

# RELIABLE AND ENERGY EFFICIENT CLUSTER HEAD SELECTION USING EVOLUTIONARY ALGORITHM IN WIRELESS SENSOR NETWORK

**S. Mageshwaran, P. Sivananaintha Perumal, R.S. Rajesh and P. Sundareswaran**

*Department of Computer Science and Engineering, Manonmaniam Sundaranar University, India*

## Abstract

*One of the most pressing problems in the industry at the moment is figuring out how to make wireless sensor networks (WSN) more reliable and extend their lifespan. The processes of selection and the development of clusters are incredibly significant; however, carrying them out is challenging and time-consuming despite the significance of the tasks. In the most recent study, researchers began their hunt by selecting a particular cluster head to use as a basis for their investigation. On the other hand, the model that was suggested utilizes evolutionary cluster head selection as one of its components. This contributes to the acceleration of computing, the improvement of selection precision, and the prevention of the selection of duplicate nodes. When the results of the simulation of the suggested model are compared to the results of simulations using other methods and techniques, we find that our method is both more accurate and more efficient. This was discovered when the results of the simulation of the proposed model were compared to the results of simulations using other approaches and techniques.*

## Keywords:

*Cluster, WSN, Nodes, Network Lifetime*

## 1. INTRODUCTION

A WSN can be identified by the absence of infrastructure as well as a limited footprint in terms of the physical structures that it contains. Each sensor node, also known as an SN, in a WSN works in conjunction with the other nodes in the network to detect its exact location and collect data about its immediate surroundings. There is a well-organized variant of WSN, in addition to an unorganized variant. A collection of SNs is the term used to describe a WSN that does not have any structure. These transmit information in an arbitrary fashion and can be used in any environment. As soon as the data transfer is complete, the network reverts back to its normal state in which it is undetectable and continues to perform its regular duties of monitoring and giving information [1].

The fact that the WSN was established in the appropriate fashion, all of the SNs are stored within it in an ordered fashion. Because of the way in which the WSN is constructed, it is possible to send particular nodes while simultaneously reducing the expenses associated with their administration and maintenance. When compared to the ad hoc arrangement, which may have revealed specific regions due to the fact that all of the nodes are now linked to specified regions to ensure inclusion, the quantity of data that needs to be provided is far fewer. This is because all of the nodes are now related to the regions that need to be included. The primary goal of a WSN installation is to establish a connection between the user natural physical surroundings and the virtual world in a way that is completely undetectable by the user [2].

Random deployment can take place in constrained environments thanks to the WSN SNs, which make this capability possible. The self-composed nature of the wireless sensor convention that has been formed is alluded to by this method of deployment. Assisting the SNs in the job that they are performing is another one of the crucial functions that the WSN is responsible for performing. While in a given condition, SNs will collect data, do analysis on that data, and then send that information to the base station (BS). anytime a sensor node (SN) sends in a sensor field, the BS acts as a bridge between the client and the web and offers the basic engineering for the wireless sensor network [3].

Collaborating with one another and the world around them is necessary for them to successfully collect data and send it on to the BS. Data is able to be communicated via the internet because BS, in its most fundamental form, acts as a gateway. This makes it possible for data to be transmitted. Because clients have a unique connection to the web, the SNs create data by depending on the perceptual skills of their detecting components. This is because clients have a unique link with the web. The data packet that is generated as a consequence of this process is then sent to the BS [4].

This process basically coordinates transmission with the goal that more effective methods use a smaller number of nodes to convey information to the BS. This is done because it is possible that the BS will be located a significant distance away from the SNs, and it takes a greater amount of energy to transfer information across such distances. These nodes are referred to as aggregator nodes inside of a WSN, and the process that corresponds to them is known to as information aggregation.

A great number of research have been conducted over the course of the last several years to study whether or not it is possible to arrange sensor networks into clustered structures. As a consequence of these investigations, an abundance of protocols that are designed expressly for this purpose have been developed. When it comes to developing efficient, durable, and highly adaptable dispersed sensor networks, clustering is one of the most important strategies that can be implemented. By employing clusters, the strain of maintaining consistent correspondence between SNs is reduced, which in turn leads in a reduction in both the amount of energy that is consumed and the impedance [5].

