Ammari [37] for on-demand event coverage using mobile nodes. For a fair comparison with DAMSEL we designed a simulation scenario with $600 \times 600m^2$ square area of interest with nodes

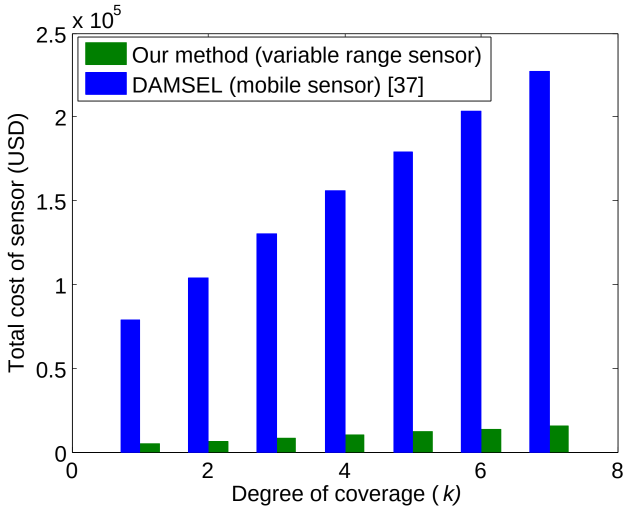


Figure 4.12: Deployment cost comparison (Mobile vs. Variable range static sensor).

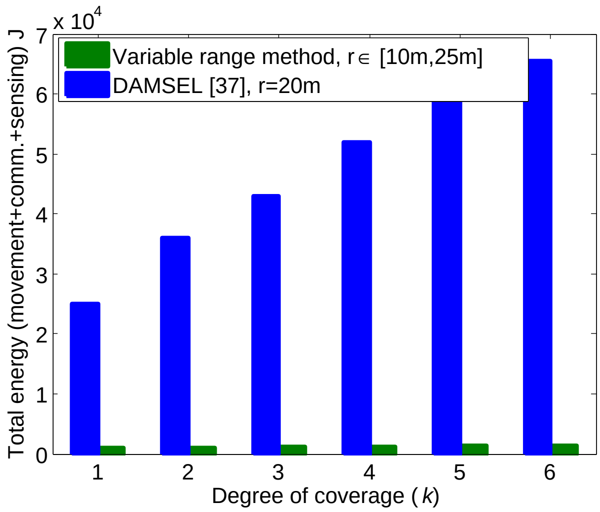


Figure 4.13: Energy comparison (Mobile vs. Variable range static sensor).

having sensing range $r = 20m$ in normal mode of operation. We accomplished the event detection task with static sensors having adjustable sensing range in $[10m, 25m]$. The results are presented in Fig. 4.11, 4.12 and 4.13. Fig. 4.11 shows that our method requires more nodes compared to the mobile nodes in DAMSEL to provide a certain degree of coverage to any event location. However, considering the cost of expensive mobile nodes and significant energy consumption due to mobility, the trade-off in number of nodes is justified in our case. We have used the commercial price information for iRobot mobile nodes [297] and EQ-501 [267] variable range nodes to demonstrate the cost implication of these two methods in Fig. 4.12. It is quite evident from the figure that high cost of mobile units makes the real life deployments of them infeasible in many event detection applications, especially when high degree of coverage is required. Use of adjustable sensing range makes it quite feasible to attain this goal of higher performance gain at a lower cost. Fig. 4.13 shows the total energy (movement+communication+sensing energy) consumed by all nodes in a WSN in DAMSEL compared to our method for 1000 hours of operation maintaining same degree of coverage. The high energy consumption is primarily due to mobility while the energy spent in our on-demand k-coverage for adjusting sensing range is negligible.

While, on-demand event detection using variable range sensing is an attractive solution, the capability of adjusting range is limited mostly to active sensing based devices. This necessitates the search for alternative mobile node based solution that can ensure efficient use of node mobility to make such scheme feasible from energy consumption point of view. Below, we propose a dynamic event coverage technique employing node mobility.

4.5 Dynamic Coverage using Mobile Nodes

Studies presented in Chapter 2 explored several research attempts to exploit node mobility to improve dynamic coverage and detection. These works mostly focus on maintaining connectivity and minimising coverage hole. But in case of event detection, the movement strategy in many cases may lead to random movements and unbalanced energy consumption among mobile nodes due to mobility. This may deteriorate the detection performance by reducing network life and detection capability. We focus on the issue of event detection in such a mixture of mobile and static sensor network, (i.e., in a hybrid network) with a view to enhancing the detection performance by emphasising on fair energy consumption due to mobility, minimising movement and keeping node density balanced. To achieve these through better node selection and movement strategy, we exploited the spatial locality of the occurrences of events.

For dynamic coverage, it is intuitive to keep the mobile nodes roaming around the region of interest for enhanced coverage. But mobility is a costly operation for resource limited sensor nodes and excessive movement can lead to early demise. Therefore, minimising the overall distance travelled by a node is a major issue. This is usually addressed by moving the nodes towards event proximity only when necessary [37, 257]. But considering the inherent nature of event detection systems, several other factors should also be considered.

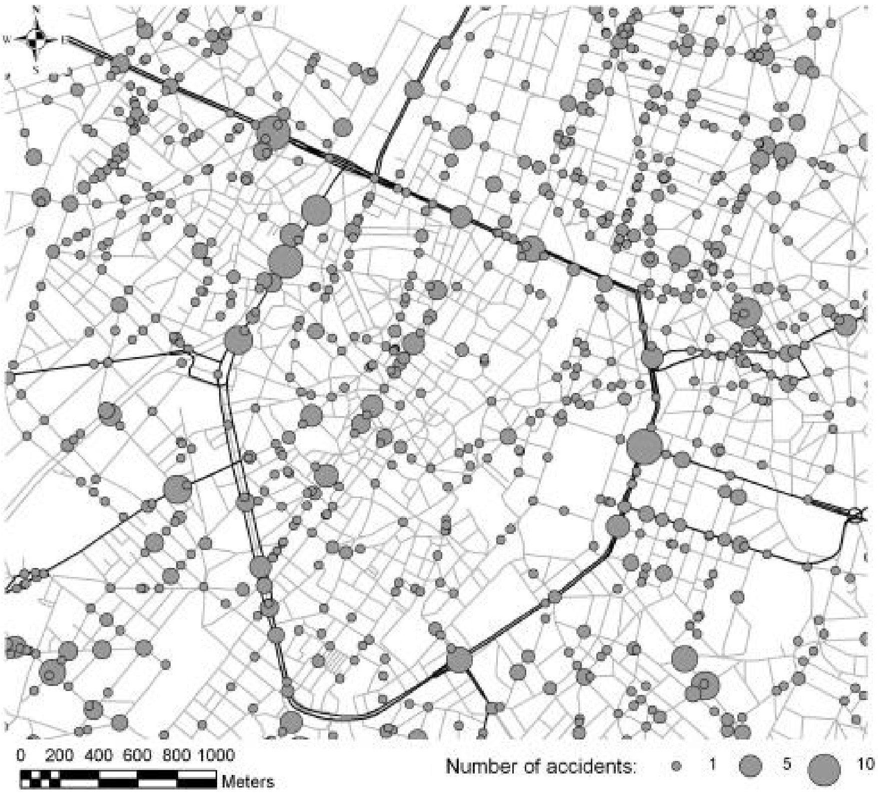


Figure 4.14: Number of accidents at each accident location demonstrating event clustering [24].

4.5.1 Spatial Locality of Events

An interesting phenomena observed in most event detection systems is that events usually tend to cluster around some points of interest over time. Steenberghen *et al.* in [24] attempted to identify this inherent clustering nature among traffic events in road networks and proposed a method to compute spatial concentrations of point-based events in a network. They studied the dense road network of Brussels and determined the distribution of accidents over the accident locations (Fig. 4.14) based on the accident data from the year 1997 to 1999. In our work, we argue that exploiting this nature of events can be advantageous to event-centric wireless sensor networks. In such context, mobility in sensor network can be useful to a great extent as mobile sensor nodes are capable of adapting to the dynamic nature of event distribution. Using *a priori* domain knowledge and keeping track of event locations, our model attempts to position the mobile nodes in the proximity of the high event occurring regions. When two distant nodes are equally likely to be relocated to cover an event, we assign priority to the one whose current location is less susceptible to future event than the other. We introduce a new concept in WSN namely, *event occurrence probability*, and divide the sensor field into a set of regions based on the frequency of event occurrence in that region. This plays a major role in designing our node selection method in dynamic event coverage as a node from lower frequency region is a better candidate.

4.5.2 Other Factors in Movement Strategy

Another significant observation from the studies in Chapter 2 is that, in most cases the movement strategies give the highest priority to a node's distance from target location [37, 257]. This can cause mobile nodes around a region with high event occurrence frequency to get selected recurrently and consequently they will be depleted of energy required for mobility quickly while much healthier node (in terms of energy) may reside a little farther. Such phenomena may degenerate to unbalanced energy consumption over the network. That is why the selection and mobility strategy in the proposed model takes the remaining energy into consideration. Lastly, the density of the areas from where nodes are being relocated can also be an issue since it is better to move nodes from high density region rather than sparsely deployed region for the sake of uniformity. Moving a node from a low density region while its closest competitor resides in relatively higher density region will cause imbalance in node density. Our method will attempt to keep this selection fair from the density point of view as well as the other factors mentioned above. Such a model should be parametrised enough to assign appropriate priority to each factor.

To the best of our knowledge, the proposed method is the first to concomitantly address all the aforementioned factors, namely, i) distance, ii) remaining energy, iii) density and iv) event occurrence probability, in an on-demand event coverage approach in a hybrid sensor network. We adopt a sparse deployment of mobile nodes in conjunction with a 1-coverage of stationary nodes. We propose a fair policy for node mobility in order to provide dynamic event coverage and our method ensures k-coverage with significantly fewer number of nodes. We have characterised the problem of selecting nodes to move to ensure coverage as a coalition formation game among nodes and employed a simple game theoretic approach that facilitates the automated coalition formation among mobile nodes without any central intervention. The following contributions are made in this regard,

- A self-organised autonomous node movement strategy to provide dynamic k-coverage in event-centric mobile WSN.
- Introduction of the concept of spatial event occurrence probability in different regions of a sensing field. The local clustering of events is utilised to enhance detection performance.
- Simple game theory based distributed scheme that minimises energy spent due to mobility.
- Minimisation of movement distance in a way that attains balanced consumption of mobility energy and uniform node density.

Another research area relevant to our work is the implementation of game theory in communication which has gained attention in recent literature. The network entities usually tend to work selfishly by seeking performance advantage over others. Each entity prefers to save its own resources to prolong its lifetime and perform better in the network. This very nature fits the inherent idea of game theory [298]. Game theory can model the actions and preferences of independent players in order to capture the interaction of players in a competitive or cooperative environment. Even though it originated from the field of Economics, recent studies have revealed huge potential of utilising game theory in communication networks and multi-agent systems [299]. This work employs a major class of cooperative game theory called Coalitional Game that aids in forming group or coalition among a set of agents considering their multi-objective preferences.

4.6 System Model for Hybrid WSN

4.6.1 Network Model

So far in this thesis, we have used only static nodes. Here, we consider a hybrid sensor network with N_s number of static sensor nodes and N_m number of mobile sensor nodes deployed over an arbitrary shaped area of interest. Sensor nodes are location aware via a localisation technique such as Global Positioning System (GPS) [289] and both static and mobile nodes have the same sensing radius, r and a communication radius, R. The number of static nodes are sufficient to ensure at least 1-coverage which is calculated according to (2.10). Mobile sensors are uniformly deployed over the sensor field initially and N_m is taken to be large enough so that each static sensor is within the communication range of at least $k-1$ mobile nodes, k being the dynamic degree of coverage. Since communication range is usually much greater than sensing range ($R \geq 2r$), required number of mobile nodes for such communication coverage will be much less than that required for k sensing coverage. Each mobile node is equipped with a sensing unit and a locomotion unit and capable of movement with a constant velocity. The movement energy is directly proportional to the distance travelled.

4.7 Proposed Dynamic Event Coverage Model

4.7.1 Event Occurrence Probability

To meet our goal of keeping more nodes in higher event density region, the centralised entity (base station) keeps record of event occurrence statistics with spatial information. The entire region is then divided into an $B_1 \times B_2$ rectangular grid (as shown by the 3×3 dotted grid in Fig. 4.15). We define the event occurrence probability in any grid

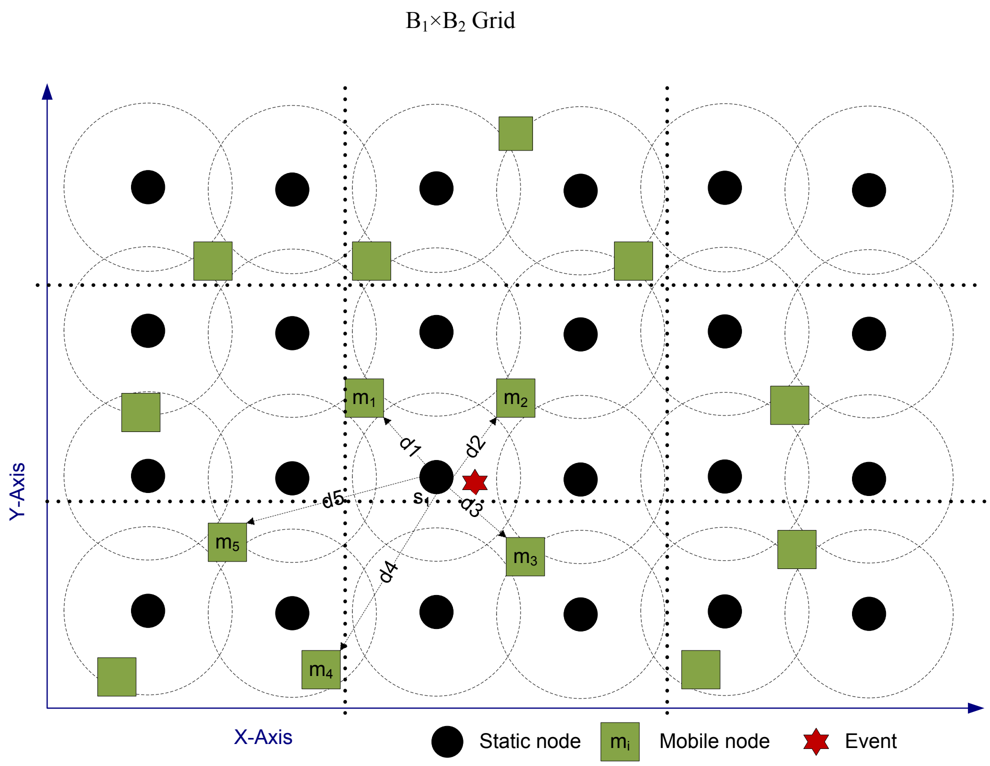


Figure 4.15: System model.

cell (a_1, a_2) at the end of each observation cycle of period, t_c by,

$$\varpi(a_1, a_2) = \frac{E(a_1, a_2, t_c)}{\sum_{i=0}^{B_1-1} \sum_{j=0}^{B_2-1} E(i, j, t_c)}, \tag{4.23}$$

where $0 \leq a_1 \leq B_1$, $0 \leq a_2 \leq B_2$, and $E(a_1, a_2, t_c)$ are the number of events occurred in cell (a_1, a_2) within the observation period $[0, t_c]$. For any mobile sensor m_i, the event occurrence probability in its current location (x_i, y_i) can be given by,

$$\zeta_i = \varpi(\lfloor \frac{x_i}{B_1} \rfloor, \lfloor \frac{y_i}{B_2} \rfloor).$$

Our base station advertises an *UPDATE* packet containing the cell co-ordinate and probability $(< (a_1, a_2), \varpi(a_1, a_2) >)$ periodically after every observation cycle of time t_c. Each node listening to the packet, compares its location (x_i, y_i) with (a_1, a_2) and updates its local estimation of ζ_i with the relevant value. If the spatial distribution is known *a priori*, sufficient number of cells can be employed to properly distinguish the differences in event occurrence probabilities in different regions. In absence of such knowledge, equi-probable event occurrence is assumed and any arbitrary $B_1 \times B_2$ grid can be taken in the design phase. After initial design, a cell exhibiting wide variation of event occurrence frequency within its area can be further subdivided.

4.7.2 Node Density Formulation

We define the density around a mobile node by the number of nodes per square unit area within its communication range. To compute the density without any additional message passing, we have incorporated the *Ad Hoc On Demand Distance Vector* (AODV) routing in our model. AODV [6] is a pure on-demand routing acquisition algorithm that does not depend on periodic routing table exchange. Rather a node acquires the route information by broadcasting discovery packets only when it needs to communicate. Thereby, whenever a mobile node receives a *REINFORCE* request, it initiates the *Path Discovery* process which eventually identifies its immediate neighbours. Based on this observation, we define the density around a mobile node s_m as, $\rho_m = \frac{neighbour(s_m)}{\pi R^2}$, where $neighbour(s_m)$ is the number of single hop neighbours. Due to the on-demand route discovery method in AODV, this provides the freshest estimation of density that is used in our on-demand event coverage algorithm. Density is an important metric since when two nodes from different density regions are to be considered, having other factors remaining same, the one from the higher density region should receive higher preference.

