EFFICIENT WIRELESS SENSOR NETWORKS DEPLOYMENT IN 3D ENVIRONMENTS

BY

AHMED ALI AHMED BAABOOD BAWAZIR

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This thesis, written by **AHMED ALI AHMED BAABOOD BAWAZIR** under the direction of his thesis advisor and approved by his thesis committee, has been presented and accepted by the Dean of Graduate Studies, in partial fulfillment of the requirements for the degree of **MASTER OF SCIENCE IN COMPUTER NETWORKS.**

Dr. Abdulaziz Barnawi
(Advisor)

Dr. Tarek Sheltami
(Member)

Dr. Talal Al-Kharobi
(Member)

Dr. Ahmad Almulhem
Department Chairman

Dr. Salam A. Zummo
Dean of Graduate Studies

23/4/19

Date

Dedication

I dedicate this work to the persons who believed in me with endless love and support, to my father and my mother, to my wife, brothers, sisters, aunts, and all people who help me through the way of making this achievement.

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In the name of Allah, all praise be to him, the most Merciful and most Gracious. The one who has power overall. Blessings and peace be upon the most noble of Messengers, the Prophet Mohammad and upon his family and companions.

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LIST OF ABBREVIATIONS

ABC	:	Artificial Bee Colony
BMS	:	Building Management System
BS	:	Base Station
CCPSO2	:	Cooperative Coevolutionary Particle Swarm Optimization 2
CH	:	Cluster Head
CLPSO	:	Comprehensive Learning Particle Swarm Optimizer
CPCP	:	Coverage-Preserving Clustering Protocol
DE	:	Deferential Evolution
DEEHC	:	Distributed Energy Efficient Heterogeneous Clustering
DPCCMOLSEA	:	Distributed Parallel Cooperative Coevolutionary Multi-Objective Large- Scale Evolutionary Algorithm
EECC	:	Energy-Efficient Connected Coverage
GA	:	Genetic Algorithm
GADV-Hop	:	Genetic Algorithm Distance Vector Hop
GSA	:	Gravitational search algorithm
kVDPR	:	k-Vertex Disjoint Path Routing

MAC	:	Medium Access Control
MILP	:	Mixed Integer Linear Program
MODS	:	Metal Oxide Semiconductor
MOEA/D-DE	:	Multi-Objective Evolutionary Algorithm/ Differential Evolution
MOEAD-CCP	:	Multi-Objective Evolutionary Algorithm Decomposition-Coverage-aware Clustering Protocol
MOGA	:	Multi-Objective Genetic Algorithm
MPI	:	Message Passing Interface
MST	:	Minimum Spanning Tree
NSGA-CCP	:	Non-dominated Sorting Genetic Algorithm- Coverage-aware Clustering Protocol
NSGA-II	:	Non-dominated Sorting Genetic Algorithm-II
O3DwLC	:	Optimized 3D grid deployment with Lifetime Constraint
PSO	:	Particle Swarm Optimization
QoS	:	Quality of Service
RN	:	Relay Node

RSS	:	Received Signal Strength
SN	:	Sensor Node
3D	:	Three Dimension
WSN	:	Wireless Sensor Network
WTDS2-SGA	:	Wavelet Transformation based Sensor Deployment Strategy with a Steady state Genetic Algorithm

ABSTRACT

Full Name : Ahmed Ali Ahmed Baabood Bawazir

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Wireless Sensor Networks (WSNs) are expected to serve different types of environmental monitoring applications. Sensors in such applications have limited energy supply and processing power. They are also deployed in unattended areas. Randomly, deploying sensor nodes in the filed may generate an initial communication gap resulting in low energy and communication efficiencies. These gaps may still exist even when these sensor nodes are deployed in a structured manner. Similarly, deploying large number of nodes or using relay and cluster head nodes to improve communication efficiency could result in increasing the overall cost of the network with no guarantees on energy efficiency. Therefore, in order to achieve better communication and extend the lifetime of the network, nodes have to be deployed in a careful manner. Extending network lifetime while maximizing energy efficiency and minimizing network cost is a challenging task due to the conflicting nature of these objectives. It is even more challenging when nodes are deployed in 3-D dimensional space. In, this thesis, we propose a 3-D WSNs deployment based on heuristic optimization approach in order to achieve an approximate solution for a set of desired objectives; extending network lifetime, maximizing connectivity and reducing cost. Based on a two-layer hierarchical structure, which consists of sensor nodes, clusters heads and the base station, a genetic algorithm is used to optimize the positions (placement) of cluster heads in order to achieve the aforementioned objectives. We have proposed a multi-objective function to evaluate the generated solutions. In addition, a simulation evaluation of different deployment scenarios were carried out using MATLAB to assess the proposed scheme using Genetic Algorithm (GA) and Binary Particle Swarm Optimization (BPSO) then compare it with the non-optimal placement.

Keywords *Genetic Algorithm, Binary Particle Swarm Optimization, Multi-objective optimization, CHs placement, Connectivity, Lifetime, Cost*

ملخص الرسالة

الاسم الكامل: أحمد علي أحمد باعبود باوزير

عنوان الرسالة: التوزيع الامثل لشبكات الاستشعار اللاسلكية في بيئة ثلاثية الابعاد

التخصص: شبكات حاسوب

تاريخ الدرجة العلمية: ديسمبر 2018

من المتوقع أن يتم استخدام شبكات الاستشعار اللاسلكية (WSNs) مستقبلاً في العديد من التطبيقات المختلفة وفي بُنَى بيئية متعددة. ومما يعيب تلك المستشعرات في أي تطبيق واقعي، أنها تمتلك طاقة وقدرة محدودتين خصوصاً وأنها قد تُستخدم في مناطق غير مأهولة وصعبة الوصول، لذا فإن التوزيع العشوائي لتلك المستشعرات قد يسبب فجوة اتصال في منظومة الشبكة اللاسلكية المتواجدة فيها، مما يؤثر سلباً على كفاءة الاتصال وكفاءة الطاقة المستهلكة. حتى وإن تم توزيع المستشعرات في الشبكة بشكل هندسي منتظم، فإن الفجوة في الاتصال قد تظل موجودة. وبالمثل، فإن توزيع المستشعرات بأعداد كبيرة في الشبكة واستخدام نقاط تجميع رئيسية للاتصال (Cluster Head) من أجل تحسين كفاءة الاتصال، قد يزيد من التكلفة الإجمالية مع عدم ضمان كفاءة عالية في الطاقة. وبالتالي من أجل تحقيق اتصال ذا جودة أفضل وزيادة العمر الافتراضي للشبكة، فإنه يجب توزيع المستشعرات بطريقة مثلى .

يعتبر تمديد عمر الشبكة وزيادة كفاءة الطاقة وتقليل التكلفة الإجمالية أهداف مرجوة لكنها صعبة التحقيق عند التوزيع بسبب الطبيعة المتعارضة لكل منها. وتزداد صعوبة تحقيق هذه الأهداف إذا كان توزيع المستشعرات في فضاء ثلاثي الأبعاد .

تقدم هذه الرسالة دراسة لتوزيع مستشعرات الشبكات اللاسلكية في فضاء ثلاثي الأبعاد وفقاً لخوارزميات التحكم الذكية للوصول إلى التوزيع الأمثل واضعة في الحسبان الأهداف المنشودة ألا وهي تمديد عمر الشبكة، وتحقيق أقصى قدر من الاتصال وخفض التكلفة.

لقد تم إستخدام خوارزمية تحكم ذكية تعرف بخوارزمية التحسين الجيني (GA) وضع تركيب هرمي محسن يتكون من طبقتين; وهما طبقة المستشعرات اللاسلكية وطبقة نقاط التتبع والتجميع الرئيسية، حيث تقوم الخوارزمية باختيار

المواضع المثلى لكل من تلك النقاط في الشبكة اللاسلكية. وتقترح هذه الرسالة أيضاً معادلة تحسين متعدد الأهداف خاصة بالخوارزمية المستخدمة.

بالإضافة إلى ذلك، تعرض الرسالة نتائج محاكاة التوزيع باستخدام برنامج MATLAB وكذا مقارنة التوزيع الأمثل باستخدام خوارزمية التحسين الجيني بالتوزيع الغير العشوائي الغير محسّن، إضافة إلى المقارنة باستخدام خوارزمية أخرى وهي خوارزمية تحسين حركة الأسراب(PSO).

CHAPTER 1

INTRODUCTION

Basically, Wireless Sensor Networks (WSNs) consists of sensor nodes (SNs), which are deployed in a specific area called sensing area to measure or detect required physical phenomena and send all the collected data to a central source called base station (BS). Sensor nodes are small, cheap, low-power, and multifunctional sensing devices, in wireless sensor networks. Sensor nodes are used for sensing, computation, communication and operate in integrating manner to achieve their deployment objective. The base station is considered as an access point that allows the user to access the network data. It is usually located at a fixed position and has its own power supply.

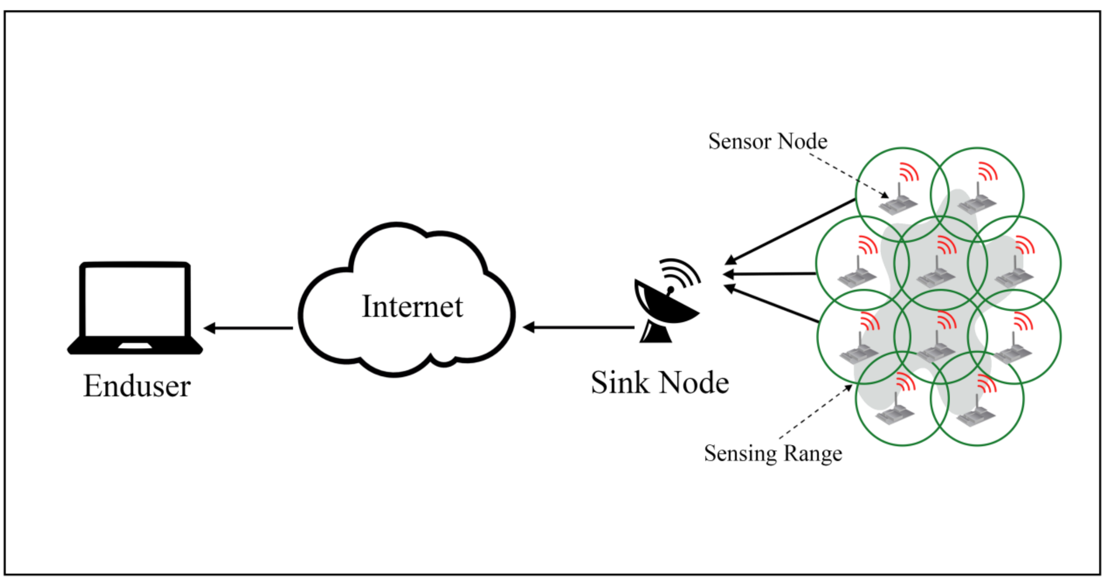

Figure 1: Wireless sensor Network Architecture

Figure 1 shows the architecture of the wireless sensor networks where the main components are the sensor nodes that may use to measure and monitor some physical phenomena in targeted area as shown in the figure. Sensor nodes usually deployed in the sensing area in order to achieve the sensing task accurately and efficiently. SNs collecting the data about the sensing area and send it to the sink node or base station periodically; either directly or via other nodes that follow routing path. On the other hand, the base station is responsible for processing and extracting the data that received from other nodes in the topology to make it readable and meaningful to the end user. In sensor nodes there are some limitations that restrict the functionality of sensor nodes such as:

- Limited transmission range: the communication unit of the sensor nodes has limited transmission range.

- Limited power supply: sensors are powered by tiny battery. In wireless sensor networks, charging or exchanging those batteries is not an easy task and considered as a costly process. Therefore, once the energy of the sensor nodes are completed, the sensor nodes will be out of service and will lost their functionality [1] [2].

To design wireless sensor network with such challenges, the main concerns is the energy management [3]. Deploying the sensor nodes with initial energy can allow the sensor nodes to work for a short and limited period especially if it is deployed in large area and the data transmitted over a long distance. Thus, an energy-aware design is directly related to the lifetime of the network.

Hierarchical Two-Tiered Wireless Sensor Networks

In this work, the network basically consists of several types of network devices; mainly sensor nodes, relay nodes and the base station. In this work, a two-layer hierarchical structure are considered. Figure 2 illustrates the network structure type.

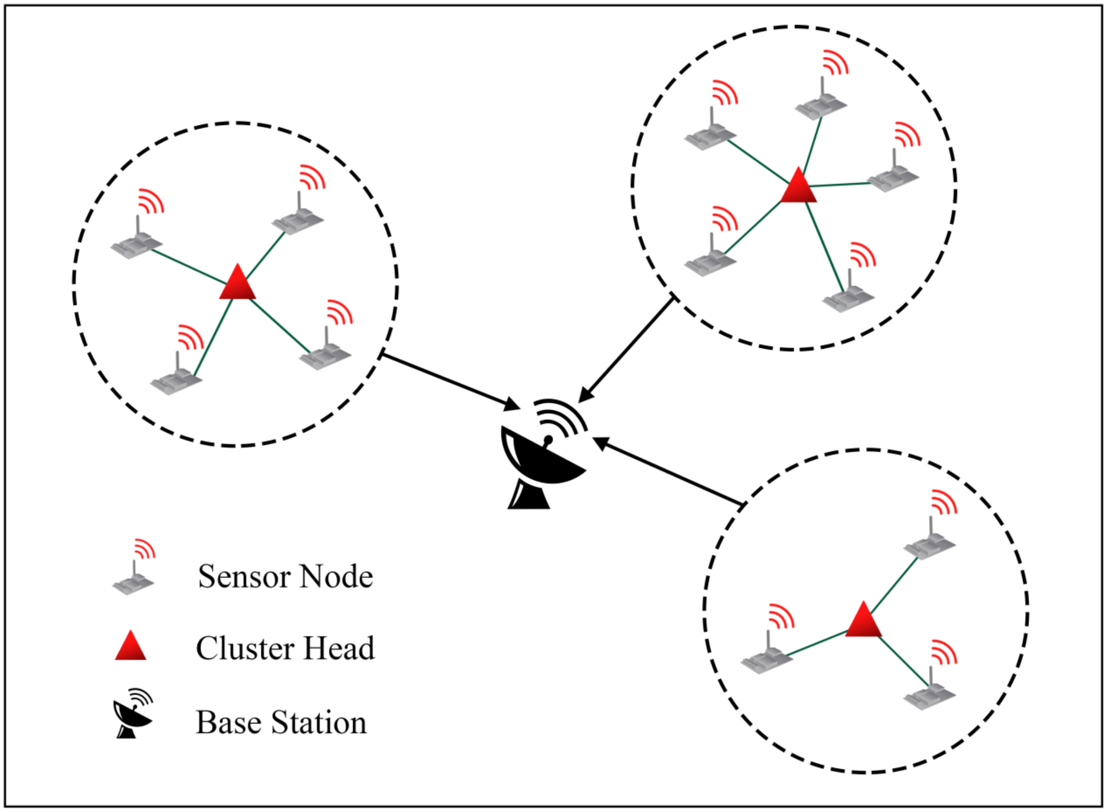

Figure 2: Hierarchical Two-Tiered Wireless Sensor Networks

The functionality of the devices which will be placed in the layers are:

- Sensor nodes: the nodes which are placed in the lower layer and responsible for sensing the targeted area and sending the collected data to cluster heads (CHs) in the upper layer.

- Cluster Heads (CHs): These nodes will be placed in the upper layer and they are responsible for collecting the data from the sensor nodes in the lower layer based on their locations and send it to the base station.

The lower layer compromises of sensor nodes. The transmission ranges of sensor nodes are fixed and limited, so they cannot handle the data exchange with CHs that are beyond their fixed range. The upper layer composes of cluster heads, and base station. The transmission range of the devices in this layer is enough. They have periodically communication with the base station to deliver the collected data from the lower layer [4].

1.1 Problem Statement

Basically, the main problem is defined to find an optimal or near optimal placement of sensors for an indoor and outdoor application in WSN that satisfies the desired application requirements such as maximizing the network lifetime, minimizing the cost, and achieving connectivity by using different types of devices (sensors) such as normal sensors and Cluster Heads (CHs). A cluster head is a more eligible node with significantly more energy reserve and large communication range than sensors which facilitates and accelerates the connectivity restoration among the disjoint segment.

The main objective is to determine the optimal locations and optimal number of cluster heads to maximize the network lifetime and achieve satisfied connectivity under specific application constraints such as batteries capacity, cost, maximum number of CHs, and limited communication range of SNs. In conventional WSN designs, the most salient performance metric is chosen as the optimization objective, while the remaining performance metrics are normally treated as constraints of the optimization problem [5].

There are some constrains of the network lifetime such as:

- Energy constraint: The total energy consumed by the nodes should be less than the initial energy of each node.
- Connectivity constraint: The sensor nodes in the network should relate to at least one relay node, the distance between the sensor nodes and the nearest relay node should be within the communication range of the nodes.

The number of cluster heads that are deployed in this work should not be exceeding the maximum cost provided by the decision maker.

1.2 Motivations

In two-layer wireless sensor networks, the first layer is assumed to has sensor nodes which have been uniformly deployed in the targeted area with a uniform random method to cover the application area. Cluster heads in the second layer are used as cluster heads to work as a connection link between the sensor nodes in the first layer and the base station in the second layer. The main issue is to find the optimal placement of the cluster heads in the second layer.

Meanwhile, in WSNs the deployed nodes have a limited communication range and limited energy, and they are required to monitor wide areas such as industrial fields, forests, mines and other applications. Therefore, deploying cluster heads (CHs) make the SNs spend their power in collecting data only. In wireless sensor networks applications, it is mandatory to minimize the amount of the energy consumed in collecting data and send it to the base station (BS). Hence, maximize the network lifetime. The redundancy and heterogeneity of the nodes (SNs, CHs, BS) in outdoor applications should be considered as a part of definition of the network lifetime.

This optimization problem turns out to be more challenging when applied in 3D environment. In outdoor or indoor applications, sensor nodes will be deployed not only in different horizontal planes, but also in different vertical altitudes such as on trees, soil surface, underground or industrial constructions. For instance, monitoring a phenomenon in trees environment (forest) or industrial constructions for a scientific researches purpose, needs sensors placement at various altitudes that may reach to some tens of meters.

The placement strategy is the main part in this work which is responsible for finding the optimal position of the cluster heads. The more optimal placement for cluster heads, the more constrains achieved. Every sensor node in the first layer should be covered by at least one cluster head. In other words, there will be at least one cluster head in the transmission range of each sensor node in the lower layer. The consumption energy of the nodes should be minimized as much as possible to extend the lifetime of the whole wireless sensor network. The mentioned constrains should be achieved with minimum number of cluster heads needed.

A successful and widely used placement strategy in 3D space is the grid-based deployment [6]. As an alternative way for finding optimal node locations in the large 3D space. This deployment strategy looks for the optimal locations within specific number of grid vertices. Consequently, the deployed CHs will be located at these vertices to focus on the fundamental properties of the WSNs such as connectivity, energy consumptions, and cost. hence, there are many advantages of grid-based deployment. In grid-based deployment we can exclude the impossible positions to deploy nodes on. The grid-based deployment also shows the routing paths from any node at any vertex to any other vertex (node) in the same graph. hence, guarantee the connectivity between nodes.

