IMPROVED NATURE INSPIRED ALGORITHMS FOR OPTIMIZATION PROBLEMS IN WIRELESS SENSOR NETWORKS

Thesis

Submitted in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

by

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June, 2022

Dedicated to

My Family and Teachers

DECLARATION

By the Ph.D. Research Scholar

I hereby declare that the Research Thesis entitled **IMPROVED NATURE INSPIRED ALGORITHMS FOR OPTIMIZATION PROBLEMS IN WIRELESS SENSOR NETWORKS** which is being submitted to the **National Institute of Technology Karnataka, Surathkal** in partial fulfillment of the requirements for the award of the Degree of **Doctor of Philosophy** in **Mathematical and Computational Sciences** is a bonafide report of the research work carried out by me. The material contained in this Research Thesis has not been submitted to any University or Institution for the award of any degree.

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CERTIFICATE

This is to certify that the Research Thesis entitled **IMPROVED NATURE INSPIRED ALGORITHMS FOR OPTIMIZATION PROBLEMS IN WIRELESS SENSOR NETWORKS** submitted by **Pradeep Kanchan**, (Reg. No.: 155055 MA15F05) as the record of the research work carried out by him, is accepted as the Research Thesis submission in partial fulfilment of the requirements for the award of degree of **Doctor of Philosophy**.

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"A hundred times every day I remind myself that my inner and outer life are based on the labors of other men, living and dead, and that I must exert myself in order to give in the same measure as I have received and am still receiving"
- Albert Einstein

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ABSTRACT

In a Wireless Sensor Network (WSN), the nodes are placed in random positions and connected to each other through networks. The nodes collect data from each other, perform processing and the results are sent to a Base Station (BS).

In simple words, Optimization is selecting the best element, with respect to some criterion, from a given set of alternatives. Most of the research in the field of WSNs have concentrated on optimizing clustering, energy efficiency, network lifetime, coverage, load balancing, fault tolerance, quality of service, etc. Multi Objective Optimization deals with optimizing more than one objective at the same time.

This thesis concentrates on developing nature inspired algorithms for energy efficient clustering and for improving network lifetime in conjunction with Quantum computing. Also, the aim is to develop an efficient nature inspired algorithm for optimizing target coverage in Homogeneous as well as Heterogeneous WSN using Quantum Computing.

For achieving the first 2 objectives (Optimizing Energy Efficiency and Improving Network Lifetime), the nature inspired algorithm, PSO (Particle Swarm Optimization) is used in conjunction with Quantum computing. For the 3rd objective (Optimizing Target Coverage), another nature inspired algorithm, MOEAD (Multi Objective Evolutionary Algorithm with Decomposition) is used in conjunction with quantum computing.

Keywords: Optimization, WSN, Quantum computing, Nature inspired algorithms.

Table of Contents

List of Figures

List of Tables

Acronyms

1. ACO - Ant Colony Optimization
2. ABC - Artificial Bee Colony
3. WSN - Wireless Sensor Network
4. BS - Base Station
5. PSO - Particle Swarm Optimization
6. MOEAD - Multi Objective Evolutionary Algorithm with Decomposition
7. PBA - Physics Based Algorithms
8. CBA - Chemistry Based Algorithms
9. BBA - Biology Based Algorithms
10. CBO - Colliding Bodies Optimization
11. GSA - Gravitational Search Algorithm
12. HSA - Harmony Search Algorithm
13. SA - Simulated Annealing
14. CRO - Chemical Reaction Optimization
15. ACPA - Artificial Chemical Process Algorithm
16. ACROA - Artificial Chemical Reaction Optimization Algorithm
17. CRA - Chemical Reaction Algorithm
18. EA - Evolutionary Algorithms
19. BIA - Bio-inspired Algorithms

20. SIA - Swarm Intelligence based Algorithms
21. GA - Genetic Algorithm
22. GP - Genetic Programming
23. DE - Differential Evolution
24. CA - Cultural Algorithm
25. FA - Firefly Algorithm
26. CS - Cuckoo Search
27. BFOA - Bacterial Foraging Optimization Algorithm
28. LEACH - Low - Energy Adaptive Clustering Hierarchy
29. PSOECHS - Particle Swarm Optimization based Energy efficient Cluster Head Selection
30. SEP - Stable Election Protocol
31. NSGA II - Nondominated Sorting Genetic Algorithm II
32. PEGASIS - Power - Efficient GAthering in Sensor Information Systems
33. TL-LEACH - Two-Levels hierarchy for Low-Energy Adaptive Clustering Hierarchy
34. QPSO - Quantum Particle Swarm Optimization
35. EB- QPSO - Elitist Breeding QPSO
36. MOO - Multi Objective Optimization
37. MOP - Multi Objective Problem

CHAPTER 1

Introduction

1.1 Nature Inspired Inventions

Nature has always inspired mankind to invent and continues to do so. Examples are so many but only 3 have been given to illustrate how nature inspires invention.

The *kingfisher* (Hennighausen (2017)), a fish-eating bird, inspired the Japanese Engineer Eiji Nakatsu. It barely creates a ripple when it darts into water in search of fish. He redesigned the nose of high-speed train inspired by the beak of kingfisher to look like a 50 foot long steel beak. This reduced the high level noise caused by high-speed trains and also reduced power use and enabled higher speeds

The bumps on the shell of *Namibian beetle* (Hennighausen (2017)) catch water droplets, which then run down chutes toward its mouth. Inspired by this, Pak Kitae of Seoul National University of Technology developed *'Dew Bank Bottle'*. Morning dew condenses on it and conveys it to a bottle, which has a drinking spout.

When insects of the genus Photuris (*Fireflies*)(Hennighausen (2017)) light fires in their bellies, the radiance is amplified by their anatomy — sharp, jagged scales, according to research by scientists from Belgium, France, and Canada. Based on this observation, the scientists then built and laid a similar structure on a light-emitting diode (LED), which increased its brightness by 55 percent.

1.2 Nature Inspired Algorithms / Nature Inspired Computing

Nature Inspired Algorithms / Nature Inspired Computing refers to a class of meta heuristic algorithms that imitate or are influenced by some natural phenomena explained by natural sciences. A common feature shared by all nature-inspired meta heuristic algorithms is that they combine rules and randomness to imitate some natural phenomena.

The nature inspired algorithms can be grouped into 3 broad classes (Siddique and Adeli, 2015) : Physics Based Algorithms (PBA), Chemistry Based Algorithms (CBA) and Biology Based Algorithms (BBA) as shown in Figure 1.1 :

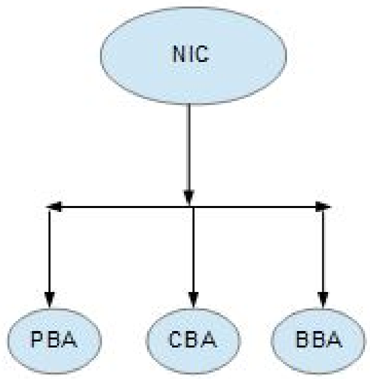

Figure 1.1 Classes of Nature Inspired Algorithms / NIC

1. **Physics-based Algorithms (PBA):**

   Examples:

   - Colliding Bodies Optimization (CBO) - inspired by Newton's laws of motion
   - Gravitational Search Algorithm (GSA) - inspired by Newton's gravitational force
   - Harmony Search Algorithm (HSA) - inspired by Acoustics

- Simulated Annealing (SA) - inspired by Thermodynamics

2. **Chemistry-based Algorithms(CBA):**

   Examples:

   - Chemical Reaction Optimization (CRO) algorithm - based on simulation of molecules' movements and their resultant chemical reactions
   - Artificial Chemical Process Algorithm (ACPA)
   - Artificial Chemical Reaction Optimization Algorithm (ACROA)
   - Chemical Reaction Algorithm (CRA)

3. **Biology-based Algorithms (BBA):**

   Biology based algorithms can be classified into 3 groups : Evolutionary Algorithms (EA), Bio-inspired Algorithms (BIA) and Swarm Intelligence based Algorithms (SIA) as shown in Figure 1.2 :

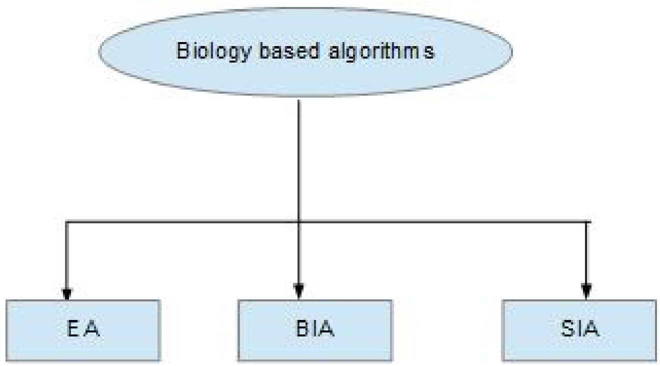

Figure 1.2 Classification of Biology based algorithms

   (a) **Evolutionary Algorithms (EA):**

   - Evolutionary Programming (EP)
   - Evolutionary Strategies (ES)
   - Genetic Algorithm (GA)
   - Genetic Programming (GP)

- Differential Evolution (DE)
- Cultural Algorithm (CA)

(b) **Bio-inspired Algorithms (BIA):**

- Particle Swarm Optimization (PSO)
- Bird Flocking (BF)
- Fish School (FS)
- Biogeography Based Optimization (BBO)
- Artificial Immune Systems (AIS)
- Lindenmayer Systems (LS)

(c) **Swarm Intelligence based Algorithms(SIA):**

- Ant Colony Optimization (ACO)
- Artificial Bee Colony (ABC)
- Bat Algorithm (BatA)
- Firefly Algorithm (FA)
- Cuckoo Search (CS)
- Bacterial Foraging Optimization Algorithm (BFOA)

1.3 Wireless Sensor Network

1.3.1 Basics of WSN

The basic structure of a node is given in Figure 1.3 (Kuila and Jana, 2017).

As shown in the above figure, a sensor node consists of 4 components:

1. Sensing unit
2. Processing unit
3. Transceiver unit
4. Power supply unit

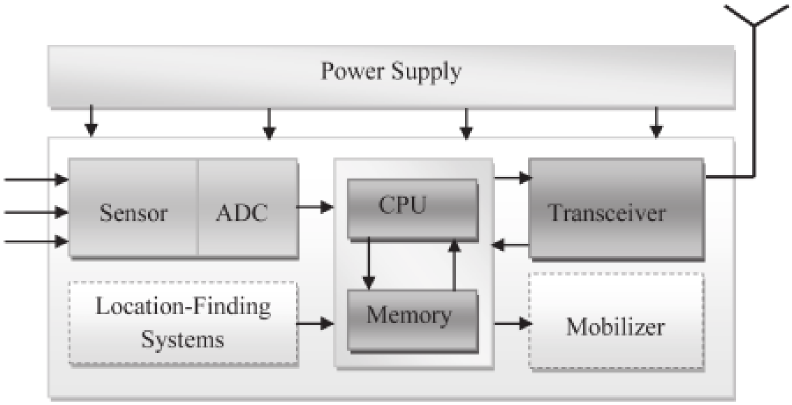

Figure 1.3 Basic Components of WSN

Sensing Unit:

The sensing unit usually consists of many sensor units which allow it to gather information from the physical world. The sensor unit can gather information like light, temperature, humidity, etc. It consists of 2 subunits- a sensor and an ADC (Analog to Digital Converter). The sensor observes the phenomenon for which it is designed and generates analog signals. The ADC converts these analog signals into digital signals. These digital signals are then sent to the processing unit.

Processing Unit:

This part serves as the sensor node's 'heart.' The processor unit may include onboard memory or be linked to a tiny storage device. This unit is in charge of the procedures that allow the sensor node to perform sensing activities, run accompanying algorithms, and communicate with other nodes via wireless communication.

Transceiver unit:

The transceiver units are responsible for communication between any two sensor nodes. The operations for converting bits to be transferred into radio frequency (RF) waves and recovering them at the other end are implemented by a transceiver unit. This unit helps in connecting the WSN to the network.

Power supply unit:

The power unit is one of the most crucial components of a sensor node. The most common power source is battery power, even though there can be other energy sources also. Each component in the wireless sensor node is powered by the power unit, and the power unit's limited capacity necessitates energy-efficient operation for each component's functions.

1.3.2 WSN Architecture

A WSN is made up of a large number of small, low-power, and low-cost sensor nodes that are distributed randomly or manually over an unmanaged target region. Sensor nodes collect local data on a regular basis, process it, and then transfer it to a remote base station (BS), also known as a sink, via single-hop or multi-hop communication. The sink is connected to the internet in order to bring the phenomenon to the attention of the general public. The detected data is conveyed to the sink in a continuous, event-driven, query-driven, or hybrid manner, depending on the many applications of the sensor network. In continuous data communication, all sensor nodes communicate data to the sink on a regular basis. In some applications, a sensor node only communicates observed data to the sink if an event occurs, which is known as event-driven. The BS or sink sends a query to all sensor nodes in the sensing zone via flooding or direct communication in the query-driven paradigm. The sensor nodes with data matching the query will then respond to the sink. A hybrid model, which combines continuous, event-driven, and query-driven data delivery, is used by several applications. There are 2 types of WSN architecture:

1. Flat

2. Hierarchical

Flat Architecture:

Each sensor node in a Flat sensor network is responsible for efficiently performing the sensing duty. Single-hop or multi-hop communication is used by the sensor nodes to send the detected data to the sink.

Figure 1.4 (Kuila and Jana, 2017) depicts both Single-hop and Multi-hop communication. Single-hop communication is used for small area sensor networks and when sink is located near the region. In Multi-path communication, each sensor node selects another sensor node as a next-hop relay node for forwarding data to the sink.

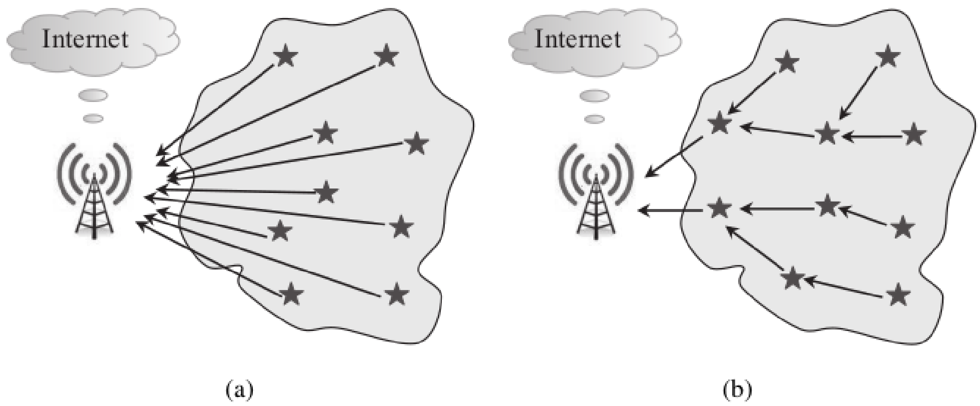

Figure 1.4 Flat wireless sensor network architecture: a) Single-hop communication and b) Multi-hop communication between sensor nodes and sink

Hierarchical architecture:

Sensor nodes in a Hierarchical network are organised into groups called Clusters. A Cluster Head (CH) is the leader of each cluster. All sensor nodes detect local data and transmit it to the corresponding CH. The local data is then aggregated by the CHs before being sent to the base station (BS) directly or via other CHs.

The working of Cluster-based WSN with Single-hop and Multi-hop are shown in Figures 1.5 and 1.6 respectively. (Kuila and Jana, 2017)

1.3.3 Design Challenges in WSN

The majority of sensor networks are application-specific, with varying application requirements. This is one of the primary reasons why it is not feasible to address all design challenges in a single network. Instead, only a portion of these challenges are considered in the design of an application-specific network based on the application requirements. The following is a list of important challenges which researchers of WSN have worked on: (Labrador and Wightman, 2009)

- **Network Lifetime:** Since WSNs run on batteries, it is important that these batteries can last longer to get better network lifetime. When WSNs are deployed on a large scale or deployed in dangerous applications, the number of times the batteries are changed should be kept to a minimum. Network lifetimes in the order

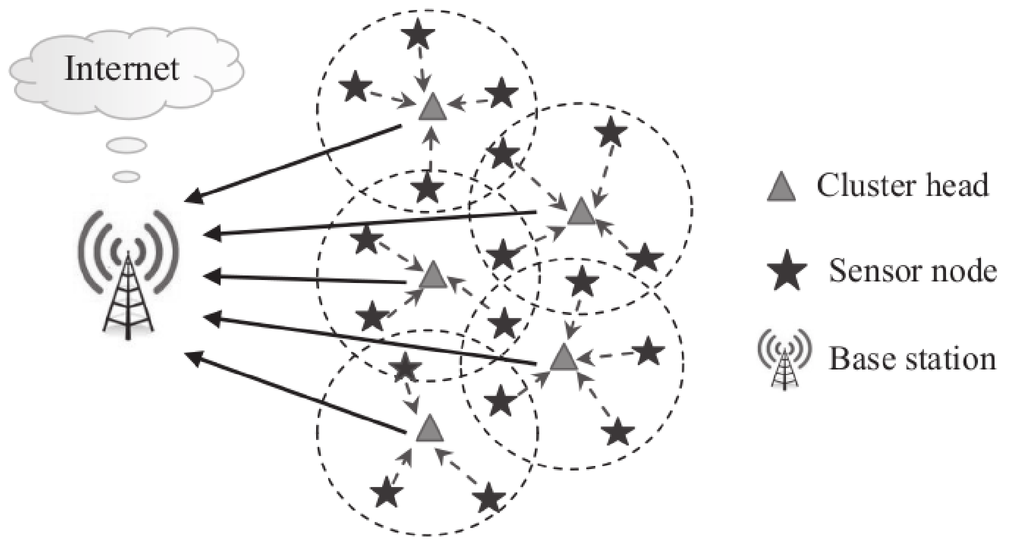

Figure 1.5 A cluster-based wireless sensor network architecture with Single-hop communication between CHs and base station. Small dashed arrows show the communication between sensor nodes and their corresponding CHs, and large arrows for the same between CHs and CHs or CHs and base station.

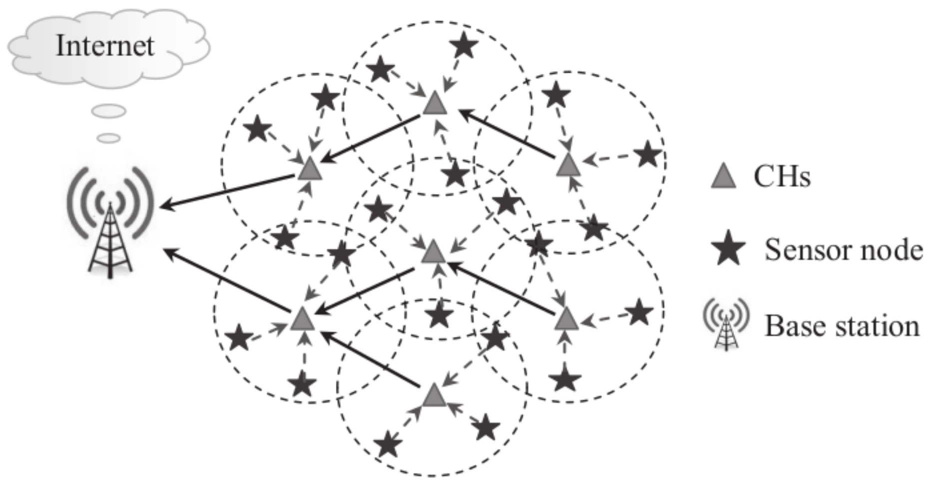

Figure 1.6 A cluster-based wireless sensor network architecture with Multi-hop communication between CHs and base station

of many years would be ideal.

- **Scalability:** Depending on the application, hundreds to thousands of wireless sensor devices maybe required. As an example, suppose WSNs are used to monitor the India-Pakistan border. The one size fits all approach will not work here.

Some of the algorithms and protocols which work in small scale networks may not work in large scale ones. One example is of Routing. Using Dijkstra's shortest path algorithm, small-scale networks can easily run well-known proactive or reactive routing protocols. This approach, however, will not be energy-efficient for large-scale wireless sensor networks. Instead, location-based routing mechanisms based on local information are better suited.

- **Interconnectivity:** WSNs must be interconnected in order for data to reach its intended destination for storage, analysis, and possible action. WSNs are connected to each other using various technologies. To achieve these interconnections and allow data transfer to and from WSNs, new protocols and mechanisms must be developed.

- **Reliability:** The devices used are cheap and more prone to failure. Available energy plays an important role in the reliability of a node.

- **Heterogeneity:** The newly developed WSNs may require the development of algorithms and protocols which never existed before.

- **Privacy and security:** As is normal in networking, privacy and security are of concern in WSNs too. Algorithms which are not too complex and need less energy are in demand.

- **Coverage:** In simple words, Coverage means that each point in a particular area will be monitored by a sensor node. Ideally, a large area would need to be covered using minimum number of nodes.

  All the above challenges are influenced by one factor : Energy. The energy available in the individual nodes has an effect on the lifetime of the network. This is one of the reasons due to which there are so many research publications on energy efficiency of WSNs and related protocols.

  In our thesis, we have restrained ourselves to the study of the 3 issues :

  – Energy Efficiency

- Network Lifetime
- Coverage

1.3.4 Homogeneous Vs Heterogeneous WSNs

Sensor networks can be classified into 2 types, Homogeneous and Heterogeneous (Kuila and Jana, 2017) . In Homogeneous networks, the sensor nodes are similar as far as energy of nodes, memory capacity, etc are concerned. In Heterogeneous networks, some of the nodes may differ in the above properties.

