Collaborative Sensing and Communication Schemes for Cooperative Wireless Sensor Networks

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Abstract

Energy conservation is considered to be one of the key design challenges within resource constrained wireless sensor networks (WSNs) that leads the researchers to investigate energy efficient protocols with some application specific challenges. Dynamic clustering scheme within the deployed sensor nodes is generally considered as one of the energy conservation techniques. However, unbalanced distribution of cluster heads, highly variable number of sensor nodes in the clusters and high number of sensor nodes involved in event reporting tend to drain out the network energy quickly, resulting in unplanned decrease in network lifetime. Performing power aware signal processing, defining communication methods that can provide progressive accuracy and, optimising processing and communication for signal transmission are the challenging tasks. In this thesis, energy efficient solutions are proposed for collaborative sensing and cooperative communication within resource constrained WSNs.

A dynamic and cooperative clustering as well as neighbourhood formation scheme is proposed that is expected to evenly distribute the energy demand from the cluster heads and optimise the number of sensor nodes involved in event reporting. The distributive and dynamic behaviour of the proposed framework provides an energy efficient self-organising solution for WSNs that results in an improved network lifetime. The proposed framework is independent of the nature of the sensing type to support applications that require either time-driven sensing, event-driven sensing or hybrid of both sensing types.

A cooperative resource selection and transmission scheme is also proposed to improve the performance of collaborative WSNs in terms of maintaining link reliability. As a part of the proposed cooperative nature of transmission, the transmit-receive antennae selection scheme and lattice reduction algorithm have also been considered. It is assumed that the channel state information is estimated at the

receiver and there is a feedback link between the wireless sensing nodes and the fusion centre receiver. For the ease of system design engineer to achieve a predefined capacity or quality of service, a set of analytical frameworks that provide tighter error performance lower bound for zero forcing (ZF), minimum mean square error (MMSE) and maximum likelihood (ML) detection schemes are also presented. The dynamic behaviour has been adopted within the framework with a proposed index derived from the received measure of the channel quality, which has been attained through the feedback channel from the fusion centre. The dynamic property of the proposed framework makes it robust against time-varying behaviour of the propagation environment.

Finally, a unified framework of collaborative sensing and communication schemes for cooperative WSNs is proposed to provide energy efficient solutions within resource constrained environments. The proposed unified framework is fully decentralised which reduces the amount of information required to be broadcasted. Such distributive capability accelerates the decision-making process and enhances the energy conservation. Furthermore, it is validated by simulation results that the proposed unified framework provides a trade-off between network lifetime and transmission reliability while maintaining required quality of service.

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Dedicated to my family. . .

List of Published Work

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J02 M. K. Naeem, M. N. Patwary, A. H. Soliman and M. Abdel-Maguid, “Cooperative transmission schemes for energy-efficient collaborative wireless sensor networks,” in IET Science, Measurement & Technology, vol. 8, no. 6, pp. 391-398, 11 2014, doi: 10.1049/iet-smt.2013.0194.

J03 M. K. Naeem, M. N. Patwary, A. H. Soliman and M. Abdel-Maguid,“Tighter Receiver Performance Lower Bound for MIMO Wireless Communication Systems. Journal of Applied Sciences ”, 2014. doi: 10.3923/jas.2014.95.100

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Abbreviations

BER	**B**it **E**rror **R**ate
BPSK	**B**inary **P**hase **S**hift **K**eying
CQI	**C**hannel **Q**uality **I**ndex
CSI	**C**channel **S**tate **I**nformation
CCT	**C**onventional **C**ooperative **T**ransmission
DEEC	**D**istributed **E**nergy **E**fficient **C**lustering
DDEEC	**D**ynamic **D**istributed **E**nergy **E**fficient **C**lustering
EDEEC	**E**nhanced **D**istributed **E**nergy **E**fficient **C**lustering
EDDEEC	**E**nhanced **D**eveloped **D**istributed **E**nergy **E**fficient **C**lustering
FND	**F**irst **N**ode **D**ied
FCR	**F**usion **C**entre **R**eceiver
HND	**H**alf **N**ode **D**ied
HEED	**H**ybrid **E**nergy **E**fficient **D**istributed
ICC	**I**ntersection **C**ruise **C**ontrol
LND	**L**ast **N**ode **D**ied
LR	**L**attice **R**eduction
LEACH	**L**ow **E**nergy **A**daptive **C**lustering **H**ierarchy
LLL	**L**enstra **L**enstra **L**ov*á*sz
LMS	**L**east **M**ean **S**quare
MMSE	**M**inimum **M**ean **S**quare **E**rror
ML	**M**aximum **L**ikelihood
MIMO	**M**ultiple **I**nput **M**ultiple **O**utput

ML	**M**aximum **L**ikelihood
MSE	**M**ean **S**quare **E**rror
PH	**P**roposed **H**ybrid
PNS	**P**roposed **N**ode **S**election
PAT	**P**roposed **A**daptive **T**ransmission
QoS	**Q**uality **O**f **S**ervice
RF	**R**adio **F**requency
SNR	**S**ignal to **N**oise **R**atio
SER	**S**ymbol **E**rror **R**ate
USN	**U**biquitous **S**ensor **N**etwork
WSN	**W**ireless **S**ensor **N**etwork
ZF	**Z**ero **F**orcing

Symbols

d_n	Distance between the sensor nodes
c	Minimum power required to tx-rx signal
ξ	Signal strength attenuation factor
$\mathbf{a}$	Sensing data
μ	Prediction of the sensing range location
Σ	Covariance of the sensing data
K	Number of total samples
$\mathbf{r}$	Received data
$\mathbf{n}$	Additive white gaussian noise
$\mathbf{h}$	Channel coefficients
$\mathbf{H}$	Channel matrix
N_t	Number of transmit antennae
N_r	Number of receive antennae
n	Number of sensor nodes in the network
$A \times B$	Dimensions of the sensing field
R	Coverage radius of each sensor node
G	Set of sensor nodes within the network
$S_{(.)}$	Sensor node
$a_c \times b_c$	Dimensions of a virtual grid
q	Number of clusters in the network
$\mathbf{S}$	Set of sensor nodes within network
n_p	Number of sensor nodes within a cluster

$Q_{(.)}$	Set of sensor nodes within a cluster
C_H	Set of the cluster heads within the network
p	Index for denoting cluster heads
$\mathbf{x}$	Transmitted signal vector
$\breve{k}$	Index for transmitted signal vectors
$\mathbf{y}$	Received signal vector
$\sigma^{\mathbf{2}}$	Noise variance
i	Index for the transmit antennae
j	Index for the receive antennae
$\sigma^{\mathbf{2}}_{\mathbf{h}}$	Variance of channel coefficients for $i = j$
$\sigma^{\mathbf{2}}_{\mathbf{s}}$	Variance of channel coefficients for $i \neq j$
d_c	Distance of a sensor node from the centre of a cluster
λ_{d_c}	Energy threshold of a cluster head
(x_e, y_e)	Coordinates of a sensor node
e	Index for sensor nodes
(x_f, y_f)	Coordinates of a cluster head
f	Index for cluster heads
k	Number of events
t	Time
n_b	Number of sensor nodes in a neighbourhood
N_e	Neighbourhood
$\hat{d}$	Distance of a sensor node from an event
$(x_{\hat{f}}, y_{\hat{f}})$	Coordinates of a neighbourhood
λ_{d_n}	Optimum distance of a sensor node from an event
λ_s	Sensitivity threshold
$\hat{f}$	Index for neighbourhood
n_c	Number of sensor nodes in all neighbourhoods
n_{opt}	Optimum number of sensor nodes
$\hat{j}$	Index for optimum sensor nodes
$\mathbf{x}_{\hat{f}}$	Data vector from a neighbourhood

$\mathbf{H}_s$	Channel matrix of a possible combination of tx-rx antennae
$\mathbf{I}$	Identity matrix
$\tilde{\mathbf{H}}$	Channel matrix with reduced basis
$\mathbf{Y}$	Received data matrix
λ	Set of Eigen vector
μ_s	Expected value of Eigen vector
$\mathbf{E}$	Expected value
λ	Eigen value
E_{Cc}	Energy required by LR algorithm
β	Number of error for each transmission
λ_β	Outage probability threshold
N_b	Number of bits in one transmission
v	Index for bits in one transmission
$\hat{n}$	Total number of transmissions
$\mathbf{x}_o$	Transmitted data at each transmission
$\tilde{\mathbf{x}}_o$	Received data at each transmission
$\hat{v}$	Index for transmissions
n_b	Number of sensor nodes within neighbourhood
$\hat{q}$	Number of non-cooperative CHs
$\hat{n}_t$	Number of cooperative CHs
$d_{1(n,q)}$	Distance of n^{th} sensor node from q^{th} grid centre
$d_{2(n,q)}$	Distance of n^{th} sensor node from q^{th} CH
d_3^q	Distance of q^{th} CH from fusion centre receiver
$d_{4(\hat{q})}^{\hat{n}_t}$	Distance of $\hat{q}^{th}$ CHs to $\hat{n}_t$ cooperative CH
d_5	Distance between cooperative cluster heads (CCH)
$d_6^{\hat{n}_t}$	Distance of $\hat{n}_t^{th}$ CCHs to fusion centre receiver
$d_{7(n_b,q)}$	Distance of n_b^{th} sensor node from q^{th} CH
δ_{ch}	Energy threshold for cluster head election
$\hat{p}$	Number of sensing nodes within a cluster
k	Number of neighbourhoods within the network

Chapter 1

Introduction

1.1 Background and Motivation

From an engineering prospective, a sensor node is a small device which is comprised of the following basic components, which are described as follows: a sensing subsystem that is responsible for acquiring the data from the physical environment, a processing subsystem which performs data processing, a storage subsystem, a communication subsystem for wireless transmission and reception of data and a power subsystem. Wireless sensor nodes are capable of transmitting and receiving data within a particular communication range. The main tasks of sensor nodes are to monitor environmental conditions, to perform data processing and to transmit it to the Fusion Centre Receiver (FCR). Usually sensor nodes can be equipped with a variety of sensors based on the application requirements i.e. seismic, thermal, visual, infrared etc., in order to monitor various conditions e.g. temperature, humidity, motion, fire detection, smoke detection, pressure, flood detection, noise level, mechanical stress level etc. Wireless sensor nodes can be used for a diverse range of applications in military, health, chemical processing, ocean monitoring, disaster management etc.

"Wireless Sensor Networks (WSNs) are usually composed of a number of wireless sensor nodes which collectively monitor and distribute information to the desired destinations. A wireless sensor node is a battery powered device which is expected to perform several tasks such as sensing of physical quantities, wireless communication, data storage, computation and signal processing. Ideally within a WSN, sensor nodes are expected to perform these tasks collaboratively to achieve a common objective as discussed in [1]". The main aim of such collaborative scheme is to optimise network communication, to reduce the number of nodes involved in decision making and the amount of information required to exchange between them. One of the design challenges is to introduce such collaborative techniques which are dynamically self-configurable and adaptive to the environmental conditions [2].

Usually WSNs are "deployed in a hostile environment which make it impractical to recharge or change the batteries as discussed in [1]". Energy conservation is a key issue in the design of WSNs because they should have a lifetime long enough to fulfil the application requirements. The lifetime of WSNs can be defined in several ways such as the time when the first sensor node runs out of battery, a certain percentage of sensor nodes energy depletes as well as when all the sensor nodes run out of energy as described in [3]. If a sensor node within a WSN runs out of energy, the other sensor nodes around it will start to run out of energy quickly. Consequently, it could result in loss of network connectivity, coverage and reliability. The factors that contribute to the rapid depletion of energy within sensor nodes are: retransmission of data due to link failure, inappropriate transmission strategies, lack of cooperation among sensor nodes and improper deployment strategies. Generally, WSNs are deployed to monitor events, e.g. static events such as humidity, vibration, temperature etc. or dynamic events, e.g. battlefield surveillance, ocean monitoring etc. Based on the types of sensing environments, the sensing methods are expected to be different as described in [4]. Dynamic events can only be observed if the sensor nodes are constantly monitoring the environment. One of the main goals in the design of WSNs is to keep it alive for the maximum possible time.

In WSNs, the parameter requirements may vary because of the dynamic environmental conditions which makes it difficult for sensor nodes to determine appropriate parameter values, e.g. voltage, frequency, radio transmission power, packet size etc. WSNs are expected to be adaptive with the sensing environment, while demanded or allocated with resources such as energy consumption, available bandwidth etc. to ensure required Quality of Service (QoS) as discussed in [5]. The required QoS is generally defined in terms of the error rate that can be guaranteed by adopting a dynamic behaviour according to the time-varying conditions of the propagation environment. In WSNs, thousands of sensor nodes could be collecting data which makes it difficult to combine the distributed data synchronously. Centralised decision making is one of the well accepted collaborative signal processing model in which each sensor node transmits its data to the FCR for further processing. In large sensor networks, the number of sensor nodes could be thousands which can cause longer processing delays and potential drops at the FCR as discussed in [6]. It is also discussed in [7] that centralised decision making based models are not appropriate for data integration in WSNs as they cannot respond to load changing in real time because a fixed set of sensor nodes are used for data fusion which requires more battery power and network bandwidth.

WSNs usually suffers from a number of inevitable problems because of resource constrained sensor nodes deployed randomly in hostile environments which make it difficult to change or replace them as discussed in [8]. "Consequently, lifetime enhancement is one of the key constraints while designing the WSNs regardless of the type of application, without compromising the required QoS. As stated earlier, sensor nodes are expected to collaborate to involve an optimised number of sensor nodes while reporting an incident or to select a set of transmission schemes that can guarantee minimum energy consumption without compromising the required QoS. Recently, a significant amount of research has been carried out on sensor node selection while exploiting the advantages provided by the multiple sensor nodes involved in transmission and reception. While optimising WSNs, the key challenge is the selection of transmitting sensor nodes as well as receiving antennae at the FCR that provide with assurance of optimum utilisation of radio resources as discussed in [9]. Traditionally multiple antennae have been used to achieve transmit or receive diversity to combat fading or to achieve spatial multiplexing to increase the data rate by transmitting the independent information streams through the spatial channels. In the context of WSNs, several sensor nodes are expected to achieve a virtual Multiple-Input Multiple-Output (MIMO) system, that can obtain all the benefits of both transmit-receive diversity as well as spatial multiplexing as attainable with conventional MIMO based communication systems as discussed in [1, 10, 11]".

To achieve scalability and energy efficiency within WSNs, clustering is defined that virtually divides the sensor nodes of the whole network into logical groups. It also enhances load balancing, fault tolerance and network connectivity within the network [12]. Generally, cluster heads are selected within WSNs to perform special tasks for its sensor nodes i.e. coordination among sensor nodes, data aggregation, communication with other cluster heads and the FCR etc. The cluster heads selection criterion is usually based on certain parameters i.e. residual energy, distance from the FCR etc. As a result of the aforementioned tasks, the energy of the cluster heads drains out at a much faster rate than the other nodes within the network. Therefore, the self-organisation of the network is a desirable feature as no centralised or external entity is required. Dynamic clustering is introduced within WSNs which is expected to balance the energy consumption among the sensor nodes by re-selecting the cluster heads and redefining the cluster boundaries; hence enhancing the lifetime of the WSN [13]. Most of the dynamic clustering schemes presented in the literature [14, 15] are based on random selection of cluster heads which results in uneven distribution of cluster heads that leads to low network coverage and uneven energy consumption. As a result, it also increases the chance of selecting a low energy sensor node as a cluster head which will force frequent re-clustering. Subsequently, controlled size clustering is one of the solutions to overcome the aforementioned challenges that is expected to conserve energy by evenly distributing the energy demand among sensor nodes throughout the network.

Within WSNs, most of the energy is consumed during communication, especially data transmission to the FCR which is denoted as long-haul transmission. Generally, conventional single node transmission techniques are used for long-haul communication. However, such high dependency on a single node during long-haul transmissions may lead to reliability risk in severe network conditions such as least amount of available energy at a sensor node or deep channel fading etc. Hence, energy efficient communication schemes are needed to be defined to focus on minimising the energy consumption during communication. Cooperation among sensor nodes during data transmission allows resource saving within WSNs by implementing virtual MIMO concepts for energy efficient communication to increase reliability and enhance energy efficiency [16].

The power consumption of a sensor node is also directly proportional to the uncertainty of channel propagation conditions. Thereafter, one of the key design challenges within WSNs is to make them adaptive with the dynamic propagation environmental conditions of radio frequency to guarantee the QoS based on application requirements. "It is also expected to obtain maximum transmit-receive reliability with optimum usage of radio resources i.e. power and bandwidth. To obtain maximum optimisation performance, knowledge of the channel quality features at the transmitter is required as discussed in [1]". Hence, classification of such channel quality features as estimated at the receiver can be fed back to the transmitter with negligible spectral resources as required.

Several key issues have been addressed in the existing work to produce energy efficient solutions for WSNs. However, it is found that the existing works do not provide a unified framework of collaborative sensing and cooperative communication for resource constrained WSNs that can utilise the dynamic nature of the sensing environment and also be adaptive to the varying channel conditions during wireless communication. This study aims to provide an energy efficient collaborative sensing and communication framework for resource constrained WSNs that is expected to be adaptive to the dynamic sensing and communication environment. Moreover, the framework is expected to enhance the operational efficiency of WSNs and also their robustness against the prevailing variable channel conditions.

1.2 Aim and Objectives

The aim of this research is to obtain an adaptive sensing and communicative scheme for resource constrained cooperative WSN. The nature of collaboration is thus aimed to be the prime focus of adaptivity. This involves: adaptation of collaborators with the aim of achieving the required quality of service, without any loss of information content, whilst maintaining data sharing reliability as well as guaranteed intended performance robustness on the network response in the presence of adverse channel conditions.

The main objectives of this research project are stated below:

- To conduct research on collaborative wireless sensing and its applications, such as: security, assisted living, tele-health care, and environmental and remote area monitoring etc.
- To investigate the nature of resource constraints within the co-operative WSN and to explore the suitability of collaborative wireless sensing in order to improve the performance with the constraints on resources, such as energy, processing complexity, channel capacity, etc.

- To investigate the challenges within cooperative WSN with the existing collaborative transmit-receive schemes.
- To propose an improved collaborative wireless sensing scheme that optimises the performance degradation due to the resource constraints within WSN.
- To propose an adaptive cooperative communication scheme within WSN, for enhanced receiver performance with the available physical resources such as the number of sensing nodes involved in the cooperation.
- To propose a unified framework of collaborative sensing and communication scheme for sensor networks, where performance is expected to be independent of the application.
- To build a simulation model of the proposed unified model and analyse its performance in terms of reliability and robustness in the resource constrained environment.

1.3 Research Contributions

The main contributions of this study are as follows:

- A dynamic clustering as well as neighbourhood formation framework for wireless sensor networks is proposed where collaborative sensing is permitted. The proposed framework provides an energy efficient solution by uniformly distributing the network load among sensor nodes and carefully selecting the candidate sensor nodes for event reporting.
- The proposed framework is universal in nature for its functionality requirement within a WSN, i.e. independent of the sensing parameters. This provides the system design engineer with a tool for lifetime approximation modelling to configure the network for a diverse range of applications by

fine-tuning the following parameters: cluster head selection threshold and neighbourhood selection criterion.

- The analytical frameworks of the MIMO receiver performance, which provides a tighter lower bound in comparison to the existing bounds for the ZF, MMSE and ML detection schemes within MIMO wireless communication systems are proposed. This is to ease system design in order to achieve a predefined capacity or quality of service requirement.
- A measure of channel quality is "proposed that maps directly to the frame error probability. This is defined as the channel quality index (CQI) to enable adequate decisions on the selection of appropriate optimisation scheme adaptively. The CQI is designed in a manner to ensure robustness against signal distortions caused by the propagation and interference conditions of the channel. As well as to guarantee the optimised utilisation of resources while maintaining the required quality of service" [1].
- A CQI-centric transmitter-receiver antennae selection scheme is proposed. This is expected to maintain the required QoS by turning off the transmitter-receiver antennae pairs that are suffering from deep channel fading. This will be "based on the information from the FCR through a feedback link. Lattice reduction based signal design scheme is also proposed with the aim of minimising the effect of leakage interference on the signal. To achieve a high detection reliability while minimising energy consumption, a hybrid scheme is proposed. The hybrid scheme is expected to achieve high detection reliability and to minimise energy consumption by turning off the transmit-receive antennae pair which is affected by deep fading" [1].
- A unified framework is proposed for collaborative sensing and communication schemes for resource constrained WSNs. The dynamic behaviour of the proposed framework is adopted with a proposed CQI scheme in the context of WSNs. This scheme provides a trade-off model for transmission reliability

and network lifetime by dynamically reconfiguring the network according to radio frequency propagation environment conditions while maintaining the required QoS.

A flow chart is presented in Figure 1.1, which highlights the research contributions and limitations within the context of the existing works.

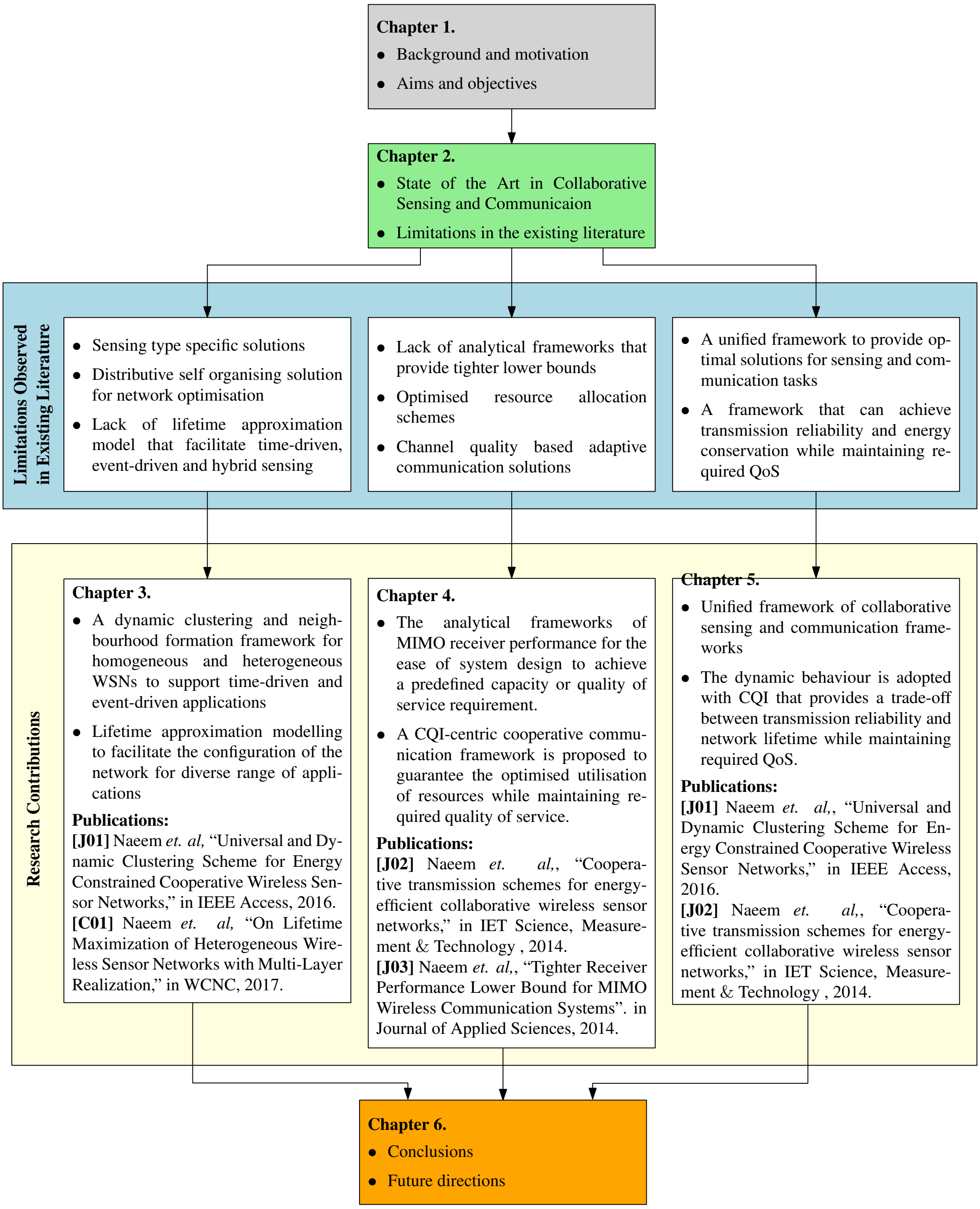

FIGURE 1.1: A flow chart highlighting the research contributions and limitations within the context of existing works.

1.4 Thesis Organisation

The rest of the thesis is organised as follows:

In Chapter Two, the characteristics requirements of WSNs, the optimisation goals to overcome the challenges and to achieve the characteristics requirements; the state of the art techniques in collaborative sensing and communication schemes within resource constraints WSNs are all discussed. A literature review of the dynamic clustering schemes, event-driven sensing, challenges to exploit MIMO techniques, cooperative sensor node selection, dynamic adaptivity to maintain link reliability, and optimisation problems within the context of WSNs are presented.

In Chapter Three, a universal and dynamic clustering framework for collaborative sensing within WSNs is presented. This supports the applications that require either time-driven sensing, event-driven sensing or both. Moreover, a network lifetime model is also derived to observe the performance of the proposed framework with homogeneous and heterogenous WSNs.

Chapter Four presents a channel quality based resource allocation framework for cooperative communication within WSNs. An adaptive transmit-receive antennae selection as well as lattice reduction based transmit signal design schemes are proposed. Moreover, a measure of channel quality to enable adequate decision on the selection of appropriate cooperation scheme is also presented. Thereafter, analytical frameworks are presented for the ease of the system design engineer to achieve predefined QoS requirements.

In Chapter Five, a unified framework of collaborative sensing and communication schemes for cooperative WSNs is presented. The proposed framework is expected to be adaptive based on the channel quality to attain transmission reliability while utilising optimum resources. Moreover, the proposed unified framework provides a trade-off between energy efficiency and transmission reliability while maintaining the required QoS.

Finally, in Chapter Six, research challenges are discussed, concluding remarks and future work based on the proposed work presented for this study.

Chapter 2

State of the Art Techniques for Collaborative Sensing and Communication Schemes

2.1 Introduction

This chapter explores the state of the art techniques for collaborative sensing and cooperative communication schemes and their implementation challenges within the context of resource constrained WSNs. Moreover, the characteristics of WSNs such as energy efficient operation, adaptive reconfiguration, collaboration, in-network processing, decentralised management, multi-hop wireless communication and scalability are discussed briefly. The optimisation goals in the design of WSNs are also discussed. Recent developments in WSNs design and optimisation techniques are elaborated along with their limitations within the context of the problem domain.

2.2 Wireless Sensor Networks: Applications and Demands

Recent developments in the technology have contributed a significant transformation within WSNs that makes it possible to produce low cost, small size and multi-functional sensor nodes. Depending on the application requirements, a wireless sensor node can comprise of multiple sensor types such as thermal, seismic, acoustic, magnetic, infrared, visual etc. So, WSNs can be used to monitor a diverse range of ambient conditions such as: pressure, humidity, temperature, direction, speed, noise level, light, stress etc. Consequently, WSNs can be used for a large range of applications such as: habitat monitoring, climate monitoring, home automation, ocean monitoring, disaster management, support for logistics etc. The existing WSN applications can be categorised as shown in Figure 2.1 and some of the applications are described as follows.

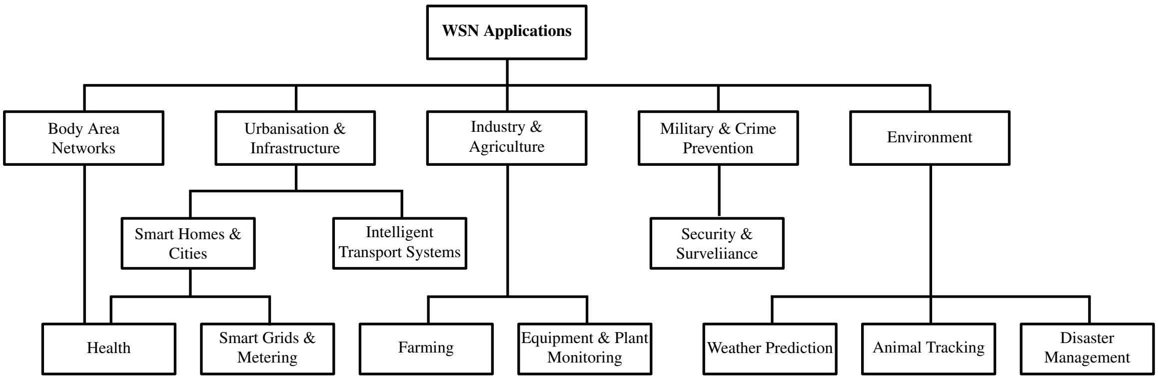

FIGURE 2.1: Classification of WSN Applications.

- One of the applications of WSNs for environmental monitoring is disaster management. The occurrence of environmental events either naturally or caused by humans can result in mass destruction. Recently, WSNs can play a key role in disaster early warning systems. It is required from WSNs to provide efficient detection and recovery mechanisms such as surveillance, detection, intruder warning and to facilitate emergency response. A semantic sensor web architecture has been proposed in Gray, Sadler, Kit, Kyzirakos, Karpathiotakis, Calbimonte, Page, García-Castro, Frazer, Galpin, et al. [17] to support environmental decision applications e.g. flood emergency response. It can provide support to different authorities in emergency by updating them with real time data. It is claimed by the authors that the proposed semantic sensor web will provide support to identify the relevant data sources, real time access of sensor data and correlate the data from multiple sources which will facilitate flood forecasting and thus help the emergency response units.

- As the world advances in technology, our environment is becoming polluted because of the harmful gases mainly due to the high density of industries and transports especially in urban areas. Consequently, the increase in air pollution is continuously increasing global warming. As a result, the climate temperature is increasing around the world and glaciers in north and south poles are melting. Therefore, it is becoming mandatory to monitor and regulate air pollution for the protection of our future generations as discussed in [18]. A ubiquitous sensor network (USN) is proposed in [19] to monitor air pollution. The USN provides efficient data distribution, security and long distance deployment readiness to support the relevant authorities by monitoring temperature, humidity, pressure, CO_2 and ten other gases. The acquired information is broadcast through ZigBee and GSM technologies, and is accessible to the users by making use of Google Maps.

- Tele-healthcare is one of the key applications within WSNs for the improvement of the quality of life. The tele-healthcare systems can continuously monitor patients which minimises the need of caregivers. Moreover, it can provide continuous support to the elderly people and help them to lead an independent life as described in [20]. A tele-homecare system has been presented by Chung *et al.* in [21] that provides assistance to elderly people in their home. The patient's physiological parameters such as body temperature and heart beat are measured continuously and stored in a database at a control centre using ZigBee communication. The control centre analyses the patient's data and in case of an emergency it sends alerts to caregivers and the family. The caregiver can remotely control the patient's environmental conditions and can also monitor through cameras when an emergency occurs.

- With the advances in technology, smart homes and cities have become a popular area of research. One of the applications of WSNs for smart homes and cities is the smart grid which integrates renewable and alternate energy sources in the existing power systems. In recent years, major blackouts have occurred due to the congestion within the power systems caused by the high demand of electricity, lack of monitoring, fault diagnostic, effective communication and automation. The basic concept of a smart grid is to control the power systems remotely with intelligent decision making and to perform automated actions in various aspects e.g. generation, delivery and utilisation. To fulfil these requirements, an extensive network monitoring is required. The challenges of WSN's deployment in power systems such as harsh environments, reliability, and latency as well as the application requirements such as remote monitoring, automatic meter reading and managing equipment faults are discussed in [22]. Moreover, it presents a comprehensive analysis to statistically characterise the wireless channel's link quality for the outdoor substation, power control room and underground transformer vault.

- In recent days, the industry marketplace is very competitive which demands improvement in process efficiency while complying with environmental regulations as well as meeting the financial objectives. To improve the productivity and efficiency of the industrial systems, low cost automation systems are required with smart features such as intelligent processing, self-organisable capabilities, flexibility, reliability and which can also be deployed rapidly.

WSNs can play a key role in industrial systems by providing real time monitoring and responding to events with appropriate actions as discussed in [23]. The detection of toxic gases in petrochemical plants is one of the significant issues, as the leakage can threaten the life of working staff. So, it is required from WSNs to detect the boundary of the toxic gases which are invisible, fast moving and have irregular shapes. Therefore, a boundary area detection scheme is proposed in [24] that is expected to detect the boundary area of toxic gases and provide this information to the rescue teams for evacuation of workers.

- The advancement in the technology provides an inexpensive and reliable solution for surveillance applications. Conventional surveillance systems require huge computation and manpower to analyse the surveillance data. WSNs provide a cost-effective surveillance system that allows the devices to share detected information with each other and with the server to achieve an overall picture of the situation. An integrated mobile surveillance and wireless sensor system named as iMouse is proposed by Tseng *et al.* in [25] that incorporates static as well as mobile sensor nodes to provide surveillance of urban areas. Its basic functionality is to detect and analyse unusual events such as fire incidence. If an event occurs, the static sensors detect that event and report it to the server. Then the server commands mobile sensors to investigate the event and provide additional information such as the cause of the event occurrence.

- As the growth of the population in urban areas is increasing, the need of efficient transportation has become a very important issue as traffic congestions cause wastage of time and unpleasant experience. Moreover, congestion also has a huge impact on economy and environment. A series of small incidents can result in congestion such as a car breakdown can cause huge traffic jams especially in highly loaded roads. To overcome this issue Yang *et al.* proposed a self-organised traffic flow at intersections without the need of traffic lights in [26] to improve the traffic flow. As a result, the proposed scheme results in reducing fuel consumption and emission level. The lightless traffic flow can be achieved by installing intersection cruise control (ICC) in vehicles which allows vehicles to communicate with each other and dynamically adapt the traffic density at the intersections. The ICC incorporates a dedicated short range communication device, global positioning system and a digitised road map. A vehicle is selected as a leader that controls the traffic flow at the intersection by communicating with nearby roads and tracking its location with respect to other vehicles.

2.3 Characteristics of WSNs

The architecture of a wireless sensor node is generally consists of a sensing, processing, transceiver and power units. The sensing unit may consist of several sensors and is responsible for monitoring environment conditions such as temperature, humidity, light etc. The main controller of a sensor node is the processing unit that may also consists of a memory unit. It is responsible for performing sensing operations, running algorithms and collaboration with other sensor nodes. But due to the size and cost limitations, a sensor node is constrained in processing and memory e.g. Smart Dust mote has 4 MHz micro-controller with 512 bytes of RAM as discussed in [27]. Another example of a micro-controller with higher capability is SunSpot with 180 MHz processor with 4 MB flash and 512 KB of RAM [28]. These specifications have been increased in the Imote2 platform with 416 MHz micro-controller, 256 KB SRAM, 32 MB flash and 32 MB of SDRAM as discussed in [29].

Although the processing capabilities of sensor nodes are increasing, However, these capabilities are significantly lower than the capabilities of embedded devices. As a result, computationally low softwares are required for the efficient operation of WSNs. The sensor nodes communicate through the transceiver unit and it performs the essential procedures to transmit data via radio frequency and vice versa to receive information. It is the most important unit because it provides connectivity with the network, but it also consumes most of the energy in order to perform the functions such as modulation, filtering, demodulation and multiplexing. Moreover, due to path loss, sensor nodes are expected to transmit small packets with low data rates over short distances. Therefore, it is a challenging task to design low cost, low duty cycle and energy efficient transceivers. The power unit is the most constrained unit in sensor nodes because of the size requirement and its deployment in harsh environments, which makes it impossible to change its batteries. Consequently, the lifetime of the sensor network is also limited. The power capacities of Smart Dust, MicaZ and SunSpot platforms are 33 mAh, 1400 - 3400 mAh and 750 mAh respectively as discussed in [30]. Therefore, energy efficiency is one of the key design issues in WSNs.

WSNs are expected to be deployed for diverse range of applications. So, it is required from WSNs to be adaptable with the characteristics and mechanisms required by the applications. Such adaptation in a real time environment without any intervention from outside is the major challenge of the vision of WSNs. Some of the characteristics required from WSNs are discussed as follows:

2.3.1 Energy-efficient Operation

Within WSNs, sensor nodes rely on a limited energy supply and it is impractical to replace or recharge the energy supply in most of the applications. Hence, energy efficient operation of the sensor nodes is one of the main tasks in the design of WSNs. There are several key techniques described in [31–34] that can be used for energy efficient operation of WSNs, such as: avoiding low energy sensor nodes for data transmission to the FCR, i.e. energy efficient routing; turning off the sensor nodes which are not in use i.e. duty cycling; minimising the number of samples which reduces the amount of data to be processed and transmitted to the FCR, i.e. adaptive sampling; uniform energy usage and minimising the transmission of redundant data among sensor nodes i.e. clustering.

2.3.2 Adaptive Reconfiguration

WSNs are expected to configure its operational parameters based on the application requirements without any external intervention i.e. configuration, adaptation and maintenance must be performed autonomously. The sensor nodes should be able to: find their geographical locations through other sensor nodes within the network; should be able to act as cluster heads when required; should be able to cooperate with other sensor nodes to form topologies or agree on sensing, processing and communication strategies; should be able to adjust transmission power to maintain a certain degree of reliability; should be able to adapt the changes in the environment; should be able to tolerate dead sensor nodes and should be able to integrate new sensor nodes as described in [35].

2.3.3 Collaboration and In-network Processing

In some applications, sensor nodes are required to collaborate to perform decisions e.g. detection of an event, tracking of a target etc. It is because only collaboration among sensor nodes can provide enough information to make that final decision. Network processing is used to perform the collaboration among the sensor nodes and to aggregate the redundant sensor data. This provides a trade-off between computational complexity and communication cost, hence achieve energy conservation.

2.3.4 Decentralised Management

The resource constraints within WSN make it infeasible to perform network management through centralised algorithms. Instead, WSNs are expected to be managed through decentralised algorithms and sensor nodes are expected to collaborate to perform decisions locally. Consequently, the decentralised solution might not be optimal but it will reduce the number of communications required to perform a decision and hence will conserve energy.

2.3.5 Multi-hop Wireless Communication

Within WSNs, one of the most energy consuming tasks performed by the sensor nodes is wireless communication. As the received power of a wireless signal is inversely proportional to inverse of the square of the distance from the source signal, the increasing distance between the transmitter and receiver requires an increase in transmission power. Therefore, multi-hop communication is the energy efficient solution which requires the sensor nodes to cooperate and relay the data to the receiver. Consequently, multi-hop wireless communication is a key requirement in most of the applications within WSNs.

2.3.6 Scalability

WSNs are expected to be scalable which is a very important characteristics requirement for most of the applications. The protocols and techniques considered in WSNs are expected to be scalable to the changes in the topology of the network. It is expected that the sensor nodes should be able to establish a communication network, divide the tasks among themselves in an energy efficient manner, adapt the overall tasks load to the remaining resources and reconfigure upon sensor failures. Moreover, WSNs are also expected to be able to accommodate new sensor nodes if required at a later stage after the network design as described in [36].

2.3.7 Quality of Service (QoS)

The increasing demand of WSNs for wide range of applications makes QoS to be one of the paramount optimisation goals. Optimisation of WSNs in terms of QoS is very challenging due to energy and computational constraints, harsh environmental conditions, random deployment and interdependency between QoS properties. For example, multi-path routing can improve reliability but it can also increase energy consumption as discussed in [37]. So, it is important to provide a means to control the balance while optimising the quality of support in WSNs. The parameters such as energy efficiency, reliability, scalability, data throughput etc., should be considered to measure the QoS for WSNs.

