

# Grid based Energy-Efficient Cross-Layer Optimization Model in WSN Using Dual Mobile Sinks

Vimala D (✉ [vimalamcs@gmail.com](mailto:vimalamcs@gmail.com))

Vellore Institute of Technology: VIT University

Manikandan K

Vellore Institute of Technology: VIT University

---

## Research Article

**Keywords:** Clustering, Routing, Mobile Sink, WSN, Lifetime

**Posted Date:** April 6th, 2021

**DOI:** <https://doi.org/10.21203/rs.3.rs-306247/v1>

**License:**  This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

---

# **Grid based Energy-Efficient Cross-Layer Optimization Model in WSN Using Dual Mobile Sinks**

**<sup>1</sup>Vimala D**

Research Scholar

School of Computer Science and Engineering (SCOPE)  
Vellore Institute of Technology, Vellore, Tamil Nadu, India.  
[vimalamcs@gmail.com](mailto:vimalamcs@gmail.com)

**<sup>2</sup>Manikandan K**

Associate Professor

School of Computer Science and Engineering (SCOPE)  
Vellore Institute of Technology, Vellore, Tamil Nadu, India.  
[kmanikandan@vit.ac.in](mailto:kmanikandan@vit.ac.in)

**Corresponding author email id : [vimalamcs@gmail.com](mailto:vimalamcs@gmail.com)**

## **Abstract**

In recent days, wireless sensor network (WSN) gained more attention among researchers as well as industries. It is composed with massive number of sensors which are independently organized cooperate with one another for collecting, processing and transmitting data to the base station (BS) or sink. Since sensors undergo random deployment in harsh environment, it is difficult or not even possible to replace the batteries. So, energy efficient clustering and routing techniques are preferable to reduce the dissipation of energy and improve the network lifetime. This paper introduces a new Grid based Energy-Efficient Cross-Layer Optimization Model in WSN Using Dual Mobile Sink (GEECLO). The proposed method involves three main processes namely grid partitioning, clustering and routing. Initially, the entire network is partitioned into different zones and then sub zones. Then, type II FL process gets executed to select the CHs and construct the clusters. Finally, dolphin swarm optimization algorithm (DSOA) based routing process takes place to select the optimal path for inter-cluster communication. A detailed simulation analysis takes place to ensure the betterment of the GEECLO algorithm. The obtained experimentation outcome depicted that the GEECLO model offers maximum energy efficiency and network lifetime.

**Keywords:** Clustering, Routing, Mobile Sink, WSN, Lifetime

## 1. Introduction

The rapid development in wireless communication and micro-electronic models enable a fast growth in tiny, minimum-cost, multi-operational sensors and so on. Some of the sensors are generally applied in target region by random monitoring of external features present in ecological factors like moisture, humidity, temperature, pressure etc. Then, the observed information is transmitted to data collector or sink under the application of cooperative model which is termed as multi-hop where the sink forwards the data to remote server in order to perform data examining process. On the other hand, a sensor has the potential of self-organizing the local collaboration which tends to build a Wireless Sensor Networks (WSN) [1]. Some of the most useful features of WSNs are fast deployment, maximum fault tolerance, self-organized, realistic data transfer and so on. This forms an adaptive environment to be fixed in an unmanned platform, specifically in armed forces or disaster monitoring. In addition, WSNs have been used in observing commercial product line, farming as well as wildlife analysis, healthcare, modern homes, and so on. [2,12].

In general, Sensors are recharged by using energy-filled batteries which is impossible to replace battery often due to massive number of sensors are expensive. To resolve the limitation, the sensors must be equipped with higher-constrained batteries. Unfortunately, if the battery attains its choke point then, it is complex to enhance the battery [3]. Thus, energy limitation issue in WSN is reported by obtaining energy effective protocols [4]. Also, WSN has the shortcoming of uneven energy of sensors. Every sensor is comprised with a monitoring limit in case of a node expiry, and then fade zones would arise, which results in decreased network performance. The mechanism of irregular energy in WSN is same as energy holes where it is caused due to “hot spots” issue. Generally, “hot spots” problems occur in WSN by static sink as well as permanent network topology. Some of the nodes in the sink are loaded with engaged data as it has to forward the data packages from external layer to sink which leads to drain out the energy in a rapid manner. As it is comprised with static sink as well as with fixed network topology, energy becomes more heterogeneous in further process. Here, the network lifespan is a significant

evaluation procedure to calculate the function of network which is generally described as the duration of first node expiry.

A major challenge in this work is to deal with problem of energy efficiency as well as energy maintenance where optimal solutions are attained. The clustering model reduces the power utilization of WSN by classifying the sensors as clusters on the basis of specified patterns. For every cluster, more than one cluster heads (CHs) has been selected and fed as relay nodes for the cluster members. Clustering helps to simplify the network topology architecture as well as eliminates the direct communication among sensors and sink. In addition, data fusion is applied in CHs for extracting the unnecessary information to reduce the overhead of CHs. Conventional routing protocols use clustering with Low-Energy Adaptive Clustering Algorithm (LEACH); but, the model is used to select the CH for unreasonable as well as more additional function has to be performed which is relied on LEACH protocol respectively.

Here, Sink mobility method is evolved which is assumed to be an effective model to solve the uneven energy constraint in WSN. For mobile sink-supported WSN, sink is adopted by smart robots; also it has the capability of freely moving over sensing field. There are few benefits which are emerged by establishing the sink mobility approach . Initially, “hot spots” issues could be reduced by motion of sink. Usually, area of sink is traffic hubs and if sink is in motion, then traffic hub is transferred. Subsequently, sensors act as “hot spots” for balanced application of energy. Secondly, overall power application is alleviated by minimizing the transmission distance from communication pairs by considering that sink mobility criteria is properly developed. Followed by, delay of network could be decreased and throughput of network is maximized by applying the sink mobility. Consequently, the network link has to be assured, especially at the case of disconnected sensors. Though it has mobile sink existence which has several measures, it meets various challenging issues [5]. Hence, position of mobile sink must be frequently broadcasted or detected by sensor networks that tend to improve the workload of network. In addition, sink mobility has to be developed more accurately to comply with local nodes for transmitting data.

Here, [6] presented a technique named Load Balanced Clustering and Dual Data Uploading (LBC-DDU). For LBC-DDU, the entire network is segmented to 3 layers: sensor layer, CH layer, and SenCar layer. Initially, SenCar is able to measure an optimal path and use the path to

collect data by applying single-hop transmission. Once the selected point has been visited, SenCar would come back to base station (BS) and prepare for the upcoming process. Hence, it is constrained with 2 antennas where it is capable of interchanging data using 2 CH at same time by consuming the Multi-User Multiple-Input and Multiple-Output (MU-MIMO) that reduces the delay as well as to improve the efficiency. [7] introduced a Tree-Cluster-Based Data-Gathering Algorithm (TCBDGA). In TCBDGA, the node weight is a measure of various aspects like remaining energy, number of neighbors as well as distance to BS. Every node selects the corresponding neighbor along with higher weight as parent node. Similarly, a tree-construction is applied and all trees are degraded to various sub-trees which are based on the depth and data traffic. Hence, the final outcome reveals that, it is optimal with respect to power application.

This paper introduces a new Grid based Energy-Efficient Cross-Layer Optimization Model in WSN Using Dual Mobile Sink (GEECLO) [8 -10]. The proposed method involves three main processes namely grid partitioning, clustering and routing. Initially, the entire network is partitioned into different zones and then sub zones. Then, type II FL process gets executed to select the CHs and construct the clusters [11]. Atlast, DSOA based routing process takes place to select the optimal path for inter-cluster communication. A detailed simulation analysis takes place to ensure the betterment of the GEECLO algorithm. The obtained experimentation outcome depicted that the GEECLO model offers maximum energy efficiency and network lifetime.

## **2. System model**

### **2.1. Network model**

A sensor is constrained with N number of sensor nodes that is deployed in a random manner in which has to be observed and some considerations are developed.

- Sensor nodes and BS are immobile
- Every nodes has same quantity of energy after node deployment
- All nodes are homogeneous
- The distance among nodes and BS could be estimated by Received Signal Strength Indicator (RSSI)
- Node death is due to exhaustion of energy

- Sensor nodes are capable of changing the power of transmission by applying power control based on its the distance to receiving node

## 2.2. Energy model

A simple first order radio method is used as energy model of network. The energy drained for transmission and reception of  $l$  bit packet across distance  $d$  is given in Eq. (1) and Eq. (2).

$$E_{TX}(l, d) = \begin{cases} l \times E_{elec} + l \times \varepsilon_{fs} \times d^2 & \text{if } d \leq d_0 \\ l \times E_{elec} + l \times \varepsilon_{mp} \times d^4 & \text{if } d > d_0 \end{cases} \quad (1)$$

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

where  $E_{elec}$  denotes dissipated energy in transmitter or receiver unit,  $d_0$  indicates threshold distance that is measured by  $A = \sqrt{\varepsilon_{fs}/\varepsilon_{mp}}$ . According to the transmission distance  $d$ , free space ( $\varepsilon_{fs}$ ) or multipath fading ( $\varepsilon_{mp}$ ) is employed in transmitter amplifier.

## 2.3. Mobility model

The mobility model defines the moving principle of the nodes in a network and estimates velocity, location, as well as node's acceleration of network region. The purpose of introducing mobility model is to examine the operation of routing protocol. Assume 2 two nodes as  $N_i$  and  $N_k$  that is placed in  $(u_i, v_i)$  and  $(u_k, v_k)$  so that  $S^i \in (u_i, v_i)$ ;  $S^k \in (u_k, v_k)$ . Thus,  $N_i$  and  $N_k$  migrate to a specific dimension using variable velocity by forming the angle  $\varphi_1$  and  $\varphi_2$ . Generally, nodes  $N_i$  and  $N_k$  occupy distance  $D_1$  and  $D_2$ , then, the nodes attain novel location  $(u_i^{new}, v_i^{new})$  and  $(u_k^{new}, v_k^{new})$ , correspondingly. Hence, Euclidean distance at primary duration for nodes that are placed at  $N_i (u_i, v_i)$  and  $N_k (u_k, v_k)$  which is provided in the following,

$$D_{(uv,0)} = \sqrt{|u_i - u_k|^2 + |v_i - v_k|^2} \quad (3)$$

Let nodes  $N_i$  and  $N_k$  is iterated by a velocity  $\vartheta_{N_i}$  as well as  $\vartheta_{N_k}$  that forms an angle  $\varphi_1$  as well as  $\varphi_2$  to enclose a distance  $D_1$  and  $D_2$  that is given as,

$$D_1 = \vartheta_{N_i} \times t \quad (4)$$

$$D_2 = \vartheta_{N_k} \times t \quad (5)$$

In time  $t$ , the node is transferred to a new position which is accomplished by node  $N_i$  that is given as follows,

$$u_i^{\text{new}} = u_i^{\text{old}} + \vartheta_{N_i} \times t \times \cos \varphi \quad (6)$$

$$v_i^{\text{new}} = v_i^{\text{old}} + \vartheta_{N_i} \times t \times \cos \varphi \quad (7)$$

If  $N_k (u_k, v_k)$  is moved at  $D_2$  by creating an angle  $\varphi_2$ , it concentrates on new position which is depicted as,

$$u_k^{\text{new}} = u_k^{\text{old}} + \vartheta_{N_k} \times t \times \cos \varphi \quad (8)$$

$$v_k^{\text{new}} = v_k^{\text{old}} + \vartheta_{N_k} \times t \times \cos \varphi \quad (9)$$

If nodes attain a novel position, then the distance from nodes  $N_i$  and  $N_k$  are formulated as,

$$D_{(u^{\text{new}}, v^{\text{new}}, t)} = \sqrt{|u_i^{\text{new}} - u_k^{\text{new}}|^2 + |v_i^{\text{new}} - v_k^{\text{new}}|^2} \quad (10)$$

### 3. The proposed GEECLO model

The proposed GEECLO model incorporates different sub processes namely grid partitioning, clustering and routing. Initially, the entire network is partitioned into different zones and sub zones. Then, type II FL process gets executed to select the CHs and construct the clusters. Finally, DSOA based routing process takes place to select the optimal path for inter-cluster communication.

#### 3.1. Grid partitioning

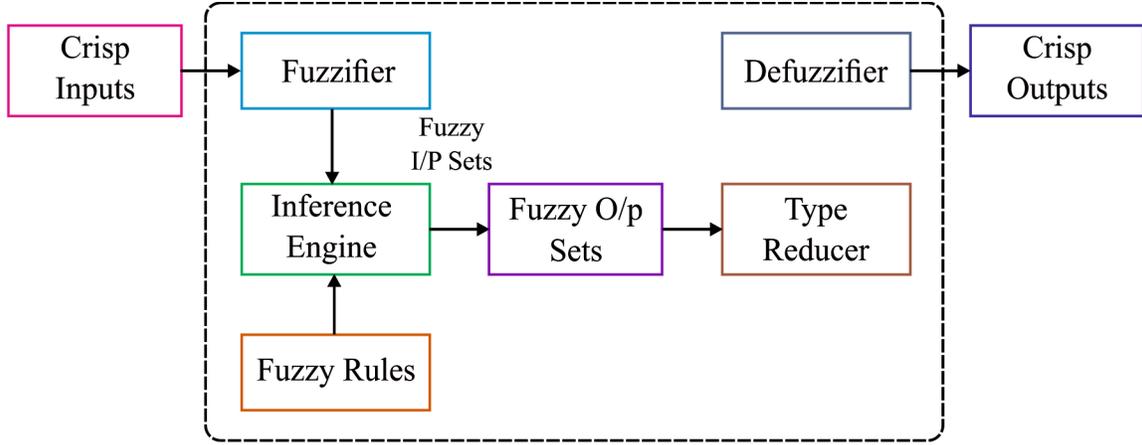
Consider a network area of  $1000 \times 1000 \text{m}^2$  which undergo the deployment of sensor nodes in a random manner. Then, the network area is partitioned into different zones of  $200 \times 200 \text{m}^2$ . Afterwards, clustering process takes place at every zone. The cluster process will construct different clusters or sub-zones under every zone and separate CHs will be elected in each subzone.

#### 3.2. Type II FL based clustering process

After the zones are constructed, clustering process is carried out at every zone and a number of clusters are organized along with CHs selection mechanism. A set of three parameters namely residual energy, distance to BS and node mobility are used to elect the probability of becoming CHs. A node with maximum residual energy, minimum distance to BS and low mobility has the higher chance of becoming CHs.

The T2FL generates an optimal computation and performs far better than T1FL method. Some of the inference methods as well as fuzzy system applied to presented technique as provided Fig. 1. There are 3 fuzzy input parameters which are adopted to choose the tentative CH. The three input variables are constrained with 3 Membership Functions (MF) individually. Here, fuzzy set denotes 3 input attributes like residual battery, distance to BS, as well as mobility. There are few linguistic variables in fuzzy set i.e., minimum, moderate and maximum. A triangular MF is adopted the three linguistic features. Then, third fuzzy input variable is that concentration, which refers to count the available sensors in specified position. Followed by, linguistic parameters for concentration are assumed to lower, medium and higher.

