COMPUTATIONAL INTELLIGENCE ALGORITHMS FOR ENERGY OPTIMIZATION PROBLEMS IN WIRELESS SENSOR NETWORKS

Thesis

Submitted in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

by

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August, 2022

Dedicated to
My Family, Teachers, and Friends

DECLARATION

By the Ph.D. Research Scholar

I hereby declare that the Research Thesis entitled **Computational Intelligence Algorithms for Energy Optimization Problems in Wireless Sensor Networks** which is being submitted to the **National Institute of Technology Karnataka, Surathkal** in partial fulfilment of the requirements for the award of the Degree of **Doctor of Philosophy** in Department of Mathematical and Computational Sciences is a bonafide report of the research work carried out by me. The material contained in this Research Thesis has not been submitted to any University or Institution for the award of any degree.

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Date: August 16, 2022

CERTIFICATE

This is to *certify* that the Research Thesis entitled **COMPUTATIONAL INTELLIGENCE ALGORITHMS FOR ENERGY OPTIMIZATION PROBLEMS IN WIRELESS SENSOR NETWORKS** submitted by **Mr. Chandra Naik**, (Register Number: 177033MA001) as the record of the research work carried out by him, is *accepted as the Research Thesis submission* in partial fulfillment of the requirements for the award of degree of **Doctor of Philosophy**.

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Abstract

Recent advancements in hardware and wireless technology enabled the development of low cost and energy-constrained tiny devices known as sensors that communicate with each other at short distances through a wireless link. The collaborative settings of these tiny devices form a Wireless Sensor Network (WSN). In the recent past, it has gained tremendous interest among researchers and industrial communities due to its wide spectrum of applications in the real world. One of the important issue is coverage of the given set of targets under specified connectivity constraint. The other main issue is the interference of signals in the wireless media. This results in message drop and requires message retransmission which in turn affects the energy efficiency of the network. Energy conservation is the most critical problem in WSN to extend stability or lifetime of the network. Many artificial intelligence methods are proposed in the literature to solve these problems in the wireless sensor network. The first objective of the thesis work is to deploy an optimal number of sensor nodes with k-coverage and m-connectivity constraints in an area of interest. The problem of ensuring all the targets are covered by at least k number of sensor nodes and all the sensor nodes have at least m connectivity with other sensors nodes is termed as k-coverage and m-connectivity problem in WSN. Many meta-heuristic algorithms have been proposed to solve different problems like clustering and localization in WSN. In this work, a novel meta-heuristic based differential evolution algorithm to solve k-coverage and m-connectivity problem in WSN is proposed. The second objective of the thesis is interference minimization in wireless sensor network. Therefore biogeography based optimization and multi-attribute decision making techniques are proposed for sensor placement which minimizes the interference of sensors by preserving connectivity and coverage constraints. The third objective of the thesis is to propose an energy efficient clustering technique using artificial intelligence methods. Therefore a hybrid of game theory and fuzzy logic based hierarchical clustering algorithms are proposed to increase stability of the network. Also, an interference aware clustering technique is proposed using TOPSIS to extend stability of the network. Simulations are carried out to check validity of the proposed methods and compared with other methods.

Keywords: wireless sensor networks; k-coverage and m-connectivity; interference; clustering; meta-heuristic; optimization; fuzzy logic; game theory; artificial intelligence

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Abbreviations and Notations

Abbreviations

WSN	:	Wireless Sensor Network
DE	:	Differential Evolution
BBO	:	Biogeography-Based Optimization
SIR	:	Sensing Interference Ratio
TCR	:	Target Coverage Ratio
SPPR	:	Sensor to Potential Positions Ratio
SSCR	:	Sensor to Sensor Connectivity Ratio
CH	:	Cluster Head
SCH	:	Super Cluster Head
LEACH	:	Low Energy Adaptive Clustering Hierarchy
CROSS	:	Clustered Routing for Selfish Sensors
FLAG	:	Fuzzy Logic Augmented Game theory
CHEF	:	Cluster Head Election mechanism using Fuzzy logic
MADM	:	Multi-Attribute Decision Making
TOPSIS	:	Technique for Order Preference by Similarity to Ideal Solution
SAW	:	Simple Additive Weighting

Notations

α_{ij}	:	Sensing interference between sensor node i and j
β_{ij}	:	Target i is covered by sensor node j
γ_i	:	Potential position i for sensor placement
δ_{ij}	:	Connectivity between sensor node i and sensor node j
S_R	:	Sensing range of sensor node
C_R	:	Communication range of sensor node

p_i	:	Probability for selecting CH node
E_o	:	Initial energy of sensor node i
E_i	:	Current energy of sensor node i
d_i	:	Distance of sensor node i to base station
d_{max}	:	Distance of farthest sensor node to base station
R_{energy}	:	Residual energy of sensor node
$CH_{centrality}$	:	Cluster head centrality
$BS_{distance}$	:	Distance between cluster head to base station
$S(t_i)$	:	Set of sensor nodes which monitor target t_i
$T(s_i)$	:	Set of target points monitored by sensor node s_i
$C(s_i)$	:	Set of sensor nodes having direct communication range of sensor node s_i
E_{ele}	:	Energy consumed for 1-bit computation
$E_{Tx}(l,d)$	:	Energy consumed to transmit l-bit data over d distance
$E_{Rx}(l)$	:	Energy consumed to receive l-bit data
ε_{mp}	:	Amplifier characteristics of the multi path channel
ε_{fs}	:	Amplifier characteristics of the free space channel
E_{DA}	:	Energy consumed for aggregate data
w_{min}	:	User defined variable to avoid negative value during CH probability calculation
A	:	Actions available for sensor nodes
$U_i(a_i)$	:	Utility gained by a sensor node i after choosing an action a_i
D	:	Sensor node declared to be cluster head
ND	:	Sensor node not declared to be cluster head
v	:	Payoff for being cluster member
c	:	Energy overhead for being cluster head
R	:	Average radius of a cluster
E_{chi}	:	Energy drain of sensor node i to become CH

E_{cmi}	:	Energy drain by a cluster member node i to transmit data to CH
D_{ri}	:	Degree of sensor node i
$CH_{centrality}$	:	Centrality of a CH
E_{spent}	:	Energy spent so far by the CH
N_{br}	:	Neighbors of CH
β	:	Random variable takes the value between 0 and 1
Q	:	CHEF local distance

Chapter 1

Introduction

This chapter gives an overview of Wireless Sensor Network (WSN), its components and architectures. Further, discusses various design challenges and categories of WSN. Furthermore, this chapter presents few of the applications of WSN in the real world.

1.1 Background of Wireless Sensor Networks

Recent advancements in microelectromechanical systems (MEMS) and wireless technology have enabled production of low power, inexpensive, and multifunctional tiny devices with inbuilt communication, computing, and sensing capabilities known as sensor nodes. These sensor nodes forms a collaborative settings called a Wireless Sensor Network (WSN) which collects useful information from a field of interest (Akyildiz et al. (2002)). Wireless sensor networks gained tremendous interest in a wide variety of applications like disaster management, home automation, traffic control, environment monitoring, agriculture, health care, and military target tracking. Generally, sensors are equipped with irreplaceable, limited capacity batteries, and deployed in a hostile or harsh environment such as deep forest and under water to collect required information. The sensors are deployed in either a random or pre-planned manner. The deployed sensors are required to ensure full coverage and connectivity with other sensors. Sensor deployment strategy must reduce overall network cost. That is, minimize the number of sensors to be deployed. A major part of these sensors energy is drained in data transmission and receipt. Another main reason for the quick power drain in WSNs is due to the interference of signals in the wireless media. This results in message drop and requires message retransmission, which in turn affects the energy efficiency of WSNs. Moreover, the deployed network must be able to monitor all the target points by preserving connectivity of the network. Thus, an energy management of sensors plays an important role in prolong lifetime of the WSNs. There are many methods proposed to achieve energy efficiency of the WSNs which includes target coverage solutions for WSNs (Slijepcevic and Potkonjak (2001a); Cardei et al. (2005)), interference minimization methods for WSNs (Buchin (2008); Bilò and Proietti (2008); Panda and Shetty (2011); Shetty and Lakshmi (2016)), combined target coverage and connectivity solutions for WSNs (Jehan and Punithavathani (2017); Gupta and Jha (2019)), and energy efficient clustering and routing methods for WSNs (Kuila and Jana (2014); Lalwani et al. (2018); Nomosudro et al. (2019)).

1.2 Structure of Sensor Node

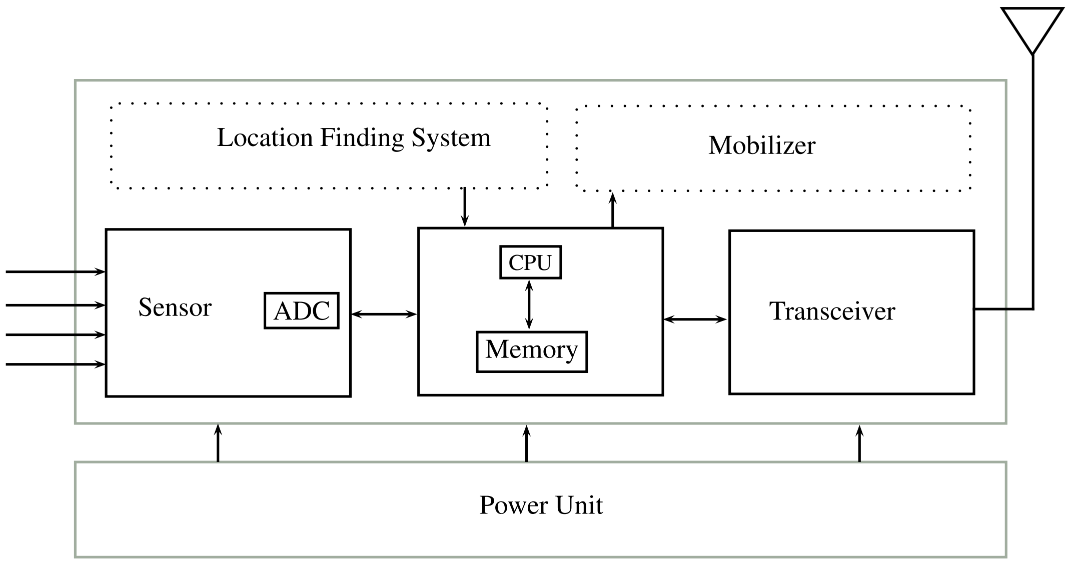


Figure 1.1 Block diagram of a sensor node

In general sensor has four subsystems: (i) a sensing subsystem which includes one or more sensors with associated analog-to-digital converters for data acquisition (ii) a processing subsystem consists of a micro-controller and memory for local data processing (iii) a transceiver for data communication and (iv) a power unit. In few applications, sensor nodes equipped with additional components, like location finding system such as global positioning system (GPS) to locate their position, a mobilizer to give mobility to the sensors. The Figure 1.1 depicts the block diagram of a sensor node.

1.2.1 Sensing Unit

The sensing unit of a sensor node differentiates it from other embedded hardware with its communication capabilities. Each sensing unit may consists of several sensors units and each sensor unit is responsible for collecting information of a certain type, like temperature, humidity, and light. The sensing unit has two sub units, a sensor and an analog-to-digital converter (ADC). The analog signals generated by sensors corresponds to observed phenomenon of a physical world and are converted to digital signals by the ADC, and finally send to the processing unit.

1.2.2 Processing Unit

The processing unit controls and manages every other units of sensor node. It may associated with onboard memory or a separate storage unit. The processing unit enables other subsystems to perform sensing operation, runs algorithms, and collaborate with other sensor nodes.

1.2.3 Transceiver Unit

The Transceiver unit is responsible for performing communication between any two sensor nodes. It implements the necessary procedures to convert bits into radio frequency (RF) waves and recover at the other end.

1.2.4 Power Unit

Power unit is the essential component of a sensor node. Generally, sensor is equipped with a battery, but other energy sources are also available. Each unit in the sensor node gets power through the power unit. The limited capacity of this unit demands energy efficient operation and tasks, which are performed by the other units.

1.2.5 Location Finding System

Many of the wireless sensor network applications, sensing and routing techniques demands knowledge of the physical location of a node. Thus, sensor node is equipped with a location finding system. This subsystem may consist of a GPS module for high end sensor node or may be a software module that implements the localization algorithm, which provide location information.

1.2.6 Mobilizer

The mobilizer unit is responsible for the movement of a sensor node. Mobility demands extensive energy resources and should be provided efficiently.The mobilizer operates by interaction with the sensing unit and processing unit to manage the movements of the sensor node.

1.3 WSN Architecture

A WSN consists of large number of spatially distributed tiny, battery operated sensor nodes with one or more base stations. These sensor nodes monitors physical phenomena of environments in real time such as temperatures, pressure, vibration, or motion and produce sensory data, finally send to the base station, either via single-hop or multi-hop communications. The generated data is forwarded to the base station in a continuous, event-driven, query-driven or hybrid manners depending on the applications of the sensor network. In continuous data forwarding, all sensors forwards the sensed data in periodically to the base station. In event-driven, sensed data is forwarded whenever event has occurred. In case of query-driven model, the BS sends a query to all the sensor nodes to get sensed data of interest from the environment. Some application demands combination of continuous, event-driven, and query-driven for data forwarding in WSN. There are two types of WSN architecture, flat and hierarchical discussed in the literature (Kuila and Jana (2017).

1.3.1 Flat Architecture

In this type of network, each sensor node has the same responsibility of performing the task. The sensor nodes forward sensed data to the base station through single-hop or multi-hop communication.

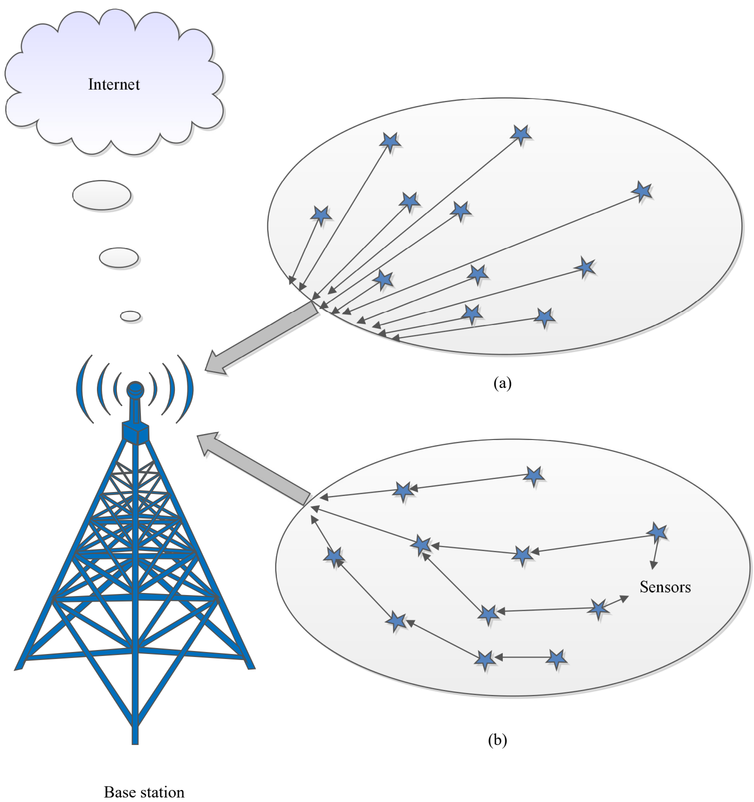


Figure 1.2 Flat wireless sensor network architecture: (a) single-hop communication (b) multi-hop communication

The Figure 1.2 (a) depicts a single-hop communication model, which is suitable for small area networks. The Figure 1.2 (b) shows a multi-hop communication model, which is suitable for a large area network. In this architecture the sensor node may select another sensor node as a relay-node to forward the sensed data to the base station.

1.3.2 Hierarchical Architecture

In this model, the sensor nodes are divided into several groups called clusters and each cluster has a cluster head (CH).

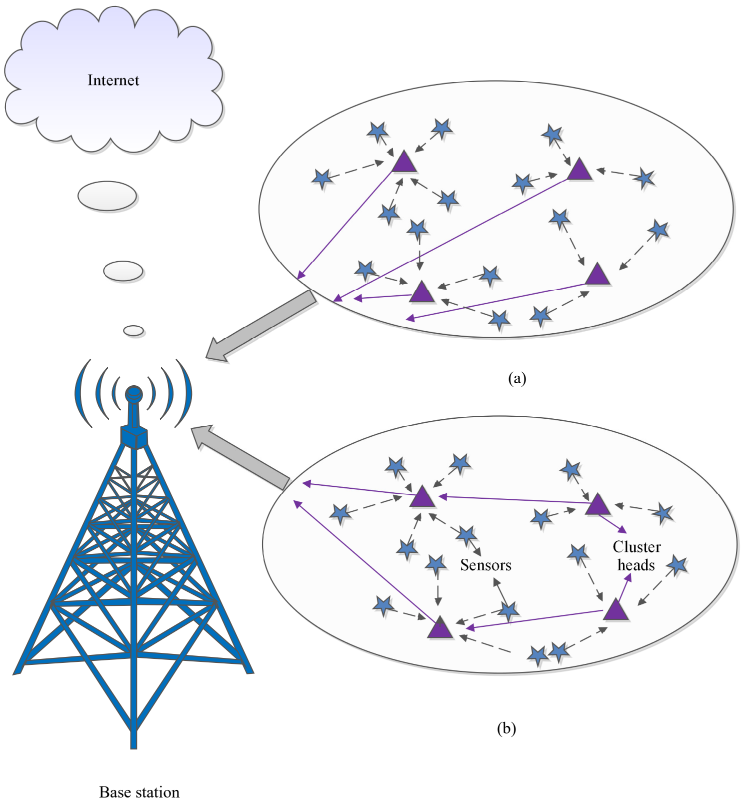


Figure 1.3 Hierarchical wireless sensor network architecture: (a) CHs to base station single-hop communication (b)CHs to base station multi-hop communication

All sensor nodes forward sensed data to the base station via CH. The CHs are responsible for aggregating data received from its members send data directly to the base station with single-hop communication as shown in Figure 1.3(a) or through multi-hop communication between CHs as shown in Figure 1.3 (b)

1.4 Challenges in WSN Design

Main characteristics of wireless sensor networks and their applications are to overcome various challenges in the design of sensor networks. The WSN demands different requirements based on application and hence it is not feasible to answer all the design challenges of WSN. However, a few of the main challenges are described in the following subsections (Akyildiz and Vuran (2010)).

1.4.1 Power Consumption

Generally, sensor nodes are equipped with a limited power source (< 0.5Ah, 1.2V) and frequent recharge or replacement of battery is not feasible. Each sensor node in a sensor field is responsible for detecting events, performing local data processing, and then transmitting the data to the base station. Power consumption in WSN is divided into three domains, sensing, communication, and data processing, which are performed by the sensors, the radio, and the CPU respectively. It is observed that, among these three, a sensor node spends maximum energy for data communication. WSN lifetime has a strong dependency on battery lifetime. Therefore the design of hardware, power-aware protocols, and energy-efficient algorithms for a WSN are given highest importance.

1.4.2 Production Cost

The WSN consists of a large number of sensor nodes and hence cost of each sensor node decides the cost of the network. If the cost of the network is more expensive than deploying traditional single-sensor devices, then the sensor network cost will not be justified. The cost for Bluetooth is usually less than $10 and the cost of the sensor node should be less than $1 to have a practically feasible network. Further, sensor nodes may be equipped with additional units like a location-finding system and mobilizer. which adds cost to the sensor devices. As a result, keeping the cost of a sensor node reasonably low is very challenging for a given number of functionalities.

1.4.3 Scalability

The number of sensor nodes deployed in a sensing field may be in the order of hundreds to thousands. Thus, the networking protocols and algorithms developed for this network should be able to handle such a large network efficiently. The high-density deployment of sensor nodes in a field provides redundancy and improves the fault tolerance of the network and also creates scalability challenges.

1.4.4 WSNs Topology

A large number of sensors are deployed in an inaccessible and harsh environment and prone to frequent failures making topology maintenance a challenging task. The major task of deployment of sensor nodes is to monitor required field efficiently and topology maintenance. After the deployment of sensor nodes, the protocol parameters and operations must be adapted according to the network topology. Sometimes, the redeployment of sensor nodes may be necessary if several nodes fail or deplete their energy to prolong the network lifetime.

1.4.5 Self Organization

In most applications, sensor nodes are deployed in harsh environments, and in such scenarios network expects to function less or without human intervention or sensor nodes are capable of self-organization.

1.4.6 Sensing, Processing, and Communication Capabilities

The sensor nodes have limited sensing, processing, and communication capabilities. Thus, they can perform limited computational functionalities and communicate within a short-range. These hardware constraints bring many challenges in protocols and algorithms design for WSNs. All the algorithms and protocols for sensor networks should consider energy, processing, and communication limitations.

1.5 Categories of WSN

The wireless sensor networks are divided into different categories based on several factors such as types of nodes, node mobility, and deployment environment. Considering these factors WSNs are broadly categorized as follows (Pal and Misra (2016)).

1.5.1 Wireless Underwater Sensor Network

The advancement of wireless underwater sensor network provides opportunities for exploring the flora and fauna of oceanic environments. These networks help in monitoring underwater resources and structures, such as oil rigs. The networks use acoustic signal instead of radio signal for communication. The acoustic signal are more suitable for the underwater environment than radio signal due to their high attenuation. The challenges of these networks involve high propagation delay, low link capacity, inherent mobility of nodes, sparse deployment of costly nodes, and failure due to environmental conditions.

1.5.2 Wireless Underground Sensor Network

This type of networks is used in intelligent agriculture and irrigation, monitoring soil quality, and border patrol. Both electromagnetic and magnetic induction are used as the communication medium to interact with ground nodes and underground nodes. The different parameters like soil temperature, moisture, composition, and depth affect the quality of communication, maximum communication range of the node is around 4.5 m when soil moisture is high and the burial depth of the node is 35 cm.

1.5.3 Wireless Multimedia Sensor Network

The nodes of the network are equipped with low cost CMOS cameras and microphones. The multimedia nodes are deployed in a pre-planned manner for providing proper target coverage. The nodes communicate the monitored data in the form video, audio, and image. In this type of networks, multimedia data is of high volume and faces the delay in data communications.Thus, multimedia networks demands high bandwidth and high energy for quality and reliable services.

1.5.4 Wireless Mobile Sensor Network

Recently, mobile sinks and mobile sensors are used in this type of network to reduce communication overhead of the static nodes. Mobile networks provide good connectivity, better reliability, and energy efficiency. The networks pose some challenges such as mobility management, mobility aware transmission, timely detection of mobile nodes, and data transfer.

1.6 Applications of WSN

The WSN emerged as a attractive technology for development of various commercial and academic applications. This spectrum of applications include safety and security systems, weather and climate monitoring system, crop and irrigation systems, and exploration of solar systems. Some of the important applications are discussed below and summarized in Figure 1.4 (Akyildiz and Vuran (2010)).

1.6.1 Military Applications

The rapid deployment, fault tolerance, and self organizations nature of WSN made it an integral part of military command, control and communication systems. Some of the military applications include military operations, sniper detection, battle field surveillance and damage assessment, also used in nuclear, biological, and chemical attack detection.

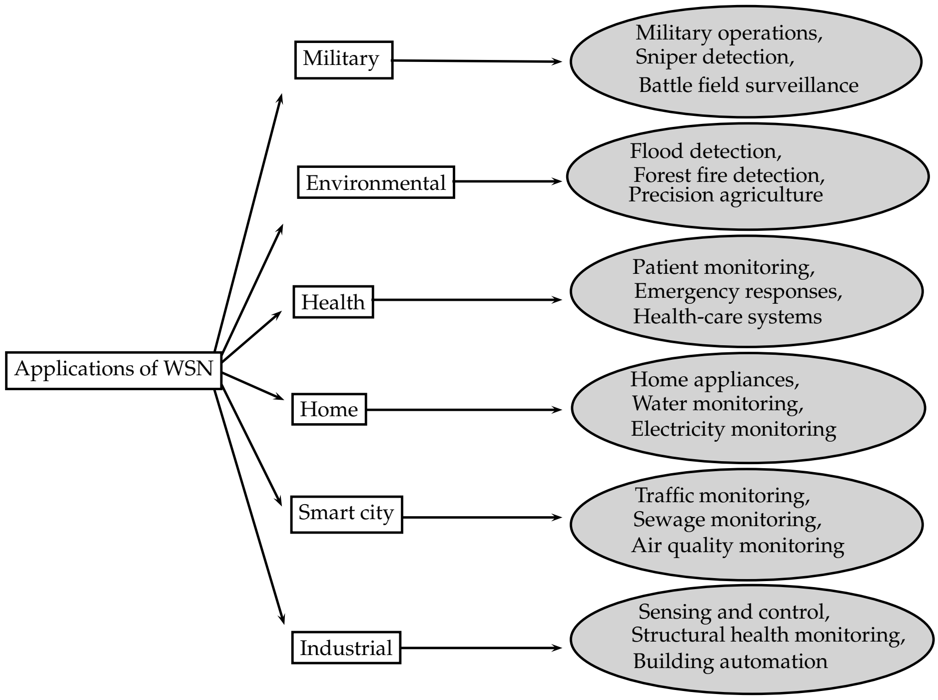


Figure 1.4 Summary of wireless sensor network applications

1.6.2 Environmental Applications

The self coordination nature of the WSN has an advantage in building various environmental applications such as disaster detection and monitoring systems which are results of natural forces. Few environmental applications include forest fire detection, early flood detection, precision agriculture and irrigation, tsunami and volcano detection and monitoring, and pollution studies.

1.6.3 Health Applications

The development of smart integrated and implanted biomedical devices enhanced usage of WSN in health applications. Few health-care applications include patient monitoring and emergency response systems.

1.6.4 Home Applications

Sensors and actuators are inbuilt into home appliances such as washing machines, refrigerators, vacuum cleaners, heaters. The sensors that are inside domestic devices interact with each other or the outside world using the internet. Few other applications include electricity monitoring, water monitoring, and air conditioner monitoring systems.

1.6.5 Smart City Applications

In the recent past, various WSN applications are developed for urban and metropolitan cities to make human life smooth and comfortable. Some applications include congestion and traffic monitoring systems, vehicle navigation systems, road surface monitoring systems, sewage chemical monitoring systems, and air quality monitoring systems.

1.6.6 Industrial Applications

Technological advancement in the industrial internet of things (IIOT) increased the usage of WSN in a wide variety of applications in industries such as industrial sensing and control systems, preventive maintenance systems, building automation, and structural health monitoring. Few commercial applications include material fatigue monitoring and product quality monitoring systems.

1.7 Thesis Overview

The thesis is organized as follows. **Chapter 1** provides a brief introduction to wireless sensor network. **Chapter 2** presents related work on sensor placement and clustering techniques in WSN, also gives proposed research objectives and contributions of the thesis. **Chapter 3** gives DE based sensor placement in WSN with target coverage and connectivity requirements. **Chapter 4** describes the BBO based method for minimum interference sensors placement in WSN with target coverage and connectivity constraints. **Chapter 5** presents a hybrid artificial technique for clustering in WSN. **Chapter 6** presents a combined goal of interference aware sensor placement and clustering using a multi-attribute decision making method. **Chapter 7** outlines the thesis contributions and provides future research directions.

1.8 Chapter Summary

In this chapter, background of WSNs, structure of a sensor node, WSNs architecture, and categories of WSN are discussed. Various WSN design challenges are addressed in the chapter. Few real-world applications of the WSNs are also discussed in the chapter. Finally, the structure of the thesis is presented in the chapter.

Chapter 2

Literature Review

This chapter discusses some of the prominent works on wireless sensor networks. Our discussion is limited to three problems on WSNs that include target coverage problem, interference minimization problem, and clustering problem. The chapter also briefs about motivation of the work, research objectives, and contributions of the thesis.

2.1 Target Coverage Problem in WSNs

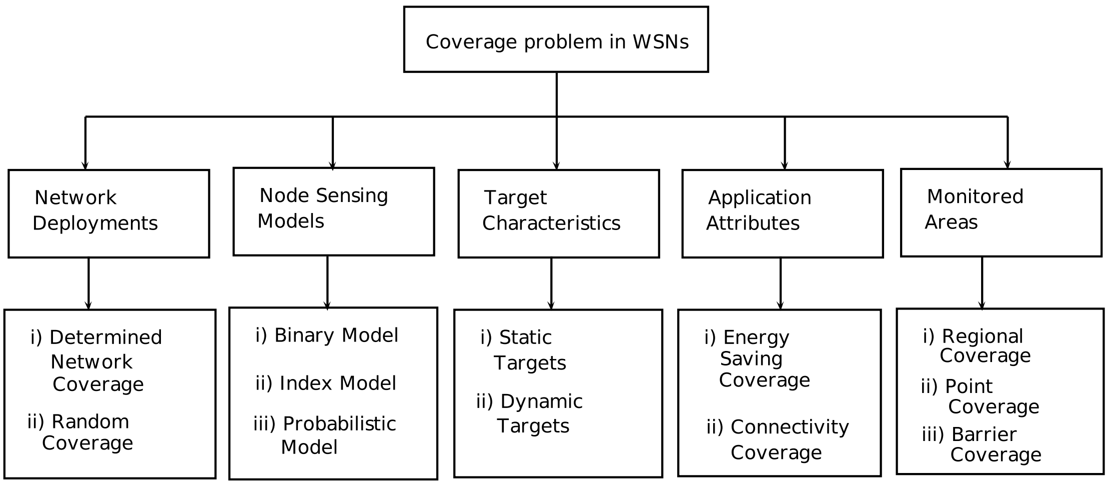


Figure 2.1 Classifications of coverage problem

Coverage and connectivity are two crucial issues for the quality of service in the WSNs. The coverage in the WSNs defines how well each target point of a deployed network is under the vigilance of a sensor node. Also, the connectivity of WSNs defines every node pair that can directly or indirectly communicate with each other. There is a need to monitor different targets or regions in the sensor field for effective information transmission to the base station. Various class of coverage problems are studied in the literature (Wang (2011b)). The coverage problems are divided based on network deployment type, node sensing models, target characteristics, application attributes, and monitored areas as shown in the Figure 2.1. The classifications of coverage problems are detailed below:

2.1.1 Network Deployment

2.1.1.1 Determined Network Coverage

These networks based on predefined settings like the shape of the network, the location of a sensor node, etc., are known in advance. In this type of coverage, sensor nodes are deployed in a predefined manner; however, many cases sensor nodes cannot be deployed in a deterministic pattern. In this type of placement, coverage is easier than a random coverage.

2.1.1.2 Random Coverage

In this type of network, there is no prior information regarding the type of topology structure or node position in the network. The placements of sensors in an inaccessible or hostile area demands random deployment. In this type of settings, location for sensors are unevenly distributed, hence some regions are highly dense and some regions are sparse. In the dense regions, targets are covered by more sensors than the sparse regions.

