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Energy And Load Balancing Platform Based Smart Routing Protocol For WSN

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ABSTRACT

The lifetime of a wireless sensor network is greatly influenced by three key factors: clustering nodes, determining routing patterns, and cluster maintenance. In order to enhance network load balancing and energy efficiency, a clustering routing protocol with fuzzy logic is presented in this study along with these three properties. By determining the best possible route, the routing algorithm is used to determine the optimal routing paths and to choose the best cluster heads (CHs). The algorithm converges swiftly thanks to fuzzy logic rules based primarily on a unique fitness function that takes load balancing and lowest energy usage into account together with new determination conditions. Additionally, an adaptive behavior that takes load balance and energy into account is offered to sustain the clusters and further minimize energy use. According to simulation results, the suggested strategy outperforms LEACH, PEGASIS, and Q Learning based routing in terms of longevity, load balancing, convergence speed, and energy efficiency.

INDEX TERMS : *Multi-hop routing **,**WSNs, energy & oad balancing CHs and clustering.*

I. INTRODUCTION

Because of the fast growth of information technology, WSNs are used widely in environmental monitoring, intelligent transportation, disaster avoidance, space exploration, and other applications. WSNs make use of several sensors that are linked together in hubs [1], [2]. Because WSN nodes have limited resources and energy, the most important issue has always been energy conservation, which enhances network lifetime. Clusters are formed by grouping nodes, and clustering leaders (CHs) are appointed for supervising the clustering. Clustering routing that saves energy has been[1] proved to be efficiency, reliability, and scalablity [2-5]. The fundamental WSN grouping guiding convention was low-energy flexible bunching ordered progression (Filter) [3]. It has various benefits, including less above from grouping and collection, an equivalent possibility turning into a CH by choosing CHs at irregular, less crashes thanks to the TDMA system, and a more drawn out network lifetime from pivoting CHs in adjusts. However, LEACH also has a lot of problems. These incorporate the arbitrary CH determination and fixed round time prompting an expansion in control message above, the inconsistent dispersion of groups, the determination of hubs with low remaining energy as CHs, and a lopsided energy utilization. Since then, tremendous efforts have been done to enhance LEACH's performance from many angles for clustered routing techniques, and the anticipated outcomes have been attained. [6]–[10]. The three primary stages of a clustering routing

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approach are typically clustering, routing, and cluster maintenance. Selection of CHs and construction of clusters are the typical steps in clustering. There are numerous ways available for choosing CHs; these can be divided into four categories: approaches based on probability [4]–[6], [11]–[14], approaches based on weight [7], [15]–[17], and approaches based on heuristics [9], [10], [18]–[20]. Nodes are identified as CHs in probability-based approaches if the values of threshold observed to be lower to random selection of integer as 0 or 1. Even yet, a number of nodes with lower standards of threshold picked as the head nodes, causing them to die prematurely. As a result, in weight-based approaches, only nodes with high weights are expressly chosen as CHs to solve the problem. However, choosing the optimal CHs may be difficult owing to local decision-making, network dynamics, and ignoring uncertainty. Furthermore, probability and weight-based approaches have not been demonstrated to be helpful in tackling the non-deterministic polynomial (NP) issues of hard decision for cluster formation [1]. For the purpose of choosing CHs, heuristic-based techniques are utilised to obtain approximations of solutions to NP-hard problems [21]. Heuristic algorithms, a type of significant optimisation method, can use local or global search to obtain the correct solutions for clustering. Several procedures, including fluffy rationale derivation [22], bat calculation [19], molecular swarm advancement calculation [23], hereditary calculation [20], differential development & agreement searching [21], is applied for estimating the optimal number of cluster heads. To establish homogenous and energy-efficient clusters, each of the chosen CHs sends an advertising message stating its identification. The cluster head residual energy govern through the received signal intensity and other parameters, and the normal nodes pick which CHs to connect [5], [11], [12], [15], [21]-[23]. To save even more energy, intra-cluster communication employs TDMA scheduling similar to that of LEACH [3]-[23].

