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Research Article

Energy efficient trust ware routing protocol for improving heterogenous wireless sensor network for maximizing lifetime using swarm intelligence optimization algorithm

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Abstract:

In the realm of wireless sensor networks (WSNs), the increasing demand for energy efficiency and prolonged network lifetime is paramount, particularly in heterogeneous environments where sensor nodes exhibit varying capabilities and energy constraints. Preliminary model has so many routings congestion and energy consumption degrade he throughput latency to downgrade the network life time. This paper presents an innovative Energy Efficient Trust Ware Routing Protocol (EETWRP) designed to enhance the operational longevity of heterogeneous WSNs by leveraging swarm intelligence optimization algorithms. The proposed protocol addresses critical challenges in energy consumption and trust management, which are essential for maintaining network integrity and performance. EETWRP employs a multi-layered approach that integrates trust evaluation mechanisms with energy-aware routing strategies. Based On Traffic Intensive Behaviour Rate (TIBR) And Cross Layer Multicasting Energy Aware-Route Selection (CLM-EARS). By utilizing swarm intelligence, specifically inspired by the collective behaviors of social organisms, the protocol dynamically adjusts routing paths based on real-time energy availability and trustworthiness of sensor nodes. This adaptability not only optimizes energy utilization but also mitigates the risks associated with malicious activities and unreliable data transmission, which are prevalent in WSNs. Simulation results demonstrate that EETWRP significantly outperforms traditional routing protocols in terms of network lifetime, energy consumption, and data accuracy. The findings indicate a marked improvement in the overall efficiency of data transmission, with a reduction in energy expenditure and an increase in the reliability of the network. Furthermore, the protocol's ability to adapt to changing network conditions and node behaviors underscores its potential applicability in various domains, including environmental monitoring, smart cities, and industrial automation.

1. Introduction

Wireless Sensor Networks (WSNs) represent distributed systems with dispersed autonomous sensor nodes that jointly perform physical or environmental measurements such as temperature reading, pressure and humidity, and motion detection. The nodes relay data by wireless connections while functioning in cooperative groups to send information to a central base station, performing subsequent data processing. WSNs serve multiple applications because they cover diverse monitoring scenarios and operate automatically in distant locations with minimal supervision. In WSNs, the network lifetime is a significant performance indicator since it measures the duration of effective operation until the major sensor nodes use up their energy reserves [1].

The extended operation period of WSNs depends on crucial power management because sensor nodes deploy limited rechargeable or replaceable batteries, especially when deployed in challenging remote conditions. By extending the operational time of the network, organizations can maintain continuous data flow while decreasing repair expenses and improving system reliability. The long-term operation faces multiple obstacles, mainly from limited energy reserves, changing network layouts, and uneven energy consumption patterns [2]. Senior node energy unbalance causes node failure before its time, producing network fragmentation, data loss, and diminished coverage area. Research shows that inefficient routing operations, high communication expenses, and insufficient energy-aware cluster strategies severely shorten wireless sensor networks' operation time [3-4].

Heterogeneous WSN environments using existing routing techniques demonstrate inadequacies because sensor nodes have different energy and processing power levels. The requirement for adaptive routing systems stems from network adaptations, where these systems need to balance power consumption across different nodes. Traditional protocols work inefficiently with available energy because they create an imbalance in energy drainage throughout the system, reducing system effectiveness [5]. This study now concentrates on developing robust and adaptive solutions by combining Machine Learning (ML) with swarm intelligence to produce dynamic routing decision optimization.

The proposed Energy-Efficient Trust-Aware Routing Protocol (EETARP) uses swarm intelligence-based optimization methods to boost the operational life of heterogeneous WSNs. The protocol deals with conventional routing weaknesses by combining trust evaluation and energy efficiency for route selection. The network identifies untrustworthy nodes through trust management, allowing security enhancement and robustness improvement. Using swarm intelligence algorithms, which derive inspiration from collective natural behaviors, the system selects optimal routing paths that distribute energy load uniformly among the nodes. The proposed method leverages swarm-based optimization search capabilities to guarantee reduced energy usage, enhanced data transmission, and extended network operation time. Implementing trust metrics and the protocol ensures communication reliability, making it suitable for essential WSN applications that demand dependable operations. This new method delivers an adaptable energy-efficient solution that provides scalability and security through its deployment in heterogeneous WSN environments.

2. Literature Survey

The authors of [6] developed the Energy-efficient Fault-tolerant Routing Protocol (EFRP) to align energy-aware clustering with multipath routing for better energy usage and fault tolerance. A main disadvantage of this protocol is generating higher control operations that decrease scalability in extensive networks. The author developed an Improved Grey Wolf Optimization (IGWO) algorithm [7] to modify cluster heads by assessing distance and residual energy parameters. The proposed energy balancing solution achieved better results but displayed a drawback because its convergence rate was notably slow, which resulted in impaired real-time performance capabilities.

