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Mathematically Engineered Adams Optimizer for Energy Efficient and Optimal Routing Approach for the Wireless Sensor Network

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Abstract

Wireless Sensor Network (WSN) comprises numerous Sensor Nodes (SN) scattered across a network to observe the atmospheric condition where the SN is the minimum cost. Vast usage of energy during data transmission is the primary design issue in WSNs that can be addressed by routing and clustering techniques. WSN has diverse transmission paths with unstable nodes, where the energy consumption is high, and the Quality of Service (QoS) is affected. The high data transmission delay and inefficient throughput indicate the ineffectiveness of WSN. To overcome this issue, this research concentrates on energy-efficient optimal routing formulated with the assistance of a mathematical approach and Adams optimizer. The mathematics-based Pareto optimization is utilized to optimize the Adam Moment Estimation (Adam) that trains Deep Learning (DL) network that is deployed in both heterogeneous and homogeneous networks. The learning process is enhanced with the support of Pareto optimization, and the multi-objective problem is efficiently handled. In this context, Pareto optimization balances the path construction, and the equitable distribution issue is rectified by the Adams-based DL network. The proposed Pareto-integrated Adams Optimizer for Energy Efficient Routing (PAOEER) sustains the WSN performance by enhancing network parameters. The PAOEER achieves a higher Packet Delivery Ratio (PDR) of 97.18% and minimal Energy Consumption (EC) of 112.34 J. The simulation analysis shows that the proposed PAOEER is effective and outperforms the existing state-of-the-art techniques, indicating PAOEER is a promising alternative.

Keywords: Optimization, Sensor Node, Deep Learning, Pareto, Adams, PDR, Wireless Sensor Network, Energy Consumption, Routing

1. Introduction

Information processing has changed because of the invention of the computer and the communication network. Professionals, government entities, and other sectors have already used network features [1]. Two methods connect to a network they are wired connections and wireless connections. In contrast to wireless communication, which uses waves to transmit data, a wired connection is formed through wires. Wireless communication and data transfer technology have been designed to accommodate the rapidly rising use of mobile and electronic devices. Also, as wireless technology develops, the efficiency and capacity of networks need to be increased [2].

WSN consists of a few low-power, multipurpose, and communication nodes that monitor and record one or more parameters at various locations [3]. Subsequently, it transforms the captured data into signals that may be analyzed further to get the required information [4,5]. Their success in offering voice and messaging capabilities has fostered their adoption in numerous sectors including private and commercial enterprises, as well as biological research [6]. A WSN is characterized by a system where data is transmitted via wireless connections, involving multiple nodes interconnected with different networks [7,8]. Each sensor node (SN) in the network houses components for radio communication, power management, and data processing and sensing, facilitating direct communication with a base station or sink, which serves as an interface between users and the network, streamlining data retrieval and analysis.

The WSN is connected to the internet or an existing telecommunications network via the BS, which can be either a mobile or fixed node [9]. Since the WSNs have grown to be a significant component of digital communication systems [10]. Power consumption and maximizing network longevity have become essential routing protocol parameters for optimal information transmission [11].

In the WSN application, when the transmission is initiated with a clustering mechanism, the observer in the network must report the status of the network. Sensors from diverse fields can function together in the transmission context to offer a more specific report about local region information [12,13]. To enrich the aggregation of information, a group is formulated with nodes that are small clubs or clusters. In the absence of a Cluster Head (CH), each cluster poses a member for the cluster. The clustering formation indicates a two-level hierarchy with high energy of CH and minimizes the member node energy level [14]. The latency in this context is expected to be much lower than in the multi-hop framework [15].

Clustering permits intrinsic optimization capabilities for the CHs, is prominent in a more active way, and has a better-systematized topology of the network [16]. This framework is more suitable for multi-hop and single-hop systems. The overall routing process in the inter and intra-clustering scheme is illustrated in Figure 1. In WSN, the member nodes in the cluster transmit their data to corresponding CHs in the clustering mechanism [17]. Every CH collects cluster formulations and data from the relevant cluster, which is then sent to the BS via other CHs in the cluster [18].