CMs can only communicate with CHs that are related, so routing is used to figure out the best route for each CH. Following receipt of all data from its CMs, After compiling the data, a CH transfers it to the base station either direct or through the single-bounce mode [4]- [7], [19] - [23], or as an indirect manner in mode of multi-hpping [7], [24]. As the clustyer head is far off to the BS, one bounce mode communication between CHs and BSs typically costs excessive energy and inhibits the organization's adaptability. To minimize energy consumption, forwarding of data in mode of multi-hop routing has increasingly replaced traditional routing by selection of the suitable relaying nodes to link to the base station [25]. Heuristics-based [8, 10], [20], [21], [26] and Weight-based [7, 11], [18] methods, which are comparable to cluster selection, are used to locate routing paths. The following bounce still up in the air by choosing the hubs with more noteworthy weight values. The weight depends on the distance to the next bounce CHs [18], the energy left in the subsequent jump CHs [7], etc. [11]. Essentially, deciding the best directing ways is trying because of nearby navigation and the disregarding of organization elements and vulnerability. Hence, the best directing examples for each CH are found utilizing fluffy rationale [9], molecule swarm streamlining [8], subterranean insect province enhancement [20], [26], and hereditary calculations [10], [13], [17], and [20]. This considers adjusted energy utilization of CHs and longer organization lifetime. They can also, to some extent, mitigate the hot spot issue brought on by hop-by-hop routing and other uneven clustering routing techniques [12], [15], [24], and [27] by modifying size of cluster, selection of CHs, and calculating counts of hops.

Maintenance of clusters is applied to spin around the cluster heads to guarantee that the energy consumption of each node is allocated appropriately. Round is commonly used to rebuild network clusters, such as those in LEACH, but determining the optimal round duration is difficult. Furthermore, specified round periods usually lead CHs with low residual energy to die too soon, halting communication [5, 9, 11, 12, 15, 16, and 24]. This issue worsens as the network continues to operate. Variable round time is thus recommended [5]-[12], [23], or substitution of CH is applied for replacement of heads whose residual energy is less to a predefined threshold [12], [16], or hybrid] for preventing the remaining energy of CHs from being drained while maintaining normal network communication. As a result, the number of rotations is decreased considerably, consumption of energy is lowered, and the lifetime of network is enhanced.

Fuzzy Logic based routing protocol:

Under this section the proposed routing protocol describes, an energy-efficient clusterering-based fuzzy logic-based routing system for wireless networks. It enables devices to learn how to save energy and improve next-hop selection by sharing local knowledge with the community. Every sensor node in the vicinity that is capable of receiving a packet collects the data from the head and adjusts its route table accordingly. Packet header includes knowledge about the sender's location. The ID of device, energy remaining, coordinates of location, and count of hops are among the local data delivered. This technique, like prior cluster-based routing systems, consists of three steps: creation of cluster, transmission of data, setting up the network & selection of cluster head.

(a) Network Configuration and Cluster Head Election. This step is separated into two parts: first, owing to the network configuration, devices may compute the initial fitness value using their local information. In a heartbeat broadcast, the base station initially communicates its location coordinates. Following package reception from the base station, each gadget records the location of the last option and uses conditions (1), (2), and (3) to calculate the underlying wellbeing esteem based on the underlying energy level and bounce count. We also set up a distance edge among the heads of cluster (CHs) and the monitoring unit to reduce overhead on network and empower sensing nodes that are away of the base station. In addition, we assume that each device has varying levels of energy. The standard divergence of the average residual power allotted to every load on a cluster head shown in Equation 1:

$$= \sqrt{\quad} \; \Sigma \; (\; ( ) \; - \; \Sigma \; ( ) \;) \; ( ) \qquad ( )$$

where r is the number of rounds covered, $E_{residual}(h_i)$ represents residual power of cluster head h_i , & $n_L(h_i)$ representing load on CH h_i

n_L= Load = Number of packets collected at the CH for sending the BS.

NH=Number of hop counts = D_{link}/TX_{range} (2)

By reducing the transmission distance between members when they submit data to the CH, the WSN nodes can be clustered into several tight clusters, which will reducing the consumption under communication energy inside clustering. The clustering loss function is represented by equation (3):

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^{m} \left\| x_i - c_j \right\|^2, \quad 1 \le m \le \infty$$

where x_i is the i^{th} sample point, c_j is the j^{th} cluster center, $\|x_i - c_j\|$ is the separation between the cluster centre and sample I. The degree of sample I's membership in the cluster centre is denoted by cj, uij. N represents number of samples, C is representing the number of clusters j, m is the weighting factor equals to 2. The clustering procedure uses continuous iteration to minimise the clustering loss function Jm. Every iteration results in an update to the membership matrix.