2.1.2 Node Sensing Models

2.1.2.1 Binary Disk Model

In this model, a node senses a region of disk shape which has a radius R (sensing range) and is centered at c. The target z is sensed or not is indicated by the value 1 or 0. If $dis(z,c) \leq R$, then the value is 1, which means that target is within the sensing range of the sensor and the value is 0 otherwise. Here, $dis(z,c)$ stands for the Euclidean distance between centre and target. Figure 2.2(c) illustrates such a binary disk model, which covers target z and Figure 2.2(d) shows the target point z is 3-covered by three disks.

2.1.2.2 Index Model

This model gives information about the chances to sense a target in the network. The state of a target to be sensed is inversely proportional to the k^{th} power of the distance between the target (T) and sensor node (S), i.e., sensing chances = $c(\frac{1}{[dis(T,S)]})^k$, where $k \leq 2$ and c is a constant which is determined by network characteristics.

2.1.2.3 Probabilistic Model

It is an extension of the binary sensing model. For probabilistic model a quantity, R_u is defined such that $R_u < R_s$ where R_s is the radius of a circular disk and an interval $(R_s - R_u, R_s + R_u)$ is defined for the the probability to detect an object is p. Based on the given probabilistic model, the sensing of a point $C(x,y)$ by a sensor S_i is given below:

$$C_{(x,y)}(S_i) = \begin{cases} 0 & : R_s + R_u \leq d(S_i, p) \\ e^{-\omega a^{\beta}} & : R_s - R_u < d(S_i, p) < R_s + R_u \\ 1 & : R_s - R_u \geq d(S_i, p) \end{cases}$$

Where $a = d(S_i, p) - (R_s - R_u)$, and ω, β are measured parameters for detection probabilities, when an object is within a certain distance from a sensor.

2.1.2.4 Binary Sector Coverage Model

The Binary sector coverage model is a Boolean directional coverage model, Figure 2.2(a) illustrates such a sector model, where ϕ_s is is called orientational angle and ω is called visual angle of the sector model, and R_s is called sensing range.

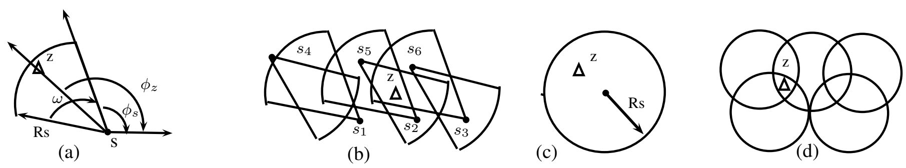


Figure 2.2 Illustrations of (a) a directional binary sector coverage model; (b) a space point being 3-covered by three sectors; (c) an isotropic binary disk coverage model; (d) a space point z being 3-covered by three disks.

The coverage function of the sector model is given by,

$$f(d(s,z),\phi_z) == \begin{cases} 1 & : d(s,z) \leq R_s \;\; and \;\; \phi_s \leq \phi_z \leq \phi_s + \omega \\ 0 & : othewise \end{cases}$$

where $d(s,z)$ is the Euclidean distance between a sensor s and a space point z, and ϕ_z is their angle. The coverage function defines a sector and all space points within such a sector have a coverage measure of 1 and are said to be covered by this sensor. All space points outside such a sector have a coverage measure of 0 and are said to be not covered by this sensor. In Figure 2.2(a), the space point marked by a triangle has a coverage measure of 1 and is covered by the sensor sector. Figure 2.2(b)shows 3-covered by three sensor sectors s_2, s_5, and s_6.

2.1.3 Target Characteristics

2.1.3.1 Static Target Coverage

Static targets are stationary targets to the sensing node. This type of coverage works to maximize coverage and minimize the redundancy of sensor nodes. This approach is observed in daily life situations such as monitoring temperature.

2.1.3.2 Dynamic Target Coverage

The dynamic targets can move and are not stationary to the sensing node. The main focus of such a coverage is the movement of the dynamic target. It is complicated as compared to the static one. This coverage is very useful for military purposes as it can be used for battlefield surveillance.

2.1.4 Application Attributes

2.1.4.1 Energy-Saving Coverage

Energy-Saving coverage focuses on the energy consumption by the network. Due to the limited energy resource, coverage is achieved by dividing the sensing nodes into the subsets of **active** and **sleep** nodes in different rounds. This type of coverage is suitable for maximizing network lifetime with energy preservation.

2.1.4.2 Connectivity Coverage

Connectivity coverage focuses on connectivity constraints like m-connectivity coverage. This coverage type finds application in monitoring critical targets. k-coverage of WSN defines each sensor covers at least k target points. k-coverage and m-connectivity of WSN define that each sensor covers k targets points by maintaining m connectivity with their neighbour sensor nodes.

2.1.5 Monitored Areas

2.1.5.1 Regional Coverage

In regional coverage, a portion of the area or monitored space is under the surveillance of at least one sensor. This coverage type finds application in forest protection against fire. Here, sensing nodes are densely deployed that results in overlapped coverage.

2.1.5.2 Point Coverage

Under the point coverage, only a limited number of discrete objects or target points are to be monitored. In this type of coverage, the sensor nodes are divided into node subsets under the stochastic distribution. In this type of division, each subset works at a time that results in the maximization of the network lifetime.

2.1.5.3 Barrier Coverage

Barrier coverage computes the probability of objects movement in the targeted area. The probability is determined by the movement rate of the object and sensing intensities of the sensors for every point on the path followed by the object. Based on the calculation the density of sensor nodes can be computed.

2.2 Prominent Works on Coverage Problems in WSNs

A wide range of deployment methods are presented in the literature. These sensor deployment techniques are proposed to satisfy certain objectives like target coverage, connectivity, energy efficiency and network cost.

To solve the target coverage problem, the authors Slijepcevic and Potkonjak (2001b) have discussed a heuristic that produces a disjoint sensor cover, That is, sensor do not present in more than one sensor cover set. The authors Cardei et al. (2005) have proposed an approximation algorithm to solve a coverage problems in WSNs. Here, the lifetime of the network is extended without considering a disjoint set and hence sensor nodes can present in more than one sensor cover set. The authors Mini et al. (2013) have used an artificial bee colony algorithm to solve target coverage problem. Here, the objectives are identifying optimal locations for sensor placement and scheduling these sensors to maximize the lifetime of the network with the required coverage level. The authors Panda et al. (2017) have proposed a heuristic method for a target coverage problem to increase the lifetime of the network. The heuristic method supports 2-connected target coverage property which provide fault tolerant to the network. The authors Singh et al. (2018) have proposed a heuristic technique that maximizes the lifetime of the network by generating maximum coverage set and each coverage set can monitor a given target set. The authors Gupta and Jha (2019) have proposed a solution for a coverage and connectivity problem using Biogeography-based optimization meta-heuristic approach. It finds a minimum number of potential positions to place sensor nodes to achieve k-coverage of targets and m-connectivity with other sensors for a given set of location points. The authors Moh'd Alia and Al-Ajouri (2017) have adopted a Harmony Search Algorithm (HSA) for sensor placement to maximize the coverage and minimize the network cost. The authors Barkhoda and Sheikhi (2020) have proposed a k-coverage and m-connected sensor placement problem in WSNs using Immigrant imperialist competitive algorithm (IICA).

The authors Mini et al. (2012) have discussed three coverage issues such as simple, Q-coverage, and k-coverage. In this scheme, the authors solved the coverage problem by designing cover optimization in the first phase, and M-connected optimization in the second phase. The main drawback of this algorithm is its high computational complexity. The authors Kalayci et al. (2007) have proposed a solution for k-coverage of the network field by maintaining connectivity between the sensor nodes. The authors Chand et al. (2018) have found a cover set with a minimum number of sensors to prolong the total network lifetime using a Genetic algorithm (GA) based approach.

Table 2.1 Comparisons of various works on coverage problems in WSNs

References	Methods	Parameters			
		Coverage	Connectivity	Energy	Cost
Slijepcevic and Potkonjak (2001b)	Heuristic	√			
Cardei et al. (2005)	Heuristic	√			
Panda et al. (2017)	Heuristic	√	√		
Jehan and Punithavathani (2017)	GSA	√	√		√
Gupta et al. (2016)	GA	√	√		√
Moh'd Alia and Al-Ajouri (2017)	HSA	√			√
Wang et al. (2019)	PSOA	√			
Gupta and Jha (2019)	BBOA	√	√		√
Barkhoda and Sheikhi (2020)	IICA	√	√		√
Jaiswal and Anand (2021)	GWOA	√	√	√	√

To achieve that, the authors defined target coverage problem as the maximum network lifetime problem (MLP) and designed using the linear programming. Besides, the authors Rebai et al. (2015) have developed a genetic algorithms to identify the optimal positions to deploy sensor nodes in a way that the set of sensors cover the entire field and also ensures connectivity among them. The drawback of this technique is that the crossover operation may produce an invalid offspring. This problem handled by authors Gupta et al. (2016) and solved both coverage and connectivity problem using an improved GA approach. The methods obtains the minimum number of potential positions to place sensor nodes to achieve k-coverage of targets and m-connectivity. The authors Jehan and Punithavathani (2017) have proposed a Gravitational Search Algorithm (GSA)-scheme for wireless sensor node deployment in the network. This scheme provides l-coverage and n-connectivity in the WSN. The authors Gupta and Jha (2019) have proposed a Biogeography-Based Optimization (BBO) scheme for solving the target coverage problem, where optimal sensor locations are computed for achieving k-coverage and m-connectivity of the given WSN. The authors Jaiswal and Anand (2021) have proposed a Grey Wolf Optimization Algorithm (GWOA) to deploy sensors to achieve a good quality of service in the Internet of Things (IoT) applications. This technique considers coverage, connectivity, energy efficiency, and network cost as parameters to decide the appropriate locations to deploy sensors. The authors Wang et al. (2019) have proposed a sensor deployment method for target coverage solution using Particle Swarm Optimization Algorithm (PSOA). Mobile sensors are used for coverage patching in the proposed technique. Various sensor deployment methods and performance indicators considered are summarized in Table 2.1

2.3 Interference Problem in WSNs

One of the fundamental problems of energy drains in WSNs is due to the interference of signals during sensing, transmission, and receiving data in wireless media. The interference leads to packet loss and requires re-transmission of packets, that in turn affects the energy efficiency of the networks. Therefore, it is essential to minimize the interference of the networks to enhance the lifetime.

Consider a network model that is denoted by a graph $G(V,E)$. The graph consists of vertex set V that represents n sensors, edge set E that represents transmission (communication) range of the sensors. Then, the number of transmission range that covers node $v \in V$ gives the communication interference of node v. In the WSN, if a node v has a communication range $C(v)$, then we can construct a communication disk centred at v with a radius equal to its communication range.

The **communication disk** of a vertex v is defined as a circle centred at v and its communication range $C(v)$ as its radius, denoted by $D(v,C(v))$. Let S_r and C_r be the sensing radius and communication radius of each sensor respectively. There are two types of transmission interference found in the literature namely Sender interference and Receiver interference as detailed below Shetty and Lakshmi (2016).

2.3.1 Sender Interference

The number of vertices that lie in v's communication disk determines the ***Sender interference*** of v, and formally defined as follows:

$$I_s(v) = |\{u \in V \setminus \{v\}, u \in D(v, C(v))\}| \tag{2.3.1}$$

2.3.2 Receiver Interference

The ***Receiver interference*** of a vertex v is defined as the number of vertices having the vertex v in their communication disk and given as follows:

$$I_r(v) = |\{u \in V \setminus \{v\}, v \in D(u, C(u))\}| \tag{2.3.2}$$

2.4 Prominent Works on Interference Minimization Problems

To minimize the interference of the WSNs, researchers proposed variants of topology control-based interference minimization solutions in WSNs. The author Buchin (2008) has proved that the problem of minimizing maximum receiver interference of the network is NP-hard. The authors Bilò and Proietti (2008) gave algorithms for minimizing the maximum sender interference. The authors Agrawal and Das (2013) have proposed an algorithm for minimizing maximum interference as well as total interference of the network. The Authors Panda et al. (2012) have proposed a heuristic that assigns different power levels to sensors such that resulting networks have minimum interference by preserving connectivity of the network

The authors Panda and Shetty (2011) have proposed two new models SUM and MAX, and presented algorithms for minimizing maximum and average node interference for WSN. The author Rangwala et al. (2006) have presented an algorithm that produces the best Sender interference spanning tree for the input distribution of the nodes

Table 2.2 Comparisons of various works on interference minimization problems in WSNs

		Interference minimization parameters		
References	Methods	Sender	Receiver	Total
Buchin (2008)	Heuristic		$\surd$	
Bilò and Proietti (2008)	Heuristic	$\surd$		
Agrawal and Das (2013)	Heuristic			$\surd$
Shetty and Lakshmi (2016)	Heuristic		$\surd$	
Mohanty and Udgata (2020)	Heuristic		$\surd$	

in the plane and gives minimum interference value for the WSN. The author Lou and Lau (2011) try to minimize the average interference of the WSN. The authors Shetty and Lakshmi (2016) have proposed an algorithm for WSN and broadcast networks that minimizes maximum receiver interference. The authors Mohanty and Udgata (2020) have proposed a probabilistic interference model for minimizing the maximum receiver interference. The summary of various interference problems are presented in Table 2.2

2.5 Clustering in WSNs

Various methods and techniques are found in the literature for clustering in WSNs to achieve the energy efficiency of the network. The most famous clustering algorithm LEACH Heinzelman et al. (2000) selects CHs on a rotation basis and ensures energy consumption is evenly distributed in the network. However, the random rotation to select CHs leads to uneven distribution of CHs in the network. To overcome this issue, LEACH-C Heinzelman et al. (2002) algorithm is proposed. In this technique, the base station elect CHs based on their distance to the base station and energy of the node. The authors in DEEC Qing et al. (2006) used ratio between residual energy of sensor node and average energy of the network for the election of appropriate CHs in the network. The algorithm HEED Younis and Fahmy (2004) selects CHs periodically using residual energy and degree of nodes. Many meta-heuristic techniques are proposed

Table 2.3 Comparisons of various cluster heads selection techniques

References	Method	Parameters: Residual energy	Node degree	Distance to BS	Competition radius	Avg. distance to neighbour nodes
Heinzelman et al. (2002)	Random	√		√		
Qing et al. (2006)	Random	√				
Younis and Fahmy (2004)	Random	√	√			
Lalwani et al. (2018)	Meta-heuristic	√		√		
Nomosudro et al. (2019)	Meta-heuristic	√		√		√
Panchal and Singh (2021a)	Fuzzy-C means	√		√		
Yang et al. (2016)	Game theory	√				
Baranidharan and Santhi (2016)	Fuzzy logic	√	√	√		
Toloueiashtian and Motameni (2018)	Fuzzy logic	√	√	√		
Logambigai and Kannan (2016)	Fuzzy logic	√	√	√		
Agrawal and Pandey (2018)	Fuzzy logic	√	√	√	√	

for clustering in the network. The authors Lalwani et al. (2018) have consider energy and distance to the base station for selecting appropriate CHs. The authors Nomosudro et al. (2019) have used residual energy, distance to the base station, and distance to neighbouring nodes (member nodes) for selecting CHs.The authors in Edla et al. (2019) have proposed a load balanced clustering method by considering mean cluster distance, gateways load and number of heavily loaded gateways in the WSN. The authors Panchal and Singh (2021a) have proposed a Fuzzy-C means based hybrid hierarchical structure for clustering that considers energy and distance parameters for CHs selection. The authors in Panchal and Singh (2021b) have proposed an optimum cluster head selection method based on residual energy, Euclidean distance, and location of the grid-centroid of CHs. The authors Yang et al. (2016) have used a game theory based technique for selecting appropriate CHs. It uses energy and distance to neighbouring CHs to elect final CHs. The authors Baranidharan and Santhi (2016) have a proposed a fuzzy logic based clustering algorithm. The algorithm considers residual energy, node degree, and distance to the base station as fuzzy input parameters. The authors in Toloueiashtian and Motameni (2018) have proposed a fuzzy logic based approach for clustering by considering residual energy, distance to base station, and degree of the node. The clustering by Logambigai and Kannan (2016) have used a fuzzy logic method with residual energy, node degree, and distance to the base station as fuzzy input variables. The authors Agrawal and Pandey (2018) have proposed a fuzzy logic based clustering technique. The authors consider residual energy, node degree, distance to the base station, and competition radius as fuzzy input variables. It is observed that the cluster head selection based on node degree drains the energy of the node faster and affects the stability period of the network. The various clustering methods for WSNs are summarized in Table 2.3.

2.6 Motivation of the Work

In the recent past, WSNs have gained wide attention among researchers and industrial communities due to their diverse usage in the Internet of Things (IoT) applications. The primary goal of WSN is to observe and detect events in the given targets and barriers. One of the fundamental issues of WSN is to monitor or track events by covering required targets and maintaining reliable connectivity of the network. Also, it is necessary to extend the stability of the WSN for data-sensitive and critical applications. In this context, many works on sensor placement and clustering have been proposed by researchers. However, these works never consider interference during the sensor placement and clustering. The interference of nodes cause a message drop and results in quick energy drain during data transfer between member nodes and cluster heads. It is also essential to note that the various artificial intelligence techniques or hybridization of these methods are gaining importance in solving a wide spectrum of science and engineering problems. Hence, the design of a reliable and robust WSN by considering different network performance parameters like target coverage, connectivity, interference, network stability, and network cost are essential for many real-world applications.

2.7 Research Objectives (RO's)

Problem Statement

To design and develop computationally intelligent algorithms for minimum interference, energy-efficient clustering, and target coverage with connectivity constraints in wireless sensor networks.

2.7.1 Objectives

RO1. To design and develop a novel algorithm for k-coverage and m-connectivity problem in wireless sensor networks.

RO2. To design and develop an intelligent interference minimization algorithm for wireless sensor networks.

RO3. To design and develop a hybrid clustering technique for wireless sensor networks.

2.8 Research contribution and mappings

The research contributions and mappings of the RO's to chapters are shown in Table 2.4.

Table 2.4 Details of contributions of the Thesis

Specifics of research contribution	**Research objective addressed**	**Thesis chapter presenting contribution**	**Journal publication derived from each chapter**
k-coverage and *m*-connectivity solution for WSN	RO 1	Chapter 3	C Naik and Shetty D P: "Differential evolution meta-heuristic scheme for k-Coverage and m-Connected optimal node placement in wireless sensor networks", IJCISIM **[Scopus]**.
Interference minimization with coverage and connectivity for WSN	RO 2	Chapter 4	C Naik and Shetty D P:" Optimal sensors placement scheme for targets coverage with minimized interference using BBO" Journal of Evolutionary Intelligence, Springer **[ESCI, Scopus]**.
Hierarchical fuzzy logic augmented game theoretic clustering algorithm for WSN	RO 3	Chapter 5	C Naik and Shetty D P: "FLAG: fuzzy logic augmented game theoretic hybrid hierarchical clustering algorithm for wireless sensor networks", IJTS, Springer **[SCIE]**
Interference aware MADM for sensor placement and clustering for WSN	RO2 & RO3	Chapter 6	C Naik and Shetty D P: "MADM: multi-attribute decision making approach for energy efficient sensor placement and clustering in wireless sensor networks" [Communicated]

2.9 Chapter Summary

In this chapter, prominent works on target coverage, interference minimization, and clustering for WSNs are discussed. Further, motivation for the research work is presented. The research objectives are listed in the chapter. Finally, the research contributions and their mappings to the chapters are tabulated.

Chapter 3

k-Coverage and m-Connected Sensor Placement Scheme

This chapter discusses the coverage problem in wireless sensor networks. The coverage problem is centred around, how well sensors are covered the physical space in a deployed area (Cardei et al. (2005)). It plays a vital role in extending the lifetime of wireless sensor networks. Many real-world applications demand a high degree of sensors connectivity and efficient target coverage. Therefore, a novel differential evolution based scheme is presented in the chapter to solve the k-coverage and m-connectivity problem of the WSN.

.

3.1 Background

The coverage problem can be termed as a target coverage problem where the sensor is required to monitor the set of specific locations in the region of interest. The target coverage problem is divided into *simple*-coverage, k-coverage and Q-coverage. In *simple*-coverage, each target is covered by at least one sensor. In k-coverage, each target is monitored by at least k sensors. In Q-coverage, each target t_j is covered by q_j sensors, where $1 \leq j \leq n$ and n is a number of targets. Similarly, a sensor is m connected if at least m sensors are in the transmission range of the sensor.

Sensor node placement is one of the most sought challenges of WSN, where it finds optimal locations to place sensor nodes so that some design objective under given constraints must be satisfied (Wang (2011b)). Two types of sensor node placement are found in the literature namely random deployment and deterministic deployment Wang (2011b); Deif and Gadallah (2014a). A random deployment of the sensor might be the best choice whenever the sensing field is hostile(e.g.disaster areas). In this type of deployment, some parts of the sensor field may have a high density of sensor nodes, and some other parts of the field may have low density. In deterministic deployment, optimal locations to place sensors are known in advance such that one or many design objectives of the network must be fulfilled (Wang (2011b)). Therefore, many heuristic algorithms are proposed to solve target coverage problems like the work in Slijepcevic and Potkonjak (2001b). Heuristic techniques are adopted to provide near optima solutions, whenever exact solutions are unachievable. Thus, most of the real world problems find solutions by adopting meta-heuristic techniques that do require objective function and the domain of the variable instead of detailed information about domain space (Rajpurohit et al. (2017)).

Differential Evolution (DE) is a meta-heuristic technique used in many optimization problems. This algorithm is useful whenever other bio-inspired algorithm fails (Storn and Price (1997)). It takes a name from a differentiation operation that is used in the process of evaluation. The DE algorithm uses similar characteristics of the Genetic Algorithm (GA) such as mutation, crossover, and selection. The variants of DE, applications, and its advancement are discussed in the work of Das and Suganthan (2011); Das et al. (2016); Fan et al. (2018). More detailed technical information and discussion also available in Rajpurohit et al. (2017). The DE based technique used in solving the clustering problem in WSNs (Kuila and Jana (2014)). The authors Céspedes-Mota et al. (2018) have adopted DE to place sensor nodes on different geometric shapes which minimize the energy and increase the coverage area of the network. To the best of our knowledge no researcher attempted to solve "k-coverage and m-connectivity" problem of WSNs using DE. The GA has limitations over DE in solving different combinatorial optimization problems due to its premature convergence. Therefore, we propose a DE-based approach to solve the "k-coverage and m-connectivity" problem of WSN and compared it with the GA approach.

3.2 Classical Differential Evolution

Differential evolution is a widely used evolutionary algorithm in many real-world applications. It is also used in diverse streams of engineering to solve a wide set of optimization problems. The algorithm is divided into five stages that include initialization of population vector, fitness computation, mutation, crossover, and selection. The algorithm begins with a random population of a specified size. Each vector is a solution to the optimization problem. The quality of the individual vector is determined using the fitness value of that vector. Once the vectors are ready, the DE passes through mutation, crossover, and selection process to obtain feasible solution vectors. Finally, depending on the fitness value the best vector is selected as the best solution (Kuila and Jana (2014)). The various stages of classical DE is shown in Fig. 3.1.

3.3 Assumption and Problem Formulation

3.3.1 Assumption

The proposed model is based on how targets are identified and are spread across an area of interest. A few candidate positions are predetermined to place sensors to sense the targets. We assume targets, candidate positions, and sensors are stationary. A wireless sensor node is said to be covering a target if it is in its sensing range. Every sensor may cover one or more targets. Data acquisition rounds are similar to the technique proposed in Gupta and Jha (2019). Each sensor node forwards sensed data to the base station either directly or via other sensor nodes that are in its transmission range as

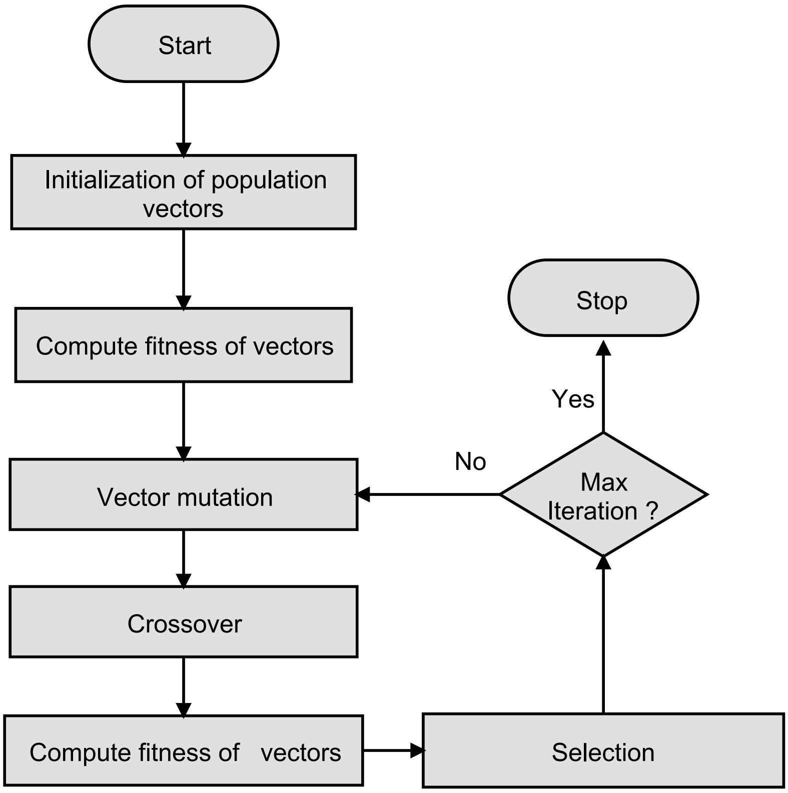


Figure 3.1 Flowchart of classical differential evolution

shown in Fig. 3.2.

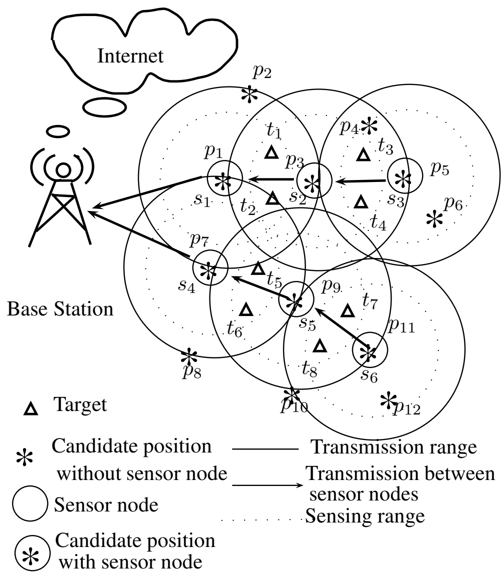


Figure 3.2 2-covered and 1-connected wireless sensor network

3.3.2 Problem Formulation for Node Deployment

Let $C = \{p_1, p_2 \ldots, p_N\}$ denotes the set of the N candidate positions that are predetermined locations on a field of interest and the set of m targets $T = \{t_1, t_2, \ldots, t_M\}$ that are to be monitored. Then the objective is to select an optimal number of candidate locations to deploy wireless sensors such that it fulfills "k-coverage and m-connectivity" for a predetermined value of k and m. Let C_R and S_R represent communication and sensing range of the wireless sensor nodes respectively.

Let $S(t_i)$, $T(s_i)$, and $C(s_i)$ represents set of sensor nodes monitors target t_i, set of target points monitored by sensor node s_i, and set of sensor nodes with in the communication range of sensor node s_i respectively. Formally defined as follows:

$$S(t_i) = \{S_j \mid distance(t_i, s_j) \leq S_{range}\},\ \forall j\ 1 \leq j \leq N \tag{3.3.1}$$

$$T(s_i) = \{t_j \mid distance(t_j, s_i) \leq S_{range}\},\ \forall j\ 1 \leq j \leq M \tag{3.3.2}$$

$$C(s_i) = \{s_j \mid distance(s_i, s_j) \leq C_{range}\},\ \forall j\ 1 \leq j \leq N \tag{3.3.3}$$

To define the coverage of target, connectivity between sensor nodes, and selection of final candidate positions, we use variables t_{ij}, s_{ij}, and u_i respectively. And formally defined as follows,

$$t_{ij} = \begin{cases} 1, & \text{if target } t_i \text{ is in the range of sensor node } s_j \\ 0, & \text{otherwise} \end{cases} \tag{3.3.4}$$

$$s_{ij} = \begin{cases} 1, & \text{if sensor } s_i \text{ in the communication range of sensor node } s_j \\ 0, & \text{otherwise} \end{cases} \tag{3.3.5}$$

$$
u_i = \begin{cases} 1, & \text{if a candidate location } p_i \text{ is selected for node deployment} \\ & \forall i,\ 1 \leq i \leq N \\ 0, & \text{otherwise} \end{cases} \tag{3.3.6}
$$

Final LP-problem formulation is expressed as follows,

$$
\text{Minimize } Z = \sum_{i=1}^{N} u_i \tag{3.3.7}
$$

Subject to

$$
\sum_{j=1}^{P} t_{ij} \geq k,\ \forall i,\ 1 \leq i \leq M \tag{3.3.8}
$$

$$
\sum_{j=1}^{P+1} s_{ij} \geq m,\ \forall i,\ 1 \leq i \leq P \tag{3.3.9}
$$

3.4 Proposed Differential Evolution Based Algorithm

Here, we discuss a k-coverage and m-connectivity wireless sensor node deployment in a wireless sensor network.

Definition 3.4.1. ***k-coverage and m-connectivity Problem***

Let $C = \{p_1, p_2 \ldots, p_N\}$ denote the set of N candidate positions for deploy sensor nodes to cover set of M targets $T = \{t_1, t_2, \ldots, t_M\}$, find optimal sensor node placement positions so that

1. *Each target is monitored by at least k sensor nodes, where $1 \leq k \leq N$*

2. *Each wireless sensor node in C is in the range of at least m other nodes in C, where $1 \leq m \leq N$*

3. Minimize $\frac{P}{N}$, where P is the obtained candidate locations for deploy sensor nodes, and N is the total number of candidate locations.

3.4.1 Vector Encoding

In the proposed technique, an array of Boolean values represent each vector. The length of each vector equals the number of candidate positions on a target area. For a vector, the i^{th} entry value 1 to indicates a wireless sensor node is deployed on the i^{th} candidate location, and the entry value 0 represents no wireless sensor node is deployed at the i^{th} candidate location.