1.3 Thesis Objectives

Our research objectives are focusing mainly on the optimization of the wireless sensor networks deployment for outdoor applications, through deploying two types of sensors on grid structure. Number of SNs and cluster heads (CHs) are deployed to ensure the connectivity between all the SNs with the BS in the network. In other scenarios, the second stage of the CHs that responsible of relaying the data between the cluster heads and the base station are deployed through different paths in the grid, to optimize the objectives of the WSN deployment primarily by maximizing the connectivity, increased the lifetime, and minimizing the deployment cost as well. We propose a novel deployment approach to deploy the sensor nodes on any grid model. The main objectives of this work are stated as follows:

1. Review the state-of-the-art in wireless sensor networks placement and nodes deployment schemes in these networks.

2. Propose sensor deployment solution that will meet application requirements such as guarantee the required connectivity, maximize the lifetime, and minimize the cost with constrains on the implementation cost, and battery capacity.

3. Implement and evaluate the proposed solution using a properly selected simulation tool.

4. Compare the performance of the proposed solution with some other previous approaches.

1.4 Thesis Structure

The thesis is comprised of five chapters. A brief summary of each chapter is illustrated here.

- **Chapter 1** presents a background overview of the basic idea of this work and states the general background of WSNs in last years. Additionally, the basic objectives and the scope of the study have briefly discussed along with the thesis outline.
- **Chapter 2** presents the literature review from previous research about placement problem in WSNs, and the main challenges of the WSNs that we tried to overcome in this work.
- **Chapter 3** addresses the problem formulation; covers the developed mathematical model for all components includes energy, network, communication models, and other components specifications. This chapter also introduces the optimization process in detail and present the heuristic technique that used in this work. It gives a comprehensive explanation of optimizing the CHs placement by minimizing the number of CHs while achieving full connectivity and maximizing the network lifetime. The simulation scenarios that followed in this work are also explained.

- **Chapter 4** discusses and compares the results of the simulation work, illustrates the significant outcomes of this thesis and concludes by offering several recommendations for further work.
- **Chapter 5** illustrates the significant outcomes of this thesis and conclude by offering several recommendations for further work.

CHAPTER 2

LITERATURE REVIEW

Deployment planning is the utmost importance in the context of WSNs as it decides the available resources and their configuration for system setup. This in turn plays a major role in the performance of wireless sensor networks. A lot of research has been conducted to improve and develop the performance of WSNs through improving the data routing and enhance the Medium Access Control (MAC) protocols [7]. However, despite proposed good routing protocols of the WSNs, the performance of the WSNs still cannot achieve the targeted performance level unless it has been properly installed in advance. In simple words, if the number of deployed devices is insufficient or there is a design shortage caused by ineffective deployment plan, the connectivity between the network nodes and the nodes lifetime will be decreased.

Accordingly, recent approaches are focusing on optimizing the network deployment strategies in order to enhance the network performance. Different WSNs properties considered as deployment objectives and constrains have led to rich research field. Depending on the classification presented in [5], we categorized the approaches which have been done in the literature into two groups; non-deterministic deployment (random) and deterministic deployment (Grid-based). In the first group, the nodes are deployed randomly in the targeted area and then managed in an Ad Hoc manner. On the other hand, in deterministic deployment, the nodes are deployed in specific places in the grid called grid vertices. A number of the approaches that have been conducted in this filed are presented below.

Extending to the above mentioned challenges and properties of the WSNs, we will discuss the most significant properties in the wireless sensor deployment strategies, such as network lifetime, connectivity, coverage. In general, the proposed solutions which are presented to optimize the placement issue are connected with each other. For example, if we decrease the distance between the connected nodes this will lead to maximize the connectivity between nodes and decreases the energy consumed during the transmission and receiving process at the same time. On the other, some solutions can improve and tackle one of the WSNs issues while neglect the other properties.

2.1 Connectivity

Connectivity is one of the main challenges in the WSNs that have addressed in the literature. Connectivity is defined as the ability of the network nodes to stay connected to the BS earthier through one hop or multi-hop communication. Authors in [8] presented an approach that enhanced the algorithm for deployment range-free localization in three-dimensional WSN called Genetic Algorithm Distance Vector Hop (GADV-Hop). The main objectives are to reduce the distance between the targeted nodes and the anchor nodes by minimize the number of hops. Based on that find, the optimal hop size of the anchor nodes reduces the localization error. The nodes are deployed randomly and the nodes that localized at the required coordinates promoted to be anchor nodes and that leads to increase the localization accuracy and coverage accuracy. In [9], authors enhanced their work based on Coverage-Preserving Clustering Protocol (CPCP) with homogenous nodes. The proposed Non-dominated Sorting Genetic Algorithm- Coverage-aware Clustering Protocol (NSGA-CCP) and Multi-Objective Evolutionary Algorithm Decomposition-Coverage-aware Clustering Protocol (MOEAD-CCP) were implemented by dividing the field into M number of virtual cubes and check each cube by calculating the number of sensors. The sensors monitor and cover the cube to check the percentage of the active nodes that are connected and covered the targeted area. Another contribution in [10] has been proposed by using weighted relay node in a single-tire WSNs architecture. Heterogeneous sensor nodes was used with different communication ranges, relay nodes have larger sensing range than sensor nodes. The terrain has a dedicated place for the base station (BS) and set of points for the sensor nodes and set of points for relay nodes. The connectivity based in this approach is the Euclidean distance between the nodes, the distance between the nodes should be within the communication range to assure that the connectivity between them is achieved. The authors present the results by built a full connected WSN with minimum cost by calculating the weights of the relay nodes as the network cost.

The work in [11] deployed two phases of RNs to overcome some of the WSNs issues and maximize the network connectivity as one of their main objectives. The RNs deployed in dedicated positions in grid vertices based on their communication ranges. The connectivity between the nodes can be calculated by using some mathematical formulas which gave probability of successful communication. The probability of the communication should exceed the threshold, and that threshold specifies the maximum distance between any two nodes communicate directly. Authors in [12] proposed a new formulation of k-connected relay node localization issue, their approach have been built base on two different algorithms; GA and greedy approach. The main objective in this work is to cover all the target area with sensor nodes while all the sensor nodes must be connected to the backbone network. Based on the results they conclude that GA achieves k-connectivity better than greedy deployment strategy. In addition, if the candidate locations are prepositioned, an optimal number of relay nodes can harvest energy that helps them to live and be able to achieve connectivity and survivability in the network [13]. Even though there is an interesting in using the algorithm that is capable to detect and recover the connectivity and partitioning of the network by utilizing mobility relay nodes, however, this type of approaches includes mobile robots and further electronic circuitry, which could make the cost ineffectual to execute especially in rough environment [14].

However, placing nodes without considering grid connectivity properties could affect the solution through chose the properly nodes that should to be moved to the right direction of that movement [15].In [16], the work focused in RNs placement in multi-hop scenario. In their approach, they optimized the network connectivity and throughput with a two-step procedure which are initial distribution and solution selection along with third step by using PSO algorithm. The main difference compared to our work is that our work focuses in optimizing the network lifetime with constrains of network connectivity and cost.

2.2 Lifetime

Lifetime is one of the most significant issues in the WSNs. Because the deployed nodes are energy constrained, and the networks in some applications required to have a long lifetime that may reached to a number of years[17][18].

Knowing the lifetime of deployed nodes is very important for the purpose of recharging or placement especially in rough outdoor. Accordingly, the accuracy of the lifetime prediction in the early stage of the deployment design is highly recommended [11]. The lifetime definition in the literature is classified into two types: node lifetime prediction and network lifetime prediction. Node lifetime can be measured in different methods. The lifetime can be measured based on the number of rounds which determines when the data should be collected. It can be also measured based on the total time that node was active before it is dead. In other way, it can be calculated based on the total traffic size of the node before its energy is consumed.

Basically, energy in WSNs is consumed in three main domains: Sensing, communication, and data processing. Due to the fact that the main consumer of the nodes is the communication, many works in the literature focused on proposing energy model that measures the energy of transmitting and receiving data in the network. There are different definitions of the network lifetime in the literature. In [19] the definition of the network lifetime stated as "it is the time until the first node death occurs". Such a definition may not be efficient if we are monitoring some phenomena, for instance, if the network is monitoring a temperature or weather humidity for a specific environment, hence we cannot depend on the previous definition as long as we can still get information from other alive nodes in the same filed. Other works define the network lifetime as "it is the time until the last node death occurs", which may not be suitable as well. Therefore, both of the above definitions are impractical for outdoor monitoring applications. Another method to define the network lifetime is presented as the time until percentage of the deployed nodes still alive [19].

In [20], Roselin and et al presented an algorithm called Energy-Efficient Connected Coverage (EECC), which targeted to maximizing the WSNs lifetime by preserving Quality of Service (QoS) factors like coverage, connectivity, and residual energy while constructing non-disjoint connected cover. The algorithm also saves the network energy by minimizing the network data traffic through preventing the redundant coverage at CPs.

In [21-23], the objectives mainly focused on optimizing specific objectives by placing the sensor nodes optimally along with constrains to maximize the network lifetime. Heuristic-based RN deployment is proposed in order to improving the network lifetime by using minimum number of RNs along with achieving required connectivity. In [24], the authors introduce a method for RNs placement in 3D industrial environment with obstacles to maximize the network coverage and lifetime. Two particle swarm optimizers are utilized; which are cooperative coevolutionary particle swarm optimization 2 (CCPSO2) and the comprehensive learning particle swarm optimizer (CLPSO) to achieve network connectivity and prolong network lifetime. In addition, distributed parallelism based on message passing interface (MPI) where used to minimize the computation time through dividing the 3D space.

In [15], Turjman and et al proposed a 3D grid-based deployment model of heterogeneous WSNs consists of SNs, RNs, and mobile RNs. They aim to optimize the network lifetime, fault tolerance, and cost with an approach called Mixed Integer Linear Program (MILP). The work expects maximum network lifetime with no node or link failures in a rough outdoor environment applications. A 3D Genetic Algorithm Distance Vector Hop (GAIDV) was proposed in [8] to optimize the network coverage and lifetime with best positioning of the targeted nodes. The work approach focuses on minimizing the number and the size of hops between the sensor nodes and BS. In [25], two technique based on particle swarm optimization (PSO), dimensionality and hybrid dimensionality PSO were utilized to minimize the computational power and reduce the error rate in location estimation by calculating the received signal strength (RSS). This leads to solve the disjunctive between received signal strength and distance estimates. In [26] the authors aimed to optimize the energy consumption with constraints of achieving full network connectivity, and clustering coverage in smart buildings. They proposed a new system called Building Management System (BMS) that is responsible for managing the building components. The system minimizes the amount of the consumed energy by the users in that building taking in consideration achieving good level of comfortable in automation and also achieving high efficiency way using human behavioral models.

In [9], the authors proposed a protocol that focus on optimizing the coverage and clustering of sensors while minimize the energy consumption in a 3D environment. A Coverage-Preserving Clustering Protocol (CPCP), homogenous nodes were used to achieve the targeted objectives. The proposed NSGA-CCP and MOEAD-CCP were implemented by dividing the field into M number of virtual cubes and check each cube by calculating the number of sensors that monitor and cover the cube. Then find the total number of active sensors and calculate the energy consumed per node and the number of packet delivery rate. The work concludes that NSGA-CCP outperforms the other approaches that have been proposed before.

2.3 Deployment Strategies

In wireless sensor networks deployment, nodes can be deployed randomly in the targeted area to reduce the deployment cost. The nodes can be deployed based on weighted deployment in order to minimize the cost by minimizing the total weight of the points where the RNs are deployed [10]. In [27], the authors formulated the placement problem in a form that network connectivity and cost where constrained in a desired range simultaneously. The same authors Artificial bee colony algorithm (ABC) to optimize the efficient deployment of the relay nodes deployment and maximize the network lifetime with constrains of connectivity and cost. Forthurmore in [28] they also used two evolutionary techniques called Deferential Evolution (DE) and Gravitational search algorithm (GSA) to compare them with their old approach.

In [29] the authors proposed a clustering algorithm called Distributed Energy Efficient Heterogeneous Clustering (DEEHC) that selectes the cluster heads in the network based on their remaining energy. They also presented a k-Vertex Disjoint Path Routing (kVDPR) algorithm that allows cluster heads to find the disjoint nodes in that clusters and relay their collected data to the base station. We can conclude that the main objectives from the aforementioned approaches are maximizing the connectivity in the network and increase the network performance while take care of maximizing the network lifetime.

Table 1 shows a simple comparison among number of the presented works that focuses on relay nodes placement in 3D model.

Table 1: Comparison of Deployment Strategies

Year	Algorithm	Type of nodes	Topology	Environment	Objectives	Reference
2009	MOGA	Homogenous	flat	3D	Maximizing coverage and maximize the accuracy of detection level	[30]
2012	WTDS2-SGA	Homogenous	Flat	3D terrain	Maximize quality of coverage and minimize the consumed power.	[31]
2013	O3DwLC	Heterogeneous	Hierarchical	3D	Maximize connectivity , lifetime and minimize cost	[11]
2013	MOEA/D-DE	Homogenous	Tree structure	3D	Maximize the coverage, lifetime, and connectivity with constrains on cost.	[32]
2014	(EECPS)	Homogenous	Hierarchical	3D bridge	Extend the network lifetime	[33]

2014	VLGA	Heterogeneous	Hierarchical	2D	Maximize the coverage and lifetime while minimize the cost.	[34]
2015	3MOEA MO-GSA NSGA-II SPEA2	Heterogeneous	Hierarchical	3D	Maximize the coverage with constraint in cost.	[23]
2015	PSO	Homogenous	flat	3D	Maximize the coverage over the terrain.	[35]
2016	ABC	Heterogeneous	Hierarchical	3D	Maximize the lifetime with constrains in cost.	[28]
2016	Greedy Algorithm	Heterogeneous	Hierarchical	2D	Maximize the coverage with k-connectivity with constrains on cost.	[12]
2017	MODS	Homogeneous	flat	2D	Deploy sensor nodes optimally with constrains on cost, coverage, and connectivity.	[36]

2018	DPCCMOLSEA	Heterogeneous	Hierarchical	3D	Maximize the lifetime and reliability of industrial Wireless sensor networks.	[37]
2018	CCPSO2 CLPSO	Heterogeneous	Hierarchical	3D	Maximize coverage and lifetime with reliability.	[24]
2018	DEA & GSA	Heterogeneous	Hierarchical	3D	Maximize the network lifetime and connectivity, with constrains in cost.	[27]

CHAPTER 3

3D Deployment Model

3.1 Network Model

In this work, the network is basically consists of several types of network devices which are sensor nodes, cluster heads and the base station. As mentioned earlier, a two-layer hierarchical structure is considered to address the heterogeneous nature of wireless sensor network as shown in Figure 3 and Figure 4. The functionality of the devices that chosen for this purpose is stated as follows:

1- Sensor nodes: the nodes that are placed in the lower layer of the network and responsible for sensing and collecting data from the targeted area and send it to Cluster Heads (CHs) in the upper layer.

2- Cluster Heads: These nodes placed in the upper layer and they are more powerful compared with the sensor nodes. Cluster heads (CHs) are responsible for aggregating the collected data from the sensor nodes in the lower layer based on their locations, and relaying collected data from their member nodes to the base station.

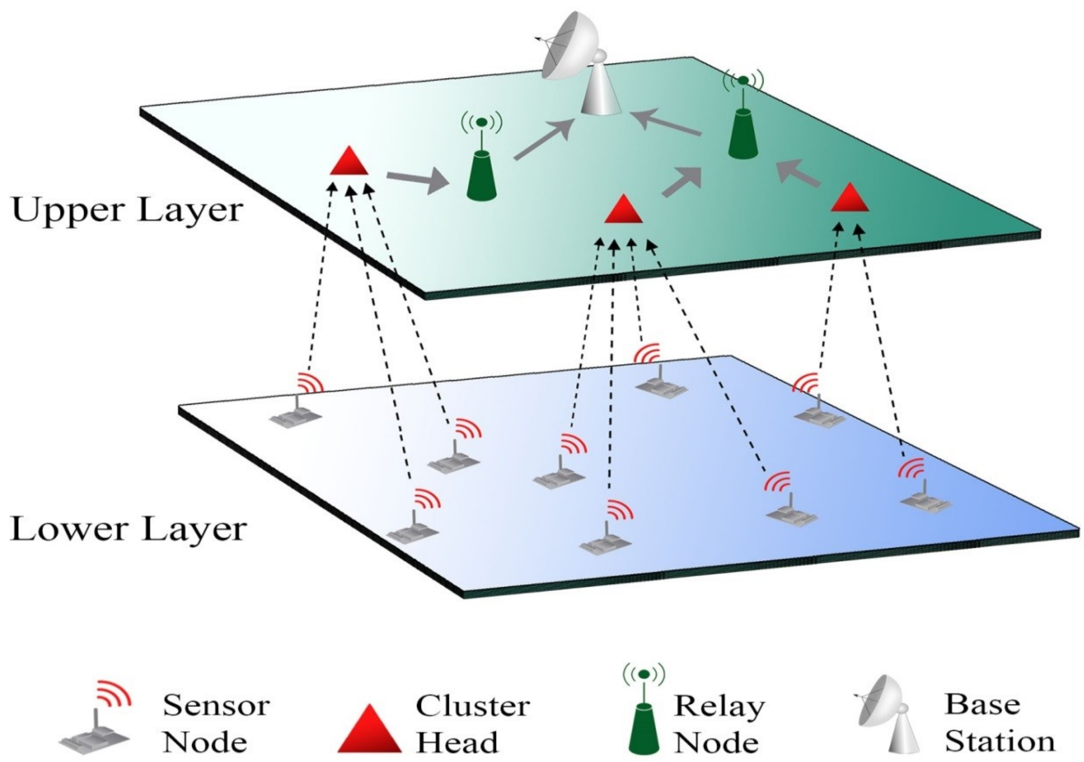

Figure 3: Network Model Architecture

The transmission ranges of sensor nodes that form the lower layer are fixed and limited so they cannot handle the data exchange with CHs that are beyond their limits, hence, the energy consumed in the transmission process can be reduced. The upper layer composes of cluster heads and base station. The transmission range of the devices in this layer is better, and they have periodically communication with the base station to deliver the collected data from the lower layer [1]. The structure of the upper layer is modeled as a graph $G = (V, E)$ where $V = \{n\_0, n\_1, n\_2, \ldots, n\_m\}$ which is the set of the candidate grid vertices (positions) and E is the set of the graph G edges.

The energy given to the sensor nodes is assumed to be enough to perform the sensing tasks meanwhile fixed and large (relative to the network lifetime) power supply is given to the cluster heads in the deployed WSN.

