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Enhancing Quality of Service in WSN Through a Routing Algorithm Based on Self-Organizing Maps

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Abstract

Many scholars have focused their attention on Wireless Sensor Networks (WSN) within the last ten years. QoS control, Energy intake, MAC protocols, routing protocols, statistics aggregation, self-organizing net algorithms, Internet of Things (IoT), and so forth are among the research topics that have been thoroughly studied recently. Historically, the potential of artificial intelligence (AI) has not been fully realized due to constraints in data processing capabilities and energy efficiency. Nonetheless, the unique characteristics of neural networks can be harnessed for complex tasks, such as the role of travel advisors. This research aims to combine IoT and WSN technologies to enhance Quality of Service (QoS) parameters including reliability, energy, conservation, system scalability and response time. It provides an overview of the key components and techniques utilized in WSNs to achieve QoS. The objective of the proposed article is to compare the performance of two widely used route paradigms, Energy-Aware Routing and Directed Diffusion, with the proposed routing technique called Sensor Intelligence Routing (SIR). The foundation of Sensor Intelligence Routing (SIR) is the incorporation of neural networks into discrete sensor networks. WSN simulation, OLIMPO (an ad-hoc wireless sensor network simulator for optimal scada-applications) has been used in multiple simulations to examine how well neural networks perform within the system. The results obtained from every routing method have been compared and analyzed. The paper also aims at fostering the use of IoT-based synthetic intelligence techniques.

Keywords: Artificial Neural Networks (ANN), Ad hoc Networks, Routing, Self-organizing Maps (SOM), and IoT.

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1. INTRODUCTION

Recent technological advancements have made it technically and commercially viable to manufacture small, low-cost sensors. These sensors allow one to monitor the impact of the surrounding environment on them. These sensor nodes are commonly found in thousands or hundreds within the IoT and WSNs. Because of the sensor features, self-organizing networks are the optimal network design for programs in this type of scenario. With the IoT, the significance of requirements such as effective energy organization [1], dependability, high availability communication security, and resilience has risen significantly.

Investigations into this kind of network have been conducted globally, with notable emphasis in the United States and Europe. The state-of-the-art in this field has been extensively defined by Willig & Karl [2], and Akyildiz et al. [3]. ”Path discovery” is one of the newest WSN study areas in IoT. It is concluded by Bernard, M. S. et al. that “the IoT-based paradigm that enables objects to connect and exchange structured and unstructured data with one another to enable multimedia-based services and applications” [4]. However, the defeating algorithm design must take into account the QoS that the application has provided due to sensor limitations in order to further fulfill the previous objectives. The development of software-defined platform based on the recent developments in 5G system architecture were also design to address this issue [5].

Although many solutions have been proposed by both academia and industry to tackle QoS limitations in current networking, most either fell short or were never implemented, paving the way for the emergence of the Software Defined Networking (SDN) paradigm [6].

WSNs are critical components of the IoT ecosystem because they enable data collection and transmission from a wide range of physical settings. Within WSN, QoS routing techniques offer consistent and efficient data delivery. Many academic efforts have been made in the last few years to provide QoS routing algorithms for IoT-based WSNs [7]. Some of the major contributions made to this field are listed below.

- **Energy-Aware Routing:** Because sensor nodes have a limited battery life, energy efficiency is one of the main concerns with WSNs. In order to improve network lifetime while accounting for energy constraints, researchers have developed QoS routing algorithms. These algorithms pick energy-efficient pathways for data transmission dynamically by considering factors including distance, data aggregation, and residual energy levels [8].
- **Traffic Load Balancing:** For peak network efficiency, evenly distributing traffic load across sensor nodes is crucial. To achieve this, routing strategies aimed at QoS have been suggested, which help in spreading traffic evenly across the network, thereby mitigating congestion in particular areas [9]. These techniques protect certain nodes from becoming overloaded by modifying routing decisions in response to real-time traffic monitoring.
- **Dependability and Tolerance for Errors:** Because WSNs are often employed in difficult and unexpected scenarios, they are vulnerable to node breakdowns and disruptions in communication. Different WSN models were made for two different applications, spatial mapping and target tracking, in which QoS were explicit [10]. The goal of QoS routing methods is to ensure reliable and resilient data transmission, taking into account multiple routes, the reliability of

nodes, and the quality of connections. These algorithms are designed to dynamically adapt to changing network conditions even in the case of a breakdown, ensuring data delivery.

- **Scalability and Network Dynamics**: As the count of sensor nodes increases or when there are changes in the network structure, the adaptability and scalability of QoS routing methods become imperative. Algorithms have been crafted by researchers to handle extensive WSNs efficiently and adapt seamlessly to changes in network conditions, including the mobility, addition, or elimination of nodes [11].

With the aid of these contributions, the field has advanced and dependable algorithms for QoS routing in IoT-based WSNs have been developed [12]. The aim of these algorithms is to satisfy numerous application objectives in the IoT ecosystem by enhancing network performance, energy economy, reliability, and adaptability.

2. BACKGROUND OF THE STUDY

IoT-equipped WSN explores the integration of IoT technologies with WSN, presenting a convergence that holds significant promise for various applications. WSN serves as a foundational infrastructure for collecting and disseminating data from the physical world, while IoT extends this capability by enabling seamless connectivity and communication between a myriad of devices [13]. This fusion offers enhanced sensing, data analytics, and real-time monitoring capabilities, revolutionizing industries such as healthcare, agriculture, and smart cities. Investigating the historical context, technological advancements, and challenges associated with IoT-equipped WSN's the contributions of the prominent authors can be categorized in terms of the Energy Aware Routing, Traffic Load Balancing, Dependability and Tolerance for Errors and Scalability and Networks Dynamics discussed in previous section are as follows.

Literature Review on Energy Aware Routing:

Priyanka, et al. [14], addressed the increasing demands of IoT applications, such as video/audio streaming in surveillance, disaster recovery, multimedia, and healthcare, which necessitate improved QoS delivery. The authors introduced a congestion management technique utilizing the Hierarchical Token Bucket (HTB) for bandwidth management in Software-Defined IoT (SDIoT) networks. The findings demonstrated that their approach significantly reduced end-to-end delay and increased average throughput respectively.