Illustration 1

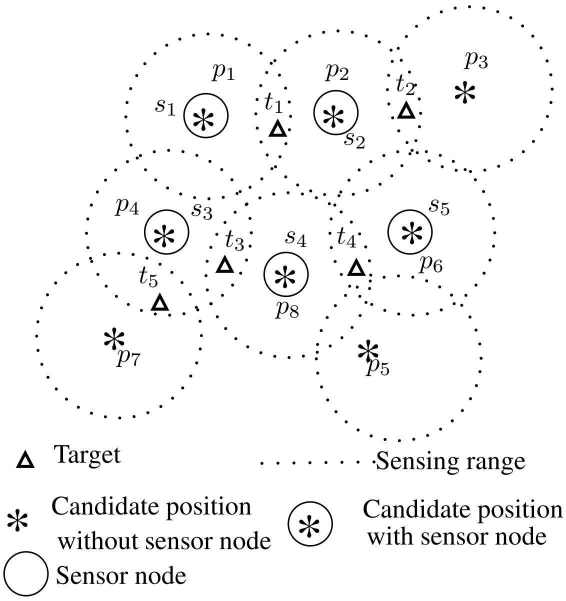
Let a target based WSN with 5 targets $T = \{t_1, t_2, \dots, t_5\}$ and 8 candidate positions $C = \{p_1, p_2, \dots, p_8\}$ as shown in Fig 3.3(a). The length of the vector is 8 as according to the number of candidate positions. Fig 3.3(b) represents a vector in which vector positions $p_1,\ p_2,\ p_4,\ p_6$ and p_8 have value 1 that indicates sensor nodes are deployed on these candidate positions and vector positions $p_3,\ p_5,$ and p_7 have value 0 that implies no sensor node is placed on these candidate positions.

3.4.2 Initialization of the Population Vector

The scheme represent vectors as follows. Each vector represent a selection of candidate positions to place sensors. The G^{th} generation of i^{th} vector having N components is indicated as $X_{i,G} = [x_{1,i,G}, x_{2,i,G}, x_{3,i,G}, \dots, x_{N,i,G}]$.

3.4.3 Derivation of Fitness Function

Our design objective is to obtain an optimal number of candidate locations to place the sensor so that each target is k-covered and each sensor node is m-connected with other sensor nodes for some predetermined values of k and m. We adopt the following paa



b

Candidate Positions	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8
Vector Values	1	1	0	1	0	1	0	1

Figure 3.3 a. A WSN with 5 targets and 8 candidate positions b. Vector representation

rameters to design the fitness function.

1. ***k*-coverage of the targets(f_1)** To achieve k-coverage of a target at least k wireless sensor node must monitor the target. So we obtain the first objective of fitness function as follows:

$$\text{Maximize } f_1 = \frac{1}{M \times k} \sum_{i=1}^{M} CovCost(t_i) \tag{3.4.1}$$

Where M is number of target points and $CovCost(t_i)$ is defined as follows:

$$CovCost(t_i) = \begin{cases} k, & \text{if } |S(t_i)| \geq k \\ k - |S(t_i)|, & \text{otherwise} \end{cases} \tag{3.4.2}$$

2. ***m*-connectivity of the sensor nodes(f_2)** To fulfill m-connectivity, each deployed sensor node is required to maintain at least m-connectivity among other sensors.

So we define the second objective of the fitness function as follows:

$$\text{Maximize } f_2 = \frac{1}{P \times m} \sum_{i=1}^{P} ConCost(s_i) \tag{3.4.3}$$

Where P is the number of selected candidate positions from N candidate positions to deploy sensor nodes and $ConCost(s_i)$ is defined as follows:

$$ConCost(s_i) = \begin{cases} m, & \text{if } |C(s_i)| \geq m \\ k - |C(s_i)|, & \text{otherwise} \end{cases} \tag{3.4.4}$$

3. **Selection of optimal candidate positions**(f_3) The main objective of our scheme is to determine optimal candidate locations (P) so that each target point must satisfy k-coverage and each sensor monitor the target must fulfill m-connectivity with other sensors for the predetermined value of k and m. Therefore, we define the third objective of the fitness function as follows:

$$\text{Maximize } f_3 = (1.0 - \frac{P}{N}) \tag{3.4.5}$$

On the basis of individual objectives f_1, f_2, and f_3, we devise the final fitness function F as follows:

$$\text{Maximize Fitness } F = w_1 \times f_1 + w_2 \times f_2 + w_3 \times f_3 \tag{3.4.6}$$

Where w_i is weight, with $0 < w_i \leq 1, \ 1 \leq i \leq 3$ and $w_1 + w_2 + w_3 = 1$. The objective is to find the better vector having highest fitness value.

3.4.4 Mutation

We adopted DE/best/1/bin scheme (Storn and Price (1997)) for mutation and crossover operation. DE mutation process is performed on vectors of the population to obtain a mutation vector. In this scheme, out of three vectors, the best vector and two random distinct vectors are selected that are different from the current target vector. Let $X_{i,G}$, $X_{best,G}$, and $V_{i,G}$ are target, best, and donor vectors respectively. Then the mutation chromosome is obtained as follows:

$$V_{i,G} = X_{best,G} + \mu \times D_{i,G} \tag{3.4.7}$$

The scaling factor μ that lies in the interval [0.4, 1] (Storn and Price (1997)). We set μ as 1.0 and $D_{i,G} = X_{r,G} - X_{s,G}$ with $r,s \in [1,P]$, such that $r \neq s \neq best$. This classical mutation operation does not work for our scenario. The vectors consist of 0's and 1's and subtraction of two components of the vectors gives a difference vector with negative values. Therefore, we adopted the scheme proposed in Kuila and Jana (2014).

$$D_{j,i,G} = \begin{cases} 1 + X_{j,r,G} - X_{j,s,G} & \text{if } X_{j,r,G} - X_{j,s,G} \leq 0 \\ X_{j,r,G} - X_{j,s,G} & \text{otherwise} \end{cases} \tag{3.4.8}$$

Again, the same problem may occur at the time of the addition operation. Therefore, donor vectors are generated as mentioned in **?**.

$$V_{j,i,G} = \begin{cases} X_{j,best,G} + \mu \times D_{j,r,G} - 1 \text{ if } X_{j,best,G} + X_{j,r,G} & \\ & > 1 \\ X_{j,best,G} + \mu \times D_{j,r,G} \quad \text{otherwise} & \end{cases} \tag{3.4.9}$$

3.4.5 Crossover

A trial vector $U_{i,G}$ is derived from the target vector $X_{i,G}$ and the donor vector $V_{i,G}$ as shown below:

$$U_{j,i,G} = \begin{cases} V_{j,i,G} & \text{if Rand()} \leq C_r \\ X_{j,i,G} & \text{otherwise} \end{cases} \tag{3.4.10}$$

The crossover probability C_r is set to 0.2. A random number is obtained between 0 and 1 to generate a j^{th} component of a trial vector. If the random number is less than or equal to C_r, then we select j^{th} component of donor vector as j^{th} component of the trial vector; otherwise, it is selected from the target vector. The entire process of crossover is depicted in Fig. 3.4.

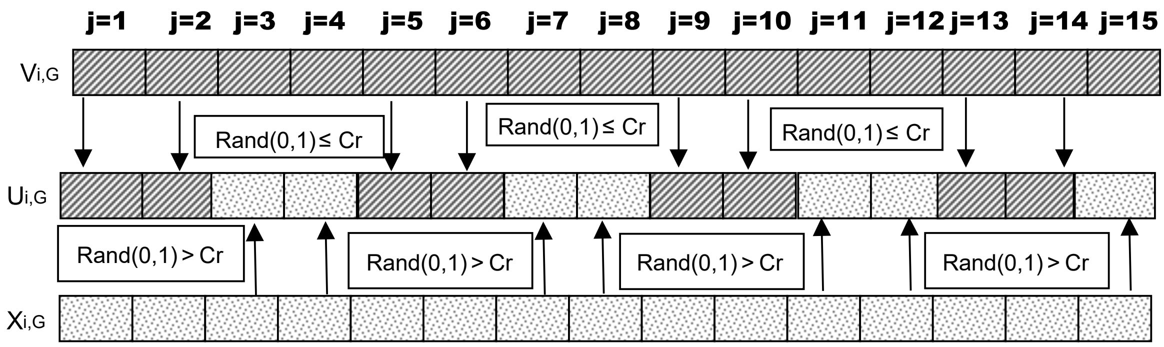


Figure 3.4 Crossover operation

3.4.6 Selection

The selection process determines the vector that survives for the next generation, either the target vector or the trial vector. The vectors are evaluated to find fitness values. The target vector $X_{i,G}$ is compared with the trial vector $U_{i,G}$ and one with the highest fitness value is selected for the next generation as shown below,

$$X_{i,G+1} = \begin{cases} U_{i,G} & \text{fitness } U_{i,G} \geq \text{ fitness } X_{i,G} \\ X_{i,G} & \text{otherwise} \end{cases} \tag{3.4.11}$$

Illustration 2

Consider a wireless sensor network with 5 candidate positions to place sensors $C = \{p_1, p_2, \ldots, p_5\}$ and 4 targets $T = \{t_1, t_2, \ldots, t_4\}$ as shown in Fig. 3.5. An optimal node placement shown in Fig. 3.5 (a), which obtains a vector as shown in Table 1. The integer 1 in the cell indicates selection, the integer 0 indicates non selection, and the symbol '-'

Algorithm 3.4.1 The DE based k-coverage and m-connected algorithm for WSN

Input: Set of m targets, set of n candidate positions, values of k and m
Output: Set of optimal candidate positions with k-coverage and m-connectivity.

1. // Generate initial popualtion of size P
2. **for** $i = 1$ **to** P
3. Initialize each i^{th} individual
4. // Using random function.
5. // Differential algorithm starts
6. **for** $itr = 1$ **to** $Max_{iteration}$ // Generation
7. **for each** member vector of population $X_{i,G}$
8. Compute the fitness using Eq. 3.4.6
9. Select best member vector $X_{best,G}$ using best fitness value.
10. Select two random $X_{r,G}$ and $X_{s,G}$, such that $r,s \in [1,P]$, $r \neq s \neq best$, and set μ=1.0.
11. Perform mutation operation using Eq. 3.4.7
12. Set crossover probability(C_r=0.2).
13. Perform crossover operation using Eq. 3.4.10
14. Perform selection operation using Eq. 3.4.11
15. Obtain $Best_{fitness}$ and $X_{Best,G}$
16. // Obtain optimal positions from $X_{Best,G}$
17. Obtain set of candidate positions that satisfies k-coverage and m-connectivity.

indicates the empty cell. The variable $CovCost(t_i)$ and $ConCost(s_i)$ represents coverage cost of targets and connectivity cost of sensors respectively. The fitness value of vector is computed using the Eq. 3.4.6 is given by, $F_1 = w_1 \times f_1 + w_2 \times f_2 + w_3 \times f_3$, where $w_1 = 0.3,\ w_2 = 0.3,\ w_3 = 0.4$ and $f_3 = 1.0 - \frac{P}{N} = 1.0 - \frac{3}{5}$

$F_1 = 0.3 \times 1 + 0.3 \times 1.3 + 0.4 \times 0.4 = 0.85$, here f_1, f_2 taken from Table 3.1.

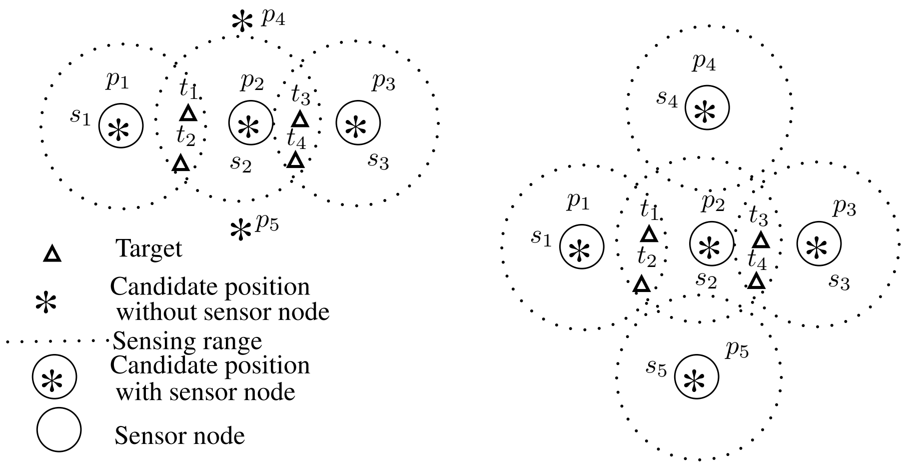
The Table 3.2 represents a vector with an extra sensors node placement as shown in Fig. 3.5(b). The fitness value of vector computed using the Eq. 3.4.6 is given by,

$F_2 = w_1 \times f_1 + w_2 \times f_2 + w_3 \times f_3$, where $w_1 = 0.3$,

$w_2 = 0.3,\ w_3 = 0.4$ and $f_3 = 1.0 - \frac{P}{N} = 1.0 - \frac{5}{5}$

$F_2 = 0.3 \times 1 + 0.3 \times 1.6 + 0.4 \times 0.0 = 0.78$, here f_1, f_2 taken from Table 3.2.

Since our objective is to maximize the fitness function, the vector whose fitness value $F_1 = 0.85$ is better than the vector whose fitness value $F_2 = 0.78$.



a b

Figure 3.5 2-coverage and 1-connected network scenarios (a) optimal number of placed wireless sensor nodes and (b) unnecessary and extra placed wireless sensors nodes.

Table 3.1 Optimal sensor nodes placement

(a) CovCost determination

Targets	Sensors					$CovCost(t_i)$
	p_1	p_2	p_3	p_4	p_5	
	1	1	1	0	0	
t_1	1	1	0	-	-	2
t_2	1	1	0	-	-	2
t_3	0	1	1	-	-	2
t_4	0	1	1	-	-	2
$f_1 = \frac{1}{M \times k} \sum_{i=1}^{M} CovCost(t_i) = 1$						

(b) ConCost determination

Sensors	Sensors					$ConCost(s_i)$
	p_1	p_2	p_3	p_4	p_5	
	1	1	1	0	0	
p_1	-	1	0	-	-	1
p_2	1	-	1	-	-	2
p_3	0	1	-	-	-	1
p_4	-	-	-	-	-	-
p_5	-	-	-	-	-	-
$f_2 = \frac{1}{P \times m} \sum_{i=1}^{P} ConCost(s_i)$=1.3						

Table 3.2 Unnecessary extra sensor nodes placement

(a) CovCost determination

Targets	Sensors					$CovCost(t_i)$
	p_1	p_2	p_3	p_4	p_5	
	1	1	1	1	1	
t_1	1	1	0	0	0	2
t_2	1	1	0	0	0	2
t_3	0	1	1	0	0	2
t_4	0	1	1	0	0	2
$f_1 = \frac{1}{M \times k} \sum_{i=1}^{M} CovCost(t_i) = 1$						

(b) ConCost determination

Sensors	Sensors					$ConCost(s_i)$
	p_1	p_2	p_3	p_4	p_5	
	1	1	1	1	1	
p_1	-	1	0	0	0	1
p_2	1	-	1	1	1	4
p_3	0	1	-	0	0	1
p_4	0	1	0	-	0	1
p_5	0	1	0	0	-	1
$f_2 = \frac{1}{P \times m} \sum_{i=1}^{P} ConCost(s_i)$=1.6						

3.5 Experimental Results

In this section, we discuss the simulation results of the proposed scheme. For simulation, we have used MATLAB R2017b. In our experiment, we have considered random and grid scenarios for sensor deployment as shown in Fig. 3.6 and Fig. 3.7. We used the parameters mentioned in Table 3.3 to carry out simulations.

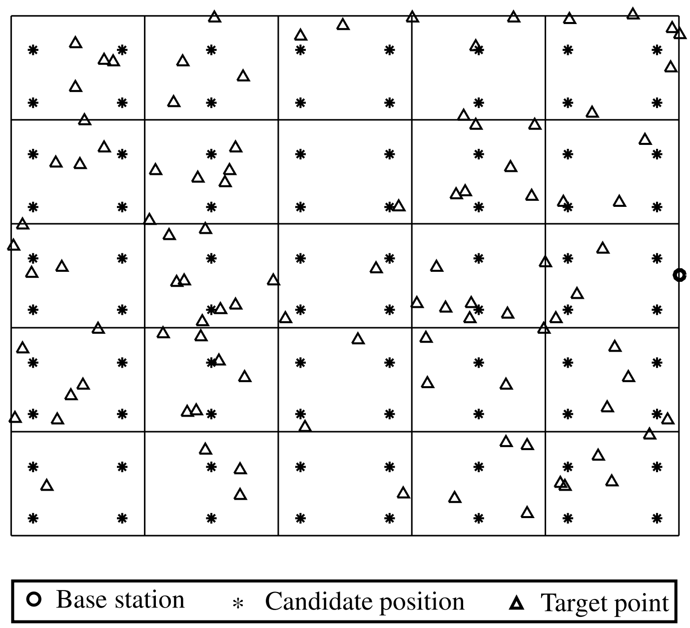


Figure 3.6 The first scenario, where candidate positions are on a grid

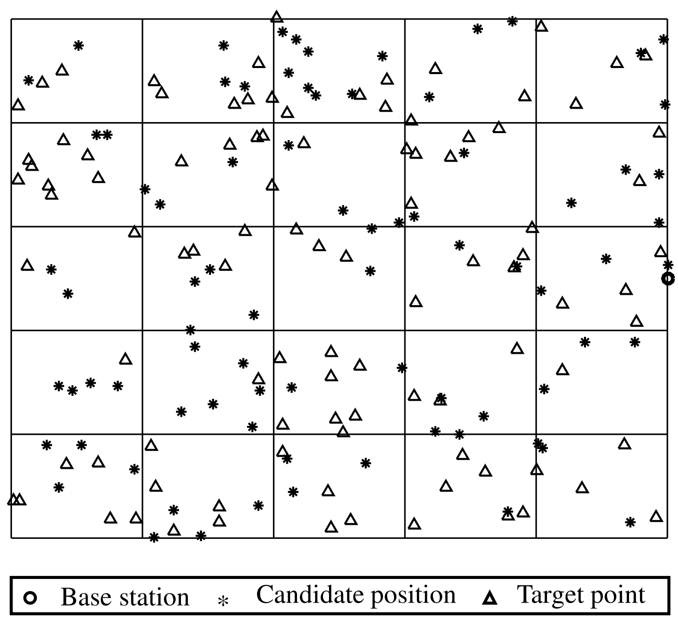
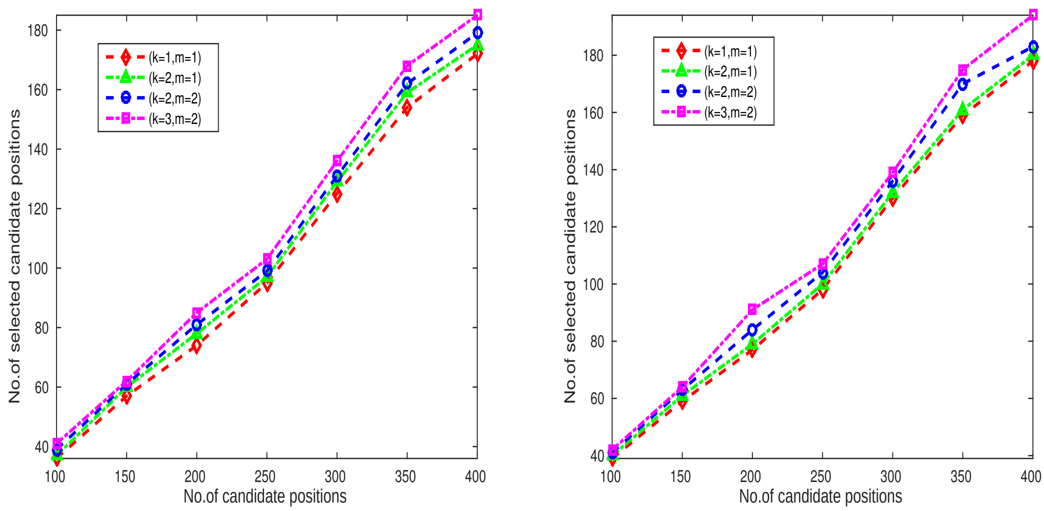


Figure 3.7 The second scenario, where candidate positions are random

Table 3.3 Simulation parameters

Parameters	Values
Size of the network field (m^2)	300×300
Location of the sink	(300,300)
Number of target points	100
Number of potential positions	100-400
Sensing range (m)	15
Communication range (m)	30
Maximum Iteration	100
Population Size	100
Crossover Probability	0.2
Mutation factor (μ)	1.0



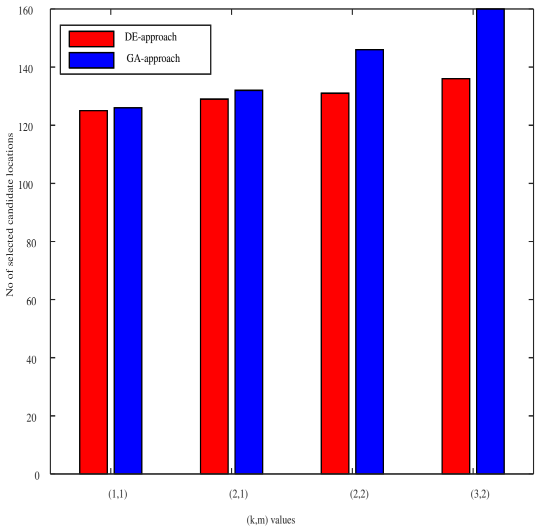
(a) Performance comparison of DE-based scheme in terms of number of selected candidate locations for grid scenario

(b) Performance comparison of DE-based scheme in terms of number of selected candidate locations for random scenario

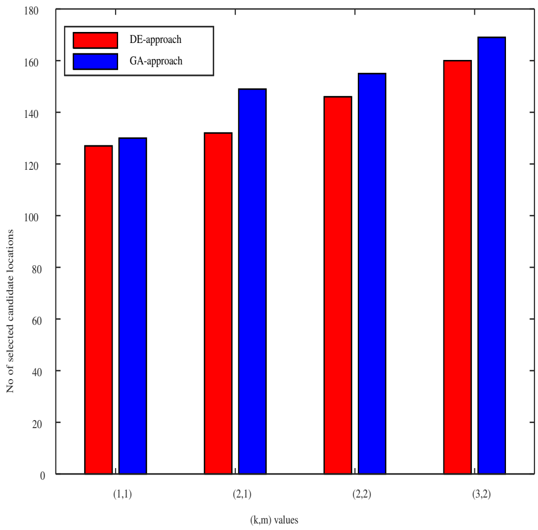
Figure 3.8 Proposed DE scheme

A set of random and grid based wireless sensor networks are generated within a field size of 300×300 m^2. The number of candidate positions are varied from 100 to 400 in steps of 50; The 100 targets randomly placed on both the scenarios. The network is assumed to be homogeneous, the initial energy of each sensor is $1J$, and sensing range and communication range of each sensor is 15 m and 30 m respectively. For our proposed approach, we considered a population of 100 vectors and 100 generations. We have considered a crossover rate (C_r) and scaling factor (μ) as 0.2 and 1.0 respectively.

The Fig. 3.8a shows performance comparison of different coverage and connectivity



(a) Performance comparison of DE-based scheme Vs GA-based scheme in terms of number of selected candidate locations for grid scenario



(b) Performance comparison of DE-based scheme Vs GA-based scheme in terms of number of selected candidate locations for random scenario

Figure 3.9 Performance of DE scheme Vs GA scheme

requirements for the grid scenario. The Fig. 3.8b show comparison results of different coverage and connectivity requirements for random scenario. Both the scenarios show optimal selected candidate positions by satisfying *k*-coverage and *m*-connectivity demands of the wireless sensor networks. The Fig. 3.9a and Fig. 3.9b shows a comparison between the DE-based approach and the GA-based approach for both the grid and random network scenarios respectively, where we considered 100 targets points and 300 sensor nodes. It can be noted that the proposed technique selects a minimum number of candidate positions for deploying sensor nodes compare to GA-based scheme. It is also viewed that the selected candidate positions are more for random scenarios compare to grid scenarios since candidate positions are decided uniformly on a grid. The under performance of GA-approach over DE-approach is due to premature convergence of GA-approach.

3.6 Chapter Summary

In this chapter, DE-based technique for solving k-coverage and m-connectivity problem in WSN is presented. The technique finds the optimal number of selected candidate positions for deploying sensor nodes with specified k-coverage and m-connectivity constraints. The simulations are performed by varying candidate sensor node positions and targets points. Finally, the proposed technique is compared with the GA-based approach. The results confirm that the proposed approach is superior to the GA-based approach.

Chapter 4

Interference Aware Sensor Placement Scheme

This chapter addresses obtaining an optimal number of sensors to place in the region of interest for maximizing target coverage and minimizing the interference of the sensors while maintaining the connectivity of the network. A novel BBO-based algorithm for optimal sensor deployment scheme is presented in the chapter. A novel fitness function with an elegant vector encoding scheme is presented. The proposed method is tested on random and grid deployment scenarios. Results are compared with other methods and presented in the later section of this chapter.

4.1 Background

In recent fast, numerous sensor deployment schemes are widely studied by researchers. Deployment of sensors in a region of interest is categorized into random deployment and deterministic deployment. Placement of sensors in an inaccessible or hostile area allows random deployment. Placement of sensors in predetermined locations allow deterministic deployment or grid deployment (Deif and Gadallah (2014b); Tripathi et al. (2018); Wang (2011a)).

In random deployment, location for sensors are unevenly distributed, and hence some regions are highly dense and some regions are sparse. In the dense regions, there is a possibility for more sensor nodes are interfering during the sensing and transmitting of the data. One of the main reasons for the quick power drain in WSNs is due to the interference of signals in the wireless media. This results in message drop and requires message retransmission which in turn affects the energy efficiency of WSNs. Moreover, the deployed network must be able to monitor all the target points by preserving the connectivity of the network. Therefore, It is important to minimize the interference of nodes during their deployment to maximize the coverage while maintaining network connectivity. Due to the advancement of computational intelligence, scientists have adopted nature inspired techniques to solve real world combinatorial science and engineering problems such as applications in industry 4.0 (Azizi (2019)). These techniques have been adopted to solve some optimization problems such as k-coverage and m-connectivity (Barkhoda and Sheikhi (2020)) clustering (Nomosudro et al. (2019); Lalwani et al. (2018)), and node localization problems in WSNs (Annepu and Rajesh (2019); Arora and Singh (2017); Nagireddy et al. (2018)).

The proposed scheme employs the Biogeography Based Optimization (BBO) meta-heuristic technique which is motivated by the study of the geographical distribution of living beings (Simon (2008)). These geographic regions are well suited for living beings called habitats or islands. The quality of habitat is determined using Habitat Suitability Index (HSI). The Suitability Index Variables (SIVs) characterize each habitat. The high HSI habitat has a high emigration rate, where as low HSI habitat has a high immigration rate. Therefore, low HSI habitats are more dynamic in their species distribution than high HSI habitats (Simon (2008)). The BBO is considered to be a powerful search technique because it includes both exploration and exploitation strategies (Ma et al. (2017)). It shows the same characteristic of Genetic Algorithm (GA) and Differential Evolution (DE) in information sharing among neighbour solutions. The BBO is adopted in solving combinatorial problems in WSNs such as k-coverage and m-connectivity (Gupta and Jha (2019)), clustering and routing (Lalwani et al. (2018); Nomosudro et al. (2019)). Various meta-heuristic techniques are used to solve target coverage problem alone or target coverage with connectivity problem in WSN. However, none of them solve a combination of interference and target coverage problems by

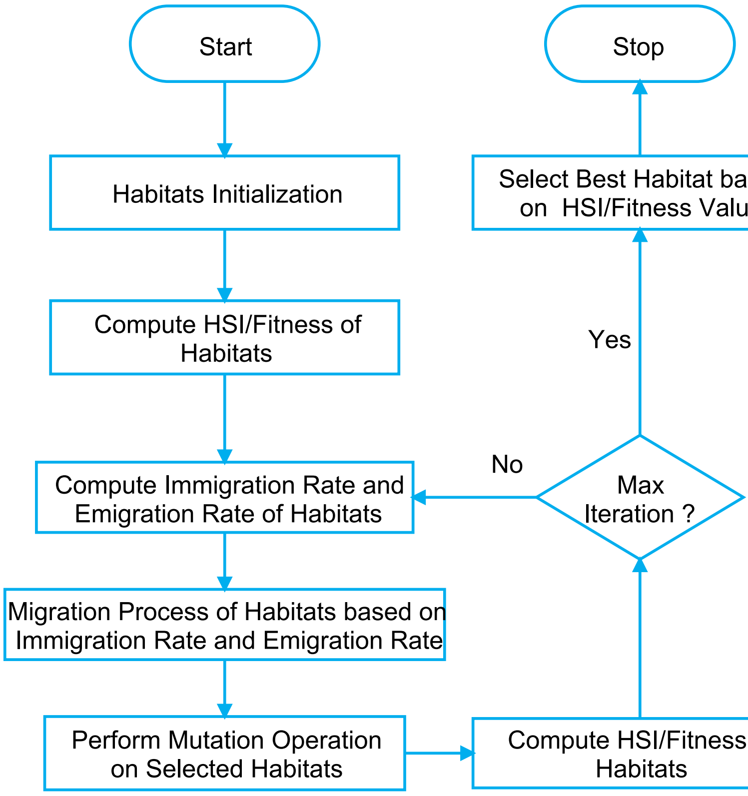


Figure 4.1 Flowchart of classical Biogeography-Based Optimization

maintaining connectivity of the WSN and hence a meta-heuristic scheme is adopted to solve the said combined problem.

4.2 Classical Biogeography-Based Optimization

Biogeography-Based Optimization (BBO) is a widely accepted meta-heuristic algorithm to solve many real world combinatorial problems. It is employed in solving many science and engineering optimization problems. The algorithm has five stages which consist of initialization of habitats, fitness calculation, migration, mutation, and selection. The entire process of BBO is shown in Fig. 4.1.

Fig. 4.2 represent species abundance in a single habitat, where λ and μ are immigration and emigration rate of species respectively. The variables I and E are maximum immigration and emigration rates respectively. The variable S_0 denotes equilibrium number of species at which immigration and emigration rates are equal. The maximum

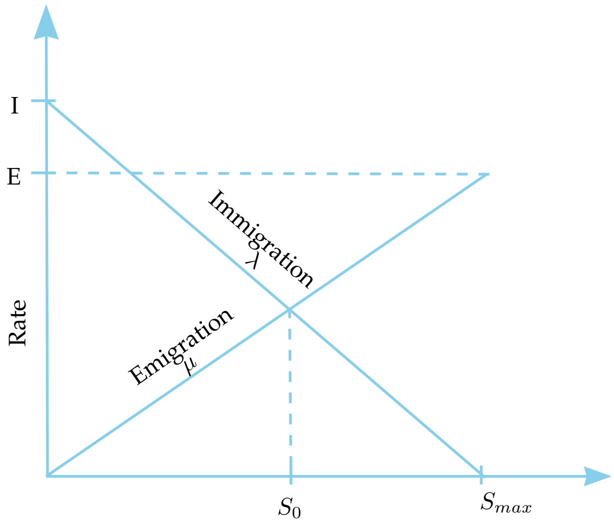


Figure 4.2 Species model of a single habitat in BBO

number of species that can live in a habitat is indicated by S_{max}.

The species count at habitat i is given by,

$$S_i = S_{max} * \frac{HSI_i}{\sum_{i=1}^{H_{max}} HSI_i} \tag{4.2.1}$$

Where H_{max} is the number of habitats. The immigration rate of habitat i is given by,

$$\lambda_i = I * (1 - \frac{S_i}{S_{max}}) \tag{4.2.2}$$

The emigration rate of habitat i is given by,

$$\mu_i = E * \frac{S_i}{S_{max}} \tag{4.2.3}$$

The essential phases of the BBO algorithm are migration and mutation stages as described below.

4.2.1 Migration Phase

In this stage, information is shared among habitats. High HSI habitat shares information with low HSI habitat to obtain a better habitat. The habitats are exchanging their information using SIVs. These SIVs are moved between habitats using their immigration and emigration rates. Suppose the first habitat H_i is chosen based on its immigration rate and second habitat H_j is chosen using the emigration rate, then some SIVs are moved from H_j to H_i.

4.2.2 Mutation Phase

Habitats are prone to undergo sudden changes due to natural catastrophes. The BBO adopts SIV mutation to model these changes. Each habitat i is associated with a probability P_i to obtain mutation rate M_i. The value of the P_i is computed using λ_i and μ_i. The high P_i vector has less chance for mutation and a low P_i vector has a high chance for mutation (Simon (2008))

. The mutation rate is computed using the following formula,

$$M_i = M_{max} * (\frac{1 - P_i}{P_{max}}) \tag{4.2.4}$$

Where M_{max} is user-specified maximum mutation rate, P_i is mutation probability of i^{th} habitat, P_{max} is the maximum mutation probability among habitats, and M_i is the mutation rate of i^{th} habitat.

4.3 Network Model and Preliminaries

The network is formed using homogeneous nodes having equal energy, same sensing, and communicating capabilities. Initially, different potential positions for deploying sensors are identified randomly to monitor set of target points. The sensors that are deployed in identified locations forward data to the base station directly or via other nodes. The adopted network architecture for the proposed work is shown in Fig. 5.2.

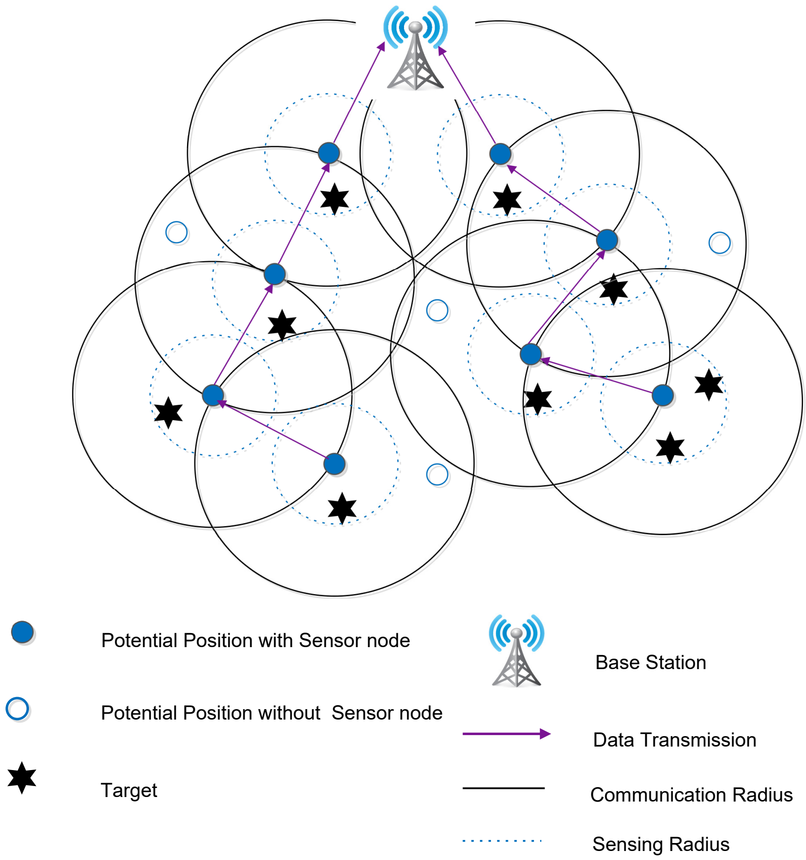


Figure 4.3 An instance of a network model

4.3.1 Preliminaries

Suppose P is the set of n potential positions $P = \{p_1, p_2 \ldots, p_n\}$ which are identified positions on a region of interest. Let T denotes the set of k targets $T = \{t_1, t_2, \ldots, t_k\}$ are to be monitored. Let $S = \{s_1, s_2 \ldots, s_m\}$ denotes the set of sensors placed in selected m potential positions.

Let C_R and S_R represents the communication and sensing range of the wireless sensor nodes respectively. Euclidean formula is adopted to calculate distance measure between two points. If $p = (x_1, y_1)$ and $q = (x_2, y_2)$ two points on two dimensional plane then the distance is computed as follows:

$$\text{distance}(p,q) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{4.3.1}$$

Let α_{ij}, β_i, γ_i, δ_{ij}, ψ_i^{BS} are sensing interference, target coverage, selection of potential positions, connectivity between sensors, and connectivity of base station with at least one sensor respectively. And formally defined as follows:

$$\alpha_{ij} = \begin{cases} 1 & distance(s_i, s_j) \leq 2 \times S_R \\ & \forall i,\ \forall j,\ 1 \leq i, j \leq m \\ 0 & \text{otherwise} \end{cases} \tag{4.3.2}$$

$$\beta_i = \begin{cases} 1 & \exists s_j \in S,\ Scov(s_j, t_i) = 1 \\ & \forall i,\ 1 \leq i \leq k \text{ and } \forall j,\ 1 \leq j \leq m \\ 0 & \text{otherwise} \end{cases} \tag{4.3.3}$$

Where $Scov(s_j, t_i)$ defined as follows,

$$Scov(s_j, t_i) = \begin{cases} 1 & distance(s_j, t_i) \leq S_R \\ 0 & \text{otherwise} \end{cases} \tag{4.3.4}$$

$$\gamma_i = \begin{cases} 1 & \gamma_i \text{ is selected for node deployment} \\ & \forall i,\ 1 \leq i \leq n \\ 0 & \text{otherwise} \end{cases} \tag{4.3.5}$$

$$\delta_{ij} = \begin{cases} 1 & \exists s_j \in S, distance(s_i, s_j) \leq C_R \\ & \forall i,\ \forall j,\ 1 \leq i, j \leq m \\ 0 & \text{otherwise} \end{cases} \tag{4.3.6}$$

$$\psi_i^{BS} = \begin{cases} 1 & \exists s_i \in S,\ distance(s_i, BS) \leq C_R \\ & \forall i,\ 1 \leq i \leq m \\ 0 & \text{otherwise} \end{cases} \tag{4.3.7}$$

Definition 4.1.1

Sensing Interference Ratio (SIR) of the network is the ratio of total sensing interference experienced by the network to the sum of currently deployed sensors. The underlying formula for *SIR* is given in Eq. 4.4.3.

Definition 4.1.2

Target Coverage Ratio (TCR) of the network is the ratio of the sum of target points covered by the sensors to the total number of target points in the region of interest. The underlying formula for TCR is given in Eq. 4.4.5.

Definition 4.1.3

Sensor to Potential Position Ratio (SPPR) of the network is the ratio of sum of potential positions considered for sensor placement to the total number of potential positions. The underlying formula for *SPPR* is given in Eq. 4.4.6.

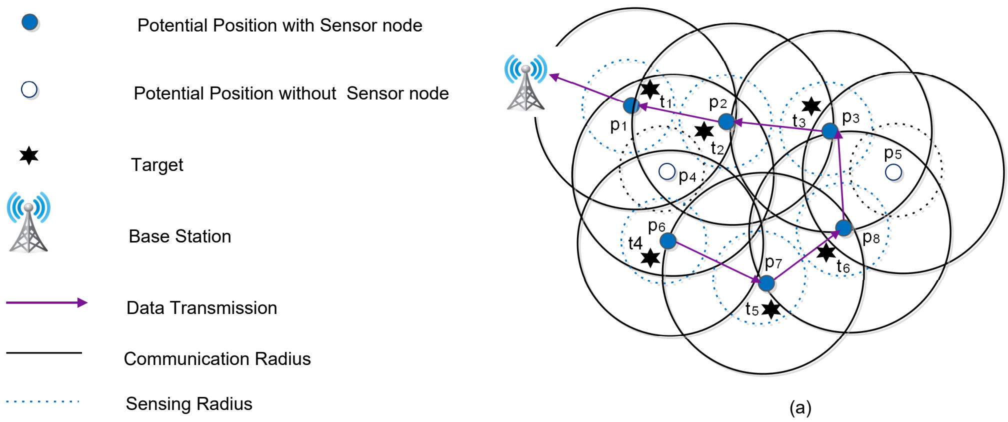
4.4 Proposed Algorithm

Illustration 1

In this work, a BBO based optimal sensor placement algorithm that provides maximum target coverage and minimum interference is proposed.

Given $P = \{p_1, p_2, p_3, \ldots, p_n\}$ and $T = \{t_1, t_2, t_3, \ldots, t_k\}$, the objective is to choose optimal number of sensors and their positions such that,

1. Minimize the sensing interference for the sensor network
2. Maximize the target point coverage of the sensor network
3. Minimize the selection of potential positions to deploy sensors in the network while preserving the connectivity of the network.



(a)

Potential Positions	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8
Vector values	1	1	1	0	0	1	1	1

(b)

Potential Positions	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8
Vector values	1	1	1	1	1	0	0	1

(c)

Figure 4.4 An instance of vector encoding

4.4.1 Representation of Habitats

In the proposed technique, initial habitats are generated using boolean values. The number of potential positions in a habitat gives the length of a vector. Placement of a sensor in i^{th} position is indicated by a boolean value 1 and non placement of a sensor is indicated by a boolean value 0.

4.4.2 Initialization of Habitats

Each habitat represents selection of potential positions to place sensors. The g^{th} generation of i^{th} habitat having length n is represented as follows:

$$H_{i,g} = [SIV_{1,i,g}, SIV_{2,i,g}, SIV_{3,i,g}, \ldots, SIV_{n,i,g}] \tag{4.4.1}$$

The Habitat Suitability Index (HSI) measures the fitness or goodness of i^{th} habitat as indicated below:

$$HSI_{i,g} = f([SIV_{1,i,g}, SIV_{2,i,g}, SIV_{3,i,g}, \ldots, SIV_{n,i,g}]) \tag{4.4.2}$$

Suppose there are 6 targets $T = \{t_1, t_2, \ldots, t_6\}$ and 8 potential positions $P = \{p_1, p_2, \ldots, p_8\}$ are considered as shown in Fig. 4.4(a). The number of potential position is the length of the habitat, which is 8 as according to Fig. 4.4(b).

Fig. 4.4(b) represents a encoded habitat. The binary value 1 in the positions p_1, p_2, p_3, p_6, p_7 and p_8 indicates that the sensor nodes are deployed on these potential positions. The binary value 0 in the positions p_4 and p_5 denotes that the sensor nodes are not placed on these potential positions.

4.4.3 Derivation of Fitness Function

Objective 1

It is to minimize *SIR* and is formally defined as follows:

$$\text{Minimize } o_1 = \frac{1}{m} \sum_{i=1}^{m} \sum_{j=i+1}^{m} \alpha_{ij} \tag{4.4.3}$$

where m is the number of position selected to deploy sensor nodes.

OR

$$\text{Maximize } {o_1}' = 1 - \frac{1}{m} \sum_{i=1}^{m} \sum_{j=i+1}^{m} \alpha_{ij} \tag{4.4.4}$$

Objective 2

It is to maximize *TCR* and is formally defined as follows:

$$\text{Maximize } o_2 = \frac{1}{k} \sum_{i=1}^{k} \beta_i \tag{4.4.5}$$

Objective 3

It is to minimize *SPPR* and is formally defined as follows:

$$\text{Minimize } o_1 = \frac{1}{n}\sum_{i=1}^{n}\gamma_i \tag{4.4.6}$$

OR

$$\text{Maximize } o_3{}' = 1.0 - \frac{1}{n}\sum_{i=1}^{n}\gamma_i \tag{4.4.7}$$

Since all the objectives are conflicting in nature, a final objective function(O) is devised by applying a weighted sum approach (Atta et al. (2019); Harizan and Kuila (2019)) as shown below:

$$\text{Maximize } \ O = w_1 \times o_1{}' + w_2 \times o_2 + w_3 \times o_3{}' \tag{4.4.8}$$

Subject to

$$\frac{1}{m}\sum_{i=j=1}^{m}\delta_{ij} \times \gamma_i + \psi_i^{BS} = 2 \tag{4.4.9}$$

Here w_i is a weight variable, with $0 < w_i \leq 1,\ 1 \leq i \leq 3$, $w_1 + w_2 + w_3 = 1$, $\delta_{ij} \in \{0,1\}$, $\gamma_i \in \{0,1\}$ and $\psi_i^{BS} \in \{0,1\}$

The total *interference energy loss* (E_{Loss}^{Total}) of the network is defined as the total energy drain due to interference in the network and formally defined as follows:

$$E_{Loss}^{Total} = I_{Count}^{Total} \times E_{Loss}^{Interference} \tag{4.4.10}$$

Where I_{Count}^{Total} and $E_{Loss}^{Interference}$ are interference number of the network and the energy loss per interference respectively.

Illustration 2

Consider an optimal placement of sensors as shown in Fig. 4.4(b) and corresponding SIR determination and TCR determination are shown in Table 4.1.

Table 4.1 Optimal sensor nodes placement

(a) SIR determination

Sensors	Sensors and Positions						$I_{cnt}(s_i)$
	p_1	p_2	p_3	p_6	p_7	p_8	
	s_1	s_2	s_3	s_4	s_5	s_6	
s_1	0	0	0	0	0	0	0
s_2	0	0	0	0	0	0	0
s_3	0	0	0	0	0	0	0
s_4	0	0	0	0	0	0	0
s_5	0	0	0	0	0	0	0
s_6	0	0	0	0	0	0	0
$o_1{}' = 1 - \frac{1}{m}\sum_{i=1}^{m}\sum_{j=i+1}^{m}\alpha_{ij} = 1$							

(b) TCR determination

Targets	Sensors and Positions						$S_{cov}(t_i)$
	p_1	p_2	p_3	p_6	p_7	p_8	
	s_1	s_2	s_3	s_4	s_5	s_6	
t_1	1	0	0	0	0	0	1
t_2	0	1	0	0	0	0	1
t_3	0	0	1	0	0	0	1
t_4	0	0	0	1	0	0	1
t_5	0	0	0	0	1	0	1
t_6	0	0	0	0	0	1	1
$o_2 = \frac{1}{k}\sum_{i=1}^{k}\beta_i = 1$							

Table 4.2 Non optimal sensor nodes placement

(a) SIR determination

Sensors	Sensors and Positions						$I_{cnt}(s_i)$
	p_1	p_2	p_3	p_4	p_5	p_8	
	s_1	s_2	s_3	s_4	s_5	s_6	
s_1	0	0	0	1	0	0	1
s_2	0	0	0	1	0	0	1
s_3	0	0	0	0	1	0	1
s_4	0	0	0	0	0	0	0
s_5	0	0	0	0	0	1	1
s_6	0	0	0	0	0	0	0
$o_1{}' = 1 - \frac{1}{m}\sum_{i=1}^{m}\sum_{j=i+1}^{m}\alpha_{ij} = 0.33$							

(b) TCR determination

Targets	Sensors and Positions						$S_{cov}(t_i)$
	p_1	p_2	p_3	p_4	p_5	p_8	
	s_1	s_2	s_3	s_4	s_5	s_6	
t_1	1	0	0	0	0	0	1
t_2	0	1	0	0	0	0	1
t_3	0	0	1	0	0	0	1
t_4	0	0	0	0	0	0	0
t_5	0	0	0	0	0	0	0
t_6	0	0	0	0	0	1	1
$o_2 = \frac{1}{k}\sum_{i=1}^{k}\beta_i = 0.67$							

The variable $Icnt(s_i)$ and $Scov(t_i)$ represents interference count of the sensor s_i and sensor coverage of the target t_i respectively. The value 1 in the cell indicates whether the sensor covers another sensor or target and the value 0 indicates the sensor or target is not covered by another sensor.

The fitness value of the vector is computed using the Eq. 4.4.8 is given by,

$O_1 = w_1 \times o_1' + w_2 \times o_2 + w_3 \times o_3'$, where $w_1 = 0.3,\ w_2 = 0.4,\ w_3 = 0.3$ and

$o_3' = 1.0 - \frac{m}{n} = 1.0 - \frac{6}{8}$

$O_1 = 0.3 \times 1 + 0.4 \times 1.0 + 0.3 \times 0.25 = 0.775,$

here o_1', o_2 are taken from Table 4.1.

The non optimal sensor placement of sensors vector is shown in Fig. 4.4(c). The fitness value of vector computed using the Eq. 4.4.8 is given by,

$O_2 = 0.3 \times 0.33 + 0.4 \times 0.67 + 0.3 \times 0.25 = 0.442$, Here o_1' and o_2 are taken from

Table 4.3 Pictorial view of migration process

Step 1: Randomly generated habitat with 0 and 1 from H_1-H_5 as shown below	Step 2: Fitness value for each habitat calculated using Eq. 4.4.8
H_1 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 |	$HSI_1 = 0.775$
H_2 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 1 |	$HSI_2 = 0.442$
$H3$ | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |	$HSI_3 = 0.5$
H_4 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 |	$HSI_4 = 0.4325$
H_5 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 1 |	$HSI_5 = 0.4365$
Step 3: Let $S_{max} = 1000$. Species count of each habitat are as follows	Step 4: Immigration and Emigration rate $\lambda_i = I(1 - S_i/S_{max})$ and $\mu_i = E(S_i)/S_{max}$
$S_1 = 1000 \times (0.775/2.586) = 299$	$\lambda_1 = 1 \times (1 - 299/1000) = 0.701$ and $\mu_1 = 1 \times (299/1000) = 0.299$
$S_2 = 1000 \times (0.442/2.586) = 172$	$\lambda_2 = 1 \times (1 - 172/1000) = 0.828$ and $\mu_2 = 1 \times (172/100) = 0.172$
$S_3 = 1000 \times (0.5/2.586) = 193$	$\lambda_3 = 1 \times (1 - 193/1000) = 0.807$ and $\mu_3 = 1 \times (193/1000) = 0.193$
$S_4 = 1000 \times (0.4325/2.586) = 167$	$\lambda_4 = 1 \times (1 - 167/1000) = 0.833$ and $\mu_4 = 1 \times (167/1000) = 0.167$
$S_5 = 1000 \times (0.4365/2.586) = 169$	$\lambda_5 = 1 \times (1 - 169/1000) = 0.831$ and $\mu_5 = 1 \times (169/1000) = 0.169$
Step 5: Migration process between selected habitats	
H_1 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 |	
| | | | | ↓ | ↓ | ↓ | ↓ |	
H_4 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 |	
H_4' | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 |	

Table 4.2. where $w_1 = 0.3,\ w_2 = 0.4,\ w_3 = 0.3$ and $o_3' = 1.0 - \frac{m}{n} = 1.0 - \frac{6}{8}$.

Since it is a maximization problem, the habitat having fitness value $O_1 = 0.775$ is better than that of the habitat having fitness value $O_2 = 0.442$. The computed interference energy loss for the network with non optimal sensor nodes placement using Eq. 4.4.10 is $0.08 Joule$ and which is ideally zero in the network with optimal sensor node placement.

4.4.4 Migration

In this stage, habitats H_i and H_j are selected stochastically based on immigration rate λ_i and emigration rate μ_j respectively. After choosing habitats, a random number is generated between $(0,1)$. If the random number is less than λ_i, then migration is performed

Table 4.4 Pictorial view of mutation process

<table>
<tr><td>Step 1: Emigration rate of habitats H_1 to H_5

$\mu_1 = 0.299$

$\mu_2 = 0.172$

$\mu_3 = 0.193$

$\mu_4 = 0.167$

$\mu_5 = 0.169$</td><td>Step 2: Mutation probability of habitat H_i using $M_i = M_{max} * (\frac{1-P_i}{P_{max}})$, where $M_{max} = 0.2$

$M_1 = 0.2 \times (1-0.299)/0.299 = 0.469$

$M_2 = 0.2 \times (1-0.172)/0.299 = 0.554$

$M_3 = 0.2 \times (1-0.193)/0.299 = 0.540$

$M_4 = 0.2 \times (1-0.167)/0.299 = 0.557$

$M_5 = 0.2 \times (1-0.169)/0.299 = 0.556$</td></tr>
<tr><td colspan="2">Step 3: Mutation process of the selected habitat
$H_4^{'}$ 1 1 1 1 0 1 1 1
↓
$H_4^{''}$ 1 1 1 0 0 1 1 1</td></tr>
</table>

between habitats. To perform the migration, a random position is selected between $(1,n)$, and SIV are shifted from habitat H_j to habitat H_i from the selected position to the last position of habitat H_j. The Table 4.3 depicts the pictorial representation of the migration process.

4.4.5 Mutation

This process involves the selection of a vector based on the mutation probability of the respective vector. Once the habitat is selected, check for value at the position, if the value is 1 then it is changed to 0; otherwise to 1. The Table 4.4 depicts the pictorial representation of the mutation process.

4.4.6 Pseudo-code of BBO-based Sensor Placement Algorithm

The proposed scheme is depicted in Algorithm 4.4.1. The algorithm consists of two main stages. They are the migration process (lines 18-29) and the mutation process (lines 30-36). Initially, the $best_{fitness}$ and M_{max} are set to value 0 and value 0.2 respectively (line 1). The habitats are initialized with 0's and 1's (lines 2-4). The initial iteration is set to 1 (line 5) and the entire procedure for the BBO is presented (lines 6-38). Firstly, fitness computation for each habitat and selection of best habitat that has highest fitness value is performed (lines 7-11). The species count of each habitat is calculated (lines 12-14). Next the immigration rate and emigration rate are computed for each habitat (lines 15-17). In lines 18-29, the migration procedure is presented. Each habitat H_i, a associated habitat H_j is selected based on the emigration rate to perform SIV's migration from habitat H_j to habitat H_i (lines 18-19). In this process, a random number is generated (line 20). If the generated random number is less than the emigration rate of habitat H_j (line 21), then a random position p_1 is selected in habitat H_j (line 22). Next, all SIV's from position p_1 to position n are moved from habitat H_j to habitat H_i (lines 23-26). In lines 30-36, a habitat mutation procedure is presented. Firstly, immigration rate and emigration rate of the each habitat is used to compute its mutation probability (line 30). A habitat H_i is selected which has maximum mutation probability (p_{max}). A random number is generated (line 32). If the generated random number is less than the maximum mutation probability, then a random position p_2 is selected in habitat H_i (lines 33-34).

Next, if the value of the position p_2 is 1, then replace it is with 0; otherwise it is with 1 (line 35). Go to line 6 and repeat the process till the maximum iteration is reached and the algorithm terminates. Finally, the habitat with best solution is selected for placing sensors (line 39).

4.5 Simulation and Discussion

This section discusses the performance analysis of the proposed scheme and gives comparative analysis with other schemes. The experiments are carried out using MATLAB 2018a on an Intel(R) Core(TM) i5-8250U CPU@1.60 GHz 1.80 GHz and 8 GB RAM running on Microsoft Windows 10, 64-bit operating system, x64-based processor.

Algorithm 4.4.1 BBO based Sensors Deployment for Target Coverage with Interference Minimization

Input: Set of n candidate positions $P = \{p_1, p_2, p_3 \ldots, p_n\}$, Set of k target points $T = \{t_1, t_2, t_3 \ldots, t_k\}$, and set of habitats H_n

Output: Optimal sensor nodes placement positions

// Habitat initialization

$best\_fitness = 0$, $M_{max} = 0.2$
for $habitat\ i = 1$ to H_n **do**
    Initialize habitat H_i with 0's and 1's
end for
$itr = 1$

// BBO algorithm starts

while $itr < MAX_{itr}$ **do**
    for $habitat\ i = 1$ to H_n **do**
        Evaluate habitat HSI/fitness($f(H_i)$)
    end for
    Sort habitats based on HSI's
    $best\_fitness = \max(f(H_i), best\_fitness)$
    for $habitat\ i = 1$ to H_n **do**
        Map habitat species count (S_{count}) for each habitat (H_i)
    end for
    for $habitat\ i = 1$ to H_n **do**
        Compute immigration rate(λ_i) and emigration rate (μ_i)
    end for

    // Habitat migration

    for $habitat\ i = 1$ to H_n **do**
        for $habitat\ j = 1$ to H_n **do**
            Generate random number r_1 , $0 \le r_1 \le 1$
            if $r_1 < \mu_j$ **then**
                Select random position p_1 , $1 \le p_1 \le n$
                while $p_1 > n$ **do**
                    $H_i[p1] = H_j[p1]$
                    $p_1 = p_1 + 1$
                end while
            end if
        end for
    end for

    // Habitat mutation

    Compute mutation probability(M_i) of each habitat H_i using immigration rate (λ_i) and emigration rate (μ_i) using Equation 4.2.4
    Select a habitat H_i with maximum mutation probability P_{max}
    Generate random number r_2, $0 \le r_2 \le 1$
    if $r_2 < P_{max}$ **then**
        Select a random position p_2, $1 \le p_2 \le n$
        if the value of the position p_2 is 1, then replace it is with 0; Otherwise it is with 1
    end if
    $itr = itr + 1$
end while
Finally, the habitat with highest fitness value is selected for placing sensors.

A WSN is created with n number of potential positions and k number of target points. A 300×300 network field is created and sink is placed at the centre of the field $(150,150)$. The potential positions and target points are randomly generated on the field. The parameter values for the WSN are mentioned in Table 4.5.

Table 4.5 Simulation parameters

Parameters	Values
WSN Field Size	$300 \times 300\ m^2$
Sink Position	$(150,150)$
Target points	$50-200$
Potential Positions	$100-200$
Sensing Range	$10m$
Communication Range	$50m$
Initial Energy of node	2 *Joule*
Per interference energy loss	0.02 *Joule*

The proposed technique is compared with Random scheme and GA based scheme for performance comparisons. In a Random scheme, the potential positions to deploy sensors to cover the given target points are identified randomly using a uniform distribution. If the identified potential positions form the connected network, then these potential positions are considered for placing sensors. The SIR and TCR are computed for these sensors. The GA algorithm is an optimization technique or heuristic solution-search method proposed by John Holland. The main components of the GA algorithms are the chromosome representation, the fitness function evaluation, cross over, mutation, and selection (McCall (2005)). We adopted single-point cross over and roulette wheel selection method in this algorithm.

The parameter settings for heuristic techniques are decided as follows. The 200 potential positions and 200 target points are used to find appropriate simulation parameters. A population size of 100 habitats and 100 generations are considered for the experiments. Experimentally verified that these generic parameter values are enough for proper convergence of the proposed algorithm. However, the control parameter mutation probability M_{max} for BBO method is adopted from Gupta and Jha (2019) and also verified with different values of M_{max} and confirmed that results are comparatively better for $M_{max} = 0.2$. It is observed in the literature that the control parameter like mutation rate for GA is set between 0.01 to 0.05. Therefore, the mutation rate is set to 0.02 and varied the crossover rate from 0.1 to 0.9 and confirmed through repeated experiments that the result is better when crossover rate is 0.2. The final parameter settings for heuristic methods for the simulations are mentioned in Table 4.6.

Table 4.6 Parameter settings for BBO and GA

Algorithm	Parameters	Values
BBO	Population Size	100
	Maximum Iteration	100
	Mutation Probability	0.2
GA	Population Size	100
	Maximum Iteration	100
	Crossover Probability	0.2
	Mutation Probability	0.02

Table 4.7 Weight values and multi-objective results (potential positions=200 and targets=200)

Weight values			BBO			GA		
w_1	w_2	w_3	SIR	TCR	SPPR	SIR	TCR	SPPR
0.45	0.1	0.45	0.9704	0.9617	0.7780	1.0808	0.9580	0.7903
0.40	0.2	0.40	0.9735	0.9620	0.7853	1.1056	0.9583	0.7923
0.35	0.3	0.35	0.9776	0.9626	0.7910	1.1103	0.9586	0.8060
0.30	0.4	0.30	0.9809	0.9646	0.7970	1.1175	0.9606	0.8186
0.25	0.5	0.25	0.9889	0.9650	0.8050	1.1238	0.9614	0.8257
0.20	0.6	0.20	1.0103	0.9653	0.8113	1.1297	0.9623	0.8326
0.15	0.7	0.15	1.0953	0.9663	0.8236	1.1324	0.9628	0.8360
0.10	0.8	0.10	1.1076	0.9670	0.8260	1.1331	0.9631	0.8386
0.05	0.9	0.05	1.1093	0.9673	0.8286	1.1397	0.9636	0.8423

In the Equation 4.4.8, the second component (TCR) is the maximization component and other two components (SIR and SPPR) are the minimization components. Therefore, weight of second component w_2 is varied from 0.1 to 0.9 in steps of 0.1 and

Table 4.8 BBO multi-objective results (normalized)

BBO			BBO (normalized results)		
SIR^{-1}	TCR	$SPPR^{-1}$	SIR^{-1}	TCR	$SPPR^{-1}$
1.0305	0.9617	1.2853	0.3501	0.3323	0.3446
1.0272	0.9620	1.2733	0.3489	0.3324	0.3414
1.0229	0.9626	1.2642	0.3474	0.3326	0.3390
1.0194	0.9646	1.2547	0.3475	0.3333	0.3364
1.0112	0.9650	1.2422	0.3435	0.3334	0.3331
0.9898	0.9653	1.2325	0.3362	0.3335	0.3305
0.9129	0.9663	1.2142	0.3101	0.3339	0.3256
0.9028	0.9670	1.2106	0.3066	0.3341	0.3246
0.9015	0.9673	1.2068	0.3062	0.3342	0.3236

Table 4.9 GA multi-objectives results (normalized)

GA			GA(normalized results)		
SIR^{-1}	TCR	$SPPR^{-1}$	SIR^{-1}	TCR	$SPPR^{-1}$
0.9252	0.9580	1.2653	0.3658	0.3323	0.3457
0.9045	0.9583	1.2621	0.3576	0.3324	0.3448
0.9007	0.9586	1.2407	0.3561	0.3325	0.3389
0.8949	0.9606	1.2216	0.3538	0.3332	0.3338
0.8898	0.9614	1.2111	0.3518	0.3334	0.3309
0.8852	0.9823	1.2011	0.3499	0.3337	0.3282
0.8831	0.9628	1.1962	0.3491	0.3339	0.3268
0.8825	0.9631	1.1925	0.3489	0.3340	0.3258
0.8774	0.9636	1.1872	0.3469	0.3342	0.3244

accordingly equal weights are assigned to w_1 and w_3 to decide appropriate weight values. The results are computed for 15 instances of experiments for each set of weight values for w_1, w_2 and w_3 and mean result is tabulated in Table 4.7. The multi-objective results for BBO and GA approaches are presented in the normalized form in Table 4.8 and Table 4.9 respectively using the Equation 4.5.1.

$$x_i^{normalized} = \frac{x_i}{\sqrt{\sum_1^n {x_i}^2}} \tag{4.5.1}$$

Here, x_i denotes each data value and n represents the number of data values present.

The Pareto solution (Atta et al. (2019)) for SIR, TCR, and SPPR on different weight values is shown in Fig. 4.5. It is required to note that the selection of weight values in a precise and accurate manner is very difficult even for someone familiar with the

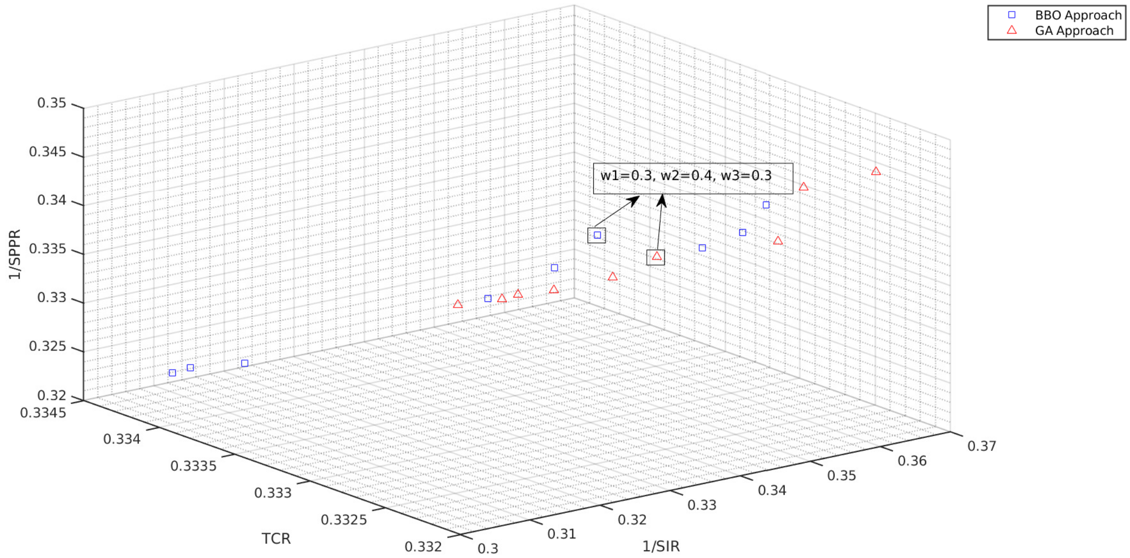


Figure 4.5 Pareto solutions for SIR, TCR and SPPR on different weight values

problem domain (Konak et al. (2006)). Therefore, we adopted weight values $w_1 = 0.3$, $w_2 = 0.4$ and $w_3 = 0.3$ in both heuristic methods for simulations.

4.5.1 Result and Analysis

This section details the result analysis of the experiments that are carried out. The experiments are performed using the same data on all three algorithms. The 30 instances of experiments are carried out for each set of targets to handle the random nature of these algorithms. Fig. 4.6 shows the performance analysis of BBO-based scheme when the number of target points increase from 50 to 200. The 30 instances of experiments are carried out on each set of target points and the graph is drawn by taking the best and mean of the results. Here, 200 potential positions are identified to deploy sensors. It is observed that that there is a increase in BBO_SIR when the number of target points increase. It is because more potential positions are selected to place sensors, which

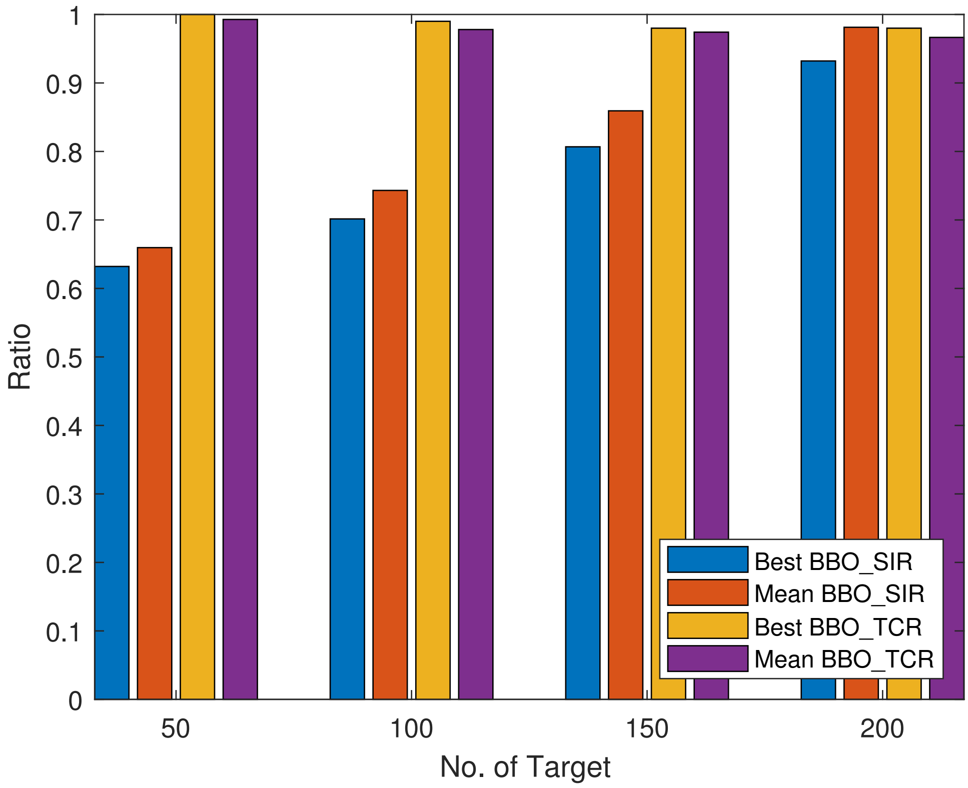


Figure 4.6 Performance of proposed scheme

gives scope for more interference of signals. The simulations are performed on grid and random scenarios as shown in Fig. 4.7 and Fig. 4.8. The Fig. 4.9a and Fig. 4.9b illustrates the best and mean comparison of SIR and TCR for grid and random scenarios respectively when target points increase from 25 to 100. The 30 instances of the experiments are carried out on each set of target points and graph is drawn by taking the best and mean of the results. In these experiments, 100 potential positions are identified to deploy sensors. In both the graph, it is observed that the best and mean Grid_SIR is zero, which is to indicates no sensors are interfering with each other because potential positions are identified on grid cross points. It is also seen that the Random_SIR increases as the number of target points increase. Grid_TCR is better than that of the Random_TCR because the targets are optimally covered in grid scenario as compared to random scenario.

Table 4.10 Comparison results for SIR (30 instance of experiments are conducted)

Targets	Parameters	BBO_SIR	GA_SIR	Random_SIR
50	Best	0.6321	0.6529	0.7984
	Worst	0.6872	0.7548	0.9921
	Mean	0.6596	0.7257	0.933
	SD	0.0169	0.0209	0.0390
	95% CI	[0.6537, 0.6655]	[0.7181, 0.7333]	[0.9197, 0.9463]
100	Best	0.7015	0.7898	0.9128
	Worst	0.7842	0.8465	1.0861
	Mean	0.7431	0.8215	1.0229
	SD	0.0193	0.0155	0.0440
	95% CI	[0.7363, 0.7499]	[0.8161, 0.8269]	[1.0074, 1.0384]
150	Best	0.8068	0.8942	1.0617
	Worst	0.9025	0.9678	1.842
	Mean	0.8593	0.9329	1.1815
	SD	0.0281	0.0189	0.158121629
	95% CI	[0.8495, 0.8691]	[0.9263, 0.9395]	[1.1259, 1.2371]
200	Best	0.9321	0.9806	1.142
	Worst	1.0787	1.2386	1.956
	Mean	0.9813	1.1201	1.3443
	SD	0.0414	0.0578	0.2097
	95% CI	[0.9667, 0.9959]	[1.1003, 1.1399]	[1.2705, 1.4181]

Table 4.11 Comparison results for TCR (30 instance of experiments are conducted)

Targets	Parameters	BBO_TCR	GA_TCR	Random_TCR
50	Best	1	1	1
	Worst	0.98	0.98	0.92
	Mean	0.9927	0.9813	0.9707
	SD	0.0098	0.0036	0.0179
	95% CI	[0.9893, 0.9961]	[0.9796, 0.983]	[0.9647, 0.9767]
100	Best	0.99	0.98	0.98
	Worst	0.97	0.96	0.9
	Mean	0.978	0.9665	0.9633
	SD	0.0071	0.0052	0.0440
	95% CI	[0.9755, 0.9805]	[0.9648, 0.9682]	[0.9587, 0.9679]
150	Best	0.98	0.98	0.9733
	Worst	0.96	0.95	0.88
	Mean	0.9742	0.9623	0.9533
	SD	0.0038	0.0067	0.0199
	95% CI	[0.9724, 0.976]	[0.9599, 0.9647]	[0.9463, 0.9603]
200	Best	0.98	0.97	0.97
	Worst	0.965	0.945	0.86
	Mean	0.9665	0.9605	0.9508
	SD	0.0023	0.0078	0.0181
	95% CI	[0.9657, 0.9673]	[0.9576, 0.9634]	[0.9425, 0.9591]

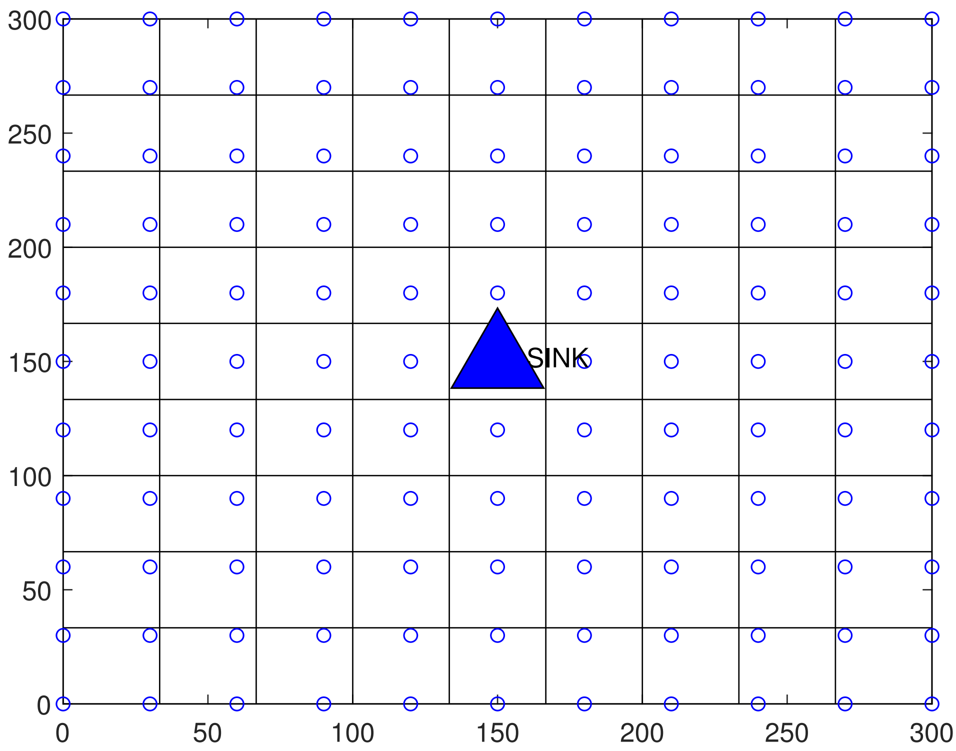


Figure 4.7 Scenario 1: candidate positions are on a grid

The comparison results for SIR for different values of targets are tabulated in Table 6.5 as best, worst, mean, standard deviation, and 95% Confidence Interval (CI). It is observed that in all algorithms SIR is increased with an increase in target points. It is due to more sensors are required to cover as number of target point increases and hence more scope for interference. Similarly, the comparison results for TCR for different values of targets is tabulated in Table 6.6 as best, worst, mean, standard deviation, and 95% Confidence Interval (CI). It is noted that the TCR decreases as number of target points increase in all algorithms. It is also observed that the BBO_TCR decreases when number of targets increase. Fig. 4.10a and Fig. 4.10b depict the performance comparisons of the BBO-based scheme, GA-based scheme, and Random-based scheme for SIR and TCR respectively. Here, the number of target points increases from 50 to 200. The 30 instances of experiments are carried out for each set of target points. The best and mean of these results are depicted in the graph. In these experiments, 200 po-

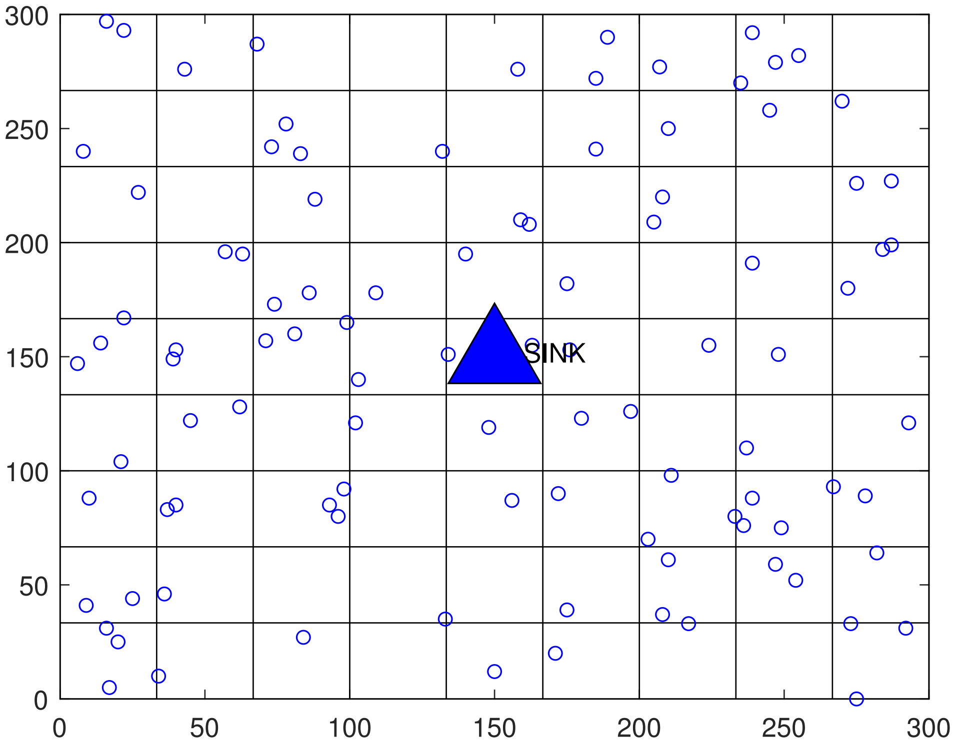
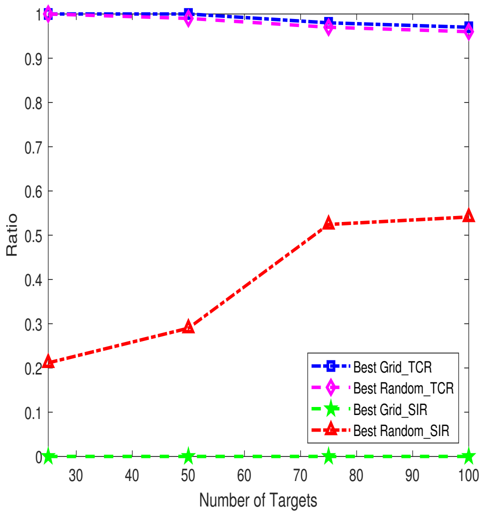
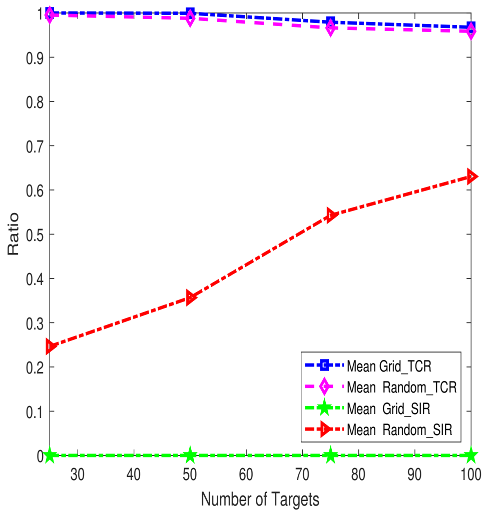


Figure 4.8 Scenario 2: candidate positions are random



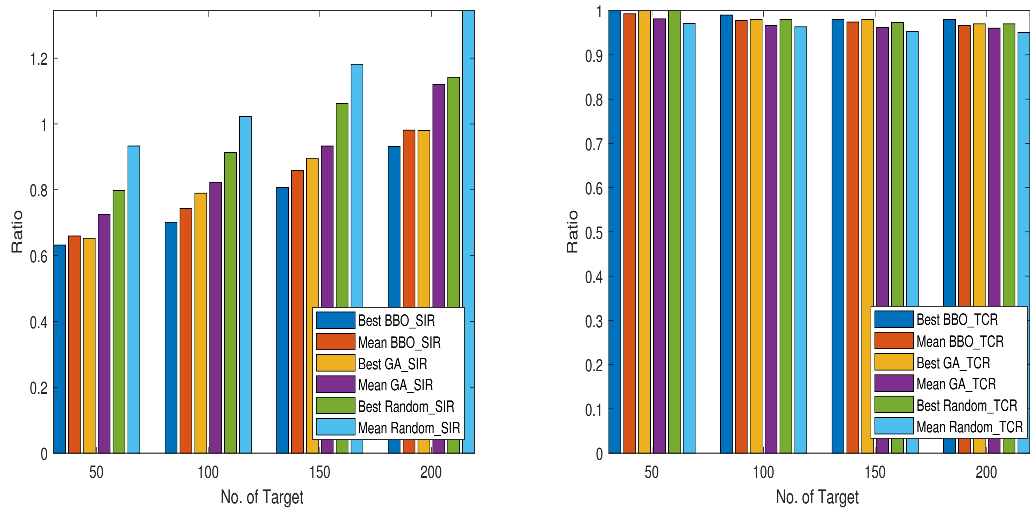
(a) Best performance on grid and random scenario



(b) Mean performance on grid and random scenario

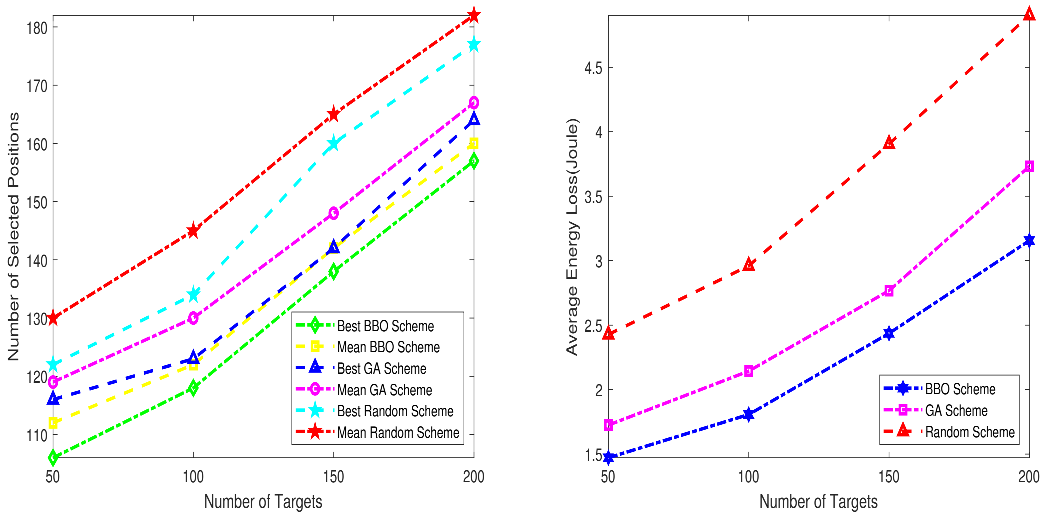
Figure 4.9 Performance of BBO scheme

tential positions are identified to deploy sensors. It is observed that the SIR is low in the BBO-based scheme as compared to the other scheme and TCR is better than that



(a) SIR performance comparisons (b) TCR performance comparisons

Figure 4.10 Performance comparisons between BBO, GA, and Random schemes



(a) Selected positions comparisons (b) Energy loss comparisons

Figure 4.11 Performance comparisons between BBO, GA, and Random schemes

of the other schemes. Fig. 4.11a illustrates the number of selected positions between BBO-based scheme, GA-based scheme, and Random scheme when number of target points increase from 50 to 200. The 30 instances of experiments are carried out to obtain results. The graph shows the best and mean of these results. In these experiments, 200 potentials positions are identified to deploy sensors. It is observed that the number of selected positions to place sensors is less in BBO-based scheme as compared with other schemes. The BBO-based scheme outperforms the GA-based scheme due to the premature convergence behaviour of the GA over BBO. Finally, Fig. 4.11b depicts performance of the average network energy loss due to interference when number of target points increases from 50 to 200. In these experiments, 200 potential positions are identified to deploy sensors. Fig. 4.11b shows average energy loss in network of the BBO-based scheme is better than that of other schemes. It is also noted that the average energy loss in network due to interference in BBO-based scheme is 16% less than that of GA-based scheme and 60% less than that of the Random-based scheme.

4.6 Summary

In this chapter, optimal sensors placement BBO-based scheme is proposed with a combined goal of maximizing target coverage and minimizing interference while maintaining connectivity of the network. An elegant vector encoding for habitat representation and novel fitness function are formulated for the proposed scheme. The working of the proposed scheme is illustrated with a suitable example. The performance study of sensing interference ratio and target coverage ratio on grid and random scenarios were conducted. A comparison study of the BBO-based scheme with other schemes was carried out. The least energy loss due to interference in the BBO-based scheme confirms its superiority over other schemes.

Chapter 5

Hybrid Hierarchical Clustering Algorithm

This chapter presents a hybrid of game theory and fuzzy inference-based clustering algorithms for wireless sensor networks to improve the stability period of the network, named FLAG and I-FLAG. The FLAG protocol is a combination of CROSS and fuzzy inference system, where as I-FLAG is a hybrid of fuzzy inference system and improved version of CROSS protocol which considers the energy of a sensor node and its distance to the BS as additional parameters.

5.1 Background

Energy conservation of sensors play an important role in prolonging the lifetime of the WSNs. There are many methods proposed to achieve the energy efficiency of the WSNs. Among them, one of the most influential technique is clustering which divides the entire network into clusters. Each cluster has a cluster head (CH) and many cluster members. The cluster head is responsible for collecting data from its members, fuse it, and forward to the base station. Many state-of-the-art algorithms are proposed for clustering in WSNs.

Game theory is a branch of mathematics and heavily used to analyse the problem of economics, social science, and computer science. In recent past, It is employed to solve clustering, routing, resource allocation, and coverage optimization problems in WSN (Yang et al. (2016)). The first game theoretic algorithm proposed for clustering in WSN is called CROSS (Clustered Routing for Selfish Sensors). Here, each sensor node act as a player and each node plays a clustering game with other players within the network to decide whether to be CH or not. Later, the authors in Xie et al. (2013) proposed localized algorithm by considering clustering game within close neighbours.

In the proposed work, a hybrid of game theory and fuzzy inference-based algorithms are proposed to improve the stability period of the network, named FLAG and I-FLAG. The FLAG protocol is a combination of CROSS and fuzzy inference system, where as I-FLAG is a hybrid of fuzzy inference system and an improved version of CROSS protocol which considers the energy of a sensor node and its distance to the BS as additional parameters.

The contributions of the work are listed below:

- An improved version of CROSS game theoretic protocol for CHs selection.
- A fuzzy logic system is proposed to elect appropriate SCHs from CHs in FLAG and I-FLAG.
- Residual energy, centrality, and distance to base station are considered as member functions to compute SCH election probability.
- The proposed algorithms are compared with other clustering techniques like LEACH, CHEF, CROSS, and an improved CROSS.

5.2 Network Model and Radio Model

5.2.1 Network Model

The proposed network model consist of homogeneous nodes having equal energy, the same sensing, and communicating capabilities as shown in Fig. 5.2. Initially, CHs are selected using game theoretic algorithm (Koltsidas and Pavlidou (2011)). Secondly, SCHs are selected among CHs using fuzzy logic. The working procedure for proposed model is similar to the work in Nayak and Devulapalli (2015); Verma et al. (2020).

5.2.2 Radio Model

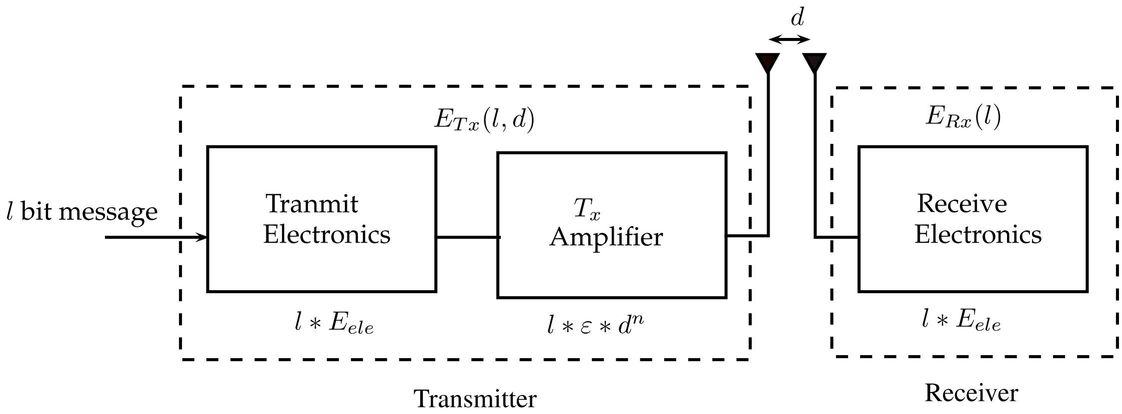


Figure 5.1 Energy radio model

The radio model adopted from Heinzelman et al. (2000) for communication and computation energy dissipation and it is shown in Fig. 5.1. The multipath fading channel (d^4 power loss model) is employed whenever distance between sender and receiver is more than threshold value d_0; otherwise, the free space model (d^2 power loss model) is employed as shown in Eq. 5.2.1. Therefore, energy required to transmit l-bit of information over distance d from sender to destination is calculated as follows

$$E_{Tx}(l,d) = \begin{cases} lE_{ele} + l\varepsilon_{fs}d^2 & \text{for } d \leq d_0 \\ lE_{ele} + l\varepsilon_{mp}d^4 & \text{for } d > d_0 \end{cases} \tag{5.2.1}$$

Here, E_{ele} is the energy dissipated per bit by the transmitter or receiver circuitry. The constants ε_{fs} and ε_{mp} are amplifier characteristics of free space channel and multipath channel respectively. The variable d is the distance between transmitter and receiver; The variable $d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}}$, distinguishes two types of path loss model.

The amount of energy dissipated by the receiver after receiving l-bit data packet is calculated as follows:

$$E_{Rx}(l) = lE_{ele} + lE_{DA} \tag{5.2.2}$$

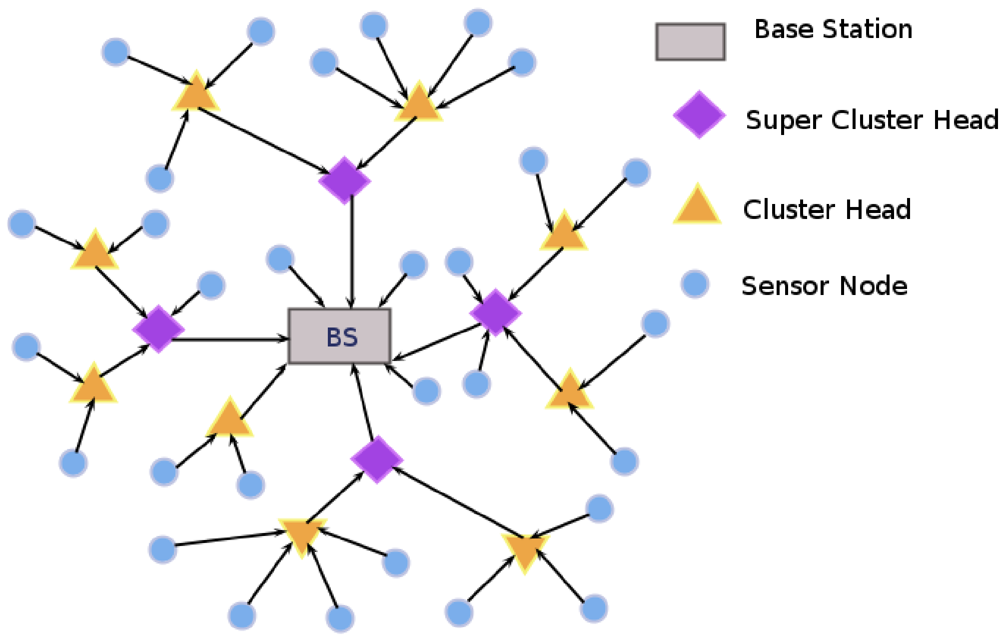


Figure 5.2 An instance of network model

Here, E_{DA} is the energy dissipated by the CH for aggregating a one bit information.

5.3 Proposed Model

5.3.1 Assumptions

- All sensor nodes in the network are homogeneous and having same initial energy, memory, and communicating capabilities.
- Sensor nodes and base station are stationary after deployment.
- Cluster setup phase is similar to the LEACH or CROSS algorithm to select appropriate cluster heads.

Table 5.1 List of notations

Notation	Description
d	distance
l	Data packet size in bits
E_{ele}	Energy consumed for 1-bit computation
$E_{Tx}(l,d)$	Energy consumed to transmit l-bit data over d distance
$E_{Rx}(l)$	Enery consumed to recieve l-bit data
ε_{mp}	Amplifier characteristics of the multi path channel
ε_{fs}	Amplifier characteristics of the free space channel
E_{DA}	Energy consumed for aggregate data
w_{min}	User defined variable to avoid negative value during CH probability calculation
N	Number of sensor nodes
A	Actions available for sensor nodes
$U_i(a_i)$	Utility gained by a sensor node i after choosing an action a_i
D	Sensor node declared to be cluster head
ND	Sensor node not declared to be cluster head
v	Payoff for being cluster member
c	Energy overhead for being cluster head
R	Average radius of a cluster
E_{chi}	Energy drain of node i to become CH
E_{cmi}	Energy drain by a cluster member node i to transmit data to CH
D_{ri}	Degree of node i
E_i	Residual energy of a sensor node i
E_o	Initial energy of a sensor node
d_i	Distance between the sensor node i and base station
d_{max}	Distance between farthest alive node to the base station
$BS_{distance}$	Distance to base station
R_{energy}	Residual energy of a CH
$CH_{centrality}$	Centrality of a CH
E_{spent}	Energy spent so far by the CH
N_{br}	Neighbors of CH
β	Random variable takes the value between 0 and 1
Q	CHEF local distance

- Elected cluster heads notify their residual energy, distance to base station and centrality to BS.