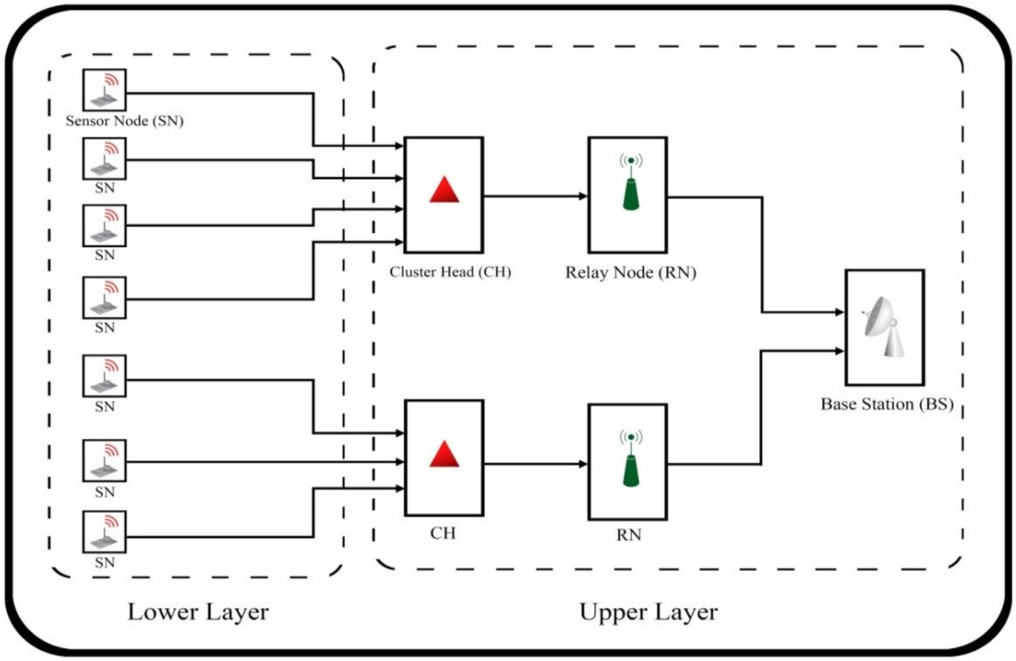

Figure 4: Network Model Diagram

3.1.1 Assumptions

The network in this work consists of sensor nodes (SNs), cluster heads (CHs), and base station (BS), formed as Two-Tire hierarchical architecture with heterogeneous network as described in Figure 3 and Figure 4. We assumed that SNs in the network has equal initial energy of (0.5 Joule) and cluster heads have (20 Joule) as well. Sensor nodes in the lower layer are assumed to be responsible only for data sensing and transmitting with short rang. The other nodes in the upper layer such as CHs and BS have stronger transceiver circuitry that has the ability to transmit and receive with long rang. There are another assumptions in this work stated as follows:

- All nodes are static.

- A periodic data gathering application where data is collected and is transmitted by each sensor to its cluster head (CH) and from the CH to BS.
- The communication in this network is multi-hop communication.
- The transmission range of all sensor nodes is same.
- The transmission range of all CH is same.
- The MAC layer with no collisions and retransmissions.

3.2 Network Communication Model

For the communication model, if the communications range of sensor node i is equal or higher than the Euclidean distance between sensor node i and point j, the connectivity is established. Otherwise, these nodes cannot communicate with each other. Based on one of the main objectives of this work are designed to achieve the desired connectivity and lifetime with minimum number of CHs. The CH at position j with coordinates (x,y,z) is assumed to be one of the cluster heads that collect the data from sensor nodes if it is selected as a CH by at least one sensor node in position i with coordinates (x,y,z). The following equation is used to calculate the Euclidean distance between the nodes in the network.

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2} \tag{1}$$

Where x,y, and z are the coordinates of the nodes location.

By counting the number of CHs in the topology we can calculate the cost of the network which considered as one of the objectives of this work. Based on this, we can also obtain the percentage of the sensor nodes that has CHs which is one of the objectives of this work.

Based on the main objectives of this work, the desired connectivity and lifetime with minimum number of CHs will be achieved. The sensor node *i* can communicate with CH *j*, only if the distance between the sensor node at position *i* and the CH at position *j* is less or equal to transmission range of the sensor node *i*, in other words, if the location of the CH *j* within the transmission range of sensor node *i* the communication will be established. Figure 5 shows how sensor nodes covered by CHs.

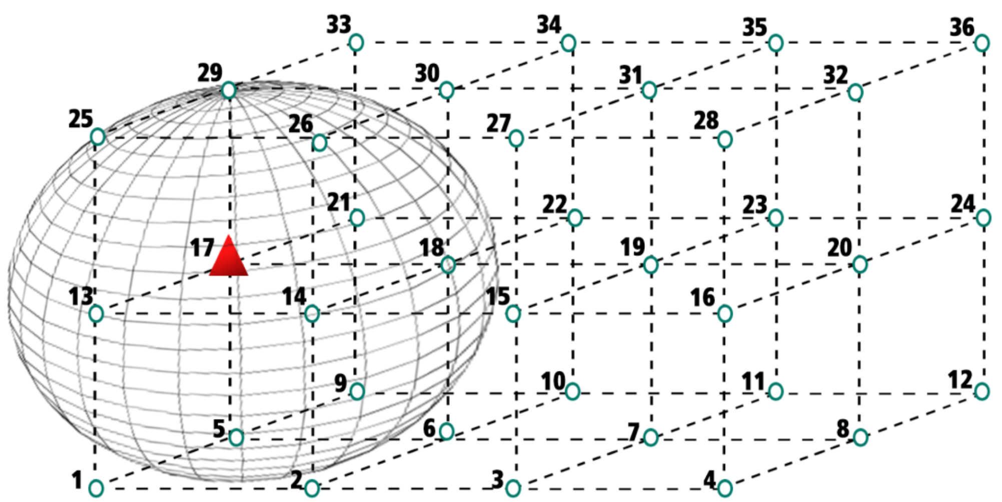

Figure 5: Sensing Range of CHs

Furthermore, if the CH at position *j* is selected as a cluster head by either one or more sensor nodes, then it must be added to the number of needed CHs to achieve the work objectives. Contrariwise, if the CH at position *j* is not selected as a cluster head by either one sensor node in the network, typically, it will not be counted as a CH in the network. Moreover, every sensor node in the network should be under only one cluster head. In another concept, each sensor node in the network can transmit its data to only one CH in that network. Overall, we can consider the above definitions as constraints that must be taken into consideration in this topology.

3.3 Network Lifetime Model

The definition of network lifetime is application dependent. One possible definition is the time until the first node dies. Another definitions is the time until the network is partitioning into several partitions or the time until a specific percentage ($x\%$) of nodes die [19]. The latter is the definition we have adopted in this work.

In fact, nodes in WSNs consume energy in three main processes: collecting data about the environment which called sensing process, sending and receiving data between the nodes which called communication process, analyzing and extracting the data which called data processing. In reality most of the power consumed in wireless sensor networks is consumed by the communication process. Therefore, the majority of the related work in literature has focus on proposing energy consumption models for receiving and transmitting wireless signals.

In this work, we will select the general energy consumption model proposed in [38] and [5]. In many outdoor applications such as environmental monitoring, sensing and processing the data into packets is lower in cost than transmission and receiving those packets [39]. Consequently, the energy which will be used in communication model will be taken into consideration.

In this work, we will use the lifetime definition which is the time from deploying the sensors until the percentage of live nodes reached a specific threshold. Using this lifetime definition, we benefit from device localization to keep the network operate as long as the percentage of cluster heads that providing the collected data are still alive.

In order to translate the aforementioned lifetime definition, we assume the network lifetime is divided into equal time periods called rounds that a WSN can stay operate. The definition of the round (R_time) is the total time that each sensor node can transmit at least once to the base station without cutoff.

3.3.1 Transmitting Energy

The transmission energy is the amount of energy which required by any node wants to send data to any other node in the network. The transmission energy is depending on some metrics such as the data packet length and the distance between the nodes. If one or both of the above metrics is increased this will lead to increase the consumption of the transmission energy.

The energy consumed by the transmitter (E_{trns})

$$E\_trns = L * P\_tx \qquad (2)$$

where P is transmiter power which can be defind by $P_{tx} = (\epsilon_1 + \epsilon_2 d^{\gamma})$

Where ϵ_1 and $\epsilon_2$are a designed hardware parameters of a particular transceiver [2], and L is the length of the packet, d is the Euclidean distance between the transmitter and receiver, (γ) is the path loss exponent (the difference between the transmitted and received power of the signal) calculated based on experimental data.

3.3.2 Receiving Energy

The receiving energy is the amount of energy consumed by the nodes when receiving data packets from other nodes. The energy consumed by the receiver (E_{recv}) is calculated by:

$$E_{\mathrm{recv}} = L\beta \tag{3}$$

Where β is designed hardware parameter of a particular transceiver [2].

The remaining energy E_r is calculated by:

$$E_r = E_i - A_{\mathrm{trns}} * E_{\mathrm{trns}} - A_{\mathrm{recv}} * E_{\mathrm{recv}} - A_{rely} * E_{rely} \tag{4}$$

Where E_i is the initial energy of each node, A_{trns} is the arrival rate of the transmitted packets, E_{trns} is the energy per unit time consumed by each node for a single packet transmission, A_{recv} is the arrival rate of the received packets, E_{recv} is the energy per unit time consumed by each node for a single packet receiving, A_{rely} is the arrival rate of the relayed packets, and $E_{rely}$is the energy per unit time consumed by each node for relaying a single packet.

The energy model that is used in this work is considering the impact of the traffic processed at the CH due to their neighboring to the sink nodes. The total energy E_{Total} consumed by a node is thus given by:

$$E_{Total} = A_{\mathrm{trns}}\, LP + A_{\mathrm{recv}}\, L\beta + A_{rely} * E_{rely} \tag{5}$$

3.4 Network Cost Model

The cost of the devices used in environmental applications depends on its functionalities and hardware components. The more functionality device has, the more expensive will be. In this work, cluster heads are considering as an expensive devices due to their functionality such as long communication range, significantly more energy reserve. In other words, cluster heads are assumed to have more functionality and dominate other devices in terms of transmission range. Consequently, the cost is modeled in this work as the number of cluster heads deployed in the work area.

3.5 Design of Objective Function

The main purpose of this work is to find an optimal or near optimal placement of CHs for an application in the vertices of grid topology as shown in figure 5. The objective is to maximize the network lifetime through minimizing the total energy consumption that are mainly caused be data exchanges between nodes through communication process. As we mentioned earlier, the literature presents that consumed energy affected by the Euclidean distance between the communicating nodes. Therefore, three main objectives are taken into consideration.

1. Maximize the network lifetime

   We define the network lifetime as the time from deploying the sensors until (*20%*) of sensor nodes die. Using this lifetime definition, we benefit from device localization to keep the network operate as long as the percentage of sensor nodes that providing the collected data are still alive. We aim to make the sensor nodes stay alive as much as possible and this can be identified through the round of data cycle by counting the number of rounds that sensor sends data in.

$$Net_{lifetime} = \sum_{i=1}^{n}\sum_{j=1}^{k} E_r \tag{6}$$

Where E_r is the nodes remaining energy

2. Maximize the network connectivity

The network connectivity in our proposed approach is considered making every sensor node in the first layer connected with at least one CH in the upper layer. As described previously in the communication model, any sensor node covered by the communication range of the cluster head considered as member of that cluster, the sensor nodes at the same time should have only one cluster head so every sensor nodes will calculate the distance between him and the CHs that located within his communication range and then will chose only one of them as a cluster head based on the minimum distance between them. The connectivity is calculated by sum the children of all CHs in the network, in other words, the connectivity is the percentage of the sensor nodes in the network that has cluster heads. Thus, we can say that we achieved 100% connectivity if the total number of children of the CHs in the network is equal to the total number of sensor nodes that deployed in the topology.

$$Net_{conectivity} = \sum_{i=1}^{k} CH_{child} \tag{7}$$

Where CH_{child} is the member node of cluster.

3. Minimize the number of CHs in the network

The network cost in this work as mentioned previously is calculated by counting the number of CHs that will be deployed in the network.

$$Net_{cost} = \sum_{i=1}^{k} K_i \tag{8}$$

Where K_i is the total number of CHs in the network.

All these three objectives should be formulated in one integrated formula. However, data and the results for each of them have different values and units; this means we should convert these three objective functions into on multi-objective function. To come up with one multi-objective function that has all the three objectives, we first normalize the values of all three objectives and make it between *0* and *1*. Then give weights w_i to each objective based on the decision maker and objective's priority.

$$\text{Minimze.}\ (\text{w1} * Net_{cost}) - (\text{w2} * \ Net_{lifetime}) - (\text{w3} * Net_{conectivity}) \tag{9}$$

The sum of all weights must be equal 1, so w_1+w_2+w_3=1.

3.6 The Proposed approach

Figure 6 depicts the 3D grid model that assumed in this work, where the distance between the nodes (grid edges) is assumed to be equal to the sensor nodes transmission range. In this cubic grid model, the Sensor Nodes (SNs) are placed randomly in the sensing area to get the collected data more accurately and cover almost all the area. Cluster Heads (CHs) are then placed on the most suitable vertices of the grid; which can cover the largest number of sensor nodes that distributed in the lower layer around the cluster heads. The base station is placed in a fixed position which is in the middle of the grid topology in our case.

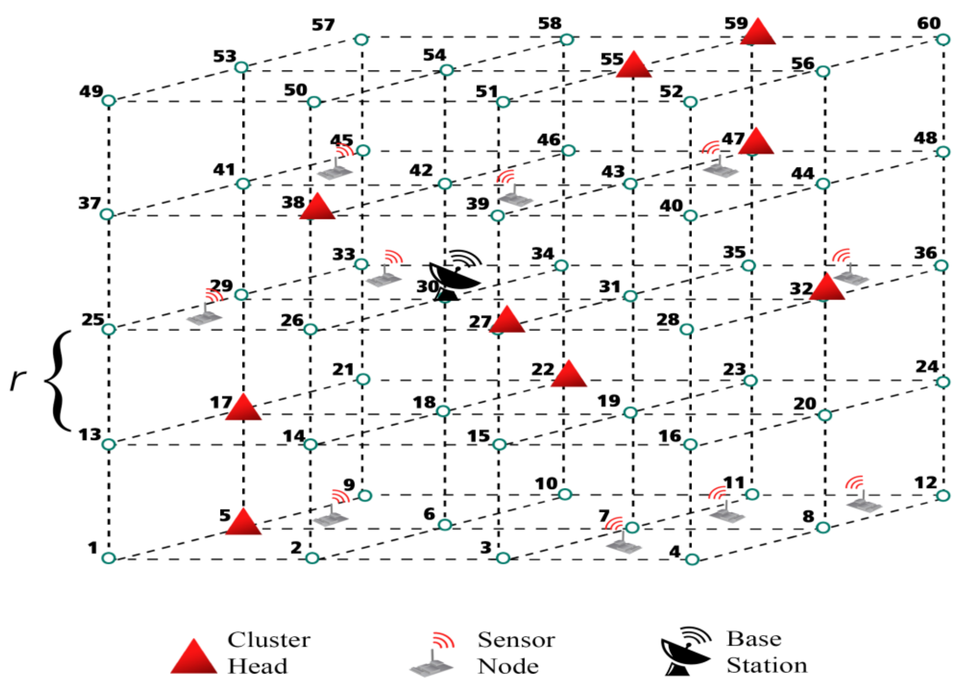

Figure 6: 3D Grid Model

3.6.1 Simulation Scenario

All simulation scenarios have been done using MATLAB, we simulate WSNs having hierarchal architecture that deployed in the 3D grid topology. We deployed a number of sensor nodes randomly with uniform distribution on the 3D grid and each SN has known location coordinates (*x,y,z*). After that we deploy a random number of CHs on the grid vertices and each CH should be placed in one vertex and each vertex in the grid has a known coordinates. The BS located in a fixed place for all scenarios which is the middle of the 3D grid. After deploying all nodes, the approach first calculate the Euclidean distance between the sensor nodes and the CH by using formula in (4), and any CH that located in the communication range of the SN will be a cluster head for that sensor node. In other words, every SN will search if there is any CH located within its transmission range. If so, it will chose it as a cluster head and it will be child for that cluster heads. In addition to that, the approach also calculates the distance between every CH in the topology and the BS. Thus, every sensor node in the network must know its CH, and every cluster head in the network must know its children. As a result of that, we can calculate the percentage of the sensor nodes that are connected to the cluster heads and calculate the connectivity quality in the network. Figure 7 illustrates the procedure of scenario.

In this scenario, each CH in the network can directly communicate with BS and send the data received from its children (SNs) to the BS periodically. Based on our model constrains, if there is a CH that has no children (SNs) it will not be considered as a CH node and will not send data to the BS. The transmission range of the SNs is equal to the length of the edge between any two vertices in the grid. Hence, the sensor nodes that located in any cube of the grid have four vertices that can send to. The CH should be located at any one of these four vertices to cover that SN as well. For more illustration, Figure 5 illustrates this process. On the other hand, the transmission range of the CHs is about four times larger than that in sensor nodes, so CH can transmit the data directly to the BS in the middle of the grid. The network cost in this scenario is calculated based on the number of CHs that have been used in the network to achieve the required objectives.

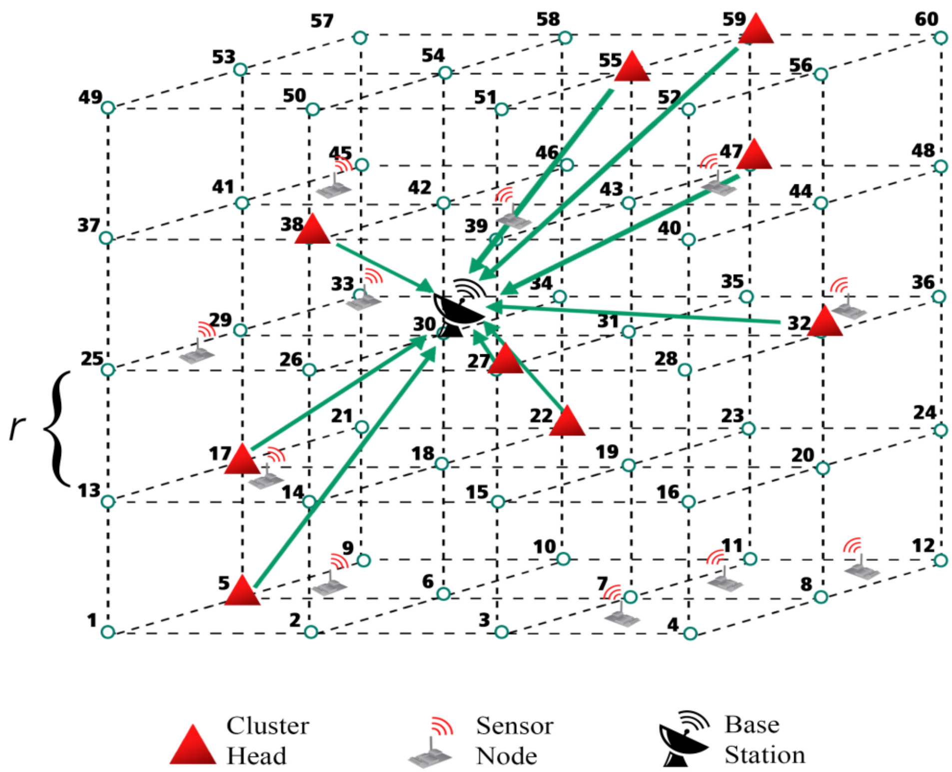

Figure 7: Simulation Scenario Architecture

3.7 Optimization Techniques

To maximizing the network lifetime and connectivity while minimizing the cost of the deployment by the number of CHs, two intelligent optimization techniques conducted to solve the problem; one of them is the genetic algorithm (GA) technique, and the other one is particle swarm optimization (PSO) technique.