Cluster association is a common method that can be used in a wide variety of contexts to bring together SNs that are situated geographically close to one another in close proximity to one another. The utilization of the connection is going to be utilized with the purpose of removing the requirement for the surplus of sensors. By combining data that was previously collected with data that was gathered from sensors positioned at the cluster heads (CHs), it is feasible to significantly reduce the overall quantity of data that is conveyed to the sink, which results in significant savings in both energy and transmission capacity [2].

Numerous programs need constant access to data that was acquired from the entirety of the territory that is being monitored in order to keep providing a quality of service that is considered to be acceptable. The entire region that is being monitored needs to be secured, and one way that this might be done on a specific location of the sensors. When sensors are given a profile that is thicker than what is required to meet inclusion criteria, unsecured nodes have the option to save power by adopting a low-control rest state [1].

In the past, both association support methods and inclusion support methods for cluster-based sensor networks have gained a significant amount of attention, but they have not previously been coordinated with one another.

The SN prior migration as a CH [5], the technique with the biggest residual energy [2], the CH area relative to alternative nodes [3], topological data [4], and so on are a few examples of the parameters that are taken into consideration by the various approaches that are now available for selecting CH nodes. The majority of these strategies for picking CHs are geared toward controlling the quantity of energy that is consumed by SNs.

These techniques pay no attention to the necessity that the network satisfy a complete inclusion mandate over lengthy time periods. This condition must be met in order for the network to be considered successful. The energy-adjusted clustered network association does not provide any assurance that the WSN will be able to cover the entire observed region, despite the fact that this is absolutely within the WSN capabilities. However, sensor integration is one of the fundamental QoS measures of the network because it characterizes the network capacity to reliably monitor and detect a specific region of interest [6]. This makes sensor integration a crucial QoS measure.

It is realistic to expect that not every SN contributes the same amount of information to the overall network diversity. This would make the overall network diversity more complex. If an SN were to pass away in an area that had a high population density, the passing of that SN would not have nearly as great of an influence on the network as it would have had if it had occurred in an area that had a low population density [7].

In this research, we analyze the differences between wireless sensor networks that are deployed in dense clusters and energy-efficient sensor networks that make optimal use of the available power. The WSNs are given a lot of priority here. When it comes to choosing CH, the technique that has been used in the past with great success is not effective at all.

## 2. RELATED WORKS

Simulated annealing was used to assist in the development of the decentralized version of LEACH known as LEACH-C [7]. The base station selects the CHs that are going to be used with a great deal of attention, the performance of LEACH-C is significantly better than that of LEACH. When deciding which CHs to use, both the distance between nodes and the energy level of the nodes themselves are taken into account. As a consequence of this, LEACH-C has the ability to select CHs in an efficient manner by taking into consideration their level of energy efficiency, hence extending the amount of time the network would remain operational. On the other hand, the possibility of an increase in the amount of energy that is wasted across the network

of the creation of clusters receives just a cursory consideration here.

In the article [8] recommend utilizing a PSO strategy in order to figure out where CHs should be placed for the greatest efficiency. However, it paid little attention to how far nodes were from the sink, which is an essential factor to take into consideration when trying to maximize the network efficiency throughout the data travel. The primary goal of this algorithm was to reduce the distances between clusters; however, it paid little attention to how far the distances between clusters were. Because CHs are utilized to determine placement, there may be an imbalance in the distribution of energy as a result of the fact that nodes that are not CHs have been placed in CHs based solely on distance.

The author of [10] suggestion for a PSO-based technique of cluster development advise employing a modified fitness function that takes into account both the intra-cluster distance and the sink distance. This is one of the aspects of the cluster generation process that needs to be taken into consideration. On the other hand, it does not take into consideration the amount of energy that is still left in the sensor nodes.

In the article [11] named FL-LEACH as a means of enhancing the LEACH protocol. This approach was proposed by the researchers. The authors make use of fuzzy logic in the process of putting the LEACH protocol into action. Both the process of fuzzification and defuzzification are part of the same overall procedure, although they are challenging and lead to incorrect results.

