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IMPROVING THE EFFECTS OF SECURITY MEASURES ON QOS FOR IOT BASED WSN IN HETEROGENEOUS DATA TRAFFIC

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ABSTRACT

Systems of wireless sensor networks (WSNs) usually consist of thousands of sensors that are powered by finite amounts of energy. Clustering strategies have been implemented to improve energy efficiency and lengthen the network's lifespan. Three common goals are considered while analyzing the existing protocols from a quality of service (QoS) standpoint: energy efficiency, dependable communication, and latency awareness. In intelligent systems, it is essential to comprehend user expectations in order to facilitate the capacity to serve a variety of situations. One difficult clustering issue that has to be resolved is user awareness or user-oriented design. Consequently, the possible difficulties in applying clustering techniques to Internet of Things (IoT) devices in network environments. WSNs are not suitable for, or perhaps unable to operate in, highly dynamic Internet of Things systems with a wide variety of user situations, as existing research on the topic is either carried out in homogeneous or low-level heterogeneous networks. Furthermore, the issue will get more complicated than it was in earlier, more basic WSNs when 5G is eventually implemented. However, when WSN expands, there is a significant raises in the amount of data that sensor nodes must collect, analyze, and distribute. The limited energy of the sensors makes it impossible to process and send such a big volume of data. Applying Machine Learning (ML) methods in WSNs is thus necessary. To maximize the performance of WSN, a number of issues pertaining to the application of clustering methods to IoT must be examined in conjunction with machine learning techniques. The goal of this research project was to create an energy-efficient method that would lower energy use and increase network connection longevity.

INTRODUCTION

In recent years, the Internet of Things (IOT) has gained interest. This technology has the ability to provide several solutions for problems that crop up in different industries. The communication backbone of a network for resource exchange amongst platforms globally is the Internet. The name "IOT" was first used in 1999 by Kevin Ashton at MIT's Auto-ID lab, while the idea itself dates back to 1998 [1]. It is an intelligent, impenetrable system that uses embedded systems to interact with one another. These systems are capable of detecting, regulating, and reprogramming. IOT offers fast access to information about any device with significant productivity gains. Approximately 50 billion smart devices are now online, according to the CISCO team [2].

The Internet of Things (IOT) consists of a billion interconnected devices that can detect, collect, and transfer data across devices without requiring human intervention. A few examples of IOT-enabled services that improve people's lives include health care monitoring, building automation, logistics, connected vehicles, smart city development, smart grid, smart home, smart retail, smart agricultural, and others. In this scenario, networked smart gadgets will become the new standard and the Internet would become outdated. IOT has the power to change the Internet in a manner that will make machine-to-machine (M2M) learning a reality [3]. The reconfiguration will take place when physical objects are become "smart," or capable of doing tasks independently, giving rise to the Internet of Things. IOT promises to increase the availability of modern gadgets by enabling connections at any time and from any place.

IOT essentially makes it possible for real-world things to communicate safely and autonomously. Regular procedures are automated by IOT, which decreases physical labor. The quantity of items linked to the Internet is always growing. Numerous sensors included in smartphones are able to gather data, process it, and then transmit the pertinent information via the Internet. Many apps that provide compelling benefits may be created by using that system with various sensor-equipped devices. IOT devices have unique identifiers. These devices read barcodes or radio-frequency identification (RFID) tags, which are picked up by sensor devices [3]. Through the Internet, the processing system receives and analyzes the data that the sensors have collected. The decision-making and action-invoking system receives the processed results and takes the necessary action. A new way of living may be contributed to by designing new applications, introducing new work, connection, and leisure methods, and so on, all thanks to the continual availability of vital information and facilities. Because of this, there will be a lot of traffic, with humans making up a small percentage of both traffic producers and receivers [4]. IOT is being studied for a number of study topics because to the challenges and possibilities it presents. In this case, effectively storing all the data necessitates keeping a consistent design. The IOT architecture