Equation for selecting the best route is:

$$y = F(\sigma, NH, J_m) \quad (4)$$

F: Fuzzy logic based decision system for the selection of cluster heads (y=zero : node not considered as CH, y=1 : node is considered as CH). The fuzzy logic approach is based on expert human knowledge embedded in the computing systems. The experts knowledge based rules may vary from person to person. But these rules are simple interpretation for approaching a decision for output action on the basis of specified input. Presently the function $F(\sigma, NH, J_m)$ is the output that depends upon the deviation from average residual energy. The nodes having higher deviation from E_{res} may indicate the large energy consumption due to large cluster size ,low density of cluster nodes or frequent use as a CH. Hence it will not be preferred to select as node in the proposed route with higher value of σ.Another predictor is NH, it is the number of hop counts. It is very critical factor because if the hop count small in a route then the instance in between the nodes will be large hence the consumption of energy within transmission phase is high and if the hop counts is large then the data receiving, processing and re transmission may increase the propagation delay. Hence this factor should neither be high nor low. Third factor to determine the selectivity criteria for inclusion of a node in the route is J_m. Since J_m is representing the 'clustering loss function' thus it is a kind of indication of the losses that has to be bear on behalf of clusters made within a network. More or less the number of clusters, selected cluster head and nodes within the clusters are related to network performance and energy consumption. It is representation of hence it should be as low as possible. In this way the fuzzy rule base may be generated on the basis of above discussed impacts of σ, NH and J_m on the next neighbor node selection criteria under the developing route for multi hop data transmission. The infrernces developed for selection of node under an efficient routing scheme now may be described as:

σ: Node with lower σ value has higher probability of selectivity as node in next hop while routing.

NH: Node with medium NH value has higher probability of selectivity as node in next hop while routing.

J_m: Node with lower J_m value has higher probability of selectivity as node in next hop while routing.

The specified rule under this scheme are given below:

Table 1: Rules for selection of sensor nodes as the next hop under routing by the fuzzy inference mechanism.

Fuzzy Rule	Input 1 σ	Input 2 NH	Input 3 J_m	Output $F(\sigma,NH,J_m)$	Fuzzy Rule	Input 1 σ	Input 2 NH	Input 3 J_m	Output $F(\sigma,NH,J_m)$
1.	Low	Low	Low	Medium	15.	Medium	Medium	High	Low
2.	Low	Low	Medium	Low	16.	Medium	High	Low	Low
3.	Low	Low	High	Low	17.	Medium	High	Medium	Medium
4.	Low	Medium	Low	High	18.	Medium	High	High	Low
5.	Low	Medium	Medium	High	19.	High	Low	Low	Low
6.	Low	Medium	High	Medium	20.	High	Low	Medium	Low
7.	Low	High	Low	Medium	21.	High	Low	High	Low
8.	Low	High	Medium	Low	22.	High	Medium	Low	High
9.	Low	High	High	Low	23.	High	Medium	Medium	Low
10.	Medium	Low	Low	Low	24.	High	Medium	High	Low
11.	Medium	Low	Medium	Low	25.	High	High	Low	Low
12.	Medium	Low	High	Low	26.	High	High	Medium	Low
13.	Medium	Medium	Low	High	27.	High	High	High	Low
14.	Medium	Medium	Medium	Medium	28.				

Table 1 is showing the rules for selection of sensor nodes as the next hop under routing by the fuzzy inference mechanism. In this table the selection is labeled as the Low ,medium or high as the degree of membership taken as probability of becoming a node as the next hop neighbor during the routing as a cluster head. Here if any of the two condition satisfies out of three i.e.

σ is 'Low' ,N_H is medium or J_m is high the probability of selection of that node is high. If only one condition satisfies then that nodes has low chances of selection to be involved under routing.