In their new PSO-based CH selection algorithm [12] included a fitness function that takes into consideration residual energy, distance, and node density. This function was part of their introduction of the algorithm. On the other hand, it does not pay any attention to the stage of cluster formation, which may lead to a significant reduction in the network ability to use energy in an efficient manner. This could be a significant problem. However, it does not take into account the clustering phenomenon that might sometimes occur. There is a chance that there will be an effect on the amount of energy that is used by the network.

PSO-C is an energy-conscious variation of PSO that picks cluster heads. It was presented by Latiff et al. [11]. Variables such as the average distance traveled inside a cluster and the ratio of the total starting energy of all nodes to the total current energy of all CHs are factored into this variation. However, it does not take into consideration the role that sink distance has in minimizing the amount of energy that is consumed by the network. This is particularly important for the CH direct transmission to the BS, but it is also important for the transmission of other sorts of communications. It also allocates non-CH sensor nodes to the CH that is the closest during the time that the clusters are being formed. This may cause the network to be less efficient in its use of energy and may cause its lifespan to be shortened.

The author of [14] came up with a solution to the issue of hot spots in wireless sensor networks that is a method that is founded on the nCRO technology. The authors have previously employed this strategy in an effort to find a solution to the scalability problem. It gives no consideration whatsoever to concerns pertaining to delay or fault tolerance in WSNs.

Rao et al. [15] developed a new clustering system that is based on a new variable population-based chemo-inspired technique. In order to accomplish this, they were able to reduce the amount of energy that was required to run the system. The optimization of novel chemical reactions is the name given to this method. The network is significantly more resistant to the effects of wear and tear. On the other hand, it is probable that it would not be practical for CHs to connect with the BS in a large-scale network. This is something that should be considered.

Rao et al. [16] provide PSO-based solutions as an alternative for time-sensitive initiatives that could use their assistance. The network lifetime as well as its energy efficiency are both significantly enhanced. Nevertheless, it does not take into account the tolerance for broken connections in the network.

### 3. ENERGY EFFICIENT CLUSTER HEAD SELECTION

#### 3.1 ENERGY MODEL

In this research, we develop our energy model by making use of a radio model that is analogous to the one that was utilized in [7], which was utilized in the study that came before this one. The radio electronics and power amplifier included in this kind of receiver are dependent on the electricity that is lost from the transmitter in order to operate correctly. The energy that could have been utilized to power the radio circuitry in the receiver is instead converted into heat, which is a waste of that energy.

The quantity of energy that is consumed by a node is influenced not just by the amount of data that is being transferred but also by the distance  $d$  between the nodes. If the distance between a node and the threshold distance, which is denoted by  $d_0$ , is less than the propagation distance, then the quantity of energy that a node consumes is proportional to  $d^2$ , and if it is greater than the propagation distance, then it is proportional to  $d^4$ , according to this model. The following equations can be used to determine the total amount of energy that is expended by each node in the network in order to transmit the  $l$ -bit data packet:

$$ETX(l,d)=\{l \times E_{elec} + l \times \epsilon_{fs} \times d^2, l \times E_{elec} + l \times \epsilon_{mp} \times d^4, \text{if } d < d_0 \text{ if } d \geq d_0$$

(1)

where,

$E_{elec}$  - dissipated energy per bit

$\epsilon_{fs}$  - amplification energy

$\epsilon_{mp}$  - transmitter amplifier model and

$d_0$  - threshold distance.

The amount of energy that must be expended by the receiver, which is represented by the  $E_{RX}(l)$ , in order to receive  $l$  bits of data is denoted by the variable:

$$E_{RX}(l) = l \times E_{elec} \quad (2)$$

where,

$E_{elec}$  - factor of modulation, digital coding, signal spreading and filtering.

#### 3.2 CH SELECTION PROBLEM

The selection of CHs from among the conventional sensor nodes is the primary purpose of the algorithm that has been developed, and doing so while keeping in mind the amount of energy that may be conserved is of utmost importance. We take into account a variety of distance metrics, such as the average distance between sensor nodes within the cluster and the distance between those nodes and the sink, in order to select a CH that uses the least amount of energy possible. This allows us to select a CH that uses the least amount of energy possible.