2.4 Optimisation Goals

As discussed earlier, there are various challenges and requirements presented by WSNs which are not handled by traditional wireless networks. As a result, it is required from the research communities to design new algorithms and protocols to overcome the challenges and requirements of WSNs. Several forms of solutions can be found in the literature for a diverse range of applications. However, optimisation of a network, comparison of the existing solutions and selecting the best approach for a given application are challenging tasks as discussed in [38]. The key optimisation goals to enhance the network performance are discussed below.

Energy is a precious resource which makes lifetime enhancement of the network an evident optimisation goal in the design of sustainable WSNs. Sensor nodes are expected to be alive for longer period of time because it may be cost prohibitive or impossible to change or replace the batteries as most are deployed in hostile environments. Moreover, WSNs are designed for a wide range of applications and are expected to satisfy requirements that differs from one application to another. Therefore, it is very challenging for the design engineer to select efficient solutions to optimise the energy efficiency within WSNs. There are several energy efficient solutions proposed in the literature for energy constrained WSNs, however, most of the proposed solutions are not universally applicable as discussed in [39]. Therefore, energy efficient solutions that can address application requirements in a more systematic manner are desirable.

One of the main requirement of WSNs for most of the applications is its functionality in spite of the occurrence of sensor failures. To provide robustness against node failures, the clustering schemes and routing protocols are expected to be fault tolerant. The low-cost components may cause sensor nodes to be non-operational. As a result, the routing protocols are expected to provide robustness by finding other routes between the source and destination. Moreover, several factors contribute to the packet loss in wireless communication which require from the routing protocol to ensure efficient delivery of packets between the source and destination as discussed in [40].

In order to overcome the above-mentioned challenges and achieve the requirements within WSNs, the sensor nodes are expected to perform the required tasks collaboratively in order to attain common objectives. These being: optimising the network communication; reducing the number of nodes required in the decision making; dynamically adapting to the variable environmental conditions and minimising the amount of information needed to exchange between them. Also, dynamic clustering can be achieved with collaboration among sensor nodes that can improve load balancing, fault tolerance and network connectivity to attain scalability and energy efficiency within WSNs. Moreover, cooperation among sensor nodes during data transmission can provide optimisation with assurance of optimal utilisation of radio resources. The existing notable schemes for collaborative sensing and communication presented in the literature are described in the following sections along with their limitations.

2.5 Collaborative Sensing

WSNs are required to overcome challenges posed by several factors such as: random deployment, decentralised management, limited power source and variable environmental conditions. This can be achieved by incorporating collaboration among sensor nodes to achieve adaptivity and energy efficiency. Existing network segmentation and lifetime approximation techniques in the literature can be grouped into two categories: time-driven sensing and event-driven sensing. Some of the notable schemes developed to overcome the aforementioned challenges while acquiring the essential data from the physical environment are discussed as follows.

2.5.1 Dynamic Clustering

The state of the art research studies that provide solutions to resolve the issues within WSNs are elaborated in this section such as: uniform energy consumption among sensor nodes within the network by performing dynamic network segmentations and dynamic adaptation to variable network conditions. In most of the applications, it is not feasible to access and monitor the WSNs. Therefore, WSNs must have the ability to operate in the harsh environments. In many applications, the sensor nodes are also deployed randomly and considering that they need to cover the entire target area, large populations of sensor nodes are also expected. In such environments, it is not feasible to recharge their batteries. Therefore, energy aware routing and data gathering protocols should be introduced to preserve the network lifetime as long as feasible as discussed in [41].

Within WSNs, a group of sensor nodes is called a 'cluster', which has been widely adopted by the researcher communities. Clustering within WSNs is expected to contribute to the overall system scalability and lifetime longevity. Sensor nodes periodically transmit their data to the corresponding cluster head nodes which are responsible in aggregating the data and transmitting it to the FCR. Cluster head nodes spend energy at higher rates because they transmit all the data to the FCR. To balance the energy consumption among all the sensor nodes, the cluster head role should be rotated periodically among all the sensor nodes within each cluster. Cluster formation procedures, cluster head selection and their adaptivity for different applications are important considerations in the design of clustering algorithms as discussed in [42].

There are two most common classifications of clustering algorithms in the literature for WSNs. The first is based on the characteristics and functionality of the sensor nodes within the clusters- these are called clustering algorithms for heterogeneous or homogeneous networks. The second is based on the method used to form clusters - these are called centralised and distributed clustering algorithms. In heterogeneous sensor networks, there are generally two types of sensor nodes; common sensor nodes and special sensor nodes with higher processing capabilities, energy etc. These special sensor nodes are used as the cluster heads to process and transmit the data sensed by the common sensor nodes as discussed in [43, 44].

A significant amount of research has been conducted in the literature for lifetime approximation of time-driven sensing scenarios with dynamic clustering schemes. A Low Energy Adaptive Clustering Hierarchy (LEACH) scheme is proposed in [45] and [46] that designates cluster heads in a distributive manner with a predetermined random probabilistic approach. It is expected that LEACH will provide adaptive clustering to improve energy efficiency, but the random election of cluster heads can lead to early energy depletion because the sensor nodes with low residual energy can be elected as cluster heads. A residual energy and communication cost based Hybrid Energy Efficient Distributed (HEED) clustering algorithm scheme is proposed in [47]. The proposed HEED scheme considers heterogeneous WSNs with multiple power levels in sensor nodes. Moreover, cluster heads are elected through an iteration process that take into account each sensor node's residual energy and its proximity to neighbouring sensor nodes. Consequently, constant communication between the candidate cluster heads and their neighbouring sensor nodes results in extra communication cost. An energy efficient clustering scheme is proposed by Ye *et al.* in [48] that is expected to support the periodical sensing applications. This scheme considers the election of cluster heads based on their residual energy. The authors in [49] proposed a Distributed Energy Efficient Clustering (DEEC) algorithm to provide an adaptive clustering solution for multi-level heterogeneous WSNs. The cluster heads are elected by considering the ratio of the residual energy of candidate cluster heads as well as the average network energy that results in extra load on the network by calculating the average energy of the network.

An energy efficient cluster head election protocol is proposed by Kumar *et al.* in [50] to extend the lifetime and stability within heterogenous WSNs. This scheme is applicable for limited applications because the authors' have assumed that the sensor nodes are uniformly distributed. A dynamic clustering scheme named as the Develop Distributed Energy Efficient Clustering (DDEEC) scheme is proposed in [51] for two level heterogeneous WSNs. The DDEEC scheme elects cluster heads based on the residual energy of the network to ensure energy efficient adaptive clustering. This scheme does not consider the extra communication cost required to calculate the average energy of the network. A three level heterogeneous sensor nodes based Enhanced Distributed Energy Efficient Clustering (EDEEC) scheme is presented by Saini *et al.* in [52]. This approach considers election of cluster heads based on the residual energy of the network. Such methodology requires calculating the residual energy of the network in each round that imposes extra load on the network. Javaid *et al.* proposed an Enhanced Developed Distributed Energy Efficient Clustering (EDDEEC) scheme presented in [53] for heterogeneous

WSNs. This scheme considers that the sensor nodes are deployed with different energy levels. The clustering is performed by electing cluster heads based on the ratio of the remaining energy of the sensor nodes and the average energy of the network. The authors claimed that this scheme distributes an equal amount of energy between the sensor nodes.

The aforementioned schemes perform cluster heads selection randomly which can lead to an unbalanced energy consumption throughout the network. Moreover, most of the schemes consider the residual network energy as a key parameter to elect cluster heads but this can actually impose an extra communication cost on the network. To address this issue Soro *et al.* proposed an unequal clustering size model in [54], that considers small size clusters near to the FCR and large size clusters as the distance increases from the FCR. This methodology is adapted to compensate for the extra energy consumed by the cluster heads near to the FCR to relay data from the other clusters. The authors have assumed that the size of clusters is fixed throughout the lifetime of the network. An unequal cluster-based routing is presented by Chem *et al.* in [55] that considers the same approach with small clusters nearer to the FCR than those of farther from the FCR as considered by Soro *et al.* In order to relay data to the FCR, a routing protocol is also proposed that provides a trade-off between the remaining energy of the sensor nodes and the routing path energy cost. A fuzzy logic approach based unequal clustering algorithm is proposed in [56] that is expected to manage the uncertainties caused in radius estimations of the cluster heads. This approach is expected to minimise the effect of the hot spot problem in the clusters that are near to FCR. Another scheme is proposed to address hot spot problem by Logambigai *et al.* in [57]. The authors presented an unequal clustering approach that considers fuzzy logic with the aim of minimising the communication overhead on the cluster heads that are nearer to the FCR. However, the authors did not consider the energy required to execute the complex algorithms to enable the fuzzy logic as discussed by Afsar *et al.* in [58]. Moreover, the aforementioned unequal clustering schemes assume that the FCR is in the centre of the sensing field. This is clearly not the case in most of the applications within WSNs. Pal *et al*. elaborated in [59] that the uneven clustering can result in uneven distribution of the energy load throughout the network. The authors further discussed the significance of a fixed number of clusters in order to evenly distribute the communication overhead and energy consumption in the network.

2.5.2 Event-driven Sensing

Considering WSNs for detection and reporting of events is another attractive approach for a significant amount of applications. The authors in [60] discussed that the occurrences of events are generally considered as random and transient, which involves the handling of a large amount of sensing data that can lead to uneven energy consumption. To address this issue, an event triggered based cluster formation scheme and multi-hop routing technique is presented by Quang *et al*. in [61], where the relay nodes are selected based on their residual energy and distance from the FCR. An adaptive and energy efficient clustering algorithm is presented to support event-driven applications in [62]. This scheme considers the residual energy of sensor nodes as the cluster head election criteria. Lucchi *et al*. proposed a distributive event detection scheme in [63] where decisions are made locally by the sensor nodes based on their observations. The authors considered a chain based configuration of sensor nodes to detect events such as fire detection.

An efficient event detecting protocol is presented by Liang et al. in [64] that considers the event detection locally with the help of cooperation among sensor nodes and forwards a single alarm to the FCR. Adulyasas *et al*. proposed an event-triggered based cluster formation scheme in [65] that reports data to the FCR only when the necessary data changes are detected. The clusters are operated only when the event is being detected. The sensor nodes switch to sleep mode once the situation is stable. The spatiotemporal correlation of the sensed data can achieve a higher energy efficiency and detection reliability as discussed by Andelic *et al.* in [66]. The authors also considers collaboration among sensor nodes during long-haul transmission. A spatial and temporal correlation based clustering architecture has been proposed for event detection in [67]. This approach takes into account the weight of the sensors and the spatial proximity of the sensor nodes to perform the decisions. In order to minimise the delay in the detection of events, a neural network based algorithm has been proposed by Damuut *et al.* in [68]. This algorithm is expected to select sensor nodes for the reliable detection of events.

A self-learning threshold based event detection scheme is proposed in [69]. This scheme considers mapping of sensor readings into symbol sequences. As a result, it is expected to reduce the amount of data needed to be transmitted to the FCR and simplify the description of events. A supervised learning algorithm based hybrid approach has been proposed by Oladimeji *et al.* in [70] that considers the k-means algorithm with neural networks. This approach is required to extract the patterns and follow the trends hidden in the complex data for the reliable detection of events. A distributed algorithm has been presented in [71] for the detection and reporting of events within WSNs. The authors considered an event-triggered based clustering approach for the energy efficient detection of events.

Observations: Most of the existing schemes presented in the literature consider random election of cluster heads. This approach can deplete the energy of the network quickly by electing neighbouring cluster heads near or far to each other. This will result in the formation of some very small size and some very big size clusters. Therefore, it increases the chance of selecting the sensor nodes with low remaining energy as cluster heads. Moreover, some clustering schemes require the calculation of the residual network energy in order to elect a cluster head. This technique imposes an extra communication overhead on the network by measuring and broadcasting the average remaining energy of the network in each round. Also, some of the schemes have been presented in the literature with unequal clustering where the size of the cluster increases with the increase in distance from the FCR. This approach is best suited for applications that have the FCR in the middle of sensing field. Furthermore, in this approach the cluster sizes are fixed throughout the lifetime of the network, which is not suitable, because of the dynamic and adaptive requirements in most of the applications. Although, a significant amount of research has been conducted in the literature to optimise WSNs by performing dynamic clustering, the existing schemes do not provide a framework that can provide energy efficient collaborative sensing; especially for applications that considers either time-driven sensing, event-driven sensing or unification of both.

2.5.3 Data Reduction

Within WSNs, data reduction techniques play an important role in energy conservation. Communication is one of the most energy consuming tasks which can be optimised by minimising the communication overhead. This can be achieved through data aggregation. The aim of data aggregation is the elimination of redundant data needed to be transmitted to the FCR and minimisation of unnecessary sensor readings. A normal distribution algorithm has been proposed by Ren *et al.* in [72] that is expected to provide lossless data compression by analysing the probability distribution of the acquired data. This algorithm specifically supports applications that monitors slow varying data. A dictionary based data aggregation scheme is proposed by Tsagkatakis *et al.* in [73] that is expected to reconstruct and classify randomly sampled data acquired by the sensor nodes. The authors claimed that this approach minimises the number of samples required to reconstruct the sensor data. Moreover, it is assumed that the acquired data exhibit intra-sensor correlations. A lossless data compression scheme is proposed in [74] that incorporates multiple code options. This technique divides the data into small blocks before performing compression.

A data aggregation algorithm that incorporates geographic location based virtual grid segmentation and optimal path selection is presented by Liu *et al.* in [75]. This scheme performs data aggregation at each grid and transmits it to the FCR through multi-hop path. Chen *et al.* proposed an algorithm in [76] that provides a trade-off between the cost of data aggregation and path to the FCR. This scheme is expected to find the best trade-off point. An energy aware data aggregation scheme is presented in [77]. This scheme considers aggregation if the residual energy of a sensor node is low. Moreover, the radio of low energy sensor node is turned off and only allowed to store the sensed data.

During the data acquisition process, the sensor nodes that are not involved in acquiring data can be kept in a 'listen' state to conserve energy. A data driven approach for data aggregation based on scheduling of sensor nodes has been proposed by Tang *et al.* in [78]. This scheme is expected to achieve energy efficiency but it provides a trade-off between sleep time and communication latency. A data aggregation algorithm is presented by Xu *et al.* in [79] for multi-hop WSNs. The authors focus on the scheduling problem during data aggregation. This approach is expected to attain collision free schedules to minimise latency. The problem of contiguous link scheduling is addressed by Ma *et al.* in [80]. This technique assigns consecutive time slots to each node for data acquisition. The aim is to perform scheduling with interference free link with minimum time slots. An energy efficient data aggregation algorithm is proposed by Guo *et al.* in [81] that is based on distributed scheduling. This study addresses the problem of minimum latency aggregation scheduling. Moreover, the authors also presented an adaptive schedule updating strategy to enable a dynamic network topology.

In-network data aggregation can also be achieved with deterministic routing that can pre-construct the stationary structure. A probabilistic routing based adaptive data aggregation protocol has been proposed by Lu *et al.* in [82] for periodical data collection events. The authors discussed that the spatial and temporal aspects for data aggregation and adaptive timing strategy can reduce the transmission delay.

A data aggregation scheme has been presented by Ebrahimi *et al.* in [83] that is based on compressive data gathering. This approach addressed the construction of a gathering tree and link scheduling problems to minimise latency and transmissions. The problem of maximum lifetime data aggregation tree scheduling has been addressed in [84] by Nguyen *et al.* The authors proposed a scheduling algorithm that is based on a local tree reconstruction and achieves energy conservation with multi-hop communication.

2.6 Cooperative Communication

As discussed earlier, a significant amount of research has been conducted in the literature for network specific optimisation with collaborative information sharing. This has been achieved "by sub-dividing the whole network into multiple clusters, where each cluster consists of relatively a small number of sensor nodes as compared to the total number of sensor nodes within the overall network. For each cluster, a sensor node is proposed to be selected as the cluster head that processes the required data for their member sensor nodes. Moreover, collaboration among sensor nodes is expected to provide real time processing while using minimum physical resources as well as requiring minimal processing. However, such high dependency on a single node during a long-haul transmission link may adversely put link reliability at risk. This specially in severe network conditions such as during least amount of available energy being available at the sensor node or during a deep channel fading, etc. Subsequently, having more than a single representative from each cluster during long distance communication has come to the attention of the researchers to provide transmit-receive diversity as Multiple-Input Multiple-Output (MIMO) based communication schemes" as discussed in [1]. The cooperation among sensor nodes within WSNs is expected to achieve the performance of traditional MIMO systems.

Within WSNs, cooperation can be introduced while communicating by utilising the collaborative nature of sensor nodes. It is claimed by the authors in [85] and [86] that cooperation among sensor nodes during data transmission can achieve energy conservation and transmission reliability as well as not being affected by the same fading effects as of the direct link. Therefore, less transmission power is required for communication. In order to achieve the required QoS, link adaptation schemes are required to be exploited which can select the appropriate degree of cooperation and processing intelligence schemes that are best suited to the channel conditions. It is expected that the link adaptation can achieve an energy efficient and reliable data transmission within WSNs. Furthermore, WSNs are also expected to achieve transmission reliability with optimum utilisation of resources that can be achieved by attaining implicit or explicit knowledge of the channel quality information at the transmitter side. Such channel quality information can be estimated and classified at the receiver and fed-back to the transmitter with negligible spectral resources.

2.6.1 Virtual/Cooperative MIMO

"A significant amount of research has been conducted in the literature for MIMO based communication architectures to improve the signal detection reliability, spectral efficiency and information capacity without increasing the transmit power or bandwidth as compared to single antenna systems. Traditionally multiple antennae have been used to achieve transmit or receive diversity to combat fading as well as to achieve spatial multiplexing to increase the data rate by transmitting the independent information streams through the spatial channels. In the context of WSNs, instead of using multiple antennae on each sensor node, several sensor nodes are expected to cooperate to transmit or receive data. Thus, cooperation among sensor nodes can achieve a virtual MIMO system, that can obtain all the benefits of both transmit-receive diversity as well as spatial multiplexing as attainable within conventional MIMO based communication systems" [1].

A communication architecture for cooperative WSNs has been proposed in [87] which exploits the virtual MIMO system. The authors considered space time block codes to explore energy and delay efficiencies of the virtual MIMO systems by using analytical techniques. Moreover, this approach analysed the relation of the energy efficiency of MIMO systems with fading coherence time. A systematic analysis on the energy consumption of WSNs has been presented by Zhou *et al.* in [88]. This scheme considered distributed space time block code based cooperative transmission scheme, where the degree of cooperation is dependent on the channel as well as noise realisations. The effect of the transmission power and the degree of cooperation on the energy consumption is also investigated. Hussain *et al.* proposed a virtual MIMO based communication scheme in [89] to achieve the energy efficiency within WSNs. The authors investigated the virtual MIMO systems for fixed as well as variable rate constellations. An energy efficient cooperative communication scheme has been presented by Gao *et al.* in [90]. This scheme adopted virtual MIMO and data aggregation techniques with the aim of reducing the amount of data required for transmission and optimise network resources through cooperative communication. The authors also analysed the relation of cluster size and the energy consumption of sensor nodes.

A multi-hop virtual MIMO schemes has been proposed in [91] by Chung *et al.* This scheme is expected to provide data transmission reliability by selecting the best set of cooperative sensor nodes for each hop. Therefore, a minimum energy consuming route is configured by dividing the long communication hops into two hops. However, the long communication hops are only divided when a gain in energy conservation is possible. A Vertical-Bell Labs Layered Space-Time (V-BLAST) based virtual MIMO architecture has been proposed in [92] to evaluate the performance of WSNs with multi-carrier modulation techniques. The authors analysed the performance of the proposed architecture for error probability, spectral efficiency and energy consumption. Peng *et al.* proposed a cooperative MIMO scheme to improve energy efficiency in [93] which is based on spatial modulation.

This scheme finds an optimal hop length for multi-hop WSNs to improve energy efficiency. A virtual MIMO based distributed cooperative scheme is proposed by Nguyen *et al.* in [94] that is expected to exploit diversity. This scheme optimally selects the cooperative sensor node to balance the energy consumption throughout the network. Moreover, this approach provides an upper bound on the optimal number of cooperative sensor nodes to reduce the computational complexity of the proposed architecture.

An energy balanced routing algorithm to exploit virtual MIMO has been proposed by Li *et al.* in [95] that is expected to evenly distribute the cluster heads and balance the energy consumption throughout the network. The cooperative nodes are selected based on the ratio of their residual energy and distance from the next hop. Moreover, a comprehensive energy consumption model is presented to analyse the effect of the number of cooperative sensor nodes and cluster head nodes on the lifetime of the network. A cooperative communication scheme based on virtual MIMO has been presented by Xu *et al.* in [96] to exploit spatial diversity. The authors also considered a dynamic routing protocol to improve the energy efficiency of the proposed system. A general routing structure based virtual MIMO scheme is presented in [97]. The authors proposed a virtual cooperative graph to find the shortest routing path for energy conservation and lifetime optimisation of the network.

2.6.2 Cooperative Sensor Node Selection

Recently, "a significant amount of research has been carried out on sensing nodes selection while exploiting the advantages provided by the multiple sensor nodes involved in transmission and reception. While optimising WSNs, the key challenge is the selection of sensor nodes as well as antennae at the FCR that provide assurance of optimum utilisation of radio resources. A distributed cooperative sensor nodes selection scheme is presented in [98]. This scheme is expected to select an optimum number of sensor nodes" [1] for cooperative communication with the aim of achieving link reliability. The authors also presented an upper bound for Symbol Error Rate (SER) with multi-phase shift keying. A sensor node selection scheme for cooperative WSNs is proposed by Elfituri *et al.* in [99]. This scheme is expected to improve network connectivity as well as detection reliability. Moreover, an upper bound for bit error rate is also presented for multi-phase shift keying transmission. A QoS requirement based sensor node selection scheme for cooperative communication is proposed by Zhang *et al.* in [100]. This technique is expected to optimise the number of sensor nodes for cooperation while minimising the computational complexity. Liang *et al.* presented a set of sensor nodes selection scheme for cooperative communication in [101]. The authors analysed the proposed scheme for capacity and probability of error within resource constrained scenarios. This technique provides a trade-off between capacity and probability of error. A geographical information based sensor nodes selection scheme is proposed by Wang *et al.* in [102]. This scheme is expected to achieve transmission diversity through cooperation among selected sensor nodes. The authors claimed that the proposed scheme can minimise symbol error and computational complexity of WSNs.

An adaptive transmission based sensor nodes subset selection scheme is proposed by Choi *et al.* in [103]. This scheme provides a trade-off between the performance and complexity of the proposed framework. Moreover, the performance analysis of the proposed scheme is also presented by quantifying the outage probability and spectral efficiency. Pal *et al.* proposed a channel selection scheme for cooperative transmission within WSNs in [104]. The proposed scheme is expected to improve the lifetime of the network by selecting the subset of sensor nodes in a distributive manner. An energy efficient cooperative nodes selection scheme is presented in [105] for uniformly distributed WSNs. This scheme is expected to select the least number of sensor nodes required for cooperation while optimising the outage probability. An adaptive sensor nodes selection based cooperative MIMO communication scheme is proposed in [106]. The authors considered the single-hop as well as multi-hop transmissions to analyse the performance of the proposed scheme. This approach is expected to achieve the uniform energy distribution throughout the network.

A cooperative MIMO scheme is proposed in [107] with the aim of conserving energy within WSNs. This scheme presented a selection criteria to select sensor nodes for cooperative communication based on channel conditions. Zhang *et al.* presented a cooperative node selection scheme in [108] that considers the residual energy as well as link quality between the cluster heads and the FCR. This approach is expected to achieve energy efficiency for long-haul transmissions. Cho *et al.* proposed a cooperative communication scheme in [109] to optimise the number of nodes involved in the cooperation. This technique is expected to minimise the overhead required for Channel State Information (CSI) and local data exchange. Therefore, the proposed scheme optimises the transmissions within the network and increases the throughput gains.

Hanninen *et al.* proposed a sensor nodes selection mechanism in [110] that is based on the channel's link quality. This scheme is expected to select the transmission paths that are affected with low interference to improve transmission reliability and throughput. This approach grades the channel based on the reliability of the link. A CSI based sensor nodes selection scheme for cooperative WSNs is presented by Moualeu *et al* in [111]. The authors discussed the effect of the delay on the CSI on the sensor nodes selection process during transmission. An upper bound for Bit Error Rate (BER) is also presented. Mousavi *et al.* proposed a cooperative nodes selection scheme in [112]. The authors considered the time varying fading channel and assumed perfect channel estimation at the cooperative sensor nodes. The FCR is expected to select the least number of cooperative nodes based on the channel estimation information.

Observations: WSNs are expected to be optimised by defining the cooperation among sensor nodes during data transmission based on channel conditions. There is a need to define the energy efficient scheme to select the sensor nodes for cooperation which are lest affected from deep fading and interference. Moreover, cooperation among the sensor nodes during data transmission need to exploit diversity and spatial multiplexing to provide a trade-off between the transmission reliability and data capacity while maintaining the required QoS.

2.6.3 Channel Quality Estimation

WSNs are "expected to provide maximum transmit-receive reliability with optimum usage of radio resources e.g. power, bandwidth, etc. To obtain maximum optimisation performance, explicit or implicit knowledge of the channel quality features at the transmitter is required. Hence, classification of such channel quality features as estimated at the FCR can be fed-back to the transmitter with negligible spectral resources required. Channel adaptive processing intelligence schemes such as Lattice Reduction (LR) is expected to support MIMO systems to perform near optimal data detection" [1]. A LR based channel quality estimation scheme for MIMO systems is proposed by Adeane *et al.* in [113]. This technique is expected to improve the link reliability based on the information estimated at the FCR. Ma *et al.* proposed a LR based channel estimation scheme for MIMO systems in [114]. The authors also presented an analytical framework to quantify the diversity order of linear detectors to optimise the spectral efficiency and complexity of MIMO systems. A near Maximum Likelihood (ML) scheme for MIMO systems is proposed by Wu *et al.* in [115]. This scheme is based on sphere decoding that is expected to optimise complexity.

A normalised Least Mean Square (LMS) based channel estimation scheme is proposed by Wang *et al.* in [116] for cooperative WSNs. The authors claimed that the proposed scheme can achieve low computational complexity and reduce the power consumption by estimating the complex channel parameters. A fixed error bound is also presented that can adjust adaptively with the channel estimations even in time varying environments. A channel estimation scheme based on recursive least square algorithm is proposed in [117] with the aim of achieving low computational complexity and power consumption. The authors also presented the analysis of the proposed scheme in term of Mean Square Error (MSE), BER and robustness against time varying conditions. A reduction strategy for sphere decoding based on permutations and unimodular transformations is proposed by Zhang *et al.* in [118]. A theoretical analysis is also proposed to define the reduction process. The authors claimed that the proposed scheme is more efficient than the permutation based reduction schemes. Ning *et al.* proposed a cooperative and distributed algorithm based on LMS in [119] to estimate the channel coefficients. This scheme is expected to improve the energy efficiency and convergence of the estimation process by incorporating collaboration among the sensor nodes. Optimal ML "detection with sphere decoding can achieve full diversity but less complex suboptimal detectors with LR perform close to optimal and have the potential to achieve full diversity" [1].

Observations: "WSNs are required to perform adequate decisions on the selection of appropriate optimisation scheme adaptively. Such adaptation requires transmission quality information over given channel conditions. To optimise energy consumption and communication overhead required at the transmitting sensor nodes, a measure of channel quality is needed to be defined that maps directly to the frame error probability; which is defined as channel quality index (CQI). It is expected to be designed in a manner to ensure reliability against variable channel conditions and optimised utilisation of available resources while maintaining the required QoS" [1].

2.6.4 Link Adaptation

Within WSNs, the "available power within a sensing node is inversely proportional to the uncertainty of the channel propagation conditions, with reference to the budgeted consumption of power as designed. WSNs are expected to be adaptive with the dynamic Radio Frequency (RF) propagation environment conditions, while demanded or allocated with resources such as physical resources as well as processing intelligence to ensure the QoS based on application requirements. The required QoS is defined in terms of the error rate, delay and degree of information security. The QoS can be guaranteed by exploiting the effective link adaptation schemes. The purpose of link adaptation is to select the appropriate physical resources and processing intelligence schemes that are best suited to the channel conditions to offer the QoS based on the application requirements" [1]. Van *et al.* proposed a communication scheme in [120] with the aim of optimising energy efficiency during transmission within WSNs. This scheme defines a threshold based on the channel conditions to avoid unsuccessful transmissions. Moreover, the sensor nodes are selected for data transmission with better channel conditions to increase the link reliability.

A CSI based adaptive transmission scheme is proposed by Ren *et al.* in [121]. The authors considered the data transmission decisions based on the channel conditions to conserve the network energy that is otherwise wasted by failed transmissions. To enhance the energy efficiency, an adaptive optimisation scheme for multi-hop communication within WSNs is proposed in [122]. This scheme is based on adaptive modulation and power control to ensure certain QoS requirements such as end-to-end delay and BER conditions are met. Temperature aware link adaptive scheme for energy efficient transmission within WSNs are proposed in [123] and [124]. These schemes estimate link quality that changes due to temperature variations and the sensor nodes are expected to adapt transmit power according to the link quality. Atitallah *et al.* proposed a cooperative communication based energy efficient transmission scheme for clustered WSNs in [125]. This scheme is expected to minimise energy consumption by allocating the least amount of transmission power among transmitting sensor nodes while achieving the required level of reliability. Jayasri *et al.* proposed a link quality based adaptive transmission scheme for WSNs in [126]. The authors proposed a link quality estimation technique to minimise data loss during transmissions. This is achieved by adapting transmission rate to the link quality.

Observations: Although, the existing literature provides solutions for cooperative communication within WSNs. However, there is a need for a framework that can attain transmission reliability by adopting variable channel conditions while optimising the energy consumption. Channel selection schemes for efficient and reliable data transmission as well as selection of intelligent processing based on the channel's link quality are required to provide a robust solution against variable channel conditions.

2.7 Summary

In this chapter, the state of the art techniques to address the key issues and challenges in the design of WSNs are elaborated. The solutions proposed in the literature to resolve these issues and to overcome the challenges are summarised, and the limitations of the existing works are discussed. Although the existing studies in the literature address several key issues and propose solutions leading to energy efficiency such as collaborative sensing techniques e.g. dynamic cluster formation, cluster head selection, data reduction, dynamic adaptivity etc. and cooperative communication techniques e.g. virtual MIMO, cooperative sensor nodes selection schemes, resource selection, channel quality estimation and link adaptation. However, the existing scheme does not provide a universal framework to support applications that are required by either time-driven sensing, event-driven sensing or unification of both scenarios. Moreover, the clustering techniques do not consider all aspects such as the unbalanced distribution of the cluster heads, highly variable number of sensor nodes in the clusters and the high number of sensor nodes involved in the event reporting that can deplete the network energy thus quickly resulting in premature decrease in the network lifetime. Consequently, dynamic and cooperative clustering and a neighbourhood formation framework is needed to evenly distribute the energy demands from the cluster heads and optimise the number of sensor nodes involved in event reporting that can support the applications independently of the nature of sensing type.

WSNs are also expected to be optimised by defining cooperation among sensor nodes during data transmission based on channel conditions. There is a need to define energy efficient scheme to select the sensor nodes for cooperation which are least affected from deep fading and interference. Moreover, cooperation among sensor nodes during data transmission are needed to exploit the diversity and spatial multiplexing to provide a trade-off between the transmission reliability and data capacity while maintaining the required QoS. In order to perform adequate decisions on the selection of appropriate optimisation schemes adaptively, the transmission quality information is required over the given channel conditions. Such adaptation is expected to be designed in a manner to ensurethe reliability against variable channel conditions and the optimised utilisation of the available resources while maintaining the required QoS. Although, the existing literature provides solutions for the cooperative communication within WSNs. However, there is a need for a framework that can attain transmission reliability by adopting variable channel conditions while optimising the energy consumption. Channel selection schemes for efficient and reliable data transmission as well as selection of intelligent processing based on the channel's link quality are expected to provide robust solutions against variable channel conditions.

The research studies in the literature consider time-driven and event-driven scenarios separately and do not provide a universal solution. In this study, a dynamic clustering and neighbourhood formation scheme is proposed that provides a framework which is independent of the nature of sensing application. It is expected that the proposed framework will provide an energy efficient solution by rotating the role of cluster head among all the sensor nodes while trying to keep the size of the clusters uniform and minimising the frequency of re-clustering. Furthermore, considering the residual energy threshold in the cluster heads selection process and their location in the network, the proposed framework is expected to avoid any unbalanced energy consumption and energy holes in the network for time-driven, event-driven as well as unification of both sensing scenarios. In order to attain transmission reliability, the dynamic behaviour is adopted to minimise the effect of variable channel conditions on data transmission. Such adaptation can be achieved by deriving an index from the received measure of channel quality that is attained at the transmitter through a feedback link from the FCR. The dynamic behaviour of the proposed framework is expected to provide a robust solution against variable conditions of the propagation environment. This study is also expected to present a unified framework of collaborative sensing and cooperative communication schemes to provide energy efficient solutions for resource constrained WSNs.

The next Chapter builds on a collaborative sensing framework that comprises of a universal and dynamic clustering scheme with the aim of evenly distributing the energy demand from the cluster heads and optimising the number of sensor nodes involved in event reporting. A network lifetime model is also derived to evaluate the performance of the proposed framework.

Chapter 3

A Universal and Dynamic Clustering (UDC) Framework for Collaborative Sensing

3.1 Introduction

Within WSNs, lifetime enhancement is one of the key design issues, regardless of the type of application, without compromising the required QoS. The sensor nodes are expected to collaborate to maximise the energy consumption within the network by involving a minimum number of sensor nodes as well as optimising the network communication required to report events. Moreover, events are generally considered as random and transient which involves the handling of a large amount of sensed data that can lead to uneven energy consumption. To overcome this issue, self-organisation of the network is required to balance the energy consumption among the sensor nodes by dynamically rotating the cluster head role and adaptively redefining the cluster boundaries. Also, dynamic clustering is expected to enhance load balancing, fault tolerance and connectivity within the network.

The research studies in the literature consider time-driven and event-driven scenarios separately and do not provide a universal solution. In this chapter, a dynamic clustering and neighbourhood formation scheme based on collaborative sensing framework is proposed that provides a universal behaviour to support applications independent of the nature of sensing type. It is expected that the proposed framework will provide an energy efficient solution by dynamically rotating the role of the cluster head among all the sensor nodes while trying to keep the size of the clusters uniform and minimising the frequency of re-clustering. Furthermore, considering the residual energy threshold in the cluster heads election process and their location in the network, the proposed framework is expected to avoid any unbalanced energy consumption and energy holes in the network. The framework for universal and dynamic clustering is presented in the following section.

3.2 Proposed Framework for UDC

In this section, a WSN model is described, which assumes a random distribution of n number of sensor nodes within the sensing field of dimensions $(A \times B)$. Each sensor node is assumed to be capable of measuring homogeneous and heterogeneous data sets based on the application requirements. It is assumed that the locations of the sensor nodes are implicitly deterministic and that all the sensor nodes within the network are homogenous in terms of processing and computational capability at initial deployment. Moreover, it is also assumed that the FCR is not energy limited, it is equipped with multiple antennae and its coordinates are known. A block diagram summarising the methodological steps of the proposed universal dynamic clustering framework is presented in Figure 3.1.

Let $\mathbf{S}$ be a set of all the sensor nodes in the network which is defined as:

$$\mathbf{S} = \{S_1, S_2, \dots, S_n\} \tag{3.1}$$

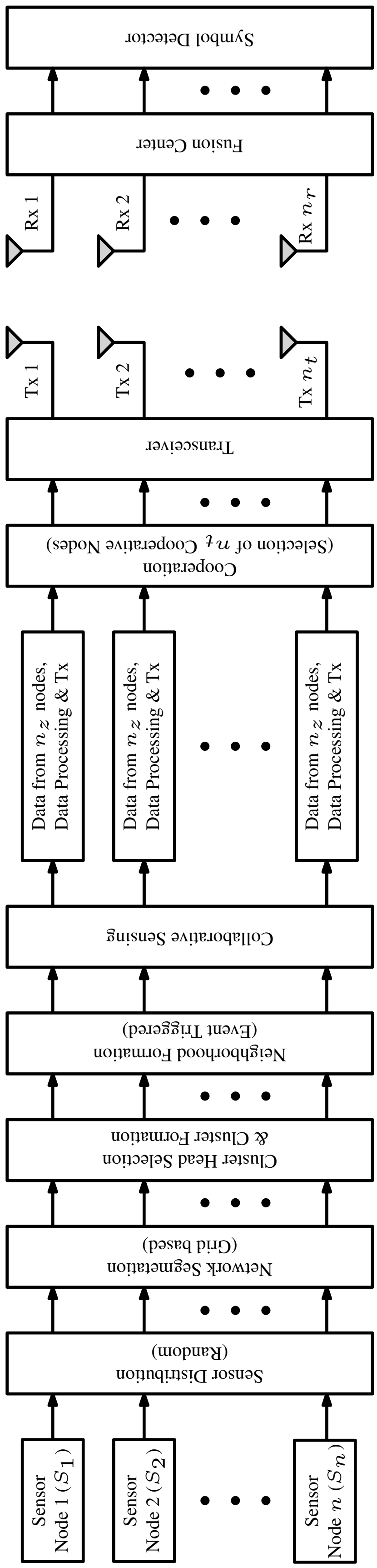

Figure 3.1: Block diagram summarising the methodological steps of the proposed universal dynamic clustering framework.

where $S_{(.)}$ represents the sensor nodes. To limit the communications overhead within large scale WSNs, several segmentation schemes have been proposed in the literature. Network segmentation is expected to achieve high energy efficiency, hence contribute to prolong the lifetime of WSNs [42]. In this study, the whole network is divided into non-overlapping uniform virtual grids of dimensions $(a_c \times b_c)$. The information of virtual grids realisation is required only at deployment phase by the sensor nodes to perform energy efficient cluster head election.

Let $\mathbf{Q}$ be a set of all the virtual grids within the network which is defined as:

$$\mathbf{Q} = \{Q_j \ ; j = 1, 2, \ldots, q\} \tag{3.2}$$

where q is the number of virtual grids in the network and each virtual grid consists of p_j number of sensor nodes. The set of sensor nodes within each virtual grid can be defined as $\{S_i; i = 1, 2, \ldots, p_j\}$. The total number of sensor nodes within the network can be expressed as:

$$n = q \times \sum_{j=1}^{q} p_j \tag{3.3}$$

Consider $Q_{(\cdot)}$ represents a set of sensor nodes within a virtual grid, then j^{th} virtual grid is represented as Q_j and defined as:

$$Q_j = \{S_i^j \ ; i = 1, 2, \ldots, p_j\} \tag{3.4}$$

where S_i^q denotes i^{th} sensor node of the q^{th} virtual grid. In each virtual grid, a sensor node is selected as the cluster head to coordinate with other sensor nodes within the cluster based on certain criteria. Cluster heads act as coordinators between the member sensor nodes and the FCR e.g. collect data from the sensor nodes, perform data aggregation, forward it to the FCR, take instructions from the FCR, etc. Dynamic cluster architectures are expected to gain energy efficiencies by selecting cluster heads in order to effectively react and adjust appropriately on network topology.

As discussed earlier, wireless communication is the most energy consuming task within WSNs. A new approach for an improved lifetime of wireless sensor nodes is required that is expected to process the sensed data locally. Each sensor node is expected to decide locally whether to transmit the sensed data to the cluster head based on the predefined application specific threshold value provided by the FCR through their respective cluster heads. To reduce the unnecessary communication within the network, the cluster heads for time-driven reporting mode, the cluster heads are expected to aggregate the data in order to remove redundant information. All the cluster heads are also expected to collaborate with each other.

