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A Hybrid Routing Algorithm using Artificial Neural Network and Swarm intelligence for Wireless Sensor Networks

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ABSTRACT

In Wireless Sensor Networks, reducing energy consumption is a crucial aspect while designing routing algorithms in order to increase throughput, improve network lifetime, and promise efficient network operations. Herein, a hybrid approach using Artificial Neural Networks (ANN) combined with Particle Swarm Optimization (PSO) is employed to develop an energy-efficient routing algorithm where, ANN with MLP Regressor is trained to find the shortest path and PSO to compute the optimized sink position. Results prove that the proposed ANNMLP-PSO outperforms as compared to Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Grey Wolf Optimization (GWO), and Reposition Particle swarm Optimization (RA-RPSO) for a network size of 50 nodes up to 300 nodes in terms of performance metrics: network lifetime, non-functional sensor nodes, energy usage, and packet delivery ratio. For a network size of 300 nodes, ANNMLP-PSO shows 0.43J of energy consumption whereas GA uses 0.88J, GWO uses 0.72J, PSO uses 0.82J, and RPSO uses 0.70J. At the end of 3000 rounds the count of dead nodes is 195 in the proposed method, while it is 300, 270, 280, and 290 nodes in the other methods. In this method, ANN is used to identify the shortest path between sensor nodes whereas PSO is employed to achieve optimized sink positioning. Due to the optimized sink position, the number of retransmissions and distance between the sink and SNs are decreased which results in overall reduction in energy usage.

Keywords: *Wireless Sensor Networks, Routing, Artificial neural network, Energy, Particle Swarm Optimization, Sink movement*

1. INTRODUCTION

Wireless Sensor Networks (WSNs) are an important part of modern life, significantly contributing to various aspects of technological advancement, and applications like data sensing and collection across numerous fields within engineering and science, showcasing their versatility and importance (1). WSNs comprises numerous sensor nodes (SNs) with constrained battery life, deployed to gather environmental data and send the same to a Base station (BS) or sink (2). The lifespan of a WSN depends on its ability to fulfill its intended function, which can end when the first sensor node fails, which leads to cluster of nodes becomes inactive, or the majority of nodes stop transmitting data (3). To maximize the sensor node's battery life and network longevity, reducing energy consumption during data transmission is vital, and achievable through efficient routing protocols (4). If maximum energy is consumed by SNs, it degrades the function of WSN. Consequently, path selection becomes a significant challenge in data transmission (5). The SNs selected to transfer the data may vary depending on the technique used (6). Therefore, the research paper proposes an unique path selection method to identify the optimum sink position considering a group of major parameters associated with the SNs. Intelligent algorithms are employed to identify optimal shortest paths for routing data to the sink (7). In earlier works objectives considered are to achieve efficient routing, power consumption, network lifespan, and packet-delivery-ratio(8). The Particle Swarm Optimization (PSO) algorithm, proposed in 1995 by Kennedy and Eberhart, and Yang and Press (2010), is recognized as the most common metaheuristic approach. However, experimentally, the PSO algorithm is hindered by two major issues it gets trapped in local-minima and premature-convergence (9), resulting in weakened global search capabilities. Efforts have been made to address these limitations (10). In real-world scenarios, environmental factors or dynamic conditions can affect network performance. Optimizing the sink's position allows the network to adapt to these changes effectively, maintaining efficiency over time.

Overall, the optimized sink position is a crucial factor in making the WSN more energy-efficient, reliable, and robust. This optimization directly addresses the hurdles faced by energy constraints in WSNs, ensuring smoother and long-lasting operation.

Optimizing sink positioning involves balancing multiple metrics to improve energy management and prolong network lifetime(11). The most commonly used metrics include: Energy Consumption, Network Lifetime**,** Path Length**,** Energy Balance, Data Throughput**,** Communication Latency**,** Coverage**,** and Scalability(12)**.** These metrics are often combined in multi-objective optimization algorithms like PSO, where the trade-offs between different goals are carefully considered to achieve the best overall performance. Thus, the research work introduces an unique hybrid algorithm for energy efficient routing process. The objectives are outlined below.

1. To select Optimum number of nodes (50-300) are considered for faster execution.
2. To present a novel multi-objective fitness function to efficiently balance the residual energy in SNs. Optimized distance calculations using vectorized operations are to be performed**.**
3. To adjust ANN parameters (hidden_layer_sizes, max_iter) for quicker training. To carry out parallel processing to compute paths efficiently.
4. To develop a novel hybrid routing algorithm named as ANNMLP-PSO aim to extend lifetime of SNs by selecting optimum values for PSO parameters to speed up optimization.

Further, paper is designed as: In Section 2, literature review is done. The Methodology of the presented ANNMLP-PSO path selection is discussed in Section 3. The Results and discussions of the presented algorithm as compared with existing works are carried out in Section 4. Lastly, the conclusion with insights on future works is presented.

2. LITERATURE REVIEW

Most routing algorithms focus solely on static sink positions or predefined criteria for routing. Traditional methods often optimize a single metric, such as path length or energy consumption. Many routing strategies rely on predefined or static datasets.

