

Management of Energy Consumption in Wireless Sensor Networks

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ABSTRACT:

Wireless sensor networks (WSNs) contains an enormous number of sensor nodes deployed in huge numbers which are able to sense, process and transmit environmental data to the base station for plenty of applications. Clustering is one of the important issues for prolonging the network lifetime in wireless sensor networks. It includes grouping of sensor nodes into clusters and selecting cluster heads for all the clusters. Cluster heads collect the data from respective cluster's nodes and forward the aggregated data to base station. Some important challenges in wireless sensor networks are to find optimal number of clusters, clustering and to select appropriate cluster heads. In this direction, we present a method that includes three phases. At first, the optimum number of clusters is calculated. In the second, clustering is done by use of k-means algorithm. In the last phase, a multi criteria decision-making approach is presented for the selection of cluster heads. This approach is used to select cluster heads based on criteria including residual energy, the distance (the distance from the cluster and the distance from the base station), the number of neighbors (the one-step neighbor and the two-step neighbor), the centrality of the nodes and the number of times a node has been cluster head. We implement the proposed method in the NS2 environment and evaluate its effect and compare it with the NEECP and E-LEACH methods. The simulation results demonstrate that this approach is more effective in prolonging the network lifetime than the NEECP and E-LEACH methods in homogeneous environments.

KEYWORDS: Clustering, Energy, Multi-criteria Decision Making, Sensor Networks, AHP Method.

1. INTRODUCTION

Wireless sensor network (WSN) is a network formed by a large number of sensor nodes where each node is equipped with a sensor to detect physical phenomena such as light, heat, pressure, etc. WSNs are regarded as a revolutionary information gathering method to build the information and communication system which will greatly improve the reliability and efficiency of infrastructure systems. Compared with the wired solution, WSNs feature easier deployment and better flexibility of devices.

The most important reason for the emergence and development of wireless sensor networks has been the continuous monitoring of contexts that are difficult or impossible to achieve by human beings [1]. In order to carry out the duties for a long time, these networks should be autonomous without the involvement of individuals. Such a network, according to its application, collects information about various events from its operating context and reports this information

to the base station during initial processing, for instances, applications such as industry [4], crisis management [35], [5], health [2], [6] and military [3]. Each sensor node has a limited energy supply and in most applications, it is not possible to replace energy sources. Therefore, sensor node life is heavily dependent on the energy stored in its battery. Hence, extending the life span of such network is one of the most important issues [7], [8].

One of the main reasons for high energy consumption of cluster heads is sending data to the base station. This is due to the distance of the base station from the cluster heads. Moreover, one of the important issues of energy consumption in wireless sensor network is clustering. In the clustering method, the network is divided into a number of independent sets referred to as sets of clusters. So each cluster has a number of sensor nodes and cluster heads. The cluster nodes send their data to their cluster head node. The cluster head node aggregates the data and sends it to the

base station. Therefore, clustering in sensor networks has some advantages such as supporting data aggregation, facilitating data collection, organizing an appropriate structure for scalable routing, and disseminating data efficiently over a network.

Research has proved that cluster head selected on single criterion does not have energy efficiency. Hence, an ideal cluster head is the one which is selected on multiple criteria. Solution of using multiple criteria can be solved via Multiple Criteria Decision Making (MCDM) technique. MCDM methods are used to solve the decision-making problem in engineering and sciences, with multiple attributes. MCDM techniques compare and rank multiple alternatives based on degree of desirability of their respective attributes. There are different types of MCDM approach. In this paper, the AHP (Analytic hierarchy process) method is used [32]. The AHP is a structured technique for organizing and analyzing complex decisions, based on mathematics and psychology. It was developed by Thomas L. Saaty in the 1970s and has been extensively studied and refined since then. It is used around the world in a wide variety of decision making situations, in fields such as government, business, industry, healthcare, shipbuilding and education [33].

The rest of the paper is organized as follows: Section 2 reviews the related work. In Section 3, the base station selects the cluster head using AHP method. Section 4 analyzes experiments with existing nodes. Finally, in Section 5, it will be summarized discussion and conclusion.