In some applications, sensor measurements are sent directly to the FCR from the sensor nodes e.g. traffic surveillance system to monitor traffic on congested roads, watches to monitor health (e.g. blood pressure, pulse rate etc.), wireless motion sensors for the monitoring of stroke patients, etc. In most of the applications, sensor nodes are densely deployed in harsh environments to monitor large scale areas e.g. environmental monitoring, infrastructure protection, agriculture, water management, military surveillance, etc. The energy and sensing range of a sensor is limited in such a scenario. So, sensor nodes can be organised in a multi-hop fashion that is expected to achieve long distance communication and lifetime improvement of the network. Within WSNs, the FCRs are responsible to collect the information from the network, process and analyse the information and also to send instructions to the sensor nodes in the network. They are usually connected to the internet through either wireless or wired communication such that sensing data can be requested any time by an end user.

3.2.1 Dynamic Clustering Scheme

In order to conserve the energy of the sensor nodes within the WSNs, it is expected to distribute the load of performing the tasks among the sensor nodes. This is to balance the energy consumption within the network by selecting the optimum number of sensor nodes to report any significant occurrences and to perform reliable communication to relay the sensing data back to FCR. Generally, sensing within WSNs can be realised as either time-driven or an event-driven scenario. In time-driven sensing, the sensor nodes relay the acquired data to the FCR on a periodic basis. While in event-driven sensing the sensor nodes are responsible for the detection of any significant occurrences and reporting it to the FCR. In this study, a dynamic clustering and neighbourhood formation scheme is proposed for time-driven and event-driven applications. Moreover, a universal framework is proposed for adaptive utilisation of both the aforementioned sensing scenarios to further enhance the feasibility of implementation for a diverse range of applications. Within the proposed UDC framework, all the decisions such as the selection of cluster heads, formation of clusters as well as neighbourhoods and the selection of cooperative sensor nodes for reporting to the FCR are all made locally within the respective clusters throughout the network. Such a distributive decision making ability facilitates the proposed UDC framework to be energy efficient, as this reduces the amount of information to be broadcasted or transmitted wirelessly to represent an event.

A distributed cluster head selection scheme is proposed such that all the sensor nodes that can serve the role with minimum energy consumption have a chance to become cluster heads. It is expected that all the sensor nodes will broadcast their location to their respective cluster heads. The cluster heads will then broadcast this information within the network. Initially, all the sensor nodes are expected to calculate their distance from the centre of their respective virtual grids. Then each sensor node is expected to be ranked based on its respective distance from the centre of their respective virtual grid. The sensor node which is nearest to the centre of the virtual grid has the highest priority to become the cluster head. A threshold energy δ_{ch} is carefully defined, such that if the energy of a cluster head falls below δ_{ch}, the role of cluster head is expected to be handed over to the second highest ranking node. Once all the cluster heads are selected, the remaining nodes find the nearest cluster heads and join them, irrespective of their initial cluster assignment. The election of cluster heads and the formation of new clusters is explained below.

Let $\mathcal{F}(x_1, y_1, x_2, y_2)$ represents the Euclidean distance function which is defined as:

$$\mathcal{F}(x_1, y_1, x_2, y_2) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \tag{3.5}$$

where x_1, y_1, x_2 and y_2 represents the coordinates of two points. Once all the sensor nodes are deployed in the network, the sensor nodes are then expected to calculate their distances from the centre of their respective virtual grids, by using the function presented in Equation 3.5 and expressed as:

$$d_1 = \mathcal{F}(c_x, c_y, s_x, s_y) \tag{3.6}$$

where

$$\mathcal{F}(c_x, c_y, s_x, s_y) = \mathcal{F}(x_1 = c_x, y_1 = c_y, x_2 = s_x, y_2 = s_y) \tag{3.7}$$

(c_x^j, c_y^j) are the coordinates of the centre of the virtual grids while $j = \{1, 2, \ldots, q\}$ and (s_x^i, s_y^i) are the coordinates of the sensor nodes where $i = \{1, 2, \ldots, p_j\}$. Consider $S_{(j,i)}$ denotes a sensor node and p denotes the maximum number of sensor nodes belonging to a particular grid, given by $p = \max\{p_j; j = 1, 2, \ldots, q\}$. Let $\mathbf{Q}$ be a matrix of all the sensor nodes in the network which is defined as:

$$\mathbf{Q} = \begin{bmatrix} S_{(1,1)} & S_{(1,2)} & \dots & S_{(1,p)} \\ S_{(2,1)} & S_{(2,2)} & \dots & S_{(2,p)} \\ \vdots & \vdots & \ddots & \vdots \\ S_{(q,1)} & S_{(q,2)} & \dots & S_{(q,p)} \end{bmatrix} \tag{3.8}$$

where each row of matrix $\mathbf{Q}$ represents the sensor nodes in each virtual grid. Although the number of sensor nodes in each virtual grid is not the same, however, for the sake of mathematical representation, $\mathbf{Q}$ is defined as a matrix. Consider $S_{(j,i)}$ is assigned with a value to classify the existence of a sensor node which is defined as:

$$S_{(j,i)} = \begin{cases} 1, & \text{if } i \leq p_j \\ 0, & \text{if } i > p_j \end{cases} \tag{3.9}$$

where 0 represents the existence of a sensor node and -1 represents the non-existence of a sensor node. Let $\mathbf{D}_1$ be a matrix of dimensions $(q \times p)$ which represents the distance of all the sensor nodes from the centre of their respective virtual grids and expressed as:

$$\mathbf{D}_1 = \begin{bmatrix} d_{1(1,1)} & d_{1(1,2)} & \dots & d_{1(1,p)} \\ d_{1(2,1)} & d_{1(2,2)} & \dots & d_{1(2,p)} \\ \vdots & \vdots & \ddots & \vdots \\ d_{1(q,1)} & d_{1(q,2)} & \dots & d_{1(q,p)} \end{bmatrix} \tag{3.10}$$

where each row of matrix $\mathbf{D}_1$ represents the distance of sensor nodes from their respective virtual grid centre. Let $\mathbf{d}_{1(q)}$ represent the distance of the sensor nodes from the centre of the q^{th} virtual grid, which is expressed as $\mathbf{d}_{1(q)} = \{d_{1(q,1)}, d_{1(q,2)}, \dots, d_{1(q,p)}\}$. All the sensor nodes are then characterised as either normal nodes or cluster head nodes. Let ξ_q constitute the information of the sensor node which is at a minimum transmission distance from the q^{th} virtual grid centre and can be defined as: $\xi_q = min(abs(\mathbf{d}_{1(q)} \backslash \psi))$. Where "\" represents the difference between two sets. Consider, initially $\psi = \emptyset$ and it will keep the record of the sensor nodes that are elected as cluster heads throughout the lifetime of the network. Let the p^{th} sensor node be at a minimum transmission distance from the q^{th} virtual grid centre which is denoted as $d_{1(q,p)}$ and defined as $d_{1(q,p)} \backslash \psi = \{d_{1(q,p)} \in \mathbf{d_{1(q)}} | d_{1(q,p)} \notin \psi\}$. In addition to the minimum transmission distance requirement, the energy of the candidate sensor node is compulsory to be greater than the threshold δ_{ch}. Once a sensor node is designated as a cluster head, it is assigned with $\varsigma = 1$, which shows its status as cluster head. This process iterates until all q number of cluster heads are defined and in each iteration $\psi = \xi$ is updated. Let $\mathbf{Q}_s$ be a matrix of dimensions $(q \times p)$ and represent the status of the sensor nodes which is defined as:

$$\mathbf{Q}_s(i,j) = \begin{cases} \text{Cluster Head (CH)}, & \text{if } \varsigma = 1 \\ \text{Normal Node (N)}, & \text{Otherwise} \end{cases} \tag{3.11}$$

Let Q_{ch} be a set of all the cluster heads in the network which is defined as:

$$Q_{ch} = \{S_j^{ch}; j = 1, 2, \ldots, q\} \tag{3.12}$$

where q is the total number of cluster heads and S_j^{ch} denotes the cluster head from the j^{th} cluster. All the sensor nodes with status N are expected to join the cluster head which is at minimum transmission distance. Let $\mathbf{D}_2$ contain the distances of all the normal sensor nodes with q number of cluster heads, which is defined as:

$$\mathbf{D}_2 = \begin{bmatrix} d_{2(1,1)} & d_{2(1,2)} & \ldots & d_{2(1,q)} \\ d_{2(2,1)} & d_{2(2,2)} & \ldots & d_{2(2,q)} \\ \vdots & \vdots & \ddots & \vdots \\ d_{2(n,1)} & d_{2(n,2)} & \ldots & d_{2(n,q)} \end{bmatrix} \tag{3.13}$$

where $\mathbf{D}_2$ is a matrix of dimensions $(n \times q)$ and d_2 is calculated by using the function presented in Equation 3.5 and expressed as:

$$d_2 = \mathcal{F}(ch_x, ch_y, s_x, s_y) \tag{3.14}$$

where

$$\begin{aligned} \mathcal{F}(ch_x, ch_y, s_x, s_y) = \mathcal{F}(&\lambda_x^1 = ch_x, \lambda_y^1 = ch_y, \\ &\lambda_x^2 = s_x, \lambda_y^2 = s_y) \end{aligned} \tag{3.15}$$

(ch_x^j, ch_y^j) are the coordinates of the cluster heads while $j = \{1, 2, \ldots, q\}$ and $(s_x^{\breve{i}}, s_y^{\breve{i}})$ are the coordinates of the sensor nodes where $\breve{i} = \{1, 2, \ldots, n\}$. Let $\mathbf{d}_2^{\breve{i}}$ be the $\breve{i}^{th}$ row of $\mathbf{D}_2$ which provides the transmission distance information of the $\breve{i}^{th}$ sensor node from q number of cluster heads. The $\breve{i}^{th}$ sensor node is expected to join the cluster head, which is at minimum transmission distance that is defined as $min\{\mathbf{d}_2^{\breve{i}}\}$. New boundaries of the clusters are defined as shown in Figure 3.2.

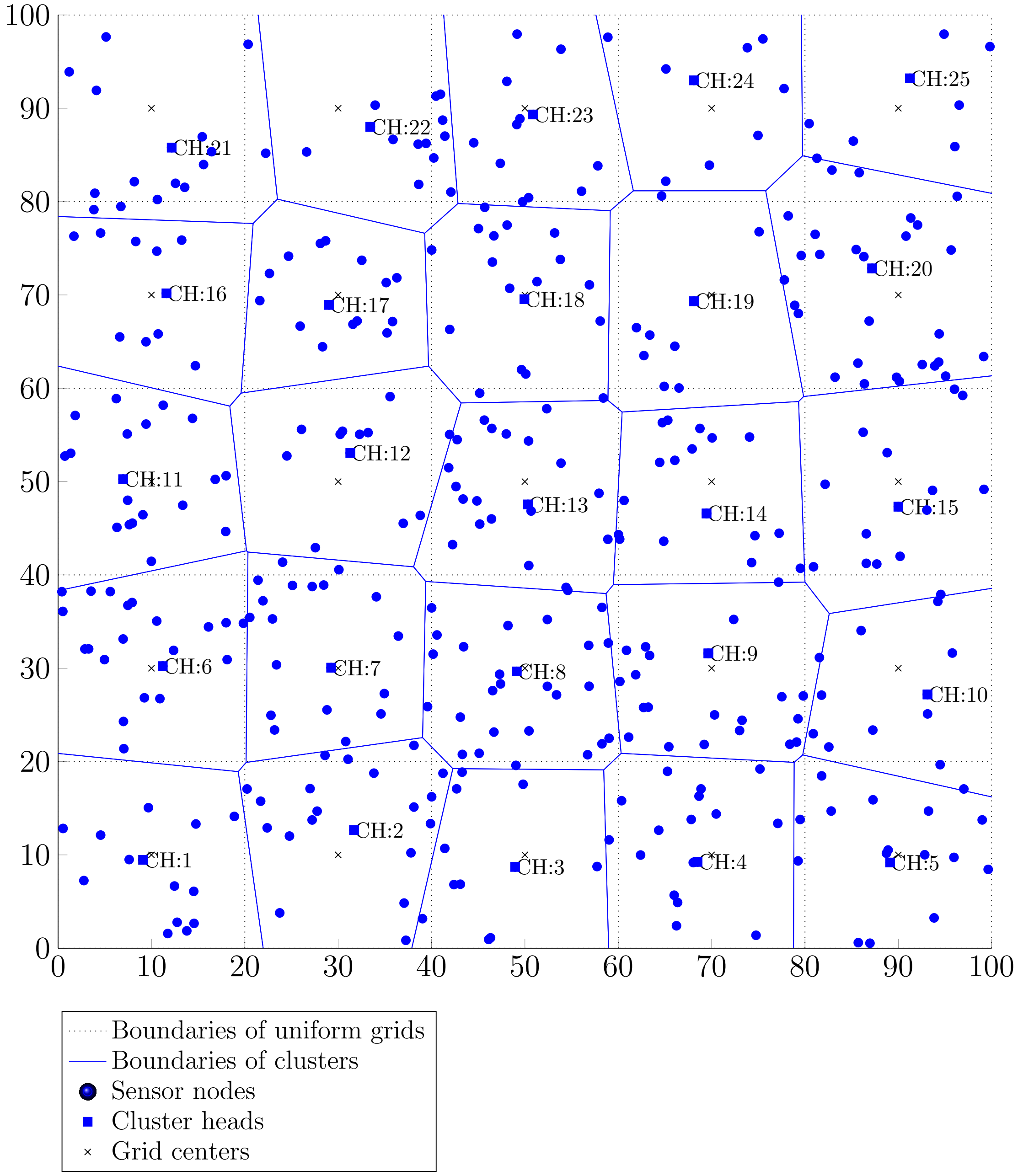

FIGURE 3.2: Implementation of dynamic clustering within WSNs.

The proposed dynamic clustering scheme is summarised in Algorithm 3.1.

Algorithm 3.1 Proposed Dynamic Clustering Scheme

Require:

The number of sensor nodes n within the network, their coordinates $(x_{\breve{i}}, y_{\breve{i}})$; $\breve{i} = 1, 2, \ldots, n$ of each sensor node, their energy which is denoted as $S_{\breve{i}}^{E}$, the coordinates of the centre of each grid (x_j, y_j) ; $j = 1, 2, \ldots, q$ and cluster head selection threshold energy δ_{ch}

Ensure:

$S_{(.)}^{ch} \leftarrow \min\{\mathbf{d}_1\}$ and $S_{\breve{i}}^{E} \geq \delta_{ch}$

$\mathbf{D}_1 \leftarrow \varnothing$, $\mathbf{d}_1 \leftarrow \varnothing$
$\mathbf{P}_1 \leftarrow \varnothing$, $\mathbf{p}_1 \leftarrow \varnothing$
$\mathbf{Q}_s \leftarrow \varnothing$
for $j \leftarrow 1$ **to** q **do**
    for $\breve{i} \leftarrow 1$ **to** n **do**
        $\mathbf{d}_1(\breve{i}) \leftarrow d_1$ where d_1 is calculated from Equation 3.6
    end for
    $\mathbf{d}_1 \leftarrow$ Sort $\{\mathbf{d}_1\}$, (Sort in ascending order and save their respective indices in $\mathbf{p}_1$)
    $\mathbf{D}_1(j) \leftarrow \mathbf{d}_1$
    $\mathbf{P}_1(j) \leftarrow \mathbf{p}_1$
end for
$\tau \leftarrow 0$
for $j \leftarrow 1$ **to** q **do**
    for $\breve{i} \leftarrow 1$ **to** n **do**
        $\mathbf{Q}_1(j, \breve{i}) \leftarrow$ Mapping of sensor nodes based on $\mathbf{D}_1$ and $\mathbf{P}_1$
        if $S_{(.)}^{E} \geq \delta_{ch}$ & $\tau = 0$ **then**
            $\mathbf{Q_s} \leftarrow$ Update the status of $S_{(j,\hat{i})}$ as Cluster Head (CH) or Normal Node (N)
            $\tau \leftarrow 1$
        end if
    end for
end for

Algorithm 3.1 (continued) Proposed Dynamic Clustering Scheme

$\mathbf{D}_2 \leftarrow \varnothing$, $\mathbf{d}_2 \leftarrow \varnothing$
for $j \leftarrow 1$ **to** q **do**
  for $\breve{i} \leftarrow 1$ **to** n **do**
    $\mathbf{d}_2(\breve{i}) \leftarrow d_2$ where d_2 is calculated from Equation 3.14 & Equation 3.15
  end for
  $\mathbf{D}_2(j) \leftarrow \mathbf{d}_2$
end for
for $\breve{i} \leftarrow 1$ **to** n **do**
  $\mathbf{Q}_{ch}(\breve{i}) \leftarrow \min\{\mathbf{D}_2(1:q, \breve{i})\}$
  Assign the task of cluster head to the sensor nodes in $\mathbf{Q}_{ch}$
end for
return $\mathbf{Q}_{ch}$

Let $\hat{Q}_j$ represent a set of sensor nodes in the j^{th} cluster which is defined as:

$$\hat{Q}_j = \{S_i^j \ ; \ i = 1, 2, \ldots, \hat{p}_j\} \tag{3.16}$$

and $\hat{\mathbf{Q}}$ is the set of all the clusters with the network which is expressed as:

$$\hat{\mathbf{Q}} = \{\hat{Q}_j \ ; \ j = 1, 2, \ldots, q\} \tag{3.17}$$

Since cluster heads are required to carry out additional tasks for their respective sensor nodes, their energy gets depleted more quickly than the non-cluster head sensor nodes. As the proposed dynamic clustering scheme is expected to rotate the cluster head role among all sensor nodes while minimising the frequency of re-clustering, it is important to define δ_{ch} carefully.

3.2.1.1 Hard Threshold

It is defined as a function of residual energy in the cluster heads. Let $\Psi = \{\psi_1, \psi_2, \ldots, \psi_{\ddot{n}}\}$, where Ψ represents the range of energy within a sensor node i.e. $\Psi \in [0, 1]$. Therefore the task for the system design engineer is to find the optimum value from Ψ to define δ_{ch} which requires extensive simulation experiments. As the distribution of sensor nodes is expected to be random in most of the applications, dynamic clustering is required to be implemented to adapt with varying conditions within the network. Consequently, the criteria to find the optimum threshold might change throughout the lifetime of the network. This can lead to erroneous decisions on the selection of δ_{ch}, which can consequently cause an unbalanced energy consumption within the network. To overcome these limitations with the aforementioned threshold selection method, a soft decision based threshold selection method is defined as follows.

3.2.1.2 Soft Threshold

It is defined based on an iterative method that computes $\ddot{k}$ number of optimum threshold values from Ψ, which are denoted as $\delta_{ch}^1, \delta_{ch}^2, \ldots, \delta_{ch}^{\ddot{k}}$ and defined as:

$$\delta_{ch}^{\hat{k}} = \frac{|\psi_1 - \psi_{\ddot{n}}|}{\Gamma^{\hat{k}}} \quad where \quad \hat{k} = \{1, 2, \ldots, \ddot{k}\} \tag{3.18}$$

where Γ is a tuneable parameter. The sensor nodes within each cluster are expected to serve as cluster heads until their energy depletion level reaches the threshold value δ_{ch}^1. Once all the sensor nodes within a cluster are served as cluster heads, the cluster head role will repeat among the nodes with energy depletion level δ_{ch}^2 and so on. It is expected that by defining the soft threshold, energy consumption is balanced throughout the network at the cost of higher rate of re-clustering than would have been with the use of a hard threshold.

3.2.2 Dynamic Neighbourhood Formation Scheme

The selection of a group of sensors, in response to an incident is one of the core elements of the proposed optimisation process. Hence, this section describes the set out criterion of such incident triggered dynamic grouping schemes, such as neighbourhood. One of the main tasks of sensor nodes is to monitor, detect and collect various significant occurrences of events within WSNs. The occurrence of the behavioural change that sensor nodes are expected to detect is called an event. Let there be k number of events that have occurred within a cluster at time instant t. It is assumed that the locations of the events are implicitly deterministic. The trend of the sensing parameters and the knowledge of that trend at the cluster heads make the location of events implicitly deterministic. Consider, the coordinates of the location of events are denoted as $(e_x^{\hat{f}}, e_y^{\hat{f}})$, where e_x and e_y denote the coordinates of the location of an event and $\hat{f} = \{1, 2, \ldots, k\}$. A neighbourhood consists of a group of sensor nodes which are selected based on certain criterion i.e. distance from the location of an event, sensing capability etc. that are expected to take part in the detection of the events. All the sensor nodes within a neighbourhood are expected to cooperate with each other. For the sake of simplicity, it is assumed that each neighbourhood at time instant t will consist of n_b number of sensor nodes where n_b varies from neighbourhood to neighbourhood as shown in Figure 3.3. Let there be k number of neighbourhoods formed by the occurrence of k number of events at time instant t. The total number of sensor nodes involved to form the k^{th} number of neighbourhood is denoted as $\mathcal{N}_e^k$ and is defined as:

$$\mathcal{N}_e^k \mid_t = \{s_{\hat{e}}^k \ ; \ \hat{e} = 1, 2, \ldots, n_b^k\} \tag{3.19}$$

It is assumed that all the neighbourhoods formed at time instant t will not overlap with each other which is defined as:

$$\mathcal{N}_e^1 \mid_t \cap \, \mathcal{N}_e^2 \mid_t \cap \cdots \cap \mathcal{N}_e^k \mid_t \ \in \ \emptyset \tag{3.20}$$

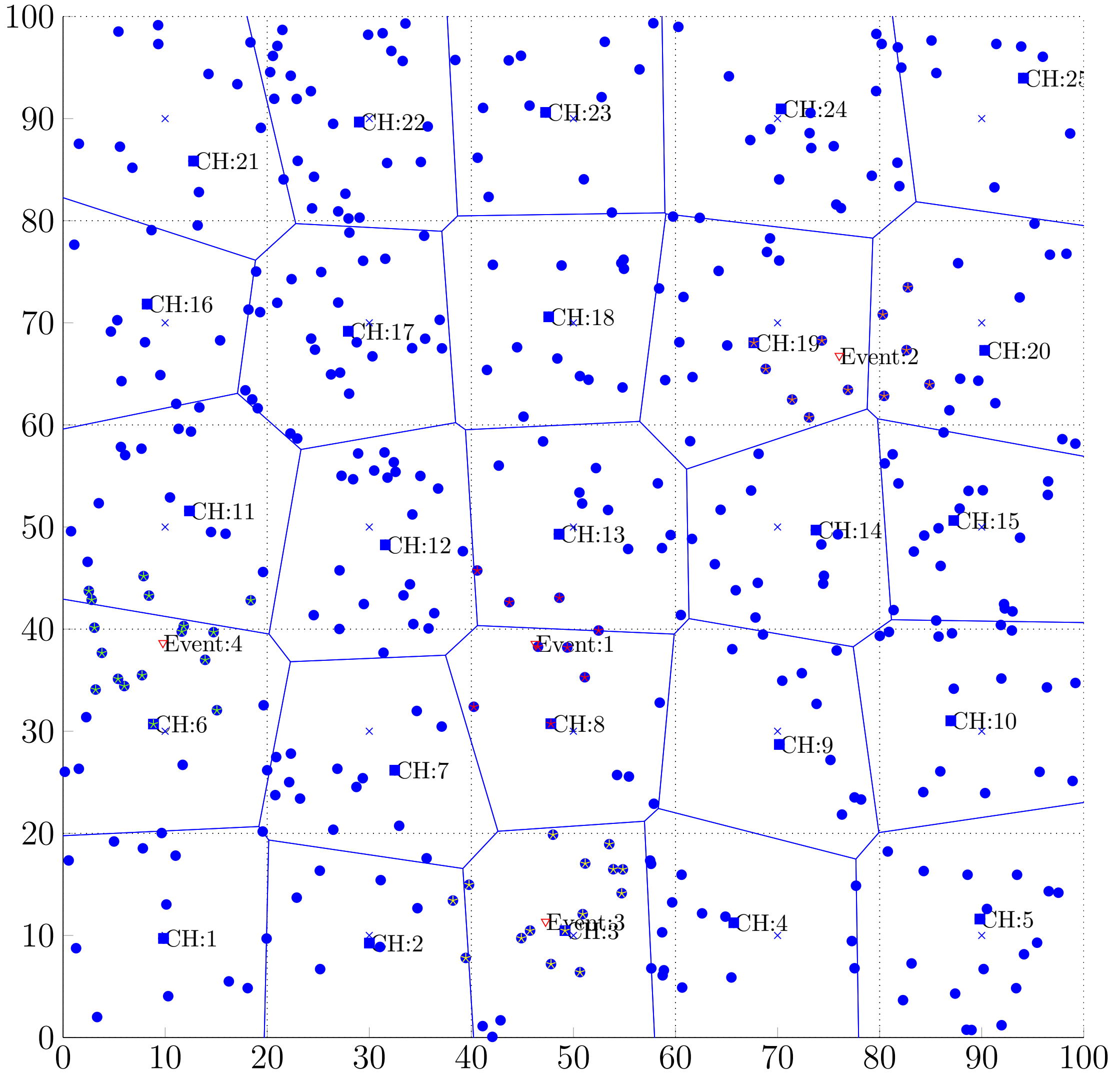

FIGURE 3.3: Event-triggered based Neighbourhood Formation within WSNs.

Depending on the depth of the event, the set of sensor nodes involved to form a neighbourhood for an event detection at time instant t can be the same or it can be different from an event that will be detected at time instant $t+1$, even if both events occur at the same location. With the aim of achieving energy conservation, the sensor nodes are expected to form a neighbourhood by fulfilling the following criteria:

3.2.2.1 Criterion 1

It is defined based on the Euclidean distance of the sensor nodes from the location of an event. Let $\mathcal{N}_e^{\hat{f}}$ be the $\hat{f}^{th}$ neighbourhood, which is defined as:

$$\mathcal{N}_e^{\hat{f}} = \begin{cases} S_{\hat{e}}^{\hat{f}} \in S_{(.)}, & \text{if } \hat{d}_{\hat{e}}^{\hat{f}} \leq \delta_d \\ S_{\hat{e}}^{\hat{f}} \notin S_{(.)}, & \text{otherwise} \end{cases} \tag{3.21}$$

where $\hat{d}_{\hat{e}}^{\hat{f}}$ denotes the distance of the $\hat{e}^{th}$ sensor node from the $\hat{f}^{th}$ event and δ_d is the threshold distance defined by the FCR.

3.2.2.2 Criterion 2

This criterion is based on the sensitivity threshold δ_s defined by the FCR. Each sensor node is expected to be a part of the neighbourhood, if it can sense the event with the predefined sensitivity threshold δ_s. Let $\mathcal{N}_e^{\hat{f}}$ be the $\hat{f}^{th}$ neighbourhood, which is defined as:

$$\mathcal{N}_e^{\hat{f}} = \begin{cases} S_{\hat{e}}^{\hat{f}} \in S_{(.)}, & \text{if } \nu_{\hat{e}}^{\hat{f}} \geq \delta_s \\ S_{\hat{e}}^{\hat{f}} \notin S_{(.)}, & \text{otherwise} \end{cases} \tag{3.22}$$

where $\nu_{\hat{e}}^{\hat{f}}$ denotes the sensitivity range of the $\hat{e}^{th}$ sensor node from the $\hat{f}^{th}$ event.

3.2.2.3 Criterion 3

This criterion is the unification of both the aforementioned criteria. On the occurrence of an event, the sensor nodes are selected to form the k^{th} neighbourhood based on the criterion which is defined as:

$$\mathcal{N}_e^{\hat{f}} = \begin{cases} S_{\hat{e}}^{\hat{f}} \in S_{(.)}, & \text{if } \hat{d}_{\hat{e}}^{\hat{f}} \leq \delta_d \cap \nu_{\hat{e}}^{\hat{f}} \geq \delta_s \\ S_{\hat{e}}^{\hat{f}} \notin S_{(.)}, & \text{otherwise} \end{cases} \tag{3.23}$$

The detailed procedure of neighbourhood formation is explained in Algorithm 3.2.

Algorithm 3.2 Proposed Neighbourhood Formation Scheme

Require:

The number of sensor nodes n, the coordinates (s_x^i, s_y^i) ; $i = 1, 2, \ldots, n$ of each sensor node, Total number of events k, the coordinates $(e_x^{\hat{f}}, e_y^{\hat{f}})$; $\hat{f} = 1, 2, \ldots, k$ of each event, desired neighbourhood selection criteria parameter α and β, Optimum distance threshold δ_d and Optimum sensitivity level threshold δ_s.

Ensure: $\hat{d}_{\hat{e}}^{\hat{f}} \leq \delta_d$ and $\nu_{\hat{e}}^{\hat{f}}$, where $\hat{d}$ is the distance and $\hat{s}$ is the sensitivity level of $\hat{e}^{th}$ sensor node from $\hat{f}^{th}$ event.

$\mathbf{D_n} \leftarrow \varnothing$, $\mathbf{d_n} \leftarrow \varnothing$
$\mathbf{P_n} \leftarrow \varnothing$, $\mathbf{p_n} \leftarrow \varnothing$
$\mathbf{s_n} \leftarrow \varnothing$
if $(\alpha = 1) \cup (\alpha \cap \beta = 1)$ **then**
  for $\hat{f} \leftarrow 1$ **to** k **do**
    for $\hat{e} \leftarrow 1$ **to** n **do**
      $\mathbf{d_n}(\hat{e}) \leftarrow \hat{d}_{\hat{e}}^{\hat{f}}$
    end for
    Sort $\{\mathbf{d_n}\}$ in ascending order and save the indices in $\mathbf{p_n}$
    $\mathbf{D_n}(\hat{f}) \leftarrow \mathbf{d_n}$
    $\mathbf{P_n}(\hat{f}) \leftarrow \mathbf{p_n}$
  end for
  for $\hat{f} \leftarrow 1$ **to** k **do**
    for $\hat{e} \leftarrow 1$ **to** n **do**
      if $\mathbf{D_n}(\hat{e}, \hat{f}) \leq \delta_d$ **then**
        Assign the corresponding sensor nodes to $\mathcal{N}_e^{\hat{f}}$
      end if

Algorithm 3.2 (continued) Proposed Neighbourhood Formation Scheme

        end for
    end for
end if
if $(\beta = 1) \cup (\alpha \cap \beta = 1)$ **then**
    for $\hat{f} \leftarrow 1$ **to** k **do**
        for $\hat{e} \leftarrow 1$ **to** n **do**
            $S_{\hat{e}}^{\hat{f}} \geq \delta_s(\hat{f})$
        end for
        Assign corresponding sensor nodes to $\mathcal{N}_e^{\hat{f}}$
    end for
end if
return $\mathcal{N}_{\mathbf{e}}^{\mathbf{k}}$

To evaluate the performance of the proposed universal and dynamic clustering framework, a network lifetime model is also proposed. Network lifetime is defined as the operational time of the network during which it is able to perform the dedicated task. Network lifetime has become the key characteristic for evaluating the WSNs such as: availability of sensor nodes, coverage, connectivity etc.

3.3 Network Lifetime Model

Network lifetime can be defined as the time span over which the network operates effectively. Several WSN lifetime definitions have been introduced in the literature e.g. the network connectivity is used to define the WSN lifetime. But the most commonly used WSN lifetime definition is based on the percentage of alive nodes or dead nodes in the network, which reflects the quality of the network coverage and connectivity as discussed in [127]. In this section, a network lifetime model is presented based on the energy model described in [85]. It is assumed that each cluster consists of $\hat{p}$ number of sensor nodes. Each sensor node is expected to sense L bits and transmit it to the respective cluster head node. As sensor nodes in a cluster are closely spaced, the sensed data is expected to be correlated. So, cluster heads are expected to aggregate the received data. All the sensor nodes are expected to be equipped with one transceiver. The transmitter and receiver blocks used in this model to estimate the energy consumption are shown in Figure 3.4(a) and Figure 3.4(b) respectively.

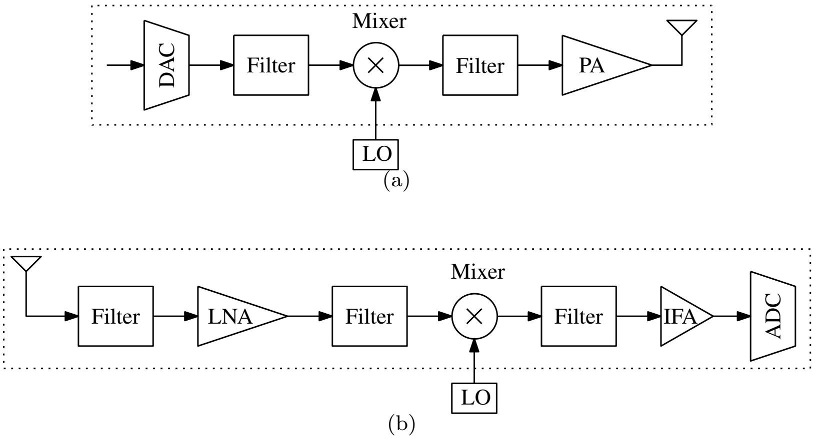

FIGURE 3.4: (a) Transmitter circuit blocks, (b) Receiver circuit blocks.

For a fixed rate system, the total energy per bit presented in [85], is denoted as E_{bit} and defined as:

$$E_{bit} = \frac{P_{PA} + P_c}{R_b} \tag{3.24}$$

where P_{PA} is the power consumption of the power amplifier, P_c is the power consumption at the transceiver circuitry and R_b is the bit rate. P_{PA} is presented in [85] and expressed as:

$$P_{PA} = (1 + \alpha)P_{out} \tag{3.25}$$

where $\alpha = (\xi/\eta) - 1$ with ξ is the peak to average ratio and η is the drain efficiency of the radio frequency power amplifier. P_{out} represents the transmit power, which can be calculated based on the link budget relationship, particularly when the channel experiences only a square law path loss as described in [128] and expressed as:

$$P_{out} = \bar{E}_b R_b \frac{(4\pi d)^2}{G_t G_r \lambda^2} M_l N_f \tag{3.26}$$

where $\bar{E}_b$ represents the required energy per bit at the receiver for a given bit error rate requirement, R_b represents the bit rate, d represents the transmission distance, G_t and G_r represent the transmitter and receiver antenna gains respectively, λ represents the carrier wavelength, N_f represents the receiver noise figure which is defined as $N_f = N_r/N_o$, where N_r is the power spectral density (PSD) of the total effective noise at the receiver input and N_o is the single sided thermal noise PSD at room temperature, and M_l represents the link margin for compensating the hardware processing variations and additive background noise. Let

$$\mathcal{P} = (1+\alpha)\bar{E}_b R_b \frac{(4\pi)^2}{G_t G_r \lambda^2} M_l N_f \tag{3.27}$$

Therefore, Equation 3.25 can be represented as:

$$P_{PA} = \mathcal{P} d^2 \tag{3.28}$$

The power consumption of the transceiver circuitry is further divided into power consumption at the transmitter and the receiver circuitry, which is $P_c = P_{c_{tx}} + P_{c_{rx}}$, where $P_{c_{tx}}$ is defined as:

$$P_{c_{tx}} = P_{DAC} + P_{filt} + P_{mix} \tag{3.29}$$

where P_{DAC}, P_{filt} and P_{mix} represents the power consumption at the digital to analogue converter, filter and mixer respectively. $P_{c_{rx}}$ is defined as:

$$P_{c_{rx}} = P_{LNA} + P_{mix} + P_{filt} + P_{IFA} + P_{ADC} \tag{3.30}$$

where P_{LNA}, P_{IFA} and P_{ADC} represents the power consumption at the low noise amplifier, intermediate frequency amplifier and analogue to digital converter respectively.

3.3.1 Local Communication

The communication between the sensor nodes and their respective cluster heads is referred to as local communication.

3.3.1.1 Energy Consumption of Intra-Cluster Communication

The energy required by the sensor nodes to communicate with their cluster heads is denoted as E_{IntraC} and defined as:

$$E_{IntraC} = \sum_{j=1}^{q} \left(\sum_{\breve{i}=1}^{\hat{p}} LE^{j}_{s(\breve{i})} + LE^{j}_{ch}\hat{p} \right) \tag{3.31}$$

where E^{q}_{ch} represents the energy required by the q^{th} cluster head to receive one bit data from its $\hat{p}^{th}$ sensor node which can be defined as:

$$E^{q}_{ch} = \frac{E_{da}P_{c_{rx}}}{R_b} \tag{3.32}$$

where E_{da} represents the energy required to aggregate one bit. Let $E^{j}_{s(\breve{i})}$ for $\hat{p}^{th}$ sensor node of q^{th} cluster be denoted as $E^{q}_{s(\hat{p})}$ and defined as:

$$E^{q}_{s(\hat{p})} = \frac{1}{R_b} \left(\mathcal{P} \times (d^{q}_{2(\hat{p})})^2 + P_{c_{tx}} \right) \tag{3.33}$$

where $d^{q}_{2(\hat{p})}$ represents the distance of the $\hat{p}^{th}$ sensor node from the q^{th} cluster head. All the sensor nodes within the network are expected to forward their sensing data to their respective cluster heads. Once a cluster head receives data from all of its member sensor nodes within the cluster, it performs data aggregation. As the sensor nodes within a cluster are closely spaced, their sensing data is correlated. Therefore, data aggregation at the ratio of 10:1 is assumed and the sensing data after aggregation is denoted as L_{da}.

3.3.2 Global Communication

Two types of global communication approaches have been considered in this study, which are defined as:

3.3.2.1 Direct Communication between Cluster Heads and FCR

The energy required for direct communication between cluster heads and FCR is denoted as E_D and defined as:

$$E_D = \sum_{j=1}^{q} L_{da} E^{j}_{sh} \tag{3.34}$$

where E_D is the energy required by q cluster heads to forward the sensed data to the FCR in one round and E^{j}_{sh} is the energy consumed by j^{th} cluster head to forward one bit of sensed data to the FCR e.g. the energy required by q^{th} cluster head is defined as:

$$E^{q}_{sh} = \frac{1}{R_b}\left(\mathcal{P}\times(d^{q}_{3})^{2} + P_{c_{tx}}\right) \tag{3.35}$$

where d^{q}_{3} is the transmission distance of q^{th} cluster head from the FCR. The total energy required by the network for one round can be defined as:

$$E_{or.sh} = E_{IntraC} + E_{SH} \tag{3.36}$$

By substituting Equation 3.31 and Equation 3.34, Equation 3.36 can be defined as:

$$E_{or.sh} = \sum_{j=1}^{q} \left(\sum_{\check{i}=1}^{\hat{p}} LE^{j}_{s(\check{i})} + LE^{j}_{ch}\hat{p} \right) + \left(\sum_{j=1}^{q} L_{da} E^{j}_{sh} \right) \tag{3.37}$$

For a simplified solution it is assumed that the transmission distance of the sensor nodes from its cluster heads is d_2 and that the transmission distance from the cluster heads to the FCR is d_3. Therefore, Equation 3.36) can be further simplified by substituting; Equation 3.32, Equation 3.33 and Equation 3.35 combined can be represented as:

$$\begin{aligned} E_{or.sh} = \frac{Lq\hat{p}}{R_b} \left(\mathcal{P} \times (d_2)^2 + P_{c_{tx}} + E_{da} P_{c_{rx}} \right) \\ + \frac{qL_{da}}{R_b} \left(\mathcal{P} \times (d_3)^2 + P_{c_{tx}} \right) \end{aligned} \tag{3.38}$$

$$\begin{aligned} E_{or.sh} = \frac{q}{R_b} \Bigg[(1+\alpha)\bar{E}_b R_b \frac{(4\pi)^2 M_l N_f}{G_t G_r \lambda^2} \left(\hat{p} L d_2^2 + L_{da} d_3^2 \right) \\ + (L\hat{p} + L_{da}) P_{c_{tx}} + E_{da} L \hat{p} P_{c_{rx}} \Bigg] \end{aligned} \tag{3.39}$$

3.3.2.2 Multi-Hop Communication between Cluster Heads and FCR

A) Selection of Cooperative Cluster Heads: As mentioned in the previous section $\mathbf{d}_3$ represents the transmission distance of all the cluster heads from FCR which is defined as $\mathbf{d}_3 = \{d_3^1, d_3^2, \ldots, d_3^{\hat{p}}\}$ and $\xi^{\hat{n}_t}$ represents the distance of $\hat{n}_t^{th}$ cooperative cluster heads which, is defined as:

$$\xi^{\hat{n}_t} = min(abs(\mathbf{d}_3 \backslash \omega)) \tag{3.40}$$

where initially $\omega = \emptyset$ and $d_3^{\hat{n}_t} \backslash \omega$ is defined as:

$$d_3^{\hat{n}_t} \backslash \omega = \{ d_3^{\hat{n}_t} \in \mathbf{d_3} | d_3^{\hat{n}_t} \notin \omega \} \tag{3.41}$$

The sensor nodes presented by ξ^k are classified as cooperative cluster head if their energy is greater than the threshold δ_{coop}, where $k = \{1, 2, \ldots, \hat{n}_t\}$. Once $\hat{n}_t$ number of cooperative cluster heads are selected, the sensor nodes status matrix $\mathbf{Q}_s$ is updated. This process is summarised in Algorithm 3.3.