4.7.3 Event Coverage Protocol

According to the aforementioned network model, our network is at least 1-covered and any event will be captured by at least one static sensor. To improve the cooperative sensing performance, additional mobile sensor nodes are needed to participate in the collaborative detection. On detection of an event individually, the static sensor broadcasts a *REINFORCE* packet containing its current location as target destination. The request is received by a set of mobile nodes within its communication range (Fig. 4.15). A mobile node receiving the request measures its distance from the target and calculates the density around its current location. An weight factor is calculated using this distance, density and remaining energy, and sent back as a *REINFORCE_ACK* packet to the requesting node. The set of nodes responding to the *REINFORCE* request is called the *candidate set* and a subset of them is to be selected according to our proposed technique presented in Section 4.8.2. Selected nodes are then informed to move towards the event and start sensing. The mobile nodes move towards the destination location and stops when they can start sensing the event. The final decision on detection of event occurrence is taken in collaboration among those nodes using a distributed decision fusion rule as demonstrated in Section 2.4.3.2.

For convenience, a mobile node will be represented by its distance from the target event (d), remaining energy (E_{rem}), density (ρ) and event occurrence probability in the current location (ζ). That is, node m_i is represented by, $m_i\langle d_i, E_{rem_i}, \rho_i, \zeta_i\rangle$. We call this tuple, $\langle d, E_{rem}, \rho, \zeta\rangle$, a node profile of a mobile node.

4.7.4 Problem Formulation

According to the proposed model, any event is covered by at least one stationary sensor and on detection of an event, the stationary node requests a set of mobile nodes to collaborate and improve the overall detecting performance. Let the mobile nodes listening to the *REINFORCE* request be denoted as candidate nodes. Our primary problem is to select the optimal combination of candidate nodes that will provide dynamic k-coverage while balancing among the following objectives,

1. Move nodes preferably from lower event probability regions.
2. Minimise node movement
3. Balance the consumption of energy among nodes due to mobility.
4. Minimise the diversity in density around the mobile nodes, i.e., nodes in higher density region should get greater priority

4.8 Game Theoretic Approach to Node Selection

According to our formulation, selection of the most suitable subset of mobile nodes and their relocation to improve coverage can be characterised as a coalition formation problem among mobile nodes to perform collaborative detection. Each mobile node may have individual preference about joining a coalition based on their profile ($\langle \varepsilon, d, \rho, \zeta\rangle$). So they need to agree on common course of actions. This is a classic characterisation of coalition formation games. It is evident that our problem of selecting suitable combination of nodes can easily be mapped into such coalition formation games. Considering the resource constraints of sensor nodes, we choose the simplest class of coalitional games called *simple weighted voting game* as defined next.

4.8.1 Preliminary Definitions

Definition 1. A coalitional game is defined by a pair $(N_G, \mathcal{V})$ where $N_G = \{1, 2, ..., n\}$ is a set of players or agents and $\mathcal{V} : 2^{N_G} \to \Re^+$ is the characteristic function of the game. For every $S_G \subseteq N_G, \mathcal{V}(S_G)$ denotes the worth of the coalition.

The problem of group formation is closely related to the concept of coalition formation in economics domain.

Definition 2. A Colaitional Game is called simple if the characteristic function is given by $\mathcal{V} : 2^{N_G} \to \{0, 1\}$. Coalitions with $\mathcal{V}(S_G) = 1$ are called winning and those with $\mathcal{V}(S_G) = 0$ is called losing.

In our work we are going to focus on a special class of simple coalitional games known as Weighted Voting Games (WVG) since each of our candidate nodes may have different weights on different criteria. The concept is to assign each mobile node a numerical weight based on its profile that can be used to measure its expected contribution to a coalition.

Definition 3. A Weighted Voting Game (WVG) is given by a set of agents $N_G = \{1, 2, ..., n\}$, a vector of agents' weights $\mathbf{w} = (w_1, w_2, ..., w_n)$ and a quota $q \in [0, \sum w_i]$. The weight of a coalition, $w(S_G) = \sum_{i \in S_G} w_i$. The characteristic function v is given by, $\mathcal{V}(S_G) = 1$ if $w(S_G) > q$ and $\mathcal{V}(S_G) = 0$, otherwise. A coalition S_G with $\mathcal{V}(S_G) = 1$ is called a winning coalition.

A power index of an agent in a coalition is the measurement of its voting power in that coalition. It eventually measures the ability of an agent to affect the final goal. The Banzhaf index is considered to be the most suitable voting power of voting game theorists [300].

Definition 4. A player i is critical in a coalition S_G, when S_G is a winning coalition and $(S_G \setminus i)$ is a losing coalition. For each $i \in N_G$ let the number of coalitions in which i is critical be denoted by n'_i. The Banzhaf index in weighted voting game is defined as, $\mathcal{B}_i = \frac{n'_i}{\sum_{i \in N_G} n'_i}$. The probabilistic Banzhaf index, $\mathcal{B}'_i$ is, $\mathcal{B}'_i = \frac{n'_i}{2^{n-1}}$.

4.8.2 Node Selection Algorithm

The objective is to form a coalition among the candidate mobile nodes that will eventually lead to provide dynamic coverage to an event location. Conceptually the weight, i.e., voting power of an agent should be proportional to its capability of contribution to the coalition. In our formulation a node's voting power depends on : i) distance from the target location - closer is better; ii) remaining energy of the node- higher energy means better candidate because it is less likely to die by taking part in collaboration and consideration of this criteria helps the low energy nodes to preserve their energy; iii) density around its current location - a node from densely deployed region is a better candidate because such region can afford to spare nodes; and finally iv) the event occurrence probability in the node's current cell - higher probability means nodes are highly likely to be needed here in future. We call the selected set of nodes, the winning coalition. The inclusion of a mobile node in a winning coalition is based on its voting power or weight. We define the binary preference relation $\succeq_C$ that orders the candidate nodes according to their weight w.r.t. the criterion, C. "$i \succeq_C j$" is read as, node m_i is preferred over node m_j in the winning coalition for criterion C. For two different nodes $m_i\langle d_i, E_{rem_i}, \rho_i, \zeta_i\rangle$ and $j\langle d_j, E_{rem_j}, \rho_j, \zeta_j\rangle$,

1. $d_i \leq d_j \Longrightarrow m_i \succeq_d m_j$
2. $E_{rem_i} \geq E_{rem_j} \Longrightarrow m_i \succeq_{E_{rem}} m_j$
3. $\rho_i \geq \rho_j \Longrightarrow m_i \succeq_\rho m_j$
4. $\zeta_i \leq \zeta_j \Longrightarrow m_i \succeq_\zeta m_j$

It is obvious that each of the individual preference relation is a total order w.r.t. the corresponding criterion. However, one ordering may not be completely complying with the others. Each node may have different preferences for different coalitions. That is why, it is suitable to assign a numerical weight to them combining their preferences. We express the weight for node m_i as,

$$w_i = c_1 \left(1 - exp(\frac{-R}{d_i})\right) + c_2 \left(\frac{\rho_i - \varphi}{\rho_{max} - \rho_{min}}\right) + c_3 \frac{E_{rem_i}}{E_{in}}. \tag{4.24}$$

Here, R is the communication radius, φ is a constant denoting the density with k-coverage, ε_{in} is initial node energy, ρ_{max} and ρ_{min} are maximum and minimum

Algorithm 4.2: SimpleWVG($\mathcal{M}$, q, $\mathbf{w}$)

Input: $\mathcal{M}$: set of mobile nodes

$\mathbf{w}$: vector of node weights

Output: MWC: set of selected mobile nodes for relocation

$WC \leftarrow \emptyset$
for $S \in 2^{\mathcal{M}}$ **do**
    $W(S) \leftarrow \sum_{i \in S} w_i$
    if $W(S) \geq q$ **then**
        $WC \leftarrow S$
    end if
end for
$MWC \leftarrow \emptyset$
$\zeta_{min} \leftarrow \infty$
for $S \in WC$ **do**
    $\zeta_S \leftarrow \sum_{m_i \in S} \zeta_i$
    if $\zeta_S \leq \zeta_{min}$ **then**
        $MWC \leftarrow S$
        $\zeta_{min} \leftarrow \zeta_S$
    end if
end for
return MWC

achievable density, respectively and $c_1, c_2, c_3 \in [0, 1]$ are adjustment constants. Our formulation of weight considers the first three of the above four preference relations. The fourth preference relation ($\zeta_i \leq \zeta_j \Longrightarrow m_i \succeq_{\zeta} m_j$) is employed to break ties among multiple solution sets and to ensure the uniqueness of solution.

Now, we can model our problem of coalition formation among candidate nodes as a weighted voting game defined by the set of n mobile nodes, $\mathcal{M} = \{m_1, m_2, ..., m_n\}$ that receive the *REINFORCE* request towards an event, a vector of nodes' weights, $\mathbf{w} = (w_1, w_2, ..., w_n)$, where $\mathbf{w}$ is defined by (4.24) and a threshold, $q = cw_{avg}$, where c is an adjustment constant. First an straightforward solution to this problem is given in Algorithm 4.2 (SimpleWVG).

Combinatorial complexity of Algorithm 4.2 is given by $\sum_{i=k-1}^{n} \binom{n}{i} \sim O(2^{n-1})$. But this exponential computation complexity is not suitable in case of a dense deployment of mobile nodes where a candidate set contains more than ten nodes. To tackle this, the winning coalition is formed by enumerating the mobile nodes according to their voting power indices because the power index actually measures the capability of a mobile node to affect the coalition's wining prospect. We will use the Banzhaf index as described in Section 4.8.1 as the voting power measure in our approach. Since computing Banzhaf index is computationally hard [300], our proposed algorithm is based on probabilistic Banzhaf Index ($\mathcal{B}'_i$) and exploits an approximation approach similar to [301]. We assume that node weights can be defined by a normal distribution with average weight μ_w and variance σ_w. Now, a node m_i can turn a losing coalition into a winning one if current weight of this coalition is in the interval $[q - w_i, q - \epsilon]$ (where ϵ is a small quantity). For any coalition size X, the expected marginal contribution (EMC) of a node m_i to the coalition is:

$$EMC_i^X \leftarrow \frac{1}{\sqrt{2\pi\sigma_w X}} \int_{lim_1}^{lim_2} e^{-X\frac{(x-X\mu_w)^2}{2\sigma_w}} dx,$$

where $lim_1 = q - w_i$ and $lim_2 = q - \epsilon$. Based on this measure, the Banzhaf indices of all candidate nodes can be computed using Algorithm 4.3. Then our desired coalition of mobile nodes are formed by selecting according to descending order of their Banzhaf power indices. It is quite likely that two or more nodes will have similar voting power. In such cases, ties are broken based on the ordering of event occurrence probability, $\zeta_i \leq \zeta_j \implies i \succeq_\zeta j$, as mentioned earlier. It is straightforward to see that the worst case complexity of this algorithm is $O(n^2)$.

The stability of a this solution depends on *the core*, which is the most significant solution concept of coalitional games. The core of a weighted voting game is non-empty if and only if there is a player i, that is present in all winning coalitions. Since WVG is a subclass of simple game, this property follows straightforward from the definition of simple game as proved in [302]. This ensures the stability of our solution.

4.9 Simulation and Results

To evaluate the performance and effectiveness of our dynamic coverage model, we designed and implemented our model in MATLAB, conducted a series of simulations. We compared results of our model with *Distributed Approach for Mobile Sensor Selection* (DAMSEL) [37], which also takes an approach to employ on-demand k-coverage with

Algorithm 4.3: MobileNodePBI($\mathcal{M}, q, \mathbf{w}, \mu_w, \sigma_w$)

Input: $\mathcal{M}$: set of mobile nodes

$\mathbf{w}$: vertor of node weights

for i=1 to n **do**

  $J_i \leftarrow 0$

  for X=1 to n **do**

    $lim_1 \leftarrow q - w_i$

    $lim_2 \leftarrow q - \epsilon$

    $EMC_i^X \leftarrow \frac{1}{\sqrt{2\pi\sigma_w X}} \int_{lim_1}^{lim_2} e^{-X\frac{(x-X\mu_w)^2}{2\sigma_w}} dx$

    $J_i^X \leftarrow EMC_i^X \times \binom{n}{X}$

    $J_i \leftarrow J_i + J_i^X$

  end for

end for

for $i = 1$ to n **do**

  $\mathcal{B}'_i \leftarrow \frac{J_i}{2^{n-1}}$

end for

return $\mathcal{B}'_i$

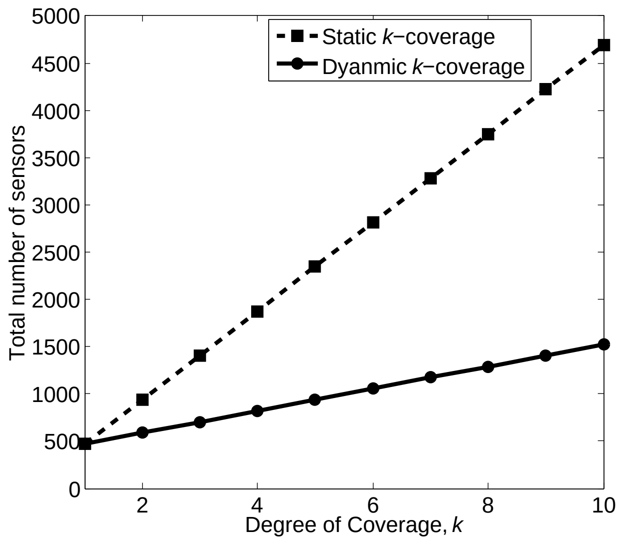


Figure 4.16: Number of sensors in static vs. dynamic coverage.

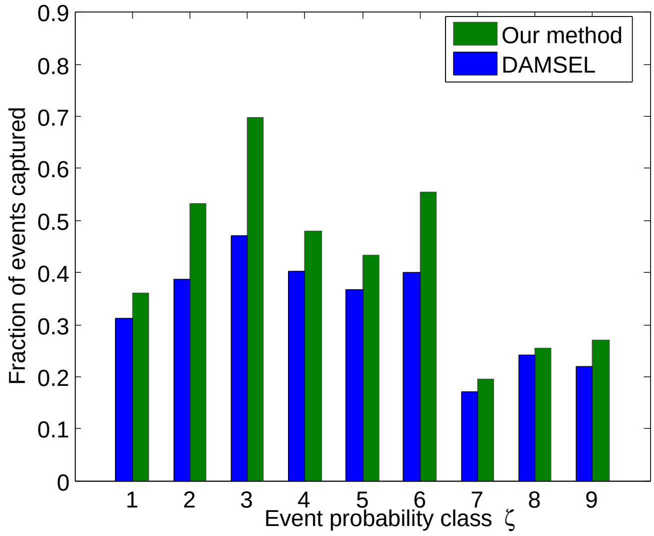


Figure 4.17: Fraction of events captured in different event probability classes given by $\zeta = \{0.10, 0.15, 0.25, 0.1, 0.1, 0.15, 0.05, 0.05, 0.05\}$

mobile nodes. 400 static sensors were deterministically deployed over a $600m \times 600m$ sensor field. Sensing and communication radii were taken to be $r = 10m$ and $R = 40m$, respectively. Energy ratings to drive the mobile nodes are taken from [303]. Initially 200 mobile nodes were deployed randomly but it was varied in some cases (Fig. 4.21). Event arrival rate was taken to be $1/hour$. To observe the impact of different event occurrence probabilities in different regions as described earlier, we divided the sensor field in nine $200m \times 200m$ square grids with event occurrence probabilities, $\zeta = \{0.10, 0.15, 0.25, 0.1, 0.1, 0.15, 0.05, 0.05, 0.05\}$ and generated a series of events according to this spatial distribution. Upon detection of an event by a stationary node, a subset of mobile nodes within its communication range were selected based on their profiles $\langle E_{rem_i}, d, \rho, \zeta \rangle$, measuring weights with $c_1 + c_2 = 0.7$ and $c_3 = 0.3$ as per (4.24). We have experimented with other values of c_1, c_2 and c_3 as well which showed comparative trends.

We consider that, the network life ends when the first mobile node dies out of energy and each simulation was run until the network dies. All the experiments were carried out 1000 times and average results are presented. First, in Fig. 4.16, we show a comparison between the number of sensors required to provide full k-coverage in a static sensor network and in our hybrid network . In case of static coverage, k nodes

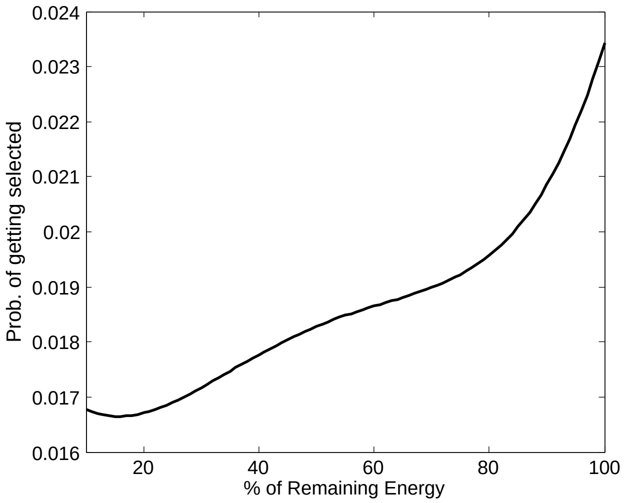


Figure 4.18: Impact of remaining energy on selection.