1.3.5 Static Vs Mobile Sink

Sinks can be Static or Mobile (Kuila and Jana, 2017) . In harsh environments, the sink maybe static and kept near sensing region. The sensor nodes can report to the static sink. The disadvantage of Static sinks is that energy of sensor nodes near the sink will deplete fast due to relaying of sensed data to sink. These nodes will die and sink is cutoff from the network. This problem is commonly known as the hot-spot or sink-hole problem. Mobile sinks can help in solving these problems. Even though mobile sinks prolong network lifetime, there is considerable overhead required to develop routing protocols for them.

1.3.6 Clustering in WSN

In a Clustered WSN, the nodes are grouped into various Clusters. For each cluster, there is a leader, the CH (Cluster Head). The job of the nodes is to sense data and send it to their respective CH. It is the job of the CH to collect all the data and send it to Base Station (BS), either directly or through other CHs. Cluster based WSNs have some advantages:

1. Data aggregation at the CH avoids redundant data. Therefore, the network does not have to transmit high volume of redundant data and this reduces Energy consumption.

2. Only CHs need to have information about the routes of other CHs and this decreases routing information required. The Scalability of the network is improved due to this.

3. Since the sensor nodes communicate with only CHs and not among themselves, Communication bandwidth is conserved.

1.3.7 Challenges in Clustered WSNs

1. **Cluster Head Selection:** Selection of CHs from normal sensor nodes is an important step and a lot of care has to be taken for this.

2. **Cluster formation:** Once the CHs are selected, the assigning of normal nodes to corresponding CHs has to be done efficiently.

3. **Load balancing:** During the assignment of nodes to CHs, if nodes are not properly assigned, some CHs maybe Overloaded and some may not have Load. This has to be avoided. Also, assigning of nodes to CHs located far from them may lead to more energy consumption and lead to decreased network lifetime.

4. **Fault tolerance:** Failure of nodes can hamper the network. But, failure of CHs may be dangerous since the non CHs connected to these failed CHs also become inaccessible. Clustering algorithms should handle this scenario.

1.4 Bioinspired algorithms and WSN

Bioinspired algorithms have been used to optimize various parameters of a WSN. In (Martins et al., 2010), the Genetic Algorithm (GA) has been used to optimize connectivity and coverage. In (Mohamed et al., 2020), energy is optimized using the Coyote Optimization Algorithm (COA). (Bouzid et al., 2020) optimizes coverage and connectivity using GA. Network lifetime and energy are optimized in (Osamy et al., 2020) using Chicken Swarm Optimization algorithm. In (Balasubramani et al., 2021), the Grey Wolf Optimization algorithm is used to optimize energy. The work of (Al-Otaibi et al., 2021) uses Human Brainstorm Optimization algorithm to optimize energy and lifetime.

1.5 Quantum Computing

In Traditional computing, the operations are done using bits which can be either 0 or 1. In Quantum computing, the bits, called Qubits, can be either 0 or 1 or both simultane-

ously and this makes quantum computing very powerful in solving complex problems. A sample problem will help us to understand the power of quantum computing. Suppose one item has to be found from a list of N items. On a classical computer N/2 items would have to be checked on the average, and in the worst case all the N items would need to be checked. Using a quantum algorithm, Grover's search, the item is found after checking roughly $\sqrt{N}$ of them. This represents a remarkable increase in processing efficiency and time saved. If one item has to be found in a list of 1 trillion, and each item takes 1 microsecond to check, in a classical Computer, about 1 week would be needed and in a quantum computer, only about 1 second would be enough.
At a particular moment in time, a qubit can be in 0 state, 1 state or a superposition of these 2 states. Its state can be derived from :

$$|\psi>= \alpha|0> + \beta|1> \tag{1.1}$$

where α and β are the probability amplitudes of the corresponding states. $|\alpha|^2$ is the probability that a qubit will be in '0' state and $|\beta|^2$ is the probability that the qubit will be in '1' state.

$$|\alpha|^2 + |\beta|^2 = 1 \tag{1.2}$$

The state of a qubit changes through quantum gates. We change the state of qubits by using rotation gates. The Q bit string of m bits is represented as a quantum matrix:

$$\begin{bmatrix} \alpha_1| & \alpha_2| & .... & |\alpha_m \\ \beta_1| & \beta_2| & .... & |\beta_m \end{bmatrix} \tag{1.3}$$

where

$$|\alpha_i|^2 + |\beta_i|^2 = 1, i = 1, 2, ..., m \tag{1.4}$$

The state of the quantum bits are updated using the Rotation gate method as below:

$$\begin{bmatrix} \alpha_{new} \\ \beta_{new} \end{bmatrix} = \begin{bmatrix} cos(\theta) & -sin(\theta) \\ sin(\theta) & cos(\theta) \end{bmatrix} \begin{bmatrix} \alpha_{old} \\ \beta_{old} \end{bmatrix} \tag{1.5}$$

where θ is the rotation angle of each qubit toward either 0 or 1 depending on the sign, α_{new} and β_{new} denote the updated values and α_{old} and β_{old} denote the values in previous iteration.

The value of θ is determined by a certain adjustment strategy in conventional quantum genetic algorithm and the value of θ is generally a constant value around 0.01π (Wang et al., 2013). A large rotating angle is set early in the evolutionary process to quickly facilitate the entire interval and find the region with the optimal values. To accurately find the optimal value, the value of rotating angle is reduced while the evolution is increased.

1.6 Research objectives

The following are the objectives fulfilled by our research:

1. Develop an *Energy Efficient* nature inspired Clustering algorithm using Quantum computing

2. Develop a nature inspired Clustering algorithm using Quantum Computing to improve the *Network Lifetime*

3. Develop an efficient nature inspired algorithm for *Target Coverage* in Homogeneous as well as Heterogeneous WSN using Quantum Computing

1.7 Problem Statement

The aim is to develop Nature inspired algorithms which also use the concept of Quantum computing for the problems of Energy efficient clustering, Improving Network Lifetime and Target coverage

1.8 Organization of the thesis

The organization of the thesis is as follows.
Chapter 1, provides an introduction about the various topics central to this thesis. A brief introduction about some of the topics like Nature Inspired inventions, Nature Inspired Computing, Wireless Sensor Networks and Quantum Computing is also given. Further, the Research Objectives and Problem statement have been mentioned.

Chapter 2, explains the literature survey done on the Design challenges of WSN which have been highlighted in the thesis i.e. Energy Efficient Clustering, Improving Network Lifetime and Target Coverage. Some of the standard schemes are also explained, which are useful for performance comparison with our proposed schemes in these areas.

In **Chapter 3**, the Energy Efficient scheme for Clustered WSNs using Quantum Inspired Computing is explained. The scheme is called Quantum-inspired PSO for Energy Efficient Clustering (QPSOEEC). It is compared with some of the widely popular approaches for energy efficient clustering, LEACH (Heinzelman et al., 2002) and PSOECHS (Rao et al., 2017) through simulation. In comparison with the mentioned schemes, the performance of our proposed scheme is better.

In **Chapter 4**, the Quantum PSO Algorithm for Clustering in WSNs is explained. The scheme is called Quantum PSO Clustering algorithm to Improve Network Lifetime (QPCINL). A term Network Lifetime Factor (NLF) is introduced here. The scheme is compared with existing algorithms, LEACH (Heinzelman et al., 2002) and PSOECHS (Rao et al., 2017). In comparison with the mentioned schemes, the performance of our proposed scheme is better.

In **Chapter 5**, the Quantum Inspired Multiobjective Optimization in Clustered Homogeneous WSN is explained. This scheme is called the Quantum inspired Multi Objective Evolutionary Algorithm based on Decomposition (QMOEAD). The scheme is compared with LEACH (Heinzelman et al., 2002), SEP (Smaragdakis et al., 2004), NSGA II (Deb et al., 2002) and MOEA/D (Özdemir et al., 2013) by simulation for Homogeneous WSNs and our scheme proves to be better than the mentioned schemes.

In **Chapter 6**, the Quantum Optimizer based on MOEAD for Optimizing Lifetime and Coverage in WSN is discussed. The scheme is compared with LEACH (Heinzelman et al., 2002), SEP (Smaragdakis et al., 2004), NSGA II (Deb et al., 2002) and MOEA/D (Özdemir et al., 2013) by simulation for Homogeneous as well as Heterogeneous WSNs and our scheme proves to be better than the mentioned schemes.

Chapter 7, concludes the thesis with the summary of contributions of research and future work.

CHAPTER 2

Literature Survey

2.1 Related work

2.1.1 Nature inspired approaches for clustering

The PSO (Particle Swarm Optimization) was proposed by (Tillett et al., 2002) for the problem of Clustering. The drawback of this method is that it can cause imbalance in the energy in the network due to the assignment of non CH nodes to CH nodes based on the distance. (Guru et al., 2005) discuss cluster formation based on PSO. The drawback of this work is that it ignores residual energy in the nodes. The PSO-C algorithm (Latiff et al., 2007) is used for energy aware CH selection. Here, during the formation of clusters, non CH nodes are assigned to CH nodes which are nearer than other nodes. It may not be energy efficient. The lifetime of the network also is decreased here. In (Rao et al., 2017), CH selection is done by using PSO. A weight function is used during cluster formation. This weight function is the basis on which non-CH nodes are joining the CH nodes.

2.1.2 Heuristic approaches for clustering

LEACH (Heinzelman et al., 2002) is one of the classic algorithms used in clustering. Cluster formation happens with one node taking up the role of CH. The work of non-CH nodes is to send the data to the CH nodes. The CH nodes have to now gather the data and send it forward to the BS. The drawback here is that a low energy CH maybe selected which may affect the working. In PEGASIS (Lindsey and Raghavendra, 2002), a node communicates with only its closest neighbour and the nodes transmit to the BS in turns. PEGASIS outperforms LEACH in terms of energy efficiency but may not perform so well when there are large size networks. In TL-LEACH (Two-Levels hierarchy for Low-Energy Adaptive Clustering Hierarchy) (Loscri et al., 2005), the local cluster base stations are rotated randomly. These local base stations are designated as Primary and Secondary CHs. The drawback of this method is that there maybe extra overhead due to the Secondary CHs selected. Also, the assignment of non-CH nodes to CHs may cause energy imbalance. In V-LEACH (Yassein et al., 2009), there is the concept of Vice CHs. These Vice CHs are supposed to take over when the main CHs die. The drawback is that extra effort is required in the selection of the Vice CHs. In E-LEACH (Energy LEACH) (Xiangning and Yulin, 2007), nodes for future rounds are chosen based on the residual energy present in the nodes. The advantage of this method is it improves the lifetime of the network.

2.1.3 Quantum Computing based algorithms

In the Quantum PSO (Sun et al., 2004), a single particle moving around in quantum multidimensional space is studied. In the EB- QPSO (Elitist Breeding Quantum Particle Swarm Optimization) (Yang et al., 2015), elitist breeding guides the swarm towards more efficient search. In (Sun et al., 2012), the QPSO is analyzed. A parameter known as the Contraction Expansion (CE) coefficient influences a particle's behaviour. That particular value of the CE coefficient is found which makes sure that the position of the particle converges. (Pant et al., 2008) developed their own version of QPSO which they call Q-QPSO . Here, a recombination operator which uses interpolation is used. In the Quantum PSO (Yin et al., 2010), quantum rotation gates update the quantum bits and quantum non-gates perform mutation. Their algorithm outperforms GA and traditional PSO.

2.1.4 Algorithms on Network Lifetime

In (Chen and Zhao, 2005), the network lifetime is found in such a way that there is no dependence on the network model. In (Rahman and Matin, 2011), the authors have proposed an efficient algorithm for locating the optimal sink position using PSO. This helps in saving energy and prolonging network lifetime. In (Yetgin et al., 2015), the authors have proposed a technique in which 2 stages are used and the network lifetime is maximized. In (Dietrich and Dressler, 2009), the authors have given a review on lifetime and the pros and cons of the different methods related to lifetime.

2.1.5 Coverage

Table 2.1 Coverage

Paper	**Parameter optimized**	**Evolutionary**	**WSN Type**
(Tian and Georganas, 2002)	Coverage, lifetime	No	Heterogeneous
(Zhang et al., 2005)	Coverage, lifetime	No	Heterogeneous
(Soro and Heinzelman, 2009)	Coverage	No	Heterogeneous
(Lin et al., 2009)	Coverage, lifetime	No	Heterogeneous
(Thomas et al., 2021)	Coverage, connectivity	No	Homogeneous
(Deepa and Venkataraman, 2021)	Coverage	Yes	Homogeneous

Table 2.1 lists the salient features of papers on Coverage. The details about the parameter(s) optimized, whether they are based on Evolutionary algorithms and the type of WSN (Homogeneous / Heterogeneous) are mentioned in this table.

2.1.6 Energy Efficiency and Lifetime

Table 2.2 Energy Efficiency and Lifetime

Paper	**Parameter optimized**	**Evolutionary**	**WSN Type**
(Heinzelman et al., 2002)	Lifetime	No	Homogeneous
(Smaragdakis et al., 2004)	Lifetime	No	Heterogeneous
(Cardei and Du, 2005)	Lifetime	No	Homogeneous
(Khalil and Bara'a, 2011)	Lifetime, energy	Yes	Heterogeneous
(Bara'a and Khalil, 2012)	Lifetime, energy	Yes	Heterogeneous
(Abidi and Ezzedine, 2020)	Lifetime, energy	No	Heterogeneous
(Alaei and Yazdanpanah, 2019)	Lifetime, energy	No	Homogeneous
(Li et al., 2019b)	Lifetime, energy	Yes	Homogeneous
(Daneshvar et al., 2019)	Lifetime, energy	Yes	Homogeneous
(John and Rodrigues, 2019)	Energy	Yes	Homogeneous
(Singh and Nagaraju, 2020)	Lifetime, energy	No	Heterogeneous
(Hung et al., 2020)	Lifetime, energy	Yes	Heterogeneous
(Lata et al., 2020)	Lifetime, energy	No	Heterogeneous
(Krishnan et al., 2021)	Lifetime, energy	No	Both

The salient features of papers on Energy efficiency and network lifetime are listed in Table 2.2. The details about the parameter(s) optimized, whether they are based on Evolutionary algorithms and the type of WSN (Homogeneous/Heterogeneous) are mentioned in this table.

2.1.7 Energy Efficiency and Coverage

Table 2.3 lists the salient features of papers on Energy Efficiency and Coverage.

Table 2.3 Energy Efficiency and Coverage

Paper	Parameter optimized	Evolutionary	WSN Type
(Ye et al., 2003)	Energy, coverage, lifetime	No	Heterogeneous
(Martins et al., 2007)	Energy, Coverage, Connectivity	No	Heterogeneous
(Özdemir et al., 2013)	Energy, Coverage	Yes	Both
(Chowdhury and De, 2021)	Energy, Coverage	Yes	Homogeneous

2.1.8 Nature Inspired Algorithms for WSN Optimization

Table 2.4 Nature Inspired Algorithms for WSN Optimization

Paper	Parameter optimized	Based on	WSN Type
(Martins et al., 2010)	Connectivity, coverage	Genetic Algorithm	Heterogeneous
(Mohamed et al., 2020)	Energy	Coyote Optimization Algorithm	Heterogeneous
(Bouzid et al., 2020)	Coverage, connectivity	GA	Heterogeneous
(Osamy et al., 2020)	Lifetime, Energy	Chicken Swarm Optimization	Homogeneous
(Balasubramani et al., 2021)	Energy	Grey Wolf Optimization	Homogeneous
(Al-Otaibi et al., 2021)	Energy, Lifetime	Human Brainstorm optimization	Heterogeneous

Table 2.4 lists the salient features of papers on Nature Inspired Algorithms for WSN Optimization.

2.1.9 Quantum based Nature Inspired algorithms for WSN Optimization

Table 2.5 lists the salient features of papers on Quantum based Nature Inspired algorithms for WSN Optimization.

Table 2.5 Quantum based Nature Inspired algorithms for WSN Optimization

Paper	**Parameter optimized**	**Based on**	**WSN Type**
(Li and Huo, 2016)	Energy, Lifetime	Quantum, GA	Homogeneous
(Kanchan and Pushparaj, 2018)	Energy	Quantum, PSO	Homogeneous
(Li et al., 2019a)	Energy, Lifetime	Quantum, ACO	Heterogeneous
(Kanchan et al., 2021)	Lifetime, Coverage	Quantum, MOEAD	Homogeneous
(Zhang et al., 2021)	Location sensing	Quantum, PSO	Heterogeneous

2.1.10 Multi Objective Optimization (MOO)

In optimization, the aim is to come up with the best / most favorable solution for a problem, given a set of criteria. The decision maker is the one taking this decision. In MOO (Coello et al., 2007), the optimization results in a solution which consists of objective functions acceptable by the decision maker. The solution must also satisfy some constraints which are specific to that problem. In single objective optimization, maximizing or minimizing a single objective function is the aim.

The Multi Objective Problem (MOP) can be defined as :

$$\begin{gathered} Minimize/Maximize\; F(x) = (f_1(x), f_2(x), \ldots, f_n(x)) \\ subject\; to\; x \varepsilon \Omega \end{gathered} \tag{2.1}$$

where x represents the decision variable, F:$\Omega \rightarrow R^n$ is used to represent the n objective functions, Ω is used for representing Search Space and R^n for representing Objective Space. Global optimization deals with search for one solution whereas in MOP's, we are satisfied with a solution which is good enough.

2.1.11 Multi Objective Evolutionary Algorithms (MOEA)

In multi-objective optimization, the aim is to come up with solutions which are a trade-off between the various objectives which we want to optimize. In MOO, Dominance determines how good a solution is.

In general, x_1 is said to dominate x_2 if

- x_1 is no worse than x_2 in all objectives
- x_1 is strictly better than x_2 in at least one objective

Given a set of solutions, the Non-Dominated solution set is a set of all the solutions that are not dominated by any member of the solution set.

Several MOEA variations have been explored by researchers. In NSGA (Srinivas and Deb, 1994), a non-dominated solution is that set of solutions where many solutions are there but none of them dominate the others. (Deb et al., 2002) is a better version of NSGA and it achieves better convergence. The MOEA/D in (Özdemir et al., 2013) performs optimization of network lifetime and coverage of a WSN. It outperforms LEACH (Heinzelman et al., 2002), SEP (Smaragdakis et al., 2004) and NSGA II (Deb et al., 2002). In the multiobjective optimization method in (Pan et al., 2021), the authors propose a binary crossover method based on rotation which improves the performance of multiobjective evolutionary algorithms. The MOEA/D (Zhang and Li, 2007) splits the multiobjective problem into a number of subproblems. These subproblems are optimized simultaneously. A population which consists of solutions is evolved. In each generation, the population consists of the best solution which has been found for a subproblem.

CHAPTER 3

Energy Efficient scheme for Clustered WSNs using Quantum Inspired Computing

3.1 Introduction

In this chapter, the Quantum inspired PSO for Energy Efficient Clustering (QPSOEEC) is presented which is inspired by Nature. This algorithm tries to take advantage of the best features of PSO and Quantum Computing.

3.2 Preliminaries

3.2.1 PSO Introduction

Particle Swarm Optimization (PSO) was proposed by Kennedy and Eberhart in 1995 (Kennedy and Eberhart, 1995). The main idea of PSO is that in a swarm consisting of birds, the birds can share their discovery about food and this helps the entire group of birds to maximize their chances of getting food. A bird in the swarm can be compared to a particle. N represents the total number of particles in the swarm. A particle P is defined by a Position Vector and a Velocity Vector. A Position Vector denoted by X = $(x_1, x_2, ..., x_D)$ represents the solution and the Velocity Vector represented by V = $(v_1, v_2, ..., v_D)$ performs exploration of search space. Here, the dimension of the search space is D. It is the same for all particles. A fitness function is used to evaluate each particle. The PSO aims to find an optimal position of the particle which yields the best fitness. The first step is Initialization in which each particle is assigned with a position and velocity. During every iteration, P_{best_i} which is personal best value of the particle and G_{best} which is the global best value of the whole swarm are calculated. Finally, it should attain the global solution which is the best. X, the position of the particle and V, the velocity of the particle are updated using :

$$V_{i,d}(t+1) = \omega V_{i,d}(t) + C_1 r(X_{P_{best,d}} - X_{i,d}) + C_2 R(X_{G_{best}} - X_{i,d}) \tag{3.1}$$

$$X_{i,d}(t+1) = X_{i,d}(t) + V_{i,d}(t+1) \tag{3.2}$$

Here, ω is the Inertia weight with values between 0 and 1.
C_1, C_2 are Acceleration coefficients with $0 \leq C_1$ and $C_2 \leq 2$
r , R are two random numbers uniformly distributed in the interval (0,1)
d is the Dimension component which has value between 1 and D
i is the number of the particle
This updation continues till a value of G_{best} which is acceptable is generated. P_{best_i} and G_{best} are calculated as follows :

$$\begin{aligned} P_{best_i} &= P_i, if\ [Fitness(P_i) < Fitness(P_{best_i})] \\ &= P_{best_i}, otherwise \end{aligned} \tag{3.3}$$

$$\begin{aligned} G_{best} &= P_i, if\ [Fitness(P_i) < Fitness(G_{best})] \\ &= G_{best}, otherwise \end{aligned} \tag{3.4}$$

3.2.2 PSO Encoding for CH Selection problem of WSN

The aim of PSO is to find the optimal position of the particle. In case of the CH selection problem, it is the optimal position of the Cluster Heads (CH). Assume that $P_i = [X_{i,1}(t), X_{i,2}(t), ..., X_{i,D}(t)]$ represents the i^{th} particle of the generation. Here, we have to keep in mind that $1 \leq i \leq N$ where N represents the number of particles and also $1 \leq d \leq D$ where D is the number of dimensions and in the encoding, it is the number of Cluster Heads.
$X_{i,d}(t) = (x_{i,d}(t), y_{i,d}(t))$ represents the coordinates of the sensors which are going to be selected as CH. Therefore, we can represent the i^{th} particle as

$$P_i = [(x_{i1}(t), y_{i1}(t)), (x_{i2}(t), y_{i2}(t), ..., (x_{id}(t), y_{id}(t))] \tag{3.5}$$

Figure 3.1 shows the particle representation for PSO. In the figure, CH refers to the index for the CH's, s indicates the index for the Sensors and o indicates the coordinates of the sensors which are generated in random.