The IOT architecture is composed of the network layer, application layer, and perception layer [5]. The sensors are initially placed at the perception layer, from where they generate data and wirelessly transfer it to the network layer. Lastly, the application layer, which is connected to the network layer, is where the user obtains sensor data. IOT devices have often been designed using a five-layered architecture. Perception, network, middleware, application, and business layers make up the Internet of Things (IOT) layers. An IOT architecture diagrammatic depiction is shown in Figure 1.1

Layer of Perception The tangible item implanted in the sensor devices at the perception layer both receives and produces an electrical signal in response to a physical, biological, or chemical signal. Thermal sensors measure temperature and heat flow; magnetic sensors measure flux density and moment; electrical sensors measure current, voltage, and inductive reactance; mechanical sensors measure size, stream, pressure, and velocity; chemical sensors measure pH and proportions; and image devices measure light intensity and polarization [5] Data packets are sent wirelessly from sensors to the network layer.

Layer of Transmission It makes safe communication possible between middleware and the physical layer. Information may be sent by wired or wireless media, depending on the specifications. Data routing from the user to the target network is the responsibility of the network layer. Coaxial cable and fiber optics are examples of conventional wired techniques. Wi-Fi, Bluetooth, Zigbee, UMTS, infrared, 3G, and 4G are a few examples of communication networks.

Layer of Middleware Services are supplied by this layer to a range of diverse IOT-connected heterogeneous items. It gathers sensor data at the network layer and stores it locally in a database or on the cloud. After then, it decides what to do depending on the data gathered and the needs of the user.

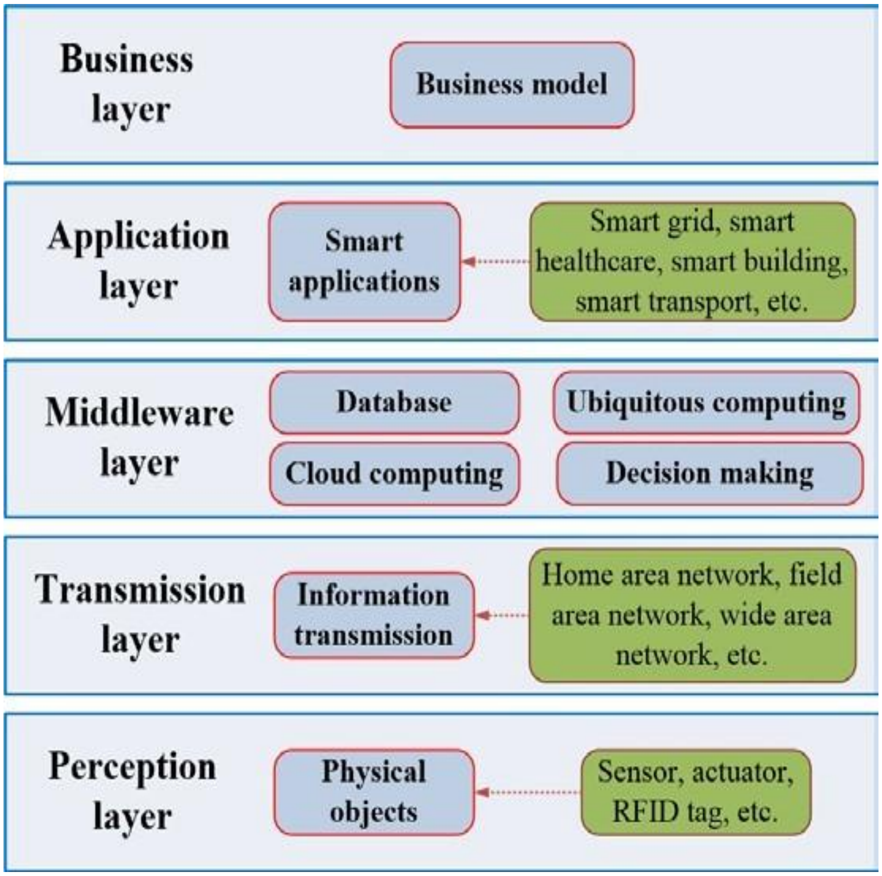

Figure 1 Architecture for the Internet of Things

Layer of Application It responds to user requests from connected devices by providing services. It submits the request as a query to the service layer, and upon receiving the response, it notifies the relevant user. In addition, it fulfills the needs of the client or customers and offers services. Restricted Use A popular IOT application framework called Protocol reduces processing time and connection bandwidth [6].