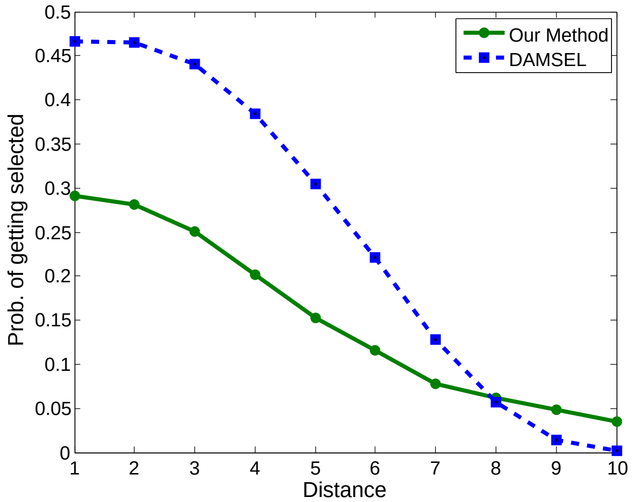


Figure 4.19: Impact of target distance on selection

need to be within the *sensing range* of the event while in our model, additional nodes are only required to be within the *communication range* of the detecting static node. That is why the number of sensors is significantly low compared to static configuration, indicating huge cost saving especially in higher value of k.

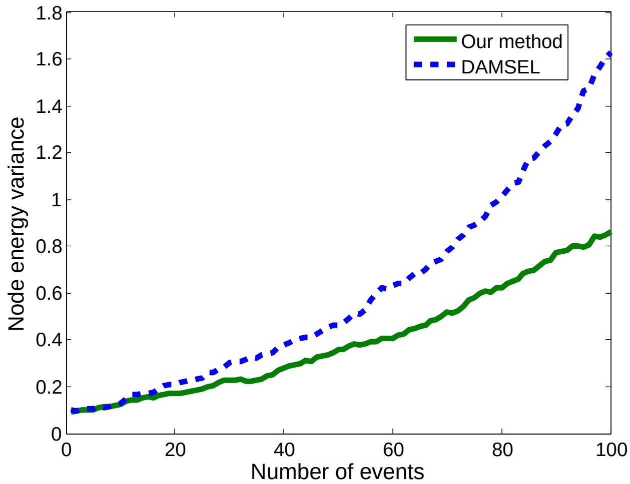


Figure 4.20: Variance of node energy vs. number of events.

Figure 4.17 shows comparison of the fraction of events captured in each of the nine ζ classes between our method and DAMSEL. Evidently, our method outperforms DAMSEL and the gain is significant in regions with high event occurrence probability ($\zeta_2 = 0.15$, $\zeta_3 = 0.25$, and $\zeta_6 = 0.15$). This is an important gain by our method, as in practice, event-prone regions need more attention, and our method performs equally good as DAMSEL in other regions. The *t-test* comparing the two methods at various probability of occurrence yielded p-values, $p \leq 1.75 \times 10^{-11}$ at 99% confidence level, validating their performance difference being statistically significant. This gain follows from two main features of our model. First, if two different nodes have similar strengths in other components of the profiles, the one currently located in low event occurring area will be relocated. Thus our method promises to provide better coverage in the vicinity of high event frequency region. Second, in DAMSEL, always the nearest nodes are selected irrespective of their remaining energy, which causes nodes in the neighbourhood of high event frequency to die out quickly. But our method prefers a distant healthier node than a closer node low in energy. The comparison of the probability of a node getting selected w.r.t. its remaining energy is presented in Fig.

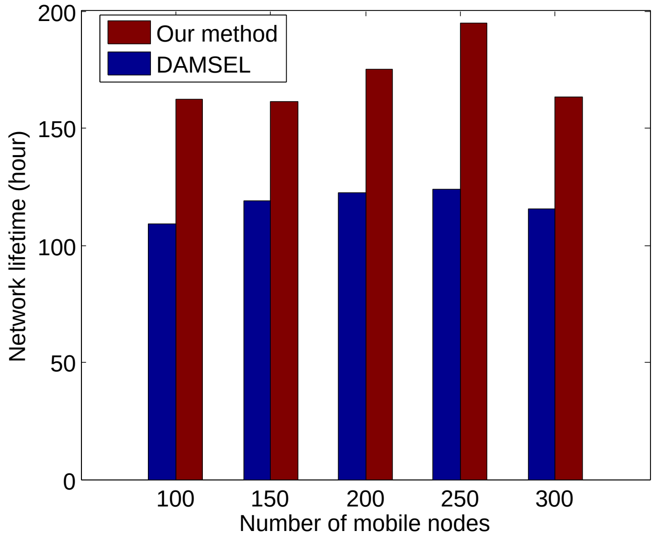


Figure 4.21: Comparison of network lifetime.

4.18. This shows that the nodes superior to others in energy have the greater probability of getting selected. However, as a result of this, our method exhibits a slightly higher node displacement compared to DAMSEL which is depicted in Fig. 4.19. It shows that DAMSEL is highly likely to select the closest nodes while our method may select a slightly distant nodes with moderate probability. However, our method hardly selects any node from the farthest region. But DAMSEL has to drag nodes from those regions since the closer nodes die out quickly. The probability of distant mobile nodes getting selected falls near-exponentially in our method as well.

Figure 4.20 plots the change of variance in node energy among the mobile nodes due to mobility vs. number of event occurrences. It shows that, approaches that always select the nearest nodes without considering remaining energy (such as DAMSEL), cause imbalance in energy consumption. But our method ensures moderate growth in the energy variance. As a consequence, our method achieves greater lifespan considering the aforementioned definition of network life. Such gain is depicted in 4.21. Joint impact of energy and event distance is shown in Fig. 4.22. The results are consistent with our idea to prefer nodes with higher energy even if they are little farther from event, when nearby nodes are low in energy. In that way, we ensure that the nodes will not die out quickly when they are in the vicinity of frequently occurring event. Fig. 4.23 presents the joint effect of distance and node density in selection. It shows that, nodes

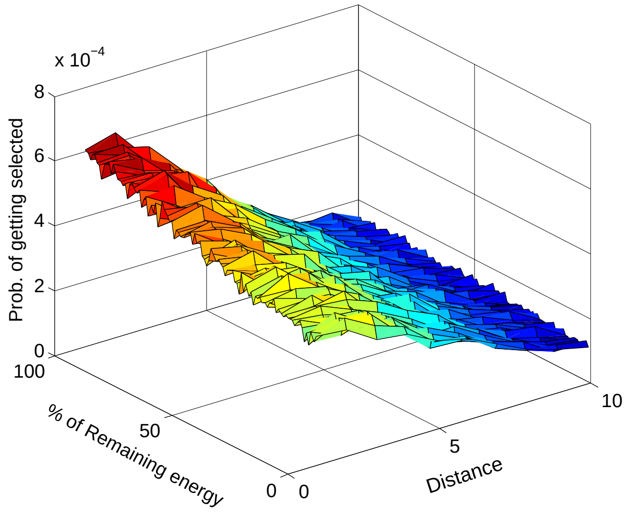


Figure 4.22: Joint impact of distance and remaining energy.

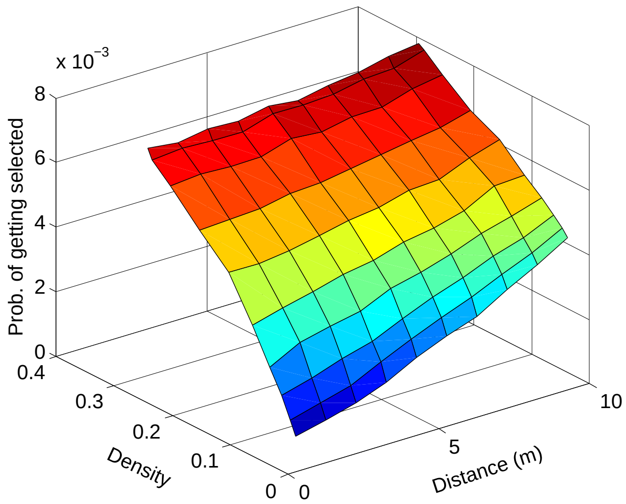


Figure 4.23: Joint impact of distance and node mobility

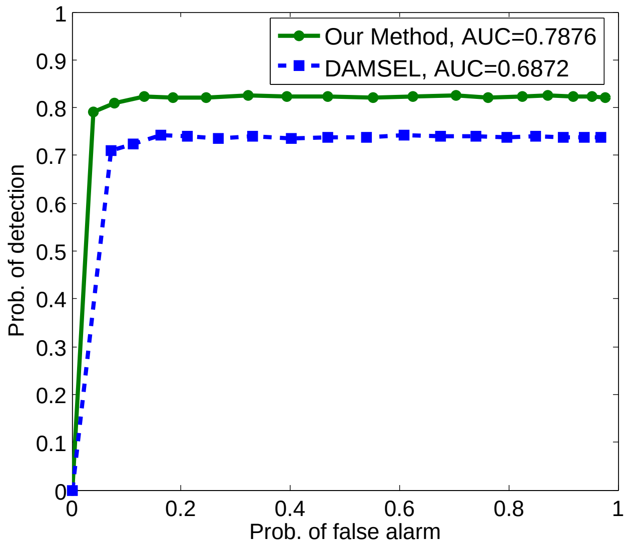


Figure 4.24: Accuracy comparison between DAMSEL and our on-demand k-coverage [37]

in highly dense regions get preference over nodes in sparse density region. This nature of our method prevents the possibility of leaving some regions out of mobile nodes at a time when some other regions may have greater concentration of nodes. Finally Fig. 4.24 plots the ROC curve for our method and also for DAMSEL which shows the gain in overall accuracy in the proposed method (Area under ROC 0.7876 vs. 0.6872).

4.10 Conclusion

In this chapter we introduced the idea of on-demand event coverage that can ensure desired performance metrics using much lower number of nodes than the fixed coverage schemes presented in the previous chapter. The on-demand event detection using variable range technique is suitable for the sensor devices with active sensing capability and easily implementable as the node selection overhead is very low. We developed a theoretical foundation to make such technique applicable considering the key issues in event-centric WSNs such as detection performance, energy consumption and deployment strategy. Simulation results show the effectiveness of our approach yielding enhanced network lifetime and improved detection performance compared to traditional fixed range sensing used in static coverage or dynamic coverage using mobile nodes.

The mobility based strategy is also made feasible by minimising the node movement exploiting the spatial locality in event occurrence distribution. However, all events are treated uniformly in both of the proposed method. In the following chapter, we explore the scenario of multiple concurrent events and the potential gain in providing differentiated treatment to them.

Chapter 5

Priority Sensitive Event Detection

In the earlier chapters, we have considered single event detection task and treated all events uniformly. However, this may not be the case in critical event detection applications such as nuclear reactor monitoring [164] or fault detection in highly expensive system. For example, in some mission critical applications like nuclear leakage detection or tusmani warning, particular events need to be detected immediately after their occurrences with high accuracy to avoid human and financial losses [129, 138]. On the other hand, non-critical applications, such as inventory alarm notification system or smart home WSN systems, are not such crucial phenomena like the previous examples, and thereby can tolerate certain delay and loss in accuracy. In the worst case scenario, even occasional failure to detect these type of phenomena will not bear the same level of consequences as that of the previous examples. This means there is a need to treat each type of phenomena/events differently according to their priorities as indicated by their natures of application. To the best of our knowledge, all event detection techniques available in the existing literature treats all events equally and uniformly [29, 37, 257] which clearly lacks practical consideration. With the decreasing cost of sensors, it is expected that sensors will be deployed in mass scale, and the advancements of multi-modal nodes will enable sensing of simultaneously occurring events, possibly of varied priorities, in the same monitoring area. In such cases a detection technique should be geared to detect high priority events with very high accuracy, even at the cost of missing some occurrences of low risk events. Such a task is not trivial, but requires the consideration of severity and cost of missed-detection of different events. To accomplish this, we introduce the notion of priority sensitive event detection in WSN under such circumstances.

5.1 Necessity of Priority Consideration

The concept of priority sensitive detection/classification stems from the wider machine learning domain where false positive (falsely detecting an event) and false negative (missing an event) decisions are often treated differently [304], [305]. Especially in the case of imbalanced data classification where the occurrences of most important and sensitive class are rare, misclassifying a rare class member is more significant than missing a regular one. To easily understand the idea, let us consider a disease diagnosis system. Missed detection of a cancer cell in body is much more sensitive than missing a benign mole or cyst on the body. Clearly, the diagnosis system should devote more sophisticated measures to ensure accurate detection of cancer than any other less lethal disease. The same scenario occurs in event detection too. An event inside a nuclear plant core is much more sensitive than an event outside the core or an event in the parking bay of the plant. Unfortunately, no existing even detection technique in the WSN addresses this issue. Jiang *et al*. [306] observed such concepts in the software fault prediction model. They established the fact that the cost implication of mistakenly classifying a faulty module as fault free and the cost of predicting a fault-free module as faulty are rarely equal in reality. In case of high risk sensitive software projects, such as safety related spacecraft navigation system or nuclear reactor monitoring system, the cost of missing a fault may lead to extreme consequences. Fig. 5.1 presents the cost implications of 13 different software projects with 11 different cost matrices. Their analysis clearly shows how the costs are associated with the risk level of the component faults. It is evident from the above discussion that events in real-world WSN applications should be treated according to priority. Priority of any specific type of event is determined by the cost implications of the damage resulting from missing that event in the sensor field. Usually, event centric WSN applications exhibit multiple simultaneous events occurring in close proximity, especially in disaster monitoring, sensitive structure/plant monitoring or in military applications [89, 108, 124, 138, 139, 164]. In March 2011 the world experienced one of the most horrifying disaster of this decade in Japan. First

Cost of FN	Cost of FP	Cost Ratio	Risk Type
1	75	1/75	Low
1	50	1/50	Low
1	25	1/25	Low
1	10	1/10	Low
1	5	1/5	Low
1	1	1	Medium
5	1	5	High
10	1	10	High
25	1	25	High
50	1	50	High
75	1	75	High

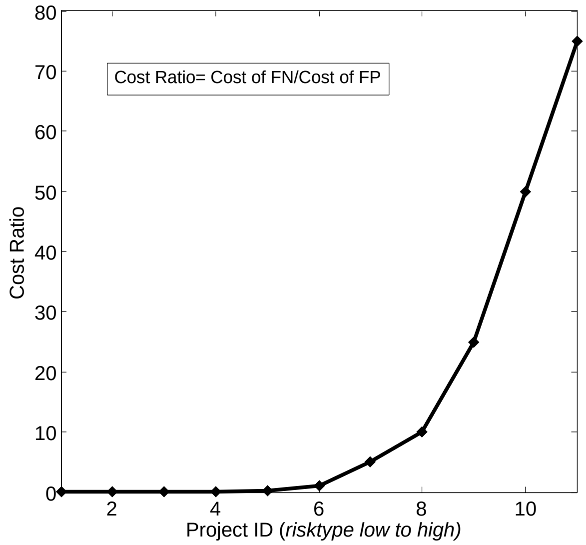


Figure 5.1: Misclassification Cost for 13 different projects.

came the earthquake and then a tsunami quickly followed. The tsunami shockwaves caused a core meltdown occurring at the Fukushima Daichi nuclear reactor along with an explosion of the reactor's housing structure causing fire hazard. These all lead to the understanding that disaster or hazard monitoring can no longer be thought of as a homogenous event detection task. Also, same type of events may have different impact and sensitivity depending on its origin of occurrence. A fire event originating near a fuel reservoir is much more sensitive than similar events in other places near non-flammable object.

Majority of the research in event detection literature treat events uniformly and equally, which is not always true in event-centric WSNs as discussed above. A range of different events with varied priority can occur in the sensor field and available mobile nodes need to be efficiently allocated to those events. Basnik *et al*. and others [28, 29, 70] devised an algorithm to assign series of tasks to multiple mobile robots in a hybrid sensor network consisting of low cost static nodes and mobile robots. Their attempt minimises the communication cost and message passing for the static nodes but does not consider any priority among different types of events. When multiple events with varied priority occur at the same time, there is no way to distinguish between them. We formally introduce variable priorities for multiple simultaneous events and incorporate this in our on-demand event coverage scheme presented in Chapter 4 to attend them in best possible way. In a hybrid WSN, this scheme requires efficient allocation of mobile nodes to different events to satisfy varied performance requirements.

In the light of the above discussion on the necessity of differentiated treatment in detecting events, we propose an event detection system, that would consider event priority and missed-detection cost to reflect the actual system performance. However, several challenges exist in the aforementioned priority sensitive event model in WSN-

1. **Priority management:** Events need to be assigned different priority values depending on the projected loss or damage caused (materialistic, financial or social). This is application specific and needs to be consistent with the real life cost incurred by respective events. No notable work has been done in WSN literature addressing this.

2. **Scalable QoS support:** QoS support techniques for event detection as described in Chapter 3 are not scalable with respect to event sensitivity. Events with different priorities demand different performance requirements.

3. **Resource allocation:** The limited WSN resources (relocatable mobile nodes) need to be allocated to multiple simultaneous events according to priority. To ensure superior detection performance for high priority events, the low priority events may suffer. The trade-off between higher and lower priority events need to be balanced to achieve acceptable overall detection performance.