3.7.1 Genetic Algorithm Optimization

Genetic Algorithm (GA) is a stochastic search technique that mimics the natural selection and evolution process proposed by Charles Darwin 1858. GA has been applied to majority of the optimization problems. Basically, GA modeled depending on the natural selection process in nature [38]. At the beginning, initial populations are randomly generated from a solution space. These populations (chromosomes) are generated to be developed towards the optimal solution via good generations through number of steps such as selection, crossover, and mutation processes. The GA is an iterative technique which responsible for generating new solutions (chromosomes) in every iteration. Each chromosome from the initial population is evaluated by calculating the fitness function. Then the fittest solutions (chromosomes) have big chance to be selected to share in generating the new generation at each step of the GA operations to improve the solutions quality. Figure 8 shows a simple flowchart of GA process.

The mechanism of GA is explained as follows:

First, the GA generates a population on (n) chromosomes along with their fitness value. Parents are chosen to mate based on their fitness values, and generating children via reproductive plane. Thus, as mentioned earlier the chromosomes who are more fit, have a good opportunity to reproduce. Hence, the generated children inherit features from their parents. As parents mated and generated children, matrix should be built for the new children since the population size is fixed. The worst generated solution will be replaced by the new good solutions. Consequently, it is expected that over sequential generation, a good solution will be saved while the solutions with least fit is considered as bad solutions and will be deleted.

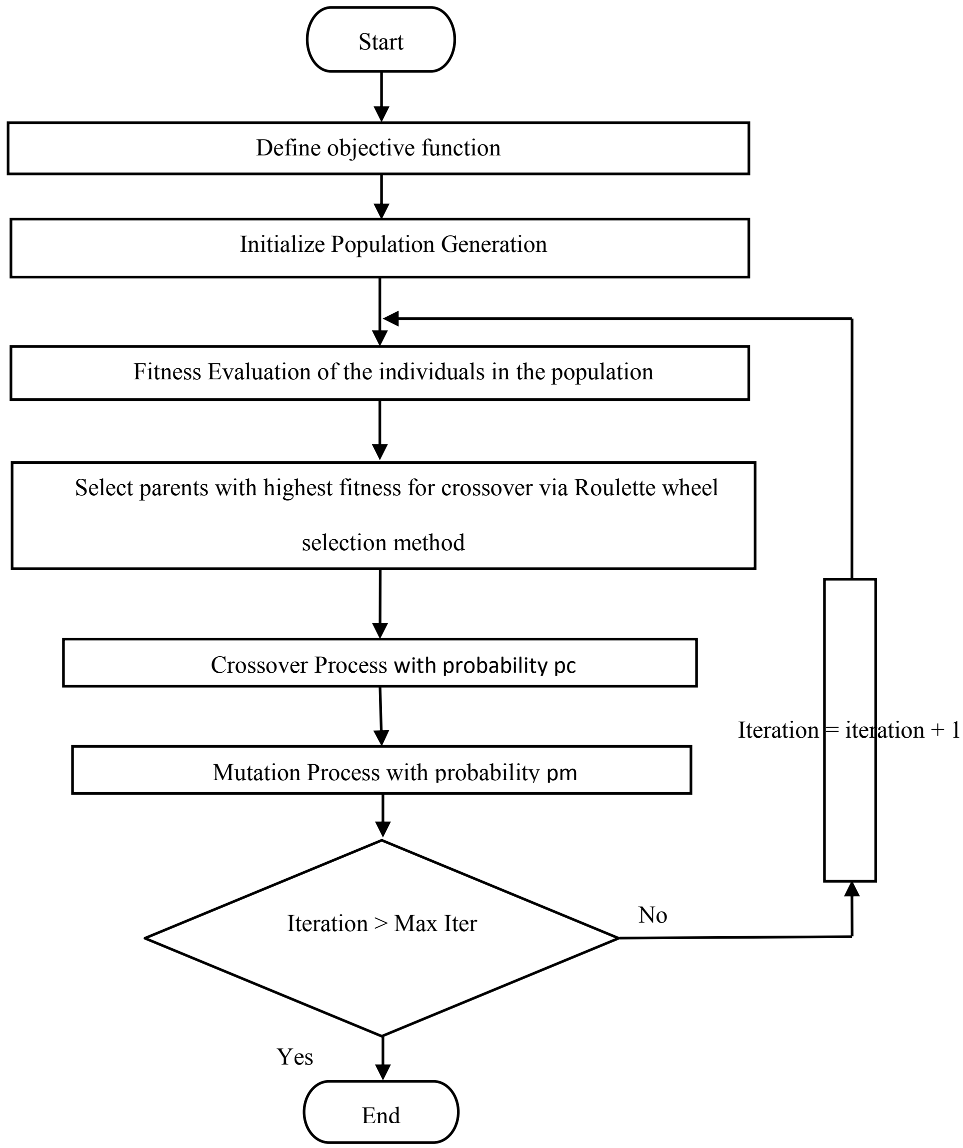

Figure 8: Genetic Algorithm Flowchart

Multi-Objective Genetic Algorithm Implementation

In this section, multi-objective genetic algorithm is used to get the optimal topology of the CHs placement in the 3D grid topology. The efficiency of obtained topology can be measured by the success of the objectives of this work through maximize the network lifetime and connectivity, with least number of CHs and minimize the cost. In the following subsections, the GA implementation is discussed in details.

Chromosome Coding

At the beginning of GA, we have to represent our problem with one of the encoding types that used to represent the problem to a mathematical way. Thus, in our case we use binary encoding to represent the problem clearly and make it suitable for the genetic algorithm. The first step in genetic algorithm is representing the problem with chromosomes. To do so, the chromosomes (solutions) in this work are represented by ($1 \ x \ m$) matrix where m is the number of grid vertices (points) that represents the CHs positions that deployed in the second layer. Each element in the chromosome's matrix called (gen) which represents one node position (vertex) in the grid. In binary coding, the chromosome represented by a string of bits, *0* or *1*. For the sensor placement in grid vertices, we have two possibilities represented by the binary coding scheme; being a sensor placed at the position means the gen value is (*1*) or being an empty position without sensor means the gen value is (*0*). In our network model, the grid has 144 positions that can be placed with CHs, so the length of the matrix that represents the chromosome will be 1 x 144. In other words, every chromosome consists of 144 gens as shown in Figure 9.

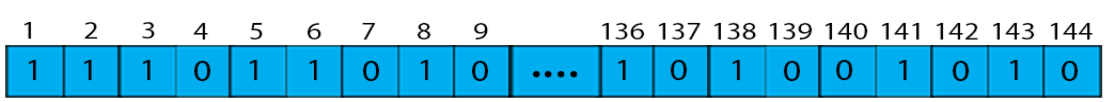

Figure 9: Chromosome Encoding

Initial Population

Based on our deployment strategy described in section 0, we start of genetic algorithm steps by first randomly generate the initial population which consists of 25 chromosomes (solutions) along with their fitness values that calculated by evaluate them using our fitness function which that explained in the next subsection. The chromosomes generated randomly by deploying a random number of CHs in the grid. In each chromosome (solution), the number of nodes is different and the positions of those nodes are different as well.

Fitness Function

Our goal is to arrange the WSNs nodes in a 3D grid meanwhile the network lifetime, connectivity, and cost are optimized simultaneously. Based on what we have explained in section 3.5, our fitness function is a weighting function that consists of three key objectives. The main job of the fitness function is to evalue the quality of the solutions that will be generated using genetic algorithm. A fitness function must include the most significant parameters that affect the quality of the solutions. Another important factor in our weighting fitness function is the objective's weights that decide the importance of the each objective in the work. The final form of the weighting linear fitness function f is given by

$$f = (\mathrm{w1} * Net_{cost}) - (\mathrm{w2} * Net_{lifetime}) - (\mathrm{w3} * Net_{conectivity}) \qquad (10)$$

The significant of each objective is defined by the weight coefficients w_i , $i = 1,2,3$. The values of these coefficients are determined based on the importance of the objective. The fitness function in this work will be minimized using the genetic algorithm (GA).

Selection

In this step, the parents chromosomes will be selected from the initial population to participate in generating the new population using one of the common known method called Rolette Wheel selection [38]. In this selection scheme, each solution from the solutions that have been generated initially will have a chance to be selected according to its fitness value. Based on our fitness function the smaller the fitness value the more probability to be selected they have.

Genetic Algorithm Operators

The main operators in genetic algorithm (GA) are crossover and mutation. So, they consider as the most significant parameter that affects the genetic algorithm (GA) performance. The implementation of these operators depends on the problem representation and encoding type. Crossover and mutation can be implemented using many ways, so in this section we will explain in details the ways that we follow to implement each one of them.

The main function of crossover operator is to reproduce new chromosomes (solutions) through combined two old chromosomes. Crossover usually executed with probability less than one, in our model we assume that the crossover probability is 0.8. The main ways to execute the crossover are single point crossover, double point crossover, uniform crossover, and arithmetic crossover. In our work, we used the single and double point crossover.

In single point crossover, one random point between (1 - 144) selected from the chromosome string. The offspring will be generated of the two selected parents in the previous step. The first part will be from the beginning of the first parent chromosome string to that crossover point and the second part will be the rest of the second parent. Figure 10 shows the process clearly.

In double point crossover, two random points between (1 – 144) picked from the chromosome string. Due to that, the parents will be partitioned into three parts as shown in Figure 11. The offspring will be the generated of the two selected parents in the previous step. The new chromosome will be combined of three different parts, First part will be taken from the beginning of the first parent's chromosome string to the first crossover point, the second part will be taken from middle part of the second parent, and the third part will be copied from last part of the first parent. For more illustration Figure 11 explains how that implemented.

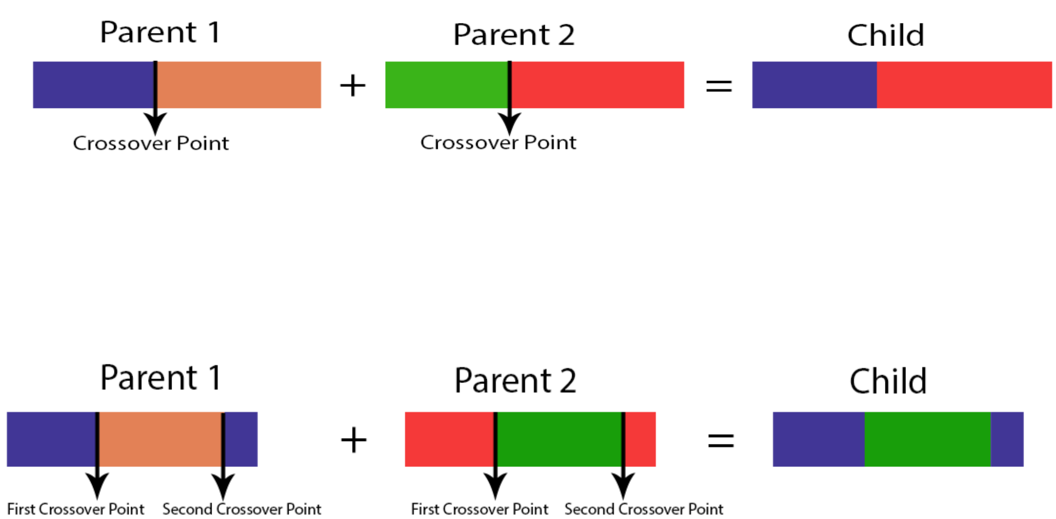

Figure 11: Double Point Crossover

Mutation is the second main operator in genetic algorithm (GA). In mutation a number of gens in each chromosome are selected randomly and mutate them. In our work we assumed that the probability of mutation is (0.3), so three random bits in every chromosome are mutated. In more details, the selected gens values are mutated, so if the value of the selected gen is *0* the mutation operation will change its value to *1* and vies versa. For more understanding Figure 12 illustrates the process.

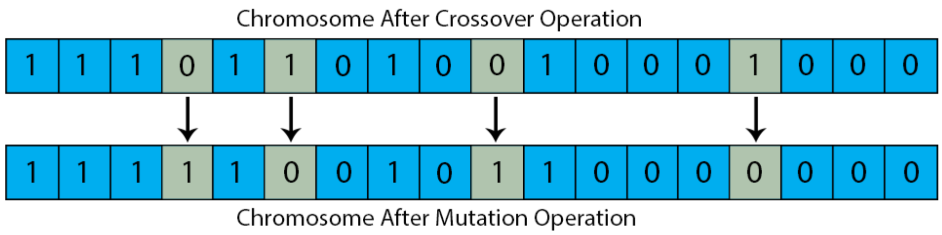

Figure 12: Mutation Operation

3.7.2 Particle Swarm Optimization (PSO)

PSO is an intelligent technique used for optimizing formulated problem inspired by the natural behavior of the fish and birds swarm. It was first proposed by Kennedy and Eberhart 1n 1995 [39] and modified later by Shi and Eberhart [40]. The concept of this algorithm is that each particle in the search space has its own co-ordinates and represents a probable solution for the problem. These particles update their position and velocity in each iteration according to their best-known solution. Finally, all particles contribute in obtaining the best global solution.

Binary Particle Swarm Optimization (BPSO)

Generally, there are many problems that have intrinsic discrete binary search spaces, like feature selection and dimensionality reduction. In addition, problems with continuous real search space can be converted into binary problems by converting their variables to binary variables. Regardless of binary problems' types, a binary search space has its own structure with some limitations.

Let vectors $\mathrm{Y_i} = [\mathrm{Y_{i1}}, \mathrm{Y_{i2}}, \mathrm{Y_{i3}}, \dots, \mathrm{Y_{in}}]$ and $\mathrm{S_i} = [\mathrm{S_{i1}}, \mathrm{S_{i2}}, \mathrm{S_{i3}}, \dots, \mathrm{S_{in}}]$ represent the position and velocity of the PSO algorithm. Vectors $\mathrm{L_{besti}} = [\mathrm{Y_{i1Lbest}}, \mathrm{Y_{i2Lbest}}, \mathrm{Y_{i3Lbest}}, \dots, \mathrm{Y_{inLbest}}]$ and $\mathrm{G_{best}} = [\mathrm{Y_{1Gbest}}, \mathrm{Y_{2Gbest}}, \mathrm{Y_{3Gbest}}, \dots, \mathrm{Y_{nGbest}}]$ represent the best position of the particle and the best position of particle neighbors respectively which is the global best solution.

$$S_i^{k+1} = S_i^k * \omega + C_1 * rand(0,1) * \left(L_{besti} - Y_i^k\right) + C_2 * rand(1,0) * (G_{best} - Y_i^k) \qquad (11)$$

$$Y_i^{k+1} = Y_i^k + S_i^{k+1} \qquad (12)$$

where S_i^k and Y_i^k are the particle velocity and position at iteration k respectively. C_1 and C_2 are the acceleration factors. ω is inertia weight.

In binary space, due to dealing with only two numbers (‘0’ and ‘1’), the position updating process cannot be performed as in the PSO by adding velocities to positions using formula in (12).

Basically, in Binary Particle Swarm Optimization, the position updating means switching between *‘0’* and ‘*1*’ values. This switching should be done based on the velocities of agents. The question here is how the concept of velocity in a real space should be employed in order to update the positions in a binary space. According to [41], the idea is to change the position of the nodes with the probability of its velocity. In order to do this, a sigmod function is used to map velocity values to probability values for updating the positions.

$$S_i^k = \frac{1}{1+e^{-S_i^k(t)}} \qquad (13)$$

where S_i^k is the particle velocity at iteration k.

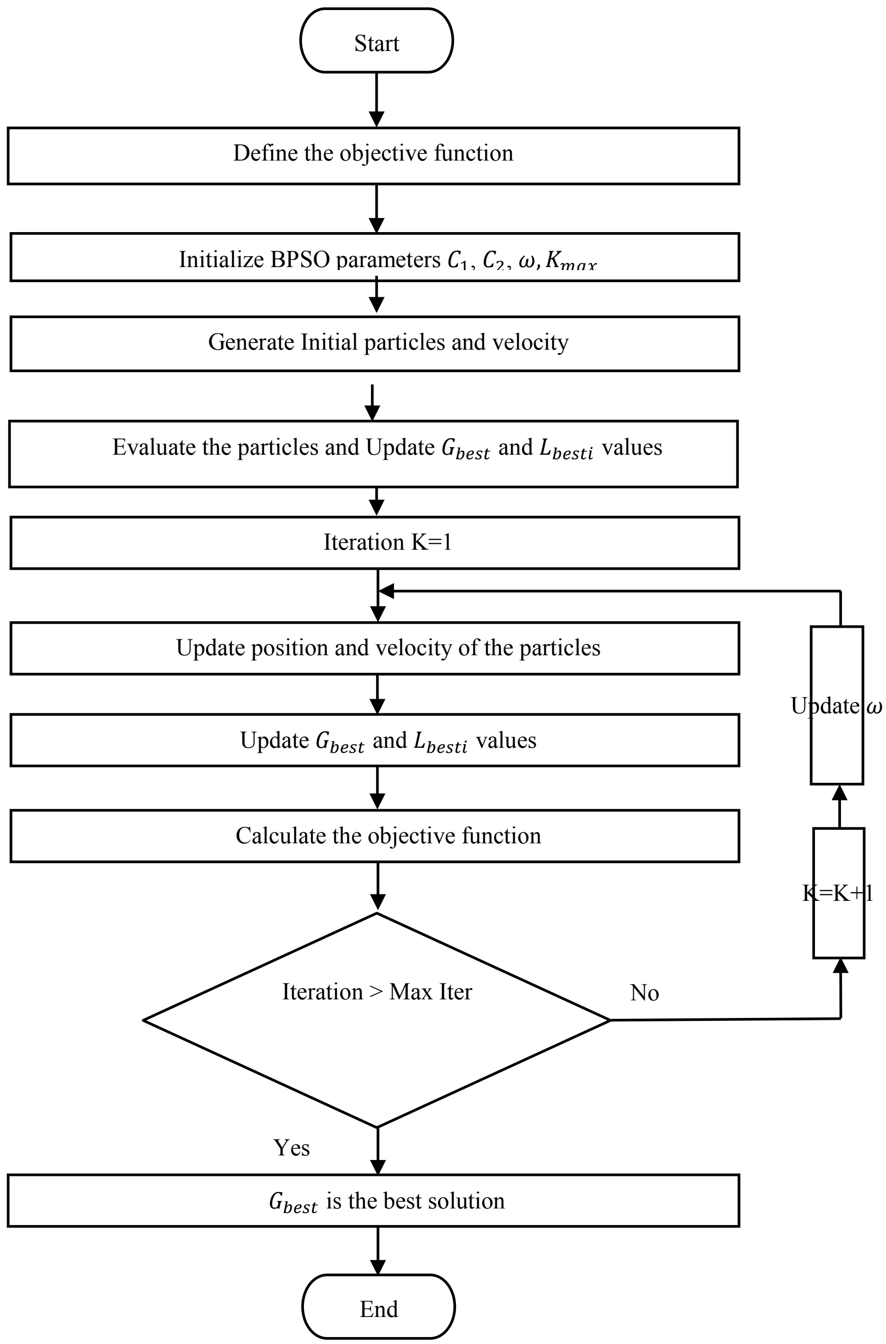

Figure 13: Binary Particle Swarm Flowchart

The original BPSO was proposed by Kennedy and Eberhart [41], to allow PSO to operate in binary problem spaces. In this version, particles could only fly in a binary search space by taking values of '*0*' or '*1*' for their position vectors. The roles of velocities are to present the probability of a bit taking the value *0* or *1*. A sigmoid function as in

(13) was used to convert all real values of velocities to probability values in the interval [0,1]. After converting velocities to probability values, position vectors could be updated with the probability of their velocities as follow

$$S_i^k = \begin{cases} 0 & if\ rand(0,1) < S_i^k \\ 1 & if\ rand(0,1) > S_i^k \end{cases} \tag{14}$$

The objective function of the problem used in this stage is defined previously in section 3.5 Figure 13 illustrates the flow chart of BPSO algorithm for solving our problem.

CHAPTER 4

Results and Discussion

In this section, we will show the simulation results of our proposed approach to achieve the objectives that aim to prolong the network lifetime and maximize the network connectivity with minimum number of CHs. Different scenarios have been simulated by setting different values of the parameters in our thesis formulation.

As mentioned in chapter 1, the simulation and the optimization using GA and BPSO of the aforementioned objectives is simulated using MATLAB 2018a simulation tool. The weights (w_1, w_2, w_3) in our objective functions in equation (10) are determined based on the objectives importance for system's design maker. Since the network cost is the primary goal in our work we focused in minimizing the number of nodes in the second layer, while the secondary objective is saving the network energy to maximize the network lifetime, finally the last objective is achieving the best connectivity by covering as large number of SNs in the first layer as much by the minimum number of CHs in the second layer. We have deployed different number of SNs in random distribution over a 3D grid 150x150x90 m^3which divided into equal cubes and each cube has four vertices or grid points, so the second layer in each simulated deployment can have up to 144 nodes which are the total grid vertices. Figure 14 shows the grid points that considered as candidate pointes to have the optimal number of CHs. Due to equal length of edges between the adjacent grid vertices we assumed that the theoretical transmission range of the SNs in the first layer is equal to the edge length $r_{max} = 30m$.

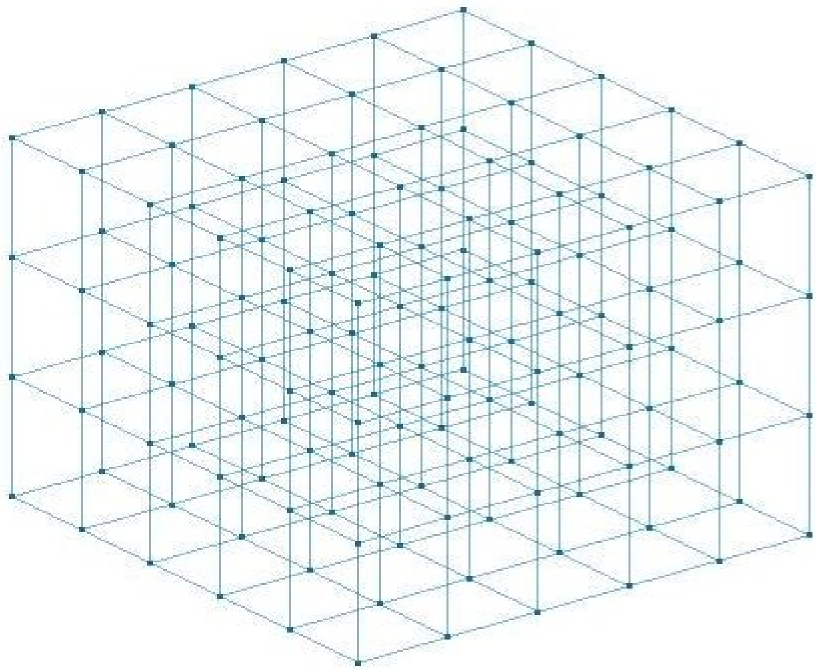

Figure 14: 3D Grid graph which used in the simulation

The following Table 2 shows the parameters that we assumed in our simulation.

Table 2 Network Parameters for Simulation

Parameter	Setting	Parameter	Setting
Number of Grid points	144	β	$50\text{x}10^{-9}$ J/bit
L	512 bits	Initial energy for SNs	0.5 J
ϵ_1	$50\text{x}10^{-9}$ J/bit	Initial energy for CHs	20 J
ϵ_2	$10\text{x}10^{-12}$ J/bit/m^2	Crossover Probability	0.8
γ	4	Mutation Probability	0.3

The first section of this chapter presents the assumed scenarios in this thesis and explains the architecture of each scenario with focusing on the performance of grid-based deployment in terms of the network lifetime, percentage of connectivity and network cost.

We have simulated our model with different number of sensor nodes SNs such as 200 SNs and 300 SNs. In each network, the size of SNs deployed using a random uniform distribution in the grid area. Then, we generate 25 different solutions as initial population, where each of them has 60 CHs with different locations in the grid points. The main responsible factor for enhancing the solution performance in our proposed approach is the optimization technique~~s~~; Genetic Algorithm (GA) and Binary Particle Swarm Optimization (BPSO).

Finally, GA and BPSO were used separately to solve the optimization problem. After applying both methods, the results were collected and the behavior of those methods analyzed.

4.1 Genetic Algorithm (GA)

As explained in the previous chapter, we proposed that we have deployed random number of SNs to cover almost the whole targeted area. Using the genetic algorithm optimization technique we deploy number of CHs to cover as much number of SNs as possible to assure that all the SNs that connected with CHs can send their data to the BS.

The main idea in the simulation scenario is sending the data from the SNs to the CHs then by the CHs nodes, the data which collected from the SNs will be send directly through long distance to the BS. Thus, in the following sections we will show how the objectives' weights can affect the performance of the network. The following Figure 15 illustrates the idea of the simulation scenario.

In the following sections, we are mainly focusing on assessing the performance of the network design in terms of lifetime, connectivity and network cost while changing the weights of the objectives in our fitness function in equation (10).

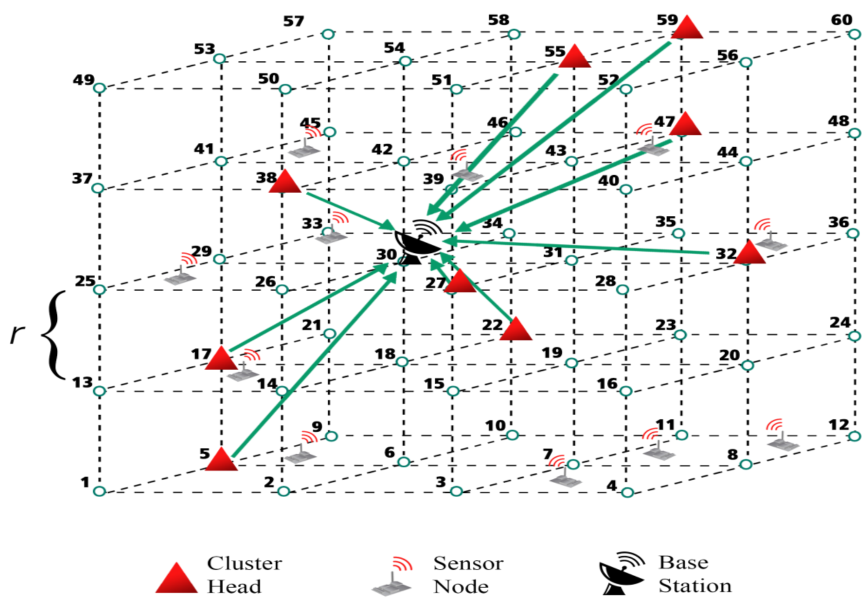

Figure 15: Simulation Scenario

In all cases we validate our approach using MATLAB simulation results. Initial experimental setup in our work consists of two sets of SNs either 200 SNs or 300 SNs with random number of CHs and one BS on predetermined location. The main functions of our approach is finding the optimal number and locations of the deployed CHs. Due to genetic algorithm iterations the locations of the CHs will change to better locations that close to their cluster members in each iteration.

The following two sub-sections exhibit the results for multi-objective optimization using Genetic Algorithm. In all simulation scenarios, the following parameters of the GA were used: Initial population = 25, number of iteration = 200, crossover probability (P_c) =0.8 and mutation probability (P_m) = 0.3.

4.1.1 Genetic Algorithm with 200 SNs

In this subsection, we optimize our multi-objective problem using GA for 200 iterations. The number of SNs that assumed to be deployed randomly in the simulation area is 200 SNs. Then 60 CHs will be deployed randomly in the initial solutions. So, finding the best locations of these CHs will improve the performance and achieve the required objectives for this problem. In this part, we will show the results of giving different weights to the objectives in our fitness function in equation (10).

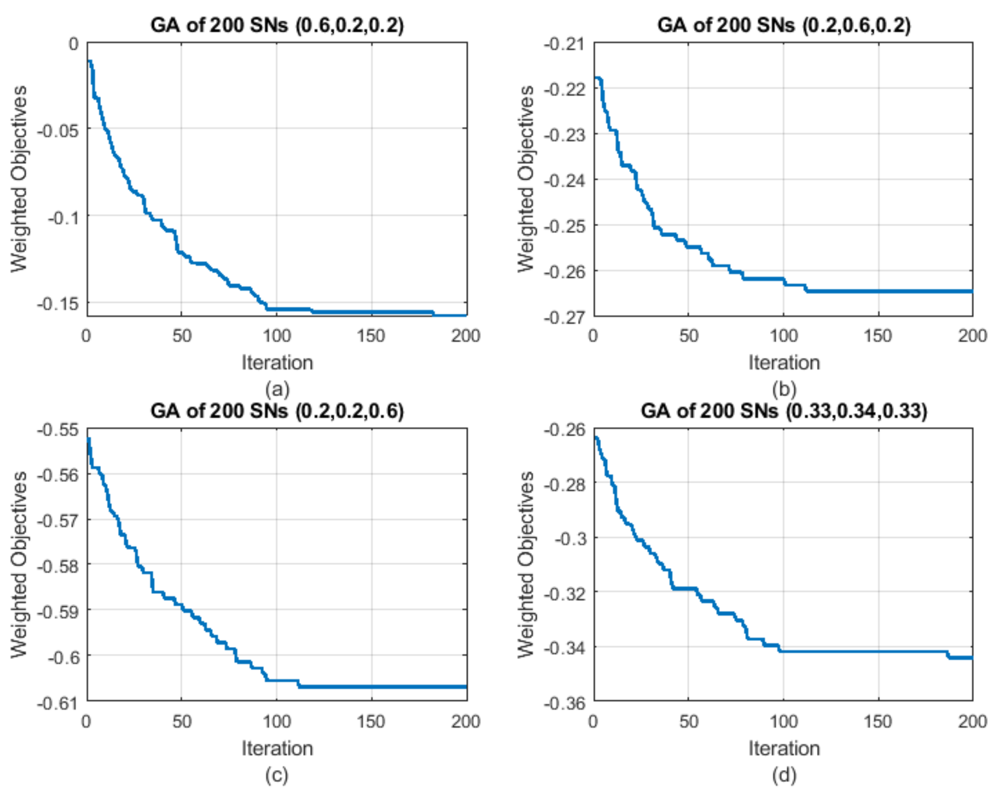

Figure 16: Convergence of GA of 200 SNs

In all the experiments, the maximum number of iteration is set to 200. The weights given to the objectives are shown above each sub graph as (number of CHs, remaining energy, and percentage of connectivity) respectively.

In Figure 16, the convergence behavior of the optimization technique during search process of the optimized parameters can be observed. Four different weighted objectives of 200 SNs using GA have been optimized. The heuristic reduces the cost of the network as expected in all simulation scenarios. The GA converged to optimal solution almost after 110 iterations and remained steady thereof. In the following results, we will show the enhancement in all objectives by comparing non-optimal solutions with the optimal solutions for each of our work objectives.

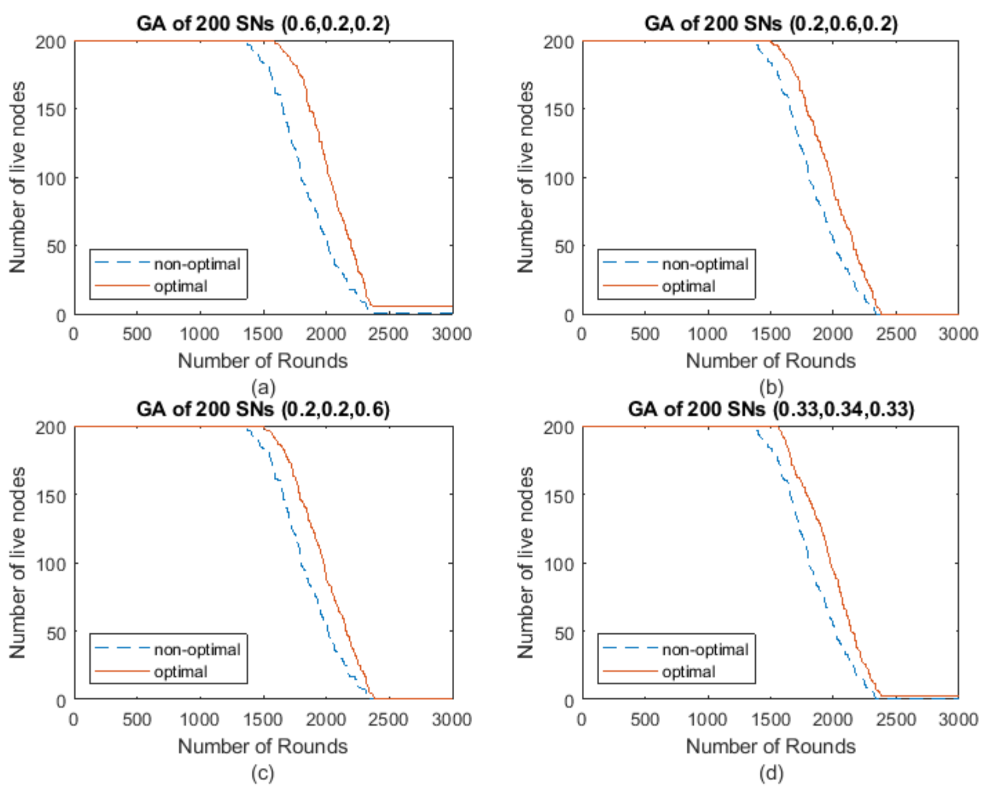

Figure 17: Total number of alive sensor nodes for 200 SNs using GA

Figure 17 depicts the enhancement of the network lifetime. The results show that the lifetime of the optimized solutions increased clearly compared to non-optimal solutions. Since the CHs are responsible for collecting data from member nodes that are inside its communication range, the algorithm trying to find the optimal locations of CHs by minimizing the distance between the CHs and their member nodes to improve the network lifetime.

Using four different weights, Figure 18 and Figure 19 show the optimization of number of CHs and their connectivity objectives respectively after 200 iteration using GA. From Figure 18 we observed that in the first scenario from the left (0.6,0.2,0.2); the number of CHs objective was given 60% of the total weight which lead to minimize their number from 60 to 15 CHs. we can conclude that: the cost of the network was reduced by more than 70% and the optimal number and location of CHs shows better performance as compared to non-optimal.

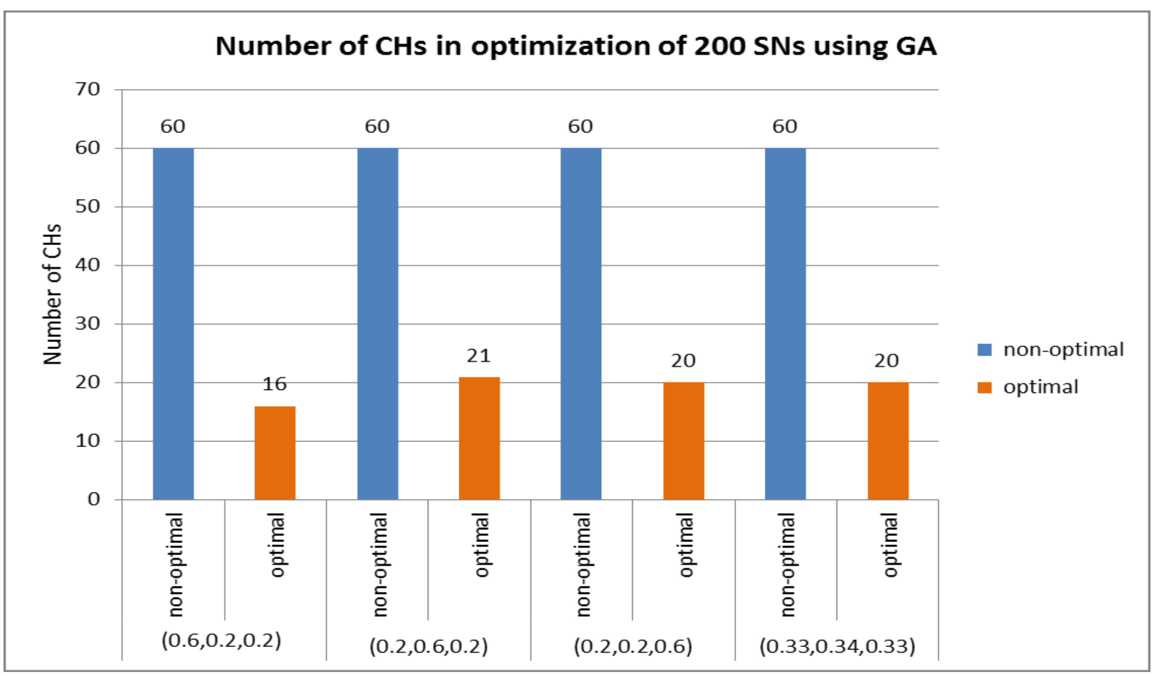

Figure 18: Optimization of number of CHs of 200 SNs using GA

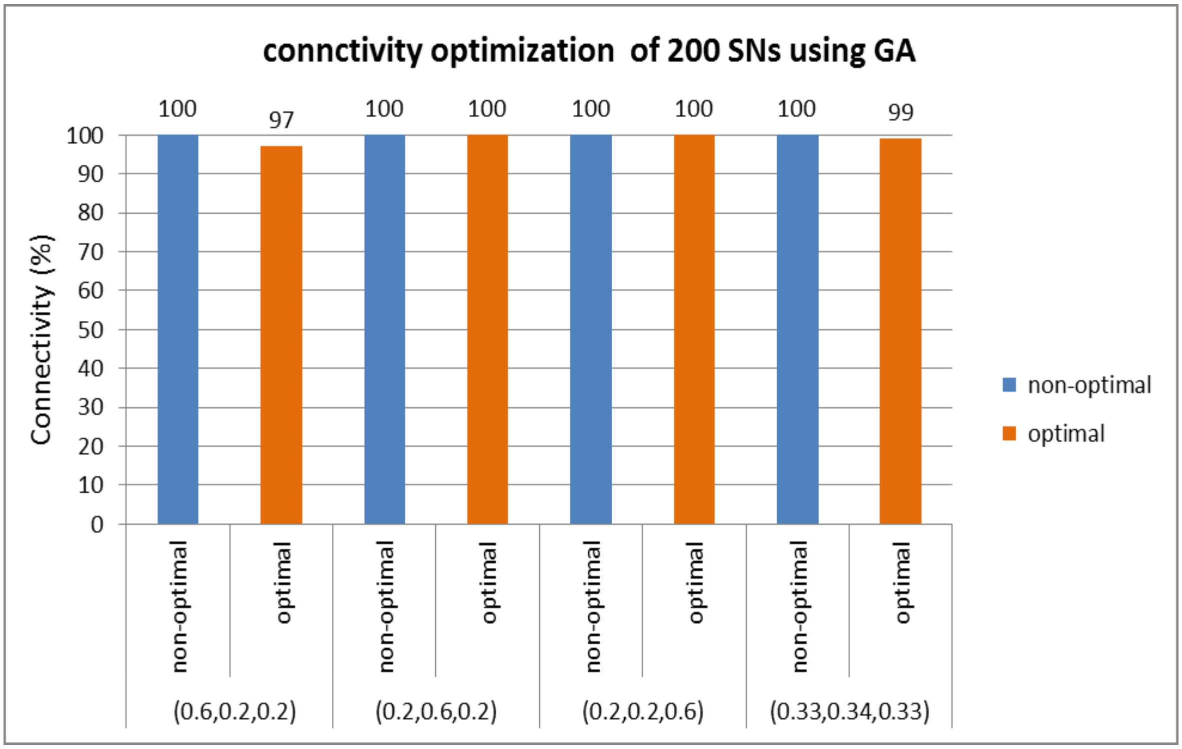

Figure 19: Connectivity optimization of 200 SNs using GA

In order to guarantee the connectivity between the CHs and their member nodes as much higher as possible while reducing the number of CHs in the network, the percentage of connectivity is achieved 97% and above in all scenarios after 200 iteration of optimization using GA as shown in Figure 19.