Thenmozhi, et al. [15], addressed the critical need for QoS communication protocols in real-time IoT applications, where the collection and processing of heterogeneous IoT data present unique challenges in terms of energy, reliability, latency, and priority. The study introduced the Energy-Efficient Priority-based Multi-Objective QoS routing (PMQoSR) mechanism to ensure energy efficiency and QoS in IoT networks by regulating routing performance based on QoS parameters. The results showed that PMQoSR excelled in managing network traffic, forwarding packets, and prioritizing routes, leading to better traffic load management, throughput, end-to-end delay, and packet delivery ratio compared to existing systems.

Nilesh, et al. [16], described WSN, including next-generation intelligent IoT applications. WSN nodes with restricted resources were powered by batteries that have a finite capacity. Energy consumption on each node and the lifetime of the network as a whole were concerns for IoT applications due to the lengthy lifespan of WSNs. The approach presented in this study is a cross-layer variation of AODV, substituting link quality and collision count for the hop count metric. This helps the Network layer make wise routing decisions by utilizing the Z-Score method. An evaluation of current approaches in comparison to one's own shows progress in terms of network longevity, energy efficiency, path stability, and delay.

Tirupati, et al. [17], explained that WSN offers location awareness, status updates for various environmental entities, and data collection for extended IoT surveillance. Data routing require a significant energy investment. Their paper presented an enhancement of the current stable election protocol (SEP) for a heterogeneous network, using a threshold-based Cluster Head (CH) selection. The threshold keeps the energy distribution between CH and member nodes constant.

Mohammad Ahmed, et al. [18], addressed the crucial role of VANET (Vehicular Ad Hoc Network) in enhancing intelligent transportation systems and addresses its challenges, including high mobility, rapid topology changes, link failures, delays, congestion, and security threats. It introduces a new routing protocol, QoS+, that merges QoS-aware CH selection with a hybrid cryptographic method, aiming to boost network stability, connectivity, and security using AES and ECC. Tested on a custom VANET simulator in NS2 software showed superior performance over existing methods in various parameters like message success rate, routing load, throughput, efficiency, and end-to-end delay, highlighting improved efficiency of CHs, cluster member performance, and an increased average number of clusters at various speeds and transmission ranges.

Parvinder and Rajeshwar [19], explained that WSN, utilizing low-power microsensor devices, were utilized for various applications like remote sensing and surveillance. Advances in these devices spurred the creation of smart WSN applications, though issues like energy efficiency and communication reliability posed limitations. Cluster-based routing protocols were key in optimizing data collection and transmission by grouping sensor nodes. Their paper proposed a multi-objective clustering strategy to enhance energy efficiency, network lifetime, throughput, and delay, employing a fitness function for optimal CH selection in both heterogeneous and homogeneous networks.

Literature Review on Traffic Load Balancing

Yaozhong, Stephen, et al. [20], investigated how the IoT is transforming infrastructures for smart communities through intelligent device connectivity. It highlighted the practice of offloading compute-intensive tasks from resource-constrained IoT devices to more capable systems, such as cloud servers, to overcome limitations. To optimize edge computing for IoT, the paper introduced a task management strategy that periodically redistributes tasks to enhance the network's processing capacity and meet QoS standards. Simulation results confirmed the strategy's effectiveness in increasing the completion rate of tasks, thus boosting the network's efficiency and effectiveness.

The challenge in the IoT era focused on efficiently and cost-effectively managing traffic from a multitude of smart devices to the Internet. A strategy was proposed to equip only gateways with full capabilities, while other devices used simpler, cheaper transceivers for forwarding traffic, ensuring adherence to specific QoS standards for each device. To address the issue authors Ilias, Prodromos, et al. [21], formulated the network planning problem of IoT to identify the optimal number and placement of gateways and the appropriate transceivers for devices, aiming for a cost-effective, QoS-aware network infrastructure.

Kavita and Veena [2], discussed the challenges faced by WSN-based IoT applications, including end-to-end delay, packet loss during transmission, and reduced sensor node lifetimes due to energy depletion. To tackle these issues, the authors designed an energy-efficient routing protocol aimed at improving network performance and QoS for IoT applications experiencing unfairness and high traffic load. The protocol selected the optimal path based on three criteria: lifetime, reliability, and traffic intensity at the next-hop node. The results demonstrated that the proposed protocol outperformed others in terms of energy savings, packet delivery ratio, end-to-end delay, and network lifetime.

Literature Review on Dependability and Tolerance for Errors

Manisha and Gaurav [22], highlights the significance of defining QoS metrics in the IoT to enhance its adoption and utility. By automating human life, IoT has the potential to simplify daily tasks. However, the success and popularity of IoT services largely depend on the clear definition of QoS metrics. This study identified and outlined various QoS metrics for IoT, considering its foundational pillars: Computing, Communication, and Things. The goal is to aid IoT service providers in describing their offerings, enable users to articulate their requirements, and assist researchers and professionals in developing IoT models with a focus on the importance of QoS metrics.

Dongwan, et al. [23], addressed the need for simultaneous assurance of both security and quality-of-service (QoS) in numerous WSN applications. Nonetheless, achieving both security and QoS in WSNs presented a significant challenge, since security measures often adversely affected QoS. In this study, the authors introduced an energy-efficient secure forwarding technique that reduced energy usage while simultaneously satisfying both security and QoS criteria. The simulation outcomes demonstrated that this approach surpassed competing methods in energy efficiency while fulfilling the dual requirements of QoS and security.

Karunuzhali, et al. [24], discussed in their paper that the IoT improved daily machine optimization through smart data processing and enhanced communication. A new software framework for IoT applications and an optimal QoS-aware routing technique, OQR-SC, were developed, utilizing IoT-enabled WSN. The optimal decision-making (ODM) algorithm determined the best data transmission paths. The effectiveness of the OQR-SC technique was verified using the NS2 simulation tool, demonstrating superior performance compared to existing techniques.