**1) Rule Base and Inference Engine:** This system is comprised with 27 rules in Fuzzy Inference model. The rules might be as, if X, Y, Z then C. Here X denotes residual battery power, Y implies distance to BS, Z signifies node mobility and C indicates probability of become CG. Hence, simulation outcome of CF is constrained with seven MF such as Very poor, Poor, Below Average, Average, Above Average, Strong, and Very Strong. Then, CH is measured by assuming 3 input variables like retaining battery power, distance to BS, as well as node mobility under the application of Mamdani's Fuzzy rule. The T1FL method is comprised with 4 levels: a fuzzifier, fuzzy inference engine, fuzzy rules and a defuzzifier. It is mainly applied to manage the uncertainty level to a partial distance, but not for the entire set of Type - 1 fuzzy sets as it is definite one. Besides, Type - 2 Fuzzy Logic (T2FL) technique is applicable in complex environment where an accurate numeric MF has to be attained. The purpose of using T2FL in WSN is to select an effective CH which helps to distribute the overhead over sensor networks. In T2FL is simplified with the help of superior MF as well as inferior MF. The block diagram of Fuzzy Inference System is illustrated in Fig. 1.



**Fig. 1.** T2FL process

The above functions might be denoted as Type - 1 fuzzy set MF. Thus, the time period among 2 functions indicates Footprint of Uncertainty (FOU) that is applied for characterization of T2FL set. Assume FOU is implied as  $f$ , when  $f \in [0, 1]$ , and  $f \rightarrow 0$ , then MF is named as T1FL whereas  $f \rightarrow 0$  to 1, then T2FL has a wider range of FOU which is from 0 to 1. However, the rule formation is similar to T1FL. It is represented as:

$$Type2FL = PrincipalMF(Type1FL) + FOU \quad (11)$$

T2FL method has 4 elements as given below:

- 1) **Fuzzifier:** Converts inputs values to fuzzy values.
- 2) **Fuzzification Module:** Inference engine integrates rules and provides a mapping of input type-2 fuzzy sets to output type-2.
- 3) **Defuzzifier:** The type-reducer produces a T1FL result which is translated to numeric outcome by implementing the defuzzifier.
- 4) **Knowledge base:** Consist a group of fuzzy rules, and a MF set is termed as data base.

Hence, the rules are obtained from a formula that is shown in Eq. (12).

$$C = \sum_0^5 RBP + \sum_0^5 DistancetoBS + \sum_0^5 Mobility \quad (12)$$

### 3.3. DSOA based routing process

Once the CHs were chosen and clusters are effectively constructed, the CM starts to sense the environment and transmits the data to its respective CHs. Then, it is necessitating forwarding the data to sink by the optimal path. At this point, effective routing mechanism plays a vital role which offers a set of optimal paths between two nodes. The dolphin technique is emerged from the extension of dolphin population's hunting model. In this method, dolphins achieve predation by using 4 significant levels, namely as given below:

- Searching stage
- Call stage
- Receiving phase
- Predation stage

Thus, the related searching links has been developed by applying the nature of 4 combined levels where the optimal solution is attained by frequent processing.

#### 3.3.1. Initialization

In an optimization problem, every dolphin denotes a possible solution. Dolphin in this work is described as  $Dol_i = [x_1, x_2, \dots, x_D]^T (i = 1, 2, \dots, D)$ , like, a viable D-dimensional solution, where  $N$  represent the count of dolphins and  $x_j (j = 1, 2, \dots, D)$  indicate the unit of all dimensions must be optimal. Therefore, unique solution (implied as  $L$ ) as well as neighborhood optimal solution (represented as  $K$ ) are 2 parameters correlated with dolphin. For every  $Dol_i (i = 1, 2, \dots, N)$ , it has 2 adjacent variables  $L_i (i = 1, 2, \dots, N)$ , and  $K_i (i = 1, 2, \dots, N)$ , where  $L_i$  is best solution from which  $Dol_i$  identifies in individual duration and  $K_i$  resembles better solution of  $Dol_i$  component obtained by itself or others. Fitness  $E$  is assumed to be the fundamental unit to predict the optimal solution. In DSOA,  $E$  is estimated using fitness function where the adjacent one is zero, which shows a better process. There are 3 kinds of distances which is applied in throughout the network. Initial phase is the distance from  $Dol_i$  and  $l_j$ , termed as  $DD_{i,j}$ , and  $DD_{i,j} = \|Dol_i - Dol_j\|, i, j = 1, 2, \dots, N, i \neq j$ . Alternatively, distance among  $Dol_i$  and  $K_i$ , called as  $DK_i$ , and  $DK_j = \|Dol_i - K_i\|, i = 1, 2, \dots, N$ . Followed by, the distance between  $L_i$  and  $K_i$ , known as  $DKL_i$ , and  $DKL_j = \|L_i - K_i\|, i = 1, 2, \dots, N$ .

### 3.3.2. Pivotal stages

**Search stage.** In search stage, all dolphins undergo searching for neighborhood by applying a sound wave. Here, sound is described as  $V_i = [v_1, v_2, \dots, v_D]^T (i = 1, 2, \dots, M)$ , where  $M$  signify the count of sounds as well as  $V_j = (j = 1, 2, \dots, D)$  is the element for every direction, like direction variable of sound. Additionally, sound convinces the  $\|V_i\| = \text{speed} (i = 1, 2, \dots, M)$  feature, where speed represents the speed variable of sound respectively. The major searching duration is  $T_1$ . With limited search time  $T_1$ , sound  $V_j$  which  $Dol_i (i = 1, 2, \dots, N)$  is formed in time  $t$  would search novel solution  $X_{ijt}$  that is given as:

$$X_{ijt} = Dol_i + V_j t \quad (13)$$

To gain an effective solution  $X_{ijt}$  for  $Dol_i$ , the fitness  $E_{ijt}$  is:  $E_{ijt} = \text{Fitness}(X_{ijt})$ . The unique optimal solution  $L_i$  of  $Dol_i$  is computed as  $L_i = X_{iab}$ . While  $\text{Fitness}(L_i) < \text{Fitness}(K_i)$ ,  $K_i$  is substituted by  $L_i$ ; else,  $K_i$  remains unchanged.

**Call stage.** In call stage, all dolphins generate a sound which is a signal for provided for alternate dolphins regarding the search outcome along with identifying optimal solution.

**Reception stage.** Alternate dolphins make a comparison with the solution derived and gained solution, and selecting an optimized solution as  $K_i$ . In DSOA, interchanging mechanism, along with call stage as well as reception stage has been executed by an  $N \times N$  order matrix termed as transmission time matrix  $TS$ . From  $TS$ ,  $TS_{i,j}$  denotes the remaining voice from  $Dol_j$  to  $Dol_i$ . In  $K_i, K_j$  and  $TS_{i,j}$ , when  $\text{Fitness}(K_i) \ll \text{Fitness}(K_j)$  and  $TS_{i,j} > \left[ \frac{DD_{i,j}}{A \cdot \text{speed}} \right]$  the  $TS_{i,j} = \frac{DD_{i,j}}{A \cdot \text{speed}}$  where  $A$  implies constant acceleration which creates rapid sound. In this point,  $TS_{i,j}$  is renamed as major contact time  $T_2$ . If  $\text{Fitness}(K_i) > \text{Fitness}(K_j)$ ,  $K_i$  is substituted using  $K_j$ ; else,  $K_i$  does not change. The multi fitness function is relied on the aspects of energy, distance to BS and mobility.

#### ***Fitness based on energy***

The energy constraint has been determined by applying the Eq. (15). The overall energy of a cluster is the combination of residual energy in  $j$ th CH as well as power unique nodes. Hence,

the residual energy existed in nodes must be improved where the network functions are retained with prolonged lifespan of the network.

$$f_1 = \frac{1}{2} \left[ \frac{1}{m * n} \left( \sum_{j=1}^m \sum_{i=1}^n \varepsilon_{ji} \right) + \frac{1}{m} \sum_{j=1}^m \varepsilon_j \right] \quad (15)$$

where  $m$  and  $n$  implies total number of CH and nodes present in network,  $\varepsilon_{ji}$  signify the energy present in  $i$ th node from  $j$ th cluster whereas  $\varepsilon_j$  indicate the power of  $j$ th CH.

### ***Fitness based on Distance to BS***

Inter-cluster distance is defined as distance measured from CH and nodes present in the corresponding cluster which must be lower to obtain optimal network. Therefore, fitness applying the inter-cluster distance can be written as,

$$f_2 = \frac{1}{m * n} \left( \sum_{j=1}^m \sum_{\substack{i=1 \\ i \in j}}^n \left\| \frac{S_j, S_i}{\eta} \right\|^2 \right) \quad (16)$$

where  $S_j$  and  $S_i$  represent the position of  $j$ th CH and place of  $i$ th node.  $\left\| \frac{S_j, S_i}{\eta} \right\|^2$  shows the distance among position of  $j$ th CH as well as  $i$ th node in respective cluster. Thus, the variable  $\eta$  resembles normalizing factor.

### ***Fitness based on mobility***

Mobility of the  $j$ th cluster from past and present location is obtained to estimate the mobility of node which is measured by,

$$f_4 = \frac{1}{m} \sum_{j=1}^m \frac{\|S_j^t, S_j^{t-1}\|}{\eta} \quad (17)$$

### **Predation stage**

In predation stage, every dolphin requires to estimate surround radius  $R$  and compute distance from dolphin neighborhood optimal solution and location after predation stage which is relied on the predefined data. This process tends to obtain a novel position.

#### **4. Performance Validation**

A brief explanation of the performance evaluation of the presented GEECLO model is provided here. The presented model has been simulated using OMNET++ 4.6 tool. Consider a network area of  $1000 \times 1000 \text{m}^2$  which undergo the deployed of sensor nodes in a random manner. Then, the network area is partitioned into different zones of  $200 \times 200 \text{m}^2$ . Afterwards, clustering process takes place at every zone. The cluster process will construct different clusters or sub-zones under every zone and separate CHs will be elected in each subzone. The results are analyzed in terms of energy utilization, network lifetime, throughput, delay and number of survival nodes under varying hop count and varying number of rounds.

##### **4.1. Energy Consumption Analysis**

Fig. 2 portrayed the total amount of energy consumed by the nodes under varying hop count. The technique which results in minimum energy consumption of the network can be considered as an effective technique. The figure apparently indicated that the GEECLO model is found to be energy efficient and shows least energy consumption over other methods. It is found that the LEACH protocol consumes maximum amount of energy compared to other methods. It is because of the probabilistic nature of CH selection and its ineffectiveness to select the CHs in an effective way. At the same time, it is observed that the TEEN protocol reports slightly better energy consumption over LEACH due to the reactive nature of data transmission. However, it also fails to shows better energy efficiency over the other methods due to improper CH selection. Followed by, the FUCHAR method offers slightly better lower energy dissipation over other methods. But, it is revealed that it does not outperform the two methods namely GEECLO and ECDRA methods. At the same time, it is apparent that the ECDRA method exhibits energy efficient characteristic over the other methods except GEECLO. The presented GEECLO is found to be highly energy efficient and consumes only limited amount of energy due to the proper election of CHs and optimal route selection.

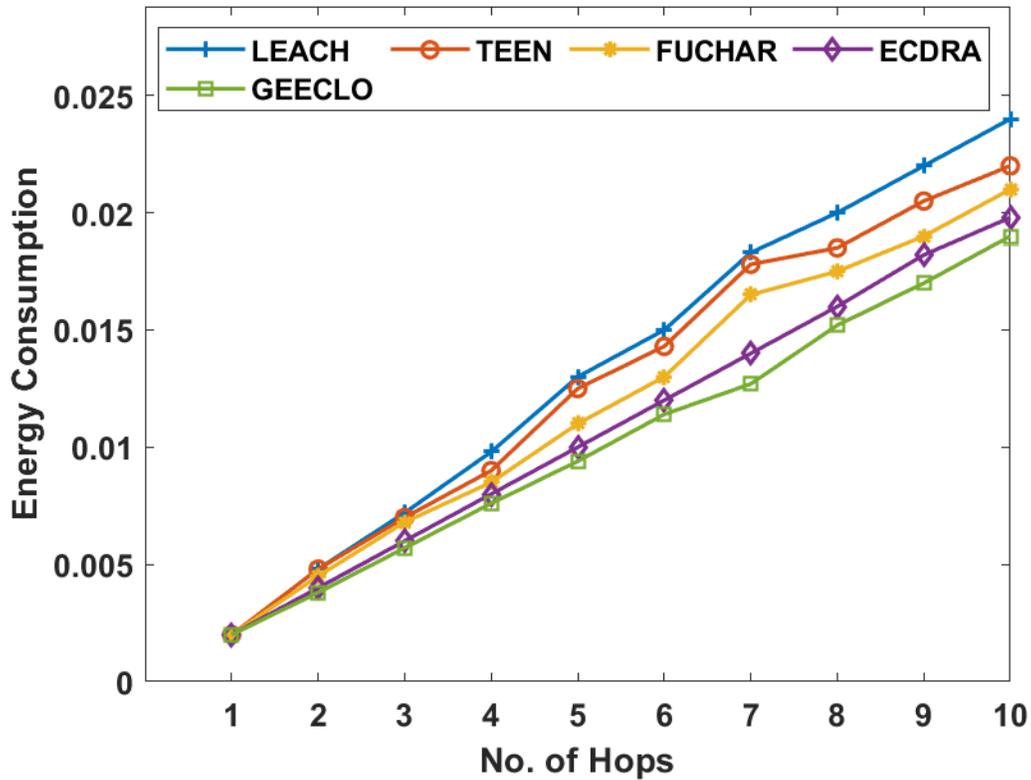
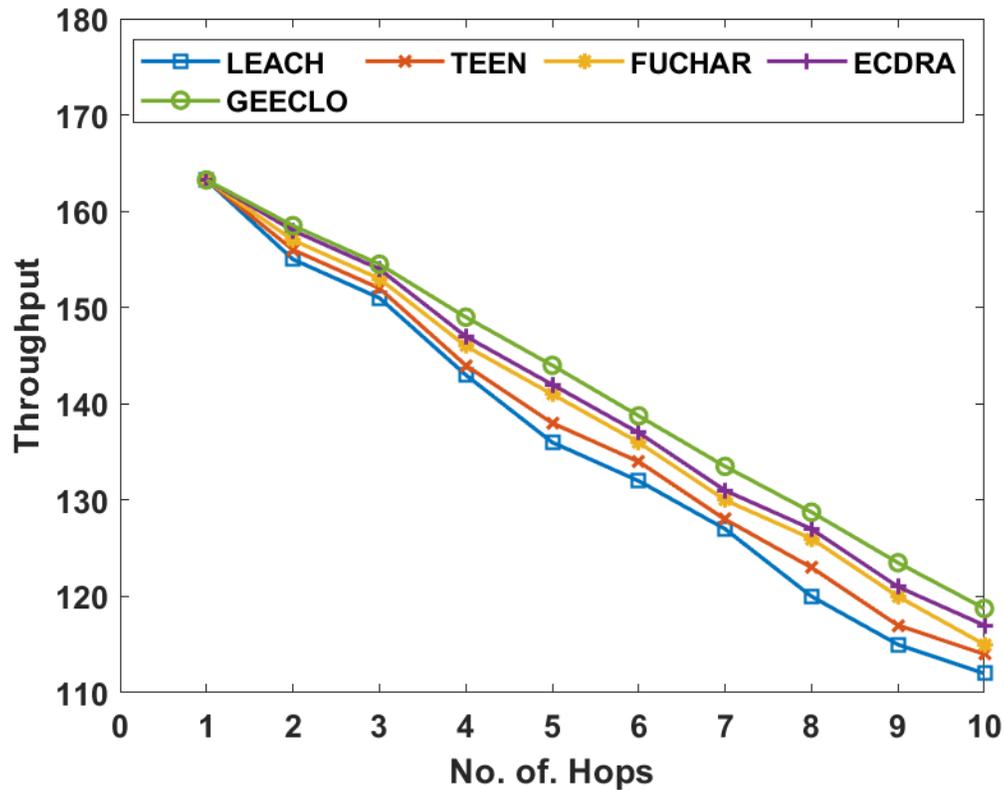