Layer of Business The overall management of IOT is under the business layer's control. It generates the business plan, graphs, and charts using application layer data. The business plan provides a straightforward means of accelerating organizational growth and supports the formulation of subsequent business plans. To raise the quality of service provided to the customer, it also compares the output of each layer to the most probable result.

Features of Internet of Things

IOT's fundamental qualities [7] are as follows:

Interconnection of Networks: One of the main topics of IOT in recent years has been the exponential expansion of Internet-based apps. The requirements may differ significantly due to the diverse variety of IOT technology applications, but the most essential components are always present. It is feasible to achieve several breakthroughs using IOT. One crucial component of an IOT system is the network, which enables communication between the various devices. Several wired and wireless technologies may play this function.

Sensing: IOT cannot generate data that can map or interact with surrounds if it does not have sensors that can detect and measure any changes in the environment. Recognizing gadgets provide a means of constructing skills that demonstrate the true knowledge and awareness of the physical environment.

Heterogeneity: Heterogeneity is one of the IOT's main focuses. IOT devices may link to other service platforms or devices via specific networks as they are designed on specific hardware and Internet platforms. IOT facilitates direct communication between non-homogeneous systems. These items and their related IOT environments include specifications for scalability, expandability, interoperability, and modularity.

Connectivity: The Internet of Things makes it possible to connect common objects together. It stabilizes everything and offers connections to a network. With the use of this link, intelligent devices and apps may be networked to create new IOT business prospects [8].

Security: There are network safety concerns with these sensors. Customers are more prone to ignore security issues as they become more efficient and encounter new things. Numerous technologies with high levels of security enable the Internet of Things. The features of IOT technology listed above provide human actions purpose and motivate them. By working together, they improve the functioning of the IOT network and integrate into the overall structure [9].

Intelligence: IOT is clever because it has a computer, hardware, and software combination. By using its full potential, environmental intelligence allows intelligent things to carry out specific duties. IOT is concerned with computer interaction using conventional input techniques and a visual user interface that facilitates user engagement, even with the growing popularity of intelligent technology.

Adaptable Nature: IOT's main responsibility is to gather data from its environment. IOT devices dynamically modify the temperature, location, and speed of an item. Along with the device status, the number of devices changes dynamically depending on the user, location, and time.

Massive Scale: There will be a considerably larger number of gadgets to interact with and control other Internet-connected devices. It is increasingly crucial for applications to handle and interpret the data produced by these devices.

REVIEW OF LITERATURE

Adnan, M., Ahmad, et al., [1] Utilizes mobile agent techniques for data fusion First, we will discuss the WSN model and mobile agent framework. Then, we will propose a data fusion routing mechanism that utilizes an enhanced ant colony method to determine a more effective approach. When analyzing migration flows of a mobile user, it's important to consider more than just the separation of two endpoints. The average energy usage is also taken into account to ensure that the operator doesn't move to an incorrect node. Finally, the computational results show that the proposed approach effectively reduces network latency and improves system reliability.

Sharma, N., Singh et al., [2] Due to significant advancements in technology, the combination of nano-sensors, wireless networks, and smart software has greatly increased the relevance of WSNs. One of the key challenges faced by WSNs is the fast depletion of sensor energy. Utilizing clustering techniques and selecting suitable cluster heads can be effective strategies for addressing this issue. The optimization of Mamdani fuzzy rule-base tables is achieved through the utilization of the Fuzzy Shuffled Frog Leaping Algorithm, which is tailored to meet specific requirements. Before deploying the network, this approach enhances the five adjustable parameters of the fuzzy system's input in an offline manner, while also dynamically modifying the if-then rule base. Energy and distance are two inputs used in fuzzy systems. Inputs for fuzzy systems consist of residual power, proximity to the base station, and neighboring nodes. The clustering technique being recommended has two specific criteria for transforming contender nodes into ultimate cluster heads. The FSFLA method is compared to LEACH, LEACH-DT, SIF, and ASLPR in terms of bandwidth, energy, and packets successfully received. The results indicate that the FSFLA clustering protocol demonstrates superior performance compared to previous protocols.