2. RELATED WORKS

Most of the clustering algorithms [9-12] have been established for WSNs according to heuristic methods. LEACH [9] is one of the popular distributed clustering algorithm where the sensor nodes designate themselves as a cluster head with some probabilities. LEACH offers substantial energy saving and extends the period of the network in comparison with the static clustering and minimum transmission energy. However, the chief difficulty of this algorithm is that there is a probability to choose a cluster head with very low energy, which may expire quickly and therefore reduces the performance of the network. Consequently, the amount of algorithms has been established to advance LEACH protocol, PEGASIS [13] and HEED [14] are prevalent among them. PEGASIS classifies the nodes into the chain in an attempt to make opportunity for each node to convey and obtain the data only from its neighbor nodes. In each turn, an arbitrarily designated node from the chain as a cluster head is chosen. PEGASIS is more efficient than LEACH; nevertheless, it is unbalanced for huge networks. Furthermore, the delay is expressively high. Recently, many algorithms [15-19] have been established for data gathering structures for

prolonging the lifetime of WSNs. Loscri et al. [20], have suggested TL-LEACH protocol presenting a novel level of hierarchy. It advances the network period over LEACH, however, with an extra overhead for selecting subordinate cluster heads and also non-cluster head nodes allocate to the cluster heads according to distance only, which may cause severe energy imbalance to the network. Xiaoyan et al. [22], have argued that M-LEACH algorithm is comparable with LEACH and only difference is that it forward to cluster head node in next hop rather than sending the data directly to the base station and thus it keeps energy in comparison with LEACH and TL-LEACH. However, in multi-hop data transfer between cluster heads, it does not regard the significant metrics like energy, node degree etc.

Yassein et al. [21] discussed that V-LEACH protocol improves the LEACH protocol where some cluster heads referred as vice cluster heads are designated along with the chief cluster heads and once the main cluster heads die, the vice cluster heads play as a cluster heads. It is revealed that it acts better than unique LEACH. However, sensor nodes require additional processing energy for choosing cluster heads. Also, it does not mind of development of clusters, which may cause severe energy incompetence of the WSN. In [23], the researchers have argued that E-LEACH protocol, which is similar to LEACH protocol, in the selection of cluster heads, remaining energy of the cluster heads was taken into consideration, which can spread the life of the network by saving the low energy of cluster heads. Means, it may not select the cluster head with low energy. Bari et al. [24], have argued the least distance clustering (LDC) for enhancing the lifetime of WSNs. The value of their method is that it performs faster, due to the assigning of non-cluster head nodes to the nearest cluster head. The chief difficulty of LDC is the unsuitable creation of clusters. Nevertheless, it is problematic to discover the optimal clusters for large scale networks, since the computational difficulty differs exponentially. The studies [26-28], have planned energy well-organized cluster based routing arrangements for dependable networks and in [29] a framework for energy assessment in WSNs has proposed.

A Novel Energy-Efficient Clustering Protocol (NEECP) is developed to improve the lifetime of sensor network. NEECP elects cluster heads in an influential manner and each cluster possesses various sensing range to balance the load on the cluster head. The protocol also uses the chain based data aggregation arrangements to spread the period of WSN. Furthermore, NEECP evades redundant data spreads that further advance the network lifetime. NEECP applies stochastic cluster head election procedure to select cluster heads [30].

In the most of articles, authors have considered residual energy or number of neighbors or combination of these factors as criteria for selecting cluster heads and showed that network lifetime significantly increased [14], [15], [23], [34]. But these methods have been overhead due to sending messages to all nodes. Among the methods that have been proposed for clustering in wireless sensor networks, multi criteria decision making method (MCDM) rarely has been used. However, MCDM models are capable of selecting the best options based on certain criteria. [35-38] considered node's residual energy, the distance from node to the base station and the distance between neighboring nodes as criteria for selecting cluster heads. By studying the papers published concerning energy efficiency in wireless sensor networks, it is found that the higher the number of criteria for selection of the cluster heads, the better the cluster heads are selected. For this approach, in this paper, it is presented a multi criteria decision-making approach for the selection of cluster heads. This approach is used to select cluster heads based on criteria including residual energy, the distance (the distance from the cluster head and the distance from the base station), the number of neighbors (the one-step neighbor and the two-step neighbor), the centrality of the nodes and the number of times a node has been cluster head. The proposed method is implemented in the NS2 environment and evaluated its effect as well as compared it with the NEECP and E-LEACH methods. The simulation results demonstrate that this approach is more effective on prolonging the network lifetime than the NEECP and E-LEACH methods in homogeneous environments.

