Energy Efficient Clustering Algorithm for Wireless Sensor Networks

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Received: 04/Jan/2020

Revised: 24/Apr/2020

Accepted: 08/May/2020

Abstract

In Wireless Sensor Networks (WSNs), sensor nodes are usually deployed with limited energy reserves in remote environments for a long period of time with less or no human intervention. It makes energy efficiency as a challenging issue both for the design and deployment of sensor networks. This paper presents a novel approach named Energy Efficient Clustering Algorithm (EECA) for Wireless Sensor Networks which is based on two phases clustering model and provides maximum network coverage in an energy efficient way. In this framework, an effective resource-aware load balancing approach applied for autonomous methods of configuring the parameters in accordance with the signaling patterns in which approximately the same bit rate data is provided for each sensor. This resource-efficient clustering model can also form energy balanced clusters which results in increasing network life time and ensuring better network coverage. Simulation results prove that EECA is better than LEACH, LEA2C and EECS with respect to network lifetime and at the same time achieving more network coverage. In addition to obtained an optimal cluster size with minimum energy loss, the proposed approach also suggests new and better way for selecting cluster heads to reduce energy consumption of the distributed nodes resulting in increased operational reliability of sensor networks.

Keywords: Wireless Sensor Networks; Energy-Efficient Clustering; Cluster Head Selection; Network Coverage; Network Life Time.

1- Introduction

With recent advancement in micro electro mechanical system (MEMS) technologies, low cost and low power micro electro nodes have become popular. WSN consists of tiny sensor nodes forming an ad hoc distributed data sensing and propagation network which collects the information from the surrounding environment. These networks combine wireless communication (i.e. transceiver) and minimal onboard computational facilities (i.e. processor or microcontroller) with sensing and monitoring. All these components together in a single device constitute a so called 'sensor node' or simply a 'sensor'. Wireless sensor networks lifetime mainly depends on battery, which are small and generally irreplaceable. Among all the task performed by Wireless Sensor Networks radio communication consumes most of the energy. It is therefore important to design proper

clustering algorithm, so that the inter cluster and intra cluster communication cost is minimum.

These networks are widely used in both the military and civilian applications such as target tracking, surveillance, and security management [1], [2]. With their capabilities for monitoring and control the network can provide a fine global picture of the target area through the integration of the data collected from many sensors each providing a coarse local view.

The main objective of sensor network is to collect data from monitoring environment and finally send it to base station via multi hop communication [3]. Based on network structure data routing protocols are divided into three structures [4]. Among them Hierarchical (cluster based) routing protocols are most energy efficient and widely used [5]. For e.g. say LEACH [6], LEACH-C [7], LEA2C [8], [9], EECS [10] and so on. In case of clustering those nodes which are geographically closer nodes form cluster. Each cluster we have a cluster head which acts as local base station. [6], [7] have proposed the LEACH protocol and a centralized version of this protocol, called LEACH-C. These protocols are based on clustering. Among various approaches available for energy efficient wireless sensor networks, the clustering approach in which data are gathered by one representative sensor of each group. It allows good scalability for the sensor network consisting of hundreds and thousands of nodes. Another advantage of clustering approach is balanced energy consumption among the nodes and thus increased network lifetime. The chain based approach tries to save the energy by forming a chain from the source to the sink, and so only one node will be transmitting data to the base station in any given transmission time frame. Here data fusion occurs at every node in the sensor network which allows all relevant information to permeate across the network.

In case of LEACH the job of cluster head is to collect data from their surrounding node and pass it to the base station. It is dynamic algorithm because the job of cluster head is rotated among the nodes but, this rotation is based on some probability for becoming a cluster head in each round [4]. LEACH-C, LEACH-N are modified version of LEACH but all of them failed to prevent the nodes from early energy dissipation of energy and hence leading to early end of network lifetime. The authors of [11] propose a protocol called Tree based clustering (TBC) here nodes in a cluster form a tree with cluster head as root. It effectively reduces and balances the energy consumption among the nodes. Compared with last dead node, improvement of TBC over LEACH is by 70%. However, the tree structure becomes complicated with number of rounds passing a more and more number of nodes get dying. The author of [12] has proposed a zone based hierarchical framework (ZBHF). Key feature in this scheme is to minimize the energy consumption during the self-organizing clustering scheme for energy efficient WSNs. Though the result obtained in this scheme is better than that of LEACH and LEACH-C but their network topology constraint them from being applied in a large scale network.