Detection performance of events in WSN are typically enhanced using k-coverage as demonstrated in Chapter 3. In this chapter, we adhere to the on-demand k-coverage model for QoS guarantee for event detection presented in the previous chapter. Under such model, in an event centric WSN with static-mobile intermix, mobile sensors will move closer to an event and increase the fidelity of detection through the collaboration with other nodes. Due to the deployment cost, it is not realistic to assign adequate additional mobile nodes to equally over-provision for all the simultaneous events. The limited number of additional mobile nodes, which are costly and higher energy consuming, needs to be assigned carefully to events on-demand in such a manner as to ensure better performance for higher priority events while still not ignoring lower priority events. The timeliness of detection should also be maintained. The proposed *Priority Sensitive Event Detection (PSED)* scheme deals with the aforementioned challenges. To the best of our knowledge, this scheme is the first to handle simultaneous occurrence of priority sensitive events in an event centric hybrid WSN. Our contributions in this chapter are :

- Introduction of the concept of event priority and cost of missed-detection in WSN based event detection.
- Quality of Service (QoS) of event detection such as accuracy and timeliness are provisioned on a priority basis, which ensures superior overall detection performance.
- Analytical modelling of event detection in our proposed model.
- Finally, maximising the overall priority sensitive detection performance through the optimisation of mobile node allocation to events.

5.2 System Model for PSED

5.2.1 Network Model

We modify the hybrid WSN model described in Section 4.5 to account for the presence of multiple events at the same time. We consider a hybrid sensor network with N_s number of static sensor nodes and N_m number of mobile sensor nodes deployed over an arbitrary shaped area of interest. We assume that sensor nodes are location aware via some localisation technique (e.g. GPS or other systems). Mobile sensors are initially uniformly deployed over the sensor field. Static sensors provide 1-coverage to cover every point of the WSN and to maintain connectivity and the number of nodes N_s

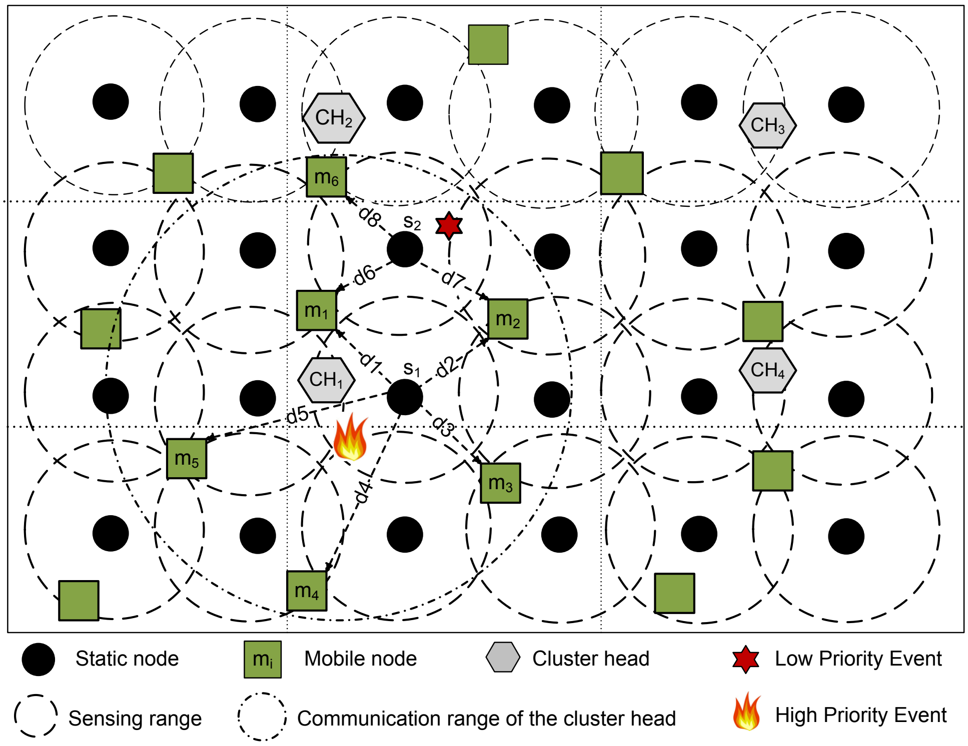


Figure 5.2: System Model.

required for such coverage is computed using the technique described in [180]. Each mobile node is equipped with a sensing unit and a locomotion unit and capable of movement with a constant velocity, v. The movement energy is directly proportional to the distance travelled. In Fig. 5.2, solid circles denote static node and squares denote mobile nodes. Sensing range for the static nodes are shown by concentric dotted circles.

5.2.2 Priority Scheme

In the PSED case, a range of different types of events may occur in a sensor field. Each type of event has an associated priority value $\pi \in [0, 1]$ depending on the severity and risk of damage caused by the corresponding event. Each event has one or more designated sensing attributes and each sensor node stores a lookup table to assign priority to the event depending on the specific sensed attributes for corresponding event types.

5.2.3 Event Detection Model

Here, we adopt a two phase detection model where each event is first detected by one or more static sensor nodes. Each static node notifies a local cluster head of the event and the corresponding priority. The cluster head determines which mobile nodes can move forward to enhance the fidelity of detection, assigns mobile nodes to specific events and sends request to them. The mobile nodes within the communication range of that cluster head are candidate for all those simultaneous events. Consider the scenario presented in Fig. 5.2 where two events with different priorities take place at the same time and are detected by two static sensors s_1 and s_2 first. Those two static sensors inform the cluster head CH_1. The cluster head requests the six mobile nodes (m_1, m_2, m_3, m_4, m_5, m_6) within its communication range denoted by the large dotted circle. These six mobile nodes will be referred to as *the candidate nodes*. We see that nodes m_1 and m_2 are candidates for both events but they can move towards only one at a time. In such case, the priority has to be taken into consideration and the high priority event should get preference.

We employ the sensing and noise model well established in the literature of signal detection and event sensing as described in Chapter 2. An event is characterised by the power of the signal it emits. When a sensor senses the emitted signal from an event for a duration of time T, the total energy measured by sensor s is given by,

$$\hat{U}_s = U(x_s).T + \aleph_s^2(T). \tag{5.1}$$

where $U(x_s)$ is the total power measured by a sensor at distance x_s without the noise and $\aleph_s^2(T)$ is the noise having a Gaussian distribution with zero mean. After the initial detection of an event by at least one sensor close to the event, a set of mobile nodes are assigned to collaborate and enhance the detection performance. Those mobile nodes move forward to sense the assigned event and send their measurements to a local cluster head. The cluster head decides on the presence or absence of the event comparing the average power to a threshold η_v. Such multi-sensor fusion model was explored in [45].

5.2.4 Problem Formulation

In this model, mobile nodes are allocated to events depending on the event's priority. Higher priority events are attended by greater number of nodes. However, critical events require faster detection while allocating more mobile nodes may slow down the detection process as all the assigned nodes need to move forward before detection decision can be taken. That is why we formulate the problem as a bi-criteria optimisation problem as described below. Consider,

n events occurring simultaneously, $E = \{e_1, e_2, \ldots, e_n\}$.

l candidate mobile nodes, $\mathcal{M} = \{m_1, m_2, \cdots, m_l\}$.

q different priorities, $\Pi = \{\pi_1, \pi_2, \cdots, \pi_q\}$.

$t_{i,j}$ is the normalised movement delay for node m_j to reach event e_i.

Event coverage is represented as a $n \times l$ allocation matrix, $Cov = [c_{ij}]$, where,

$$c_{ij} = \begin{cases} 1, & \text{if event } e_i \text{ is covered by mobile node } m_j. \\ 0, & \text{otherwise.} \end{cases}$$

$f_{det}(x)$ is the detection accuracy of an event covered by x nodes which can be defined according to the k-coverage detection model in Chapter 3. We define the following optimisation problem with the goal to determine the optimum allocation matrix, Cov, for event coverage,

$$\begin{aligned} &maximise \quad && \sum_{i=1}^{n} \pi_i f_{det}\Big(\sum_{j=1}^{l} c_{ij}\Big) \\ &minimise && \sum_{i=1}^{n} \pi_i \left(\max_{1 \le j \le l} c_{ij} t_{ij} \right) \\ &s.t., && \sum_{i} \sum_{j} c_{ij} = l \\ & && \sum_{i} c_{ij} = 1, \text{ for all } 1 \le j \le l \end{aligned} \tag{5.2}$$

In determining the allocation matrix, i.e. to select the best positioned nodes, the first objective in the above formulation aims to maximise the overall prioritised accuracy while the second objective aims to minimise delay in detection. The cluster head in our detection model will run an algorithm to compute the allocation matrix.

5.3 Solving the PSED problem

5.3.1 Probabilistic Approach

The most intuitive solution to the described problem is the probabilistic assignment of mobile nodes to events based on the priority. First, we approach the problem as a priority based resource scheduling task. We adopt the lottery scheduling [307] from operating system domain which is a proportional-share scheduling algorithm. We allocate the mobile nodes to events in proportion to their normalised priority. For n events occurring simultaneously, normalised priority of event e_i is defined as,

$$\pi_{N_i} = \frac{\pi_i}{\sum_{j=1}^{n} \pi_j}.$$

A total of $n_L = \sum_j^n \lceil \pi_{N_i} m \rceil$ lottery tickets are allocated to n events in proportion to their normalised priority values. Event e_i gets $n_l = \lceil \pi_{N_i} l \rceil$ tickets. For each m candidate mobile nodes, cluster head picks a ticket randomly and assigns the node to the corresponding ticket owner. The expected number of mobile nodes allocated to event e_i is $\frac{l n_l}{n_L}$.

Proposition 1. For two simultaneous events e_i and e_j with priority π_i and π_j,

1. $\pi_i \geq \pi_j \implies P_{F_i} \leq P_{F_j}$.
2. $\pi_i \geq \pi_j \implies P_{D_i} \geq P_{D_j}$.

where P_F and P_D are the corresponding false alarm probability and detection probability, respectively.

Proof. Let us consider the multi sensor value fusion model as discussed in Chapter 2. Suppose there are k sensors sensing an event. Each sensor measures the signal energy for duration T. False alarm probability P_F can be expressed as,

$$\begin{aligned} P_F &= P\left(\frac{1}{k}\sum_{s=1}^{k} \aleph_s^2(T) > \eta_v\right) \\ &= 1 - P\left(\sum_{s=1}^{k} \aleph_s^2(T) \leq k\eta_v\right) \end{aligned} \tag{5.3}$$

Since the signal strength follows a zero mean normal distribution, $\sum_{s=1}^{k} \aleph_s^2(T)$ follows the Chi-square distribution with k degrees of freedom. Denoting its cumulative distribution function as $\chi_k(.)$,

$$P_F = 1 - \chi_k(k\eta_v). \tag{5.4}$$

Let the expected number of mobile nodes allocated to events e_i and e_j are k_i and k_j. Then the false alarm rates are $P_{F_i} = 1 - \chi_{k_i}(k_i\eta_v)$ and $P_{F_j} = 1 - \chi_{k_j}(k_j\eta_v)$, respectively. According to the method described above, $k_i = \lceil \pi_{N_i} m \rceil$ and $k_j = \lceil \pi_{N_j} m \rceil$. The condition $\pi_i \geq \pi_j$ leads to,

$$\begin{aligned} \pi_i \geq \pi_j &\implies \pi_{N_i} \geq \pi_{N_j} \\ &\implies k_i \geq k_j \\ &\implies 1 - \chi_{k_i}(k_i\eta_v) \leq 1 - \chi_{k_j}(k_j\eta_v) \end{aligned} \tag{5.5}$$

Therefore, $\pi_i \geq \pi_j \Longrightarrow P_{F_i} \leq P_{F_j}$.
Again the probability of detection is,

$$\begin{aligned} P_D &= P\left(\frac{1}{k}\sum_{s=1}^{k}\left(U(x_s).T + \aleph_s^2(T)\right) > \eta_v\right) \\ &= P\left(\sum_{s=1}^{k}\aleph_s^2(T) > k\eta_v - \sum_{s=1}^{k}U(x_s).T\right) \\ &= 1 - \chi_k\left(k\eta_v - \sum_{s=1}^{k}U(x_s).T\right). \end{aligned} \tag{5.6}$$

$$\begin{aligned} \pi_i \geq \pi_j &\Longrightarrow k_i \geq k_j \\ &\Longrightarrow \sum_{s=1}^{k_i}U(x_s).T \geq \sum_{s=1}^{k_j}U(x_s).T \\ &\Longrightarrow k_i\eta_v - \sum_{s=1}^{k_i}U(x_s).T \leq k_j\eta_v - \sum_{s=1}^{k_j}U(x_s).T \\ &\Longrightarrow 1 - \chi_{k_i}\left(k_i\eta_v - \sum_{s=1}^{k_i}U(x_s).T\right) \\ &\quad \leq 1 - \chi_{k_j}\left(k_j\eta_v - \sum_{s=1}^{k_j}U(x_s).T\right). \end{aligned} \tag{5.7}$$

Therefore, $\pi_i \geq \pi_j \Longrightarrow P_{D_i} \geq P_{D_j}$. $\square$

5.3.2 Combinatorial Optimisation

Probabilistic approach described above is fast and requires very little computational resource. However, it does not meet the delay constraint. To achieve both the objectives formulated in (5.2), we view this as combinatorial optimisation problem which considers all the possible combinations of the coverage matrix. Naturally the problem is NP-hard. Considering the computational limitation, energy and delay constraint, the exact optimisation is not always feasible in the sensor node. That is why, we need to use a heuristic based algorithm to mitigate the exponential time complexity. We consider the meta heuristic for randomised priority search (Meta-RaPS) [308] algorithm to solve the optimisation problem stated in Section 5.2.4.

The philosophy behind Meta-RaPS stems from three basic ideas: (i) the incorporation of randomness in a particular heuristic may dramatically improve the solution quality, (ii) random combinations of heuristics may lead to better results than each heuristic individually, and (iii) it basically depends on one heuristic - *the priority rule.* Meta-RaPS has been proved to be highly effective and efficient in resource allocation problem [309]. We approach the aforementioned problem as a resource constrained allocation problem which motivates us to exploit Meta-RaPS here.

5.3.3 Delay Analysis

To model the detection delay for any event, let us revisit our two phase detection model. In the first phase, the event gets detected by nearest sensor. In the second phase a set of mobile nodes are allocated by the cluster head to move forward and increase the quality of detection. Since all the allocated nodes need to move to within the sensing distance to complete the decision fusion, detection delay is determined by the time required for the furthest node to move within sensing range, assuming constant velocity for all mobile nodes. We ignore the decision fusion delay and transmission latency here as they are negligible compared to the time required for node motion.

Definition 1. We define the *Allocation Radius*, A_R, of an event as the distance of the furthest node among the set of nodes allocated to that event. Let the number of mobile nodes allocated to event e_i be k_i. Allocation radius, A_{R_i} is given by,

$$A_{R_i} = \max_{1 \leq j \leq k_i} x_{ij}. \tag{5.8}$$

where, x_{ij} is the distance of node m_j from event e_i.

Definition 2. *Detection Delay* is defined as the time required for the furthest node to move to within the sensing range of the event. For k_i nodes assigned to event e_i, this delay is given by,

$$D_i = \frac{\max_{1 \leq j \leq k_i} x_{ij}}{v} = \frac{A_{R_i}}{v}. \tag{5.9}$$

where, v is the constant velocity of the mobile nodes.

Theorem 2. *For uniform node distribution, the expected detection delay becomes an increasing function of the number of nodes allocated to that event. The expected detection delay, $\bar{D}_i$ for an event e_i with k_i nodes allocated to it, with the nodes selected from a circle of radius R, is given by,*

$$\bar{D}_i = \frac{R\left(1 - (2k_i + 1)^{-1}\right)}{v}. \tag{5.10}$$

Proof. For a circle of radius R having uniform node distribution, it is known [310] that the pdf of the distance of any point from the centre is

$$f_X(x) = \frac{2x}{R^2}. \tag{5.11}$$

The probability distribution function for a node to be at most at distance x from the target is,

$$g_X(x) = \int_0^x f_X(x) = \frac{x^2}{R^2}. \tag{5.12}$$

For a set of k_i nodes allocated to an event, the probability distribution for the maximum distance of any node from event is expressed as,

$$G_X(x) \quad = \quad \binom{k_i}{1} f_X(x) \left(g_X(x)\right)^{k_i-1} = \tfrac{2k_i x^{2k_i-1}}{R^{2k_i}}. \tag{5.13}$$

The expected value of the allocation radius as defined above is derived from (5.13) as,

$$\begin{aligned} \bar{A}_{R_i} &= \int_0^R xG_X(x)\mathrm{d}x \\ &= \int_0^R \tfrac{2k_i x^{2k_i}}{R^{2k_i}}\mathrm{d}x \\ &= R\left(1-(2k_i+1)^{-1}\right). \end{aligned} \tag{5.14}$$

Therefore, the expected detection delay,

$$\bar{D_i} = \frac{\bar{A}_{R_i}}{v} = \frac{R\left(1-(2k_i+1)^{-1}\right)}{v}. \tag{5.15}$$

□

Now, let us consider two events e_i and e_j with respective priority π_i and π_j and the number of nodes assigned to them are k_i and k_j, respectively. From (5.5), $\pi_i \geq \pi_j \implies k_i \geq k_j$. From (5.10), $k_i \geq k_j \implies \bar{D_i} \geq \bar{D_j}$. Therefore, $\pi_i \geq \pi_j \implies \bar{D_i} \geq \bar{D_j}$.