Algorithm 3.3 Cooperative Sensor Nodes Selection Scheme

Require:

q number of cluster heads Q_{ch}, their transmission distances from the sink node which is denoted with $\mathbf{d}_3$, the cooperative sensor node selection threshold energy value δ_{coop} and the sensor nodes status matrix $\mathbf{Q}_s$

Ensure:

$S_{(.)}^{coop} \leftarrow \min\{\mathbf{d}_3\}$ and $E_j^{ch} \geq \delta_{coop}$

$\hat{\mathbf{d}}_3 \leftarrow \varnothing, \hat{\mathbf{Q}}_{ch} \leftarrow \varnothing$

$\mathbf{Q}_{c.coop} \leftarrow \varnothing, \hat{\mathbf{Q}}_{c.coop} \leftarrow \varnothing$

$\hat{\mathbf{d}}_3 \leftarrow sort\{\mathbf{d}_3\}$

$\hat{\mathbf{Q}}_{ch} \leftarrow sort\{Q_{ch}\}$ corresponding to $\hat{\mathbf{d}}_3$

for $j \leftarrow 1$ **to** q **do**

  $S_{c.coop} \leftarrow S_j^{ch}$

  if $S_{coop}^{E} \geq \delta_{coop}$ **then**

    $\mathbf{Q}_{c.coop}(j) \leftarrow S_{c.coop}$

  end if

end for

$\hat{\mathbf{Q}}_{c.coop} = \mathbf{Q}_{c.coop}(\mathbf{Q}_{c.coop} \neq 0)$

for $k \leftarrow 1$ **to** $\hat{n}_t$ **do**

  $\mathbf{Q}_{coop}(k) \leftarrow \mathbf{Q}_{c.coop}(k)$

end for

return

B) Energy Consumption of Inter-Cluster Communication: The energy required by the cluster heads to communicate with each other is denoted as

E_{InterC}. Let $\hat{n}_t$ be the number of cluster head nodes to be selected to cooperate and communicate with the FCR, then the remaining $q-\hat{n}_t$ number of sensor nodes are denoted as $\hat{q} = q - \hat{n}_t$.

$$E_{InterC} = \sum_{\hat{j}=1}^{\hat{q}} L_{da} E_{n.coop}^{j} + q_1 L_{da} E_{coop} \tag{3.42}$$

where E_{coop} represents the energy required by the cooperative cluster head node to receive the one bit data from the non-cooperative cluster head nodes which is defined as $E_{coop} = P_{c_{rx}}/R_b$. Consider $E_{n.cop}^{\hat{q}}$ represents the energy required by the $\hat{q}^{th}$ non-cooperative cluster head node to transmit the one bit of data to the cooperative cluster heads, which is defined as:

$$E_{n.coop}^{\hat{q}} = \frac{1}{R_b} \left(\mathcal{P} \times d_4^{q_1})^2 + P_{c_{tx}} \right) \tag{3.43}$$

C) Energy Consumption of Long-haul Communication: The $\hat{n}_t$ number of selected cooperative cluster head nodes are expected to collaborate and act as the virtual MIMO antennae to transmit the sensed data to the FCR. The energy consumed in this process can be categorised into E_{Lh-SM} if cooperation among the transmitting nodes is exploited to achieve spatial multiplexing and E_{Lh-DIV} if transmission diversity is required, which are described as:

i) Case I

$$E_{Lh-SM} = \sum_{k=1}^{\hat{n}_t - 1} \frac{q L_{da}}{\hat{n}_t} E_{col.}^{k} + \sum_{k=1}^{\hat{n}_t} \frac{q L_{da}}{\hat{n}_t} E_{lh}^{k} \tag{3.44}$$

ii) Case II

$$E_{Lh-DIV} = \sum_{k=1}^{\hat{n}_t - 1} q L_{da} E_{col.}^{k} + \sum_{k=1}^{\hat{n}_t} q L_{da} E_{lh}^{k} \tag{3.45}$$

where

$$E_{col.}^{\hat{n}_t} = \frac{1}{R_b}\left(\mathcal{P}\times(d_5^{\hat{n}_t})^2 + P_{c_{tx}} + P_{c_{rx}}\right) \tag{3.46}$$

where $d_5^{\hat{n}_t}$ is the distance of the $\hat{n}_t^{th}$ cooperative cluster head from the other cooperative cluster heads

$$E_{lh}^{\hat{n}_t} = \frac{1}{R_b}\left(\mathcal{P}\times(d_6^{\hat{n}_t})^2 + P_{c_{tx}} + P_{syn}\right) \tag{3.47}$$

where d_6 is the distance of the cooperative cluster head from the FCR and P_{syn} represents the power required to synchronise the transmitting data from multiple nodes. Let $E_{o.r}$ represent the total energy required to transmit L_{da} bits. It is assumed that one round is the transmission of data from all the sensor nodes to the FCR. $E_{o.r}$ is defined as:

$$E_{o.r} = E_{IntraC} + E_{InterC} + E_{Lh} \tag{3.48}$$

Therefore, Equation 3.48 can be simplified for E_{Lh-SM} into Equation 3.49, which is defined as:

$$\begin{aligned} E_{o.r} \;=\; & \sum_{j=1}^{q}\left(\sum_{i=1}^{\hat{p}} LE_{s(\check{i})}^{j} + LE_{ch}^{j}\hat{p}_j\right) + \left(\sum_{j=1}^{\hat{q}} L_{da}E_{n.coop}^{j} + \hat{q}L_{da}E_{coop}\right) \\ & + \left(\sum_{k=1}^{\hat{n}_t-1}\frac{qL_{da}}{\hat{n}_t}E_{col.}^{k} + \sum_{k=1}^{\hat{n}_t}\frac{qL_{da}}{\hat{n}_t}E_{lh}^{k}\right) \end{aligned} \tag{3.49}$$

As $\hat{q} \gg n_t$, so let us assume $q \approx \hat{q}$, so it can further be simplified into Equation 3.50 and Equation 3.51, which are derived as:

$$= \frac{Lq\hat{p}}{R_b}\left(\mathcal{P}\times(d_2)^2 + P_{c_{tx}} + E_{da}P_{c_{rx}}\right) + \frac{\hat{q}L_{da}}{R_b}\left(\mathcal{P}\times(d_4)^2 + P_{c_{tx}} + P_{c_{rx}}\right)$$
$$+\frac{qL_{da}}{R_b}\left(\mathcal{P}\times(d_5)^2 + P_{c_{tx}} + P_{c_{rx}}\right) + \frac{qL_{da}}{R_b}\left(\mathcal{P}\times(d_6)^2 + P_{c_{tx}} + P_{syn}\right) \tag{3.50}$$

$$= \frac{\mathcal{Q}}{R_b}\Bigg[\left((1+\alpha)\bar{E}_b R_b \frac{(4\pi)^2}{G_t G_r \lambda^2} M_l N_f \left(\mathcal{N}L\mathcal{D}^2 + L_{da}(d_4^2 + d_5^2 + d_6^2)\right)\right)$$
$$+(\mathcal{N}L + 3L_{da})P_{c_{tx}} + (\mathcal{N}LE_{da} + 2L_{da})P_{c_{rx}} + L_{da}P_{syn}\Bigg] \tag{3.51}$$

where Equation 3.51 provides a generalised equation for the energy consumption of time-driven, event-driven or hybrid sensing scenario. Based on the type of sensing, the parameters in Equation 3.51 are obtained as follows:

$$\begin{cases} \mathcal{Q} = q, \mathcal{N} = \hat{p}, \mathcal{D} = d_2 & \text{Time-driven} \\ \mathcal{Q} = k, \mathcal{N} = n_b^k, \mathcal{D} = d_7 & \text{Event-driven} \end{cases}$$

3.3.3 Energy Consumption for Event Reporting

The energy required by the sensor nodes to transmit event data to the cluster head is denoted as $E_{IntraNH}$ and defined as:

$$E_{IntraNH} = \sum_{\hat{m}=1}^{k}\left(\sum_{\hat{l}=1}^{\hat{n}_b^{\hat{m}}} LEs_{\hat{l}}^{\hat{m}} + LE_{ch}^{\hat{m}}\hat{n}_b\right) \tag{3.52}$$

where $Es_{\hat{l}}^{\hat{m}}$ for $\hat{n}_b^{th}$ sensor node of k^{th} neighbourhood is denoted as $Es_{\hat{n}_b}^k$ and defined as:

$$Es_{\hat{n}_b}^k = \frac{1}{R_b}\left(\mathcal{P}\times(d_{7(\hat{n}_b)}^k)^2 + P_{c_{tx}}\right) \tag{3.53}$$

where $d_{7(\hat{n}_b)}^k$ represents the distance of $\hat{n}_b^{th}$ sensor node from k^{th} neighbourhood head. E_{ch}^k represents the energy required by the k^{th} cluster head to receive the event data from n_b sensor nodes, which is defined as:

$$E_{ch}^k = \frac{E_{da}P_{c_{rx}}}{R_b} \tag{3.54}$$

The cluster head receives the sensed data from all the sensor nodes within the neighbourhood, it then performs the data processing locally, detects the event and transmits the decision to the FCR through the cooperative nodes. This approach will accelerate the decision making process by making the cluster heads self-reliant and also minimises the number of transmissions to the FCR which all results in energy conservation.

3.4 Performance Analysis

This section demonstrates the performance analysis of the proposed dynamic and cooperative clustering and neighbourhood formation schemes for WSNs. The proposed framework is expected to facilitate the applications that consider either time-driven sensing, event-driven sensing or both denoted as hybrid sensing. To demonstrate the effectiveness of the proposed schemes, a WSN model is simulated. Moreover, all the proposed schemes are analysed in terms of their network lifetime i.e. the number of alive nodes and residual energy.

A WSN model is simulated with a sensing area of $100\times100\ m^2$ with $n = 100$ sensor nodes with an initial energy $E_o = 1$ J, which are randomly distributed within the network. Furthermore, the simulation environment is composed of a FCR that is located at a distance of 50 m from the nearest boundary of the sensing region. After deployment, the network is expected to perform dynamic clustering that will divide the sensor nodes into clusters. Once settled, all the sensor nodes within the network are expected to sense the environment and transmit the sensed data to their respective cluster heads. These are then responsible to perform the data correlation and relay it to the FCR through the cooperative nodes. The process from re-clustering to data transmission to the FCR is defined as one round. At each round, the cluster heads are expected to evaluate themselves and withdraw from the cluster head role if they do not fulfil cluster head role criteria, and trigger the re-clustering process. To generate events, a data set is obtained by using the heat equation presented in [129]. Table 3.1 presents the parameter values considered in the simulations as described in [130].

3.4.1 Performance Analysis of Proposed Dynamic Clustering Scheme with Soft Threshold and Hard Threshold

The performance of the proposed dynamic clustering scheme with the cluster head selection criterion based on either soft or hard threshold is presented in Figure 3.5. It is observed that the soft threshold based cluster head election criterion enhances the lifetime of the network by increasing the degree of load balancing among the sensor nodes and reducing the uneven energy consumption within the network. The results demonstrate that the soft threshold based dynamic cluster head election enhances the network life represented as number of alive nodes by 21%, 16% and 12% for rounds 33%, 50% and 67% respectively, where number of alive nodes and rounds are denoted as $\mathcal{N}_A$ and R respectively.

Table 3.1: Simulation parameters and their values.

Parameter	Value
Central Frequency (f_c)	2.5 GHz
Transmitter Gain (G_t)	5 dBi
Receiver Gain (G_r)	5 dBi
Bandwidth (B)	10 kHz
Power Consumption Value (PCV) at Mixer (P_{mix})	30.3 mW
PCV at Tx Filter (P_{filt})	2.5 mW
PCV at Rx Filter (P_{filr})	2.5 mW
Targeted Probability of Error ($\bar{P}_b$)	10^{-3}
Receiver Noise Figure (N_f)	10 dB
PCV at Intermediate Frequency Amplifier (P_{IFA})	3 mW
PCV at Frequency Synthesiser (P_{syn})	50 mW
PCV Low Noise Amplifier (P_{LNA})	20 mW
PCV at A/D Convertor (P_{ADC})	6.566 mW
PCV at D/A Convertor (P_{DAC})	15.435 mW
Link Margin (M_L)	40dB
Drain Efficiency (η)	0.35
σ^2	-174 dBm/Hz
β	1

3.4.2 Performance Comparison of Proposed Dynamic Clustering Scheme with Existing Clustering Schemes

This section demonstrates the performance evaluation of the proposed dynamic clustering scheme with the existing clustering schemes in the literature. In order to perform a fair comparison, the simulation platforms have been simulated in this section and denoted as Model 1 and Model 2, for performance comparison with homogeneous and heterogeneous WSNs respectively, which are described as:

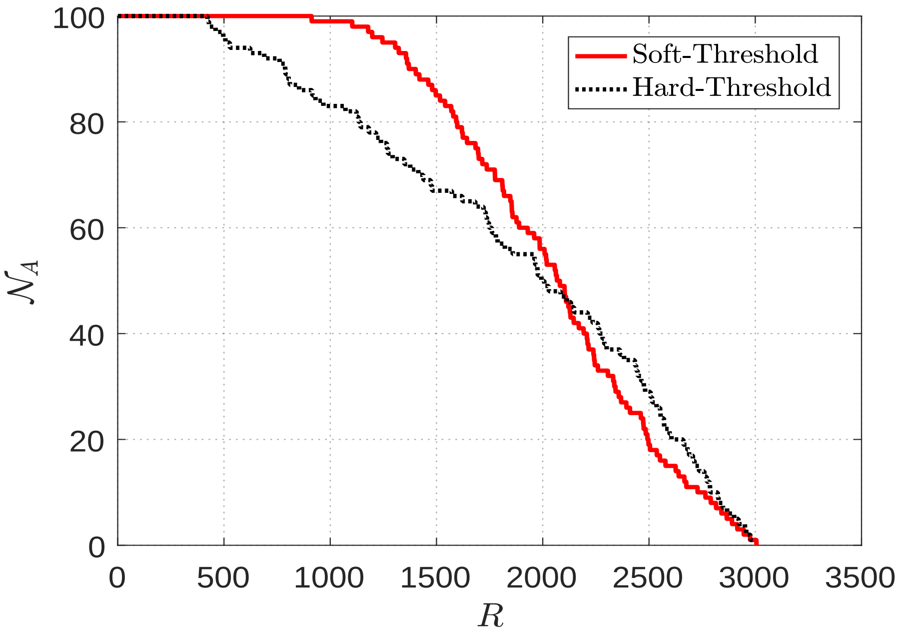

FIGURE 3.5: Performance analysis of the proposed dynamic clustering scheme with Soft threshold and Hard threshold for number of alive nodes $\mathcal{N}_A$ and rounds R.

3.4.2.1 Model 1

Model 1 provides a platform to compare the performance of the proposed dynamic clustering scheme with LEACH as proposed by Heinzelman *et al.* in [45]. It is assumed that all the sensor nodes are homogeneous and that the cluster heads are responsible for relaying the data to FCR. It is observed from Figure 3.6 that the first node died (FND) for the proposed dynamic clustering scheme at 1370 rounds while the FND for LEACH at 903 rounds. Also, half nodes died (HND) for the proposed scheme and for LEACH at 2334 and 1198 rounds respectively. Moreover, the last node died (LND) at 3415 and 1862 rounds for the proposed scheme and existing scheme (LEACH) respectively. Hence, the proposed scheme enhances the lifetime of the sensor nodes by 51%, 94% and 83% rounds for the number of alive nodes at 100%, 50% and 1% respectively.

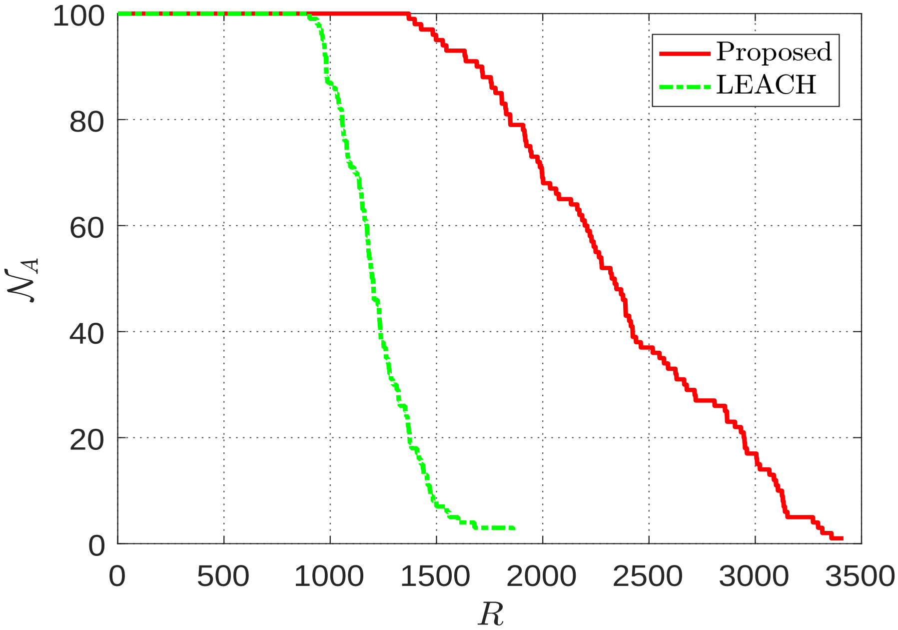

FIGURE 3.6: Performance analysis comparison of the proposed scheme with LEACH considering homogeneous network for number of alive nodes $\mathcal{N}_A$ and rounds R.

3.4.2.2 Model 2

To evaluate the performance of the proposed dynamic clustering scheme for heterogeneous WSNs, Model 2(a) and 2(b) are simulated for two level and three level heterogeneous sensor nodes respectively. The performance of the proposed dynamic clustering scheme is compared against the existing clustering scheme for heterogeneous WSNs i.e. DEEC [51], DDEEC [51] with two level heterogeneity and EDEEC [52] and EDDEC [53] with three level heterogeneity as presented in Figure 3.7 and Figure 3.8 respectively. In Model 2(a) the WSN is comprised of sensor nodes which are categorised as normal sensor nodes and advanced sensor nodes based on their initial energy, where the number of normal sensor nodes and advanced sensor nodes are $n \times (1 - m)$ and $n \times m$. While in Model 2(b), the sensor nodes are categorised as normal sensor nodes, advanced sensor nodes and super sensor nodes. Where the number of normal sensor nodes, advanced sensor

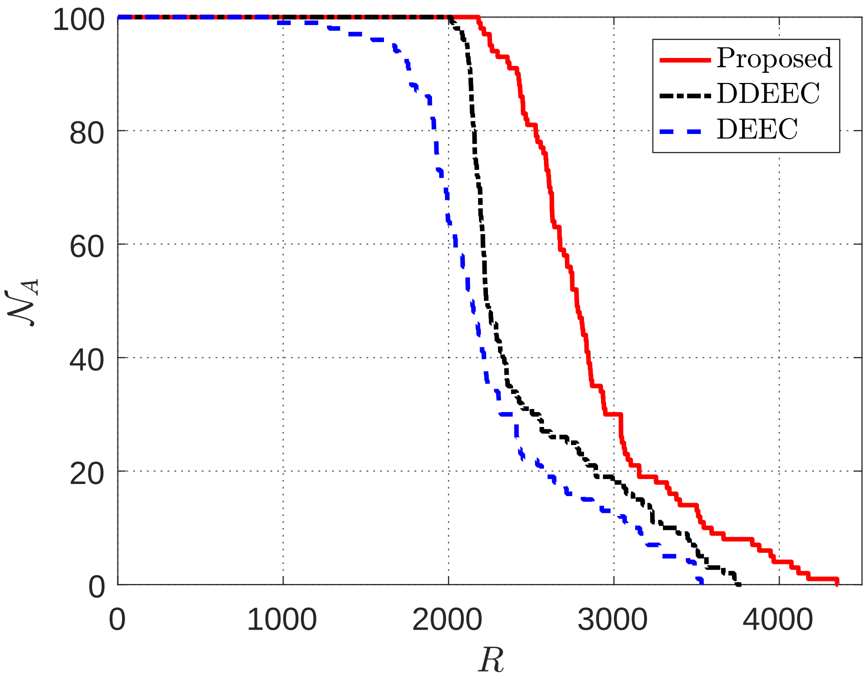

FIGURE 3.7: Performance analysis comparison of the proposed scheme with DEEC and DDEEC considering two level of heterogeneous network for the number of alive nodes $\mathcal{N}_A$ and rounds R.

nodes and super sensor nodes are calculated as $n \times (1 - m)$, $n \times m \times (1 - m_o)$ and $n \times m \times m_o$ respectively; where m and m_o are assumed as 0.3. The advanced sensor nodes and super sensor nodes energy can be calculated as $(1 + a)E_o$ and $(1 + b)E_o$ respectively, where a and b are assumed as 2 and 3.5.

It is observed from Figure 3.7 that the FND, HND and LND for the proposed scheme are at 2151, 2777 and 4351 rounds respectively. While the FND for DEEC and DDEEC are at 936 and 2013 respectively, the HND at 2145 and 2232 rounds respectively, and the LND at 3531 and 3770 rounds respectively. Hence, the proposed scheme extends the network lifetime by 23.2% and 15.4% rounds as compared against DEEC and DDEEC respectively. Also, Figure 3.8 validates that the FND,HND and LND for the proposed scheme are at 2158, 3391 and 4635 respectively. While the FND for EDEEC and EDDEEC are at 1813 and 1761 respectively, the HND at 2401 and 2492 rounds respectively, and the LND at 4157 and 4520 rounds respectively. Therefore, the proposed scheme enhances

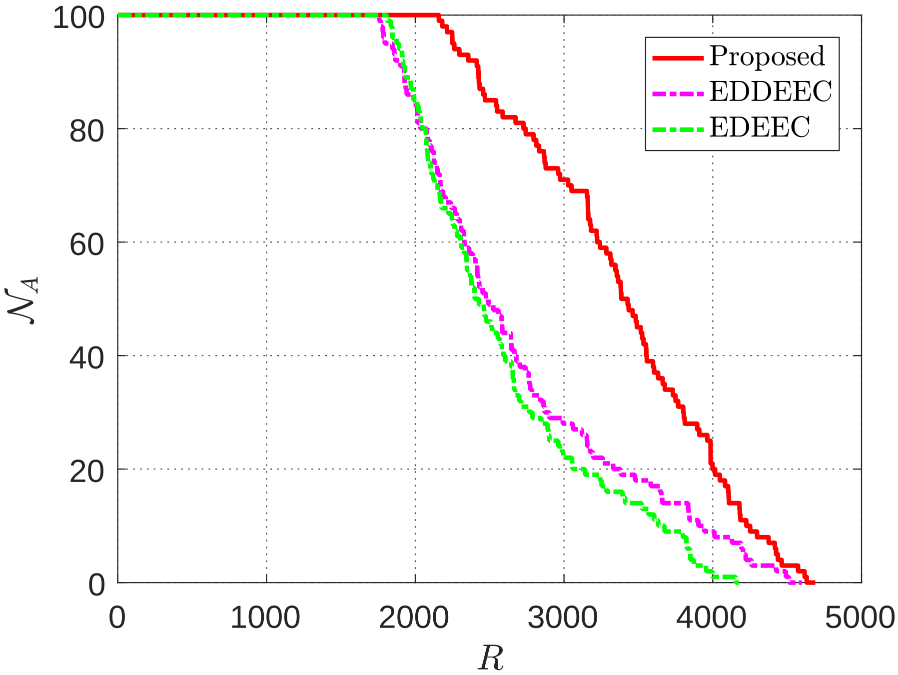

FIGURE 3.8: Performance analysis comparison of the proposed scheme with EDEEC and EDDEEC considering three levels of the heterogeneous network for the number of alive nodes $\mathcal{N}_A$ and rounds R.

the network lifetime by 11.5% and 2.6% as compared to EDEEC and EDDEEC respectively.

A detailed comparison analysis of the proposed dynamic clustering scheme with the aforementioned existing schemes is presented in Table 3.2. It is validated from the Table 3.2 that the proposed dynamic clustering scheme outperforms the existing schemes for both homogeneous and heterogeneous WSNs.

Table 3.2: Comparison of the proposed dynamic clustering scheme with existing schemes for homogeneous and heterogeneous WSNs.

Scenerio	Reference	Sensors Type	Protocols	Activity Factor		
				100%	50%	0
Model 1	Figure 3.6	Homogeneous	LEACH [45]	902	1197	1861
			Proposed	**1369**	**2333**	**3414**
Model 2(a)	Figure 3.7	Heterogeneous (Level 2)	DEEC [49]	935	2144	3530
			DDEEC [51]	2012	2231	3769
			Proposed	**2150**	**2776**	**4350**
Model 2(b)	Figure 3.8	Heterogeneous (Level 3)	EDEEC [52]	1812	2400	4156
			EDDEEC [53]	1760	2491	4519
			Proposed	**2157**	**3390**	**4634**

3.4.3 Performance Analysis of Proposed Universal Framework

The performance analysis of the proposed dynamic clustering and neighbourhood formation framework is presented in this section. To evaluate the performance of the proposed framework with universal behaviour, three possible sensing scenarios are considered i.e. time-driven sensing, event-driven sensing and hybrid sensing. For simulations, it is assumed that the location of the events is randomly distributed and that their occurrences is at least 10 m away from each other. Figure 3.9 represents the network lifetime analysis of the proposed framework for time-driven sensing, event-driven sensing and hybrid sensing scenarios. Moreover, the performance analysis of the proposed schemes in terms of their average residual energy per node is presented in Figure 3.10. It is observed that the FND for time-driven sensing, event-driven sensing and hybrid sensing are at 913, 951 and 923 number of rounds, HND at 2074, 2906 and 2390 number of rounds and LND at 2980, 4741 and 3739 number of rounds respectively. Moreover, the network has 50% of residual energy for time-driven sensing, event-driven sensing and hybrid sensing at 1002, 1600 and 1252 number of rounds and 20% of residual energy at 1687, 2817 and 2095 number of rounds respectively. A comprehensive analysis of the proposed framework for network lifetime and residual energy is presented in Table 3.3.

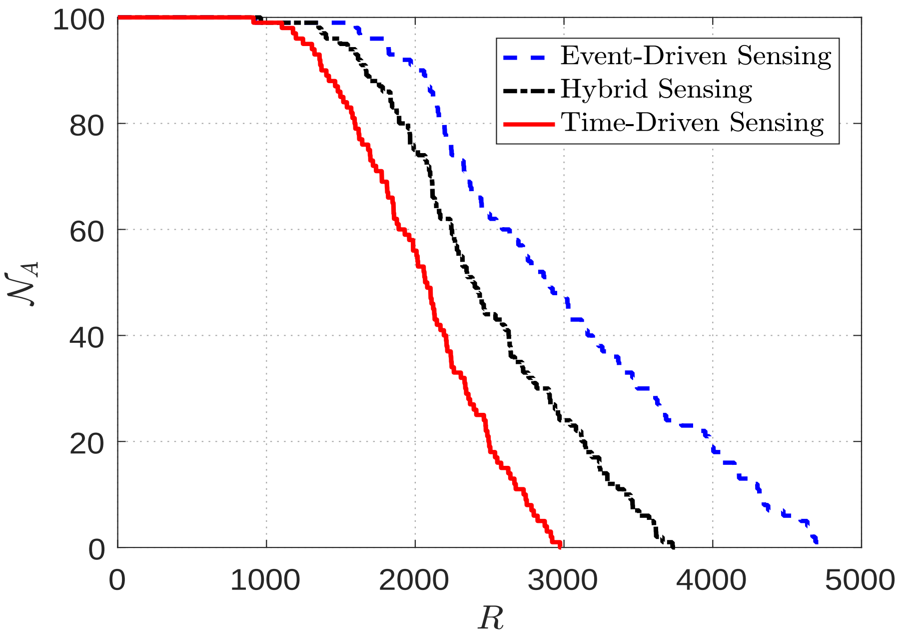

FIGURE 3.9: Performance analysis of the proposed UDC framework for time-driven, event-driven and hybrid applications for the number of alive nodes $\mathcal{N}_A$ and rounds R.

TABLE 3.3: Performance analysis of the proposed universal framework for time-driven, event-driven and hybrid scenarios within WSNs.

Sensing Type	**Activity Factor**			**Residual Energy**	
	100%	**50%**	**0**	**50%**	**20%**
TD	912	2073	2979	1002	1687
ED	950	2905	4740	1600	2817
Hybrid	922	2389	3738	1254	2095

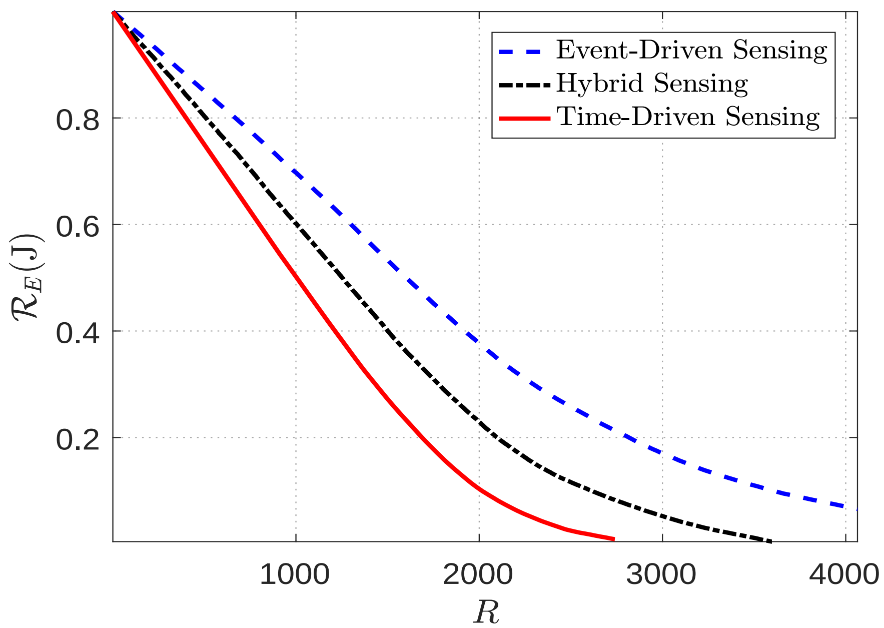

FIGURE 3.10: Performance analysis of the proposed UDC framework for time-driven, event-driven and hybrid applications for the average residual energy $\mathcal{R}_E$ and rounds R.

3.5 Summary

In this chapter, the issues of optimising the energy consumption within the network by involving a minimum number of sensor nodes and optimising the network communication required to report events are addressed. The dynamic clustering scheme ensures a balanced energy consumption within the network by rotating the cluster head role among all the sensor nodes. Moreover, the virtual grids are defined at the initial deployment phase to support the dynamic clustering scheme. This approach dynamically selects cluster heads such that the clusters are approximately uniform in size to avoid any unbalanced energy consumption and energy holes throughout the network. Soft and hard threshold based cluster heads' selection criteria are also presented that provides a trade-off between the balanced energy consumption throughout the network and the frequency of the re-clustering. The neighbourhood formation scheme provides an energy efficient grouping of sensor nodes in response to events. This approach provides a reliable and energy efficient solution to monitor, detect and collect various significant occurrences of events throughout the network.

A collaborative sensing framework is proposed that incorporates dynamic clustering and neighbourhood formation schemes. This framework is independent of the nature of the sensing application, providing with universal behaviour to enhance its feasibility for a diverse range of applications. Moreover, the UDC framework is distributive in nature as all the decisions such as cluster heads' selection, cluster's formation and neighbourhood formation are all made locally. This decision making ability minimises the amount of information to be transmitted to represent an event which facilitates the UDC framework to be energy efficient.

A WSN's lifetime model is also derived to observe the performance of the UDC framework. The cooperation among sensor nodes is considered during data transmission towards the FCR. The performance of the proposed UDC framework is evaluated for homogeneous and heterogeneous networks as well as for time-driven, event-driven and hybrid sensing. Moreover, the performance of the proposed UDC framework is analysed against several notable existing models in the literature. It is observed from the simulation results that the proposed UDC framework outperforms the existing schemes in terms of energy conservation.

The next chapter builds on the resource allocation framework for cooperative communication within WSNs which is expected to optimise resource usage while maintaining the required QoS.

Chapter 4

CQI-centric Resource Allocation Framework for Cooperative Communication within WSNs

4.1 Introduction

To conserve the energy of the sensor nodes within WSNs, it is expected to optimise the allocation of resources such as: the selection of the minimum number of sensor nodes involved with active transmission as well as the minimum the data required to represent the incident to the FCR, while maintaining the required QoS. It is proposed to obtain such optimisation in a cooperative manner, among a selected group of sensor nodes, in response to the presence of any reportable data, within the group originated due to an incident. The involvement of sensor nodes within such a group varies from one set of incidents to the other. To serve the same purpose at a higher layer, it is also expected to obtain an optimum amount of power from each representative sensor node from each group, collectively adapted with the channel conditions in the perspective of the FCR. Moreover, for the ease of the system design engineer to achieve a predefined QoS requirement, analytical frameworks are extremely useful that provide a performance benchmark.

In this chapter, such kind of optimisation is proposed to achieve with collaborative and dynamic selection of transmit power coefficients. This is done with respect to the depth of channel fading, or the degree of sparsity that is to be attained from the candidate sensor nodes - selected to participate in the transmission of the reportable data to the FCR. An adaptive transmit receive antennae selection scheme is proposed that is expected to mitigate the effect of dynamic radio frequency propagation conditions. Moreover, a lattice reduction based signal design scheme is proposed that is expected to minimise the effect of noise on data transmissions. Thereafter, a hybrid scheme is presented that incorporates both aforementioned schemes that is expected to provide a robust solution against deep channel fading and noise in variable channel propagation conditions. An adaptive transmission scheme is also proposed that provides an adequate decision on the selection of the appropriate aforementioned proposed schemes. An analytical framework is also presented in this chapter to facilitates the system design engineer to select the required optimisation scheme for a given QoS, in terms of bit error rate or symbol error rate. The proposed framework is expected to provide a robust solution against variable channel conditions while providing the required QoS.

4.2 CQI-centric Resource Allocation Framework

The transmitted data vector from n_t number of transmitting sensor nodes is denoted as $\mathbf{x}$ and expressed as:

$$\mathbf{x} = [x_1, x_2, \ldots, x_{n_t}]^T \tag{4.1}$$

The received signal vector at the FCR can be expressed as:

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n} \tag{4.2}$$

where $\mathbf{y}$ is the received signal vector with dimensions $(n_r \times 1)$, $\mathbf{H}$ is the Rayleigh fading channel matrix of size $(n_r \times n_t)$ and $\mathbf{n}$ is the noise vector with dimensions $(n_r \times 1)$. The noise is considered to be additive white Gaussian noise with zero mean and unity variance σ^2. The Rayleigh fading channel matrix is defined as:

$$\mathbf{H} = \begin{bmatrix} h_{(1,1)} & h_{(1,2)} & \dots & h_{(1,n_t)} \\ h_{(2,1)} & h_{(2,2)} & \dots & h_{(2,n_t)} \\ \vdots & \vdots & \ddots & \vdots \\ h_{(n_r,1)} & h_{(n_r,2)} & \dots & h_{(n_r,n_t)} \end{bmatrix}$$

where $h_{\hat{j},\hat{i}}$ denotes the channel coefficients from $\hat{i}^{th}$ transmitter sensor node to $\hat{j}^{th}$ receiving antenna at the FCR with $\hat{i} \in \{1, 2, \dots, n_t\}$ and $\hat{j} \in \{1, 2, \dots, n_r\}$ respectively. It is also assumed that there is a feedback link between the sensor nodes and the FCR, which is expected to enable the sensor nodes to exploit the channel conditions and adapt accordingly. Employment of the feedback channel requires cooperation between the sensor nodes and the FCR. Where, the FCR is expected to estimate the channel and feedback the CSI to the sensor nodes that can use this information to adapt the transmitted signal according to the channel conditions.

Energy conservation is expected to be achieved by optimising the allocation of resources within the network while maintaining the targeted QoS. Two approaches are under consideration to optimise the WSN i.e. Intra-neighbourhood optimisation and Inter-neighbourhood optimisation. Intra-neighbourhood optimisation is expected to take place by defining the cooperative characteristics of WSNs. The cooperation criterion is expected to be defined by observing the channel quality based on the fading or interference depth, while transmitting to the FCR. If transmit diversity or spatial multiplexing is intended to be achieved, multiple sensor nodes from each neighbourhood are expected to participate in the transmission. To attain the collaborative nature of the network, inter-neighbourhood optimisation is to be considered. The collaboration criterion is to be defined by mutual agreement between the candidate transmitting sensor nodes and the FCR. In this study, processing intelligence based signal design is expected to be considered. For both of these methods, channel state information is required at the transmitting sensor nodes. It is assumed that the channel state information is known to the candidate transmitting sensor nodes through a feedback link from the FCR. A block diagram summarising the methodological steps of the proposed CQI-centric resource allocation framework for cooperative communication within WSNs is presented in Figure 4.1.

4.2.1 Adaptive Transmitter-Receiver Antennae Selection Scheme

Energy conservation and data transmission reliability is expected to be achieved by defining adaptive cooperation between the sensor nodes and the FCR. The cooperation criterion is defined based on the channel quality. The sensor nodes which suffer from deep fading and interference will not participate in the transmission. Transmit diversity or spatial multiplexing can be achieved if more than one sensor nodes will participate in the transmission. Subsequently, this will help to maintain a communication link with certain required QoS. A CQI-centric transmitter-receiver antennae selection scheme is presented which is expected to maintain the required QoS by turning off the transmitter-receiver antennae pairs that are suffering from deep channel fading based on the information from the FCR through a feedback link.