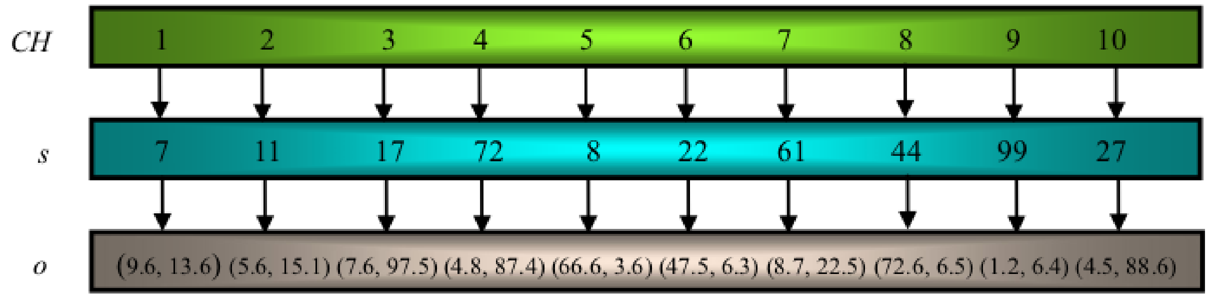

Figure 3.1 Particle representation for PSO

In the scenario shown , s_7 is selected as CH_1, s_{11} is selected as CH_2 and so on. The coordinates for the sensor nodes are assigned randomly (number between 0 to 100). For example, s_1 is assigned the coordinates (9.6,13.6), s_{11} is assigned the coordinates (5.6,15.1) and so on.

Let us assume there are 10 particles (D=10) and the velocities of these particles are 0. For the first iteration, every particle is itself the Personal best P_{best_i}. Let us assume that the 3^{rd} particle is the Global Best, G_{best}. Assume that (8.0,58.2) is the first dimension of P_3. P_1 is the input particle. Assuming r = 0.5 and R = 0.7 and ω = 0.7, C_1=C_2=2, we can calculate the velocity of P_1 in the first dimension using (3.1) as shown below:

$V_{1,1}$ (t+1) = 0.7 * 0 + 2 * 0.5 * (9.6-9.6) + 2 * 0.7 * (8.0-9.6) = -2.2

$x_{1,1}$ (t+1) = 9.6-2.2 = 7.4

The calculations shown above illustrate how velocity updation along the X-axis of $X_{1,1}$ (t) is done. Similarly, the velocity updation along Y-axis is done as follows:

$V_{1,1}$ (t+1) = 0.7 * 0 + 2 * 0.5 * (13.6-13.6) + 2 * 0.7 * (58.2-13.6) = 62.5

$y_{1,1}$ (t+1) = 13.6 + 62.5 = 76.1

This is how the first dimension of P_1 i.e. $X_{1,1}$ (t) = (9.6,13.6) is updated to a new position $X_{1,1}$ (t+1) = (7.4,76.1). The other dimensions of P_1 are updated similarly.

3.2.3 QPSO Introduction

According to Clerc and Kennedy (Clerc and Kennedy, 2002), the PSO converges if every particle converges to a local attractor p_i :

$$p_{i,d}^t = \psi_d^t * P_{best}{}_{i,d}^t + (1-\psi_d^t) * G_{best}{}_d^t \tag{3.6}$$

where $\psi_d^t = C_1 r \,/\, (C_1 r + C_2 R)$

In Quantum PSO (QPSO) (Sun et al., 2004), every particle is a spinless entity moving in quantum space. A particle appears at the position x_i^t where t is the iteration number depending on a probability density function (Liu et al., 2006). The way a particle flies is determined according to the Monte Carlo method:

$$\begin{aligned} X_{i,d}^{t+1} &= p_{i,d}^t + \alpha|x_{i,d}^t - m_{best}{}_d^t| ln(1/u_{i,d}^t), if\ (randv \geq 0.5) \\ &= p_{i,d}^t - \alpha|x_{i,d}^t - m_{best}{}_d^t| ln(1/u_{i,d}^t), if\ (randv < 0.5) \end{aligned} \tag{3.7}$$

Here

α = Contraction - Expansion (CE) coefficient

$u_{i,d}^t$ and randv are random numbers distributed randomly in the range [0,1]

m_{best} = Mean Best

m_{best} is calculated as follows :

$$m_{best}{}_d^t = (1/N)\sum_{i=1}^{N} P_{best}{}_{i,d}^t \tag{3.8}$$

where N = Swarm Size

The CE coefficient is found by (Sun et al., 2012) using the formula :

$$\alpha = \alpha_1 + ((T-t)(\alpha_0 - \alpha_1)/T) \tag{3.9}$$

where

α_0 = Initial value of α

α_1 = Final value of α

T = Number of maximum possible iterations

t = Current iteration number

The QPSO has an advantage over the PSO in that in QPSO only a position vector is required as compared to PSO where position vector as well as velocity vector are required.

3.2.4 The Energy model used

The Energy required by a node for transmission of a data packet which is l-bit long is :

$$\begin{aligned} E_{Transmit} &= lE_{elec} + l\varepsilon_{fs}d^2, if\ d < d_0 \\ &= lE_{elec} + l\varepsilon_{mp}d^4, if\ d \geq d_0 \end{aligned} \tag{3.10}$$

where

l = No of bits in the data packet

E_{elec} = The energy dissipated / bit for running the transmitter / receiver circuit

ε_{fs} = Amplification energy (using free space method)

ε_{mp} = Amplification energy (using multipath model)

d = Propagation distance

d_0 = Threshold distance

The Energy required for receiving data which is l-bit long is :

$$E_{Receive} = lE_{elec} \tag{3.11}$$

The total energy expended for transmission and receiving data is :

$$E_{Total} = E_{Transmit} + E_{Receive} \tag{3.12}$$

3.2.5 The Network model

The sensors are stationary but they are randomly deployed. A node can be a Sensor or a Cluster Head (CH). Data is sent to CH or BS by the node. The convention is that there will be more sensors than CH's. The transmission power required by CH or BS also will be different and the distance to which the data is sent plays a role in this. Usually, the nodes are Homogeneous.

3.3 The QPSOEEC (Quantum inspired PSO for Energy Efficient Clustering) Algorithm

The Quantum inspired PSO for Energy Efficient Clustering (QPSOEEC) is inspired by Nature and takes advantage of features of PSO and Quantum computing. A single parameter, the position vector, is required during the updation of position by our algorithm. The steps of the QPSOEEC algorithm are listed below:

1. Updating the position
2. Selecting the CH
3. Forming the clusters
4. Calculating the total energy consumed

QPSO (Yang et al., 2015) is used for the position updation phase and PSO-ECHS (Rao et al., 2017) is used for the CH selection. During CH selection, the sensors send details about their location and their residual energy to the base station. A node becomes a CH node only if it has a particular value of Threshold energy. At the base station, the algorithm for selection of CH is run. This is followed by cluster formation. Here, a weight function is developed with distance, energy and node degree as the deciding factors (Rao et al., 2017). The CH with the maximum weight value is joined by the sensor node.

3.3.1 Calculation of the Fitness

The method used by (Rao et al., 2017) is used for calculating the fitness function, f_1. The fitness function depends on two factors: the average of the distance between the clusters and the average of the distance between the BS and the CH. *Minimizing* f_1 is our objective.

$$f_1 = \sum_{j=1}^{m} (1/l_j) \sum_{i=1}^{l_j} (dist(s_i, CH_j + dist(CH_j, BS)) \tag{3.13}$$

where

m = number of cluster heads

l_j = number of sensors in cluster j
$dist(s_i, CH_j)$ = Distance between sensor s_i and its selected cluster head CH_j
$dist(CH_j, BS)$ = Distance between Cluster Head CH_j and the BS

f_2 is found by taking the reciprocal of the sum of energies of all the CH's. *Minimizing* f_2 is our objective.

$$f_2 = \frac{1}{\sum_{j=1}^{m} E_{CH_j}} \tag{3.14}$$

where
E_{CH_j} is the energy of Cluster head CH_j

$$Fitness = \alpha f_1 + (1-\alpha) f_2, 0 < \alpha < 1 \tag{3.15}$$

Minimization of the fitness is our objective.

3.3.2 Updating of the position

QPSO (Yang et al., 2015) is used for updating the position. (3.7) is used for position updation of the particle.

3.3.3 Selecting the CH

The method used in PSO-ECHS (Rao et al. (2017)) is used for selecting the CH. Energy efficiency decides which are the CH's selected from a group of sensor nodes. The fitness function minimizes the total energy consumption.

3.3.4 Forming the clusters

A weight function (Rao et al. (2017)) is used for forming the clusters. A weight function CH_{weight} is used by sensors to join the cluster head :

$$CH_{weight}(s_i, CH_j) = L * Energy\,factor \tag{3.16}$$

where

$$Energy\,factor = \frac{E_{residual}(CH_j)}{dist(s_i, CH_j) * dist(CH_j, BS) * deg(CH_j)} \tag{3.17}$$

Here

L has the value 1

$E_{residual}(CH_j)$ is the residual energy of the CH, CH_j

$dist(s_i, CH_j)$ is the distance between Sensor s_i and CH_j

$dist(CH_j, BS)$ is the distance between CH_j and BS

$deg(CH_j)$ = Degree of node CH_j

The sensor nodes use (3.16) in order to calculate CH_{weight} when clusters are formed and they join the cluster head which has maximum value for the weight.

In Table 3.1, the energies consumed for LEACH, PSOECHS and QPSOEEC are tabulated with 300 sensors, 15 CH's and the BS being located at the position (100,100). When QPSOEEC is used, the energy consumed is less as compared to LEACH and PSOECHS. The QPSOEEC proved to be better than LEACH and PSOECHS even when number of sensors ranged from 400 to 700 and number of CH's ranged from 30 to 50. The graphs which illustrate this are depicted later. The QPSOEEC algorithm is shown below (Algorithm 1).

Table 3.1 Comparing the Energies Consumed - LEACH, PSOECHS, QPSOEEC - No of Sensors = 300, CH's = 15, BS position (100, 100)

Rounds	**Energy Consumption LEACH**	**Energy Consumption PSOECHS**	**Energy Consumption QPSOEEC**
0	0	0	0
200	423.05	21.03	6.93
400	505.86	40.77	11.76
600	508.68	58.96	15.32
800	541.05	78.51	21.53
1000	544.79	96.95	28.35
1200	563.71	113.12	31.26
1400	571.39	131.37	36.46
1600	584	146.16	42.02
1800	585	169.7	44.86
2000	587.4	189.53	52.12
2200	589.28	209.83	58.67
2400	592.3	227.95	61.82
2600	595	246.95	66.77
2800	595.3	266.57	73.07
3000	598.21	286.81	76.01
3200	598.85	303.54	80.31
3400	599.8	310.75	85.3
3600	600	316.79	86.39
3800	600	321.58	91.48
4000	600	329.03	94.84
4200	600	335.02	97.56
4400	600	341.28	100.74
4600	600	347.23	104.83
4800	600	353.41	108.15
5000	600	359.5	111.4

Input: Collection of sensor nodes $S = [s_1, s_2, ..., s_{sen}]$, N which is the size of the swarm, the dimensions of the particle D
Output: Optimized position of CHs with energy consumption also minimized
begin
  Randomly initialize the particles
  Initialize TELEACH, TEPSOECHS and TEQPSOEEC to 0
  (These are the Total Energies using LEACH, PSOECHS and QPSOEEC)
  Store the randomly generated particle values in a file
  Using 3.15, find the fitness
  Calculate ELEACH, the Energy for LEACH
  Calculate EPSOECHS, the Energy for PSOECHS
  Calculate EQPSOEEC, the Energy for QPSOEEC
  for *i = 0 to number of Rounds* **do**
    Get the values for the particle from the file
    Use same particle values from file for calculation of ELEACH, EPSOECHS and EQPSOEEC
    Position updation through QPSO
    3.15 is used for fitness calculation
    TELEACH = TELEACH + ELEACH
    TEPSOECHS = TEPSOECHS + EPSOECHS
    TEQPSOEEC = TEQPSOEEC + EQPSOEEC
    Find the personal best, P_{best} and the global best, G_{best}
    Use P_{best} and G_{best} for CH selection
    Cluster formation
  end
  Compare the Total energies TELEACH, TEPSOECHS and TEQPSOEEC
  Stop
end

Algorithm 1: Quantum Inspired PSO for Energy Efficient Clustering (QPSOEEC)

3.4 Performance Evaluation

3.4.1 Simulation Environment

The algorithm is coded using C (Dev C++) and the plots are done using MATLAB (R2015a). The varying number of sensor nodes ranged from 300 to 700 and varying CH's ranged from 15 to 50. The initial energy of the node is 2J. The sensing field is of 200x200 m^2 (Table 3.2). Initially, the BS was stationed at (100,100), (200,200) and (300,300) with 300 Sensors and 15 CH's. Later, the sensors were varied as 400, 500 and 700. The number of CH's were varied as 35, 40, 50.

Table 3.2 Network Parameters

Parameters	Value
Area	200x200 m^2
Base Station	(100,100), (200,200), (300,300)
No of Sensors	300 - 700
No of CH's	15 - 50
E_{elec}	50 nJ/bit
ε_{fs}	10 $pJ/bit/m^2$
ε_{mp}	0.0013 $pJ/bit/m^4$
Packet length	4000 bits
Message size	500 bits

Table 3.3 PSO Parameters

Parameters	Value
No of particles	30
C_1	2.0
C_2	2.0
α	0.3
ω	0.7
D	15 - 50
No of iterations	100

Table 3.3 shows the parameters of PSO (Rao et al., 2017).

3.4.2 Performance Metric used

Energy Consumption has been used as the performance metric. The algorithm is allowed to run for many rounds (we have done for 5000) and the total energy consumed is found. It is observed that as number of rounds increases, the energy consumption also increases. A comparison of LEACH, PSO-ECHS and QPSOEEC are done with respect to the total energy consumed with number of sensors varying between 300 to 700 and CH's varying between 15 to 50. The total energy consumed using QPSOEEC is *89% better* than LEACH and *71% better* than PSOECHS. QPSOEEC proved to be superior compared to LEACH and PSO-ECHS even when BS position was changed to (200,200) and later to (300,300).

Figure 3.2 , Figure 3.3 and Figure 3.4 show the scenarios where keeping the number of sensors as 300 and number of CH's as 15, the base station position is varied as (100,100), (200,200) and (300,300).

Figure 3.5, Figure 3.6 and Figure 3.7 show the scenarios where with 300 sensors and 30 CH's, base station position is varied as (100,100), (200,200) and (300,300). Figure 3.8, Figure 3.9 and Figure 3.10 show the scenarios where there are 400 sensors and 40 CH's with base station position varying as (100,100), (200,200) and (300,300). Figure 3.11, Figure 3.12 and Figure 3.13 show the scenarios where there are 500 sensors and 50 CH's with base station position varying as (100,100), (200,200) and (300,300). Finally, Figure 3.14, Figure 3.15 and Figure 3.16 show the scenarios when there are 700 sensors and 35 CH's and base station position is varied as (100,100), (200,200) and (300,300).

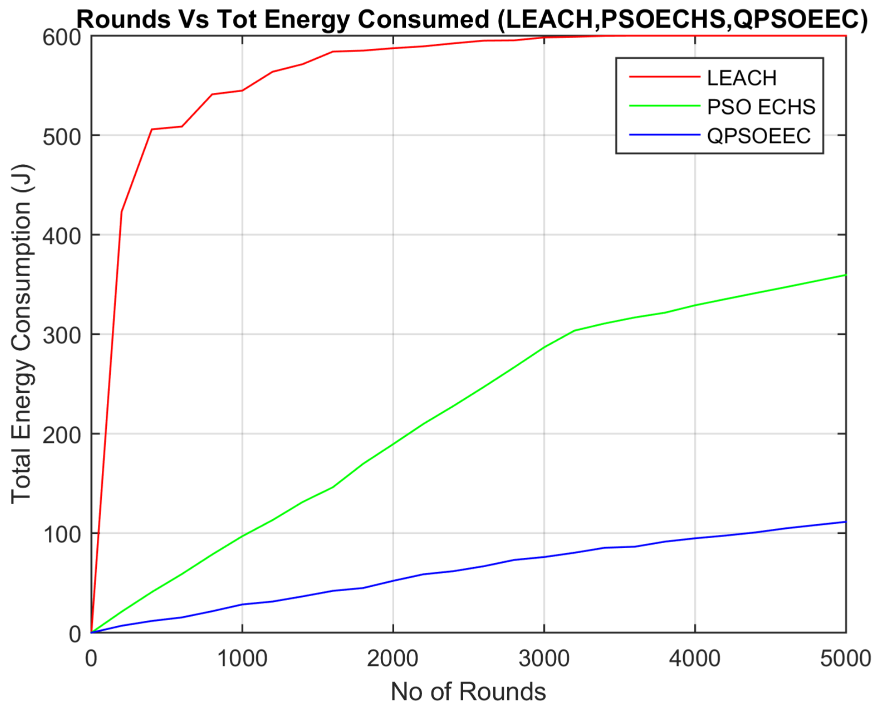

Figure 3.2 Sensors = 300, CH's = 15, BS position (100,100)

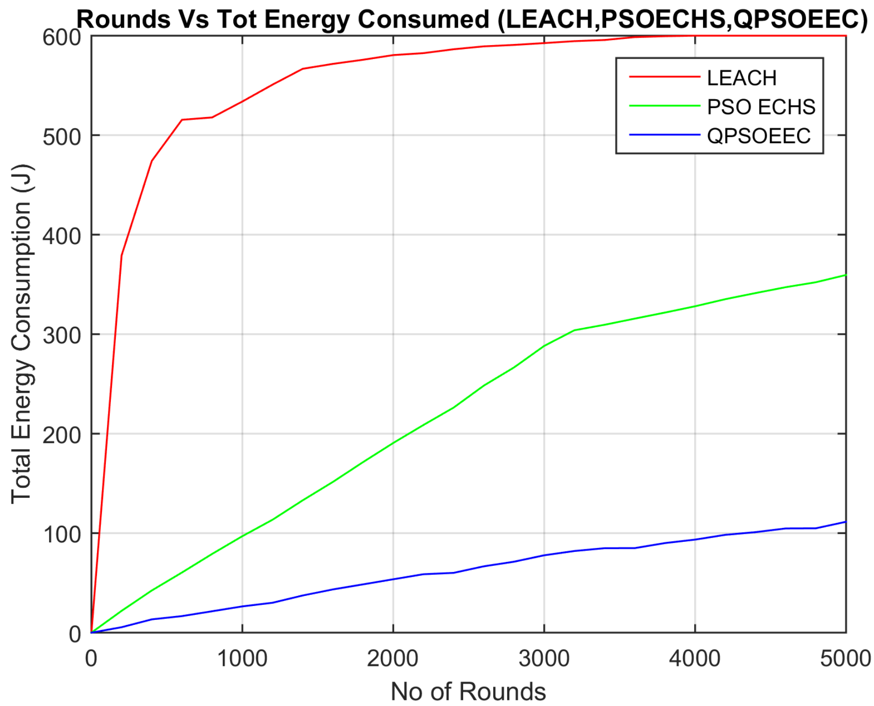

Figure 3.3 Sensors = 300, CH's = 15, BS position (200,200)

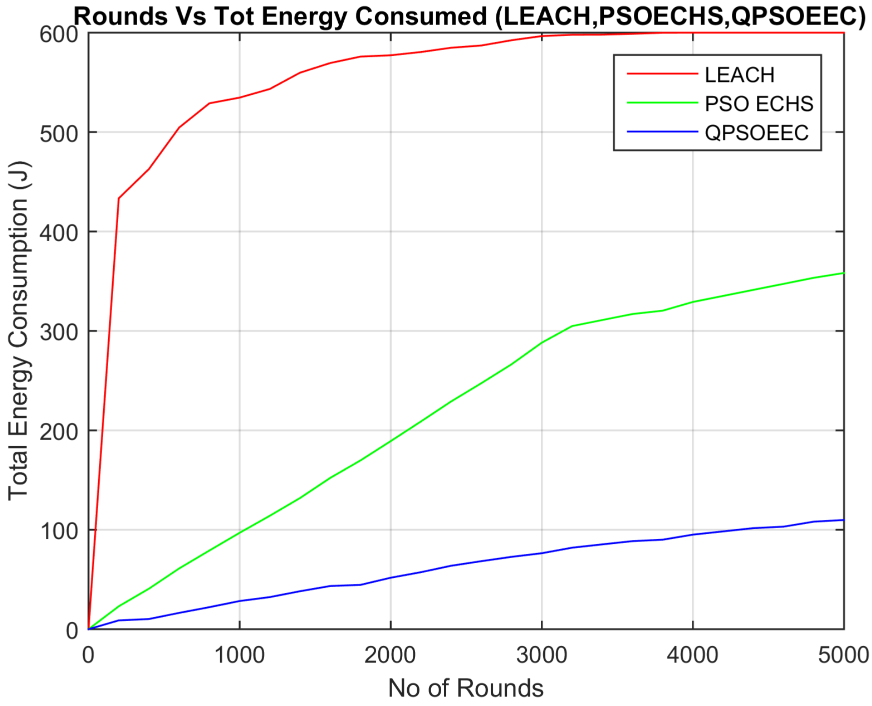

Figure 3.4 Sensors = 300, CH's = 15, BS position (300,300)

