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Distance based Modelling and Optimization of Wireless Sensor Network Energy Consumption with Adaptive Clustering using Genetic Algorithm

Safa A. E. Elhaj [1] , Awadallah M. Ahmed [2] , Yousif E. E. Ahmed [3]

[1] *University of Gezira Faculty of Mathematical and Computer Sciences safabatch5@gmail.com*
[2] *University of Gezira Faculty of Mathematical and Computer Sciences awadallah@uofg.edu.sd*
[3] *University of Gezira Faculty of Engineering and Technology Yousif.hadi@uofg.edu.sd*

INFORMATIONs

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ABSTRACT

Wireless sensor network (WSN), as one of the most important technologies due to its wide variety of applications, consists of various densely deployed sensor nodes inside or very near to application area. WSNs work with several limitations related to resources like battery power, bandwidth, memory and etc. and hence node goes out of energy where it's impossible to recharge or replace the battery of nodes. It has been proved that, long communication distance between sensor nodes and base station (BS) can drain the energy. This paper proposes an approach to optimize the WSN energy consumption of nodes via optimizing the number of clusters that minimizes the transmission distance, for maximizing network lifetime. A genetic algorithm is proposed for sensor nodes clustering to find the optimal number of cluster heads that reduces the energy consumption. The proposed solution considers the communication distance, as a main factor, which is formulated as an objective function to be optimized for the mathematical model constrained by the number of cluster heads. The results were conducted using the proposed GA for different instances with different settings such as the population size, number of cluster-heads, and number of generations. The experimental results show that the algorithm achieved good results and it converges toward the optimal solution through the generations for the different instances. Moreover, the proposed approach reduces the energy consumption more efficient when compared with hierarchical clustering algorithm on minimizing the communicating distance. It is recommended to scale the algorithm to consider a trade-off between the total intra-cluster communication distance and total distance of cluster-heads to BS as a future work.

KEYWORDS: ***Wireless Sensor Network, Cluster heads, Genetic Algorithm, Energy Consumption, Modelling and Optimization***

1. INTRODUCTION

Wireless sensor networks (WSNs) have been considered as one of the most important technologies that have received tremendous attention from both academia and industry all over the world [1]. WSN is a system composed of large number of sensor devices (nodes) that are deployed randomly in a geographical area, where, each device consists of sensing, processing, communication, and power units. These sensors have the ability to communicate either among each other or directly to an external Base-Station (BS) [2]. WSNs have a wide area of applications such as health monitoring, military, environmental surveillance, office and commercial smart houses, smart farms, distributed robotics, and industrial automation [3]. One of the most important challenges in WSNs belongs to the limited battery of sensor nodes, when nodes are being placed in a specific field with difficulties to replace batteries or supply additional energy and the network may disconnect if one sensor node consumes completely its energy. Therefore, energy conservation has become a very important issue in WSNs, and so, more efforts have been paid and techniques have been needed to save battery life as long as possible. Clustering based mechanisms are effective means for managing such high population of nodes have been developed to reduce the nodesô energy consumption [4]. Clustering refers to division of sensor nodes in virtual group (clusters) which comprises cluster member nodes and Cluster Head (CH) receives data from member nodes and transfers it to the base station, illustrated in Fig 1. [5].