The authors in [8] introduced the Fuzzy Clustering Algorithm (FCA), which evaluates trust and energy parameters to enhance reliability and life span during clustering procedures. The fuzzy rule processing requirements make FCA experience performance degradation, together with improved fault detection and connectivity reliability. Data correlation combined with residual energy forms the basis of the Correlation-based Node Selection Algorithm (CNSA) developed by the author [9]. The effectiveness of CNSA for reducing redundant transmissions becomes less significant in dynamic or mobile sensor networking environments because it does not provide robust features.

The researchers introduced FL-LEACH-PSO by fusing Fuzzy Logic-based LEACH and Particle Swarm Optimization (PSO), respectively, in [10]. The combined model enhances network longevity through optimized cluster head selection, though it results in performance delays because it incorporates multiple algorithms. The author [11] presented HEMA, which merged different routing and clustering methods to manage energy distribution for longer sensor network operation. While HEMA reaches high energy conservation levels, it presents excessive complexity, which reduces its suitability for deployment in resource-limited technological environments.

The author [12] developed an Energy-Efficient Multi-Sensor Decision (EEMSD) that implements conditional decision procedures on heterogeneous sensor information. The EEMSD technology enables flexibility for various sensor types and conditions, yet becomes less flexible when using an elevated number of conditional parameters. The authors [13] introduced a Metaheuristic-Based Lifetime Enhancement (MBLE) strategy that selects optimal paths through evolutionary techniques. MBLE achieves effective results only when networks remain stationary, whereas dynamic networks that enable node movement reduce their operational effectiveness.

In [14], the researchers outline the Hybrid Energy-Efficient Layered clustering protocol (HEEL) that combines layered clustering with adaptive re-clustering techniques to enhance energy efficiency. HEEL decreases energy usage within individual clusters but encounters limitations when used between clusters because of its scalability issues. The author created the Enhanced LEACH protocol with Angle Sector-based Energy-Aware TDMA (ELEACH-AS-TDMA) to improve scheduling efficiency and reduce collisions [15]. The approach benefits from its scheduling capabilities but fails to perform well when nodes need rearranging due to restricted adaptability in unpredictable network structures. Table 1 shown literature.

Table 1. *Literature*

Author/Year	Proposed Methodology	Scalability	Objective	Limitation
[16]	Mobile Sink Optimization (MSO)	Medium	Data Gathering	The mobile sink node concept improves energy efficiency. However, it adds extra complexity to path planning and movement forecasting, reducing its practicality in real-time use or where mobility is constrained.
[17]	Energy Efficient Clustering Protocol (EECP)	High	Lifetime Enhancement	The fixed clustering style restricts network flexibility in changing conditions, thus causing unbalanced energy patterns as the network structures develop.
[18]	Stability-Enhanced Routing (SER)	Low	Lifetime Maximization	The protocol provides better stability in early operations, yet leaves unaddressed energy breakdowns for later phases, producing unbalanced power consumption and possible communication failures.
[19]	Firefly Optimization (FO)	Medium	Lifetime Optimization	The Firefly algorithm proves effective but has a drawback: its convergence slows down when operating on sizable or sophisticated wireless network systems, potentially influencing real-time application speed.
[20]	Graphical Neural Network (GNN)-based routing	High	Lifespan Extension	The model presents excessive computational requirements, which prevent it from being employed on resource-limited sensor nodes commonly used in typical WSN applications.
[21]	Hybrid Cluster Head (CH) Selection	Medium	Lifetime Maximization	The combined operational elements of the protocol produce higher complexity for algorithms, thus causing slower decision times and increased computational energy needs.
[22]	Advanced Distributed Clustering (ADC)	High	Load Balancing	The technique works well in a thick network but proves inefficient in dynamic conditions. This is because continual cluster configuration changes enhance communication system costs.
[23]	Improved EECP	Medium	Lifetime Enhancement	The protocol performs effectively in uniform networks but is unbaled heterogeneous elements or system mobility structures, making large-scale implementation difficult in actual WSN environments.
[24]	Prediction-Based Scheduling	Medium	Lifetime Improvement	The method's performance strongly depends on the accuracy of the prediction model. Imprecise forecasting might create inefficient scheduling, which wastes energy and increases idle listening duration.
[25]	Mobility based CH selection	High	Lifetime Enhancement	The scheme enhances energy distribution within mobile networks, yet the repetitive cluster head selection generates excessive control expenses and Funny link usage.

The authors in [26] created the Energy Centroid Clustering Algorithm (ECCA) to establish clusters through the energy-weighted centroid selection process that minimizes communication paths from nodes to the cluster head, thus both saving power reserves and extending network operational time. The algorithm operates with fixed clustering that reduces its capability to adjust when topologies shift or become mobile, thus causing disparate energy distribution throughout the system operation time.

The Optimal Base Station Location (OBSL) technique from [27] activates an approach to find the most suitable base station position by placing it at the point that minimizes total communication distance throughout all network nodes. The geometrical optimization minimizes transmission power usage, mainly when networks operate at high densities. Despite its effectiveness, the constant station position of the base station fails to optimize event-driven applications alongside mobile-node deployment needs for adaptable station moving strategies.