- After receiving information from CHs base station employs fuzzy logic inference system to select SCHs.

- Election of SCHs probability is decided on three input parameters residual energy, distance to base station, and centrality of CHs.

- Association of member nodes with cluster nodes and association of cluster nodes with super cluster nodes are established according to their distance metric as described in LEACH.

- The data transmission in the network happens in the steady phase of the network. Firstly, from sensor nodes to CHs and secondly, CHs to SCHs, and finally from SCHs to Base station as shown in Fig. 5.2.

The proposed FLAG and I-FLAG hybrid hierarchical clustering models are divided into cluster heads selection phase and super cluster heads selection phase. Table 6.1 shows all the definitions of variables and acronyms that are used in this chapter.

5.3.2 Cluster Heads Selection Phase

In this phase, an existing CROSS and an improved version of CROSS game theoretic protocol are used.

According to the definition of game theory, clustering game (CG) of WSN with N nodes, A actions, and U utility function are represented with three tuples as $CG(N,A,U)$. where tuples N, A, and U denote the player set, strategy set, and payoff set of the game respectively. Suppose sensor nodes adopt a pure strategy to play the clustering game, then the strategy space or action profile has two choices; either node is declared (D) to be cluster head or not declared (ND) to be cluster head. With regard to utility, if none of the sensor nodes select strategy D, then utility for each sensor node will be 0. Sensor node payoff will be v, if at least one of its neighbour sensor node is declared to be cluster head and such cluster head payoff will be $v-c$, since it plays the role of forwarding packets to the base station. Suppose there are only two players, then the Table 5.2 gives utility values of the two player game. Therefore, in general the utility value for any player i which plays action a_i from action profile set A in a N player game will take the following form

$$U_i(a_i) = \begin{cases} 0 & \text{if } a_{j \neq i} = ND,\ \forall j \in N \\ v_i - c_i & \text{if } a_i = D \\ v_i & \text{if } a_i = ND,\ \exists j \in N, \\ & \text{such that } a_{j \neq i} = D \end{cases} \tag{5.3.1}$$

Table 5.2 Utility for two player clustering game

Choices	D	ND
D	$(v-c, v-c)$	$(v-c, v)$
ND	$(v, v-c)$	$(0,0)$

The payoff or utility value v_i for player i when it choose action ND, and if at least one other player choose action D can be computed as follows (Yang et al. (2016))

$$v_i = \frac{l}{Ecm_i} \tag{5.3.2}$$

where l is the size of the data packet and Ecm_i is the energy drain to transmit the packet to its respective CH (Yang et al. (2016)), and can be computed as follows

$$Ecm_i = lE_{ele} + \frac{4}{9} l \varepsilon_{fs} R^2 \tag{5.3.3}$$

Here, R is the average radius of each cluster. Suppose node i chooses the action D, then its utility value is computed as discussed in Yang et al. (2016).

$$v_i - c_i = \frac{(Dr_i + 1)\, l}{Ech_i} \tag{5.3.4}$$

where c_i is the overhead of a node for becoming CH, Dr_i is the node degree of a palyer i, and Ech_i is the energy drain for node i for becoming CH (Yang et al. (2016)). Its value is obtained as follows:

$$Ech_i = Dr_i l E_{ele} + (Dr_i + 1)\, l E_{DA} + l \varepsilon_{mp} \left({d_i}^{toBS} \right)^4 \tag{5.3.5}$$

From Eq.5.3.2 and 5.3.4, c_i value can be calculated as follows:

$$c_i = \frac{l}{Ecm_i} - \frac{(Dr_i + 1)\, l}{Ech_i} \tag{5.3.6}$$

Eq.5.3.6 takes the form by denoting $w_i = \frac{c_i}{v_i}$, as follows

$$w_i = 1 - \frac{(Dr_i + 1)\, Ecm_i}{Ech_i} \tag{5.3.7}$$

To avoid the w_i value to be negative, a parameter w_{min} is introduced, and w_i is obtained as follows.

$$w_i = \max\left(w_{min},\ 1 - \frac{(Dr_i + 1)\, Ecm_i}{Ech_i} \right) \tag{5.3.8}$$

Suppose the sensor node i that chooses the action D with probability p_i and the action ND with probability $q_i = 1 - p_i$. Then, there exists an equilibrium probability p_i based on mixed strategy Nash equilibrium as discussed in CROSS protocol (Koltsidas and Pavlidou (2011)), and is formally defined as follows:

$$p_i = 1 - (w_i)^{\frac{1}{N-1}} \tag{5.3.9}$$

Along the above equation we use residual energy and distance of the node to the base station to get appropriate probability for cluster head selection. The new improved version of CROSS for cluster head selection can be expressed as follows

$$p_i = 1 - (w_i)^{\frac{1}{N-1}} \times \left[\left(\frac{E_i}{E_o} \right)^{\beta} + \left(\frac{d_i}{d_{max}} \right)^{1-\beta} \right] \tag{5.3.10}$$

where $\beta \in (0,1)$ is a weight factor, E_i is the remaining energy and the E_o is the initial energy of a node i respectively. The variables d_i and d_{max} are distance between node i

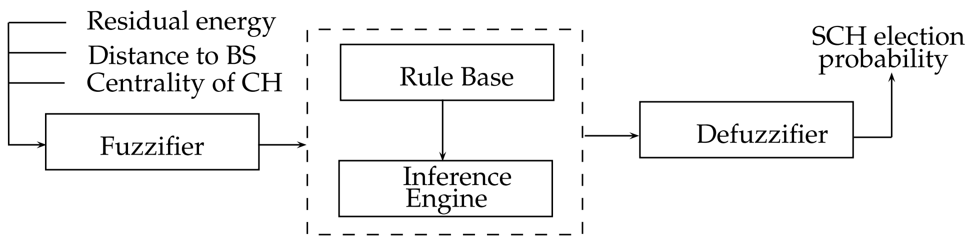


Figure 5.3 Outline of fuzzy model

and BS and the distance to the farthest alive node to the BS respectively .

5.3.3 Super Cluster Heads Selection Phase

In this phase, Fuzzy inference System (FIS) is employed to elect appropriate SCHs from set of CHs.

FIS is a data base generally employed to handle uncertainties and imprecise information in the system. It consists of member functions and fuzzy rules. There are three types of FIS: Mamdani, Sugeno, and Tsukamoto. The Mamdani FIS is a popular and widely adopted technique in different applications because of its intuitive characteristic and simple structure (Toloueiashtian and Motameni (2018)).

The main components of FIS are Fuzzifier, Fuzzy rules, Inference engine, and Defuzzifier as shown in Figure 5.3. In the first step, crisp set inputs are transformed into fuzzy sets using membership functions, and the process is known as fuzzification. In the second step, The fuzzy inference engine uses “IF-THEN" rules to map fuzzy input sets for fuzzy output sets. At last, fuzzy outputs are transferred to crisp values, and the process is called defuzzification.

Input membership function variables considered for FIS are residual energy, distance to base station, and centrality of CHs.

Table 5.3 Fuzzy membership functions

SerialNo	Input variable	Linguistic variables		
1	Residual energy	Low	Medium	High
2	Distance to BS	Near	Average	Far
3	Centrality of CH	Close	Reachable	Distant

- Residual Energy of CH (R_{energy}): Selection of higher residual energy CH node to be SCH prolongs the stability of the network.

$$R_{energy} = E_o - E_{spent} \tag{5.3.11}$$

- Centrality of CH ($CH_{centrality}$): This value corresponds to position of CH in compared to its neighbours with in the entire network. CHs with low centrality values have been given high priority than the CHs with high centrality values.

$$CH_{centrality}(j) = \frac{\sqrt{\frac{\sum_{i \in Nbr(j)} d^2(CH_j, CH_i)}{|Nbr(j)|}}}{M} \tag{5.3.12}$$

  where $d(CH_j, CH_i)$ is the distance between the j^{th} CH node to the i^{th} CH node, M is the dimension of the network.

- Distance to Base Station ($BS_{distance}$): This value corresponds to distance between CH to the BS, the lower the value, lower the energy consumption. And hence CHs which are nearer to the BS have given higher priorities than CHs that are far away from the BS. The distance is computed using Euclidean formula.

$$BS_{distance}(i,j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2)} \tag{5.3.13}$$

The FIS input membership functions for SCH selection with their linguistic variables are given in Table 5.3.

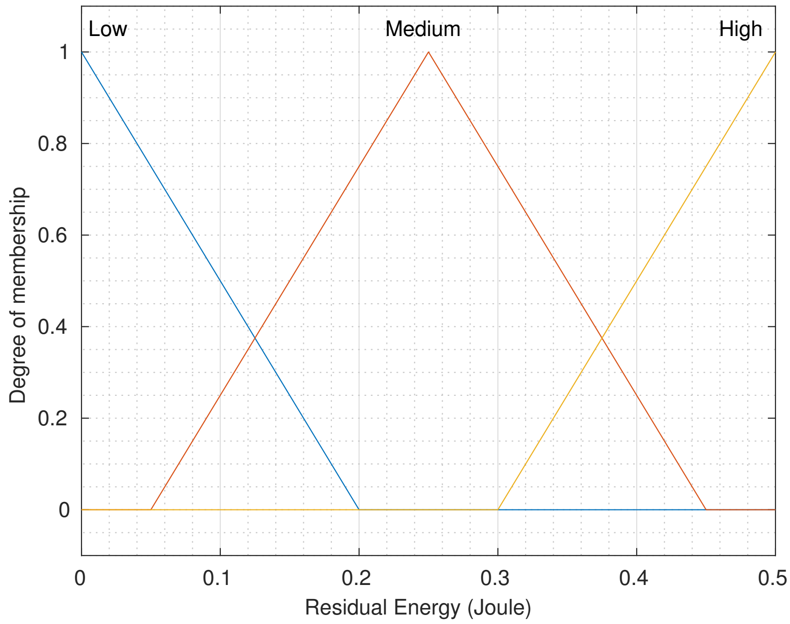


Figure 5.4 Residual energy of CH

The membership functions for R_{energy}, $CH_{centrality}$, and $BS_{distance}$ are represented in Figure 5.4, 5.5, and 5.6 respectively. These membership functions are mapped to “IF-THEN" rules which are mentioned in Table 5.4 and Mamdani FIS is employed to handle the uncertainty of selecting appropriate SCHs. There are 27 rules containing all combination of 3 input variables. The member function of the output fuzzy variable is called probability having 9 combinations of linguistic values as shown in Fig.5.7. The triangular member ship function is used for all input and output variables. The final value for probability is defuzzified to crisp value using the centroid method. The centroid is computed as follows

$$Centroid = \frac{\sum_i \mu(x_i)x_i}{\sum_i \mu(x_i)} \tag{5.3.14}$$

Here, $\mu(x_i)$ is the membership value for the point x_i in the universe of discourse. The surface view of input/output of membership functions with fuzzy rules are shown in

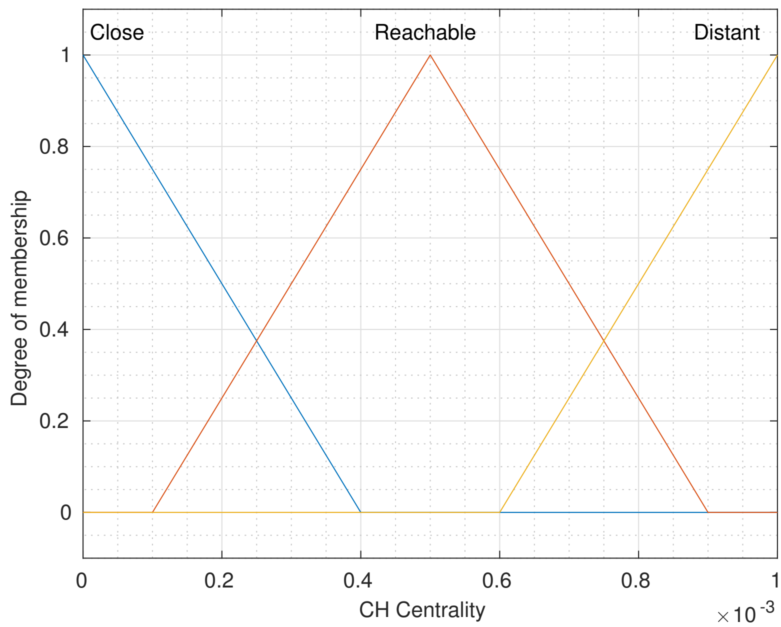


Figure 5.5 Centrality of CH

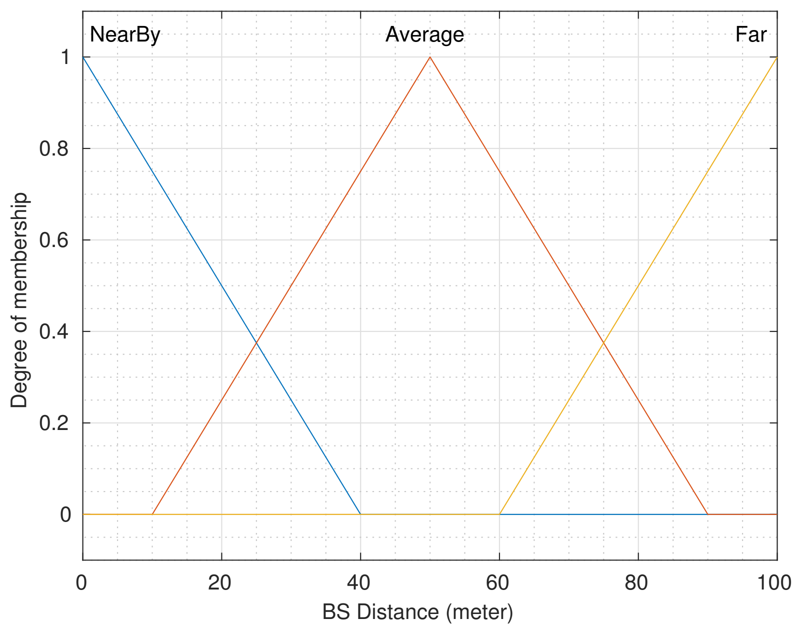


Figure 5.6 Distance between CH to BS

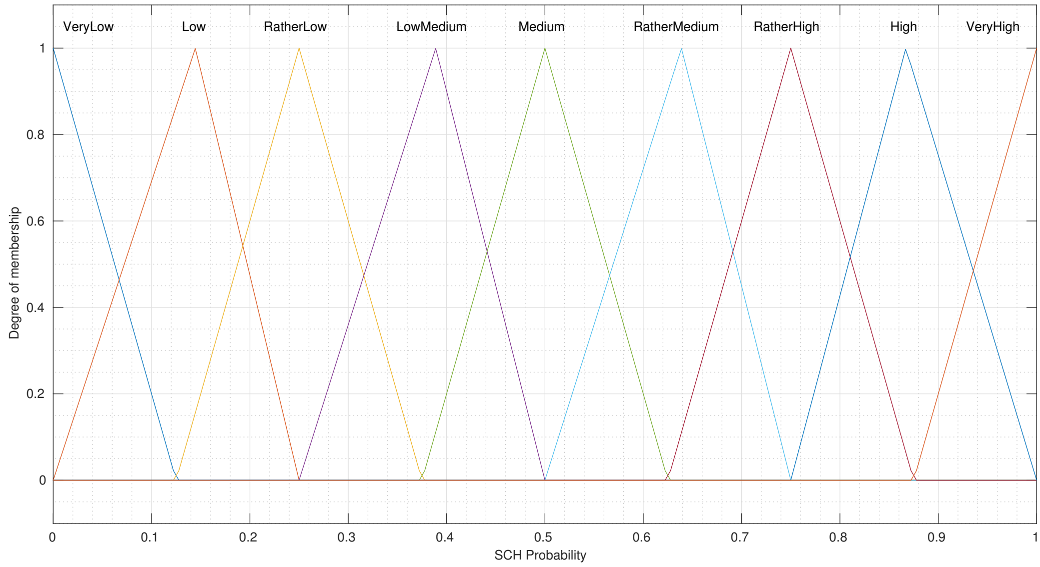


Figure 5.7 SCH selection probability

Figures[5.8-5.10]

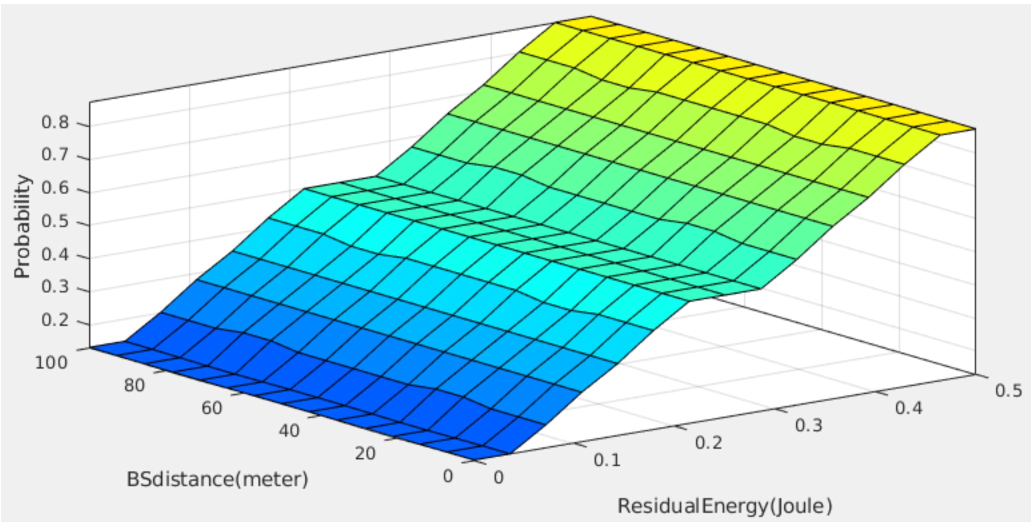


Figure 5.8 Surface view of Distance to BS, Residual energy, and Probability

The complete flow of the proposed scheme is depicted in Algorithm 6.3.1.

Algorithm 5.3.1 FLAG a hybrid hierarchical clustering algorithm

Input: Wireless sensor network with n randomly deployed homogeneous sensors in 100×100 field

Output: Stability period of the wireless sensor network

$itr = 1$
while $itr < max\_itr$ **do**
    if any node alive **then**
        Elect probable CHs using Eq.5.3.10
        Apply fuzzy inference rules to elect right SCHs
        for each CH **do**
            Associate nodes to their CHs using distance metric
            Aggregate the data received from its member nodes at CHs
            Send fused data to SCHs
        end for
        for each SCH **do**
            Associate CHs to SCHs using distance metric
            Aggregate the data received from its CHs at SCHs
            Send fused data to BS
        end for
    end if
    $itr = itr + 1$
end while

5.4 Results and Discussion

Experiments are carried out using MATLAB R2019a software to evaluate and compare the performance of proposed protocols with the existing protocols like LEACH (Akyildiz et al. (2002)), CHEF (Kim et al. (2008)), and CROSS (Koltsidas and Pavlidou (2011)). To conduct experiments 200 sensor nodes are randomly placed on $100m \times 100m$ field with the base station location at coordinate $(50, 50)$. All sensors are homogeneous and the initial energy of each sensor is set to 0.5Joule. The sensed data size by each sensor is identical and equal to 4000 bits. The energy consumption for transmitter (receiver) electronic is set to 50nJ/bit. The energy drain for data fusion is set to 5nJ/bit/message. All simulation parameters used in experiments are mentioned in Table 5.6.

Table 5.4 Fuzzy rules

RuleNo	R_{energy}	$BS_{distane}$	$CH_{centrality}$	$SCH_{probability}$
1	Low(0)	Near(0)	Close(0)	Rather Low(2)
2	Low(0)	Near(0)	Reachable(1)	Low(1)
3	Low(0)	Near(0)	Distant(2)	Very Low(0)
4	Low(0)	Average(1)	Close(0)	Rather Low(2)
5	Low(0)	Average(1)	Reachable(1)	Low(1)
6	Low(0)	Average(1)	Distant(2)	Very Low(0)
7	Low(0)	Far(2)	Close(0)	Rather Low(2)
8	Low(0)	Far(2)	Reachable(1)	Low(1)
9	Low(0)	Far(2)	Distant(2)	Very Low(0)
10	Medium(1)	Near(0)	Close(0)	Rather Medium(5)
11	Medium(1)	Near(0)	Reachable(1)	Medium(4)
12	Medium(1)	Near(0)	Distant(2)	Lower Medium(3)
13	Medium(1)	Average(1)	Close(0)	Rather Medium(5)
14	Medium(1)	Average(1)	Reachable(1)	Medium(4)
15	Medium(1)	Average(1)	Distant(2)	Lower Medium(3)
16	Medium(1)	Far(2)	Close(0)	Rather Medium(5)
17	Medium(1)	Far(2)	Reachable(1)	Medium(4)
18	Medium(1)	Far(2)	Distant(2)	Lower Medium(3)
19	High(2)	Near(0)	Close(0)	Very High(8)
20	High(2)	Near(0)	Reachable(1)	High(7)
21	High(2)	Near(0)	Distant(2)	Rather High(6)
22	High(2)	Average(1)	Close(0)	Very High(8)
23	High(2)	Average(1)	Reachable(1)	High(7)
24	High(2)	Average(1)	Distant(2)	Rather High(6)
25	High(2)	Far(2)	Close(0)	Very High(8)
26	High(2)	Far(2)	Reachable (1)	High(7)
27	High(2)	Far(2)	Distant(2)	Rather High(6)

Table 5.6 Simulation parameters

Parameters	Values
Network size (number of nodes)n	200
Network area (m^2)	100×100
Initial node energy(J)	0.5
Data packet size l (bits)	4000
E_{ele}(nJ/bit)	50
E_{Tx}(nJ/bit)	50
E_{Rx}(nJ/bit)	50
ε_{mp}(pJ/bit/m^4)	0.0013
ε_{fs}(pJ/bit/m^2)	10
E_{DA}(nJ/bit/message)	5
w_{min}	0.000001
LEACH p (percentage)	5
CHEF average cluster size(m)	25
BS location(coordinates)	(50,50)
R(m)	10

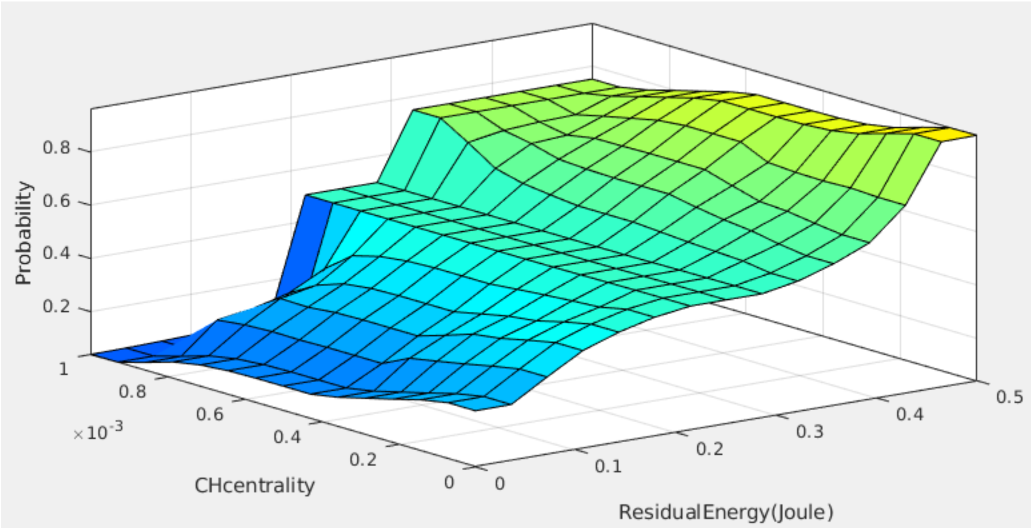


Figure 5.9 Surface view of Residual energy, CH centrality, and Probability

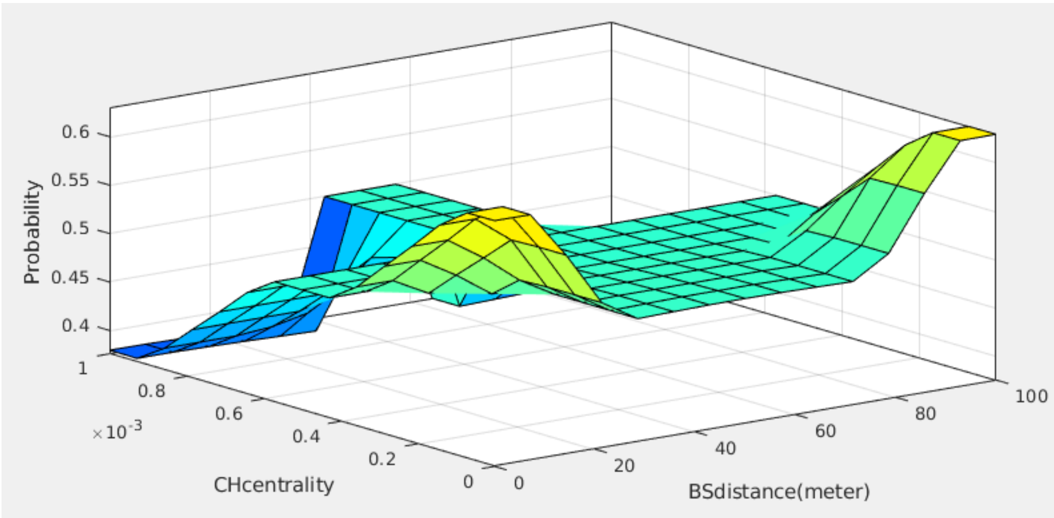


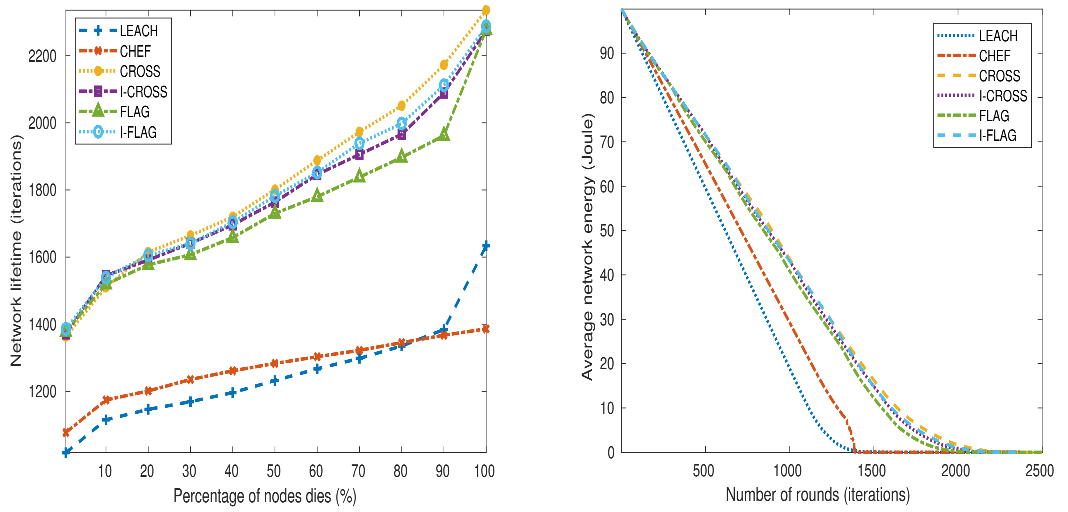
Figure 5.10 Surface view of CH centrality, Distance to BS, and Probability

Two hybrid clustering protocol for WSN is designed by augmenting fuzzy logic to basic CROSS and improved-CROSS to increase the stability of the network. Fig. 6.7b shows lifetime of the network. It is observed that the first node dies faster in other protocols compared to FLAG and I-FLAG, besides the network stability period is better in proposed protocols until 10 % of nodes die in the network. Network stability period, stability period throughput, and network lifetime are tabulated in Table 5.5.