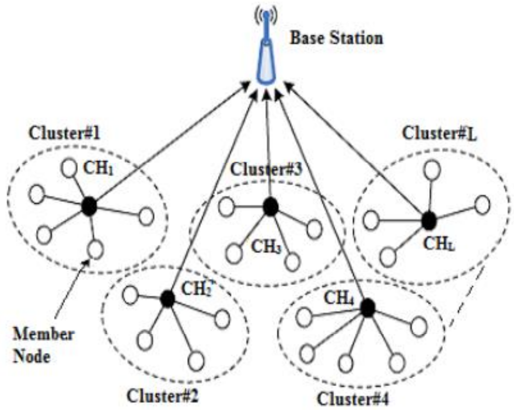

Fig 1: Clustering Architecture

Base on, energy-efficiency routing techniques and algorithm have been investigated under this category such as Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol. Moreover, minimizing the communication distance between the sensor nodes can minimize the energy consumption of the network. However, clustering a network for keeping the total distance to minimum is the NP-HARD problem [6]. The heuristics and met-heuristics such as genetic algorithm have been used for many NP-HARD optimization problems like the Travelling Salesman Problem (TSP). Many researchers used genetic algorithm to maximize the network lifetime [7]. The Genetic Algorithm (GA) is a technique for randomized search and optimization and has been applied to a wide range of studies. A basic operation flow of GA includes creating initial population, evaluating fitness, selection, crossover, mutation, updating optimal chromosome, and checking termination condition. GA can be effectively used in searching for optimal clusters. In this paper genetic algorithm is used to improve the network lifetime based on distance, also generates an optimal number of sensor-clusters with cluster-heads [8]. The problem of WSNs lifetime has been addressed from different points of view using many tools as illustrated in the next section.

2. RELATED WORKS

The problem of energy consumption in wireless sensor network has been widely addressed as a prime design issue. The LEACH-B (LEACH-Balanced) was proposed based on the analysis on the defect in LEACH including the fluctuation of the number of cluster heads and the ignorance of the nodes residual energy and simulation result shows that LEACH-B provides better energy efficiency and longer network life span than LEACH [9]. The genetic algorithm have been used to solve sensor network optimization problem with a fitness function of some fitness parameters such as direct distance to sink, cluster distance, transfer energy, and number of cluster head and experimentally proofed that it maximizes the fitness function, find appropriate number of cluster heads, minimizing the communication distance, as well as greatly decreased the consumed energy [10]. In [11]. The primary approach in cluster based routing protocols is to maintain network-cluster lifetime because node displacement and network failure (node energy level). Due to the cluster-lifetime maximization, a new GA was proposed to identify the optimal position for sensor placement and to cover maximum possible number of targets with less sensor ratio. Having control over the position and number of cluster heads and also the number of clusterĝs member is always a challenge. The author introduce dynamic clustering to determine clustering and the place of the cluster heads using genetic algorithm, which takes different parameters to increase the network lifetime, this parameters are: the residual energy of the nodes as a main parameter for selecting the cluster head. The second parameter that is considered is the required energy to send a message toward the sink node. The lower the communication distance, the less energy will be consumed during transmission. Finally, since cluster heads use more energy than other nodes, reducing the number of cluster heads has a considerable effect on decreasing the energy consumption [12]. In addition, the GA is proposed in order to evaluate the energy consumption of WSN. Which used a multi-objective algorithm that generates an optimal number of sensor clusters with the cluster heads and minimize the cost of transmission with two fitness functions: one evaluates total node fitness for each system of Sensor networks that is going to be maximized. The other one evaluates the cost of transmission for each system of sensor networks that is going to be minimized [4]. Long communication distance between sensor nodes and base station is the main factor that drains the energy of sensor nodes. The genetic algorithm was incorporated with hierarchical clustering for the sake of reducing the communication distance. Which it's applied to cluster the nodes in WSN, after finishing the genetic algorithm, the hierarchical clustering was performed by the following steps:

- Each cluster head calculates its distance to the sink and all cluster heads.
- Is the distance to the sink is the minimum distance compared with distances to reach other cluster heads, then the cluster head will be connected directly to the sink, otherwise the cluster head connected to the nearest cluster head.
- The number of cluster heads connected to each other forms a group. The nearest to the sink is selected to be a super cluster head and gather the required data from cluster heads within its group to be then relayed to the sink [13].

The energy consumption of WSN has been considered by LEACH protocol which its hierarchical routing protocol randomly divide data collection area into several clusters while each cluster has a cluster head and some cluster members [14].

