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OPTIMAL PLACEMENT OF CLUSTER HEAD IN TRANSMIT ONLY WIRELESS SENSORS NETWORKS

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بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

(قَالَ يَا أَيُّهَا الْمَلَأُ أَيُّكُمْ يَأْتِينِي بِعَرْشِهَا قَبْلَ أَنْ يَأْتُونِي مُسْلِمِينَ * قَالَ عِفْرِيتٌ مِنَ الْجِنِّ أَنَا آتِيكَ بِهِ قَبْلَ أَنْ تَقُومَ مِنْ مَقَامِكَ وَإِنِّي عَلَيْهِ لَقَوِيٌّ أَمِينٌ * قَالَ الَّذِي عِنْدَهُ عِلْمٌ مِنَ الْكِتَابِ أَنَا آتِيكَ بِهِ قَبْلَ أَنْ يَرْتَدَّ إِلَيْكَ طَرْفُكَ فَلَمَّا رَآهُ مُسْتَقِرًّا عِنْدَهُ قَالَ هَذَا مِنْ فَضْلِ رَبِّي لِيَبْلُوَنِي أَأَشْكُرُ أَمْ أَكْفُرُ وَمَنْ شَكَرَ فَإِنَّمَا يَشْكُرُ لِنَفْسِهِ وَمَنْ كَفَرَ فَإِنَّ رَبِّي غَنِيٌّ كَرِيمٌ)

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OPTIMAL PLACEMENT OF CLUSTER HEAD IN TRANSMIT ONLY WIRELESS SENSORS NETWORKS

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BY

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Abstract

In the recent years, wireless sensor networks (WSNs) have emerged as new technology in various applications to obtain information from the environment such as temperature, humidity, pressure, etc. WSNs are primarily characterized by a limited, non-renewable power supply. Hence, the need to improve energy efficiency is becoming increasingly important as it affects the lifetime of the network. In order to minimize the energy consumption in WSN, this thesis presents models to reduce the consumed energy and extend the network lifetime by proposing two cases. The first case discusses five scenarios. In each scenario, the proposed model is divided into a certain number of clusters, and the proposed model is compared with two other models. In this case, the model minimizes the number of active sensor nodes, and determines the optimal position for the single cluster head (CH). To minimize the energy consumed by the transmit-only sensor nodes, k-mean algorithm is employed to perform node clustering, and determine one sensor node from each cluster to represent this cluster. Particle Swarm Optimization (PSO) is used to solve the non-convex optimization problem of finding optimal location of the CH. In the second case, the optimal position for the cluster heads (CHs) in the networks where natural obstacles are studied, such as mountains, buildings or a group of trees, exist within observer field. These obstacles may block the communication between transmit-only sensor nodes and a CH in WSNs. In this case, the observer field is divided into k-groups, where each group has the greatest number of sensor nodes that have a line-of-sight (LOS) among them. This sub-problem is formulated as a graph partitioning problem. Moreover, the optimal position of the CHs is determined in each groups such that LOS is maintained between the CH and its sensors nodes. In order to minimize the energy consumed by each group within the target field, PSO algorithm is used to find the optimal location of the CH. Simulation results show that the first proposed case achieves better network lifetime compared to its comparators. While the second proposed case shows that the proposed model achieves the best partitioning of the network, the best communications between sensor nodes and its CH, and the best network lifetime compared with a model that splits the sensor nodes using the coordinates of the obstacles (heuristic model). The percentage of lifetime improvement is 22% and 16% in the first and second scenarios, respectively.

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Declaration

I hereby declare that the work in this thesis is my own except for quotations and summaries which have been duly acknowledged.

2021 Name: Zahraa Hammodi Baqer

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List of Abbreviations

Abbreviations	Description
BS	Base Station
CCGA	Clustering approach based on Cluster head using Genetic Algorithm
CH	Cluster Head
D-LEACH	Deterministic Low-Energy Adaptive Clustering Hierarchy
EELP	Energy Efficient Leveling Protocol
EESSTBRP	Energy Efficient Sleep-Scheduled Tree-Based Routing Protocol
ESCHS	Energy Saving Cluster Head Selection
EUCRP	Energy-balanced Unequal Clustering Routing
GA	Genetic Algorithm
GM	Geometric Mean
GPT	Graph Partitioning Technique
HEED	Hybrid Energy Efficient Distributed
ID	Identification
LEACH	Low-Energy Adaptive Clustering Hierarchy
LEACH-C	Low-Energy Adaptive Clustering Hierarchy- Centralized
LEACH-GA	Low-Energy Adaptive Clustering Hierarchy-Genetic Algorithm
LOS	Line-Of-Sight
NP	Nondeterministic Polynomial-time
O-LEACH	Optimize Low-Energy Adaptive Clustering Hierarchy
PEGASIS	Power-Efficient Gathering in Sensor Information Systems

PSO	Particle Swarm Optimization
SN	Sensor Node
TDMA	Time Division Multiple Access
TO	Transmit-Only
WSN	Wireless Sensor Network

List of Symbols

Symbol	**Definition**	**Unit**
α	Constant associated with the transmitter and receiver circuits.	nJ/bit
β	Constant associated with the transmitter and receiver circuits.	$pJ/(bit.m^2)$
c_1,c_2	Learning factors.	....
CH_X, CH_Y	The two-dimensional location of the CH.	….
CH_{Xopt}, CH_{Yopt}	The optimal two-dimensional location of the CH in the first case.	….
CH_{Xoptj}, CH_{Yoptj}	The optimal location of the j^{th} CH in the j^{th} group in the second case.	….
$C_j \equiv (C_{Xj}, C_{Yj})$	The two-dimensional location of the j^{th} centroid node.	….
$Cut(A, B)$	The definition of cut technique between two subgroups A and B.	….

d_b	The Euclidian distance between the CH and the BS.	m
d_i	The Euclidian distance between the i^{th} transmit-only sensor node and the CH.	m
d_{ij}	The Euclidian distance between the i^{th} transmit-only sensor node and the j^{th} cluster head in the second case.	m
d_j	the Euclidian distance between the j^{th} cluster head and the BS.	m
E_{CH}	The total energy consumed by the CH as receiver and transmitter.	Joule
E_{CHj}	The total energy consumed by the j^{th} cluster head in the second case.	Joule
E_{CHTR}	The total energy consumed by CH in the first case.	Joule
E_{CONS}	The total energy consumed for the entire observer field in the first case.	Joule
E_{RX}	The energy dissipated by the CH as a receiver.	Joule
E_{RXO}	The amount of energy dissipated by a CH as a receiver in the first case.	Joule
E_{TX}	The total energy consumed by TO sensor nodes in the whole network.	Joule
E_{TXCN}	The total energy consumed by all centroid nodes in the observer field as transmitter in the first case.	Joule
E_{TXi}	The energy dissipated by the i^{th} transmit-only sensor node.	Joule

E_{TXj}	The total energy consumed by all TO sensor nodes in the j^{th} group in the second case.	Joule
E_{TXOj}	The amount of energy dissipated by the j^{th} centroid node as a transmitter in the first case.	Joule
E_{tot}	The total energy dissipated in the entire network by the TO sensor nodes and the CH.	Joule
E_{totj}	The total energy dissipated in the j^{th} group by the transmit-only sensor nodes and its CH in the second case.	Joule
G_j	The number of TO sensor nodes in the j^{th} cluster.	….
GM_X, GM_Y	The location of the CH within two dimensional observer field.	….
$I_{LOS}(i)$	Indication function that represents the absence of LOS between the CH and the i^{th} transmit-only sensor node.	….
k	The number of clusters.	….
l_j	The Euclidian distances between the j^{th} centroid node and the CH.	m
M_{Cut}	The min-max function in graph partitioning algorithm.	….
μ	The path loss exponent.	….
N	The number of the TO sensor nodes in the network.	….
N_j	The number of the TO sensor nodes in the j^{th}	….

	group.	
p	The number of data bit.	bit
p_{id}	The best position of the i^{th} particle.	….
p_{gd}	The global best position.	….
r_1, r_2	Random numbers.	….
t	The iteration index.	….
v_{id}	The velocity of the i^{th} particle.	….
w	The inertia weight.	….
$W(A)$	The aggregate of all edge weights in group A.	….
$W_{i,j}$	The cost of the edge between node i and node j.	….
x_{id}	The position of the i^{th} particle.	….
Z_i	The two-dimensional location of i^{th} sensor node.	….
Z_{XN} , Z_{YN}	The locations of TO sensor nodes in two dimensional field.	….
γ	Constant that is related to the receiver circuit and its value is equivalent to α.	nJ/bit
ρ	A trade-off factor that is used to increase the cost of the sensor nodes that do not have LOS with their CH.	….
δ	A trade-off factor that is used to reduce the weight of the total energy consumed by the j^{th} cluster head when determine its optimal location within its group.	….

Chapter One

Introduction to Wireless Sensor Networks

1.1 Background

Wireless sensor networks (WSNs) have attracted the interest of researchers in the recent years due to their wide applications. WSN is a kind of wireless ad hoc networks [1] that is widely used in civilian, military, environment monitoring, and security approaches [2], [3]. The WSNs used broadcast communication pattern whereas ad hoc networks use point-to-point communication, the number of nodes in WSN is greater than in an ad hoc network, and the battery of a WSN is not rechargeable or replaceable, while the battery of ad hoc network is replaceable.

WSNs are composed of a set of nodes equipped with one or more sensors, memory, simple process, an RF antenna and limited energy sources. A sub-set of WSNs is Transmit-Only (TO) sensor Network. These networks are composed of sensor nodes with TO ability, and cluster head(s) (CH) that have the transmit-receive ability. The CH bears the additional workload that receives the sensed data from sensor nodes, collects it and sends it to the base station (BS).

WSNs consist of sensor nodes with the ability to sense and monitor different types of environment conditions from the observer field such as temperature, pressure, moisture, vehicle motion, soil features, lightning state, levels of noise, levels of mechanical stress on annexed objects, the presence or absence of a specific types of things in an environment, and the existing properties such as directions, sizes, and velocities of objects [4].

For many WSNs, normal nodes inside the scene are chosen as CHs, which affects the lifetime of the chosen sensors due to the extra workload [5]. Several researchers have suggested the use of nodes equipped with additional energy (special nodes) called gateways, and these gateways are similar in their work to the CHs [5]. TO sensor nodes are spread in large numbers and usually randomly in the monitoring field to form WSNs. Energy efficiency is an important factor in the design of WSNs [6]. Moreover, energy efficiency depends on various parameters for its improvement, such as the distances between sensor nodes and the corresponding CHs, the position of the BS, and the residual energies of the TO sensor nodes. BS is usually rich of energy, while the energy of the sensor nodes is limited (1.5 volts) [7]. There are several types of batteries used in WSNs such as nickel-cadmium, nickel metal hydride, alkaline, reusable alkaline, zinc-carbon, and lithium polymer [8]. The energy of the sensor nodes is the most valuable resource in the network. Therefore, the efficient consumption of the energy to extend the lifetime of the network is the focus of recent research on WSNs. Despite the different definitions of WSN network lifetime (number of rounds), the most common definition is adopted, where lifetime of a network represents the different time between the operation time of the network to the depletion and death of the first TO sensor node.

WSNs consist of big number of small, multifunctional, and inexpensive sensor nodes that are capable to sense, process, and communicate data from the physical environment to a remote node. These sensor nodes act as transmit-only devices as in [9].

The base station (BS) is one of the components of the WSNs with much more computational, energy, and communications resources. It acts as a gateway between sensor nodes and the user end as they usually forward sensed data from the observer field to a remote server. WSN includes a mediator device between the sensor nodes and the BS called a cluster head (CH), which is responsible for receiving data from the TO sensor nodes and forwarding them to an off-the-field BS for further processing. CHs deplete their energy by reception and transmission processes, while TO sensor nodes consume their energy by sensing, processing, and transmitting the sensing data to the CH. The energy consumed by TO sensor nodes as transmitter is proportional to the distance between the transmitter and the receiver. Thus, reducing the transmission distances leads to reduction in energy consumption in TO sensor nodes. In this thesis, the work considers only the energy dissipated in the network by transmission and reception process, and do not take into account the energy dissipated by sensing the observer field and processing the sensing data because the energy consumption in these two cases is almost constant among sensor nodes.

Figure 1.1 shows the typical structure of the WSNs, where the SN represents the transmit-only sensor nodes that are distributed in the observer field, and the CH is responsible for collecting the data from corresponding sensor nodes and transmitting it to BS.

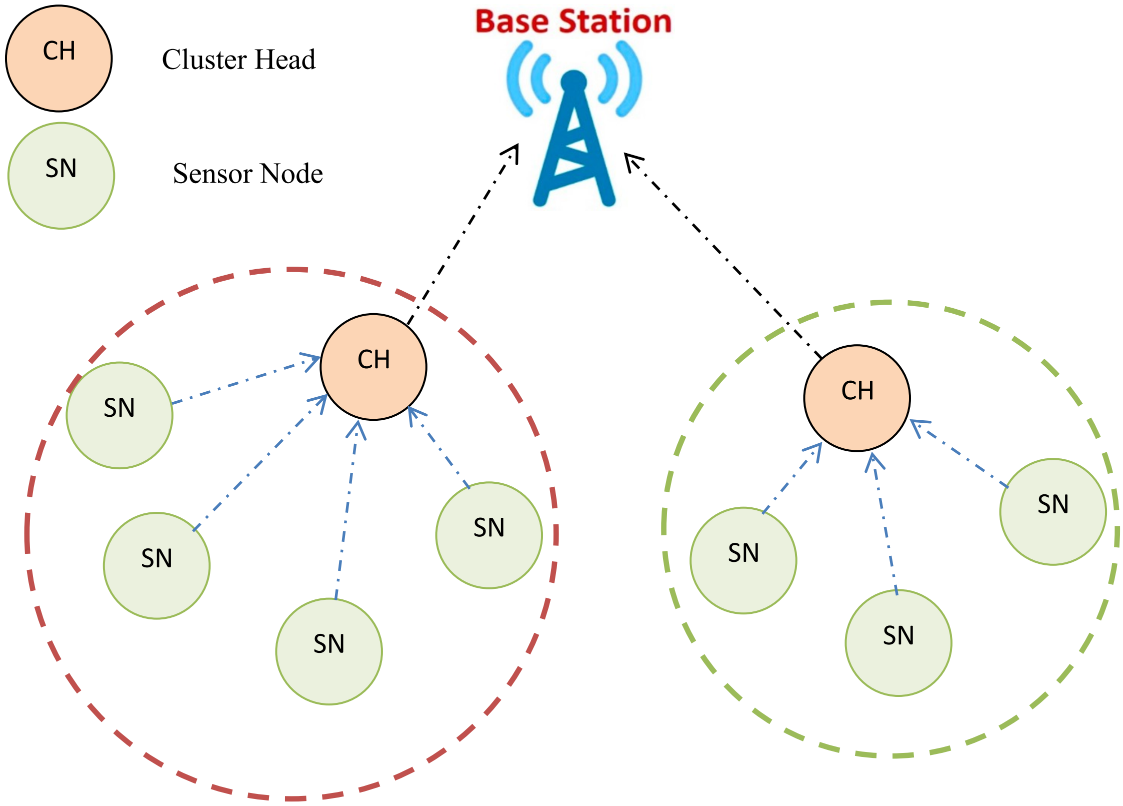

Figure 1.1. An illustration of wireless sensor networks [10].

1.2 Problem Definition

The limited energy sources of the wireless sensor nodes are one of the most factors affecting the lifetime of the WSNs [11]. It is usually difficult to recharge and replace the energy supply of the sensor nodes due to their spread in harsh environment [6]. This problem has driven a wave of researches that aim at optimizing energy consumption and thus prolonging the lifetime of the network. In some applications, it is impossible to replenish the energy source of the sensor nodes, and therefore the network lifetime depends on the lifetime of the sensor nodes' batteries.