However, in case of LEA2C which based on two phase clustering, the lifetime of network improved remarkably around 50 percent [8, 9]. In case of LEA2C the cluster head was selected on the basis of maximum energy node. Our study on increasing network lifetime has seeded the idea for EECA from LEA2C.

In this paper we've done initial regrouping of clusters using K-means concept over multi criteria; energy and distance. This regrouping provides uniform energy distribution in all clusters. The difference of our proposed protocol with the previous clustering protocol lies in using multi criteria. We are able to adaptively cluster the nodes not only based on their topological closeness but also based on their energy levels by using K-means concept. We are able to reduce the computation time. Simulation results show that our new protocol can extend the network lifetime by 144% over

EECS and 62% over LEA2C, when the cluster head retained takes maximum energy criteria. Also random dying of the sensor nodes ensures more network coverage. Energy-performance trade-off for sensors processor operations is undergoing intense research considering the challenges with the evolving technology of wireless sensor computing. However, to guarantee energy-efficient processor operation, layout and architecture, it is necessary to identify and integrate optimization techniques and parameters influencing energy-performance trade-off in various energy efficiency domain. Existing literature on energy optimization in sensors focuses primarily on individual sub-domains such as offloading methods.

Our paper is organized as follows: first we present an energy consumption model in the WSNs. We have then given our proposed protocol followed by its explanation, where we have also described our proposed method K-Means_Initial, which by using multi criterion for clustering is helping us in building an energy efficient clustering model. Finally, we show through a series of experiments, some validation of our new algorithm and we present the future prospects.

2- Energy Consumption Model

Theoretically, our study is focused on power utilization of the wireless sensors nodes. But segregating the energy drained by it from the total energy drain is quite a difficult task given the association of network, and operating structure for sensor operations along with several other external factors influencing the network performance. Apparently, these factors have made this study very challenging task.

- Categorizing subcomponents of wireless sensor domain and defining their behavior w.r.t. the power consumption.
- Detecting uneven energy drains observed for a wide range of operations in WSN and identifying their root causes is quite a difficult task given the substantial amount of operations performed concurrently by the device.
- The energy minimization techniques applied varies with the varying functional and operation domains of the device processor. Assembling these techniques and finding application of common approach over varying domains is quite a challenging task.

Apparently, most of the current schemes focus on the subcomponents as a discrete entity. Due to these challenges, modeling a perfect optimal-energy system for wireless sensor networks turns out to be a challenging task. Energy optimization has become a crucial factor in wireless sensors as evolution of battery technology has failed to keep pace with evolution of computational sensor network technology. Moreover, the limitations imposed on

battery size intended to keep the device lightweight has made energy consumption by various software and hardware components a critical factor. Numerous energy models have been proposed so far depicting various factors playing crucial roles in WSN energy consumption. Eventually, the power consumed by sensor has been broadly described by as:

$$P_{Sensor} = P_{Display} + P_{Processor} + P_{Network}$$

where, P_{Sensor} is the overall node's power consumption, which is the sum of power drain by processor, network, and display components individually. These major consumers have been further classified into their specific functional areas consuming the device energy. The gravity of power issue for sensors can be seen through the exponential growth of the device processing capabilities along with the unwanted energy drains which go undetected for most of the times.

The communication consumes maximum energy than other tasks, in emission as well as in reception. Fig 1 shows an antenna model and the energy consumption rules associated [1].