4.1.2 Genetic Algorithm with 300 SNs

Here, again we use GA optimization technique. The number of SNs that deployed in the simulation area changed to 300 SNs. The number of CHs deployed in the initial solutions is 60 CHs. Finding the optimal number and locations of these CHs will lead to achieve the required objectives for this problem.

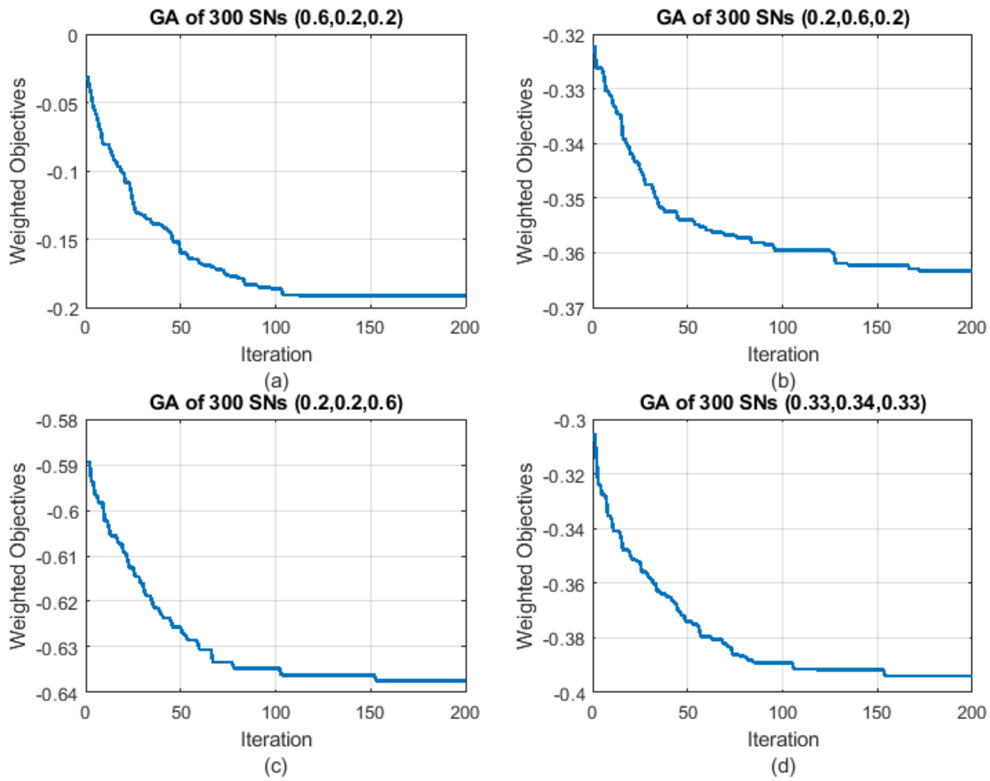

Figure 20: Convergence of GA of 300 SNs

In Figure 20, the convergence graphs of 300 SNs using GA after 200 iterations of algorithm search have been shown. After about 110 iterations the GA convergence graph almost reaches the optimal solution. The cost of the weighted objectives has been minimized using GA as shown in Figure 20. The WSN desired requirements have been achieved by finding the optimal solution.

Figure 21, clarify the network lifetime enhancement. The results showed that the lifetime of the SNs in the optimal solutions has been extended compared to non-optimal solutions. Placing the CHs in the optimal positions plays the main role in improving the network lifetime.

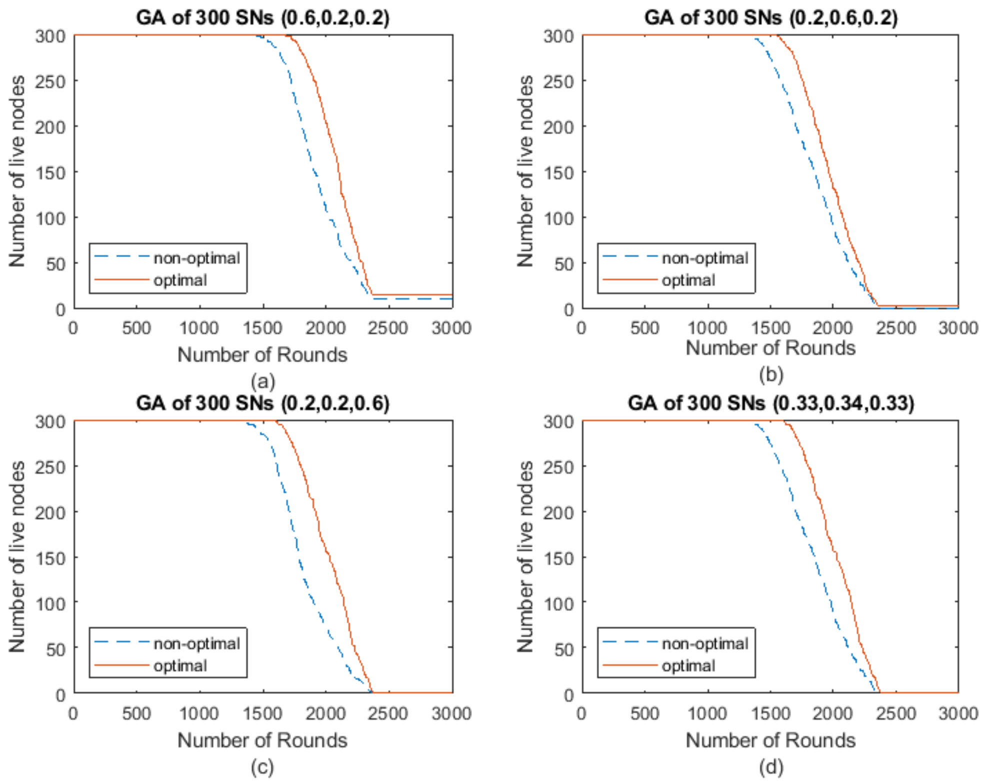

Figure 21: Total number of alive sensor nodes for 300 SNs using GA

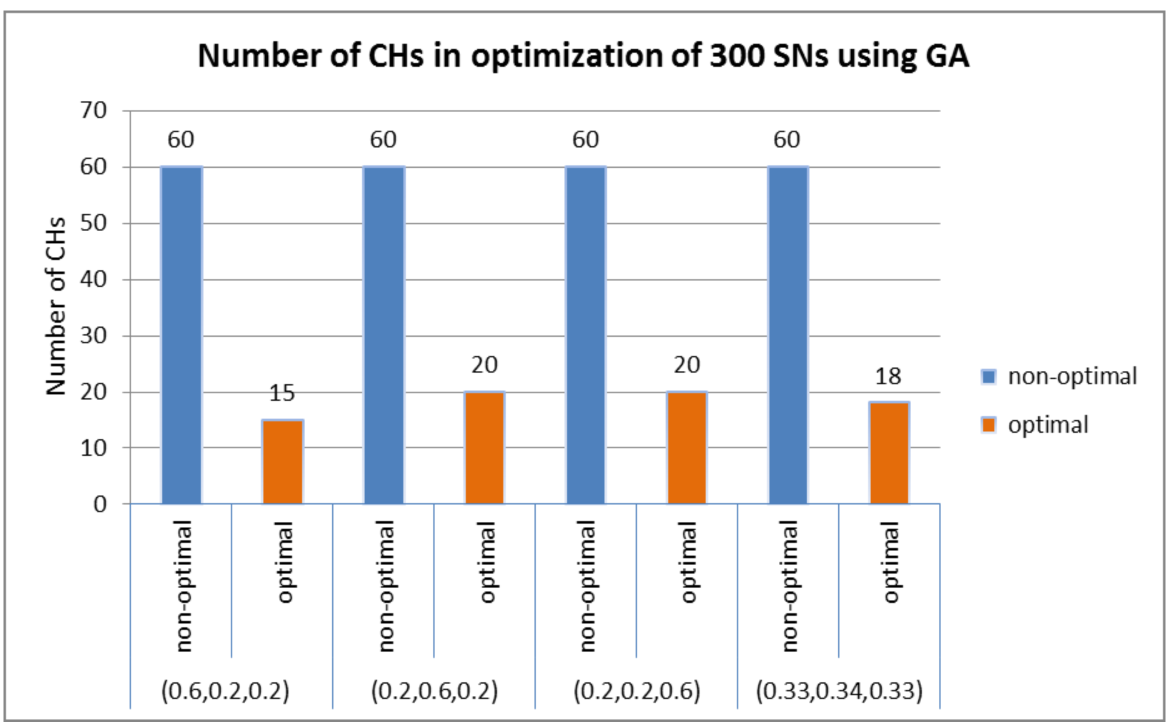

Figure 22: Optimization of number of CHs of 300 SNs using GA

The optimal number of CHs after 200 iteration using GA that satisfies the objectives of our approach, can be seen in Figure 22. The number of CHs in the network was minimized by 66% to 75% as observed from Figure 22.

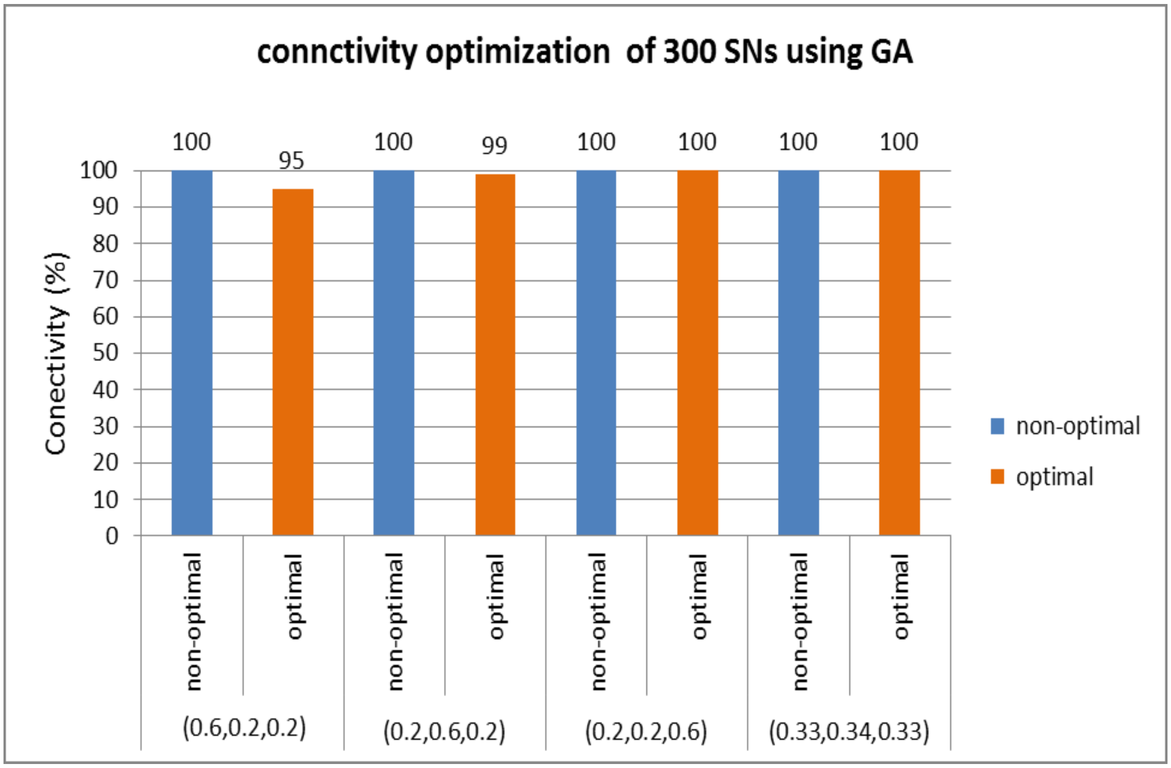

Figure 23: connectivity optimization of 300 SNs using GA

Connectivity is one of the objectives that we optimized using GA. Despite the percentage of connectivity before and after the optimization process is almost full, thanks to optimization we noted that the number of CHs used in optimal solutions is 70% lower than that used in non-optimal solutions.

4.2 Binary Particle Swarm Optimization (BPSO)

The following two sub-sections present the results for the multi-objective optimization using Binary Particle Swarm Optimization (BPSO). We optimized the same objectives that we assumed in the previous section. The main scenario that we proposed in section 3.6.1 will be simulated with 200 and 300 number of SNs. In addition, each of these has been simulated with four different weights of the objectives. In all figures, the weights given to the objectives are shown above each sub graph as (number of CHs, remaining energy, and percentage of connectivity) respectively. In all of the simulation scenarios, the following parameters of the BPSO were used: initial population = 25, number of iteration = 200, number of intervals = 10, inertia weight= 0.99 and velocity constants c1=c2=0.5.

4.2.1 Binary Particle Swarm Optimization with 200 SNs

Using the objective function presented in equation (10) a multi-objective optimization using PSO was simulated with all parameters as mentioned before.

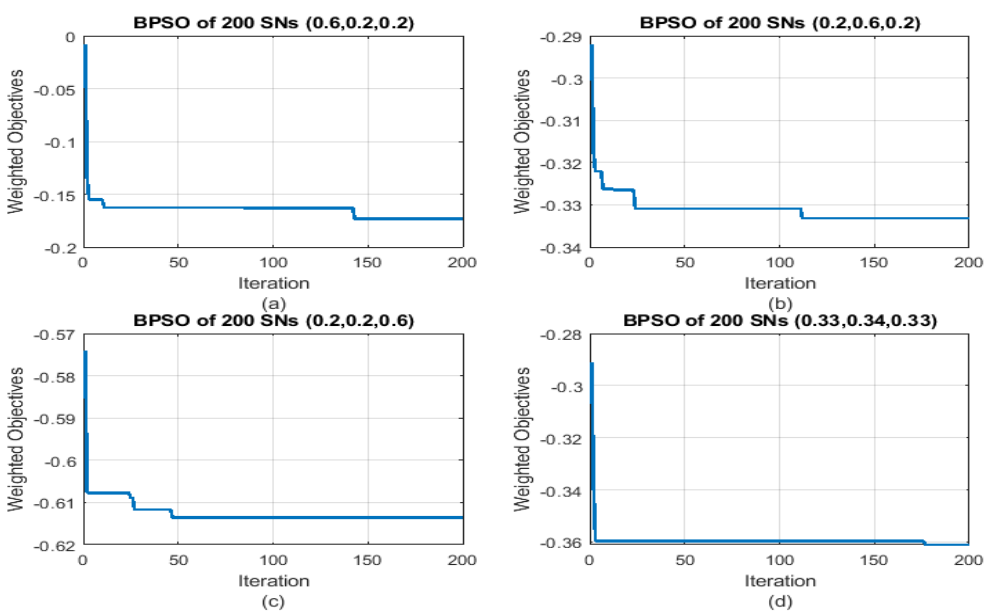

Figure 24: Convergence of BPSO of 200 SNs

Figure 24 shows the convergence behavior of the optimization technique during search process of the optimal solutions. From the all sub-graphs in the figure, we observed that the cost function minimized during the algorithm iteration.

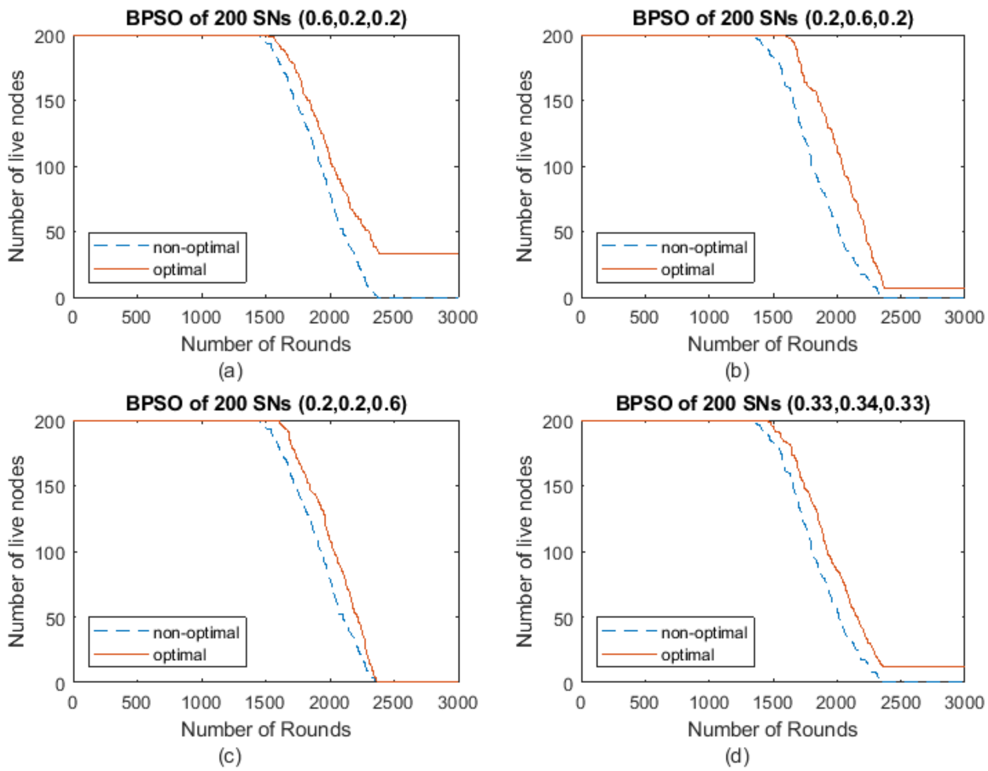

Figure 25: Total number of alive sensor nodes for 200 SNs using BPSO

Figure 25 shows the number of alive nodes for the optimal and non-optimal network layouts having total number of nodes equals 200. All sub-figures, presented the improvement in optimal network compared to the non-optimal network. This leads to a longer network lifetime. Increasing the network lifetime means increasing the number of data samples taken from the region of interest.

The optimal numbers of CHs that have been selected using the BPSO are shown in Figure 26. The proposed objective function selects the number and location of cluster heads that can achieve the desired objectives.