The author [28] brings forward a Multi-Objective Metaheuristic Optimization (MOMO) system that optimizes network coverage and lifetime enhancement. The method combines various objectives between energy efficiency and sensing coverage via evolutionary algorithms to find a perfect equilibrium. The multiple-objective problem-solving complexity creates substantial computational demands that hinder real-time operation because it extends computing time and slows convergence rates. The authors in [29] introduce the Scalable Cluster-based Data Aggregation (SCADA) approach to improve both network performance and operating duration. The method builds a data hierarchy that reduces superfluous data transfers while lowering the energy needed to broadcast information across the network. The SCADA data aggregation technique lowers communication expenses. Still, it will degrade data accuracy because of sweeping aggregation practices, and it loses efficiency in network patterns with infrequent nodes and inconsistent data patterns.

In [30], the author developed Hierarchical Routing with Optimal Clustering using Fuzzy Approach (HROCF), using fuzzy logic to choose cluster heads by assessing energy supply, base station proximity, and node population density. The technique shows efficient responsiveness to network condition modifications and extends network duration. The utilization of fuzzy inference systems increases the computational requirements of sensor nodes with limited resources, while requiring possible adjustments to membership functions for peak performance.

3. Proposed Methodology

The proposed solution presents EETWRP as a reliable routing approach for heterogeneous systems within WSNs. The protocol was developed to resolve problems concerning different WSN environments and their energy efficiency, as well as trust management and routing reliability challenges. EETWRP implements an intelligent trust evaluation method that works with energy-aware path selection and adaptive optimization using swarm intelligence concepts. The TIBR serves as the fundamental element of this protocol since it uses the trust-based model to monitor packet drop rates together with unusual response delays for detecting untrustworthy nodes. Accurate node reliability assessments are included in routing decisions through this approach. Within its framework, the protocol utilizes CLM-EARS to choose energy-efficient paths supported by stable links by assessing cross-layer metrics, including multicast delivery efficiency and link quality, and buffer load change rates against topology alterations.

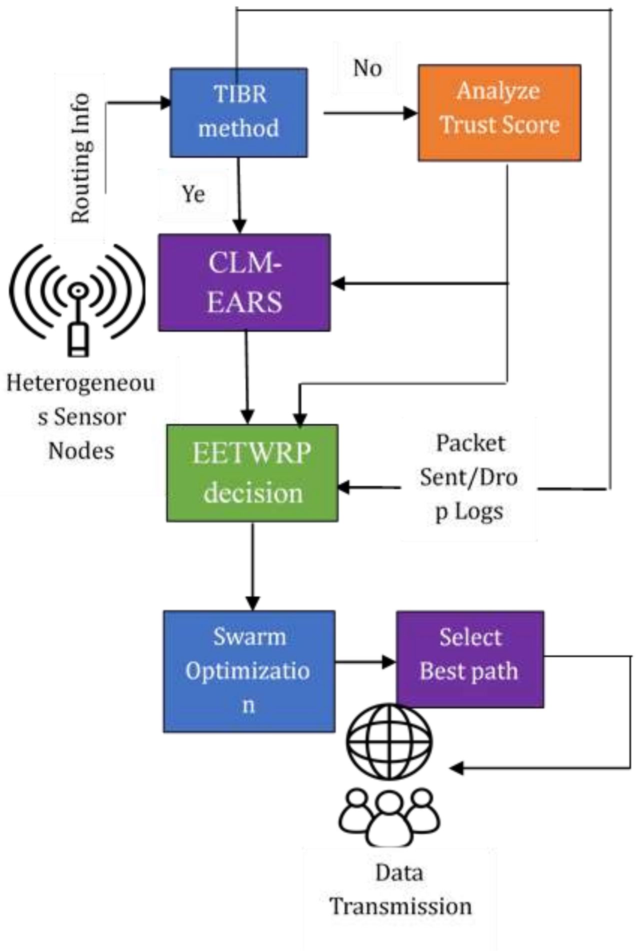

Figure 1. *Architecture diagram of the proposed method*

The heterogeneous sensor nodes start the process by collecting and transmitting data and routing information with packet sent/drop logs. The TIBR method evaluates node trust behavior. An insufficient trust score results in the system diversion to examine trust score parameters before continuing data transmission. After the trust evaluation, the CLM method processes the trusted nodes to determine the best energy-efficient routing paths through residual energy assessment, link quality measurements, and multicast efficiency checks. The decision engine accepts the data, after which trust metrics and energy parameters are processed for routing path guidance. A global optimization technique based on Swarm Optimization operates during this block to identify and choose the most secure and efficient routing path. The "Select Best Path" module implements the optimal route using a swarm intelligence-derived fitness function. The selected path serves as the data transmission avenue because it includes reliable nodes that maintain energy efficiency, thus extending network performance and security measures.