The authors in (11) proposed an enhanced routing algorithm for WSNs called RA-RPSO "Routing Algorithm based on Reposition Particle Swarm Optimization". It improves energy efficiency and extends the network's lifetime by addressing local minima and premature convergence often encountered in standard PSO. The paper (13) introduces an energy-saving routing algorithm by optimizing a multi-function formulation within a WSN. The algorithm incorporates the Adaptive Remora Optimization Algorithm (AROA) for cluster head selection. Key factors considered include energy usage, distance calculation, throughput, Packet-Delivery-ratio (PDR), and path loss. The Simulation results promised that the developed routing protocol majorly enhances WSN lifetime and its energy efficiency. The study (14) shows the effects of sink mobility on routing protocols, highlighting how these effects can vary based on the application architecture and network context. The work in (15) concentrates on innovative self-adaptive coyote optimization algorithm is employed for DN and CCH selection. By this next CH can be easily selected. Simulation results show that the model outperforms the self-adaptive whale optimization algorithm and other algorithms efficiently.

In (16), the authors have developed a Genetic algorithm for cluster development, choosing the CH and equilibrium optimizer for routing data between CH and BS. Gagandeep Kaur et al.,(17) presented a heuristic routing method using Deep Reinforcement learning for IoT-enabled WSNs. They have considered many objectives like lifetime, throughput, and delay for intra-cluster path selection and the same for inter-cluster routing. The algorithm outperforms compared to existing works in packet delivery, efficiency in power, delay in communication, and time complexity. In (18), authors have shown an energy-efficient routing algorithm employing reinforcement learning which makes devices adapt to WSN dynamics like energy modifications and movement by improving the routing decisions. The output depicts its better power efficiency and scalability. Another metaheuristic algorithm proposed in (19) is Ant Colony optimization (ACO) which considers the node mobility. The results show that it has almost 50% reduced energy consumption compared to traditional ACO. The authors in(20) have shown a hybrid form of trajectory scheduling using ACO (21) and PSO (22) where the anchor node of every cluster head is chosen within the communication range. From simulation experiments, it is evident that the results depict less energy consumption and gathers data efficiently. In (23), the authors have tackled the critical challenge of planning a sink's movement to balance energy consumption across the network. Ten different types of WSN maps are considered including dynamic and large scale networks. But, the additional processing required for implementation may introduce energy overhead. The authors in (24) presented a heuristic routing algorithm for autonomous vehicles by examining criteria such as robustness, explain ability, reproducibility, and transparency. The study highlights edge cases where extreme agent parameters can challenge algorithm performance but demonstrates robustness through adaptive parameters like B-spline interpolation. In (25), authors have proposed an advanced routing solution for Mobile Ad Hoc Networks (MANET) in Internet of things (IoT) environments. Simulation outputs show major improvements in through-put, delay, data packet loss ratio and detection rate compared to existing techniques.

3. METHODOLOGY

The assumptions of the WSN topology considered are outlined in this section. The energy consumed by the radio model used within the specified WSN area is examined. Lastly, the operation of the developed ANNMLP-PSO is described in detail.

3.1 Energy consumption model

A radio communication model is employed to compute energy consumption. The transmitter present in the SN needs energy for running the electronic components in it and also for amplifying transmitting power, while the receiver only utilizes energy for running the electronic components. The energy dissipated is denoted as E_e per bit at both the transmitter and receiver circuit. Table.1 shows the energy model parameters considered (26). Channel coding, modulation, filtering, and spreading influence energy usage. Optimizing energy usage is important for prolonging the network's lifespan and ensuring efficient operation.

Table 1.Energy Model parameters

Sl.No	Parameters	Value
1.	Initial_energy	Variable for each node
2.	Transmission_energy per unit distance	0.1J
3.	Receiving_energy	0.05J
4.	Idle_energy	0.001J
5.	Data_packet_size	1
6.	Area_size	100 X 100

Energy consumption in a WSN refers to the energy spent by SNs during data transmission and reception. Key Parameters are

1. Transmission Energy (E_t)**:** Energy required to transmit data over a given distance. Typically depends on the distance and data size.
2. Receiving Energy (E_r**)**: Energy consumed by the receiving node.
3. Idle Energy (E_i**)**: Background energy consumed by nodes when they are idle (not transmitting or receiving data).
4. Distance Matrix: Represents distances between SNs in the network.

Energy consumed for information transmission from one node (n_i) to another node (n_j) I given by Eq. 1.

$$E_{ij} = (Et\,.\ d_{i,j} + E_r\,) \tag{1}$$

Where:

Where,

E_t : Transmission energy per unit distance

d_{ij}: Distance between nodes i and j.

E_r: Receiving energy.

Considering an entire path connecting multiple nodes ($n_1 \rightarrow n_2 \rightarrow n_3$), the energy consumed is given in Eq.2.

$$E_{path} = \sum_{i=1}^{N-1}(E_t\, d_{i,i+1} + E_r\,) \tag{2}$$

The additional E_r accounts for the sink node consuming energy.

The function calculate_energy_consumption() implements this process of calculating energy consumption. It loops through the nodes in the path. Also, adds transmission and receiving energy for each hop (pair of connected nodes). It calculates the receiving energy consumed by the sink node. Factors Affecting Energy Consumption are distance between nodes: Longer distances increase transmission energy. Data Size: Larger packets consume more energy during transmission. Path Configuration is identifying direct paths to the sink since it is more energy-efficient than indirect or multi-hop routes. Placing the sink closer to nodes minimizes energy consumption.

3.2 Mathematical equations

Euclidean distance between Nodes

To compute the distance between two SNs i and j, the Euclidean-distance formula is used as given in Eq. 3. This is employed to create the "distances" matrix, which provides the pairwise distances between all nodes.