Literature Review on Scalability and Networks Dynamics

Chérifa, et al. [25], explored the crucial role of reliable communication in the success of the IoT by focusing on the optimization of protocols through the estimation of wireless link quality, which in turn reduces latency, and enhances both reliability and network longevity. The research investigated the link quality within Time Slotted Channel Hopping (TSCH) networks by analyzing received signal strength (RSSI) and error rates, aiming to understand the temporal characteristics of these factors. This knowledge was vital for selecting optimal channels for critical applications and improving the network's QoS.

Guo-Cin and Kuochen [26], in their study addressed the challenges posed by the proliferation of IoT devices, which generate large volumes of data, leading to potential network congestion and massive bandwidth consumption when this data is transmitted to cloud or fog layers. It noted the particular demands of IoT applications that require the transfer of multimedia data, each possessing unique QoS demands. Although the advanced MINA algorithm was designed to cater to these varied QoS necessities, it did not fully ensure the QoS expectations for critical IoT applications nor did it effectively adapt to changing network situations.

Salvica, Walter, et al. [1], discussed that the major challenge within the IoT landscape involved managing and orchestrating environments that span multiple technologies and vendors. Their amalgamation facilitated the governance of countless smart devices through sophisticated orchestration and provisioning systems. SDN's distinct advantage lies in its ability to enable network virtualization and the automated rollout of new services over this virtualized infrastructure. In pursuit of this forward-thinking model, a framework based on SDN for the virtualization of IoT networks was developed.

Vu Khanh, et al. [27], discussed that WSN and Mobile Ad hoc Networks (MANET) drew special attention for their role as communication channels in various sectors, including healthcare, military, smart traffic, and smart cities. With the evolution of the IoT, where every device can be network-connected, integrating WSN, MANET, and other networks into IoT became essential. The research focused on the merging of WSN and MANET within IoT, addressing a critical issue: the ability of a unified WSN-MANET network to offer QoS guarantees to multimedia applications.

Omjee, Tankala, et al. [28], discussed that the limitations of conventional WSN such as limited radio range and lack of scalability which hinder wide area connectivity among IoT devices, Low-Power Wide-Area Networks (LPWANs) have been developed. These networks offer long-range communication capabilities while maintaining low power consumption for end devices. To address these issues, a multi-hop data routing method for LPWANs was proposed. The method tackled the inherent challenges of multi-hop transmission, including increased data latency, higher interference, and reduced throughput, by employing a reinforcement learning approach.

Mukesh, et al. [29], addressed the challenges of maintaining network longevity in WSNs integrated with the IoT, focusing on the high energy demands of IoT operations. A significant contribution of this research was the introduction of a multi-objective optimization model that selects optimal packet transmission routes using a trust model for CH selection, followed by a hybrid algorithm combining particle swarm optimization (PSO) and genetic algorithm (GA), named PSOGA. Simulations demonstrated that PSOGA outperforms existing methods like LEACH and PSO in energy efficiency, network throughput, packet delivery rates, and residual energy, offering a promising approach to improving WSN longevity.

In this paper, Idris S, et al. [30], conducted an in-depth examination of IoT and wireless sensor network (WSN) simulators, with a particular emphasis on the performance of these simulators when utilizing LoRa (Long Range), a Low Power Wide Area Network (LPWAN) communication technology that has recently garnered significant attention. Employing a systematic approach, they created a chronological survey of available IoT and WSN simulation tools. Key performance metrics such as Packet Delivery Ratio (PDR), CPU utilization, memory usage, execution time, and the number of collisions were evaluated to provide a comprehensive assessment. This detailed analysis offered valuable insights into the strengths and weaknesses of various simulators within the context of IoT and WSN applications

3. ARCHITECTING NETWORK STRUCTURE

Various factors needed the consideration while designing a WSN for IoT devices. These included protocol design, data aggregation techniques, QoS, redundancy for dependability, scalability, and connection of WSNs into larger systems, data-centric addressing structures, energy geographic needs, and addressing structures for communication procedures.

This emphasized the use of Open Systems Interconnection model (OSI) where lower layers made use of our special WSN Arachne protocol, IoT devices, 802.15.4 protocol, and additional protocols like ping, base station, and broadcast clock for data aggregation originating in the upper levels. If a program, such as a representative SCADA system, worked well with data from several unique sensor sets, arrangements were made to expand the quantity and duration of sensing based on the schedule of the sensors [31]. Paths were chosen considering how advanced usage would affect the network's longevity, with a general rule to avoid key WSN nodes for IoT devices.

Numerous scholars and authors have explored the challenge of maintaining robust connectivity in IoT device WSNs in their publications [32]. Our study examined a random distribution of devices, focusing on the average radio range determined by individual node radio ranges, radio transmitter power, and radio receiver sensitivity. Within the realm of IoT devices, we assessed various network routing strategies applicable to wireless networks [33], including strategies for minimizing transmission energy, multi-hop routing, and direct communication.

In the direct communication protocol, each WSN node transmitted data directly to the base station. Meanwhile, WSN utilized an algorithm for minimum-transmission-energy routing, where selected nodes acted as routers for others. This approach focused on choosing intermediary nodes strategically to minimize global energy consumption.

The primary types of routing in IoT-based WSNs were location-based, flat-based, and hierarchical-based. For networks with equal responsibilities for each node, flat-based routing was effective. Energy-aware routing (EAR) and directed diffusion were chosen as samples to test the impact of AI among the flat routing protocols already in use. Directed diffusion was used by sensors to measure events, maintaining several paths and selecting them based on the likelihood of energy consumption. This approach prevented rapid depletion of energy in any single path at various IoT junctures.