Natural obstacles in the observed field can present a problem, due to the absence of line-of-sight (LOS) among TO sensor nodes and the CHs, and thus affect the connectivity and coverage of the WSN. Some of TO sensor nodes will prevent transmitting information to the CH, because there is no LOS between them, which may reduce the area monitored in the observer environment. Hence, this may result in coverage holes. To get the coverage of the entire network, one CH is identified for each specific group of TO sensor nodes. The presence of a LOS was also confirmed between each TO sensor nodes and its CH.

1.3 Research Aim and Objective

The aim of this work is to extend the lifetime of the network and reduce the energy consumption in the whole network by selecting the optimal location of the CH within its group after clustering the network into clusters. In addition to that, this study aims at ensuring the coverage of the entire network, as well as making a balance in energy consumption among the partitions in the whole network. The objective of first case is achieved by proposed a clustering method that schedules the operator sensor nodes in each cluster, after that determine the optimal location of the CH within the observer field. The objective of the second case is achieved by splitting the network with obstacles into k-groups using graph partitioning technique and determine the optimal location of the CHs within their groups that minimize energy consumption of the network and provides a LOS between the network components, to ensure that the entire network is covered.

1.4 Motivation

WSNs have gained significant research attention in recent years due to its versatile applications. In WSNs, sensor nodes are usually equipped with limited, non-rechargeable, and non-renewable power supplies, especially in harsh and hard-to-reach environments. This power limitation imposes a practical challenge that researchers face in the field deployment of sensors, which is to keep the network running for as long time as possible by reducing the energy consumption of the sensor nodes. This can be realized by the use of different types of technologies, such as the method of network partitioning, as well as finding the optimal location of the CHs.

1.5 Contribution

- In the first case, the network lifetime is extended by scheduling the operation of the sensor nodes in each cluster thus prevent redundant sensed data, and determine the best CH location.
- In the second case, the best division of the sensor nodes which have approximately equal number of sensor nodes in each group which leads to the balance of the energy consumption of the groups. The best communication between the CHs and their sensor nodes as LOS is provided between them to ensure the coverage of the whole network. Thus,

extend the network lifetime by determine the optimal location of the CHs within their groups that reduce the energy consumption of the network and provide a LOS between the network components.

1.6 Outline of the Thesis

- **Chapter two:** This chapter includes a brief explanation of the wireless sensor networks (WSNs) in terms of the network model and the mathematical model, as well as a background on the algorithms used in the work. Those techniques include particle swarm optimization (PSO), graph partitioning technique, and k-mean clustering algorithm. Finally, a review of some published literature related to the work is presented.

- **Chapter three:** It covers the proposed model for the first case with five scenarios. In each scenario, the proposed model is compared with other two models, where the first model uses Geometric Mean, finding the location of the CH. In contrast, the second model uses the PSO algorithm to find the position of the CH. Finally, the presentation and simulation of the results are presented in detail in this chapter.

- **Chapter four:** This chapter focuses on studying the presence of obstacles in the network that may prevent communication link between the network components, as it is called the second case. The proposed model is compared with another model that is non-intelligent in dividing the network into k-groups (it is called heuristic model) in two scenarios. The results are shown at the end.

- **Chapter five:** This chapter states summary conclusions of the proposed model, and provides suggestions for improving future work.

Chapter Two

Theoretical Background and Literature Review

In this chapter, the models of the power optimization of wireless sensor networks (WSNs) are introduced, in addition to the required theoretical background regarding PSO, graph partitioning algorithm, and k-means clustering algorithm. The chapter ends with a summary of some published papers related to the work.

2.1 Wireless Sensor Networks

WSNs consist of a large number of low cost and small sensor nodes, which operate as transmitter-only (TO) devices, and which are usually randomly distributed in two-dimensional observer field. Each TO sensor node is able to sense, process, and send the sensed data to a cluster head (CH) or a base station (BS), as the sensor nodes transmit their sensed data directly to the BS when there is no CH in the network. The CH acts as a mediator point between the networks' nodes and a remote node.

The energy is consumed by TO sensor node for sensing the observer field, and transmitting the sensed data to the BS. The limited energy sources of the sensor nodes are the key drawback of WSNs due to the difficulty associated with replacing and/or recharging the nodes' batteries because of their large numbers and hostile environments distributions [12]. Energy conservation and prolonging lifetime of WSNs are the main challenges in building and implementing these networks [13].

In the transmission phase, the CHs create a time division multiple access (TDMA) schedule to organize the transmissions and also to avoid interferences during transmissions [14]. They assign a frame to each cluster, and this frame consists of a time slot, each sensor node has one time slot to send its data to the corresponding CH, and remain in sleep state in the rest of the frame. The number of time slots in the frame depends on the number of sensor nodes in the cluster. After all sensor nodes transmit their data (at the end of the frame), the CH transmits the collected data to the BS.

The energy dissipation model that is used here is similar to the model considered in [9], [15], [16]. The energy dissipated by the i^{th} transmit-only sensor node E_{TXi} for transmitting p-bits of sensed data, and the energy dissipated by the CH as a receiver E_{RX} for receiving p-bits of data from TO sensor nodes are depicted as follows:

$$E_{TXi} = \left(\alpha + \beta . d_i^{\mu}\right) . p \qquad (2.1)$$

$$E_{RX} = N . \gamma . p \qquad (2.2)$$

where $i = 1,2, \ldots., N$, and N is the number of TO sensor nodes in the observer field. d_i is the Euclidian distance between the i^{th} transmit-only sensor node and the CH. α and β are constants associated with the transmitter and receiver circuits [17]. μ is the path loss exponent ($2 \leq \mu \leq 5$) [17], [18]. p is the number of data bits. γ is a constant that is related to the receiver circuit and its value is equivalent to α [17].

The total energy consumed by TO sensor nodes in the whole network is given as follows:

$$E_{TX} = \sum_{i=1}^{N} \left(\alpha + \beta . d_i^{\mu}\right) . p \tag{2.3}$$

Hence, based on Equations 2.1 and 2.2, the total energy consumed by the CH for receiving the sensed data from N transmit-only sensor nodes and forwarding them to the BS is given by:

$$E_{CH} = N . \gamma . p + N . \left(\alpha + \beta . d_b^{\mu}\right) . p \tag{2.4}$$

where E_{CH} is the total energy consumed by the CH in the observer field, d_b is the Euclidian distance between the CH and the BS.

The energy consumed during transmission processes is proportional to the distance between the transmitter and the receiver. Figure 2.1 shows a simple example of the amount of energy consumption, where the dotted arrows represent the direction of transmission and the transmission distance of the TO sensor nodes and the CH in the observer field. The first sensor node (SN1) consumes higher energy during sending its data to the CH due to the large distance between the SN1 and the CH. The second sensor node (SN2), however, consumes less energy during transmission owed to the shorter distance between the SN2 and the CH.

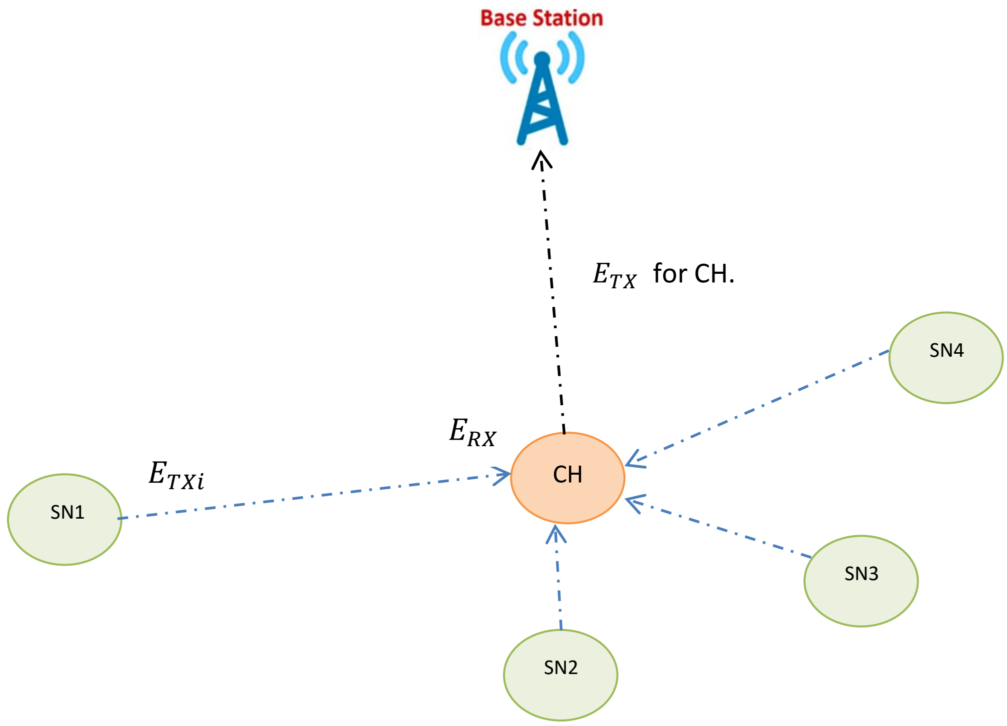

Figure 2.1. An example showing the energy consumed in the WSNs and its relation to the distance between the transmitter and receiver.

The total energy dissipated in the entire network by the TO sensor nodes and the CH is the sum of Equations 2.3 and 2.4, which is given as follows:

$$E_{tot} = \sum_{i=1}^{N}(\alpha + \beta . d_i^{\mu}). p + N. \gamma. p + N. (\alpha + \beta . d_b^{\mu}). p \qquad (2.5)$$

2.2 Particle Swarm Optimization (PSO)

PSO algorithm is an evolutionary computing technique that has been extremely popular recently. It is one of the effective algorithms that is inspired from natural life. In general, PSO techniques are inspired by the social demeanor of biological organisms. PSO is usually chosen to numerically solve complex optimization problems due to its state of implementation, quality of the solution, ability to eloping from local idealism, and rapid convergence [19]–[21]. It can be used to solve nonlinear and multi-peak optimization problems, especially in the fields of science and engineering [22]. PSO can be used in many fields, such as neural network, mechanical design, image processing and communication [23], precisely, the ability of groups of some kinds of animals to act together to search for a desired location in a target area, for example, a flock of birds searches for a source of food. This search behavior is linked to optimal searching for solutions to nonlinear equations in a search area [19].

PSO uses a sequence of iterations in an attempt to improve a particle solution regarding given measurement quality or application [24]. PSO technique is usually used to find the position of the particle associated with the best evaluation of a particular fitness function. The fitness function is used to assess the significance of each particle in the search area. In the first case, the PSO algorithm was used to minimize the total energy consumed in the entire network by TO sensor nodes through minimizing the total transmission distance between TO sensor nodes and a CH. In the second case, the PSO algorithm was used to minimize the number of TO sensor nodes that do not have line-of-sight (LOS) with their corresponding CHs. In addition, PSO was used to minimize the total energy consumed in each group by TO sensor nodes and their corresponding CHs through minimizing the total transmission distance between them. The optimization problem here is convex, which is to find the optimal location for CH, so using any optimization algorithm will give the same results.

In the PSO problem, each particle is defined by its position and velocity along each dimension of the problem. Initially, the particles of the swarm are drawn randomly from a pre-defined probability distribution within the search space. The particles iteratively update their position and velocity until they reach a possible best solution. In each iteration, the particles utilize the information of their previous best individual position and the global best position to converge to the final answer. The position and velocity update equations can be stated as follows:

$$v_{id}(t) = w * v_{id}(t-1) + c_1 r_1\big(p_{id} - x_{id}(t-1)\big) + \; c_2 r_2 \left(p_{gd} - x_{id}(t-1)\right) \tag{2.6}$$

$$x_{id}(t) = x_{id}(t-1) + v_{id}(t) \tag{2.7}$$

where x_{id} and v_{id} are, respectively, the position and velocity of the i^{th} particle. (c_1,c_2) are learning factors, and (r_1, r_2) are two different random numbers uniformly distributed between 0 and 1. p_{id} is the best position of the i^{th} particle, and p_{gd} is the global best position. t is the iteration index, and w is the inertia weight [19]. There is a lot of literature in WSN that uses PSO algorithm to solve problems in these networks as in [5], [12], [20].

2.3 Graph Partitioning Technique

Graph partitioning technique (GPT) has attracted the interest of many researchers in various fields due to its wide range of application. GPT is nondeterministic polynomial-time complete problem (NP-complete problem) [25]. Hence, no algorithm can solve this problem in polynomial time, and thus, it is approximately solved.

The basic idea of this algorithm is as follows: giving an undirected weight graph $G = (V, E)$, where V is the set of vertices (here represent the TO sensor nodes), and E is the set of edges. The edges, E, represent the presence of a LOS path between two TO sensor nodes, and their weight is determined by the distance between these two TO sensor nodes. If the number of vertices (number of TO sensor nodes) is $N = |V|$ and the number of edges is $m = |E|$, the TO sensor nodes can be divided into k-groups, which form a set of non-overlapping partitions $P = \{V_1, V_2, \ldots\ldots, V_k\}$, i.e., $V_i \cap V_j = \emptyset$ and $V_1 \cup V_2 \cup \ldots\ldots \cup V_k = V$ [25], where P is the set of non-overlapping partitions.

The cost (weight) of the edges in the work is inversely proportional to the distances among endpoints. Also, the objective of the GPT is to partition the vertices into k-partitions and simultaneously reduce the number of edges that have endpoints in multiple partitions (aka edge-cut) [25].

When applying the GPT method to WSNs, the algorithm works as follows: the nodes in the target field are split into k-partitions by cutting the edges that have low cost (weight) between partitions, minimizing the number of edges that have endpoints in different groups (edge-cuts), and maximizing the aggregate of all edge weights in the same partition [26].

The definition of cut technique between two subgroups A and B is depicted in [26], [27] as follows:

$$Cut(A,B)=\sum_{i\in A,j\in B} W_{i,j} \tag{2.8}$$

where $W_{i,j}$ is the cost of the edge between node i and node j. The aggregate of all edge weights in group A is represent by $W(A) \equiv W(A,A)$. The goal is to minimize $\mathrm{Cut}(A,B)$ and maximize $W(A)$ and $W(B)$ simultaneously (the min-max partitioning principle), which can be achieved by minimizing the following objective function (aka min-max cut function) [26]:

$$M_{Cut}=\frac{Cut(A,B)}{W(A)}+\frac{Cut(A,B)}{W(B)} \tag{2.9}$$

where M_{Cut} is the min-max function. Figure 2.2 shows a simple example of GPT, where the circles represent the vertices (TO sensor nodes) and the blue dotted lines represent the undirected edges between endpoints. The red dashed line represents the cut line of the edges to create two groups.

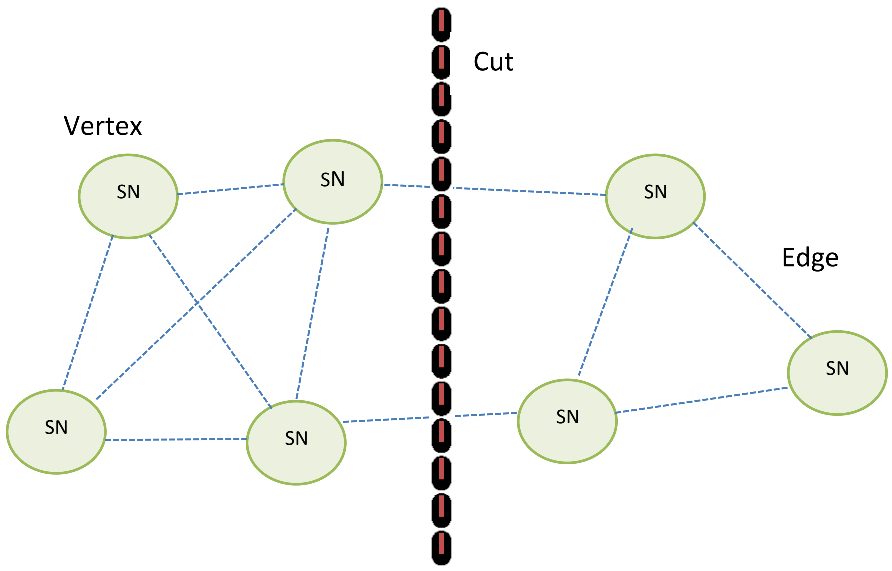

Figure 2.2. An example of a graph partitioning problem.