The value of the function  $f_1$  will be determined based on the average intra-cluster distance as well as the sink distance of the CHs. Both of these distances will be taken into consideration. In order for the CH selection to function at its optimal level, we need to bring  $f_1$  down. Determine the value of the square root inverse of the sum of the current energies of the chosen CHs, which is denoted by  $f_2$  in the equation. Keep in mind that the ratio will be maximized to the greatest extent feasible when the ideal choice of CH will take place. This suggests that the magnitude of its square root,  $f_2$  should be kept at a level that is as close as feasible to its smallest potential value. In order to effectively minimize linear combinations of the two goals, we first normalize the two goal functions so that they fall within the range of 0 to 1. This makes the range of possible values for the functions.

The EACH-based approach that has been developed will generate its fitness function by making use of  $f_1$  and  $f_2$ , and the objective is to reduce the magnitude of these two functions to the greatest extent possible. Their linear combination should be simplified as much as feasible in order to achieve the most beneficial outcomes imaginable. As a result, the problem of selecting the CH with the optimal value can be formulated as a linear programming (LP) problem:

$$\text{Min } F = \alpha \times f_1 + (1-\alpha) \times f_2$$

s.t.

$$D(s_i, CH_j) \leq d_{max}, \forall s_i \in S \text{ and } CH_j \in C$$

$$D(CH_j, BS) \leq R_{max}, \forall CH_j \in C$$

$$E_{CH_j} > TH, 1 \leq j \leq m$$

$$0 < \alpha < 1$$

$$0 < f_1, f_2 < 1$$

In order for there to be communication inside the cluster between the sensor nodes and the CH nodes, as the constraint mandates, the sensor nodes must be within communication range of the CH nodes. In addition, restriction directs that in order for the BS to be operational, it must be positioned within the CH authorized range of communication. This range is specified in meters. The value of the threshold is established by computing the mean of the energy possessed by each of the sensor nodes. In order for the energy of all of the CH nodes to be in accordance with the limitation, this figure needs to be exceeded. The parameter  $\alpha$ , which determines the relative significance of the distance and energy parameters, is used in both constraints to ensure that the two values of the objective function are normalized within the range of 0 to 1, with 0 being the minimum and 1 being the maximum. This is done to make certain that the values are within a range that is considered to be acceptable.

### 3.3 CLUSTER FORMATION

When a cluster is being formed, the sensor nodes consult a weight function known as  $CH_w$  in order to decide whether or not they should be included in the CH. This helps ensure that only the most relevant nodes are included. These are the several factors that can be changed to influence the weighting function.

- **CH Residual Energy:** CH residual energy If a sensor node, denoted by  $s_i$ , can only communicate with one cluster of nodes (CH), then it should join  $CH_j$  because it has the greatest energy left over. This is the case if it can only interact with one CH.

$$CH_w(s_i, CH_j) \propto E_{res}(CH_j)$$

- **Distance to CH:** It is recommended that a sensor node initiate communication with the CH that is located in the area that is geographically closest to it in order for it to save electricity. When traveling a shorter distance, there will be a reduction in the amount of work and energy necessary.

$$CH_w(s_i, CH_j) \propto ldis(s_i, CH_j)$$

- **Distance to BS:** The sensor nodes are in constant communication with the CHs that are situated in close proximity to the base station (BS).

$$CH_w(s_i, CH_j) \propto ldis(CH_j, BS)$$

- **CH node degree:** If a sensor node is within the range of communication for more than one CH, it should join the CH that has the fewest number of other nodes already connected to it.

$$CH_w(s_i, CH_j) \propto$$

$$CH_w(s_i, CH_j) \propto E_{res}(CH_j) \times dis(CH_j, BS) \times dis(CH_j, BS) \times lnd(CH_j)$$

$$CH_w(s_i, CH_j) = L \times E_{res}(CH_j) \times dis(CH_j, BS) \times dis(CH_j, BS) \times lnd(CH_j)$$

where,  $L$  – constant, each sensor node will first determine its  $CH_w$ , and then it will join the cluster that has the highest  $CH_w$ . This process will continue until all sensor nodes have joined a cluster.

