Journal of Computer Science

Research Article

Dynamic Weighting Technique Based Arctic Puffin Optimization for Energy Efficient Data Transmission in Wireless Sensor Networks

M. Bharathraj Kumar[1], S. Avinash[1], Prakash G. Gani[2] and Prathapchandra Shetty[1]

[1]*Department of Electronics and Communication Engineering, Shri Dharamasthala Manjunathaeshwara Institute of Technology, Ujire, India*
[2]*Department of Electrical and Electronics Engineering, S D M College of Engineering and Technology, Dharwad, India*

Article history
Received: 17-09-2025
Revised: 30-07-2026
Accepted: 06-08-2026

Corresponding Author:
M. Bharathraj Kumar
Department of Electronics and Communication Engineering, Shri Dharamasthala Manjunathaeshwara Institute of Technology, Ujire, India
Email: bharathrajkumar100@yandex.com

Abstract: Wireless Sensor Networks (WSNs) are designed using various sensor nodes, which are employed for communication in diverse applications that include healthcare, industrial areas, and smart cities. Specifically, WSNs demand energy-efficient clustering and routing mechanisms that assist in extending network lifetime due to the limited battery capacity of sensor nodes. However, many existing meta-heuristic-based approaches incorporate fixed objective weights that struggle to adapt under dynamic network conditions and result in premature convergence and uneven energy depletion among cluster heads. To address these challenges, this manuscript proposes a Dynamic Weighting Technique-based Arctic Puffin Optimization (DWT-APO) algorithm for cluster head selection and optimal routing in WSNs. The DWT-APO introduces an adaptive weight adjustment mechanism that dynamically helps balance exploration and exploitation throughout the optimization process. Finally, a unified multi-objective fitness function is formulated by combining residual energy, communication distance, delay, and node degree, which enhances cluster stability and routing efficiency. The simulation outcomes illustrate that the proposed DWT-APO attains improved network lifetime up to 60%, enhancing residual energy by 66.7%, and throughput by 24% when compared to the Ultra-Scalable Ensemble Clustering Technique (U-SENC) with Flamingo Search Algorithm (FSA) under high-round network conditions.

Keywords: Arctic Puffin, Cluster Head Selection, Data Transmission, Dynamic Weighting Technique, Optimal Route

Introduction

Wireless Sensor Networks (WSNs) play a significant part in recent transmission models by enabling distributed data collection across various applications, including smart cities, healthcare systems, and industrial automation (Senkumar et al., 2024; Priyanka et al., 2022). A representative WSN comprises several small sensor nodes that are deployed across a geographical area to sense, process, and transmit environmental data. However, these nodes are controlled by limited battery power, restricted processing capabilities, and short communication range (Alsuwat and Alsuwat, 2025; Chaurasia et al., 2023). Owing to these constraints, energy-efficient data transmission remains an essential challenge in WSN design.

The energy consumption in WSNs is largely affected by communication operations. Frequent data transmission results in rapid battery depletion, which significantly reduces network lifetime and overall system reliability (Zeng et al., 2024; Rajaram et al., 2025). To mitigate this issue, clustering and routing strategies are widely incorporated, as these techniques assist in balancing energy consumption among nodes. Currently, metaheuristic optimization algorithms are utilized for cluster head selection, routing optimization, and efficient data aggregation because of their ability to address complex multi-objective problems (Srividhya and Shankar, 2023; Zulfiqar et al., 2023). Algorithms like Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and other bio-inspired algorithms illustrate intelligent search mechanisms that help improve energy efficiency while improving data delivery performance (Gupta and Rout, 2024; Prakash et al., 2024).

DOI: 10.3844/jcssp.2026.2723.2735

By incorporating these optimization techniques, WSNs demonstrate an enhanced network lifetime, reduced packet loss, and improved data accuracy (Karthikeyan et al., 2024; Kumar et al., 2022). Existing research approaches have focused on optimizing parameters including node deployment, routing path selection, and data aggregation, which help increase overall network performance (Kumar and Agrawal, 2023; Wilson et al., 2024). Energy-efficient transmission mechanisms utilizing metaheuristic approaches have been extensively explored (Sheeja et al., 2023).

Despite these improvements, most existing metaheuristic-based clustering and routing protocols depend on fixed-weight multi-objective fitness functions. Such static weighting mechanisms struggle to adapt to dynamic network conditions, including residual energy variations, node density, and traffic load. Consequently, these methods result in suboptimal cluster head selection, inconsistent energy depletion, and a decrease in routing stability. Furthermore, adaptive mechanisms to adjust objective priorities dynamically during the optimization process remain insufficiently explored in existing literature.

Therefore, there is a need for an adaptive optimization model that dynamically balances exploration and exploitation while integrating cluster head selection and routing within a multi-objective model. To address this limitation, this research proposes a Dynamic Weighting Technique-based Arctic Puffin Optimization (DWT-APO) algorithm that has the ability to adaptively adjust weight parameters during the optimization process, which facilitates the enhancement of energy efficiency, extension of network lifetime, and improvement of routing stability in WSNs. The contributions of this manuscript are described below.

The major technical contributions of this work are summarized as follows:

- The proposed DWT-APO approach is designed for cluster head selection and optimal routing in WSNs
- An adaptive dynamic weighting technique is introduced that continuously adjusts the objective weights during the optimization process, thereby enhancing the balance between exploration and exploitation stages
- The unified multi-objective fitness function is formulated by combining the residual energy, communication distance, delay, and node degree, which helps achieve balanced energy consumption and improved routing stability
- The proposed model conducts coordinated cluster head selection and routing optimization within a single optimization structure that reduces communication overhead and enhances the network lifetime

Literature Review

Literature reviews are provided by existing works that are related to energy-efficient transmission using metaheuristic approaches in WSN.

Abraham and Vadivel (2023) developed the Ultra-Scalable Ensemble Clustering technique (U-SENC) to manage huge data. The Flamingo Search Algorithm (FSA) was performed with high stability in Cluster Head (CH) selection. The Q-learning model was used to choose a small distance between CHs and BSs, and it has the ability to select routes in complex network situations. A reward point system was designed depending on the objective function, which reflected distance between the CH and BS, energy consumption, and coverage area. The developed ultra-scalable ensemble clustering improved energy efficiency performance with optimal CH and route selection methods.

Ram and Ilavarasan (2024) developed a Multi-Objective May-Badger (M2B). The World Cup Optimization (WCO) was designed as a CH selection process that considered various objectives during the selection strategy.

The objective function was employed to choose CH in each cluster, considering energy and distance between the base station and nodes. An M2B approach was utilized to enhance routing to find an optimal way. The proposed M2B technique helped process CH selection and optimal routing for the base station.