3. PROPOSED METHOD

The most important issues regarding clustering are to improve cluster structure, optimize the selection of cluster heads and reduce energy consumption for data transmission. This motivates us to propose an energy efficient clustering protocol to resolve these issues.

3.1. Network Model and Assumptions

In this Section, some assumptions, relevant definitions and system models are described and then the details of the proposed method are stated.

3.1.1. Network model

The wireless sensor networks studied in this paper mainly focus on typical application for data acquisition, the network contains a large number of sensor nodes and several sink nodes. To simplify the system model, it is assumed that the WSNs have the following properties and some reasonable assumptions are made: let N be the number of homogeneous sensor nodes which are distributed randomly in the Rectangle monitoring field with the sides of length L and width

P , each node has the power control capacity and adjusts itself to a fixed transmission radius r , the network is dense and connected, the base station is deployed in a fixed position, the source nodes are far from the base station, they send data packets to the base station via multi-hop routing method, each sensor node is assumed static and carries internal battery to support sensing and communication functions, the battery cannot be replaced or recharged, the node dies once its energy is used out.

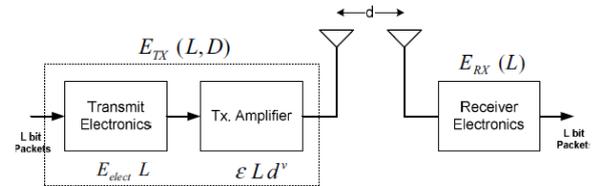


Fig. 1. Radio energy model.

The energy pattern as the same radio pattern in [31] is applied in this study. In this model, transmitter disperses energy to run the radio electronics and the power amplifier. The receiver dissipates energy to run the radio electronics. The energy consumption of the node depends on the amount of the data and distance to be sent. In this model, when the transmission distance d is less than the threshold distance d_0 , the energy consumption of a node is relative to d^2 , otherwise it is relative to d^4 [31]. The whole energy consumption of each node in the network for conveying the k -bit data packet is given by the following equations. (Fig.1) shows the radio energy model.

$$E_{TX}(k, d) = E_{TX-elect}(k) + E_{TX-amp}(k, d) \quad (1)$$

$$= k(E_{elect} + E_{amp}d^\alpha)$$

$$= \begin{cases} k(E_{elec} + \epsilon_{fs}d^2), & d < d_0 \\ k(E_{elec} + \epsilon_{mp}d^4), & d \geq d_0 \end{cases} \quad (2)$$

Where the threshold distance d_0 is:

$$d_0 = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}} \quad (3)$$

Where E_{elect} is the energy required for the run of the radio, ϵ_{mp} and ϵ_{fs} is the energy required to run the transmitter amplifier contingent on the distance d . To receive a k -bit message, energy consumed is:

$$E_{Rx}(k, d) = E_{Rx-elec}(k) = k.E_{elec} \quad (4)$$

3.1.2. System assumptions

Throughout the paper, assumptions regarding the network model in the proposed method are the following:

- All nodes are constant and have resource constraints.
- The sensor nodes and the base station are all static after deployment.
- There is only one base station far from the sensing region which has no resource constraints.
- All nodes are located within one or more steps of the base station.
- All nodes have data to send at specific moments.
- Data aggregation happens in each of the cluster head.
- All cluster head ultimately send aggregated data to the base station.
- All nodes are aware of their locations.
- The base station is aware of the location of all nodes.
- The energy of all nodes is constant.

3.2. Optimum Number of Clusters

Energy efficiency is one of the most important performances metric for sensor networks. It has been established by research that energy efficiency can be enhanced using hierarchal clustering or multi clustered approach. Generally, energy efficiency depends upon the optimum number of clusters selected. Optimal numbers of clusters depend upon the spatial distribution of nodes in the sensor region and remaining energy available with each node. Initially when the sensors are just deployed and all nodes have new batteries, the optimal number of clusters will depend more on the distribution of nodes. To get the optimal number of clusters, the initial state of deployment is considered as the following.