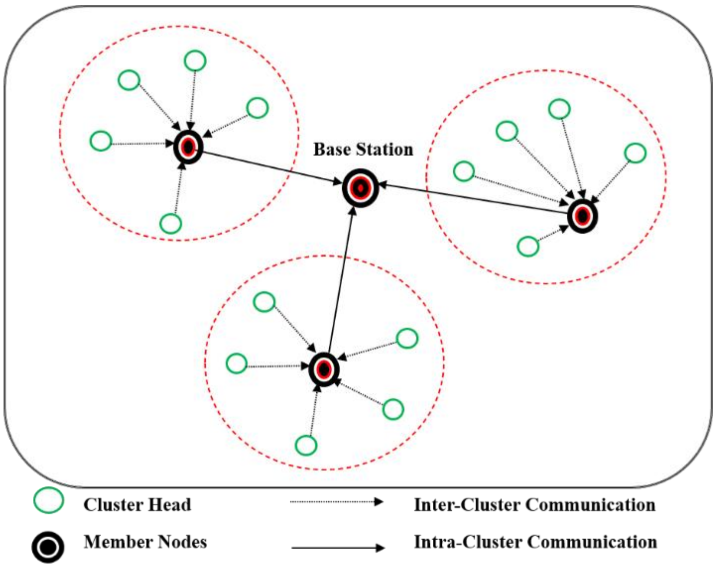

Figure 1. Formulation and Alignment of Clusters

The CHs communicate data to a BS in a distant region and utilize higher energy than other sensor nodes. Thus, dissemination of the load consistently increases across every node under dense load [19]. Routing assists in the identification of the enhanced path for the transmission of data from the location of CH to BS. Data gathering and clustering constantly prolonged the network's lifespan, the only metric for testing the efficiency of the network. The network's lifetime relies on the latency until the initial node drains the time and energy necessary, where all nodes die [20].

Routing protocols are mainly utilized for minimizing Energy Consumption (EC) during data transmission in WSN. The quantity of sensor nodes will establish and run the network. The sink node will offer the service to the users while linked to the base station. Numerous categories, including flat-based routing, hierarchical-based routing, and location-based routing, are used to categorize the routing procedures in WSN [21]. All nodes are given the same functions in flat-base routing [22]. SPIN, or the Sensor Protocol for Information Negotiation, is used in this situation. Large data sets will be sent to the neighbouring nodes [23]. The BS distributes the query to the remaining nodes via diffusion [24]. The research objectives address the following:

The deployment of many SNs may allow for better monitoring with high precision. The objectives of this research are concentrated on:

• To determine the best way to extend the life of WSNs.

• To assess optimal paths that minimize the total EC along the transmission path and balance the load between the nodes.

• To observe these dispersed NS can gather and transfer data to an internal SB or other sensors.

• To identify optimal route identification with the support of mathematics-based Pareto optimization integrated with the Adam Moment Estimation (Adam) that trains deep learning networks.

• To discover optimal routes from multiple possible paths is effectively identified through Pareto optimization, and the methodology is detailed in Section 3.

The contributions of this paper offer the following:

• This Work investigated, reviewed, and broadly classified almost all the recent detections of WSN routing and CH-based optimal routing mechanisms.

• The researcher conducted a quantitative and mathematical analysis of the existing mechanisms of each category by understanding various aspects.

• This paper highlights some critical challenges and balances the load between the nodes to extend the lifespan of the WSNs.

• Finally, this work aims to explore a novelty adaptive Pareto-integrated Adams Optimizer technique to support the WSN performance by enhancing network parameters.

The research work is given as follows: an overview of WSN and CH-based optimal routing mechanism is detailed in Section 1, the literature survey about the WSN routing mechanisms and the research gap is described in Section 2, the proposed Pareto-integrated Adams Optimizer for Energy Efficient Routing (PAOEER) is elucidated in Section 3, simulation outcome is compared and contrasted with existing technique in Section 4, and the proposed PAOEER is concluded with the future recommendation in Section 5.

2. Related Works

An article designed a Deep Learning-based Defence Mechanism (DLDM) to detect and isolate attacks in the Data Forwarding Phase (DFP) [25]. This technique detects successful attacks caused by weariness, jamming, homing, and flooding. Comprehensive simulation studies can isolate the enemies accurately and are more resilient to attacks. The result of this simulation revealed that a high detection rate, throughput, Packet Delivery Ratio (PDR), and precision could be achieved. Energy usage and False Alarm Rate (FAR) are also minimized.

Fu et al. proposed an Environment-Fusion Multipath Routing Protocol (EMFRP) to provide a durable message transmission service under severe circumstances [26]. EFMRP makes routing decisions with respect to depth, residual energy, and the environment according to a mixed potential area. The fundamental idea of this approach is to teach data packets to choose optimum routes. Experimental studies have shown that the EFMRP can considerably increase package delivery and the life period of the network.

Jemili et al. presented a multi-path routing approach to creating unrelated and node disjoint paths [27]. It also transports multimedia content from the source to the sink, considering diverse contextual information. The report was presented to adapt and normalize wake-up planning for nodes' involvement in the forwarding phase. The approach depends on close cooperation between Routing and Multi-Access Control (MAC) layers.

A two-step algorithm for optimizing the allocation of resources has been developed by Hao et al. to analyze various resources' dependencies [28]. Interference between links is regulated to achieve a trade-off between increased network capacity and improved energy efficiency. The challenge of joint energy control and canal allocation is researched and formulated as a multi-objective optimization problem for the purpose of analysis.

Sundhari & Jaikumar addressed optimization difficulties in a WSN design. The energy optimization problem for smart city control has been developed [29]. During the information processing phase, the energy-constrained SN will negotiate multiple network-related activities to select the sensor cluster node, which will optimize both the EC and the sensing accuracy. Experiment results reveal that these techniques have improved energy efficiency in the experimental laboratory validation of wireless network sensors and cluster node selection.

