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RESEARCH ARTICLE

Differential Evolutionary Optimization Algorithm for Energy-Efficient Routing Strategy in Wireless Sensor Networks

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Abstract – Modern communication systems depend mostly on wireless sensor networks (WSNs), yet resource constraints and dynamic topologies cause major difficulties in energy efficiency and safe data transmission. Dealing with these problems, this work presents Exponentially-Enhanced Whale- Differential Evolution Optimisation (E-WDEO), a new routing system meant to improve network longevity and performance. The proposed model runs in two phases: first, cluster heads are chosen by a hybrid metaheuristic combining Differential Evolution (DE) and Whale Optimisation Algorithm (WOA), therefore guaranteeing best resource distribution. Then effective routing paths are found via a fitness-driven path selection technique including parameters including distance, energy, and latency. The E-WDEO model reduces the problems of high packet loss, energy depletion, and latency rather successfully. Over 1000 rounds, simulations on a 500-node network show notable performance gains including 85.2 J energy savings, 750 kbps throughput, 0.07 seconds latency, and a 9% packet loss. Compared to present techniques, the proposed approach considerably reduces computing cost and preserves 480 active nodes. These results demonstrate E-WDEO's capacity to deliver robust and efficient data transfer, hence extending the lifetime of the network. Future studies aimed at additional advancements in energy economy and Quality of Service (QoS) combine metaheuristics with deep learning approaches.

Index Terms – Wireless Sensor Networks, E-WDEO, Whale Optimization Algorithm, Differential Evolution, Energy Efficiency, Routing Protocol, Quality of Service, Network Performance, Packet Loss, Throughput.

1. INTRODUCTION

Emerging as a transforming technology, wireless sensor networks (WSNs) allow seamless monitoring and data collecting in many sectors including environmental surveillance, industrial automation, and military uses. These networks provide insightful analysis of monitored surroundings since geographically scattered sensor nodes independently gather and send data to base stations [1][2]. Particularly in applications like gas monitoring, intrusion detection, and object tracking [3], the strategic placement of sensor nodes inside the region of interest determines network efficiency and coverage in great part.

WSNs rely on limited resources, especially battery-operated sensor nodes, which presents important issues even if they are quite versatile. The autonomous running of these nodes without outside energy sources requires effective energy management to minimise early failures and increase network lifetime [4]. Major causes of energy depletion are transmission and sensing operations, so power optimisation is crucial to keep network functionality. Moreover, changing topologies resulting from mobile nodes complicate path building and routing especially in mobile or distant situations where infrastructure deployment or battery replacement is not feasible [5].

In WSNs, efforts to save energy have concentrated on methods include lowering transmission ranges, using sleep and idle modes, and so minimising the number of active nodes [6]. While sleep modes lower energy usage by halting data transmission and reception, idle nodes run selectively during significant events. These techniques especially apply in situations where WSNs enable the Industrial Internet of Things (IIoT), therefore supporting sectors such home automation, environmental monitoring, national security [7][8].

Still, low power and limited resources inherent in sensor nodes cause great attention to energy efficiency [9]. Apart from energy problems, ensuring safe and efficient data flow complicated network architecture even further. Equally distributing loads among nodes has helped clustering-based routing systems show promise in extending network lifetime and reducing energy usage [10]. These methods improve scalability and system performance even while they reduce routing costs [11].

This work proposes exponentially-enhanced Whale-Differential Evolution Optimisation (E-WDEO) using a novel routing protocol to overcome the dual issues of energy economy and safe data transfer in WSNs. Using hybrid evolutionary algorithms, this approach maximises cluster head selection and routing patterns, thereby enhancing data dispersion, reducing energy consumption, and extending network lifetime. The proposed method offers a powerful response for modern WSN problems by way of simulations since it demonstrates superior performance in terms of energy savings, latency, throughput, and packet delivery than present alternatives [12].

1.1. WSN Architecture

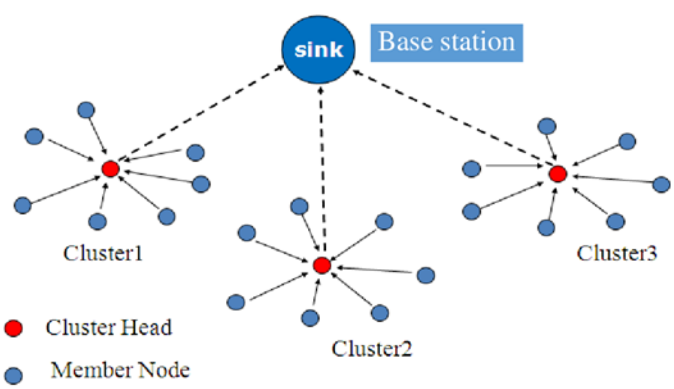

Figure 1 Clustering Topological Structure of WSN

Figure 1 shows the topological structure of clustered WSNs. Every cluster or cluster is defined essentially by two elements: a Cluster Member (CM) and a Cluster Head (CH). The CM gathers data and forward it to the CH, which aggregates the cluster's data and distributes it to the Base Station (BS) by means of multi-hop communication This process consists in two distinct phases: (i) the phase of network topology creation in duty of head selection and clustering; (ii) the steady-state phase, in charge of data flow, communication, and data fusion.

Routing algorithms/protocols in WSNs have evolved fundamentally with time. Liu et al. (2019) presented a multi-channel AODV routing technique based on the Dijkstra algorithm to identify optimal transfer paths and project energy consumption during data transmission [11]. Likewise, Abderrahim et al. (2019) looked at a Dijkstra algorithm-based clustered routing technique [12]. Under their paradigm, the BS generates a weight matrix and the method determines the optimal path from source to destination. Chen et al. (2019) presented the LEACH protocol, a widely used traditional routing method designed to divide the task among clusters. LEACH has a major disadvantage as well since it compromises energy efficiency by ignoring the residual energy of sensor nodes when selecting relay nodes for transmission [13].

Recent studies on overcoming these obstacles have concentrated on developing WSN energy-efficient routing systems. Even if they may minimise energy use in homogeneous networks and lower hop distances, current approaches find difficult management of energy in heterogeneous systems. Particularly, the low energy efficiency of these models can reduce the running lifetime of the network. Consequently, one has to consider node variability and build routing solutions to increase network lifetime and reduce energy consumption.

Designed to boost throughput while saving energy and extending network lifetime, this work offers WSNs a novel energy-efficient routing technique called Exponentially-Whale Differential Evolution Optimisation (E-WDEO). The key contributions of the proposed model include:

Two-phase routing process: The first phase involves the selection of cluster heads using hybrid evolutionary algorithms, combining whale optimization with differential evolution techniques.

Fitness-based CH selection: The choice of the cluster head is determined by fitness measures such as energy and delay, with the node exhibiting the highest fitness score selected as the CH for data transmission.

Optimal path discovery: The second phase of E-WDEO employs fitness criteria (e.g., energy, distance, and latency) to identify the most efficient path for packet delivery.

Comprehensive performance evaluation: The proposed model is simulated and compared with existing approaches, demonstrating improved performance in terms of residual energy, latency, network lifetime, packet loss, and throughput.

Global optimization using WOA: The population-based Whale Optimization Algorithm (WOA) helps the model

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achieve global optima rather than being limited by local solutions. This flexibility allows WOA to address a variety of constrained or unconstrained optimization problems without requiring structural modifications, making it suitable for real-world applications.

The E-WDEO approach thus offers a robust solution for enhancing WSN performance while addressing the challenges of energy efficiency and network scalability.

1.2. Problem Statement

Wireless sensor networks (WSNs) are increasingly employed in important applications including environmental monitoring, industrial automation, and healthcare where they gather and broadcast data over great distances. Particularly with regard to network scalability, energy economy, and dependability of communication, WSNs offer considerable challenges even if their increasing value is evident. The most urgent problem is the fast depletion of sensor node energy resulting from strong transmission and sensing operations, therefore greatly restricting the operational lifetime of the network. Although current routing systems, including PSO-ECHS, EERL, and ELAW, somewhat address energy consumption, they often fall short in optimising energy usage, ensuring load balancing, and minimising packet loss across extended periods (Akyildiz et al., 2006; Alomari et al., 2022; Padmalaya Nayak et al., 2021) [14-16]. The necessity of more scalable, resilient, and efficient energy management techniques in WSNs is clear-cut; hence, the proposed Exponentially-Whale Differential Evolution Optimisation (E-WDEO) model is developed to solve these problems by improving energy efficiency and network performance.

This paper is arranged such that the results and analysis might be carefully presented. Examining the body of present research, Section 2 covers metaheuristic algorithm application, energy-efficient routing in wireless sensor networks (WSNs), and current clustering techniques. This section provides the basis and highlights areas of research lacking the proposed focus. Section 3 addresses the methodologies and the Exponentially-Enhanced Whale-Differential Evolution Optimisation (E-WDEO) model. Stressing the hybrid optimisation techniques and fitness measurements applied helps to clarify the two-phase approach for optimal routing path determination and cluster head selection. Section 4 presents, by means of comparison with current methods, the results and analysis of the performance of the proposed model under numerous conditions. Section 5 highlights the results with future directions for research including the combination of metaheuristic algorithms with deep learning for extra optimisation.

2. RELATED WORK

Because of issues related to limited energy resources and changeable network topologies, the field of wireless sensor networks (WSNs) has attracted a lot of research aiming at energy-efficient routing methods. To improve network performance, several strategies stress hybrid approaches, optimisation strategies, and clustering.

RLBEEP, a reinforcement learning-based routing protocol presented by Abadi et al. (2022), makes use of reinforcement learning methods to maximise routing pathways and therefore increase energy economy. Learning optimal routing algorithms over time allowed this approach to show notable increases in energy economy [17]. Aiming to balance node energy usage, Adnan et al. (2021) also presented an unequally clustered multi-hop routing protocol based on fuzzy logic. This approach lowers the energy load on nodes close to the base station by dynamically changing cluster sizes [18].

To provide adaptive energy management, Adumbabu and Selvakumar (2022) presented a strengthened optimization-based dynamic cluster head selection method. Using optimisation methods, this method finds ideal cluster heads, hence lowering energy consumption while preserving network stability [19]. Alansari et al. (2022) have developed a fuzzy clustering method called FCERP that maximises cluster development to enhance network performance [20]. Apart from energy savings, security and dependability in WSNs have been somewhat prominent topics of research. Approaching trust and security challenges, Ahmad et al. (2022) proposed a trust-based framework for 6LoWPAN networks to provide safe and reasonably priced data transit [21].

By means of clustering methods, Kaur et al. (2023) developed a learning-based optimisation strategy for sensor node localisation, so enhancing routing efficiency and reducing energy waste. Combining route optimisation and localisation [22] this approach delivers enhanced scalability. Suresh Kumar and Vimala (20211) simulated natural behaviours using the Antlion-Whale Optimisation Algorithm for energy-aware routing, hence prolonging network lifetime and improving node stability [23].

Many research has focused on traditional and hybrid clustering techniques. Khan and Awan (2022) presented a hybrid model that extends the LEACH protocol by integrating residual energy and node density issues for better scalability and energy economy [24]. Yanfei et al. (2021) chosen cluster heads based on residual energy using a heterogeneous energy model for both single- and multi-hop communication, so enhancing network lifetime [25].

We have also investigated advanced clustering and energy optimisation methods. Hu et al. (2022) developed an energy-balanced WSN model by combining K-means clustering with Dijkstra's algorithm, hence extending network lifetime by choosing cluster leaders based on residual energy [26]. By means of a centroid-based routing system to balance network

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loads and improve sensor node lifetime by means of cluster head selection, Kumar and Gnanadhas (2020) presented By simulating natural hunting behaviours for ideal cluster head selection [27], Daneshvar et al. (2019) enhanced energy economy using the Grey Wolf Optimiser (GWO)[28].

To improve routing performance, optimisation strategies such the fractional particle lion method by Bhardwaj and Kumar (2019) taken many parameters including energy, latency, and cluster density [29]. Using residual energy, concentration, and centrality as measurements for clustering, Alami and Najid (2019) developed the Energy-Aware Fuzzy Clustering Algorithm (EAFCA), therefore guaranteeing strong energy management [30].

Apart from energy efficiency, security and dependability in WSNs have been quite important subjects of investigation. Approaching trust and security issues, Ahmad et al. (2022) suggested a trust-based framework for 6LoWPAN networks to guarantee safe and affordable data transfer [21]. Extending this by creating a QoS-aware trust-based routing algorithm that gives energy efficiency and safe data transfer first priority by [31], Kalidoss et al. (2020). Haseeb et al. (2019) improved the energy economy for IoT-based WSNs by means of a multi-hop routing method applied with secret-sharing mechanisms [6].

Furthermore, very helpful in optimising WSN performance have been machine learning methods. Deep Q-learning was used by Bouzid et al. [32] for dynamic path selection, hence improving network lifetime and responsiveness to changing network conditions. Particularly in large-scale WSNs Alharbi and El-kenawy (2021) shown the efficacy of machine learning algorithms in data analysis and energy-efficient routing [33]. Examining AI-driven approaches for urban WSNs, Sharma et al. (2021) showed how smart city networks might use machine learning for improved scalability and resource management [34].

Recent research have also included sophisticated WSN applications. Focussing on best sink location to reduce energy consumption, Ashween et al. (2020) devised a mobile sink-based data collecting approach to increase network lifetime [35]. Emphasising energy-efficient clustering methods, Fatima et al. (2021) [36], used K-means clustering to improve network vitality. To preserve energy efficiency in multi-hop WSNs, Huan et al. (2020) [37] presented a beaconless, asymmetric synchronising mechanism. For UAV-assisted WSNs, Poudel et al. (2021) developed a residual energy-based clustering technique allowing efficient monitoring and surveillance [38].

Though it lacked experimental validation, Wu et al. [39] conducted a review of security threats in space networks, so providing a comprehensive analysis of vulnerabilities and mitigations, so restricting their practical relevance. Lăzăroiu et al. [40] effectively combined wireless sensor networks (WSNs) with robotics and geospatial data, so integrating deep learning into IoT and manufacturing, but the approach demands advanced computational resources, so creating a barrier to implementation. Although Prabhu et al. [41] used multi-agent reinforcement learning to increase network lifespan by means of adaptive routing, they encountered convergence time problems that affected the method's effectiveness.

These works address issues of scalability, security, and dynamic topologies by collectively showing how clustering methods, optimisation algorithms, and machine learning approaches support energy-efficient routing and stable performance in WSNs. A summary of literature review with each works, contribution and limitation is listed in table 1.

Table 1 Summary of Literature Review

Reference	Methodology	Contribution	Limitation
Abadi et al. (2022) [17]	Reinforcement learning for energy-efficient routing	Developed RLBEEP protocol for improved energy management	High computational overhead
Adnan et al. (2021) [18]	Fuzzy logic-based unequal clustering	Enhanced energy balancing via multi-hop routing	Limited scalability
Adumbabu& Selvakumar (2022) [19]	Enhanced optimization algorithms	Dynamic cluster-head selection for energy-efficient routing	Complex optimization algorithms
SureshKumar & Vimala (2021) [23]	Ant-lion whale optimization (E-ALWO)	Trust-based routing combining ant-lion and whale optimization	Limited generalization to all WSNs

Bouzid et al. (2020) [32]	Deep Q-learning-based routing	Dynamic path selection to maximize network lifetime	Training complexity in large networks
Khan & Awan (2022) [24]	Hybrid energy-efficient clustering	Addressed LEACH protocol limitations to improve scalability	Potential communication delays
Yanfei et al. (2021) [25]	Heterogeneous energy model	Efficient cluster-head selection based on residual energy	Requires node heterogeneity
Hu et al. (2022) [26]	K-means clustering and Dijkstra algorithm	Energy-balanced high-throughput WSN model	Limited to static topologies
Kumar &Gnanadhas (2020) [27]	Centroid-based routing model	Balanced load through cluster-based head selection	Not tested in dynamic environments
Daneshvar et al. (2019) [28]	Grey Wolf optimizer-based clustering	Improved energy efficiency by mimicking wolf behavior	Lacks QoS considerations
Bhardwaj & Kumar (2019) [29]	Fractional particle lion algorithm	Optimized routing using multiple performance metrics	High computational overhead
Alami & Najid (2019)[30]	Fuzzy logic-based clustering (EAFCA)	Energy-aware clustering based on remaining energy and frequency	Needs a stronger head node selection mechanism
Ahmad et al. (2022) [21]	Adaptive trust-based framework	Secure, cost-effective data transmission in 6LoWPAN networks	Potential delays in trust evaluation
Kalidoss et al. (2020) [31]	QoS-aware trust-based routing	Enhanced data security and transmission reliability	Not evaluated in dynamic settings
Haseeb et al. (2019) [6]	Multi-hop energy-aware routing with secret sharing	Improved energy economy for IoT-based WSNs	Complex cluster management
Wu et al. (2022) [39]	Review of security threats in space networks	Comprehensive analysis of vulnerabilities and mitigations	Lacks experimental validation
Alharbi & El-kenawy (2021) [37]	Machine learning optimization for sentiment analysis	Enhanced social media sentiment analysis	Limited to specific datasets
Lăzăroiu et al. (2022) [40]	Deep learning for IoT and manufacturing	Integrated WSNs with robotics and geospatial data	Requires advanced computational resources

Sharma et al. (2021) [34]	Survey on machine learning in WSNs	Overview of AI applications for smart city WSNs	Lacks implementation details
Ashween et al. (2020) [35]	Mobile sink optimization for data gathering	Extended network lifespan with optimal sink placement	Assumes static sink nodes
Fatima et al. (2021) [36]	K-means clustering	Efficient energy routing through clustering	Sensitive to initial cluster centers
Huan et al. (2020) [37]	Asymmetric time synchronization scheme	Energy-efficient synchronization in resource-constrained WSNs	Complex implementation
Poudel et al. (2021) [38]	Residual energy-based clustering for UAV-aided WSNs	Optimized clustering for UAV-based surveillance	Limited to UAV-assisted networks
Prabhu et al. (2023) [41]	Multi-agent reinforcement learning	Improved network lifespan through adaptive routing	Convergence time issues

Although the above listed research has achieved great progress in WSNs' energy efficiency, scalability, and robustness, important difficulties still exist especially in balancing energy consumption across nodes, adjusting to changing network topologies, and guaranteeing long-term sustainability. Many clustering-based techniques depend on heuristic approaches or stationary setups, which could not be sufficient to handle the complexity of practical WSN implementations. Likewise, even if they are efficient, optimisation methods may have to compromise real-time adaptability against computational expense. Another major issue is security since current systems find it difficult to smoothly combine safe and energy-efficient routing. These constraints make a thorough routing model that dynamically optimises clustering, guarantees balanced energy usage, and integrates strong decision-making systems even more urgently needed. By combining advanced evolutionary algorithms and fitness-based routing measures, the proposed Exponentially-Enhanced Whale- Differential Evolution Optimisation (E-WDEO) model tries to fill in these gaps, hence improving network lifetime, data throughput, and general performance. This creative method seeks to close the distance between theoretical developments and useful applications in WSNs with energy economy.

3. PORPOSED ARCHITECTURE

This section discusses the proposed system model for the routing process from the sensor node to the base station for packet transfer via CH. The proposed system network model for WSN is shown in Figure 2.