Fig. 2. Energy Consumption Analysis

#### 4.2. Throughput Analysis

Fig. 3 portrayed the throughput analysis of the presented and other methods under varying hop count. An effective cluster based routing model should exhibit maximum throughput. It is shown that the GEECLO model offers maximum throughput over the compared models. It is depicted that the LEACH model offers least throughput over the compared methods. But, the TEEN protocol outperforms LEACH by offering a higher throughput. But, it does not outperform the rest of the methods by offering maximum throughput. Next to that, it is depicted that the FUCHEAR model reported moderate and manageable throughput outcome. But, it is revealed that it does not outperform the two methods namely GEECLO and ECDRA methods. In the same way, it is evident that the ECDRA method provides high throughput over the compared models. Interestingly, the presented GEECLO exhibits maximum throughput under varying hop count in a significant way.



**Fig. 3.**Throughput Analysis

### 4.3. Delay Analysis

Fig. 4 portrayed the average delay incurred by the presented and other methods under varying hop count. The technique which necessitates minimum time delay can be considered as an effective technique. The figure actually represented that the GEECLO model requires minimum amount of time compared to other methods. It is shown that the LEACH protocol results in maximum delay compared to other methods. Next to that, it can be seen that the TEEN protocol reports slightly lower delay over LEACH. However, it also fails to shows better results over the other methods. Followed by, the FUCHAR method offers slightly lower delay over other methods. But, it is revealed that it does not outperform the two methods namely GEECLO and ECDRA methods. At the same time, it is apparent that the ECDRA method exhibits lower delay requirement over the other methods except GEECLO. The presented GEECLO requires least delay time over the compared methods in a significant way.

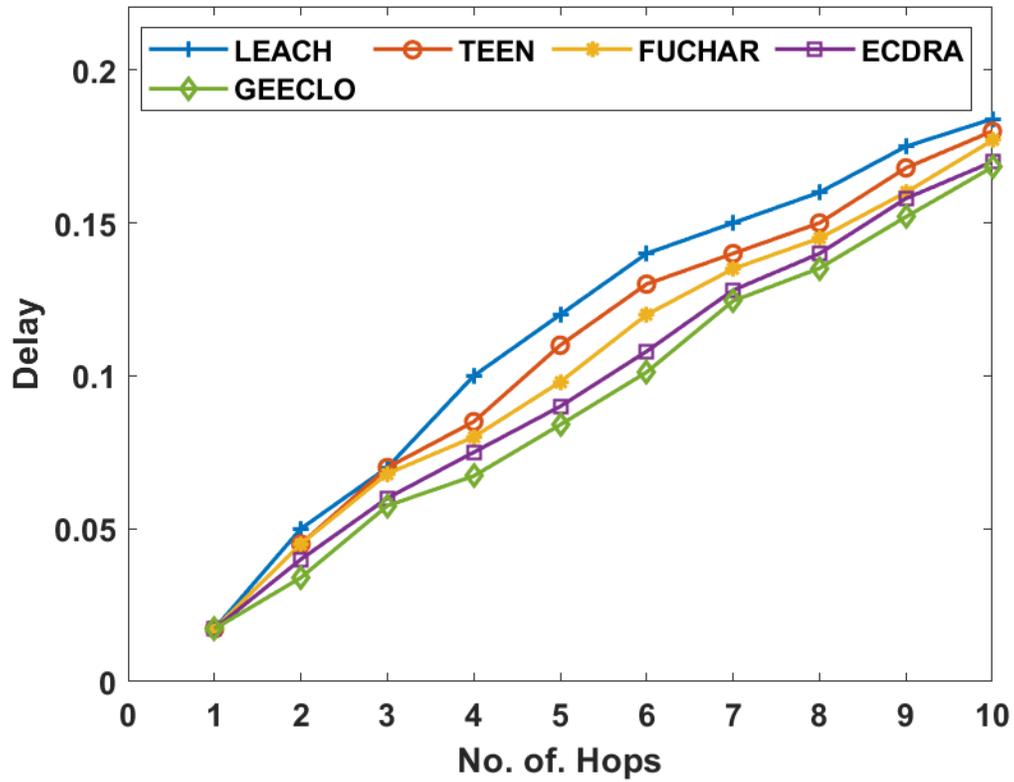


Fig. 4. Delay Analysis

#### 4.4. Network Lifetime Analysis

Fig. 5 represented the network lifetime analysis of the presented and other methods under varying node count. An effective cluster based routing model should exhibit maximum network lifetime. It is shown that the GEECLO model offers maximum network lifetime over the compared models and the lifetime gets increased with an increase in number of nodes. It is shown that the LEACH model offers least network lifetime over the compared methods. But, the TEEN protocol outperforms LEACH by offering a higher network lifetime. But, it does not outperform the rest of the methods. Next to that, it is depicted that the FUCHAR model reported moderate and manageable network lifetime outcome. But, it is revealed that it does not outperform the two methods namely GEECLO and ECDRA methods. In the same way, it is evident that the ECDRA method provides high network lifetime over the compared models. Interestingly, the presented GEECLO exhibits maximum network lifetime under varying hop count in a significant way. From the detailed experimental analysis, it is found that the presented

GEECLO is found to be highly energy efficient and consumes only limited amount of energy due to the proper election of CHs and optimal route selection.