3.1 Traffic Intensive Behaviour Rate (TIBR)

Traffic Intensive Behaviour Rate (TIBR) provides a dynamic trust assessment system that evaluates reliability among sensor nodes found in heterogeneous WSNs. The fundamental trust assessment component, TIBR, performs behavior analysis and monitoring on nodes when they handle different traffic loads. The evaluation mechanism assesses three essential factors, data delivery consistency, response duration, and network reliability, to perform node behavior analysis during demanding network usage periods. The process of behavioral integrity evaluation leads TIBR to produce trust scores, resulting in decision support for network routing that enables dependable nodes to take part in data forwarding. The first-stage trust evaluation plays a vital role in protecting network security and energy efficiency while improving data longevity throughout WSNs. Each node i calculates its Traffic Load through the following calculation at the initial stage,

$$TL_i = P_{sent}^i + P_{recev}^i \qquad (1)$$

The total data processing through the node equals to P_{sent}^i combined with P_{recev}^i based on packet transmission statistics. The recorded workload serves as vital information for executing subsequent behavioral evaluation. In equation 2, the Packet Delivery Ratio (PDR) (D) evaluates the effectiveness with which a node transmits received packets.

$$D_i = \frac{P_{fwd}^i}{P_{recv}^i} \qquad (2)$$

The assessment of packet forwarding success is demonstrated through P_{fwd}^i. A high value of D_i confirms that the node establishes dependable service for routing activities. The Response Time Score (RTS) (S) defines node response efficiency as the reciprocal of average response duration according to equation 3.

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$$S_i = \frac{1}{ART_i} \qquad (3)$$

The response time average in nodes can be calculated using ART_i to obtain the average response time score in a node according to equation 3. A combination of security measures is achieved by calculating the Malicious Drop Rate (MDR) (R) using equation 4 to detect malicious or overloaded nodes.

$$R_i = \frac{P_{drop}^i - P_{norm\_drop}}{TL_i} \qquad (4)$$

The ratio utilizes P_{drop}^i, which signifies the number of packets the node drops, while P_{norm_drop} defines the normal packet drop threshold. The ratio enables the detection of nodes that show unexpected performance characteristics, specifically when traffic levels reach maximum intensity. The node i TIBR Trust Score (B) results from aggregating multiple metrics using assigned weights

$$B_i = w_1 . D_i + w_2 . S_i - w_3 . R_i \qquad (5)$$

The weight coefficients w_1, w_2, and w_3 predetermine how much influence each factor of successful delivery, node speed, and risk behaviors will have in this calculation. The resultant value $B_i \in [0,1]$ is an evaluation metric for CLM-EARS to find trustworthy nodes that minimize energy consumption during route selection. The overall evaluation method ensures better security and decreased energy consumption while improving network reliability throughout heterogeneous wireless sensor networks.

3.2 Cross Layer Multicasting Energy Aware-Route Selection (CLM-EARS)

The data transmission path optimization mechanism in heterogeneous WSNs is accomplished through the Cross Layer Multicasting Energy Aware Route Selection protocol (CLM-EARS). The route selection process within CLM-EARS uses cross-layer information gathering, which integrates data from physical, MAC, and network layer protocols to guide its routing decisions. This comprehensive evaluation method enables the protocol to assess regular routing measurements in conjunction with parameters such as node trustworthiness obtained from B_i and remaining energy, link quality, and multicast efficiency. Implementing energy awareness in CLM-EARS gives preferences to nodes with more residual energy to increase overall network lifetime. CLM-EARS integrates multicast capabilities that enable optimum group communication functionality required by environmental monitoring systems and intelligent infrastructure networks. CLM-EARS runs in real-time to automatically choose the best routes by balancing energy distribution across the network and minimizing retransmissions while avoiding untrusted or weak nodes. The proposed method starts by calculating the residual energy ratio R for node i through a mathematical computation.

$$R_i = \frac{E^i_{residual}}{E^i_{max}} \qquad (6)$$

The equation uses $E^i_{residual}$ to represent the current node energy level and E^i_{max} to define its initial maximum energy capacity. The protocol selects nodes with substantial energy reserves to extend the network lifespan. Equation 7 calculates the link quality indicator Q between nodes i and j.

$$\mathrm{Q_{ij}} = \frac{\mathrm{P^{ij}_{success}}}{\mathrm{P^{ij}_{attempt}}} \qquad (7)$$

The calculation considers $P^{ij}_{success}$, which represents the received packet count, and $P^{ij}_{attempt}$, which shows the total number of transmission attempts. Using this metric, CLM-EARS finds reliable communication connections that facilitate improved network performance through reduced retransmission operations. Equation 8 determines the Multicast Efficiency (ME) evaluation for each node.

$$ME_i = \frac{N^i_{group\_delivered}}{N^i_{group\_attempted}} \qquad (8)$$

This measurement shows the effectiveness of a node in delivering multicast messages. Combined with traffic behavior trustworthiness scores of B_i, all system metrics become part of the Cross Layer Route Score (C).

$$C_i = \alpha . R_i + \beta . D_i + \gamma . Q_{ij} + \delta . ME_i \qquad (9)$$

The components operate within the framework under four weight parameters α, β, γ, and δ that define their relative importance. CLM-EARS bases its routing decision on selecting the most suitable next-hop node using the maximum scoring criterion

$$BR = arg\max_i(C_i) \qquad (10)$$

The selection process leads to adaptive routing, which combines energy-saving measures with security protocols to achieve protocol goals in real-time WSN operations.

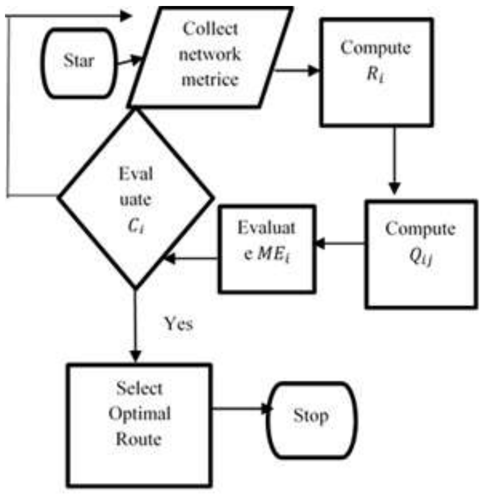

Figure 2. *Flowchart diagram of the CLM-EARS method*

The initial stage of the procedure in figure 2 starts with accepting multicast routing metrics that consist of residual energy, link quality, buffer status, and multicast delivery efficiency. The initial decision block confirms whether the node fulfills the energy standards for secure transmission operations. The node becomes ineligible if its energy level proves insufficient, which results in exclusion from routing duties. The system moves to link quality and delivery ratio assessment if the energy level satisfies the minimum requirement. The system only selects dependable paths that provide fast data delivery times for its forwarding operations. The system evaluates buffer load after link checking to prevent selecting nodes with heavy traffic congestion that could result in delivery problems. The checking procedure for buffer status completes the node performance evaluation, which ensures dynamic network stability by assessing topology adaptability. CLM-EARS routing adds the eligible path to its list for consideration by EETWRP after satisfactory evaluation completion.

3.3 Swarm Intelligence Optimization (SIO)

The dynamic improvement of routing operations and network flexibility depends on Swarm Intelligence Optimization (SIO). The behavior of animal groupings like ants and flocking birds, and bee colonies directs swarm intelligence into distributed decision-making via decentralized communication between nodes instead of centralized governance. The algorithms base swarm optimization helps select optimal routing paths by automatically balancing factors including link quality alongside trust levels (B_i), energy reserves, and multicast performance. The autonomous agents at sensor nodes determine their routing score through CLRS and adjacent network information to help generate global avoidance of congested or unreliable paths. Reliable network routing functions become possible through automatic decision making and organization, enabling operation without human assistance in facing node failures, energy exhaustion, and malicious threats. The decentralized swarm intelligence system maintains scalability through heterogeneous WSN environments, consisting of various node qualities and robust operation. In algorithm 1 we briefly illustrated the SIO algorithm.

Algorithm 1:
Input:
Set of all nodes N, source node S, destination node D, maximum number of iterations (MaxIterations), weight coefficients for energy α, trust β, link quality γ, multicast δ, and set of candidate paths P.
Output:
Best path from S to D with highest C_i score
Start
Set P with random paths from S to D
For each path $p \in P$ do
For each i in p do
Evaluate residual energy ratio R
$R[i] \leftarrow E_r[i]/E_{max}[i]$
Evaluate trust score by utilizing B_i
$B_i[i] \leftarrow CalcualteB_i(i)$
Evaluate average Q_{ij} for outgoing links
$Q_{ij}[i] \leftarrow Avg\left(P_{success}[i][*]/P_{attempt}[i][*]\right)$
Evaluate ME_i
$ME_i[i] \leftarrow N_{group\_delivered}[i]/N_{group\_attempted}[i]$
Evaluate the score of i fitness
$C_i[i] \leftarrow \alpha * R_i[i] + \beta * D_i[i] + \gamma * Q_i[i] + \delta * ME_i[i]$
End for
Evaluate fitness F of p
$F[p] \leftarrow Avg(C_i[i])$ for all i in p
End for
While iteration < MaxIterations do
For each $p \in P$ do
Update velocity on the basis of $F[p]$
New routes of exploration and exploitation
Compute $F[p]$ for updates p
Update Bestpath if new global best found
iteration ← iteration + 1
End while
Return Bestpath
End

The process represents each possible routing path as an intelligent agent and other candidate paths in a swarm. The evaluation process considers a combined fitness score from these specific criteria: $R[i]$, $B_i[i]$, $Q_{ij}[i]$, and $ME_i[i]$ combined with weighting factors of $\alpha, \beta, \gamma,$ and δ. The swarm optimization method starts with randomly selecting various paths that extend from the source to the destination. The swarm optimization system improves path fitness by utilizing velocity-position operations that depend on assessment results from prior strategic decisions. During repeated execution, the swarm arrives at the best possible route by optimizing energy efficiency alongside trustworthiness and communication reliability. A self-regulating, integrating mechanism allows for network response to instant network changes as the method skips congested and compromised nodes to maximize total system longevity.

