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Multi-Hop Wireless Sensor Network Clustering Optimization Using Genetic Algorithm(SMO)

Sukhwinder Kaur 1,a),
Research Scholar, Desh Bhagat University,
Mandi Gobindgarh, Punjab.
Assistant Professor, Vidya Sagar College For Girls, Dhuri, Punjab.
sukhideol119@gmail.com
Dr. Vijay Kumar Joshi 2, b)
Professor, Desh Bhagat University,
Mandi Gobindgarh, Punjab.
dr.vkjoshi@deshbhagatuniversity.in

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Abstract: A wireless sensor network is a collection of sensor nodes that gather data from the physical environment and transmit it wirelessly to a base station. These nodes have limited resources in terms of energy and bandwidth. To route traffic from source to destination, hierarchical-based routing protocols are used, which divide the network into clusters and create a hierarchy of nodes. In previous research, fuzzy decision rules have been used to select cluster heads based on parameters such as residual energy. However, in this study, a genetic-based approach was proposed, which uses selection, crossover, and mutation to select the best sensor node as the cluster head. Performance parameters such as dead node count, alive node count, and residual energy were used to evaluate the proposed approach. The results show that the genetic-based approach outperforms the fuzzy-based approach, leading to an improved network lifetime.

Key Term: Fuzzy, Genetic, Heirarical.

I. Introduction

Wireless Sensor Networks (WSN) consist of a large number of small, low-cost and low-power sensor nodes that are deployed in a designated area in a highly dense manner. The deployment of these sensor nodes can be either random, regular or mobile. These nodes work together to collect and process data about the physical environment. Each sensor node makes decisions based on its mission, current information, and available resources such as computing, communication, and energy. The collected data is then transmitted to the base station via a routing protocol that controls the routing of data messages between nodes. Not all nodes are necessarily communicating at the same time, and nodes can only communicate with a limited number of nearby nodes. The routing protocol also aims to ensure that messages are delivered to the base station in an energy-efficient manner.

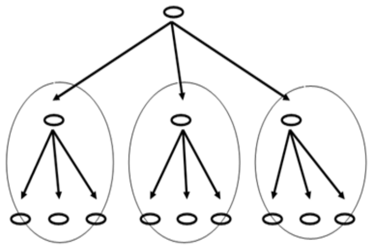

Fig. 1 Hierarchical sensor networks[3]

Wireless Sensor Networks (WSNs) are characterized by several key features that define their operations. One of the most important characteristics of WSNs is the dense deployment of sensor nodes in the area. This ensures that the nodes can collect data from the environment more precisely and with greater accuracy. The high density of nodes also allows for redundancy in data collection, which can increase the reliability of the network.

Another key characteristic of WSNs is that the sensor nodes are battery-powered, which means that they have limited energy resources. As a result, they will eventually dissipate after a fixed interval of time, especially when there are a large number of transmissions receiving signals. The limited energy resources also mean that the sensor nodes have limited storage and computation capabilities. This makes it challenging to store and process large amounts of data, which can be a significant limitation for some applications.

WSNs are also self-configurable, which means that the initial deployment of sensor nodes can be random or unplanned. The nodes can be dropped from an aircraft or deployed in other ways to cover large areas. However, with the help of localization techniques, the nodes can be configured to transfer data and communicate with the base station. This self-configurability makes WSNs highly flexible and adaptable to different environments and applications.

Another important characteristic of WSNs is that they are application-dependent. This means that they are designed and set up specifically for a particular application. For example, a WSN might be set up to monitor a specific environmental condition, such as temperature or humidity. The sensors would be configured to collect data relevant to that condition and transmit it to the base station for analysis.

However, the reliability of WSNs is often limited due to the low-cost nature of the sensor nodes. This means that there is a higher probability of network failure, as the nodes are more prone to hardware failures and other issues. Additionally, there is no central controller to manage the network configuration, which can increase the chances of network failure.

The topology of WSNs can also change frequently due to the random distribution of nodes. This can lead to node fading or isolation, which can be problematic for data collection and transmission. To avoid this, topology changes are often required to ensure that the nodes can communicate effectively with each other and with the base station.