Clustering is the main factor responsible for the energy conservation in LEACH algorithm. Main objectives of clustering are equal distribution of energy and equal distribution of nodes in space, so that less energy is consumed and early death of nodes can be delayed. In LEACH both of these objectives can't be achieved. Further to achieve these objectives a modified genetic algorithm was proposed, in which cluster heads are chosen based on residual energy instead of random selection. The improved GA has been compared with random LEACH, MAX energy LEACH, K-means algorithm, and simple GA which cluster only space equal-distribution not for the load balancing among clusters. The performance of GA cluster based routing protocol show improvements in lifetime but MAX energy LEACH perform better in network disintegration criterion [15].

In [16], Efficient Energy Clustering Protocol (EECP) based on Genetic Algorithm (GA) was proposed, which is a clustering procedure for WSNs based on meta-heuristic, is used by CH and cluster members for improved solution of search equation. The proposed EFCP protocol with genetic algorithm utilizes an energy efficient method, which picks optimal CHs based on an enhanced search equation with effective fitness function to improve exploitation competences in addition to convergence rate of existing meta-heuristic. The proposed algorithm was assessed in terms of throughput, packet delivery ratio, energy consumption and end to end delay.

This paper investigates the WSNs lifetime maximization via minimizing the transmission energy consumption through: minimizing the total transmission distance between sensor nodes and their cluster heads (CH), and distance between cluster heads and BS and utilizing the efficiency of optimization techniques to finding optimal solution with minimum computation time.

3. PROPOSED METHOD

This section describes the problem formulation, modelling and more details about applying GA for solving energy consumption of wireless sensor nodes.

a. Problem formulation

For any set of sensors nodes, $S = \{S_1, S_2 \ldots S_m\}$ and a set of CHs as a subset of S with n sensors, $Cn = \{S_1, S_2 \ldots Sn\}$, finding appropriate cluster heads is critically important for minimizing the distance and thus the energy consumption. The following notation will be used to describe the objective function.

m: number of sensors

n: number of cluster heads

α: threshold value (maximum number of cluster heads)

□: Distance between nodes and cluster heads

□: Distance between cluster heads and base station

The communication distance between sensor nodes and their cluster heads and distance between cluster heads and base station depend on the number of cluster heads. Hence this number is determined by a threshold value and must not be exceeded, as in Equation 1.

$$n <= \alpha \quad \ldots\ldots\ldots\ldots\ldots (1)$$

Then, the Direct Distance to CH, (DDCH) represents total direct distance between the whole sensor nodes and the CHs, denoted by □, and is calculated as in Equation 2.

$$DDCH = \sum \square \quad \ldots\ldots\ldots (2)$$

The energy for direct distance to cluster head is:

$$E = DDCHE \ldots\ldots\ldots\ldots\ldots\ldots (3)$$

And the cluster to BS, (CD): this parameter is the sum of the distances between CHs and BS.

$$CD = \sum \square \ldots\ldots\ldots\ldots\ldots\ldots (4)$$

The energy for cluster distance is:

$$E = CDE \ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

Thus, objective function to minimized is formulated as in Equation 6.

$$TE = DDCHE + CDE \ldots (6)$$

From the above formula, one can observe that the objective function is total transmission energy, which describes the relation between communication distance and energy. The communication distance is the main factor that can drain the energy of sensor nodes as a factor to be minimized.

b. The Proposed Genetic Algorithm

There are many ways to represent a sensor node as a chromosome in a genetic algorithm. A binary representation of the chromosome is proposed for the application of the GA. Each chromosome encodes a binary (bit) string. Each bit in the string can represent some characteristics of the solution. Every bit string therefore is a solution. Binary coded strings with 0s and 1s to represent the sensor nodes and CHs respectively as in **Error! Reference source not found.** presents an example of the binary representation used.

Table 1: Example of binary representation of sensor node

Sensor set(S)	□	□	□	□	□	□	□	□	□	□
Chromosome	1	0	0	0	1	0	0	0	0	1

Then, specifying the initial population size is the important step in the genetic algorithm. There are set of nodes (sensors) need to be distributed on a network. This strategy is used to generate an initial population of the specified size randomly.

– ***Selection stage:***

For the Selection stage roulette wheel selection will be applied. Evaluate the population and determine which members are fit to be selected as parents for the next generation. The process of selection can be divided into two steps.