3.4 Energy Efficient Trust Ware Routing Protocol (EETWRP)

The Energy Efficient Trust Ware Routing Protocol (EETWRP) is a novel routing framework designed to enhance the performance and longevity of heterogeneous WSNs by integrating intelligent trust evaluation and energy-aware routing mechanisms. In environments where sensor nodes differ in capabilities and face energy constraints, EETWRP introduces a multi-layered, adaptive approach that addresses the dual challenges of energy consumption and trust management. EETWRP significantly improves network lifetime, data reliability, and energy efficiency. The proposed method effectively balancing load, avoiding unreliable nodes, and adapting to fluctuating network conditions making it highly suitable for applications like environmental monitoring, and smart cities. The Residual Energy Ratio of a node i is denoted as R_i, ensures energy-aware routing by quantifying available power using equation 11,

$$\mathrm{R_i} = \frac{\mathrm{E_r(i)}}{\mathrm{E_{max}(i)}} \qquad (11)$$

The computing method utilizes the remaining energy ($E_r(i)$) and maximum energy capacity ($E_{max}(i)$) of individual nodes. The trustworthiness evaluation of nodes is determined by the traffic-intensive behavior rate D_i, which detects irregularities in delivery patterns and latencies through equation 12.

$$R_i = \frac{E_r(i)}{E_{max}(i)} \quad (12)$$

The number of dropped and transmitted packets is denoted by$P_d(i)$ and $P_s(i)$, and communication delay irregularities are assessed through $RTT_a(i)$ and $RTT_t(i)$. The Q_{ij} link quality indicator shows that the network relies only on dependable connections, which depend on successful packet transmission from node i to node j.

$$Q_{ij} = \frac{P_z(i,j)}{P_b(i,j)} \quad (13)$$

The value of $P_z(i,j)$ refers to delivery successes while $P_b(i,j)$ counts total transmission efforts between nodes i and j. The multicast efficiency ME_i for group-based communication can be determined through Equation 14.

$$ME_i = \frac{N_{gd}(i)}{N_{ga}(i)} \quad (14)$$

The total multicast attempts consist of $N_{ga}(i)$, while $N_{gd}(i)$ represents successful multicast packets. The load balance penalty L_i functions to discourage network traffic through nodes experiencing high congestion volumes.

$$L_i = \frac{Q_c(i)}{Q_t(i)} \quad (15)$$

The algorithm evaluates candidate nodes through the formula, with $Q_c(i)$ representing the current queue length and $Q_t(i)$ representing the acceptable threshold. A_i of the adaptability index selects stable nodes that remain fixed during topology changes.

$$A_i = \frac{1}{1+\Delta C_t(i)} \quad (16)$$

This rate is indicated by $C_t(i)$ in the equation. The scoring model assesses candidate nodes using the composite metric expressed by equation number 17.

$$G_i = w_1.R_i + w_2.D_i + w_3.Q_{ij} + w_4.ME_i - w_5.L_i + w_6.A_i \quad (17)$$

The algorithm includes six adjustable weights indicated by w_1 through w_6, which control parameter importance according to network objectives. The evaluation of potential routes for route discovery depends on the fitness metric in equation 18.

$$\mathrm{F(p)} = \frac{1}{|\mathrm{p}|} \sum_{\mathrm{i \in p}} \mathrm{G_i} \quad (18)$$

The path length measurement uses $|p|$ to represent this value. The complete framework enables EETWRP G_i to operate dynamically under network changes and identity untrustworthy nodes. It delivers energy-efficient data with enhanced security for critical applications, including smart cities and environmental monitoring networks.

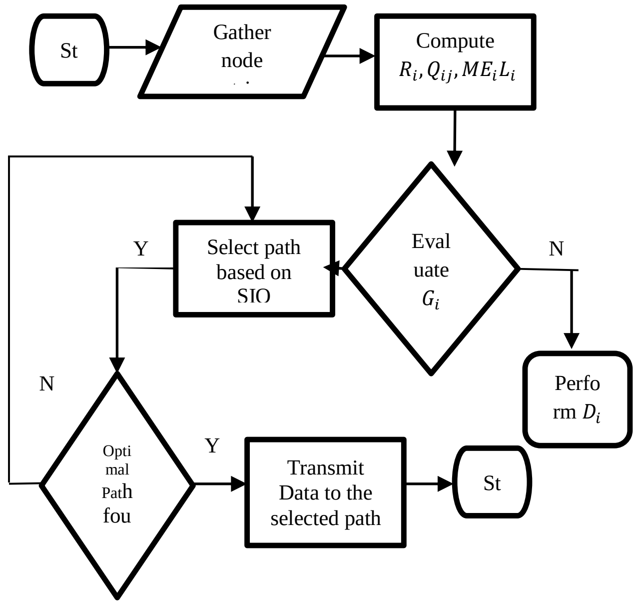

Figure 3. *Flowchart diagram of the EETWRP*

The routing process begins by gathering trust levels and node statistical data from figure 3 before obtaining measurements for residual energy and packet delivery statistics from each node. The EETWRP Decision Module selects eligibility from nodes that pass trust and energy evaluations. The Swarm Intelligence Optimization engine processes the candidate nodes to pick the most optimal path based on real-time trust and energy values through a nature-inspired metaheuristic operation. The protocol implements the optimized path for data transmission, ensuring reliable and energy-efficient data communication throughout the WSN.

