

Original Article

Tent Mapping Reverse Learning-Elk Herd Optimization Algorithm for Trust-aware and Energy Efficient Clustering and Routing in Wireless Sensor Networks

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Received: 18 November 2025

Revised: 20 February 2026

Accepted: 28 February 2026

Published: 29 April 2026

Abstract - Wireless Sensor Networks (WSNs) emerge as an important development for tracking and monitoring applications in a wide range. WSN captures environmental information, acquires data, and communicates to a sink node for processing and analysis. The important task in deploying WSNs is to enhance the network lifetime, particularly when the energy is constrained. Moreover, maintaining trust in WSN becomes complex, which establishes consistent trust relationships among nodes that are important for achieving reliable communication. Hence, this research proposes a new approach of the Tent Mapping Reverse Learning-Elk Herd Optimization Algorithm (TMRL-EHO) for energy-effective Cluster Head (CH) selection and routing in WSN. In TMRL-EHO, an objective value for CH selection considers multiple factors, including distance among nodes, trust, traffic rate, density of the cluster, and remaining energy. The simulation findings indicate that an introduced approach enhances a better throughput of 97% with 500 nodes, as compared to the existing Quantum Behavior and Gaussian Mutation-assisted Archimedes Optimization Algorithm (QGAA).

Keywords - Cluster Head, Elk Herd Optimization Algorithm, Energy efficiency, Tent Mapping Reverse Learning, Wireless Sensor Network.

1. Introduction

Wireless Sensor Networks (WSNs) primarily deploy a monitoring system, which consists of diverse distributed Sensor Nodes (SNs) for various applications that include concentrating on data gathering, processing, and transformation [1]. Over the years, WSNs have evolved into a crucial technology for enabling intelligent decisions through recent computational competencies across various expanded applications [2, 3]. Through advancements in wireless communication and micro-electronics, WSNs have enhanced their footprint over various fields such as healthcare, underwater communication, agriculture, Internet of Things (IoT), and disaster management [4, 5]. The clusters are formed to arrange arbitrarily designed nodes and routing protocols that involve Cluster Members (CMs) and Cluster Head (CH). Basically, CH is crucial for the network due to its more capabilities that include data acquisition, aggregation, transmission, and cluster management than CMs [6, 7]. Clustering is a famous approach for enhancing energy efficiency; it helps identify an optimal path between the receiver and the transmitter [8]. In WSN, there is a binary way for each cluster, which contains an individual CH boundary among its individual CMs and Base Station (BS) or sink node.

The CH transmits data to BS using a multi-hop hierarchical clustering approach during inter-cluster communication, while each CM sends data to its particular CH through a single-hop method during intra-cluster transmissions [9, 10].

The energy-efficient protocols extend the network sustainability, which is needed for practical applications of WSNs. Over the past years, more clustering and routing protocols have been introduced to address this issue, which are assumed to be an effective approach [11]. WSNs are inherently vulnerable to various security threats because of the open communication medium as well as exposure to traffic analysis, security breaches, and physical attacks. [12, 13]. In this framework of WSN, trust management mechanisms assess and estimate the trustworthiness of nodes according to their previous behaviors and the recommendations (reputation feedback) received from other nodes [14]. Deploying the trust management devices precisely personalized to WSN is a problematic task. As compared to conventional networks, the WSNs function under resource constraints, including limited energy, processing power, and memory capacity [15, 16]. Furthermore, the heterogeneous nature of Wireless Sensor Networks (WSNs) with nodes frequently joining and leaving



the network makes trust management increasingly challenging [17]. Attaining security and energy efficiency causes the researcher to concentrate on the cluster-assisted trust routing approaches [18]. Moreover, various researchers have employed methods that deploy secure and suitable clustering with routing approaches in WSN, but these methods still need to be improved [19]. Hence, the researchers utilize a meta-heuristic approach to convert the CHs and a routing path selection into an optimization issue through a particular aim function. Consequently, the process iterates until the optimal problem-solving function is identified [20].

1.1. Problem Statement and Objective

WSNs pose significant challenges in ensuring both energy efficiency and communication trustworthiness during data transmission. Conventional clustering and routing approaches often suffer from premature convergence, high energy consumption, and vulnerability to malicious nodes, which constrain the network's sustainability and reliability. The aim of this manuscript is to design and implement a Tent Mapping Reverse Learning–Elk Herd Optimization (TMRL-EHO) algorithm that enhances energy efficiency, trust-based routing, and cluster stability in WSNs.

The important development of this research is arranged as follows:

- This research proposes a TMRL-EHO algorithm that integrates tent mapping and reverse learning to overcome local optima stagnation to enhance the convergence in CH selection and routing.
- Developed a multi-objective fitness function, combining trust, distance, residual energy, cluster density, and traffic rate to ensure both secure and energy-balanced communication.
- Demonstrated superior energy effectiveness that enhances network sustainability and greater data reliability, which is compared to FFO, GWO, RDA, and conventional EHO through extensive simulation.

This research paper is positioned as follows. Section 2 provides related works. Section 3 designates the proposed methodology. Section 4 presents the simulation results, and a conclusion is presented in Section 5.

2. Related Works

Recent research conducted trust and energy optimization in WSN, each proposed various approaches. This portion accomplished a development for implementing the introduced energy optimization method by reviewing the existing research, which determined its limitations and highlighted the prevailing limitations in WSN. