Efficient Clustering Protocol for WSN Based on Particle Swarm Optimization with Fault Recovery

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***ABSTRACT*-- Clustering is one of most efficient energy saving techniques for maximizing network lifetime in wireless sensor networks (WSNs). In the multi-hop approach, cluster heads (CHs) close to the base station (BS) deplete their energy very quickly due to high inter-cluster relay traffic load, causing the hot spot problem. Thus, a clustering protocol is required to be energy efficient as well as fault tolerant. This paper presents a particle swarm optimization (PSO) based unequal and fault tolerant clustering protocol referred as PSO-UFC. The proposed protocol addresses imbalanced clustering and fault tolerance issues in the existing energy-balanced unequal clustering (EBUC) protocol for the long-run operation of the network. To solve the imbalanced clustering problem, the PSO-UFC protocol utilizes unequal clustering mechanism to balance intra-cluster and inter-cluster energy consumption between the Masterclusters heads(MCHs). Also, in PSO-UFC protocol the network connectivity is restored by electing an extra CH called Surrogate cluster head (SCH) due to sudden failure of MCH. The obtained simulation results demonstrate that the PSO-UFC protocol prolongs the network lifetime.**

***Index Terms*— Wireless Sensor network, clustering, routing, energy saving, lifetime.**

I. INTRODUCTION

Wireless sensor networks (WSNs) have come across as one of the emerging technologies in the recent years. The early research on WSN is mainly directed towards the monitoring applications, but with immense proliferation in micro-electro-mechanical systems (MEMS), there has been a widespread utilization of WSNs in different environments and for different purposes like Healthcare, Military Surveillance, Smart Grid, and Industrial Automation. They incorporate automated sensing, embedded processing, and wireless transmission into tiny embedded devices referred as sensor nodes. Each sensor node is constrained to energy supply due to its limited and non-rechargeable battery source. Nevertheless, their processors have limited onboard processing power and storage capabilities. Such constraints require the energy resources of sensor nodes should be used wisely for the long run of WSNs. In the recent past, clustering has been studied extensively for the energy conservation of WSNs.

The clustering mechanism splits the network into small clusters, where each cluster has a Cluster Head (CH) node and member nodes. Once the network is partitioned into clusters, the communication among the nodes can be classified into: intra-cluster and inter-cluster communication. Non-CH nodes transmit their data to the CH, and then the CH transmits aggregated data to the base station (BS) either directly or through multi-hop routing. However, in multi-hop routing, CHs near to the BS involved in high inter-cluster relay traffic load and deplete their energy very quickly compared to the other CH nodes. In literature, this issue is popularly known as the hot spot problem. Moreover, sensor nodes are prone to failure due to quick depletion of their limited battery power or some malfunctioning of hardware components. The failure of a CH node interrupts the network communication not only with its member nodes as well as with the neighbor CHs. Therefore, this paper addresses the hot spot problem, imbalanced clustering and fault tolerance issues in a joint manner.

Note that the CH-election is a Non-Deterministic Polynomial (NP)-hard optimization problem because the election of m optimal CHs among sensor nodes give possibilities. Swarm intelligence approaches have been applied successfully to a variety of such NP problems. Particle swarm optimization (PSO) is swarm intelligence based stochastic optimization technique which is inspired by social behavior of bird flocking, and fish schooling. It generally optimizes an issue by performing a series of iterations to improve the candidate solution regarding the given quality of the application. It can be a better choice for optimal CH selection because of its ease of implementation on hardware or software and ability to converge to an optimal solution very quickly. As clustering is a repeated process; therefore, simpler the optimization algorithm, the better the network efficiency is. This is another reason why PSO has been adopted widely to optimize the CH election process by several clustering protocols.

Some of the existing clustering protocols in wireless sensor networks are given below

- **LEACH-C**

LEACH-C is a centralized clustering protocol where the BS governs the entire CH election phase to maximize the network lifetime. The BS employs simulated annealing technique to select the optimal number of CHs throughout the network. The main drawback of LEACH-C is single-hop routing for inter-cluster communication that may cause imbalanced energy distribution, especially when a large number of CHs is placed far away from the BS.

$$T(n) = \begin{cases} \frac{p}{1-p*(r \bmod \frac{1}{p})} & \text{, if } n \epsilon G \\ 0 & \text{, otherwise} \end{cases} \quad (1.1)$$

- **PSO-C**

An energy-aware clustering using PSO algorithm (PSO-C) is a centralized clustering protocol in which BS controls the entire CH election and cluster formation process to enhance the lifetime of network. The BS considers both the intra-cluster distance between nodes and current energy of all CH nodes for efficient CH election.

- **EBUC**

EBUC is a centralized unequal clustering protocol which addresses hot spot problem by using PSO algorithm at the BS. The protocol creates unequal clusters in such a way that the CHs closer to the BS has smaller cluster size in order to preserve their battery energy for high inter-cluster relay traffic load.

Communication is the activity of conveying information. Communication requires a sender, a message, and an intended recipient, although the receiver need not be present or aware of the sender's intent to communicate at the time of communication; thus communication can occur across vast distances in time and space. Communication requires that the communicating parties share an area of communicative commonality. The communication process is complete once the receiver has understood the sender.

Wireless data communications are an essential component of mobile computing. The various available technologies differ in local availability, coverage range and performance, and in some circumstances, users must be able to employ multiple connection types and switch between them. To simplify the experience for the user, connection manager software can be used, or a mobile VPNdeployed to handle the multiple connections as a secure, single virtual network.

1.1 SCOPE OF THE PROJECT

Energy- balanced unequal clustering (EBUC) protocol addresses the hot spot problem by using PSO algorithm at the BS. The protocol creates unequal clusters to support high inter-cluster relay traffic load. EBUC does not consider fault tolerant issues, node degree and residual energy of CHs. To imbalanced clustering and fault tolerant a new particle swarm optimization based fault tolerant clustering protocol referred as PSO-UFC. The main contribution of this paper can be summarized as follows:

- PSO based clustering mechanism to solve hot spot problem in WSN.
- Derivation of the cost functions for unequal clustering mechanism to balance the intra-cluster and inter-cluster energy consumption.
- Construction of a multi-hop routing tree to ensure the network connectivity among the MCHs.
  Election of Surrogate Cluster Head in each cluster to address the fault tolerant issue.**1**

3.2 BLOCK DIAGRAM

Clustering is the most efficient energy saving technique for maximizing network lifetime. It is an ability of several servers or instances to connect to a single server or instances to connect to a single database. The clustering mechanism splits the network into small clusters. Non-CH nodes transmit their data to the CH and then the CH transmits aggregated data to the BS directly or through multi-hop routing. Initially the data is introduced in the wireless sensor network. WSN is a wireless network consisting of spatially distributed autonomous device using sensor to monitor physical or environmental condition. Each CH has different amount of energy, and are located at random locations. The energy and locations of each nodes are detected initially. The selection of Cluster Head CH is made using these parameters through the PSO method. LEACH (Low Energy Adaptive Clustering Hierarchy) is used for routing. The network connectivity is restored by electing a SCH in case of failure oh Master Cluster Head (MCH). The basic block diagram of the proposed method is shown below.

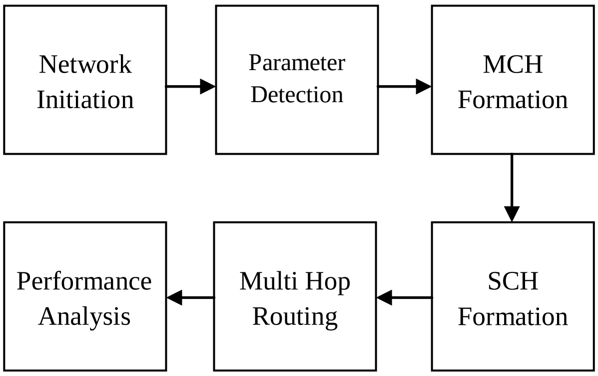

Fig: 1.1 Basic Block Structure

3.3 MODULES DESCRIPTION

- Wireless Sensor Network(WSN)
- PSO-MCH
- Multi-hop Routing
- Performance Analysis

A Wireless Sensor Network (WSN)

The WSN is built of nodes from a few to several hundreds or even thousands, where each node is connected to one (or sometimes several) sensors. Each such sensor network node has typically several parts: a radio transceiver with an internal antenna or connection to an external antenna, a microcontroller, an electronic circuit for interfacing with the sensors and an energy source, usually a battery or an embedded form of energy harvesting. The topology of the WSNs can vary from a simple star network to an advanced multi-hop wireless mesh network. The propagation technique between the hops of the network can be routing or flooding.

B PSO-MCH

In computational science, Particle Swarm Optimization (PSO) is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. It solves a problem by having a population of candidate solutions, here dubbed particles, and moving these particles around in the search-space according to simple mathematical formulae over the particle's position and velocity. Each particle's movement is influenced by its local best known position, but is also guided toward the best known positions in the search-space, which are updated as better positions are found by other particles. This is expected to move the swarm toward the best solutions.

PSO is a metaheuristic as it makes few or no assumptions about the problem being optimized and can search very large spaces of candidate solutions. However, metaheuristics such as PSO do not guarantee an optimal solution is ever found. Also, PSO does not use the gradient of the problem being optimized, which means PSO does not require that the optimization problem be differentiable as is required by classic optimization methods such as gradientdescent and quasi-newton methods.

Formally, let f: $\mathbb{R}^n \rightarrow \mathbb{R}$ be the cost function which must be minimized. The function takes a candidate solution as an argument in the form of a vector of realnumbers and produces a real number as output which indicates the objective function value of the given candidate solution. The gradient of f is not known. The goal is to find a solution a for which $f(a) \leq f(b)$ for all b in the search-space, which would mean a is the global minimum. Maximization can be performed by considering the function h = -f instead.

Let S be the number of particles in the swarm, each having a position $x_i \in \mathbb{R}^n$ in the search-space and a velocity $v_i \in \mathbb{R}^n$. Let p_i be the best known position of particle i and let g be the best known position of the entire swarm.

1. **Parameter selection**

The choice of PSO parameters can have a large impact on optimization performance. Selecting PSO parameters that yield good performance has therefore been the subject of much research. The PSO parameters can also be tuned by using another overlaying optimizer, a concept known as meta-optimization, or even fine-tuned during the optimization, e.g., by means of fuzzy logic. Parameters have also been tuned for various optimization scenarios.

2. **Neighbourhoods and topologies**

The topology of the swarm defines the subset of particles with which each particle can exchange information. The basic version of the algorithm uses the global topology as the swarm communication structure. This topology allows all particles to communicate with all the other particles, thus the whole swarm share the same best position g from a single particle. However, this approach might lead the swarm to be trapped into a local minimum, thus different topologies have been used to control the flow of information among particles. For instance, in local topologies, particles only share information with a subset of particles. This subset can be a geometrical one for example "the m nearest particles" – or, more often, a social one, i.e. a set of particles that is not depending on any distance. In such cases, the PSO variant is said to be local best (vs global best for the basic PSO). A commonly used swarm topology is the ring, in which each particle has just two neighbours, but there are many others. The topology is not necessarily static.

3. **Convergence**

In relation to PSO the word convergence typically refers to two different definitions:

- Convergence of the sequence of solutions (aka, stability analysis, converging) in which all particles have converged to a point in the search-space, which may or may not be the optimum,
- Convergence to a local optimum where all personal bests p or, alternatively, the swarm's best known position g, approaches a local optimum of the problem, regardless of how the swarm behaves.

Determining convergence capabilities of different PSO algorithms and parameters depends on empirical results. One attempt at addressing this issue is the development of an "orthogonal learning" strategy for an improved use of the information already existing in the relationship between p and g, so as to form a leading converging exemplar and to be effective with any PSO topology. The aims are to improve the performance of PSO overall, including faster global convergence, higher solution quality, and stronger robustness.

4. **Variants**

Numerous variants of even a basic PSO algorithm are possible. For example, there are different ways to initialize the particles and velocities (e.g. start with zero velocities instead), how to dampen the velocity; only update p_i and g after the entire swarm has been updated, etc. Some of these choices and their possible performance impact have been discussed in the literature.

A series of standard implementations have been created by leading researchers, "intended for use both as a baseline for performance testing of improvements to the technique, as well as to represent PSO to the wider optimization community. Having a well-known, strictly-defined standard algorithm provides a valuable point of comparison which can be used throughout the field of research to better test new advances. The latest is Standard PSO 2011 (SPSO-2011).

5. **Hybridization**

New and more sophisticated PSO variants are also continually being introduced in an attempt to improve optimization performance. There are certain trends in that research; one is to make a hybrid optimization method using PSO combined with other optimizers e.g., combined PSO with biogeography-based optimization and the incorporation of an effective learning method.

6. **Binary, discrete, and combinatorial**

As the PSO equations given above work on real numbers, a commonly used method to solve discrete problems is to map the discrete search space to a continuous domain, to apply a classical PSO, and then to demap the result. Such a mapping can be very simple (for example by just using rounded values) or more sophisticated. However, it can be noted that the equations of movement make use of operators that perform four actions:

- Computing the difference of two positions. The result is a velocity (more precisely a displacement)
- Multiplying a velocity by a numerical coefficient
- Adding two velocities
- Applying a velocity to a position

Usually a position and a velocity are represented by n real numbers, and these operators are simply -, *, +, and again +. But all these mathematical objects can be defined in a completely different way, in order to cope with binary problems (or more generally discrete ones), or even combinatorial ones. One approach is to redefine the operators based on sets. Once the sensor nodes are deployed, the BS broadcasts an Info-Collect message to gather all the necessary information of the sensor nodes in the network. Each sensor node replies by sending an Info-Receive message contains its location (X) and residual energy (RE) to the BS. The BS tends to elect optimum MCHs with higher residual energy, lesser intra-cluster communication cost and better location (closer to the BS) to solve the hot problem and to maximize the network lifetime.

C PSO based Master Cluster Head (MCH) Election

Once the sensor nodes are deployed, the BS broadcasts an Info-Collect message to gather all the necessary information of the sensor nodes in the network. Each sensor node replies by sending an Info-Receive message contains its location (X) and residual energy (RE) to the BS. The BS tends to elect optimum MCHs with higher residual energy, lesser intra-cluster communication cost and better location (closer to the BS) to solve the hot problem and to maximize the network lifetime. This problem can be described as the optimization problem with the following three objectives:

Average intra-cluster communication distance (f1):

It is defined as the average distance between the sensor nodes and theirassociated MCHs. By minimizing f1, sensor nodes with lesser intra-cluster communication cost tend to be elected as the MCHs. Thus,

Minimize $f_1 = \sum_{j=1}^{m} \frac{1}{Ij} (\sum_{i=1}^{Ij} \|Ni - MCHj\|)$Multi-hop Routing

The PSO-UFC protocol constructs the multi-hop routing tree among the elected MCHs. Before electing the next hop node, each MCH maintains a neighboring by equation:

$$Com\ (MCH_i)=\{MCH_j \| MCH_i - MCH_j \| < d_o\} \quad (3.2)$$

The neighboring MCHs which are in the direction from MCH $_i$ to the BS, are added to the next hop node set of MCH $_i$ denoted as which is defined in equation

$$NH(MCH_i)=\{MCH_j | \forall MCH_j \in Com(MCH_j) \ \|MCH_j - BS\| \nleq \|MCH_i - BS\|\} \quad (3.3)$$

There may be more than one MCHs in the NH (MCH_i) and therefore, the PSO-UFC protocol determines the best next hop node (NH_{best}) for each MCH by deriving the cost function based on the following parameters:

1) **Residual energy of Next Hop:**

A MCH_i should select that MCH from its NH (MCH_i) which has higher residual energy. Therefore,

$$NH\_Cost(MCH_i, MCH_j) \alpha\ E_R(MCH_j)$$

2) **Distance between MCH and its Next Hop:**

A should select the nearest MCH from its NH (MCH_i). Therefore,

$$NH\_Cost(MCH_i, MCH_j) \alpha \frac{1}{|MCHi - MCHj\|} \quad (3.5)$$

3) **Distance of Next Hop from the BS:**

A MCH_i should select that MCH from its NH (MCHi) which has lesser distance from the BS. Therefore,

$$NH\_Cost(MCH_i, MCH_j) \alpha \frac{1}{\|MCHj - BS\|} \quad (3.6)$$

4) **Node degree of Next Hop:**

A MCH_i should select that MCH from its NH (MCH_i) which has lower node degree. Therefore,

$$NH\_Cost(MCH_i, MCH_j) \alpha \frac{1}{Node\_Degree(MCHj)} \quad (3.7)$$

3.4 SYSTEM REQUIREMENTS

3.4.1 Hardware Requirement

The minimal hardware requirements are as follows,

- System : Dual core processor
- Hard Disk : 160 GB
- RAM : 2 GB

3.4.2. Software Requirement

The minimal software requirements are as follows,

- Os : Windows Xp,
- Language : Mat lab

CHAPTER 4

RESULTS AND DISCUSSION

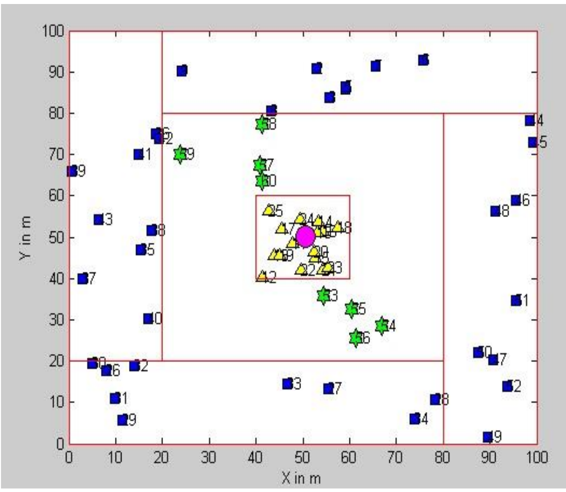

Fig: 4.1 Wireless Sensor Network

The above figure shows WSN model with Region Division depending on distance from the base station. Each region has number of nodes. The base station is marked with a circle.

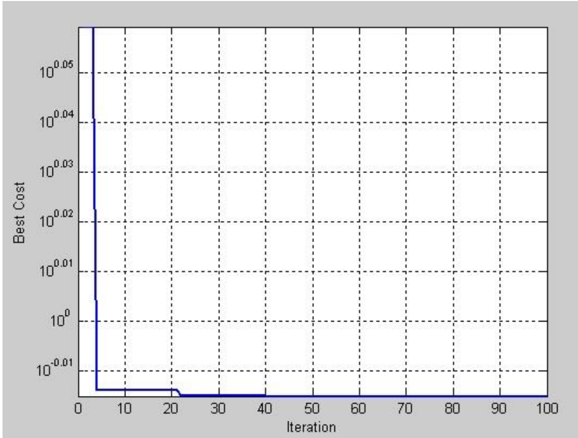

Fig: 4.2 PSO Optimization

The above diagram shows PSO optimization for Cost minimization. The fitness function is related to Distance and Energy Consumption. Energy consumption of each cluster is detected and corresponding efficient CH is selected as MCH.

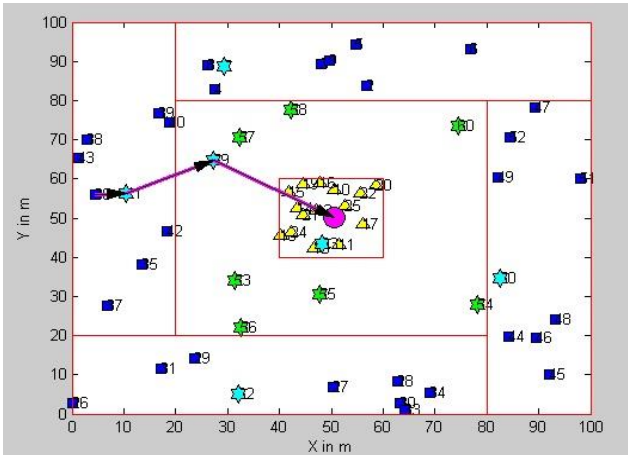

Fig: 4.3 Test Case 1

This is test case 1 where a node from region 3 transmits data to BS through node in region 2.

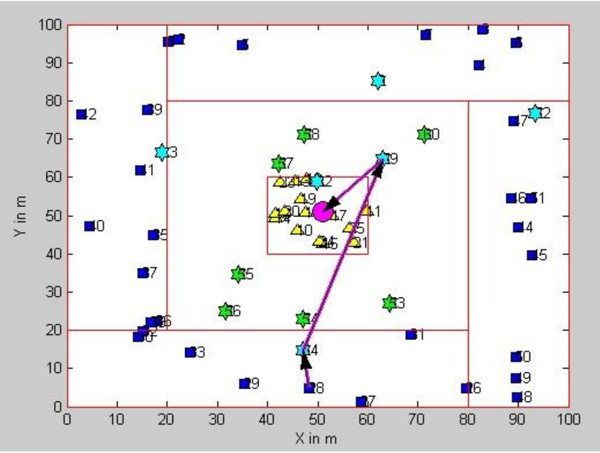

Fig: 4.4 Test Case 2

This is test case 2 where a node from region 3 transmits data to BS through a different node in region 2.

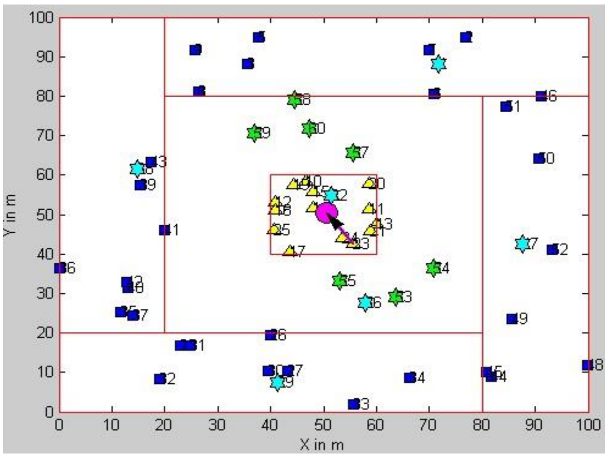

Fig: 4.5 Test Case 3

This is test case 3 where a node from region 1 transmits data to BS directly.

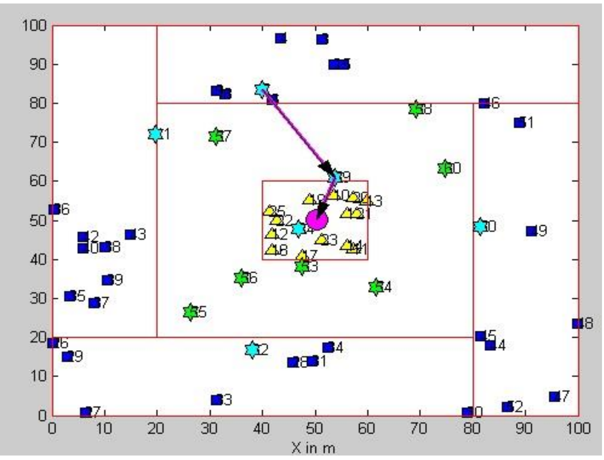

Fig: 4.6 Test Case 4

This is test case 4 where a node at border of region 2 and 3 communicates with BS.

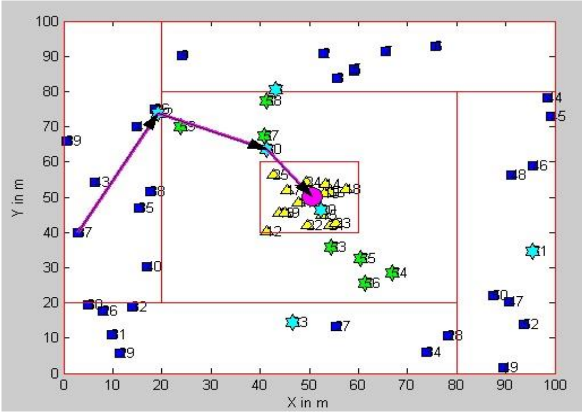

Fig: 4.7 Test Case 5

This is test case 5 where a node from region 3 transmits data to BS through node in region 2.

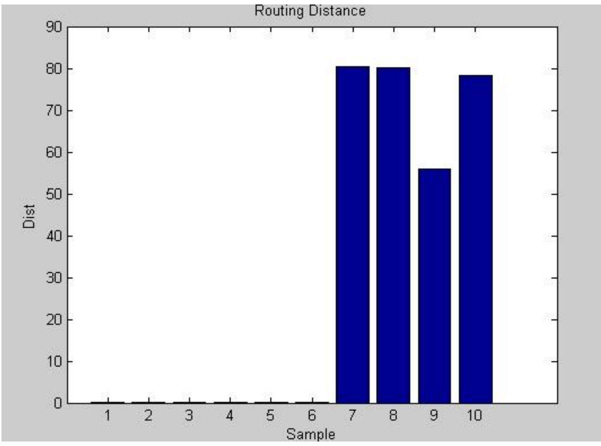

Fig: 4.8 Routing Distance

The above diagram shows the routing distance for 10 test cases. As the number of sample increases the routing distance will be increased.

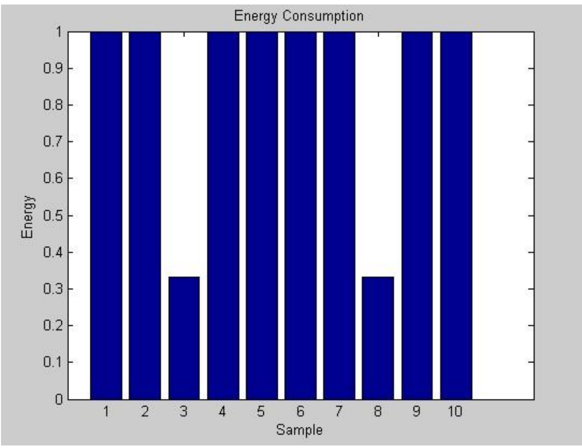

Fig: 4.9 Energy Consumption

The above diagram shows the energy consumption for 10 Test cases. Energy tends to change between different nodes in the network.

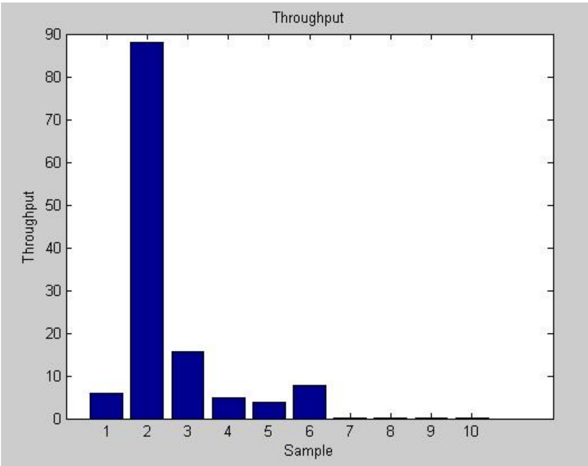

Fig: 4.10 Throughput

This diagram shows the throughput for 10 Test cases.

4.2 CONCLUSION

In this paper, a particle swarm optimization based unequal and fault tolerant clustering protocol is proposed to address the hot spot problem, imbalanced clustering, and fault tolerance issues. The aim of PSO-UFC protocol is to elect more number of MCHs in the area closer to the base station to solve the hot spot problem. By utilizing unequal clustering mechanism, the PSO-UFC constructs an optimum number of clusters and multi-hop routing tree between the MCHs in order to balance the intra-cluster and inter-cluster energy consumption. Moreover, the fault tolerance mechanism prevents the MCHs from sudden failure due to their complete energy depletion. We have shown that PSO-UFC protocol delivers better performance in terms of network lifetime and total energy consumption. As a future work, we plan to study the design of a TDMA frame in the case of variable traffic load.

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