Roberts et al. (2024) introduced Sailfish Optimization (SFO) and Spotted Hyena Optimization (SHO) for effective cluster-based routing in WSNs. The dual method influenced SFO exploration for effective clustering and optimal CH selection. SHO had the capability of optimizing an efficient routing path and enhancing the performance of metrics like energy efficiency and Packet Delivery Ratio (PDR).

Manoharan et al. (2024) produced an Entropy-Based Bald Eagle Search (EBES), which was utilized for the most energy-efficient routing. The nodes in the network were selected via Density based Adaptive Soft (DAS) and Beetle Swarm Optimization (BSO). These techniques were used to select a CH and its node that had the highest entropy data to transmit data by estimating each node's entropy value weight. Moreover, BSO was performed to select an optimal CH based on the entropy values of the nodes, which helped enhance the data accuracy. El Khediri et al. (2024) presented an Artificial Bee Colony (ABC) and Ant Colony Optimization (ACO) for energy efficiency. The ABC and ACO were designed to select a CH from a set of terminals. The ACO determined a path between a CH and BS by choosing an effective route depending on factors like distance, residual energy, and node degree. A combination of ABC and ACO optimization was performed for both CH and routing paths to reduce energy consumption.

The literature indicates that various recent metaheuristics for cluster head selection and routing optimization mostly apply hybrid optimizations. These include FSA, M2B, SFO-SHO, EBES, and ABC-ACO, which demonstrate an increase in performance in terms of energy efficiency and packet delivery, but all have similar limitations. First, the objective weight parameters utilized by these methods are fixed or hand-tuned, which determines their ineffectiveness in adapting to change under WSN conditions. Second, hybrid combinations of metaheuristic methods have increased complexity and parameter tuning, and as a result, they do not attain the best solutions. Lastly, existing research considers cluster head selection and routing as separate processes. This decreases the level of coordination across the two processes and leads to problems such as received data loss due to information dropping. This research proposes a Dynamic Weighting Technique-based Arctic Puffin Optimization (DWT-APO) algorithm framework that combines cluster head selection and routing into a single efficient computation. Table 1 demonstrates a comparative analysis of existing meta-heuristic approaches for WSN clustering and routing, highlighting their strengths and limitations.

Table 1: Comparative Analysis of Existing Meta-Heuristic Models for WSN Clustering and Routing

.	Algorithm Used	Key Strength	Identified Limitation	Research Gap Leading to This Work
Abraham and Vadivel (2023)	U-SENC with FSA	Improved cluster stability and Q-learning-based routing	Performance degradation in large-scale and dynamic environments	Lack of adaptive weight control for scalable and dynamic networks
Ram and Ilavarasan (2024)	M2B	Effective multi-objective CH selection and routing	High parameter tuning complexity and overfitting risk	Need for adaptive parameter adjustment to reduce tuning overhead
Roberts et al. (2024)	SFO with SHO	Balanced exploration–exploitation for clustering and routing	Assumes static network conditions; limited adaptability	Requirement for dynamic adaptation during optimization
Manoharan et al. (2024)	EBES with DAS clustering	Improved data accuracy using entropy-based CH selection	Sensitive to node density assumptions and topology changes	Need for a density-independent adaptive clustering framework
El Khediri et al. (2024)	ABC with ACO	Reduced energy consumption through hybrid routing	Slow convergence under high node variability	Need for improved convergence stability using adaptive weighting
Proposed Work	DWT-APO	Adaptive dynamic weighting technique with unified CH selection and routing optimization	Moderate computational overhead	Addresses adaptability, convergence balance, and unified multi-objective optimization

Proposed Methodology

Energy Model

An energy model is crucial for optimizing the energy consumption of each node in a network. The energy consumed and total energy expense $ETX(K,d)$ are based on the energy required to improve the signals. To enhance the signal strength, energy is needed, which depends on the distance between the transmitter and the receiver. When the distance is greater than $d0$, a multi-path (d^4) is utilized instead of free-space (d^2). Energy is required for transmission, which is denoted as $Etx(k,d)$ given in Eq. (1):

$$E_{tx}(m,d) = \begin{cases} E_{elec} \times K \times \varepsilon_{fs} \times K \times d^2, \ d \le d_0 \\ E_{elec} \times K \times \varepsilon_{amp} \times K \times d^4, \ d > d_0 \end{cases} \tag{1}$$

Where E_{elec} represents the power required to track a transmitter circuit to transfer one bit, ε_{fs} is a free-space model of the amplification factor, ε_{amp} is a multi-path model of the amplification factor, and d_0 is a distance-threshold value estimated in Eq. (2):

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{amp}}} \tag{2}$$

The energy required $E_{RX}(k)$ to receive an n-bit packet is given in Eq. (3):

$$E_{RX}(k,d) = K \times E_{elec} \tag{3}$$

$E_{aggregation}$ signifies the energy expended through a particular CH aggregating member node. The energy consumption is estimated using the following Eq. (4):

$$E_{aggregation} = n * E_{DA} \tag{4}$$

DOI: 10.3844/jcssp.2026.2723.2735

Where E_{RX} illustrates the energy required to receive a single bit, and E_{DA} represents the energy required to aggregate a single bit.

Network Model

The considered WSN comprises M homogeneous sensor nodes that are uniformly distributed across a two-dimensional sensing region of area O. A single Base Station (BS) is expected to be fixed either at the center or outside the sensing field. All sensor nodes are fixed after execution and are initialized with equal initial energy. The communication links are considered to be symmetric:

- Node Deployment Strategy: The M sensor nodes are randomly and uniformly distributed across the sensing region (O). The node density ρ is symbolized as the ratio of the total number of deployed nodes to the sensing area and is illustrated by Eq. (5):

$$\rho = \frac{M}{O} \tag{5}$$

The node density remains constant during the optimization process:

- Evaluation of Node Separation Proximity: To determine balanced cluster formation, average separation distance (d) among nodes within a cluster is estimated based on node density and sensing area. The standard distance across nodes is evaluated using Eq. (6):

$$d = \sqrt{\frac{O}{\pi \times M}} \tag{6}$$

This metric is incorporated to assess the proximity during cluster head selection:

- Cluster Organization: The network is divided into K clusters to improve energy-efficient communication. The total number of clusters (K) is defined on the basis of the maximum communication range of nodes and network density and is represented using Eq. (7):

$$C = \sqrt{\frac{M}{5 \times \pi \times R_M}} \tag{7}$$

Where R_M represents the maximum transmission range of the sensor node. Each cluster chooses a CH, which is responsible for intra-cluster data aggregation and inter-cluster communication with the BS. This structured organization facilitates efficient energy utilization and assists the proposed DWT-APO algorithm.