Suppose N is the total number of sensor nodes distributed in a $L \times P$ rectangle sensing region. The optimum number of clusters k_{opt} can be obtained as follows [40].

$$K = \sqrt{\frac{\epsilon_{fs}}{\pi(\epsilon_{mp}d_{to\ BS}^4 - E_{elect})}} L \cdot P \sqrt{N} \quad (5)$$

Here $d_{to\ BS}$ is the distance from cluster head to the base station, ϵ_{fs} is the parameter for free space model and ϵ_{mp} is the parameter for multipath model. It is assumed that BS is informed about the geographical positions of all sensor nodes. For clustering, BS uses K-means algorithm that is described in the next section.

3.3. Clustering by K -means Algorithm

The basic idea of k -means clustering algorithm is to classify a given set of data items into k number of disjoint clusters where the value of k is predefined. The k -means clustering algorithm uses iterative

refinement to produce a final result. The algorithm inputs are the number of clusters k and the data set. The data set is a collection of features for each data point. The algorithms starts with initial estimates for the k centroids, which can either be randomly generated or randomly selected from the data set [39].

For clustering, the sensing region is divided into k section where k is the optimum number of clusters. Then, in each section, a node is randomly chosen as cluster center by BS. BS assigns each node to the cluster with the nearest cluster head and then calculates the mean value of the cluster. Mean values of the clusters are considered new cluster centers and again clustering is done. This way is repeated until mean values of the clusters are fixed. The following flow chart (Fig.2) shows the Flowchart of K-means algorithm.

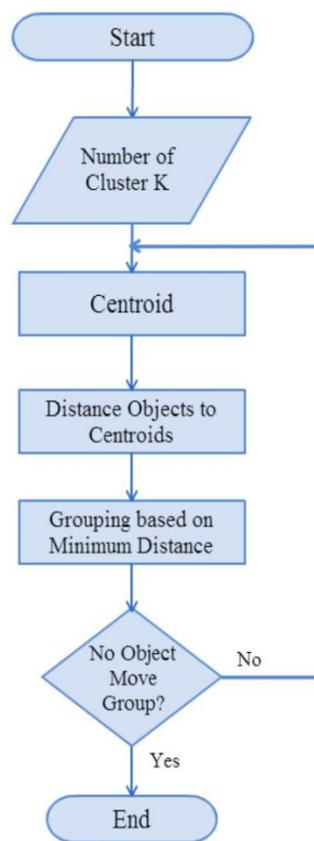


Fig. 2. Flowchart of k-means algorithm.

K -Means clustering intends to partition n objects into k clusters in which each object belongs to the cluster with the nearest mean. This method produces exactly k different clusters of greatest possible distinction. The best number of clusters k leading to the greatest separation (distance) is not known as a priority and must be computed from the data. The objective of K-Means clustering is to minimize total intra-cluster variance, or, the squared error function:

$$j = \sum_{j=1}^k \sum_{i=1}^n \|x_i^{(j)} - c_j\|^2 \quad (6)$$

example:

Suppose that. We cluster the set A into two groups by k-means algorithm.

Initial clusters (random centroid or average):

$$A = \{2, 4, 10, 12, 3, 20, 30, 11, 25\}$$

$$k = 2$$

$$c_1 = 3$$

$$c_2 = 4$$

Iteration 1:

$$k_1 = \{2, 3\} \quad k_2 = \{4, 10, 12, 20, 30, 11, 25\}$$

$$c_1 = 2.5 \quad c_2 = 16$$

Iteration2:

$$k_1 = \{2, 3, 4\} \quad k_2 = \{10, 12, 20, 30, 11, 25\}$$

$$c_1 = 3 \quad c_2 = 18$$

Iteration3:

$$k_1 = \{2, 3, 4, 10\} \quad k_2 = \{12, 20, 30, 11, 25\}$$

$$c_1 = 4.75 \quad c_2 = 19.6$$

Iteration4:

$$k_1 = \{2, 3, 4, 10, 11, 12\} \quad k_2 = \{20, 30, 25\}$$

$$c_1 = 7 \quad c_2 = 25$$

- i. Cluster the data into k groups where k is predefined.
- ii. Select k points at random as cluster centers.
- iii. Assign objects to their closest cluster center according to the Euclidean distance function.
- iv. Calculate the centroid or mean of all objects in each cluster.
- v. Repeat steps 2, 3 and 4 until the same points are assigned to each cluster in consecutive rounds.

