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Performance Tuning of 5G WSN and IOT Using Machine Learning Based Efficient Technique

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***Abstract:** Wireless sensor network (WSN) systems are typically composed of thousands of sensors that are powered by limited energy resources. To extend the networks longevity, clustering techniques have been introduced to enhance energy efficiency. The Existing protocols are analyzed from a quality of service (QoS) perspective including three common objectives, those are energy efficiency, reliable communication and latency awareness. Understanding the user's requirements is critical in intelligent systems for the purpose of enabling the ability of supporting diverse scenarios. User awareness or user-oriented design is one remaining challenging problem in clustering. Therefore, the potential challenges of implementing clustering schemes to Internet of Things (IoT) systems in networks. As the current studies for WSNs are conducted either in homogeneous or low-level heterogeneous networks, they are not ideal or even not able to function in highly dynamic IoT systems with a large range of user scenarios. Moreover, when 5G is finally realized, the problem will become more complex than that in traditional simplified WSNs. But when WSN grows, the volume of data to be gathered processed and disseminated by the sensor nodes increases largely. Processing and transmitting such a large amount of data is impractical because of the limited energy of the sensors. Thus, there is a need for applying Machine Learning (ML) algorithms in WSNs. Several challenges related to applying clustering techniques to IoT need to be analyzed along with machine learning techniques to optimize the performance of WSN. This research study focused to design an energy efficient technique which can reduce the energy consumption and prolong the lifetime of network communication.*

***Keywords:** IOT, LEACH, WSN, IoT, sensor, Machine Learning,5G, heterogeneous etc.*

I. INTRODUCTION

The Internet of Things (IoT) has been attracting attention in recent years. This is a potential technology that provides various legal remedies for challenges arising in different sectors. The Internet acts as the communication backbone of the network for exchanging resources from one platform around the world to another. The IoT concept was created in 1998 and 1999, and Kevin Ashton shaped the term IoT in the Auto-ID Institute as "1], a mysterious but intelligent system that can be recognized, regulated and reprogrammed by using embedded systems for communication. With highly productive improvements, IoT allows instant access to information on any device. According to the Cisco team, around 50 billion intelligent devices are already connected to the web [2].

A billion connected devices form the IoT and can recognize, collect and transmit data from one device to another without the necessary human interactions. Healthcare systems persecution, automation, logistics, linked cars, smart city development, smart grids, smart homes, smart retail, smart agriculture and other IoT-enabled services can help improve people's lives. In this scenario, the Internet becomes obsolete and creates new concepts for Connected Smart' products. IoT allows the Internet to change so that machine-to-machine learning (inter machine learning) becomes a reality [3]. New conFigureurations are generated by intelligent physical devices, giving them the opportunity to achieve things on their own, leading to the development of IoT. Since it was connected everywhere back then, IoT is committed to making it even more accessible to the expansion devices.

IoT generally enables autonomous and secure communication of real objects. IoT reduces physical work through the usual automation process. The number of objects connected via the internet is constantly increasing. Smartphones contain many sensors that recognize data, calculate them, and send corresponding data over the Internet. With a variety of devices with sensors, this system can create numerous applications that offer compelling benefits. IoT smart things can be uniquely identified. These devices use RFID tags (radio frequency identification) or barcodes recognized by the sensor device [3]. Data recorded by the sensor is sent over the Internet to the processing system for analysis.

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The processed findings are sent to the system approved for the selection and action that performs the corresponding action. Important information and facilities are always available. This makes it easier to design new apps and contributes to a new lifestyle by introducing new work, connections and entertainment approaches. As a result, there is a lot of traffic and people become a small number of traffic generators and wearers [4]. Because of the problems and possibilities that bring things on the Internet, it is being studied in a variety of fields of research. In this case, consistent architecture maintenance is required to store all data efficiently.

II. IOT AND WSN CONVERGENCE

The WSN acts as a connection between the virtual and physical worlds. The small combined sensors are used to transfer values to the Internet. Sensors are implemented in a network and monitor the various physical and surrounding functions of the WSN. This network consists of many nodes, each with a specific function. WSNs can connect to the Internet using IP-based sensor network technology. A WSN consists of nodes that can be used in a variety of applications, including healthcare, agriculture, and military applications. WSNs are used to monitor many applications over the Internet. Collect data by enabling physical objects connected with knots, activators, and connections. Several scholars have proposed many WSN systems created for real applications based on different requirements. By taking into account the example of intellectual cities, we can explain how WSN acts as the backbone of IoT [2-4]. Intelligent cities collect and analyze data using IoT devices such as linked sensors, lights and measuring devices. This data will be used in cities to improve infrastructure, public supply companies and services. These intelligent objects can create a secure and intelligent environment. Vehicle Internet (IOV) is an IoT subclass that makes transportation systems more intelligent. The IOV has three communication options: vehicles to vehicles, vehicles on roadways, and roadside pages. Vanz is used in a variety of applications, including vehicle speed monitoring, avoiding traffic congestion, optimal route gaps, and communication between external vehicles and interior [2-5]. As a result, WSN is a collection of specialized objects that provide sensor services to the IoT device. WSN is a lucrative network for monitoring, persecution and recognition of various environmental activities. Various intelligent (unmanned) service networks must be designed, built and used

III. RESEARCH GAPS

As mentioned in the previous section, clustering strategies are also important for highly dynamic IoT systems. Using 3GPP standard communication, this provisioning is more flexible and connectivity issues are addressed quickly. When migrating IoT systems to 5G networks, various hard clustering challenges need to be addressed.