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{3}$$

3.2.1. Energy Consumption for Data Transmission

The total energy consumed when transmitting data between two nodes i and j is given by Eq.1. This is calculated for each segment of a path and summed up to find the total energy consumed along a routing path.

Total Energy Consumption for a path: For a path P = [n_1,n_2,n_3,….., n_k], the total energy consumption is shown in Eq.4. This finds the energy needed for data to move from the SN to the sink.

$$E_{path} = \sum_{i=1}^{k-1}(E_t * d_{i,i+1} + E_r) + E_r \tag{4}$$

3.2.2 Network Lifetime

The network-lifetime is calculated depending on energy reserves of SNs and their consumption rates are given in Eq.5. The minimum lifespan among all SNs determines the overall network lifetime.

$$L = min(\frac{E_i}{E_{i,consumption}} + \frac{1}{E_i^{idle}}) \tag{5}$$

where**,**

E_i: Initial energy of SN i.

$E_{i,consumption}$: Energy usage by node i for transmission and reception.

E_i^{idle} **:** Idle energy consumption rate of node i.

3.3.3 Objective Function for Sink Optimization

The objective function combines energy consumption and network lifetime into a single cost metric for PSO optimization is shown in Eq.6. guides the Particle Swarm Optimization (PSO) algorithm to find the best sink position by minimizing f(x).

$$f(x) = E_{total} - w * L \tag{6}$$

where,

E_{total}: Total energy consumed by all nodes.

L: Network lifetime.

w: Weight factor to balance energy minimization and lifetime maximization.

3.2.3 Path Cost Prediction Using Artificial Neural Network (ANN)

The ANN is trained by using input features to enable it to predict the cost of a path as shown in Eq.7. It predicts the path cost for routing between SNs by employing machine learning, instead of calculation of distances repeatedly.

$$Loss = \frac{1}{N}\sum_{i=1}^{N}(y_{predicted,i} - y_{actual,i})^2 \tag{7}$$

These equations provide a strong foundation for energy calculation efficiently, routing mechanism, and optimized positioning of sink.

3.3 Proposed Model

The presented model demonstrates a novel approach to developing a hybrid energy-efficient routing algorithm for WSN, which is a combination of Artificial Neural Networks (ANN) with Multilayer Perceptron (MLP) Regressor and Particle Swarm Optimization (PSO). The novelty of the algorithm is due to the following aspects:

3.3.1 Synthetic Dataset Generation

A Synthetic dataset is created which offers different scenarios like node density variation and changes in the area size impacting in efficient simulation of real-world WSN dynamics.

3.3.2 Integration of ANN for Shortest Path Prediction

It is a unique idea to use ANN model for shortest path prediction. Hence, the model is trained to predict path costs dynamically. The ANN considers the coordinates of SNs, the distance between SNs, and changes in sink positions to make real-time predictions, enabling adaptability to changes in the network.

3.3.3 Optimization via PSO

Particle swarm optimization (PSO) is made use of to optimize the sink's position, which is a unique aspect here since; it uses swarm intelligence to find the best solution by balancing energy consumption and network lifetime. PSO is versatile as it handles multi-objective optimization effectively in comparison to gradient-based methods which find it difficult to perform in non-linear or complex scenarios. A combination of Multiple Metrics is considered where energy consumption is reduced and network lifetime is extended providing overall efficient network design.

Dynamic Sink movement is created based on network conditions resulting in minimal energy consumption among SNs. A clear understanding of network operation is achieved by visualizing node positions, path optimization, and sink movement. The hybrid algorithm of ANN predictions and PSO optimization ensures adaptability to dynamic conditions for both small and large network scenarios.

3.3.4 ANNMLP-PSO Algorithm

The proposed hybrid algorithm is comprehensive and consists of concepts like Wireless sensor networks (WSN), Artificial Neural Networks (ANN), Particle Swarm Optimization (PSO), and energy-efficient routing strategies using MLP regressor. The Algorithm steps are:

Steps	Description
I.	Initialization: Packages like NumPy, Pandas, scilit-learn, matplotlib, pyswarm and networkx are initialized.
II.	Synthetic data is generated using a function and the network is modeled as a group of nodes randomly distributed in space.
III.	Define the sink node and energy-related parameters.
IV.	The energy consumption calculation function calculates the energy consumed when data is transmitted along a path of nodes.
V.	A Network lifetime calculation function determines how long the network can operate before a node runs out of energy.
VI.	An objective function for PSO that guides the Particle swarm optimization by evaluating each potential solution (sink node position).
VII.	An ANN is trained to predict shortest path costs between nodes a function to find the shortest distance from SN to the sink is developed.
VIII.	The search space for the sink's position is defined and the "pso" function iteratively adjusts the sink's position to minimize the objective function and the optimized sink position is stored.
IX.	Final path calculation: Once the sink's position is optimized, the shortest paths from all nodes to the sink are recalculated.
X.	Evaluation of Energy Consumption and Lifetime for Optimized Configuration. A Scatter plot of nodes and sink, and path Connection between nodes and the sink are drawn. A plot showing the energy consumption of individual nodes.