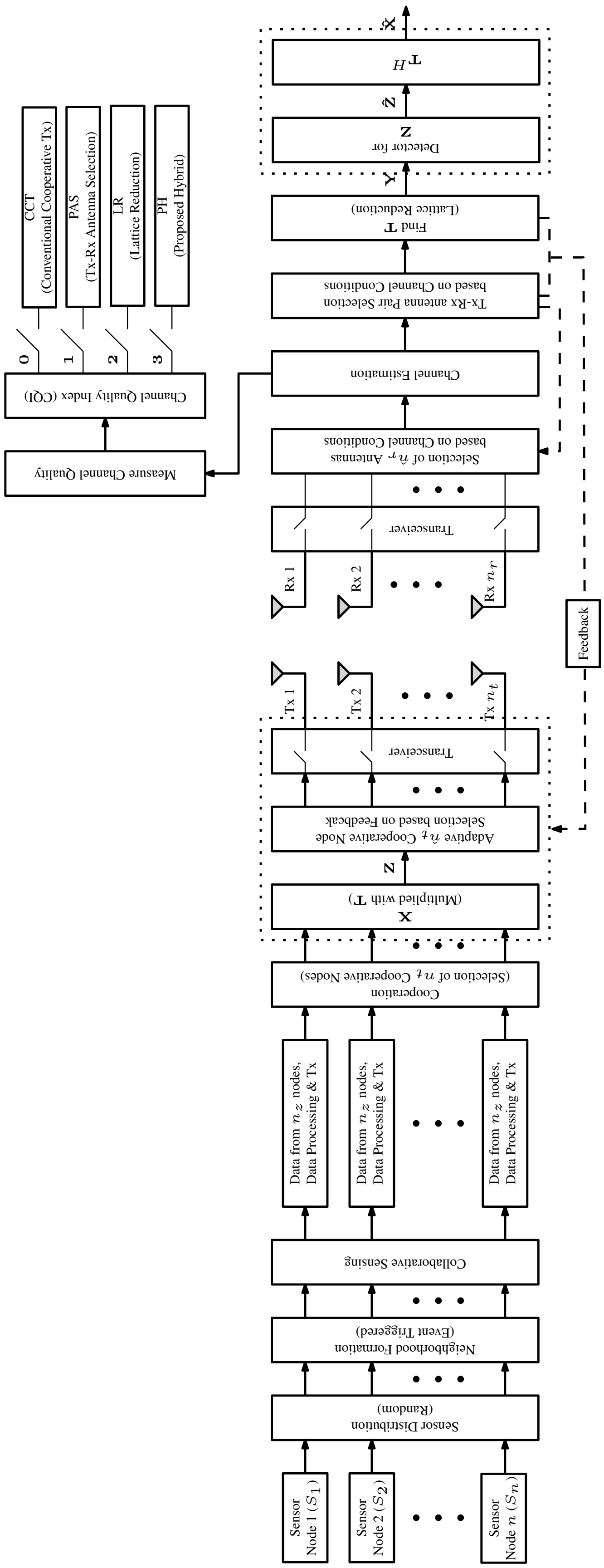

FIGURE 4.1: Block diagram summarising the methodological steps of the proposed CQI-centric resource allocation framework for cooperative communication within WSNs.

Consider **H**, the channel matrix of dimensions $(n_r \times n_t)$ with n_t number of cooperative sensor nodes and n_r number of antennae at the FCR. Suppose, some of the channel links are causing a decrease in the QoS, as they are suffering deep channel fading. To maintain the QoS, it is desirable that such transmitting and receiving antennae pairs should not participate in the data transmission as shown in the block diagram presented in Figure 4.2.

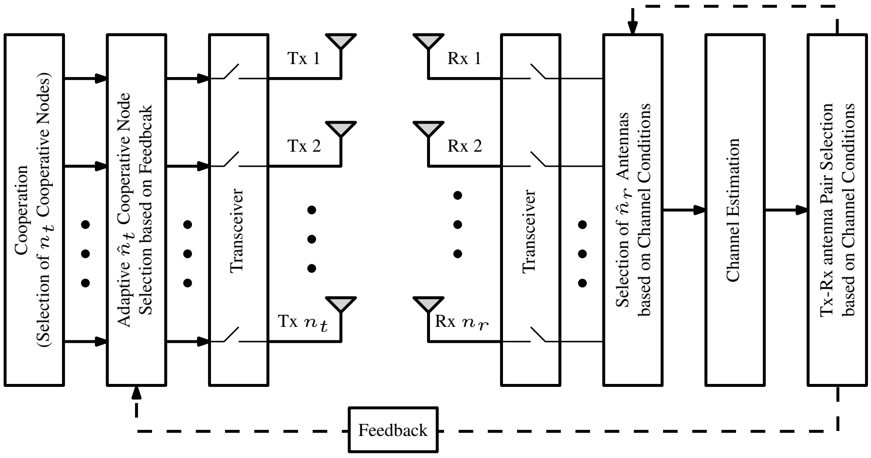

Figure 4.2: Block diagram of the proposed Tx-Rx antennae selection for cooperative communication within WSNs.

Let $\mathcal{N}_{tr}$ represents the total number of transmit-receive antennae pairs and $\hat{\mathcal{N}}_{tr}$ denotes the desirable number of transmit-receive antennae pairs. The total number of possible $\hat{k}$ combinations of $\hat{\mathcal{N}}_{tr}$ transmit-receive antennae pairs from the channel matrix **H** can be derived as:

$$\hat{k} = \frac{\mathcal{N}_{tr}!}{\hat{\mathcal{N}}_{tr}!(\mathcal{N}_{tr} - \hat{\mathcal{N}}_{tr})!} \tag{4.3}$$

Let $\mathbf{H}_s$ be a matrix that represents $\hat{k}$ number of sub-matrices extracted from the channel matrix **H** which is expressed as:

$$\mathbf{H}_s = [\mathbf{H}_1, \mathbf{H}_2, \ldots, \mathbf{H}_l]^T \tag{4.4}$$

where $\hat{k} = \{1, 2, \ldots, l\}$. Let $\mathbf{H}_l$ represents a sub-matrix with l^{th} combinations of transmit-receiver antennae pairs from the channel matrix $\mathbf{H}$ with dimensions $(\hat{n}_r \times \hat{n}_t)$ and $\mathbf{I}$ is the identity matrix of dimensions $(\hat{n}_r \times \hat{n}_t)$.

$$\varrho_l = \frac{1}{\hat{n}_r \hat{n}_t} \sum_{\hat{u}=1}^{\hat{n}_r} \sum_{\hat{v}=1}^{\hat{n}_t} \left(\mathbf{H}_{l_{(\hat{u},\hat{v})}} \mathbf{H}^H_{l_{(\hat{u},\hat{v})}} - \mathbf{I}_{(\hat{u},\hat{v})} \right) \tag{4.5}$$

where ϱ_l is the performance parameter of the $\mathbf{H}_l$. Consider $\mathbf{e}$ represents the performance status of all the possible transmit-receive antennae combinations against the varying environment propagation conditions which is expressed as:

$$\mathbf{e} = [\varrho_1, \varrho_2, \ldots, \varrho_l] \tag{4.6}$$

The best possible transmit-receive antennae combination against the current channel conditions can be defined as $\min\{\mathbf{e}\}$. The criterion to select the best possible transmit-receive antennae combination to mitigate the effect of deep channel fading is described by Algorithm 4.1.

Algorithm 4.1 Adaptive Transmitter-Receiver Antennae Selection Scheme

Require:

The matrix $\mathbf{H}_s$.

Ensure:

Obtain $\mathbf{H}_k$ with $\min\{\mathbf{e}\}$, where dimensions of $\mathbf{H}_k$ is $\hat{n}_r \times \hat{n}_t$, $\hat{u} = n_r - 1$, $\hat{v} = n_t - 1$ and $n_t = n_r$

$\mathbf{e} \leftarrow \varnothing$

for $\hat{l} \leftarrow 1$ **to** $\hat{k}$ **do**

find $\ddot{\mathbf{H}}_l$ for l^{th} combination

Algorithm 4.1 (continued) Adaptive Transmitter-Receiver Antennae Selection Scheme

$\mathbf{E} \leftarrow \left[\mathbf{H}_l \mathbf{H}_l^T - \mathbf{I}\right]^2$

$\mathbf{e}(l) \leftarrow \frac{1}{\hat{n}_r \hat{n}_t} \sum_{\hat{u}=1}^{\hat{n}_r} \sum_{\hat{v}=1}^{\hat{n}_t} \mathbf{E}_{(\hat{u},\hat{v})}$

end for

$er \leftarrow \min\{\mathbf{e}\}$

Find the position $\hat{l}$ of er in $\mathbf{e}$

$\mathbf{H}_k \leftarrow \mathbf{H}_s$

return $\mathbf{H}_k$

4.2.2 Lattice Reduction based Transmit Signal Design

Within WSNs, collaboration among sensor nodes is expected to optimise the usage of resources. It is assumed that the FCR will cooperate with the neighbourhoods through a feedback link. It is intended to design the transmit signal based on a lattice reduction scheme proposed in [131]. The "design criterion is to be based on feedback information from the the FCR. The signal is designed with the aim of minimising the effect of noise on the signal. The Lenstra-Lenstra-Lovász (LLL) lattice basis reduction algorithm is considered to determine a corresponding reduced basis $\widetilde{\mathbf{H}}$ with better properties by searching for the reduced lattice basis of the lattice defined by the channel matrix. Figure 4.3 shows the block diagram for a MIMO system with lattice reduction based detection" [1].

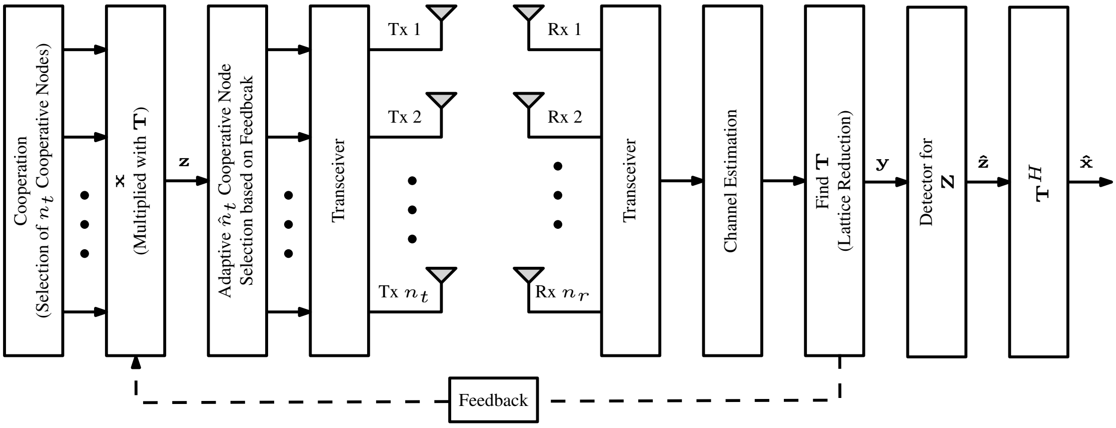

FIGURE 4.3: Block diagram summarising the methodological steps of the MIMO system with lattice reduction aided data detection.

The received signal $\mathbf{y}$ at the FCR is defined as:

$$\mathbf{y} \quad = \quad \tilde{\mathbf{H}}\mathbf{x} + \mathbf{n} \tag{4.7}$$

where $\tilde{\mathbf{H}} = \mathbf{H}\mathbf{T}$, $\tilde{\mathbf{z}} = \mathbf{T}^{-1}\mathbf{x}$ and $\mathbf{T}$ represents the reduced basis of $\mathbf{H}$. Moreover $\widetilde{\mathbf{H}}$ is obtained from Lenstra Lenstra Lovśz (LLL) lattice basis reduction algorithm and it is the LLL-reduced basis of $\mathbf{H}$. Let $\mathbf{H} = [\mathbf{h}_1, \mathbf{h}_2, \ldots, \mathbf{h}_{n_t}]$, where $[\mathbf{h}_1, \mathbf{h}_2, \ldots, \mathbf{h}_{n_t}]$ are the column vectors of $\mathbf{H}$. For zero-forcing detector $\tilde{\mathbf{z}}_{LR-ZF}$ can be defined as:

$$\begin{aligned}\tilde{\mathbf{z}}_{LR-ZF} &= \mathbf{T}^{-1}\tilde{\mathbf{x}}_{ZF} \\ &= \mathbf{T}^{-1}\mathbf{H}^{H}\mathbf{y} \\ &= \tilde{\mathbf{H}}^{H}\mathbf{y} \\ &= \mathbf{z}+\tilde{\mathbf{H}}^{H}\mathbf{n}\end{aligned} \tag{4.8}$$

The LLL Lattice reduction algorithm is summarised in Algorithm 4.2.

Algorithm 4.2 The LLL Lattice Reduction Algorithm

Require:

The channel matrix $\mathbf{H}$.

$\widetilde{\mathbf{H}} \leftarrow \mathbf{H}$

$[\widetilde{\mathbf{Q}}, \widetilde{\mathbf{R}}] \leftarrow qr(\widetilde{\mathbf{H}})$

$\mathbf{T} \leftarrow \mathbf{I}_m$, where m is number of columns of $\mathbf{H}$

$l \leftarrow 2$

$\frac{1}{4} < \delta < 1$

do

  $\mu = \left\lceil \frac{\widetilde{\mathbf{R}}(l-1,l)}{\widetilde{\mathbf{R}}(l-1,l-1)} \right\rfloor$

  $\widetilde{\mathbf{h}}_l \leftarrow \widetilde{\mathbf{h}}_l - \mu\widetilde{\mathbf{h}}_{l-1}$

  $\zeta = \|\widetilde{\mathbf{R}}(l,l) + \widetilde{\mathbf{R}}(l-1,l)\|^2$

  if $\delta|\widetilde{\mathbf{R}}(l-1,l-1)|^2 > \zeta$ **then**

    Swap columns $l-1$ and l in $\widetilde{\mathbf{H}}, \widetilde{\mathbf{R}}$ and $\mathbf{T}$

    Calculate rotation matrix $\mathbf{\Theta}$ such that the elements $\widetilde{\mathbf{R}}(l,l-1) = 0$

$$\mathbf{\Theta} = \begin{bmatrix} \alpha & \beta \\ -\beta & \alpha \end{bmatrix} \quad \textit{with} \quad \alpha = \frac{\widetilde{\mathbf{R}}(l-1,l-1)}{\zeta}, \quad \beta = \frac{\widetilde{\mathbf{R}}(l,l-1)}{\zeta}$$

Algorithm 4.2 (continued) LLL Lattice Reduction Algorithm

```
        R̃(l − 1 : l, l − 1 : m) = ΘR̃(l − 1 : l, l − 1 : m)
        l ← max(l − 1, 2)
    else
        l ← l + 1
    end if
while l < m
```

4.2.3 Adaptive Signal Transmission

An adaptive signal transmission scheme is required to achieve intra-neighbourhood optimisation and inter-neighbourhood optimisation adaptively. An adaptive transmission scheme based on the channel quality is proposed which selects either the proposed transmit receive antennae selection scheme, the lattice reduction based transmit signal design or the hybrid of both schemes to maintain required QoS as shown by the block diagram presented in Figure 4.4.

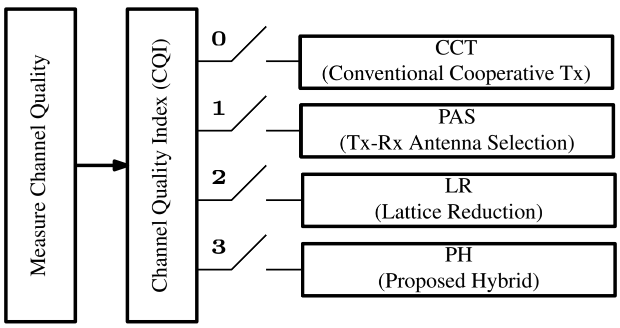

FIGURE 4.4: Block diagram for the channel quality index.

4.2.3.1 Channel Quality Index (CQI)

In order "to enable adequate decisions on the selection of the appropriate optimisation scheme adaptively, link adaptation mechanisms require knowledge of the received transmission quality over the given channel conditions. The transmission quality is generally based on the frame error probability conditioned on the particular realisation of the channel, but such information is not accessible directly. Hence, there arises the need to define a measure that maps directly to the frame error probability which is defined as the CQI. It is designed in a manner to ensure robustness against signal distortions caused by the propagation and interference conditions of the channel as well as to guarantee the optimised utilisation of resources while maintaining the required QoS. In this study, a measure of the channel quality index is proposed such that the link between the transmitter and the receiver is maintained for a given QoS" [1]. The CQI is defined as:

$$\mathrm{CQI} \quad = \quad f(\tilde{\mathrm{E}}[(\boldsymbol{\Lambda} - \boldsymbol{\mu})^2]) \tag{4.9}$$

where $\tilde{\mathrm{E}}$ denotes the expectation value and CQI can be simplified as:

$$\mathrm{CQI} \quad = \quad \frac{1}{n_t}\sum_{\hat{i}=1}^{n_t} \mid \boldsymbol{\Lambda}_{\hat{i}} - \mu \mid^2 \tag{4.10}$$

where

$$\mu = \frac{1}{n_r}\sum_{\hat{j}=1}^{n_r} \boldsymbol{\lambda}_{\hat{j}} \tag{4.11}$$

where $\boldsymbol{\Lambda}$ is a set of eigen vector channel coefficient matrix $\mathbf{H}$ of dimension $(n_r \times 1)$, which is defined as:

$$\boldsymbol{\Lambda} = \{\boldsymbol{\lambda}_{\hat{j}}\ ;\ \hat{j} = 1, 2, \ldots, n_r\} \tag{4.12}$$

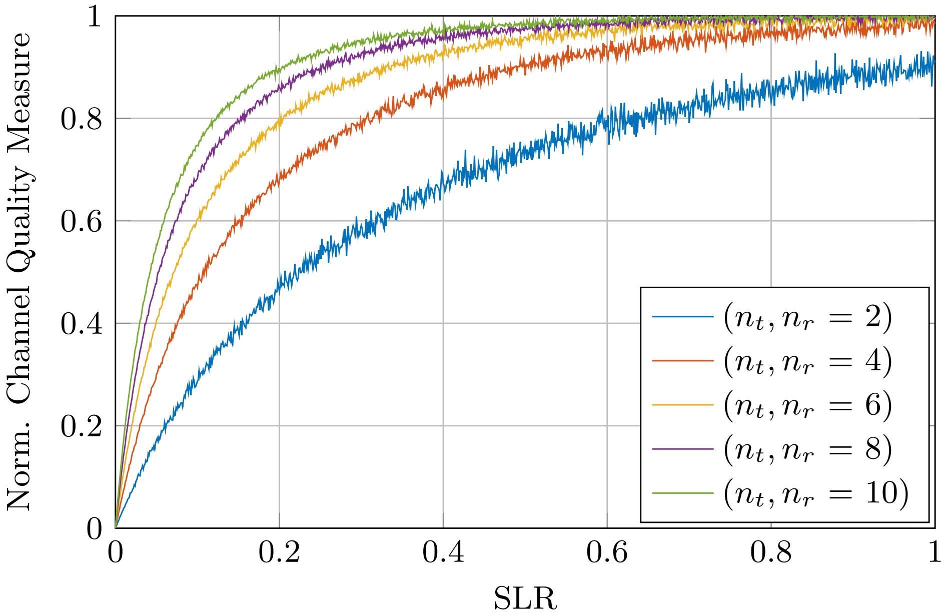

FIGURE 4.5: Normalised channel quality measure for $(n_t, n_r) = 2$, 4, 6, 8 and 10.

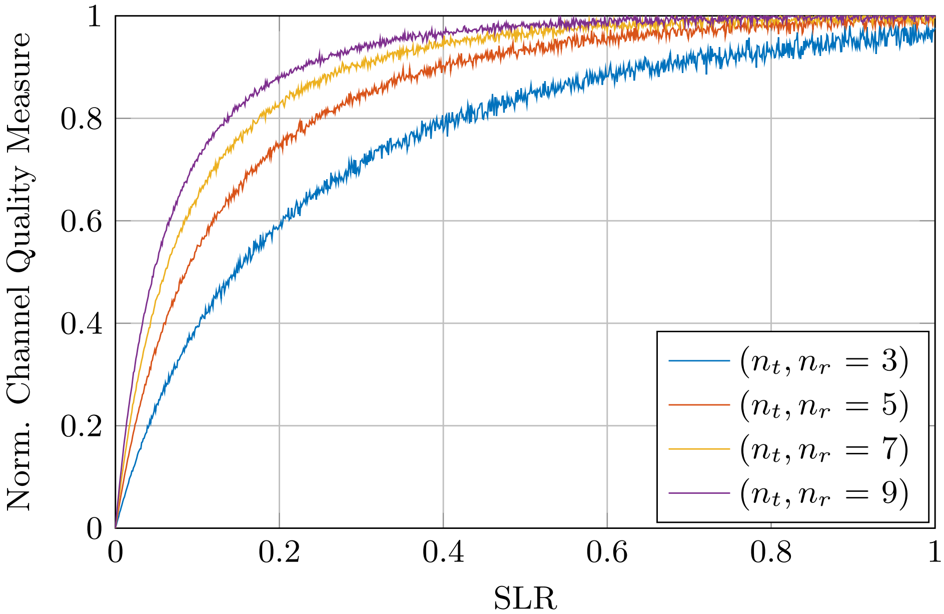

FIGURE 4.6: Normalised channel quality measure for $(n_t, n_r) = 3$, 5, 7 and 9.

where $\lambda_{\hat{j}}$ represents the eigen values of the $\hat{j}^{th}$ channel coefficient. Figure 4.5 and Figure 4.6 present the measurement of the CQI. "The selection of the transmission scheme is proposed to be based on the classification of the propagation condition, which can be obtained from the list of CQI as presented in Table 4.1. CQI is indexed based on the condition of the channel from 0 to 3. The higher index represents the higher requirement of cooperation from sensor nodes and the FCR to maintain the required link reliability" [1].

TABLE 4.1: Proposed channel classification and scheme selection criterion.

CQI	**0**	**1**	**2**	**3**
Normalised Channel Quality Measure	< 0.4	0.4 - 0.6	0.6 - 0.75	> 0.75
Selection of Transmission Scheme	Conventional Cooperation Scheme	Proposed Resource Selection Scheme	Proposed Hybrid Scheme	Lattice Reduction

4.2.3.2 Proposed Receiver Performance Bound

For ease of system design to achieve a predefined capacity or quality of service requirement, analytical frameworks are extremely useful that provide a performance benchmark. Multiple antennae based future communication systems are expected to be adaptive with available capacity or QoS to offer as trade off with each other. A simplified analytical framework is expected to lead towards designing such resource adaption algorithm more easily. However, to achieve the effectiveness of such a framework, a tighter bound is required. With the given resources, the most commonly used detection schemes found in the existing literature are: zero forcing (ZF), minimum mean square error (MMSE) and maximum likelihood (ML). Most of the available lower bounds in the existing literature are lacking tightness with the actual performance. Several performance analyses frameworks for ZF and MMSE detection have been presented in [132–135]. However, within the scope of the author's knowledge there are few analytical frameworks which facilitate communication system design engineers to select the required transmit-receive antennae combination for a given QoS in terms of the BER or SER. Most of such frameworks for MIMO wireless systems in the existing literature are lacking tightness between theoretical approximation and actual simulation results.

The simplified analytical frameworks of the MIMO receiver performance, which provides a tighter lower bound in comparison to the existing bounds for ZF, MMSE and ML detection schemes within MIMO wireless communication are presented. The channel state information is assumed to be known at the FCR. In ZF detection, the received signals are sent through the ZF filter denoted as $\mathbf{G}_{ZF}$ and can be defined as:

$$\mathbf{G}_{ZF} = \left(\mathbf{H}^H\mathbf{H}\right)^{-1}\mathbf{H}^H \tag{4.13}$$

Subsequently, the recovered spatially multiplexed data streams recovered from the detected received signals are denoted as $\hat{\mathbf{x}}_{ZF}$ and can be written as:

$$\begin{aligned} \hat{\mathbf{x}}_{ZF} &= \mathbf{G}_{ZF}\mathbf{y} && (4.14) \\ &= \left[(\mathbf{H}^H\mathbf{H})^{-1}\mathbf{H}^H\right]\mathbf{y} && (4.15) \end{aligned}$$

During the detection process, the ZF detector is aimed to null out interfering components, which can cause noise amplification. Subsequently, it is well established that ZF is not the best possible detection scheme. Although, it is simple and easy to implement. MMSE is another widely used detection scheme which provides a trade-off between minimising the inter-symbol interference and noise amplification. The MMSE filter matrix is denoted as $\mathbf{G}_{MMSE}$ and defined as:

$$\mathbf{G}_{MMSE} = \left[(\mathbf{H}^H\mathbf{H} + \sigma^2\mathbf{I})\right]^{-1}\mathbf{H}^H \tag{4.16}$$

Hence, the estimation of the transmitted signal vector can be written as:

$$\begin{aligned} \hat{\mathbf{x}}_{MMSE} &= \mathbf{G}_{MMSE}\mathbf{y} && (4.17) \\ &= \left[(\mathbf{H}^H\mathbf{H} + \sigma^2\mathbf{I}))^{-1}\mathbf{H}^H\right]\mathbf{y} && (4.18) \end{aligned}$$

The ML detector is known to be the optimal detector in terms of minimising the probability of the bit error rate. The criterion required to satisfy the maximum likelihood detection can be defined as:

$$\hat{\mathbf{x}}_{ML} = \arg\min_{k\in 1:2^{N_t}} \|\mathbf{y} - \mathbf{H}\mathbf{x}_k\|^2 \tag{4.19}$$

where x_k is the k^{th} candidate symbol vector out of 2^{n_t} number of possible symbol vectors. However, the computational complexity of these detection schemes grows exponentially with the number of antennae elements when used within MIMO systems. While designing MIMO systems, the selection of the detection scheme along with the resources required to be provided to achieve a given QoS, is challenging. Moreover, to design an adaptive receiver with a predetermined power constraint, a lower number of iterations are desirable to converge to a true performance pattern from an initial approximation. One possibility of approximating the performance of these systems is to design a framework which provides tighter error performance bound.

The bit error rate is a critical measure of the system performance which defines the QoS of any telecommunication system. An intended achievable QoS threshold is required to be determined, to allocate resources during any given telecommunication system. To find such a threshold, analytical frameworks have been studied in the literature that provide a benchmark of the required resources.

A) Existing Framework: The most commonly used linear detection schemes e.g., ZF, MMSE and ML have been the prime topic of interest for such analytical performance measure. Recent work in [132, 133] provides a frame work for the analyses of error performance for ZF and MMSE detection schemes which is defined as:

$$P_{b,ZF} = \left[\frac{1}{2}\left(1-\sqrt{\frac{snr}{1+snr}}\right)\right]^{N_r-N_t+1} \sum_{n=0}^{N_r-N_t+1} \binom{N_r-N_t+n}{n} \left(\frac{1+\sqrt{\frac{snr}{1+snr}}}{2}\right) \tag{4.20}$$

$$P_{b,MMSE} = \mathbb{E}\left[e^{-\eta_{\infty,n}}\right] P_{b,ZF} \tag{4.21}$$

where

$$\eta_{\infty,n} = \left(\mathbf{U}_n^T \mathbf{h}_n\right)^T \Lambda^{-2} \left(\mathbf{U}_n^T \mathbf{h}_n\right) \tag{4.22}$$

where $\mathbf{U}_n$ is the upper triangular matrix and Λ is the eigen values matrix of $\mathbf{H}_n$, and $\mathbf{H}_n$ is the sub-matrix obtained by taking $\mathbf{h}_n$ out of $\mathbf{H}$. $\mathbf{h}_n$ is the n^{th} column of $\mathbf{H}$. Equation 4.19 can be simplified into Equation 4.23 for a symmetric MIMO system, i.e.

$$P_{b,ZF} = \frac{1}{2}\left(\frac{1}{1+snr}\right) \tag{4.23}$$

ML detection is widely known to be optimum in terms of bit error rate performance with the cost of intensive computational complexity. Different upper bounds on SER and BER probability of ML detection within MIMO communication systems have been presented in [136–138]. The upper bounds for the probability of the bit error rate defined in the existing literature are the function of the input signal to noise ratio and the number of receive antennae. A generalised model is found in [138] and given as follows:

$$P_{b,ML} = \left[\frac{1}{2}\left(1 - \sqrt{\frac{snr}{1+snr}}\right)\right]^{N_r} \sum_{n=0}^{N_r-1} \binom{N_r - 1 + n}{n} \left(\frac{1+\sqrt{\frac{snr}{1+snr}}}{2}\right)^n \tag{4.24}$$

As mentioned earlier, the frame work presented in Equation 4.24 provides the error performance upper bound for ML detection. According to authors knowledge, there is no framework which provides an error performance lower bound for ML detection without error correction code in the existing literature.

B) Proposed Framework: For a symmetric MIMO system, the existing approximated performance bounds presented in the literature [132, 133] for ZF and MMSE are quite loose with respect to the actual simulation results. In this context, simple analytical frameworks that provide tighter lower bounds for ZF, MMSE and ML detection schemes are proposed. The proposed frameworks are simple and accurate in the context of performance tightness that depends on the MIMO dimension as well as the input signal to noise ratio. Denoting $\mathcal{N}_{tr}$ to be the symmetric MIMO dimension, the proposed analytical framework of the bit error rate performance lower bound with ZF detection at the receiver derived from simulation results presented in Figure 4.7 and can be written as:

$$P_{b,ZF} = e^{\left(\sqrt{\frac{3}{\mathcal{N}_{tr}}}\right)} erfc\left(\frac{1}{\sqrt{n_t n_r}}\right) log_{10}\left(\sqrt{\mathcal{N}_{tr}}\right)\left(\frac{1}{1+\sqrt{2\ snr}}\right) \tag{4.25}$$

The error performance bound for the receiver with MMSE detection is derived from simulation results presented in Figure 4.9 and and presented in Equation 4.26, which depends on the input signal-to-noise ratio and the MIMO dimension.

$$P_{b,MMSE} = \frac{1}{\sqrt{\mathcal{N}_{tr}}} erfc\left(\frac{1}{\sqrt{n_t n_r}}\right)\left(\frac{1}{2\ snr}\right)^{\frac{1}{4}}\left(\frac{1}{1+\sqrt{2\ snr}}\right) \tag{4.26}$$

As mentioned earlier, there is no error performance lower bound framework for a receiver with ML detection in the existing literature; a framework is derived from simulation results presented in Figure 4.11 and presented in Equation 4.27, which defines the error performance lower bound.

$$P_{b,ML} = \frac{e^{-\sqrt{snr}}}{2}\left(\frac{\sqrt{\mathcal{N}_{tr}}\left(1+\sqrt{snr}\right)}{\left(\sqrt{\mathcal{N}_{tr}}+snr\right)\left(1+snr\right)^2}\right) \tag{4.27}$$

4.3 Performance Analysis

The performance analysis of the proposed adaptive transmit receive antennae selection and lattice reduction based transmit signal design schemes are presented. Moreover, the performance of a hybrid scheme is also presented which is the combination of the adaptive transmit receive antennae selection and the lattice reduction based transmit signal design schemes. Thereafter, the performance of the

CQI based adaptive transmission scheme is presented that dynamically selects the aforementioned schemes based on the channel conditions, in order to maintain the link reliability. All the proposed schemes are analysed in terms of their probability of error, computational complexity and outage probability. Moreover, spatial multiplexing is considered for MIMO transmissions.

4.3.1 Performance Analysis of the Proposed Receiver Performance Bound

In this section, new analytical performance bound frameworks with tighter lower bounds have been presented for different receivers for MIMO systems. On the basis of the presented analytical framework, a simulation platform has been established. The channel state information as well as the expected QoS is assumed to be known for simplicity. To evaluate the performance of the proposed framework, a MIMO communication system with Rayleigh fading channel is considered. It is assumed that the channel is changing after every transmitting symbol vector $\mathbf{x}_{n_t}$ with dimension $(n_t \times 1)$ and Binary Phase Shift Keying (BPSK) modulation schemes is considered for simplicity.

Figure 4.7 and Figure 4.8 present comparative results for performance lower bound for MIMO systems with dimension ranges $d = \{2,\ 4,\ 6,\ 8\}$ for ZF, MMSE and ML detection schemes respectively. Tightness of the analytical frameworks with respect to actual simulation results is the main focus of this work. The proposed performance lower bound provides tighter lower bound with respect to simulation results as compared to the existing framework fora receiver with ZF detection. At 5 dB of signal-to-noise ratio with MIMO dimension ranges $d = \{4,\ 6,\ 8\}$, the proposed performance bound is 4 dB tighter than the existing lower bound as compared to the actual simulated results. At a higher signal-to-noise ratio, the proposed lower bound becomes tighter with respect to the actual simulation results.

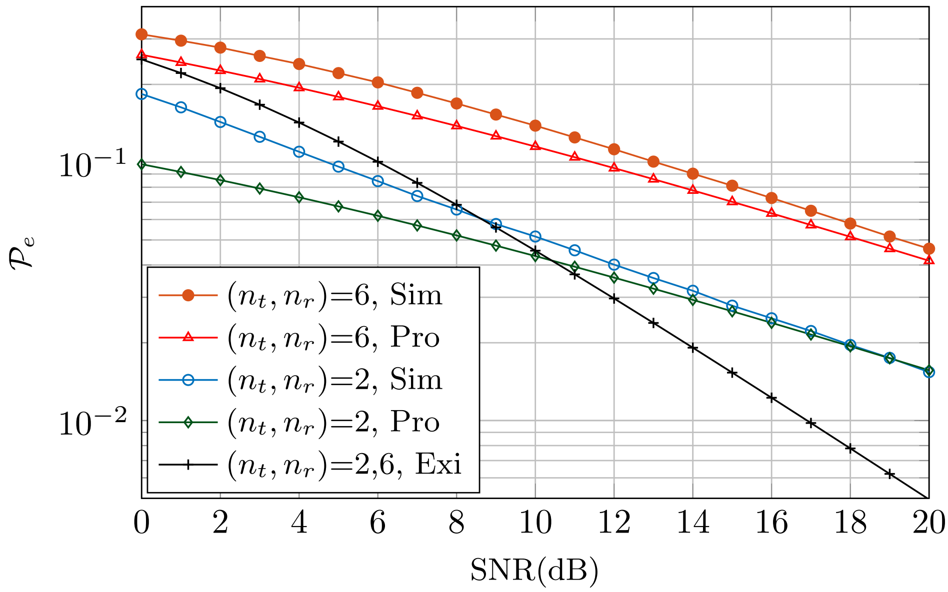

FIGURE 4.7: Error performance bound comparison of the Proposed (Pro) framework with Simulations (Sim) and Existing (Exi) frameworks for Zero Forcing (ZF) detection, where transmit and receive antennae (n_t, n_r) are 2 and 6.

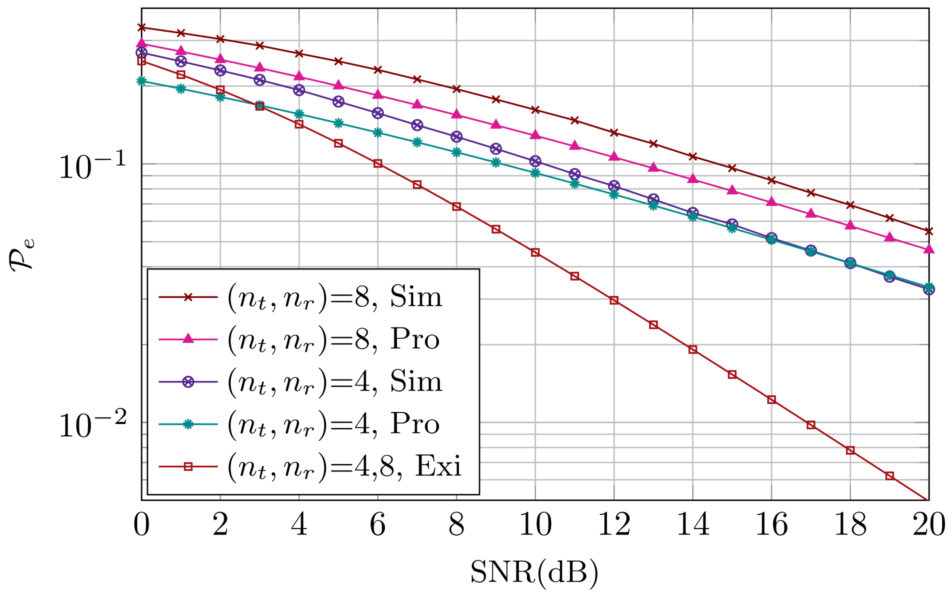

FIGURE 4.8: Error performance bound comparison of the Proposed (Pro) framework with Simulations (Sim) and Existing (Exi) frameworks for Zero Forcing (ZF) detection, where transmit and receive antennae (n_t, n_r) are 4 and 8.

A comparative study of the existing and proposed analytical frameworks along with actual simulated bit error rate performance for a MIMO receiver with MMSE detector is presented in Figure 4.9 and Figure 4.10. As shown in the figures, at 10

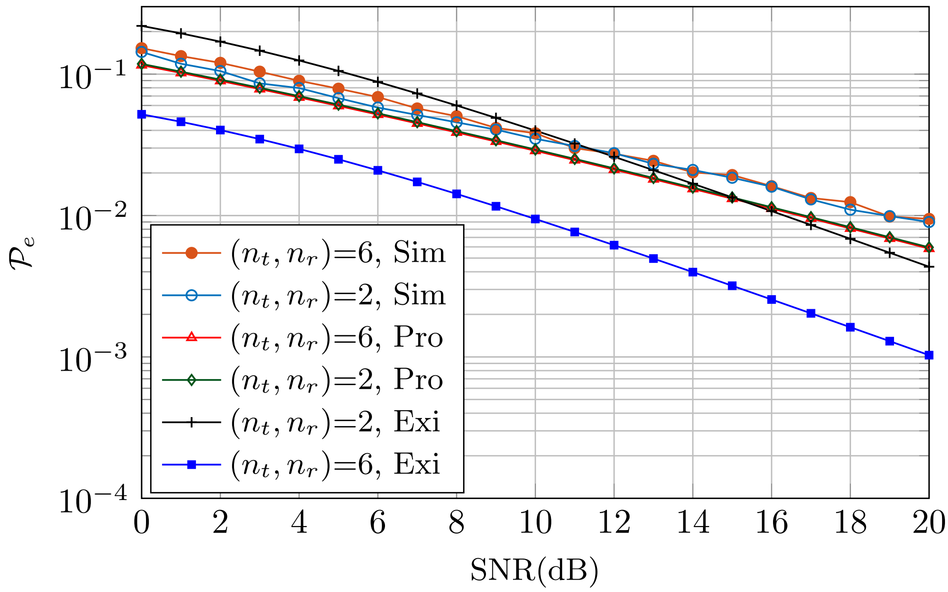

FIGURE 4.9: Error performance bound comparison of the Proposed (Pro) framework with Simulations (Sim) and Existing (Exi) frameworks for Minimum Mean Square Error (MMSE) detection, where transmit and receive antennae (n_t, n_r) are 2 and 6.

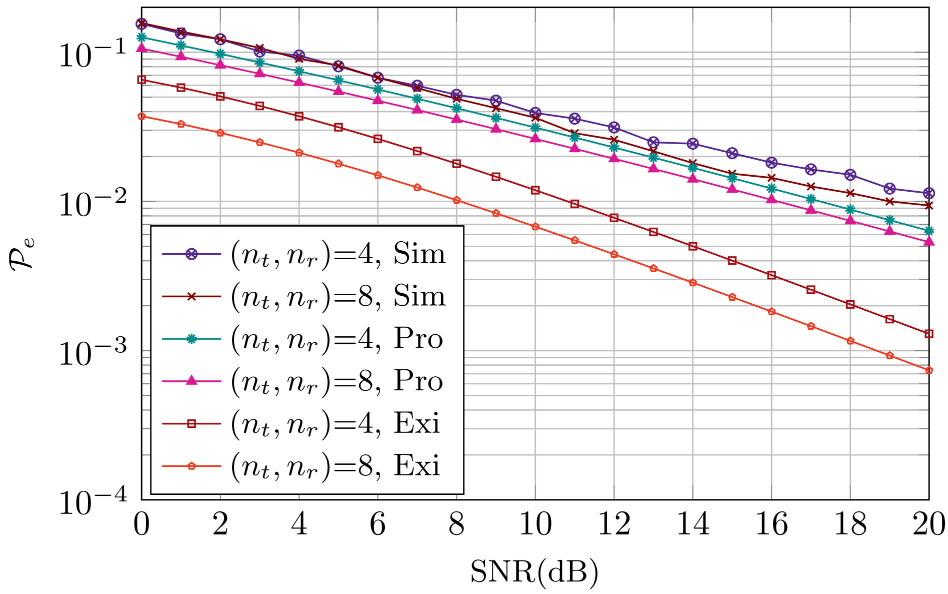

FIGURE 4.10: Error performance bound comparison of the Proposed (Pro) framework with Simulations (Sim) and Existing (Exi) frameworks for Minimum Mean Square Error (MMSE) detection, where transmit and receive antennae (n_t, n_r) are 4 and 8.

dB of signal-to-noise ratio, the proposed performance bound is 4 dB tighter than the existing error performance bound, in comparison with the actual simulated results for $d = \{2, 4, 6, 8\}$.