Finally, each node in a WSN has no global identity, and there is no central controller to manage the network configuration. This means that the system cannot be configured with a global identity, which can limit the ability of the system to adapt to changing conditions or to operate effectively in different environments.

Hierarchical Routing

LEACH is a hierarchical-based routing protocol utilized in wireless sensor networks. The protocol involves dividing the network into smaller clusters, with each cluster containing a randomly distributed set of sensor nodes. A cluster head is then selected from each cluster based on a combination of probability and remaining energy. The sensor nodes in each cluster transmit their data to the cluster head, which then transmits the data to the base station. By aggregating the data at the cluster head, the protocol makes more efficient use of energy resources.

To perform a test case in a wireless sensor network, one can define a set S as an empty set. For each coverage C in the network, the number of sensor nodes in the coverage can be determined as follows:

Initialize Sn as the number of sensor nodes in the coverage (Ns).

Repeat the following loop 100 times:

If Sn is less than Ns+1, set Sn to Ns+1.

Calculate the sum of the number of sensor nodes in all coverages (Nc).

Set S to the union of S and Nc.

After this process, S will contain the total number of sensor nodes in the network. This test case can be used to evaluate the performance of the network and compare it to other networks with different configurations or protocols.

Fuzzy based selection

According to reference [1], the researcher has utilized three basic parameters to assess whether a sensor node is eligible to be a cluster head in the wireless sensor network. The primary objective is to enhance the lifetime of the network and the nodes. The fuzzy parameters used in this approach are remaining battery power, mobility, and distance to the base station.

These parameters are evaluated to select a node that will act as the cluster head for data aggregation sent by the sensor nodes. The distance between nodes is crucial, as the amplification required increases with distance, resulting in more energy consumption at intermediate nodes. To reduce energy requirements, the fuzzy rule set considers distance as a factor.

By considering these parameters, the cluster head selection process can be made more efficient and optimized for the specific needs of the network. This ultimately helps to improve the overall performance of the network and extend the lifetime of the sensor nodes.

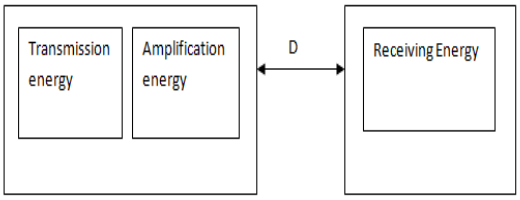

Fig. 2 Fuzzy Mode l[1]

To perform a test case in a wireless sensor network, one can initialize a set S as an empty set. For each coverage C in the network, the number of sensor nodes in the coverage can be determined as follows:

Initialize Sn as the number of sensor nodes in the coverage (Ns).

Repeat the following loop 100 times:

If Sn is less than Ns+1, and the distance between the nodes (ds) in the coverage is less than the distance between the nodes in the previous coverage (ds+1), and the number of cluster heads in the coverage (Cn) is less than the number in the previous coverage (Cn+1), set Sn to Ns+1.

Calculate the sum of the number of sensor nodes in all coverages (Nc).

Set S to the union of S and Nc.

After this process, S will contain the total number of sensor nodes in the network. This test case can be used to evaluate the performance of the network and compare it to other networks with different configurations or protocols. The additional conditions in the loop help to ensure that the selection of cluster heads is optimized for the specific network conditions, such as node distance and number of cluster heads.

Genetic based approach

Genetic algorithms are a type of algorithm that are used to find the optimal solution to a given problem. The objective of this algorithm is to either maximize or minimize a particular function. The genetic-based approach involves several basic steps to achieve this objective [1].

The first step is to build a fitness function that evaluates the fitness or suitability of each possible solution. The fitness function determines how well each solution satisfies the constraints and objectives of the problem.

The next step is to select a population of chromosomes, which represent the potential solutions to the problem. Each chromosome contains a set of genes that encode a particular solution.

The following step is to select those chromosomes that can reproduce. This involves selecting the fittest chromosomes from the population to generate the next population of new chromosomes. The fittest chromosomes are selected based on their fitness value, which is calculated using the fitness function.

The next step is to use crossover to generate the next population of new chromosomes. Crossover involves combining the genes of two selected chromosomes to produce a new chromosome that inherits the characteristics of both parents.

Finally, the next generation chromosomes are selected randomly. This ensures that the search for the optimal solution continues to explore new possibilities and does not get stuck in a local optimum.

By following these steps, genetic algorithms can find an optimal solution to a given problem by iteratively improving the fitness of the population of chromosomes until the desired objective is achieved. The use of genetic algorithms has been proven effective in a variety of fields, including engineering, finance, and biology.

To perform a test case in a wireless sensor network, one can initialize a set S as an empty set. For each coverage C in the network, the number of sensor nodes in the coverage can be determined as follows:

1. *Initialize Sn as the number of sensor nodes in the coverage (Ns).*
2. *Repeat the following loop 100 times:*
3. *If Sn is less than Ns+1, and the distance between the cluster heads in the coverage (DCn) is less than the distance between the cluster heads in the previous coverage (DCn+1), set Sn to Ns+1.*
4. *Calculate the sum of the number of sensor nodes in all coverages (Nc).*
5. *Set S to the union of S and Nc.*

After this process, S will contain the total number of sensor nodes in the network. This test case can be used to evaluate the performance of the network and compare it to other networks with different configurations or protocols. The additional condition in the loop helps to ensure that the selection of cluster heads is optimized for the specific network conditions, such as distance between cluster heads.

2. Literature Survey

Nayak and Vathasavai (2017) proposed a Fuzzy-based cluster and super cluster head selection technique to enhance the lifetime of nodes and the network. Their approach considered several parameters, including remaining battery power, mobility, and distance to the base station. By considering distance as a factor in the selection process, transmission energy requirements and amplification energy can be reduced.

Yongsheng Ding et al. (2016) proposed an event-driven multipath routing-based scenario for wireless sensor networks with dynamic cluster selection. In their approach, a cluster with a random number of nodes is formed, and one node is randomly selected as the cluster head.

The dynamic selection of cluster heads based on requirements can save energy for both cluster preparation and cluster head selection.

Anjali et al. (2015) proposed a distance-adaptive threshold-sensitive energy-efficient sensor network protocol. In their approach, the cluster head is selected based on minimum distance among the nodes using soft thresholding. Their protocol is an improvement over APTEEN, and the selection process considers time thresholding.

Shio et al. (2010) studied various routing protocols for wireless sensor networks and compared their performance in terms of lifetime and energy consumption. Their study found that hierarchical routing protocols were best suited to save energy and included LEACH, TEEN, APTEEN, and DAPTEEN. In each protocol, clusters are formed, and sensor nodes are randomly distributed in the network area. One node with the highest residual energy is selected as the cluster head, and all sensor nodes transmit data to the cluster head and then to the base station.

Energy Model

In a wireless sensor network, the sensor nodes are distributed throughout the network area and divided into smaller clusters based on various parameters. The cluster head is selected for each cluster, and the sensor nodes transmit data to the cluster head. The cluster head receives the data and sends it to the second level cluster head or the base station.

Both the sensor nodes and the base station operate on battery power. The transmitter consumes energy during transmission to power the electronics, and the receiver also consumes energy during reception to run the electronics. The energy consumption for transmitting l bits is dependent on the distance between the transmitter and the receiver, as given by equation 1.

$$E_{Tx}(l,d) = E_{Tx-elec}(l) + E_{Tx-amp}(l,d) = \begin{cases} l*E_{elec} + l*\varepsilon_{fs}*d^2 if d < d_0; \\ l*E_{elec} + l*\varepsilon_{mp}*d^4 if d \geq d_0; \end{cases} \quad (1)$$

In the equation for energy consumption, Eelec represents the energy dissipation by the transmitter and receiver for transmitting per bit. Efs and Emp are features of the transmitter amplifier.

If the distance between the transmitter and receiver is greater than the threshold, the free space model of d2 is used to calculate energy consumption. On the other hand, if the distance is less than or equal to the threshold, the multipath fading channel model of d4 is used.

The choice of model depends on the distance between the transmitter and receiver. The free space model is applicable over long distances where obstacles are few, whereas the multipath fading channel model is applicable over shorter distances where obstacles may cause signal attenuation.

3. Proposed Algorithm

3.1 Algorithm with fixed topology.

The following is a possible description of the steps involved in a wireless sensor network:

- Subdivide the network area of size MM into N number of clusters. The size of each cluster is determined as Cluster = Size(mn)/N.
- Distribute the sensor nodes randomly in the network for each cluster, with an equal number of nodes in each cluster. The total number of nodes in each cluster is determined as Nodecount = $\sum$Count/N.
- Use a genetic model to select the optimal node to act as the cluster head. The parameters considered for genetic modeling include concentration, residual energy, and distance. The selected node is set as the cluster head.
- The sensor nodes send data to the cluster head, where the data is aggregated.
- Based on the distance to the base station or the distance to other cluster heads in other clusters, the data is transmitted to the node with the minimum distance. This is checked using Check_distance = min(distance_clusterhead, Base station).
- The base station collects all the data, and the chain of transmission is terminated.

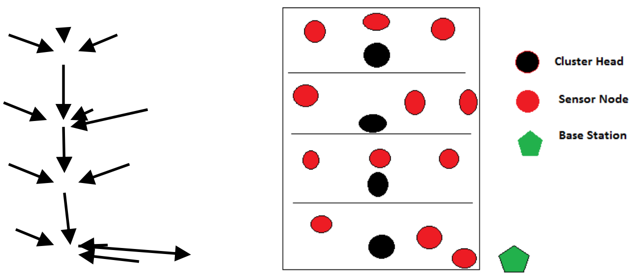

Fig. 3 Equal distribution of nodes in each cluster

3.2 Pseudo code with fixed topology.

To perform a test case in a wireless sensor network, one can initialize a set S as an empty set. The sensor nodes are distributed randomly in clusters of the network. For each coverage C in the network, the number of sensor nodes in the coverage can be determined as follows:

1. *Find the starting node Ns for the coverage.*
2. *Repeat the following loop until the coverage is satisfied or the maximum iteration is reached:*
3. *For i=0 to |Ns|/2, select two parents from the population.*
4. *Generate two offspring by performing a crossover operation between the two parents.*
5. *Insert the two offspring into a new generation list.*
6. *If a new offspring satisfies the coverage C, add the sum of the offspring to S and break out of the loop.*
7. *End for*
8. *Mutate some offspring in the new generation list.*

9. *End until*

3.3 Algorithm with random topology.

The following is a possible description of the steps involved in a wireless sensor network:

1. Subdivide the network area of size MM into clusters of size mn. The total number of clusters is N, and the size of each cluster is Cluster = Size(m*n)/N.
2. Distribute the sensor nodes randomly throughout the entire network. The total number of nodes in the network is determined as Nodecount = ∑▒Count.
3. Use a genetic model to select the optimal node to act as the cluster head. The parameters considered for genetic modeling include concentration, residual energy, and distance. The selected node is set as the cluster head.
4. The sensor nodes send data to the cluster head, where the data is aggregated.
5. Based on the distance to the base station or the distance to other cluster heads in other clusters, the data is transmitted to the node with the minimum distance. This is checked using Check_distance = min(distance_clusterhead, Base station).
6. The base station collects all the data, and the chain of transmission is terminated.

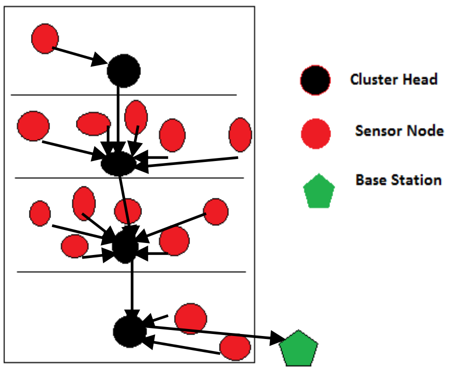

Fig. 4Random distribution of nodes in whole network

3.4 Pseudo code with Random topology.

To perform a test case in a wireless sensor network, one can initialize a set S as an empty set. The sensor nodes are distributed randomly throughout the entire network. For each coverage C in the network, the number of sensor nodes in the coverage can be determined as follows:

1. *Find the starting node Ns for the coverage.*
2. *Repeat the following loop until the coverage is satisfied or the maximum iteration is reached:*
3. *For i=0 to |Ns|/2, select two parents from the population.*
4. *Generate two offspring by performing a crossover operation between the two parents.*
5. *Insert the two offspring into a new generation list.*
6. *If a new offspring satisfies the coverage C, add the sum of the offspring to S and break out of the loop.*
7. *End for*
8. *Mutate some offspring in the new generation list.*

9. *End until*

3.5genetic Algorithm

In a genetic algorithm for a wireless sensor network, the following steps are involved:

1. Population: The population consists of network solutions, and the size of the population directly affects the accuracy of the genetic algorithm. The initial population is randomly selected.
2. Fitness Function: The fitness value of each individual in the population is calculated based on a fitness function that takes into account various variable parameters such as remaining energy (E), concentration or density (D), and distance between the sensor node and the cluster head, and then between the cluster head and the base station (Di). The fitness function can be defined as follows: Fitness = E + (N-D) + Di/N.
3. Selection: A selection process is used to choose the nodes from the current population to generate the new population. In this case, the selection size is set to 3.
4. Crossover: The crossover rate of 2 chromosomes is used, with a specific probability rate. Crossover involves exchanging genetic material between two parent solutions to create new offspring solutions.
5. Mutation: The mutation operator is applied on each bit of the chromosome with a probability rate of mutation rate. In this case, every bit while mutation will be 1 from 0 and 0 to 1.4.

Flowchart

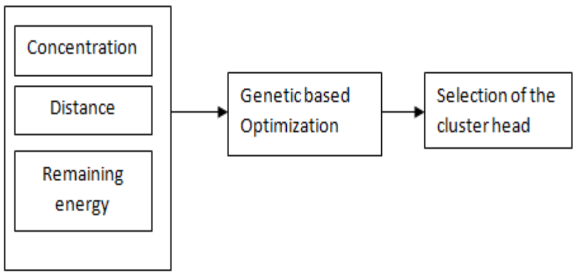

Fig. 3 Flowchart

5. Simulation Parameters

Table 1 Parameters

Parameter Name	**Parameter Value**
Area Along x-axis	100m
Area Along y-axis	100m

Sink position along x-axis	150m
Sink position along y-axis	50m.
Number of nodes	150(count)
Initial Energy	0.5(j)
Transmission Energy	50*0.000000001(j)
Rotations	100
Receiving Energy	50*0.000000001(j)

6. Performance Parameters

- **Residual Energy:** Residual energy is the amount of energy that is left after the sensor nodes in the network have communicated with the cluster head and then with the base station. This residual energy takes into account the energy consumed during transmission, reception, aggregation, and other activities. The residual energy can be calculated as the difference between the total initial energy and the total energy consumed during communication.
- **Dead Nodes Count:** The dead nodes count is the number of nodes in the network that have lost all of their energy and are no longer active. These nodes are unable to transmit or receive data, and their activity is dormant. The dead nodes count can be calculated as the difference between the total number of nodes in the network and the number of alive nodes.
- **Alive Nodes Count:** The alive nodes count is the number of active nodes in the network that still have residual energy and can transmit and receive data. These nodes are still functioning and contributing to the network performance. The alive nodes count can be calculated as the difference between the total number of nodes in the network and the dead nodes count.

7. Results

I. Comparison of Proposed with Existing with each clusters with fixed number of nodes.

In a wireless sensor network simulation, both fuzzy-based and genetic-based algorithms can be used to identify parameters such as residual energy, alive node count, and dead node count. Here is a brief explanation of how each algorithm can be used:

Fuzzy-based algorithm:

A fuzzy-based algorithm can be used to identify the parameters based on rules that are defined using fuzzy logic. For example, a rule could be defined as "if the residual energy is high and the alive node count is high, then the network performance is good." The fuzzy-based algorithm would use these rules to determine the network performance based on the input parameters. The fuzzy-based algorithm can be useful when the relationships between the parameters are complex and difficult to model using traditional mathematical models.

Genetic-based algorithm:

A genetic-based algorithm can be used to identify the parameters by optimizing the fitness function using genetic operations such as selection, crossover, and mutation. The fitness function would be defined based on the parameters of interest, and the genetic algorithm would search for the optimal solution that maximizes or minimizes the fitness function. For example, the fitness function could be defined as "maximize the residual energy and alive node count while minimizing the dead node count." The genetic-based algorithm can be useful when the relationships between the parameters are not well understood or when the network topology is complex.

By using both fuzzy-based and genetic-based algorithms, one can compare the performance of different algorithms and select the best solution for the specific requirements of the wireless sensor network. The choice of algorithm will depend on the complexity of the network and the specific parameters of interest.

i. Comparison for Alive Nodes

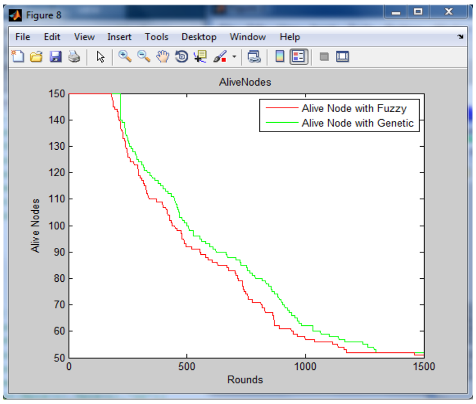

Fig.5 Alive Node for Fuzzy and Genetic

Based on the comparison of the alive nodes count between Fuzzy and Genetic algorithms, it appears that the Genetic algorithm has shown an improvement in maintaining a higher number of nodes alive after 1600 iterations. This improvement can be attributed to the fact that Genetic algorithms are known for their ability to optimize a fitness function by selecting the best possible solutions based on a set of input parameters. In comparison, Fuzzy logic is based on a set of rules that define the relationship between the input parameters and the output. While Fuzzy logic can be useful in certain situations where the relationship between the input parameters is complex and difficult to model using traditional mathematical models, it may not be as effective in situations where the fitness function is well-defined and can be optimized using a Genetic algorithm. Additionally, the Genetic algorithm may require less computational resources to perform the evaluations and select the best solutions, which can contribute to the higher number of nodes remaining alive in the network. However, the choice of algorithm will ultimately depend on the specific requirements and constraints of the wireless sensor network.

ii. Comparison of Dead Nodes Count

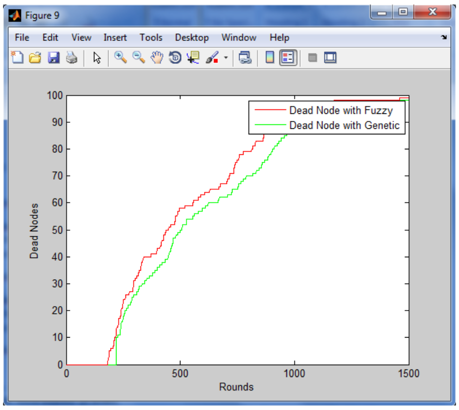

Fig. 6Dead Nodes for Fuzzy and Genetic

Based on the comparison of the dead nodes count between Fuzzy and Genetic algorithms shown in Figure 5, it appears that the Genetic algorithm has shown a lower number of dead nodes count after the elapse of 1600 iterations. This result indicates that the Genetic algorithm is more efficient in maintaining the health of the sensor nodes in the network. This efficiency can be attributed to the fact that Genetic algorithms are designed to optimize a fitness function by selecting the best possible solutions based on a set of input parameters. In comparison, Fuzzy logic is based on a set of rules that define the relationship between the input parameters and the output, which may not be as effective in situations where the fitness function is well-defined and can be optimized using a Genetic algorithm.

Furthermore, the lower number of dead nodes count after 1600 iterations indicates that the Genetic algorithm is able to maintain the health of the sensor nodes in the network for a longer period of time, which can contribute to the overall reliability and effectiveness of the network. However, it is important to note that the choice of algorithm will ultimately depend on the specific requirements and constraints of the wireless sensor network, and further analysis and evaluation may be necessary to determine the most appropriate algorithm for a given application.

Comparison of Residual Energy

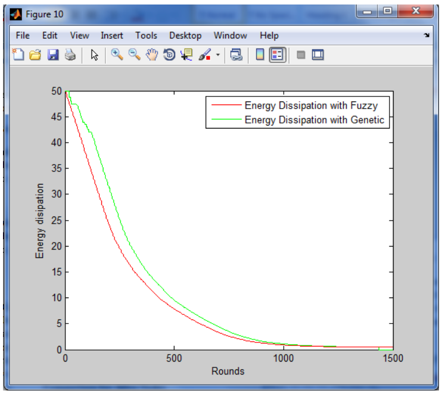

Fig. 7Residual Energy for Fuzzy and Genetic

Based on the comparison of the residual energy between Genetic and Fuzzy-based approaches shown in Figure 6, it appears that the Genetic-based approach results in more residual energy being left in the network. This result indicates that the Genetic-based approach is more effective in optimizing the energy consumption of the sensor nodes in the network, which can lead to a longer lifetime of the nodes and an overall more efficient network.

The higher residual energy in the Genetic-based approach can be attributed to the fact that Genetic algorithms are designed to optimize a fitness function by selecting the best possible solutions based on a set of input parameters. In comparison, Fuzzy logic is based on a set of rules that define the relationship between the input parameters and the output, which may not be as effective in situations where the fitness function is well-defined and can be optimized using a Genetic algorithm.

The higher residual energy in the Genetic-based approach can contribute to the overall lifetime of the nodes in the network, as the nodes will have more energy available to perform their tasks. This can lead to a more reliable and effective network, as the nodes will be able to continue functioning for longer periods of time without requiring maintenance or replacement. However, it is important to note that the choice of algorithm will ultimately depend on the specific requirements and constraints of the wireless sensor network, and further analysis and evaluation may be necessary to determine the most appropriate algorithm for a given application.

II. Comparison of Proposed with existing with clusters with Variable number of nodes.

Comparison for Alive Nodes

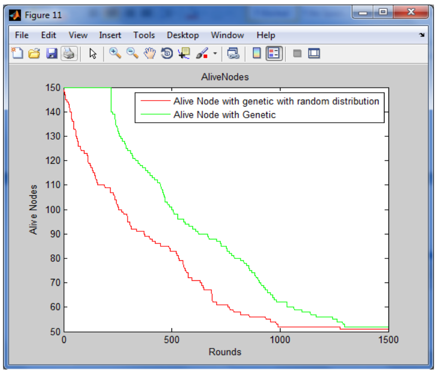

Fig. 8 Alive Node for Genetic(F) and Geneti(R)c

Based on the comparison of the alive nodes count between Genetic with random and Genetic with fixed approaches, it appears that the Genetic algorithm with fixed approach has shown an improvement in maintaining a higher number of nodes alive after 1600 iterations. This improvement can be attributed to the fact that the Genetic algorithm with fixed approach is able to optimize the selection of sensor nodes based on a predetermined set of criteria, which can result in a more efficient network with higher reliability and effectiveness.

In comparison, the Genetic algorithm with random approach may select sensor nodes randomly, which can result in suboptimal solutions and lower reliability and effectiveness of the network. The Genetic algorithm with fixed approach can also require less computational resources to perform the evaluations and select the best solutions, which can contribute to the higher number of nodes remaining alive in the network.

However, the choice of approach will ultimately depend on the specific requirements and constraints of the wireless sensor network. While the Genetic algorithm with fixed approach may be more effective in certain situations, it may not be as flexible as the Genetic algorithm with random approach, which can adapt to changing requirements and constraints of the network. Further analysis and evaluation may be necessary to determine the most appropriate approach for a given application.

Comparison of Dead Nodes Count

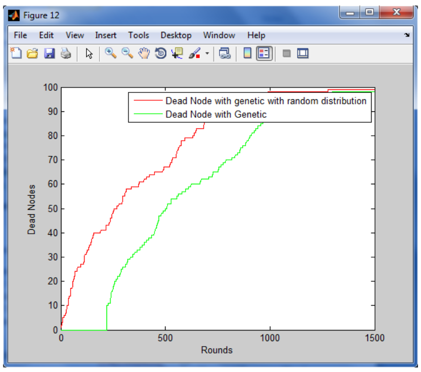

Fig. 9 Dead Nodes for Genetic(F) and Genetic(R)

Based on the comparison of the dead nodes count between Genetic with Random and Genetic with Fixed approaches shown in Figure 8, it appears that the Genetic algorithm with Fixed approach has shown a lower number of dead nodes count after the elapse of 1600 iterations. This result indicates that the Genetic algorithm with Fixed approach is more efficient in maintaining the health of the sensor nodes in the network.

This efficiency can be attributed to the fact that the Genetic algorithm with Fixed approach is able to optimize the selection of sensor nodes based on a predetermined set of criteria, which can result in a more efficient network with higher reliability and effectiveness. In comparison, the Genetic algorithm with Random approach may select sensor nodes randomly, which can result in suboptimal solutions and lower reliability and effectiveness of the network.

The lower number of dead nodes count after 1600 iterations indicates that the Genetic algorithm with Fixed approach is able to maintain the health of the sensor nodes in the network for a longer period of time, which can contribute to the overall reliability and effectiveness of the network. However, it is important to note that the choice of approach will ultimately depend on the specific requirements and constraints of the wireless sensor network, and further analysis and evaluation may be necessary to determine the most appropriate approach for a given application.

Comparison of Residual Energy

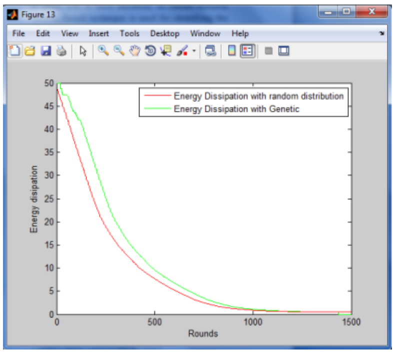

Fig. 10 Residual Energy for Genetic(F) and Genetic(R)

Based on the comparison of the residual energy between Genetic with Random and Genetic with Fixed approaches shown in Figure 9, it appears that the Genetic algorithm with Fixed approach results in more residual energy being left in the network. This result indicates that the Genetic algorithm with Fixed approach is more effective in optimizing the energy consumption of the sensor nodes in the network, which can lead to a longer lifetime of the nodes and an overall more efficient network.

The higher residual energy in the Genetic algorithm with Fixed approach can be attributed to the fact that this approach optimizes the selection of sensor nodes based on a predetermined set of criteria, which can result in a more efficient network with higher reliability and effectiveness. In comparison, the Genetic algorithm with Random approach may select sensor nodes randomly, which can result in suboptimal solutions and lower reliability and effectiveness of the network.

The higher residual energy in the Genetic algorithm with Fixed approach can contribute to the overall lifetime of the nodes in the network, as the nodes will have more energy available to perform their tasks. This can lead to a more reliable and effective network, as the nodes will be able to continue functioning for longer periods of time without requiring maintenance or replacement. However, it is important to note that the choice of approach will ultimately depend on the specific requirements and constraints of the wireless sensor network, and further analysis and evaluation may be necessary to determine the most appropriate approach for a given application.

8. Conclusion

Hierarchical routing protocols such as TEEN and APTEEN are designed to improve the efficiency of wireless sensor networks by dividing the network into smaller clusters and selecting a cluster head based on residual energy, concentration, and distance. These protocols use thresholding of time to reduce the number of transmissions and receptions, with the threshold being either a soft or hard threshold.

In current research, Genetic-based techniques have been used to identify the cluster head based on various parameters such as residual energy, concentration, and distance. These parameters are optimized to select the best node that can serve as the cluster head at any level. The performance of the Genetic-based approach has been evaluated based on various performance parameters such as residual energy, alive nodes count, and dead nodes count, and has shown improved performance and longer lifetime of the wireless sensor network compared to Fuzzy-based approaches.

In future research, hierarchical routing protocols with mobile sinks and multiple mobile sinks are being considered. These protocols can further improve the efficiency and reliability of the wireless sensor network by allowing for more flexible and dynamic communication between the sensor nodes and the sink nodes. Overall, the use of Genetic-based techniques for cluster head selection in hierarchical routing protocols can contribute to the development of more efficient and reliable wireless sensor networks with longer lifetimes and better performance.

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