The flowchart of the algorithm is shown in Figure. 1. It begins by importing necessary libraries for numerical computations, plotting, machine learning, and optimization (e.g., NumPy, Matplotlib, Scikit-learn, PSO). A function named "generate_synthetic_data ()" is used to create a synthetic Wireless Sensor Network (WSN). The Inputs are several SNs and area size. It results in Node positions (x,y) randomly distributed in the area. Initial energy levels for each node are set. A distance matrix representing pairwise distances between nodes is developed. An initial sink (base station) is identified at a predefined location at the center of the area. Energy-related parameters considered are Transmission energy per unit distance, receiving energy per data packet, and idle energy for nodes when not transmitting or receiving.

The Energy Consumption calculation is performed by defining a function called "calculate_energy_consumption()" to compute the energy spent by nodes for transmitting and receiving data along a routing path as in Eq. 4. The Computation of Network Lifetime is performed using the function **"**calculate_lifetime ()" to evaluate network lifetime. Lifetime is given by minimum remaining energy of SN divided by its energy consumption rate. Mainly, lifetime of the network is depending on the most energy-depleted node. To train an ANN using the "train_ann()" function, the inputs considered are Node coordinates (x, y), distances between nodes and Sink position. The Model uses Multi-Layer Perceptron (MLP) as the regressor to predict shortest path costs. The Output of training ANN model is its capability of predicting path costs dynamically.

For predicting Shortest Paths a function " find_shortest_path_ann()" is used to calculate the shortest paths from nodes to the sink node. It predicts the cost of each path using the trained ANN and selects the route with the minimum cost for each node to the sink. An objective function is defined for Particle Swarm Optimization (PSO) with inputs as Node positions, sink positions, distances, and energy levels and outputs as total energy consumption and Network lifetime. Combine these metrics into a single scalar value to minimize is given in Eq.6. To optimize Sink Position Using PSO **"**pso()" function is employed with inputs Objective function, Lower bounds (0,0), and upper bounds (100,100) for sink coordinates and Outputs as Optimized sink position (x_{opt}, y_{opt}) and Corresponding objective function value. The parameters considered are SNs position, energy, distances, sink node position, swarm size, and maximum iterations.

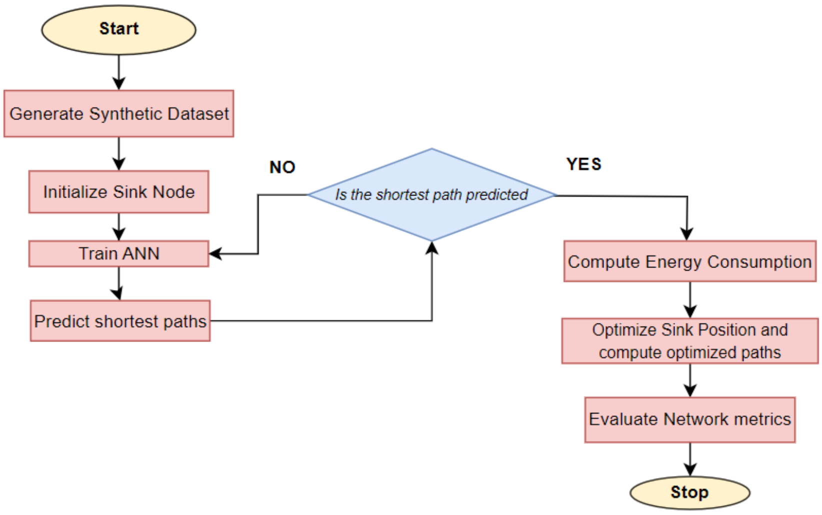

Figure.1 Flowchart of ANNMLP-PSO algorithm

Optimized Paths are computed by recalculating the routing paths from nodes to the sink using the optimized sink position. ANN model is used to find the shortest path**.** Finally, optimized total energy consumption and optimized network lifetime are evaluated and these metrics are compared with other existing algorithms. Initial and optimized sink positions, routing paths from nodes to the sink are shown in Figure. 3.

4. RESULTS AND DISCUSSION

The presented hybrid algorithm is trained and performance evaluation is carried out in Jupyter notebook. Initially, Synthetic dataset is generated for a range of 50-300 nodes. A sample of top five rows of the dataset is shown in Figure. 2.

	Node ID	X Position	Y Position	Initial Energy
0	0	37.454012	95.071431	3.142919
1	1	73.199394	59.865848	63.641041
2	2	15.601864	15.599452	31.435598
3	3	5.808361	86.617615	50.857069
4	4	60.111501	70.807258	90.756647

Figure. 2. A sample dataset showing first 5 rows

The SNs are randomly deployed and the initial sink position is at the center. The WSN is employed with 50 SNs that are randomly deployed in a 100 X 100m^2 area. The number SNs considered are 50, 150, 200, 250, and 300 for scalability verification. A single sink node is placed at the middle of the specified area. Each SN initially has variable energy. The parameters considered in the proposed algorithm are represented in Table 2. Maximum number of rounds for each node is 3000.

Table 2: Parameter values exploited while simulating the network

Parameter	Value
Network area_size	100m X 100m
No. of sensor nodes	50-300
Max. no. of rounds	3000
E_e	50nJ/bit
ε_f	10pJ/bit/m^2
ε_m	0.0013 pJ/bit/m^4
Control Packet size	500 bits
Data Packet Size	10000 bits

The optimized sink position shown in Figure. 3 exhibits a pivotal part in enhancing efficiency of WSN. It signifies a good strategy for reducing energy consumption by repositioning the sink where, the distance between the sink and the SNs is minimized. The SNs consume less energy for shorter transmission distances when sending data, which results in preserving their energy reserves for a longer time duration. Thus, energy consumption is balanced across SNs by placing the sink optimally. This minimizes the risk of particular nodes depleting their energy prematurely (a phenomenon called the "hotspot problem"), thereby increasing the overall operational network lifetime. Also, Packet delivery losses reduce when nodes are nearer to the sink which in turn avoids data packet retransmission. This influences reliability and throughput of data transmission inside the network. This ensures a fair distribution of energy consumption among all nodes.