4. NEURONS IN IoT DEVICE:

The route problem emerges because the nodes must be connected to each other. To transition from a single power source to multiple in WSN, a multi-hop method is needed. There may be a set of parameters that dictate the paths to be followed. A few instances of appropriate specifications are minimum latency, minimum hop counts, maximum data speeds, and minimal error rates. Consid-

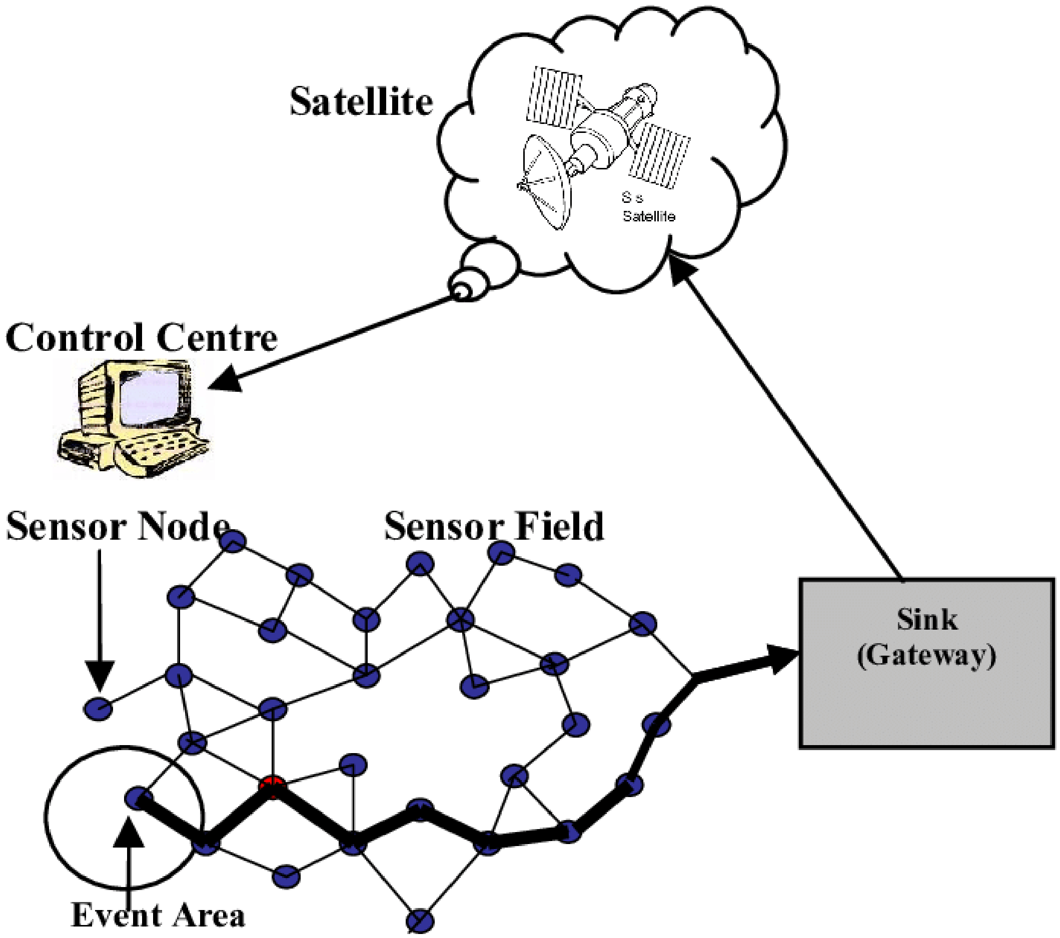


Figure 1: Event Transfer from an IoT device's Source to its Sink.

ering the situation where each node requests communicating statistics to the base station, the issue is solved via a method known as "network backbone construction".

4.1 Creation of the Network's Backbone:

Graph Theory has been used to examine how the network's establishment has grown.

Let A is a collection of edges composed of ordering pairs, and V is a set of nodes, then an ordered pair G is an absorbed graph.

$$G := (V, A)$$

It is believed that an edge by the coordinates Vxy (x, y), where x stands the edge's tail and y is its head, would stay orientated after x to y. A method to solve the distinct shortest pathway issue is proposed by E. Dijkstra for a directed network where the true edge weights of IoT devices are non-negative. We make the assumption that all of the links in our WSN are symmetrical.

To build the centralized system, we propose to alter Dijkstra's algorithm by employing the shortest paths between each network node and the incorrect station, or roots, r. Sensor Intelligence Routing, or SIR, is the name given to this method. Although IoT device directions are included in the framework of Dijkstra's approach, our modified network has edges. Since we assume that wij = wji, where wij is the mass of every edge joining two nodes Vi and Vj. There is an indication of the distance (d) among a base station and a node (Vi). The set of nodes that are either node Vi's antecedents or inheritors may be specified as follows: (Vi) = (Vj, Vi) = (Vj, Vi) = E. If Vj is a subset of p, then p(Vj) is the partitioning of the nodes preceding node Vj. We can now describe our method, which is displayed in Algorithm 1, thanks to this nomenclature. In an IoT device's first stage, each node is allocated a beginning cost to go to the sink. In the phases that follow, this price is adjusted according to the neighborhood. The algorithm terminates if there are no further changes available.

4.2 Service Quality in WSN:

Following the completion of the spine creation process, it is necessary to measure the weight's edges parameter, or wij. Wij can be taken to be true and described with a hop count as a first step. Wij = 1 $\forall$i,j$\in$ R, i$\neq$ j is the formula that was produced using this approach. But let's look at another example, node Vj, it is situated in a loud area. VJ collisions has the capacity to cause a node to fail, which would raise power consumption and reduce substance dependability. In this case, the optimal path after node Vk to the root node can be p in its place of p. This issue necessitates changing wij. This characteristic may be changed by assessing the QoS in an exact place. End-to-end interruption, delay variation, and throughput are all influenced by the following variables:

Numerous writers have put out architectural designs and integrated frameworks to assure networking performance levels [16, 34]. However, QoS studies often ignore other performance-related elements like resilience, communication security, and network access. The definition of an IoT device must be expanded if we are to use QoS as a standard to help achieve the objective of network regulation. As a result, sensors may participate fully in the networks, maintaining power and application performance requirements. Leonard Kleinrock and Ranjit Iyer provide a description of the network-based QoS of sensor networks resolutions [24]. Resolution is determined by the greatest number of cameras that can send data to information-gathering sinks, which are often base stations.