Results and discussion:

In this section the results in terms of plots and tables for representing the performance in terms of lifetime, energy consumed and throughput are assosited. The algorithm are developed under Matlab programming platform for four different algorithms known as LEACH,PEGASIS, Reinforcement learning and fuzzy based decision mechanism (proposed).The parameters for developed platform of WSN are given below:

Sensing field size 100 ×100 m Number of devices [30–100]

Transmission range 20 m Initial energy [1-2] joules

Data size 4000 bits Eelec 50 ×10-9 joules/bit

Eamp 100 ×10-12 joules/bit/m2

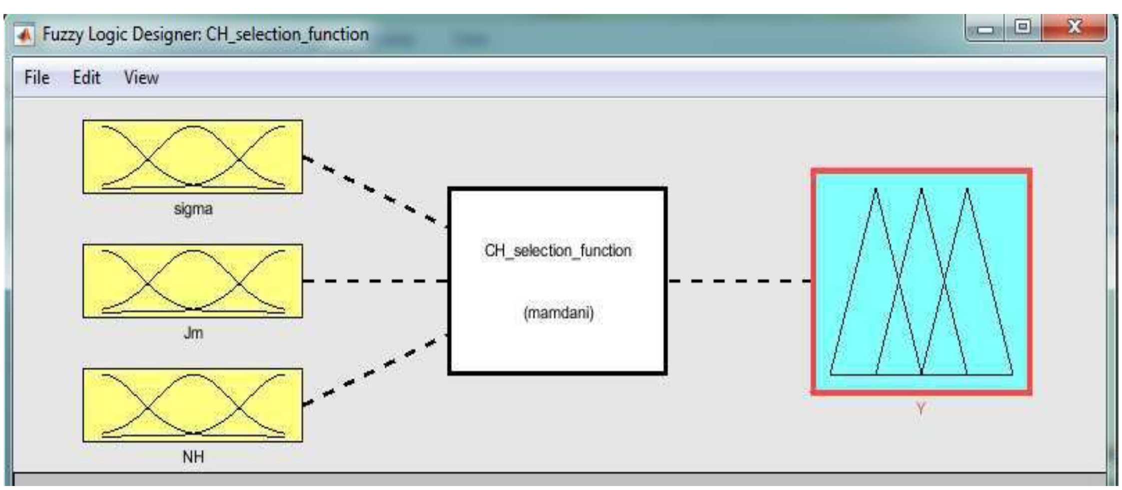

Figure 1:Proposed fuzzy logic based decision model

Figure 1 is showing the block based representation of fuzzy inference system for taking decision for node selection under smart multihop routing mechanism as per the rules described in table 1.It may be seen here that the three input as the linguistic variables are given to the rule base system (CH_ selection_function).The input are given after the fuzzification process as variable name {sigma, Jm and NH).The output also have three bifurcation as Low, medium high.

Routing Criteria: The routing process for the data transmission process considered different rules. Initially, sensor nodes that have zero or less residual energy are deemed dead and are unable to send data. Nevertheless, devices within transmission range of the base station and nodes with the greatest degree of membership as eligibility to be cluster heads can connect directly with the base station without the need for an intermediary node [27- 31]. However, if the CH is also far away, nodes that are far from the base station can send packets to it through a different closest node that is a part of the same cluster.