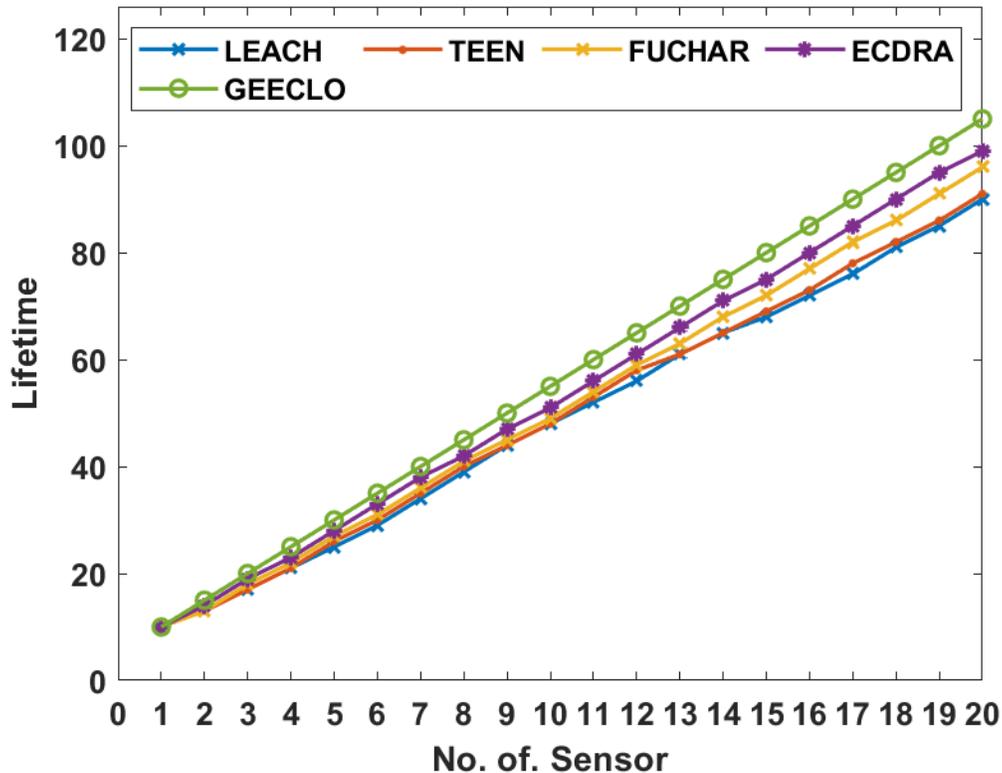


Fig. 5. Network lifetime analysis

## 5. Conclusion

This paper has introduced an energy efficient clustering and routing technique called GEECLO model to achieve energy efficiency and maximize network lifetime in WSN. The GEECLO model involves three major processes such as grid partitioning, clustering and routing. To begin with, the entire network is partitioned into different zones and then sub zones. Then, type II FL process gets executed to select the CHs and construct the clusters. Next, DSOA based routing process takes place to select the optimal path for inter-cluster communication. A detailed simulation analysis takes place to ensure the betterment of the GEECLO algorithm. From the detailed experimental analysis, it is found that the presented GEECLO is found to be highly energy efficient and consumes only limited amount of energy due to the proper election of CHs and optimal route selection. In future, the presented GEECLO model can be further improved by the use of hybrid data transmission schemes and predicting the effective position of mobile sinks.

## References

- [1] Akyildiz, I.F.; Su, W.; Sankarasubramaniam, Y.; Cayirci, E. Wireless sensor networks: A survey. *Comput. Netw.* 2002, 38, 393–422.
- [2] Chanak, P.; Indrajit Banerjee, I.; Wang, J.; Sherratt, R.S. Obstacle Avoidance Routing Scheme through Optimal Sink Movement for Home Monitoring and Mobile Robotic Consumer Devices. *IEEE Trans. Consum. Electron.* 2014, 60, 23–29.
- [3] Al-Karaki, J.N.; Kamal, A.E. Routing techniques in wireless sensor networks: A survey. *IEEE Wirel. Commun.* 2004, 11, 6–28.
- [4] Wang, J.; Gao, Y.; Yin, X.; Li, F.; Kim, H. An Enhanced PEGASIS Algorithm with Mobile Sink Support for Wireless Sensor Networks. *Wirel. Commun. Mob. Comput.* 2018, 2018, 9472075.
- [5] Khan, A.W.; Abdullah, A.H.; Anisi, M.H.; Bangash, J.I. A Comprehensive Study of Data Collection Schemes Using Mobile Sinks in Wireless Sensor Networks. *Sensors* 2014, 14, 2510–2548.
- [6] Zhao, M.; Yang, Y.; Wang, C. Mobile Data Gathering with Load Balanced Clustering and Dual Data Uploading in Wireless Sensor Networks. *IEEE Trans. Mob. Comput.* 2015, 14, 770–785.
- [7] Zhu, C.; Wu, S.; Han, G.; Shu, L.; Wu, H. A Tree-Cluster-Based Data-Gathering Algorithm for Industrial WSNs With a Mobile Sink. *IEEE Access.* 2015, 3, 381–396.
- [8] Basheer, Shakila; Mathew, Rincy Merlin; Ranjith, D; Sathish Kumar, M; Praveen Sundar, P. V; Balajee, J. M. An Analysis on Barrier Coverage in Wireless Sensor Networks, *Journal of Computational and Theoretical Nanoscience*, Volume 16, Numbers 5-6, May 2019, pp. 2599-2603(5).
- [9] Manikandan, K., and MA Saleem Durai. "Optimised layered approach on congestion control with efficient energy and QOS improvement for wireless network." *Elixir Comp. Sci. & Eng* (2013): 13227-132305.
- [10] Kumar, V. V. (2019). A Special Section on Intelligent Computational Techniques for Advanced Networking. *Journal of Computational and Theoretical Nanoscience*, vol. 16, issue 5, pp. 1828-1828, 16, 1828-1828.

- [11] Maithili, K., Vinothkumar, V., & Latha, P. (2018). Analyzing the security mechanisms to prevent unauthorized access in cloud and network security. *Journal of Computational and Theoretical Nanoscience*, 15(6-7), 2059-2063.
- [12] Karthikeyan, T., Sekaran, K., Ranjith, D., & Balajee, J. M. (2019). Personalized Content Extraction and Text Classification Using Effective Web Scraping Techniques. *International Journal of Web Portals (IJWP)*, 11(2), 41-52.