The L-bounded GPT in which all partitions have equal number of TO sensors (i.e., equal size) is considered to be a perfectly balanced. It is defined as $L = \frac{N}{k}$ (i.e., the output of $\frac{N}{k}$ is without any remainder). However, when the partitions are not of equal size (i.e., the output of $\frac{N}{k}$ with remainder), it has an ϵ percentage of imbalance, $L = \left\{(1+\epsilon).\frac{N}{k}\right\}$ [25], [28]. This thesis seeks to obtain an approximately equal number of sensor nodes in each group to ensure a balance in the energy consumption of the groups.

2.4 K-means Clustering

'k-means' is an unsupervised machine learning technique that is mainly used for grouping unlabeled data, which makes it a suitable choice for solving the problem under consideration. The concept of clustering is usually used to facilitate network operation, where the network is divided into a number of clusters based on the physical distance between TO sensor nodes. Clustering is a popular technique that can be used to reduce the communication distance between the sensor nodes (transmitter) and the corresponding CH (receiver), and reduce the energy consumption of the sensor nodes [29]. In addition, clustering reduces communication overhead, reinforces resource utilization, and scalability where sensor nodes can enter or depart the cluster without impacting the whole network [29].

Here, the 'k-means clustering algorithm' was used to split the sensor nodes in the network area into k-groups based on their Euclidian distance from the centroid nodes, each group contains a random number of sensor nodes. Thus, there is a k centroids, one for each cluster. The equation of the target function is defined as [29]:

$$S = \sum_{j=1}^{K} \sum_{i=1}^{N} \left\| Z_i^j - C_j \right\|^2 \tag{2.10}$$

where $\|.\|^2$ is the 2-norm operator, Z_i is the two-dimensional location of i^{th} sensor node, C_j is the two-dimensional location of the j^{th} centroid node, N is the number of the sensor nodes in the network, and k is the number of clusters.

2.5 Literature Review

Many researchers have focused on WSNs to extend the network lifetime due to wide applications. Therefore, in order to improve energy efficiency and to prolong the lifetime of the network, they have worked to reduce the energy consumption of the network. Some of the related published papers are summarized as follows:

W. R. Heinzelman, et al. in 2000 [15]: The authors proposed Low-Energy Adaptive Clustering Hierarchy (LEACH) to minimize energy consumption of the network. LEACH is a clustering-based protocol that uses random rotation of cluster heads to evenly distribute the energy load between sensor nodes in the field.

This protocol contains two phases, one is called set-up phase and the other is called steady-state phase. In the set-up phase, CHs selection and clusters' formation tasks are performed, while in the steady-state phase, the CHs aggregate the data from sensor nodes and forward it to BS. These phases are repeated during regular time intervals to rotate role of CH between all sensor nodes and re-clustering to balance the network load. LEACH does not take into account the remaining energy of the sensor nodes when they are selected to be CHs (i.e. each sensor nodes have equal probability to become CH).

Simulation results demonstrate that LEACH protocol can achieve up to 8 factor reduction in energy dissipation compared to traditional routing protocols. It is able to evenly distribute energy dissipation in the network, and doubling the network lifetime.

W. B. Heinzelman, et al. in 2002 [30]: In this paper, the authors aim to improve the performance of LEACH, by protocol called LEACH-Centralized (LEACH-C). In the set-up phase, all sensor nodes transmit information about their locations and energy levels to the BS. The BS utilizes these information to find a predetermined number of CHs and forms clusters. Then, BS sends a message that contains the cluster head ID with their TDMA schedules for all sensor nodes. The steady-state phase of LEACH-C is similar to LEACH protocol. Simulations show that LEACH-C protocol is better than LEACH protocol in terms of the network lifetime.

N. M. Abdul Latiff, et al. in 2007 [20]: Their proposed protocol has been compared with LEACH and LEACH-C and showed better results in terms of network lifetime and data delivery at the BS. The proposed approach is based on the energy aware cluster-based protocol to minimize energy consumption of the network, using PSO algorithm.

The main objective of this paper is to determine the CH that can reduce the intra cluster distance between it and its sensor nodes, and optimize energy management in the network. Each sensor node transmits its information regarding location and current residual energy to the BS. The BS in turn calculates the average energy of all sensor nodes. To make sure that only sensor nodes with enough energy are chosen as CHs. After that, the PSO algorithm in turn clusters the sensor nodes and select the best number of CHs that minimized the cost function. The BS sends the information about the ID of the CHs for each sensor nodes.

E. Natalizio, et al. in 2008 [18]: Proposed a mathematical model to maximize path lifetime by determine the optimal placement of the sensor nodes on a single data flow in WSNs. These sensor nodes are located between source and destination that have previously determined their location. The placement selection of the sensor nodes depends on the residual energies of the sensor nodes.

In this paper, the results do not show any specific correlation between the path length and the lifetime. The longer path will contain more sensor nodes than a shorter path. The proposed approach (energy spaced) is compared with another two approaches, first, random, and second, evenly spaced placement of the sensor nodes along the path between the source and the destination. It was observed that the proposed approach was the best of the other two approaches in term of the path lifetime.

S. Babaie, et al. in 2010 [2]: The main aim of this paper is to minimize the energy consumption by proposing Clustering approach based on Cluster head using Genetic Algorithm (CCGA). Initially, they choose k cluster heads from the sensor nodes according to some parameters, and the remaining sensor nodes become members of the closest CH (i.e. create clusters). There are several constraints that must be used in order to get the optimal CHs, and divided the network into clusters. Thus, this is done using the Genetic Algorithm (GA) to find the optimal solutions. Therefore, the constraints that determine the selection of the CHs and clustering the network are:

- The distance of the CHs should not be close to each other, rather the distance between them should be reasonable. If the distance is not reasonable, the member nodes of each CH is not equal. Hence, this leads to the CHs with largest number of member nodes to lose their energy prematurely.
- Number of cluster member (number of the sensor nodes associated to each CH to form clusters), this constraint depends on the first constraint. Thus, regulating the previous constraint leads to an approximately equal number of cluster members.
- The last constraint is the distance between the sensor nodes and their CHs. This constraint is considered one of the most important constraints, as it

specifies the sensor nodes that have a minimum distance for the CH from other CHs. In addition, the total internal distance of the cluster is the minimum for each of the cluster members to their CH.

Simulation results show that the proposed CCGA algorithm produces better clusters and extend the network lifetime.

S. Ebadi, et al. in 2010 [13]: In this paper, the authors proposed an algorithm to prolong the lifetime and minimize the energy consumption of the WSNs. They propose the hierarchical and multi-hop clustering algorithm. This algorithm seeks to divide the network into clusters and assign two CHs for each cluster, one is called low level CH and the other is called high level CH. The low level CHs is responsible for collecting, aggregating, and sending data to the high level CH. The high level CHs are responsible for receiving data from the low level CHs and sending it to another high level CHs or to the base station, where the communication process among CHs and the BS is in multi-hop. Whereas the communication between the sensor nodes and their CHs is in single-hop. Simulation results showed that the proposed algorithm is the best in terms of network lifetime compared to LEACH protocol by more than 28%.

S. E. Khediri, et al. in 2014 [31]: The authors worked to Optimize Low Energy Adaptive Clustering Hierarchy (O-LEACH) by selecting the cluster according to the remaining energies of the sensor nodes dynamically. Their proposed algorithm was compared to LEACH and LEACH-C, and showed to be the best in terms of stability of the network. Therefore, the stability of the network is that the proposed system keeps its sensor nodes alive as long as possible than LEACH and LEACH-C (the network is called stable network, when all sensor nodes are alive). Hence, the selection of the CHs among the sensor nodes is based on the residual energy after each round.

V. Pal, et al. in 2015 [32]: The authors proposed the clustering algorithm by determining a head for each cluster and optimize the number of the CHs using genetic algorithm. The authors proposed switching the role of the CHs between the sensor nodes. They compared their proposed work (LEACH-GA) with LEACH and LEACH-C protocol, LEACH-GA works to optimize number and selection of the CHs. Thus, they found that the LEACH-GA is the best in terms of the first node death and half node death.

V. Pal, et al. in 2015 [33]: The authors proposed a clustering approach for extending network lifetime by balancing cluster size using thresholds, that used initially in cluster configuration in each round. Two thresholds are used in such approach: $Th_{cluster}$ which represents the number of sensor nodes in clusters, and $Th_{distance}$ (distance threshold) that represents the maximum distances between the CH and the un-clustered sensor nodes (i.e. when the distance between un-clustered sensor node and the CH is less than $Th_{distance}$, this sensor node joins the cluster).

$Th_{distance}$ is determined initially and its value remains constant in all rounds, while $Th_{cluster}$ changes its value at each round according to the number of remaining live nodes in each round. $Th_{cluster}$ is calculated as the number of active sensor nodes divided by the number of CHs, whereas $Th_{distance}$ is determined by the trade-off between the total cluster distance and cluster size to obtain the best cluster quality. CH forms the TDMA schedule and send it to its cluster members. Hence, each sensor node has a time slot to send its sensed data to corresponding CH and remain in sleep state otherwise, i.e. in the rest of the time slots. The results demonstrate that the proposed clustering approach is better in terms of network lifetime and has a lower rate of expired sensor nodes compared to the traditional clustering approach.

M. Aldeer, et al. in 2016 [17]: In this paper, the authors proposed a new model to increase network lifetime and reduce energy consumption in the network, by clustering the static TO sensor nodes into clusters. Moreover, it involves determining the optimal location of the CH within each cluster, which reduces the energy consumption of TO sensor nodes and the CHs. Therefore, they reduced the energy consumed by the network as a whole, through minimizing the energy dissipated by TO sensor nodes and the CHs. The optimization problem is solved by minimizing the total distance between the CH and its sensor node as well as minimizing the distance between CH and the BS. They compared the proposed model with two other models in two scenarios, in each scenario, the proposed model outperforms the other two models in term of the network lifetime.

J. Wang, et al. in 2016 [34]: The Energy-balanced Unequal Clustering Routing (EUCRP) algorithm is proposed to balance the energy consumption of the network. The aim of the proposed algorithm is to divided the network into clusters using non-uniform clustering approach. Thus, creating shortest path tree to find the best multi-hop transmission paths to achieve efficient data transmission between the sensor nodes and the base station. The selection of the CHs in the proposed algorithm depends on the density of the sensor nodes in the target field, the residual energies, and the distances between the sensor nodes and the BS. Simulation results show that the EUCRP can efficiently balance the energy consumption of the sensor nodes, reducing the speed of the death of the sensor nodes, and extend the lifetime of the network.

A. John, et al. in 2017 [35]: Energy Saving Cluster Head Selection (ESCHS) method are proposed in this paper to improve network lifetime, by using of the notion of uniform clustering to form clusters and residual energy of the sensor node to select the CH in each cluster. The sensor nodes with higher residual energies than the average residual energies of their corresponding clusters are selected as CHs. The number of clusters are decided initially. They calculate the mid points by calculating the central point and the average distance between the central point and all sensor nodes. Thus, clusters are formed according to the distance between the sensor nodes and each mid point, where the sensor node with a minimum distance to a certain mid point, the sensor node belongs to that cluster. The ESCHS is compared with LEACH and D-LEACH algorithms. The results showed that the ESCHS is the best in terms of the rate of the residual energy of the sensor nodes in each round (energy saving) and of the first sensor node died.

M. Aldeer, et al. in 2019 [9]: In this work, the authors proposed to increasing the lifetime of the network (reduce energy consumption), and maintaining network coverage. The sensor nodes are randomly distributed and are static while the CH is moving among the sensor nodes in the monitoring field. The position of the CH changes with each round as the CH tends to be located near a sensor node that has less residual energy than the rest of the sensor nodes in the monitoring field. The optimization problems are solved by maximizing the total residual energies of the sensor nodes and the CH in each round.

P. Zhuojin, et al. in 2019 [36]: The researchers proposed an algorithm to minimize energy consumption of the sensor nodes in WSNs. They divided the network into four groups such that each group contains an equal number of sensor nodes. In this work, the authors proposed an Energy Efficient Sleep-Scheduled Tree-Based Routing Protocol (EESSTBRP) that corrects the formation of the chain in PEGASIS.

In [37] they proposed an improved PEGASIS protocol (Power-Efficient Gathering in Sensor Information Systems) to improve the lifetime of the sensor nodes in the network. In PEGASIS protocol, a chain is created to connect all sensor nodes with each other using the greedy algorithm, where the data is sent along the chain until reaching the chain leader. The chain leader in turn collects the data and sends it to the BS.

In EESSTBRP protocol, they assumed that every two adjacent sensor nodes at a certain distance sense similar data from the target field, and thus they make these two sensor nodes work alternately, to prevent data duplication. These sensor nodes are called paired nodes. All sensor nodes that do not have adjacent sensors are assigned with an active mode throughout the rounds until they are dead, while the paired sensor nodes are switched between active and sleep modes during rounds until they are dead.

The CH selection in each round is based on the weight value that is based on the residual energy of the active nodes and its distance to the BS. Therefore, they build a minimum spanning tree for each group, where the roots are represented by the CHs.

This procedure is done by using prim's algorithm. The child active node transmits its sensed data and residual energy data to its parent node. The parent node will collect the received data and its sensed data in addition to its remaining energy. This procedure is done throughout the tree, until data is received by the CH nodes. Therefore, the CH node in turn sends its information and the received aggregate data to the BS.

T. J. Swamy, et al. in 2019 [38]: An Energy Efficient Leveling Protocol (EELP) is proposed to ensure communication security, reduce message delay and maintain energy efficiency in military communications. The optimization problem is solved by selecting the optimal CH and determining the sensor node location in WSNs. The network is divided into clusters and each cluster is headed by a CH. Among CHs, some are important and others are normal. The important CHs are responsible for transferring data between the BS and other CHs. These important CHs are identified by reducing their depth from the BS by minimizing the number of hops. The proposed EELP protocol are compared with the LEACH and HEED protocols. The simulation results show that the proposed approach increases the network lifetime, providing secure data compared to LEACH and HEED protocols.

M. Zivkovic, et al. in 2020 [39]: The authors proposed an improved version of the firefly algorithm (IFA) to extend the lifetime of the network and reduce power consumption by dividing the network into clusters and determine the optimal CH for each cluster. Their proposed approach took two things into consideration when dividing the network into clusters, the first is the energy consumed during the transmission process from the sensor nodes to the corresponding CH, and the second is the energy consumed by the CH to collect data and send it to the BS. The proposed approach (LEACH-IFA) was compared with LEACH, LEACH-PSO, and LEACH-FA, which were conducted for the same network infrastructure. Simulation results proved that LEACH-IFA is the best in terms of the death of the first sensor node, the death of half of the sensor nodes and the death of all sensor nodes, as well as in terms of the number of data packets sent to the BS for a certain number of iterations.