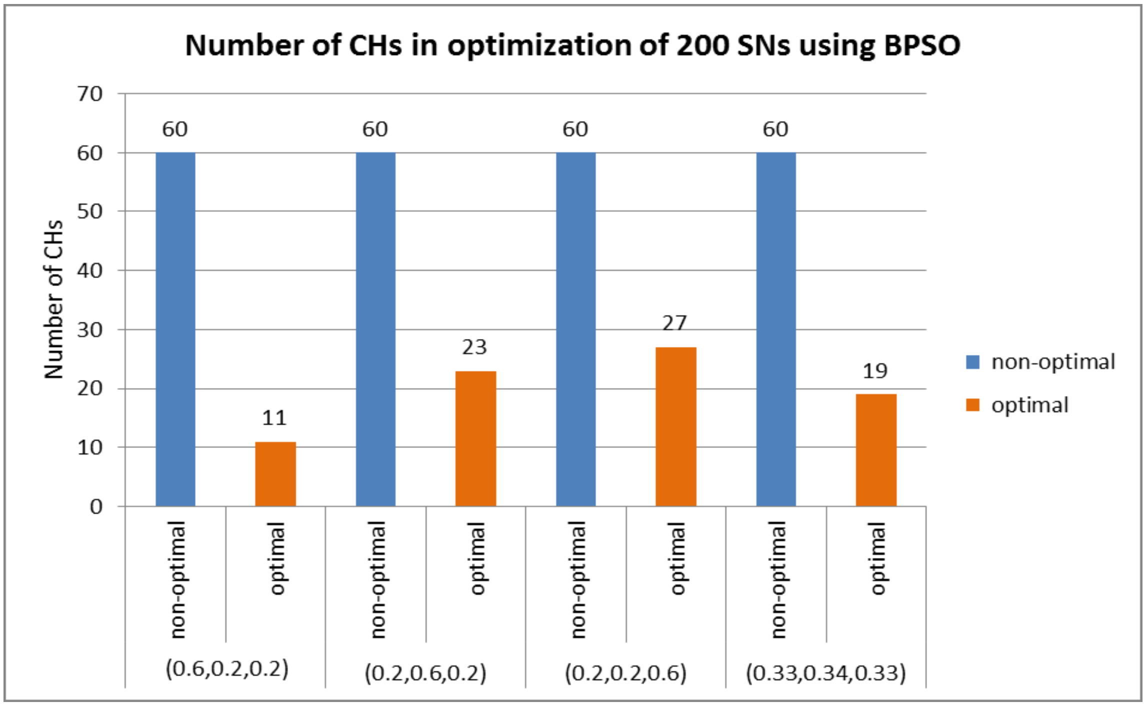

Figure 26: Optimization of number of CHs of 200 SNs using BPSO

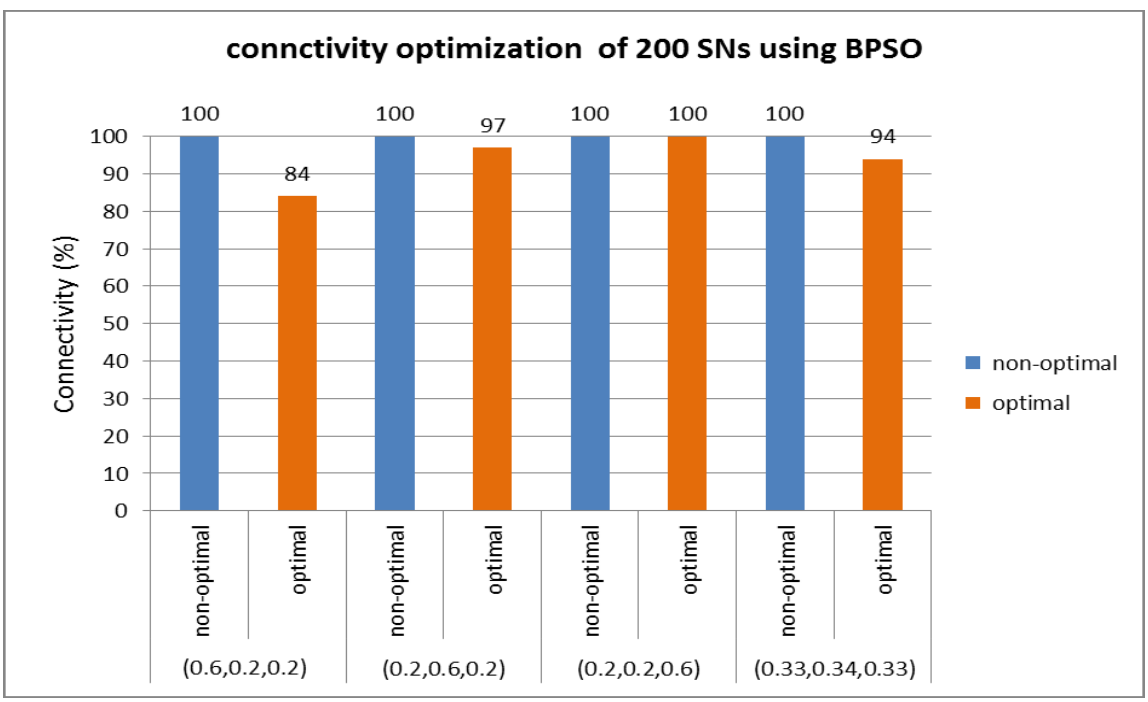

Figure 27: Connectivity optimization of 200 SNs using BPSO

In Figure 27, we show the percentage of connectivity between the CHs and their members in the network. The simulation results dictate that the percentage of network connectivity that achieved with the optimal number of CHs is good.

4.2.2 Binary Particle Swarm Optimization with 300 SNs

Here, we present the results of our proposed approach using the same simulation parameters of the above sub-section, except for the number of sensors.

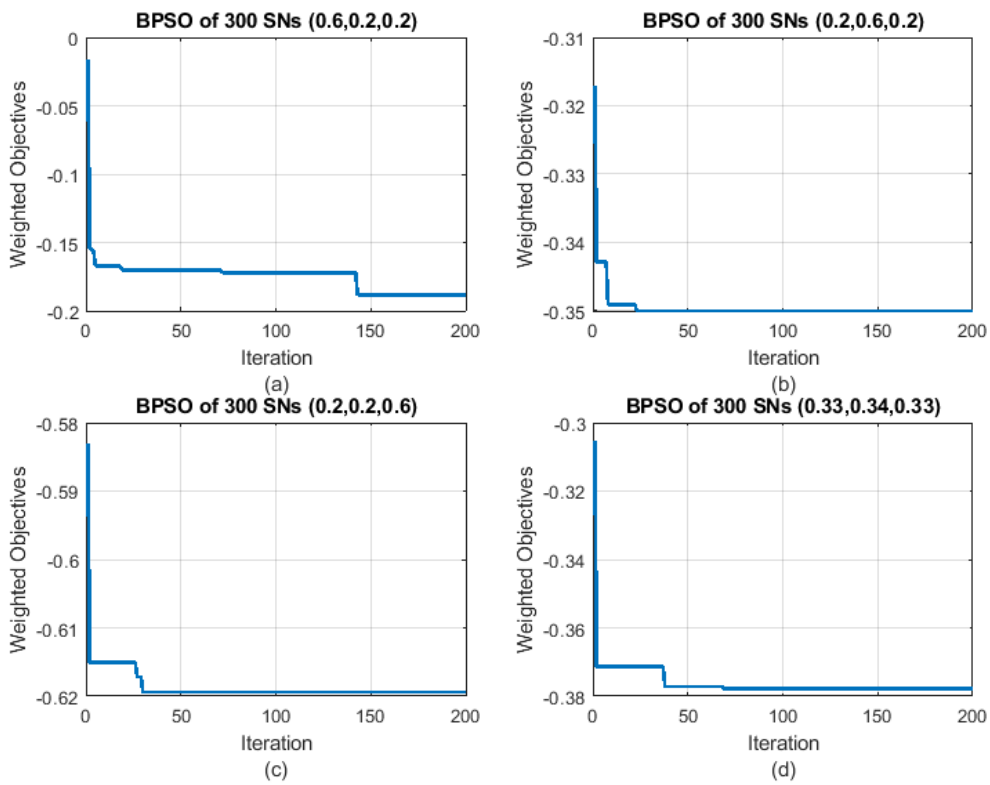

Figure 28: Convergence of BPSO of 300 SNs

Figure 28, shows that BPSO converged to the optimal solutions during search process of the optimization technique. However, it is obvious that BPSO acts efficiently in terms of minimizing cost value of the weighted objectives.

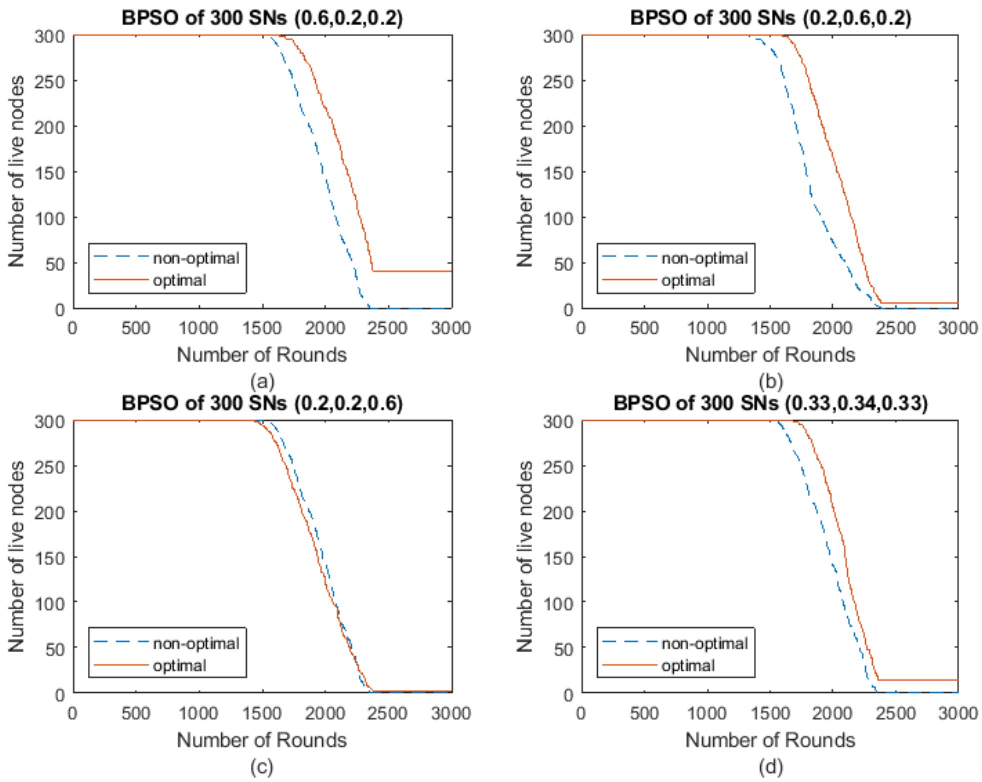

Figure 29: Total number of alive sensor nodes for 300 SNs using BPSO

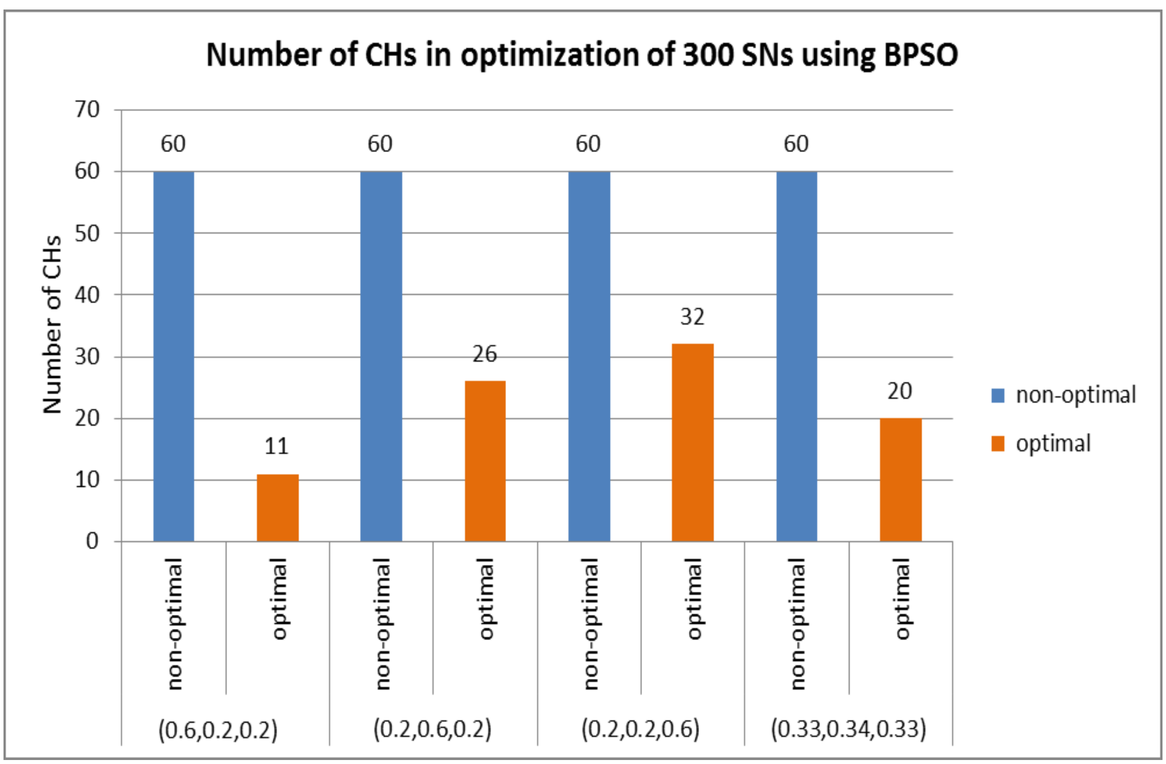

Figure 30: Optimization of number of CHs of 300 SNs using BPSO

Figure 29, compares the network lifetime of the network before and after applying the optimization technique. As expected, the optimal network lifetime gain is always higher than the non-optimal, thanks to the BPSO optimization technique.

Based on the work objectives, when the number of CHs is decreasing, the efficiency of optimization solutions is increasing. Therefore, the bar graph in Figure 30 shows the efficiency of BPSO in finding the optimal solutions. The optimal number of CHs that have been selected using BPSO optimization technique achieves 96% to 100% of the network connectivity between CHs and SNs that is presented by Figure 31.

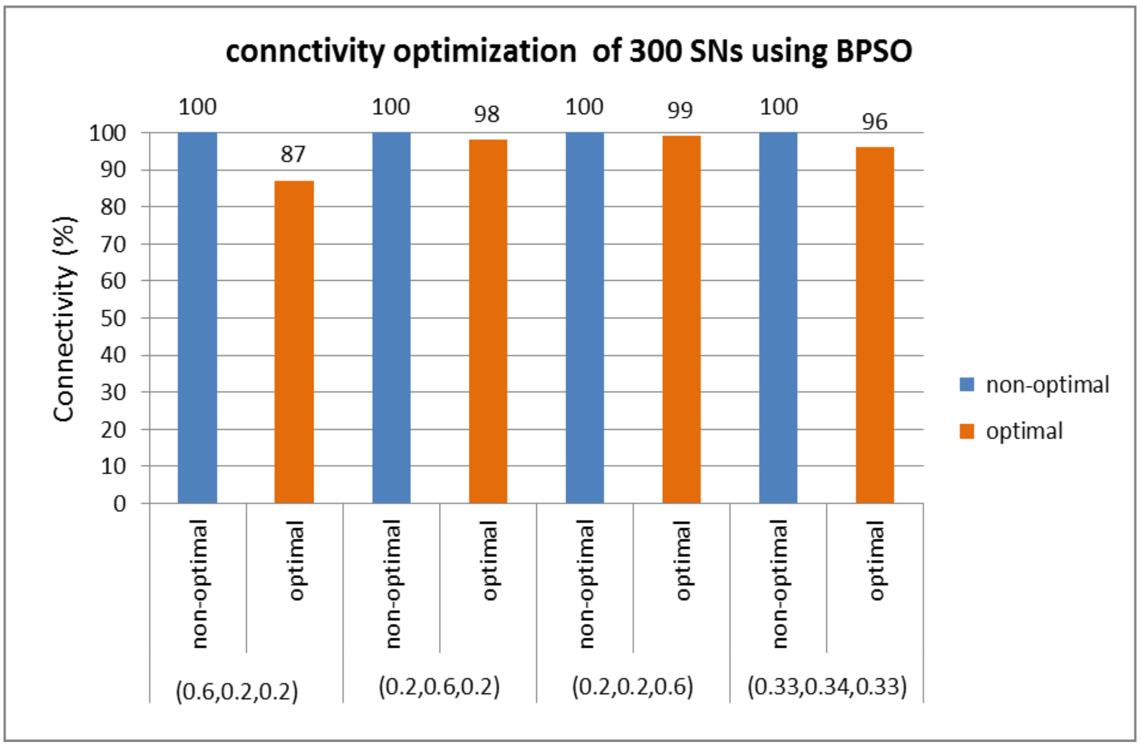

Figure 31: Connectivity optimization of 300 SNs using BPSO

4.3 Comparison between GA and BPSO

From the results in section 4.1 and section 4.2 we will present the results of comparison between GA and BPSO. In this section, multi-objectives optimization results have been simulated using GA and BPSO. Three main objectives have been optimized to deploy the WSNs efficiently.

Figure 32 and Figure 33 show a plot describing the comparison between the optimal solutions of the lifetime which optimized using two different techniques GA and BPSO for two different network sizes. From the Figure 32 we observed that BPSO shows slight improvement in the network lifetime compared to GA of 300SNs network size.

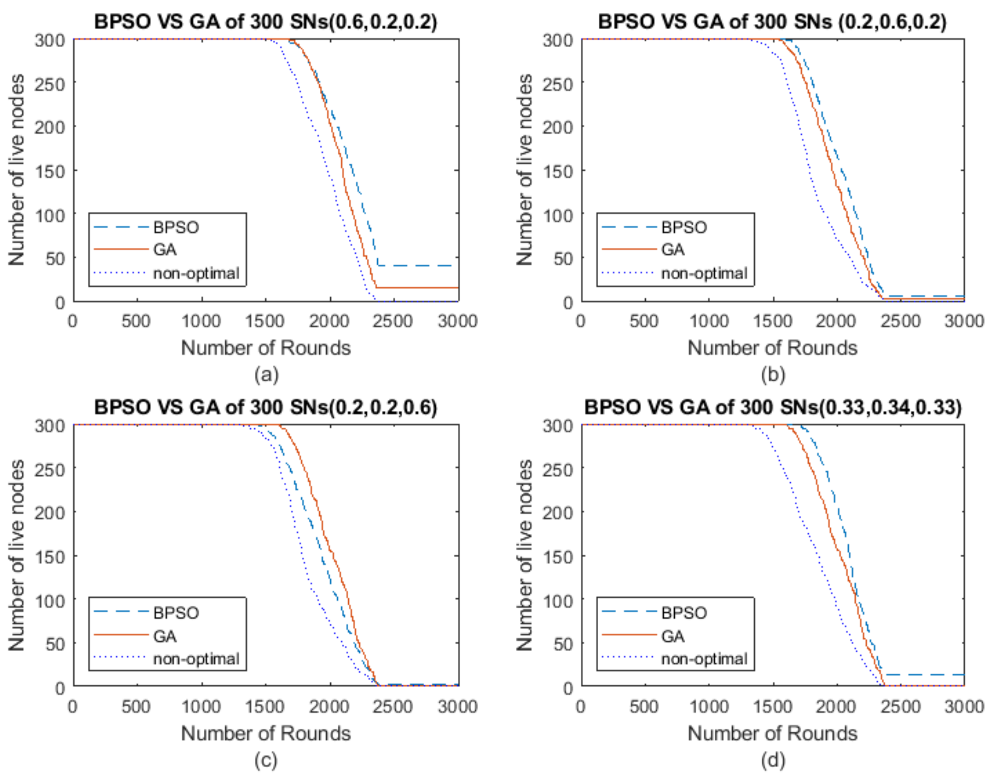

Figure 32: Comparison of alive sensor nodes for 300 SNs using BPSO and GA

Figure 33 shows the tradeoff of the network lifetime improvement between the BPSO and GA. From the figure plots we observed that BPSO and GA shows almost same improvement of the network lifetime for 200 SNs.