3.4. Selecting Cluster Heads

The cluster heads are samples of the sensor node that have been elected among all sensor nodes in WSN. Once the sensor nodes are deployed to cover a specific geographical area, the process of cluster head choice for first round operation is initiated. The election process of sensor node as a cluster head is a dominant process. So in this section, a multi criteria decision-making approach is presented for the selection of cluster heads. This approach is used to select cluster heads based on criteria including residual energy, the

distance (the distance from the cluster and the distance from the base station), the number of neighbors (the one-step neighbor and the two-step neighbor), the centrality of the nodes and the number of times a node has been cluster head.

Table 1. Numerical values of preferences in paired comparisons.

Linguistic expression to determine preference	Numerical value
Full Preference	9
Pretty strong	7
Strong preference	5
Little preference	3
The same preference	1
Preference between intervals	2,4,6,8

3.4.1 Criteria of selection

- The distance from the base station: The more cluster head node is closer to the base station, the less the energy it uses to send the data packets. If the location coordinates of the node is (x_i, y_i) and the location coordinates of the base station is (x_j, y_j) , then the distance of node from the base station is equal to:

$$d = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (7)$$

- The distance from the cluster head: The closest node of cluster to the cluster head is the better candidate for cluster head. The distance of node from the cluster head is calculated similar to (7).
- The remaining energy of the node: Since the overhead of cluster head is larger than the other nodes, so the node should be selected as a cluster head that has enough energy, otherwise the nodes will be disconnected from the base station due to the node's death.
- The number of neighbors: If r denotes the radio radius of each node, then the single-step neighbors of a node is the set of nodes that are located at a distance less than r meters from the node.
- The number of two-step neighbors: The two-step neighbors of the node are defined as the set of nodes which are located at the distance less than $2r$ meters from the node.
- Centrality: The mean distance of cluster nodes from a desired node is considered as centrality of that node. In fact reduction of centrality of the cluster head causes the energy consumption for intra-cluster communication (between nodes and cluster head).
- If C is the set of cluster nodes, the centrality of the node x_0 is defined as follows:

$$\sum_{x_s \in C} \frac{|x_0 - x_s|}{|C|} \quad (8)$$

Where x_0 denotes the coordinate of the cluster node and x_s denotes the coordinate of the node within the cluster and $|C|$ is the number of nodes of C .

- Number of times a node has been selected as Cluster Head

3.4.2. Determining the paired comparison matrices

At this stage, the decision making matrix of the paired criteria is made. The ij^{th} entry of the decision-making matrix, in fact, is the ratio of the preference of i^{th} option to the j^{th} option. If the values are quantitative, it is sufficient to divide the values. If the

values are qualitative, Table 1 is utilized to convert qualitative values to quantitative ones.

After making decision matrix, the consistency or inconsistency of matrix should be checked. In the decision matrix, if the following equality is satisfied for all i, j, k ,

$$a_{ij} = a_{ik} \cdot a_{kj} \quad (9)$$

Then it is said that the matrix is consistent, otherwise is not.

3.4.3. Calculating weights of options and criteria

In the following, the assumption of inconsistency of decision matrix is used to calculate the weights of criteria which have a very decisive role in decision-making problems which is in the form of Table 2.

Table 2. The paired comparison matrix of criteria.

Criteria	Remaining energy	Distance	Number of neighbours	Centrality	Number of times a node has been selected as Cluster Head
Remaining energy	1	a	b	c	g
Distance	$1/a$	1	$1/d$	$1/f$	h
Number of neighbours	$1/b$	d	1	e	k
Centrality	$1/c$	f	$1/e$	1	l
Number of times a node has been selected as Cluster Head	$1/g$	$1/h$	$1/k$	$1/l$	1

So the decision matrix is as follows:

$$A = \begin{bmatrix} 1 & a & b & c & g \\ 1/a & 1 & 1/d & 1/f & h \\ 1/b & d & 1 & e & k \\ 1/c & f & 1/e & 1 & l \\ 1/g & 1/h & 1/k & 1/l & 1 \end{bmatrix}$$