1) The first problem stems from the enormous diversity of the underlying structures of IoT systems. The things on the ground are really diverse. There may be limited skills for nodes, while others are extremely sophisticated. To combine all of the intelligent cities, inexpensive and energy efficient devices with only broadcasting are used in many with other highly developed sensors. Hardware limitations make it difficult to form distributed clusters because certain devices cannot receive data from other devices. The Super Sensor is an example of the opposite pole of a transmit-only gadget. It's a stronger knot that collects sensory data and in some situations acts as a relay node. As a rule, they are classified as a CHS of the network due to their great memory and arithmetic skills. As a result, IoT systems are more complex and extensive than traditional WSNs. Collecting and sending data is no longer an exclusive feature of the OTT app. You need to think about more complex situations and user scenarios. When deleting dual data, you must compile a sensor/device for equivalent use.
2) The cost of transfer is the second issue. Energy costs remain a major challenge when IoT devices are implemented in 5G networks. Financial expenses must be managed carefully as mobile networks are involved. For example, using LTE is more expensive than using WLAN. In fact, LTE can be used as a major type of communication. Some devices can be converted to Bluetooth or Zigbee. If possible, there are more efficient options (CH can meet user standards within reach). To use the MIMO method, you must distribute sufficient devices in the same cluster to allow for separate network interfaces.
3) Improving user usefulness is the third task. When it comes to 5G laws and regulations, quality of experience was prioritized. Based on the action, the user needs TaylorMade service. User profiles should be considered during catering of the described usage. Information such as user priorities, user habits, and user status can be recorded in a user profile. The first problem to solve is determining how to formalize user usefulness as quantitative statistics.

Clustering technology must take into account the requirements of network users. For example, if each cluster uses the TDMA-MAC protocol, grouping all users with high latency requirements in the same cluster is not a smart idea. These users must be in a highly relevant cluster. In the worst case scenario, you should be able to transfer directly at a Layer 2 access point. The fourth problem is to look into how the intelligent components of the main network are used. Additional elements of the core network were proposed, providing additional features to intelligently and contextualize 5G networks. A device can query information from such components. Remote monitoring elements can recognize network overload across all internet connections. If you know this information, the clustering method should be designed more intelligently. Because applications require high network performance, devices use LTE as the primary connection interface. As soon as you receive information from the core network indicating that this WLAN network is overcrowded, this should not change in the wlan

4) The fifth problem is to look at how to check and use mobility in your network. Several exams were conducted to resolve the mobility issues on WSNS. The advent of IoT systems requires rapid mobile object connectivity support (such as the automobiles of linked automotive systems) and the use of mobility to improve communication efficiency. Improved QoS and QOE is one of the broader goals of 5G. The above problems need to be solved by a cluster approach to adapt to the 5G and increasingly complex situations of IoT systems. Related research in such directions should be pursued further. To collaborate, the design of cross-layers is also highly suggested. It is highly recommended that more advanced research be conducted in this area. It is highly recommended that more complex research be conducted in current environments of 5G rather than typical WSN use.

IV. ARTIFICIAL NEURAL NETWORKS (ANNS)

ANNs are a subfield of machine learning that are based on the brain and inspired by neuroscience. It is computer network that create structure of human brain. Neurons in ANNs are connected to one another at various levels, just like in real brains. These cells are referred to as nodes. In ANN, dendrites from biological neurons serve as inputs, cell nuclei serve as nodes, synapses serve as weights, and axons serve as output. These are supervised learning algorithms that analyze labeled samples, each having an input and a desired output. After the datasets have been provided for learning, the algorithm would be able to classify for a new dataset and provide an outcome. NNs are made up of neurons connected by weighted connections that allow the input layer to be linked to the output layer via a transfer function. This function consists of the sum of the product of input values and their weight, and they don't require data storage. An artificial neuron is depicted in the diagram below.

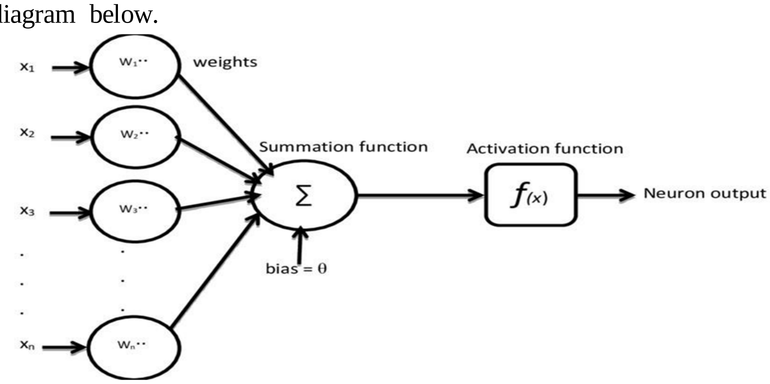

Figure 1: Artificial Neuron[4]

The training phase is referred to as supervised learning because NN learns from labelled instances. Prediction and classification are two of the most common applications for NNs. The model is organised in layers, and it can do nonlinear statistical training and detect complex relationships between variables. However, it has higher computing cost and over fitting of data. The general architecture of ANN comprises of three layers which are briefly described as follows:

1) Input Layer accepts data in a various formats determined by the developer.
2) Hidden layer lies between input and output layers. It does all of the calculations necessary to discover unseen patterns and insights.