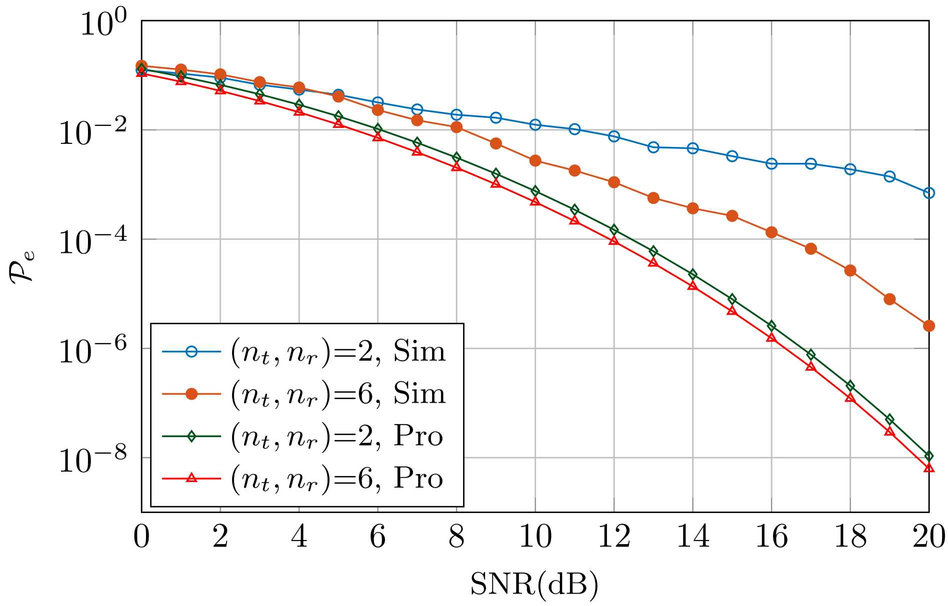

FIGURE 4.11: Error performance bound comparison of the Proposed (Pro) framework with Simulations (Sim) and Existing (Exi) frameworks for Maximum Likelihood (ML) detection, where transmit and receive antennae (n_t, n_r) are 2 and 6.

Figure 4.11 and Figure 4.12 present the performance bound of the receiver with ML detection for $d = \{2, 4, 6, 8\}$. It is validated from simulation results that the proposed performance bound for ML detection provides a tighter bound with actual simulated results for $d = \{2, 4, 6, 8\}$.

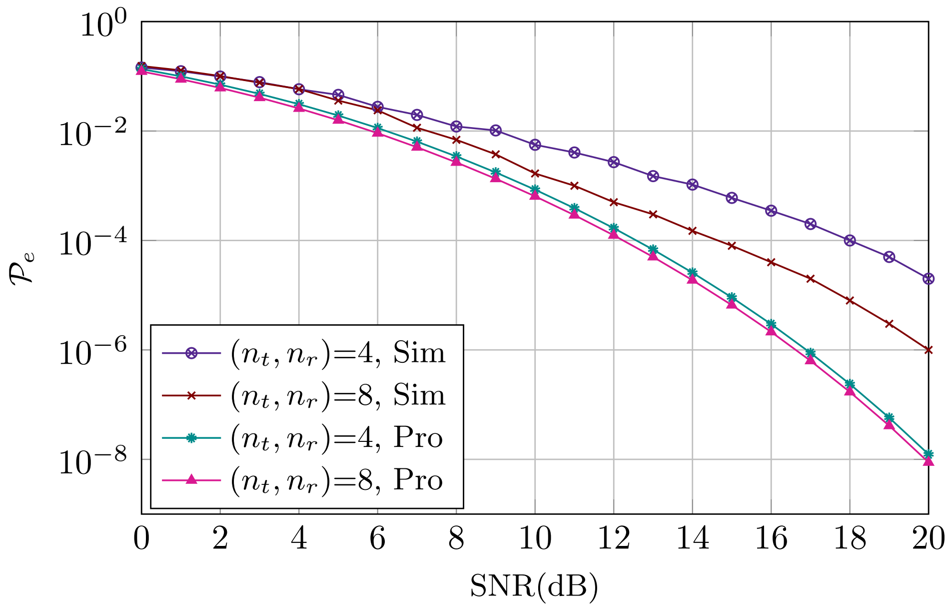

FIGURE 4.12: Error performance bound comparison of the Proposed (Pro) framework with Simulations (Sim) and Existing (Exi) frameworks for Maximum Likelihood (ML) detection, where transmit and receive antennae (n_t, n_r) are 4 and 8.

4.3.2 Performance Analysis of the Proposed CQI-centric Resource Allocation Framework for WSNs

The performance of the proposed simulation model is analysed in terms of the bit error rate for a given signal to noise ratio. A set of transmit receive antenna dimensions of three, five, eight and ten are considered. The FCR is assumed to receive data from sensing nodes with three, five, eight and ten antennae respectively. For the ease of implementation, ZF and MMSE detectors have been considered at the FCR. “It is expected that adaptive resource selection scheme will reduce energy consumption by turning off the transmit-receive antenna pair which is affected by deep fading” [1].

“Figure 4.13 presents a comparative study of the proposed adaptive node selection

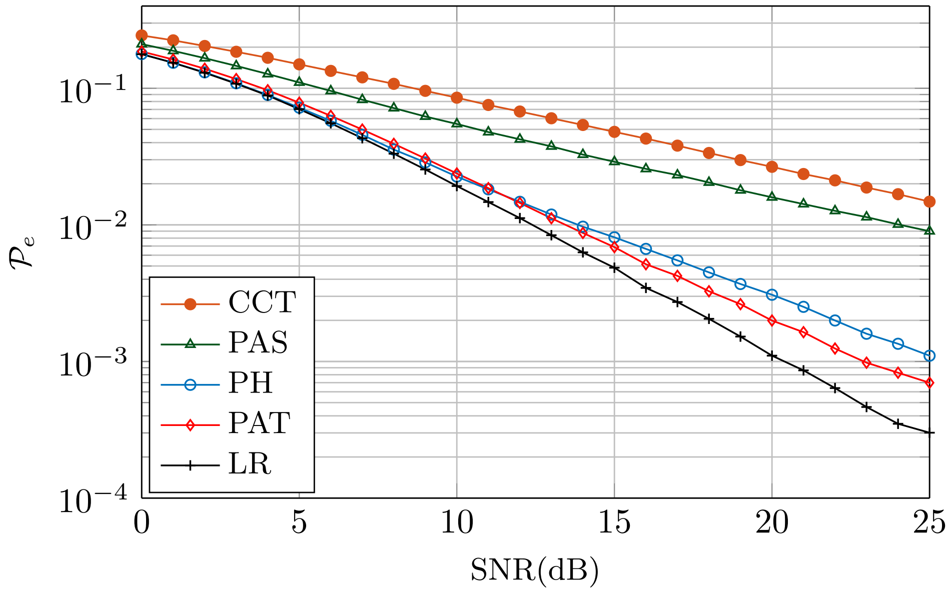

FIGURE 4.13: Performance comparison of the Proposed Adaptive Transmission (PAT), Proposed Antenna Selection (PAS) and Proposed Hybrid (PH) schemes with Lattice Reduction (LR) and Conventional Cooperative Transmission Schemes (CCT) for Zero Forcing (ZF) detection with transmit and receive antennae are 3.

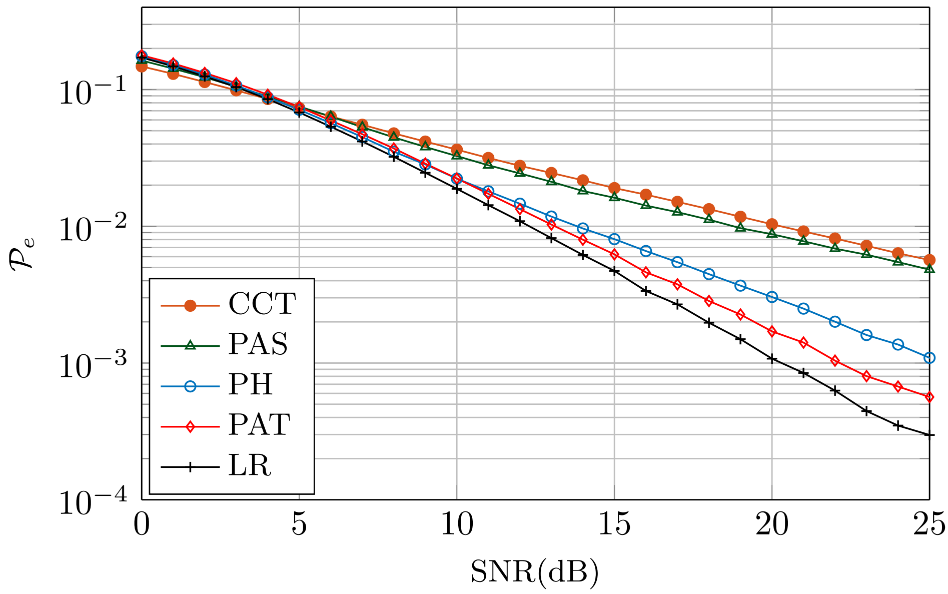

FIGURE 4.14: Performance comparison of the Proposed Adaptive Transmission (PAT), Proposed Antenna Selection (PAS) and Proposed Hybrid (PH) schemes with Lattice Reduction (LR) and Conventional Cooperative Transmission Schemes (CCT) for Minimum Mean Square Error (MMSE) detection with transmit and receive antennae are 3.

and hybrid schemes over conventional cooperative schemes (conventional virtual MIMO) and existing lattice reduction scheme as found in the literature for $n_t = n_r = 3$. It is also observed that the LR scheme achieves the highest detection reliability among the other schemes. However, LR requires a significant computational intensity within the available resources; hence it is not energy efficient. The proposed hybrid scheme is expected to provide a trade-off between computational complexity and detection reliability. An accurate CQI is the key to the performance of the proposed adaptive resource allocation scheme in energy efficient collaborative transmission. To select the appropriate optimisation scheme adaptively, based on the information from the FCR through a feedback link, a measure of the CQI has been proposed in Equation 4.9 and its normalised behaviour has been realised in Figure 4.5 and Figure 4.6. Table 4.1 presents resource allocation decision boundaries of the CQI values which have been considered to select the appropriate transmission scheme. It is expected that the proposed adaptive transmission schemes achieve a high energy efficiency and link reliability while maintaining the required QoS. It is observed from Figure 4.14 that the proposed adaptive transmission scheme and proposed hybrid scheme outperformed the conventional cooperative transmission scheme by 18 dB and 13 dB respectively for a given bit error rate of 10^{-3}, where $n_t = n_r = 3$ and detection scheme is MMSE" [1].

Figure 4.15 and Figure 4.16 present the performance comparison of the proposed CQI based adaptive transmission, hybrid and adaptive resource selection scheme with conventional cooperative transmission and LR schemes. $n_t = n_r = 5$, 8 and 10 are considered to generate the results in Figure 4.15, Figure 4.17, Figure 4.19 and Figure 4.16, Figure 4.18, Figure 4.20, whereas ZF and MMSE detection has been exploited respectively. It is observed that the proposed adaptive transmission and hybrid scheme outperform the conventional cooperative transmission scheme for $n_t = n_r = 5$, 8 and 10.

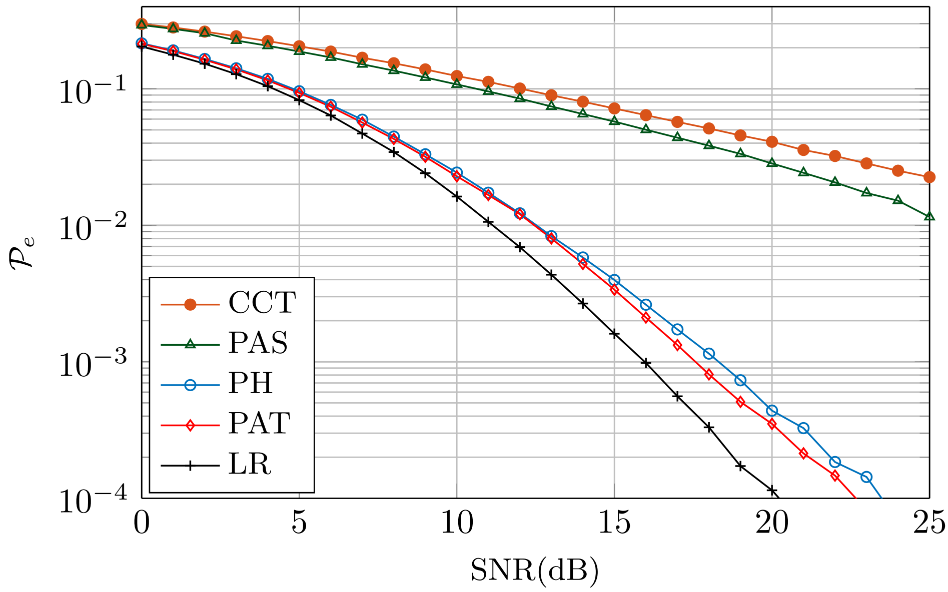

FIGURE 4.15: Performance comparison of the Proposed Adaptive Transmission (PAT), Proposed Antenna Selection (PAS) and Proposed Hybrid (PH) schemes with Lattice Reduction (LR) and Conventional Cooperative Transmission Schemes (CCT) for Zero Forcing (ZF) detection with transmit and receive antennae are 5.

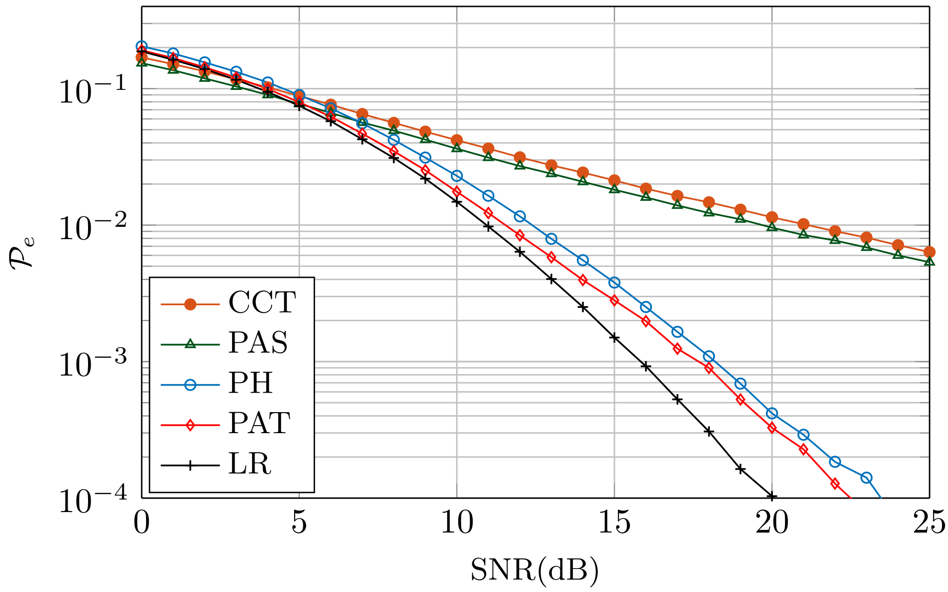

FIGURE 4.16: Performance comparison of the Proposed Adaptive Transmission (PAT), Proposed Antenna Selection (PAS) and Proposed Hybrid (PH) schemes with Lattice Reduction (LR) and Conventional Cooperative Transmission Schemes (CCT) for Minimum Mean Square Error (MMSE) detection with transmit and receive antennae are 5.

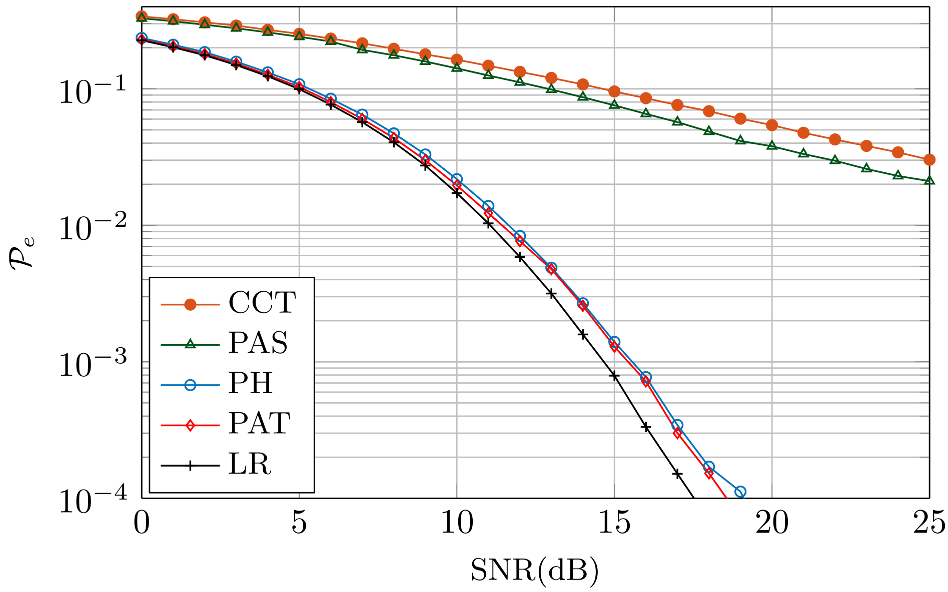

Figure 4.17: Performance comparison of the Proposed Adaptive Transmission (PAT), Proposed Antenna Selection (PAS) and Proposed Hybrid (PH) schemes with Lattice Reduction (LR) and Conventional Cooperative Transmission Schemes (CCT) for Zero Forcing (ZF) detection with transmit and receive antennae are 8.

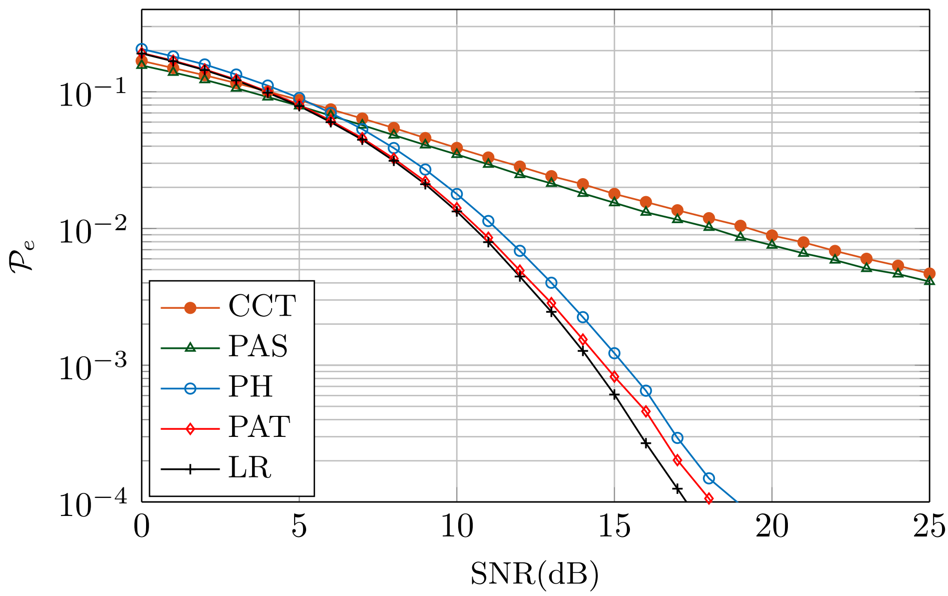

Figure 4.18: Performance comparison of the Proposed Adaptive Transmission (PAT), Proposed Antenna Selection (PAS) and Proposed Hybrid (PH) schemes with Lattice Reduction (LR) and Conventional Cooperative Transmission Schemes (CCT) for Minimum Mean Square Error (MMSE) detection with transmit and receive antennae are 8.

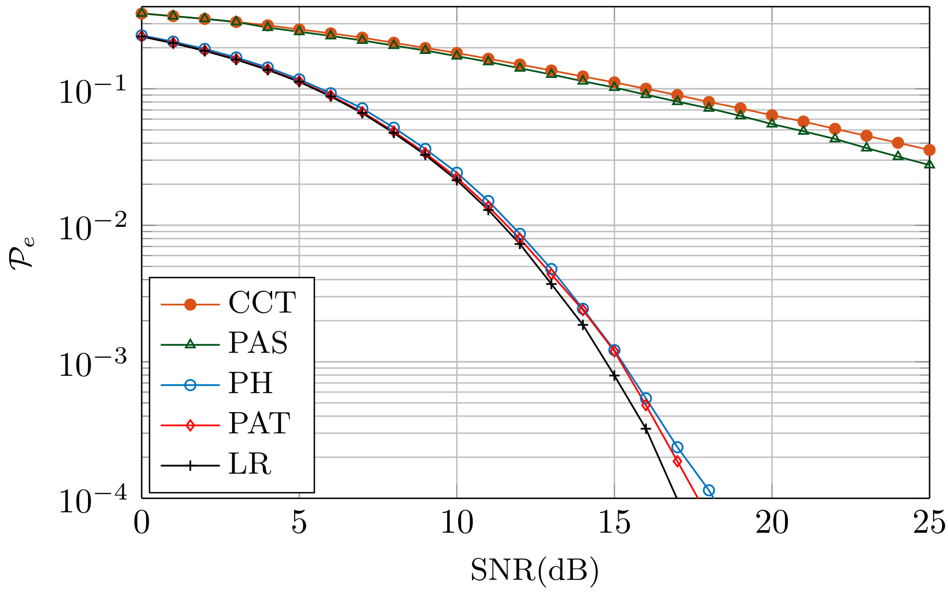

FIGURE 4.19: Performance comparison of the Proposed Adaptive Transmission (PAT), Proposed Antenna Selection (PAS) and Proposed Hybrid (PH) schemes with Lattice Reduction (LR) and Conventional Cooperative Transmission Schemes (CCT) for Zero Forcing (ZF) detection with transmit and receive antennae are 10.

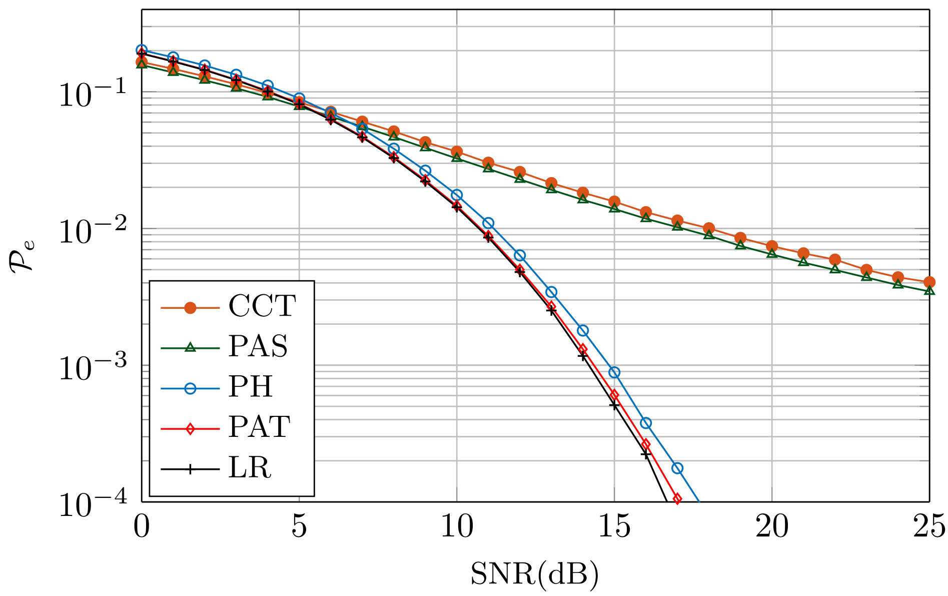

FIGURE 4.20: Performance comparison of the Proposed Adaptive Transmission (PAT), Proposed Antenna Selection (PAS) and Proposed Hybrid (PH) schemes with Lattice Reduction (LR) and Conventional Cooperative Transmission Schemes (CCT) for Minimum Mean Square Error (MMSE) detection with transmit and receive antennae are 10.

4.3.2.1 Complexity Analysis

This section presents the computational complexity analysis of the aforementioned schemes. Computational complexity is defined as the number of arithmetic operations performed by these schemes. It is assumed that each node is transmitting 15 samples and each sample contains eight bits, where different network sizes are considered i.e. from 0 to 1500 nodes. Figure 4.21 shows the computational complexity analyses for the proposed hybrid, proposed adaptive transmission, proposed antenna selection and lattice reduction schemes for $n_t = n_r = 3$.

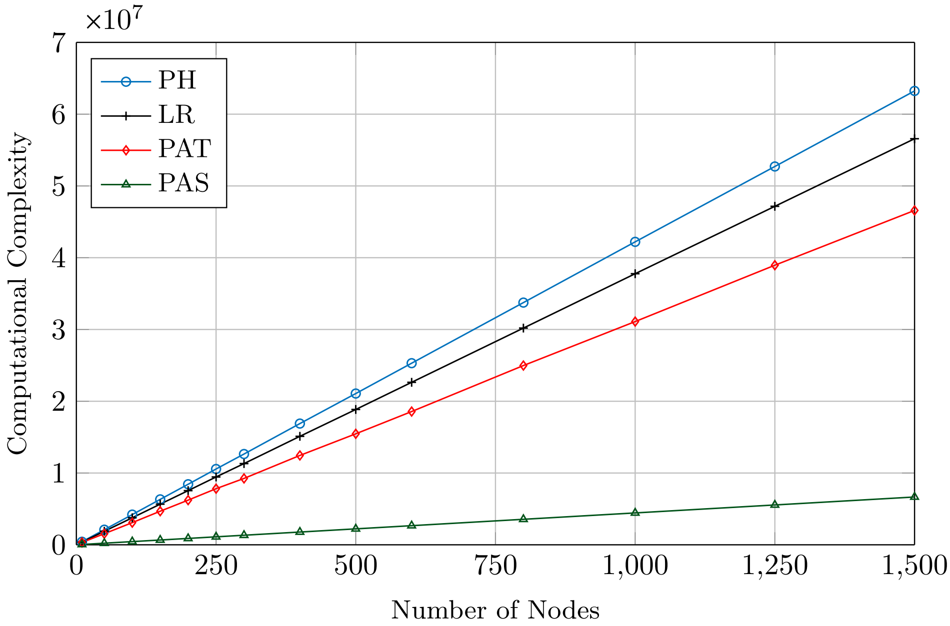

FIGURE 4.21: Computational complexity comparison of the Proposed Adaptive Transmission (PAT), Proposed Antenna Selection (PAS), Proposed Hybrid (PH) schemes with Lattice Reduction (LR) where transmit and receive antennae are three.

It can be observed from the graph that the proposed hybrid has the highest computational complexity among all the schemes because this scheme is the combination of the proposed antennae selection and lattice reduction schemes. However, this scheme achieves the same performance in terms of achieving probability of error as achieved by lattice reduction. Moreover, the proposed hybrid scheme required one less transmit-receive antennae pair that conserves energy. The proposed antennae selection scheme has the lowest computational complexity among all the schemes.

Detailed computational complexity analyses for different network sizes is presented in Table 4.2. It is assumed that LR require E_{Cc} amount of energy to perform all the computations. Then PNS and PAT are conserving 88% and 18% energy respectively as compared to LR, while PH consumes 12% additional energy as compared to LR.

TABLE 4.2: Complexity analysis (Tx-Rx = 3).

Schemes	Computational Complexity	Energy Consumption	Normalized Energy Consumption	% of Energy Saved Compared to LR
Tx-Rx = 3, Network Size = 1500 Nodes				
PAS	6.66×10^6	$C_1 \times E_{Cc}$	$\frac{C_1 \times E_{Cc}}{N} = 0.1177E_{Cc}$	$88.23 \approx 88$
PAT	4.659×10^7	$C_2 \times E_{Cc}$	$\frac{C_2 \times E_{Cc}}{N} = 0.8234E_{Cc}$	$17.66 \approx 18$
LR	5.658×10^7	$C_3 \times E_{Cc}$	$\frac{C_3 \times E_{Cc}}{N} = E_{Cc}$	0
PH	6.324×10^7	$C_4 \times E_{Cc}$	$\frac{C_4 \times E_{Cc}}{N} = 1.1177E_{Cc}$	$-11.7 \approx -12$
Tx-Rx = 3, Network Size = 1000 Nodes				
PAS	4.44×10^6	$C_1 \times E_{Cc}$	$\frac{C_1 \times E_{Cc}}{N} = 0.1176E_{Cc}$	$88.23 \approx 88$
PAT	3.11×10^7	$C_2 \times E_{Cc}$	$\frac{C_2 \times E_{Cc}}{N} = 0.8234E_{Cc}$	$17.66 \approx 18$
LR	3.777×10^7	$C_3 \times E_{Cc}$	$\frac{C_3 \times E_{Cc}}{N} = E_{Cc}$	0
PH	4.221×10^7	$C_4 \times E_{Cc}$	$\frac{C_4 \times E_{Cc}}{N} = 1.1176E_{Cc}$	$-11.7 \approx -12$
Tx-Rx = 3, Network Size = 500 Nodes				
PAS	2.22×10^6	$C_1 \times E_{Cc}$	$\frac{C_1 \times E_{Cc}}{N} = 0.1177E_{Cc}$	$88.23 \approx 88$
PAD	1.546×10^7	$C_2 \times E_{Cc}$	$\frac{C_2 \times E_{Cc}}{N} = 0.8197E_{Cc}$	$18.03 \approx 18$
LR	1.886×10^7	$C_3 \times E_{Cc}$	$\frac{C_3 \times E_{Cc}}{N} = E_{Cc}$	0
PH	2.108×10^7	$C_4 \times E_{Cc}$	$\frac{C_4 \times E_{Cc}}{N} = 1.1177E_{Cc}$	$-11.76 \approx -12$

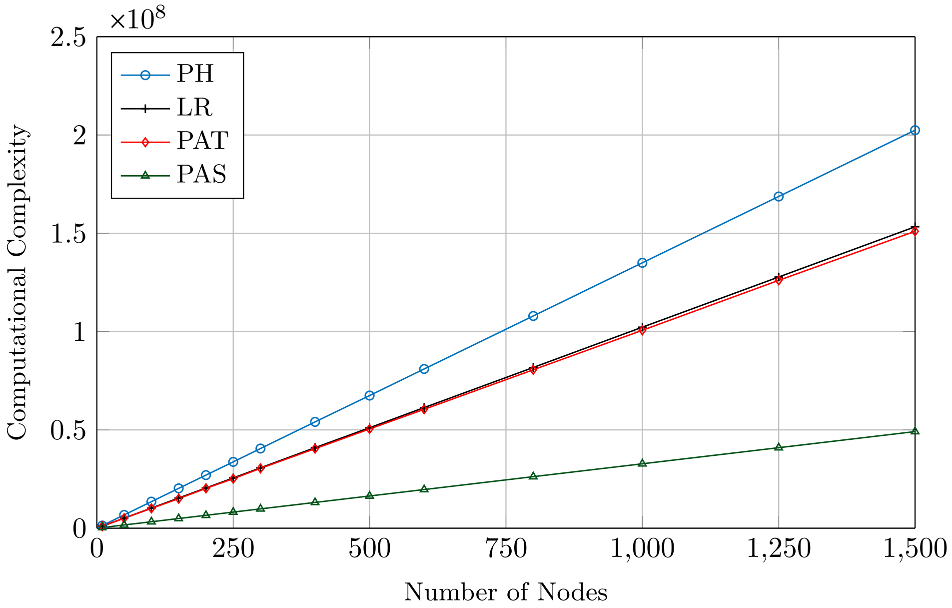

FIGURE 4.22: Computational complexity comparison of the Proposed Adaptive Transmission (PAT), Proposed Antenna Selection (PAS), Proposed Hybrid (PH) schemes with Lattice Reduction (LR) where transmit and receive antennae are five.

TABLE 4.3: Complexity analysis (Tx-Rx = 5, Network = 1500 Sensor Nodes).

Schemes	Computational Complexity	Energy Consumption	Normalized Energy Consumption	% of Energy Saved Compared to LR
Tx-Rx = 5, Network Size = 1500 Nodes				
PAS	4.914×10^7	$C_1 \times E_{Cc}$	$\frac{C_1 \times E_{Cc}}{N} = 0.3205E_{Cc}$	$67.95 \approx 68$
PAT	1.51×10^8	$C_2 \times E_{Cc}$	$\frac{C_2 \times E_{Cc}}{N} = 0.985E_{Cc}$	1.5
LR	1.533×10^8	$C_3 \times E_{Cc}$	$\frac{C_3 \times E_{Cc}}{N} = E_{Cc}$	0
PH	2.025×10^8	$C_4 \times E_{Cc}$	$\frac{C_4 \times E_{Cc}}{N} = 1.3209E_{Cc}$	$-32.09 \approx -32$

Computational complexity for $n_t = n_r = 5$ is shown in Figure 4.22 and its detailed analysis is presented in Table 4.3. It is observed from Figure 4.22 that the proposed hybrid scheme has the highest and the proposed antennae selection scheme has the lowest computational complexity among all the schemes. The proposed antennae selection and adaptive transmission scheme are 68% and 1.5% more energy efficient than lattice reduction, while the proposed hybrid required 32% additional energy compared to the lattice reduction as shown in Table 4.3. Also, the adaptive transmission and the lattice reduction have almost the same computational complexity.

Figure 4.23 presents the computational complexity for the proposed hybrid, an-

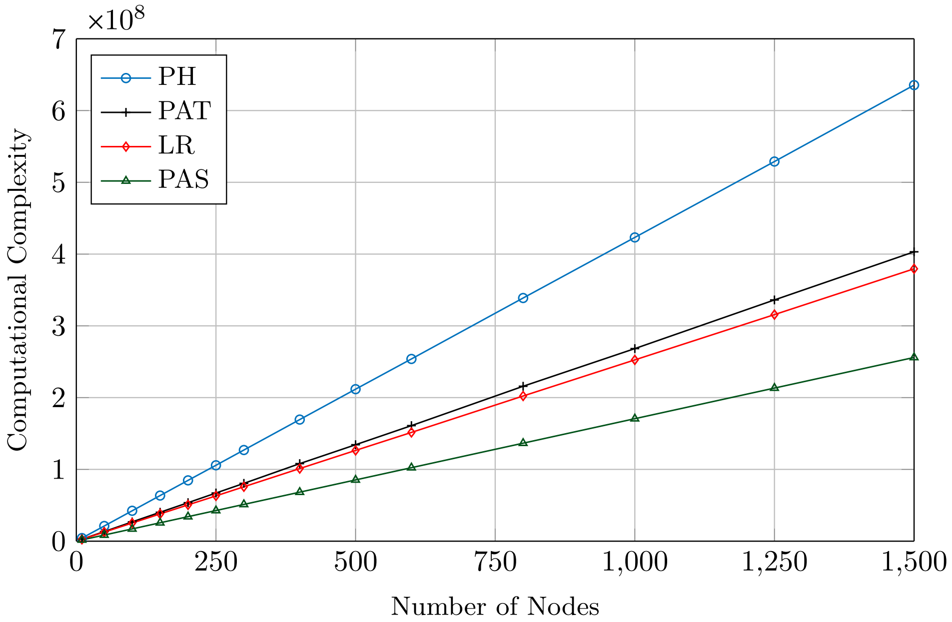

FIGURE 4.23: Computational complexity comparison of the Proposed Adaptive Transmission (PAT), Proposed Antenna Selection (PAS), Proposed Hybrid (PH) schemes with Lattice Reduction (LR) where transmit and receive antennae are eight.

tenna selection, lattice reduction and adaptive transmission schemes and its analysis is described in Table 4.4, where $n_t = n_r = 8$. The proposed antennae selection scheme is 33% more energy efficient than lattice reduction scheme as shown in Table 4.4 whereas the proposed adaptive transmission and proposed hybrid schemes are consuming 6% and 67% additional energy to perform the tasks compared to the lattice reduction.

For $n_t = n_r = 10$, the computational complexity of the proposed hybrid, antennae selection, lattice reduction and adaptive transmission schemes are shown in Figure 4.24. It is observed that the proposed hybrid scheme has the highest computational complexity among all the scheme i.e. 1.122×10^9 and the proposed antennae selection scheme has the lowest complexity i.e. 5.396×10^8. The proposed hybrid scheme require 5.824×10^8 additional computations as compared

TABLE 4.4: Complexity analysis (Tx-Rx = 8, Network = 1500 Sensor Nodes).

Schemes	Computational Complexity	Energy Consumption	Normalized Energy Consumption	% of Energy Saved Compared to LR
Tx-Rx = 8, Network Size = 1500 Nodes				
PAS	2.56×10^8	$C_1 \times E_{Cc}$	$\frac{C_1 \times E_{Cc}}{N} = 0.6746E_{Cc}$	$32.54 \approx 33$
PAT	4.032×10^8	$C_2 \times E_{Cc}$	$\frac{C_2 \times E_{Cc}}{N} = 1.0625E_{Cc}$	$-6.256 \approx -6$
LR	3.795×10^8	$C_3 \times E_{Cc}$	$\frac{C_3 \times E_{Cc}}{N} = E_{Cc}$	0
PH	6.355×10^8	$C_4 \times E_{Cc}$	$\frac{C_4 \times E_{Cc}}{N} = 1.6746E_{Cc}$	$-67.46 \approx -67$

to the proposed transmit receive antennae selection scheme. Detailed analysis of

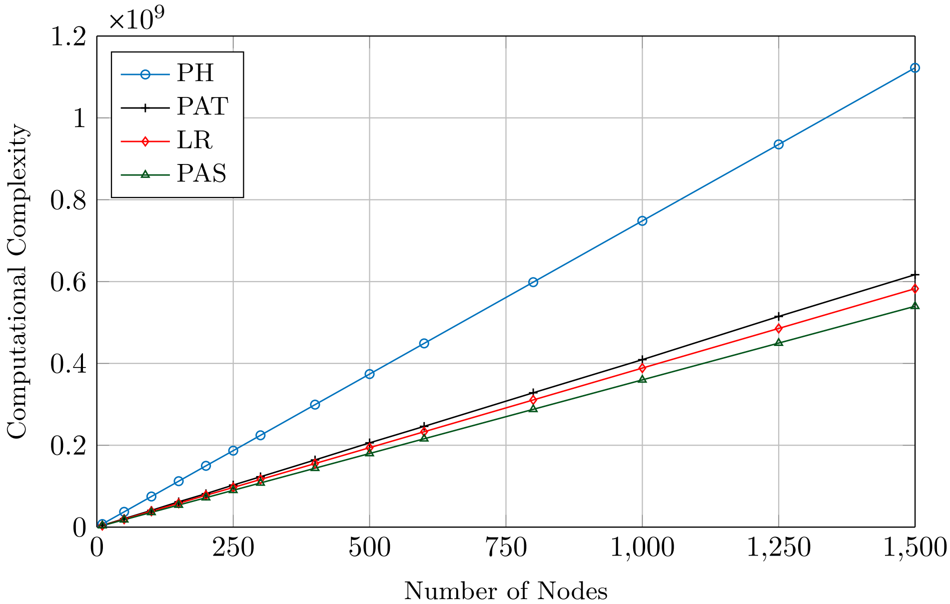

FIGURE 4.24: Computational complexity comparison of the Proposed Adaptive Transmission (PAT), Proposed Antenna Selection (PAS), Proposed Hybrid (PH) schemes with Lattice Reduction (LR) where the transmit and receive antennae are ten.

these schemes for $n_t = n_r = 10$ is presented in Table 4.5, where the network size is 1500 nodes. It is observed that the proposed transmit receive antennae selection scheme is conserving 7% energy as compared to lattice reduction, but the proposed adaptive transmission and proposed hybrid schemes are consuming 6% additional energy.