4. Result and Discussion

The section compiles a comparative analysis to demonstrate how the proposed EETWRP performs better regarding routing efficiency and network sustainability than EFRP, FL-LEACH-PSO, HEEL, and SER. Simulation results reveal that EETWRP establishes superior performance in Packet Delivery Ratio (PDR), network lifetime and energy efficiency, end-to-end delay and energy consumption and throughput across heterogeneous WSN environments compared to existing protocols. The multi-metric decision flow enhances data transmission integrity by fighting malicious nodes and congested paths, reducing overall data loss.

Table 2. *Simulation Parameter*

Parameters	Value
Simulation Area	100m x 100m
No of Sensor Nodes	100
Packet Size	4000 bits
Simulation Environment	NS2-Simualator
No of Rounds	500 – 1000 rounds
Energy for transmission	50 nJ/bit
Energy for Reception	50 nJ/bit

A comprehensive NS2 simulation environment demonstrated the performance evaluation for the proposed EETWRP, as shown in Table 2. The simulation occurred in a 100m × 100m square area containing 100 heterogeneous sensor nodes randomly positioned. The sensor nodes were programmed to exchange 4000-bit data packets representing standard wireless sensor network communication. The simulated rounds lasted between 500 and 1000 seconds to show network patterns and evaluate network operational duration. The implemented energy model follows the first-order radio model, which attributes a 50 nJ/bit cost for data transmission and reception processes.

Table 3. *Performance Analysis of Network Lifetime*

Rounds	EFRP	FL-LEACH-PSO	HEEL	SER	EETWRP
500	180	220	200	210	260
600	170	210	195	200	250
700	160	205	190	195	240
800	150	190	180	185	230
900	140	180	170	175	220
1000	130	170	160	165	210

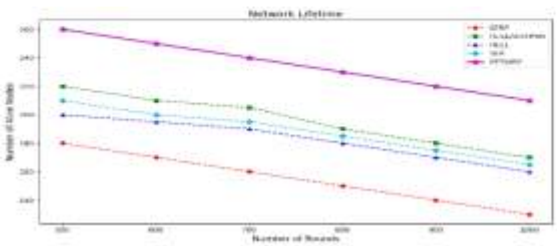

Figure 4. *Performance Analysis of Network Lifetime*

Figure 4 and table 3 highlight the proposed EETWRP's effectiveness in contrast with existing routing protocols such as EFRP, FL-LEACH-PSO, HEEL, and SER. EETWRP maintains superior performance than all other protocols throughout every testing cycle of the simulation. For instance, at the 1000th round, EETWRP retains approximately 210 alive nodes, significantly higher than 130 in EFRP, 170 in FL-LEACH-PSO, 160 in HEEL, and 165 in SER. EETWRP achieves this performance gain from its trust evaluation and energy-based routing mechanisms, which work together to reduce overall energy waste, establish routing balance, and protect network node integrity.

Table 4. *Performance Analysis of PDR*

Packet Size (bits)	EFRP	FL-LEACH-PSO	HEEL	SER	EETWRP
1000	81.4	85.2	83.6	84.2	**92.8**
2000	78.9	83.7	80.4	82.2	**90.4**
3000	74.8	80.4	78.7	79.7	**88.6**
4000	70.2	77.1	75.1	76.2	**85.4**

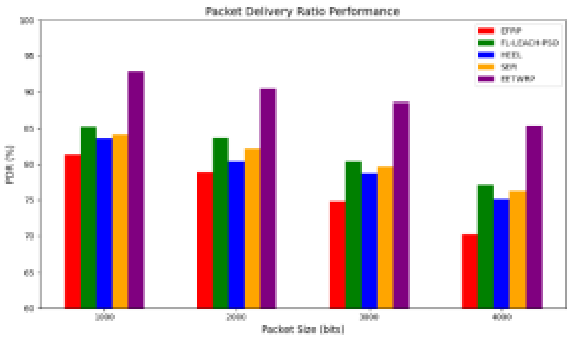

Figure 5. *Performance Analysis of PDR*

Figure 5 and table 4 highlight the proposed EETWRP's superior reliability over traditional routing protocols such as EFRP, FL-LEACH-PSO, HEEL, and SER. EETWRP's performance benefit results from its route selection mechanism based on energy and trust-related metrics, which picks reliable, stable packet-transmission routes. EETWRP effectively reduces packet loss and enhances transmission reliability under increased data transmission demand, thus enabling its application in crucial mission areas for wireless sensor networks.