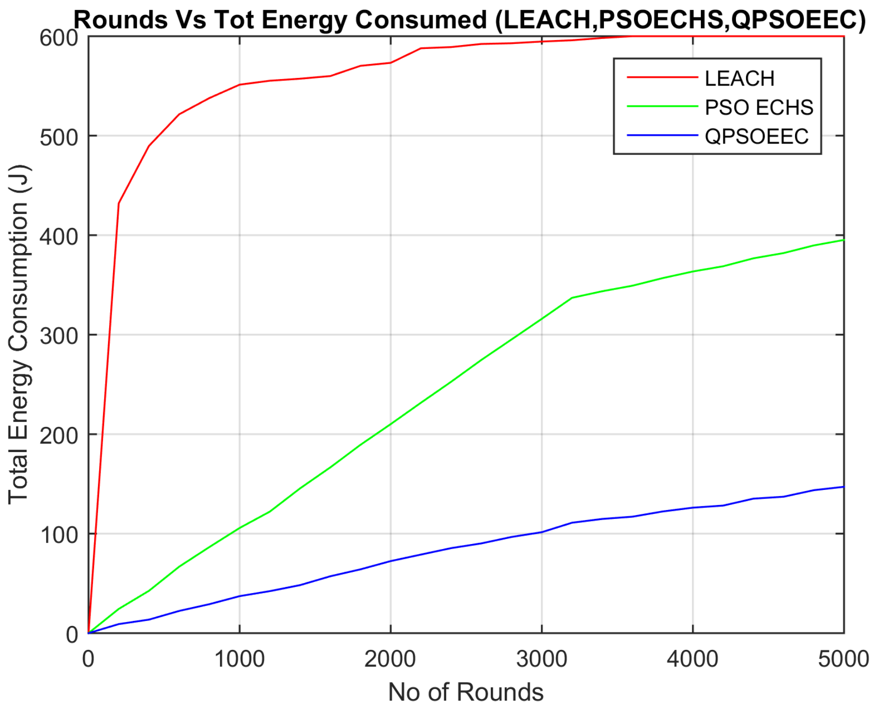

Figure 3.5 Sensors = 300, CH's = 30, BS position (100,100)

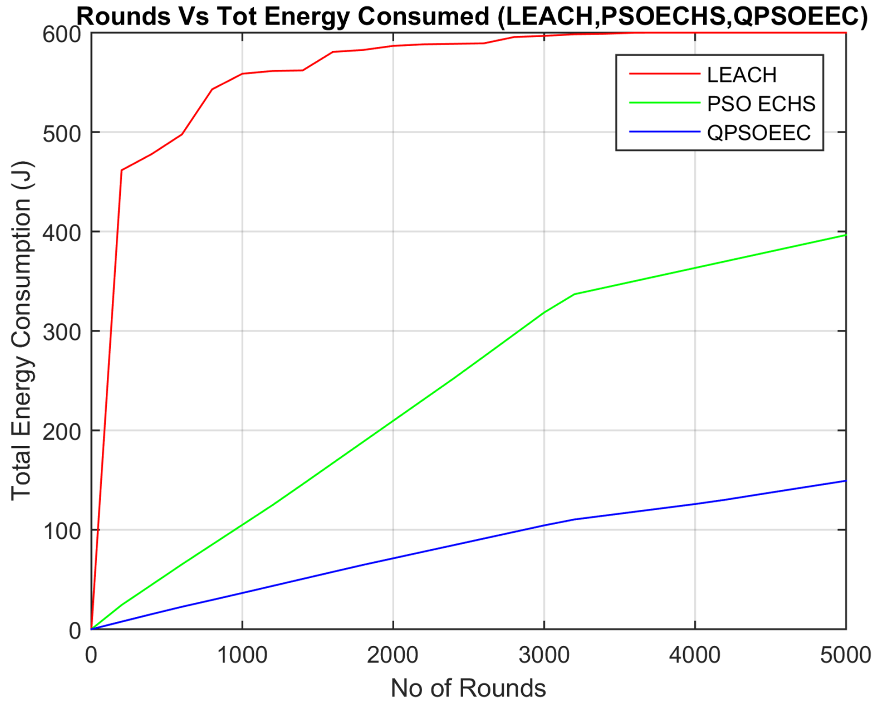

Figure 3.6 Sensors = 300, CH’s = 30, BS position (200,200)

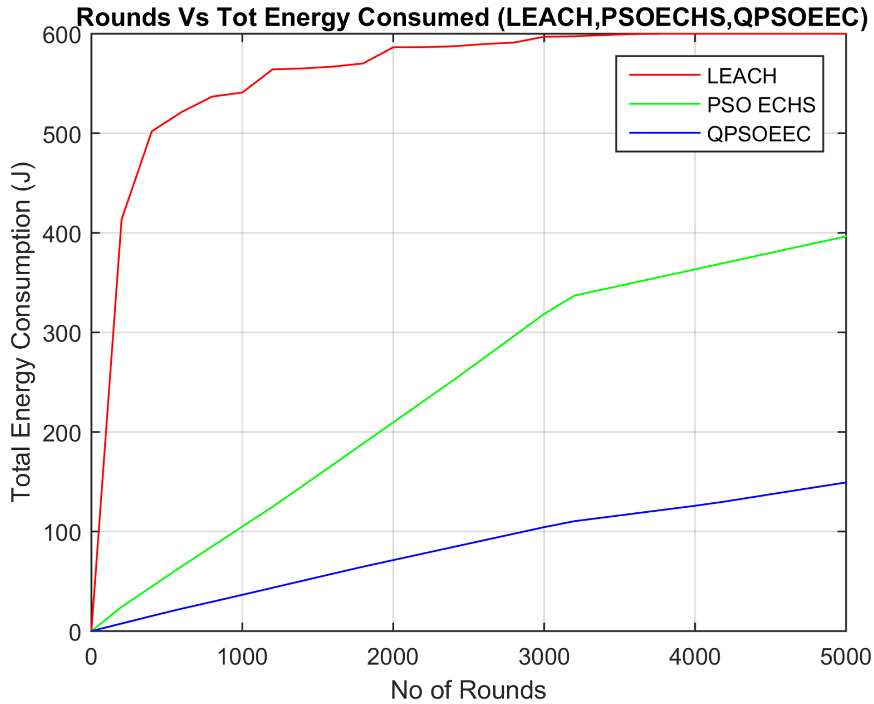

Figure 3.7 Sensors = 300, CH’s = 30, BS position (300,300)

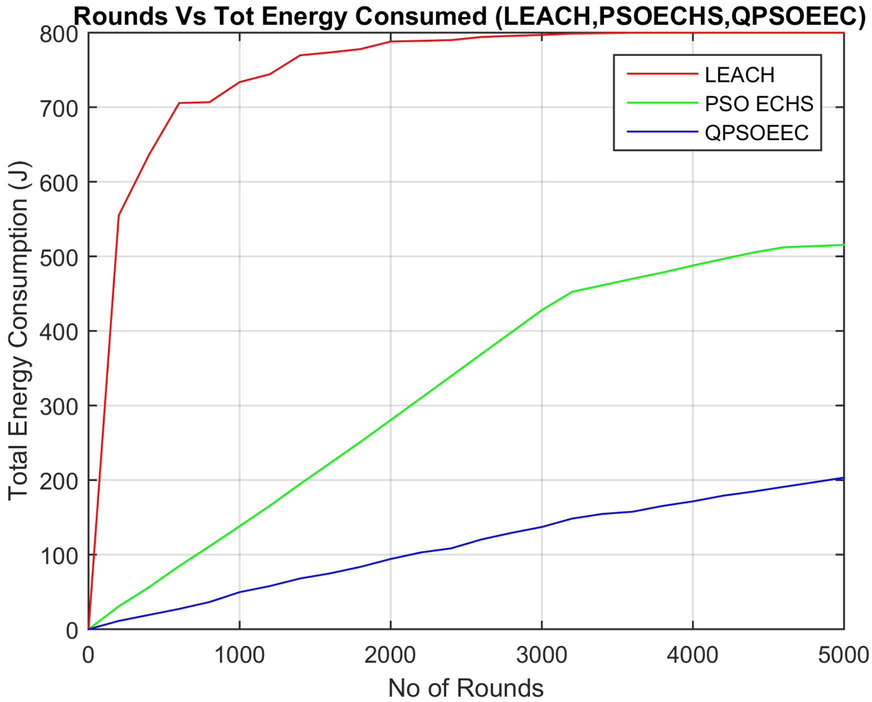

Figure 3.8 Sensors = 400, CH's = 40, BS position (100,100)

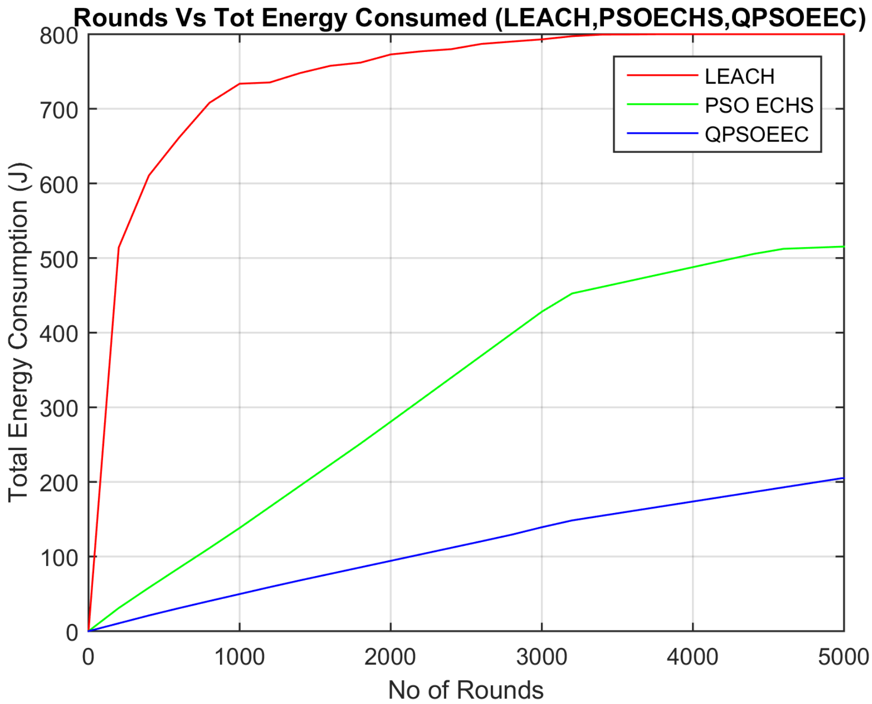

Figure 3.9 Sensors = 400, CH's = 40, BS position (200,200)

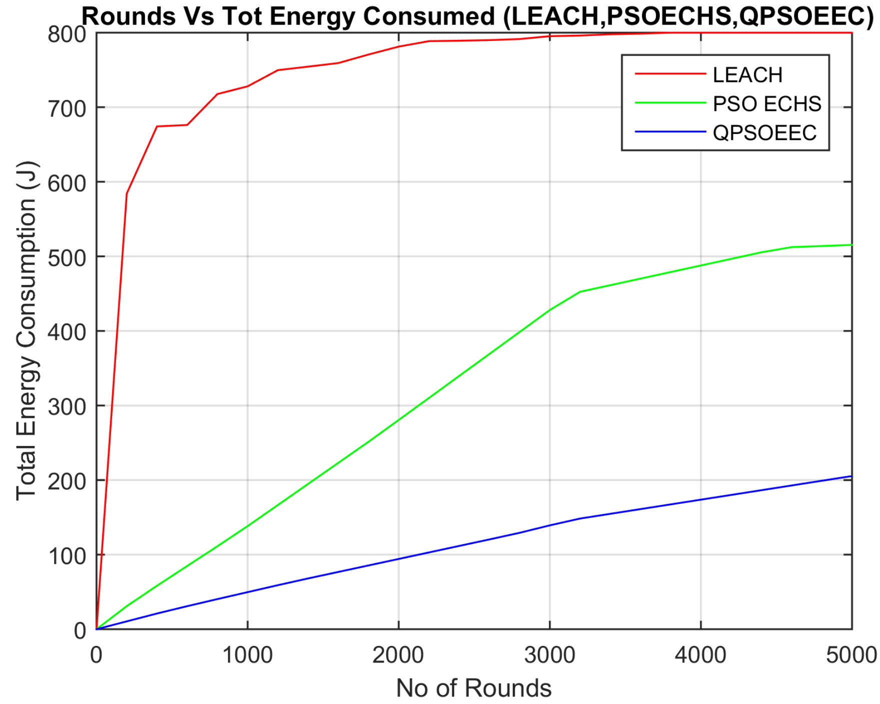

Figure 3.10 Sensors = 400, CH’s = 40, BS position (300,300)

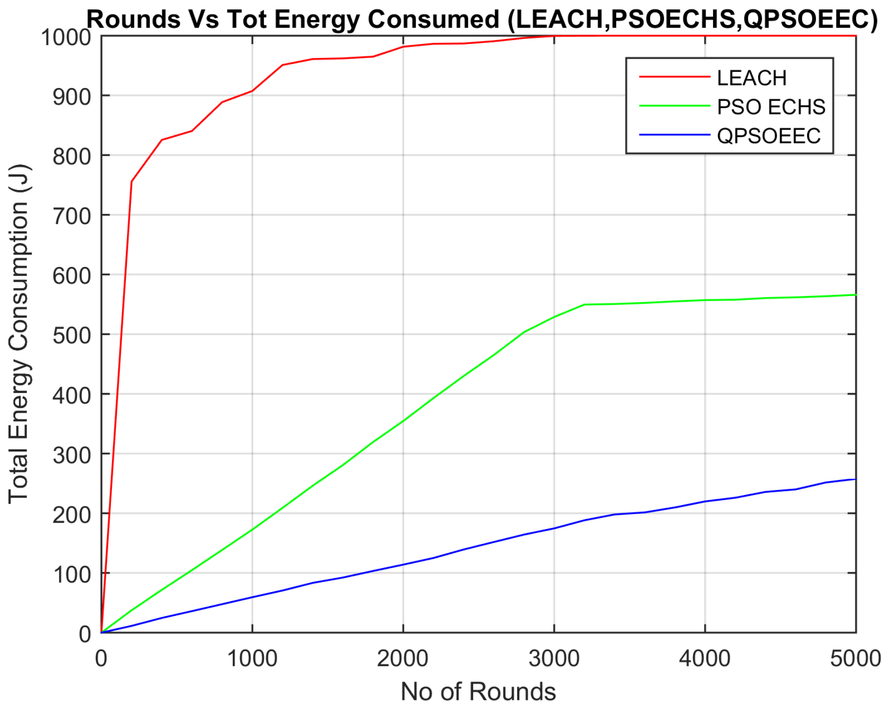

Figure 3.11 Sensors = 500, CH’s = 50, BS position (100,100)

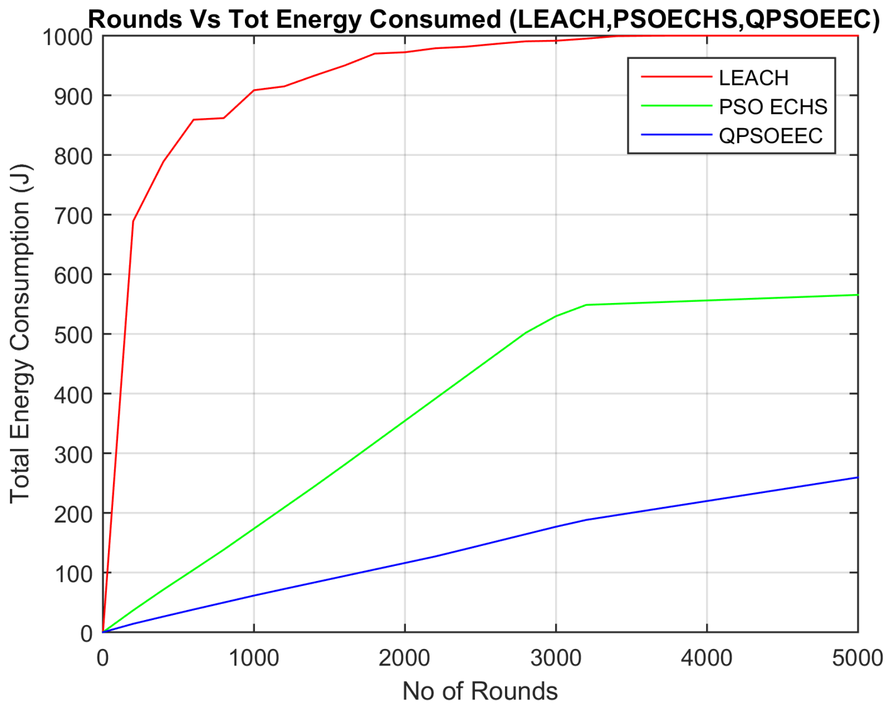

Figure 3.12 Sensors = 500, CH’s = 50, BS position (200,200)

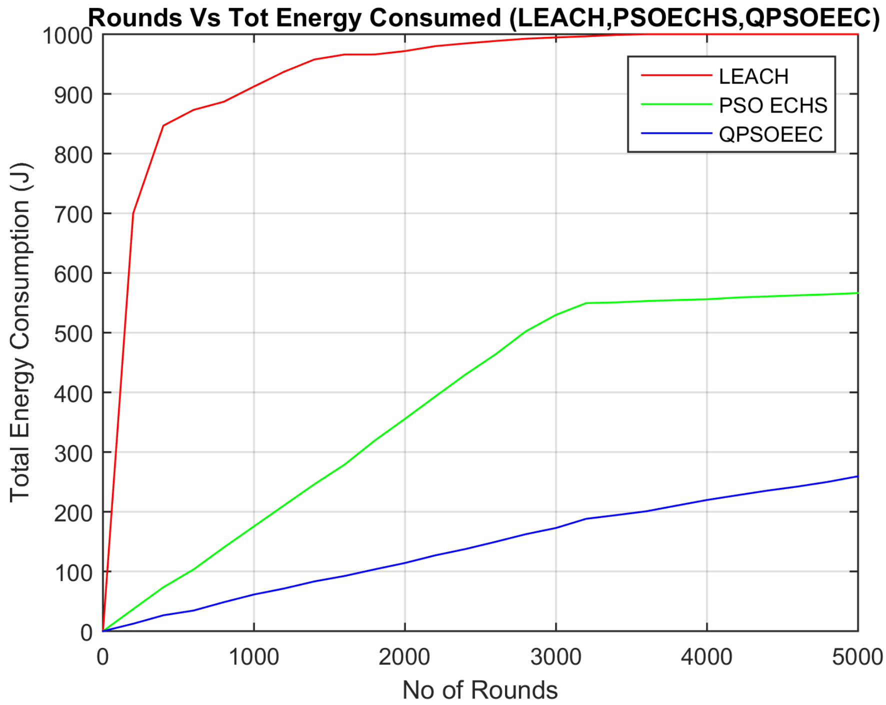

Figure 3.13 Sensors = 500, CH’s = 50, BS position (300,300)

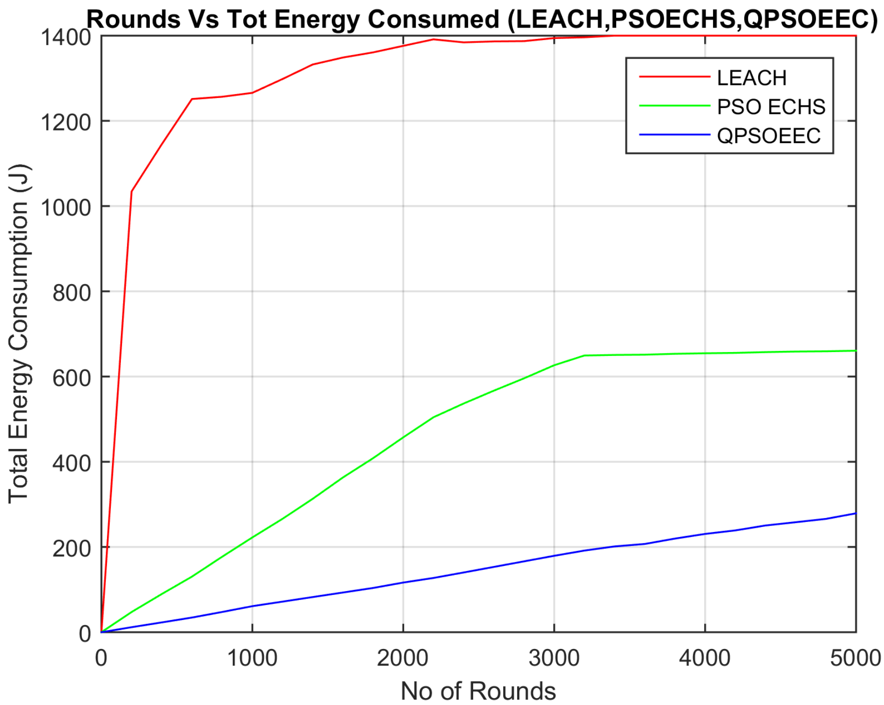

Figure 3.14 Sensors = 700, CH’s = 35, BS position (100,100)