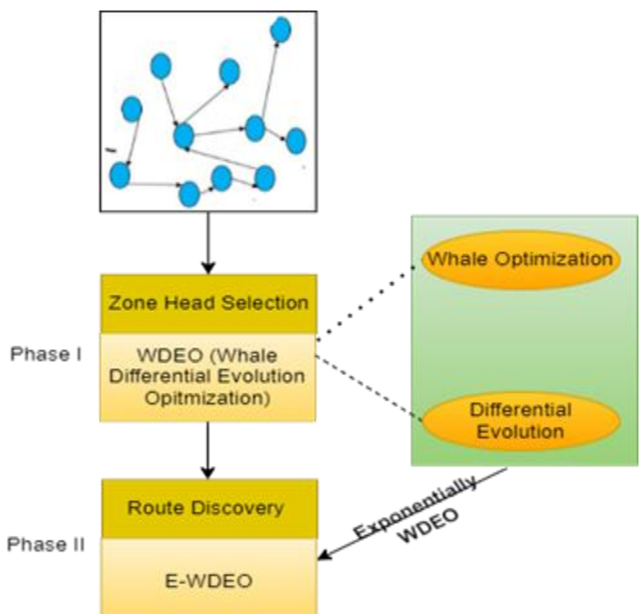

Figure 2 Architecture of Proposed Method

A wireless sensor network (WSN) is defined by a sink (base station, denoted as S) and numerous sensor nodes wirelessly interacting with one other. Every one of these equally separated nodes has a unique ID that facilitates network clusterizing. The sink node is placed deliberately to efficiently

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compile data from every sensor node. This architecture guarantees the packet flow from every sensor node to the sink via routing methods.

Let n be the total number of sensor nodes; let Cn be the number of nodes inside a given cluster group (C), hence expressing the size of every cluster split. Once clusters start to grow, every node (n) forwards its data to the designated Cluster Head (CH). Starting from its member nodes, the CH gathers information it sends to the sink (S). The proposed system model specifies a hybrid Whale Optimisation and Differential Evolution (WDEO) method that direct the CH choice.

Then the E-WDEO routing method reveals the most efficient transmission channel from the CH to the washbasin. This approach selects optimal paths depending on the dynamic characteristics of the network, therefore improving general network performance and ensuring energy-efficient data delivery.

3.1. Energy Model

Every sensor node in the network is started with a set energy level, indicated E0E_0E0, which cannot be restored. Following a multi-hop communication model, data flow from the ith node to the jth Cluster Head (CH) causes energy loss dependent on the sender-receiver distance. Data packet size SSS and the transmission distance between nodes determine the energy consumed during transmission.

Equation (1) captures the link between packet size, transmission distance, and energy loss for every data packet of size SSS bytes, therefore defining the energy dissipation suffered during transmission. This model guarantees correct quantification of the energy cost of communication, thereby stressing the need of maximising transmission channels to extend the lifetime of the sensor nodes.

$$E_d(x^i) = \begin{cases} E_{re} * S + E_{pa} * S * \left\|x^i - G^j\right\|^4 if \left\|x^i - G^j\right\| \geq S_0 \\ E_{re} * S + E_w * S * \left\|x^i - G^j\right\|^2 if \left\|x^i - G^j\right\| < S_0 \end{cases} \quad (1)$$

Where, re is denotes the radio electronics energy of sender and receiver, pa denotes the power amplifier of the sender and $\left\|x^i - G^j\right\|$ denotes the distance from normal ith node to jth Cluster head G.

The equation (2) represents the the relationship between the available work energy and the energy per unit mass to derive the initial velocity. The square root ensures that the velocity is proportional to the energy ratio, aligning with principles from mechanics or wave dynamics.

$$v_{s_0} = \sqrt{\frac{E_w}{E_{pa}}} \quad (2)$$

$$E_{re} = E_{sender} + E_{agg} \quad (3)$$

Where, Esender is the sender energy, Eagg is the data aggregation energy (equation (3)). After receiving S bytes of data, the energy dissipated by the receiver using CH is denoted as (equation (4))

$$E_d(G^l) = E_{re} * S \quad (4)$$

After receiving each S bytes of data, each node energy value Ea is updated (equation (5) and (6)).

$$E_{a+1}(x^i) = E_a(x^i) - E_d(x^i) \quad (5)$$

$$E_{a+1}(G^i) = E_a(G^i) - E_d(G^i) \quad (6)$$

This data transfer is repeated till all the network nodes are to be dead. If the node has energy less than zero, then that node is considered as dead node.

3.2. Routing Procedure

Using energy and delay observations, the WDEO technique selects nodes as Cluster Heads (CHs). Our hybrid approach combines Differential Evolution (DE) approach with Whale Optimisation Algorithm (WOA) to increase the efficiency of CH choosing.

The CHs assist data to travel from the sensor nodes to the Base Station (BS) acting as middlemen. By means of CHs rather than direct connections between individual nodes and the BS, routing data reduces the transmission time, hence improving network performance. Moreover assured by the CH-based routing is a more sensible and safe communication tool. By analysing nodes depending on their energy levels and delay properties, the fitness function applied in WDEO directs the selection of best CHs.

This method ensures minimal energy use in addition to timely data transfer, therefore extending the running lifetime of the network.

3.3. Fitness Function

Based on the fitness value utilized to transport data between the sender and receiver, the CH is chosen. The variables to be taken into account include delay and energy. The CH node is chosen based on minimal point and uncertainty and has a greater fitness score. Following is how the fitness value is calculated (equation (7), (8), and (9)):

$$f = \frac{1}{2}\left(E + (1 - l)\right) \quad (7)$$

$$E = \frac{1}{mn} \sum E_{mn} \quad (8)$$

$$l = \frac{1}{mn\eta} \sum l_{mn} \quad (9)$$

Where f is the fitness function, E is the energy, l is the delay and η denotes the normalization factor. For the selection CH, the proposed model integrates the Whale optimization with differential evolution operator.

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4. PROPOSED METHODOLOGY

Combining Differential Evolution (DE) with the Whale Optimisation Algorithm (WOA) this suggested approach generates an energy-efficient routing plan for wireless sensor networks (WSNs). The main goal is to use WOA's natural behaviour to replicate humpback whale bubble-net foraging method while improving search space exploration and convergence via DE's evolutionary processes. This hybridisation raises local convergence as well as global search capacity.

Described by Mohanty et al. (2017), [42] the Whale Optimisation Algorithm (WOA) models the spiral motions of humpback whales during bubble-net foraging. When the prey is not directly found, the whale algorithm dynamically updates positions by means of spiral and contraction movements towards the prey, therefore identifying it. Equations (10, 11) with parameters (P) and (Q) expressing the size of the surrounding area, determined using Equations (12, 13) help to mathematically model this mechanism. WOA reduces the control parameter (a) over time to strike a mix between exploration and exploitation (Equation 14). The whale moves between spiral motion and contraction paths throughout the bubble-net attack phase, therefore simulating its natural hunting behaviour (Equations 15, 16). Should it be required, the algorithm moves into a prey-seeking phase to enable worldwide exploration, hence avoiding its confinement in local optima (Equations 17, 18).

Originally put forth by Storn and Price (Szydło et al., 2019), Differential Evolution (DE) [43] addresses the shortcomings of WOA including premature convergence to local optima, therefore complementing WOA. By selecting, modifying, and crossovering an initial population, DE generates new individuals (Equations 19, 20). Equation 21 selects the fittest people to move on to the next generation, therefore assuring that the set of solutions gets better every iteration. While maintaining the global search capability of the method, the coupled WDEO (Whale- Differential Evolution Optimisation) methodology efficiently overcomes local optima convergence problems. Gaussian mutation helps to preserve population variety (Equation (23)) and a probability-based update algorithm improves the optimisation process even more. Equation 22 Equations (24–27) allow one to compute the fitness function depending on time, energy consumption, and distance thereby assuring that the most effective path for data transmission is chosen.

The suggested Exponentially-Enhanced WDEO (E-WDEO) combines into the WDEO update equation (Equation 28) an Exponential Weighted Moving Average (EWMA) factor. With a tuning value, this change maximises the position of the search agent (Equation (29)), therefore improving the search process. The E-WDEO model provides a complete solution to raise network performance by effectively routing data, minimising resource usage, and handling security, energy depletion, and dynamic topology in WSNs. The algorithm captures the main stages of the methodology, showing the sequence of whale optimization, differential evolution, and the integration of both to achieve an optimal routing path in wireless sensor networks.

$$X(t+1) = X^*(t) - P.K \quad (10)$$

$$K = Q.X^*(t) - X(t) \quad (11)$$

Where, t denotes the current number of iterations, $X^*(t)$ declares the vector of prey current position, $X(t)$ denotes vector of prey position, | | is the abosolute value and P and Q declares the vectors respresenting the size of sorrundings (or) coefficients.

The vectors P and Q are calculated as follows in the Equations (12) and (13).

$$P = 2a.r - a \quad (12)$$

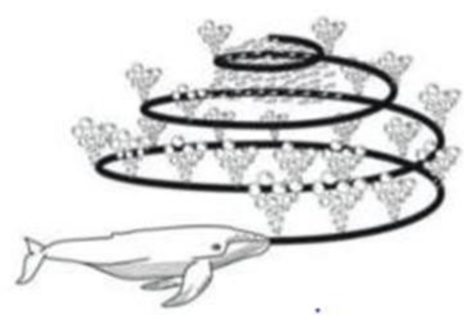
$$Q = 2r \quad (13)$$

Where, r is the random number in the range [0,1], a is the control parameter and for the number of iterations it decreases the value in the range 2 to 0 as stated in Equation (14) where $T_m is$ maximum number of iterations.

$$a = 2 - \frac{2t}{T_m} \quad (14)$$

4.1. Bubble Net Attack

The whale's bubble net behavior while being encircled, as depicted in Figure 3. The whale makes a spiraling motion in the direction of the beach. This behavior is mathematically represented using the spiral update position and the shining inspirational method.



(Source: Collier, Travis & Taylor, Charles 2004[44])

Figure 3 Whale Bubble-Net Foraging

In first step, the factor a is reduced using the Equations (12, 13 and 14). In second step, the position is updated based on the distance from whale to current position. The food capturing of the whale is computed in Equation (15)

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$$X(t+1) = K'.e^{bl}.cos(2\pi l) + X^*(t) \quad (15)$$

$$K' = |X^*(t) - X(t)| \quad (16)$$

Where in equation 16 K'- distance between whale i to current position, b is the constant to define the spiral logarathimic form, l is the random number between [-1, 1]. Spiral and contraction envelopment are performed with equal probablity to obtain the synchronous model.

4.2. Hunting Prey

It randomly selects the whale with its position if $|A| \geq 0$. It makes the whale far awary from its current target and expore the global characteristics. The best prey position is replaced by the current whale as in Equation (17).

$$X(t+1) = X_{rnd} - P.Q \quad (17)$$

$$K = |Q.X_{rnd} - X(t)| \quad (18)$$

Where X_{rnd} is the random number (vector) of the whale's position.

Differential evolution with enhanced whale optimization process is depicted in algorithm 1.

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1. Start
2. Whale Optimization Algorithm (WOA)
a. Whale identifies prey location
- If prey is not found, update other prey positions
- Calculate prey position (Equations 10, 11)
- Calculate P and Q (Equations 12, 13)
b. Reduce control parameter 'a' (Equation 14)
3. Bubble Net Attack
a. Whale creates a spiral path towards prey
b. Update position based on distance (Equations 15, 16)
c. Perform spiral contraction with equal probability
4. Hunting Prey
a. If random condition met, whale explores global search space
b. Update whale position (Equation 17)
c. Calculate new prey position (Equations 18)
5. Differential Evolution (DE)
a. Initialize DE parameters: feature length, generations, weight, population size, crossover
b. Selection, mutation, and crossover of individuals (Equations 19, 20)
c. Compute fitness for selection (Equation 21)
6. Integration of Differential Evolution and Whale Optimization (WDEO)
a. Combine DE with WOA to improve global and local search
b. Update whale positions based on current generation (Equation 22)
c. Apply Gaussian mutation to increase population diversity (Equation 23)
7. Fitness Function
a. Calculate fitness based on delay, energy, and distance (Equations 24, 25, 26, 27)
b. Select route path with maximum fitness value
8. Proposed E-WDEO Optimization
a. Integrate exponential terms in the update equation of WDEO (Equation 28)
b. Tune search agent positions using EWMA (Equation 29)
9. Output optimal route path
10. End

Algorithm 1 Differential Evolution with Enhanced Whale Optimization

4.3. Differential Evolution

Storn and Price (Szydło, Joanna et al. 2019) [43] first proposed it, and it is related to the Genetic Algorithm (GA). Five parameters make up DE: feature length, generational count, weight, population size, and crossover. DE includes selection, mutation, and crossover procedures just like GA.