TABLE 4.5: Complexity analysis (Tx-Rx = 10, Network = 1500 Sensor Nodes).

Schemes	Computational Complexity	Energy Consumption	Normalized Energy Consumption	% of Energy Saved Compared to LR
Tx-Rx = 10, Network Size = 1500 Nodes				
PAS	5.396×10^8	$C_1 \times E_{Cc}$	$\frac{C_1 \times E_{Cc}}{N} = 0.926E_{Cc}$	$7.4 \approx 7$
PAT	6.168×10^8	$C_2 \times E_{Cc}$	$\frac{C_2 \times E_{Cc}}{N} = 1.0585E_{Cc}$	$-5.85 \approx -6$
LR	5.827×10^8	$C_3 \times E_{Cc}$	$\frac{C_3 \times E_{Cc}}{N} = E_{Cc}$	0
PH	1.122×10^9	$C_4 \times E_{Cc}$	$\frac{C_4 \times E_{Cc}}{N} = 1.9255E_{Cc}$	$-92.55 \approx -93$

Figure 4.25 presents the computational complexity of the proposed hybrid, antenna selection, lattice reduction and adaptive transmission schemes, where $n_t = n_r = 3$ to 10. It is assumed that the network size is 1500 i.e. 1500 nodes and each node is sending one data sample. It can be observed that 9.292 $\times 10^6$ computations are required to transmit all the data if the proposed hybrid scheme is used. While

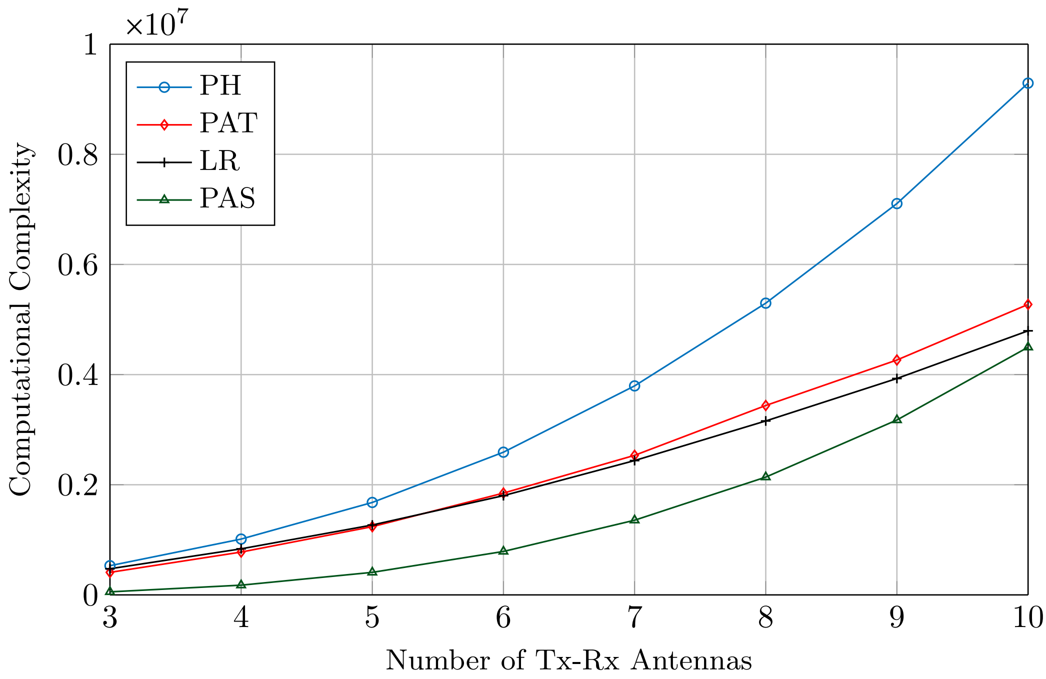

FIGURE 4.25: Computational complexity comparison of the Proposed Adaptive Transmission (PAT), Proposed Antennae Selection (PAS), Proposed Hybrid (PH) schemes with Lattice Reduction (LR) where the network size is 1500.

the proposed adaptive transmission, lattice reduction and the proposed transmit receive antennae selection schemes require a lesser number of computations i.e. 5.274 $\times 10^6$, 4.795 $\times 10^6$ and 4.497 $\times 10^6$ respectively. So, the proposed transmit receive antennae selection scheme has the lowest computational complexity among all the presented schemes for the number of transmit-receive antennae three to ten as shown in Figure 4.25. It is also observed that the computational complexity of all the presented schemes increases with an increase in the number of the transmit-receive antennae.

4.3.2.2 Outage Probability

A crucial aspect in the evaluation of wireless communication is the computation of the effect of noise and interference. The computation of the outage probability is based on finding the performance of the system that drops below a certain threshold. The mathematical model to compute the outage probability is presented in [139] and defined as:

$$\beta = 1 - \frac{\sum_{v=1}^{N} (\mathbf{x_o}^v . \tilde{\mathbf{x_o}}^v)}{N_b} \tag{4.28}$$

where β represents the number of errors for each transmission, $\mathbf{x_o}$ represents the transmitted data at each transmission, $\tilde{\mathbf{x_o}}$ represents the received data after detection of each transmission and N_b represents the total number of bits in one transmission. Let λ_β be the threshold to find the outage probability of the system, which is defined as:

$$P(\beta_{\hat{v}} \geq \lambda_\beta) = \frac{1}{\hat{n}} \sum_{\hat{v}=1}^{\hat{n}} \beta_i \tag{4.29}$$

where $\hat{n}$ represents the total number of transmissions. It is assumed that there are 500 nodes within the network and $\mathbf{x_o}$ is the data packet of N_b number of bits transmitted at each transmission i.e. $\hat{n} = 500$. Let λ_β is the outage probability

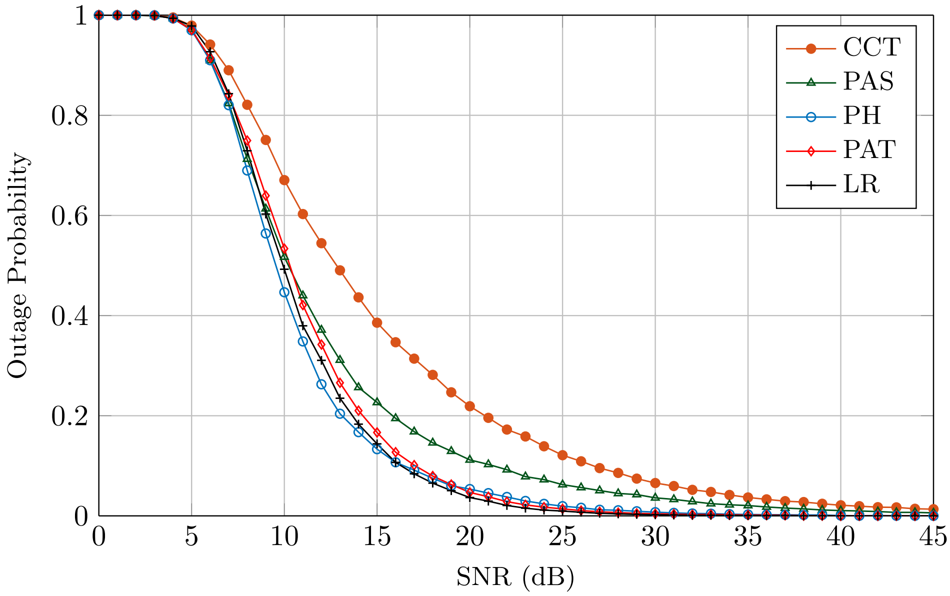

Figure 4.26: Outage Probability comparison of the Proposed Adaptive Transmission (PAT), Proposed Antenna Selection (PAS), Proposed Hybrid (PH) schemes with Lattice Reduction (LR) and Conventional Cooperative Transmission (CCT) schemes, where transmit and receive antennae are three.

threshold i.e. 10^{-3}.

Figure 4.26 and Figure 4.27 present the outage probability analysis for transmitter receiver antennae three and five respectively. It is observed from the simulation results that the proposed antenna selection scheme has low outage probability than the conventional cooperative transmission scheme. Moreover, the proposed hybrid, proposed adaptive transmission and lattice reduction schemes follow the same trend and also have the lowest outage probability among all the schemes. Also, the outage probability is maximum up to 4 dB and 6 dB of SNR and lowest at 25 dB and 20 dB of SNR, where transmit-receive antennae three and five respectively.

The outage probability analyses for the number of transmit-receive antennae eight and ten are shown in Figure 4.28 and Figure 4.29 respectively. It is validated from

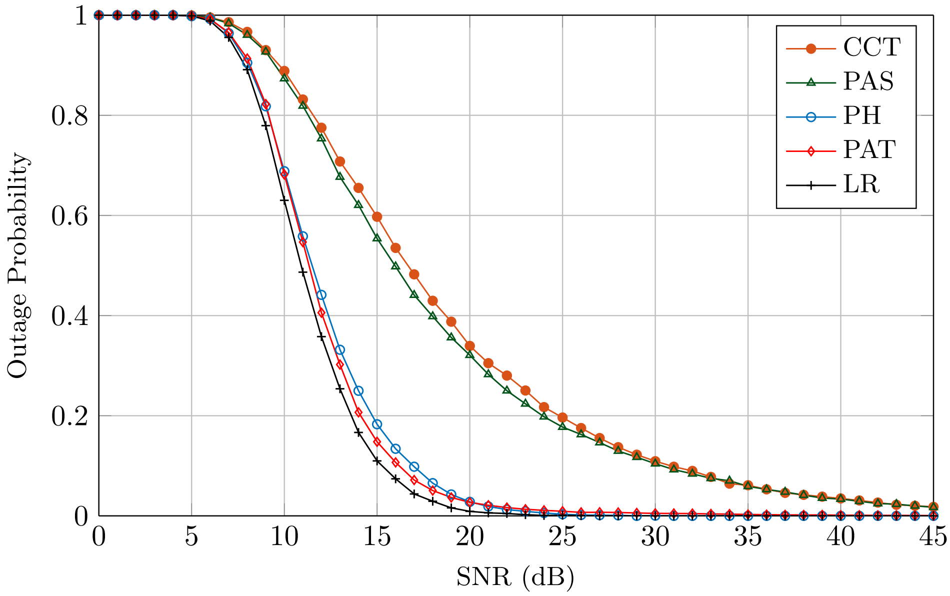

FIGURE 4.27: Outage Probability comparison of the Proposed Adaptive Transmission (PAT), Proposed Antenna Selection (PAS), Proposed Hybrid (PH) schemes with Lattice Reduction (LR) and Conventional Cooperative Transmission (CCT) schemes, where transmit and receive antennae are five.

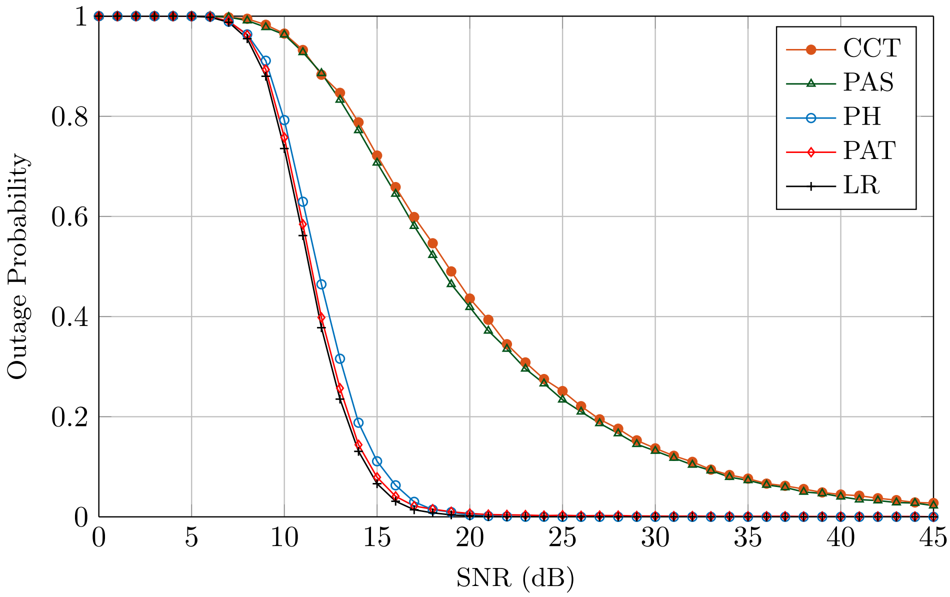

FIGURE 4.28: Outage Probability comparison of the Proposed Adaptive Transmission (PAT), Proposed Antenna Selection (PAS), Proposed Hybrid (PH) schemes with Lattice Reduction (LR) and Conventional Cooperative Transmission (CCT) schemes, where transmit and receive antennae are eight.

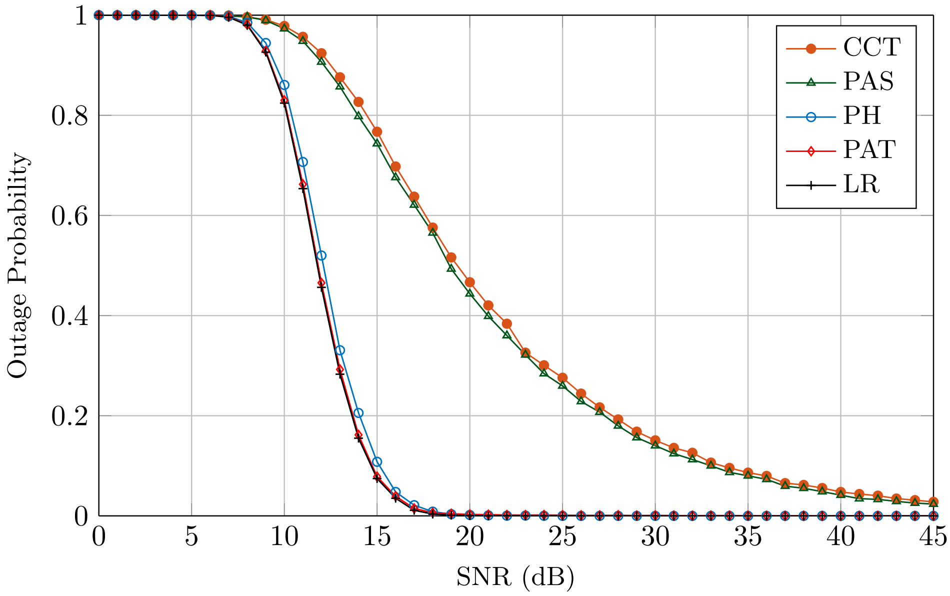

FIGURE 4.29: Outage Probability comparison of the Proposed Adaptive Transmission (PAT), Proposed Antenna Selection (PAS), Proposed Hybrid (PH) schemes with Lattice Reduction (LR) and Conventional Cooperative Transmission (CCT) schemes, where transmit and receive antennae are ten.

simulation results that the outage probability is maximum up to 6 dB of SNR, where the transmit-receive antennae are eight and achieves the lowest outage probability at 18 dB of SNR. Also the proposed hybrid, proposed adaptive transmission and lattice reduction schemes achieve the lowest outage probability as compared to the proposed transmit receive antenna selection and conventional cooperative transmission schemes. It is also observed that for $n_t = n_r = 10$, achieves the lowest outage probability at a lower SNR compared to $n_t = n_r = 8$, 5 and 3.

Although lowest outage probability is achieved at 18 dB of SNR for the proposed hybrid, proposed adaptive transmission and lattice reduction schemes, when $n_t = n_r = 10$ but 50% probability is achieved at 10 dB of SNR when $n_t = n_r = 3$. While $n_t = n_r = 5$, 8 and 10 achieve 50% outage probability at 12 dB of SNR. Also, the proposed transmit receive antennae selection and conventional cooperative transmission schemes achieving 50% outage probability at a lower value of SNR i.e. 12.5 dB for $n_t = n_r = 3$ as compared to 16 dB, 18 dB and 19 dB respectively.

So, it is observed that increasing the number of the transmit-receive antennae are helping to achieve the lowest outage probability at a lower SNR but to achieve 50% outage probability, $n_t = n_r = 3$ require 2 dB less SNR compared to $n_t = n_r = 5$, 8 and 10.

4.4 Summary

In this chapter, a CQI-centric resource allocation framework for cooperative communication within energy constrained WSNs is presented. The proposed framework incorporates an adaptive transmit receive antenna selection scheme, lattice reduction based transmit signal design scheme, a hybrid scheme that incorporates an adaptive transmit receive antenna selection scheme and lattice reduction based transmit signal design scheme, a measure of channel quality to adapt the aforementioned schemes according to the channel conditions and a receiver performance bound. The proposed adaptive transmit receive antenna selection scheme maintains the link reliability to ensure certain required QoS. This is achieved by turning off the transmit-receive antenna pairs that are suffering from deep channel fading based on the information from the FCR through a feedback link.

The design of the transmit signal based on the lattice reduction scheme is also proposed to minimise the effect of noise on the signal. This scheme requires extra processing intelligence and the design criterion is based on feedback information from the FCR. New analytical frameworks, which provide error performance lower bounds for the MIMO system with ZF, MMSE and ML detection schemes have been presented. Tighter approximation have been obtained for the receiver with all three intended detection schemes, in comparison to approximation methods within the existing literature; considering simulated results with respective detection schemes as reference. The proposed frameworks are expected to be helpful for engineers to approximate the system performance accurately for a symmetric transmitter receiver MIMO communication model. A cooperative resource selection and transmission scheme is proposed to improve the performance of the WSNs in terms of link reliability. A measure of channel quality index is proposed to obtain dynamic adaptivity and to optimise resource usage within WSNs according to environmental conditions.

The performance of the proposed analytical framework is presented for the ZF, MMSE and ML detection schemes for MIMO wireless communication systems. The proposed framework provides a tighter lower bound in comparison to the existing bounds in terms of the bit error rate or symbol error rate. This will facilitates the system design engineers to select the required transmit receive antennae combinations for a given QoS. Furthermore, the performance of the frameworks in terms of reliability, computational complexity and outage probability is also analysed. The results and analyses provide the performance comparison for the proposed adaptive transmission, proposed transmit receive antennae selection, proposed hybrid, lattice reduction and conventional cooperative transmission schemes in terms of detection reliability, computational complexity and outage probability. It is observed that the lattice reduction based signal design, CQI based adaptive transmission and hybrid schemes achieves the targeted bit error rate at a lower signal-to-noise ratio compared to other presented schemes. Moreover, the lattice reduction based signal design and CQI based adaptive transmission schemes have a lower computational complexity compared to a hybrid scheme. However, the hybrid scheme performs data transmission with one less transmit receive antennae pair compared to the lattice reduction based signal design scheme. Moreover, the adaptive transmission scheme optimises resource usage and conserves energy while selecting all the presented schemes based on the CQI which is received from the FCR through a feedback link.

The next chapter builds on a unified framework that incorporates universal and dynamic clustering schemes and a channel quality based adaptive transmission scheme. The proposed framework is expected to provide energy efficient and reliable sensing and communication in resource constrained environments. Moreover, it is expected to provide a trade-off between network lifetime and transmission reliability.

Chapter 5

Unified Framework of Collaborative Sensing and Communication Schemes

5.1 Introduction

Energy conservation is one of the key challenges in the design of WSNs. Lifetime enhancement is expected to be achieved regardless of the type of application, without compromising the required QoS. This can be achieved by introducing collaboration among sensor nodes to optimise the energy consumption while performing sensing and communication tasks. Self-organisation of WSNs is desirable to balance the energy consumption among the sensor nodes by dynamically rotating the cluster head role among the sensor nodes. Moreover, energy optimisation is expected to be achieved by involving a minimum number of sensor nodes and optimising the network communication required to report an event. Also, dynamic adaptivity and optimisation of resource usage according to the radio frequency propagation in variable environment conditions based communication methods can provide progressive accuracy, and optimise processing and communication for signal transmission.

In this chapter, a unified framework is proposed that is expected to support applications independent of the type of sensing, and provide reliable and robust performance in resource a constrained environment. The unified framework comprised of twofold: a dynamic clustering and neighbourhood formation scheme proposed in Chapter Three to provide an energy efficient and universal solution for collaborative sensing, and an adaptive transmission based on channel quality measure as proposed in Chapter 4 to provide an adequate decision on the selection of appropriate degree of cooperation. The unified framework is expected to enhance network lifetime and transmission reliability by using optimum resources during sensing and communication. The resource usage is expected to be adaptive during communication to dynamically adjust the variable environment conditions.

5.2 Proposed Unified Framework

A unified framework of collaborative sensing and communication schemes for cooperative WSNs is presented in this section. This framework incorporates a universal and dynamic clustering scheme, and channel quality based adaptive transmission scheme. Figure 5.1 presents a block diagram summarising the methodological steps of the proposed unified framework for collaborative sensing and communication within cooperative WSNs. The dynamic clustering and neighbourhood formation scheme is expected to perform energy efficient sensing. Thereafter, the sensing data is transmitted to the FCR through cooperative nodes. Transmission diversity is expected to be achieved to maintain the required QoS. The degree of cooperation among sensor nodes is adaptive based on the variable radio frequency propagation conditions to maintain the link reliability.

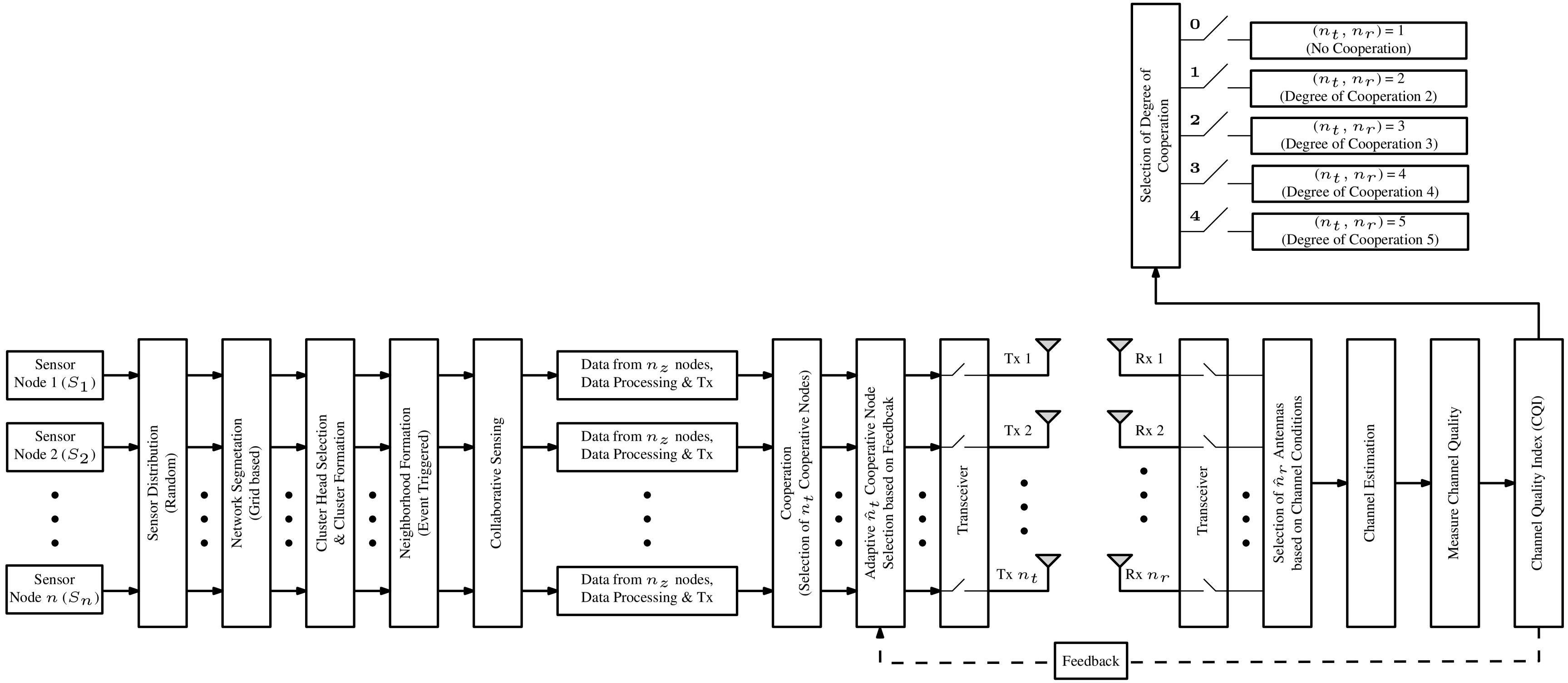

FIGURE 5.1: Block diagram summarising the methodological steps of the proposed unified framework for collaborative sensing and communication within cooperative WSNs.

The network lifetime model presented in Chapter Three. Section 3.3 is extended for cooperation among sensor nodes during data transmission to exploit the diversity. Equation 3.48 can be defined as:

$$E_{o.r_{div}} = E_{IntraC} + E_{InterC} + E_{Lh_{div}} \tag{5.1}$$

where $E_{Lh_{div}}$ defined in Equation 3.45 can be presented as:

$$E_{Lh_{div}} = \sum_{k=1}^{\hat{n}_t - 1} qL_{da}E^k_{col.} + \sum_{k=1}^{\hat{n}_t} qL_{da}E^k_{lh} \tag{5.2}$$

Therefore, Equation 5.1 can be simplified for $E_{Lh_{div}}$ by substituting Equation 3.31 and Equation 3.42 into Equation 5.3 which is defined as:

$$\begin{aligned} E_{o.r} = & \sum_{j=1}^{q}\left(\sum_{i=1}^{\hat{p}} LE^j_{s(\check{i})} + LE^j_{ch}\hat{p}_j\right) + \left(\sum_{j=1}^{\hat{q}} L_{da}E^j_{n.coop} + \hat{q}L_{da}E_{coop}\right) \\ & + \left(\sum_{k=1}^{\hat{n}_t-1} qL_{da}E^k_{col.} + \sum_{k=1}^{\hat{n}_t} qL_{da}E^k_{lh}\right) \end{aligned} \tag{5.3}$$

As $\hat{q} \gg n_t$, so let us assume $q \approx \hat{q}$, so it can further be simplified into Equation 5.4 and Equation 5.5, which are derived as:

$$\begin{aligned} = & \frac{Lq\hat{p}}{R_b}\left(\mathcal{P}(d_2)^2 + P_{c_{tx}} + E_{da}P_{c_{rx}}\right) + \frac{\hat{q}L_{da}}{R_b}\left(\mathcal{P}(d_4)^2 + P_{c_{tx}} + P_{c_{rx}}\right) \\ & + \frac{qL_{da}\hat{n}_t}{R_b}\left(\mathcal{P}(d_5)^2 + P_{c_{tx}} + P_{c_{rx}}\right) + \frac{qL_{da}\hat{n}_t}{R_b}\left(\mathcal{P}(d_6)^2 + P_{c_{tx}} + P_{syn}\right) \end{aligned} \tag{5.4}$$

$$= \frac{\mathcal{Q}}{R_b}\Bigg[\Bigg((1+\alpha)\bar{E}_b R_b \frac{(4\pi)^2}{G_t G_r \lambda^2} M_l N_f \left(\mathcal{N} L \mathcal{D}^2 + L_{da} d_4^2 + L_{da} \hat{n}_t (d_5^2 + d_6^2)\right)\Bigg)$$
$$+(\mathcal{N}L + L_{da} + 2\hat{n}_t L_{da}) P_{c_{tx}} + (\mathcal{N} L E_{da} + L_{da} + \hat{n}_t L_{da}) P_{c_{rx}} + \hat{n}_t L_{da} P_{syn}\Bigg] \tag{5.5}$$

where Equation 5.5 provides a generalised equation for energy consumption of time-driven, event-driven or hybrid sensing scenario. Based on the type of sensing, the parameters in Equation 5.5 are obtained as follows:

$$\begin{cases} \mathcal{Q} = q, \mathcal{N} = \hat{p}, \mathcal{D} = d_2 & \text{Time-driven} \\ \mathcal{Q} = k, \mathcal{N} = n_b^k, \mathcal{D} = d_7 & \text{Event-driven} \end{cases}$$

A channel quality index (CQI) model presented in Chapter Four is used to define a measure that maps the frame error probability. It is expected that CQI based adaptation will provide robustness against signal distortions and interference caused by propagation and channel conditions respectively. Also, it will provide adequate decision on the degree of cooperation in order to maintain link reliability. The measure of CQI as defined in Equation 4.9 can be presented as:

$$\text{CQI} = f(\tilde{\text{E}}[(\mathbf{\Lambda} - \boldsymbol{\mu})^2]) \tag{5.6}$$

where $\tilde{\text{E}}$ denotes the expectation value and CQI can be simplified as:

$$\text{CQI} = \frac{1}{n_t}\sum_{\hat{i}=1}^{n_t} \mid \mathbf{\Lambda}_{\hat{i}} - \mu \mid^2 \tag{5.7}$$

where

$$\mu = \frac{1}{n_r} \sum_{\hat{j}=1}^{n_r} \boldsymbol{\lambda}_{\hat{j}} \tag{5.8}$$

where $\boldsymbol{\Lambda}$ is a set of eigen vector channel coefficient matrix $\mathbf{H}$ of dimension $(n_r \times 1)$ which is defined as:

$$\boldsymbol{\Lambda} = \{\boldsymbol{\lambda}_{\hat{j}} \mid \hat{j} = 1, 2, \ldots, n_r\} \tag{5.9}$$

where $\lambda_{(\cdot)}$ represents the eigen values of the channel coefficients. The degree of cooperation is to be selected based on classification of signal propagation conditions that can be acquired from the CQI which is indexed from one to the required degree of considered cooperation. The higher index refers to the requirement of higher degree of cooperation in order to maintain the required QoS. The decision on the selection of degree of cooperation is shown in Figure 5.2 and presented in Table 5.1.

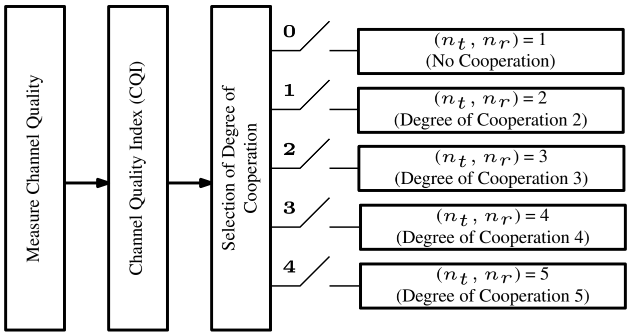

FIGURE 5.2: Block Diagram for Channel Quality Index.

TABLE 5.1: Channel classification and degree of cooperation selection criterion.

Normalised Channel Quality Measure	**<0.4**	**0.4-0.55**	**0.55-0.7**	**0.7-0.85**	**>0.85**
CQI	0	1	2	3	4
Seletion of Degree of Cooperation	$(n_t, n_r) = 1$	$(n_t, n_r) = 2$	$(n_t, n_r) = 3$	$(n_t, n_r) = 4$	$(n_t, n_r) = 5$

5.3 Performance Analysis

The performance analysis of the proposed unified framework is presented which is expected to provide energy efficient and reliable sensing and communication in resource constrained environments. Transmission diversity is expected to be achieved based on the channel conditions. To select the appropriate degree of cooperation adaptively, based on the information from the FCR through a feedback link, a measure of CQI has been proposed in Equation 5.6 and decision boundaries of CQI values which have been considered to select the appropriate degree of cooperation which is presented in Table 5.1. Table 3.1 presents the parameter values considered in the simulations.

5.3.1 Performance Analysis of the Unified Framework

The network lifetime analysis with cooperation among the sensor nodes while transmitting the data to the FCR is presented. The simulation parameters are considered as provided by the authors in [140]. The simulation results presented in Fig. 5.3 demonstrates that the FND, HND and LND for the proposed scheme at 601, 2101 and 2801 rounds respectively for $(n_t, n_r) = 2$. While for the COOP-LEACH presented in [140] the FND, HND and LND at 890, 3165 and 4643 rounds respectively for $(n_t, n_r) = 2$. Similarly, the LND for the proposed scheme and the COOP-LEACH at 4185 and 2251 rounds respectively when $(n_t, n_r) = 3$, at 3756 and 1801 rounds respectively when $(n_t, n_r) = 4$, and at 3145 and 1551 rounds respectively when $(n_t, n_r) = 5$. Hence, the proposed scheme increases the network lifetime by 50.6%, 35%, 40.5% and 49% with $(n_t, n_r) = 2$, 3, 4 and 5 respectively for 50% alive nodes as compared to COOP-LEACH; while cooperation among the sensor nodes is exploiting diversity to achieve transmission reliability.

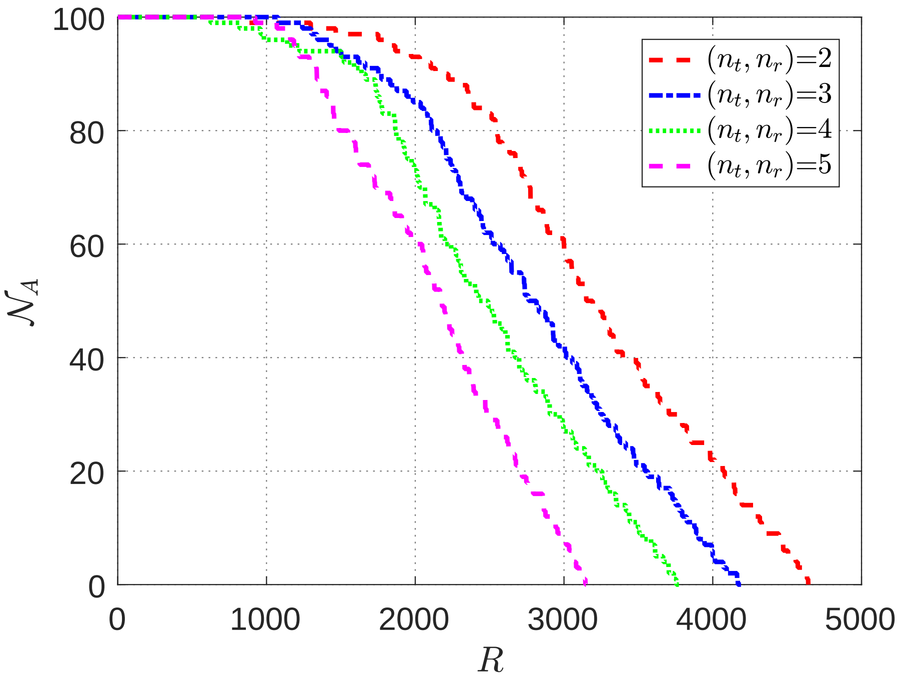

FIGURE 5.3: Performance analysis of the proposed scheme for cooperative communication realising virtual MIMO transmission and exploiting diversity for number of alive nodes $\mathcal{N}_A$ and rounds R.

A detailed comparison analysis of the proposed dynamic clustering scheme with the aforementioned existing schemes is presented in Table 5.2. It is validated from Table 5.2 that the proposed scheme outperforms the existing schemes.

Table 5.2: Comparison of the proposed dynamic clustering scheme with the existing scheme for homogeneous and heterogeneous WSNs.

Protocols	**Degree of Cooperation**	**Activity Factor**		
		100%	**50%**	**0**
COOP-LEACH	Diversity 2	600	2100	2800
Proposed		**889**	**3164**	**4642**
COOP-LEACH	Diversity 3	1030	2075	2250
Proposed		**1087**	**2794**	**4184**
COOP-LEACH	Diversity 4	1250	1750	1800
Proposed		**625**	**2461**	**3755**
COOP-LEACH	Diversity 5	1150	1450	1550
Proposed		**925**	**2179**	**3144**

5.3.2 Performance Analysis of the Proposed Unified Framework

The performance analysis of the proposed framework for time-driven, event-driven and hybrid sensing scenarios are presented in this section. It is assumed that the location of the events is randomly distributed and their occurrence is at least 10 m away from each other. The network lifetime analysis is presented in Figure 5.4, Figure 5.6 and Figure 5.8 for time-driven, event-driven and hybrid scenarios respectively. To achieve transmission reliability, cooperation among sensor nodes is considered during data transmission to the FCR. Moreover, performance analysis of the proposed schemes in terms of the average residual energy per node is presented in Figure 5.5, Figure 5.7 and Figure 5.9 for time-driven, event-driven and hybrid scenarios respectively. Figure 5.10 demonstrates that the higher degree of cooperation increases the detection reliability. It is found that by increasing the number of cooperative sensor nodes, the proposed universal framework provides a trade-off between the network lifetime and data transmission reliability. Also, exploiting diversity quantifies the signal to noise ratio (SNR) gain of 13 dB, 17.5 dB, 20 dB and 21.5 dB with a decrease in network lifetime by 20%, 35.2%, 38.4% and 50.8% for degree of cooperation 2, 3, 4 and 5 respectively to achieve 10^{-3} probability of error $\mathcal{P}_e$ compared to conventional transmission. A detailed performance comparison of the proposed scheme is described in Table 5.3.

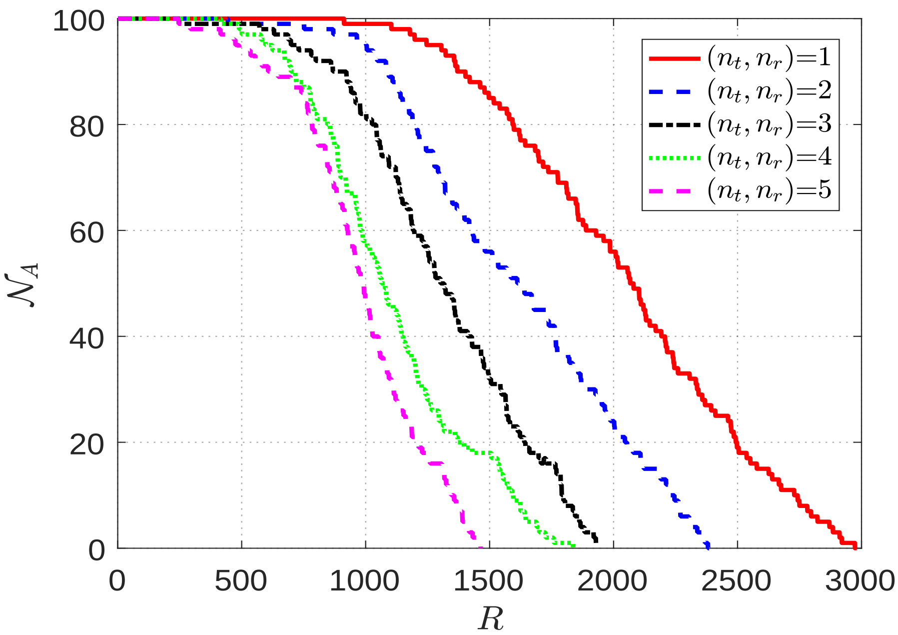

Figure 5.4: Performance analysis of the proposed scheme for time-driven applications for the number of alive nodes $\mathcal{N}_A$ and rounds R.