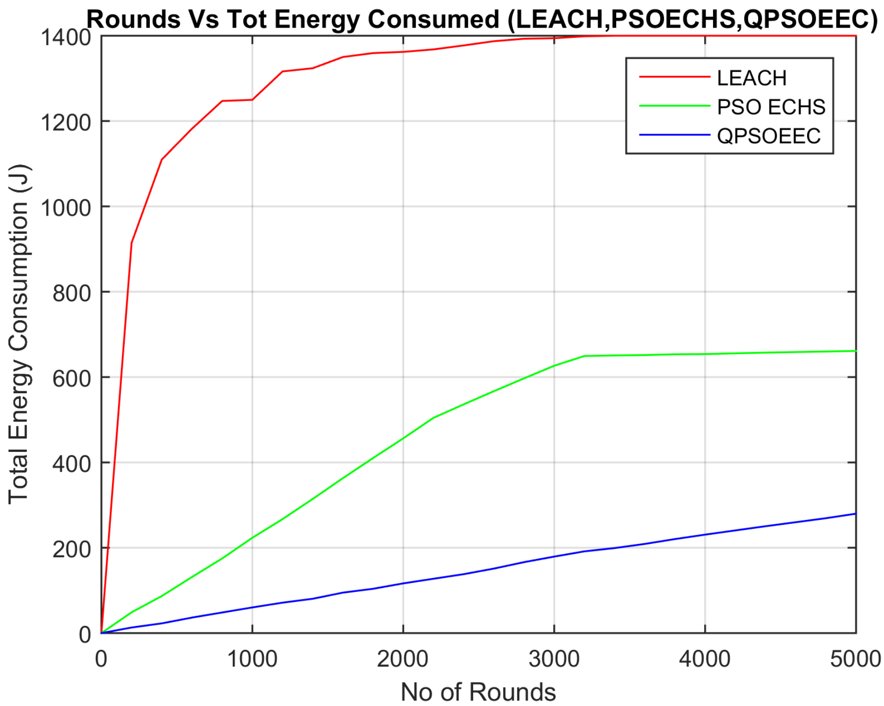

Figure 3.15 Sensors = 700, CH’s = 35, BS position (200,200)

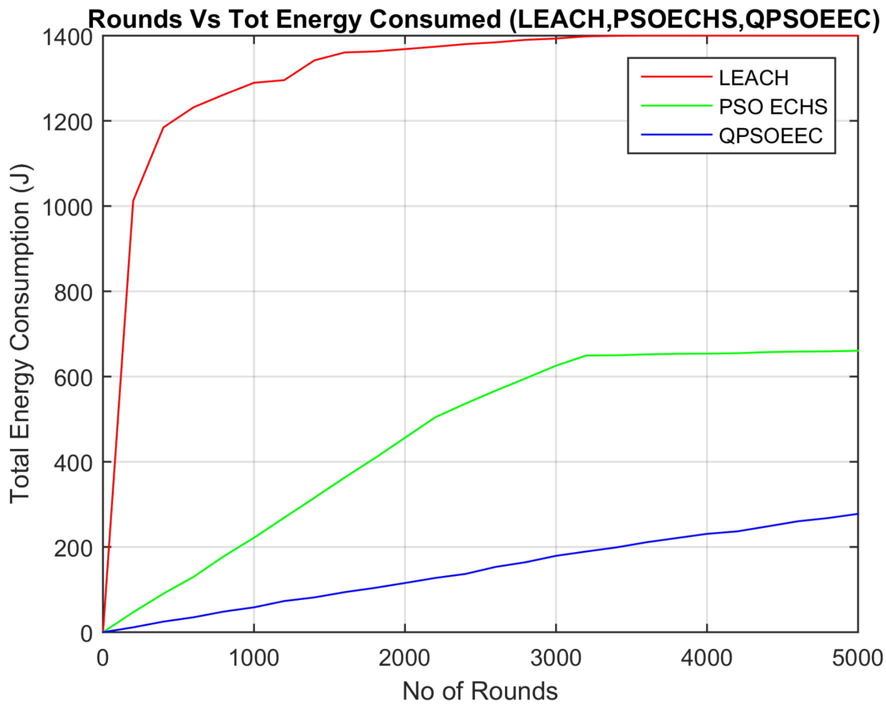

Figure 3.16 Sensors = 700, CH’s = 35, BS position (300,300)

3.4.3 Summary

In this chapter, the QPSOEEC algorithm is explained. The results are analysed for the proposed algorithm QPSOEEC by comparing with existing methods LEACH (Heinzelman et al., 2002) and PSOECHS (Rao et al., 2017). It is established that the results are consistent with the literature. The values of Total Energy consumption using QPSOEEC are *89% better* than LEACH and *71% better* than PSOECHS.

Quantum versions of other nature inspired algorithms like Artificial Bee Colony optimization and Genetic Algorithm when compared with QPSOEEC, LEACH and PSOECHS might yield better results.

CHAPTER 4

Quantum PSO Algorithm for Clustering in WSNs

4.0.1 Introduction

Network Lifetime is a measure of how long the network remains active from the time it is deployed to the time it stops. The network may stop working the moment its first node dies or it may stop when the energies in a given percentage of nodes get depleted or it may stop the moment its last node is dead. In this chapter, Quantum PSO Clustering algorithm to Improve Network Lifetime (QPCINL) is presented. Here, positions are updated with the help of Quantum PSO and CH Selection is done with the help of PSOECHS (Rao et al., 2017). The *Network Lifetime Factor (NLF)* is also found. The NLF values of proposed algorithm are compared with those for LEACH (Heinzelman et al., 2002) and PSOECHS (Rao et al., 2017). The following are the contributions of the chapter :

- Position Updates using Quantum PSO and CH Selection using PSO
- Cluster formation using a weight function.
- The number of nodes and CH's are varied to find the Network Lifetime Factor (NLF)
- The efficiency of our proposed algorithm over existing algorithms is verified by simulation.

4.0.2 Network Lifetime

In our work, Network Lifetime is defined as the time from the moment the node is deployed until the first node in the network depletes its energy. The lifetime of a single node is defined by (Rao et al., 2017) and (Rahman and Matin, 2011) using the following equation:

$$L = \frac{E_{initial}}{E_{total}} \tag{4.1}$$

where

$E_{initial}$ = The energy present initially in a node

E_{total} = The energy required by a node in order to transmit and receive data

$E_{initial}$ is initialized to 2J for all the nodes and E_{total} is calculated as in Equation 3.12

The term Network Lifetime Factor (NLF) is introduced in our work which is defined by the following equation :

$$NLF = \frac{E_{NWinitial}}{E_{NWtotal}} \tag{4.2}$$

where

$E_{NWinitial}$ = Total initial energies of nodes in the Network

$E_{NWtotal}$ = Total final energies of nodes in the Network

The algorithm with better NLF proves its superiority over the other algorithms.

4.1 The Quantum PSO Clustering algorithm to Improve Network Lifetime (QPCINL)

The Quantum PSO Clustering algorithm to Improve Network Lifetime (QPCINL) has three steps:

1. Position Updating
2. CH Selection
3. Formation of Clusters

The QPSO (Yang et al., 2015) is used for the position updation and PSO-ECHS (Rao et al., 2017) is used the CH Selection.

4.1.1 Deriving the Fitness Function

The fitness function is derived in the same way as in 3.3.1 using Eq 3.13, Eq 3.14 and Eq 3.15.

4.1.2 Position Update

Position Update is done as in 3.3.2 using QPSO (Sun et al., 2004).

4.1.3 Cluster Head Selection

Cluster Head Selection is done as in 3.3.3 using the method adopted by (Rao et al., 2017).

4.1.4 Cluster Formation

Clusters are formed using the weight function as in 3.3.4 (Rao et al., 2017).

In Table 4.1, the network lifetimes for LEACH, PSOECHS and QPCINL are tabulated with 300 sensors, 15 CH's and the BS being located at the position (100,100). At the end of round 1000, the network lifetime of LEACH is 1.090, that of PSOECHS is 6.610 and for QPCINL it is 23.880. As can be seen, the network lifetime is more for QPCINL as compared to LEACH and PSOECHS. The same kind of behavior is observed when number of rounds is increased to 2000,3000,4000 and 5000.

In Table 4.2, the network lifetimes for LEACH, PSOECHS and QPCINL are tabulated with 400 sensors, 40 CH's and the BS being located at the position (100,100).

Table 4.1 Comparing the Network lifetimes - LEACH, PSOECHS, QPCINL - No of Sensors = 300, CH's = 15, BS position (100, 100)

Rounds	Network lifetime LEACH	Network lifetime PSOECHS	Network lifetime QPCINL
0	0.000	0.000	0.000
200	1.330	28.040	89.760
400	1.170	15.960	52.920
600	1.140	10.510	39.630
800	1.110	7.960	29.290
1000	1.090	6.610	23.880
1200	1.090	5.570	19.630
1400	1.060	4.740	17.470
1600	1.050	4.140	15.190
1800	1.040	3.670	13.530
2000	1.020	3.330	12.160
2200	1.010	3.000	11.110
2400	1.010	2.750	9.880
2600	1.008	2.550	9.450
2800	1.000	2.360	8.620
3000	1.000	2.200	8.110
3200	1.000	2.080	7.850
3400	1.000	2.030	7.690
3600	1.000	2.000	7.220
3800	1.000	1.950	6.860
4000	1.000	1.910	6.620
4200	1.000	1.880	6.610
4400	1.000	1.850	6.270
4600	1.000	1.810	6.000
4800	1.000	1.780	5.821
5000	1.000	1.750	5.710

In Table 4.3, the network lifetimes for LEACH, PSOECHS and QPCINL are tabulated with 500 sensors, 50 CH's and the BS being located at the position (100,100).

In Table 4.4, the network lifetimes for LEACH, PSOECHS and QPCINL are tabulated with 700 sensors, 35 CH's and the BS being located at the position (100,100).

The following explains the algorithm :

Input: Sensor Nodes $S = [s_1, s_2, ..., s_{sen}]$, Size of Swarm N, No of dimensions of particle D
Output: Network Lifetime Factor (NLF)
begin
  Initialize the particles randomly
  Calculate fitness using 3.15
  for *i = 0 to No. of Rounds* **do**
    Update Position using QPSO
    Calculate fitness using 3.15
    Find Personal Best, P_{best} and Global best, G_{best}
    Use P_{best} and G_{best} for CH selection
    Form Clusters
  end
  Calculate Network Lifetime Factor (NLF) at the end of predefined No of Rounds
  Stop
end

Algorithm 2: Quantum PSO Clustering Algorithm to Improve Network Lifetime (QPCINL)

4.2 Performance Evaluation

4.2.1 Simulation Environment

The algorithm is coded using C (Dev C++) and the plots are done using MATLAB (R2015a). The varying number of sensor nodes ranged from 300 to 700 and varying CH's ranged from 15 to 50. The initial energy of the node is 2J. The sensing field is of 200x200 m^2 (Table 4.5). Initially, the BS was stationed at (100,100), (200,200) and (300,300) with 300 Sensors and 15 CH's. Later, the sensors were varied as 400, 500 and 700. The number of CH's were varied as 35, 40, 50.

Table 4.2 Comparing the Network lifetimes - LEACH, PSOECHS, QPCINL - No of Sensors = 400, CH's = 40, BS position (100, 100)

Rounds	Network lifetime LEACH	Network lifetime PSOECHS	Network lifetime QPCINL
0	0.000	0.000	0.000
200	1.367	28.388	70.383
400	1.212	15.100	39.871
600	1.141	10.371	28.289
800	1.100	7.912	21.776
1000	1.085	6.363	18.084
1200	1.038	5.283	14.899
1400	1.027	4.517	13.257
1600	1.018	3.944	11.742
1800	1.015	3.501	10.288
2000	1.012	3.135	9.336
2200	1.010	2.837	8.627
2400	1.009	2.591	7.878
2600	1.006	2.384	7.311
2800	1.005	2.208	6.836
3000	1.004	2.056	6.415
3200	1.003	1.945	5.932
3400	1.000	1.907	5.845
3600	1.000	1.872	5.534
3800	1.000	1.840	5.329
4000	1.000	1.804	5.064
4200	1.000	1.772	4.888
4400	1.000	1.741	4.773
4600	1.000	1.717	4.577
4800	1.000	1.712	4.420
5000	1.000	1.707	4.285

Table 4.3 Comparing the Network lifetimes - LEACH, PSOECHS, QPCINL - No of Sensors = 500, CH’s = 50, BS position (100, 100)

Rounds	**Network lifetime LEACH**	**Network lifetime PSOECHS**	**Network lifetime QPCINL**
0	0.000	0.000	0.000
200	1.421	30.256	92.971
400	1.192	15.345	48.610
600	1.109	10.330	28.882
800	1.095	7.884	22.113
1000	1.086	6.279	18.082
1200	1.060	5.308	15.583
1400	1.053	4.495	13.455
1600	1.048	3.918	11.911
1800	1.036	3.464	10.653
2000	1.035	3.088	9.476
2200	1.019	2.800	8.662
2400	1.012	2.577	8.128
2600	1.011	2.373	7.350
2800	1.008	2.186	6.703
3000	1.004	2.076	6.295
3200	1.000	2.002	5.845
3400	1.000	1.995	5.609
3600	1.000	1.988	5.390
3800	1.000	1.981	5.189
4000	1.000	1.977	5.002
4200	1.000	1.968	4.831
4400	1.000	1.967	4.746
4600	1.000	1.955	4.553
4800	1.000	1.948	4.373
5000	1.000	1.945	4.271

Table 4.4 Comparing the Network lifetimes - LEACH, PSOECHS, QPCINL - No of Sensors = 700, CH's = 35, BS position (100, 100)

Rounds	Network lifetime LEACH	Network lifetime PSOECHS	Network lifetime QPCINL
0	0.000	0.000	0.000
200	1.365	31.093	116.105
400	1.199	16.771	59.113
600	1.124	11.302	42.154
800	1.117	8.383	31.360
1000	1.097	7.506	23.634
1200	1.051	5.490	20.964
1400	1.031	4.652	17.492
1600	1.030	4.048	15.632
1800	1.027	3.584	13.949
2000	1.025	3.226	12.811
2200	1.021	2.914	11.541
2400	1.010	2.742	10.650
2600	1.005	2.599	9.872
2800	1.004	2.463	8.839
3000	1.003	2.346	8.198
3200	1.001	2.270	7.820
3400	1.000	2.262	7.299
3600	1.000	2.257	7.098
3800	1.000	2.249	6.717
4000	1.000	2.245	6.374
4200	1.000	2.241	6.109
4400	1.000	2.238	5.964
4600	1.000	2.232	5.681
4800	1.000	2.227	5.443
5000	1.000	2.223	5.252

Table 4.5 Network Parameters

Parameters	Value
Area	200x200 m^2
Base Station	(100,100), (200,200), (300,300)
Number of Sensors	300 - 700
Number of CH's	15 - 50
E_{elec}	50 nJ/bit
ε_{fs}	10 $pJ/bit/m^2$
ε_{mp}	0.0013 $pJ/bit/m^4$
Packet length	4000 bits
Message size	500 bits

Table 4.6 PSO Parameters

Parameters	Value
No of particles	30
C_1	2.0
C_2	2.0
α	0.3
ω	0.7
D	15 - 50
No of iterations	100

Table 4.6 shows the PSO parameters used by (Rao et al., 2017).

4.2.2 Performance Metric used

Network lifetime factor (NLF), a term introduced by us in this work is used as the performance metric. The algorithm is allowed to run for many rounds (we have done for 5000) and the NLF is found. It is observed that as the number of rounds increases, the value of NLF decreases. A comparison of LEACH, PSO-ECHS and QPCINL are done with respect to NLF values with number of sensors varying between 300 to 700 and CH's varying between 15 to 50. QPCINL proved to be superior to LEACH and PSOECHS. The NLF values for QPCINL are 3 times more than those for PSOECHS.
Figure 4.1 shows the scenario where with 300 sensors and 15 CH's, the base station is at (100,100). Figure 4.2 shows the scenario where with 400 sensors and 40 CH's, the base station is positioned at (100,100). Figure 4.3 shows the scenario where with 500

sensors and 50 CH's, the base station is stationed at (100,100). Figure 4.4 shows the scenario where with 700 sensors and 35 CH's, the base station is stationed at (100,100).

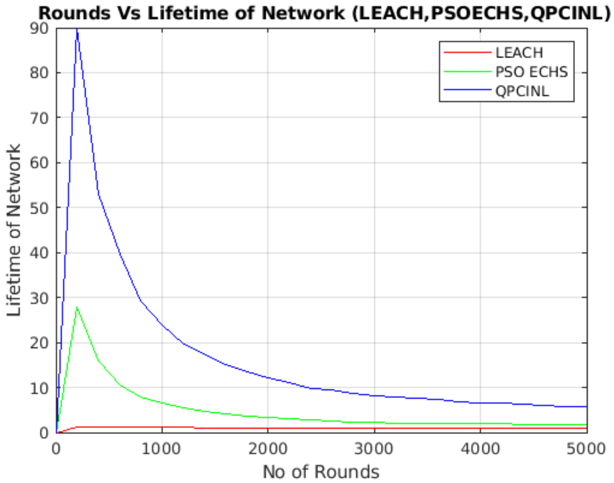

Figure 4.1 Sensors = 300, CH's = 15, BS position (100,100)

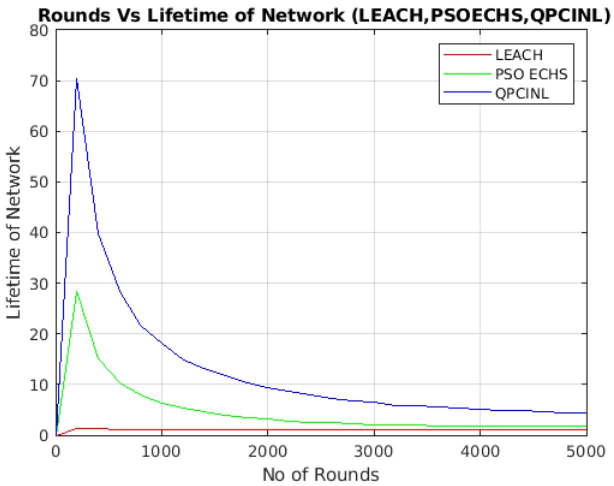

Figure 4.2 Sensors = 400, CH's = 40, BS position (100,100)

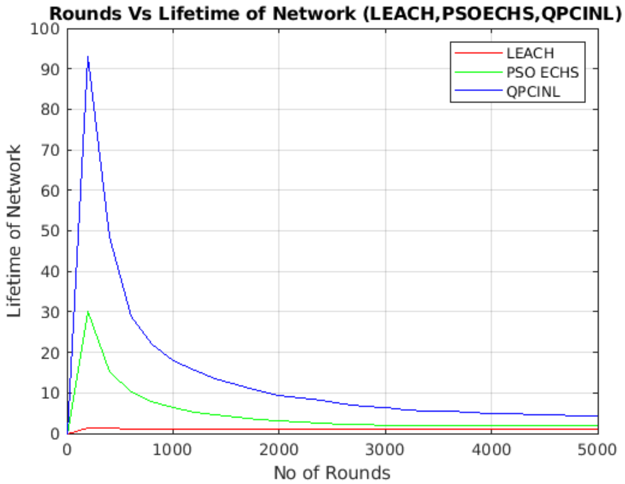

Figure 4.3 Sensors = 500, CH's = 50, BS position (100,100)

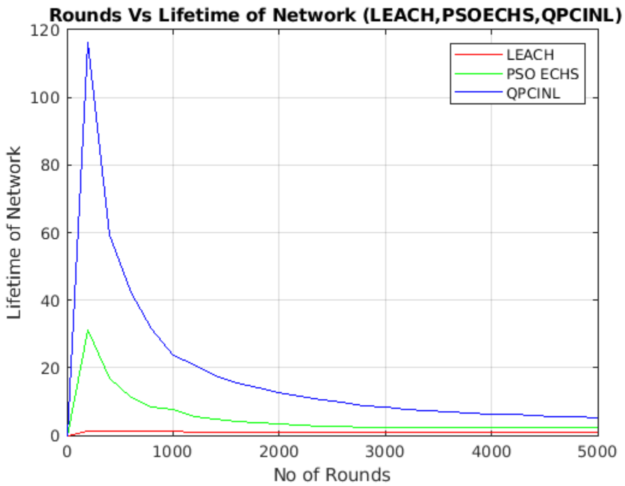

Figure 4.4 Sensors = 700, CH's = 35, BS position (100,100)

4.2.3 Summary

In this chapter, the Quantum PSO Clustering algorithm to Improve Network Lifetime (QPCINL) algorithm is explained. The detailed analysis of the Network Lifetime Factor (NLF) with increasing number of rounds is presented for various scenarios of LEACH (Heinzelman et al., 2002) and (Rao et al., 2017). The improvement factors achieved in the proposed algorithm are analyzed in detail. The NLF values obtained using QPCINL are approximately 3 times more than that of PSO-ECHS and QPCINL outperforms LEACH. The NLF values for other nature inspired algorithms like GA, ACO, ABC can be compared with QPCINL and it is possible that they may improve upon the QPCINL.