Tita et al. proposed a novel Potential Relay Information (PRI) metric that devices the WSN Node routing capabilities [30]. This PRI reflects true timeliness and illustrates the potential of nodes to efficiently send data packets to BS within an explicitly set time limit. A proactive feedback system was created that allows nodes to update their neighbour information.

Reddy et al. proposed the new Glowworm Swarm Optimization approach and integrated it with Ant Colony Optimization (GSO-ACO) [31]. The aim is to decrease the distance between CH nodes. It uses many objectives, including distance, delay, and energy, to create the fitness function. Finally, the performance is measured, and the efficiency is improved.

Yasodha et al. proposed an optimized route selection technique that uses the Cuckoo Search Algorithm (CSA) [32]. The primary need of WSN is energy saving, and this work seeks to provide an Energy-Preserving Cluster-Based Routing (EPCBR) mechanism for WSN. The clustering methodology and the best route selection form the foundation of the proposed technique. The sensor nodes are grouped into clusters, and the CH is chosen based on the nodes' level of trust. Due to battery capacity and size limitations, WSNS must deploy effective energy-saving methods.

3. Methodology

This section explains the Energy Consumption (EC) model of WSN and the cluster formation, where the intelligent routing across the clusters is accomplished using a mathematical model integrated Adams optimizer. It proposes the Pareto integrated Adams Optimizer for Energy Efficient Routing (PAOEER). The Pareto optimization is used with the Adams optimizer, which in turn identifies the optimal route effectively.

3.1 Energy Consumption Model

The energy consumption (EC) necessary for transmitting n-bit information over a distance denoted as "dis" can be found in Equation (1):

$$E_{TX} = \begin{cases} E_{expen} \times n + \epsilon_{fs} \times n \times dis^2, & if\ dis \le dis_0 \\ E_{expen} \times n + \epsilon_{mp} \times n \times dis^4, & if\ dis \le dis_0 \end{cases} \quad (1)$$

Here, the energy amplifier in the free space channel model is denoted as ϵ_{fs}, while in the multipath fading channel model, it is represented as ϵ_{mp}. The procedure for receiving an n-bit data packet over the network is detailed in Equation (2):

$$E_{RX} = E_{expen} \times n \quad (2)$$

In this scenario, E_{RX} denotes the energy consumed by the transceiver circuit, while E_{expen} signifies the energy required to transmit n-bit messages while maintaining a tolerable bit error rate. The error rate is influenced by the distance between the communicating nodes. This can be described through two models: the free space model and the multipath fading model. Here, "dis_{ij}" illustrates the Euclidean distance between sensor nodes i and j. When the transmission distance is shorter than a predetermined threshold (dis_0), the free space model is utilized. Conversely, if the distance surpasses the threshold (dis_0), the multipath fading model comes into play. The specific threshold can be determined using Equation (3):

$$dis_0 = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}} \quad (3)$$

3.2 Cluster Construction

The clustering process is constructed with CH given in Equation (4). The value of B equals one where the node 'v' selects CH as the cluster head. Otherwise, the value is assigned as '0'.

$$\sum_{CH\in\zeta} B_{vCH} = 1, \forall_v \in SN \quad (4)$$

Where CH indicates the cluster head, the sensor node in the network is indicated by SN, and the node selects CH is indicated by 'v'.

The routing process in the intra-routing region is initiated after cluster formation, and the connection between the source and CH is attained. The formulation of routing is given in Equation (5):

$$b_{sCH} = \sum_{p\in P_{sCH}} x_p, \forall_s \in S; CH \in \zeta \quad (5)$$

Where the source is indicated by 2, the set of the source is indicated by S, the intra-routing decision variable is indicated by x_p, the candidate path is indicated by P, and the path is indicated by 'p'.

There must be at least one inter-routing link that connects the CH of every source node and the sink node, as shown in Equation (6), that gives the set of data sources S from which the sink node must acquire the aggregated data.

$$B_{vCH} = \sum_{q\in Q_{CH}} \eta_p, \forall_s \in S; CH \in \zeta \quad (6)$$

Where the set of decision values is indicated by η_p, the inter-routing path is indicated by 'q,' and the set is indicated by Q.

Each CH ensures the conjunction in the condition, and there is only one intra-routing path from each cluster to the source node. Equation (7) provides the connection setup, whereas Equation (8) provides the transmission limitation.

$$the \sum_{CH\epsilon\varsigma} \sum_{p\epsilon P_{sCH}} x_p = 1, \forall_s \in S \quad (7)$$

$$\sum_{CH\epsilon\varsigma} \sum_{p\epsilon P_{sCH}} x_p\, \delta_{p(u,v)} \leq y_{(u,v)}, \forall_s \in S; (u,v) \in L \quad (8)$$

Where the link in the network is indicated by u, v, and the set of links belongs to L.