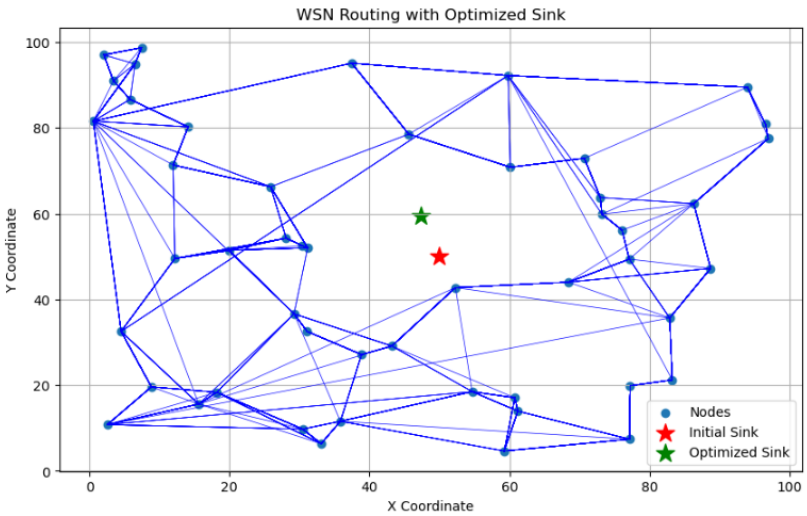

Figure. 3 Final nodes, routing paths and optimized sink position(50 nodes and 1 sink)

4.1 Performance Evaluation of proposed ANNMLP-PSO algorithm

A performance comparison of ANNMLP-PSO algorithm with other intelligent routing algorithms such as PSO, GA, GWO, and RA-RPSO is carried out considering key metrics like network lifetime, energy consumption, count of dead nodes, and throughput or Packet delivery ratio. Network Lifetime is the time during which it remains functional before any sensor node runs out of energy. A Longer lifetime indicates that algorithm balances energy usage effectively among nodes. The lifetime comparison of presented work is shown in Figure 4. The simulation output depict that presented ANNMLP-PSO algorithm offers a prolonged lifetime compared to other algorithms PSO, GWA, GA, and RA-RPSO. For 50 nodes the network maintains up to 1500 rounds for PSO, GWA, GA, and RA-RPSO, whereas the ANNMLP-PSO algorithm maintains a network lifetime of up to 2000 rounds. Further, if 300 nodes are considered, the proposed algorithm's network lifetime extends up to

3000 rounds while, other algorithm's network lifetime ends between 2500 and 2900 rounds. The performance is increased due to the efficient prediction of the algorithm in path selection, optimum sink positioning, and energy consumption maintenance.

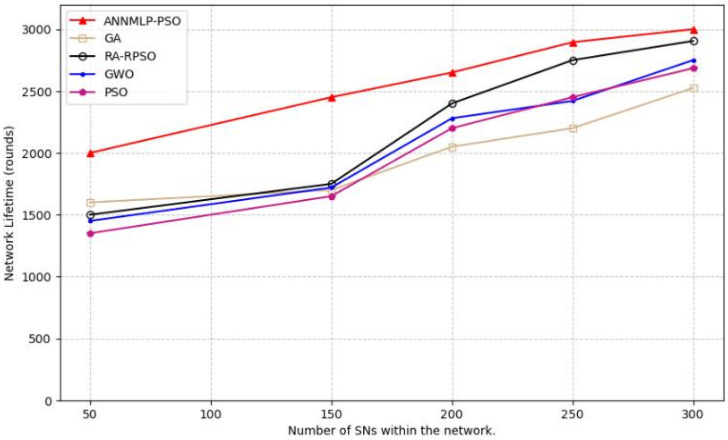

Figure.4 Network lifetime comparison for 50 nodes upto 300 nodes

Dead nodes occur due to uneven energy depletion and cause hotspots, leading to isolated or non-functional nodes. Residual energy levels at different nodes are assessed and energy balancing among nodes is checked. ANNMLP-PSO ensures that no nodes are overly depleted, it offers better load balancing compared to other methods PSO, GWA, RA-RPSO, and GA. A comparison of a number of dead SNs in various routing methods is depicted in Figure 5. At the end of 1500 rounds, all SNs of the presented algorithm are yet alive justifying the superiority of the algorithm. During the last round, it is observed that the number of dead SNs is lowest in ANNMLP-PSO algorithm in comparison to all other routing methods.