Jeff Frolik and James Kay describe the QoS of a WSN in an IoT context as the count of deployed sensors that are actively utilized, a concept also discussed by Mark Perillo and others in [18], as well as Veselin Rakocevic and colleagues in [29]. Three separate QoS categories i.e timeliness, accuracy, and precision—form the foundation of our QoS paradigm. Our method uses a scattered network strategy to estimate the QoS degree rather than an end-to-end IoT device approach since sensor networks are distributed. To ascertain the quality of each neighbor's home link, every node transmits a unique packet known as a "ping". These transmissions provide mean information for duty cycle, error rate, latency, and throughput to each node. A node calculates its distance from the IoT device root based on the QoS value it assigns after evaluating a neighboring link's QoS. The technique, outlined in expression (1), demonstrates how a node Vi estimates its distance to the root through node vj using the QoS value derived from an ANN output, a utility that is further explored in the discussion.

$$d(vi) = d(Vj).Qos \tag{1}$$

Algorithm 1: Forming the network backbone

```
import network as nx
import matplotlib.pyplot as plt
class Network Backbone Formation:
   def __init__(self):
      # Initialize an empty graph for the network backbone
      self.backbone_graph = nx.Graph()
   def add_router(self, router_id, x, y):
      # Add a router as a node to the backbone graph with specified (x, y) coordinates
      self.backbone_graph.add_node(router_id, pos=(x, y))
   def connect_routers(self, router_a, router_b, bandwidth):
      # Connect two routers with a high-bandwidth link in the backbone graph
      self.backbone_graph.add_edge(router_a, router_b, bandwidth=bandwidth)
   def form_backbone(self, routers, high_bandwidth_links):
            Form the network backbone.
      Parameters:
      - routers: List of tuples (router_id, x, y)
      - high_bandwidth_links: List of tuples representing links between routers (router_a,
router_b, bandwidth)
            # Add routers to the backbone with specified coordinates
      for router_id, x, y in routers:
         self.add_router(router_id, x, y)
      # Connect routers with high-bandwidth links in the backbone
      for link in high_bandwidth_links:
         router_a, router_b, bandwidth = link
         self.connect_routers(router_a, router_b, bandwidth)
   def visualize_backbone(self):
      # Visualize the network backbone graph with vertex labels (router_id, x, y)
      pos = nx.get_node_attributes(self.backbone_graph, ’pos’)
      labels = {router: f”{router}\n({pos[router][0]}, {pos[router][1]})” for router in pos}
edge_labels = nx.get_edge_attributes(self.backbone_graph, ‘bandwidth’)
      nx.draw(self.backbone_graph, pos, with_labels=False, node_size=700,
node_color = ‘skyblue’,font_size = 8
font_color = ‘black’,font_weight = ‘bold’, edge_color = ‘gray’
      nx.draw_networkx_labels(self.backbone_graph, pos, labels=labels, font_size=8)
      nx.draw_networkx_edge_labels(self.backbone_graph, pos, edge_labels=edge_labels,
font_size = 8
plt.show()
   network_backbone.visualize_backbone()if __name__ == ”__main__”:
   # Form the network backbone
   network_backbone.form_backbone(routers, high_bandwidth_links)
   # Visualize the network backbone
```

This approach ensures data is routed from source nodes via dynamic pathways, thereby circumventing areas with the lowest service quality.

4.3 SOM:

The SOM model was developed in 1982 by Teuvo Kohonen at the Finnish University of Helsinki [35]. In this model a two-layer, unidirectional network of neurons remains organized (FIGURE 2). The first layer is the input, or sensory layer, which consists of m neural connections for both input parameter. These neurons function as buffers, distributing the information they detect in the incoming stream. The input consists of random samples drawn from the sensory space, x(t)∈ Rm. Usually, nx* ny neurons are grouped in a rectangle to form another layer. Each neuron (i, j) is characterized by an m-dimensional vector called a synapse, which is sometimes referred to as a weight or reference vector. The vector input x's length is denoted by m(t). The neurons in the input layer are correctly linked to the output layer neurons, sometimes denoted to as the competitive Kohonen layer. This implies that each single input layer neuron is associated to every single Kohonen layer neuron device in the IoT. There are two separate stages in SOM (also called the mapping process) that are referred to as the knowledge phases (also called the training method).

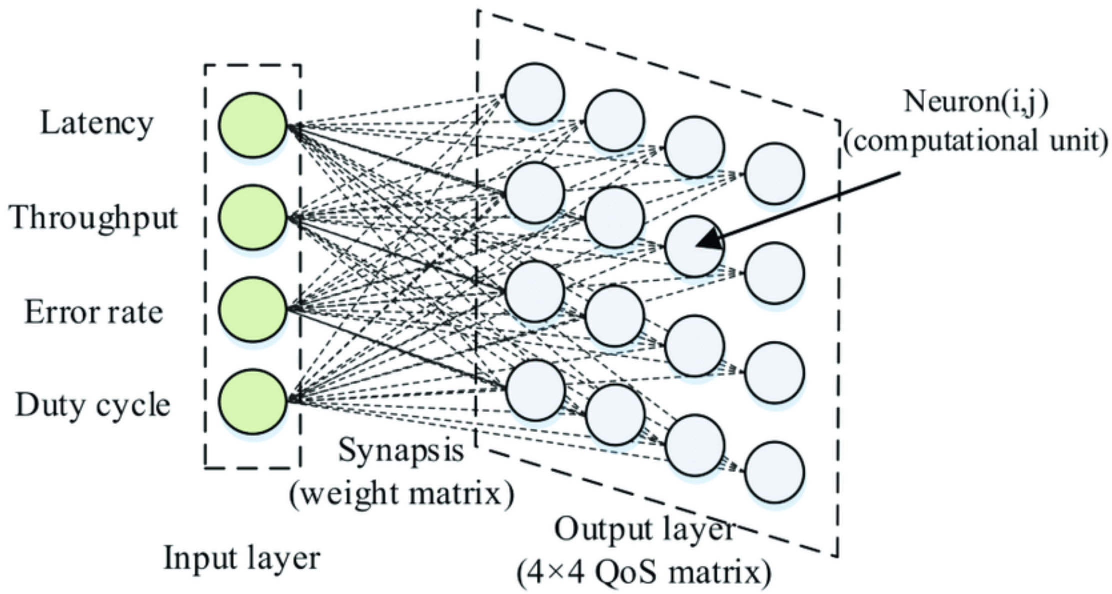


Figure 2: SOM architecture

Learning necessitates extensive computing. This is the reason that centralized statistics processing equipment, such as a personal computer, is required to carry out the exercise operation.