J. Singh, et al. in 2021 [40]: The authors proposed a clustering approach to obtain uniform size clusters (USCs) and reduce the intra-cluster communication distance, hence increasing the lifetime of the network. They compared their proposed approach (LEACH-USCs) with [30], [33] in terms of the number of sensor nodes in each cluster, the intra-cluster distance, and the lifetime of the network (in terms of first node death, half node death, and last node death). The selection of the CHs is similar to [30], [33] after which the formation of clusters begins, as the sensor nodes join the nearest CH. Each cluster after this step contains a different number of sensor nodes. Then the cluster refurbishes phase beginning, as the sensor nodes of large clusters try to join to other clusters based on the second best choice CH. Simulation results show that the LEACH-USCs outperforms the comparative methods.

In this thesis, two cases are discussed. The first proposed case aims to schedule the operation of the TO sensor nodes in each cluster to reduce energy consumption and prevent data redundancy. The sensor nodes are divided into k clusters using k-means clustering algorithm, and then one TO sensor node from each cluster is selected to represent its corresponding cluster. In addition, the optimal location of the CH is determined using PSO algorithm, such that it is closer to the sensor node that has lower initial energy than the rest of the sensor nodes to reduce the energy consumed in this sensor node during transmission. Most of the literature discusses flat, obstacle-free environments that may impede the communication links between sensor nodes and the CH in the network. In the second proposed case, the work is interested in optimizing the location of the CHs in environments where an obstacles can block the direct communication link between the TO sensor nodes and their corresponding CHs as well as extend the lifetime of this WSNs. For this purpose, the network divided into k partitions using GPT. Further, identify the location of the CH within each group to facilitate LOS communication between the TO sensor nodes and their CHs, and increasing the lifetime of the sensor nodes, as well as the entire network. This optimization problem can be solved using PSO algorithm to determine the optimal location of the CH within its partition.

2.6 Summary

This chapter presents a brief overview of the techniques that have been used in this work to facilitate and find the best solutions to the problem of improving the energy efficiency of WSNs. PSO algorithm is used to determine the optimal location of the CHs in the network, whereas k-means and GPT are used for splitting the TO sensor nodes into k-groups in the first and second cases, respectively. Previous literature discussing reducing energy consumption in WSNs and extending network lifetime has been reviewed.

Chapter Three

Simulation and Results of the First Case

3.1 Introduction

This chapter involves explaining the network and the mathematical models of the first case. It also presents simulation results of five scenarios, and compares the results of proposed model with two other models in terms of the network lifetime.

3.2 System Model

This section shows the structure of the WSN for the first case, including the method of distribution of TO sensor nodes, optimal location of the CH, statement and clarification of the three models, comprising the proposed model. In addition, the mathematical model (energy model) of the first case is shown. They are described as the following:

3.2.1 Network Model

This work considers a network model with N transmit-only sensor nodes that is randomly distributed in an $M \times M$ observer field with one CH that has large energy (i.e. the energy of the CH is not constrained) and a single stationary BS. The results of three models are compared in terms of the network lifetime. The location of the CH varies among the three models. It is assumed that the amount of energy consumed by TO sensor nodes is proportional to the distances between TO sensor nodes and the CH. The location of a CH within the monitoring field have been determined in these three models as follows.

- **First model**: In this model, the CH location is obtained by using the concept of the geometric mean (GM), where the coordinates of TO sensor nodes are used to determine the location of the CH. The coordinates of the CH can be determined as follows [41]:

$$GM_X = \sqrt[N]{Z_{X1} * Z_{X2} * \dots \dots Z_{XN}} \tag{3.1}$$

$$GM_Y = \sqrt[N]{Z_{Y1} * Z_{Y2} * \dots \dots Z_{YN}} \tag{3.2}$$

where Z_{XN} and Z_{YN} are the locations of TO sensor nodes in two dimensional spaces, and GM_X, GM_Y are the locations of the CH within two dimensional observer fields. Figure 3.1 shows the structure of the first network model in 50×50 m^2 observing field, where the blue circles represent a 50 transmit-only sensor nodes that are distributed in the monitoring field. The black star represents the location of the CH within the target field using the concept of geometric mean.

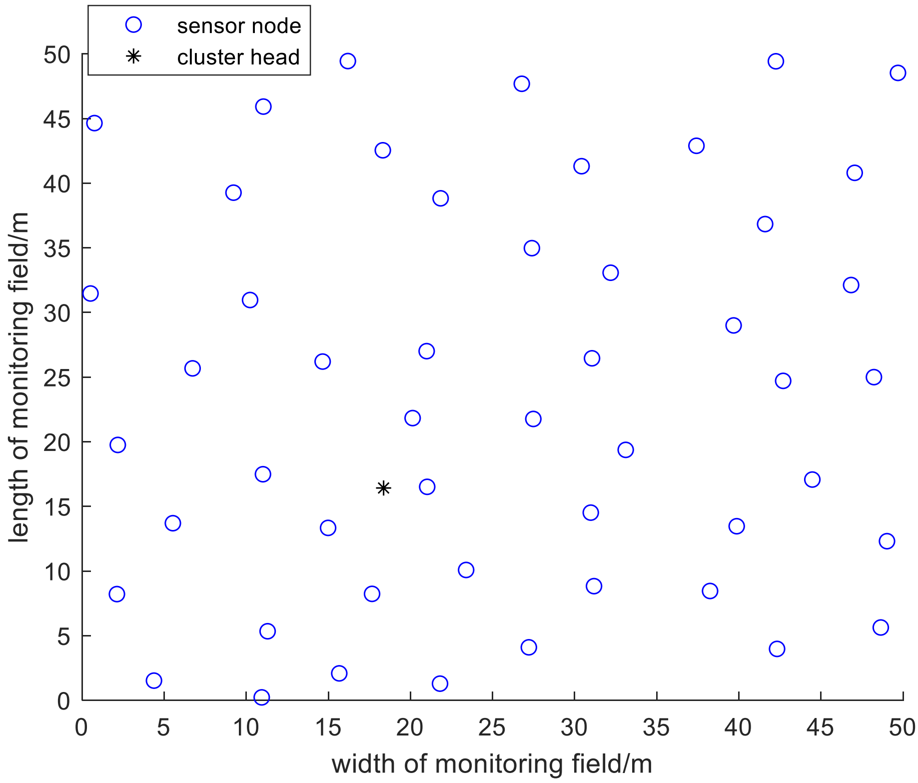

Figure 3.1. The first model of the first case.

- **Second model**: The location of the CH is similar to the concept that was used to find the location of the CHs in [17]. This model reduces the total distances between TO sensor nodes and the CH to reduce the energy consumption in the monitoring field to increase the network lifetime.

Figure 3.2 shows the network construction of the second model, showing the location of the CH in the monitoring field.

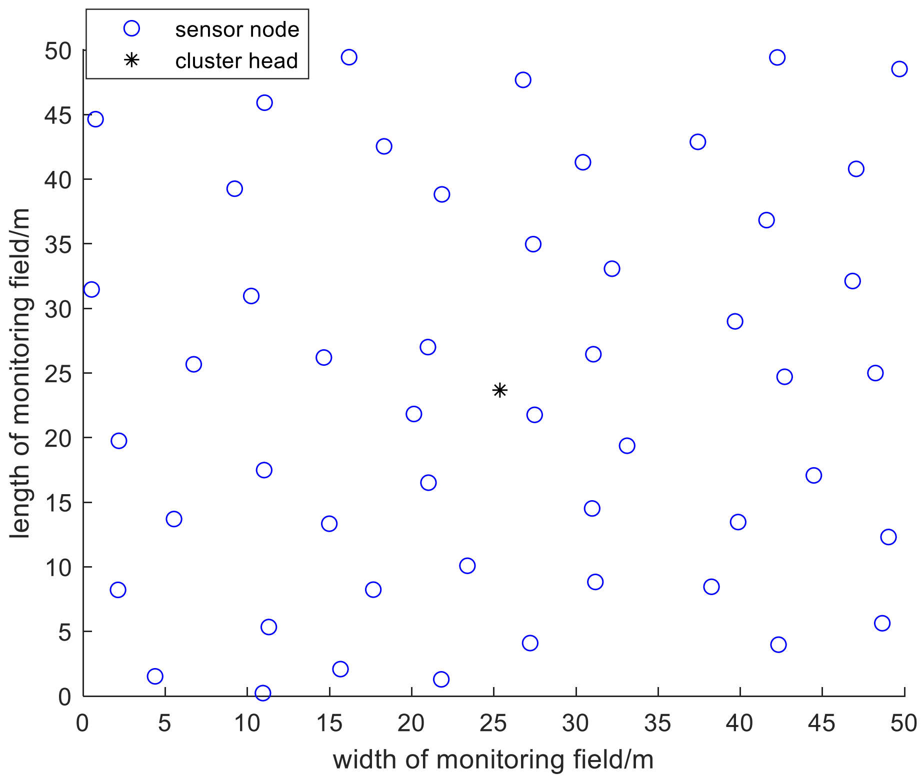

Figure 3.2. The second model of the first case.

- **Proposed model**: In this model, the sensing field is divided into k clusters according to the distances among TO sensor nodes using k-means clustering algorithm. Each cluster has unequal number of TO sensor nodes. This work assume that each cluster covers a specific area of the target field, and the sensed information are highly correlated (i.e., the sensed data of the sensor nodes in each cluster are the same). The aim is to prevent the transmission of redundant sensed data that are received from each cluster and to improve the energy efficiency of the network. The centroid node is selected in each cluster to represent its corresponding cluster and sense the corresponding part of the field. It is also assumed that the centroid node has the accumulated energy of all TO sensor nodes on its cluster, so the energy of the centroid nodes are unequal based on the number of TO sensor nodes in each cluster.

The case of a single CH that is not constrained (i.e. has large amount of energy) is considered. Finding the optimal location of the CH in the target field has been done using PSO algorithm, where the optimal location is near-by the sensor nodes that have low amount of energy (i.e. close to the cluster that has low number of TO sensor nodes). The CH receives sensing data from the centroid nodes, then forwards them to a base station.

Figure 3.3 shows the division of 50 transmit-only sensor nodes in 50×50 m^2 observer field of the proposed model when the number of clusters is ten. The proposed model is not affected by the number of sensor nodes and the network dimensions, because the network infrastructures are the same for the three models. The circles represent the TO sensor nodes that are randomly distributed in the observer field, where each color of the circles representing a particular cluster. The centroid nodes of each cluster are represented by the pink stars, and the optimal location of the CH is represented by the black star.

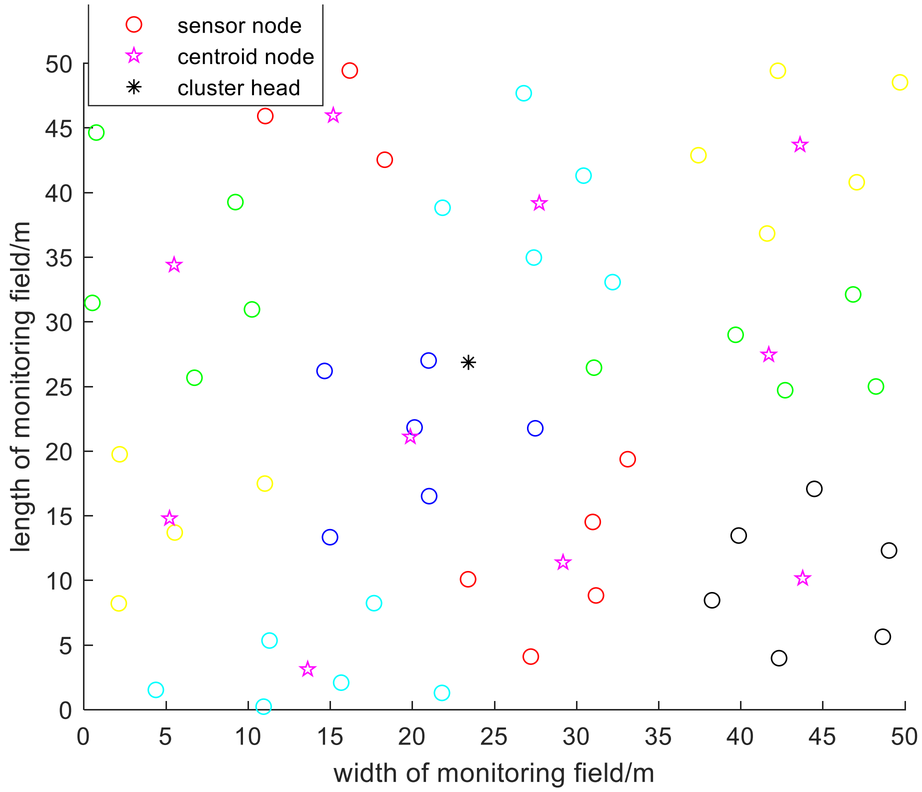

Figure 3.3. The proposed network model of the first case.

In fact, the locations of the CHs in the three models are different, as shown in the three figures above, where the position of the CH in the first model is (18.36, 16.4), the position of the CH in the second model is (25.4, 23.68), and the location of the CH in the proposed model is (23.4, 26.86).

3.2.2 Mathematical Model

Giving the observed field, and assuming that there are k clusters, the amount of energy dissipated by the j^{th} centroid node as a transmitter E_{TXOj} for transmitting p-bits of data packet is as in Equation 2.1, but is divided by the number of TO sensor nodes in each cluster. It is given as follows:

$$E_{TXOj} = \frac{1}{G_j}.\left(\alpha + \beta.l_j^{\mu}\right).p \tag{3.3}$$

where j=1,2,…., k. k is the number of clusters or the number of centroid nodes in the observer field. G_j is the number of TO sensor nodes in the j^{th} cluster. l_j is the Euclidian distances between the j^{th} centroid node and the CH, and it is given as follows:

$$l_j = \sqrt{(C_{Xj} - CH_X)^2 + (C_{Yj} - CH_Y)^2} \tag{3.4}$$

where the pairs $\left(C_{Xj}, C_{Yj}\right)$ and (CH_X, CH_Y) are the two-dimensional locations of the j^{th} centroid node and the CH, respectively. The amount of energy dissipated by a CH as a receiver E_{RXO} for receiving p-bits of data packet from all centroid nodes is as in Equation 2.2, which is given by:

$$E_{RXO} = k.\gamma.p \tag{3.5}$$

The total energy consumed by all centroid nodes in the observer field for transmitting the sensing data, E_{TXCN}, is given as:

$$E_{TXCN} = \sum_{j=1}^{k}\frac{1}{G_j}\left(\alpha + \beta.l_j^{\mu}\right).p \tag{3.6}$$

The CH consumes energy as a receiver and a transmitter, so the total energy consumed by CH, E_{CHTR}, is the sum of the total energy consumed by CH as receiver and transmitter, which is represents as follows:

$$E_{CHTR} = E_{RXO} + k.E_{TX} = k.\gamma.p + k.(\alpha + \beta.d_b^{\mu}).p \tag{3.7}$$

where d_b is the Euclidian distance between the CH and the BS. The number of clusters affects the proposed model in term of the network lifetime, so when the number of clusters is ten, it is better than if it was a large number because the energy consumed during transmission and reception changes according to the number of clusters. In other words, the energy consumption changes according to the number of transmitted and received bits of sensed data, which depends on the number of clusters (number of the centroid nodes). This work takes the number of clusters nine and not less than that because when the number of clusters is taken less than nine, clusters are formed in large areas and this may not achieve the assumption, that each group of sensor nodes are sensed similar data from their part. Therefore, the number of clusters is greater than eight was taken to achieve the assumption, as well as to ensure good coverage of the network.

In this model, the optimal location of the CH is near the cluster that has low number of TO sensor nodes (i.e. near by the centroid node that has low energy). Also, in order to conserve the energy source of the centroid node which has less energy, the distance between this centroid node and the CH can be reduced. For this purpose, the PSO algorithm is used to select the optimal location of the CH, which reduces the energy consumption for these centroid nodes, and minimizes the energy consumption of the entire network. Since the energy consumed by the CH is already reduced by reducing the number of TO sensor nodes that operating and thus reducing the number of bits received at the CH, as well as reducing the number of bits that the CH will send to the BS. So this work assumes that the CH has a high potential (the CH has a large energy).