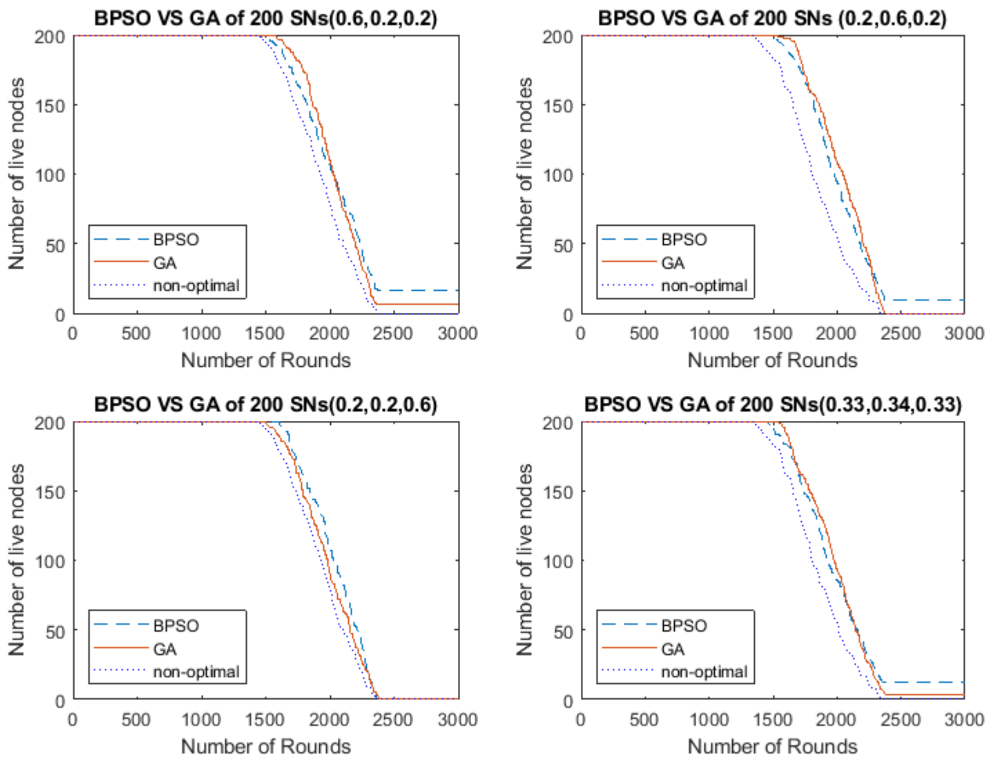

Figure 33: Comparison of alive sensor nodes for 200 SNs using BPSO and GA

The comparison between the results of finding the optimal number of CHs using BPSO and GA in the network can be show in Figure 34 and Figure 35. The optimal number of CHs in the network after using GA is slight lower than that obtained by BPSO for network size 300 SNs. While the optimal number of CHs after using GA and BPSO for network size 200SNs show little difference as compared with those in network size 300SNs.

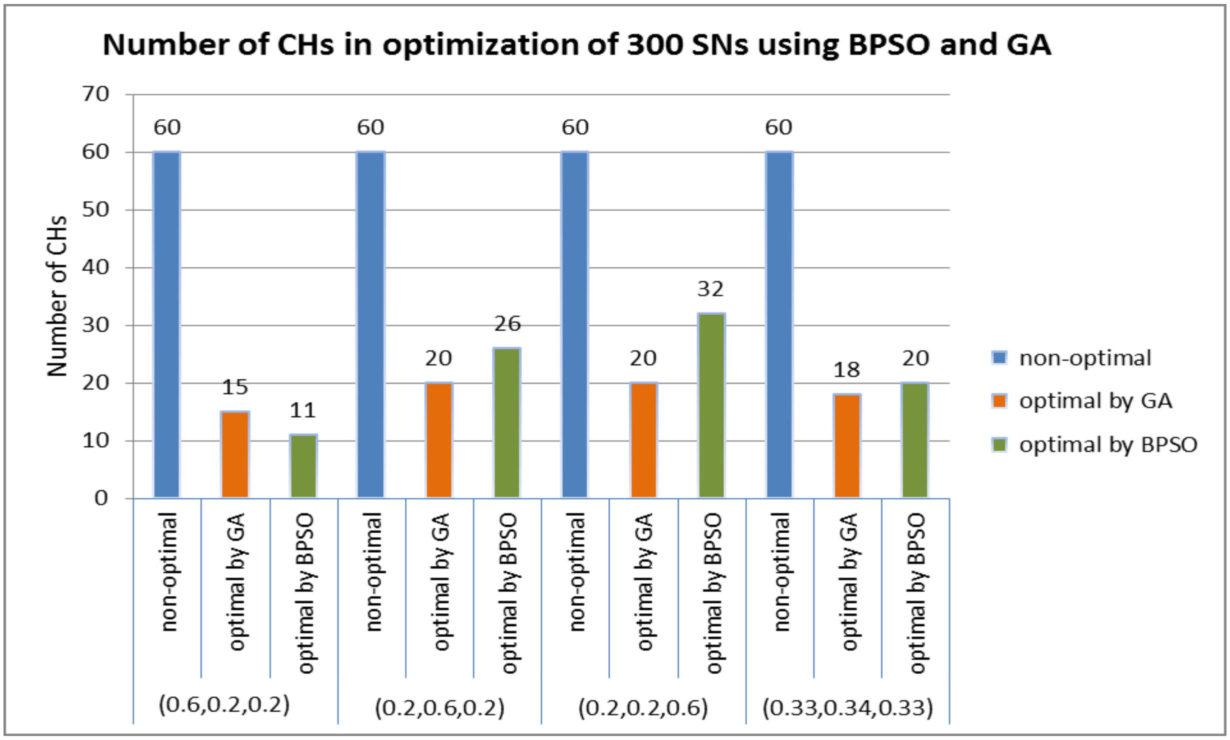

Figure 34: Optimization of number of CHs of 300 SNs using BPSO and GA

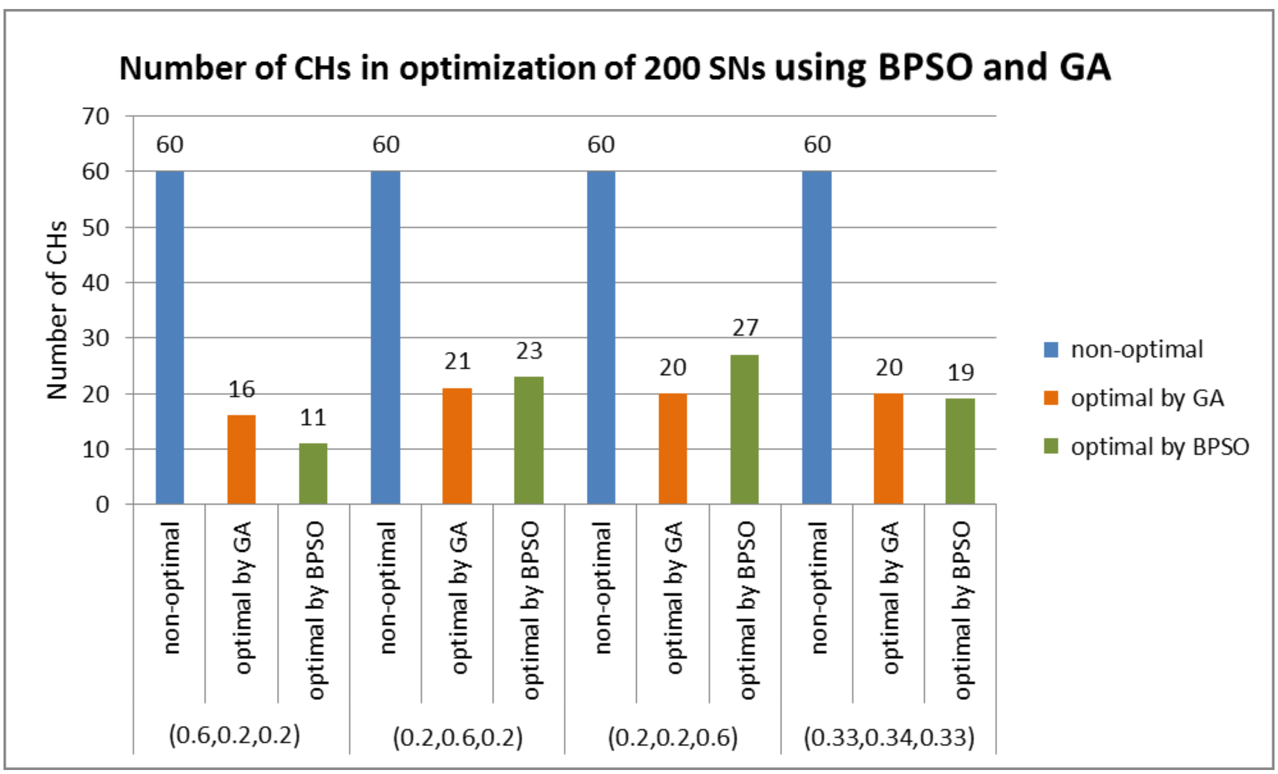

Figure 35: Optimization of number of CHs of 200 SNs using BPSO and GA

Figure 36 and Figure 37, compare the percentage connectivity of the network after applying the optimization techniques BPSO and GA of 300SNs and 200SNs respectively.

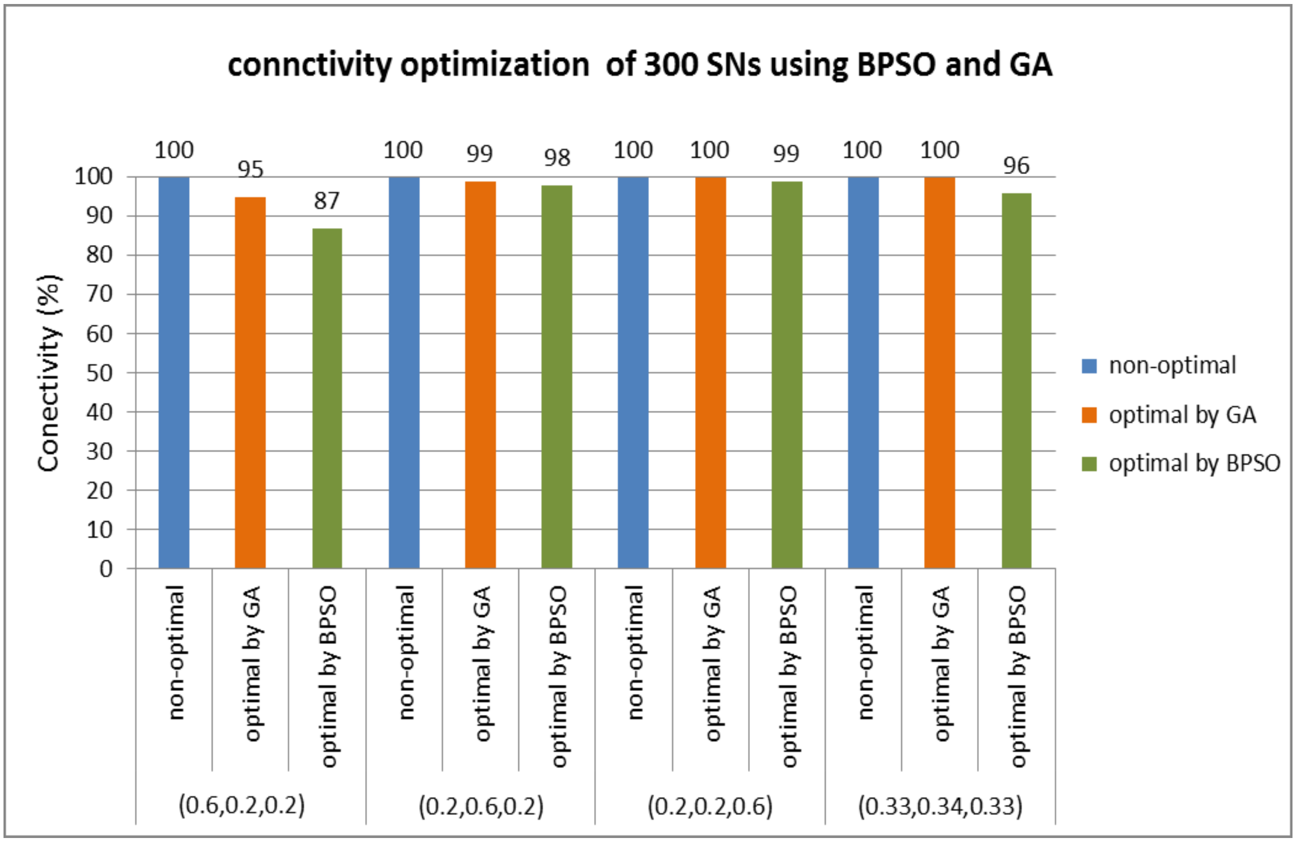

Figure 36: Connectivity optimization of 300 SNs using BPSO and GA

The percentage of network connectivity is slight better by using GA than using BPSO that can be observed from the two bar graphs in Figure 36 and Figure 37.

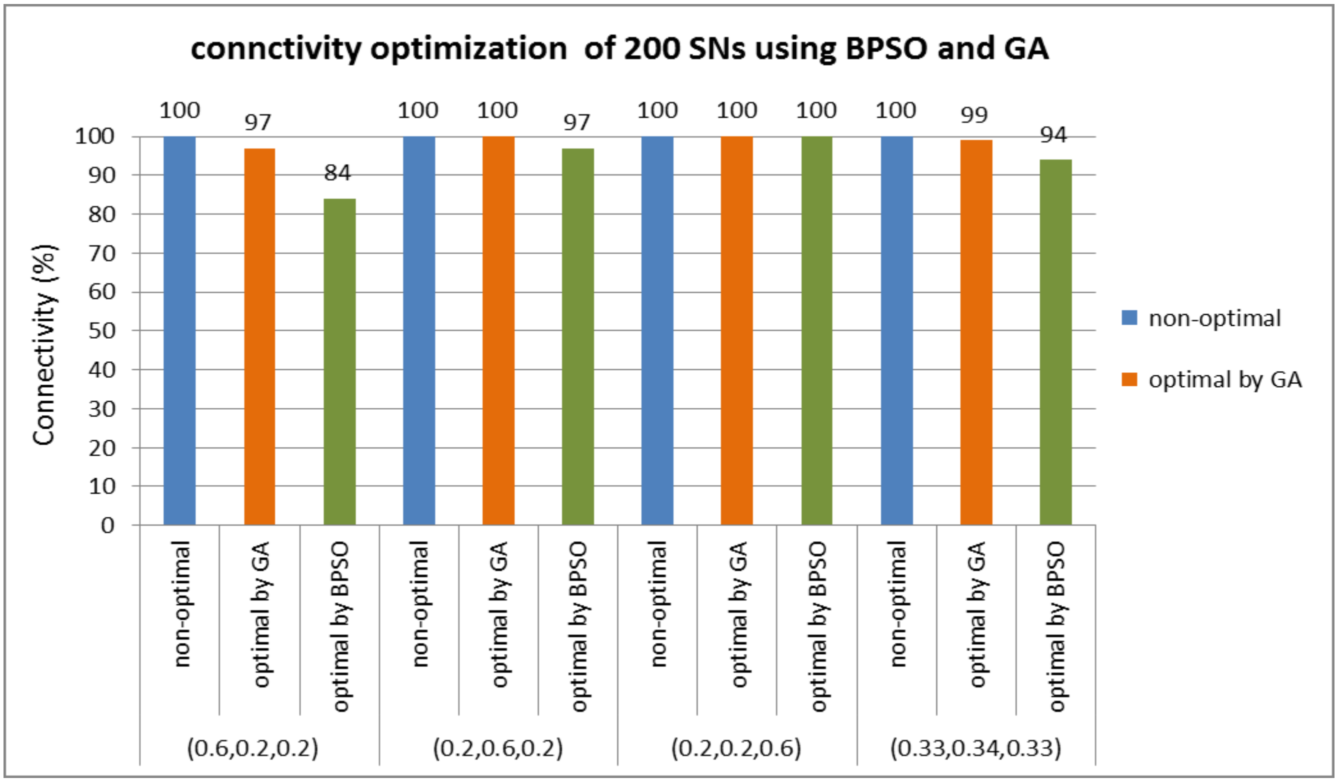

Figure 37: Connectivity optimization of 200 SNs using BPSO and GA

Overall, the results have emphasized the effectiveness of the proposed approach in finding the optimal solutions using GA and BPSO. From the above results, we observed that GA is more efficient in finding the optimal solution of the objective that has large weight whereas keeping a good level of optimization for the other objectives that has less weight. On the other hand, BPSO shows more optimization for the objective that has high weight than that value in GA, however for other objectives that have less weights are not improved as much as those in GA.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

In this thesis, the optimization of wireless sensor networks deployment in 3D environments using Genetic Algorithm (GA) has been proposed. The proposed solution aim to optimally deploy Relay Nodes in sensor networks such specific application requirements are met. Specifically, the objective is place Relay Nodes in a 3D structure while maximizing network lifetime, minimizing cost and maximizing connectivity. To achieve this purpose, a multi-objective functions has been developed and iteratively evaluated in different network and application scenarios using GA.

The proposed solution was evaluated and compared to Binary Particle Swarm Optimization (BPSO) and the results show that the proposed GA solution was able to optimize the network deployment in all simulation scenarios. When compared with BPSO, the proposed solution outperform BPSO in some scenarios and achieve comparable results in others. The GA solution was able to find the optimal deployment for the main objective, which has the largest weight while keeping a good level of optimization for the secondary objectives which have lesser weights. On the other hand, BPSO achieves better optimization for the main objective compared to GA. However for the secondary objectives, GA performs better than BPSO. Therefore, we can conclude that our proposed GA solution is well suited for optimizing 3D sensor network deployments with multi-objectives compared to BPSO.

For future work, the effect of RNs mobility on enhancing the network lifetime will be studied. In addition, the objective function will take into consideration other application requirements such as netowrk fault tolerance and mazimizing the supression of correlated data.

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Vitae

Name :Ahmed Ali Ahmed Bawazir

Nationality :Yemeni

Date of Birth :11/2/1990

Email :Ahmed77769@gmail.com

Mobile : +966-508428182

Address :Yemen – Hadhramout – Mukalla

Academic Background :

- Bachelor of Science in Computer Networks (June 2013), from University of Science & Technology, Yemen.
- M.Sc in Computer Networks, Decmber 2018 King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia.

Publications:

- Al-Baseera, A., Taliba, G., & Bawazira, A. (2016). Multi-hop Wireless Network: A Comparative Study for Routing Protocols Using OMNET++ Simulator. Journal of Ubiquitous Systems & Pervasive Networks, 7(1), 29-34.