Table 5. *Performance Analysis of End-to-End Delay*

Methodologies	Avg Delay (ms)
EFRP	310
FL-LEACH-PSO	270
HEEL	260
SER	250
EETWRP	180

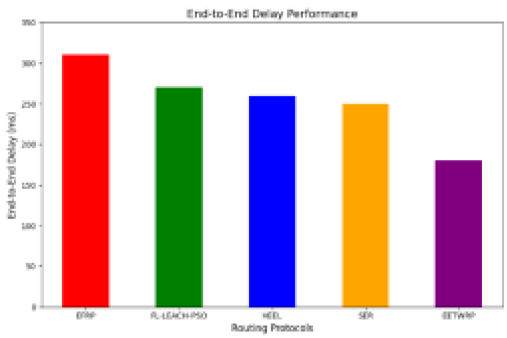

Figure 6. *Performance Analysis of End-to-End Dealy*

Figure 6 together with table 5 demonstrates that EETWRP performs better than EFRP, FL-LEACH-PSO, HEEL and SER in terms of efficiency. The total end-to-end delay measurement took 180 ms to transmit data successfully across the network through a 50 nJ/bit energy model that considered transmission and reception as power-consuming operations. The experimental results demonstrate that EETWRP reduces end-to-end delay performance to 180 ms, while SER and HEEL attain 250 ms and 260 ms, FL-LEACH-PSO uses 270 ms, and EFRP requires 310 ms. The effectiveness of EETWRP routing decisions accounts for lower delays because the system makes efficient energy-conscious selections through optimal paths that avoid congested or untrusted nodes.

Table 6. *Performance Analysis of Energy consumption*

Sensor Nodes	EFRP	FL-LEACH-PSO	HEEL	SER	EETWRP
25	0.92	0.85	0.81	0.79	0.65
50	1.78	1.68	1.55	1.48	1.12
75	2.55	2.41	2.25	2.10	1.75
100	3.45	3.25	3.02	2.87	2.38

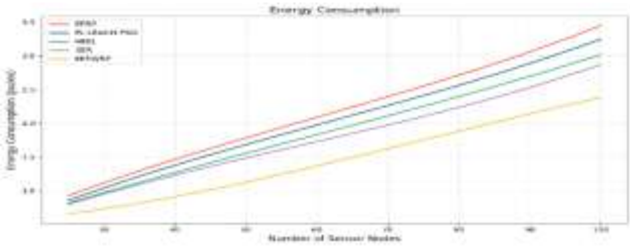

Figure 7*. Performance Analysis of Energy Consumption*

The figure 7 and table 6 compare Energy Consumption between EFRP, FL-LEACH-PSO, HEEL, SER and the proposed EETWRP as the sensor nodes range from 25 to 100. Results demonstrate that EETWRP maintains sustainable energy efficiency levels through all changes in sensor node densities. The performance enhancement of EETWRP results from its trust-aware routing and energy-efficient path selection processes that redistribute network traffic to prevent fatal damage to energy-limited nodes. The spaced graph data indicates that EETWRP demonstrates both efficient operation and flexible use in diverse WSN situations and presents a promising option for power-sensitive implementation areas like environmental observations and intelligent construction frameworks. Figure 8, and table 7, shows researchers evaluating the Throughput behavior of EFRP, FL-LEACH-PSO, HEEL, SER, and the proposed EETWRP throughout different simulation rounds spanning 500 to 1000. The

Table 7. *Performance Analysis of Throughput Performance*

Rounds	EFRP	FL-LEACH-PSO	HEEL	SER	EETWRP
500	115	130	138	142	155
750	122	138	144	150	168
1000	130	145	152	158	182

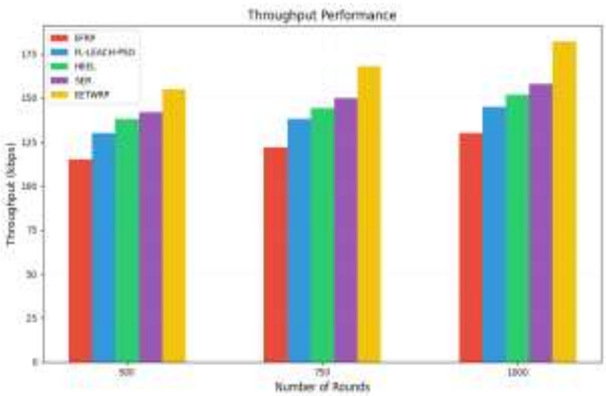

Figure 8. *Performance Analysis of Throughput Performance*

experimental results show that EETWRP exceeds all current routing approaches by consistently achieving better throughput at every simulation round. EETWRP achieves better performance results by combining its adaptive trust-based routing with efficient load distribution and energy-aware path optimization to lower packet loss and enhance communication reliability.

5. Conclusion

In conclusion, the EETWRP represents a new routing framework that unifies trust management approaches with energy-aware routing and swarm intelligence optimization functions to optimize heterogeneous WSN performance and operational lifetime. TIBR and CLM-EARS help the protocol solve routing congestion, energy depletion, and malicious node behavior. Simulation results showed that the EETWRP achieved better performance than conventional methods in all assessed metrics, including network lifetime, PDR, energy consumption, throughput, and end-to-end delay. Electronic EETWRP features adaptive intelligence to pick the best routes for data transfer among resource-constrained WSN networks because of its security capabilities, thus making it perfect for applications like environmental observation. The protocol EETWRP provides an encouraging basis for creating future routing protocols that maintain operational excellence and defensiveness in networks.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
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