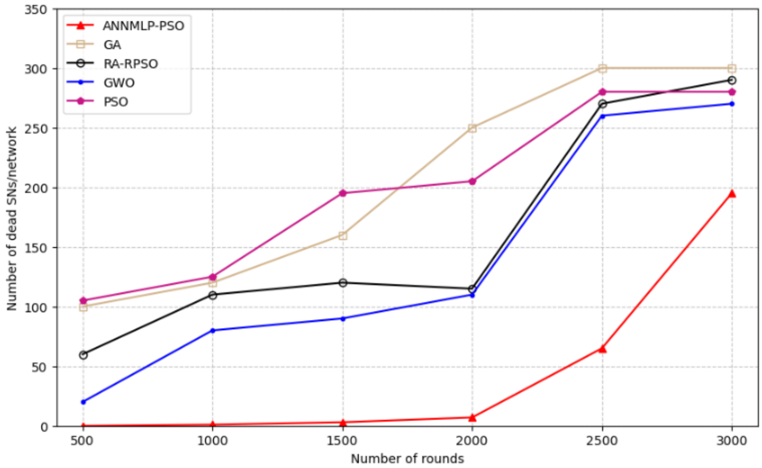

Figure. 5 Number of Dead nodes for maximum rounds

Average Energy consumption is the maximum energy used by SNs while transmitting and receiving data. Lower energy consumption indicates higher efficiency and prolonged network lifetime. The total energy consumed for all routing paths is measured and compared with existing algorithms. In Figure 6 it is observed that, ANNMLP-PSO reduces energy consumption by optimizing sink position, it demonstrates superior efficiency over other routing methods.

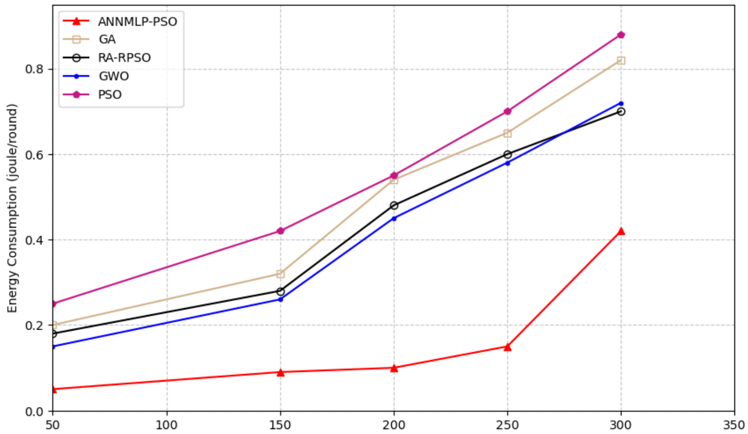

Figure. 6 Energy consumption with respect to number of nodes

Throughput measures the rate at which data packets are successfully sent to the sink. The proposed algorithm ensures reliable data transmission by optimizing sink placement. Data Packet Delivery Ratio (PDR) is the percentage of data packets successfully delivered compared to the total packets transmitted. High PDR indicates efficient communication and successful routing and is given by Eq. 9. Comparing PDR across algorithms to identify the most robust solution is shown in Figure 7, where a track of a total number of data packets sent and successfully delivered to the sink node for each algorithm is shown. It is observed that the presented method shows high throughput in comparison to existing methods for a range of 50 nodes and 300 nodes.

$$PDR = \frac{Number\ of\ Delivered\ Packets}{Number\ of\ sent\ packets}\ X\ 100 \qquad (9)$$

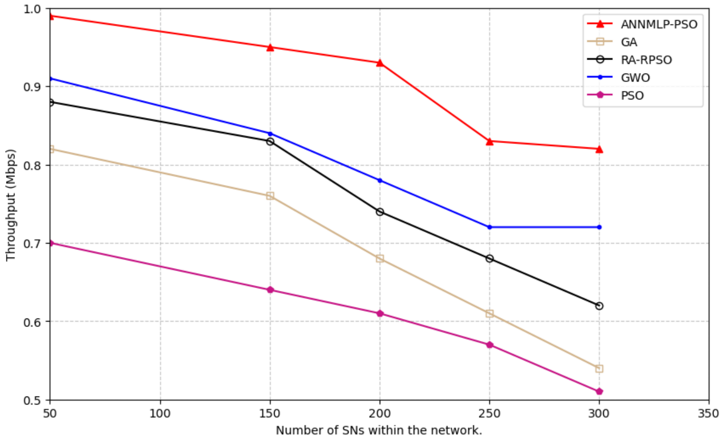

Figure. 7 Throughput compared to number of Alive sensor nodes

The Initial sink position is fixed as [50,50] and optimized sink position after a maximum number of rounds turned out to be [47.29705406, 59.52219585] for 50 nodes, [48.65214594, 60.65423585] for 200 nodes and [49.52648956, 61.54687125] for 300 nodes. It is evident that, each time when the sink position is calculated by PSO its optimum position is found. It is observed that amount of energy consumed is proportional to the increase in SN count. A comparison of energy consumption between algorithms of interest for 50 nodes and 300 nodes is depicted in Figure. 8. It proves that the presented ANNMLP-PSO algorithm consumes less energy for both 50 nodes and 300 nodes compared to other algorithms. The energy consumed for 50 nodes by ANNMLP-PSO is 150, PSO is 205, GA is 220, GWO is 200 and RA-RPSO is 160. For 300 nodes by ANNMLP-PSO is 170, PSO is 210, GA is 260, GWO is 240 and RA-RPSO is 180. This proves that presented algorithm consumes less energy in comparison with existing methods. Thus, scalability is also achieved nominally.