1) Evaluate Fitness function:

The fitness of a chromosome represents its qualification on the basis of energy consumption minimization and coverage maximization. The total transmission distance is the main factor we need to minimize. In addition, the number of cluster heads can factor into the function. Given the same distance, fewer cluster heads result in greater energy efficiency.

2) Create a mating pool:

Once the fitness has been calculated for all members of the population, we can then calculate the objective function of members are fit. After that select the minimum distance of them to become parents and place them in a mating pool**.** Better solution for the mating pool is to use a probabilistic method, which weꞌll call the ñwheel of fortuneò (also known as the ñroulette wheelò).

```
Pseudo code of roulette wheel selection
For all members of population
        Sum += fitness of this individual
End for
        For all members of population
        Probability = sum of probabilities + (fitness /sum)
        Sum of probabilities += probability
End for
Loop until new population is full
        Do this twice
         Number = Random between 0 and 1
      For all members of population
          If number > probability but less than next
probability
             Then you have been selected
      End for
    End
    Create offspring
End loop
```

– Crossover operator:

For the crossover, single-point crossover method will be used. The crossover operation takes place between two chromosomes with probability specified by crossover rate. These two chromosomes exchange portions that are separated by the crossover point for new head. This new head is detached from its previous head. If a cluster-head becomes a regular node, all of its members must find new cluster-heads as in the following is an example,

Table 2: An example of single point crossover

	First	Second
	[illegible]	[illegible]
Parent	**1 1 0 0 0 0 1 0 0 1**	**0 0 1 1 0 1 1 0 0 0**
Offspring	**1 1 0 0 0 0 1 0 0 0**	**0 0 1 1 0 1 1 0 0 1**

And the Pseudo code of single point crossover as follows:

```
Find a crossover point according to crossover probability
    For i=0 to crossover point do
        Child A gene[i] = parent A gene[i]
         Child B gene[i] = parent B gene[i]
    End for
    For i = crossover point to chromosome length do
         Child A gene [i] = parent B gene[i]
          Child B gene [i] = parent A gene[i]
    End for
    Return children
```

– Mutation operator:

Then, the mutation operator is applied to each bit of an individual with a probability of mutation rate. A bit whose value is 0 is mutated into 1 and vice versa. An example of mutation is as follow:

Table 3: An example of mutation

	Offspring 1	Offspring 2
	[illegible]	[illegible]
Original	1 1 0 0 **0** 0 1 0 0 0	0 0 1 **1** 0 1 1 0 0 1
mutated	1 1 0 0 **1** 0 1 0 0 0	0 0 1 **0** 0 1 1 0 0 1

Based on the objective function used to solve the problem, the binary encoding for the representation of chromosome, the type of crossover and mutation were experimentally used to obtain the results with different parameters values.

4. EXPERIMENTAL RESULTS

This section concerns about the obtained results and their justification, we provide a brief description about the experimental setup. Then, we show the results of the proposed solution. Finally, we established a comparison between the results obtained and hierarchical clustering based on genetic algorithm approach. The Experimental setup illustrated in Table 4.

Table 0: Setup of the experimental environment

Parameter	**Setting**
Computer Properties	
Processor	Intel® Core Ê i5-460M CPU@ 2.53GHz
RAM	4.00 GB
OS	Window 7 (**x32 bit Processor**)
Programming Language	Java Programming Language
IDE	NetBeans IDE 8.2
Parameter for genetic algorithm evaluation	
Node size	50 , 100 ,150 , 200 , 250 ,300 ,350 ,400 ,450 ,500
Population size	50, 100, 150, 200, 250, 300, 350, 400, 450,500
Selection type	Roulette wheel
Crossover type	One-point
Crossover rate	0.9
Mutation rate	0.1
Number of iteration	50 , 100 ,150 , 200 , 250 ,300 ,350 ,400 ,450 ,500
Number of cluster heads	10 ,15 ,20 ,25 ,30 ,35 ,40