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3) The output layer is the hidden layer, which is where the input goes through a series of computations before reaching the output layer. The bias component of the neural network calculates the weighted total of the inputs. A transfer function is used to express this computation. The weighted sum is used as input to activation function to generate result. Node activation is decided by the activation function. A variety of activation functions can be used, depending on the task at hand. The architecture of ANN in general is depicted in the Figure below.

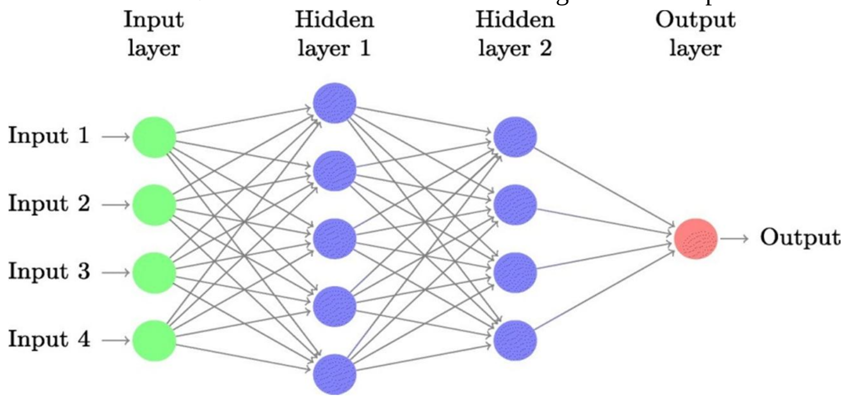

Figure 2: Artificial Neural Network[5]

V. NEED OF STUDY

Energy management and utilization in networks is a critical challenge. The researchers found that energy-conscious routing caused a number of problems in a variety of applications. Examples of routing protocols include QoS routing protocols, energy-efficient routing protocols, location-aware routing protocols, data centralized routing protocols, and hierarchically routing protocols. For WSN performance optimization in a dynamic environment without human intervention, experience and an intelligent approach to real-time decision making are necessary. Because ML algorithms use iterations, experience-based data is used to improve outcomes that both reduce errors and learn from them. The sensor network's connectivity has been improved through the use of machine learning. When simulation methods are either unavailable or too expensive, methods are practical and useful for information extraction and relationship detection in sensor networks. Cluster head selection, optimal path identification, locating useful data from collected data, decreasing packet delay, and increasing WSN lifetime are all achieved through the use of a variety of machine learning techniques.

VI.METHODOLOGY

In this section we discuss the network modeling and the proposed routing method PDORP, LEACH, ACO and GA in detail. We have created a network with randomly deployed nodes N. We have taken the area of 100 square meters. We have computed the distance d of all the nodes from their neighbors and we have compared their distance with the threshold th value of distance, so that they could be connected only when their distance is less than or equals to the threshold value. We have used this algorithm to make it sure that all the nodes are connected with a minimum distant value.

To find the optimal route in the large coverage set of nodes. If source node and destination nodes come under coverage set, then transmission will take place, otherwise again path searching will done.

If a node becomes more aggressive at the time of transfer and previously it was not in the cache memory, the other node is bound to receive a packet from it and in such a way it can cause damage to existing routes. A solution to this problem could be checking of any node at the time of receiving a data packet but this would cause unessential delay. Hence, the proposed solution creates a trustiest for the first time in each round on the basis of the parameters allocated to the nodes. After every round, the trust list is updated and after a certain number of rounds, the trust would not be checked to avoid time delays.

When a source node wants to transmit data to destination node, it calculate the distance from all the neighbors and forward the data to the node whose distance is less than or equals to the threshold distance and only in the direction of destination nodes and it also ensures that the minimum distance neighbor node should be in the direction of the destination node. After this process all the nodes in the direction of the destination are added into the trust list only in

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the first round of simulation. Whenever a new data transmission is required, then the trust list will be updated in the first round of simulation and the data will be transferred via only those nodes which are found in the trust vector. As the vector list is created only in the starting phase of the simulation so to continue the transmission thereafter vector list is stored in the cache which is created

It has been considered that each node occurs once in the trust list. To create the fitness value of trust, a hybrid algorithm, which consists of GA and ACO, has been proposed via algorithm. GA would be optimizing the node consistency based on the Received and transmitted energy. ACO would be used for searching the shortest path.

Algorithm

Step 1: Create a Network creation with following

1. Network. height=100
2. Network. Width=100; N=Total_Nodes.
3. For each n′ in N

counter = 1;
xloc(n′) = 100 * Random.
yloc(n′) = 100 * Random.
Node. name (n′) = counter; counter = counter + 1;
Endforeach

4. Cov_set = [ ]; //it would contain the limited area node.

for i =1 to N
cov_count=2;
for j=1: N
if (i! =j) // a node cannot compute distance to itself
d = √ ((x (i) – x (j)) 2 + (y (i) – y (j)) 2
th = Rand(N);
If (d ≤ th) cov_set (i, 1) = i;
cov_set (i, cov_count) =j;
cov_count = cov_count + 1;
end if end for end for

Above algorithm describes the node deployment in the whole network. In proposed network 100*100 network development takes place with coverage set = 1.

Step 2: Find the path

1. For i=1: Network.Simulation.Rounds
2. Source=Initialize. Source;
3. Source.Id=Node.name (source); Path= [ ]; Pathelement=2; Path [1] =Source;
4. Source.Packet.count=100;
5. Destination.Id=Node.name (Destination);
6. Current_cov_set_source=cov_set (source.Id,:)dest_found=0; possible_nodes=[ ];
7. While (dest_found! =1)
8. For each all n in current_cov_set

If(x(all n)>xloc(Source.Id) && (x(all n)-xloc(Destination.Id) < 0
Possible_nodes [possiblenoedcount] = all n;
Possiblenodecount+=1;
Endif

9. Selection=possible node count*Random;
10. Selected_node=Possible_nodes [selection];
11. Possible_Nodes=[ ]; Path(Path element) = selected_Node
12. End

Step 3: Set the different energy.

Step 4: Apply the random election of normal and advance Node.

Step 5: Apply the counter to count the distance between nodes, clusters and Base station and apply distance formula to find the distance.

Step 6: Choose the multiple paths with energy

S(i).E=S(i).E- ((tx_energy)*(4000) + multipath*4000*(dist*dist*dist*dist));

Step 7: Apply the ACO and GA for transmission of data from Base station to different nodes through BS.

Step8: Find the first dead, half dead and full dead nodes during transmission of data from BS to nodes and clusters.

Step 9: Calculation of Energy dissipated based on distance

```
if (distance>do)
        S(i).E=S(i).E- ((ETX+EDA)*(4000) + Emp*4000*( distance*distance*distance*distance ));
    end
    if (distance<=do)
        S(i).E=S(i).E- ( (ETX+EDA)*(4000)  + Efs*4000*( distance * distance ));
    end
```

Step 10: Draw Varnoi diagram for network.

Step 11: if Step 2 to Step 9 is completed then

Calculate

Rho1 = (number of bit error)/ (total number of bit send)

Bit Error Rate = Rho1 +Em

p= N/R

N is the number of bits, and

R is the rate of transmission (say in bits per second)

Delay=abs(p +Em),

Remaining_Energy = ETx (k, d) = Eelec * k + Єamp *k * d2, d>1

ERx (k) = Eelec * k

Energy Consumption= mean(Remaining_Energy)+Em

and

Size of the packet= abs ((abc) +Em)*packet

Transmission time =datatxperiod*10

Throughput= (Size of the packet / Transmission time)

End

VII. SIMULATION AND ANALYSIS OF PROPOSED PROTOCOL

Throughput, PDR, and latency were used to estimate the output of the recommended procedure. With the experiment conditions listed in Table 1, the findings were estimated using Matlab (version R2018a).

Table 1 Simulation Parameters

Type	Parameter	Value
Network	Area	200x200 m^2
	Number of nodes	200
	Number of CHs	10
	Initial energy of node	0.5 Joule
	Simulation rounds	2000
	Topology	Random deployment
	Data packet length	250 bytes
Radio model	Radio electronics energy (E_{elec})	50 nJ/bit
	Radio amplifier energy (E_{fs})	10 pJ/bit/m^2
	Radio amplifier energy (E_{mp})	0.0013 pJ/bit/m^4
	Threshold distance (d_o)	87.7 m
	Energy required for data aggregation(E_{DA})	5 nJ/bit/signal

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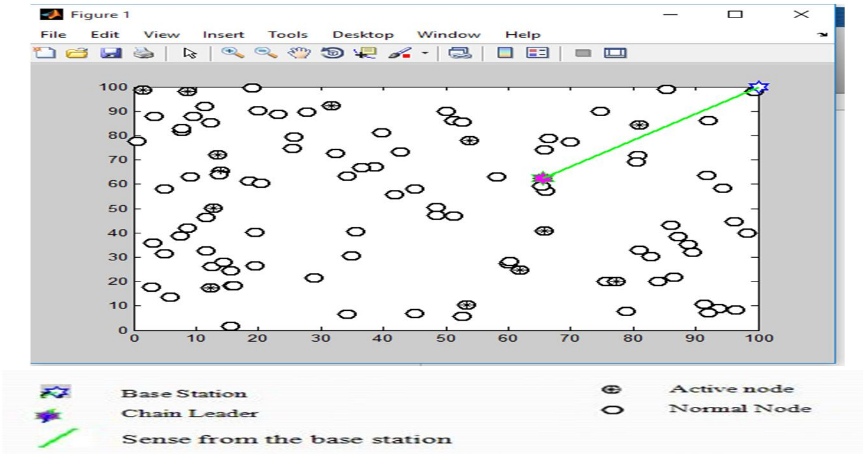

Figure 3. Initial Node Deployed on WSN with BS

The Figure 3 displays the number of nodes deployed on the wireless sensor network. In this Figure the number of nodes re connected with Base Station. Here are Active and Normal Nodes. The green line shows the sense from the base station.