Cluster Head Selection Using Dynamic Weighting Technique Based Arctic Puffin Optimization

The APO algorithm is developed to solve complex optimization problems. The optimization algorithm is performed in two phases: Exploration and exploitation. The exploration stage denotes aerial flight, and the exploitation phase denotes foraging behavior. These two phases attain a balance between global exploration and local exploitation, which helps enhance the model's efficiency in finding optimal solutions. Arctic puffins fly at low altitudes and dive underwater to catch prey, and they adjust their characteristics or behaviors depending on different environmental conditions. Fig. 1 represents the proposed methodology for the DWT-APO.

Population Initialization

Each Arctic puffin signifies a candidate solution in an APO algorithm, and these solutions of initial positions are created randomly inside predefined bounds, as expressed in Eq. (8):

$$X_i^t = rand.(ub - lb) + lb, i = 1,2,3, \dots, N \tag{8}$$

Here, X_i^t signifies the position of a i^{th} puffin, and $rand$ represents a value that is spread between 0,1. ub – lower, lb denotes upper bounds of a search space, N signifies overall population size.

Exploration Using Aerial Flight Stage

The aerial flight phase follows two models, such as velocity factors and Levy flight, to allow effective exploration of a solution space.

- Aerial Search Strategy: In puffins, their positions are efficient through a Levy flight, as given in Eq. (9):

$$Y_i^t = X_i^t + (X_i^t - X_r^t).L(D) + R \tag{9}$$

Where $L(D)$ illustrates a random value that is created depending on the Lévy flight distribution. R indicates a normal transmission factor, which helps improve exploration:

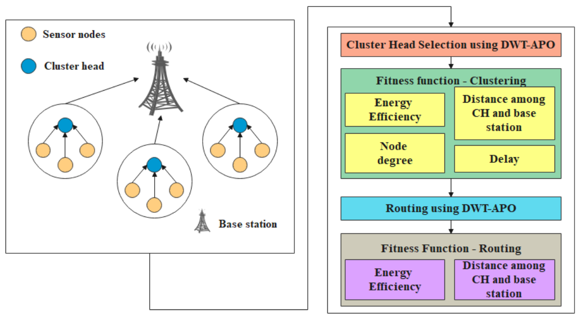

Fig. 1: Proposed methodology for the DWT-APO

- Swooping Predation Strategy: It helps adjust the displacement of puffins to evaluate a rapid dive to catch prey, as expressed in Eq. (10):

$$Z_i^{t+1} = Y_i^{t+1} * S \tag{10}$$

Here, S denotes the velocity coefficient of the puffins to catch their prey. The swoop predation model is designed to model fast convergence on good candidate locations for the solutions. In Eq. (10), adjusting the position of each puffin is performed by a controlled/measured displacement that allows for greater velocity (speed) to enable them to reach areas of acceptable high fitness. The velocity coefficient is considered to regulate the size of the movement step to allow for controlled exploration without causing large oscillations. Therefore, this helps accelerate (strengthen) convergence to the global best possible solution while still retaining diversity in the solution set during the early iterations.

Merging Candidate Positions

A top N is specifically selected to establish an updated population from this sorted pool. These merging candidate positions are represented in Eqs. (11-13):

$$P_i^{t+1} = Y_i^{t+1} \cup Z_i^{t+1} \tag{11}$$

$$new = sort\left(P_i^{t+1}\right) \tag{12}$$

$$X_i^t = new\ (1{:}N) \tag{13}$$

Exploitation Using the Underwater Foraging Stage

The underwater foraging phase includes a strategy that improves the search capability of the model. Exploitation includes intensifying searching, gathering, foraging, and avoiding predators:

- Gathering foraging: The updated locations depend on cooperative behavior, which is expressed in Eq. (14):

$$W_i^{t+1} = \begin{cases} X_{r1} + F.L\,(D).(X_{r2} - X_{r3})\ if\ rand \geq 0.5 \\ X_{r1} + F.(X_{r2} - X_{r3})\ if\ rand < 0.5 \end{cases} \tag{14}$$

Where F represents the cooperative factor with a value of 0.5 that is used to update the locations in the foraging process. Gathering foraging is a method used for exploiting local candidate locations, where the positions of these candidate solutions converge toward regions that assist in finding additional fitness. This process is achieved by cooperating with other high-quality candidate solutions. According to Eq. (14), the cooperative factor that affects position updates considers only the high-quality candidate solutions of neighboring candidates. This assists in creating a considerable local search area of potential candidates around the convergence area, improving the likelihood of selecting successful cluster head solutions and routing reliability:

- Intensifying Search: This denotes that when food resources are depleted, a search strategy is expressed in Eq. (15) and (16):

$$Y_i^{t+1} = W_i^{t+1}.(1 + f) \tag{15}$$

$$f = 0.1.\ (rand - 1).\frac{(T-t)}{T} \tag{16}$$

Where T signifies the total number of iterations, t is the current iteration, and the f factor is familiar and relies on a repetition procedure. The intensification process reduces the exploration step length in a controlled manner as the number of iterations increases. A controlled manner of decreasing the exploration step ensures that there is a smooth transition from exploratory to exploitative nature, thus improving the stability of convergence while avoiding premature stagnation:

- Avoiding Predators: To ignore a predator, a strategy is designed using Eq. (17):

$$Z_i^{t+1} = \begin{cases} X_i + F.L(D).(X_{r1} - X_{r2}\ )\ if\ rand \geq 0.5 \\ X_i + \beta.(X_{r1} - X_{r2}\ )\ if\ rand \geq 0.5 \end{cases} \tag{17}$$

Where β signifies a distributed random variable. APO uses an exploration and exploitation mechanism that is inspired by the natural behaviors of Arctic puffins. The improved exploitation mechanism is discussed in the following sections. The predator avoidance strategy is illustrated in Eq. (17), employing random weighted variables (stochastic) to perturb the candidate locations further and prevent the algorithm from reaching a local optimum by redistributing the candidates when stagnation is detected.