The network lifetime of I-FLAG is better than LEACH, CHEF, and I-CROSS, however it underperforms over CROSS because of its even energy drain distribution among

Table 5.5 Stability period, throughput and total network lifetime

Parameters	LEACH	CHEF	CROSS	I-CROSS	FLAG	I-FLAG
Stability period(rounds)	1017	1077	1363	1371	1377	1386
Stability period throughput(bits)	203400	215290	272600	274700	275242	277002
Network lifetime(rounds)	1634	1386	2336	2275	2278	2288

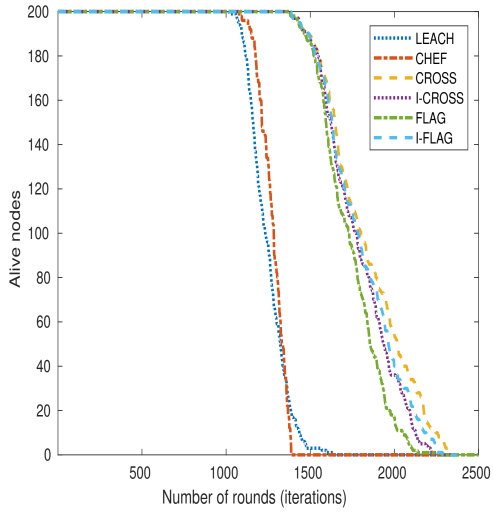


(a) Percentage of node dies Vs Network lifetime

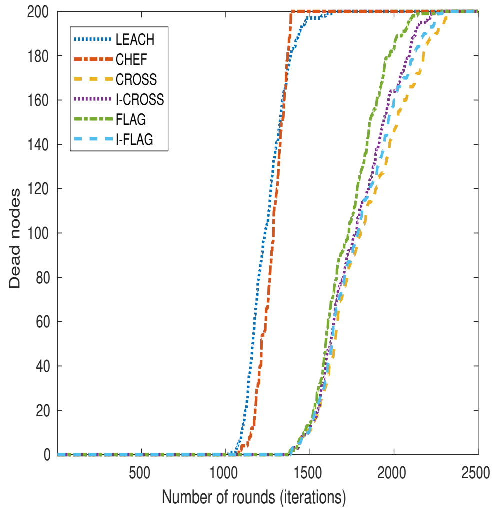
(b) Number of rounds Vs Average network energy

Figure 5.11 Network lifetime and average network energy comparison

nodes of the network. And hence it prolongs the death of the first node in the I-FLAG. Fig. 5.11b depicts the average energy drain of the network, and it is smooth in the proposed protocols compared to other protocols. Fig. 5.12a and Fig. 5.12b represents the number of alive nodes and dead nodes of the network respectively. In the initial period of the network, number of alive nodes are more, and the number of dead nodes are less in both FLAG and I-FLAG as compared to other protocols. The network stability period comparison is shown in Fig. 5.13a. The graph demonstrates that the stability period of FLAG is 26.2 %, 21.84 %, and 1.08 % better than LEACH, CHEF, and CROSS respectively. Similarly, the stability period of I-FLAG is 26.62 %, 22.29 %, and 1.08 % better than LEACH, CHEF, and I-CROSS respectively. The network throughput during stability period is depicted in Fig. 5.13b. It is observed that the throughput of FLAG during

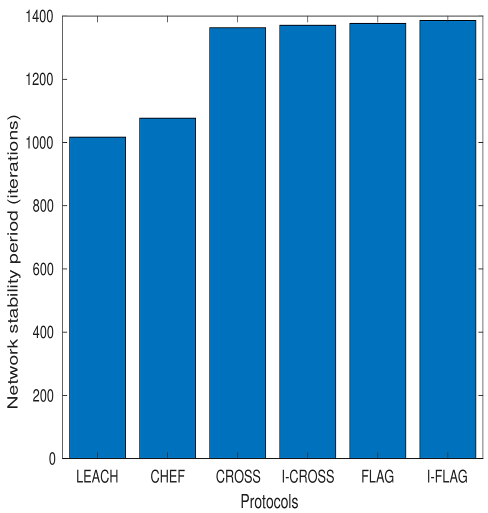


(a) Number of rounds Vs Alive nodes

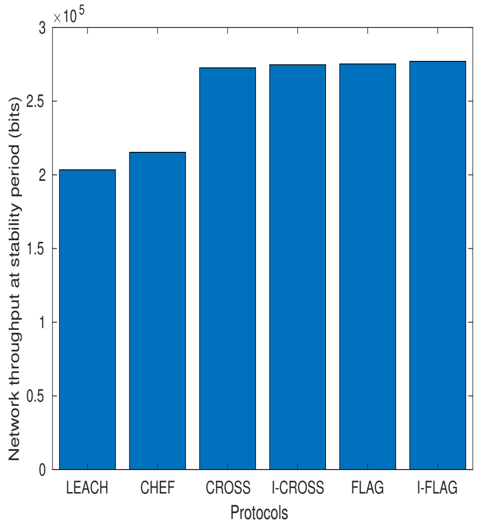


(b) Number of rounds Vs Dead nodes

Figure 5.12 Network alive and dead nodes comparison



(a) Protocols Vs Network stability period



(b) Protocols Vs Network throughput at stability period

Figure 5.13 Network stability period and throughput comparison

the stability period is 26.10 %, 21.78 %, and 0.9 % better than LEACH, CHEF, and CROSS respectively. Similarly, the stability period throughput of I-FLAG is 26.57 %, 22.28 %, and 0.84 % better than LEACH, CHEF, and I-CROSS respectively. The energy parameter and distance parameter plays a vital role in selecting CH and hence the SCH. It infers that the network stability period of I-FLAG is outperforms over all other protocols.

5.5 Chapter Summary

Hybrid hierarchical protocols named FLAG and I-FLAG are proposed in the chapter to extend network stability. Two main phases of these protocols are the CH election phase and the SCH election phase. The CH election phase is achieved through a game-theoretic protocol, and the SCH election phase is achieved through a fuzzy inference system. The simulations are carried out to verify the superiority of the proposed protocols. The results show that the network stability period of FLAG is better than LEACH, CHEF, and CROSS. The network stability period of I-FLAG is better than LEACH, CHEF, and I-CROSS. The network stability period is better in the proposed work due to the balanced energy drain compared to the other protocols.

Chapter 6

Multi-attribute Decision Making Approach for Sensor Placement and Clustering

This chapter discusses interference aware sensor deployment followed by an interference aware clustering technique on deployed sensors. Various methods and techniques are proposed for sensor deployment and clustering in wireless sensor networks. However, none of them considered MADM (Multi attribute decision making) based interference aware sensor deployment and clustering. Therefore, we proposed MADM based interference aware sensor placement and clustering techniques. Simulations are carried out and results are presented. The simulation results show that the E-TOPSIS MADM method for sensor placement and clustering outperforms over other methods.

6.1 Background

There are many works in the literature on interference minimization with target coverage and connectivity in the wireless sensor network. There are many works on clustering in WSN using different schemes and techniques to handle energy problems in wireless sensor networks. However, these works never consider interference during the sensor placement and clustering. The interference of nodes cause a message drop and results in a quick energy drain during data transfer between member nodes and cluster heads. Therefore, In the proposed work, a novel interference aware sensor deployment scheme is developed followed by a clustering technique on deployed sensors. The placement method selects suitable positions using coverage, connectivity, and interference parameters. After the deployment, the MADM method is used for clustering. Here, the cluster heads are identified using various parameters like the energy of the nodes, the distance between sensors and the base station, the communication range of the sensor nodes, and the average distance between the sensor nodes to their member nodes.

Both the sensor deployment and the clustering are multi-objective problems. Moreover, the objectives of the problems are conflicting in nature. If the problem has multiple conflicting objectives, then multi-attribute decision making technique can be used to solve such problem. Therefore, the proposed methods adopts a well known multi-attribute decision making method (MADM) E-TOPSIS for ranking potential positions for deployment of the sensors and ranking the sensor nodes for electing cluster heads. The sensor deployment scheme is compared with TOPSIS and SAW methods and the clustering technique is compared with TOPSIS, SAW, and Modified LEACH for stability period and network lifetime. Multi-attribute decision making (MADM) is a process of selecting the best alternative from available alternatives based on multiple attributes or constraints. The MADM problem is represented as a decision matrix in which rows indicate the alternatives and columns indicate the attributes of each alternative. Numerous MADM techniques have been proposed to solve real-word science and engineering decision problems. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is the state-of-the-art method received much attention from researchers and practitioners Trilok and Gnanasekaran (2021). The technique is developed by Hwang and Yoon in 1981, which choose the alternative that simultaneously have shortest distance from the positive ideal solution and farthest distance from the negative ideal solution. Here, the positive ideal solution maximizes the beneficial criteria and minimizes the non-beneficial criteria; The negative ideal solution minimizes the beneficial criteria and maximizes the non-beneficial criteria. The method uses the alternatives information to provide a ordinal ranking to each alternative. The other widely used MADM model is SAW (Simple Additive Weighting). In this technique, the score of each alternative is computed by aggregating the values of that alternative in different criteria with the weight of corresponding criteria (Ameri et al. (2018))

The main contributions of the proposed work are listed below:

- A novel entropy-weighted TOPSIS technique for an optimal sensor deployment scheme is formulated. It considers conflicting attributes like interference of sensor nodes, coverage of target points, and connectivity of sensor nodes.
- A novel entropy-weighted TOPSIS technique for clustering in wireless sensor networks scheme is formulated. It considers conflicting attributes for election of cluster heads like residual energy of nodes, interference of sensor nodes, sensor nodes distance to the base station, the communication range of sensor nodes, and average distance to its neighbour sensors.
- The deployment scheme is compared with TOPSIS and SAW methods.
- The clustering technique is compared with TOPSIS, SAW, and modified LEACH schemes.

6.2 Definitions and System Model

Sensing Interference Ratio (SIR)**:** It is defined as the ratio of total sensing interference experienced by the network to the sum of currently deployed sensors. The underlying formula for *SIR* is given in Eq. 6.3.5.

Target Coverage Ratio (TCR)**:** It is defined as the ratio of the sum of target points covered by the sensors to the total number of target points present in the region of interest. The underlying formula for TCR is given in Eq. 6.3.6.

Sensor to Sensor Connectivity Ratio (SSCR) **:** It is defined as the ratio of sum of sensor to sensor connectivity to the total number of sensors placed in the network. The underlying formula for *SSCR* is given in Eq. 6.3.7.

Table 6.1 List of notations

Notation	Description
d	distance
k	Data packet size in bits
E_{ele}	Energy consumed for 1-bit computation
$E_{Tx}(k,d)$	Energy consumed to transmit k-bit data over d distance
$E_{Rx}(k)$	Energy consumed to receive k-bit data
ε_{mp}	Amplifier characteristics of the multi path channel
ε_{fs}	Amplifier characteristics of the free space channel
E_{DA}	Energy consumed for aggregate data
n	Number of sensor nodes
D_{bs}	Distance to base station
R_e	Residual energy of a CH
C_r	Communication radius of a sensor node
C_v	Number of targets covered by the sensor node
C_n	Number of neighbouring nodes in the communication range of a sensor node
I_r	Number of neighbouring nodes in the sensing range of a sensor node
C_i	Closeness score for entropy-weighted TOPSIS
D_i	Closeness score for weighted TOPSIS
E_i	Score for SAW method
D_{nn}	Average distance of member nodes to the CH node
N_{br}	Neighbors of CH
N_d	Degree of node

6.2.1 Network model

Network architecture is adopted from Heinzelman et al. (2000) for clustering. The network consists of heterogeneous sensor nodes which have equal initial energy but different sensing and communicating capabilities. Initially, random potential positions are identified for placing sensors to monitor a set of target points. A MADM method is employed to rank potential positions by considering coverage, connectivity, and interference of the nodes as constraints. The final position for sensor placements are selected after employing Algorithm 6.3.1. After the deployment, MADM based clustering technique is proposed to elect CHs. The member nodes forward the sensed data to CHs and CHs aggregates received data and forward to the base station as shown in Figure 6.1.

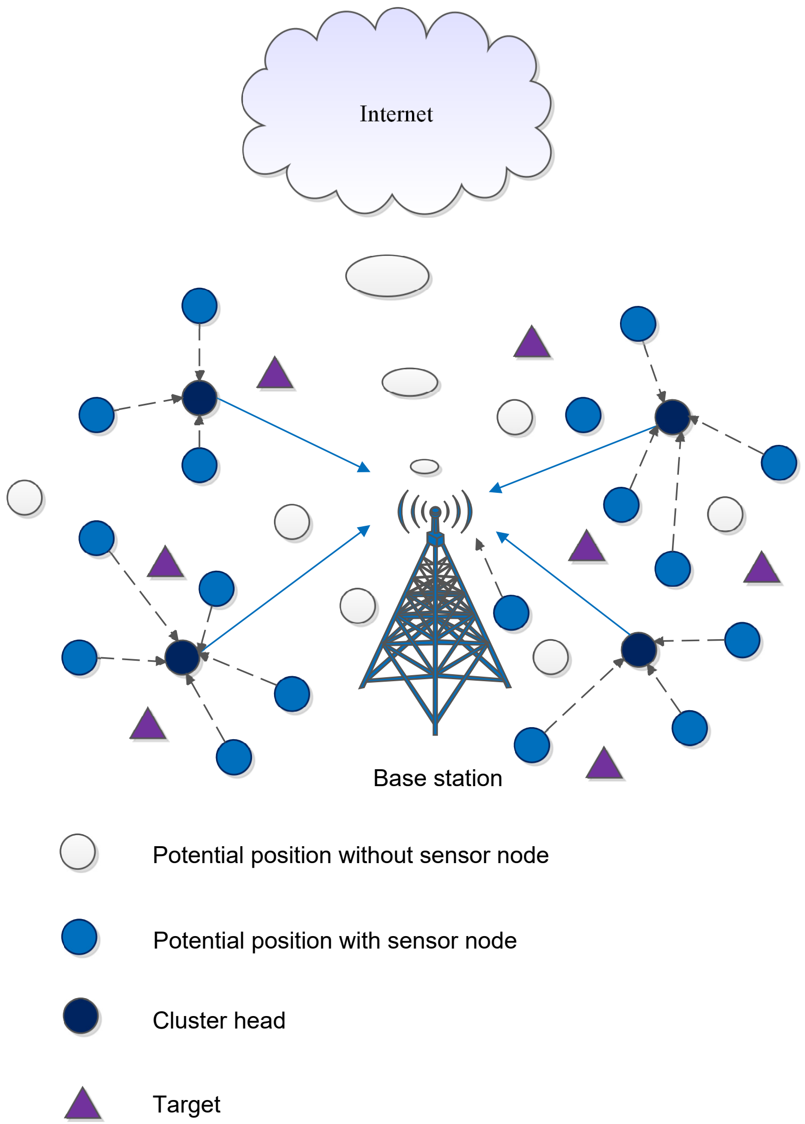


Figure 6.1 Network model

6.2.2 Radio Model

The radio model adopted from Heinzelman et al. (2000) for communication and computation energy dissipation. The multipath fading channel, that is d^4 power loss model is used whenever distance between sender and receiver is more than the threshold value d_0; otherwise, the free space model, that is d^2 power loss model is adopted as shown in Eq. 6.2.1. Therefore, the amount of energy required to transmit k-bit of information over distance d from the sender node to receiver node is calculated as follows:

$$E_{Tx}(k,d) = \begin{cases} kE_{ele} + k\varepsilon_{fs}d^2 & d \leq d_0 \\ kE_{ele} + k\varepsilon_{mp}d^4 & d > d_0 \end{cases} \tag{6.2.1}$$

Here, E_{ele} is the energy required to transmit or receive one bit information by the transmitter or receiver circuitry respectively. The constants ε_{fs} and ε_{mp} are amplifier characteristics of free space channel and multipath channel respectively. The variable d is the distance between transmitter and receiver; The variable $d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}}$, distinguishes two types of path loss model.

The energy required for receiving k-bit information by the sensor node is computed as follows:

$$E_{Rx}(k) = kE_{ele} + kE_{DA} \tag{6.2.2}$$

Here, E_{DA} is the energy dissipated by the CH for aggregating a one bit information.

6.3 Proposed Entropy-weighted TOPSIS Sensor Placement Algorithm

In this Section, a MADM based sensor placement scheme is presented. The method minimizes Sensing Interference Ratio (*SIR*), maximizes Target Coverage Ratio (*TCR*), and maximizes Sensors to Sensors Connectivity Ratio (*SSCR*) for wireless sensor networks.

Definition 6.3.1. ***MADM based sensor placement problem***
Suppose $P = \{pos_1, pos_2 \ldots, pos_p\}$ denote the set of p potential positions to deploy n sensor nodes $S = \{s_1, s_2, \ldots, s_n\}$ to cover k targets $T = \{t_1, t_2, \ldots, t_k\}$. Find appropriate sensor node placement positions such that,

1. *Sensor node s_i in S is not in the sensing range of any other node in S, where $1 \leq i \leq n$. The goal is to minimize the sensing interference ratio in the network.*

2. *Sensor node s_i in S is able to monitor maximum number of targets in T, where $1 \leq i \leq n$. The goal is to maximize the target coverage ratio in the network.*

3. *Sensor node s_i is in the communication range of the maximum number of neighbouring nodes in S, where $1 \leq i \leq n$. The goal is to maximize sensors to sensors connectivity ratio of the network.*

Let $S_r(i)$ and $C_r(i)$ represents sensing and communication range of sensor node i respectively. Euclidean formula is adopted to calculate distance measure between the two points. If $p = (x_1, y_1)$ and $q = (x_2, y_2)$ are the two points on the two dimensional plane then the distance d is computed as follows:

$$\mathrm{d}(p,q) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{6.3.1}$$

Let α_{ij}, β_{ij}, and γ_{ij} are sensing interference between the sensors, target coverage by the sensor, and connectivity between the sensors, and formally defined as follows:

$$\alpha_{ij} = \begin{cases} 1 & d(s_i, s_j) \leq S_r(i) + S_r(j) \\ & \forall i,\ \forall j,\ 1 \leq i, j \leq n \\ 0 & \text{otherwise} \end{cases} \tag{6.3.2}$$

$$\beta_{ij} = \begin{cases} 1 & d(s_i, t_j) \leq S_r(i) \\ & \forall i,\ 1 \leq i \leq n,\ \forall j,\ 1 \leq j \leq k \\ 0 & \text{otherwise} \end{cases} \tag{6.3.3}$$

$$\gamma_{ij} = \begin{cases} 1 & d(s_i, s_j) \leq C_r(i) \\ & \forall i,\ \forall j,\ 1 \leq i, j \leq n \\ 0 & \text{otherwise} \end{cases} \tag{6.3.4}$$

The objectives for sensor placement scheme is formally defined as follows,

Objective 1

It is to minimize *SIR* and is formulated as follows:

$$\text{Minimize } o_1 = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=i+1}^{n}\alpha_{ij} \tag{6.3.5}$$

where n is the number of position selected for deploy sensor nodes.

Objective 2

It is to maximize TCR and is formulated as follows:

$$\text{Maximize } o_2 = \frac{1}{k}\sum_{i=1}^{n}\sum_{j=1}^{k}\beta_{ij} \tag{6.3.6}$$

Objective 3

It is to maximize *SSCR* and is formulated as follows:

$$\text{Maximize } o_3 = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=i+1}^{n}\gamma_{ij} \tag{6.3.7}$$

6.3.1 Entropy-weight Computation Method for Sensor Placement

Step I : Construct decision matrix $\left(x_{ij}\right)_{p\times q}$, where p is the number of candidate sensor positions and q is the number of constraints employed on these candidate sensor positions.

Step II : Decision matrix consist of different types of data and comparison between these data cause inconsistent. Therefore, decision matrix required to be normalized to handle data. One of the accepted technique to normalize data is vector normalization. Suppose $\left(\bar{x}_{ij}\right)_{p\times q}$ is normalized matrix and calculated as follows:

If the constraint on the candidate position is positive, that is, maximum value is better, then normalization is done using the following equation.

$$\bar{x}_{ij} = \frac{x_{ij}}{\sqrt{\sum_i^p x_{ij}^2}} \;\; i \in [1 \dots p], \; j \in [1 \dots q]$$

If the constraint on candidate position is negative, that is, minimum value is better, then normalization is done using the following equation:

$$\bar{x}_{ij} = \frac{\frac{1}{x_{ij}}}{\sqrt{\sum_i^p \frac{1}{x_{ij}}^2}} \; i \in [1 \dots p], \; j \in [1 \dots q], \, x_{ij} \neq 0$$

In experiments, a small value $'\delta'$ is added with x_{ij} to handle divide by error.

Step III :The characteristic proportion value p_{ij} for each candidate position P_i of constraint C_j is computed as follows:

$$p_{ij} = \frac{\bar{x}_{ij}}{\sqrt{\sum_{i=1}^p \bar{x}_{ij}^2}}, \; j \in [1 \dots q]$$

Step IV : The entropy value e_j for each constraint using characteristic proportion p_{ij} is computed as follows:

$$e_j = -\frac{1}{\ln(p)} \sum_{i=1}^{p} p_{ij} \ln(p_{ij}), \; j \in [1 \dots q]$$

The entropy value range from 0 to 1 and smaller entropy value of j^{th} constraint indicates more information available from it.

Step V : The computation of degree of divergence d_j for each constraint j is performed using the equation below:

$$d_j = 1 - e_j, j \in [1 \dots q]$$

If the degree of divergence of constraint j is higher, then the degree of information

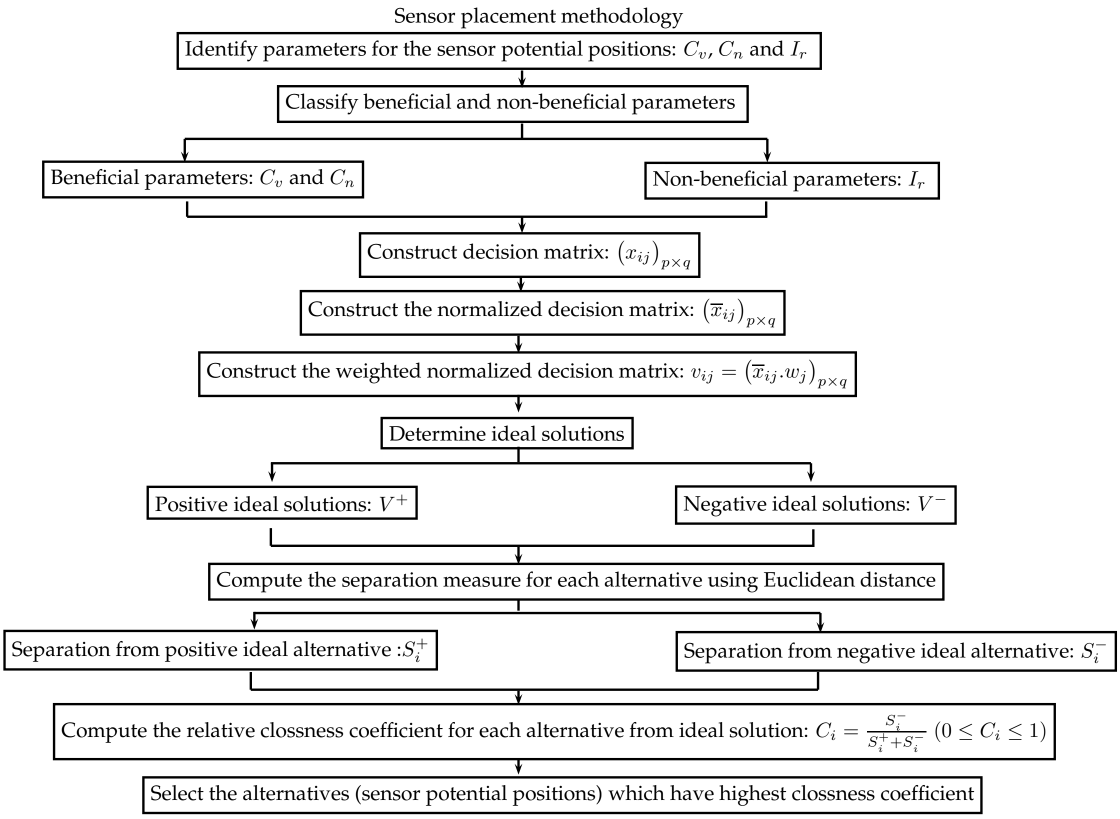


Figure 6.2 Topsis sensor placement

revealed by the constraint j is also higher.

Step VI : The entropy weight for each constraint j for all candidate positions of set P is obtained as follows:

$$w_j = \frac{d_j}{\sum_{j=1}^{q} d_j}, j \in [1, q]$$

where,

$\sum_{j=1}^{q} w_j = 1$

Finally, these weights are used in TOPSIS to rank potential positions and select best potential positions.

6.3.2 TOPSIS Method for Sensor Placement

Step I : Construction of decision matrix $(x_{ij})_{p\times q}, i \in [1 \ldots p], j \in [1 \ldots q]$

Algorithm 6.3.1 Final selection of potential positions for sensor deployment

Input: Ranked set of p candidate positions $P = \{pos_1, pos_2, pos_3 \ldots, pos_p\}$, Set of k target points $T = \{t_1, t_2, t_3 \ldots, t_k\}$

Output: Final sensor placement positions set C which covers targets T

```
Sort candidate positions according to their rank
        // Algorithm starts
for target j = 1 to k do
    for positions i = 1 to p do
        if target t_j is covered by sensor in position p_i then
            if p_i ∉ C then
                C = C ∪ p_i
                break       // To break inner loop
            end if
        end if
    end for
end for
Final potential positions set C is used for sensor deployment
Evaluate SIR, TCR, and SSCR.
```

$$x_{ij} = \begin{array}{c c} & \begin{array}{ccccc} C_1 & C_2 & C_3 & \cdots & C_q \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ A_3 \\ \vdots \\ A_p \end{array} & \begin{bmatrix} x_{11} & x_{12} & x_{13} & \cdots & x_{1q} \\ x_{21} & x_{22} & x_{23} & \cdots & x_{2q} \\ x_{31} & x_{32} & x_{33} & \cdots & x_{3q} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ x_{p1} & x_{p2} & x_{p3} & \cdots & x_{pq} \end{bmatrix} \end{array}$$

Step II : Computation of normalized decision matrix is done as follows:

$$\bar{x}_{ij} = \frac{x_{ij}}{\sqrt{\sum_i^p x_{ij}^2}} \quad i \in [1 \ldots p], j \in [1 \ldots q]$$

Step III : Weighted normalized matrix v_{ij} is computed by multiplying the normalized matrix with corresponding weights:

$$vij = \bar{x}_{ij}.w_j$$

Step IV : Computation of positive ideal solutions (PIS) V^+ and negative ideal solutions (NIS) V^- are done as follows:

$$
\begin{aligned}
V^+ &= \left\{ \max_i v_{ij}, j \in J_1; \min_i v_{ij}, j \in J_2 \right\} \\
&= \left\{ {v_1}^+, {v_2}^+, \cdots, {v_q}^+ \right\}
\end{aligned}
$$

and

$$
\begin{aligned}
V^- &= \left\{ \min_i v_{ij}, j \in J_1; \max_i v_{ij}, j \in J_2 \right\} \\
&= \left\{ {v_1}^-, {v_2}^-, \cdots, {v_q}^- \right\}
\end{aligned}
$$

where J_1 and J_2 are the sets of beneficial criteria and non-beneficial criteria respectively; ${v_j}^+$ and ${v_j}^-$ represents j^{th} column PIS and j^{th} column NIS of the weighted normalized matrix respectively.

Step V : Computation of Euclidean distance from PIS and NIS for each weighted normalized values are done as follows:

$$
\begin{aligned}
S_i^+ &= [\sum_{j=1}^{q} \left(v_j^+ - v_{ij} \right)^2]^{0.5} \\
S_i^- &= [\sum_{j=1}^{q} \left(v_j^- - v_{ij} \right)^2]^{0.5}
\end{aligned}
$$

Step VI : The closeness coefficient of alternative A_i is computed as follows:

$$
C_i = \frac{S_i^-}{S_i^+ + S_i^-} \,, (0 \leq C_i \leq 1), \; i \in [1 \ldots p]
$$

Step VII : The best alternatives are ranked according to the C_i value in descending order.

The ranked candidate positions and the targets are fed to the Algorithm 6.3.1. Firstly, the algorithm sorts the candidate positions according to their ranks (line 1). Each target t_j, a candidate position p_i that covers the target is identified. if the newly selected candidate position is not in the sensor placement positions set C, then add the position p_i to set C. In the end, a candidate positions set C is obtained and is used for sensor placement (lines 2-11). Finally, performance parameter values SIR, TCR, and $SSCR$ are computed.

In the algorithm, the sorting in line 1 requires $O(plogp)$ time in worst case to sort potential potential p. The for loop of line 2 requires $O(k)$ time in worst case to identify each target. The for loop of line 3 requires $O(p)$ time in worst case to identify potential positions to deploy sensors. The line 6 needs $O(1)$ time to execute it. So, the algorithm can be executed in $O(kp)$ time. Therefore the time complexity of the above algorithm is $O(kp)$. if $k < log\ p$, then the algorithm requires $O(p\ log\ p)$ time.

Illustration 1

Table 6.2 Potential positions ranking for sensor placement

Positions	C_v	C_n	I_r	C_i	$Rank_1$	D_i	$Rank_2$	E_i	$Rank_3$
p_1	1	2	0	0.7878	3	0.6311	6	0.8311	2
p_2	2	2	0	1.0000	1	0.6526	5	0.9167	1
p_3	2	1	1	0.6691	5	0.6763	4	0.6417	6
p_4	2	0	2	0.4033	9	0.5287	8	0.4767	10
p_5	2	0	1	0.5137	7	0.7600	2‘	0.5317	9
p_6	2	1	3	0.3999	10	0.3710	9	0.5592	8
p_7	2	0	0	0.5889	6	1.0000	1	0.6967	5
p_8	2	2	1	0.8152	2	0.5955	7	0.7517	3
p_9	1	1	0	0.6818	4	0.7184	3	0.7211	4
p_{10}	1	2	4	0.4111	8	0.3474	10	0.5671	7

Let 5 targets $T = \{t_1, t_2, \ldots, t_5\}$, 5 sensors $S = \{s_1, s_2, \ldots, s_5\}$, and 10 potential positions $P = \{p_1, p_2, \ldots, p_{10}\}$. Suppose Table 6.2 gives coverage, connectivity, and the

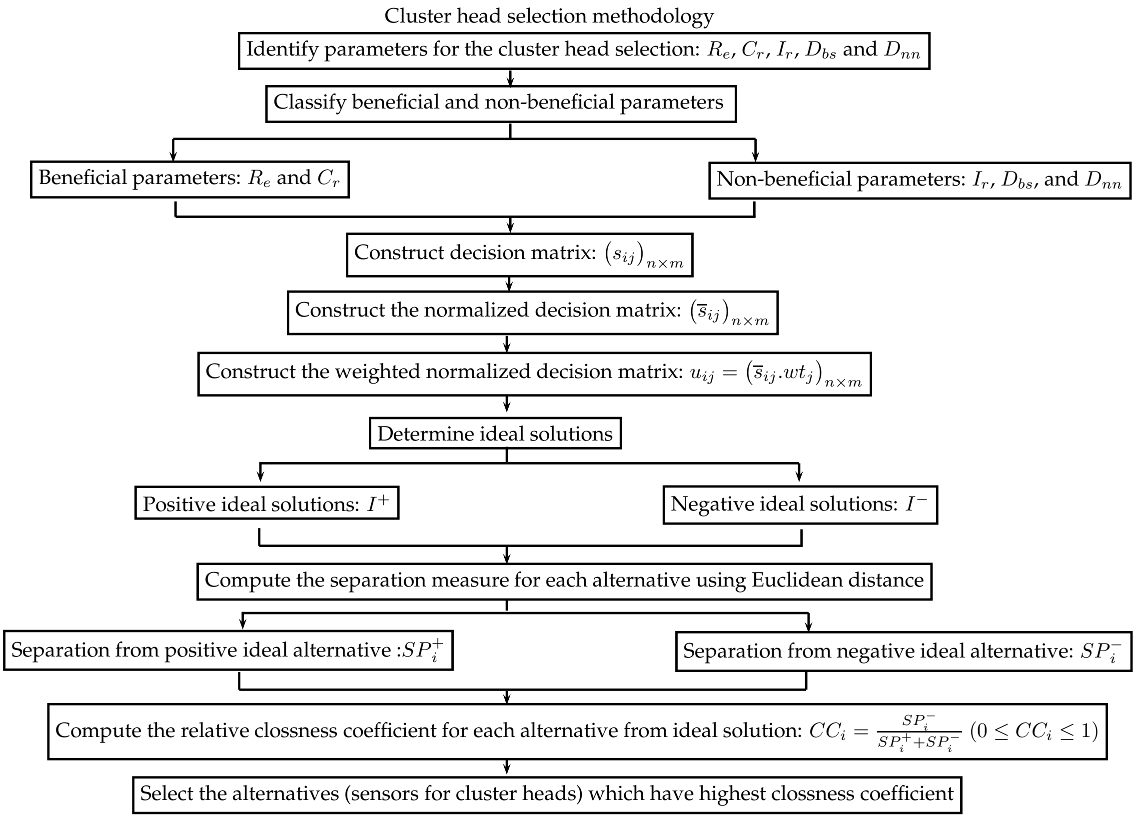


Figure 6.3 Topsis sensor head selection

interference count of potential positions that may be selected for deploying sensors. If top 5 positions are considered for sensor placement according to their rank, then *SIR*, *TCR*, and *SSCR* values are 0.4, 1.6, and 1.6 respectively and corresponding interference energy loss is 20nJ. Instead, worst 5 positions are considered for sensor placement, then *SIR*, *TCR*, and *SSCR* values are 2, 1.8, and 0.6 respectively and corresponding interference energy loss is 100nJ. The Table 6.2 shows ranking of the potential positions using E-TOPSIS, TOPSIS, and SAW methods.