The eigenvector method is used to calculate weights. Roots of the characteristic polynomial of matrix A which are the eigenvalues of the matrix are equal to solutions of equation $\det(kI - A) = 0$. Assuming that k_{max} is the largest eigenvalue of A , the eigenvector associated with it is obtained by solving the Equation (10) using the MATLAB software.

$$(k_{max} I - A)W = 0 \text{ where } \sum_{i=1}^5 w_i = 1 \quad (10)$$

Let corresponding eigenvector be $(w_e, w_d, w_n, w_c, w_t)$. So the weights of criteria are obtained as follows:

The weight of the remaining energy = w_e

The weight of distance = w_d

The weight of the neighbor numbers = w_n

The weight of the centrality = w_c

The weight of the number of times a node had been cluster head = w_t

For two criteria distance and the number of neighbors, below the paired comparison submatrices are made up.

Table 3. The paired comparison submatrices of distance.

Distance	Distance from the head cluster	Distance from the base station
Distance from the head cluster	1	r
Distance from the base station	$1/r$	1

Table 4. The paired comparison submatrices of neighbors.

The number of neighbors	One-step neighbors	Two-step neighbors
Two-step neighbours	1	s
Two-step neighbors	1/s	1

So the sub-matrices of the paired comparisons are as the following:

B_1 is the sub-matrix associated with the distance and

B_2 is the sub-matrix associated with the number of neighbors

$$B_1 = \begin{bmatrix} 1 & r \\ \frac{1}{r} & 1 \end{bmatrix} \quad B_2 = \begin{bmatrix} 1 & s \\ \frac{1}{s} & 1 \end{bmatrix}$$

Both matrices are compatible and the weights of each of the sub-criteria are as follows:

The weight of distance from cluster head = w_h

The weight of distance from base station = w_b

The weight of the number of single step neighbors = w_1

The weight of number of two-step neighbors = w_2

Now put:

$$E = \sum_{i=1}^m e_i \quad (11)$$

$$N = \sum_{i=1}^m n_i \quad (12)$$

$$M = \sum_{i=1}^m m_i \quad (13)$$

$$D = \sum_{i=1}^m \frac{1}{d_i} \quad (14)$$

$$D' = \sum_{i=1}^m \frac{1}{d'_i} \quad (15)$$

$$C = \sum_{i=1}^m c_i \quad (16)$$

$$T' = \sum_{i=1}^m \frac{1}{t_i} \quad (17)$$

Here

e_i : Remaining energy of i^{th} node

n_i : The number of one-step neighbors of i^{th} node in the cluster,

m_i : The number of two-step neighbors of i^{th} node in the cluster

d_i : The distance of i^{th} node from the cluster head

d'_i : The distance of i^{th} node from the base station

c_i : The average distance of i^{th} node from all nodes of the cluster

t_i : The number of number of times that i^{th} node has been selected as cluster head

For each node, calculate the following value, which is the final weight of the i^{th} node:

$$w_{\text{node}} = \frac{e_i}{E} w_e + \frac{1}{d_i D} w_d w_b + \frac{1}{d'_i D'} w_d w_h + \frac{n_i}{N} w_n w_1 + \frac{m_i}{M} w_n w_2 + \frac{c_i}{C} w_c + \frac{1}{t_i T} w_t \quad (18)$$

Finally, the node that has the biggest weight is selected as new cluster head.

Therefore, in the present paper, it has been tried to combine different criteria for choosing optimal cluster heads. Then it was tried to provide the possibility of changing cluster head role after each transmission. So that the consumption of cluster energy is distributed equally among all cluster members and so early death of cluster nodes is prevented. The base station chooses cluster heads based on the criteria such as number of single-step and two steps neighbors, remaining energy, the distance from the cluster head, the distance from the base station and centrality of each node. For this purpose, a target function has been proposed that should be calculated for all nodes of each cluster. The base station calculates the weight w_{node} for each node, a node that has the biggest weight is selected as new cluster head. Finally, the base station creates a packet which contains the geographic location of the nodes selected as cluster heads and then sends it to all nodes, so each node knows its cluster head.