CHAPTER 5

Quantum Inspired Multi-objective Optimization in Clustered Homogeneous WSN

5.1 Introduction

Clustering is one of the most effective methods for achieving energy efficiency in a WSN. Here, a CH (Cluster Head) is in charge of collecting data from other nodes which are then sent to the BS (Base Station). The network maybe required to monitor a large area and supply information about the area monitored by it. In such a case, the particular area is said to be "covered" by the sensors. The term "Target" is used to denote those nodes which are being covered. A node can cover a particular number of targets. Covering a large number of targets is one of the objectives of our research. The energy consumed in the network needs to be optimized which is another objective of our research. The optimization of energy consumed results in improved lifetime of the network.

Only a few researchers have considered performing routing through clusters and coverage simultaneously. Through multi-objective optimization, these 2 objectives can be achieved at the same time. One of the most referenced works on multi-objective optimization is found in (Coello et al., 2007). Multi-objective problems allow k objective functions to be optimized simultaneously. The term "optimization" is used to refer to minimization of the functions or maximization of the functions or combination of minimization and maximization. In order to deal with WSN design issues, MOEAs (Multi Objective Evolutionary Algorithms) have been used successfully on many occasions.

Some of the parameters of WSN which are used often as the multiple objectives to be optimized are lifetime, coverage, connectivity, energy, etc (Marks, 2010). The Evolutionary Multi Objective Crowding Algorithm (EMOCA) (Rajagopalan et al., 2005) takes a balanced approach towards dominance and diversity with respect to population. In the Hybrid MOEA (Martins et al., 2010), lifetime and coverage are the multiple objectives simultaneously optimized.

Optimizing WSNs using quantum computing is a recent development. A quantum adaptation of ABC (Artificial Bee Colony) algorithm optimizes the energy in WSN (Sandeli et al., 2018). A quantum version of ACO (Ant Colony Optimization) optimizes coverage in (Wang and Wang, 2017). A quantum version of PSO (Particle Swarm Optimization) optimizes energy in Clustered WSNs (Kanchan and Pushparaj, 2018). The quantum PSO optimizes coverage in (Huang et al., 2012).

Exploring the possibility of combining quantum computing with MOEA/D for WSNs with coverage and lifetime as the multiple objectives has not been done so far. This chapter deals with optimizing coverage and lifetime of a WSN using Quantum Inspired MOEA/D.

The following are the contributions of this chapter :

- The WSN is represented using quantum bits.
- The QMOEAD algorithm is developed with the aim of conserving energy and improving coverage. The lifetime of the network is also improved.
- The QMOEAD is compared with LEACH (Heinzelman et al., 2002), SEP (Smaragdakis et al., 2004), NSGA II (Deb et al., 2002) and MOEAD (Özdemir et al., 2013).

5.2 Multi - Objective Optimization (MOO)

The aim of MOO (Multi - Objective Optimization) (Coello et al., 2007) is to come up with some solution which consists of objective functions. This is a solution which is acceptable to the decision maker. In case of Single Objective optimization, the focus is on maximizing / minimizing the objective function whereas here the focus is on coming up with an acceptable solution.

Multi - Objective Problems (MOP) are denoted by :

$$\begin{gathered} Minimize/Maximize\ F(x) = (f_1(x), f_2(x), \ldots, f_n(x)) \\ subject\ to\ x \varepsilon \Omega \end{gathered} \tag{5.1}$$

where x refers to decision variable, F:$\Omega \rightarrow R^n$ denotes objective functions which are n in number, Ω denotes the Search Space and R^n denotes the Objective Space.
As far as MOP's are concerned, a fairly good enough solution is enough whereas in global optimization, a single solution is needed. *Pareto optimum* refers to such a solution. The NSGA (Non-Dominated Sorting Genetic Algorithm) (Srinivas and Deb, 1994) uses the concept of multiobjective optimization. It introduces a term "non-dominated" solution which refer to the set of solutions that are not dominated by any member of the solution set.

In the NSGA, the population is ranked based on the non domination of individual. An improved version of the NSGA is the NSGA II (Deb et al., 2002). In the MOEAD (Multi Objective Evolution Algorithm based on Decomposition), the multiobjective problem is divided into small problems which are then in turn optimized simultaneously. In (Özdemir et al., 2013), the MOEAD is used to optimize the multiple objectives - lifetime and coverage of a WSN. The algorithm yields better results compared to LEACH, SEP and NSGA II.

5.3 Quantum Computing based algorithms for WSN

Energy consumption is optimized by the Quantum ABC (Artificial Bee Colony algorithm) (Sandeli et al., 2018). It performs better than LEACH and ABC. Quantum bits / qubits form the population in this algorithm. The PSO (Particle Swarm Optimization) in conjunction with quantum computing is used to achieve energy efficiency for the clustered wireless sensor networks (Kanchan and Pushparaj, 2018). It yields better results than LEACH and PSOECHS. Quantum computing in conjunction with WSN is used in precision agriculture as illustrated by Quadrivalent Quantum Inspired GSA (QQIGSA) (Mirhosseini et al., 2017). It proved to be better than the BPSO (Binary PSO) and BGA (Binary Genetic Algorithm).

5.4 Quantum Computing based Multi Objective Evolutionary Algorithm with Decomposition (QMOEAD)

Energy consumption is minimized and coverage is increased by the QMOEAD for WSNs which use cluster based routing. The multiple objectives for the QMOEAD are lifetime and coverage. The MOEA/D (Özdemir et al., 2013) is used in this work in conjunction with quantum computing. A square field is used for monitoring. The Base Station (BS) has the coordinates (x_{BS},y_{BS}). There is a set of m sensor nodes (s_1,s_2,...,s_m) and the set ((x_{s1},y_{s1},r_{s1},E_{s1}),...,(x_{sm},y_{sm},r_{sm},E_{sm})) denote the locations (x,y). For the nodes, the radii of coverage is r_s and the initial energies are represented by E_s. The l targets are represented by set (d_1,...,d_l) where the locations are ((x_{d1},y_{d1}),...,(x_{dl},y_{dl})). Efficient coverage is achieved when every target is covered by at least one sensor at the same time optimizing the lifetime. The aim is to optimize the coverage and lifetime. The MOEA/D for the routing protocol is defined as

$$MOEA/D = (I, \Phi, \Gamma, \psi, l, N, EP, \phi) \tag{5.2}$$

where I is the individual space. An individual consists of a bit string of size m, which denotes how many nodes are there in the WSN. The bits of each gene can be any of the following : -1 in case of a *dead* node, 0 in case of *inactive* node, 1 for a *non-CH* node and 2 for a *CH* node.

The population of N individual solutions represented by IP = (I_1,...,I_N) is :

$$\forall i \in (1, \ldots, N)\, and \, \forall j \in (1, \ldots, m), \tag{5.3}$$

$$I_{i,j} = \begin{cases} \text{-1 if } E(s_j\text{=0}) \\ \text{0 if } E(s_j\text{>0}) \text{ with } s_j \text{ Inactive} \\ \text{1 if } E(s_j\text{>0}) \text{ with } s_j\text{= Non CH} \\ \text{2 if } E(s_j\text{>0}) \text{ with } s_j\text{= CH} \end{cases} \tag{5.4}$$

Only homogeneous networks are considered in this work. During the rounds of the protocol, dynamic number of CH's are formed. A random population is formed in the initial stages. Some assumptions are :

- The probability of an alive node becoming active or inactive is equal
- According to (Smaragdakis et al., 2004), an active advanced node becomes a CH with a probability :
  p_{adv}/(1-p_{adv}*(r mod 1/p_{adv}))

An active normal node becomes CH with the probability:
p_{nrm}/(1-p_{nrm}*(r mod 1/p_{nrm}))
Here,
p_{adv} = ((P_{opt}*(1+α))/(1+α*Advanced nodes percentage))
p_{nrm}=((P_{opt})/(1+α*Advanced nodes percentage))
The optimal election probability used as in LEACH (Heinzelman et al., 2002) is :
P_{opt}=K_{opt} / m
where m= Number of nodes in the network
K_{opt} = Optimal number of clusters given by

$$K_{opt}=\sqrt{\frac{m}{2\pi}}\,\frac{2}{0.765}$$

$\Phi : I \rightarrow R^2$ is used to denote that the objective function vector consisting of E, the energy consumed and NC, the number of Uncovered targets, has to be minimized. The transmission, reception and aggregating ion of signals requires energy and E represents these energies (Khalil and Bara'a, 2011).

The total energy for activation of sensor is

$$E(I) = (\sum_{i=1}^{nc}\sum_{s\in c_i} E_{TX_{s,CH_i}} + E_{RX} + E_{DA}) \\ + (\sum_{i=1}^{nc} E_{TX_{CH_i,BS}}) + TotAE \tag{5.5}$$

Here, nc denotes number of active cluster heads

$s \in c_i$ denotes active non-cluster heads linked to the i^{th} active cluster head

$E_{TX_{n1,n2}}$ is the energy for transmitting data from one node $n1$ to another node $n2$

E_{RX} is energy required for data reception

E_{DA} is energy required for data aggregation

(Smaragdakis et al., 2004) contains the detailed explanation of these terms :

$$E_{TX_{n1,n2}} = \begin{cases} E_{elec} \times l + \varepsilon_{fs} \times l \times d(s_1,s_2)^2 & \text{if } d<d_0 \\ E_{elec} \times l + \varepsilon_{mp} \times l \times d(s_1,s_2)^4 & \text{if } d \geq d_0 \end{cases} \tag{5.6}$$

$$E_{RX} = E_{elec} \times l \tag{5.7}$$

The total activation energy, $TotAE$, for cluster head and non-cluster heads which get activated during a round is :

$$TotAE = \sum_{i=1}^{nc} AE \times a_i \\ + \quad \sum_{s\in c_i} AE \times a_s \tag{5.8}$$

where

$$a_i = \begin{cases} 1 \text{ if } sensor_i \text{ gets activated during the current round} \\ 0 \text{ Otherwise} \end{cases} \tag{5.9}$$

AE is the activation energy of each node

The objective function, *NC*, minimizes the number of uncovered targets :

$$NC(I) = \sum_{i=1}^{m} Uncovered(target_i) \tag{5.10}$$

Here,

$$Uncov(t_i) = \begin{cases} 0 & \text{if } \exists\, s \in SensorActive, d(s,t_i) \leq r_s \\ 1 & \text{Otherwise} \end{cases} \tag{5.11}$$

$d(s,t_i)$ denotes the distance between sensor node s and target t_i

The usual operators used in the GA - crossover, mutation, selection - are part of the set Γ :

$$\Gamma = (c_{\Theta_c}, m_{\Theta_m}, s_{\Theta_s} \mid c_{\Theta_c}, m_{\Theta_m}, s_{\Theta_s} : I^N \to I^N) \tag{5.12}$$

The routing solutions are modified by crossover and mutation operators.

p_c is a fraction of the pairs of parents of the population chosen for recombination. For every pair of the parents, two points of crossover r_1 and r_2 are selected randomly from the set (1,.....,$m-1$). The parents I_1 and I_2 are exchanged at the bit positions between these points. Each new string of bits is also mutated with a probability of p_m. During mutation, 0 is converted into 1 or 2, 1 is converted into 0 or 2 and 2 is converted into 0 or 1. The -1s are not converted. The generation updation is denoted by :

$\psi : EP \to EP'$

This is how the current EP (External Population) is updated through the removal and / or addition of dominated and / or non-dominated solutions, also applying Γ to the current I^N.

The criteria for terminating the MOEA/D is :

$l : I^N \to \{true, false\}$

The next round of routing begins by using

$\varphi : EP \to I^*$

Here a solution I^* is selected from the EP. The selected solution is the one which needs minimum energy for achieving coverage. It then decodes it into a clustered solution $\forall i \in \{1,m\}$,

$$s_i = \begin{cases} \text{Dead if } I_i^*\text{=-1} \\ \text{Inactive if } I_i^*\text{=0} \\ \text{Non CH if } I_i^*\text{=1} \\ \text{CH if } I_i^*\text{=2} \end{cases} \tag{5.13}$$

This is the way implementation of MOEA/D is done for a WSN represented in the form of bits.

We represent the WSN state by creating a qubit population. A qubit may be in '0' state, '1' state or a superposition of these 2 states. Its state can be derived from :

$$|\psi >= \alpha|0> +\beta|1> \tag{5.14}$$

where α and β represent the probability amplitudes of the corresponding states. $|\alpha|^2$ is the probability of the qubit being in '0' state and $|\beta|^2$ is the probability of the qubit being in '1' state.

$$|\alpha|^2 + |\beta|^2 = 1 \tag{5.15}$$

The state of a quantum bit is changed by the quantum gates. Rotation gates are used in our work for changing the qubit states. The Q bit string of m bits is represented as a quantum matrix :

$$\begin{bmatrix} \alpha_1| & \alpha_2| & .... & |\alpha_m \\ \beta_1| & \beta_2| & .... & |\beta_m \end{bmatrix} \tag{5.16}$$

where

$$|\alpha_i|^2 + |\beta_i|^2 = 1, i = 1,2,.....,m \tag{5.17}$$

We have used a rotation gate for changing the state of qubit:

$$U(\Delta\theta_i) = \begin{bmatrix} cos(\Delta\theta_i) & -sin(\Delta\theta_i) \\ sin(\Delta\theta_i) & cos(\Delta\theta_i) \end{bmatrix} \tag{5.18}$$

where $\Delta\theta_i$, i=1,2,3,....,m is rotation angle of each qubit toward either 0 or 1 and it depends on the sign.

The Quantum Optimizer based on MOEAD for optimizing lifetime and coverage in WSNs is given in the Algorithm 3 below:

Input: MOP (minimizing energy consumption and increasing coverage)
The number of subproblems considered in MOEA/D, N
A Uniform spread of N weight vectors: $\lambda^1,\ldots,\lambda^N$
The number of the weight vectors in the neighborhood of each weight vector, T
The maximum number of generations, gen_{max}
Output: EP (External Population)
begin

Step 0 : Setup

EP is set to Φ

gen is initialized to 0

Step 1 : Initialization

The internal population (IP) which consists of quantum bits is randomly generated IP=$(x^1,\ldots,x^N)$ and FV^i is set to $F(x^i)$

z=$(z_1,\ldots,z_n)^T$ is initialized through a method which depends on the problem

The Euclidean distance between two weight vectors is calculated and the T closest weight vectors to every weight vector are found

$\forall i = 1,\ldots,N$, $B(i)$ is set to $(i_1,\ldots,i_T)$ where $\lambda^{i_1},\ldots,\lambda^{i_T}$ are the T closest weight vectors to λ^i

Step 2: Update: For i=1,....,N

Quantum updation: 2 indices k, l are randomly selected from $B(i)$ *and a new solution y is generated from* x^k *and* x^l *through quantum rotation gates*

z is updated, $\forall j = 1,\ldots,n$, if $z_j < f_j(y)$ and z_j is set to $f_j(y)$

The neighbouring solutions are updated: For each index $j \in B(i)$, if $g^{te}(y \mid \lambda^j, z) \leq g^{te}(x^j \mid y^j, z^*)$, set x^j to y and $FV^j = F(y^j)$

EP Updation: All vectors which are dominated by $F(y)$ are removed from EP. If no vector present in EP dominates $F(y)$, $F(y)$ is added to EP

Step 3 : Stopping criteria

If $gen = gen_{max}$, the loop is stopped and EP is given as output

Otherwise gen is incremented by 1 and control is transferred to Step 2

end

Algorithm 3: Quantum Optimizer based on MOEAD for optimizing lifetime and coverage in WSNs

5.5 Experimental Results

QMOEAD is compared with LEACH (Heinzelman et al., 2002), SEP (Smaragdakis et al., 2004), NSGAII (Deb et al., 2002) and MOEA/D (Özdemir et al., 2013). The parameters compared are number of nodes alive and number of targets covered. The simulation is done using MATLAB R2019a. The experimental setup consisted of 10 WSNs, with each WSN having 100 sensors and 50 targets and the area of interest being $100 \times 100\ m^2$. The nodes are assumed be homogeneous.

The radio model and evolutionary components used are given in Table 5.1 and Table 5.2 respectively:

Table 5.1 Radio model

Term	**Value**
E_{elec}, energy dissipated per bit	20 nJ/bit
E_0, initial energy of node	0.1 J
ε_{fs}, Free Space energy	10 pJ/bit/m^2
ε_{mp}, Multipath energy	0.0013 pJ/bit/m^4
E_{DA}, energy for data aggregation	5 nJ/bit/report
Sensing radius	10 m
Activation Energy	5.0 nJ
l, Message size	4000 bits

Table 5.2 Evolutionary components

Term	**Value**
p_c, crossover probability	0.6
p_m, mutation probability	0.03
N, Population size	20
gen_{max}, number of generations	20
E_{DA}, energy for data aggregation	5 nJ/bit/report
T, neighbourhood size	4

The results when the nodes alive are compared after a number of rounds is shown

Table 5.3 Number of Alive Nodes Vs Rounds

Rounds	**Alive Nodes LEACH**	**Alive Nodes SEP**	**Alive Nodes NSGAII**	**Alive Nodes MOEAD**	**Alive Nodes QMOEAD**
25	100	100	100	100	100
50	100	100	100	100	100
75	96.6	96.2	99.6	100	100
100	8.8	8.4	97.4	100	100
125	4	6.6	80.3	100	100
150	0	0	75.66	98.78	100
175	0	0	23.56	87.89	100
200	0	0	0.7	34.89	99.76
225	0	0	0	8.78	90.34
250	0	0	0	1.56	68.46
275	0	0	0	0	54.35
300	0	0	0	0	23.86
325	0	0	0	0	1.77
350	0	0	0	0	0.35
375	0	0	0	0	0

in Table 5.3. As can be seen from the table, in case of QMOEAD, only after round 375 the number of nodes alive will become 0. For the other algorithms evaluated, it reaches the value 0 earlier.

The results when targets covered are compared after a number of rounds is shown in Table 5.4. The table illustrates that in case of QMOEAD, only after round 350 the number of targets covered will become 0. For the other algorithms evaluated, it reaches the value 0 earlier.

The graphical results of comparison of number of nodes alive with number of rounds for LEACH, SEP, NSGA II, MOEAD and QMOEAD are shown in Figure 5.1. The usage of QMOEAD makes the number of alive nodes reach the value 0 after more rounds. The graphical results of comparison of number of targets covered with number of rounds for LEACH, SEP, NSGA II, MOEAD and QMOEAD are shown in Figure 5.2. Through the usage of QMOEAD, the number of targets covered reaches the value 0 after more rounds. Since LEACH and SEP activate all the alive nodes during their

Table 5.4 Target Coverage Vs Rounds

Rounds	**Targets covered LEACH**	**Targets covered SEP**	**Targets covered NSGAII**	**Targets covered MOEAD**	**Targets covered QMOEAD**
25	50	50	50	50	50
50	50	50	50	50	50
75	50	50	50	50	50
100	25	27.4	50	50	50
125	10	13	49.5	50	50
150	0	0	40.12	49.8	50
175	0	0	37.78	49.56	50
200	0	0	0.67	38.67	49.9
225	0	0	0	14.44	40.67
250	0	0	0	2.45	35.98
275	0	0	0	0	23.56
300	0	0	0	0	12.87
325	0	0	0	0	2.56
350	0	0	0	0	0
375	0	0	0	0	0

rounds, their performance is inferior in comparison to the other algorithms. The NSGA II and MOEAD activate only a percentage of alive nodes and therefore perform better. The QMOEAD, due to the nature of qubits, adds more diversity.

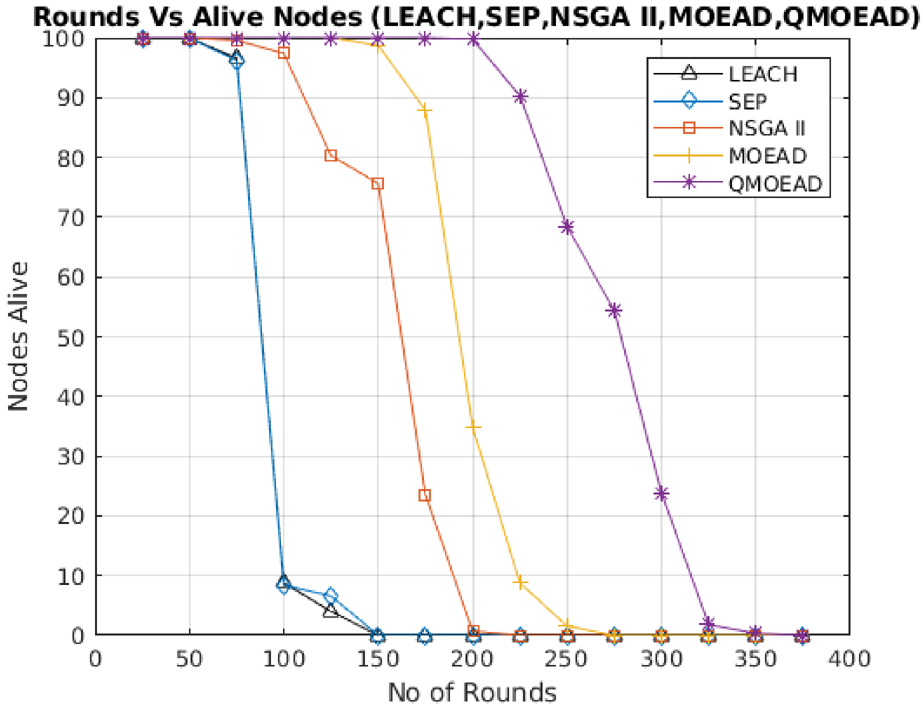

Figure 5.1 Nodes Alive Vs No of Rounds - LEACH, SEP, NSGA II, MOEAD, QMOEAD

5.6 Summary

In this chapter, the Quantum computing based Multi Objective Evolutionary Algorithm with Decomposition (QMOEAD) is presented. The number of nodes alive and number of targets covered for QMOEAD after a large number of rounds are compared with LEACH (Heinzelman et al., 2002), SEP (Smaragdakis et al., 2004), NSGA II (Deb et al., 2002) and MOEAD (Özdemir et al., 2013). Even as the number of rounds increases, the nodes remain alive for a longer time in case of QMOEAD. Also, even as the number of targets covered decreases with increasing rounds, QMOEAD covers more targets in comparison with the other mentioned algorithms. The performance of QMOEAD is therefore better than LEACH, SEP, NSGA II and MOEAD. A limitation of the proposed algorithm is that it works only for Homogeneous WSNs. Real life WSNs may be Heterogeneous and may require more robust algorithms. The Quantum Optimizer discussed in the next chapter works for both Homogeneous and Heterogeneous WSNs.