### 3.4 EVOLUTIONARY ALGORITHM FOR CH SELECTION (EACH)

An approach that is based on an evolutionary algorithm has been developed as a potential solution to the problem of how to plan work in an environment that is based on cloud computing and fog computing respectively.

#### 3.4.1 Encoding of Chromosomes:

In the field of genetic algorithms, a chromosome stands in for a solution to a problem involving task scheduling. In chromosomal encoding, an  $n$ -dimensional array is often utilized, with each dimension standing in for a different gene. Each gene has a value of an integer  $k$  that is somewhere in the range  $[1:m]$ , where  $m$  is the total number of nodes, and the responsibility for the task that corresponds to the gene is assigned to the node that has the sequence number  $k$ .

The decision to employ this way of encoding chromosomes was made in large part due to the ease with which genetic operations such as crossover and mutation can be carried out. This approach results in the generation of new individuals who have the potential to investigate the solution search space while simultaneously inheriting fully functional gene segments from

their parents. The general goals of lowering costs and raising productivity have very little to do with the order in which jobs are processed on the same machine, and changing that order has very little impact on those goals.

#### 3.4.2 Population Initialization:

The initial population refers to all of the individuals who were consulted by the GA in order to decide which option would be the most effective. Let pretend the total number of persons in the population is  $N$ . Let also assume that the initial population refers to all of the people who were consulted by the GA in order to determine which option would be the most effective. The initial seeding of the  $N$  individuals is done entirely at random, and this is done for two reasons: the first reason is to increase the number of regions found in the search space, and the second reason is to improve the diversity of the population in the first generation. The initial seeding of the  $N$  individuals is done in order to increase the number of regions found in the search space. Before going through a series of changes, each individual that will make up the next generation is painstakingly selected from the initial population so that they can become part of the next generation.

#### 3.4.3 Fitness Function:

The fitness function is a tool that may be used to determine an individual comparative advantage over other people who belong to the same group. An individual who is in peak physical condition can stand in for a response of high quality. The application of the utility function  $F$  is what happens when figuring out an individual level of physical fitness. The level of physical fitness that an individual possesses has a direct association with the likelihood that the individual will live to see the following generation.

### 3.5 GENETIC OPERATORS

#### 3.5.1 Crossover Operator:

An operation known as the two-point crossover is carried out on chromosomes that are represented by a string of numbers. This process is utilized to develop offspring that have favourable gene combinations acquired from their parents. The offspring are produced through the usage of this procedure. In the process of making a new human, a pair of genes that are inherited from each parent are arbitrarily exchanged at two places in the genome that are known as crossings. These regions are located in the middle of the genome.

The method used to choose the parents of the offspring has an effect on how well the crossover algorithm works in the population. Every single person has a unique crossover frequency, which is denoted by a unique combination of letters and numbers. It is presumed that each individual in the population has a 50/50 chance of becoming the first parent, and a roulette wheel method is utilized to determine who will play the part of the second parent in the crossover. If this method of selection is utilized, then high-quality people who have a higher value placed on their level of fitness will have a larger probability of being selected to become a parent. This will improve the likelihood that beneficial stretches of gene information will be passed on to following generations.

#### 3.5.2 Selection Strategy:

The selection mechanism picks individuals of the population from which the next generation will emerge. When the crossover

procedure has been completed, the natural selection process will begin immediately afterwards. The fitness value of the offspring is compared to the fitness value of the parent, and children with a higher fitness value are selected to continue in the population. Because the parent will have been passed down to the subsequent generation, this offspring will never be seen again after it has been born.

As long as desirable gene segments are not permitted to be replicated an excessive number of times within that population and the genes of less-fit individuals are not removed from the population at an excessively rapid rate, greedy selection will ensure that a population diversity is preserved over many generations. This is the case provided that desirable gene segments are not allowed to be replicated an excessive number of times within that population.