For a number of cluster heads equal to 10, 15, 20, 25, 30, 35 and 40, and using a population size of 100 for 100 generations, Fig 2. shows that the algorithm produces good results

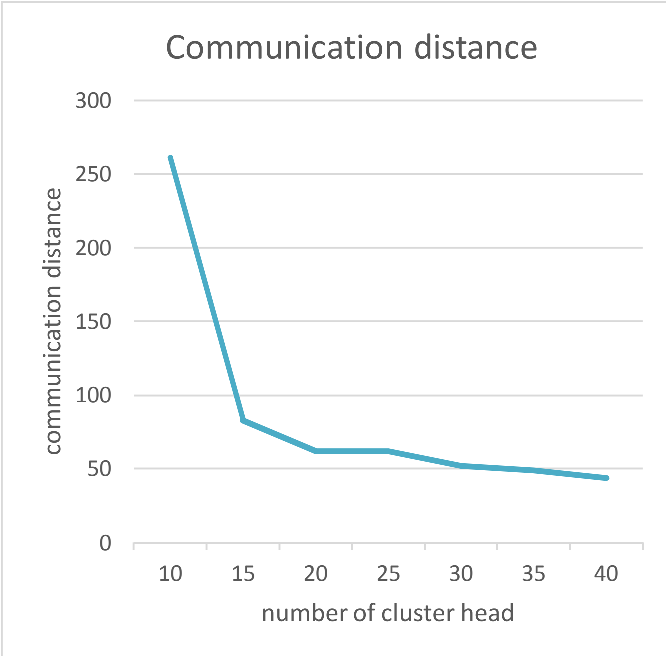

Fig 2: Communication distance with the different number of cluster heads

As observed from Fig 2, the communicating distance decreases as a number of cluster heads increases and stable in the number of cluster heads 35, and 40. Further, Fig 3 shows the communication distance with the different number of generations.

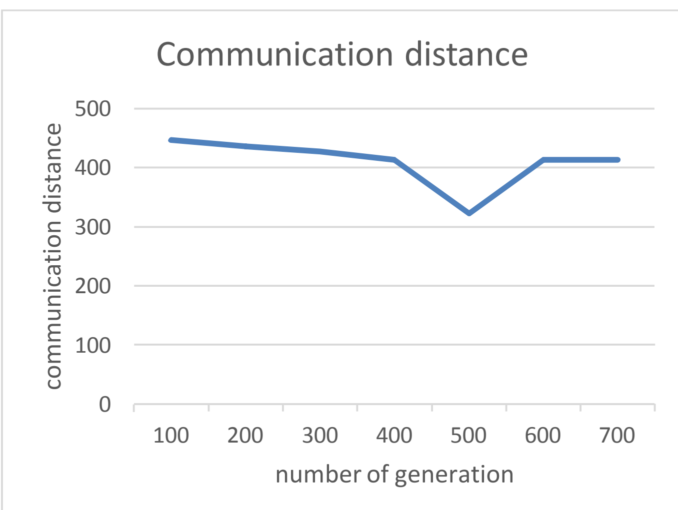

Fig 3: Communication distance with different number of generations

Actually, decreasing the long distance communications as the genetic generations increase means that our proposed approach is very efficient and performs correctly as expected. For estimating the performance of the proposed method, different instances with different node sizes were used on the proposed method and hierarchical clustering and the minimal distances were found as in Table 5.

Table 05: Comparison between our proposed solution and hierarchical algorithm

node size	long-distance decreased by (proposed solution)	long-distance decreased by (hierarchical clustering)
50	331	346
100	143	307
150	75	302
200	71	257
250	70	136
300	60	130
350	53	126
400	44	100
450	44	80

Table 5 shows the reduction in long communication distance when compared with the hierarchical clustering considering the different network sizes and different number of generations. The proposed solution reduces the long communication distance more than hierarchical clustering. The noticeable thing is that, when the network size increased, the efficiency of the proposed solution is increased. Fig 4 illustrates the distance reduction of the proposed method when compared with hierarchical clustering algorithm.

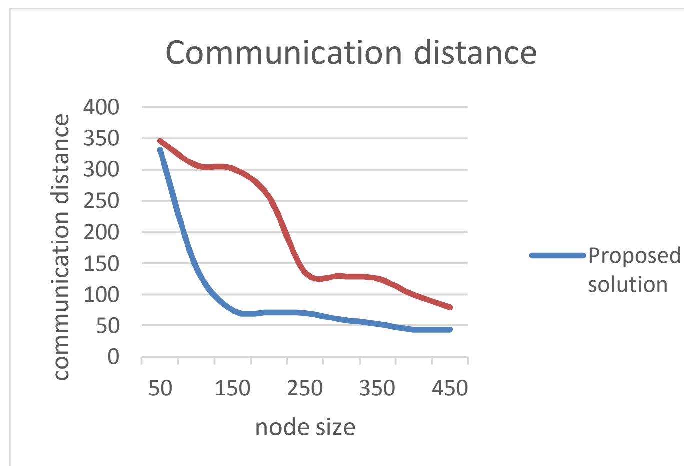

Fig 0: Comparison between the proposed approach and hierarchical clustering approach

The reduction is about 96% in the proposed solution, while in hierarchical clustering is about 92%. From the objective function described previously, the distance parameter is the only factor that affects the energy consumption, as a result, the proposed approach reduces the energy consumption more than hierarchical clustering.

The radio model is used to calculate the transmission energy as illustrated in Equation

$$E_{Tx}(k, d) = E_{elec} * k + \varepsilon_{amp} * k * d^{2} \quad \text{----------- (7)}$$

Where E_{Tx} is the transmission energy, E_{elec} is the energy being dissipated to run the transmitter or receiver circuitry and ε_{amp} as the energy dissipation of the transmission amplifier. Where E_{elec} and

□□□ □ are constants, □□□□□□ =50 nJ/bit and □□□ □ is 10 and k is the number of transmitted or received bits. We considered the transmitted data to be only one bit. Hence, the communication distance (d) is the dominant factor in affecting the power consumption, this is to say, increasing (d) increases the power consuming and vice versa.

The following Figures display the total transmission energy with different node sizes and different number of cluster heads. Fig 5 shows the total transmission energy using population size of 100 nodes and number of cluster heads are 10, 15, 20, 25, 30, 35, 40, 45, 50 and we ran the algorithm for 100 generations.

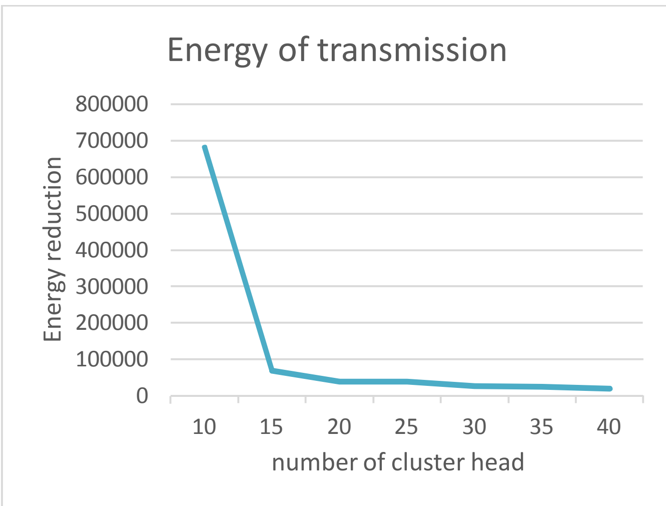

Fig 05: Total transmission energy with different number of cluster heads

It is clear that the total transmission energy decreased when the number of cluster heads increase. Fig 6 shows the total transmission energy with the different number of generations.