The total energy consumed for the entire observer field in each round is the sum of Equations 3.6 and 3.7, which is presented as follows:

$$E_{CONS} = \sum_{j=1}^{k} \frac{1}{G_j}\left(\alpha + \beta . l_j^{\mu}\right). p + k.\gamma . p + k. p. \left(\alpha + \beta . d_b^{\mu}\right) \tag{3.8}$$

where E_{CONS} is the total energy consumed in the whole network. Equation 3.8 contains two terms: the first term is the total energy consumed by the centroid nodes to transmit the sensed data to the CH, and the second term is the energy consumed by the CH to receive the sensed data from all the centroid nodes and then send it to the BS. Due to the large amount of energy associated with the CH compared to the energy associated with TO sensor nodes, the amount of energy consumed by the CH can be discarded from the Equation 3.8. Mathematically, the energy minimization problem can be formulated as follows, to get the optimal location for the CH:

$$CH_{Xopt}, CH_{Yopt} = \operatorname{argmin}_{CH_X, CH_Y} \left\{ \sum_{j=1}^{k} \frac{1}{G_j}\left(\alpha + \beta . l_j^{\mu}\right). p \right\} \tag{3.9}$$

$$\text{s.t.} \quad 0 \leq \left(CH_X, CH_Y\right) \leq \text{M}$$

where the pair (CH_{Xopt}, CH_{Yopt}) is the optimal two-dimensional location of the CH. The location of the CH must be restricted within $M \times M$ monitoring field.

3.3 Simulation and Results

Five scenarios are considered, in each scenario, the proposed model was compared with two other models for different values of k, and their results have been compared. In each scenario, the results of the proposed model are compared with two other models in terms of the number of rounds (network lifetime). The difference in the scenarios is the number of clusters in the proposed model. All models have the same way of distributing TO sensor nodes in the observer field. The first and second models are not clustering, while the proposed model is clustering using k-means clustering algorithm. The difference between the models lies in the method of determining the CH location. The simulation parameters are summarized in Table 3.1. The 50×50 m^2 observer field with 50 transmit-only sensor nodes that are randomly distributed in the observer field, a single CH with high energy, and one BS is placed at the edge of the target field are the components of the WSN. The location of the BS affects the energy consumption in the CH, as the energy consumed in the CH is proportional to the transmitting distance between it and the BS. The iterations continue until the first TO sensor node in the observer field consumes all its energy and dies.

Table 3.1. Simulation parameters.

Parameter	***value***
Observer area (M*M)	(50*50) m^2
Network size	50 nodes
Path loss exponent (μ)	2
α, γ	50 nJ/bit
β	100 $pJ/(bit.m^2)$
Initial energy of each sensor (E_o)	5 J
Packet size(P)	1000 bit
Simulation round	100000
Base station location (x, y)	(25,50)
Communication radius	35 m

All models are simulated using MATLAB software. These scenarios discuss the number of rounds (network lifetime) until the energy of the first TO sensor node in the observer field is expired. The TO sensor nodes consume a specific amount of energy in each round as transmitter. Thus, the energy of the TO sensor nodes is decreased in each round.

Figure 3.4 shows the performance of the first scenario in term of the number of rounds, where the proposed model is compared with two other models in which the number of clusters in the proposed model are nine. In the first scenario, it is noticed that the proposed model is better than the other two models. Thus, the results demonstrate that the proposed model increased in the first scenario about eight times over the first model and five times over the second model.

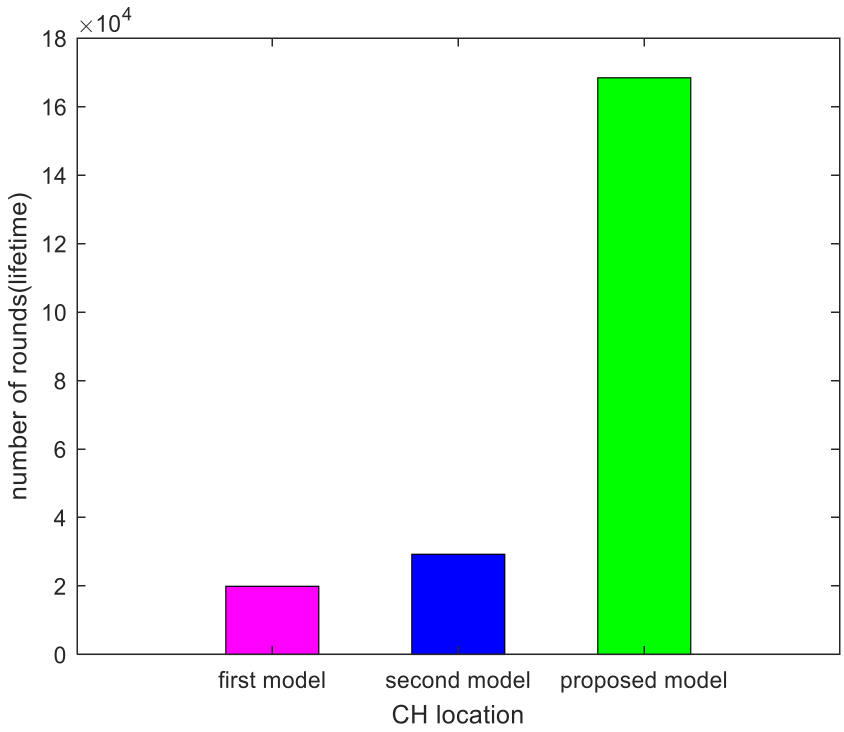

Figure 3.4. The number of rounds of the first scenario when k=9.

In general, all scenarios are the same as the first scenario, but the number of clusters is different in the proposed model, whereas the first and second models have the same results in all scenarios. Figure 3.5 shows the performance of the second scenario when the number of clusters are ten. The results of this scenario show that the proposed model increased by almost seven and four times over the first and second models, respectively.

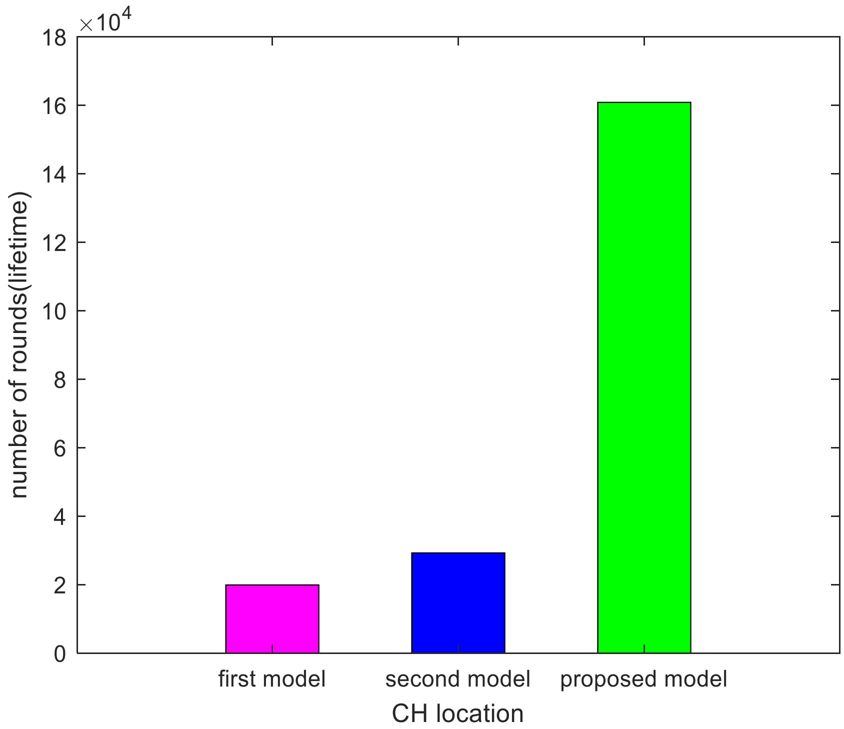

Figure 3.5. The number of rounds of the second scenario when k=10.

Figure 3.6 shows the results of the third scenario when the number of clusters of the proposed model are eleven. Thus, the proposed model outperforms the other two models in terms of the number of rounds (network lifetime), due to the reduction in the transmitting and receiving energy consumption of the TO sensor nodes, and the CH in each rounds. Therefore, the proposed model increased by about six times over the first model and three times over the second model.

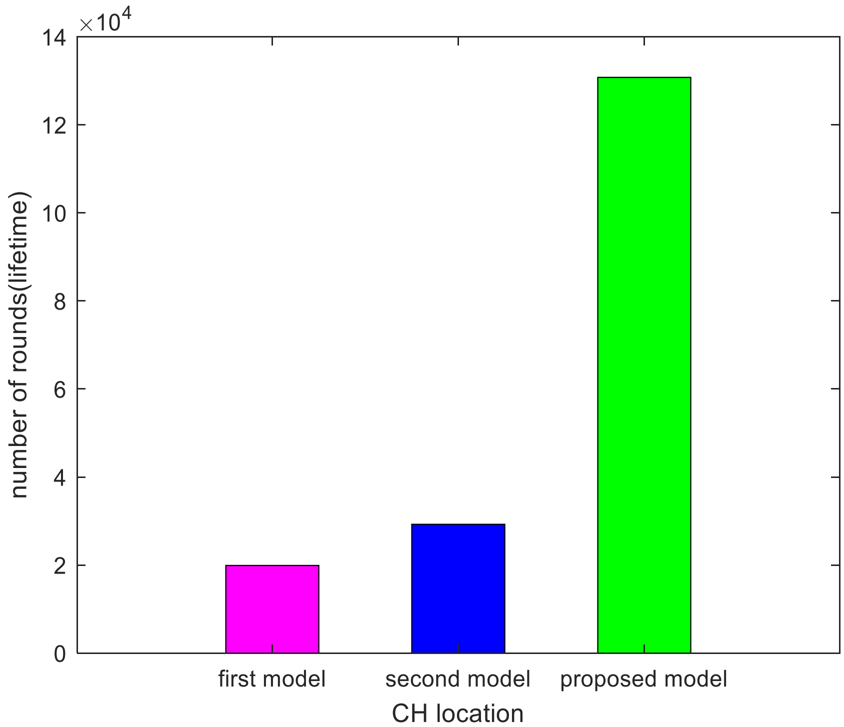

Figure 3.6. The number of rounds of the third scenario when k=11.

The fourth scenario discusses the number of rounds when the number of clusters in the proposed model are twelve as shown in Figure 3.7. The results showed that the proposed model is better than the other two models, and therefore the proposed model increased about five and three times over the first and second models, respectively.

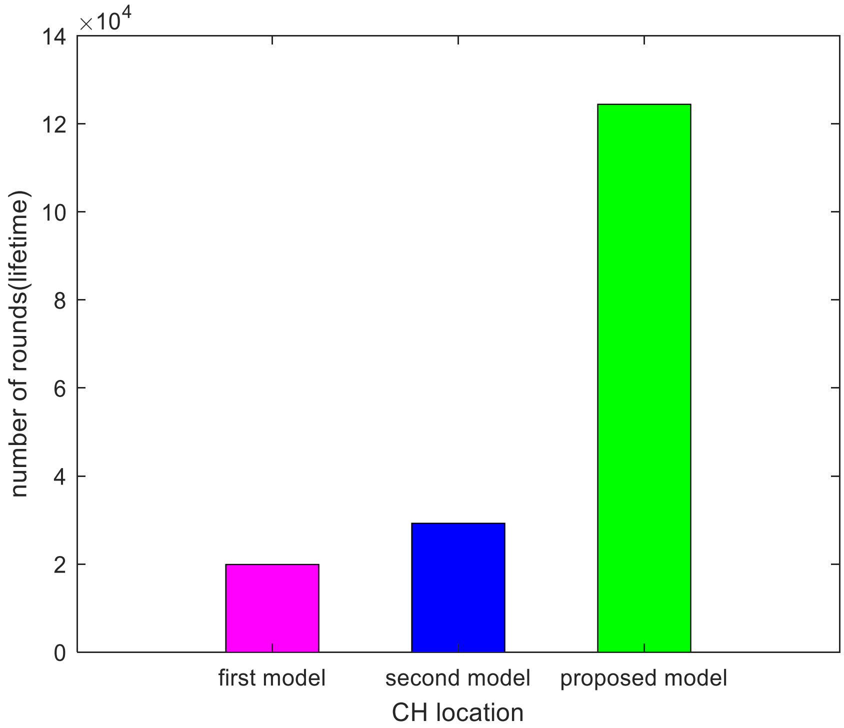

Figure 3.7. The number of rounds of the fourth scenario when k=12.

However, as the number of clusters increases in the proposed model, the number of rounds (network lifetime) gradually decreases, as in the fifth scenario depicted in Figure 3.8. The lifetime of the proposed model decreases from that of the second model when the number of clusters is 45. The reason for this behavior can be seen from Equations 3.8 and 3.9, where the total consumed energy relates to the number of clusters, and, thus, as the number of cluster increases the consumed energy increases as well. In other words, the proposed model outperforms the other two compared models when the number of clusters is small related to the number of sensor nodes in the field (i.e. when k/G is small).

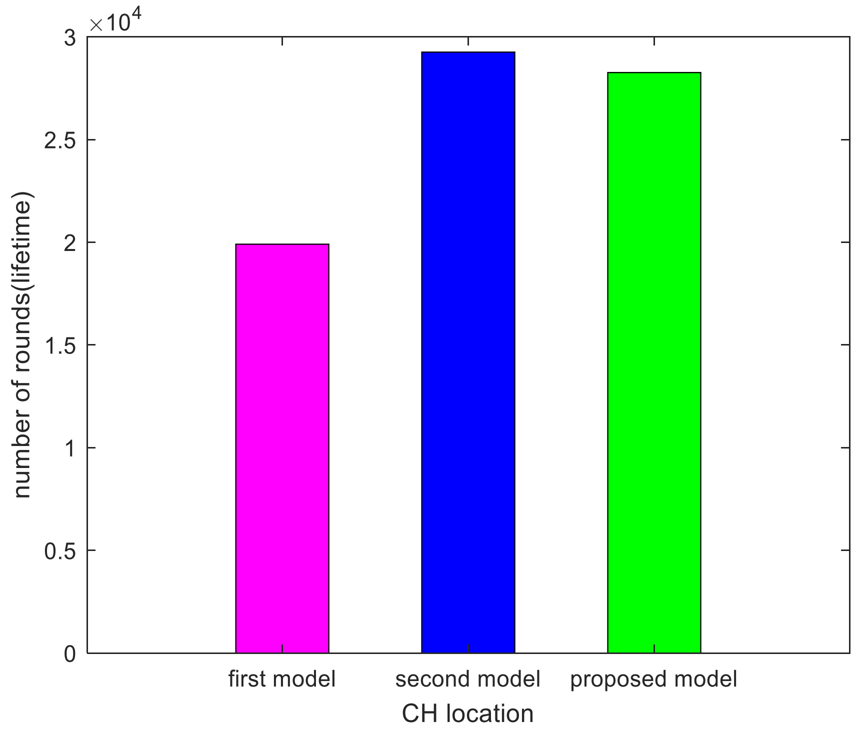

Figure 3.8. The number of rounds of the fifth scenario when k=45.

The results show that the energy consumption in the TO sensor nodes as transmitter and the energy consumed in the CH as receiver and transmitter are minimized. Since instead of receiving sensing data from all TO sensor nodes it will only receive sensing data from the centroid nodes and send it to BS. This work notes that the proposed model is better if the number of clusters is relatively small.