Adnan et al.,[3] Flexibility and energy efficiency are vital in wireless sensor networks. Given the large number of nodes in WSNs and their limited storage and battery capacity, it is crucial to prioritize energy-efficient design. Clustering has proven to be a highly effective method for enhancing energy consumption and extending the lifespan of sensor nodes, which are crucial for the overall functioning of the network. In this paper, researchers propose a multi-hop WSN clustering technique that utilizes fuzzy logic to enhance network scalability and minimize energy consumption. Researchers have put forward a method for selecting a sensor node as a CH based on inputs from fuzzy logic. The size of CHs' perimeter is determined by the fuzzy logic. Researchers select the radius size of CHs using fuzzy logic inputs to effectively balance the load. The TTDPF and CHCCF systems are being compared to the recommended strategy. The simulation findings indicate that the proposed schemes demonstrate superior performance compared to the TTDFP and CHCCF schemes in terms of network longevity.

Selvi, M., Kumar, S. S et al., [4] Developing energy-efficient routing methods for WSNs poses a significant challenge for researchers. In recent times, WSNs have become increasingly popular, with a wide range of energy-efficient routing solutions being proposed. Most routing protocols primarily concentrate on CH. Harmony search is utilized to discover an initial set of energy-efficient cluster head nodes that are appropriately spaced apart from each other. After that, temporary elections are held for cluster head nodes. The firefly approach further refines the cluster that has been provisionally selected. The Firefly approach optimizes the selection of cluster head nodes by taking into account factors such as the number of nodes, cluster density, and energy usage. The selection is divided into two phases in order to mitigate challenges arising from premature convergence of evolutionary optimization methods. A new approach is proposed for cluster formation, where each node can choose to connect to a cluster head node based on either distance or the remaining energy of the cluster head. Clustering is beneficial for energy conservation. The technique presented here relies on evaluating various parameters such as living nodes, energy utilization, packets collected by the base station, first node death, half node death, and last node death. When deployed using the Simulation Tool, a hybrid cluster formation election technique outperforms specified routing protocols.

Alabdali et al., [5] Clustering is widely acknowledged as a highly effective method for conserving energy in WSNs. Cluster-based WSNs experience higher energy consumption and a shorter network lifespan due to the increased energy consumption of CHs compared to conventional nodes. Various routing strategies have been proposed to reduce the energy consumption of CHs. Additional clustering of CHs will lead to a decrease in energy consumption in these designs. In contrast, this particular rule has not been examined in previous similar publications. One of the main concerns in the design is the uneven energy consumption of CHs, resulting in higher energy wastage and premature network failure. Many recent studies have focused on improving energy balance through the use of large and expensive energy harvesters, which can lead to increased expenses [10]. A practical solution is needed to ensure that CHs consume energy in a balanced manner.

Researchers proposed a new approach to address the limitations by introducing a wireless energy balancer for energy-efficient clustering. First, we offer an n-level clustering that optimizes the utilization of CHs and minimizes their energy consumption. Additionally, an energy balancer is employed to minimize the amount of wasted energy by equalizing the remaining energy of CHs. The performance of the suggested scheme has been compared to the CMS2TO and DGOB methods. Simulation results demonstrate that the suggested system significantly improved various aspects compared to previous schemes. The network lifespan increased by 20%, overall energy consumption rose by 52%, network overhead saw a 20% increase, calculation time was extended by 46%, and wasted energy was reduced by an impressive 86%. Ultimately, the proposed framework showcases its potential as a viable solution for prolonging the lifespan of networks and enhancing energy efficiency [10].