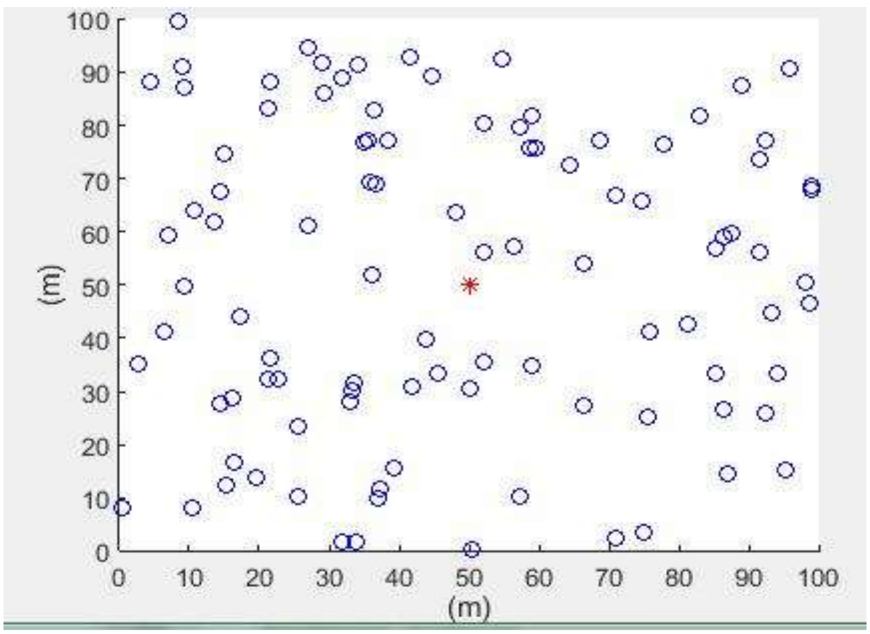

Figure 2: WSN under consideration

Figure 2 is showing the distribution of node under the heterogeneous distribution of random node deployment. The base station is considered to be located at the centre as (red asterisk symbol *) while the sensor nodes are shown here as the blue circles (○).

Table 2 : network lifetime covered under different schemes and number of nodes

	Number of Nodes:			
	30	50	70	100
Scheme:				
Q learning	712	897	1321	1428
PEGASIS	585	634	656	672
LEACH	432	483	1238	793
PROPOSED	1871	1935	1776	1576

On running the simulation for 10000 rounds the depreciation on energy of each node is calculated by standard radio model under the consideration of energy consumption in terms of free space losses, multipath losses and energy consumed in electronic circuits internally. Due to unequal distance to base station the energy consumption are different hence some of the nodes reaches a state of zero residual energy at faster rate compare to other nodes. The node whose residual energy reaches to zero is taken as dead node and remaining are considered as alive node. In figure 3 the x axis is showing umber of rounds varying from 1 to 9000 and the y-axis is showing number of alive nodes. Four different algorithms under the energy efficient routing protocol are shown in different colors (red,blue, green and black as Q Learning, Fuzzy (proposed),PEGASIS and LEACH.LEACH is the very basic protocol that has been yet widely used due to its simplicity and versatility but it is a single hop routing and randomly selects the nodes without considering the status of nodes. PEGASIS is the improved version and considers for different cluster size as per the distance from the base station. The Q learning decides the involvement of node in the routing on the basis of the while learning from the reward as per the optimal behavior of nodes. Here behavior is evaluated in terms of satisfaction of any to conditions i.e. σ is 'Low' ,N_H is medium or J_m is high the probability of selection of that node is high. If only one condition satisfies then that nodes has low chances of selection to be involved under routing. In figure 3 it may be observed that the nodes start to dead (known as first node dead FND) at round 2000 (approx.),similarly for PEGASIS ,Q learning and proposed Fuzzy decision mechanism the FND is 3402,3426,3469 rounds. The time taken to all nodes are dead (AND) is observed to be 5138,6255,6643,8087 rounds for LEACH,PEGASIS,Q Learning and fuzzy (proposed).In this way it may be concluded that the proposed Fuzzy based mechanism for routing is helpful in providing better lifetime. Variation of number of alive nodes with respect to the number of rounds. The proposed fuzzy based routing approach covers maximum number of rounds above than 8000 rounds at which all the nodes are observed to be dead.

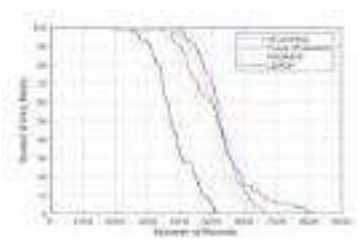

Figure 3:Variation of number of alive nodes with respect to number of rounds.

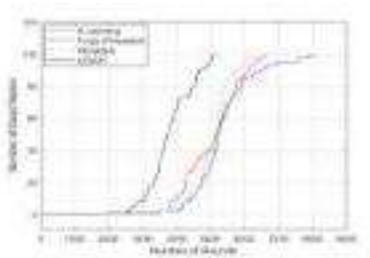

Figure 4:Variation of number of nodes with respect to number of rounds.

Similarly the simulation for 10000 rounds from the depreciation on energy of each node is calculated by standard radio model under the consideration of energy consumption. The node whose residual energy reaches to zero is taken as dead node. In figure 4 the x axis is showing number of rounds varying from 1 to 9000 and the y-axis is showing number of dead nodes. Four different algorithms under the energy efficient routing protocol are shown in different colors (red,blue, green and black as Q Learning, Fuzzy (proposed),PEGASIS and LEACH. In figure 4 it may be observed that the proposed Fuzzy based mechanism for routing is helpful in providing better lifeteime.