# Figures

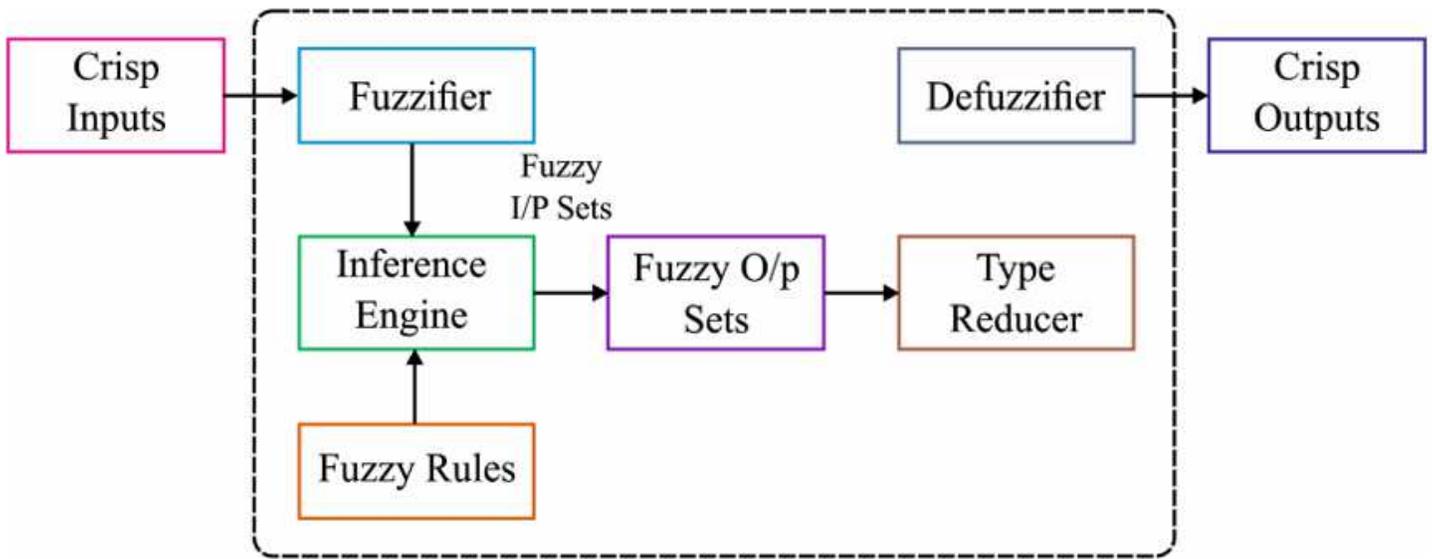


Figure 1

T2FL process

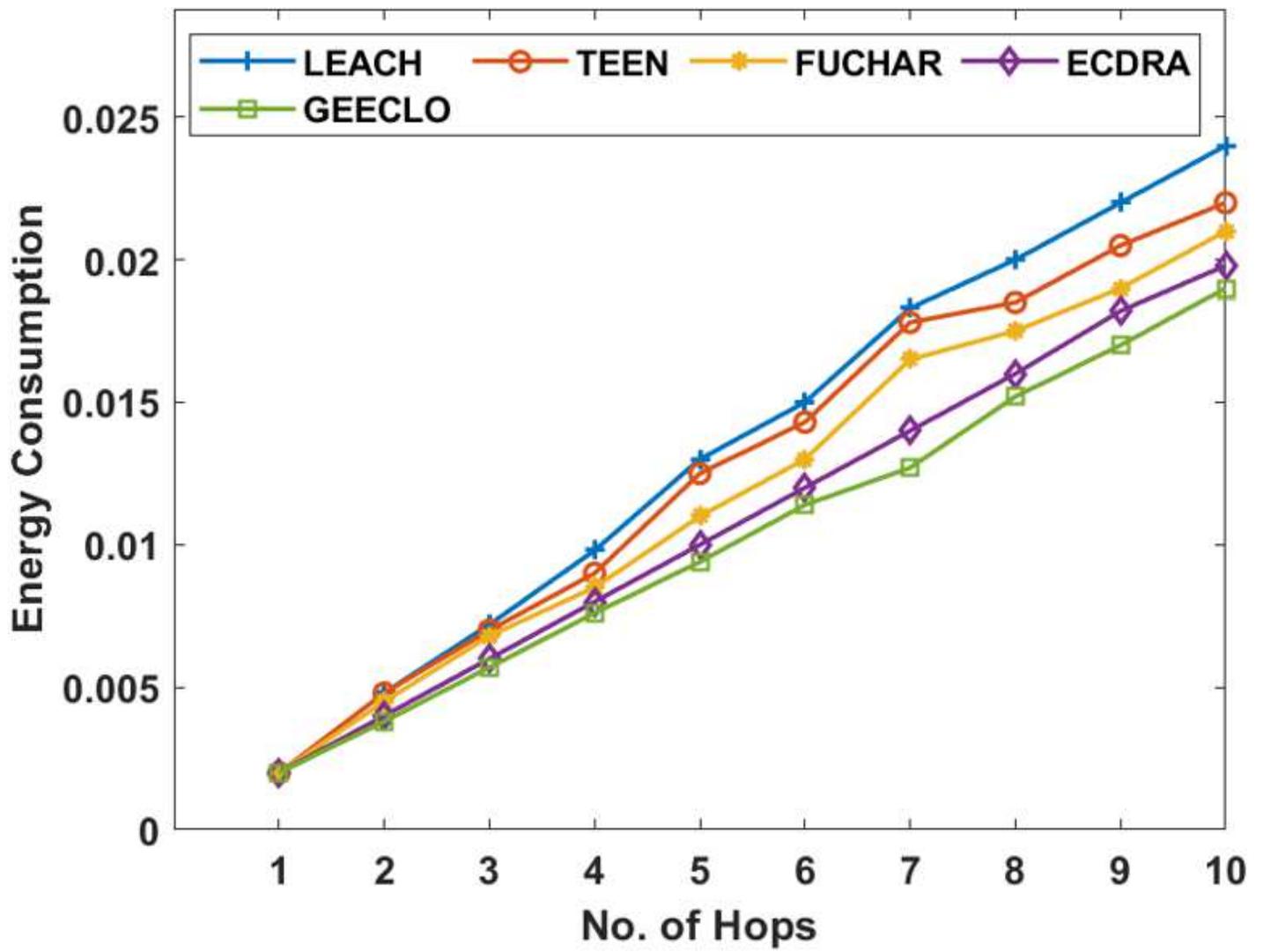


Figure 2

Energy Consumption Analysis

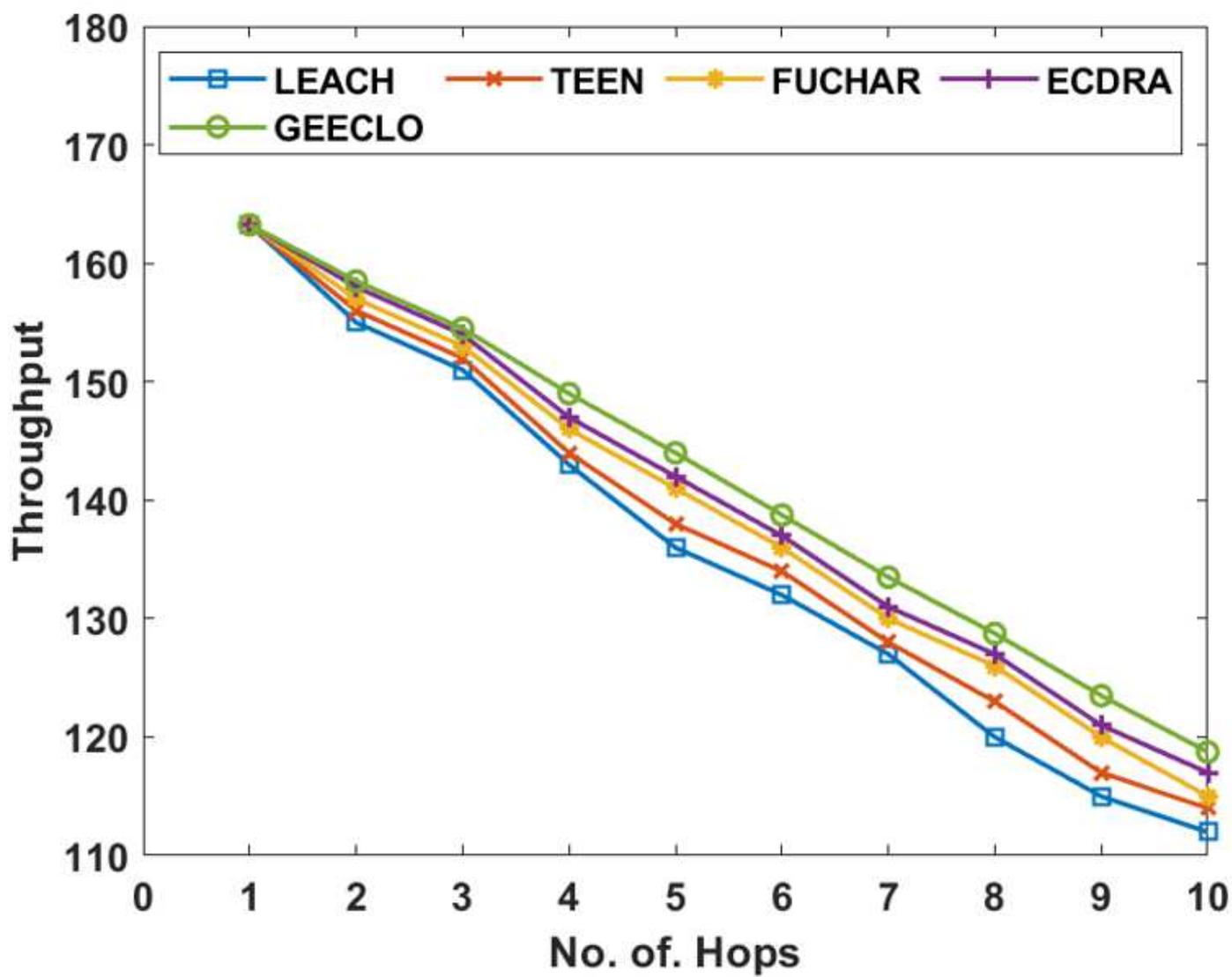