3.4 summary

In this chapter, the first proposed case is discussed, where the goal is extend the network lifetime and minimize the energy consumption of the observer field. This goal is achieved by reducing the number of operating TO sensor nodes by splitting the network into k clusters and determine one sensor nodes from each cluster to represent its corresponding cluster. In addition, the optimal location of the CH is determined within the target field that reduces the energy consumption of the TO sensor nodes, thus reduces the energy consumption of the CH, and thus, reduces the energy consumption of the whole network. The presence of obstacles in the monitoring environment caused a gape in the first proposed case, forcing work to address the presence of obstacles that may hinder direct communication links between the network components, which will be presented in the next chapter.

Chapter Four

Simulation and Results of the Second Case

4.1 Introduction

This chapter discusses the second proposed case that deals with the presence of obstacles in the monitoring field that may hinder the communication links between the sensor nodes and the CHs in the network. This work discusses the proposed case for solving the problem of power optimization of WSNs, introducing the system models (network model and mathematical model), building a simulation environment, and evaluating the generated results in a similar manner to that introduced in the previous chapter. Two scenarios are discussed in this chapter, in each scenario the proposed model is compared with a heuristic model in terms of the minimum network lifetime and the lifetime difference between the maximum lifetime and the minimum lifetime of the network groups.

4.2 System Model

This section provides an explanation of the structure of the wireless sensor network (network models) that includes the proposed model, the heuristic model and the mathematical formulation of the second case.

4.2.1 Network Model

This work considers a network model with stationary TO sensor nodes that are distributed randomly in two-dimensional monitoring field ($M \times M$). Hence, random deployment is a simple way to deploy TO sensor nodes, but it may result in unbalanced deployment [42]. In addition, there are obstacles in the target field that may block the communication link between TO sensor nodes and the CHs in the network. Therefore, the observer field is divided into two groups and one CH is allocated for each group to receive data from its TO sensor nodes and forward them to an out-of-field BS. The reason for this nodes grouping is to guarantee a LOS link between each TO sensor nodes and the CH in the presence of field obstacles that may hinder the TO-CH communications.

Two scenarios are considered in this chapter:

- The first scenario: when the energy of the CH is not constrained (i.e., the CH has sufficient source of energy and has high potential).
- The second scenario: when the energy of the CH is constrained (i.e., the CH has limited energy).

In the latter scenario, the energy consumed by the CH affects the network lifetime and the optimal location of the CH. In each scenario, the proposed model is compared with another heuristic (or a Naïve) model, where there is no intelligence involved in the solution when splitting the sensor nodes into groups. The two models are described as follow:

- **Heuristic model**: the presence of the obstacles and the knowledge of their locations may suggest that the process of splitting the TO sensor nodes can be done by using the coordinates of the obstacles, where the sensor nodes under the obstacles are in the first group and the rest are within the second group as shown in Figure 4.1 which appears later in this chapter. With this model, determining the location of the CH in each group considers the presence of a LOS path between the CH and its sensor nodes and reduces the energy consumption in each group. This is achieved using PSO algorithm. However, this partitioning leads to a large difference in the consumed energy between the two groups due to the non-optimal partitioning of the TO sensor nodes between the two groups. This makes the group with the larger number of TO sensor nodes depletes its energy faster than the other group, and thus the network lifetime expires as well.

- **Proposed model**: in this model, the sensing field is divided into two groups using GPT. Initially, a LOS paths are found among TO sensor nodes and then create an $N \times N$ binary matrix of 0's and 1's to indicate the presence (1) and absence (0) of the LOS path between every two sensor nodes in the observer field. In other words, an entry of 1 means the presence of an edge between the two sensor nodes, and an entry of 0 means there is no edge between the two sensor nodes. The distances between TO sensor nodes is taken into account when GPT is used to compute the cost (weight) of each edge. So, when the distance between two TO sensor nodes is small, the edge cost is large and it is difficult to cut it. Meanwhile, when the distance is large, the edge cost is small and it is easy to cut it. This is achieved by dividing (element-wise) the 0-1 matrix by the distance matrix, where $N \times N$ distance matrix represents the distance between each two TO sensor nodes. Finally, the optimal location of the CHs is determined using the PSO algorithm by minimizing the number of TO sensor nodes that do not have LOS with the CH, as well as minimizing the total energy consumption in each group by minimizing the total distance between each CH and corresponding TO sensor nodes.

4.2.2 Mathematical Model

The total energy consumed by all TO sensor nodes in the j^{th} group to transmit p-bits of data packet to the j^{th} CH, E_{TXj} is the sum of the dissipated energy of the individual nodes, which was given in Equation 2.1. Mathematically, this can be stated as follows:

$$E_{TXj} = \sum_{i=1}^{N_j} \left(\alpha + \beta . d_{ij}^{\mu}\right) . p \tag{4.1}$$

where d_{ij} is the Euclidian distance between the i^{th} transmit-only sensor node and the j^{th} cluster head, and N_j is the number of the TO sensor nodes in the j^{th} group.

The CH consumes energy as a receiver and a transmitter. Thus, the total energy consumed by the j^{th} cluster head is for receiving p-bits of data packet from the TO sensor nodes and transmitting them to the BS, E_{CHj}. Using Equations 2.1 and 2.2, E_{CHj} can be modeled as follows:

$$E_{CHj} = N_j . \gamma . p + N_j . \left(\alpha + \beta . d_j^{\mu}\right) . p \tag{4.2}$$

where d_j is the Euclidian distance between the j^{th} cluster head and the BS. The total energy, E_{totj}, dissipated in the j^{th} group by the TO sensor nodes and its CH is the sum of Equations 4.1 and 4.2, which is given as follows:

$$E_{totj} = \sum_{i=1}^{N_j} (\alpha + \beta . d_{ij}^{\mu}) . p + N_j . \gamma . p + N_j . (\alpha + \beta . d_j^{\mu}) . p \quad (4.3)$$

This work finds the optimal location of the CHs by minimizing the number of TO sensor nodes that do not have LOS with their CH. In addition, it aims to minimize the total energy consumed by transmitting and receiving data in each group.

Two scenarios have been considered here. In the first scenario, as the aim is to minimize the total energy in the target group, the energy consumed by the CH is not considered when determining the optimal location of the CH in the target group. This is because the CH has high potential (high energy) and the amount of energy it consumes does not affect its lifetime. Thus, this work only minimizes the total energy consumed by the TO sensor nodes in each group when determining the optimal position of the CH using PSO algorithm. Mathematically, the minimization problem for finding the location of the j^{th} cluster head in the first scenario is formulated as follows:

$$CH_{Xoptj}, CH_{Yoptj} = \text{argmin}_{CH_{Xj}, CH_{Yj}} \left\{ \sum_{i=1}^{N_j} \{ (\alpha + \beta . d_{ij}^{\mu}) . p + \rho . I_{LOS}(i) \} \right\} \quad (4.4)$$

$$\text{s.t.} \quad 0 \leq (CH_{Xj}, CH_{Yj}) \leq M$$

where (CH_{Xoptj}, CH_{Yoptj}) is the optimal location of the j^{th} CH in the j^{th} group. $I_{LOS}(i)$ is an indication function that represents the absence of LOS between the CH and the i^{th} transmit-only sensor node. The absence of this part of the above equation results in a large number of TO sensor nodes that are not connected to their corresponding CH, due to the absence of LOS among them. ρ is a trade-off factor that is used to increase the cost of the TO sensor nodes that do not have LOS with their CH. The constraint indicates that the location of the CH must be within the $M \times M$ observing field. The process of determining whether the LOS is present or not between endpoints is presented in Appendix A of this thesis.

In the second scenario, the CH has a finite energy source (the CH has limited energy) and thus its energy consumption affects the lifetime of the network. When determining the optimal location of the CH that is determined using PSO algorithm, the aim of the second scenario is to minimize the number of TO sensor nodes that do not have LOS with their CH and also minimize the total energy consumed by the TO sensor nodes and the corresponding CH in each group. Based on that, the minimization problem for determining the optimal location of the j^{th} cluster head in the second scenario is formulated as follows:

$$CH_{Xoptj}, CH_{Yoptj} = \operatorname{argmin}_{CH_{Xj}, CH_{Yj}} \Big\{ \textstyle\sum_{i=1}^{N_j} \{ (\alpha + \beta . d_{ij}^{\mu}). p + \rho . I_{LOS}(i) \} + \delta \big(N_j . \gamma . p + N_j . (\alpha + \beta . d_j^{\mu}). p \big) \Big\} \tag{4.5}$$

$$\text{s.t.} \quad 0 \leq (CH_{Xj}, CH_{Yj}) \leq M$$

where δ is a trade-off factor that is used to reduce the weight of the total energy consumed by the j^{th} cluster head when determine its optimal location within its group.

4.3 Simulation and Results

Two scenarios are considered, in each scenario the results of the proposed model are compared with the heuristic model. The simulation parameters are presented in the Table 4.1. The 80 transmit-only sensor nodes are randomly distributed in a $50 \times 50\ m^2$ monitoring field. The proposed model is not affected by the number of sensor nodes and the network dimensions, because the network infrastructures are the same for the two models. If obstacles are present in the middle of the monitoring field, they impede the communications link between the TO sensor nodes and the CH. Therefore, to facilitate the simulation, two rectangular obstacles were placed in the observer field, which are later shown in Figures 4.1 and 4.2. Thus, the observer field is divided into two sections (two groups of TO sensor nodes) to ensure that the entire network is covered, and find the optimal location of one CH within each group. This work also assumes that there is a BS located at the corner of the sensing field, because this location is better in terms of providing LOS and reduce communication distances between the CHs and the BS. The goal is to increase the lifetime of the two groups and reduce the difference in lifetime between them. Hence, the network's lifetime is computed as the moment when the first TO sensor node depletes its energy in any group and expires, so the network lifetime is determined by the minimum lifetime of the two groups. Since the lifetime for both groups are calculated separately, the smaller lifetime between the two groups is used to determine the lifetime of the entire network.

Each TO sensor node has an initial energy of 5 J. For example, the TO sensor node consumes 60 μJ of energy to transmits 1000 bits of sensed data to the CH when the communication distance between them is 10 m. Each TO sensor nodes consumes about 0.0012% of its energy in each round depending on the communication distance. The initial energy of the CH in the second scenario is $30\,J$ .The CH consumes about 8900 μJ of energy in each round as receiver and transmitter when the number of its corresponding sensor nodes is 40 and its communication distance to the BS is 35 m. Each CH consumes about 0.029% from its energy in each round in the second scenario. In each round, all TO sensor nodes send their sensed data once to the corresponding CH, and the CH in turn collects the received data and sends it to the BS.

Table 4.1. Simulation parameters.

parameter	***value***
Observer area ($M \times M$)	(50×50) m^2
Network size	80 sensor nodes
Path loss exponent (μ)	2
α, γ	50 nJ/bit
β	100 $pJ/(bit.\ m^2)$
Initial energy of each TO sensor (E_o)	5 J
Packet size (P)	1000 bit
Simulation round	100000
Base station location (x, y)	(0,50)
δ	1/30
Initial energy of each CH	30 J
Communication radius	35 m
ρ	1000000

Dimensions of the first obstacle $(x \times y)\ m^2$	$(15\times2)\ m^2$
Dimensions of the second obstacle $(x \times y)\ m^2$	$(2\times16)\ m^2$

This work uses MATLAB software to perform the simulations and extract the results. The difference between the heuristic and the proposed models is that in the heuristic model the target field is partitioned using the coordinates of the obstacles, while in the proposed model the partitioning is performed using a GPT. Compared to the proposed model, where the difference between the number of TO sensor nodes in the two groups is too small, the difference is large in the heuristic model. This is due to the more intelligent GPT used in the proposed model. This is better explained in an example. The partitioning outcomes are shown in Figures 4.1 and 4.2. In the heuristic model , whose results are shown in Figure 4.1, 29 transmit-only sensor nodes can be seen in the first group and 51 transmit-only sensor nodes in the second group. The circles represent the TO sensor nodes and the stars represent the CH in each group. TO sensor nodes and CHs are represented by different colors in each group. It is clear that the energy of the second group in the heuristic model will be drained quickly as there are 175% of the number of TO sensor nodes as that in the first group. Therefore, the network lifetime dies out faster as well.

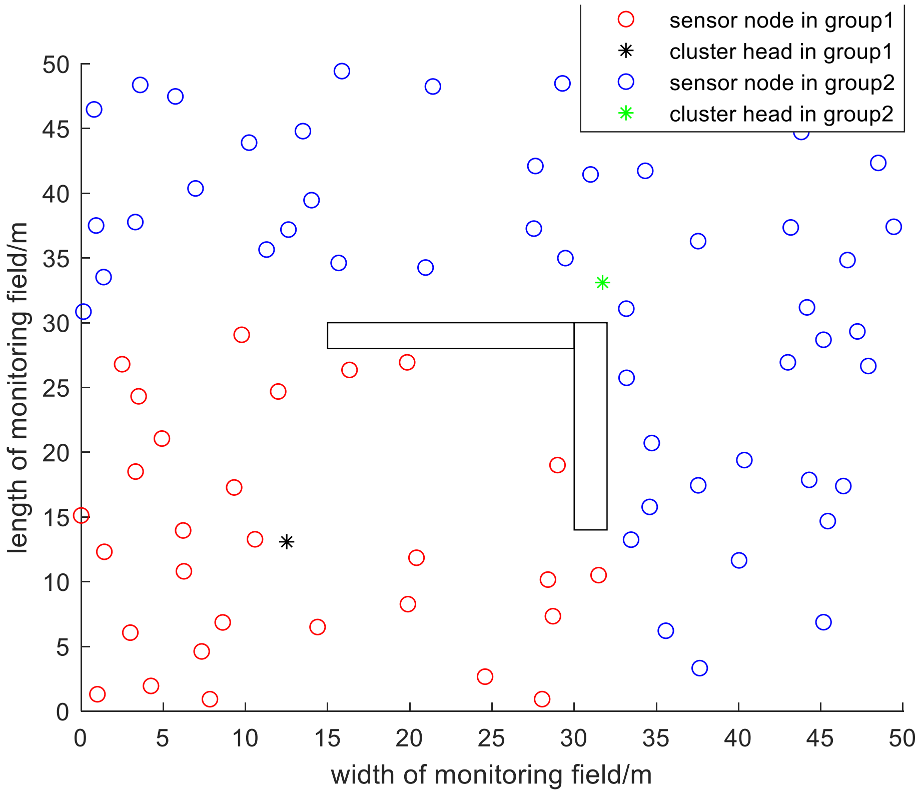

Figure 4.1. Network partitioning with the heuristic model.

However, in Figure 4.2 (the proposed model), 43 transmit-only sensor nodes are in the first group and 37 transmit-only sensor nodes in the second group. Therefore, the lifetime of these two groups is close, and in result, the lifetime difference between them is small too. These results are attributed to the fact that the number of the TO sensor nodes in the both groups in the proposed model is approximately equal.