That is, for uniform distribution, the average time required to detect an event increases with the priority of that event. However, this holds only for the initial period as long as the distribution remains uniform. But assuming that each specific type of event has a tendency to occur in a specific region of the sensor field, mobile nodes will cluster around the high priority event locations with time and the distribution of node will become non-uniform. Therefore, after sufficient number of occurrences, the overall delay will reduce for higher priority events since they are likely to have the required nodes in close proximity.

Theorem 3. *Consider two different regions reg_i and reg_j with dominant event priority π_i and π_j. Let $\hat{D_i}$ and $\hat{D_j}$ be the delay for events e_i and e_j that occurs in reg_i and reg_j respectively, with priorities π_i and π_j. For non-homogenous distribution generated after a series of occurrences of both type of events, $\pi_i \geq \pi_j \implies \hat{D_i} \leq \hat{D_j}$.*

Proof. Let us consider two circular areas of radius R around both the event locations. Since the distribution of nodes is no longer uniform, we model the regional node distribution around those two events as Poisson process, which is usually used to model the number of neighbours in non-homogenous distribution [311], [290]. From [290], for

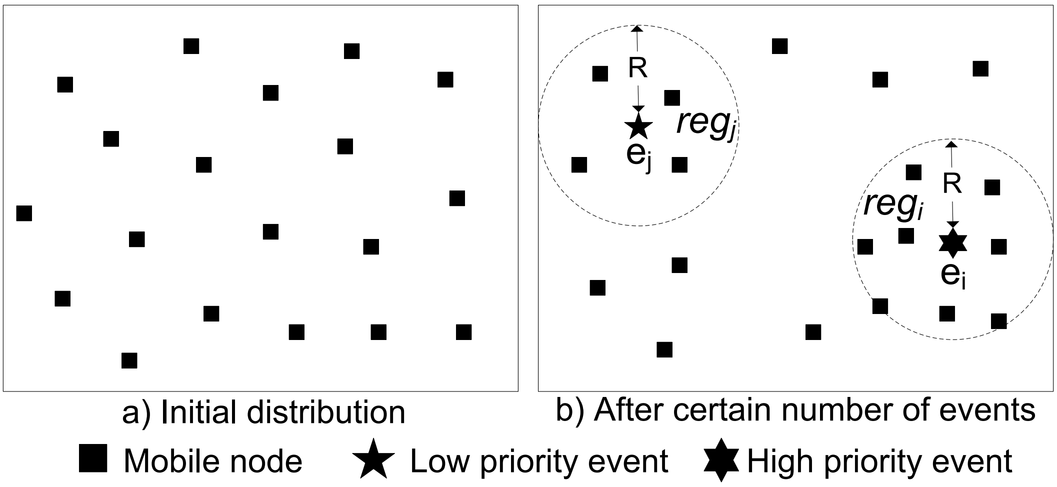


Figure 5.3: Clustering effect.

a region with poisson distributed nodes with density ρ, the pdf of the distance x from the centre of a node to its $k-th$ nearest neighbour is given by,

$$f_X(x) = \frac{2\pi\rho x^{2k-1}}{(k-1)}\mathrm{e}^{-\pi\rho x^2}. \tag{5.16}$$

Without loss of generality, let events e_i and e_j occur at the centres of reg_i and reg_j respectively and mobile nodes within the circle of radius R are requested (Fig. 5.3). The number of mobile nodes assigned to event e_i and e_j are k_i and k_j, respectively, and similarly, the node density in reg_i and reg_j are ρ_i and ρ_j. The average distance for the k_i-th node from the event e_i is then,

$$\hat{A}_{R_i} = \int_0^R x f_X(x)\mathrm{d}x = \int_0^R \frac{2\pi\rho_i x^{2k_i}}{(k_i-1)}\mathrm{e}^{-\pi\rho_i x^2}dx. \tag{5.17}$$

Similarly,

$$\hat{A}_{R_j} = \int_0^R \frac{2\pi\rho_j x^{2k_j}}{(k_j)}\mathrm{e}^{-\pi\rho_j x^2}dx. \tag{5.18}$$

Since mobile nodes tend to cluster around the high priority events with time, the non-homogenous distribution after a series of events leads to, $\rho_i \geq \rho_j$ given that, $\pi_i \geq \pi_j$. We already know, $\pi_i \geq \pi_j \implies k_i \geq k_j$. Evaluating the integrals we have, $\hat{A}_{R_i} \leq \hat{A}_{R_j}$. Now, $\hat{D}_i = \frac{\hat{A}_{R_i}}{v}$ and $\hat{D}_j = \frac{\hat{A}_{R_j}}{v}$, which leads to, $\pi_i \geq \pi_j \implies \hat{D}_i \leq \hat{D}_j$. $\square$

5.4 Simulation and Results

5.4.1 Simulation setup

To evaluate the performance and effectiveness of our PSED technique, we designed and implemented an event centric WSN in NS-3 containing both mobile and static nodes and conducted a series of simulations. We considered events with different priority values ranging from 0 to 1.0 and 3 to 5 events each run. Each experiment was carried out 500 times and the average results are presented in this section. We compared some results from our method with an otherwise similar but priority ignorant event coverage method known as *Distributed Approach for Mobile Sensor Selection (DAMSEL)*, described in [37, 257]. The mobile nodes are moved using the mobility model in [303].

5.4.2 Cost of missed detection

Table 5.1: Even classification

Sensitivity/Risk	Priority	Comment
Low	$0 \leq p < 0.4$	Low risk events, minor damage (e.g. empty space in parking lot)
Medium	$0.4 \leq p < 0.8$	Medium risk events (e.g. fire hazard in public area)
High	$0.8 \leq p < 1.0$	High risk events, missed detection is fatal (radiation leakage inside a nuclear reactor)

For better perceivability of the results we divided the available event priorities in three different classes namely- *Low*, *Medium* and *High* as shown in Table 5.1. As explained in Section 5.1, the cost implications of missing an event of *High* risk class is much higher than a missing a *Low* risk event. The cost, either monetary or in terms of fatality, indicates the loss or damage that follows from missing an event of any specific priority. From the real life example presented in Fig. 5.1, we infer that the cost increases nearly exponentially with priority. We use the following cost matrices in our simulation. Such cost matrices are widely used in machine learning domain to penalise classifier for misclassification[304, 306]. Here, TP - True Positive, FP - False Positive, TN - True Negative and FN - False Negative.

Table 5.2: Cost matrix for event class *Low*

	Event Occurred	No event
Event detected	0(TP)	1(FP)
Not detected	1(FN)	0(TN)

Table 5.3: Cost matrix for event class *Medium*

	Event Occurred	No event
Event detected	0(TP)	1(FP)
Not detected	5(FN)	0(TN)

Table 5.4: Cost matrix for event class *High*

	Event Occurred	No event
Event detected	0(TP)	1(FP)
Not detected	25(FN)	0(TN)

5.4.3 Performance evaluation

Figure 5.4 shows the event detection probability achieved by PSED and its comparison with $DAMSEL$ [37]. The experimental result establishes that our method ensures better detection performance for higher priority events while still maintaining significant detection probability for the low priority ones. It shows that, even though our PSED scheme performs little worse for the low priority events, it ensures superior detection performance for the medium and high priority events which is the primary objective of this chapter. The proposed system ensures an average of 91% detection probability for high priority event while with the priority-ignorant method there is almost 26% risk of missed detection.

Figure 5.5 compares our method with $DAMSEL$ with respect to the average degree of coverage ensured in different priority events. In our method, the overall average degree of coverage is high for the $High$ and $Medium$ priority events as would be desired in practice, while priority ignorant method results into a uniform coverage for all types of events. Even though *Low* priority events are getting better coverage in such case, the more sensitive events suffer from less than adequate coverage. In reality,

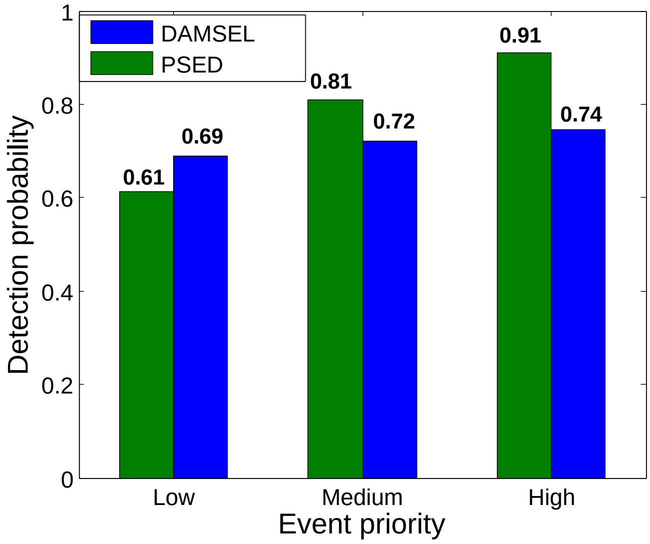


Figure 5.4: Detection probability vs. event priority.

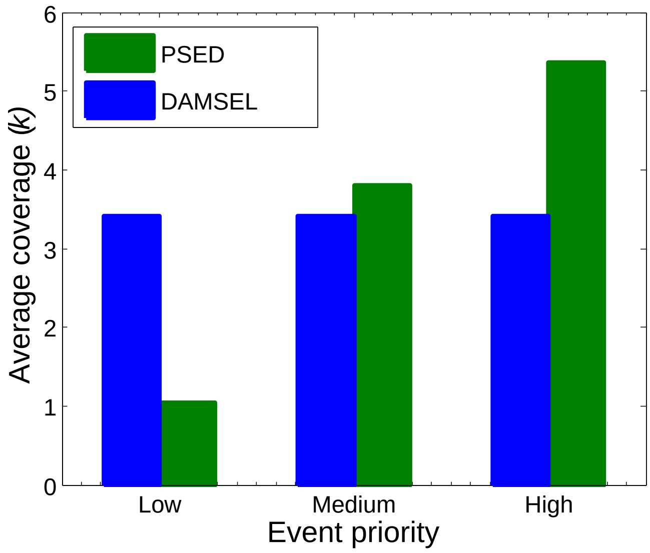


Figure 5.5: Average coverage (k) vs. event priority.

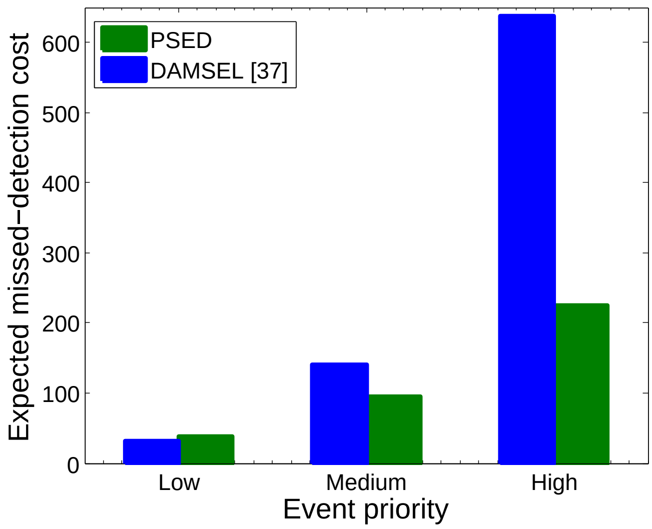


Figure 5.6: Cost of missed detection vs. event priority.

the high priority events are more sensitive and the effectiveness of a system depends on the performance guarantee ensured to them.

Figure 5.6 compares the expected cost of missed detections in PSED and the corresponding priority ignorant method using the cost matrices in Table 5.2, 5.3 & 5.4. Following [304], the expected cost is calculated as, *expected mis-detection cost= number of events *(1- probability of detection) * cost.* The rapid increase in the cost of missed detection in case of the priority-insensitive method establishes the importance of considering priority. In real world applications, high priority events have much serious consequences in terms of damage caused. Our priority sensitive method yields almost 400 units cost savings for $High$ priority events compared to its priority insensitive counterpart.

Figure 5.7 shows false alarm probability for different priority events in our priority sensitive model. This figure shows that our method maintain acceptably low false alarm for all classes of events. Fig. 5.8 demonstrates the average remaining energy of mobile sensor nodes after detecting each occurrences. DAMSEL treats each event equally and selects the nearest nodes to move which yields a moderate energy consumption. Results show that, our method spends a little more energy than DAMSEL because some nodes may have to move longer distance to provide better coverage for high priority event. However, the significant performance gain in missed detection cost in our method makes

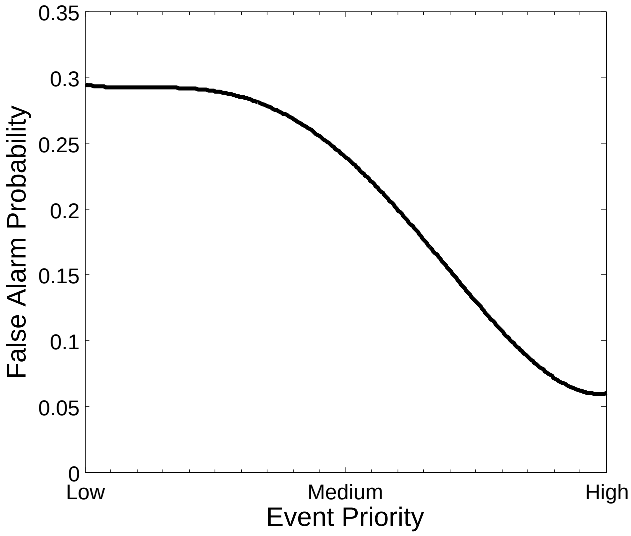


Figure 5.7: False alarm probability vs. event priority.

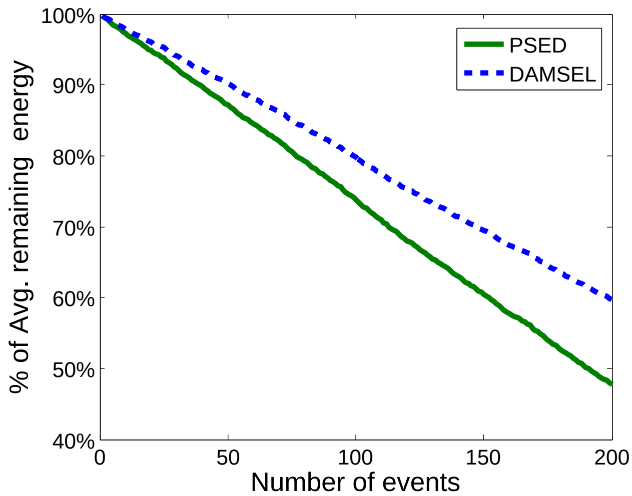


Figure 5.8: Average remaining node energy vs. number of events.

this trade-off worth.

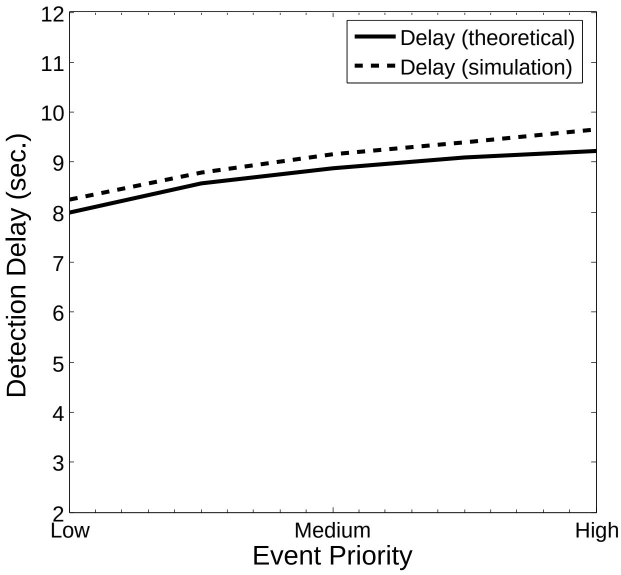


Figure 5.9: Detection delay vs. event priority.

Figure 5.9 compares the theoretical expected delay as derived in (5.15) with the value obtained in simulation for uniform node distribution at each run. Simulation shows close match between our theory and experiment. The experimental delay is little higher which follows from the fact that, we have only considered movement delay while ignoring any other source of delay such as decision fusion time or data transmission latency in theory. This is practical because movement delay is the most dominant part in case of mobile nodes.