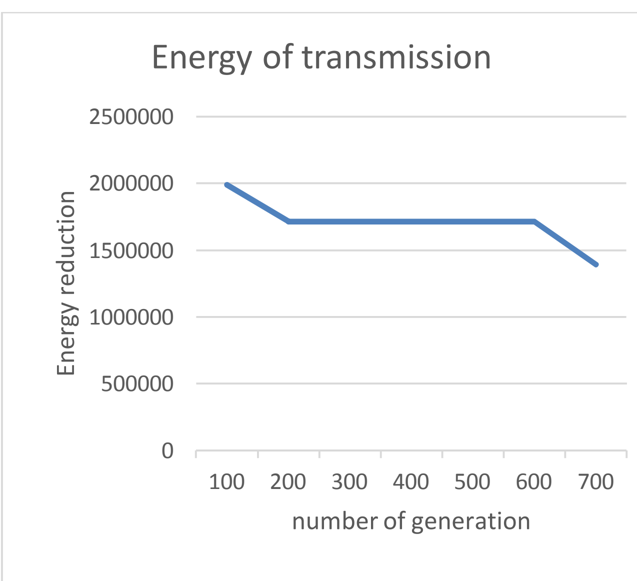

Fig 6: Total transmission energy with different number of generation

Actually, decreasing the energy as the genetic generations increase means that our proposed approach is very efficient and performs correctly as expected. The hierarchical clustering approach from the literature was used to estimate the performance of the proposed method as in table 6.

Table 6: Comparison between our proposed solution and hierarchical algorithm

node size	energy decreased by (proposed solution)	energy decreased by (hierarchical clustering)
50	1095660	1197210
100	204540	942540
150	56800	912090
200	50460	660540
250	49050	185010
300	36050	169050
350	28140	158810
400	19410	100050
450	19410	64050

One could note that the reduction in transmission energy when compared with the hierarchical clustering considering the different network sizes and different number of generations. The proposed solution reduces the energy more than hierarchical clustering. When the network size increased, the efficiency of the proposed solution is increased. Fig 7 illustrates the energy reduction for different node size.

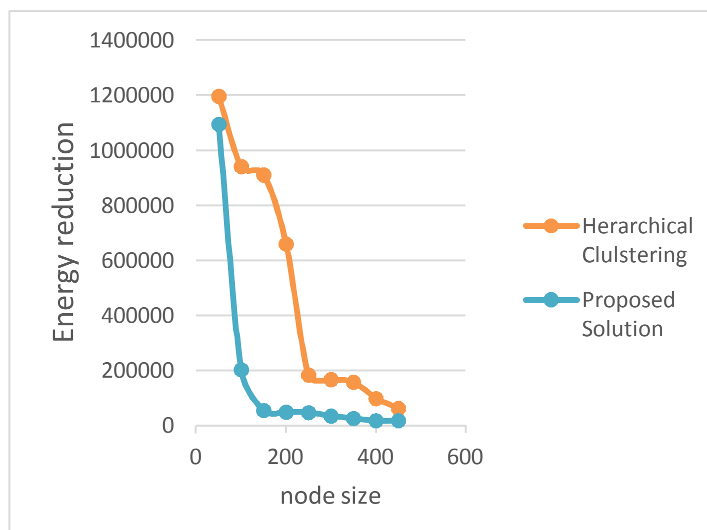

Fig 7: Comparing the proposed solution to hierarchical clustering

5. CONCLUSION

This paper has presented energy efficient clustering solution based on genetic algorithm for wireless sensor networks. The GA has been used to find near optimal solution based on the objective function in mathematical model. The proposed algorithm used the clustering technique to minimize the communication distance and so the related energy consumption required for data transmission between sensor nodes and BS also considering the number of cluster heads. The algorithm has been evaluated using different parameters' settings. The parameters that have been considered in the test are population size and number of cluster heads. The results have shown that the algorithm could achieve good results and shows fast convergence toward the optimal solution. Moreover, the results have shown positive significance in comparison with the hierarchical clustering algorithm on minimizing the communicating distance. Hence, the algorithm reduces the energy consumption of the sensor nodes prolongs the lifetime of the network.