Individuals are placed in the population at random in the search space. Using Equation (19) (Nwankwo, Wilson &Ukhurebor, Kingsley 2019[45], Tiwari, Richa & Kumar, Rajesh 2021[46]), the individual X_i^{g+1} is created from the starting population in the mutation stage.

$$X_i^{g+1} = x_{p1}^g + w\left(x_{p2}^g - x_{p3}^g\right) p1 \neq p2 \neq p3, i = 1,2, \dots N \quad (19)$$

Where x is the individual in the population p ϵ (1, N), g is the generation / iteration number, N is the size of the population and w denotes differential weight. Based on crossover probability, all the individuals not participated in mutation. The train individual called $U^{g+1}$is computed from crossover operation with the condition stated in Equation (20)

$$U_{ij}^{g+1} = \begin{cases} X_{ij}^{g+1}, rd_{ij} \leq crossover \\ X_{ij}^{g} otherwise \end{cases} \quad (20)$$

Where j=1,2,…K, rd_{ij} is the jth particle of the ith individual's random value, which ranges from 0 to 1. This trial population is provided for the selection procedure. Comparing the trial and current population, like in Equation (21), the DE selection procedure contrasts GA. The process is repeated until termination condition met from mutation and selection.

$$x_i^{g+1} = \begin{cases} U_i^{g+1}, f\left(U_i^{g+1}\right) \leq f\left(U_i^{g}\right) \\ x_i^{g} otherwise \end{cases} \quad (21)$$

The standard Whale optimization algorithm suffers from convergence factor and local optimum while the diversity decreases and minimum usage of current generation evolution data. To overcome these issues, the differential evolution is integrated with WO, can utilize the current generation data, and ensures global and local search ability. Hence, the

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optimum local issue of standard WO is updated with DE's current generation formula.

Randomly selects the probability $p \in [0,1]$ and based on the probability value, the update is as follows in equation (22):

$$X(t+1) = \begin{cases} \left(1-\frac{t}{T}\right).X_r - AKifp < 0.5and|A| \geq 1 \\ \frac{t}{T}.X^*(t) - AKif|A| < 1 \\ K'.e^{bl}.cos(2\pi l) + \frac{t}{T}X^*(t)ifp \geq 0.5 \end{cases} \quad (22)$$

Where b is initialized as 1 and, r is the random number between 0 and 1. Meanwhile, the population diversity is increased to overcome the convergence. For that, Gaussian mutation has been applied after the individual mutation of Equation (23) that takes the midpoint of current and optimal individual as mean and distance between optimal and current individual as variance. The formula for variance is as follows:

$$X(t+1) = N(0.5 * X^*(t) + X(t), |X^*(t) - X(t)| \quad (23)$$

The equations (24) to (27) collectively define a fitness function to evaluate network performance by integrating key metrics such as energy, delay, and distance. The fitness function balances these metrics, aiming to optimize overall efficiency by minimizing delay and communication distance while ensuring energy consumption is kept low. Energy is calculated as the average energy consumption across all nodes, providing a measure of efficiency in resource utilization. Delay is determined by the ratio of transmitted packets to available communication slots, reflecting the effectiveness of communication scheduling. Distance evaluates the average communication distance between nodes, aiming to minimize it for improved connectivity.

(Fitness Function) $Fit = \frac{1}{4}\left(E + (1-l) + (1-D)\right)$ (24)

(Energy) $E = \frac{1}{n}\sum_{i=1}^{n} E_k$ (25)

(Delay) $l = \frac{n}{m}$ (26)

(Distance) $D = \frac{1}{n^2 \eta}\sum_{k=1}^{n}\sum_{\frac{T-1}{T-k+1}}^{n} D(k,T)$ (27)

The proposed E-WDEO integrates the parameters of WDEO to find the optimal route path which reduces the delay of the nodes. The update equation of proposed E-WDEO integrates the Exponentially term $-X(t)$ on both ends of the update Equation (28) of WDEO.

$$X(t+1) - X(t) = \begin{cases} \left(1-\frac{t}{T}\right).X_r - AD - X(t) & ifp < 0.5and|A| \geq 1 \\ \frac{t}{T}.X^*(t) - AD - X(t) & if|A| < 1 \\ D'.e^{bl}.cos(2\pi l) + \frac{t}{T}X^*(t) - X(t) & ifp \geq 0.5 \end{cases} \quad (28)$$

Where, based on standard EWMA the term for ith search agent position $X_i(t)$ is denoted as in Equation (29),

$$X_i(t) = \frac{1}{\zeta}[X_i^T(t) - (1-\zeta)X_i^T(t-1) \quad (29)$$

Where, ζ denotes the tuning parameter in the range [0,1].

Security and energy consumption are two critical challenges faced by wireless sensor networks (WSNs) due to their limited resources and dynamic topology. Although trust-based approaches are capable of mitigating several types of malicious node behavior, challenges persist, including various attacks, high energy consumption by certain nodes, and communication bottlenecks caused by overloaded nodes. To address these issues, this study proposes a hybrid optimization approach that combines Differential Evolution (DE) with the Whale Optimization Algorithm (WOA). The following section presents the results of the proposed method and compares its performance with existing techniques.

5. RESULTS AND DISCUSSIONS

This part presents and compares results of the E-WDEO-based routing mechanism for WSNs. Among the other currently in use approaches whose performance is evaluated here are PSO with Enhanced Cluster Head Search (ECHS), the Exponential Ant Lion Whale Optimisation method (Padmalaya Nayak et al., 2021) [16], the Energy-Efficient Scalable Routing Method (Akyildiz et al., 2006) [14], and the Energy-Efficient Reinforcement Learning-based Routing Protocol (Alomari et al., 2022) [15]. These models were implemented and evaluated using MATLAB both here and elsewhere. Table 2 presents a complete inventory of simulation settings.

Table 2 Simulation Parameters

Parameters	Value
Area	500 * 500
Energy_Free_Space	0.00000002J
Energy of Sender	0.000000335J
peed	0.000000775J
Maximum iterations	10
Number of nodes (search agents)	500
Lower boundary	1
Upper boundary	100
Topology	Mesh

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The proposed model performance is evaluated in terms of residual energy, delay, packet loss, and throughput.

5.1. Residual Energy

Residual energy is a critical measure indicating the amount of energy remaining in sensor nodes after data transmission. Efficient utilization of energy directly impacts the network's lifespan and performance. It is the measurement of consumed energy of every node during the transmission which is computed using Equation (25)

Results: The residual energy of the proposed E-WDEO model was evaluated against EESR, EERL, PSO-ECHS, and ELAW. Table 3 and Figure 4 depict the higher residual energy retained by the E-WDEO model across all transmission rounds. Table 4 and table 5 shows the network life resilience through number of remaining live nodes and dead nodes after every round.