The SN is chosen as a CH and assigned zero for the intra-routing path built from the source to the sink node. If the value for η_p is 0, and there is no path, the candidate path in the network is assigned a value of 1, which is equivalent to Equation (9):

$$\sum_{q\in Q_{CH}} \eta_p \leq 1, \forall_{CH} \in \zeta \quad (9)$$

If a link is selected in the network and a path on the network is chosen, the CH indication is $\delta_{q(u,v)}$, and the inter-routing decision variable Y(u,v) is given the value 1. Equation (10) outlines the restrictions on these two pathways.

$$\sum_{q\in Q_{CH}} \eta_q \delta_{q(u,v)} \leq Y_{(u,v)}, \forall_{CH} \in \zeta, (u,v) \in L \quad (10)$$

Only when a node's CH is also on the path, as in Equation (10), can a node be chosen as an intermediate node on an inter-cluster routing path in Equation (11).

$$\sum_{q\in Q_{CH}} \eta_q . \delta_{qv} \leq \frac{\sum_{q\in Q_{CH}} \eta_q . \delta_{qCH} + b_{vCH} + L_1(1 - b_{vCH})}{2}, \forall v \in V, g \in \zeta \quad (11)$$

The data transmission over the appropriate optimal path is achieved by Pareto integrated Adams Optimizer for Energy Efficient Routing (PAOEER), which is detailed in subsequent section 3.4. The overall procedure of the PAOEER is given in Algorithm 1.

Algorithm 1. For Procedure of PAOEER

Step 1.Input: Links, clusters, set of nodes, and source nodes
Step 2.For every subgraph, **Do**
Step 3.For every link, **Do**
a. Add a link that connects CH to the destination
b. Weight of the link = 0
Step 4.End For
Step 5.Repeat
Step 6.Find the shortest path to a destination
Step 7.For Every node on the path, **Do**
a. Let mark =TRUE
b. Add link among the identified nodes and destination
c. Let weight [x, S]= 0
d. Let weight [s, y]= infinity
Step 8.End For
Step 9.Do this until all nodes are connected
Step 10. Initiates data transmission
Step 11. **End For**

3.3 Energy Consumption of CLuster

The EC of cluster member E_{clm} relies on transmitting the 'n' data bit to CH. The energy utilized by every E_{clm} is given in Equation (12).

$$E_{clm} = n \times E_{expen} + n \times \epsilon_{mp} \times dis_{CH}^{2} \quad (12)$$

The energy dissipation of CH depends on the count of received data from the cluster and aggregated data. Hence, the utilized energy in intra-clustering is given in Equation (13).

$$E_{intra_{cluster}}(CH_i) = CLM_i \times E_{RX} + (CLM_i + 1) \times E_{aggr} + E_{TX}(CH_i, NXH(CH_i)) \quad (13)$$

Where the EC across the intra-cluster is indicated by $E_{intra_{cluster}}$, the EC of data aggregation is indicated by E_{aggr}, and the next hop toward BS by CH is indicated by $NXH(CH_i)$. The EC in inter-clustering is given in Equation (14).

$$E_{inter_{cluster}}(CH_i) = OC(i) \times E_{RX} + OC(i) \times E_{TX}(CH_i, NXH(CH_i)) \quad (14)$$

Where the volume of the packet received from another cluster is indicated by $OC(i)$.

3.4 Intelligent Routing Method

Deep Learning (DL) is a distinct type of Machine Learning (ML). Both DL and ML come under Artificial Intelligence (AI) approaches. With training and testing data, a model can go through an optimization process to determine the weights that make the model best suit the data, both ML and DL process initialization. The weights in the DNN are optimized by the Pareto optimization.

The research goal is to train the WSN using the Adam optimizer, considering the quick advancement of DL techniques and their application in many fields. In order to give adjustable learning rates, Adam employs estimations of the first and second moments of the gradient, which is how the name "Adam" was created. Due to its simplicity, quick training, and practical implementation, this optimizer has been used for this research work. The most frequent and most well Adam optimizer is used in contemporary DL research. The procedure of PAOEER is given in Figure 2.

Pareto-optimization is used to achieve multi-objective optimization, and the quasi-linear utility function is defined as in Equation(15):

$$Util(ti, egc) = fnc(ti) + egc \quad (15)$$

Where the concave function of growing is shown as *'fnc,'* the time is indicated as t_i, and EC is indicated as *'egc'*. The utilization is optimized since it utilizes the necessary quantity of energy. The appropriate path with minimal EC was identified.