Fig. 5.10 shows how the average delay for different event priorities changes as the distribution of nodes changes from uniform to non-homogenous (considering that mobile nodes do not return to their original locations after the detection task). As more number of events occur the distribution of mobile nodes changes to non-homogeneous. The experimental result supports the assumption of node clustering around high priority events since the delay for higher priority events decreases with the number of occurrences. Initially higher priority events suffer higher latency which results from the fact described in (5.10). But after few occurrences of each type of events, the availability of mobile nodes increase in the proximity of high priority event locations and the average delay decreases for such events. Fig. 5.11 plots delay vs. priority for

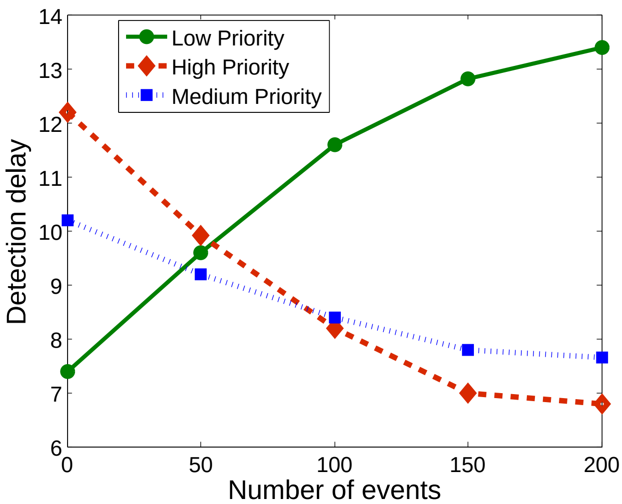


Figure 5.10: Detection delay vs. number of events

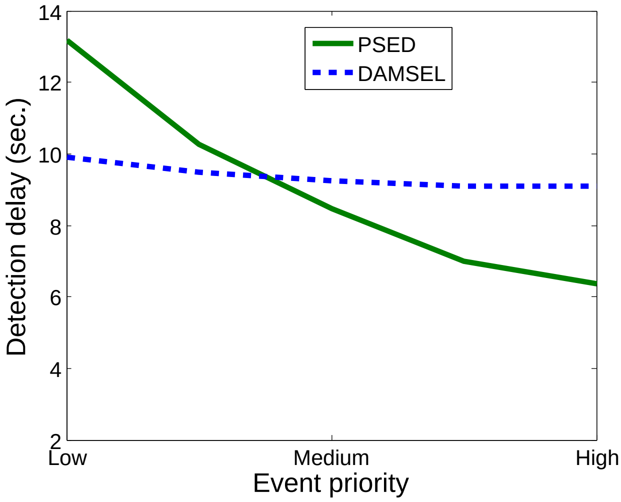


Figure 5.11: Detection delay vs. event priority (In-homogenous distribution resulted from series of events)

non-uniform distribution of node generated after a series of 200 events. Since mobile nodes cluster around high priority event locations with time, the detection delay reduces with priority which is evident from the figure. Our method is about 1.7 times faster in detecting high priority events. In other method, high priority events take about the same time as low priority events, which may lead to disastrous consequences in real world scenario.

5.5 Conclusion

In real world applications, high priority events have much serious consequences in terms of damage caused. It is evident that the efficient and timely detection of multiple simultaneous events with different performance requirements in a WSN is a practical issue. In this chapter, we introduced the idea of event priority for different types of events, and presented a novel technique to assign mobile nodes to events depending on their priority to enhance the quality of detection. Simulation results demonstrated that the proposed method outperforms existing method in overall event detection accuracy and delay.

We have considered the events in a stand-alone WSN so far in this thesis. However, interaction of nodes with external objects and consideration of surrounding context is becoming important as WSNs are becoming a part of the Internet of Things. We explore the such event detection in the following chapter.

Chapter 6

Context-Aware Event Detection in the Internet of Things

In the previous chapters, we considered the detection of event in stand-alone WSNs. However, the physical events in the real world environments are closely coupled with the surroundings atmosphere. Same event may be interpreted differently depending on the state of the environment it occurs in. This necessitates the consideration of the context defined by the state and the presence of other objects in the environment in reaching a decision on event occurrence. WSN based event detection systems need to communicate with other external objects and services to correctly capture the context of the event. This facilitates the detection of events in a more pervasive environment where WSNs coexist with other intelligent objects that are connected to the Internet to form a wider network of WSNs and objects, and builds the backbone of the Internet of things. In this chapter, we explore the potentials of integrating WSNs to the IoT for context-aware event detection.

One of the most important services expected from the IoT applications is the capability of detecting and locating events of interest. IoT is envisaged to augment our everyday objects with sensors and actuators. This augmented visibility of environment is only be useful through IoT applications if they can detect events of interest and act on them. As an example, a smart home system with embedded sensors in the environment will monitor people living inside and assist them under certain circumstances. This requires precise detection of real world phenomena. WSN technology dominates the field of such real world event detection [95] in the existing literature and is naturally paving its way in the IoT domain. Traditional WSN event detection techniques does not provide a platform for WSN-to-WSN or WSN-to-objects interactions which is necessary for event detection in a complex and dynamic environment, whereas IoT facilitates such a platform. They also lack proper framework to incorporate and handle contextual information that might strengthen detection system. WSN is deemed as one of the primary building blocks of IoT as sensors are the only means of observing the physical world. This chapter addresses such shift of event detection architecture in WSN and explores how it evolves in the IoT.

The paradigm shift of event detection technologies from traditional WSN to IoT introduces a series of new challenges. Existing approaches for event detection are mainly based on some predefined attribute values in regard to the sensed data. This is quite limiting and can be extended through the IoT platform which enables it to deal with the sensed data as well as the context of the data. The term *context*, refers to the pieces of information that capture the characteristics of sensing environments [276]. Therefore, event detection in IoT environment must be context-aware. An event of interest in such setting is inherently composite in nature and needs to be defined as a function of time, object state and context.

The way an event is defined and viewed in WSN is no longer appropriate for the IoT. In traditional WSN, an event is defined as a change of a real-world state which is characterised by the sensed measurements of one or more sensor nodes. Typically, threshold based event detection is prevalent in WSN where a sensor node reports a detected event when its average measurement of the raw sensor data is greater than the detection threshold which is an application specific parameter. However, in IoT sensors alone may not capture the event of interest since the context of the measurement defined by the state of other surrounding objects and temporal relationship among them are also important. This requires an abstract definition of event that brings the spatio-temporal relationship between sensor values and real world states together. Some of the information comes from the sensed values, some from the Internet defining user interest and some from the presence of other neighbouring objects.

Another key challenge is that imposed by the heterogeneity and interoperability of the wide range of varieties of devices present in the environment. Heterogeneity is characterised by the presence of different computing devices, such as desktop computers, PDAs and mobile phones, as well as different network technologies integrating these devices. The event detection framework should adopt a way to deal with the heterogeneity and scale the information from diverse sources up to a homogenous platform so that events can be defined and detected according to user interest defined dynamically. The event detection solution needs to manage any type of sensed information regardless of the particular information source.

The third issue in event detection in IoT is the presence of so called smart and dumb objects in the region of interest. Smart objects are those that can sense the environment and are equipped with active communication and computation capability. But there are other objects in the environment that can only identify themselves when asked (low powered RFID) but do not connect directly to the internet. Consider a smart home environment where a lot of objects in the home are only equipped with RFID so as to facilitate the identification of them. Now, consider a temperature monitoring sensor in that environment. It will be considered as a hazard if the temperature of a certain region is beyond the ignition level and there is a flammable object such as a match or a pressurised deodorant spray container. Since, such flammable objects are usually not directly connected to IoT, it is the responsibility of the smart sensor to locate and identify their presence nearby and lookup via the Internet to know if that object is introducing fire risk. So the event definition needs to be dynamic, composite and customisable via Internet.

To tackle the aforementioned challenges, it is necessary to move from the traditional threshold based detection and adapt to the IoT environment by designing a new way of event detection via a generic event representation and detection framework. Event detection in IoT is still in its infancy and to the best of our knowledge, no existing work addresses the aforementioned issues in relation to the implementation of event-centric WSN as a subsystem of IoT. In this chapter, we propose a ontology based universal event representation model in the IoT and design an event detection architecture that provides WSNs with an abstraction layer to capture event related information from heterogeneous sources in IoT. We take the advantage of the Internet connectivity of objects to push the overhead of ontology processing in the application layer that resides in the internet and provides a generic template based method to define events based on user interest. The main contributions in this chapter are -

1. Identified the key challenges to adapt event-centric WSN to the IoT architecture.

2. For generic and dynamic event definition, proposed an ontology based event definition language suitable for the event detection in collaboration of WSNs, hand-held devices and objects with RFID attached to them under the umbrella of IoT.

3. Designed and developed an event detection and notification subsystem that resides in the application layer and interpret the information retrieved from the underlying WSNs.

6.1 Preliminary Concepts

The IoT is an amalgamation of different technologies and standards such as Radio Frequency Identification (RFID), Wireless Sensor Network (WSN) and mobile communication technology with existing Internet as the communication backbone (Fig. 6.1). We describe these building blocks in brief in this section.

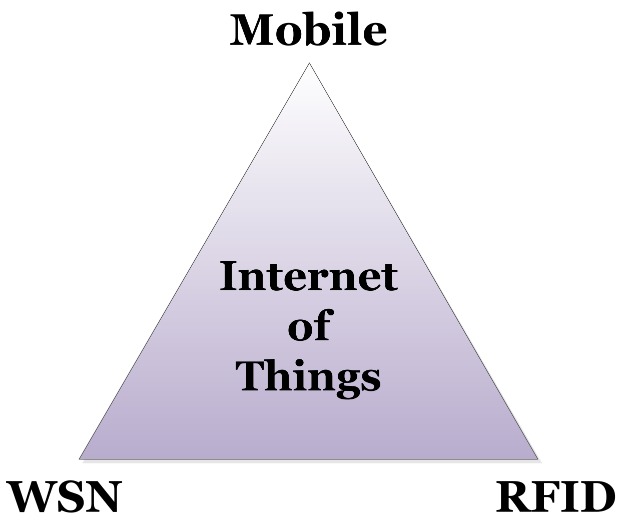


Figure 6.1: IoT Technologies.

6.1.1 RFID

RFID is a widely accepted technology for automatic identification and tracking of objects and people. It uses a wireless non-contact system based on radio-frequency to store IDs in tags attached to objects [312]. The tag contains a unique identifier (e.g.,

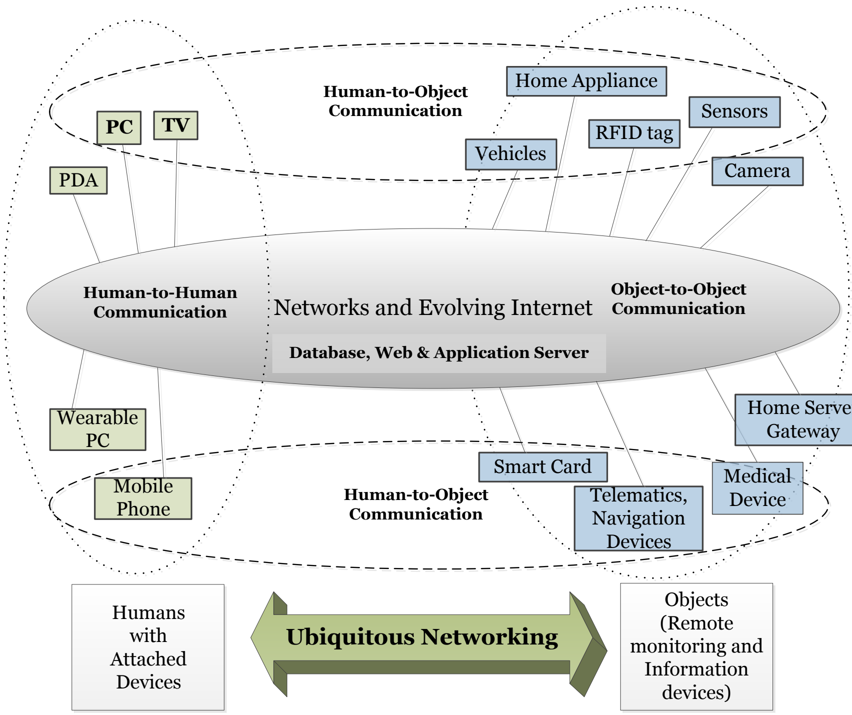


Figure 6.2: Internet of Things.

EPC code that identifies each product distinctively [313]) and an antenna for transmitting and receiving radio signals. Such an electronically stored ID can be retrieved by a reader devices that operates in a designated frequency. RFID usually uses very low powered radio and tags can be read from up to several meters of distance. RFID is one of the most important building blocks of IoT that makes it possible to identify and track trillions of physical objects or persons with a tag attached.

6.1.2 Smart Phone and PDA

Smart phones are equipped with various sensors and are capable of connecting to the Internet. With the introduction of fourth generation mobile technology, large amounts of multimedia traffic apart from the voice traffic are generated from hand held devices. Such smart devices, PDAs and similar mobile devices can capture voice, video and location data, and act as autonomous agents in the IoT architecture.

The other component is WSN which is described in previous chapters.

6.2 Key Challenges

6.2.1 Context Awareness

Context is a set of information that characterises the sensing environment and the interactions among entities (i.e. persons, objects), either directly and indirectly. IoT applications are inherently context sensitive, as they promise to bring the physical world and virtual world together. Context sensitive events cannot be defined or detected independently by sensors without considering the contextual information within the environment of interest. While traditional event-centric systems focus only on sensed information, we suggest context-aware model that integrates sensed information, user-supplied (QoS), and derived information and their contextual relationship to exploit the full power of IoT.

6.2.2 Interoperability and Integration

IoT applications face the natural challenge of interoperability among different devices and systems, and integration to standard communication protocols [314]. The underlying WSNs need to interface with all the other devices present in the environment and maintain Internet connectivity via an IPV6 addressing scheme. This communication details are beyond the scope of this work. Here we focus on the standardized data representation language for event definition and detection.

6.2.3 Data Heterogenity

As shown in Fig. 6.2, contextual information in the IoT originates from a wide range of different devices which leads to heterogeneity in data. To capture the true real world picture, the underlying WSN needs to identify and capture data streams from them apart from its on sensing devices. For example, a fire hazard detection subsystem for smart home needs to combine data from temperature and Carbon Monoxide sensors and at the same time needs to detect the presence of flammable and hazardous objects nearby. Therefore, in addition to sensing the environment, they also need to be smart enough to locate and identify other relevant devices via RFID reader or other means. Beside capturing data, there is a need for generic representation of all relevant data.

6.2.4 Event Representation

An event pattern is defined as a combination of data gathered from all or a subset of those sources. Apart from various sources, complex events often need to be defined in terms of multiple temporally or spatially related atomic events. The object state interaction is explained below with a detailed example.

Let us consider a smart home monitoring system. All the objects, like household appliances and human agents inside the home are trackable using RFID. Only the household appliances are equipped with sensors besides the standard temperature and smoke sensors mounted in fixed strategic locations. The sensor are equipped with RFID reader and directly connects to the smart home server via Internet. However, the RFID objects are usually large in number, placed randomly or change location with time, and do not directly connect to the Internet due to cost and energy restriction. So it is the responsibility of the sensors to identify the objects near them and transmit this information to the higher layer. Now let us consider a potential fire hazard and a child susceptible to the vulnerability. The $temperature > 200$ and $smoke > 100mg/L$ detects a potential fire hazard which could be detected by typical threshold based event system. However, to determine whether the child is within the danger zone or not, the sensor need to make use of RFID technology and track the RFID tag attached to the child. Thus the WSN deals with a heterogenous forms of data and enormous number of combination of information. Therefore, we require a uniform methodology of representing the IoT data and interfacing with the event detection subsystem.

6.3 Event Detection Architecture

As described in the previous example, a WSN in IoT needs to be wrapped with an abstraction layer so as to interface with the event detection subsystem. Let us consider an environment with N sensors and M passive objects identifiable via RFID. In our model, we assume that the RFID objects do not communicate with the Internet directly, rather they only store their IDs and other related description in their tags, and are readable via nearby sensors equipped with RFID reader. Sensors are location aware and equipped with RFID reader and communication module that enable them to communicate with the Internet. Each sensor can be in ϕ different states. Each object

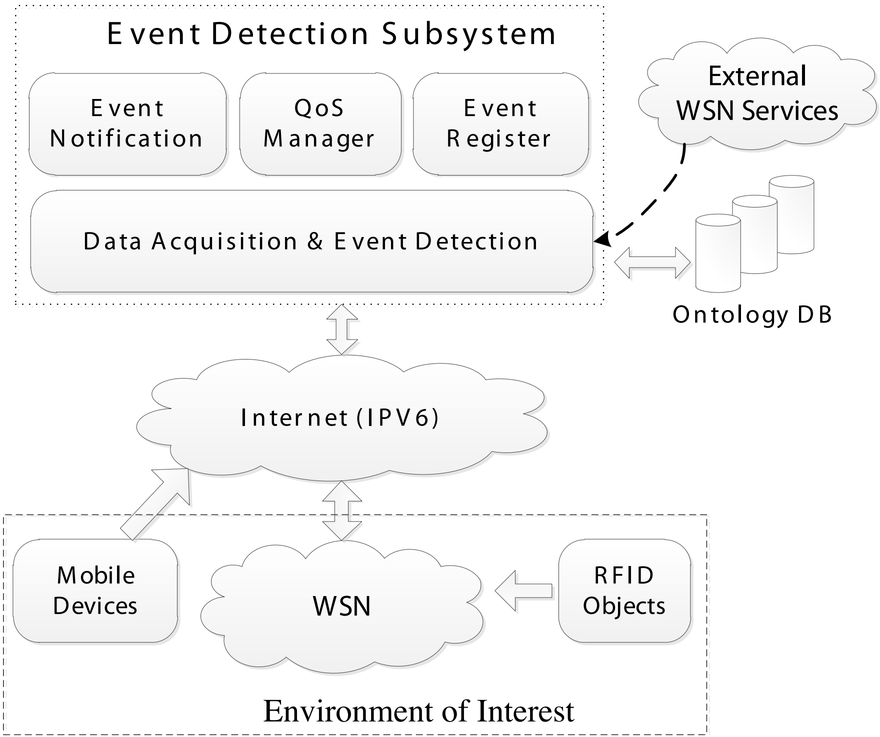


Figure 6.3: Conceptual Architecture.

can be near to one or more sensors. So there are a total of $\phi^N \times N^M$ different combinations of objects and states, only few of which denote events of interest. Because of this combinatorial explosion, the event detection algorithm is pushed in the internet layer in our detection architecture as shown in Fig. 6.3. The WSN will conform to an information exchange format provided by the higher layer IoT application and send the collected data periodically to the detection subsystem after translating them using the representation described below.