Behera et al.,[6] Introduced SEP, a method that performs threshold-based CH selection in a non-homogeneous network. The energy is distributed equally among CH and other nodes based on the threshold concept. Classifying sensor nodes into three categories (basic, intermediary, and advanced) based on their original power generation, this paper aims to distribute bandwidth requirements fairly. Based on the results of the simulation, the proposed system demonstrates superior performance compared to SEP and DEEC procedures. It shows a 30% increase in network lifespan and a 56% improvement in throughput [11].

Mishra, P. K., & Verma et al., [7] Explores the optimization of cluster size in wireless networks through the use of compartmental model-based techniques and opportunistic inputs. Utilizing various types of data, such as Wi-Fi, acoustic, and visible light, can be advantageous when considering the availability of transmissions in a specific region of interest. The compartmental attenuation model demonstrates the variations in signal power as it travels different distances. Using parameters gathered from experimental observations, a thorough analysis was conducted to evaluate the performance of the compartmental model. We will explore the potential of utilizing opportunistic transmissions in optimizing cluster size within compartmental design. When compared to the incremental and log systems, the compartmental architecture enhances average power utilization by 6% and 8%, respectively. WiFi and acoustic communications have been found to be 13 percent less effective compared to visible light signals.

Future research will focus on recommendation systems, detecting and localizing malicious sensors, implementing the SGD approach in a large WSN, and utilizing the Cramér-Rao constraint for variable prediction. These advancements will be based on the current concept.

Al-Khayyat et al., [8] A new structure for WSN has been proposed, utilizing the ACO approach. The K-means clustering technique is highly effective for secure transmission in Wireless sensor networks of any scale. It is reliable over a short period of time and does not require architecture, assistance, or particularly unique nodes. This makes it applicable to a wide range of different fields. In terms of navigation and power demand, the proposed methodology demonstrated superior performance compared to the Leach clustering method and its variations, including Fuzzy-leach and other cluster-based algorithms

Sonam Lata et al [9] An innovative centralized fuzzy-based clustering approach was employed in order to select a suitable candidate based on three key parameters: energy level, concentration, and centrality. Clusters are formed by LEACH by analyzing the signal intensity received.

Sonam Lata et al [9] An innovative centralized fuzzy-based clustering approach was employed in order to select a suitable candidate based on three key parameters: energy level, concentration, and centrality. Clusters are formed by LEACH by analyzing the signal intensity received. Additional nodes are incorporated through the utilization of fuzzy logic and three control dimensions, namely power capacity, nodal length to the Base Station, and radius to the cluster head. The authors also utilized fuzzy criteria to select a vice cluster leader, considering three variables this time. The initial two modifications aim to prolong the system's lifespan, while the third adjustment is intended to enhance the uniformity of the WSN. The proposed method has shown its effectiveness in balancing energy demand at each node, thereby enhancing the stability of WSN.

MATERIAL AND METHODOLOGY

A branch of artificial intelligence called "machine learning" examines a computer's ability to learn without the need for programming. In order to make wise decisions for new instances, process learning is carried out by looking at examples and comprehending the relationship between the general-purpose input and output values. The objective of this approach is to train a computer to comprehend without assistance from a human. Machine learning techniques are often used to identify patterns or extract features from large datasets and to find awareness information [43]. The ultimate objective of machine learning is to develop algorithms that let a system automatically collect data and use that data to learn additional features. In order for systems to make important choices by themselves, they must look for patterns in the data they gather. A crucial component of machine learning is data. Any model cannot be prepared without data. Data is any unprocessed fact, number, text, audio, or image that hasn't been examined and examined. It may be divided into the following categories

Data of Validation: This information is used when the model is being trained.

Data of Testing: Test data provides an objective assessment when the model is completely trained. When testing data is fed into the trained model, it forecasts certain values. The model's effectiveness is assessed by comparing its output to the testing data's actual output after the forecasting procedure.