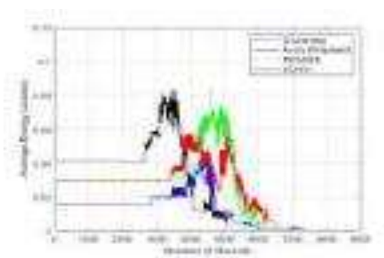

Figure 5:Variation of average energy with respect to number of rounds.

Similarly the simulation for variation of average energy due to depreciation of energy of each node is calculated. In figure 5 the x axis is showing number of rounds varying from 1 to 9000 and the y-axis is showing number average energy of nodes consumed while data packet transmission. Four different algorithms under the energy efficient routing protocol are shown in different colors (red, blue, green and black as Q Learning, Fuzzy (proposed),PEGASIS and LEACH. In figure 5 it may be observed that the proposed Fuzzy based mechanism for routing is helpful in providing lowest energy consumption. Variation of average energy consumed by the nodes with respect to the number of rounds. The proposed fuzzy based routing approach consumes minimum energy in each rounds compared to other algorithms.

Throughput is the determination of the amount of data is transmitted during a specified time period via a network. In figure 6 throughput calculated and shown as the bar chart. Here the x axis is the number of nodes and y axis is the network throughput in terms of number of packets transferred. The number of nodes are increase as 30,50,70,100 and the throughput is calculated for running the simulation for 10000 rounds under different protocols. As the number of nodes are increased higher number of packets are transferred hence the throughput is observed to be increasing as the number of nodes are increased irrespective of type of protocol. For all the network configuration at different number of nodes the Q learning and proposed fuzzy scheme are observed to be capable of giving highest throughput. The fuzzy based proposed scheme always gives slightly higher throughput compared to Q learning.

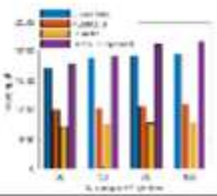

Figure 6:Network throughput at different number of nodes under different WSN protocols.

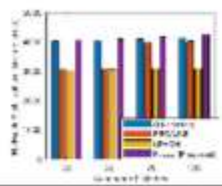

Figure 7:Network stabilization time at different number of nodes under different WSN protocols.

Network stabilization time metrics having variation in density of node, the network stability metrics under this proposed protocol giving improved performance compared to other protocols, since the protocol proposed here capable of balancing the energy consumption of network. It is showing that on comparison to other protocols, the protocol proposed in this article shows higher suitability for scenarios with high reliability requirements. In figure 7 Network stabilization time calculated and shown as the bar chart. Here the x axis is the number of nodes and y axis is the network throughput in terms of number of packets transferred. The number of nodes are increase as 30,50,70,100 and the throughput is calculated for running the simulation for 10000 rounds under different protocols. As the number of nodes are increased higher time required packets are transferred hence the throughput is observed to be increasing as the number of nodes are increased for gaining stability for all type of protocol. For all the network configuration at different number of nodes the proposed fuzzy scheme are observed to be capable of giving highest network stabilization time.

Conclusions & Future scopes: This article is useful in suggesting a clustering-based energy-efficient routing technique based on fuzzy logic in this work. The purpose of this research was to find the best data transmission channel for accomplishing the target of energy saving and extending the lifetime of the network. It has been demonstrated that the proposed cluster-based routing protocol is more scalable than the other options. This routing method was created in three steps: network configuration, CH selection, and optimization. We calculated the starting fitness value for the CH election using the beginning energy and hop count factor at this step. In the second phase, each CH encouraged all devices within its transmission range to join forces and create clusters. Following that, every distant device joining the cluster whose cluster head was closest to the base station. Finally, the learning-driven data transmission phase resulted in an energy-efficient routing strategy that considered the total number of hops & the remaining energy of the devices when selecting the optimum course of action. Furthermore, an energy cutoff value for CH substitution was determined. The results obtained on running simulation showing that the proposed system outperforming thre LEACH, Q learning, and PEGASIS in terms of energy usage & lifespan of network. We used a lightweight routing strategy in our study to speed up protocol execution and reduce energy usage. We want to consider other parameters in the future to produce an even better routing system.

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