6. REFERENCES

[1] S. N. V. Sruthi C V, "Genetic Algorithm Implementation for Cluster Head Re-election in Oceanic Environment," *International Journal of Innovative Research in Science, Engineering and Technology,* vol. 5, no. 8, p. 8, 2016.

[2] W. S. ,. S. ,. C. I.F. Akyildiz, "Wireless sensor networks: a survey," *Elsevier Science B.V,* vol. 38, p. 30, 2002.

[3] K. B. ,. M. Amit Singh, "Clustering and Energy Efficient Routing Protocol for Wireless Sensor Network using Genetic Algorithm," *International Journal of Computer Applications (0975 – 8887),* vol. 119 ï No.7, p. 4, 2015.

[4] M. H. Y. A. Zahmatkesh, "A Genetic Algorithm-Based Approach for Energy- Efficient Clustering of Wireless Sensor Networks," *International Journal of Information and Electronics Engineering,* vol. Vol. 2, p. 5, 2012.

[5] A. K. a. A. S. Buttar, "Energy efficient Clustering Techniques using Genetic Algorithm in Wireless Sensor Network: ASurvey," *International Journal for Innovative Research in Science & Technology,* vol. 2, no. 09, pp. 1-4, 2016.

[6] N. Mittal, "Moth flame optimization based energy efficient stable clustered routing approach for wireless sensor networks," *Wireless Personal Communications,* vol. 104, no. 2, pp. 677--694, 2019.

[7] S. M. A. ,. S. a. S. S. Mohammed Abo-Zahhad, "A New Energy-Efficient Adaptive Clustering Protocol Based on Genetic Algorithm for Improving the Lifetime and the StablePeriod of Wireless Sensor Networks," *International Journal of Energy, Information and Communications,* vol. 5, no. 3, pp. 47-72, 2014.

[8] S. M. a. A. S. Jamshid Shanbehzadeh, "An Intelligent Energy Efficient Clustering in Wireless Sensor Networks," *International MultiConference of Engineers and Computer Scientists,* vol. 1, pp. 1-5, 2011.

[9] M. T. Mu Tong, "LEACH-B:An Improved LEACH Protocol for Wireless Sensor Network," *IEEE,* pp. 1-4, 2010.

[10] E. H. a. A. Movaghar, "AN EFFICIENT METHOD BASED ON GENETIC ALGORITHMS TO SOLVESENSOR NETWORK OPTIMIZATION PROBLEM," *International journal on applications of graph theory in wireless ad hoc networks and sensor networks ,* vol. 3, no. 1, pp. 1-16, 2011.

[11] P. R. T.Ganesan, "Genetic Algorithm Based Optimization to Improve the Cluster Lifetime by Optimal Sensor Placement in WSNôs," *International Journal of Innovative Technology and Exploring Engineering,* vol. 8, no. 8, pp. 1-9, 2019.

[12] M. A. Mehr, "Design and Implementation a New Energy Efficient Clustering Algorithm using Genetic Algorithm for Wireless Sensor Networks," *World Academy of Science, Engineering and Technology International Journal of Computer and Information Engineering,* vol. 5, no. 4, pp. 1-4, 2011.

[13] M. F. A.-M. ,. A. N. M. ,. A. D. a. A. A. A. Mohammad M. Shurman, "Hierarchical Clustering Using Genetic Algorithm in Wireless SensorNetworks," pp. 20-24, 2013.

[14] C. S. Lalita Yadav, "Low Energy Adaptive Clustering Hierarchy in Wireless Sensor Network (LEACH)," *International Journal of Computer Science and Information Technologies,* vol. 5, no. 3, pp. 4661-4664, 2014.

[15] A. K. Jasjot Kaur, "GA Based Balanced Clustering Approach for Energy Efficiency in WSN," vol. 9, no. 1, pp. 24-31, 2015.

[16] M. S. G. P. Nandoori Srikanth, "Efficient Energy Clustering Protocol Using Genetic Algorithm in Wireless Sensor Networks," *JOURNAL OFEngineering Science and Technology Review,* vol. 11, no. 6, pp. 85-93, 2018.