Artificial Neural Networks: Neuroscience serves as the inspiration for ANNs, a branch of machine learning that is modeled after the human brain. Computer networks are responsible for the formation of the human brain [12]. Similar to actual brains, artificial neural networks (ANNs) are made up of neurons that are interconnected on various levels. Nodes are the name given to these cells. In an artificial neural network (ANN), dendrites from biological neurons serve as inputs, cell nuclei as nodes, synapses as weights, and axons as outputs. These algorithms for supervised learning examine labeled samples, each of which has an input and an intended result. Following the provision of datasets for learning, the algorithm would be capable of classifying and producing an output for a fresh dataset. Neurons in a neural network (NN) are joined by weighted connections, which enable a transfer function to connect the input and output layers. There is no need for data storage since this function is just the total of the products of the input values and their weight. An artificial neuron is shown in the figure below [12].

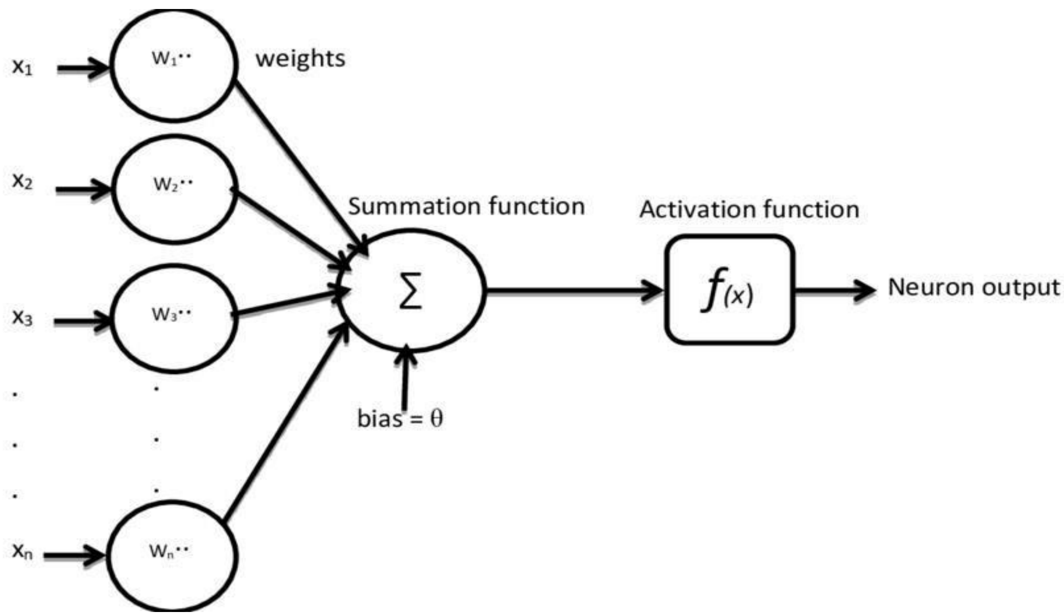

Figure 2 Synthetic Neuron

RESULT

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**
	Area	200x200 m^2

Network	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 (ε_{fs})	10 pJ/bit/m^2
	Radio amplifier energy (ε_{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

Proposed approach's output is contrasted to two recent research that used clustering to enhance WSN routing. Sharma et al. 2021 [7] offered an energy-efficient protocol based on Quality of service, while Selvi et al. 2021 [1] suggested clustered gravitational routing for energy-efficient clustering and efficient routing. In next sub- sections, simulation analysis of proposed and existing techniques is compared in terms of throughput, PDR, and latency [14].

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 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 2 Comparative analysis of Throughput

No. of Nodes	**Throughput Proposed**	**Throughput Sharma et al. 2021**	**Throughput Selvi et al. 2021**
10	1538.843	1392.266	1341.663
20	1608.392	1459.825	1474.653

40	1593.896	1431.154	1453.625
60	1629.449	1424.827	1479.475
80	1595.357	1396.751	1432.949
100	1585.909	1484.745	1499.462
120	1779.596	1567.027	1587.908
140	1860.099	1683.475	1712.214
160	1995.654	1832.415	1847.483
180	2142.395	2017.475	2101.124
200	2326.443	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.