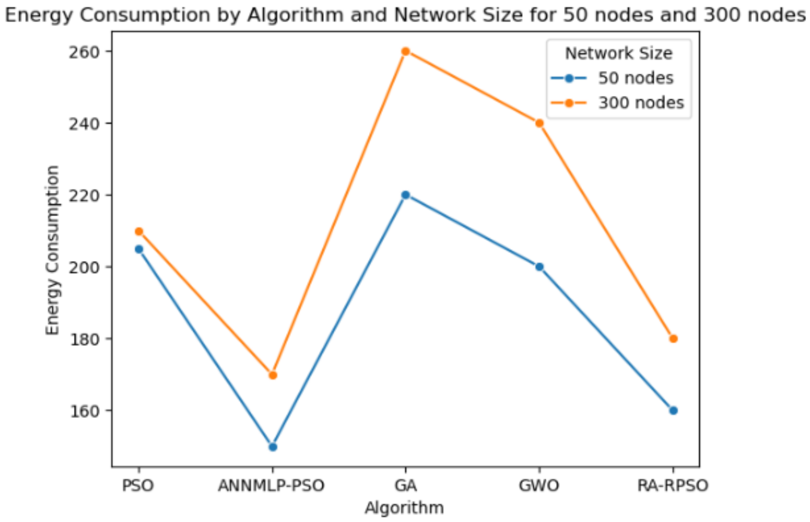

Figure. 8. Energy consumption by algorithm and network size for 50 nodes and 300 nodes.

5. CONCLUSION

The presented hybrid algorithm justifies an efficient approach to tackle crucial challenges in WSN, like optimum sink node placement and efficient routing mechanism. The novel approach used ANN's capabilities in predicting the shortest path and PSO's search optimization for sink position dynamics. This resulted in noticeable reduction in energy consumption and increased network lifetime. The results prove the importance of hybrid methodologies that combine machine learning and swarm intelligence techniques for solving complex problems in dynamic network environments. In comparison to earlier methods like GA, PSO, GWO, and RA-RPSO, it is observed that the presented algorithm shows higher performance with 48% decrease in energy consumption for 300 nodes. As the number of dead nodes is 195 which is less than the dead nodes in other algorithms shows better lifetime and improved packet delivery ratio reflects the higher throughput., Further, the proposed research work provides a robust foundation for further research in real-time applications in WSNs.

REFERENCES

[1] Kandris D, Nakas C, Vomvas D, Koulouras G. Applications of Wireless Sensor Networks: An Up-to-Date Survey. Appl Syst Innov [Internet]. 2020 Feb 25 [cited 2025 Mar 13];3(1):14. Available from: https://www.mdpi.com/2571-5577/3/1/14

[2] Al Aghbari Z, Khedr AM, Osamy W, Arif I, Agrawal DP. Routing in Wireless Sensor Networks Using Optimization Techniques: A Survey. Wirel Pers Commun [Internet]. 2020 Apr [cited 2025 Feb 2];111(4):2407–34. Available from: http://link.springer.com/10.1007/s11277-019-06993-9

[3] Chowdhury SM, Hossain A. Different Energy Saving Schemes in Wireless Sensor Networks: A Survey. Wirel Pers Commun [Internet]. 2020 Oct [cited 2025 Feb 2];114(3):2043–62. Available from: https://link.springer.com/10.1007/s11277-020-07461-5

[4] Chen J, Sackey SH, Anajemba JH, Zhang X, He Y. Energy-Efficient Clustering and Localization Technique Using Genetic Algorithm in Wireless Sensor Networks. Hassanien AEIB, editor. Complexity [Internet]. 2021 Jan [cited 2025 Feb 2];2021(1):5541449. Available from: https://onlinelibrary.wiley.com/doi/10.1155/2021/5541449

[5] R H, C B V, M S. Genetic Algorithm with Bacterial Conjugation Based Cluster Head Selection for Dynamic WSN. In: 2023 International Conference on Network, Multimedia and Information Technology (NMITCON) [Internet]. 2023 [cited 2025 Feb 2]. p. 1–6. Available from: https://ieeexplore.ieee.org/document/10275829

[6] Angadi BM, Kakkasageri MS, Manvi SS. Chapter 2 - Computational intelligence techniques for localization and clustering in wireless sensor networks. In: Bhattacharyya S, Dutta P, Samanta D, Mukherjee A, Pan I, editors. Recent Trends in Computational Intelligence Enabled Research [Internet]. Academic Press; 2021 [cited 2025 Mar 27]. p. 23–40. Available from: https://www.sciencedirect.com/science/article/pii/B9780128228449000116

[7] Fanian F, Kuchaki Rafsanjani M. Cluster-based routing protocols in wireless sensor networks: A survey based on methodology. J Netw Comput Appl [Internet]. 2019 Sep 15 [cited 2025 Apr 11];142:111–42. Available from: https://www.sciencedirect.com/science/article/pii/S1084804519301456

[8] Hung CW, Zhuang YD, Lee CH, Wang CC, Yang HH. Transmission Power Control in Wireless Sensor Networks Using Fuzzy Adaptive Data Rate. Sensors [Internet]. 2022 Dec 17 [cited 2025 Feb 2];22(24):9963. Available from: https://www.mdpi.com/1424-8220/22/24/9963

[9] Wang M, Wang S, Zhang B. APTEEN routing protocol optimization in wireless sensor networks based on combination of genetic algorithms and fruit fly optimization algorithm. Ad Hoc Netw [Internet]. 2020 May 1 [cited 2025 Apr 11];102:102138. Available from: https://www.sciencedirect.com/science/article/pii/S1570870519311436