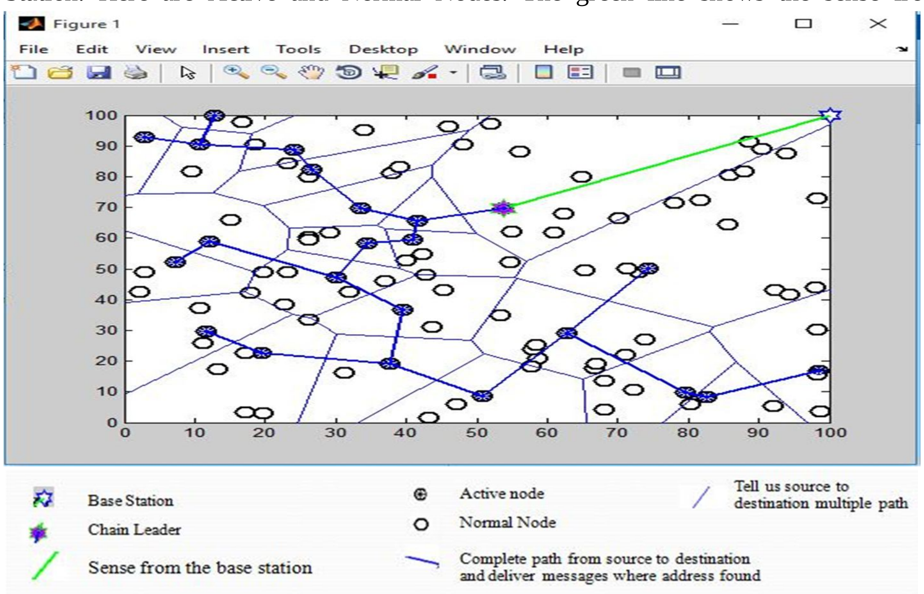

Figure 4. Source and destination Multiple Paths

Table 2: Bit Error Rate (BER)

NO. OF NODES	Existing Technique	Proposed Technique
	BER	BER
100	6.878	5.312
200	19.932	17.8542
300	25.521	23.9538
400	20.351	18.9838
500	11.595	10.2233

Formula

Bit Error Rate = (number of bit error)/ (total number of bit send)

Table 3: Delay

NO. OF NODES	Existing Technique	Proposed Technique
	DELAY	DELAY
100	0.766	0.612
200	5.281	4.2458
300	0.538	0.2538
400	2.803	1.8838
500	0.42	0.2233

Formula
Delay= N/R
N is the number of bits, and
R is the rate of transmission (say in bits per second)

Table 4: Energy Consumption

NO. OF NODES	Existing Technique	Proposed Technique
	ENERGY CONSUMPTION	ENERGY CONSUMPTION
100	5.969	4.6668
200	10.66	9.0258
300	0.235	0.1474
400	12.488	11.5314
500	4.128	3.9191

Formula
Energy Consumption
ETx (k, d) = Eelec * k + Єamp *k * d2, d>1
ERx (k) = Eelec * k
Total consumed energy of each cluster = Σ ERx + Σ ETx
= Total consumed energy of data receiving + total consumed energy of data transmitting

Table 5: Throughput

NO. OF NODES	Existing Technique	Proposed Technique
	THROUGHPUT	THROUGHPUT
100	0.785	0.9792
200	0.509	0.8209
300	0.831	1.0567
400	0.944	1.0452
500	0.452	0.5863

Formula
Throughput = (Size of the packet / Transmission time)

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Table 6: Comparison Table BER, Delay, Energy Consumption, Throughput

NO. OF NODES	Existing Technique				Proposed Technique			
	BER	DELAY	ENERGY CONSUMPTION	THROUGHPUT	BER	DELAY	ENERGY CONSUMPTION	THROUGHPUT
100	6.87	0.766	5.969	0.785	5.31	0.612	4.6668	0.979
200	19.93	5.281	10.66	0.509	17.85	4.245	9.0258	0.820
300	25.52	0.538	0.235	0.831	23.9538	0.253	0.1474	1.056
400	20.35	2.803	12.488	0.944	18.9838	1.883	11.5314	1.045
500	11.59	0.42	4.128	0.452	10.2233	0.223	3.9191	0.586