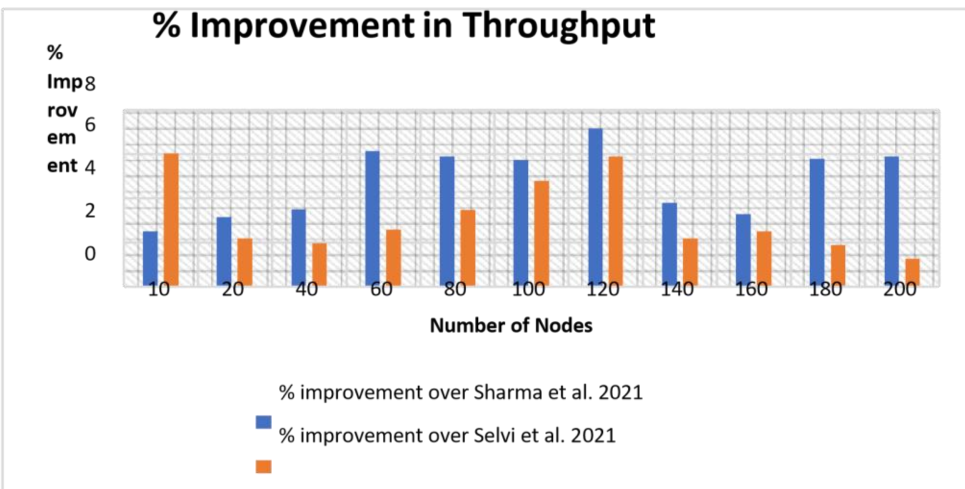

Figure 3 Improvement in Through put

PDR Analysis

PDR is used to look at differences between packets provided by source node and packets received by destination nodes. PDR of proposed, Sharma et al., and Selvi et al., and nodes used in simulation study, are compared in Table 3.

Table 3 Comparative Analysis of PDR

Number of Nodes	PDR Proposed	PDR Sharma et al. 2021	PDR Selvi et al. 2021
10	0.8082	0.6839	0.6973
20	0.8093	0.6968	0.6889
40	0.8349	0.7009	0.7073
60	0.8229	0.7023	0.7053
80	0.8295	0.7097	0.6914
100	0.8642	0.7296	0.7333
120	0.8356	0.6833	0.6968
140	0.8486	0.7191	0.7094
160	0.8499	0.7155	0.7276
180	0.8544	0.7011	0.7228
200	0.8607	0.7214	0.7397

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 [16].

The communication latency between two endpoints is investigated in this section. The recommended technique results in a communication delay of just 11.74ms at start, which is much smaller than delays found by Sharma et al. and Selvi et al. The delay seen using recommended work is slightly less than that obtained utilising Sharma et al. and Selvi et al work. The pattern is nearly unchanged when nodes are increased from 10 to 200. The comparison of observed latency with regard to collection of nodes is summarized in Table 4.

Table 4 Comparative analysis of Delay

set of Nodes	Delay Proposed	Delay Sharma et al. 2021	Delay Selvi et al. 2021
10	12.85	12.344	12.122
20	13.985	13.578	13.354
40	14.956	14.72	14.527
60	15.968	15.825	15.678
80	16.889	16.731	16.469
100	18.086	17.775	17.963
120	19.339	19.089	18.722
140	19.895	19.985	19.264
160	20.396	21.526	21.093
180	22.099	21.841	22.386
200	23.002	23.193	23.285

According to table, suggested work had average delay of 16.97 milliseconds, while Sharma et al. had average delay of 17.87 milliseconds and Selvi et al. had average delay of 17.71 milliseconds. Figure 5 depicts proposed work's enhancement analysis in comparison to two current studies for all variations in number of nodes employed for computational analysis. Overall, suggested work improved by 5.02 percent compared to Sharma et al. and 4.06 percent compared to Selvi et al. Using the suggested protocol, it indicates a significant reduction in communication latency[17].