To transmit a k bits message over a distance of d meters, the transmitter consumes:





$$E_{T_x}(k,d) = E_{T_x}(l) + E_{T_x_amp}(k,d)$$
(1)

And

$$E_{Tx}(k,d) = \begin{cases} k.E_{elec}(k,d) + k.\varepsilon.d^2 & \text{if } : d < d_{crossover} \\ E_{Tx}(k,d) = k.E_{elec}(k,d) + k.\varepsilon.d^4 \end{cases}$$
(2)

The energy consumption for receiving k bits of data is computed as:

 $E_{Rx}(k) = k \cdot E_{elec}$

(3) where:

- E elec : energy of electronic transmission/reception;
- \succ **k** : size of a message;
- d : distance between the transmitter and the receiver;
- \triangleright **<u>E</u>**_{Tx} : transmission energy,
- E Tx amp : amplification energy;

- **E** : amplification factor;
- **d** crossover : limit distance over which the transmission factors change of value.
- \triangleright **E**_{**R**x}: receiving energy

3- Proposed Protocol (EECA)

The EECA approach proposed here reduces the energy consumption of the network resulting in increased network life time. The residual energy of the node, distance, and the data overhead are taken into account for selection of cluster head in this proposed Energy Efficient Clustering Scheme (EECS). The waiting time of the mobile sink is estimated. The node having high residual energy and capable of transmitting a maximum number of packets is being chosen as CH. The transition from one state to other state is estimated using Markov model. The operation of the node and transition in Markov model are mainly based on the present state and not on the past history.



Fig. 2. The Architecture of Wireless Sensor Network



Fig. 3. Routing procedure in the energy efficient clustering algorithm

We first discuss here the system model starting from the assumptions, then after giving pseudo code for the proposed EECA algorithm, we have discussed each phase of the proposed routing scheme in detail:

3-1- Algorithm Assumptions

Our clustering algorithm is strongly related with LEA2C. The operations are divided into rounds as in LEA2C. Each round starts with a cluster setup phase, in which cluster organization takes place, which is followed by a data transmission phase. In data transmission phase data from ordinary nodes are transferred to the cluster head. Cluster head aggregate data and transmit it to the base station. In every cluster setup phase base station has to set appropriate role for each node in the cluster: we have here 0 for inactive normal node, 1 for active normal node and 2 for cluster head. We assume that there is no constraint about the energy for base station. Also base station has total knowledge about energy level and position of all the nodes of the network (most probably by the use of GPS receiver in each node). The sensor nodes are assumed to be homogenous i.e. they have same energy and communication as well as computation capabilities at algorithm start. List 1 below contains some of the term definitions used in our algorithm.

Definition:

1. aliveNodes: Number of nodes having energy more than threshold energy

- 2. element: Total number of sensor nodes initially
- 3. Olattice: It is an array of structure for cluster heads.
- 4. Centroid: Mean value of a cluster.

5. inputTemp: Array of structure of Input Nodes to hold normalized Input Nodes.

6. centroidTemp: Array of structure of Centroids to hold normalized value of Centroids.

7. m: Value for *m* is checked by Davies-Bouldin index, for *m* number of cluster heads.

8. I[N]: It is an array of structure of Input Nodes.

9. Number_of_centroids: Total number of centroids.

10. Number_of_ith_clusterElement: Total number of sensor nodes in i^{th} cluster.

11. Sumx: Variable to hold sum of x-coordinates of a cluster.

12. Sumy: Variable to hold sum of y-coordinates of a cluster.

13. x_of_newCentroid_of_ith_cluster: x coordinate value for newCentroid of ith cluster.

14. y_of_newCentroid_of_ith_cluster: y coordinate value for newCentroid of ith cluster.

15. x_of_oldCentroid_of_ith_cluster: y coordinate value for old Centroid of ith cluster.

16. newCentroid: Updated value of

Centroid. oldCentroid: Old Centroid value.

 $\label{eq:III} \textbf{17. I[N]}-\textbf{It represent array of structure of Input Nodes.}$

18. Role –Role is used to identify, normal node, cluster head node and inactive node.

19. I[i].c- Cluster Head Node or Normal Input Node. I[i].c=1 for cluster head node. I[i].c=0 for normal input nodes.

EECA Algorithm 1:

Set of Input: {Number of nodes, Deployment area, Round} Output : {Alive nodes after each round} Function Call: Algorithms 2,3,4, 5 and 6.