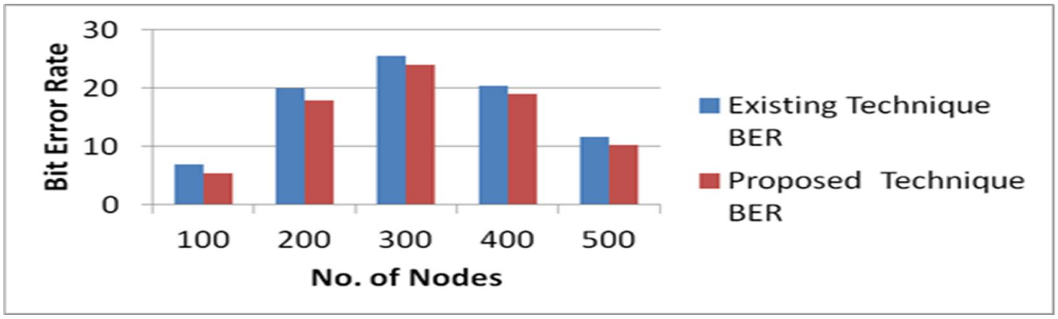

Figure 5: Bit Error Rate

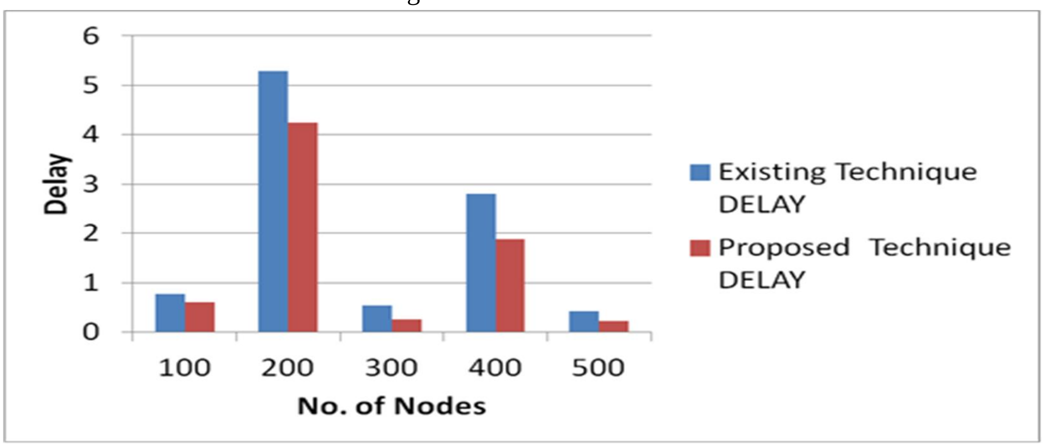

Figure .6: Delay

The Figure 5 defines the comparison of Bit Error rate of proposed work and the Existing work. Same the Figure 6 defines the Delay of existing and proposed work. Here the blue line in bar graph is the existing work and the red line is the proposed work.

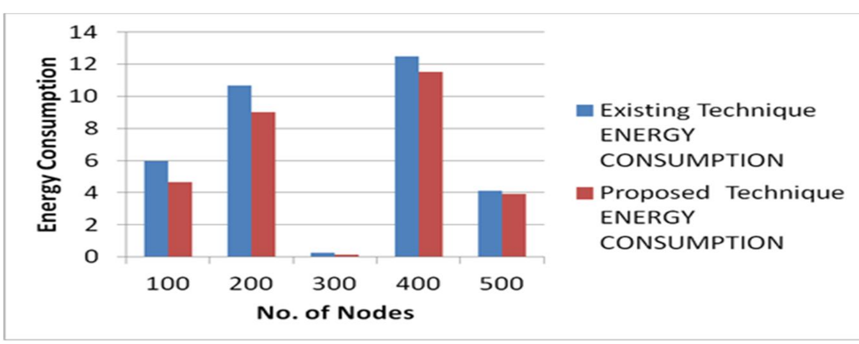

Figure 7: Energy Consumption

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The Figure 7 defines the comparison Energy consumption of proposed work and the Existing work. Here the blue line in bar graph is the existing work and the red line is the proposed work.

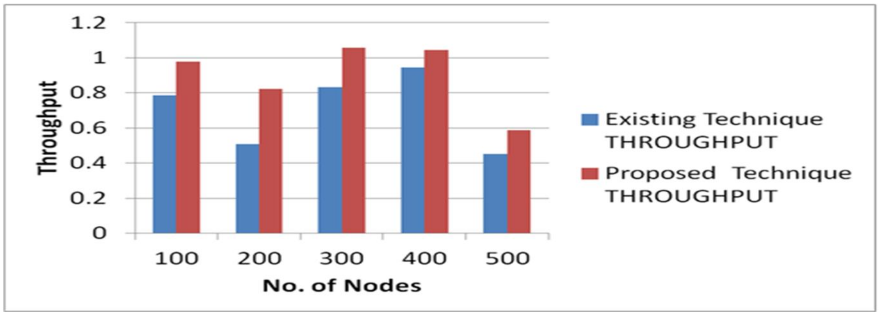

Figure 8: Throughput

The Figure 8 defines the comparison Throughput of proposed work and the Existing work. Here the blue line in bar graph is the existing work and the red line is the proposed work.

A. Throughput Analysis

Table 5.6 summarizes examination of throughput observed utilizing three approaches: suggested, Sharma et al., and Selvi et al. N odes employed in study ranges from ten to two hundred. For example, whenever a network with 10 nodes is established, proposed work's throughput is 1427.752 Kbps, while Sharma et al.' is 1392.266 Kbps and Selvi et al.'s is 1341.663 Kbps. S peeds for proposed, Sharma et al., and Selvi et al. are 2215.332 Kbps, 2084.875 Kbps, and 2187.493 Kbps respectively when nodes are increased to 200. Throughput of all three strategies is expected to improve as number of nodes increases.

Table 7 Comparative analysis of Throughput

No. of Nodes	Throughput Proposed	Throughput Sharma et al. 2024	Throughput Selvi et al. 2024
10	1427.752	1392.266	1341.663
20	1507.281	1459.825	1474.653
40	1482.795	1431.154	1453.625
60	1518.339	1424.827	1479.475
80	1484.246	1396.751	1432.949
100	1574.809	1484.745	1499.462
120	1687.495	1567.027	1587.908
140	1750.098	1683.475	1712.214
160	1894.543	1832.415	1847.483
180	2141.284	2017.475	2101.124
200	2215.332	2084.875	2187.493

According to simulation study, recommended job has average throughput of 1698.5 Kbps, compared to 1615.9 Kbps for Sharma et al and 1647.1 Kbps for Selvi et al. Figure 3 depicts proposed work's percentage improvement over two existing works. According to graphs, suggested work improves by 4.7% when compared to Sharma et al. and 3.14% when compared to Selvi et al. The findings collected on PDR variation of three approaches show that chance of packet drop decreases as number of nodes in deployed system rises. When a result, as number of nodes grew, PDR climbed somewhat. The standard PDR observed by proposed study is 0.7291, 0.7058 by Sharma et al., and 0.7109 by Selvi et al. Figure 4 depicts improvement in PDR demonstrated by proposed work as compared to two existing works. When a large number of nodes are employed in experimental analysis, larger percent improvement is found. On average, proposed work was 2.49 percent better than Selvi et al.'s work and 3.18 percent better than Sharma et al.'s work. It signifies that proposed work sends data packets to CH and then to target node with little latency.