5. PERFORMANCE ASSESSMENT THROUGH SIMULATION:

In order to evaluate the SIR performance OLIMPO, our WSN simulator, is now running three numerical simulations that we have developed [26]. Each node in the SOM neural network implementation of the OLIMPO system (online processing) of IoT devices carries out the operation described in TABLE 1. This table demonstrates how easy it is to construct this strategy for usage on a real node and how little CPU power is required.

Table 1: IoT device R.c parameter values

Noise Figureure (NF)dB	11 Db
Rate of transmission, R	4820b/s
Resonating frequency	870.75MHz
Path loss constant	n = 3
Number of radio stations	1
Radio reception sensitivity	Ps = −101 dB
Radio transmission production	Pt = 5nW
Structure loss	L = 1
modulation	FSK
Communication bandwidth +B	0.5%
Antenna gain	Gt = 1,Gr = 1
Noise input power density Nin	-175 dBm/Hz

5.1 Analytical Performance Evaluation of Radio Channels:

Specific propagation channels integrated into the WSN framework enable sensors to assess the strength of incoming signals, thus facilitating accurate simulation of an IoT device's WSN. These are incorporated into the simulation's channel objects tool. Top of Form

In this instance, there is a 218-meter gap between the two sensor networks that are trying to connect to each other via radio. We assumed in our simulations that the distance between each sensor node pair is chosen at random, as illustrated in FIGURE 1. Our emulation has been based on a 300-node WSN.

5.2 Noise Influence:

It is factual that additive Gaussian White Noise (AWGN), which begins with resistor-supplied receivers, has shown the noisy impact across a node. With equation (2) and S/Nd = 26.7 dB are present, we do not compute the signal-to-noise ratios (SNR) at the detector's input using the radio transmission physiognomies. To understand this signal-to-noise ratio, consider the following BER: If S/Nd is less than 27.3 dB, the receiver is unable to detect any data on the radio. Increases in IoT noise devices can reduce BER; alternatively, since of the link amid Eb/No and R, which is Eb/No = (S/R)/No, an increase in R can exacerbate BER.

$$(\mathrm{Ps})\mathrm{dBm} = (\mathrm{S/N})\mathrm{d} + (\mathrm{NF})\mathrm{dB} + (\mathrm{Nin})\mathrm{Db} + (10\log\mathrm{B})\mathrm{DB} \tag{2}$$

To assess the effect of noise, a node state known as failure is identified. We consider a node to be in a disappointed condition when the BER drops below a critical number, typically 103. This extent is expressed as a percentage of a node's overall lifespan. We provide the results of two studies with various node failure percentages.

5.3 Formation of SOM

The first layer of SOM consists of four input neurons, which correlates to each of the metrics given. The second layer of the IoT device is composed of twelve output neurons and (Duty cycle, error rate, throughput, and latency), forming a 4* 3 matrix. Next, we describe in full our SOM implementation.

5.3.1 Learning phase:

The following formulae must be included in the input data set: x(t) = [duty cycle (t), error rate (t), throughput (t), delay (t)]. All conceivable QoS setups for such a pair of sensor networks should be considered in these cases. In order to prepare for ubiquitous computing, we need to imitate special circumstances. Such scenarios dismiss be represented by various noise and statistics use imitations. We constructed several WSNs through a density of 300 nodes over OLIMPO for our investigation. A detailed description of the methodology used to measure each QoS link amid two friends or neighbors is provided below: There is some level of noise present in every pair of IoT device nodes, such Vi and Vj. A specific node of IoT devices has a higher noise energy capacity when this noise is added to the radio network. Consequently, this chosen node's sensor input experiences a decline in signal strength (SNR), which exacerbates the BER associated with it and its linkages across each neighbor.

In order to evaluate the QoS metrics connected to each node, we utilize a ping Programme to establish communication between a designated pair of nodes. Regularly, Node Vi forwards ping signals to Node VJ. The QoS environment is defined by the way node vi receives the acknowledgement (ACK), which is necessary for the ping to function. This ACK is obtained using the four selected metrics: duty cycle (%), error rate (%), throughput (bits/sec), and delay (seconds). As an illustration, the Node vi QoS is [0.65, 1540, 11.34, 3.45] according to the necessary metrics. This is based on the assumption that No's power density is 81 dBm/Hz due to noise, and thus Node vi and Node Vj are separated by 60 metres.

This method is repeated 100 times, changing the values of D and N. Next, we have a set of examples that cover every possible QoS situation for IoT devices. With the help of this data, we use a powerful neural network Programme like MATLAB on a home computer to create a self-organizing map. This operation, called ”training,” makes use of the learning approach outlined in Section 3.3. We call this process ”offline” since the wireless sensor network does not do the training. ”. After the layer of neurons is organized, we give each of the 100 input samples an output neuron. Using this IoT approach, the collection of 101 input data points is distributed throughout the SOM. The most difficult step is said to be the next one. The samples are grouped by the SOM so that each group comprises instances with similar attributes. This allows us to build a group-based map in which each cluster is assigned a neuron from the production layer and correlated with a certain QoS. Furthermore, a synaptic-weight medium is formed, denoted as w ij = [wij1, wij2, wij4], in which each synapse is a connection between the input and output layers. After listing the QoS for each group in the instruction, we look at their features and award. It is created to have an output meaning □(i, j), j∈[1, 4], i∈[1, 3]. using 12 values, one for every neuron in (i, j), j∈[1, 4],i∈[1, 3]. The highest grade (10) must be given to the measured connection with the lowest expected quality of service. Conversely, the lowest allocation (zero) corresponds to the case when the observed connection uses the best predicted QoS. While the assignment is being processed offline, an engineer is in charge of it.