Exploitation Using the Dynamic Weighting Technique

The APO introduces a DWT in which the dynamic inertia weight parameter is adaptively adjusted in each iteration. This strategic adaptive adjustment enhances the algorithm's convergence and improves output quality. In the enhanced version, the dynamic inertia weight $'w'$ is iteratively squeezed for an elaborate balance. The improved version is expressed in Eq. (18):

$$X_{i,j}^{P2} = X_{i,j} + W.(1 - t/t_{Max}).(2.rand - 1).X_{i,j} \tag{18}$$

W acts as a parameter that manages search scales throughout an iterative process. This process commences with a substantial value, roughly a quarter of the standard search domain scaling, which gradually diminishes to approximately 1% of a quarter of this length. The stability of an APO is expressed through the following monotonically decreasing function in Eq. (19):

$$W = \left((W_0 - W_\infty)/(1 - t_{Max})\right) \times (t - t_{Max}) + W_\infty \quad (19)$$

Where W_0 and W_∞ signify initial and final values, respectively. Essentially, W considers the control of the iteration process. W_0 and W_∞ are defined in Eqs. (20) and (21):

$$W_0 = (UB - LB)/4 \quad (20)$$

$$W_\infty = W_0/100 \quad (21)$$

Where t represents the current iteration, t_{Max} is a large number of iterations, and UB and LB are the upper and lower boundaries, respectively. In WSN optimization, using fixed-weight objectives results in early convergence and uneven power consumption in a constantly changing environment. The proposed dynamic weighting technique is formulated in the dynamic weight update equation, which dynamically modifies the weight to promote adaptive changes as the iterations progress.

In earlier iterations, a higher weight facilitates greater global exploration and solution diversity. As the optimization process continues, the weight decreases to improve local exploitation and improve the stability of the convergence process. This adaptive transition demonstrates a balanced trade-off between exploration and exploitation, ultimately improving cluster head selection and increasing the lifetime of the network relative to fixed-weight methods.

Fitness Function for Cluster Head Selection

The fitness function is validated to acquire the best results, and four fitness functions, namely energy efficiency, distance, node degree, and delay, are considered for CH selection and routing. The fitness functions are discussed in the sections below:

- Energy Efficiency: Nodes with higher energy levels are chosen as CHs. The availability of energy in a CH is represented in Eq. (22):

$$E(U) = \frac{1}{a}\sum_{i=1}^{a} E_{u+1}(C_i) \quad (22)$$

- Distance: In a WSN, the distance between the sensor nodes and their CH determines communication range. The optimal coverage distance is expressed in Eq. (23):

$$K(U) = \sum_{i=1}^{a}\sum_{j=1}^{n} S_j - C_i \;\; Vi \in j \quad (23)$$

Where nodes in the j^{th} cluster are utilized for distance calculation:

- Delay: The delay is determined by the Expected Transmission Count (ETC), along with node propagation and transmission delays of networks, which are expressed in Eq. (24):

$$Delay,\ de(u) = \sum_{j=1}^{n} I_j(u)\left(\alpha + \beta_j\right) \quad (24)$$

Where ETC of a j^{th} node present at time u is mentioned as $I_j(u)$, transmission α, and propagation delay of j^{th} node as β_j. The ETC depends on the transmission packet delivery ratio at time u:

- Node Degree: Some clusters have a large number of members, whereas others have fewer members. It depends on the neighbor nodes and load distribution, as depicted in Eq. (25):

$$ND_{min} = \sum_{i=1}^{h^T} CM_i \quad (25)$$

Where ND_{min} is the minimum node degree, h^T is the number of cluster nodes, and CM_i is derived as the overall number of neighbors of the selected CH.

Routing using Arctic Puffin Optimization

Route maintenance is a significant stage that is applied to align the load between clusters. The nearest BS clusters lose their energy due to traffic in the inter-cluster. A failed node is removed in this stage, and it extends the network lifetime. The CH range is initialized if the residual energy of the CH is above a threshold value, and an ideal route is attained using APO approaches. The dead node count is repeated until it equals the sum of the sensor nodes. Packets are communicated to the BS, which enhances the lifetime through energy efficiency by APO in WSN.

Algorithm DWT-APO: Dynamic Weighting Technique Arctic Puffin Optimization

Input: $M, O, R_M, E0, T, BS$
(Number of nodes, deployment area, max transmission range, initial energy, max iterations, base station)
Output: Optimal Cluster Headset $CH*$
Energy-efficient routing structure
1: Deploy M nodes uniformly in the O area.
2: Compute node density as in Eq. (5).
3: Estimate average node separation as in Eq. (6).
4: Determine the number of clusters as in Eq. (7).

Population Initialization
5: Initialize puffin population positions as in Eq. (8).

Exploration Phase (Aerial Flight)
6: Update positions using the aerial search strategy as in Eq. (9).
7: Apply the swooping predation update as in Eq. (10).
8: Combine candidate solutions using Eqs. (11)-(13).

Exploitation Phase (Underwater Foraging)
9: Update positions using gathering foraging as in Eq. (14).
10: Strengthen search using Eqs. (15) and (16)
11: Apply predator avoidance strategy as in Eq. (17).

Dynamic Weight Adjustment
12: Update the adaptive weight parameter as in Eq. (18).
13: Control weight stability using Eqs. (19)-(21)

Fitness Evaluation
14: Evaluate the energy metric as in Eq. (22).
15: Calculate the distance metric as in Eq. (23).
16: Assess the delay metric as in Eq. (24).
17: Compute the node degree metric as in Eq. (25).
18: Evaluate overall multi-objective fitness

Cluster Head Selection
19: Select optimal C nodes with the best fitness as CH*.

Routing Phase
20: Conduct route selection by incorporating APO-based optimization.
21: Transmit data to BS and update residual energy
22: Repeat until the termination condition T is satisfied.

End Algorithm

Experimental Results and Discussion

All simulations are performed in the MATLAB R2023a environment, with experimental results obtained from an Intel Core i7, 3.40 GHz processor with 16 GB of RAM, and running Windows 11 (64-bit). The simulation framework for the development of algorithms and performance evaluation is carried out using MATLAB's numerical computing toolbox. The static WSN performance evaluation is performed in a square monitoring area of $100 \times 100\,m$ with sensor nodes that are randomly placed within that area. The nodes are assumed to be homogeneous with the same initial energy and communication capabilities. The base station is out of reach of the sensing area to represent actual long-distance data transportation conditions. For the energy calculations, a first-order radio energy dissipation model is utilized. To ensure a fair evaluation among different algorithms, the selected parameters, such as the amplifier energy coefficient and packet size, remain the same. The performance measures, including network lifetime (alive nodes), Packet Delivery Ratio (PDR), Energy Consumption (EC), and throughput, are evaluated to assess the effectiveness of the proposed model.

To determine the scalability capabilities, the algorithms are compared at three different node density levels (100, 500, and 1,000 nodes). Each of the compared algorithms has the same number of simulation runs and energy parameters to ensure a fair analysis. All algorithms were used to determine the comparative results between the baseline and the proposed algorithms, which have exactly the same computational conditions to ensure that the results are unbiased. The simulation parameters utilized for a performance evaluation are demonstrated in Table 2.