BEGIN:

- 1. Repeat steps 1.2 to 1.4 For round=1 to aliveNodes! =0 do
 - 1.2 If round= =1 then

CALL Algorithm 2; [Initialize node energy and distance coordinate]

CALL Algorithm 3; [Initial cluster formation]

CALL Algorithm 4; [Further optimization of the initial clusters]

Else

If aliveNodes! = element then: Put the nodeID value for those nodes whose energy is below threshold as zero;

End If

CALL Algorithm 2; [Select m most energetic nodes as cluster heads.]

Save the cluster heads obtained above in Olattice;

CALL Algorithm 3; [Form initial cluster based on maximum energy.]

CALL Algorithm 4; [Further optimization, with cluster head as maximum energy.]

End If

1.3 CALL Algorithm7; [Role to each node is provided.] 1.4 CALL Algorithm 8; [Number of aliveNodes are updated.] End For [Outer for Loop Ends. Signifying end of each round.]

END

Cluster Head Selection- Algorithm 2

Set of Input: {Array of structure of Input Nodes } Output: {m cluster heads}

BEGIN

If round = = 1 then: Initialize x, y with random values; Initial energy to every node= 0.5J; Value for m is checked by Davies-Bouldin index, for m number of cluster heads; Select random cluster head values for m cluster heads: Normalize input set and cluster head set by using Min-Max Normalization; Copy Normalized Input Nodes into inputTemp; Copy Normalized Cluster Head into

Else.

y coordinates;

centroidTemp;

Select m most energetic nodes as cluster heads. Update centroidTemp with new set of normalized cluster heads:

End If END

K-means_Initial (Initial cluster formation)- Algorithm 3:

Set of Input: {m cluster heads, Array of structure of Input Nodes, inputTemp, centroidTemp} Output : {m energy balanced initial clusters} BEGIN Repeat For i=0 to i < element doIf I[i]. nodeID! = 0 Then Find the Euclidian distance of this node of inputTemp nodes of centroidTemp taking both energy and x, with all

Get the nearest node with this node;

Form cluster with ith node belonging to its nearest node; If Ends For Ends

END

Cluster Optimization- Algorithm 4:

Set of Input: { *m* Initial energy balanced clusters } : {Optimized n clusters} Output

BEGIN

Initialize old Centroid by Olattice; Initialize newCentroid by zero; CALL Algorithm 5; [Recompute centroid] Return 0;

END

Recompute Centroid - Algorithm 5:

Set of Input: { Array of structure of Input Nodes, NewCentroid, Centroids} Output : {Set of new Clusters}

BEGIN

Recompute centroid: For i=0 to i< number of centroids do If Number of ith clusterElement >1 then do For j=0 to j< number_of_ith cluster Element Sumx do sumx+x_of_jth_element_of_ith Cluster: Sumy=sumy+y_of_jth_element_of_i th Cluster: End For x_of_newCentroid_of_ith_cluster=Su mx/ Number of ith clusterElement;

y_of_newCentroid_of_ith_cluster=Sumy / Number of ith clusterElement;

Else

x_of_newCentroid_of_ith_cluster x_of_oldCentroid_of_ith_cluster; y_of_newCentroid_of_ith_cluster= y_of_oldCentroid_of_ith_cluster ;

End If

End For

If newCentroid is same as oldCentroid then: Return 0; [Returning with new cluster set]

Else

CALL Algorithm 6; [Recompute Cluster] End If

END

Recompute Cluster- Algorithm 6:

Set of Input: {Set of new centroid, Array of Structure of Input Nodes}

Output : {New cluster set of the Network}

BEGIN:

Repeat For i=0 to i< element do If I[i]. nodeID! =0 then For j=0 to j< number_of Centroids do Compute eucledian distance between ith input node and jth centroid; End For Obtain the closest centroid to which this ith node belongs; End If End For CALL Algorithm 5; [Recompute centroid] END

Role Allocation by base station -Algorithm 7:

Set of Input: {Optimized n clusters} Output: { Each node with updated Role assigned by Base Station}

4- Cluster Setup and Installation

4-1- Cluster Setup Phase

The protocol uses a two phase clustering method. K-means initial followed by K-means algorithm.