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Furthermore, performance and PDR studies demonstrate that when suggested protocols are applied, packet loss is negligible when compared to clustering techniques used by Sharma et al. and Selvi et al. In MATLAB, proposed technique was tested. This protocol specifies use of reinforcement learning and neural networks for route optimization and upkeep; we also optimized route using support vector machine and naive bayes approaches, both of which were implemented in same simulated environment, to compare its efficiency to other machine learning approaches. On basis of throughput, packet delivery ratio, and network energy usage, results are then compared. The packet delivery ratio describes proportion of transmitted packets that are finally delivered in network, whereas network throughput reflects how much data is sent to target node in network. Because this protocol concentrates on minimizing energy consumption in data transmission process and optimizing data forwarding path in addition to CH selection, parameters like throughput and packet delivery ratio become critical to examine because they describe effectiveness of route formed. The simulation was run for 1000 cycles, with 60 nodes distributed at random in network measuring 1200*1200 square metres. The base station is located in network's heart. The table below lists other simulation parameters:

Table 8: Simulation Parameters

Total Nodes	60
Maximum Initial Energy	0.2 Joules
E_{elec}	50 nJ/bit
E_{fs}	10 pJ/bit/m^2
E_{amp}	0.0013 pJ/bit/m^4
E_{da}	5 nJ/bit/signal
Base station location	Center
d_0	87 meters
Deployment Type	Random
Network area	1200 * 1200 sq meters

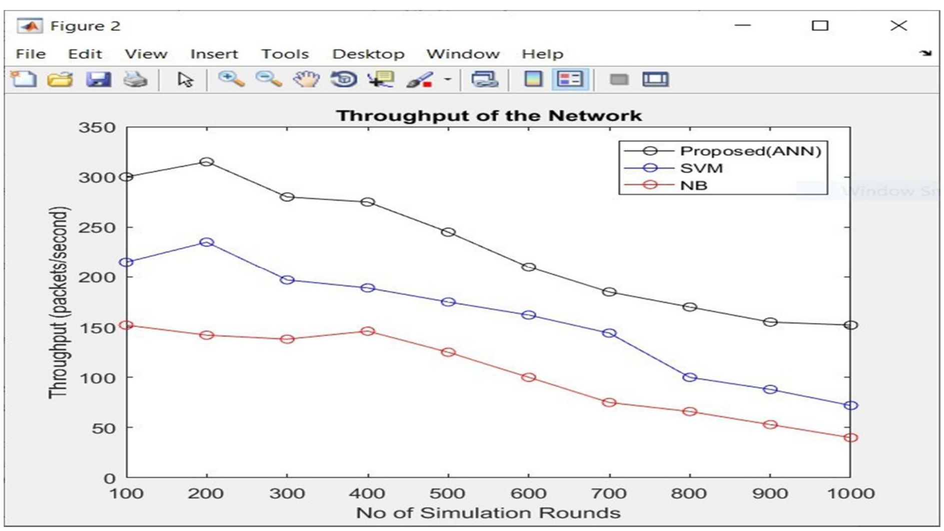

Figure 9: Throughput Comparison

The graph above displays value of network throughput vs number of simulated rounds. It has been discovered that as number of rounds increases, value of throughput drops for all three machine learning approaches. This is because as simulation develops, nodes in network consume more energy and finally die out. The lower number of living nodes, more likely the route may be broken, lowering throughput.

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When comparing performance of three strategies, suggested reinforcement learning-based neural network methodology outperforms other two. In comparison to SVM, suggested approach achieved 31% percent higher higher throughput and 54 % higher throughput than NB. This is because ANN's processing makes use of hidden layers that user may control, and data dimensionality is significantly higher in ANN. When using ANN instead of other two methodologies, it is significantly easier to forecast when node is about to run out of charge. This demonstrates that route optimised with RL based ANN supplied more data than route optimised with RL based SVM or NB, demonstrating usefulness of suggested approach.