Table 2: Simulation parameters

Parameter	Value	Unit
Network Area	100 × 100	m^2
Number of Nodes (Scenario 1)	100	Nodes
Number of Nodes (Scenario 2)	500	Nodes
Number of Nodes (Scenario 3)	1000	Nodes
Initial Energy per Node	2	J
Transmission Energy (E_{tx})	50	nJ/bit
Reception Energy (E_{rx})	50	nJ/bit
Data Aggregation Energy (E_{DA})	5	nJ/bit
Packet Size	4000	bits
Control Packet Size	200	bits
Simulation Rounds (Scenario 1)	800	Rounds
Simulation Rounds (Scenario 2)	2000	Rounds
Simulation Rounds (Scenario 3)	4000	Rounds
Base Station Position	(50, 50)	m
Number of Independent Runs	20	Runs
Optimization of Population Size	30	Agents
Maximum Iterations	100	Iterations

Furthermore, the sensor node network sizes used for the analysis of the proposed model are 100 (small-scale WSN deployment), 500 (medium-density monitoring scenarios), and 1000 nodes (large-scale, high-density deployments). The results demonstrate that the proposed algorithm can be applied to networks of different sizes, while validating its versatility in both sparse and dense network densities. Each scenario is executed across 20 independent simulation runs with variable random seeds. The reported values represent the mean performance, and variability is expressed as the standard deviation (mean ± SD).

Performance Analysis

The proposed DWT-APO algorithm's performance is evaluated with various performance metrics, namely alive nodes, energy consumption, PDR, and throughput. The proposed DWT-APO algorithm is analyzed with various approaches, such as Monarch Butterfly and Artificial Bee Colony Optimization Algorithm (MBABCOA), Hybrid Modified Artificial Bee Colony and Firefly Algorithm (HMABCFA), and Multi-Objective Grey Wolf Optimizer (MOGWO), to find the performance of the model.

Number of Alive Nodes

The DWT-APO algorithm is evaluated depending on the number of rounds and nodes. A performance analysis is conducted on the number of Alive Nodes (AN) for 100 and 500 nodes. An alive node is used for transmission. The number of ANs is higher for the DWT-APO algorithm than for the other existing methods. Various methods, such as MBABCOA, HMABCFA, and MOGWO, are evaluated with the proposed DWT-APO algorithm. The number of alive nodes for 100 and 500 nodes is analyzed across different methods. Fig. 2 represents the performance analysis of alive nodes across varying simulation rounds using 100 nodes, and Fig. 3 illustrates performance analysis of alive nodes across varying simulation rounds using 500 nodes.

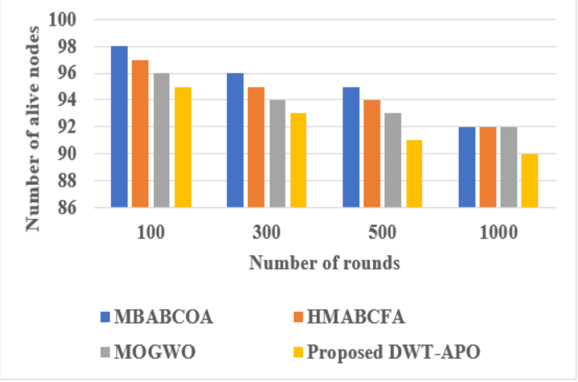

Fig. 2: Performance analysis of alive nodes across varying simulation rounds using 100 nodes

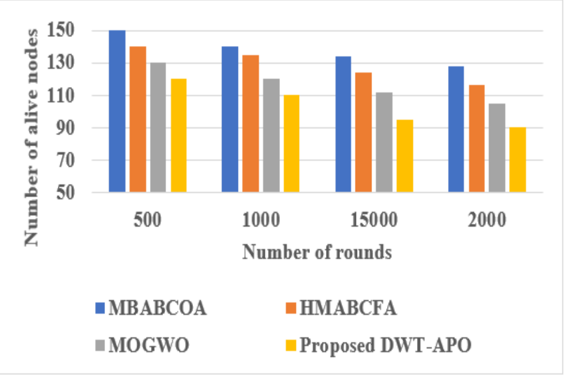

Fig. 3: Performance analysis of alive nodes across varying simulation rounds using 500 nodes

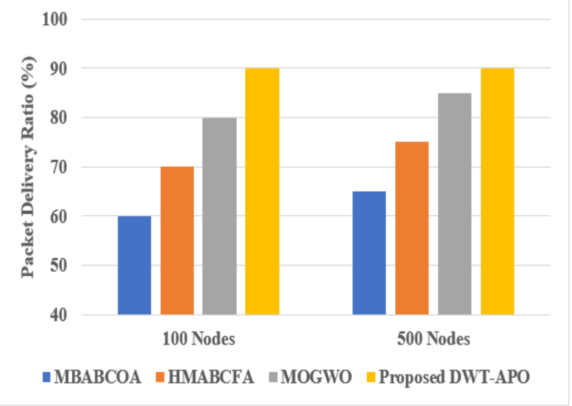

Fig. 4: Performance analysis of PDR against different node counts using 100 and 500 nodes

Packet Delivery Ratio (%)

The PDR is represented as the ratio of the number of successfully received packets through destination nodes to the total number of packets sent through source nodes. A PDR is expressed in formula (26):

$$PDR = 100 - \frac{D_{received}(n)}{T_{data}} \times 100 \tag{26}$$

Where $D_{received}(n)$ signifies the received data in values, and T_{data} illustrates the overall data. The proposed DWT-APO algorithm is compared with various methods, such as MBABCOA, HMABCFA, and MOGWO, to evaluate the performance in terms of PDR for 100 and 500 nodes. Fig. 4 depicts the performance analysis of PDR against different numbers of nodes using 100 and 500 nodes. Here, the proposed DWT-APO algorithm attains a PDR of 90% on both 100 and 500 nodes.

Energy Consumption (EC) (J)

In a WSN, EC is used to calculate energy while transferring data for network effectiveness. E C illustrates the energy consumption. The distance between the cluster nodes and energy loss is denoted as d; n is the number of nodes, and t_{energy} is defined as the energy needed for data transfer, as expressed in Eq. (27):

$$E_c\,(n,d) = (E_c \times n) + (t_{energy} \times n \times d) \quad (27)$$

The proposed DWT-APO algorithm is compared with various methods, such as MBABCOA, HMABCFA, and MOGWO, to validate the performance in terms of EC for 100 and 500 nodes. Fig. 5 represents the performance analysis of EC across varying simulation rounds using 100 nodes. Fig. 6 represents the performance analysis of EC across varying simulation rounds with 500 nodes.