### 3.5.3 Mutation Operator:

A new population of  $N$  people is produced through the processes of genetic crossover and natural selection to produce the best possible offspring. A rate of mutation that is equal to one point is possessed by each and every individual. A different value is substituted for the one that was originally located at the site of the mutant gene at random  $\gamma$ , and the task that is produced as a direct result of this process is sent to a distinct node.

Mutation either improves the solution while individuals are furious about the extremes or helps them to escape from the local extremes in order to examine other parts of the solution space. This allows for the crossover operator limits to be evaded and allows for further exploration of the solution space.

## 4. EXPERIMENTAL RESULTS

The model is analyzed making use of the NS-2 simulator, which replicated the activities of mobile WSNs so that accurate results could be obtained. The research uses NS-2, simulating a system from the bottom up is simple and rapid; you can start with the radio transmission channel and go all the way up to the application layer.

A version of the network test equipment that is the industry standard and has 150 nodes was utilized for the testing that was carried out. According to the information presented in Table.1, the nodes were dispersed in a grid that measured 100\*100m<sup>2</sup>.

Table.1. Simulation Parameters

| Parameters       | Values      |
|------------------|-------------|
| Simulator        | NS-2.35     |
| No of nodes      | 500         |
| Traffic type     | CBR         |
| Standard         | IEEE 802.11 |
| Routing protocol | AODV        |
| Agent type       | TCP         |
| Idle power       | 0.1 J       |
| Initial power    | 1000 J      |
| Packet rate      | 512 Kbps    |

At this stage, we make use of the EACH clustering algorithm, which identifies both the node and the CH cluster for us. In

addition to this, we are intending to broaden the scope of its applicability to include DT as well as CH. It was discovered that the EACH technique that was offered was superior to the traditional ways, which require picking a substantial number of clusters in order to link with the BS. This discovery was made after comparing the EACH method to the traditional ways. On the other hand, as can be shown in Table.2-Table.5, the proposed technique requires a noticeably a smaller number of clusters in order to accomplish BS.

Table.2. Delay (ms) for Cluster head selection

| Nodes | Delay (ms) |        |        |        |
|-------|------------|--------|--------|--------|
|       | Proposed   | FBCHS  | PSO    | LEACH  |
| 40    | 21.99      | 35.65  | 30.27  | 60.19  |
| 80    | 44.79      | 70.92  | 67.79  | 185.64 |
| 120   | 68.73      | 111.59 | 105.13 | 243.76 |
| 160   | 99.11      | 149.36 | 146.81 | 332.54 |
| 200   | 121.78     | 172.00 | 167.90 | 292.58 |
| 250   | 157.04     | 216.82 | 213.91 | 421.19 |
| 300   | 202.48     | 276.27 | 264.53 | 550.38 |
| 350   | 238.71     | 313.25 | 304.58 | 545.32 |
| 400   | 285.95     | 370.25 | 358.52 | 603.80 |
| 450   | 337.34     | 432.90 | 417.06 | 702.59 |
| 500   | 383.50     | 483.15 | 466.51 | 891.05 |

Table.3. Cost (\$) for Cluster head selection

| Nodes | Delay (ms) |         |         |         |
|-------|------------|---------|---------|---------|
|       | Proposed   | FBCHS   | PSO     | LEACH   |
| 40    | 165.68     | 156.03  | 156.05  | 165.38  |
| 80    | 349.60     | 333.17  | 324.86  | 344.91  |
| 120   | 534.56     | 507.65  | 496.84  | 516.80  |
| 160   | 710.52     | 681.36  | 666.22  | 689.93  |
| 200   | 846.85     | 816.86  | 795.02  | 831.52  |
| 250   | 1054.97    | 1028.74 | 991.43  | 1040.63 |
| 300   | 1296.22    | 1267.64 | 1231.75 | 1282.03 |
| 350   | 1474.28    | 1449.11 | 144.47  | 1463.61 |
| 400   | 1707.14    | 1685.37 | 169.78  | 1690.79 |
| 450   | 1947.03    | 1929.58 | 1862.01 | 1928.10 |
| 500   | 2172.99    | 2157.53 | 2081.51 | 2166.60 |