Figure 3

Throughput Analysis

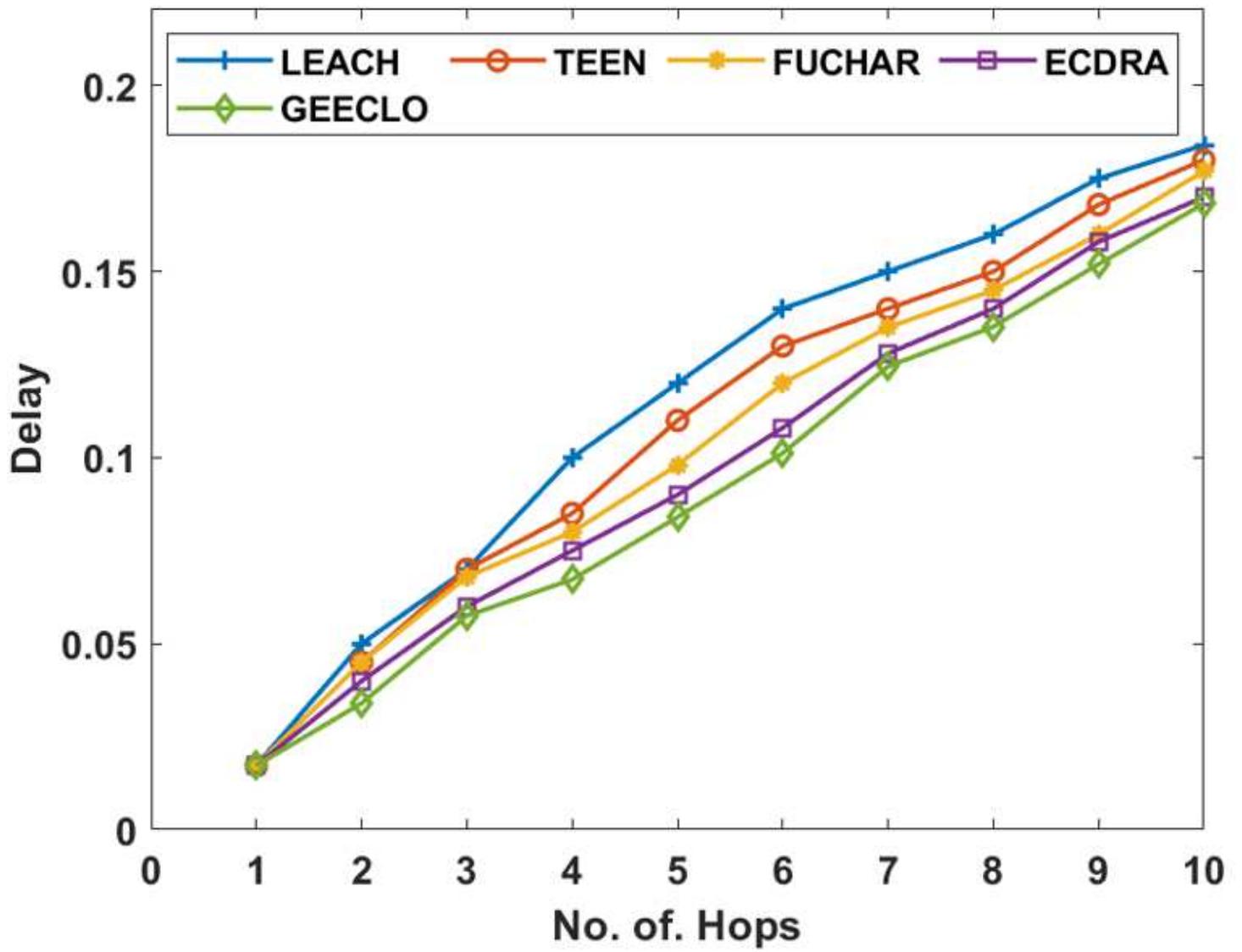


Figure 4

Delay Analysis

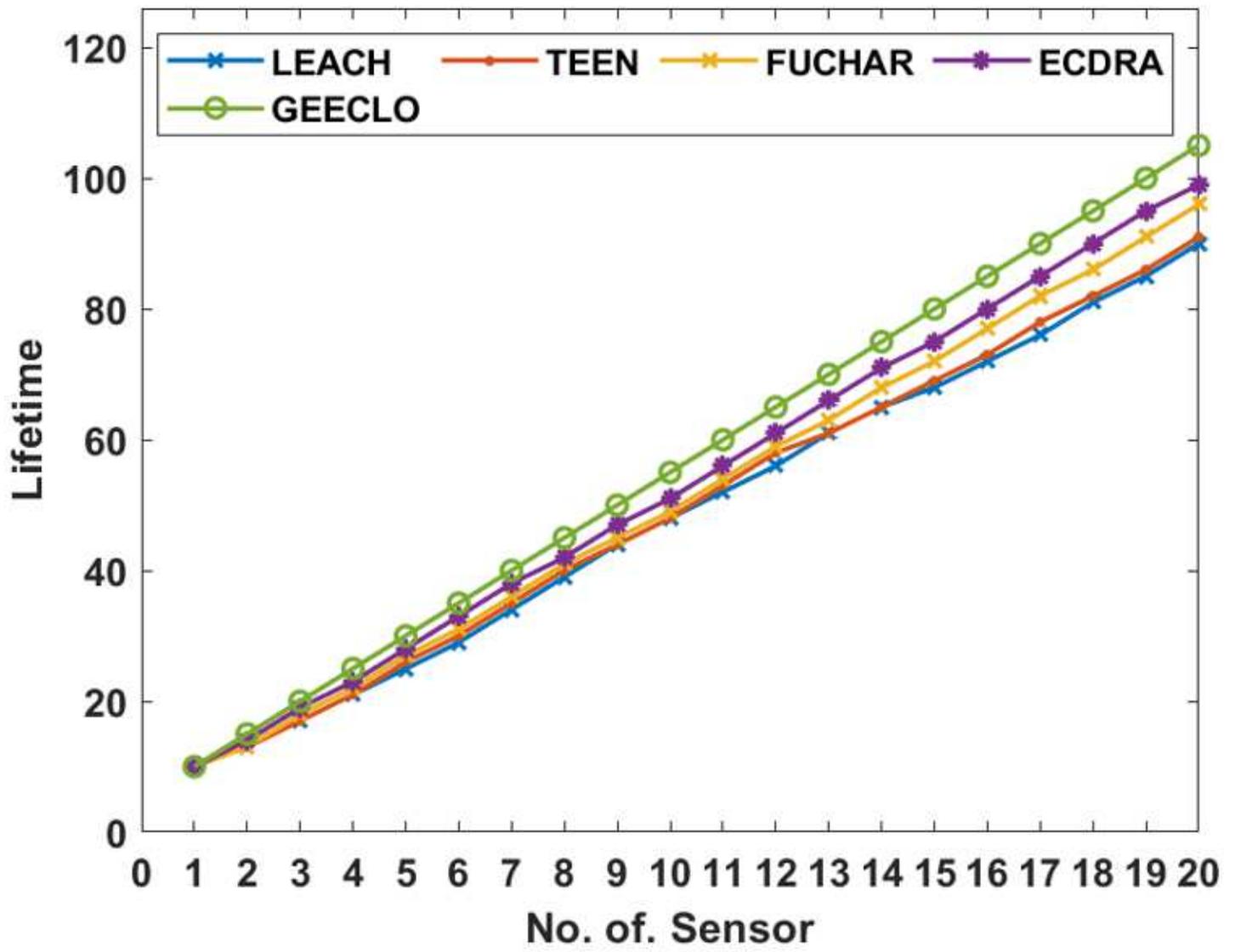


Figure 5

Network lifetime analysis