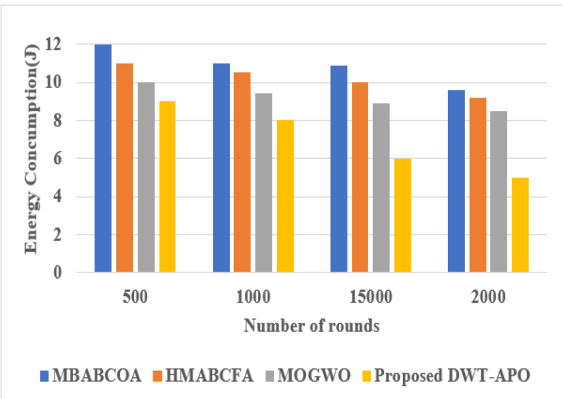

Fig. 5: EC analysis across varying simulation rounds using 100 nodes

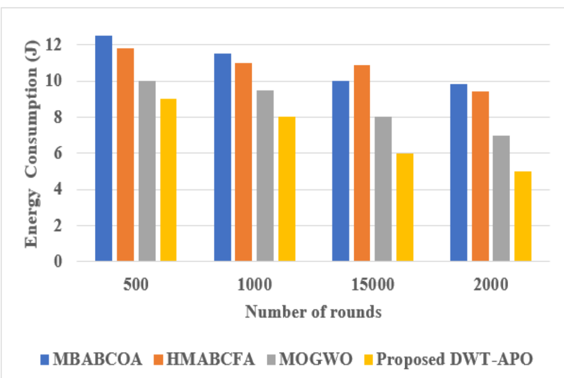

Fig. 6: EC analysis across varying simulation rounds using 500 nodes

Throughput (kbps)

The throughput is derived as the total number of connections within a considered time. The data transfer rate is observed via the route throughput expressed in Eq. (28):

$$Throughput \frac{= D_{transmitted}}{/S_{time}} \quad (28)$$

Where $D_{transmitted}$ signifies the transmitted data and S_{time} denotes the specific time. The proposed DWT-APO algorithm is compared with various methods, such as MBABCOA, HMABCFA, and MOGWO, to evaluate the performance in terms of throughput for 100 and 500 nodes. Fig. 7 represents the performance analysis of throughput with 100 and 500 nodes. The throughput is computed as the measure of total successfully delivered data bits to the base station divided by the total simulation time, which is expressed in Bits Per Second (bps). The demonstrated values signify the cumulative throughput across the simulation rounds.

Comparative Analysis

Table 3 represents the simulation parameters of different scenarios. The various existing methods, such as U-SENC with FSA (Abraham and Vadivel, 2023), M2B (Ram and Ilavarasan, 2024), and SFO-SHO (Roberts et al., 2024), are evaluated with the proposed DWT-APO algorithm. Table 4 represents a comparison of the DWT-APO algorithm with the existing U-SENC with FSA (Abraham and Vadivel, 2023). Table 5 signifies a comparison of the DWT-APO algorithm with the existing M2B (Ram and Ilavarasan, 2024). Table 6 illustrates the comparison of the DWT-APO algorithm with the existing SFO-SHO (Roberts et al., 2024).

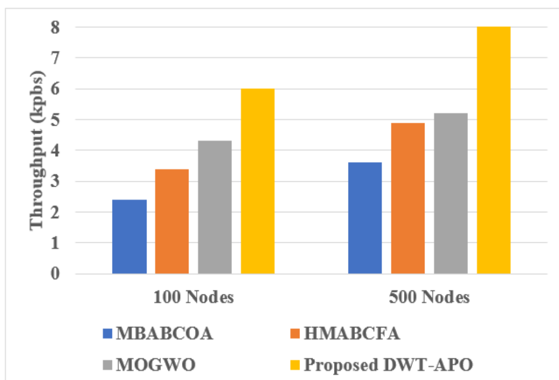

Fig. 7: Throughput analysis using 100 and 500 nodes

Table 3: Simulation parameters for the different scenarios

Parameters	Scenarios		
	1	2	3
Area	$500 \times 500m$	$300 \times 300m$	$1000 \times 1000m$
Number of nodes	100, 200, 300	500, 1000	1000
Initial energy	0.55J	0.5J	1J

Table 4: Comparison of a proposed DWT-APO algorithm with existing U-SENC with FSA (Scenario 1–100 Nodes)

Method	Metric	200 Rounds	400 Rounds	600 Rounds	800 Rounds
U-SENC with FSA (Abraham and Vadivel, 2023)	Alive Nodes	100±0	95±4	60±6	25±5
	Residual Energy (J)	110±5	75±4	40±3	18±2
	Throughput (Packets/Round)	1.8±0.05	3.0±0.08	4.5±0.12	5.0±0.15
Proposed DWT-APO	Alive Nodes	100±0	98±2	75±4	40±3
	Residual Energy (J)	120±6	85±5	55±4	30±3
	Throughput (Packets/Round)	2.0±0.04	3.5±0.09	5.5±0.13	6.2±0.14

Table 5: Comparison of a proposed DWT-APO algorithm with existing M2B (Scenario 2–500 Nodes)

Method	Metric	500 Rounds	1000 Rounds	1500 Rounds	2000 Rounds
M2B (Ram and Ilavarasan, 2024)	Alive Nodes	480±10	400±12	300±15	200±18
	PDR	0.85±0.02	0.88±0.02	0.91±0.02	0.93±0.02
	Residual Energy (J)	65±4	60±4	54±3	45±3
	Throughput (Packets/Round)	48±2	52±2	55±3	60±3
Proposed DWT-APO	Alive Nodes	500±8	450±10	380±12	300±14
	PDR	0.89±0.01	0.92±0.01	0.94±0.01	0.96±0.01
	Residual Energy (J)	72±5	65±4	60±4	52±3
	Throughput (Packets/Round)	51±2	58±3	63±3	70±4

Table 6: Comparison of the proposed DWT-APO algorithm with existing SFO-SHO (Scenario 3–1000 Nodes)

Method	Metric	1000 Rounds	2000 Rounds	3000 Rounds	4000 Rounds
SFO-SHO (Roberts et al., 2024)	Alive Nodes	980±15	650±20	450±25	250±30
	Residual Energy (J)	0.90±0.03	0.65±0.03	0.50±0.02	0.35±0.02
	Throughput (Packets/Round)	550±15	600±18	700±20	800±25
	PDR	0.87±0.02	0.92±0.02	0.95±0.01	0.97±0.01
Proposed DWT-APO algorithm	Alive Nodes	1000±12	750±18	550±20	350±22
	Residual Energy (J)	0.95±0.03	0.75±0.03	0.60±0.02	0.45±0.02
	Throughput (Packets/Round)	650±18	720±20	820±25	920±30
	PDR	0.91±0.01	0.95±0.01	0.97±0.01	0.99±0.01

The baseline algorithms that are compared with the proposed DWT-APO algorithm are re-implemented and run using the same simulation environment in which the proposed DWT-APO algorithm is evaluated. Network parameters, including node density, area of deployment, initial node energy, range of transmission, size of packet, and radio energy model across all methods, which are standardized to ensure that there is no bias or advantage to either of the compared algorithms. The implementation settings are also set up to match the configuration of the original research, while maintaining the same system conditions between the models through the simulation platform. All numerical results are illustrated as mean ± standard deviation to ensure statistical validity and numerical correctness.