Table.4. Delay (ms) for Cluster formation

| Nodes | Delay (ms) |         |         |         |
|-------|------------|---------|---------|---------|
|       | Proposed   | FBCHS   | PSO     | LEACH   |
| 40    | 191.44     | 207.57  | 215.27  | 456.11  |
| 80    | 394.69     | 416.09  | 445.35  | 963.08  |
| 120   | 607.71     | 654.92  | 686.2   | 1495.66 |
| 160   | 819.97     | 917.67  | 932.33  | 1912.08 |
| 200   | 940.87     | 1067.49 | 1065.94 | 1905.7  |
| 250   | 1,270.96   | 1490.65 | 1479.84 | 3054.8  |

|     |          |         |         |         |
|-----|----------|---------|---------|---------|
| 300 | 1,473.79 | 1765.49 | 1712.76 | 3309.14 |
| 350 | 1,649.04 | 2010.74 | 1911.27 | 3638.19 |
| 400 | 1,944.58 | 2421.98 | 2300.51 | 4347.64 |
| 450 | 2,235.16 | 2840.79 | 2751.29 | 5350.35 |
| 500 | 2,503.09 | 3174.39 | 3067.26 | 6023.74 |

Table.5. Cost (\$)for Cluster formation

| Nodes | Delay (ms)     |               |         |           |
|-------|----------------|---------------|---------|-----------|
|       | Proposed       | FBCHS         | PSO     | LEACH     |
| 40    | 733.85         | <b>730.88</b> | 740.38  | 755.98    |
| 80    | <b>1540.23</b> | 1540.85       | 1553.43 | 1581.82   |
| 120   | <b>2363.37</b> | 2367.59       | 2381.16 | 2418.9    |
| 160   | <b>3176.17</b> | 3183.8        | 3197.01 | 3246.69   |
| 200   | <b>3755.21</b> | 3767.37       | 3778.27 | 3835.4    |
| 250   | <b>4988.94</b> | 5017.17       | 5007.59 | 5079.06   |
| 300   | <b>5832.69</b> | 5877.41       | 5862.52 | 5935.94   |
| 350   | <b>6607.52</b> | 6653.37       | 6632.38 | 6738.19   |
| 400   | <b>7738.56</b> | 7816.04       | 7759.95 | 7875.39   |
| 450   | <b>8845.9</b>  | 8926.57       | 8876.3  | 9016.59   |
| 500   | <b>9902.64</b> | 9995.97       | 9921.76 | 10,097.75 |

The cluster approach will ultimately result in a decrease in the quantity of energy that is required. Only the nodes in the cluster that correspond to the route that is chosen to take instead of one of the other possible routes become active when the route is chosen.

When compared with the method of random selection, the EACH strategy produces a lifetime for the network that is noticeably greater than that achieved by the latter. Each of these prospective solutions has the capability of being put into action in the not-too-distant future in order to extend the amount of time that the sensor cluster can be used effectively. As can be seen in Figure 10, EACH has a network lifetime that is noticeably longer when compared to other methods that are more conventional.

## 5. CONCLUSION

Despite the fact that a variety of WSN models and grouping algorithms have already been created, selecting CH at random is still a vital component for an energy-efficient WSN. This is the case despite the fact that there are already available. In order to fairly distribute CH energy consumption throughout its nodes, power loss implements a probabilistic technique. Following the relocation of the cluster region, a fresh strategy was offered with the objective of locating a solution to this challenge and making it possible to conduct a DT.

Experiments that compared several cluster nodes discovered that each of them was 20% more successful than the strategies that are currently being utilized. The reduced dependence on resources that require a lot of energy is another advantage of our technology, which results in longer sensor lifetimes. In comparison to the methods that are now being utilized, the proposed method not only reduces the total amount of energy that is consumed, but it also makes the process of selecting CH much less complicated to carry out. It is hoped that the implementation

of the approach to pick pathways for clustering would lead to an improvement in the efficiency of the cluster selection process.