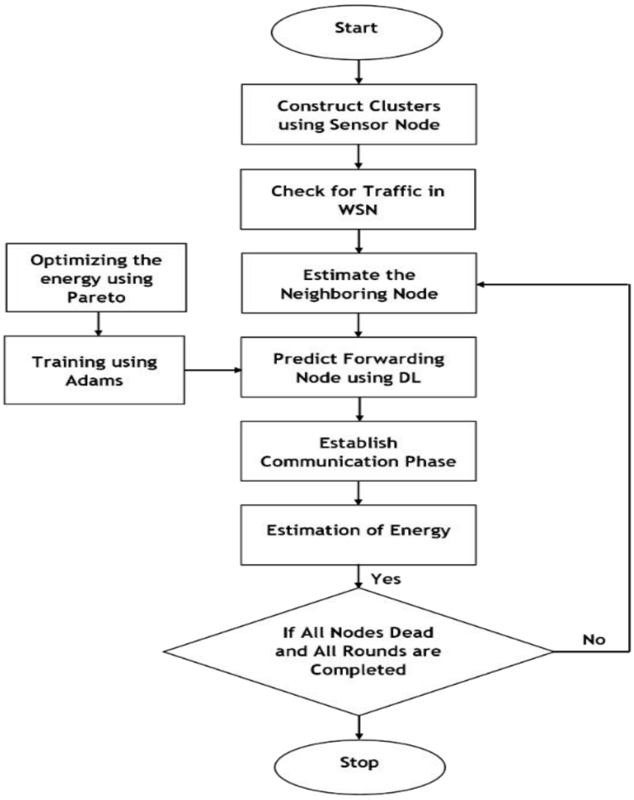

Figure 2. Flowchart of PAOEER

4. Results and Discussion

This section examines the simulation of PAOEER that uses Network Simulator 3 (NS3). The proposed PAOEER approach is investigated using the performance measures, namely PDR, Packet Loss Ratio (PLR), Network Throughput (NT), EC, Network Lifetime (NL), and End-to-End Delay (EED). The superiority of the proposed PAOEER approach is identified by comparing it with existing state-of-the-art techniques. The proposed PAOEER approach is compared with existing techniques, namely EMFRP, GSO-ACO, and CSA. The simulation setup is depicted in Table 1. The comparative analysis is given in the sub-section.

Table 1. Simulation Setup

Parameter	Description
Sensor Node Count	500
Simulation Area Size	100*100 m^2
Packet Size	512 bytes
Time Slot	2000 s
Range of Communication	20m
Initial Energy	1J

4.1 Simulation Analysis

The simulation is compared using PDR, PLR, NT, EC, NL, and EED performance metrics. The analysis is given in the subsequent section.

Packet Delivery Ratio (PDR) is the total number of packets delivered to the entire count of packets transmitted in the network. The PDR is retrieved in percentage and compared for the diverse count of nodes. The PDR of EMFRP, GSO-ACO, CSA, and PAOEER is given in Table 2 and Figure 3. The value of PDR is estimated using Equation (16):

$$PDR = \frac{Received_p}{Sent_p} \quad (16)$$

Where the count of received data is indicated by $Received_p$ and the count of sent data is indicated by $Sent_p$.

From Figure 3, it is identified that the proposed PAOEER achieved effective PDR. The PDR of the proposed PAOEER approach for 100 nodes is 1.11%, 1.44%, and 3.33 higher than CSA, GSO-ACO, and EMFRP, the PDR of the proposed PAOEER approach for 200 nodes is 0.99%, 1.89%, and 3.58 higher than CSA, GSO-ACO, and EMFRP, the PDR of the proposed PAOEER approach for 300 nodes is 1.17%, 2.37%, and 4.35 higher than CSA, GSO-ACO, and EMFRP}, the PDR of the proposed PAOEER approach for 400 nodes is 1.88%, 2.21%, and 3.84 higher than CSA, GSO-ACO, and EMFRP, and the PDR of the proposed PAOEER approach for 500 nodes is 1.35%, 2.22%, and 4.86 higher than CSA, GSO-ACO, and EMFRP. The PDR is comparatively higher for the diverse count of the nodes, and the robust transmission link assures the higher PDR in the proposed PAOEER.

Table 2. Comparison of PDR

No of Nodes	EMFRP	GSO-ACO	CSA	PAOEER
100	95.34	97.23	97.56	98.67
200	94.43	96.12	97.02	98.01
300	93.13	95.11	96.31	97.48
400	92.72	94.35	95.68	96.56
500	90.81	93.45	94.32	95.67

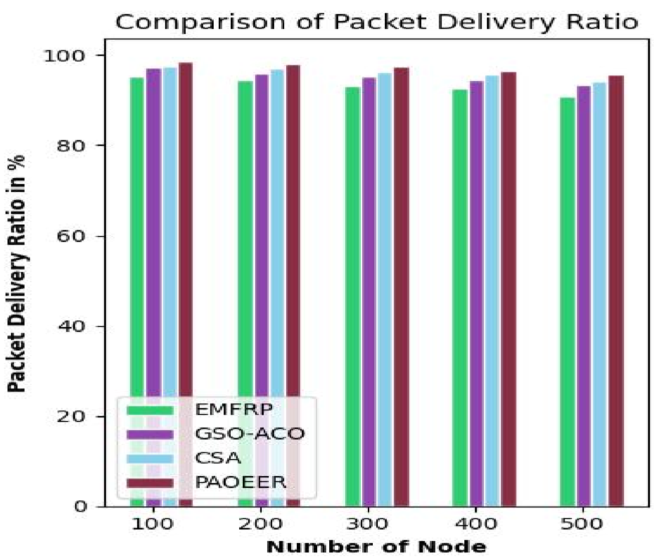

Figure 3. Comparison of Packet Delivery Ratio

Energy consumption (EC) of the SN is estimated with distinct simulation time. The residual energy of the SN is estimated and expressed in joules at a certain point in time. The EC of EMFRP, GSO-ACO, CSA, and PAOEER are given in Table 3 and Figure 4. The value of the average EC is estimated using Equation (17):

$$EC = \frac{EC_{ROUND}}{EC_{ALIVE}} \tag{17}$$

Where the EC is indicated as EC, the sum of EC of all nodes is indicated by EC_{ROUND} and the count of the alive node is indicated by EC_{ALIVE}.