Table 3 Routing Fitness Values Comparison of Proposed vs Existing Models

Methods	Number of Alive nodes				
	100	200	300	400	500
EESR	1.31	1.46	1.71	1.84	1.92
EERL	1.52	1.68	1.86	1.88	1.91
PSO-ECHS	1.42	1.53	1.61	1.73	1.82
ELAW	1.62	1.71	1.76	1.81	1.93
Proposed E-WDEO	1.69	1.78	1.85	1.91	1.98

Table 4 Number of Nodes Remained Alive During the Transmission

No of Rounds	200	400	600	800	1000
EESR	200	325	373	410	432
EERL	260	351	382	374	435
PSO-ECHS	214	300	342	360	412
ELAW	281	350	437	447	467
Proposed E-WDEO	360	441	450	475	490

Discussion: The superior residual energy of E-WDEO can be attributed to its effective use of fitness-based optimization in cluster head selection and its exponential approach to energy-aware routing. This minimizes energy dissipation during transmission and balances the load across nodes, significantly outperforming other models. Figure 4 depicts the number of live nodes per round and figure 5 pictorial shows the number of dead nodes per round for all the considered algorithms.

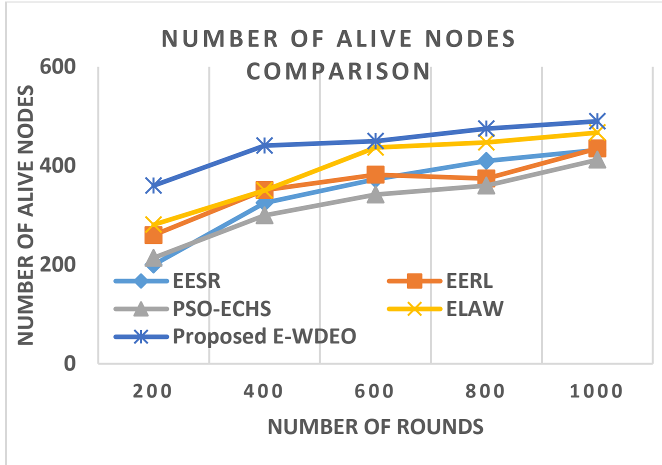

Figure 4 Number of Alive Nodes Comparison

Table 5 No of Dead Nodes After X Rounds

No of Rounds	200	400	600	800	1000
EESR	100	140	187	238	358
EERL	80	110	152	190	240
PSO-ECHS	112	153	200	246	376
ELAW	70	100	133	175	222
Proposed E-WDEO	50	75	117	146	175

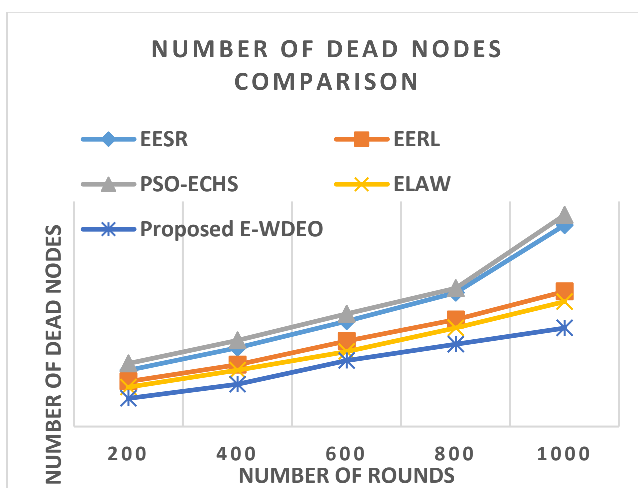

Figure 5 Number of Dead Nodes Comparison

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5.2. Throughput

Throughput is the rate at which data packets are successfully delivered to the base station. Higher throughput signifies better network performance. it is the measurement of the size of the number of packets delivered which is computed using Equation (30)

$$Throughput\left(\frac{bit}{sec}\right) = \frac{Successfully\ delivered\ packet\ count \times packet\ size}{Total\ time\ consumed\ to\ sedn\ packet\ from\ node\ to\ BS} \quad (30)$$

Results: As shown in Figure 6, the throughput of E-WDEO is 750 kbps, which outperforms EESR (550 kbps), EERL (640 kbps), PSO-ECHS (630 kbps), and ELAW (680 kbps).

Discussion: The higher throughput achieved by E-WDEO is due to its ability to minimize packet collisions and optimize transmission paths. By leveraging the fitness function for route selection, E-WDEO maximizes the successful delivery of packets, ensuring efficient utilization of network resources.

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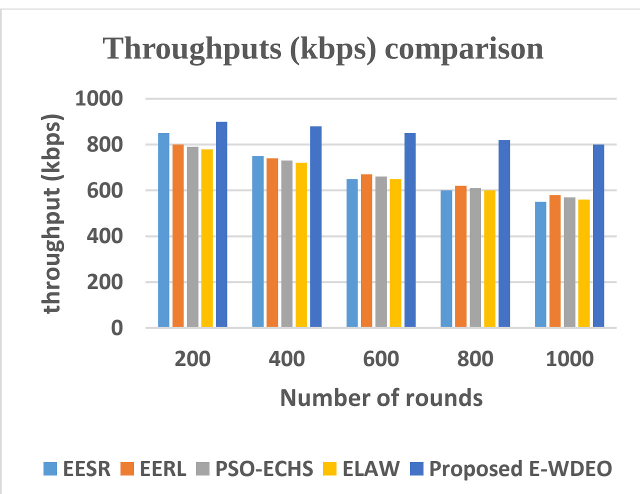

Figure 6 Throughput Comparison

5.3. Packet Loss

Packet loss is the percentage of data packets that fail to reach the destination. A lower packet loss rate indicates higher reliability. It is the percentage of not receiving packet by the base station with respect to total number of packets sensed by the sensor nodes. The computation of PL is shown in Equation (31)

$$PL = \frac{(PacketSent - PacketRcvd) * 100}{Packet\ Sent} \quad (31)$$

Results: The packet loss percentages for E-WDEO and other models are compared in Figure 7. E-WDEO achieved the lowest packet loss rate of 9%, compared to ELAW (31%), EERL (36%), and PSO-ECHS (37%).

Discussion: The significant reduction in packet loss is attributed to the proposed model's robust routing mechanism, which prioritizes reliable paths and minimizes retransmissions. The use of an exponential method ensures efficient data routing, thereby enhancing the reliability of the network.