5.3.2 Execution stage:

We also specified an output device that each WSN node of IoT devices must execute during the learning phase. This procedure is called winning neuron election algorithm. We set up a WSN including over 350 nodes. In order to obtain an input sample of IoT devices, each WSN node pings each of its neighbors on a regular basis to evaluate QoS. A node collects a batch of input samples and then executes the winning neuron election procedure. A neuron might, for example, become active if an input sample was significantly similar to the synaptic-weight vector of the neuron (2, 2). After the winning neuron has been selected, the bulge serves as the yield device to distribute the QoS approximation. Not to mention, the depth of the root may be altered using this variable (1We call this process ”processing” since the IoT device’s execution phase is implemented via a WSN”.

5.4 Evaluation of Our SIR’s Performance:

The 3 tests that have been conducted in order to assess our SIR algorithm are described below.:

5.4.1 Not a single node was disappointed in the first study

This test seeks to assess the performance of AI methods in the absence of node failure. This shows that there have been no node failures due to noise, accidents, or dead batteries. A 300-node WSN is constructed on our simulator, OLIMPO, to simulate this situation. Node 0 is identified as the source, while node 22 is identified as the drain. At an exact moment, an experience is triggered in the sources. The current problematic is figuring out how to route the signal to the specified sink after the predetermined bases. As previously said, we approach this problem with three distinct frameworks for routes: SIR, EAR, and absorbed diffusion. To assess, we choose binary parameters SIR’s performance and contrast it with other systems. These signs are as follows:

- The amount of energy wasted on average. This measure determines the average amount of work that must pass through a node in order to give sinks useful tracking. The duration of operation of the sensor nodes is also displayed by this metric. In order to get an acceptable Eb No., we disregard the transmitter’s amp usage. = 101 pJ/bit/m2 directed towards the broadcast amplifiers and Eelec = 51 nJ/bit to run utilizing Wendi Rabiner Heinzelman’s initial energy use order model for the transmitters or receiving circuits from the LEACH protocol [36]. (Scheme 3). In this strategy, the radio model must spend the following in order to broadcast a k-bit signal a certain distance.:

$$E_{Tx}(k, d) = E_{elec} \cdot k + \varepsilon_{amp} \cdot k \cdot d^2 \tag{3}$$

  and the amount of time the radio takes to play this message:

$$E_{Rx}(k) = E_{elec} \cdot k \tag{4}$$

Assuming symmetry in the radio channel, our simulation operates as a festival, whereby sensors only send data in response to environmental events. Because IoT devices have a large worldwide communication range between a sensor node and an ignoble station, the transmitted energy is much higher than that of the sector players. For this network design, the lowest level protocol offers the most energy-efficient one, as demonstrated in FIGURE 3 (a) (b) and FIGURE 4 (a) (b), respectively.

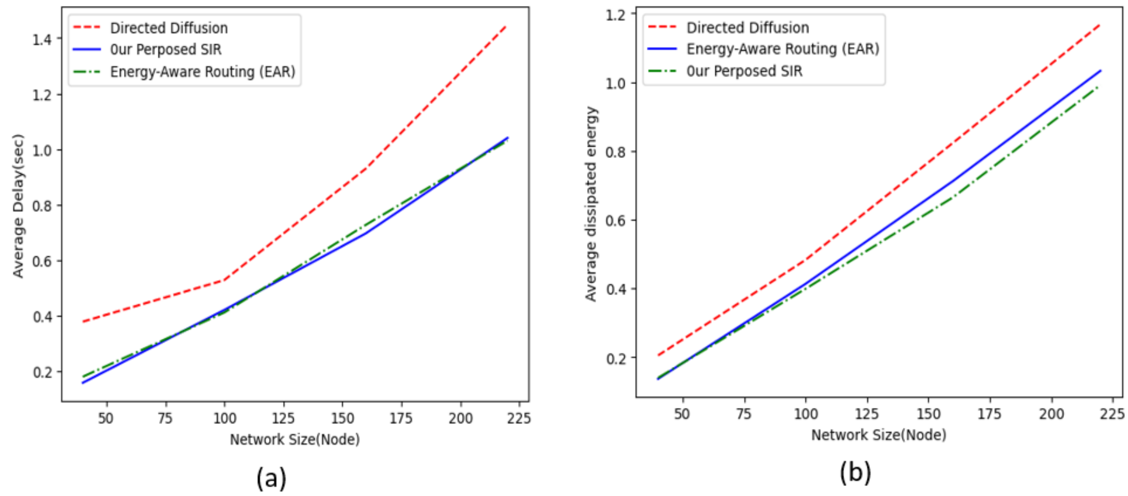


Figure 3: In the absence of concurrent node failure, average energy, average latency, and dissipated.