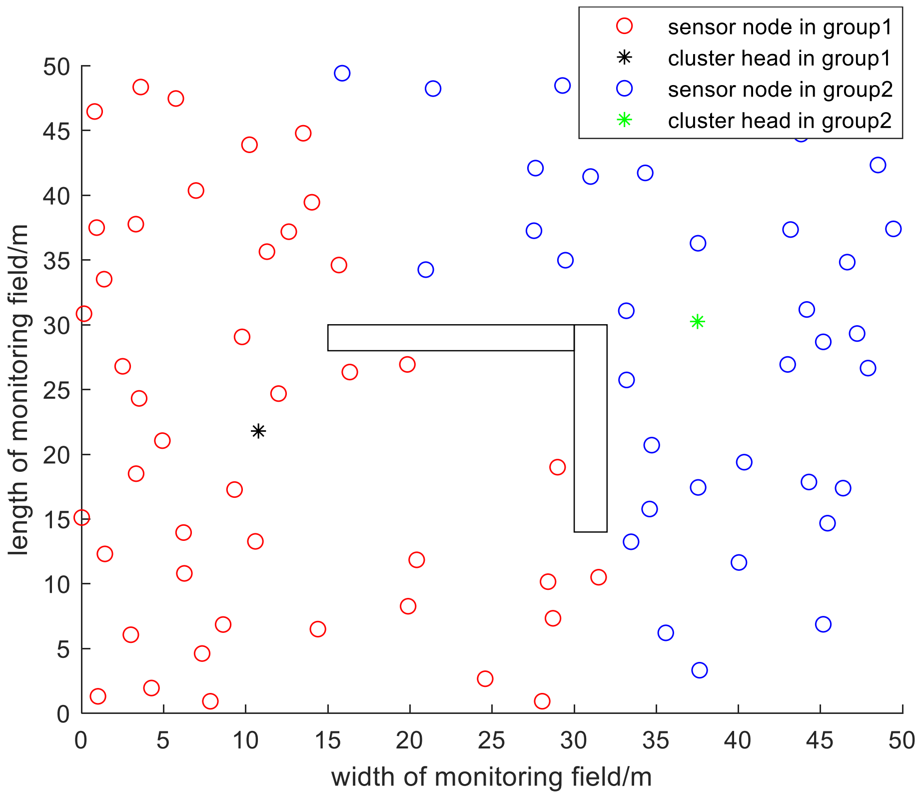

Figure 4.2. Network partitioning with the proposed model.

Figures 4.3 and 4.4 show the simulation results of the heuristic model and the proposed model, respectively, for the first scenario when the CHs are not constrained (the CHs have high energy). Figure 4.3 shows the lifetime for the first and second groups, as well as the lifetime difference between them. It can be seen that using the heuristic model, the achieved minimum lifetime is > 30,000 rounds and the lifetime difference is > 25,000 rounds. This lifetime difference between the two groups is considered to be very large as the group with more TO sensor nodes will expire faster. Thus, the entire network expires.

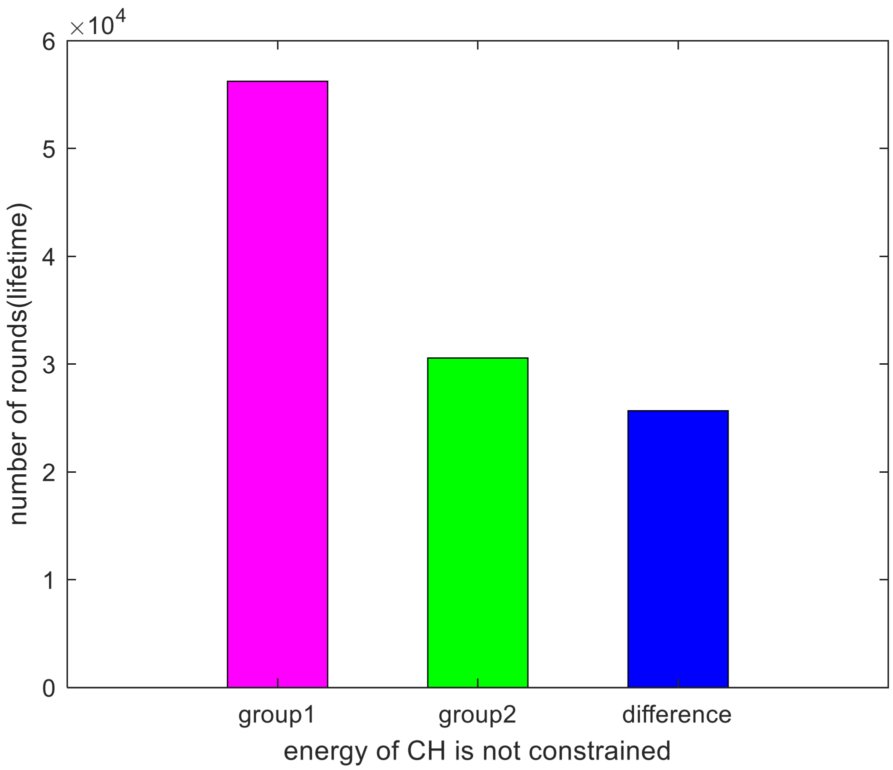

Figure 4.3. The heuristic model with the first scenario.

Figure 4.4 shows the results for the proposed model. It can be seen that the minimum lifetime among both groups is > 37,000 rounds and the lifetime difference between them is < 2,500 rounds. The reason for the small lifetime difference between the two groups in the proposed model (relative to that in the heuristic model) is that the partitioning process of the monitoring field in the proposed model is more intelligent, where the number of TO sensor nodes in the two groups is approximately equal. In result, this makes the amount of energy consumed in both groups approximately equal. Thus, achieving a balance in the energy consumption of the network.

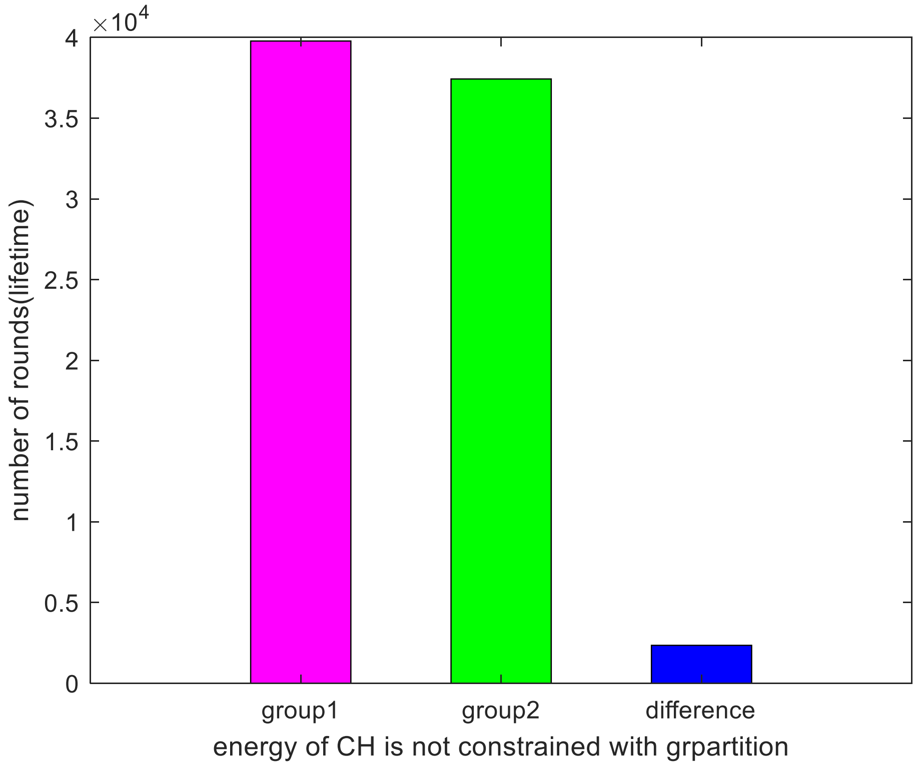

Figure 4.4. The proposed model with the first scenario.

Simulation results of the heuristic model and the proposed model are presented in Figure 4.5 and Figure 4.6, respectively, for the second scenario when the CHs are constrained (the CHs have limited energy). Figure 4.5 shows the results where the minimum lifetime and the lifetime difference are, respectively, ~ 2,600 and 1,600 for the heuristic model. Therefore, the lifetime difference between the two groups is considered to be very large. This is due to the significant difference in the number of TO sensor nodes between the two groups in the heuristic model, due to the lack of intelligence used in network segmentation.

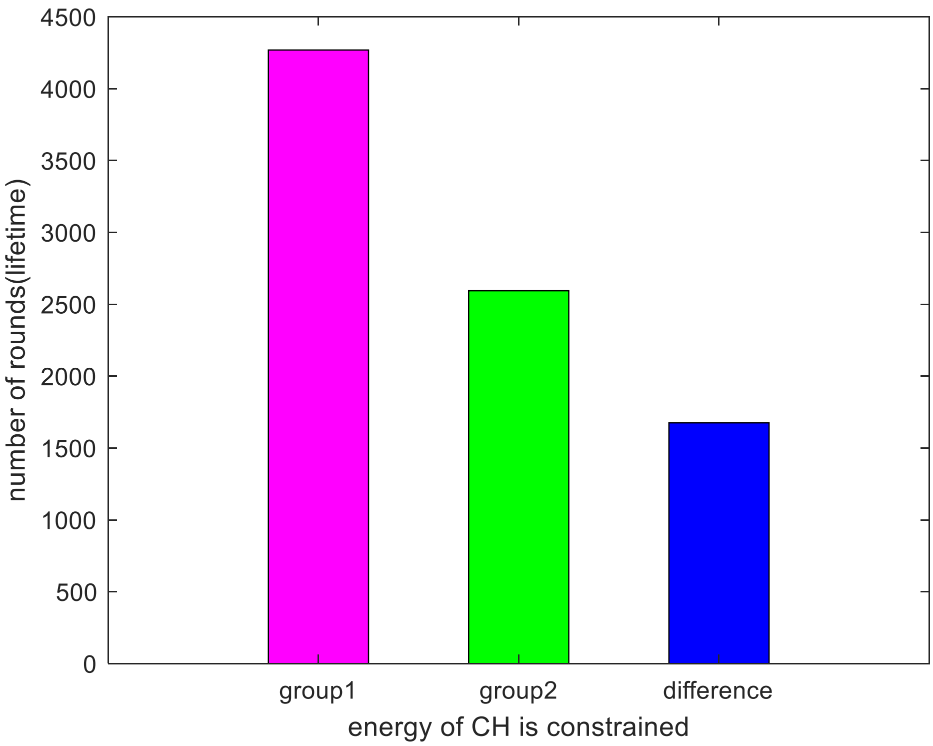

Figure 4.5. The heuristic model with the second scenario.

In the proposed model (Figure 4.6), however, the minimum lifetime found to be ~ 3,000 and the lifetime difference is ~ 750. Therefore, these results are better than the heuristic model in terms of the minimum lifetime and the lifetime difference.

The reason behind this behavior is, again, the lack of intelligence in the heuristic model relative to the GPT used in the proposed model. It is worth noting that the location of the BS is an important factor to consider in the second scenario due to the limited energy of the CH. Thus, the location of the BS and its distance from the CH is accounted for in the calculation of the network lifetime and when determining the location of the CH, where the energy consumption of the CH as transmitter is proportional to the distance between it and the BS.

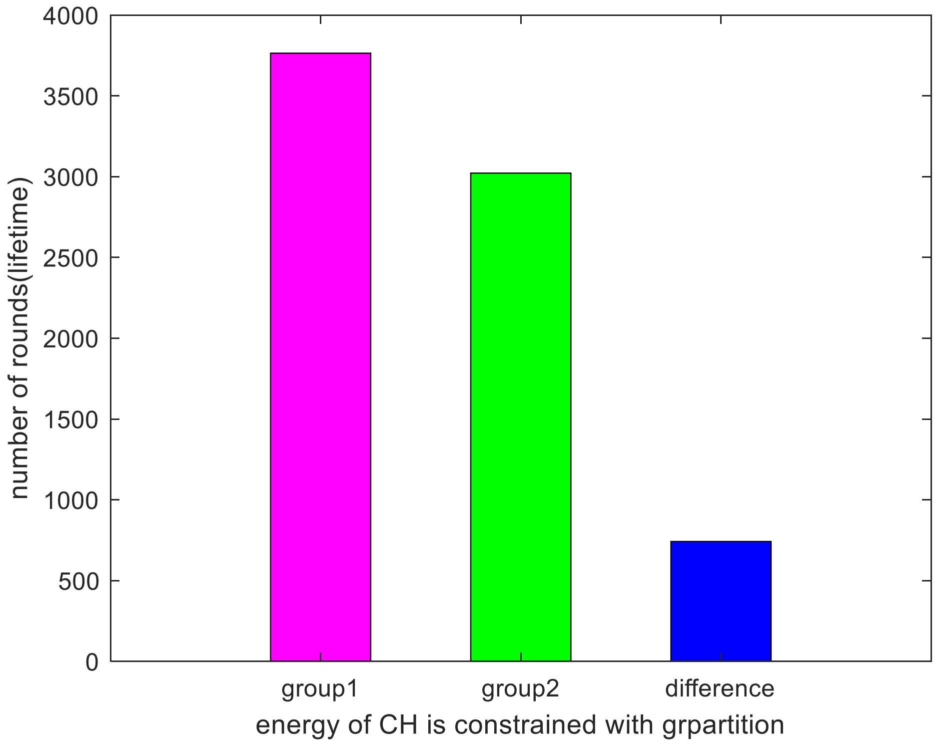

Figure 4.6. The proposed model with the second scenario.

Comparing the two scenarios, it can be seen that the lifetime of the network in the first scenario is larger than in the second scenario because the energy consumed by the CH is not taken into account in the first scenario when the lifetime of the network is calculated due to the assumption of high CH energy (i.e. unconstrained power). In comparison, in the second scenario, the network lifetime is smaller than that of the first scenario because the energy consumed in the CH is taken into consideration when calculating the network lifetime.

From the results and discussion above, It can be concluded that the energy consumption in the proposed model in both scenarios is the better in terms of the network lifetime as a whole. The improvement in the network lifetime is ~ 22% in the first scenario and 16% in the second scenario with the proposed model compared to the heuristic model.

Finally, Figures 4.7 and 4.8 show the results of a Monte Carlo simulation to study the average behavior of the two models with the two scenarios. The average of the minimum lifetime and the average lifetime difference is used as comparison metrics. The simulation is repeated 100 times for both scenarios, where the distribution of the TO sensor nodes varies in each iteration. Monte Carlo simulation is presented in a flowchart shown in Appendix B of this thesis.

Monte Carlo results for the first scenario are shown in Figure 4.7. The results show that the proposed model performs better than the heuristic model in terms of the average minimum lifetime and the average lifetime difference between the two groups in the observer field.

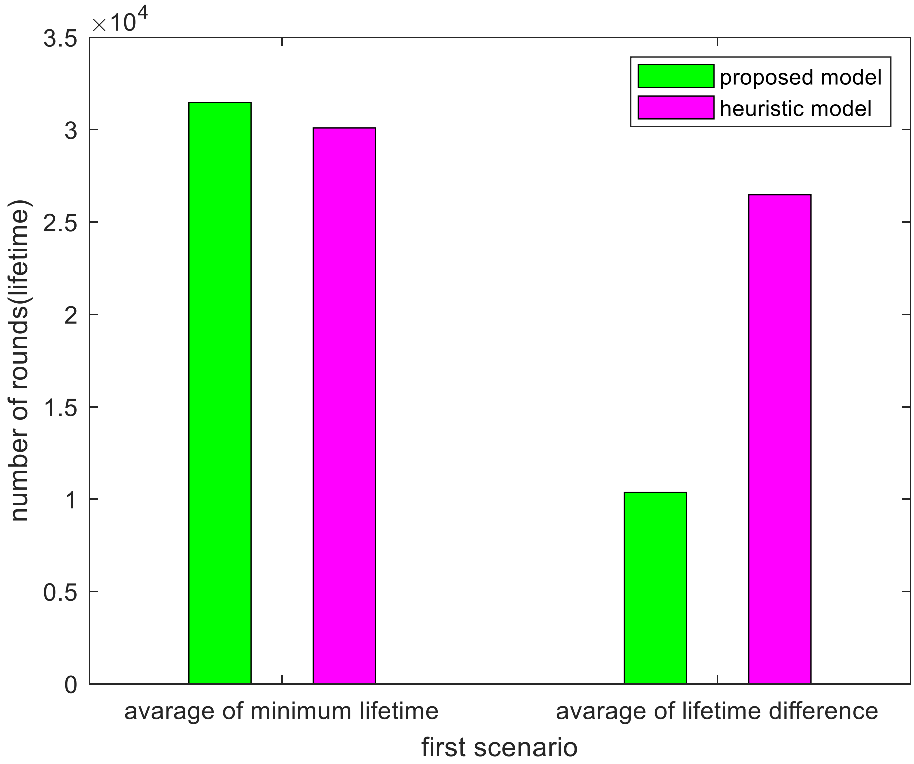

Figure 4.7. Monte Carlo simulation for the first scenario.