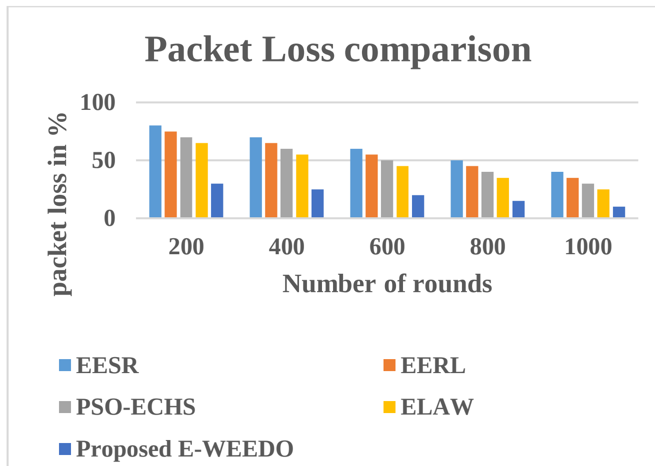

Figure 7 Packet Loss Comparison

5.4. Energy Efficiency

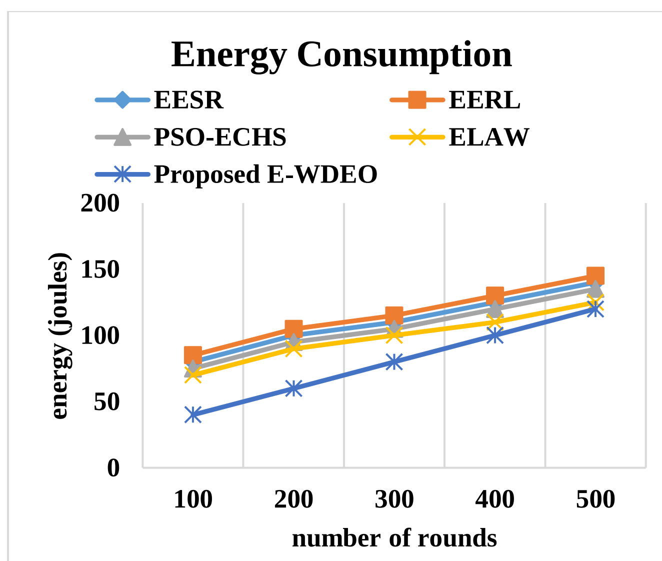

Figure 8 Energy Comparison

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Energy efficiency measures the total energy consumed during data transmission. Minimizing energy consumption extends the network's lifespan.

Results: The energy consumption comparison is illustrated in Figure 8. E-WDEO consumed only 85.2J for 500 nodes, significantly less than EESR (132.6J) and ELAW (101.2J).

Discussion: The proposed model's energy efficiency stems from its ability to evenly distribute the workload among cluster heads and select optimal routes with minimal energy expenditure. This strategic approach ensures prolonged network operation and superior performance compared to existing methods.

5.5. Delay and Computation Time

Delay measures the time taken to transfer data from the sender to the receiver as shown in equation (32 to 36.) A lower delay is critical for time-sensitive applications. It is the measurement of time taken to transfer the data from sender to receiver which is computed using equation (37). Computation time measures the processing efficiency of the model during route discovery. Lower computation times enhance scalability and responsiveness.

$$D_{total} = D_{transmission} + D_{propagation} + D_{processing} + D_{queueing} \quad (32)$$

$$D_{transmission} = \frac{\text{Packet Size}}{\text{Bandwidth}} \quad (33)$$

Where: Packet Size : Size of the data packet (bits). Bandwidth : Data transmission rate of the communication channel (bps).

$$D_{propagation} = \frac{\text{Distance}}{\text{Propagation Speed}} \quad (34)$$

Where: Distance : Distance between sender and receiver (meters). Propagation Speed : Speed of signal propagation (typically the speed of light for wireless).

$$D_{processing} = \frac{\text{Instructions}}{\text{Processing Speed}} \quad (35)$$

Where: Instructions: Number of instructions to process the packet. Processing Speed : CPU speed of the sensor node (instructions per second).

$$D_{queueing} = \frac{\text{Queue Length}}{\text{Service Rate}} \quad (36)$$

Where: Queue Length : Number of packets in the queue. Service Rate: Rate at which packets are served (packets per second).

$$T_{computation} = \frac{C}{f} \quad (37)$$

Where: C: Total number of CPU cycles required to perform the computation. f: Clock speed of the processor (cycles per second).

Results: The delay comparison between the proposed E-WDEO and existing methods is shown in Table 6. E-WDEO achieved the lowest delay of 0.07 seconds compared to EESR's 1.89 seconds and ELAW's 1.52 seconds. E-WDEO achieved the lowest computation time of 3 seconds, outperforming ELAW (6.5 seconds) and PSO-ECHS (10.3 seconds), as shown in Table 6.

Table 6 Delay and Computation Time Comparison

Methods	Delay (seconds)	Computation time (seconds)
EESR	1.89	11.2
EERL	1.84	9.7
PSO-ECHS	2.61	10.3
ELAW	1.52	6.5
Proposed E-WDEO	0.07	3

Discussion: The reduced delay in E-WDEO is a result of its efficient path selection mechanism, which minimizes route length and congestion by dynamically adapting to network conditions. This optimization reduces latency, making the model suitable for applications requiring real-time data transmission. The reduced computation time of E-WDEO highlights its streamlined optimization process. By effectively combining the Whale Optimization Algorithm with differential evolution, the model accelerates route discovery, making it ideal for dynamic and large-scale WSN deployments.

The proposed E-WDEO model consistently outperformed existing methods across all metrics, including residual energy, delay, throughput, packet loss, and energy efficiency. The integration of exponential enhancements with the WDEO algorithm contributed significantly to its superior performance. By addressing the limitations of traditional methods, the proposed model demonstrates its capability to enhance WSN performance, extend network lifespan, and meet the demands of modern applications.

6. CONCLUSION

Security and energy are main challenges for data flow in wireless sensor networks (WSNs). This paper presents E-WDEO, a novel energy-efficient routing method, to address these issues. The routing process consists in two stages. In the first phase using hybrid evolutionary techniques, a cluster head is selected combining whale optimisation with a differential evolution (DE) strategy. Fitness considerations including delay and energy level drive the cluster head's choice. The node having the best fitness score is the Cluster

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Head (CH) for data transmission. The E-WDEO-based route finding in the second phase discovers the optimum approach for broadcasting the packet according on fitness parameters including distance, time, and energy.

Performance of the proposed model was evaluated with simulations and a comparison with present energy-efficient routing methods. With regard to residual energy, latency, packet loss, and throughput, E-WDEO ranks higher than others. While increasing throughput, the proposed method drastically reduces energy consumption, latency, processing time, and packet loss relative to earlier methods. For a 500-node network, the model notably was able to retain 480 nodes alive, reduce the dead node count to 180, and save 85.2 J of energy. Furthermore, noted were a three-second computation time savings, a nine percent decline in packet loss, a 0.07 seconds delay for 1000 cycles, and a 750-kbps gain in throughput.

The results confirm that the E-WDEO model is reliable and effective in choosing the appropriate channel for data flow, hence optimising system energy and enhancing network performance. Future studies will look at how to further reduce energy use by combining more metaheuristic algorithms with deep learning models, hence improving quality of service (QoS).

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