6.3.1 Ontology Model

Ontologies can be viewed as a representation of the application domain. We describe the IoT event detection application via the ontology model which presents the underlying WSN with an information abstraction layer. The ontology model is described as a set of classes, C and properties, P. The main classes in our model are,

- **Sensor Entity:** Describes all the sensors in the IoT system such as temperature,

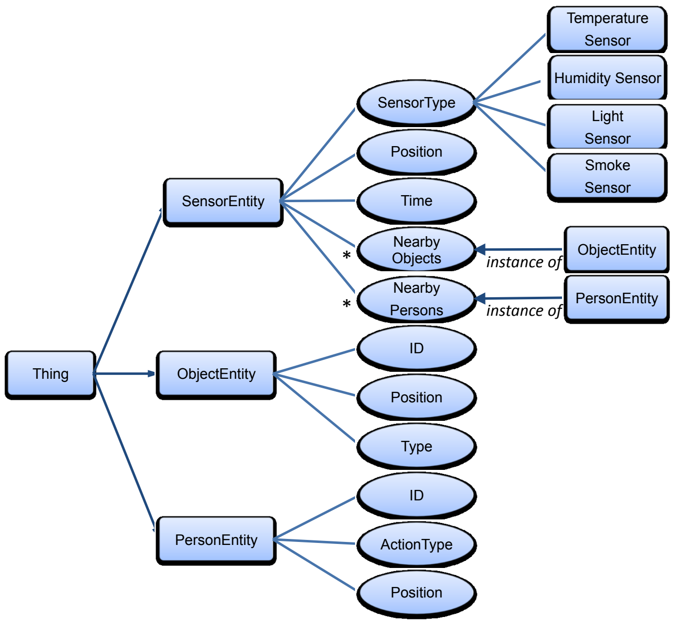


Figure 6.4: Ontology model.

pressure, smoke or light sensors.

- **Object Entity:** Any physical object with an unique ID. The entities of this class do not maintain direct connectivity with the Internet
- **Person Entity:** Mobile agents with unpredictable or random movement pattern such as human beings or pets.

Each object class has a set of attributes associated with them an can be described by a taxonomy similar to the example is shown in Fig. 6.4.

6.3.2 Data Representation

According to our model, the underlying WSN is responsible for capturing data from different sources and presenting them using a generic model suitable for information exchange within the IoT. To accomplish this, the WSN layer is provided with a common abstraction layer to manage data uniformly from different system entities such as sensors, RFID reader, hand-held devices and people. To this end, we employ the sensor model language (SensorML) described in [315] that provides the metadata model in the

```
<xs:complexType name="AbstractThing" abstract="true">
  <xs:annotation>
   <xs:documentation>Thing description in IOT
   </xs:documentation>
</xs:annotation>
<xs:complexContent>
  <xs:extension base="sml:SensorEntity">
   <xs:sequence>
     <xs:choice >
       <xs:element ref="sml:TemperatureSensor" value="0"/>
       <xs:element ref="sml:HumiditySensor" value="0"/>
       <xs:element ref="sml:LightSensor" value="0"/>
       <xs:element ref="sml:SmokeSensor" value="0"/>
     </xs:choice>
     <xs:element ref="sml:time" value=""/>
     <xs:element ref="sml:position" value=""/>
     <xs:sequence ref="sml:Nearby Objects" >
      <xs:choice >
        <xs:element ref="sml:ObjectEntity" />
      </xs:choice >
     </xs:sequence>
     <xs:sequence ref="sml:Nearby Persons" >
      <xs:choice >
       <xs:element ref="sml:PersonEntity" />
      </xs:choice >
     </xs:sequence>
  </xs:sequence></xs:extension>
 </xs:complexContent>
</xs:complexType>
```

Figure 6.5: XSD schema for sensor type ‘Thing’ in the IoT.

eXtensible Markup Language (XML) format to describe sensors and their capabilities, and other nearby objects and people reachable via the RFID reader. SensorML ensures the interoperability with other devices and the event detection application residing in the web layer. For metadata representation, we use the XML schema definition language (XSD). Our core event detection system provides the XSD for representation of relevant data in the corresponding IoT domain using the ontology description presented in the previous section. Figure 6.5 presents an example schema definition for a sensor in an IoT application that includes four different types of sensors along with the presence of passive physical objects and persons. A list of base schemas that can be customised and extended to describe an IoT environment is available online [315]. We leave the details of complete definition here, since it is application oriented. The sensor devices in the proposed method are initially aware of the schema definition and capable of generating xml strings complying with the given schema with sensed values. In reply to the query from the web layer, each device generates and delivers an xml string. The data acquisition and detection subsystem extracts the values of corresponding class from the generated string.

6.3.3 QoS Manager

The typical QoS metrics in a sensor network based event detection are detection probability, fault tolerance and detection delay. The QoS manager in our architecture defines the QoS requirement of a particular event in the corresponding IoT environment. The physical sensor network is not directly responsible for maintaining the QoS because of the possible influence of external factors, e.g., the context of the surroundings, on the event of interest. Rather the higher layer event detection subsystem decides on the data frequency and reliability required from the sensor network and asks for data accordingly. Since the detection subsystem resides in the Internet layer, it monitors all the data feeds, can aggregate data from multiple sources and introduce redundancy to guarantee expected QoS. The QoS manager enables the data acquisition subsystem to generate QoS-aware query to the sensor network when necessary. We exploit the quality adjustable query processing method of WSN described in [316]. This enables us to integrate a delay and accuracy aware query processing framework which is capable of dynamic adjustment to meet user/application requirements.

6.3.4 Detection Algorithm

The context-aware event detection algorithm in the proposed architecture is an online algorithm with two sets of inputs. One is a set of rules defining the events of interest which comes from the event register. The event register in Fig. 6.3 is populated from user input defining event pattern and can be updated anytime through the Internet. The other sets of input comes from different sources such as WSNs, mobile phones and RFID tagged objects as shown in the figure. One notable feature of the proposed architecture is the external WSN service as shown in Fig. 6.3, which enables the detection system to collect information from geographically distributed WSNs. The data acquisition submodule extracts the sensor values and proximity information of objects and person entities from the periodic WSN responses. The detection submodule then feeds the detection algorithm with the gathered data and the rule set from the event register. The algorithm detects an event as soon as finds a match against the rule set.

Since the detection algorithm runs on a server, the rules defining events can be complex and can be updated when new objects enter into the environment and augment the context. It considers all types of spatial and temporal relations among the sensor values along with the presence of different IoT objects, and accordingly define events using complex rules. In general, a event can be specified using the following format,

rule $\langle$*predicates, attributes*$\rangle$ *context*$\langle$*sensor value, object location and time*$\rangle$ *measuring accuracy* $\langle [0,1] \rangle$.

Consider the sample, *rule* $\langle$ *temprature*$> 65°C \wedge$ *distance*$< 2m \wedge$ *interval*$> 2min$ $\rangle$ *context*$\langle$*sensor T1, fuel container #1, time*$\rangle$ *measuring accuracy* $= 0.9$. The first part defines the event in terms of attribute values without context. The second part specifies the context indicating which sensor and object needs to be monitored. This rule is interpreted as, *"If the temperature data from sensor* $T1$ *exceeds* $65°C$ *while its distance of the fuel container numbered #1 is less than two metres and such observation continues for at least 2 minutes, notify the user about the event of interest.* The *measuring accuracy* denotes the required confidence for the specified event.

Each event rule corresponds to one specific entry in QoS Manager in the given architecture (Fig. 6.3). It denotes the confidence level of the corresponding sensed data to declare the event as detected. If any reading does not meet this pre-defined accuracy, the data acquisition subsystem performs a QoS aware query to the specific sensor to re-acquire values, and the detection algorithm is re-run.

6.4 System Prototype

To demonstrate the proposed event detection paradigm in the IoT using context-aware sensing, we designed and implemented a Safe Home network. This constitutes actually

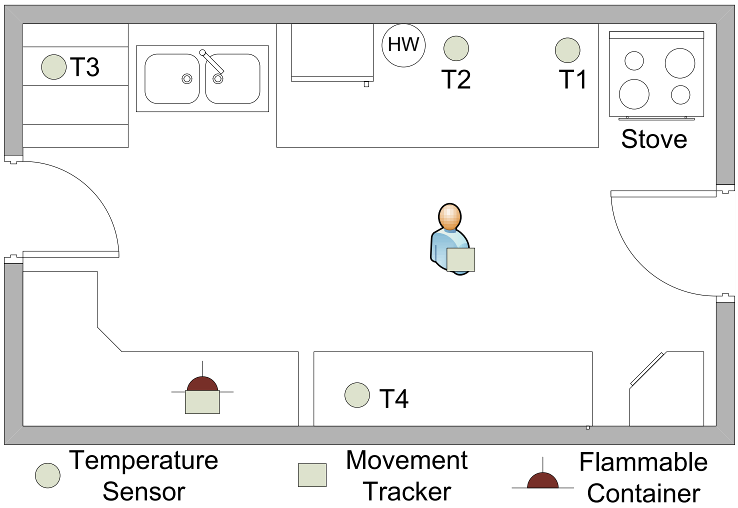


Figure 6.6: Safe Home kitchen layout.

a sub-system of the wider smart home domain. The idea is to equip the home with strategically positioned sensors and monitor the object-state interactions within it for potential hazard or unsafe activity. The layout plan of our safe home system is shown in Fig. 6.6. We define two representative context-sensitive events. They are,

- **Fire Hazard:** The placement of any flammable item in a kitchen location that exhibits a high temperature may trigger an ignition. Such as, placement of compressed oil or spray container near the stove while it is on. Temperature sensing, proximity sensing and location awareness are taken into consideration to identify the context denoting this event.

- **Unsafe Activity :** This type of event is characterised by the distance between a person in the kitchen and the stove and heat sensed at certain distance. The person's potentially dangerous movement (running or falling abruptly) in the kitchen is also monitored. We denote a speed of more than $8km/h$ in the kitchen when the stove region temperature is more than 45°C as a unsafe movement event.

6.4.1 Indoor Position Tracking

Global Positioning System (GPS) is not suitable for indoor location tracking, since high frequency signals from satellite will be attenuated and scattered by several obstructions such as roofs, walls and other objects. Therefore our prototype does not rely on GPS. To know the position of the movable objects or users in our safe home network, we employed received signal based approximations by positioning three static nodes in three fixed known locations and the co-ordinates of them are entered into the system. We call these nodes *the anchor nodes*. Each mobile node can approximate its own location by estimating the distance from these three anchor nodes using RSSI measurements from each of them [317]. This triangulation based on RSSI is illustrated in Fig. 6.7.

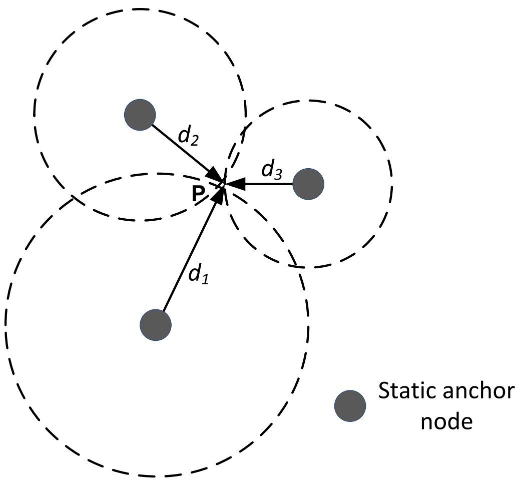
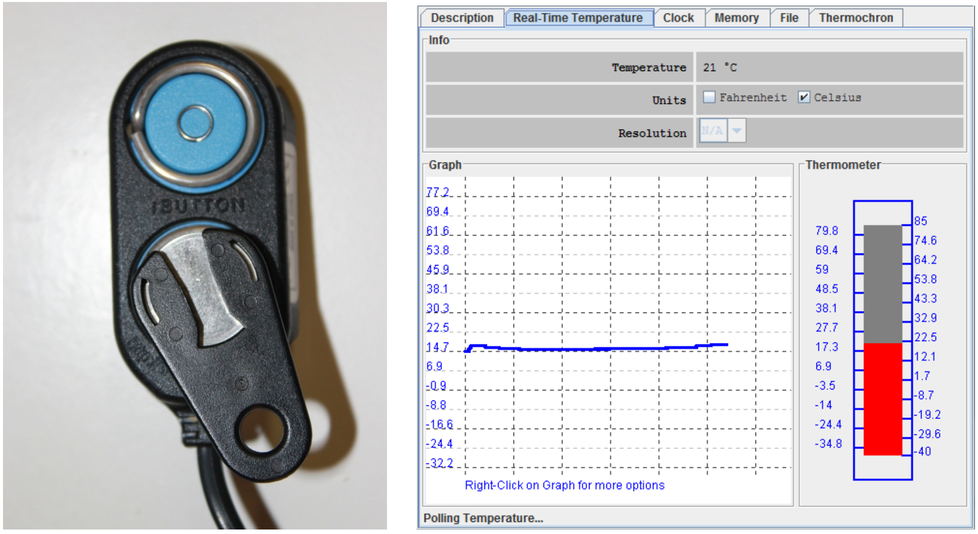


Figure 6.7: Indoor location approximation using received signal strength measurements from three static anchor nodes. The three dashed circles denotes the estimated distance of the anchor nodes from the target object. **P** indicates the estimated location.

6.4.2 Sensor types

For temperature sensing in strategic locations of our safe kitchen, we used the DS1921G thermochron iButton [318]. DS1921G is a self-sufficient system that measures temperature and records the result at a user-defined rate. Up to 2048 temperature values taken at equidistant intervals ranging from 1 to 255 minutes can be stored. It logs the time when the temperature goes beyond a user-programmable range and also records for how long the temperature stayed outside the permitted range. An additional 512



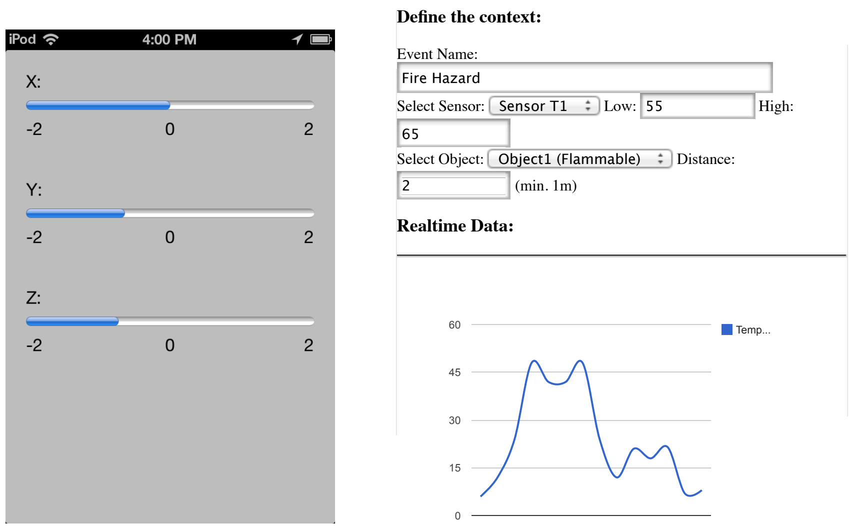
(a) Thermocon (DS1921G-F5) temperature sensor

(b) Realtime temperature monitoring

Figure 6.8: iButton temperature monitoring for our home network.

bytes of battery-backed SRAM allows storing information pertaining to the object to which the DS1921G is associated. We used the additional SRAM to store the static location of the sensor in the kitchen. To detect movement speed and direction of the users and the movable objects inside the house, we used a smartphone with built-in accelerometer, gyroscope and Wi-Fi connectivity. We developed an application that takes the raw movement data from phone sensors and transmits to a web service via Intranet. It also estimates the location of the mobile object or user using triangulation based on RSSI as explained earlier. A smart phone (iPhone) with described location tracking application running is referred to as the *movement tracker* in this prototype system. The acceleration monitoring feature is shown in Fig. 6.9(a).

In our experiment four Thermochron temperature sensors were placed in the kitchen as shown in the layout in Fig. 6.6. We attached one movement tracker to the spray container containing flammable material and another tracker to the wearable of the person (Fig. 6.6). We developed two-tier application server. A Java based console application acts as a data acquisition layer which logs data from the temperature sensors via wired connection and location data via wi-fi connection from the movement trackers and store the realtime data in a remote mysql server. A web application continuously



(a) Prototype iPhone application tracking user's acceleration in three different axes.