6.4 Proposed Entropy-weighted TOPSIS Clustering Algorithm

6.4.1 Entropy-weight Computation Method for Clustering

Step I : Construct decision matrix $(s_{ij})_{n\times m}$, where n is number of sensor nodes and m is number of constraints employed on these sensors.

Table 6.3 Sensor nodes ranking for CH selection

Sensors	R_e(Joule)	C_r(meter)	I_r(count)	$D_{bs}(meter)$	$D_{nn}(meter)$	CC_i	Rank
s_1	0.50	75	0	50	40	0.8256	1
s_2	0.30	65	0	60	35	0.7166	2
s_3	0.35	55	1	65	35	0.6559	3
s_4	0.30	85	2	100	55	0.4968	7
s_5	0.25	45	1	125	40	0.4956	8
s_6	0.15	35	3	135	15	0.3036	10
s_7	0.25	40	0	80	50	0.5921	5
s_8	0.25	55	1	70	65	0.5310	6
s_9	0.30	30	0	90	40	0.6014	4
s_{10}	0.45	80	4	100	10	0.4640	9

Step II : The normalized decision matrix is obtained as follows:

$$\bar{s}_{ij} = \frac{s_{ij}}{\sqrt{\sum_i^n {x_{ij}}^2}} \quad i \in [1 \dots n], j \in [1 \dots m] \tag{2}$$

and

$$\bar{s}_{ij} = \frac{\frac{1}{s_{ij}}}{\sqrt{\sum_i^n \frac{1}{s_{ij}}^2}} \quad i \in [1 \dots n], j \in [1 \dots m], s_{ij} \neq 0$$

In experiments, a small value $'\delta'$ is added with s_{ij} to handle divide by error.

Step III : The characteristic proportion value n_{ij} for each sensor is computed as follows:

$$n_{ij} = \frac{\bar{s}_{ij}}{\sqrt{\sum_i^n {\bar{s}_{ij}}^2}} \quad i \in [1 \dots n], j \in [1 \dots m], x_{ij} \neq 0$$

Step IV : The entropy value ev_j for each constraint using characteristic proportion n_{ij} is computed as follows:

$$ev_j = -\frac{1}{\ln(n)} \sum_{i=1}^{n} n_{ij} \ln(n_{ij}), i \in [1, n], j \in [1, m]$$

Step V : The computation of degree of divergence dd_j for each constraint j is performed using the equation below:

$$dd_j = 1 - ev_j, j \in [1,m]$$

Step VI : The entropy weight for each constraint j for all sensor set S is obtained as follows:

$$wt_j = \frac{dd_j}{\sum_{j=1}^{m} dd_j}, j \in [1,m]$$

where,

$\sum_{j=1}^{m} wt_j = 1$

Finally, these weights are used in TOPSIS to rank sensor nodes to elect suitable CHs.

6.4.2 TOPSIS Method for Clustering

Step I : Construction of a decision matrix $(s_{ij})_{n\times m}, i \in [1\ldots n], j \in [1\ldots m]$

$$s_{ij} = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ \vdots \\ A_n \end{array} \begin{array}{c} \begin{array}{ccccc} C_1 & C_2 & C_3 & \cdots & C_m \end{array} \\ \begin{bmatrix} s_{11} & s_{12} & s_{13} & \cdots & s_{1m} \\ s_{21} & s_{22} & s_{23} & \cdots & s_{2m} \\ s_{31} & s_{32} & s_{33} & \cdots & s_{3m} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ s_{n1} & s_{n2} & s_{n3} & \cdots & s_{nm} \end{bmatrix} \end{array}$$

Step II : Computation of the normalized decision matrix as follows:

$$\bar{s}_{ij} = \frac{s_{ij}}{\sqrt{\sum_i^n s_{ij}^2}} \quad i \in [1\ldots n], j \in [1\ldots m]$$

Step III : The weighted normalized matrix u_{ij} is computed by multiplying the normalized matrix with corresponding weights as shown below:

$uij = \bar{s}_{ij}.wt_j$

Step IV : Computation of the positive ideal solutions (PIS) I^+ and the negative ideal solutions (NIS) I^-.

$$\begin{aligned} I^+ &= \left\{ \max_i u_{ij}, j \in K_1; \min_i u_{ij}, j \in K_2 \right\} \\ &= \left\{ {u_1}^+, {u_2}^+, \cdots, {u_m}^+ \right\} \end{aligned}$$

$$\begin{aligned} I^- &= \left\{ \min_i u_{ij}, j \in K_1; \max_i u_{ij}, j \in K_2 \right\} \\ &= \left\{ {u_1}^-, {u_2}^-, \cdots, {u_m}^- \right\} \end{aligned}$$

where K_1 and K_2 are the sets of beneficial criteria and non-beneficial criteria respectively; ${u_j}^+$ and ${u_j}^-$ represents j^{th} column PIS and j^{th} column NIS of the weighted normalized matrix respectively.

Step V : Computation of Euclidean distance from the PIS and NIS for each weighted normalized values are done as follows:

$$\begin{aligned} SP_i^+ &= [\sum_{j=1}^{m} \left(u_j^+ - u_{ij}\right)^2]^{0.5} \\ SP_i^- &= [\sum_{j=1}^{m} \left(u_j^- - u_{ij}\right)^2]^{0.5} \end{aligned}$$

Step VI : The closeness coefficient of alternative A_i for CHs selection are computed as follows:

$$CC_i = \frac{SP_i^-}{SP_i^+ + SP_i^-} \; (0 \le CC_i \le 1)$$

Step VII: The best alternatives are ranked according to the CC_i value in descending order.

Illustration 2

Suppose Table 6.3 is constructed with random parameter values of sensors. After employing entropy weighted-TOPSIS MADM method, the order for CHs selection is s_1, s_2, s_3, s_9, s_7, s_8, s_4, s_5, s_{10}, and s_6.

6.5 Results and Discussion

Table 6.4 Simulation parameters

Parameters	Values
Potential positions p	200
Network size (m^2)	300×300
Initial node energy(J)	0.5
Sensing range (m)	[5-10]
Communication range(m)	[50-100]
Data packet size k (bits)	4000
E_{ele}(nJ/bit)	50
E_{Tx}(nJ/bit)	50
E_{Rx}(nJ/bit)	50
ε_{mp}(pJ/bit/m^4)	0.0013
ε_{fs}(pJ/bit/m^2)	10
E_{DA}(nJ/bit/message)	5
CH election probability	0.1
BS location(coordinates)	(150,150)
Energy loss per interference (nJ)	50
Sensor nodes n	42

This Section details the parameter settings for the simulations and discusses the performance analysis of MADM techniques for sensor placement and clustering. The

Table 6.5 SIR results comparison (30 instance of experiments are conducted)

Targets	Parameters	E_TOPSIS	TOPSIS	SAW
25	Best	0	0	0
	Worst	0.0909	0.0869	0.0555
	Mean	0.0149	0.0194	0.0027
	SD	0.0279	0.0285	0.0121
	95% CI	[0.0049, 0.0249]	[0.0092, 0.0297]	[0.0020, 0.0071]
50	Best	0	0	0
	Worst	0.0975	0.23075	0.0800
	Mean	0.0482	0.0557	0.0185
	SD	0.0254	0.0477	0.0185
	95% CI	[0.0392, 0.0574]	[0.0387, 0.0729]	[0.0119, 0.0252]
75	Best	0.0169	0.02040	0
	Worst	0.1694	0.2881	0.0625
	Mean	0.0874	0.0914	0.0297
	SD	0.0391	0.0474	0.0226
	95% CI	[0.0734, 0.1010]	[0.0744, 0.1080]	[0.0216, 0.0378]
100	Best	0.0140	0.0151	0
	Worst	0.1621	0.1756	0.1363
	Mean	0.0753	0.0861	0.0401
	SD	0.03571	0.0438	0.0323
	95% CI	[0.0625, 0.0881]	[0.0704, 0.1020]	[0.0286, 0.0517]

simulations are carried out using MATLAB R2019a on an Intel(R) Core(TM) i5-8250U CPU@1.60 GHz 1.80 GHz and 8 GB RAM running on Microsoft Windows 10, 64-bit operating system, x64-based processor. An initial wireless network is setup with p number of potential positions and k number of target points. A network area of 300×300 is created and a sink is placed at the centre of the field $(150, 150)$. The potential positions and target points are randomly generated on the field. The simulations are carried out for 200 potential positions and targets points are varied in the range of 25 to 100. The sensors are heterogeneous and have equal energy but with different sensing and communicating capabilities. Each sensor has initial energy of 0.5 joule. The sensing and communication range of sensors are in the range of 5 meter to 10 meter and 50 meter to 100 meter respectively. The data packet size is 4000bits. The energy required for one bit computation or transmission or receipt is 50 nanojoule(nJ). The energy drain

Table 6.6 TCR results comparison (30 instance of experiments are conducted)

Targets	Parameters	E_TOPSIS	TOPSIS	SAW
25	Best	1	1	0.76
	Worst	0.96	0.92	0.36
	Mean	0.996	0.982	0.598
	SD	0.012	0.0267	0.1098
	95% CI	[0.992, 1.000]	[0.972, 0.992]	[0.559, 0.637]
50	Best	1	1	0.76
	Worst	0.94	0.88	0.48
	Mean	0.974	0.934	0.606
	SD	0.018	0.03104	0.0834
	95% CI	[0.968, 0.980]	[0.923, 0.945]	[0.576, 0.636]
75	Best	0.9733	0.9866	0.6666
	Worst	0.92	0.88	0.48
	Mean	0.946666	0.9293	0.5846
	SD	0.01738	0.0273	0.0448
	95% CI	[0.940, 0.953]	[0.920, 0.939]	[0.569, 0.601]
100	Best	0.98	0.98	0.66
	Worst	0.89	0.86	0.5
	Mean	0.9325	0.9195	0.5835
	SD	0.0229	0.0283	0.0408
	95% CI	[0.924, 0.941]	[0.909, 0.930]	[0.569, 0.598]

for one bit transmission in multipath channel and free space channel are 0.0013 picojoule(pJ) and 10 picojoule respectively. The energy required for fusing one bit data is 5 nanojoule. The energy loss for per interference is 50 nanojoule. The cluster head election probability for all methods is 0.1. The parameter list is tabulated in Table 6.4.

6.5.1 Result Analysis

The performance analysis of novel E-TOPSIS based sensor placement scheme and clustering are presented in this chapter. Firstly, results for E-TOPSIS placement scheme are presented and compared with TOPSIS and SAW methods. The results for SIR, TCR and SSCR are tabulated in Table 6.5, 6.6 and 6.7 respectively. The 30 instance of

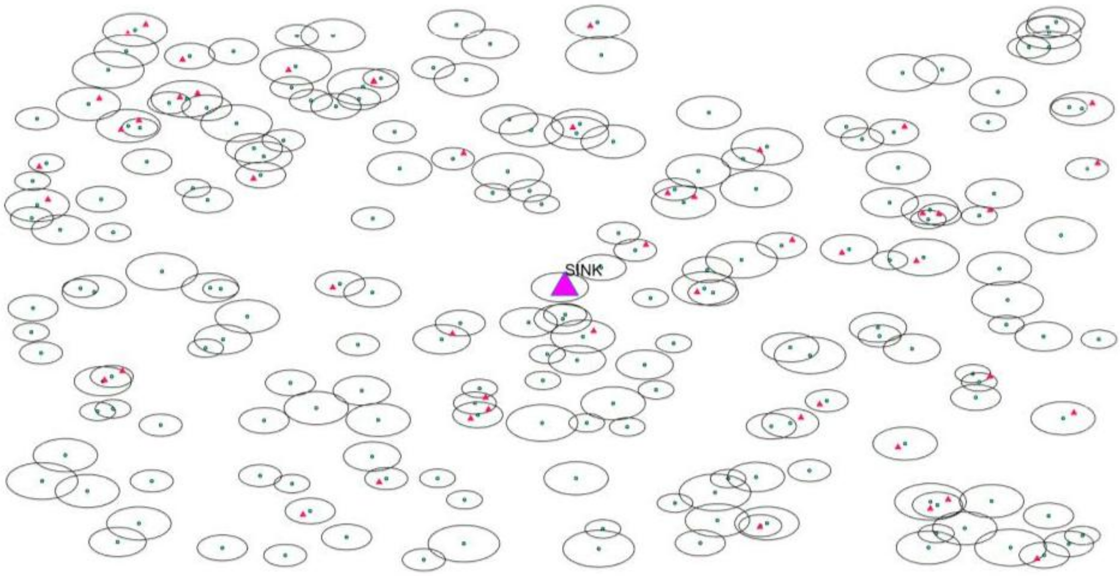


Figure 6.4 Initial Network: 200 candidate positions and 50 targets

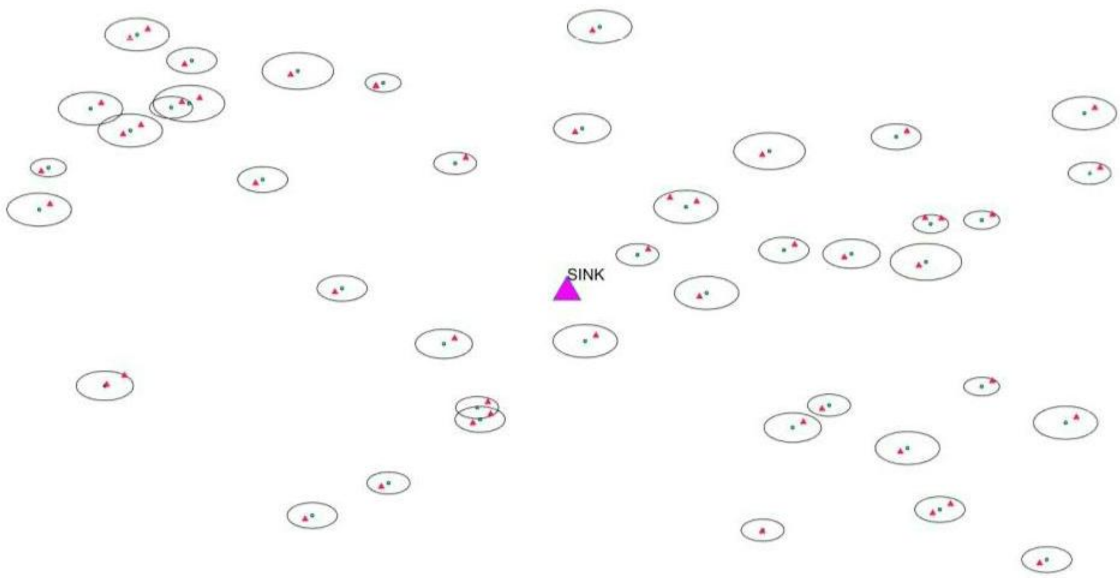
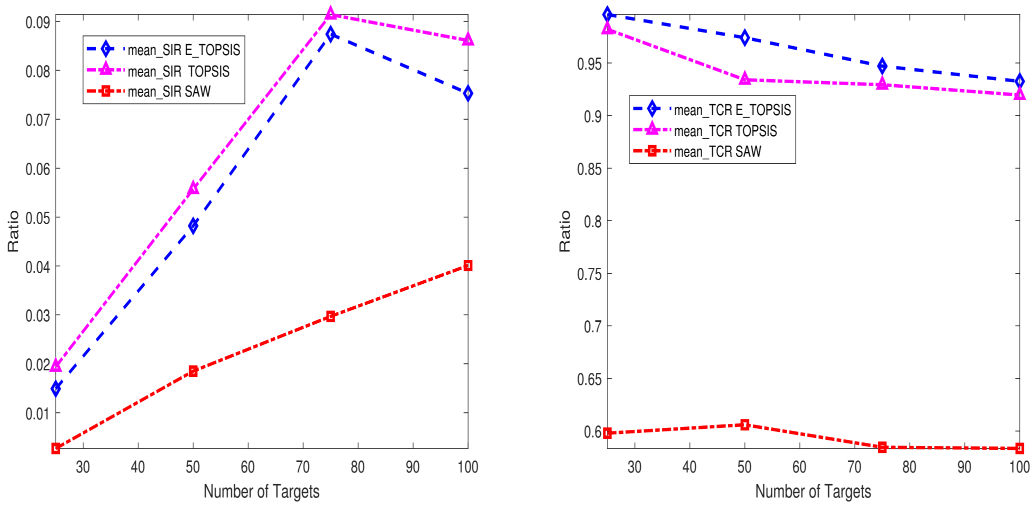


Figure 6.5 Final Network: Selected final positions with 50 targets covered

Table 6.7 SSCR results comparison (30 instance of experiments are conducted)

Targets	Parameters	E_TOPSIS	TOPSIS	SAW
25	Best	2.88	2.36	5
	Worst	1.4583	1.2272	1.1666
	Mean	1.9131	1.8103	2.9968
	SD	0.3411	0.3090	0.8678
	95% CI	[1.791, 2.035]	[1.700, 1.921]	[2.686, 3.307]
50	Best	4.1818	3.8333	6.07407
	Worst	2.9268	2.5277	2.16
	Mean	3.5300	3.2246	4.0862
	SD	0.3400	0.3417	0.8860
	95% CI	[3.408, 3.652]	[3.102, 3.347]	[3.769, 4.403]
75	Best	6.4000	5.3620	7.714
	Worst	4.0727	3.9387	3.531
	Mean	4.9946	4.7120	4.992
	SD	0.5192	0.3829	1.0394
	95% CI	[4.809, 5.180]	[4.575, 4.849]	[4.620, 5.364]
100	Best	7.1486	6.7530	7.1025
	Worst	5.3714	4.8125	4.0487
	Mean	6.19010	5.96849	5.4456
	SD	0.4611	0.5209	0.7982
	95% CI	[6.025, 6.355]	[5.782, 6.155]	[5.160, 5.731]

experiments are conducted and results are presented as best, worst, mean, standard deviation, and 95% confidence interval. The results show that the E_TOPSIS achieve better results in terms of target coverage ratio compared to other two MADM methods. In Table 6.5, the SIR increases as number of targets increase. It is due to more number of sensors being required to cover more target points and hence an increase in interference of the network. The Figure 6.6a depicts the mean SIR results of three methods. It is noted that the mean SIR for SAW method is better compared to other methods, but the technique fails to achieve the required target coverage. It is noted from the Table 6.6 is that the target coverage ratio for E-TOPSIS supersedes other MADM methods. The Figure 6.6b depicts the mean TCR results of three methods and E-TOPSIS outperforms over other methods. Figure 6.4 depicts initial network with identified potential positions and targets points. Figure 6.5 represents the final network with the selected potential

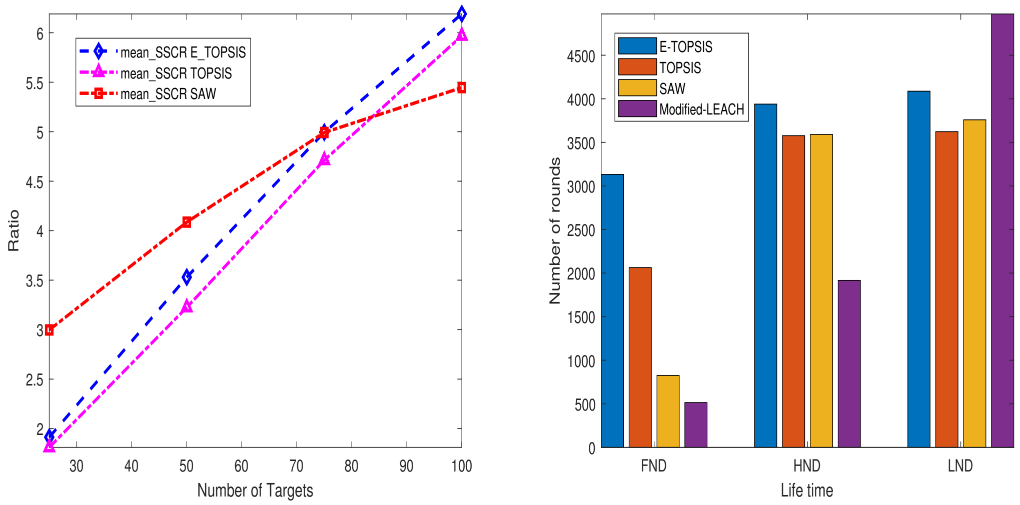


(a) mean SIR comparisons

(b) mean TCR comparisons

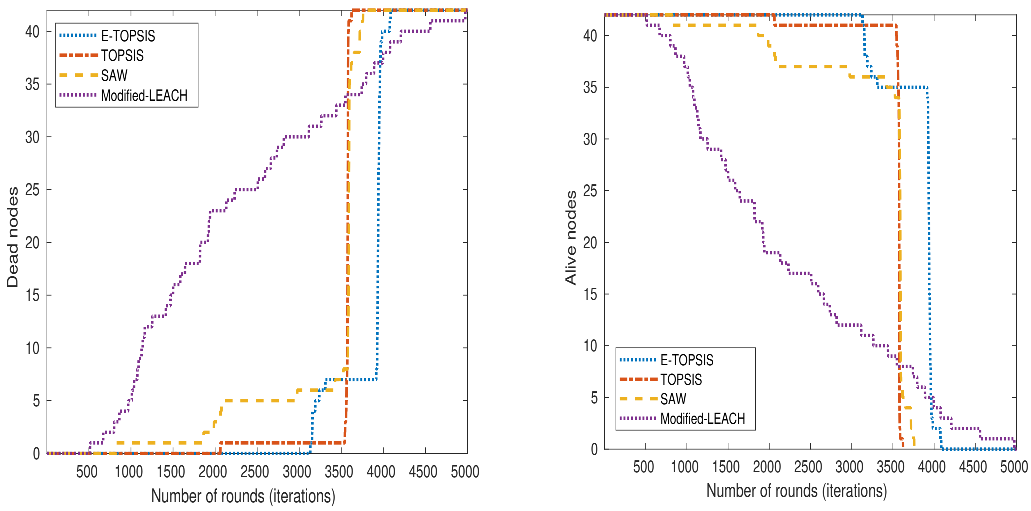
Figure 6.6 SIR and TCR comparisons

positions for sensor deployment and given target points covered. In Table 6.7, SSCR increases as the number target points increase. It is because of the increase in sensors to cover more targets and hence each node has more neighbour nodes, which results in high SSCR values. The Figure 6.7a shows the mean SSCR results and it is better as the number of targets increases. The good SSCR values are very essential for larger and reliable networks. After the placement, clustering is performed on these sensors. Again, E-TOPSIS is employed for clustering and compared with TOPSIS and SAW MADM methods. Figure 6.8 shows the lifetime of WSN on various MADM methods. It is observed that the death of first node in the E-TOPSIS later than other protocols. In other words, the network stability period for E-TOPSIS is better compared to other MADM protocols. Figure 6.7b shows that the performance indicators like first node dies (FND), Half of the node dies (HND), and last node dies (LND). Performance of MADM methods are compared with modified LEACH. Here, cluster heads are able to receive data from its member nodes, if they are in the communication range of the cluster heads. The results shows that the stability period for clustering using E-TOPSIS is 34.1%, 73.65%, and 83.5% better than TOPSIS, SAW and Modified LEACH methods



(a) mean SSCR comparisons (b) Network lifetime

Figure 6.7 SSCR and network lifetime comparisons



(a) Dead nodes Vs iterations (b) Alive nodes Vs iterations

Figure 6.8 Network stability period comparisons respectively. The network lifetime in E-TOPSIS is better than the other protocols.

6.6 Chapter Summary

The energy efficient placement and clustering play a crucial role in extending the stability period of the wireless sensor networks. To address the issues, a novel MADM based placement and clustering schemes are proposed in the chapter. The major objectives of the proposed works are multi-constrained placement and clustering in wireless sensor networks. E-TOPSIS based MADM schemes are formulated for interference aware sensor placement and clustering. The proposed schemes are illustrated with suitable examples. The performance analysis of sensing interference ratio, target coverage ratio and sensor to sensor connectivity ratio are conducted. A comparison study of the E-TOPSIS methods with other scheme is carried out. The results show that the E-TOPSIS based schemes for sensor placement and clustering are better than other schemes. The proposed sensor placement method can be adopted for the placement of under water sensors in under water environment to minimize interference among them. The results of clustering show that the stability period for E-TOPSIS is 34.1%, 73.65%, and 83.5% better than TOPSIS, SAW and Modified LEACH methods respectively.

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Chapter 7

Conclusion and Future Scope

WSNs have gained lot of attention by the researchers due to its wide spectrum of applications in industry, healthcare,military, smart city, and domestic appliances. The WSNs have various issues like coverage of targets with connectivity constraint, interference of signal during sensing the environment by the sensors or communication between the sensor nodes, and also energy conservation of the sensor nodes. In recent fast, various computational intelligence methods have developed to solve real word science and engineering problems in general and WSNs in particular to address a wide set of challenges. This includes coverage, localization, and clustering problems. In this context, the research work presented in this thesis is focused on designing and developing computational intelligence methods for solving some problems in WSNs.The research work presented in this thesis is focused on solving k-coverage and m-connectivity, interference minimization, and clustering in WSNs and contributions are summarized as follows.

In chapter 3, a differential evolution based meta-heuristic technique for solving k-coverage and m-connectivity problem in WSN is presented. The technique finds an optimal number of selected candidate positions for the deployment of sensor nodes with specified k-coverage and m-connectivity demands of the wireless sensor network. We have adopted an efficient method to represent vectors of the population as well as for fitness calculation, then applied mutation, crossover, and selection operators to choose the best vector of the population. The steps of computing fitness values are illustrated. The simulations are performed by varying candidate sensor node positions and targets points along with coverage and connectivity requirement. In addition, we have compared our proposed technique with a genetic algorithm based approach. The result confirms that the proposed approach is superior to the GA based approach.

In chapter 4, an optimal sensors placement BBO-based scheme is proposed with a combined goal of maximizing target coverage and minimizing interference while maintaining connectivity of the network. An elegant vector encoding for habitat representation and novel fitness function is formulated for the proposed scheme. The working of the proposed scheme is illustrated with a suitable example. The performance study of sensing interference ratio and target coverage ratio on grid and random scenarios were conducted. A comparison study of the BBO-based scheme with other scheme was carried out. The least energy loss due to interference in BBO-based scheme confirms its superiority over other schemes.

In chapter 5, Hybrid hierarchical protocols named FLAG and I-FLAG are proposed to extend network stability. Two main phases of these protocols are CH election phase and SCH election phase. The CH election phase is achieved through a game-theoretic protocol, and SCH election phase is achieved through a fuzzy inference system. The simulations are carried out to verify the superiority of the proposed protocols. The results show that the network stability period of FLAG is better than LEACH, CHEF, and CROSS. The network stability period of I-FLAG is better than LEACH, CHEF, and I-CROSS. Due to the balanced energy drain of the proposed work, the network stability is better over the other protocols.

Finally, in chapter 6, MADM based placement and clustering schemes are proposed. The major objectives of the proposed works are multi-constrained placement and clustering in wireless sensor networks. E-TOPSIS based MADM schemes are formulated for interference aware sensor placement and clustering. The proposed schemes are illustrated with suitable examples. The performance analysis of sensing interference ratio, target coverage ratio, and sensor to sensor connectivity ratio were conducted. A comparison study of the E-TOPSIS methods with other schemes was carried out. The results show that the E-TOPSIS based schemes for sensor placement and clustering are better than other schemes. The proposed sensor placement method can be adapted for the placement of Internet of Things (IoT) devices to minimize interference among them. The results of clustering show that the stability period for E-TOPSIS is 34.1%, 73.65%, and 83.5% better than TOPSIS, SAW and Modified LEACH methods respectively.

In future, one can develop more sophisticated model for handling following scenarios:

1. Dynamic wireless sensor networks have advantages over stationary wireless sensor networks in some applications and hence one can attempt to develop a model to handle k-coverage and m-connectivity problems in such scenarios. To adapt dynamic networks, one can consider mobile sensor nodes or mobile sinks.

2. Sophisticated model can be developed for interference minimization problems by augmenting fuzzy logic as sensor node signals have different degrees of overlapping, they can be easily modelled using fuzzy logic.

3. Zone-based hybrid clustering models can be developed which have the potential for parallelization to achieve faster computation. This is essential for time critical applications.

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2. Chandra Naik and Pushparaj Shetty D: Optimal sensors placement scheme for targets coverage with minimized interference using bbo. Evolutionary Intelligence, Springer, pp. 1-15 (2021) **[ESCI, Scopus]**

3. Chandra Naik and Pushparaj Shetty D: Flag: fuzzy logic augmented game theoretic hybrid hierarchical clustering algorithm for wireless sensor networks. Telecommunication Systems, Springer, pp. 1-13 (2022) **[SCIE]**

4. Chandra Naik and Pushparaj Shetty D: MADM: Multi-attribute decision making approach for energy efficient sensor placement and clustering in wireless sensor networks. Telecommunication Systems, Springer [Submitted]

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1. Chandra Naik and Pushparaj Shetty D: A novel meta-heuristic differential evolution algorithm for optimal target coverage in wireless sensor networks. In: In International Conference on Innovations in Bio-Inspired Computing and Applications, pp. 83-92. Springer (2018) **[Scopus]**

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Educational Qualifications :

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MTech	Computer Science and Engineering	2010	Visvesvaraya Technological University, Belagavi
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Work Experience :

1. Worked as a Faculty in the Department of Computer Science and Engineering at NMAM Institute of Technology, Nitte Karkala from July 2007 to July 2017.

2. Worked as a Asst. Lecturer in the Department of Computer Science and engineering at National Institute of Technology Karnataka, Surathkal from July 2006 to May 2007

Awards and Achievements :

1. A Student Scholarship of 20,000 INR from IISc to attend 13th International Conference on Web and Internet Economics on December 17-20, 2017, IISc Bangalore, India.

2. Qualified GATE 2017.

3. Mission10x Certificate in Teaching and Learning on January 31st, 2011 in "Pursuit of Excellence in Engineering Education through Innovation".

4. Successfully completed the Mission10x learning approach, Practitioners Certificate held on 13th September and 14th September 2010. It is in recognistion of efforts in planning, preparing and implementing MxLA in the classroom and for attending the supporting advanced workshop.

5. Sponsorship for a period of two years to do Post Graduation in MTech from NMAMIT, Nitte, Karkala.

6. S.S.L.C Examination School topper in the year 1998.