4. SIMULATION ENVIRONMENT

The NS2 simulator is one of the most popular open source network simulators. For network research, NS is used as a discrete event simulator. The NS2 simulator is the second version of NS-Simulator, NS is essentially based on the network simulator called REAL. The original version of NS was designed in 1989 and has evolved in recent years and has continued to the third version. NS2's second version is widely used in academic research and has many packages that have been developed by people who have no financial benefit. Simulation on the Redhat Linux operating system using the NS2 network simulator was done.

Table 5. Simulation parameters used for WSNs.

Parameter	Value
Number of sensor nodes	100
Target area	100*100
Energy of sensor node	2_j
Base station location	100*100
Transmission Range	50m
Number of simulations	40
Bandwidth	150Hz
Packet length	400b
Distribution	Normal

Evaluation Criteria:

To evaluate the efficiency of the proposed method, four factors have been used. The first factor is the average of consumed energy, the second factor is the number of live nodes, the third factor is the mean of end-to end delay. The fourth factor is the mean of packet delivery success which refers to ratio of the

number of packets delivered (successfully) to the base station to the number of packets generated by the source node. The four factors are evaluated in three scenarios. Four mentioned criteria have been evaluated. To evaluate the performance, the proposed method is compared with the methods of E-LEACH and NEECP. Fig.3 shows the amount of energy consumption in each period. In this figure, the E-LEACH method, the NEECP method and the proposed method are compared, so that the energy of the E-LEACH method ends at 440s, and in the NEECP method, energy ends at 560s, but in the proposed method, energy ends at 760s. The proposed approach, compared to E-LEACH and NEECP protocols, performs better in terms of energy consumption.

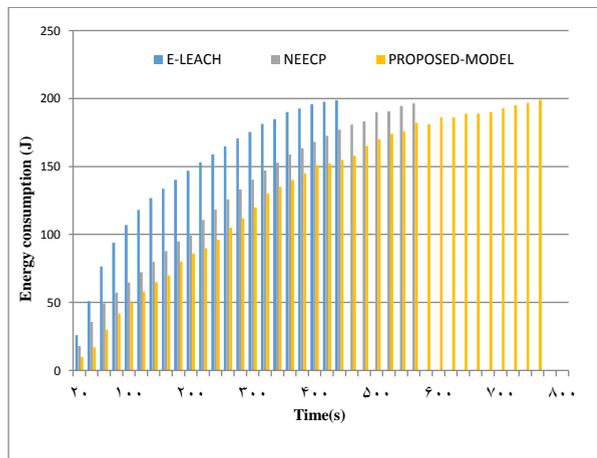


Fig. 3. Comparison of energy consumption.

In Fig.4, the lifetime of the network is compared in E-LEACH protocols, the NEECP and in the proposed method. In the E-LEACH method, in 240 seconds, nodes start to dying vigorously, and in 380 seconds they are almost energized and the network life ends, and in the NEECP method, in 560 seconds, only 8 nodes are alive. While in the proposed method, networks work with 32 live nodes in 560 seconds. The network lifetime of the proposed method is higher than the E-LEACH and NEECP methods. In the proposed method, the selection of the cluster head due to the greater remained energy causes lower energy nodes in packets not to participate and this is an important factor in increasing the lifetime of the network.

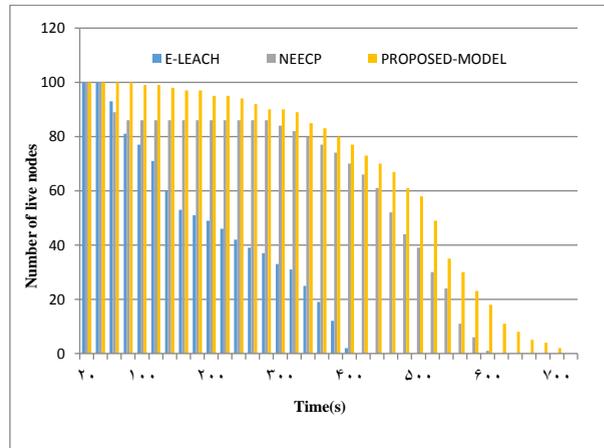


Fig. 4. The number of live nodes (network life span).

Fig.5 shows that the proposed method minimizes the minimum intermediate-to-end delay because the nodes close to the base station do not need to initially send the data to the cluster head and they can communicate directly with the base station. Therefore, the delay is reduced compared to the NEECP E-LEACH protocols.