Discussion

The comparative analysis of the proposed DWT-APO algorithm performs better than conventional approaches, including U-SENC with FSA, M2B, and SFO-SHO across all simulation rounds and network scales. In scenario 1, the proposed DWT-APO algorithm attains a large number of alive nodes in further rounds, which enhances delayed node depletion and energy balancing. This enhancement is based on an adaptive dynamic weighting technique that assists in regulating optimization priorities during routing, rather than relying on fixed objective weights and cluster head selection. In addition, residual energy ensures an increase in throughput stability and extends the network lifetime. In Scenario 2, the proposed DWT-APO algorithm demonstrates greater throughput and PDR when compared to M2B, especially under higher round-trip situations. While conventional models demonstrate increasing performance degradation because of irregular energy dissipation, the proposed DWT-APO algorithm attains a uniform energy distribution across nodes. This balance helps decrease packet loss and enhance routing reliability, thereby enhancing the overall data transmission accuracy. Furthermore, in Scenario 3, the proposed DWT-APO algorithm displays enhanced scalability over SFO-

SHO. Hence, the proposed DWT-APO algorithm achieves continued throughput under extended rounds, demonstrating robust convergence stability. Thus, the low standard deviation that occurs during frequent simulations demonstrates the consistent behavior and robustness of the optimization process.

Conclusion

This research focused on establishing an energy-efficient protocol for communicating between sensor nodes. In particular, existing studies focused on metaheuristic clustering protocols but still struggled with cluster and route selection processes, resulting in the depletion of energy across nodes at different times. To address these limitations, a new clustering and routing protocol called the DWT-APO algorithm was introduced. It utilized an energy-efficient protocol containing a dynamically adjustable weight mechanism, which regulated the weights used for selecting cluster heads and routes based on the preceding activity. The weight-regulation approach used a mathematically modeled deviation-based algorithm that enabled a balanced method of exploration and exploitation, as well as context-aware objective prioritization of sensor nodes. The experimental evaluations were conducted across several different network configurations, which demonstrated significant improvements. The proposed DWT-APO algorithm achieved up to 60% improvement in network lifetime, 66.7% higher residual energy, and 24% increased throughput compared to U-SENC with FSA, while demonstrating 40-50% better node survivability and 15-28% enhanced energy efficiency over M2B and SFO-SHO under large-scale network conditions. Ultimately, the integration of dynamic weight adaptations into the optimization algorithm allowed significant improvements in multi-objective functionality when working in an environment with constrained energy capabilities. In the future, the proposed DWT-APO algorithm will be extended into mobile WSN clusters, validating hardware deployment in real-time and integrating the DWT-APO algorithm into next-generation IoT systems by incorporating edge intelligent communication methodologies.

Notation Table

Table 7 summarizes all the mathematical symbols used in the proposed DWT-APO algorithm's formulation to ensure clarity and completeness.

Table 7: Mathematical symbols used in the proposed DWT-APO algorithm

Symbol	Description
k	Packet size
d	Distance between transmitter and receiver
$E_{TX}(k,d)$	Energy consumed during transmission
$E_{RX}(k)$	Energy consumed during reception
E_{elec}	Electronic circuitry energy
ε_{fs}	Free-space channel amplifier coefficient
ε_{amp}	Multi-path channel amplifier coefficient
d_0	Threshold transmission distance
E_{DA}	Data aggregation energy
n	Number of aggregated data packets
M	Total number of sensor nodes
O	Network deployment area
ρ	Node density
R_M	Maximum communication range
C	Estimated number of clusters
$X_i^t e$	Position of the i-th search agent at iteration t
$Y_i^t e$	Updated candidate solution
Z_i^t	Mutation-based solution
P_i^t	Combined population set
ub, lb	Upper and lower bounds of the search space
$rand$	Uniform random number in [0,1]
N	Population size
F	Mutation scaling factor
β	Adaptive perturbation coefficient
$L(D)$	Lévy flight distribution
S	Selection operator
t	Current iteration
T, t_{Max}	Maximum number of iterations
W	Dynamic inertia weight
$W_0 e$	Initial inertia weight
$W_\infty l$	Final inertia weight
X_{r1}, X_{r2}, X_{r3}	Randomly selected distinct candidate solutions
U	Utility function
a	Number of cluster heads
$E(C_i)$	Residual energy of cluster head C_i
S_j	Sensor node j
$Delay$	Transmission delay
$I_{j(u)}$	Traffic indicator function
α, β_j	Delay weighting coefficients
ND_{min}	Minimum node depletion metric
CM_i	Number of cluster members in cluster i

Abbreviation Table

Table 8 represents technical abbreviations and acronyms used in this research. This table covers essential network performance metrics, parameters, and metaheuristic optimization algorithms

Table 8: Abbreviations and definitions for optimization algorithms

Abbreviation	Description
ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
AN	Alive Nodes

Table 8: Continue

BSO	Beetle Swarm Optimization
CH	Cluster Head
CHs	Cluster Heads
DAS	Density-based Adaptive Soft
DWT-APO	Dynamic Weighting Technique based Arctic Puffin Optimization
EBES	Entropy-Based Bald Eagle Search
EC	Energy Consumption
ETC	Expected Transmission Count
FSA	Flamingo Search Algorithm
GA	Genetic Algorithm
M2B	Multi-objective May-Badger Optimization
PDR	Packet Delivery Ratio
PSO	Particle Swarm Optimization
SFO	Sailfish Optimization
SHO	Spotted Hyena Optimization
U-SENC	Ultra-Scalable Ensemble Clustering Technique
WCO	World Cup Optimization
WSNs	Wireless Sensor Networks

Acknowledgment

The authors would like to express their sincere gratitude to Shri Dharmasthala Manjunatheshwara Institute of Technology, Ujire, and S.D.M. College of Engineering and Technology, Dharwad, for their constant encouragement and support in carrying out this research work. The authors also extend their thanks to colleagues and peers for their valuable suggestions and guidance, which have contributed significantly to the successful completion of this paper.