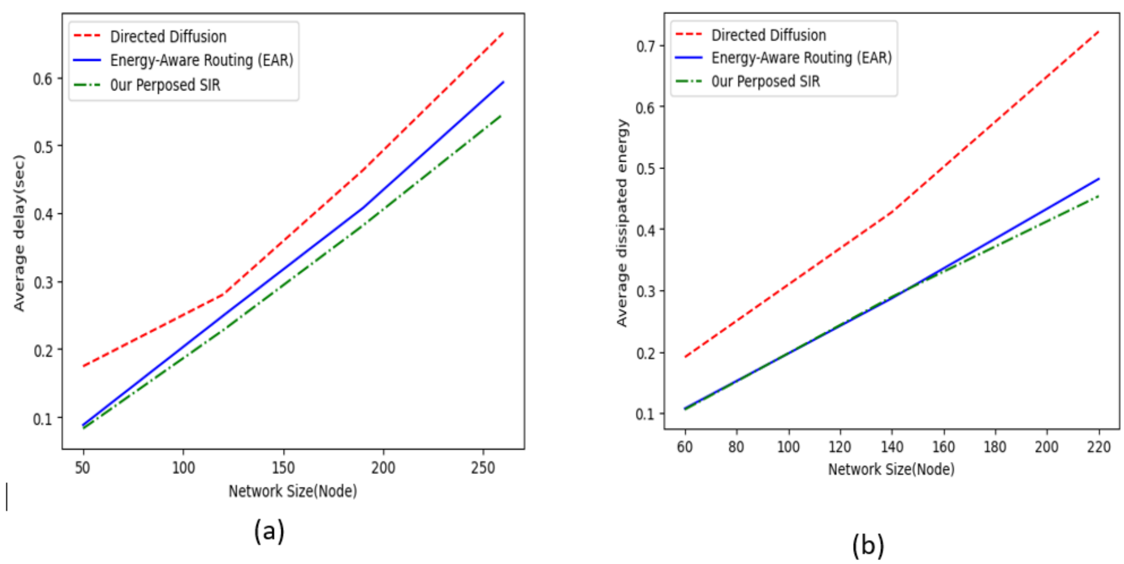
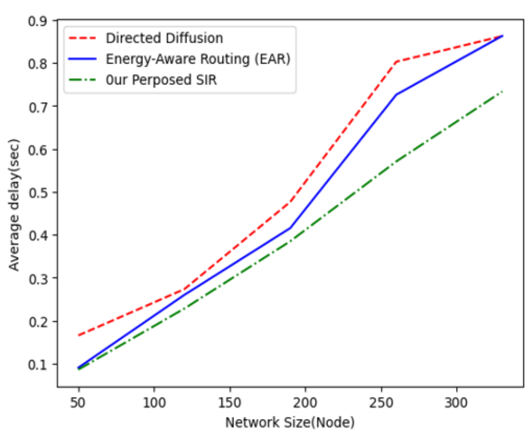


Figure 4: When 20% of the nodes failed simultaneously, the energy and delay dispersed.

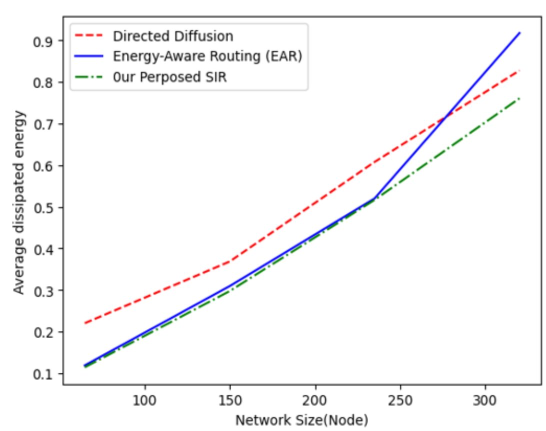
5.4.2 Dispersal of energy and latency occurred when 20% of the nodes failed simultaneously.

This experiment aims to assess the use of artificial intelligence techniques with a 20% concurrent node failure rate. Twenty percent of the nodes in the cable network are always down due to noise interference, collisions, or dead batteries. To simulate various IoT device situations, we build a 250-node WSN. We apply one of the following effects to 50 of the 20% of nodes from all of them simultaneously:

- Reduction in the S/N proportion. Because of the energy loss in the battery, radio transmission power decreases. So, the S/N ratio of its neighboring radio receivers is decreased, leading to the absence of detecting systems through a certain probability, P. In this instance, we would determine that the node that vitality is adversely impacting has a chance of P for failure.
- Sensor nodes are still often open to high noise levels caused by inductive motors. Furthermore, there are other applications that share the radio frequency band with us and might undermine our WSN.
- Adding these effects causes 20% of nodes to fail at any one moment.
- In these cases, we examine the issue examined and explained in ex. 1 using the three related paradigms. The consequences are presented in FIGURE 5(a,b). As we can see, both direct diffusion and EAR work better when we use our SIR technique. This is due to the fact that neither strategy considers the effects of a noisy environment. In contrast, our SIR technique evaluates the best course of action considering the impact of noise.



(a)



(b)

Figure 5: When 40 %of the nodes fail all at once, the average energy lost and the average delay.

5.4.3 In Experiment 3, 40% of the nodes failed at the same time.

This experiment simulates a 40% possibility of concurrent IoT device node failures. Network noise has a detrimental effect on EAR performance as shown. That being said, our SIR technique works the best because of its route management.

The use of SOM in large-scale WSNs with numerous sensor nodes is challenged by two key factors. Firstly, the compute complexity of SOMs results in significant computational costs, especially during the training and updating processes of the SOM structure. This demand for substantial computational resources that may surpass the capabilities of resource-constrained sensor nodes that operate with limited memory and processing power. Secondly, the dependency on training data is crucial for SOMs to generate topological maps. The effectiveness of SOM-based routing algorithms directly hinges on the quality and representativeness of the training data, posing challenges in obtaining meaningful data in WSNs due to issues like data transmission problems, environmental fluctuations, and the sparse deployment of sensor nodes.

6. CONCLUSION AND FUTURE WORKS:

The paper demonstrates that the variance plays a major role in contributing to link failure when results for each routing paradigm are examined. It is noteworthy that the SIR approach successfully keeps delay low even in cases where the standard deviation of waiting times increases due to direct diffusion and an increase in the number of detectors in EAR. This benefit arises from the fact that the SIR strategy uses AI algorithms to elect relay nodes, whereas EAR depends on choosing several rules-based nodes that are pertinent to transmission. As such, the pathways that are produced by the SIR approach steer clear of nodes that are susceptible to interference, loud settings, or battery-related malfunctions. Furthermore, because of the intelligent relay election, the average energy dissipation in our SIR technique lowers as the number of sensors grows. Furthermore, our SIR approach is a more effective protocol when the percentage of failure nodes increases from 20% to 40%. Although incorporating AI methods into WSN produces interesting and remarkable outcomes, it is vital to take into account a few key points.

The deployment of a SOM on every sensor enhances network performance and facilitates scalability by dispersing artificial intelligence throughout the system. Managing a variety of events and preserving network performance are made easier with this method. Even though different noisy circumstances are simulated, further investigation of the physical channel is necessary before real-world experimentation. Simulation results on IoT are consistent with the assessment of the quality-of-service assignment procedure in a real-world scenario including a station communicating with two sensor nodes in a noisy environment.

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