(b) Web interface for event definition

Figure 6.9: User interfaces of our Safe Home System.

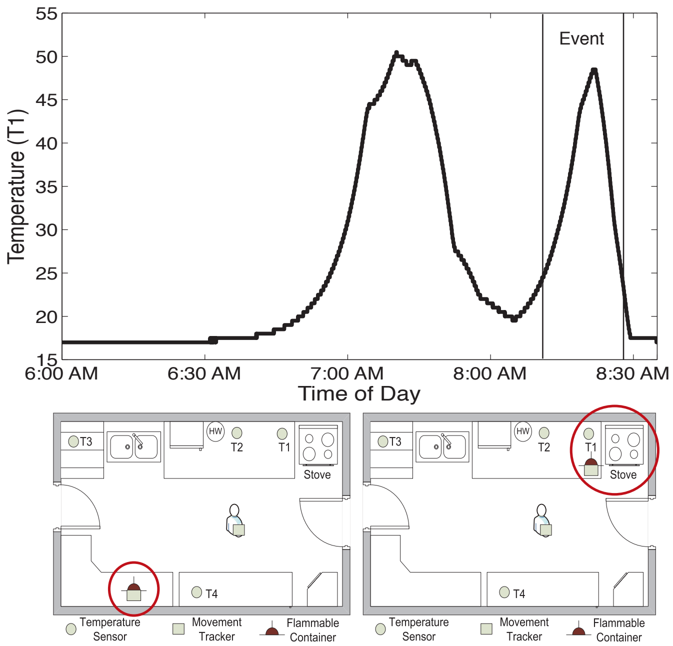


Figure 6.10: Testbed result : Fire hazard detection.

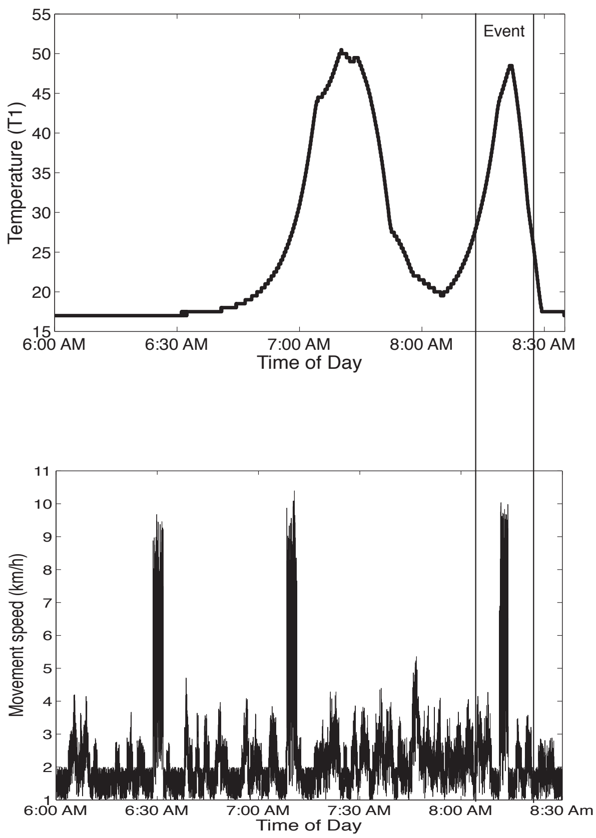


Figure 6.11: Testbed result : Unsafe movement event.

monitors this realtime data and triggers an event when the defined event context is matched. The web interface for defining context shown in Fig. 6.9 facilitates the user input for event of interest.

We logged data for about two and a half hours in the morning period of the day and used the stove twice during that time (between 7:00 - 7:30 AM and 8:15 - 8:30 AM). Fig. 6.10 plots the temperature recorded from sensor T1 which is placed within 1 m of the stove. The temperature values within the stove region was recorded and shown in the figure that exhibit a rise beyond our predefined threshold of 45°C when the stove was on. However, only the second time, the flammable container was near the stove as shown in Fig. 6.10 and thereby triggers a potential fire hazard event at around 8:15 AM as shown in the figure. Even though the Thermochron sensor itself is capable of generating an alarm when the temperature is beyond the designated range, it cannot capture the event defined here by itself since it is unaware of the surroundings. The potential fire hazard defined above was only detected when the sensor information was coupled with the location information of the flammable container.

Similarly, Fig. 6.11 plots the movement speed of a person working in the kitchen. It shows that the speed crossed the threshold of $8km/h$ on three different occasions. However, only the third occasion triggered an event (marked by the rectangle in the figure), as expected, coincided the time window while the stove was running and the temperature for the stove region was too high. Evidently, none of these two events could be captured using the threshold-based event-centric WSN. The object-state interactions are needed to be considered to capture the event.

6.5 Conclusion

In this chapter, we outlined how event centric WSNs presented in previous chapters can evolve to adapt to a broader Internet of Things domain. The proposed event detection framework provides WSNs with an abstraction layer for seamless integration with the IoT event based systems and enables them to operate with heterogenous devices and standards to accomplish reliable event detection in a pervasive IoT environment. The testbed implementation demonstrated the idea via the detection of two representative events in the IoT under the proposed event detection architecture. In the following chapter, we conclude this thesis by presenting conclusive remarks and directions on further extensions of the current work.

Chapter 7

Conclusions and Future Work

7.1 Conclusions

In this thesis, we developed a formal QoS aware event detection framework using a WSN. First, we identified the key performance metrics that characterise a detection system and investigated the factors affecting the performance. Having studied the existing WSN applications extensively, it became evident that the structure of a WSN is tightly application dependent. Therefore, we approached the goal of QoS provisioning from a design perspective. The foundation of the proposed event detection framework was laid by devising an analytical model where performance requirements are used as design parameters. The initial design was based on providing redundant coverage where the optimal degree guaranteeing a set of QoS metrics is determined in our method. Then this model was extended to incorporate a dynamic node failure model and the variable range sensing technology was exploited to attain robustness against such fault.

However, the deployment cost in fixed k-coverage detection method is not always practical. Therefore, a dynamic event coverage technique was proposed where QoS guarantee for event detection is provided on-demand in a specific region of interest after the occurrence of an event. In essence, this scheme provides the same QoS at the cost of only 1-coverage at the deployment time. This also attains energy efficiency and enhances WSN lifetime compared to maintaining complete fixed coverage throughout its lifetime. Investigating the active and passive sensing technology, we proposed two different methods for on-demand coverage. First, we exploited the variable range sensing technique to ensure redundant coverage of an event only when necessary by adjusting the sensing range of the nodes in the close vicinity of event location. However, the range adjustment technology is limited to a certain set of the physical attributes of the environment being monitored and irregular event distribution can lead to unbalanced energy consumption in some cases. To handle such a scenario, we proposed an on-demand event coverage technique using mobile nodes in conjunction with static nodes. To mitigate the random movements of mobile nodes, the proposed node movement strategy considers the spatial distribution of the occurrence of events in a network and attempts to position the mobile nodes accordingly. Our dynamic coverage scheme thereby minimises the energy spent due to mobility while taking advantage of the spatial locality tendency of event occurrences to enhance detection performance.

The prevalence of multiple simultaneous events occurring in the same WSN necessitates differentiated treatments for different events. We introduced the concept of differentiated priority and missed-detection cost of events to enhance detection performance. Our a priority sensitive event detection method facilitates the provisioning of QoS metrics, such as accuracy and timeliness, on priority basis which ensures enhanced overall detection performance. We presented detailed analysis of the delay and accuracy for the proposed model. The experimental results showed superior performance of our method compared to traditional flat priority based event detection systems in terms of both energy and accuracy.

Finally, we focused on the evolution of event detection from a WSN to the Internet of Things that connects the physical and virtual world. We identified the key challenges to fit event-centric WSN into the IoT architecture. For generic and dynamic detection of real-world phenomena, we introduced an ontology based event definition language suitable for the IoT environment where sensors, objects and persons, all collaborate in event detection. The proposed method takes the context of the surrounding environment into account in which a potential event is occurring. This approach eliminates some of the drawbacks of threshold based event detection and makes it suitable for the diverse and composite nature of the events that WSNs are responsible for in the Internet of Things.

7.2 Future Work

Our extensive study of the event detection literature identified a number of research problems that we could not solve in this thesis due to time and other limitations. We briefly outline them in the following which can be investigated in future research.

1. **3D k-coverage problem**: Traditionally, the target sensing field was considered to be a two dimensional flat plane where any location can be described using only two co-ordinates. However, recently, WSN based monitoring has been adopted in underground and underwater environments where the events can occur in any three dimensional location. This means a more complicated geometric plane needs to be handled. This change in the WSN design from a 2D to a 3D setting necessitates the extension of our QoS aware coverage presented in Chapter 3 to 3D k-coverage.

2. **Heterogeneous coverage**: In Chapter 4 we have seen that irregular spatial distribution of event occurrence is common in the real-world environment. In addition, the environmental noise considered in our model can be diverse in nature and vary largely in different areas, especially in a large-scale WSN. Therefore, the same QoS guarantee everywhere in a sensing field may lead to over provisioning and inefficient use of resources. Using variable range sensing technology, we can model a heterogenous event coverage strategy where different regions in a WSN can be monitored with different levels of performance guarantee. This needs to consider the dynamic nature of event distribution and also the temporal change in environmental noise patterns. For a large-scale sensor network, locations more susceptible to noise at the beginning may change their patterns over time. Similarly, the spatial distribution of event occurrence may also change and the network may dynamically change the degree of coverage in those locations by adjusting the sensing range accordingly.

3. **Clustering effects among mobile nodes**: In Chapter 4, we presented a dynamic event coverage scheme using mobile nodes. It was noted that the node movement delay reduces over time as the mobile nodes organise themselves in the proximity of high frequency events. While we experimentally observed such

clustering effects, we did not thoroughly analyse such phenomena. Proper investigation and modelling of such clustering effects can lead to meaningful insights that will help designing improved event detection schemes using mobile nodes.

4. **Priority sensitive coverage using variable range sensing**: In Chapter 5 we proposed a priority sensitive multiple event detection scheme using node mobility. A similar result could be achieved by exploiting variable range sensing technique where applicable. The sensor nodes can extend their sensing ranges to provide more robust detection for high priority events. Instead of moving mobile nodes on-demand, the sensors can be informed from a base station about high priority event locations and redundant coverage can be provided before the event occurs. This will further reduce missed detection of high priority events to a greater extent. In addition, it will facilitate the dynamic adaptation of the detection scheme in different locations if the priority of the event locations change over time.

5. **Time varying sensing range**: We have modelled the time-dependent node failure rates in Chapter 3. In a simpler way, the sensing range can also be subject to degradation due to ageing and battery depletion over time. A complete analytical modelling of event detection systems should account for such a scenario.

6. **QoS aware detection in Vehicular Sensor Network (VSN)**: In Chapter 4, we devised a node movement strategy to facilitate dynamic event coverage using mobile nodes. However, there are special types of mobile nodes in the practical environment where we have little control over the mobility strategy. One such domain is the vehicular sensor network mostly found in intelligent transportation. Such networks can be used to detect real-world events such as the presence of potholes in the road and rear-end collisions [319] between cars, and report them to the base station. Fig. 7.1 illustrates the example of congestion event and fog hazard detection near a gas station in a VSN. Here VS1, VS2, VS3, VS4 and VS5 detect congestion locally and transmit it through BS1 or VS8 whichever is closer. Similarly VS14 detects a local fog pocket on its way and transmits the fog hazard event via road side base station (BS3) that broadcasts this event to other cars behind. Momen *et al.* [320] proposed a random structure VSN, where the

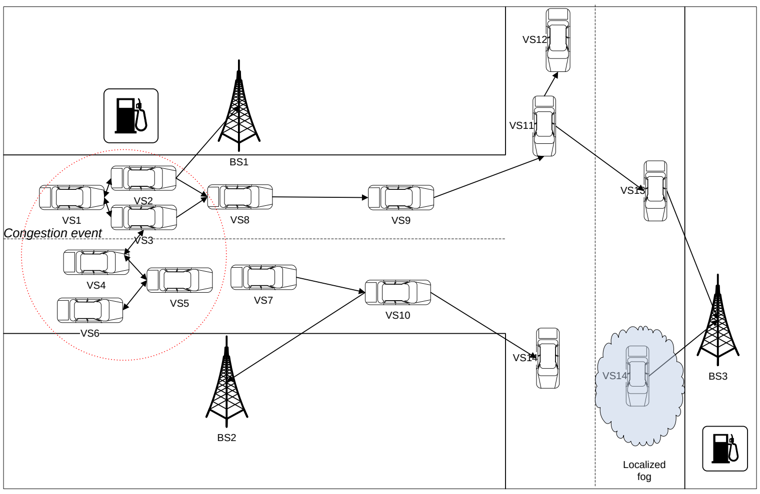


Figure 7.1: Illustration of traffic congestion and fog pocket event detection in a VSN

coverage property is managed and controlled by introducing a method for resource allocation and coverage control based on the real vehicle mobility model. But the event detection using VSN still has not yet attracted much attention. If it is possible to devise an efficient event detection technique that can be applied even in high mobility of the participating sensor nodes, we can extend the classical event detection approaches to vehicular sensor networks.

To apply the proposed QoS-aware event detection framework in such settings is not straightforward due to low control over the mobility pattern. Besides, the nodes can travel through only a predefined road network rather than randomly. The only factors that can be controlled are the node velocity (with defined speed limit) and lane change behaviours. In Hugo *et al.* [321] a methodology for characterising the mobility pattern for vehicular sensor network in the typical urban environment has been developed. They provided a framework for capturing the trajectories followed by the nodes in a typical urban setting. There are several other models of mobility outlined in literature that model the spatial distributions of mobile nodes (vehicles), direction of movement and velocity, and allows the derivation of mathematical expressions describing mobility metrics. Two such notable models are Car Following model [322] and Cellular Automaton model [323]. The car following model follows the principle that the mobility metrics (direction, velocity etc.) of one vehicle depend on the vehicle it is following. The

Cellular Automaton model divides the road into cells and modelling is done in time steps where each vehicle is allowed to move only if the following cell is empty. Based on the mobility pattern and application requirements, three different types of communication are possible: i) Inter vehicular, ii) Vehicle to roadside base stations, iii) Hybrid of the two. It will be a significant contribution in the detection domain to analyse the expected detection performance that can be achieved given a particular mobility pattern and vehicle density in any urban region.

7. **Event detection in WSAN**: The increasing application of event-based systems in our everyday life will lead to greater use of Wireless Sensor and Actuator Networks (WSANs). In the case of WSANs, the state of the environment and the context of an event must account for the current state of the actuators too. For example, if a sensor equipped with an actuator is already busy in performing one task, the system should be able to sense that and redirect any simultaneous event to the next best sensor (in terms of position, capability or energy etc.). Considering the role of WSANs in the future Internet of Things, it will be worth extending the proposed context-aware event detection described in Chapter 6 to incorporate the actuator state into the context modelling.

7.3 Broader Impact

The proposed method in this thesis facilitates efficient event detection in a pervasive intelligent environment and contributes in reducing any economic and human loss. Energy efficiency achieved by employing the state-of-the-art technology promises significant decrease in the carbon footprint and thereby promotes green communication in large scale sensor networks.

Publications from this thesis

- **Journals (Under review)**:

  1. Kh Mahmudul Alam, Joarder Kamruzzaman, Gour C. Karmakar, Manzur M. Murshed, "Event Coverage in Self-healing Wireless Sensor Networks using Variable Sensing Range", submitted to *IEEE Transactions on Mobile Computing,* January, 2013.
  2. Kh Mahmudul Alam, Joarder Kamruzzaman, Gour C. Karmakar, Manzur M. Murshed, Dynamic Event Coverage in Wireless Sensor Networks using Variable Sensing Range, submitted to *IEEE Transactions on Parallel and Distributed Systems*, November, 2012 (under review).

- **Conference papers**:

  1. Kh Mahmudul Alam, Joarder Kamruzzaman, Gour Karmakar, and Manzur Murshed, "Priority Sensitive Event Detection in Hybrid Wireless Sensor Networks", *In Proceedings of IEEE International Conference on Computer Communications and Networks (ICCCN)*, pp. 1-7, 2012. (Core rank A)
  2. Kh Mahmudul Alam, Joarder Kamruzzaman, Gour Karmakar, and Manzur Murshed, "Dynamic Event Coverage in Hybrid Wireless Sensor Nentworks", *In Proceedings of IEEE International Symposium on Network Computing and Applications (IEEE NCA11)*, Cambridge, MA, August 2011. (ERA rank A)
  3. Kh Mahmudul Alam, Joarder Kamruzzaman, Gour Karmakar, Manzur Murshed, and A K M Azad, "QoS Support in Event Detection in WSN through Optimal k-Coverage", *In Proceedings of International Conference on Computational Science (ICCS)*, Singapore, June 2011. (ERA rank A)

4. A K M Azad, Joarder Kamruzzaman, Balasubramaniam Srinivasan, KH Mahmudul Alam, Shaila Pervin, "Query Processing over Distributed Heterogeneous Sensor Networks in Future Internet: Scalable Architecture and Challenges", *In Proceedings of International Conference on Advances in Future Internet (AFIN 2010),* Venice, Italy July, 2010. (5 citations since 2010).

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