Funding Information

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Author's Contributions

M. Bharathraj Kumar: Conceptualization, methodology, software, validation, formal analysis, data curation, visualization writing original draft preparation.

S. Avinash: Conceptualization, validation, investigation, writing review and edited.

Prakash G. Gani: Resources, funding acquisition.

Prathapchandra Shetty: Writing review and edited, supervision, project administration.

Ethics

This article does not contain any studies with human participants or animals performed by any of the authors.

References

Abraham, R., & Vadivel, M. (2023). An Energy Efficient Wireless Sensor Network with Flamingo Search Algorithm Based Cluster Head Selection. *Wireless Personal Communications*, *130*(3), 1503–1525. https://doi.org/10.1007/s11277-023-10342-2

Alsuwat, H., & Alsuwat, E. (2025). Energy-aware and efficient cluster head selection and routing in wireless sensor networks using improved artificial bee Colony algorithm. *Peer-to-Peer Networking and Applications*, *18*(2), 65. https://doi.org/10.1007/s12083-024-01810-y

Chaurasia, S., Kumar, K., & Kumar, N. (2023). EEM-CRP: Energy-Efficient Meta-Heuristic Cluster-Based Routing Protocol for WSNs. *IEEE Sensors Journal*, *23*(23), 29679–29693. https://doi.org/10.1109/jsen.2023.3322631

El Khediri, S., Selmi, A., Khan, R. U., Moulahi, T., & Lorenz, P. (2024). Energy efficient cluster routing protocol for wireless sensor networks using hybrid metaheuristic approache's. *Ad Hoc Networks*, *158*, 103473. https://doi.org/10.1016/j.adhoc.2024.103473

Gupta, A., & Rout, R. K. (2024). Energy harvesting-enabled energy-efficient routing using spotted hyena optimization in wireless sensor network. *International Journal of Communication Systems*, *37*(8), e5747. https://doi.org/10.1002/dac.5747

Karthikeyan, M., Manimegalai, D., & Rajagopal, K. (2024). Optimizing energy efficiency in wireless sensor networks: dynamic routing with capuchin search algorithm. *Multimedia Tools and Applications*, *84*(15), 15453–15477. https://doi.org/10.1007/s11042-024-19625-7

Kumar, A., Mehbodniya, A., Webber, J. L., Haq, M. A., Gola, K. K., Singh, P., Karupusamy, S., & Alazzam, M. B. (2022). Optimal cluster head selection for energy efficient wireless sensor network using hybrid competitive swarm optimization and harmony search algorithm. *Sustainable Energy Technologies and Assessments*, *52*, 102243. https://doi.org/10.1016/j.seta.2022.102243

Kumar, S., & Agrawal, R. (2023). A hybrid C-GSA optimization routing algorithm for energy-efficient wireless sensor network. *Wireless Networks*, *29*(5), 2279–2292. https://doi.org/10.1007/s11276-023-03288-7

Manoharan, M., Subramani, B., & Ramu, P. (2024). An optimal energy efficient routing in WSN using adaptive entropy bald eagle search optimization and density based adaptive soft clustering. *Sustainable Computing: Informatics and Systems*, *43*, 101003. https://doi.org/10.1016/j.suscom.2024.101003

Prakash, V., Singh, D., Pandey, S., Singh, S., & Singh, P. K. (2024). Energy-Optimization Route and Cluster Head Selection Using M-PSO and GA in Wireless Sensor Networks. *Wireless Personal Communications*, *136*, 1–22. https://doi.org/10.1007/s11277-024-11096-1

Priyanka, B. N., Jayaparvathy, R., & DivyaBharathi, D. (2022). Efficient and Dynamic Cluster Head Selection for Improving Network Lifetime in WSN using Whale Optimization Algorithm. *Wireless Personal Communications*, *123*(2), 1467–1481. https://doi.org/10.1007/s11277-021-09192-7

Rajaram, V., Pandimurugan, V., Rajasoundaran, S., Rodrigues, P., Kumar, S. V. N. S., Selvi, M., & Loganathan, V. (2025). Enriched energy optimized LEACH protocol for efficient data transmission in wireless sensor network. *Wireless Networks*, *31*(1), 825–840. https://doi.org/10.1007/s11276-024-03802-5

Ram, G. M., & Ilavarasan, E. (2024). Multi-objective may-badger optimizer based energy efficient routing protocol in dense wireless sensor network. *Multimedia Tools and Applications*, *83*(25), 66897–66923. https://doi.org/10.1007/s11042-023-18057-z

Roberts, M. K., Thangavel, J., & Aldawsari, H. (2024). An improved dual-phased meta-heuristic optimization-based framework for energy efficient cluster-based routing in wireless sensor networks. *Alexandria Engineering Journal*, *101*, 306–317. https://doi.org/10.1016/j.aej.2024.05.078

Senkumar, M. R., Arafat, I. S., Nathiya, R., & Nishath, S. M. H. (2024). Enhanced Energy Efficient Clustering and Routing Algorithm in Wireless Sensor Network. *Wireless Personal Communications*, *138*(3), 1531–1558. https://doi.org/10.1007/s11277-024-11549-7

Sheeja, R., Iqbal, M. M., & Sivasankar, C. (2023). Multi-objective-derived energy efficient routing in wireless sensor network using adaptive black hole-tuna swarm optimization strategy. *Ad Hoc Networks*, *144*, 103140. https://doi.org/10.1016/j.adhoc.2023.103140

Srividhya, V., & Shankar, T. (2023). An Energy Efficient Distance-Based Spectrum Aware Hybrid Optimization Technique for Cognitive Radio Wireless Sensor Network. *Journal of The Institution of Engineers (India): Series B*, *104*(1), 51–60. https://doi.org/10.1007/s40031-022-00837-0

Wilson, A. J., S., K. W., Radhamani, A. S., & Bharathi, A. P. (2024). Optimizing energy-efficient cluster head selection in wireless sensor networks using a binarized spiking neural network and honey badger algorithm. *Knowledge-Based Systems*, *299*, 112039. https://doi.org/10.1016/j.knosys.2024.112039

Zeng, B., Deng, J., Dong, Y., Yang, X., Huang, L., & Xiao, Z. (2024). A Whale Swarm-Based Energy Efficient Routing Algorithm for Wireless Sensor Networks. *IEEE Sensors Journal*, *24*(12), 19964–19981. https://doi.org/10.1109/jsen.2024.3390424

Zulfiqar, R., Javid, T., Ali, Z. A., & Uddin, V. (2023). Novel metaheuristic routing algorithm with optimized energy and enhanced coverage for WSNs. *Ad Hoc Networks*, *144*, 103133. https://doi.org/10.1016/j.adhoc.2023.103133