In K-means initial clustering we are doing initial regrouping considering two different data, energy and coordinates. For this we have used min max normalization method [13] in which min_a and max_a are minimum and maximum values for any given attribute a, for e.g. in our case we have taken x coordinate, y coordinate and energy as attributes and have fitted each of these attributes in the range of (0,1) with the help of min max normalization. Min max normalization maps a value v in the range of (0,1) by simply computing:

$$V' = (v - \min_{v}) / (\max_{v} - \min_{v})$$
(4)

BEGIN

```
Repeat For i=0 to i< element
           do
  If ith node energy>threshold energy AND
  I[i].c==1 then:// For centroid
          ROLE
  =2; End If
   If ith node energy>threshold energy AND
   I[i].c==0 then://For cluster member
   ROLE
   =1:
   End If
   If ith node energy<threshold energy,
           then: ROLE=0:
   End If
   End For
          END
```

AliveNodes Updating-Algorithm 8

Set of Input: {n clusters with updated Role} Output : {Update Number of aliveNodes}

BEGIN

Update data for each node with ROLE=1; Aggregate data at the node with ROLE= 2; Send data to base station; Update energy of each node; If node energy < threshold energy, then: aliveNodes--; End If

Return aliveNodes;

Where *n* is the number of clusters, *ci* is the centroid of cluster *i*, δi is the average distance of all elements in cluster to centroid ci, and d (*ci*, *cj*) is the distance between centroids ci and *cj*. Since algorithms that produce clusters with low intra cluster distances and high inter cluster distances will have a low DB index, the clustering algorithm that produces a collection of clusters with the smallest DB index is considered the best algorithm based on this criterion

After every transmission phase we update energy of the network system by using equations 1, 2 and 3. Unlike previous algorithms in our proposed algorithm we reform cluster of the network and form new cluster heads with normalized data are then passed through K-means_Initial method for forming initial clusters. Value for k is checked by Davies-Bouldin index. Davies-Bouldin (DB) index actually compute the ratio of intra-clusters dispersion to inter-cluster distances by:

$$I_{db} = 1/n \sum_{i=1}^{n} \max((\delta_i + \delta_j)/d(C_i, C_{ij}))$$
(5)

4-2- Cluster Head Selection Phase

The cluster head is very important in cluster based WSN. They are responsible for data aggregation of each cluster member nodes and sending the same to the desired location. Cluster head is selected on different criterion. These are mainly based on maximum energy level or the nearest sensor to the base station. We have chosen the node as cluster head with maximum energy.

4-3- Data Transmission Phase

When clusters have been formed and cluster head has been selected, now it's time to send data packets sensed at normal nodes to their related cluster heads and after applying data aggregation function at cluster head, the same will be sent to base station. And after each round energy consumption is computed.

The criterion to be minimized in K-means is defined as:

$$\sum_{k=c}^{k=1} \sum_{x \quad Qk} \| (X - C_k) \|^2$$
(6)

Where Q_k is K^{th} cluster, C_k centroid of cluster Q_k . The K-means_Initial algorithm introduced here produces initial clusters with energy and distance both criterion. The cluster obtained here is further optimized by K-means algorithm. In eq. 6, Q_k is Kth cluster and C_k is the centroid of cluster Q_k .

Updated roles for each node. In the next section we have discussed the simulation and results of our proposed algorithm.

5- Simulation Results

The proposed algorithm is implemented using C programming language. We have also implemented LEA2C and EECS algorithm in order to compare our simulation results.

TABLE I. Parameters of si	mulation
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Sensor Deployment Area	100x100
Base Station Location	50x200
Number of Nodes	400
Data Packet Size	800 bits
Initial Energy	0.5 J
Stand by State Energy Los	0.00006 J
Energy per bit spent by transmitter Circuits	50 nJ/bit
Amplifier Energy	10 pJ/bit/m2

Table 1 shows the input sets provided to the algorithm EECA. The data provided here is containing same value as taken for LEA2C, for better comparison of results.



Fig 4. Initial random deployment of 400 nodes in 100x100 deployment area

Fig 4 shows initial random deployment of nodes in given area. We can see in the diagram that nodes are in the 100x100 area. Previous results were available under this area, for comparison purpose we have kept the area and number of nodes same.