It takes an amount of energy that is directly proportionate to the distance that separates each cluster, which means that in order to move from one cluster to another, you need to have a certain amount of energy. An alternate implementation of the shortest path algorithm is created. This strategy reduces the amount of power that is consumed during operation while keeping performance levels that are satisfactory for the vast majority of applications. The node energy was also considered as an additional consideration for choosing the CH. In the future, we plan to combine the aforementioned methods with fuzzy methods and methods that are bio-inspired in an effort to obtain predictions that are even more accurate than they are at this time.

## REFERENCES

- [1] R. Ramya and T. Brindha, "A Comprehensive Review on Optimal Cluster Head Selection in WSN-IoT", *Advances in Engineering Software*, Vol. 171, pp. 103170-103187, 2022.
- [2] R.K. Yadav and R.P. Mahapatra, "Hybrid Metaheuristic Algorithm for Optimal Cluster Head Selection in Wireless Sensor Network", *Pervasive and Mobile Computing*, Vol. 79, pp. 101504-101515, 2022.
- [3] V. Narayan, "FBCHS: Fuzzy Based Cluster Head Selection Protocol to Enhance Network Lifetime of WSN", *Advances in Distributed Computing and Artificial Intelligence Journal*, Vol. 11, No. 3, pp. 285-307, 2022.
- [4] S. Karunakaran and P. Thangaraj, "A Cluster-Based Service Discovery Protocol for Mobile Ad-hoc Networks", *American Journal of Scientific Research*, No. 11, pp. 179-190, 2011.
- [5] Danish Shehzad, Waqar Ishaq, Zakir Khan and Junaid Iqbal, "An Enhanced Weight Based Clustering Algorithm for Mobile Adhoc Networks", *Proceedings of International conference on Computer Science and Information Systems*, pp. 116-118, 2014.
- [6] Abbas Karimi, Abbas Afsharfarnia, Faraneh Zarafshan and S. A. R. Al-Haddad, "A Novel Clustering Algorithm for Mobile Ad Hoc Networks Based on Determination of Virtual Links Weight to Increase Network Stability", *The Scientific World Journal*, Vol. 2014, pp. 1-11, 2014.
- [7] Asis Kumar Tripathy and Suchismita Chinara, "Comparison of Residual Energy-Based Clustering Algorithms for Wireless Sensor Network", *International Scholarly Research Network, ISRN Sensor Networks*, Vol. 2012, pp. 1-10, 2012.
- [8] Mohamed Aissa and Abdelfettah Belghith, "A Node Quality based Clustering Algorithm in Wireless Mobile AdHoc Networks", *Proceedings of International Conference on Ambient Systems, Networks and Technologies*, Vol. 32, pp. 174 – 181, 2014.
- [9] G. Ran, "Improving on LEACH Protocol of Wireless Sensor Networks using Fuzzy Logic", *Journal of Information and Computational Science*, Vol. 7, No. 3, pp. 767-775, 2010.
- [10] B. Singh and D.K. Lobiya, "A Novel Energy-Aware Cluster Head Selection based on Particle Swarm Optimization for Wireless Sensor Networks", *Human-Centric Computing and Information Sciences*, Vol. 2, No. 1, pp. 1-18, 2012.

- [11] N.A. Latiff, "Energy-Aware Clustering for Wireless Sensor Networks using Particle Swarm Optimization", *Proceedings of IEEE International Symposium on Personal, Indoor and Mobile Radio Communications*, pp. 1-5, 2007.
- [12] P.C. Srinivasa Rao and H. Banka, "Novel Chemical Reaction Optimization based Unequal Clustering and Routing Algorithms for Wireless Sensor Networks", *Wireless Networks*, Vol. 23, pp. 759-778, 2017.
- [13] P.C. Srinivasa Rao and H. Banka, "Energy Efficient Clustering Algorithms for Wireless Sensor Networks: Novel Chemical Reaction Optimization Approach", *Wireless Networks*, Vol. 23, pp. 433-452, 2017.
- [14] H. Banka and P.K. Jana, "PSO-Based Multiple-Sink Placement Algorithm for Protracting the Lifetime of Wireless Sensor Networks", *Proceedings of International Conference on Computer and Communication Technologies*, pp. 605-616, 2016.