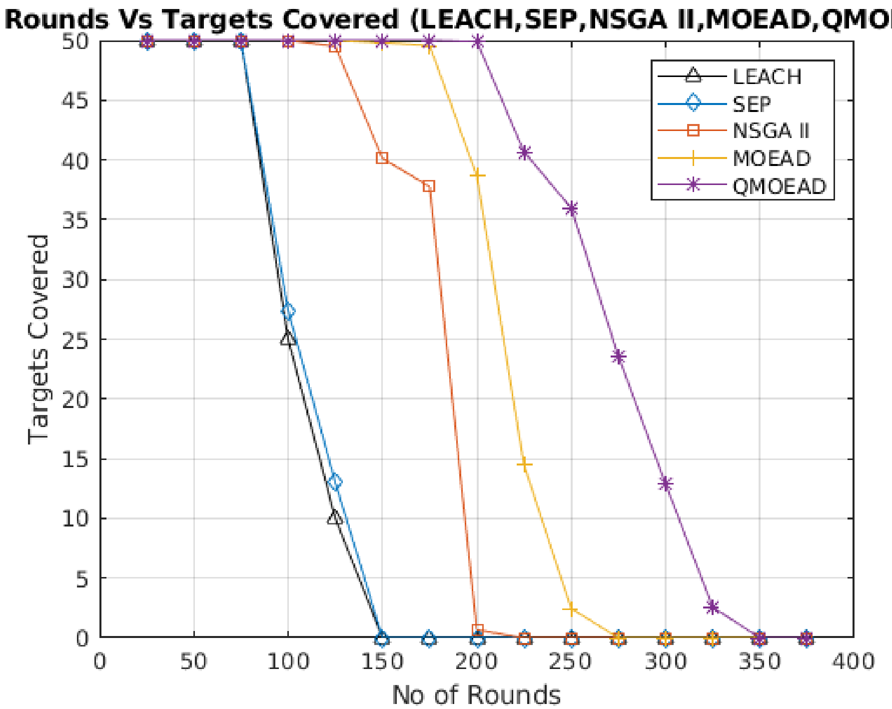

Figure 5.2 No of Covered Targets Vs No of Rounds - LEACH, SEP, NSGA II, MOEAD, QMOEAD

CHAPTER 6

Quantum Optimizer based on MOEAD for Optimizing Lifetime and Coverage in WSN

6.1 Introduction

There are various WSN parameters which researchers have been trying to optimize like energy efficiency, coverage, network lifetime, cluster head selection, quality of service, load balancing, etc. In this chapter, we have worked on simultaneously optimizing two parameters: Coverage and Network Lifetime.

Energy efficient routing has been one of the areas in which lot of research is going on (Heinzelman et al., 2002) , (Smaragdakis et al., 2004), (Cardei and Du, 2005), (Krishnan et al., 2021). Clustering is used extensively for accomplishing energy efficient routing. Clustering is a technique in which nodes are divided into Clusters which are groups of nodes. For every cluster, there is a node which is in charge and it is the Cluster Head (CH). The nodes within a cluster sense the data and send the data to the CH of that cluster. It is the job of the CH to aggregate the data and send it to the base station.

Coverage is another WSN parameter on which lot of research has been done (Tian and Georganas, 2002), (Deepa and Venkataraman, 2021). In coverage, our aim is to cover as much area as possible using as less nodes as possible.

Optimizing the Energy consumption along with Coverage is an area less explored but there are significant works on this topic (Ye et al., 2003), (Chowdhury and De, 2021).

Quantum computing has been used to optimize WSNs (Li and Huo, 2016), (Zhang et al., 2021).

There are very few efforts at using Quantum computing along with MOEAD for optimizing WSNs (Kanchan et al., 2021). This paper optimizes Homogeneous WSNs using MOEAD in conjunction with Quantum Computing.
In this chapter, Quantum computing along with MOEAD is used for optimizing lifetime and coverage of WSNs - both homogeneous and heterogeneous. *For the heterogeneous WSNs, we vary not only the energies of the nodes but also the sensing radius.* The results are compared with LEACH (Heinzelman et al., 2002), SEP (Smaragdakis et al., 2004), NSGA II (Deb et al., 2002) and MOEAD (Özdemir et al., 2013). The superiority of our method is shown by the results.

6.2 The Quantum Optimizer for Homogeneous and Heterogeneous WSNs - Experimental Results

We use the algorithm as used in Algorithm 3 in Section 5.4; the major difference is that we have considered Homogeneous as well as Heterogeneous WSNs.
We investigate the performance of Quantum Optimizer against LEACH (Heinzelman et al., 2002), SEP (Smaragdakis et al., 2004), NSGA-II (Deb et al., 2002) and MOEA/D (Özdemir et al., 2013).
The protocols are evaluated with respect to number of nodes alive and number of targets covered. The simulation is done using MATLAB R2019b. **6 scenarios are simulated. In each scenario, there are 10 WSNs with** 100 **sensors and** 50 **targets uniformly distributed in an area** $100 \times 100\,m^2$ **and the base station is located at the center.**

Scenario 1 consists of WSN Group 1 where all nodes are Homogeneous and have uniform sensing radius of 10m.

In **Scenario 2** (Heterogeneous nodes), the WSN Group 1 consists of normal nodes as well as nodes with extra energy which are called advanced nodes (10 % of the nodes are advanced in our simulation). The normal nodes have sensing radius of 10m and advanced nodes have 1.5 times the sensing radius.
In **Scenario 3** (Heterogeneous nodes), the WSN Group 1 consists of normal nodes as

well as 20 % advanced nodes. The normal nodes have sensing radius of 10m and advanced nodes have 2 times the sensing radius.

Scenario 4 consists of WSN Group 2 where all nodes are Homogeneous and have uniform sensing radius of 20m.

In **Scenario 5** (Heterogeneous nodes), the WSN Group 2 consists of normal nodes as well as 10 % advanced nodes. The normal nodes have sensing radius of 20m and advanced nodes have 1.5 times the sensing radius.

In **Scenario 6** (Heterogeneous nodes), the WSN Group 2 consists of normal nodes as well as 20 % advanced nodes. The normal nodes have sensing radius of 20m and advanced nodes have 2 times the sensing radius.

The radio model used and evolutionary components used are the same as in Table 5.1 and Table 5.2.

6.2.1 Scenario 1

In Scenario 1, all nodes of **WSN Group 1** are **Homogeneous** and have uniform sensing radius of 10m. We refer to the Quantum Optimizer as QMOEAD when Homogeneous WSN is considered.

Table 6.1 Number of Alive Nodes Vs Rounds - Scenario 1

Rounds	**LEACH**	**SEP**	**NSGAII**	**MOEAD**	**QMOEAD**
25	100	100	100	100	100
50	100	100	100	100	100
100	8	4	99	99	100
150	0	0	77	82	100
200	0	0	12	34	100
250	0	0	0	4	89
300	0	0	0	0	75
350	0	0	0	0	23
400	0	0	0	0	0

The number of nodes alive after a number of rounds for Scenario 1 is shown in Table 6.1.

Table 6.2 Target Coverage Vs Rounds - Scenario 1

Rounds	**LEACH**	**SEP**	**NSGAII**	**MOEAD**	**QMOEAD**
50	50	50	50	50	50
100	20	18	50	50	50
150	0	0	50	48	50
200	0	0	19	33	50
250	0	0	0	3	48
300	0	0	0	0	38
350	0	0	0	0	12
400	0	0	0	0	0

The number of targets covered after a number of rounds for Scenario 1 is shown in Table 6.2.

6.2.2 Scenario 2

In Scenario 2 (Heterogeneous nodes), the **WSN Group 1** consists of normal nodes as well as nodes with extra energy which are called advanced nodes (**10 % of the nodes are advanced in our simulation**). We refer to the Quantum Optimizer as QOHW when Heterogeneous WSN is considered.The normal nodes have sensing radius of 10m and advanced nodes have 1.5 times the sensing radius.

The number of nodes alive after a number of rounds for Scenario 2 is shown in Table 6.3.

The number of targets covered after a number of rounds for Scenario 2 is shown in Table 6.4.

Table 6.3 Number of Alive Nodes Vs Rounds - Scenario 2

Rounds	LEACH	SEP	NSGAII	MOEAD	QOHW
50	100	100	100	100	100
100	17	20	100	100	100
150	0	0	80	91	100
200	0	0	33	64	100
250	0	0	10	12	100
300	0	0	4	5	100
350	0	0	3	2	100
400	0	0	0	1	98
450	0	0	0	0	86
500	0	0	0	0	65
550	0	0	0	0	20
600	0	0	0	0	0

Table 6.4 Target Coverage Vs Rounds - Scenario 2

Rounds	LEACH	SEP	NSGAII	MOEAD	QOHW
50	50	50	50	50	50
100	48	50	50	50	50
150	0	0	49	50	50
200	0	0	44	50	50
250	0	0	29	33	50
300	0	0	8	13	48
350	0	0	5	10	40
400	0	0	0	6	36
450	0	0	0	4	24
500	0	0	0	0	13
550	0	0	0	0	5
600	0	0	0	0	0

6.2.3 Scenario 3

In Scenario 3 (Heterogeneous nodes), the **WSN Group 1** consists of normal as well as advanced nodes (**20 % of the nodes are advanced**). The normal nodes have sensing radius of 10m and advanced nodes have 2 times the sensing radius.

Table 6.5 Number of Alive Nodes Vs Rounds - Scenario 3

Rounds	**LEACH**	**SEP**	**NSGAII**	**MOEAD**	**QOHW**
50	100	100	100	100	100
100	21	38	99	100	100
150	7	0	55	92	100
200	0	0	44	74	100
250	0	0	17	19	100
300	0	0	12	10	100
350	0	0	6	6	100
400	0	0	2	3	100
450	0	0	0	1	100
500	0	0	0	0	90
550	0	0	0	0	79
600	0	0	0	0	45
650	0	0	0	0	23
700	0	0	0	0	0

The number of nodes alive after a number of rounds for Scenario 3 is shown in Table 6.5.

The number of targets covered after a number of rounds for Scenario 3 is shown in Table 6.6.

6.2.4 Scenario 4

In Scenario 4, all nodes of **WSN Group 2** are **Homogeneous** and have uniform sensing radius of 20m. We refer to the Quantum Optimizer as QMOEAD when Homogeneous WSN is considered.

Table 6.6 Target Coverage Vs Rounds - Scenario 3

Rounds	**LEACH**	**SEP**	**NSGAII**	**MOEAD**	**QOHW**
50	50	50	50	50	50
100	50	50	50	50	50
150	33	0	48	50	50
200	0	0	46	50	50
250	0	0	34	39	50
300	0	0	28	33	50
350	0	0	19	27	50
400	0	0	8	16	50
450	0	0	0	0	50
500	0	0	0	0	48
550	0	0	0	0	34
600	0	0	0	0	25
650	0	0	0	0	10
700	0	0	0	0	0

Table 6.7 Number of Alive Nodes Vs Rounds - Scenario 4

Rounds	**LEACH**	**SEP**	**NSGAII**	**MOEAD**	**QMOEAD**
50	50	50	50	50	50
100	34	27	50	50	50
150	0	0	50	50	50
200	0	0	50	50	50
250	0	0	15	47	50
300	0	0	0	0	50
350	0	0	0	0	38
400	0	0	0	0	23
450	0	0	0	0	12
500	0	0	0	0	0

The number of nodes alive after a number of rounds for Scenario 4 is shown in Table 6.7.

Table 6.8 Target Coverage Vs Rounds - Scenario 4

Rounds	LEACH	SEP	NSGAII	MOEAD	QMOEAD
50	50	50	50	50	50
100	34	27	50	50	50
150	0	0	50	50	50
200	0	0	50	50	50
250	0	0	15	47	50
300	0	0	0	0	50
350	0	0	0	0	38
400	0	0	0	0	23
450	0	0	0	0	12
500	0	0	0	0	0

The number of targets covered after a number of rounds for Scenario 4 is shown in Table 6.8.

6.2.5 Scenario 5

In Scenario 5 (Heterogeneous nodes), the **WSN Group 2** consists of normal as well as advanced nodes (**10 % of the nodes are advanced**). We refer to the Quantum Optimizer as QOHW when Heterogeneous WSN is considered.The normal nodes have sensing radius of 20m and advanced nodes have 1.5 times the sensing radius.

The number of nodes alive after a number of rounds for Scenario 5 is shown in Table 6.9.

The number of targets covered after a number of rounds for Scenario 5 is shown in Table 6.10.

Table 6.9 Number of Alive Nodes Vs Rounds - Scenario 5

Rounds	**LEACH**	**SEP**	**NSGAII**	**MOEAD**	**QOHW**
50	100	100	100	100	100
100	13	23	100	100	100
150	0	0	85	93	100
200	0	0	38	65	100
250	0	0	13	24	100
300	0	0	9	14	100
350	0	0	0	8	100
400	0	0	0	2	100
450	0	0	0	1	100
500	0	0	0	0	100
550	0	0	0	0	86
600	0	0	0	0	45
650	0	0	0	0	0

Table 6.10 Target Coverage Vs Rounds - Scenario 5

Rounds	**LEACH**	**SEP**	**NSGAII**	**MOEAD**	**QOHW**
50	50	50	50	50	50
100	50	50	50	50	50
150	0	0	50	50	50
200	0	0	50	50	50
250	0	0	50	50	50
300	0	0	47	49	50
350	0	0	0	47	50
400	0	0	0	44	50
450	0	0	0	35	50
500	0	0	0	0	50
550	0	0	0	0	38
600	0	0	0	0	14
650	0	0	0	0	0

6.2.6 Scenario 6

In Scenario 5 (Heterogeneous nodes), the **WSN Group 2** consists of normal as well as advanced nodes (**20 % of the nodes are advanced**). The normal nodes have sensing radius of 20m and advanced nodes have 2 times the sensing radius.

Table 6.11 Number of Alive Nodes Vs Rounds - Scenario 6

Rounds	**LEACH**	**SEP**	**NSGAII**	**MOEAD**	**QOHW**
50	100	100	100	100	100
100	23	38	99	100	100
150	9	0	89	98	100
200	0	0	49	69	100
250	0	0	38	40	100
300	0	0	25	30	100
350	0	0	17	20	100
400	0	0	14	16	100
450	0	0	10	10	100
500	0	0	8	6	100
550	0	0	3	4	96
600	0	0	0	3	76
650	0	0	0	0	45
700	0	0	0	0	24
750	0	0	0	0	0

The number of nodes alive after a number of rounds for Scenario 6 is shown in Table 6.11.

The number of targets covered after a number of rounds for Scenario 6 is shown in Table 6.12.

Table 6.12 Target Coverage Vs Rounds - Scenario 6

Rounds	LEACH	SEP	NSGAII	MOEAD	QOHW
50	50	50	50	50	50
100	50	50	50	50	50
150	50	0	50	50	50
200	0	0	50	50	50
250	0	0	50	50	50
300	0	0	50	50	50
350	0	0	50	50	50
400	0	0	48	50	50
450	0	0	44	50	50
500	0	0	42	49	50
550	0	0	36	40	48
600	0	0	0	38	38
650	0	0	0	0	23
700	0	0	0	0	13
750	0	0	0	0	0

6.3 Graphical Results

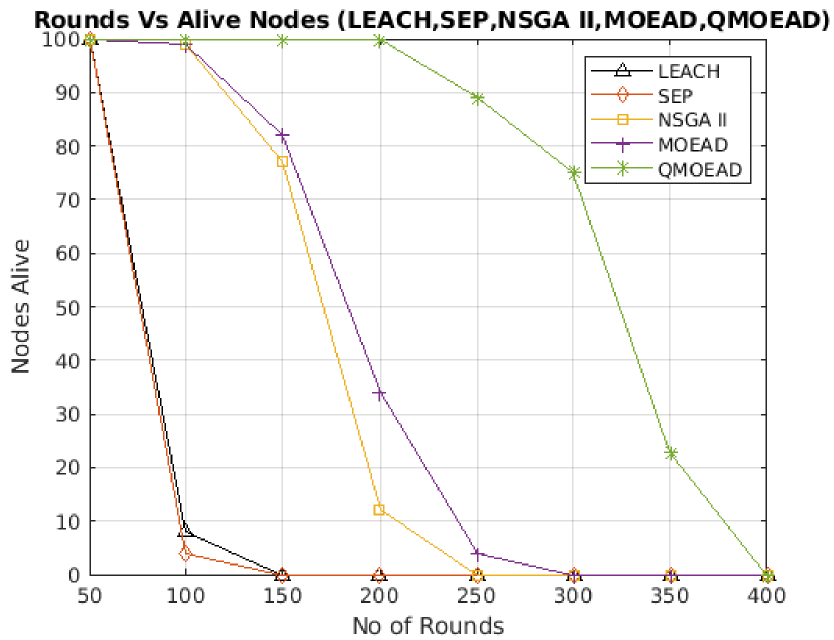

Figure 6.1 No of Nodes Alive Vs No of Rounds - LEACH, SEP, NSGA II, MOEAD, QMOEAD - Scenario 1

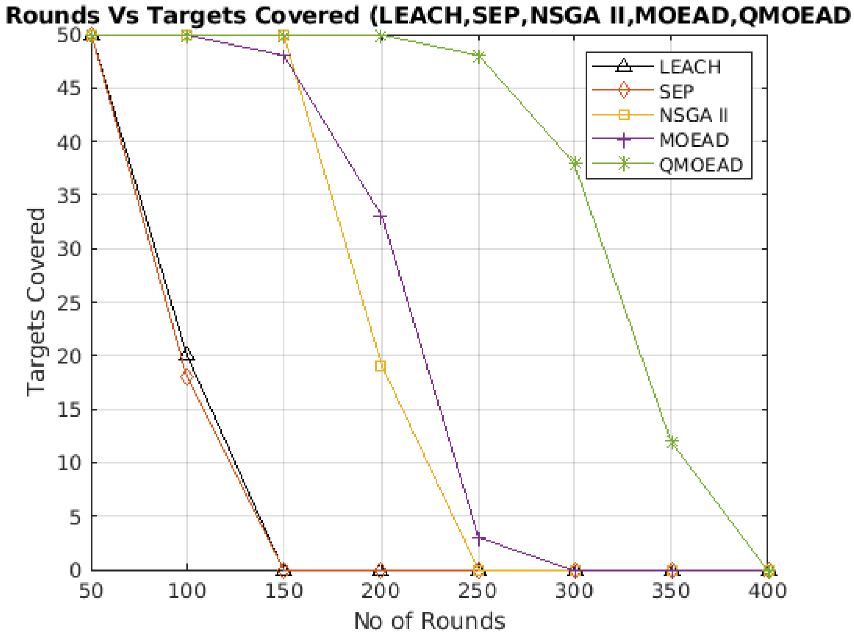

Figure 6.2 No of Covered Targets Vs No of Rounds - LEACH, SEP, NSGA II, MOEAD, QMOEAD - Scenario 1

Figure 6.1 and 6.2 show the graph obtained for Homogeneous WSN Group 1.