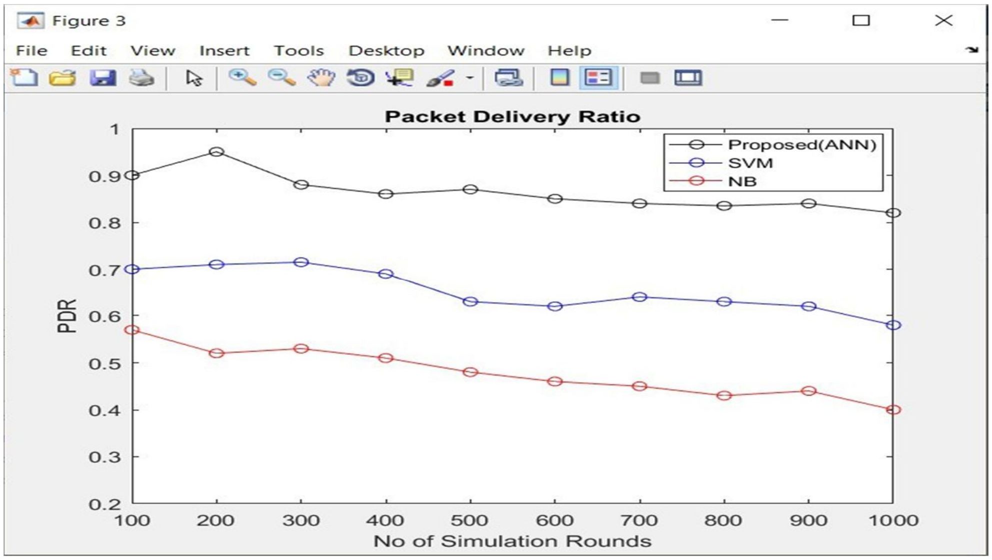

Figure 10: PDR Comparison

Results of packet delivery ratio acquired after simulating three strategies are shown in graph above. This graph is consistent with prior throughput graph. Likewise, as number of rounds grows, nodes' connectivity improves. This results in energy usage. Data packets are not transmitted properly to intended destination after nodes in optimized route die out, lowering value of packet delivery ratio. However, employing RL-based ANN approach, routes are optimized significantly more successfully, resulting in superior performance than its competitors. The greatest PDR attained was 0.95, with mean of 0.8645 maximum PDR reached by SVM was 0.715, with mean of 0.6535; and highest and mean PDR obtained by NB were 0.57 and 0.4790, correspondingly.

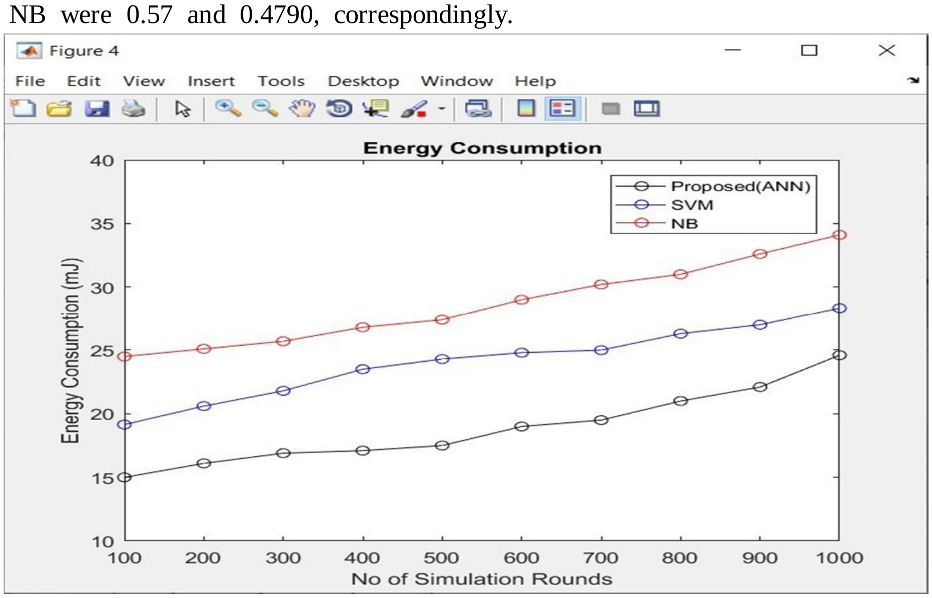

Figure 11: Energy Consumption Comparison

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The graph above depicts total amount of energy used in network for all three ways. It was discovered that energy usage increased in consistent manner, indicating that nodes were continuously detecting data from environment, sending it to cluster heads, and eventually forwarding it to target nodes. This graph also depicts network's lifespan. Because NB and SVM consume more energy than ANN-based approaches, nodes in network under simulation of these two methods quickly deplete their batteries. Energy usage is low because route creation is highly optimised using ANN, as shown by graphs of throughput and packet delivery ratio.

VIII. CONCLUSIONS

Low battery life on WSNS is a unique issue. In the past, various clustering techniques have been proposed to solve this problem, focusing on data transmission from cluster heads to base stations. Grid-based clustering in WSN solves energy balance problems by eliminating energy consumption and increasing load and energy consumption between all nodes in the system. Grid architecture offers excellent reliability and inexpensive cost for long transmission times. After conFigureuring the network in both ways, it was observed that using a single CH would improve energy efficiency on all grills. At the same time, it deals with load compensation, clustering overhead and energy efficiency. Throughput, PDR, and latency are measured to test the success of the proposed clustering-based routing system. In the performance assessment, the proposed work increases throughput by 3% to 4%, and decrease in communication latency by 4% to 5% compared to two routing algorithms based on PDR, and clustering. This conclusion is supported by the optimal CH selection approach used in the route discovery stage of the proposed procedure. Better network performance, such as throughput, PDR, and slight latency, indicates the effectiveness of the proposed work. In this study, we provided a method for selecting cluster heads based on node cosine similarity and selected neuronal network-based reinforcement learning strategies to optimize network selection. Additionally, artificial neural networks were used to maintain the route. This research element was largely overlooked in previous studies. Throughput, PDR, and network energy consumption were measured to assess performance. RL-based Ann-Technik was compared to RL-based SVM and RL-based NB approaches. The results showed that the proposed approach outperformed SVM and NB. This indicates that routes are in fact well optimized and maintained by existing technology.

A. Scope of further research

According to the final results explained in the conclusion, further research is needed to improve the effectiveness of energy efficiency. Below are suggestions for researchers to improve their research in the future.

To achieve a significant increase in the proposed model, more research is required to assess the effectiveness of artificial intelligence and machine language in other such clustering techniques that can achieve more optimized results.

1) New intelligent protocols can be designed to introduce more efficient data communication and coordination between sensor nodes. A multi-objective optimization approach with more parameters or factors can be used to select the best cluster head.
2) Most modern optimization techniques can also be implemented to improve the lifespan of your network.
3) Recognition and prevention systems can be used to improve the safety level of the proposed scheme.

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