Monte Carlo results for the second scenario are shown in Figure 4.8, and demonstrate that the proposed model has a larger average minimum lifetime and less average lifetime difference compared to the heuristic model. These average results confirm the previous results about the superiority of the proposed model as compared to the heuristic model. The reason for this improvement lies in the partitioning process of the monitoring field, where the number of the TO sensor nodes in the two groups is approximately equal in the proposed model. This makes the lifetime of the two groups approximately equal in each iteration.

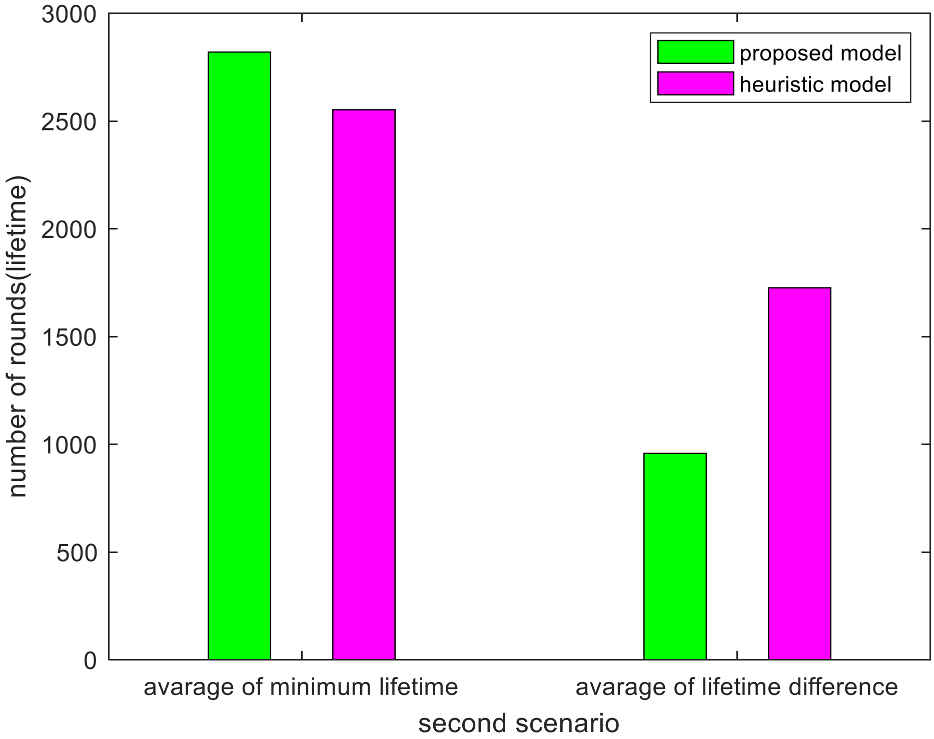

Figure 4.8. Monte Carlo simulation for the second scenario.

Chapter Five

Conclusions and Suggestions for Future Works

5.1 Conclusions

In this thesis, two cases are presented to minimize the energy consumption and prolong the lifetime of the network. These goals are achieved by splitting the observer field into k-partitions and determining the optimal location of the CHs within the observer field.

In the first case, the TO sensor nodes of the target field are divided into k-clusters using k-mean clustering algorithm. A single TO sensor node (centroid node) is selected from each cluster to represent the entire TO sensor nodes on its cluster to prevent redundant sensed data. This centroid nodes with the aggregation energy of all TO sensor nodes on its cluster. Assume that the target field contains a single CH and N transmit-only sensor nodes that are randomly distributed in the observer field. The proposed model reduces the energy consumption of the entire network by determining the optimal location of the CH using the PSO algorithm with a fitness function that represent the energy consumed by all centroid nodes in the observer field. The proposed model consumes less energy during transmissions and receptions by TO sensor nodes and the CH, due to the small number of operating TO sensor nodes in the observer field. The proposed model has been compared with two other models in five scenarios. The simulation results showed that the lifetime of the proposed model outperforms the other two compared models when the number of clusters is relatively small.

In the second case, this work has presented a model to divide the network into k-partitions using GPT, which considered the presence of a line-of-sight and the distance between every two TO sensor nodes in dividing it into k-partitions, assigning a CH to each group to collects the sensed data from corresponding TO sensor nodes and transmitting them to the BS. The two conditions considered when determining the optimal location of the CH within its partition are: maintaining a line-of-sight between the CHs and their corresponding TO sensor nodes, and minimizing the energy consumption in the observer field. The possibility of the presence of an obstacles in the monitoring field that may block the communication link between the TO sensor nodes and the CH has been considered in the analysis. The results from the proposed model have been compared with a model (called it the heuristic model) that does not use an intelligent partitioning technique. The results show that the proposed model can extend the lifetime of each partition in the observer field, it can also balance the lifetime among the partitions. In the second case, two scenarios were studied, in each scenario the proposed model was compared with the heuristic model. All partitions have close lifetime, and the difference between the minimum and maximum lifetimes is small compared with the heuristic model because the number of TO sensor nodes in each partition with the proposed model is approximately equal. In both scenarios, the results showed that the proposed model outperforms the heuristic model in terms of the minimum lifetime and the lifetime difference.

5.2 Suggestions for Future Work

The following are some suggestions for future work that could improve the network and extend its lifetime:

1. Studying the network when the sensor nodes have the ability to move over a specified distances to reduce the communication distance between them and their CH.
2. Exploring the possibility of splitting each partition in the target field into clusters to prolong the network lifetime using Grey Wolf Optimization (GWO) algorithm.
3. Studying the WSNs lifetime in Internet of Things (IoT) application.

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Appendix A

The direct distance between any two points in the 2D space (i.e. between the TO sensor nodes and the CH or between the TO sensor nodes) can be calculated using the line segment equation and the coordinates of the obstacles as follows:

$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x_1 \\ y_1 \end{bmatrix} t + \begin{bmatrix} x_2 \\ y_2 \end{bmatrix} (1-t)$$

where x and y are the coordinates of the obstacle. (x_1, y_1) and (x_2, y_2) represent the coordinates of the endpoints of the line segment (i.e. the sensor nodes and the CH). t is a parameter that characterizes the line segment, and $(t \in \mathcal{R})$ and $(0 \le t \le 1)$. From the above equation t can be calculated as follows:

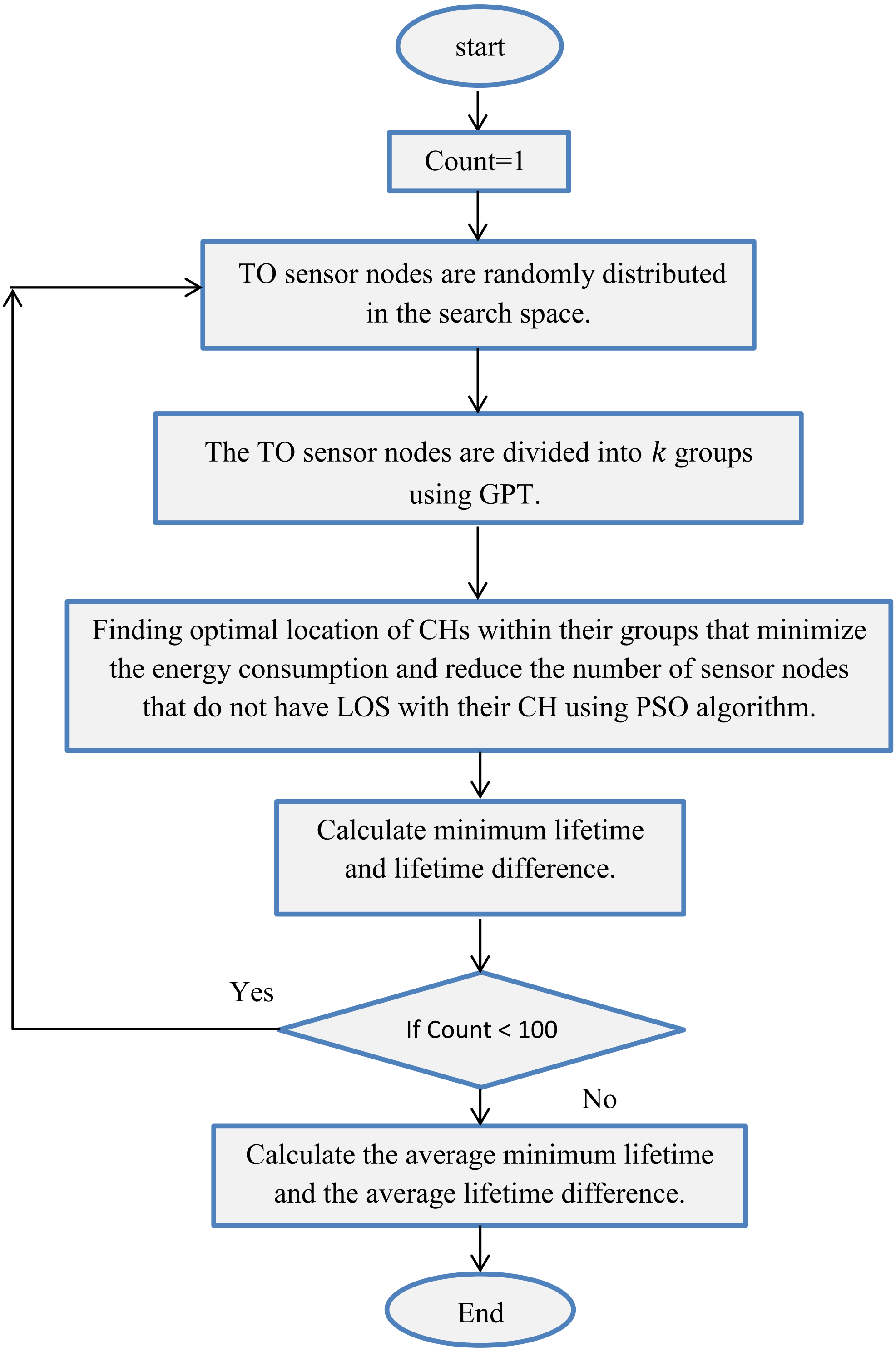
$$t_1 = \frac{x - x_2}{x_1 - x_2}$$

$$t_2 = \frac{y - y_2}{y_1 - y_2}$$

The direct path between the communicating endpoints is considered absent (i.e. passes through an obstacle) if there is an intersection between the range of values that t_1 *and* t_2 takes on. Otherwise, the LOS is present. Using these information, a 0-1 matrix is created that is later converted into a weight matrix by replacing the 1's with the inverse of the Euclidean distances between endpoints. This weight matrix is the input to the GPT to split the monitoring field into two partitions.

Appendix B

Flow chart showing the work of the Monte Carlo simulation in the second case.



List of Publications

[1] Z. Hammodi, A. Al Hilli, and M. Al-Ibadi, “Optimal Placement of Single Cluster Head in Wireless Sensor Networks via Clustering,” in *2021 IEEE 11th Annual Computing and Communication Workshop and Conference (CCWC)*, pp. 1157–1160, 2021.

[2] “Energy Optimization via Optimal Placement of Cluster Heads in Wireless Sensor Networks with Obstacles,” has been accepted in *IEEE 7th International Conference on Signal processing and Communication (ICSC) 2021.*

[3] “Energy Optimization in Wireless Sensor Networks: A Review”, *Iraqi Journal for Computer Science and Mathematics (IJCSM),* under review.

الخلاصة

في السنوات الأخيرة ، ظهرت شبكات التحسس اللاسلكية (WSNs) كتقنية جديدة في تطبيقات مختلفة للحصول على معلومات من البيئة مثل درجة الحرارة والرطوبة والضغط وما إلى ذلك. تتميز شبكات WSN بشكل أساسي بإمداد محدود وغير متجدد للطاقة. ومن ثم ، فإن الحاجة إلى تحسين كفاءة الطاقة أصبحت ذات أهمية متزايدة لأنها تؤثر على عمر الشبكة. من أجل تقليل استهلاك الطاقة في شبكة أجهزة التحسس اللاسلكية ، تقدم هذه الأطروحة نموذجًا لتقليل الطاقة المستهلكة وإطالة عمر الشبكة من خلال اقتراح نهجين. النهج الأول يناقش خمسة سيناريوهات. في كل سيناريو ، ينقسم النموذج المقترح إلى عدد معين من المجموعات ، ويتم مقارنة النموذج المقترح بنموذجين آخرين. في هذا النهج ، يقلل النموذج من عدد عقد الاستشعار النشطة ، ويحدد الموضع الأمثل لرأس المجموعة الوحيد (CH). لتقليل الطاقة التي تستهلكها عُقد تحسس الإرسال فقط ، يتم استخدام (k-mean algorithm) لأداء تقسيم العقد، وتحديد عقدة متحسس واحدة من كل مجموعة لتمثيل هذه المجموعة. تستخدم خوارزمية تحسين سرب الجسيمات (PSO) لحل مشكلة التحسين غير المحدبة المتمثلة في إيجاد الموقع الأمثل لـ CH. في النهج الثاني ، يتم دراسة الموضع الأمثل لرؤوس المجموعة (CHs) في الشبكات حيث توجد عوائق طبيعية، مثل الجبال أو المباني أو مجموعة من الأشجار ، داخل مجال المراقبة. قد تمنع هذه العوائق الاتصال بين عقد متحسس الإرسال فقط ورأس المجموعة في شبكات التحسس اللاسلكية (WSNs). في هذا النهج ، يتم تقسيم مجال المراقبه إلى k من المجموعات ، حيث تحتوي كل مجموعة على أكبر عدد من عقد التحسس التي لها خط رؤية (LOS) فيما بينها. تمت صياغة هذه المشكلة الفرعية ك graph partitioning problem. علاوة على ذلك ، يتم تحديد الموقع الأمثل ل CH في كل مجموعة بحيث يتم الحفاظ على LOS بين CH وعقد أجهزة التحسس الخاصة بها. من أجل تقليل الطاقة التي تستهلكها كل مجموعة داخل المجال المستهدف ، يتم استخدام خوارزمية تحسين سرب الجسيمات (PSO) للعثور على الموقع الأمثل لـ CHs. تظهر نتائج المحاكاة أن النهج المقترح الاول يحقق عمرًا أفضل للشبكة مقارنة بالنموذجين الاخرين. بينما النموذج المقترح الثاني يحقق أفضل تقسيم للشبكة ، وأفضل اتصالات بين عقد الاستشعار و CH الخاصة بها ، وأفضل عمر للشبكة مقارنة بالنموذج الذي يقسم عقد المتحسس باستخدام إحداثيات العوائق (heuristic model). تبلغ نسبة تحسين عمر الشبكة 22% و 16% في السيناريوهين الأول والثاني على التوالي.

الموضع الأمثل لرأس المجموعة في ارسال شبكات أجهزة التحسس اللاسلكية

الرسالة

مقدمة الى قسم هندسة تقنيات الاتصالات كجزء من متطلبات نيل درجة الماجستير في هندسة تقنيات الاتصالات

تقدمت بها

زهراء حمودي باقر

إشراف

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تشرين الثاني/2021

جمهورية العراق

وزارة التعليم العالي و البحث العلمي

جامعة الفرات الاوسط التقنية

الكلية التقنية الهندسية - نجف

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