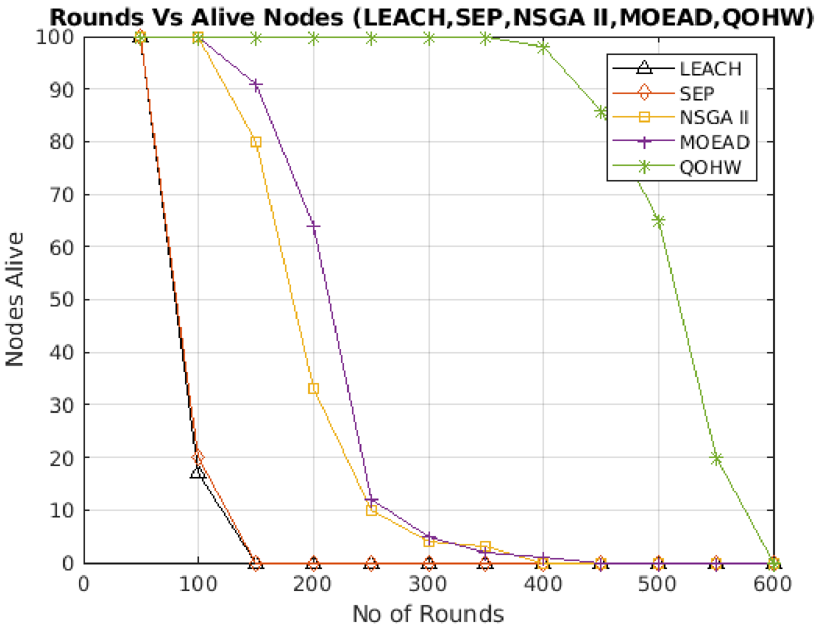

Figure 6.3 No of Nodes Alive Vs No of Rounds - LEACH, SEP, NSGA II, MOEAD, QOHW - Scenario 2

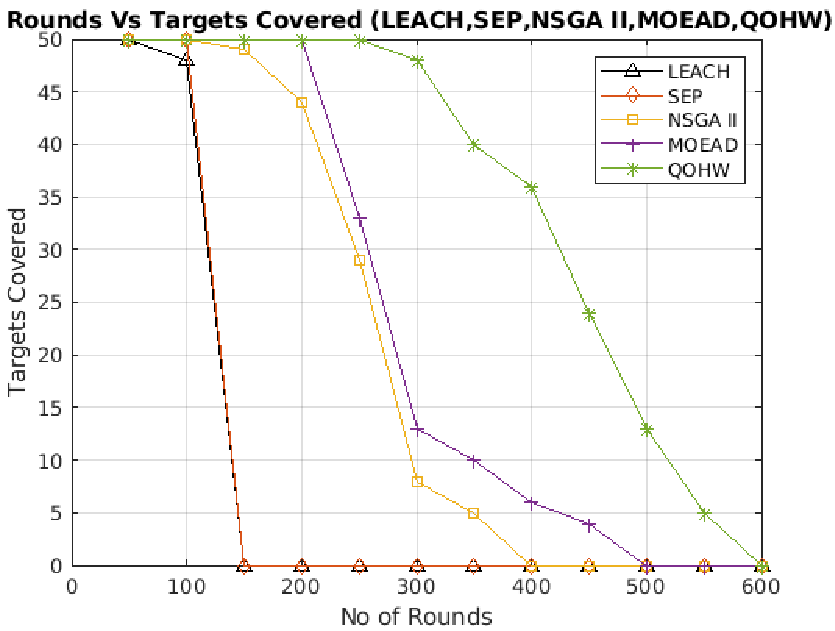

Figure 6.4 No of Covered Targets Vs No of Rounds - LEACH, SEP, NSGA II, MOEAD, QOHW - Scenario 2

Figure 6.3 and 6.4 show the graph obtained for Heterogeneous WSN Group 1 with 10 % Advanced Nodes.

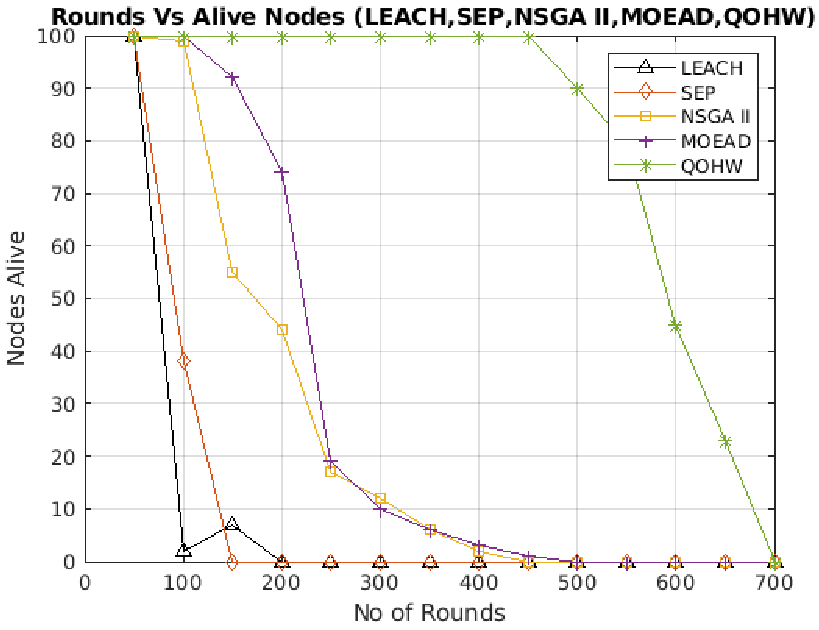

Figure 6.5 No of Nodes Alive Vs No of Rounds - LEACH, SEP, NSGA II, MOEAD, QOHW - Scenario 3

Figure 6.5 and 6.6 show the graph obtained for Heterogeneous WSN Group 1 with 20 % Advanced Nodes.

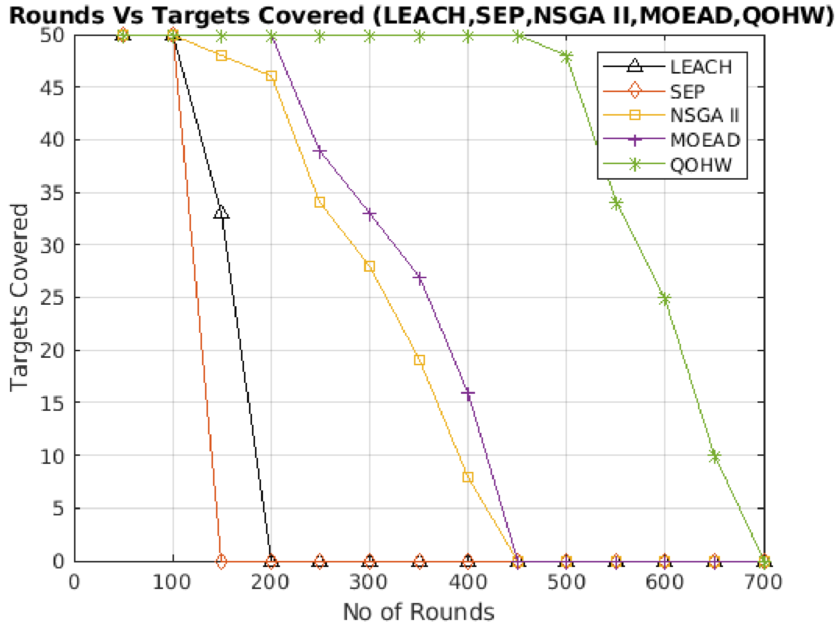

Figure 6.6 No of Covered Targets Vs No of Rounds - LEACH, SEP, NSGA II, MOEAD, QOHW - Scenario 3

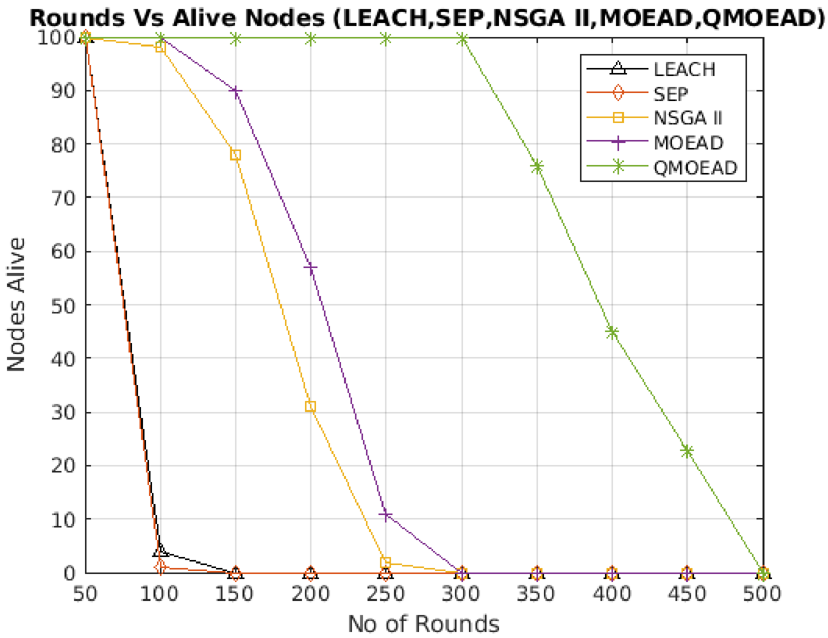

Figure 6.7 No of Nodes Alive Vs No of Rounds - LEACH, SEP, NSGA II, MOEAD, QMOEAD - Scenario 4

Figure 6.7 and 6.8 show the graph obtained for Homogeneous WSN Group 2.

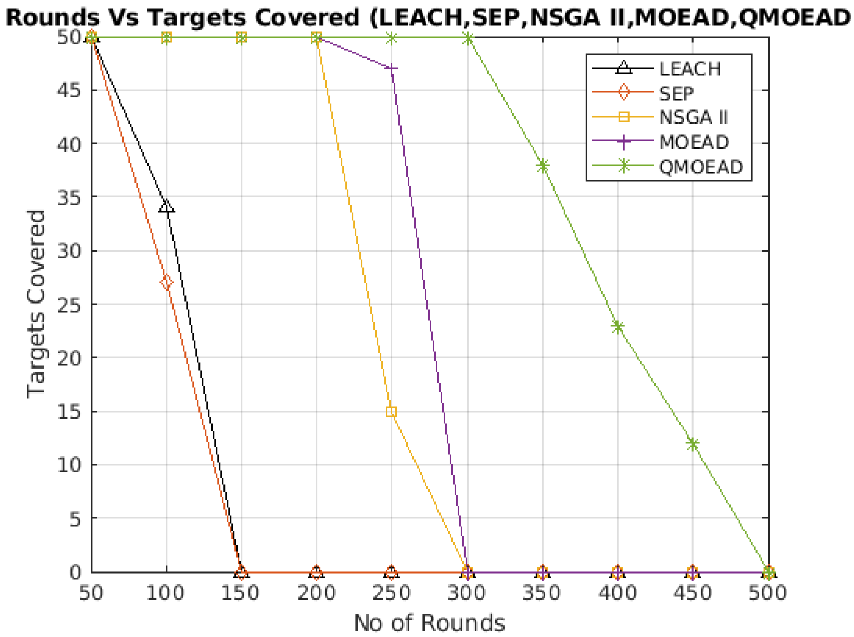

Figure 6.8 No of Covered Targets Vs No of Rounds - LEACH, SEP, NSGA II, MOEAD, QMOEAD - Scenario 4

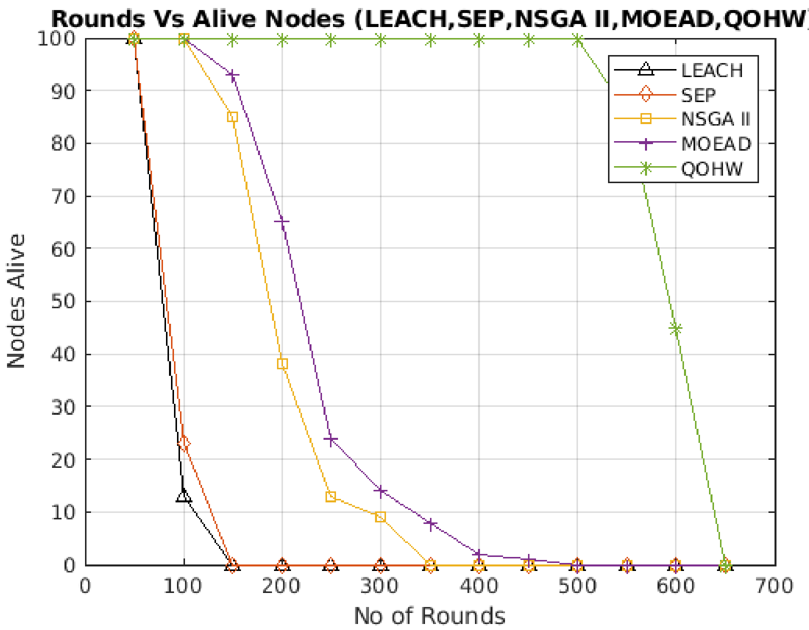

Figure 6.9 No of Nodes Alive Vs No of Rounds - LEACH, SEP, NSGA II, MOEAD, QOHW - Scenario 5

Figure 6.9 and 6.10 show the graph obtained for Heterogeneous WSN Group 2 with 10 % Advanced Nodes.

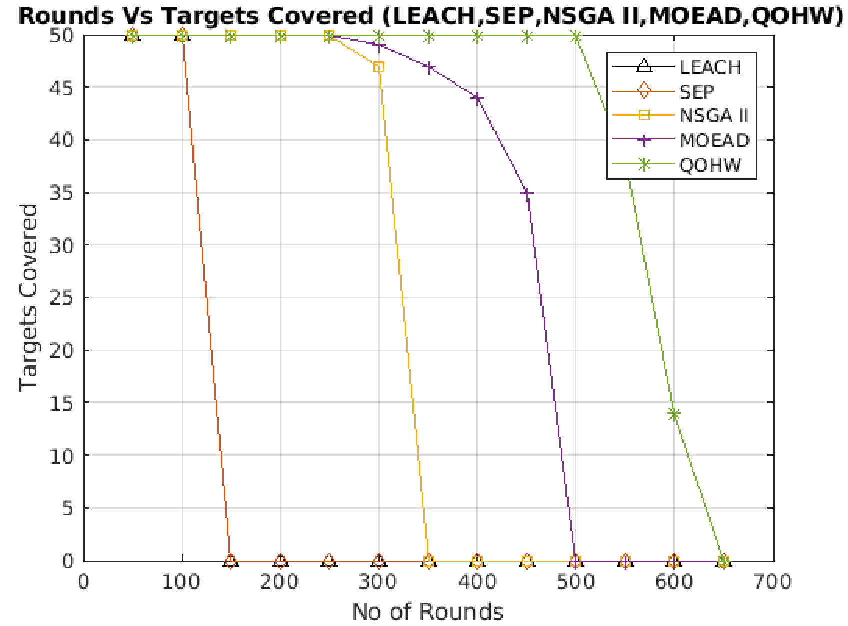

Figure 6.10 No of Covered Targets Vs No of Rounds - LEACH, SEP, NSGA II, MOEAD, QOHW - Scenario 5

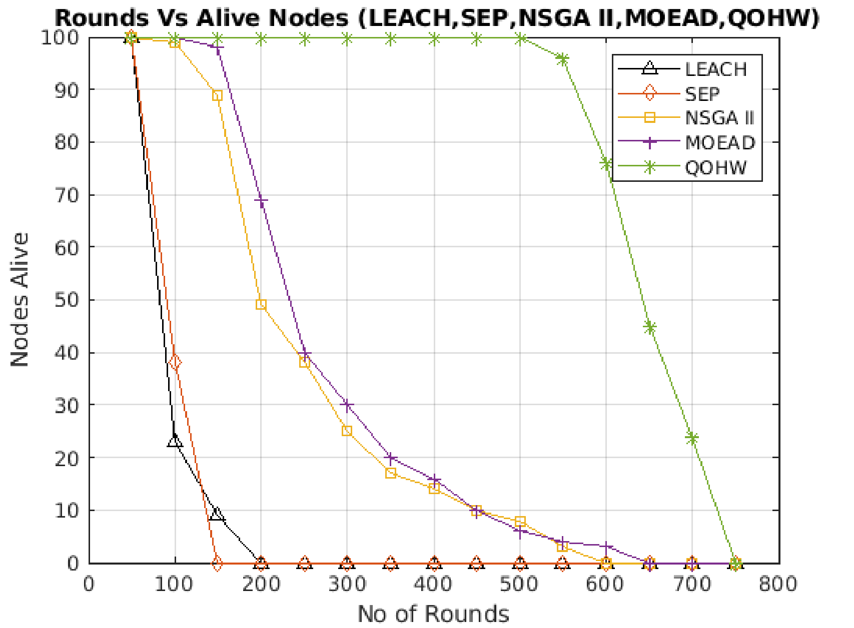

Figure 6.11 No of Nodes Alive Vs No of Rounds - LEACH, SEP, NSGA II, MOEAD, QOHW - Scenario 6

Figure 6.11 and 6.12 show the graph obtained for Heterogeneous WSN Group 2 with 20 % Advanced Nodes.

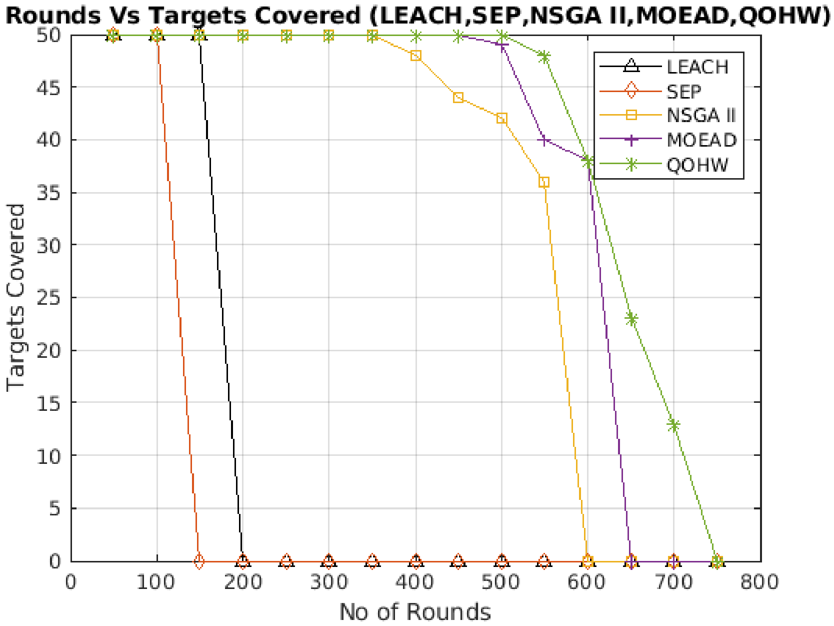

Figure 6.12 No of Covered Targets Vs No of Rounds - LEACH, SEP, NSGA II, MOEAD, QOHW - Scenario 6

6.4 Summary

The proposed Quantum Optimizer considers network lifetime and coverage as multiple objectives and optimizes them. The working of the Quantum Optimizer is compared with LEACH (Heinzelman et al., 2002), SEP (Smaragdakis et al., 2004), NSGA II (Deb et al., 2002) and MOEA/D (Özdemir et al., 2013) for 6 different scenarios and the results show that the Quantum Optimizer outperforms LEACH, SEP, NSGA and MOEA/D. Due to the activation of all alive nodes during the rounds of execution, performance of LEACH and SEP is inferior. Since in NSGA II and MOEA/D, only a percentage of alive nodes are activated during the rounds, they perform better. In case of the Quantum Optimizer, the diversity is because of quantum bits. As future work, some more WSN parameters like interconnectivity, reliability, etc along with the existing multiple objectives can be considered for improvement.

CHAPTER 7

Conclusion and Future work

7.1 Conclusion

The major contributions of the thesis are summarized in this chapter.

7.1.1 Contributions

Some Nature Inspired Algorithms are proposed in conjunction with Quantum Computing for Optimizing WSNs which are as follows:

1. Energy Efficient scheme for Clustered WSNs using Quantum Inspired Computing in which Quantum PSO is used
2. Quantum PSO algorithm for Clustered WSNs which Improves Network Lifetime
3. Quantum Inspired Multiobjective Optimization in Clustered Homogeneous Wireless Sensor Networks for Improving Network Lifetime and Coverage
4. Quantum Optimizer based on MOEAD for Optimizing Lifetime and Coverage in Homogeneous and Heterogeneous WSNs

In the first contribution **Chapter 3**, our algorithm QPSOEEC is compared with LEACH (Heinzelman et al., 2002) and PSO ECHS (Rao et al., 2017). Results show that values of total energy consumed using QPSOEEC are *89% better* than LEACH and *71% better* than PSOECHS.

In the second contribution **Chapter 4**, a new term, Network Lifetime Factor (NLF) is defined and the NLF values of LEACH (Heinzelman et al., 2002) and PSO ECHS (Rao et al., 2017) are compared with those of the proposed algorithm. The NLF values for our algorithm are better than those for LEACH and PSO-ECHS.

In the third contribution **Chapter 5**, the Quantum inspired Multi Objective Evolutionary Algorithm based on Decomposition (QMOEAD) is proposed. The scheme is compared with LEACH (Heinzelman et al., 2002), SEP (Smaragdakis et al., 2004), NSGA II (Deb et al., 2002) and MOEA/D (Özdemir et al., 2013) by simulation for Homogeneous WSNs and our scheme proves to be better than the mentioned schemes.

In the final contribution **Chapter 6**, a Quantum Optimizer for both Homogeneous and Heterogeneous WSNs is proposed. The scheme is compared with LEACH (Heinzelman et al., 2002), SEP (Smaragdakis et al., 2004), NSGA II (Deb et al., 2002) and MOEA/D (Özdemir et al., 2013). Both Homogeneous and Heterogeneous WSNs are considered for 6 different scenarios and our scheme proves to be better than the mentioned schemes.

7.1.2 Future scope

In this section, some directions for possible future work are suggested. Several research directions worth investigating are as follows :
The effect of Quantum computing in conjunction with PSO and MOEAD has been studied ; there are many more Nature Inspired algorithms with which Quantum computing can be combined (like ACO, GA, FA, CS, etc) and used to optimize some parameters of WSN. Also, we have investigated optimizing the parameters - energy,lifetime, coverage. Optimization of other parameters like Interconnectivity, Reliability can be considered.
Some scientists are of the opinion that parallel computing will improve upon the power of quantum computing. Quantum phenomena essentially allow evaluating many potential answers simultaneously, which is something parallel computers also do. However, parallel computers require an amount of hardware proportional to the number of things being simultaneously evaluated (N), while the number of qubits needed by a quantum computer is only proportional to log(N). In theory, quantum machines can also perform

the evaluation in almost zero time. On the other hand, a quantum computer simply returns a single randomly-selected correct result, while a parallel computer can directly return all valid results. Quantum computing will surely yield better performance but with increased hardware cost.

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