Table 3. Comparison of Energy Consumption

No of Nodes	EMFRP	GSO-ACO	CSA	PAOEER
100	39.67	29.67	34.53	21.34
200	59.91	39.78	52.76	44.56
300	71.82	51.69	63.54	51.98
400	85.81	72.75	83.78	59.67
500	109.45	89.33	98.56	82.56

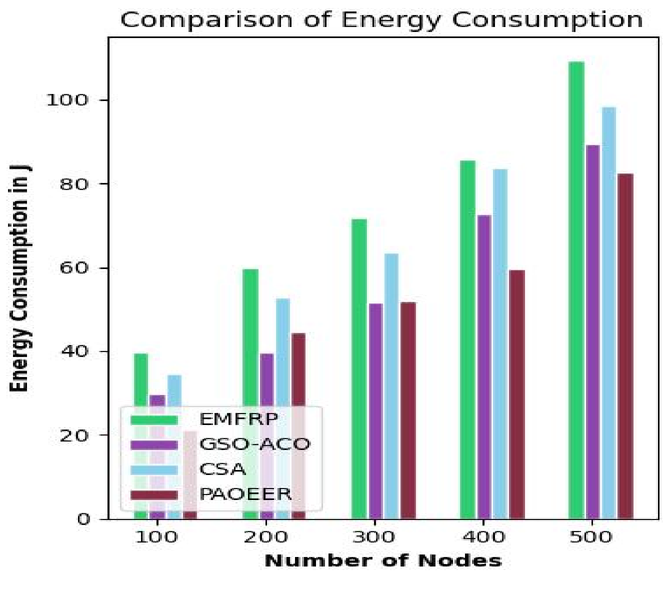

Figure 4. Comparison of Energy Consumption

The EC of the PAOEER technology is compared with other methods in Figure 4. The PAOEER approach uses the least volume of energy for data transmission compared to the others, as seen in Figure 4. Also, it has been seen that as the number of SNs increases, EC also increases. Due to the even energy distribution throughout the WSN system's nodes, the PAOEER approach reduces energy exploitation. For instance, under the WSN nodes of 100-500, the PAOEER approach has shown reduced energy usage of 21.34, 44.56, 51.98, 59.67, and 82.56 J, respectively.

The successive rate of transmitted data in a distinct time across the network is estimated by Network Throughput (NT). The NT is retrieved in Mbps and compared for the diverse count of nodes. The NT of EMFRP, GSO-ACO, CSA, and PAOEER is given in Table 4 and Figure 5. The value of throughput is estimated using Equation (18):

$$Throughput = \frac{Total\ size\ of\ packet}{Duration\ of\ data\ transmission} \times \frac{1}{\sqrt{data\_packet}} \quad (18)$$

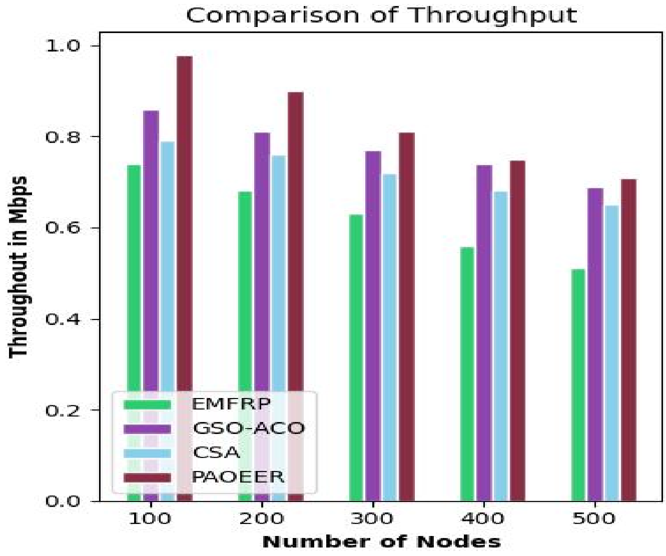

Figure 5. Comparison of Throughput

Figure 5 compares the PAOEER method with other methods regarding throughput. The results obtained showed that the PAOEER technique outperforms all other approaches. The PAOEER technique has achieved greater performance with higher throughputs of 0.98, 0.90, 0.81, 0.75, and 0.71 Mbps under the sensor nodes of 100-500, respectively.

Table 4. Comparison of Network Throughput

No of Nodes	EMFRP	GSO-ACO	CSA	PAOEER
100	0.74	0.86	0.79	0.98
200	0.68	0.81	0.76	0.90
300	0.63	0.77	0.72	0.81
400	0.56	0.74	0.68	0.75
500	0.51	0.69	0.65	0.71

The number of Packet Loss Ratio (PLR) during data transmission over the total number of packets transmitted throughout the network is indicated by the PLR. The ability to send data without a loss can be achieved by an algorithm with an efficient routing and transmission mechanism. The PLR is retrieved in percentage and compared for the diverse count of nodes. The PLR of EMFRP, GSO-ACO, CSA, and PAOEER is given in Table 5 and Figure 6. The value of PLR is estimated using Equation (19):

$$Packet\ Drop\ Rate = \frac{Count\ of\ lost\ data\_packet}{Total\ count\ of\ the\ data\_packet} \quad (19)$$

Table 5. Comparison of Packet Drop Ratio

No of Nodes	EMFRP	GSO-ACO	CSA	PAOEER
100	4.66	2.77	2.44	1.33

200	5.57	3.88	2.98	1.99
300	6.87	4.89	3.69	2.52
400	7.28	5.65	4.32	3.44
500	9.19	6.55	5.68	4.33

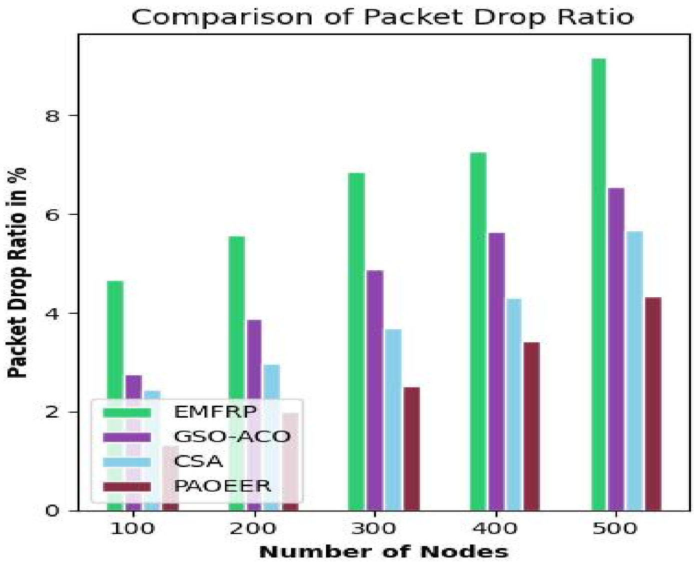

Figure 6. Comparison of Packet Loss Ratio

From Figure 6, it is identified that the proposed PAOEER achieved effective PDR. The PLR of the proposed PAOEER approach for 100 nodes is 1.11%, 1.44%, and 3.33 minimal than CSA, GSO-ACO, and EMFRP, the PLR of the proposed PAOEER approach for 200 nodes is 0.99%, 1.89%, and 3.58 minimal than CSA, GSO-ACO, and EMFRP, the packet drop ratio of the proposed PAOEER approach for 300 nodes is 1.17%, 2.37%, and 4.35 minimal than CSA, GSO-ACO, and EMFRP, the PLR of the proposed PAOEER approach for 400 nodes is 1.88%, 2.21%, and 3.84 minimal than CSA, GSO-ACO, and EMFRP, and the PLR of the proposed PAOEER approach for 500 nodes is 1.35%, 2.22%, and 4.86 minimal than CSA, GSO-ACO, and EMFRP. The packet drop ratio is comparatively minimal for the diverse count of the nodes, and the optimal path with an efficient transmission link assures the minimal PLR in the proposed PAOEER.

In proportion to the simulation time, the Network Lifetime (NL) is calculated. When the sensor's longevity increases, the network's lifetime also increases. The entire count of active nodes over a specific time calculates the NL. The lifetime efficiency improves with the count of active nodes. The NL of EMFRP, GSO-ACO, CSA, and PAOEER is given in Table 6 and Figure 7. The value of NL is estimated using Equation (20):

$$Network\_Lifetime = \frac{Initial\ level\ of\ energy}{Consumption\ of\ energy\ per\ unit\ times} \tag{20}$$

Table 6. Comparison of Network Lifetime

No of Nodes	EMFRP	GSO-ACO	CSA	PAOEER
100	4671	5324	4988	5819
200	4198	4981	4471	5181
300	3891	4781	4100	4956
400	3681	4198	3891	4781

500	3517	3981	3671	4512

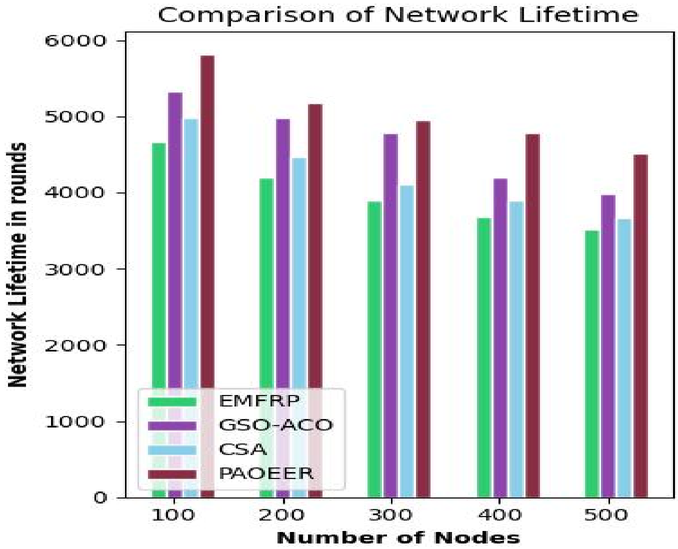

Figure 7. Comparison of Network Lifetime

Figure 7 shows the PAOEER method's NL estimation using existing models with different numbers of SNs. The findings demonstrated that the CSA and EMFRP approaches had reduced NL. In addition, the GSO-ACO approaches have a little longer NL than the CSA and EMFRP procedures. The proposed PAOEER approach has shown superior performance and significantly extended the NL, while the GSO-ACO technique has achieved the closest optimal NL. For instance, under the sensor node count of 100-500, the proposed PAOEER approach has increased the NL of 5819, 5181, 4956, 4781, and 4512 rounds, respectively.

Estimating the time takes for data to travel from the source to the destination node is the average latency of data transmission. The End-to-End Delay (EED) time must be kept to a minimum range. The latency of EMFRP, GSO-ACO, CSA, and PAOEER is given in Table 7 and Figure 8. The typical data transmission EED is computed using Equation (21):

$$Latency = data_{received_{time}} - data\_transmission_{start_{time}} \quad (21)$$

Table 7. Comparison of Latency

No of Nodes	EMFRP	GSO-ACO	CSA	PAOEER
100	1780	1250	1320	1010
200	3320	2580	2910	2090
300	4980	3750	4320	3290
400	5990	4420	5160	3910
500	7240	5130	6230	4120

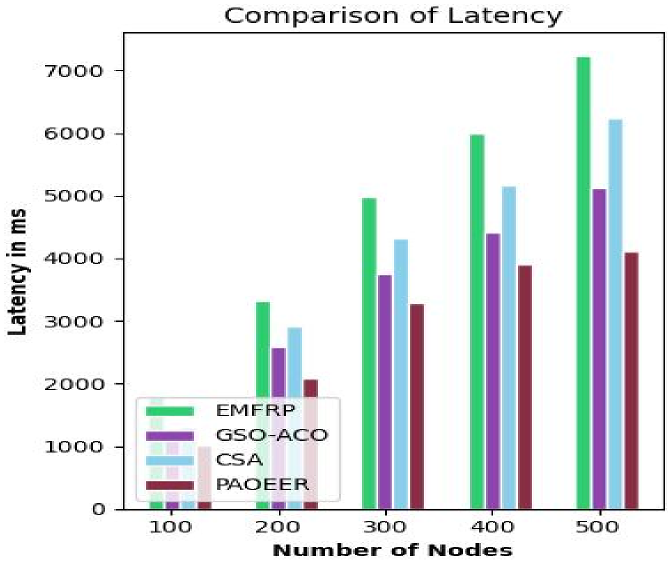

Figure 8. Comparison of EED

Figure 8 investigates the PAOEER procedure's latency analysis using existing techniques for multiple SNs. The PAOEER approach attains lower Latency than all the other methods, as is shown in the figure. Also, as the count of SNs increases, the latency increases. Because of the consistent distribution of energy throughout the WSN systems, the PAOEER approach achieves the lowest possible latency. For instance, the minimal latency under SNs of 100-500 has been validated by the PAOEER approach to be 1010, 2090, 3290, 3910, and 4120 milliseconds, respectively.

5. Conclusion and Future Works

Routing is an important operation of WSN that finds the appropriate path to the destination, and it has still been quite a challenging area of research. To address this challenge, the Adam Moment Estimation (Adam) that trains Deep Learning (DL) networks that are deployed in heterogeneous and homogeneous networks is optimized using Pareto optimization. Mathematics-based Pareto optimization supports the learning process and effectively addresses the multi-objective problem. Pareto optimization balances the path construction in this scenario, and the Adams-based DL network resolves the problem of fair distribution. By improving network parameters, the proposed Pareto-integrated Adams Optimizer for Energy Efficient Routing (PAOEER) maintains the WSN performance. The PAOEER has attained lower Energy Consumption (EC) of 112.34 J and a higher Packet Delivery Ratio (PDR) of 97.18%. The proposed methods provide improvements in most of the factors and are validated.

Future expansions will focus on developing cryptographic methods for safe and dependable data delivery. Also, in order to minimize lengthy delays and extend the simulation scenario, efficient MAC protocols can be developed. High bandwidth is provided by the multi-channel routing protocol, but it necessitates an efficient algorithm for assigning channels to transmission in active nodes. New protocols are necessary to distinguish the services supplied by WSNs. It's also necessary to create protocols that allow for dispersed instead of centralized control.

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