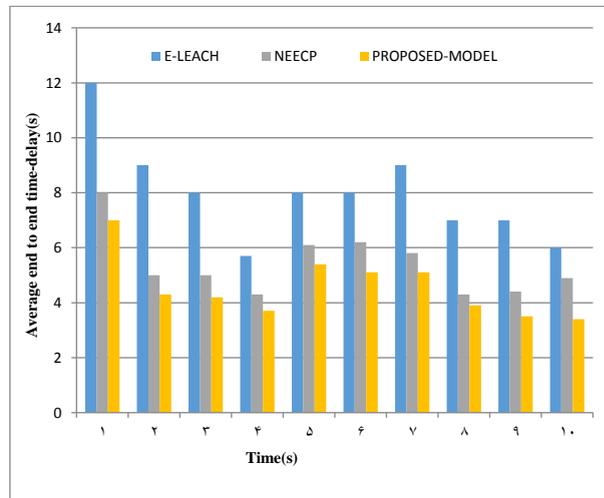


Fig. 5. The mean of end to end delay.

In this way, the base station sends a message to the cluster head by receiving 10 packets from a cluster head and the cluster head uses packets that are delivered to base station. It removes from its buffer and it resends the lost packages. In this way, the cluster nodes attempt to send missing packets. The proposed method uses better backup paths because it repossesses lost packets. As shown in Fig.6, the proposed method is better than the E-LEACH and NEECP methods in terms of packet delivery.

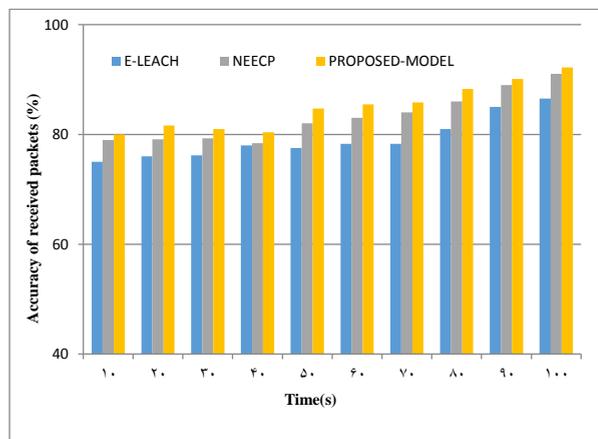


Fig. 6. Package delivery.

5. DISCUSSION AND RESULTS

In the most of articles, authors have considered residual energy or number of neighbors or combination of these factors as criteria for selecting cluster heads and showed that network lifetime significantly increased [14], [15], [23], [34]. But these methods have been overhead due to sending messages to all nodes. Among the methods that have been proposed for clustering in wireless sensor networks, multi criteria decision making method (MCDM) rarely has been used. However, MCDM models are capable of selecting the best options based on certain criteria. [35-38] considered node's residual energy, the distance from node to the base station and the distance between neighboring nodes as criteria for selecting cluster heads. By studying the papers published concerning energy efficiency in wireless sensor networks, it is found that the higher the number of criteria for selection of the cluster heads, the better the cluster heads are selected. For this approach, in this paper, it is presented a multi criteria decision-making approach for the selection of cluster heads. This approach is used to select cluster heads based on criteria including residual energy, the distance (the distance from the cluster head and the distance from the base station), the number of neighbors (the one-step neighbor and the two-step neighbor), the centrality of the nodes and the number of times a node has been cluster head.

The method was proposed for energy efficiency in order to increase the life span of wireless sensor networks. Based on the proposed method, the base station focuses on the remaining energy, the distance (distance from the cluster and the distance from the base station), the number of neighbors (the single-step neighbor and the two-step neighbor), the centrality for the network nodes and Number of times a node has been selected as cluster head. So the cluster heads are selected using AHP method. The proposed method has been compared with NEECP's E-LEACH methods in terms of energy consumption, life span, average delay

and delivery. The simulation results show that the proposed method increases the network lifetime by choosing optimal cluster heads. The proposed method balanced the energy consumption in all sensor nodes and avoids unbalanced energy consumption in a subset of nodes, which increases network lifetime. In the proposed method, the average packet delivery and average delay were also improved by choosing the optimal cluster heads in terms of the mentioned criteria.

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