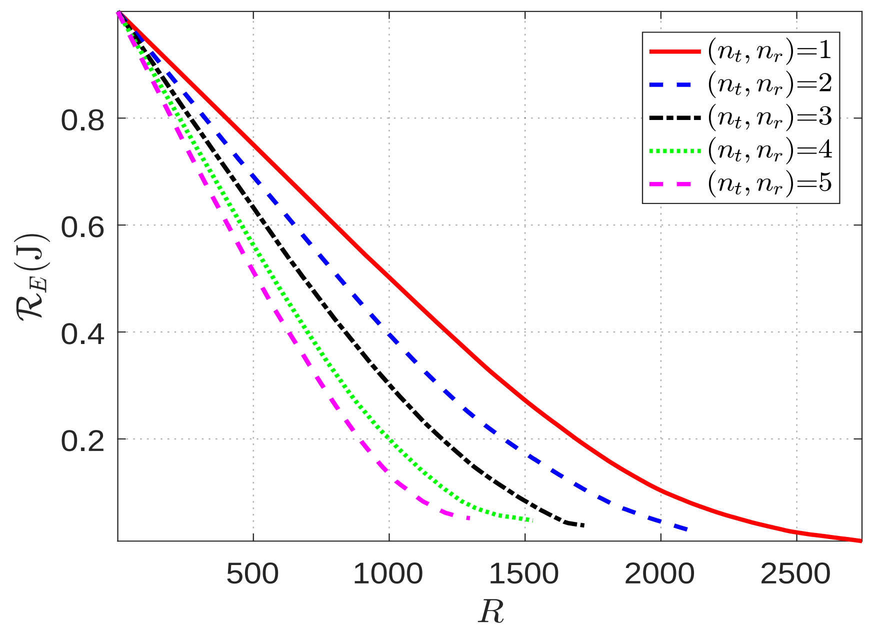

FIGURE 5.5: Performance analysis of the proposed scheme for time-driven applications for the average residual energy $\mathcal{R}_E$ and rounds R.

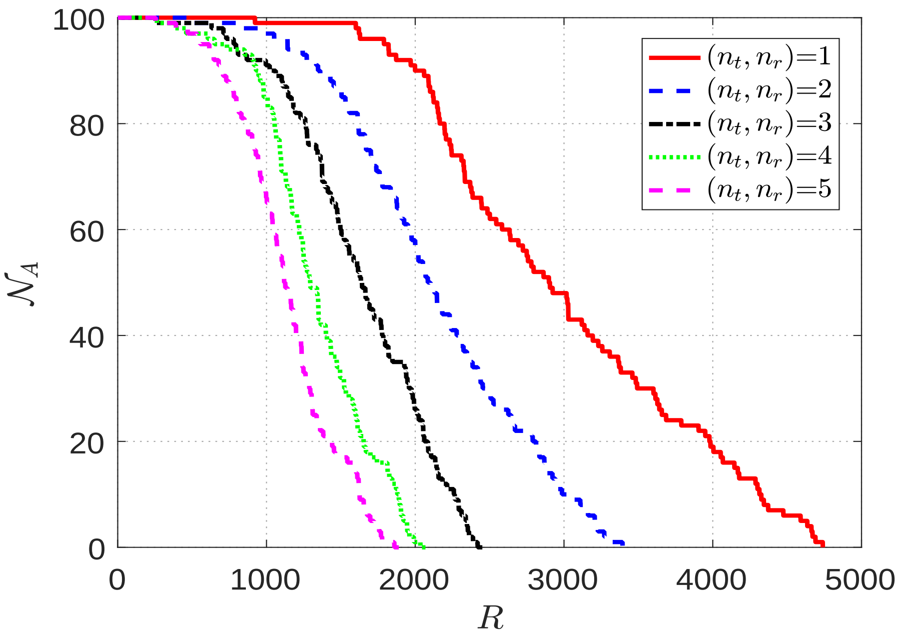

FIGURE 5.6: Performance analysis of the proposed scheme for event-driven applications for the number of alive nodes $\mathcal{N}_A$ and rounds R.

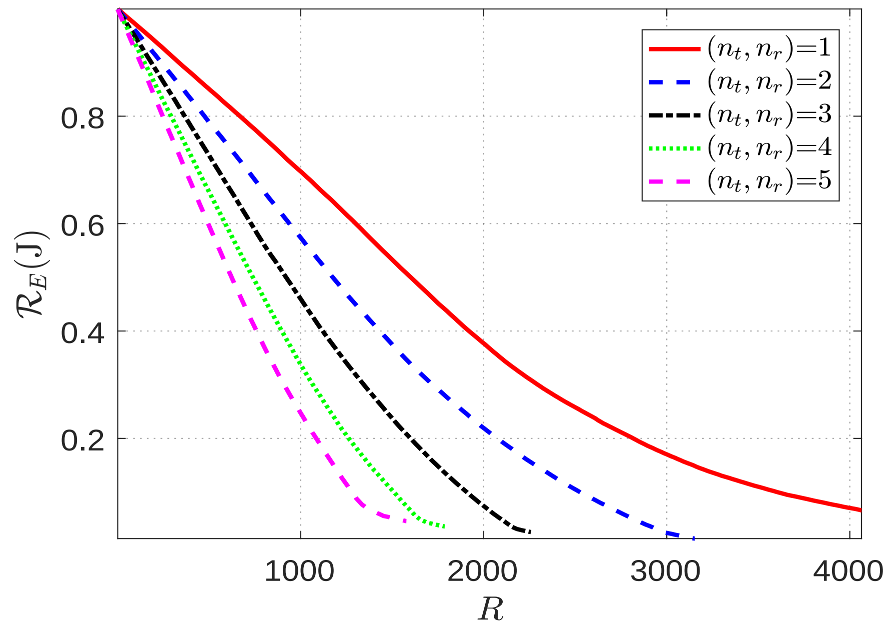

FIGURE 5.7: Performance analysis of the proposed scheme for event-driven applications for the average residual energy $\mathcal{R}_E$ and rounds R.

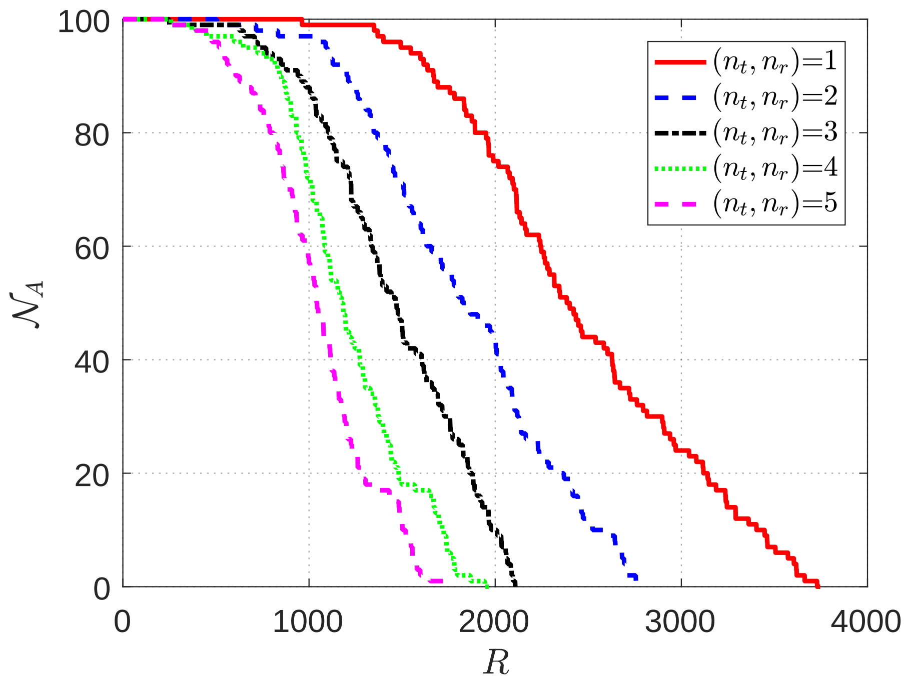

FIGURE 5.8: Performance analysis of the proposed scheme for hybrid applications for the number of alive nodes $\mathcal{N}_A$ and rounds R.

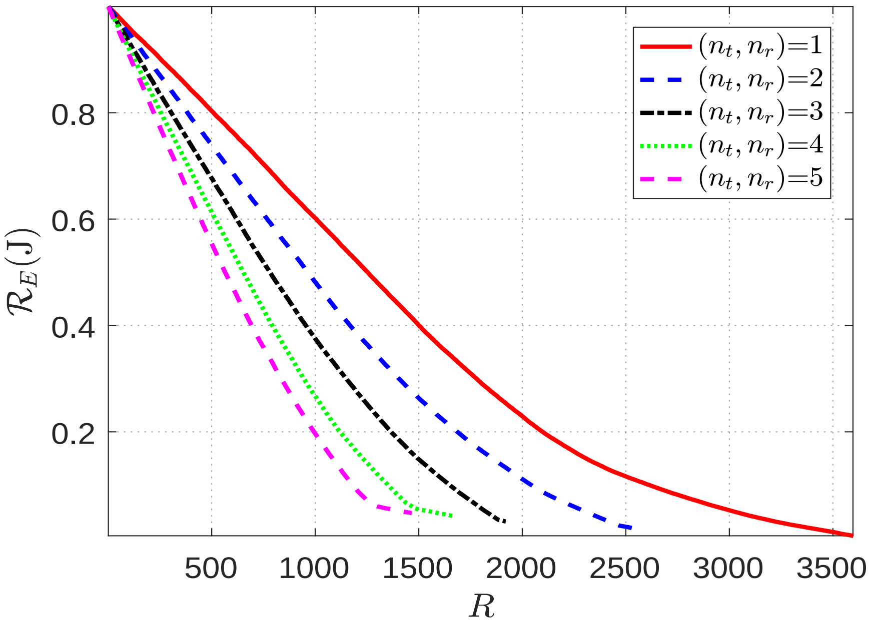

FIGURE 5.9: Performance analysis of the proposed scheme for hybrid applications for the average residual energy $\mathcal{R}_E$ and rounds R.

TABLE 5.3: Performance analysis of the proposed universal framework for time-driven, event-driven and hybrid scenario within WSNs.

Cooperation (No. of Nodes & Type)	**Sensing Type**	**Activity Factor**			**Residual Energy**		**SNR (dB) for $\mathcal{P}_e$ (10^{-3})**	**Trade-off**	
		100%	**50%**	**0**	**50%**	**20%**		**Reduction in Active Time**	**SNR Gain**
1	TD	912	2073	2979	1002	1687	27 dB	-	-
	ED	922	2905	4740	1600	2817		-	
	Hybrid	950	2389	3738	1254	2095		-	
2 Diversity	TD	439	1616	2381	816	1425	14 dB	20%	13 dB
	ED	507	2085	3394	1178	2080		28.4%	
	Hybrid	505	1839	2760	965	1689		26.16%	
3 Diversity	TD	245	1314	1929	682	1193	9.5 dB	35.25%	17.5dB
	ED	260	1642	2420	920	1601		48.9%	
	Hybrid	250	1468	2108	782	1366		43.6%	
4 Diversity	TD	412	1074	1837	573	998	7 dB	38.34%	20dB
	ED	255	1294	2064	739	1263		56.46%	
	Hybrid	246	1183	1966	648	1117		47.41%	
5 Diversity	TD	245	989	1464	516	889	5.5 dB	50.86%	21.5dB
	ED	249	1125	1863	623	1082		60.7%	
	Hybrid	245	1041	1743	564	994		53.3%	

5.3.3 Performance Analysis of the Proposed Universal Framework with CQI

In this section, the performance analysis of the proposed framework with the adaptation of variable conditions of channel propagation is presented. It is assumed that the FCR is equipped with multiple antennae to act as a virtual MIMO system, while receiving data from the cooperative sensor nodes. Figure 5.10 demonstrates the probability of error for a given range of signal quality i.e. 0 to 40 dB which is simulated from Equation 5.10 as stated in [141].

$$\mathcal{P}_b = \left[\tfrac{1}{2}(1-\mu)\right]^L \sum_{\hat{l}=0}^{L-1} \binom{L-1+\hat{l}}{\hat{l}} \left[\tfrac{1}{2}(1+\mu)\right]^{\hat{l}} \tag{5.10}$$

where $\mu = \sqrt{\frac{\gamma}{1+\gamma}}$ with average received SNR γ and L represents the total number of bits in one transmission. The effect of dynamic adaptation in the selection of number of cooperative nodes based on the signal propagation conditions to maintain the required QoS are presented in Figure 5.11, Figure 5.12 and Figure 5.13 on probability of error, number of alive nodes and average residual energy of the network respectively. Let's τ_5 represent the set of transmit receive antennae $\{1, 2, 3, 4, 5\}$, τ_5^- is $\min\{\tau_5\}$ and τ_5^+ is $\max\{\tau_5\}$.

It is observed that the adaptive selection of number of cooperative nodes enhances the detection reliability and network lifetime compared to τ_5^- and τ_5^+ number of cooperative nodes. For $\tau_4 = \{1, 2, 3, 4\}$, the CQI based cooperative transmission for the hybrid scheme can enhance network lifetime by 12.5% and achieve a 17.5 dB SNR gain compared to τ_4^+ and τ_4^- respectively. The performance comparison of the hybrid scheme with adaptive transmission, conventional cooperative transmission $(n_t, n_r) = 1$ and virtual MIMO diversity for $(n_t, n_r) = 2$ are presented in Figure 5.14 and Figure 5.15. It is found that the dynamic property of the proposed framework provides a trade-off between network lifetime and detection reliability. It is observed that proposed scheme enhances the network lifetime by

14% compared to τ_2^+ with a cost of 3 dB SNR. Moreover, it achieves 5 dB SNR gain compared to τ_2^- with a cost of 15.8% network lifetime. A detailed comparison of the proposed hybrid scheme with adaptive cooperative transmission is summarised in Table 5.4.

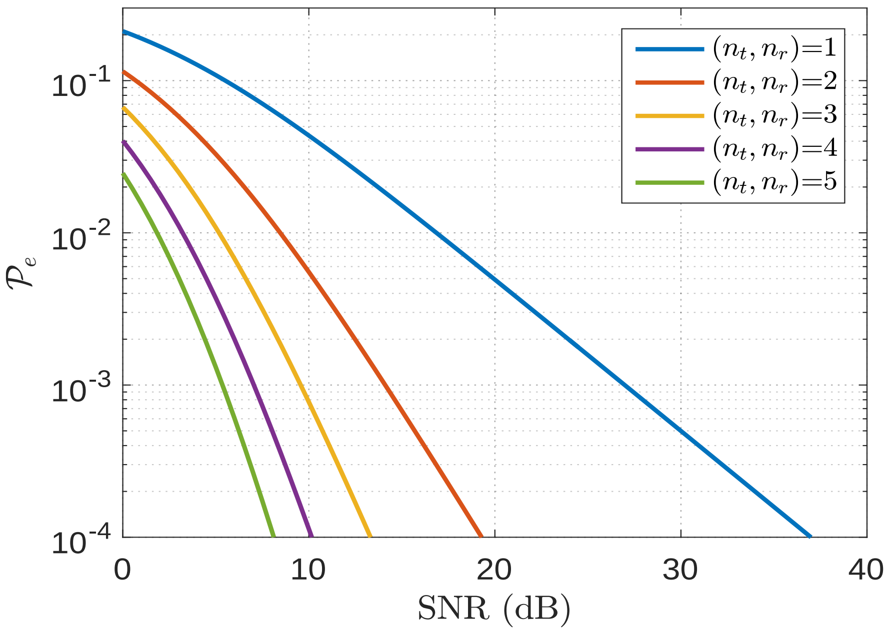

Figure 5.10: Probability of error for conventional transmission with one transmit-receive antennae pair and cooperative transmission for degree of diversity two, three, four and five.

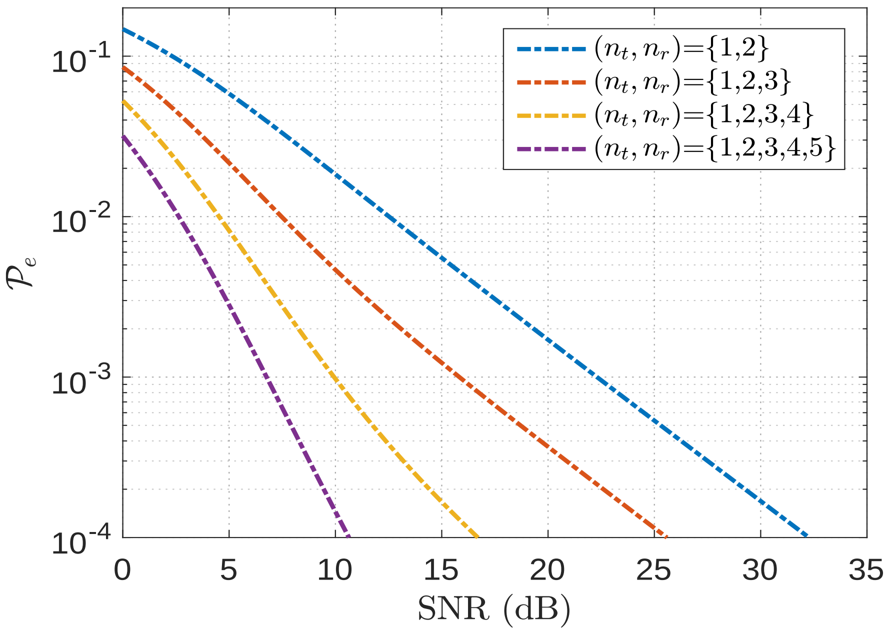

FIGURE 5.11: Probability of error for cooperative transmission with channel quality index (CQI) based adaptation for degree of diversity two, three, four and five.

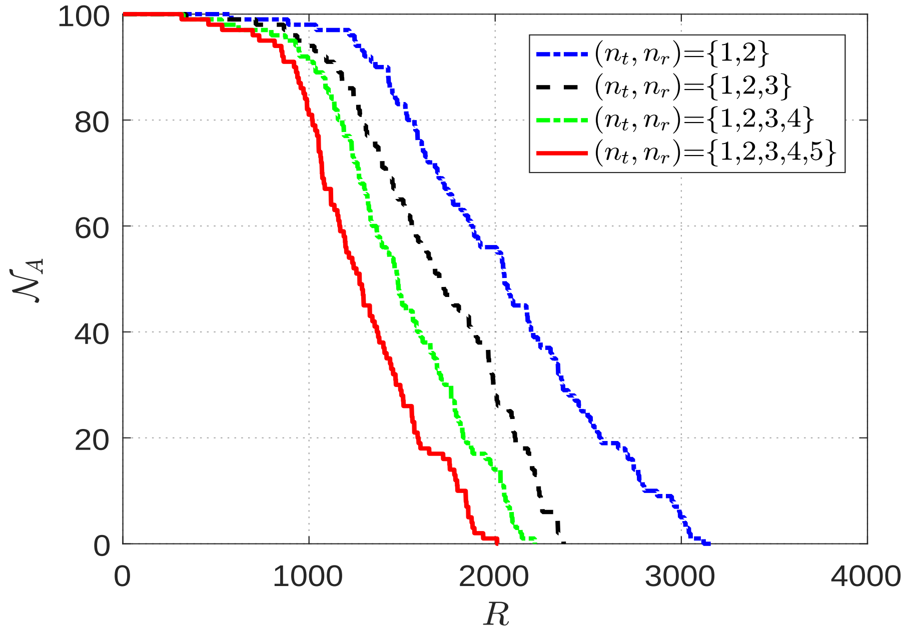

FIGURE 5.12: Performance analysis of the proposed universal framework with channel quality index (CQI) based adaptation for number of alive nodes $\mathcal{N}_A$ and rounds R.

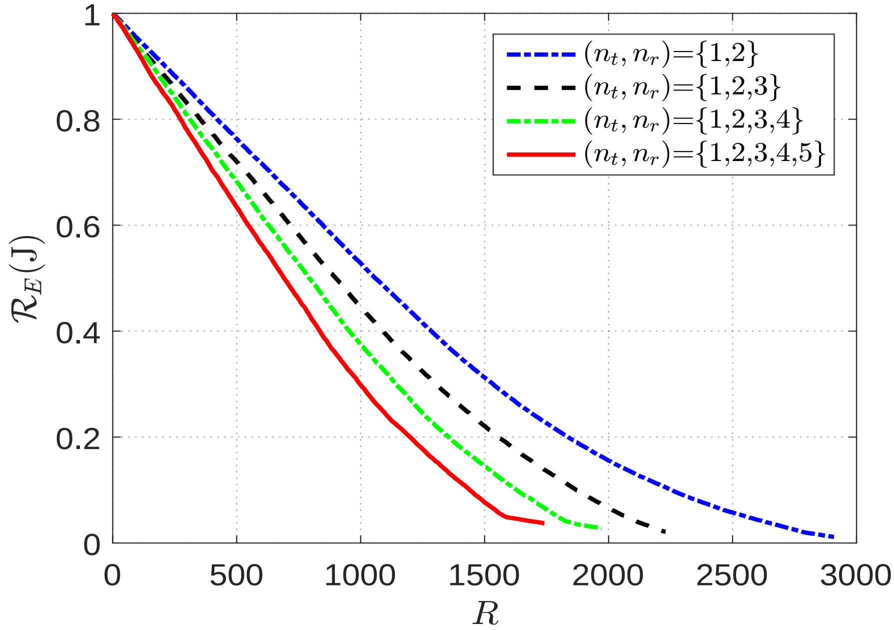

FIGURE 5.13: Performance analysis of the proposed universal framework channel quality index (CQI) based adaptation for average residual energy $\mathcal{R}_E$ and rounds R.

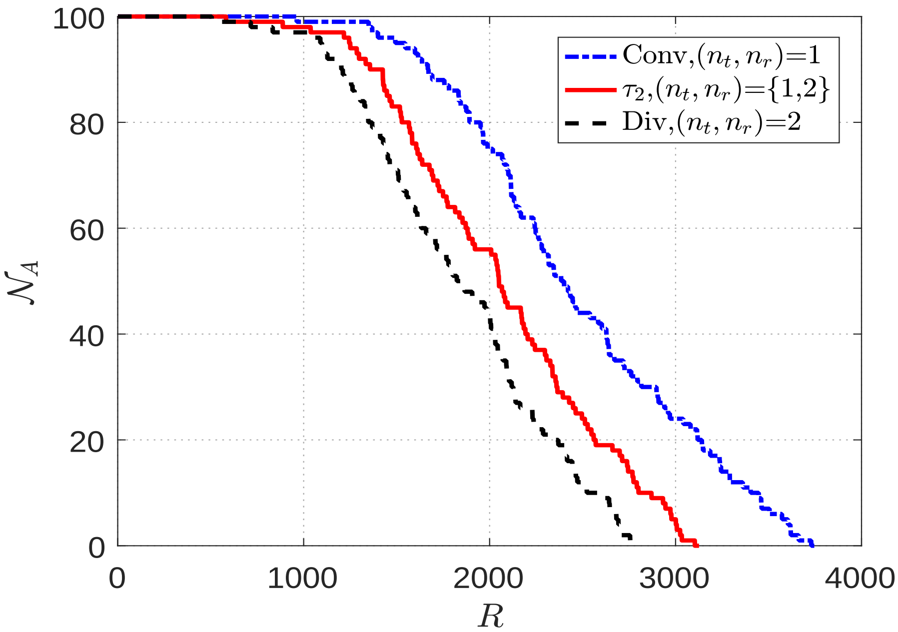

FIGURE 5.14: Performance comparison of the proposed universal framework channel quality index (CQI) based adaptation (n_t, n_r) = {1,2}, conventional cooperative transmission (n_t, n_r) = 1 and virtual MIMO diversity for (n_t, n_r) = 2 for number of alive nodes $\mathcal{N}_A$ and rounds R.

TABLE 5.4: Performance analysis of the proposed universal framework with CQI based adaptation for network lifetime and detection reliability.

CQI based Adaptation ($\tau_{(\cdot)}$)	**Activity Factor**			**Res. Energy**		**SNR (dB) for** $\mathcal{P}_e$ (10^{-3})	**Trade off**					
							Activity Factor		**Res. Energy**		**SNR Gain**	
	100%	**50%**	**0**	**50%**	**20%**		τ^-	τ^+	τ^-	τ^+	τ^-	τ^+
$\tau_2 = [1,2]$	582	2050	3147	1054	1837	22dB	-15.8%	14%	-12.3%	8.7%	5dB	-3dB
$\tau_3 = [1,2,3]$	356	1705	2367	898	1525	15.5dB	-36.6%	12.2%	-27.2%	11.6%	11.5dB	-6dB
$\tau_4 = [1,2,3,4]$	340	1474	2213	792	1353	9.5dB	-40.8%	12.5%	-35.4%	21.1%	17.5dB	-2.5dB
$\tau_5 = [1,2,3,4,5]$	315	1272	2011	689	1195	7dB	-46.2%	15.4%	-42.9%	20.2%	20dB	-1.5dB

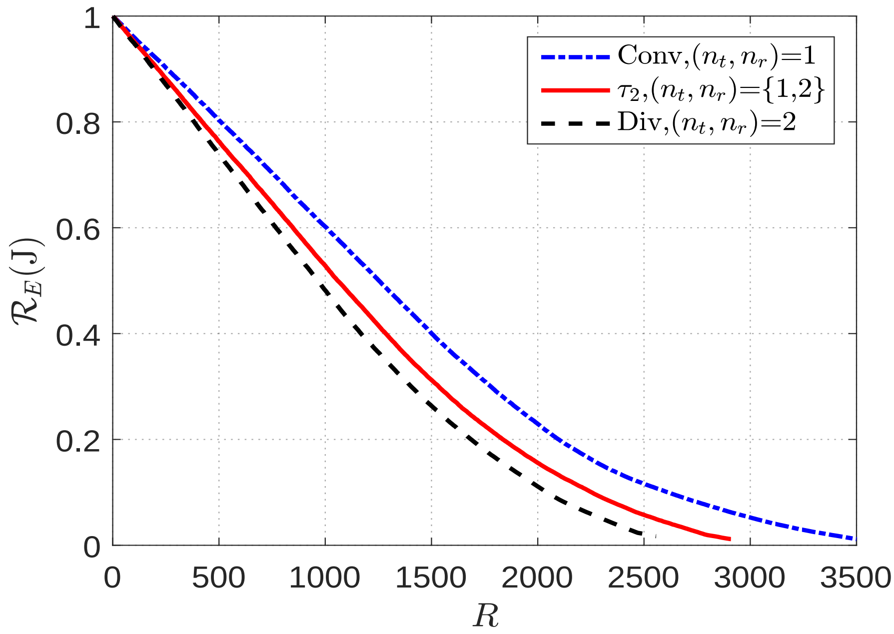

FIGURE 5.15: Performance comparison of the proposed universal framework channel quality index (CQI) based adaptation (n_t, n_r) = {1,2}, conventional cooperative transmission (n_t, n_r) = 1 and virtual MIMO diversity for (n_t, n_r) = 2 for average residual energy $\mathcal{R}_E$ and rounds R.

5.4 Summary

In this chapter, a unified framework of collaborative sensing and communication schemes is presented for cooperative WSNs that comprises of dynamic clustering and neighbourhood formation scheme as well as a channel quality based adaptive transmission scheme. The dynamic grouping of sensor nodes and adaptive configuration of the network provides a reliable and energy efficient solution to monitor, detect and collect various significant occurrences of events throughout the network. Moreover, the adaptive transmission based on channel quality provides a robust solution against time-varying behaviour of the propagation environment. The proposed framework is universal in behaviour as it is applicable to the applications which require either time-driven sensing, event-driven sensing or both. Moreover, it dynamically adapts the resource usage according to the channel quality while providing the required QoS.

The performance analysis of the proposed unified framework is presented for time-driven sensing, event-driven sensing and hybrid sensing scenarios. It is validated from the simulation results that the proposed framework ensures an even distribution of energy demand among the sensor nodes and minimises the number of sensor nodes involved in detection and reporting of events. Moreover, it provides an energy efficient solution, independent of the sensing type. An adaptive cooperation among sensor nodes and the FCR based on the channel quality, attains transmission reliability while utilising optimum resources. A measure of channel quality is presented that provides an adequate decision on the adaptation of the appropriate degree of cooperation. A network lifetime model is also presented for transmission diversity based on communication between the sensor nodes and the FCR. The proposed framework is analysed for network lifetime, average residual energy and transmission reliability for different sensing scenarios and degree of cooperation. It is observed from the simulation results that the proposed unified framework provides a trade-off between the network lifetime and transmission reliability.

The next chapter builds on the research challenges, concluding remarks and future work based on the proposed work presented in this study.

Chapter 6

Conclusions and Future Directions

6.1 Conclusions

The recent advances in technology and significant amount of efforts from the research communities make the implementation of WSNs possible to fulfil the unique requirements of diverse range of applications. Regardless of the nature of sensing application requirements, WSNs are usually formed with spatially dispersed and dedicated sensor nodes which collectively monitor and distribute information to the desired destinations. Sensor nodes are inexpensive resource constrained devices that consist of a sensor, embedded processors, limited memory, low power radio, and are normally powered by a battery. WSNs usually suffers from inevitable problems because of resource constrained sensor nodes deployed randomly in hostile environments which makes it difficult to change or replace their batteries. Consequently, lifetime enhancement is one of the key issues while designing the WSNs regardless of the type of application, without compromising the required QoS. Moreover, the implementation of WSNs in inaccessible terrains or hostile environments necessitates random deployment of sensor nodes which requires the development of self-organising protocols. Such protocols are expected to achieve scalability and energy efficiency by enhancing load balancing, fault tolerance and network connectivity within the network. Moreover, self-organising of the network is a desirable feature as no centralised or external entity is required and can contribute to energy conservation by evenly distributing the energy demand among sensor nodes throughout the network.

Within WSNs, sophisticated and efficient protocols are essential to support most of the applications. High dependency on a single node for data transmission to the FCR may lead to a reliability risk in severe network conditions such as the least amount of available energy at a sensor node or deep channel fading etc. Hence, energy efficient communication schemes are needed to be defined to focus on minimising the energy consumption during communication. Cooperation among sensor nodes during data transmission allows resource saving within WSNs by implementing virtual MIMO concepts for energy efficient communication to increase the reliability and enhance the energy efficiency. One of the design challenges of WSNs is to make them adaptive with the dynamic propagation environmental conditions of radio frequency to guarantee the QoS based on application requirements. It is also expected to obtain maximum transmit-receive reliability with optimum usage of radio resources such as power and bandwidth. In order to resolve the aforementioned research challenges within resource constrained WSNs, this study proposed energy efficient and reliable design solutions for collaborative sensing and communication schemes.

6.1.1 Universal and Dynamic Clustering Framework for Collaborative Sensing

In this thesis, a dynamic clustering and neighbourhood formation scheme is presented to evenly distribute the network load among sensor nodes throughout the network and optimise the number of sensor nodes required to report events. It is pertinent that the network is self-organising and the cluster heads are elected in distributive manner. The cluster head's election criterion is supported by soft decision and hard decision, based on the residual energy of candidate sensor nodes. The soft decision based cluster head's election criterion balances the energy consumption throughout the network at the cost of a higher rate of re-clustering as compared to hard decision. The cluster heads are elected in a manner to dynamically form the optimal size cluster heads. Within the context of event-driven sensing, the neighbourhood formation scheme provides an energy efficient solution by selecting the optimum number of sensor nodes to detect and report events. Furthermore, a cooperation based multi-hop communication approach between the cluster heads is considered for data transmission to the FCR which minimises the energy consumption. The distributive and dynamic behaviour of the proposed framework provides an energy efficient self-organising solution for WSNs that results in an improved network lifetime.

The performance of the proposed dynamic clustering and neighbourhood formation scheme is evaluated through simulations. Assuming random deployment of sensor nodes, the cluster heads are elected in a distributive manner utilising the soft or hard decision criterion. Once all the cluster heads are elected in the network, the non-cluster head sensor nodes join the cluster heads which are at minimum transmission distance to form optimal size clusters. Moreover, grouping of sensor nodes in response to an event is also presented. The neighbourhoods are formed to minimise the number of sensor nodes involved in event reporting. Afterwards, a network lifetime model is derived to find the performance of the proposed framework that reflects the quality of network coverage and connectivity. The performance of the proposed framework is evaluated for homogeneous and heterogenous WSNs. It is observed from simulation results that the proposed framework enhances the network lifetime by 83% and 15.4% for homogeneous and heterogeneous WSNs respectively. Moreover, it is observed that the proposed framework facilitates the applications independently of the sensing type requirement. It is validated from simulation results that the proposed dynamic clustering and neighbourhood formation scheme outperforms the existing solutions in energy conservation.

6.1.2 CQI-centric Resource Allocation Framework for Cooperative Communication

Considering the energy constraints within WSNs, "an adaptation criterion-based resource selection model is proposed. By adopting collaborative nature of WSNs, a set of cooperative transmission frameworks have been proposed. The basis of adaptation criterion is a perfect estimate of the channel state information at the receiver, which has been assumed to be fed back to the transmitter" [1]. A channel quality based transmit receive antennae selection is presented to mitigate the effect of channel fading. This approach saves energy as well as achieves the required QoS by turning off the antennae pairs that are suffering from deep channel fading. To minimise the effect of noise and interference on the transmit signal, a lattice reduction based transmit signal design scheme is also presented. Afterwards, a measure of the channel quality is presented to enable the appropriate decisions on the selection of suitable optimisation scheme adaptively according to the variable channel conditions. Such adaptation is based on the information estimated at the FCR and fed-back to the transmitter. For the ease of the system design engineer to achieve a predefined capacity or QoS, analytical frameworks that provide tighter error performance lower bound for ZF, MMSE and ML detection schemes are also presented.

The performance of the proposed CQI-centric resource allocation framework for cooperative communication is evaluated through simulations. It is observed from simulation results that the transmit receiver antennae selection scheme achieves transmission reliability by minimising the effect of deep channel fading based on the channel quality information. Moreover, the lattice reduction based transmit signal design achieves the highest detection reliability at the expense of higher computational complexity. It is found that the hybrid scheme which incorporates the transmit receiver antennae selection and lattice reduction based transmit signal design schemes "achieves the required detection reliability with significantly lower energy requirement compared with its existing counterparts" [1]. A measure of the channel quality index is proposed to obtain dynamic adaptivity and to optimise resource usage within WSNs according to environment conditions. Tighter approximation has been obtained for the receiver with all three intended detection schemes, in comparison to approximation methods within the existing literature; considering simulated results with respective detection schemes as reference. "Besides this, with the expense of a set of negligible computational complexity, the proposed adaptive transmission scheme is found to be able to save additional energy requirement while providing the same detection reliability" [1]. It is validated from simulation results that the proposed CQI-centric resource allocation framework required only 15% of energy compared to conventional cooperative transmission to achieve 99.99% detection reliability.

6.1.3 Unified Framework of Collaborative Sensing and Communication Schemes

In this thesis, a unified framework of collaborative sensing and communication schemes for cooperative WSNs to provide energy efficient solutions within resource constrained environments have been proposed. The proposed framework is adaptive to the dynamic sensing environment and channel conditions while performing sensing tasks and transmitting data to the FCR respectively. The unification of frameworks comprises of dynamic clustering and a neighbourhood formation scheme as well as a channel quality based adaptive transmission scheme. The dynamic grouping of sensor nodes and adaptive configuration of the network provides a reliable and energy efficient solution to monitor, detect and collect various significant occurrences of events throughout the network. Moreover, the channel quality based adaptive transmission provides a robust solution against time-varying behaviour of the channel conditions. The proposed framework supports the applications which require either time-driven sensing, event-driven sensing or both. Moreover, it dynamically adapts the resource usage according to the channel quality while providing the required QoS.

The performance of the proposed unified framework is evaluated through simulations for time-driven sensing, event-driven sensing and hybrid sensing scenarios while considering variable channel conditions during data transmission. It is observed from the simulation results that the dynamic grouping of sensor nodes and adaptive configuration of the network ensures an even distribution of energy demand among the sensor nodes and minimise the number of sensor nodes involved in the detection and reporting of events. Moreover, it provides an energy efficient solution for time-driven sensing, event-driven sensing and hybrid sensing scenarios. An adaptive cooperation among the sensor nodes and the FCR is considered to exploit transmission diversity. Such adaptation is based on the channel quality to attain transmission reliability while utilising optimum resources. A measure of the channel quality is presented that provides an adequate decision on the adaptation of the appropriate degree of cooperation.

A network lifetime model is also presented for transmission diversity based communication between the sensor nodes and the FCR. The proposed framework is analysed for network lifetime, average residual energy and transmission reliability for different sensing scenarios and degree of cooperation. It is observed from the simulation results that the proposed unified framework enhances the network lifetime by 14% with adaptive transmission compared to conventional cooperative transmission with a cost of 3 dB SNR, while the degree of cooperation is two. Moreover, it achieves 5 dB SNR gain as compared to conventional cooperative transmission with the cost of 15.8% network lifetime. It is validated from simulation results that the unified framework provides a trade-off between the network lifetime and transmission reliability while maintaining the required QoS.

6.2 Future Directions

This thesis contributes to the area of sensing and communication within WSNs by resolving some research challenges faced due to their resource constrained nature by exploiting collaborative and cooperative techniques. There are several directions of the future extension of the work presented in this thesis which are discussed as follows:

6.2.1 Latency-Aware Self-Reconfiguration of Future Generation Networks

Within the future generation of Internet-of-Things (IoT) networks, smart devices are widely distributed. Within predefined coverage, devices can form self-reconfigurable networks as required by smart sensing applications for IoT. Considering large amounts of data handling due to a large number of sensing devices in future networks, latency will be a critical issue. Latency can be considered in the proposed framework to facilitate the networks to be self-reconfigurable based on their residual energy and latency. Moreover, the distributive and dynamic behaviour of the proposed framework can facilitates an energy efficient self-organising solution for future generation networks.

6.2.2 QoS-based Cooperative Communication for IoT

IoT networks are multi-service that can support more than one applications simultaneously. There are two application specific classes for IoT i.e. real time and non-real time with different QoS requirements. Therefore, an adaptive framework is required to serve different applications while fulfilling their required QoS. To provide guaranteed coverage with maximum lifetime, more frequent cooperation would be demanded from smart sensing devices. This can be achieved with real time or non-real time cooperation to optimise connectivity, latency and scalability. The adaptive resource allocation framework proposed in this thesis can be considered to develop optimal solutions that can guarantee QoS requirements for future generation networks.

6.2.3 Context-Aware and Self-Adaptive Routing for IoT Applications

The routing of sensing data from IoT devices to the outer world is a critical task which requires energy efficient routing protocols. The individual IoT device can drop out for several reasons which requires the routing protocol to be self-adaptive and supportive for multi-path routing if needed. Most of the existing solutions for routing protocols are based on energy. Multi-hop routing are considered for energy conservation within WSNs and can be categorised into data-centric, location based and hierarchical. In IoT applications, more intelligent routing techniques based on the environment and network conditions are required. The decisions on the routing path are required to be based on the context analysed from different parts of the network. An energy aware multi-hop routing protocol proposed in this thesis can be considered to develop a context aware routing protocol to provide reliable and energy efficient data transportation for IoT applications.

6.2.4 Energy Efficient and Reliable Sensing and Communication for Smart Cities

Smart city architectures will be based on a diverse range of IoT devices. Advance communication methods are required to support the services needed for the management of the city. Significant developments in heterogeneous communication techniques have facilitated smart city objects to communicate with each other. However, participation of a large number of devices requires energy efficient collaborative sensing and cooperative communication techniques for data transmission. The proposed unified framework presented in this thesis can facilitate dynamic and adaptive sensing and communication solutions for energy efficient data transmission.

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