Fig. 5. Alive nodes VS rounds in EECA, LEA2C and EECS

We can observe in figure 5 the lifetime of the network in case of EECS, LEA2C and EECA. Initially all the algorithms are provided with 400 nodes as input. All these three algorithms are compared under same unit of scale for better comparison. We can see clearly that when cost function for EECS is applied, life span of network is up to

950 rounds and first node is dying near 780 rounds. In case of LEA2C, because of maximum energy criterion for cluster head selection, first node death time increases remarkably compared to other conditions. The result of LEA2C can be observed clearly which is giving better result over EECS in terms of both first node death time, as well as total network life time. In this case first node is dying at around 800 rounds. Total life time of the network is about 1010 rounds.

In case of EECA the first node dies at 700 rounds and after that it decreases with rounds. Lifespan of the network is up to 2893 rounds as can be seen from figure 5. We can see that network lifetime in case of our proposed algorithm EECA has a remarkable improve over the other two algorithms LEA2C and EECS. In figure 5 we can see that node is first dying nearly close with LEA2C and EECS but the network lifespan taking maximum energy as criterion is remarkably noticeable.



Fig 6. Total Energy of the Network available during each round in EECA

In figure 6 we can see total energy of the network has been shown during each round. Total energy available is represented here with bold blue curve for 400 sensor nodes and the one in bold red is for only 100 sensor nodes. We can see from the figure 6 that energy loss during each round is very less. As each time in our algorithm we are taking the node as cluster head which has maximum energy, thus it prevents early exhausting of energy of any particular node. Initially for 400 nodes total energy of the network available is 200 J and 50 J for the curve of 100 nodes in figure 6, as 0.5 J of energy is the initial assumed energy. It can be seen clearly that it is only during the near to last round that there is a severe fall in network energy level.



Fig. 7. Average energy consumed per round

In figure 7 average energy consumption of the network in each round has been shown for network containing 400 nodes and 100 nodes. In the column bar graph shown in figure 7 one in red color is representing result for 400 nodes and the other bar in blue is for network having 100 nodes only. Energy consumption is represented in terms of joules. We can observe clearly that average energy consumed during each round is very low because of energy efficient clustering. Unlike previous algorithms like LEACH, EECS, etc. We are having two phase clustering. The K-means_Initial algorithm proposed in our algorithm creates an initial energy efficient cluster which is then further optimized by K-means algorithm. Thus the average energy consumed is very low, which certainly impact in life enhancement of the network lifetime. We can also observe from figure 7 that though the number of nodes is increased by 4 times in case of network having 400 nodes as compared to network having only 100 nodes, the average energy consumed per round is increased by 0.005 only, which is certainly very small change.

In comparison with the proposed Cluster-based Dynamic Routing Approach (CDRA), we have compared the performance of the proposed scheme with [14] which applied a long short term memory (LSTM) to detect the channel characteristics automatically.

In Figure 8, the performance of the proposed CDRA approach and LSTM have been compared from the perspective of total consumption energy for different number of connected subscribers. As it is obvious in this figure, the total consumed energy of LSTM is completely close to CDRA.



Fig. 8. Network energy consumption (mj) versus the Number of connected users (#)

Figure 9 demonstrates the effect of Number of resource block on the energy consumption. This result proves that we can decrease the consumed energy by increasing the number of resource blocks. It has been also exhibited that CDRA has better performance than other two cooperative distributed resource allocation approaches.



Fig. 9. Total energy consumption (mj) versus the Number of resource block (#)

The CDRA frameworks are able to dynamically choose the transmit power of all nodes according to their current channel conditions in every TS. Compared with other alternative approaches, our framework is able to provide better EE under different transmit power limitations, and are applicable in various moving speed conditions by adjusting the parameters of networks, which proves the effectiveness of our proposed frameworks as it is exhibited in the achieved results.

6- Conclusions

In this paper we tried to improve the total network lifetime using our proposed approach. Energy Efficient Clustering Algorithm (EECA), for wireless sensor networks. EECA ensures a positive benefit compared with EECS and LEA2C. The results obtained are very promising as compared with respect to network life time. We have obtained an optimal cluster size where the nodes send their data with minimum energy loss. Two phase clustering has been performed where initial clusters has been done using both criteria energy and distance. Initial balanced clusters thus obtained by Kenergy means_Initial algorithm has been further optimized by Kmeans clustering algorithm. Our maximum energy as criterion for cluster head selection has established better result when simulate as compared to other popular clustering algorithm. As future work we can improve results by working on initial energy efficient clustering by using certain optimizing algorithms like topological selforganizing map, which will produce a complete energybalanced cluster before passing it to second phase clustering. In our proposed algorithm we have done the initial energy efficient clustering by enhancing K-means

concept itself. Also the integration of other parameters in the clustering process, such as the moving speed of the sensors in case of mobiles sensors can also be considered for the future works.

References

- El-mawla, Nesma Abd, Mahmoud Badawy, and Hesham Arafat. "SECURITY AND KEY MANAGEMENT CHALLENGES OVER WSN (ASurvey)." International Journal of Computer Science & Engineering Survey (IJCSES) 10, no. 1 (2019): 15-34.
- [2] Mohajer, Amin, Maryam Bavaghar, Rashin Saboor, and Ali Payandeh. "Secure dominating set-based routing protocol in MANET: Using reputation." In 2013 10th International ISC Conference on Information Security and Cryptology (ISCISC), pp. 1-7. IEEE, 2013.
- [3] Singh, Omkar, and Vinay Rishiwal. "QoS Aware Multi-hop Multi-path Routing Approach in Wireless Sensor Networks." International Journal of Sensors Wireless Communications and Control 9, no. 1 (2019): 43-52.
- [4] Habib, Md Ahsan, and Mohammad S. Hasan. "A performance analysis of backbone structures for static sink based starfish routing in wsn." In 2017 4th International Conference on Networking, Systems and Security (NSysS), pp. 1-6. IEEE, 2017.
- [5] Ghosh, Indranil. "Study on hierarchical cluster-based energyefficient routing in wireless sensor networks." International Research Journal of Engineering and Technology (IRJET) 5 (2018): 688-691.
- [6] Mohajer, Amin, Morteza Barari, and Houman Zarrabi. "An Efficient Resource Allocation Mechanism including Loadaware Handover Decision."
- [7] Nam, Deok. "Comparison Studies of Hierarchical Cluster-Based Routing Protocols in Wireless Sensor Networks." Proceedings of 35th International Confer 69 (2020): 334-344.
- [8] Kaur, Khushpreet, and Er Lovepreet Kaur. "Energy Efficient Protocol On Wireless Sensor Network: A Review." International Journal of Scientific Research in Science, Engineering and Technology 3, no. 3 (2017): 40-46.
- [9] Shukla, Anurag, and Sarsij Tripathi. "An Effective Relay Node Selection Technique for Energy Efficient WSN-Assisted IoT." Wireless Personal Communications (2020): 1-31.
- [10] Ramesh, Dr V. "Energy-Efficient Clustering Scheme (EECS) With Secure Data Aggregation for Mobile Wireless Sensor Networks." International Journal of Electrical Electronics & Computer Science Engineering 4, no. 5 (2017).
- [11] Sohan, Radhika, Nitin Mittal, Urvinder Singh, and Balwinder Singh Sohi. "An Optimal Tree-Based Routing Protocol Using Particle Swarm Optimization." In Nature Inspired Computing, pp. 117-124. Springer, Singapore, 2018.
- [12] Swathi, N., S. Santosh Kumar, KN Sunil Kumar, and P. Rajendra Prasad. "Zone based hierarchical energy efficient clustering scheme for WSN." In 2016 IEEE International Conference on Recent Trends in Electronics, Information & Conference on Recent Trends in Electronics, Information

Communication Technology (RTEICT), pp. 136-140. IEEE, 2016.

- [13] Aksu, Gökhan, Cem Oktay Güzeller, and Mehmet Taha Eser. "The Effect of the Normalization Method Used in Different Sample Sizes on the Success of Artificial Neural Network Model." International Journal of Assessment Tools in Education 6, no. 2 (2019): 170-192.
- [14] Gui, Guan, Hongji Huang, Yiwei Song, and Hikmet Sari. "Deep learning for an effective nonorthogonal multiple access scheme." IEEE Transactions on Vehicular Technology 67, no. 9 (2018): 8440-8450.

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