[10] An Improved Particle Swarm Optimization Based on Total Variation Regularization and Projection Constraint with Applications in Ground-Penetrating Radar Inversion: A Model Simulation Study [Internet]. [cited 2025 Apr 11]. Available from: https://www.mdpi.com/2072-4292/13/13/2514

[11] Lakshmi Narayanan S, Kasiselvanathan M, Gurumoorthy KB, Kiruthika V. Particle swarm optimization based artificial neural network (PSO-ANN) model for effective k-barrier count intrusion detection system in WSN. Meas Sens [Internet]. 2023 Oct [cited 2025 Apr 11];29:100875. Available from: https://linkinghub.elsevier.com/retrieve/pii/S2665917423002118

[12] Haripriya R, Vinutha CB, Nagaraja M. An Investigation on Computational Intelligent Solutions for Highly Dynamic Wireless Sensor Networks. In: Smys S, Tavares JMRS, Balas VE, editors. Computational Vision and Bio-Inspired Computing. Singapore: Springer; 2022. p. 301–12.

[13] Kaviarasan S, Srinivasan R. Developing a novel energy efficient routing protocol in WSN using adaptive remora optimization algorithm. Expert Syst Appl [Internet]. 2024 Jun 15 [cited 2025 Feb 2];244:122873. Available from: https://www.sciencedirect.com/science/article/pii/S0957417423033754

[14] Naveen G, Prathap PMJ. Network energy optimization and intelligent routing in WSN applicable for IoT using self-adaptive coyote optimization algorithm. Int J Commun Syst [Internet]. 2023 [cited 2025 Feb 2];36(9):e5464. Available from: https://onlinelibrary.wiley.com/doi/abs/10.1002/dac.5464

[15] Clustering routing algorithm of wireless sensor network based on swarm intelligence | Wireless Networks [Internet]. [cited 2025 Apr 11]. Available from: https://link.springer.com/article/10.1007/s11276-023-03584-2

[16] A novel approach for clustering and routing in WSN using genetic algorithm and equilibrium optimizer - Heidari - 2022 - International Journal of Communication Systems - Wiley Online Library [Internet]. [cited 2025 Apr 11]. Available from: https://onlinelibrary.wiley.com/doi/abs/10.1002/dac.5148?msockid=3f8c07480dda6a0d389a16800c776b10

[17] Kaur G, Chanak P, Bhattacharya M. Energy-Efficient Intelligent Routing Scheme for IoT-Enabled WSNs. IEEE Internet Things J [Internet]. 2021 Jul 15 [cited 2025 Feb 2];8(14):11440–9. Available from: https://ieeexplore.ieee.org/document/9324772/

[18] Mutombo VK, Lee S, Lee J, Hong J. EER-RL: Energy-Efficient Routing Based on Reinforcement Learning. Ko H, editor. Mob Inf Syst [Internet]. 2021 Apr 19 [cited 2025 Feb 2];2021:1–12. Available from: https://www.hindawi.com/journals/misy/2021/5589145/

[19] Energy-Efficient Scalable Routing Protocol Based on ACO for WSNs | IEEE Conference Publication | IEEE Xplore [Internet]. [cited 2025 Apr 11]. Available from: https://ieeexplore.ieee.org/document/8952053

[20] Singh A, Sharma S, Singh J. Nature-inspired algorithms for Wireless Sensor Networks: A comprehensive survey. Comput Sci Rev [Internet]. 2021 Feb [cited 2025 Feb 2];39:100342. Available from: https://linkinghub.elsevier.com/retrieve/pii/S1574013720304421

[21] An Effective Hybrid Routing Algorithm in WSN: Ant Colony Optimization in combination with Hop Count Minimization [Internet]. [cited 2025 Apr 11]. Available from: https://www.mdpi.com/1424-8220/18/4/1020

[22] Gao Y, Wang J, Wu W, Sangaiah AK, Lim SJ. A Hybrid Method for Mobile Agent Moving Trajectory Scheduling using ACO and PSO in WSNs. Sensors [Internet]. 2019 Jan 30 [cited 2025 Feb 2];19(3):575. Available from: https://www.mdpi.com/1424-8220/19/3/575

[23] Han X, Mu X, Zhong J. HGFF: A Deep Reinforcement Learning Framework for Lifetime Maximization in Wireless Sensor Networks [Internet]. arXiv; 2024 [cited 2025 Apr 12]. Available from: http://arxiv.org/abs/2407.07747

[24] Trustworthiness analysis of heuristic routing algorithm with special constraints for autonomous vehicles in surveillance and coverage operations [Internet]. [cited 2025 Apr 20]. Available from: https://www.tandfonline.com/doi/epdf/10.1080/00207721.2025.2455998?needAccess=true

[25] Yuvaraja P. Hybrid Optimization to Trust Enhanced Secure Routing Optimization with IABC and CGWAA for MANET. Commun Appl Nonlinear Anal [Internet]. 2025 Feb 14 [cited 2025 Apr 20];32(9s):1536–54. Available from: https://internationalpubls.com/index.php/cana/article/view/4196

[26] Wang J, Gao Y, Liu W, Sangaiah A, Kim HJ. An Improved Routing Schema with Special Clustering Using PSO Algorithm for Heterogeneous Wireless Sensor Network. Sensors [Internet]. 2019 Feb 7 [cited 2025 Feb 2];19(3):671. Available from: https://www.mdpi.com/1424-8220/19/3/671