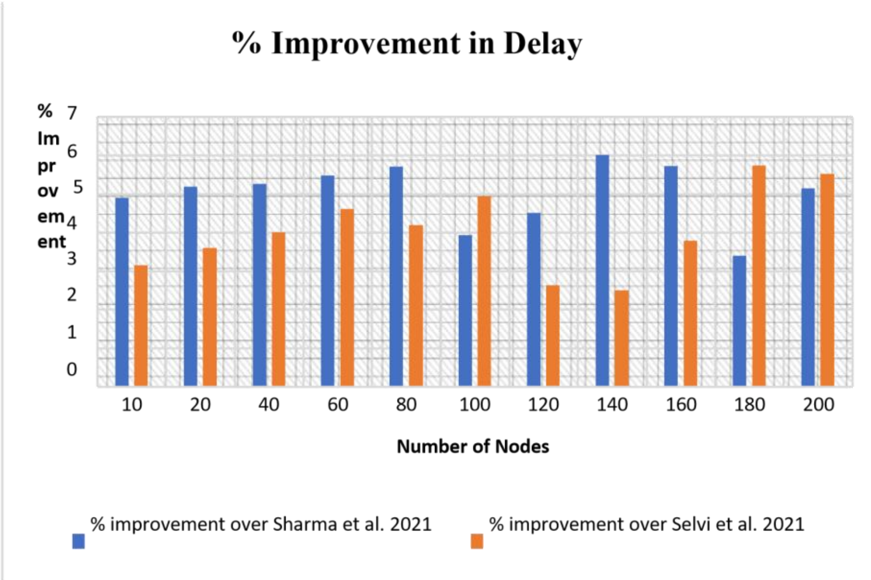

Figure 4 : % Improvement in Delay

CONCLUSION

The low battery life of WSNs is an inherent problem. Various clustering techniques have been proposed in past to resolve this concern, with focus on CH selection or data transfer from cluster head to the base station. Grid-based clustering in WSN eliminates energy usage and resolves the energy balance issue by spreading load and energy consumption among all nodes in system. Grid architecture provides great reliability and cheaper costs over lengthy transmission durations. After establishing the network with both methods, it was observed that utilizing a single CH in each grid increased energy efficiency. At the same time, it handles load balancing, clustering overhead, and energy efficiency routing. To test the success of the proposed clustering-based routing system, its throughput, PDR, and latency are measured. In performance evaluation, proposed work demonstrates a 3% to 4 % increase in throughput, 2 %to 3 % percent increase in PDR, and 4 % to 5% decrease in communication latency when compared to two clustering-based routing algorithms. This conclusion is supported by optimum CH selection approach employed during route discovery phase of proposed procedure. Better network performance, as evaluated by throughput and PDR, and least latency, demonstrate suggested work's efficacy.

This research offered a method for selecting cluster heads based on nodes' cosine similarity, as well as feed forward neural network-based reinforcement learning strategy for optimizing network route selection. Additionally, artificial neural network was employed for route maintenance; this element of study has been mostly overlooked in prior studies. The throughput, PDR, and energy consumption of network have all been measured to assess its performance. RL-based ANN technique was compared to RL- based SVM and RL-based NB approach. The findings shown that suggested approach outperforms SVM and NB. This demonstrates that with existing technique, routes have indeed been better optimized and maintained.

Scope for Further Research

As per the final results discussed in the conclusion, more research is required to enhance the effectiveness of energy efficiency. The following are the suggestions for the researchers to enhance the research work in future.

- To bring significant increases to the proposed model, more research is required to assess the effectiveness of artificial intelligence and machine language on any other such clustering technique which can give more optimized results.
- New More Intelligent protocol can be designed to introduce more efficient data communication and coordination between the sensor nodes.
- The multi objective optimization approach with more parameters or factors can be used to select optimal cluster head[18].
- The latest optimization techniques can also be implemented for improving the network lifetime.

Detection and prevention system can be deployed to enhance the security level of the proposed scheme.

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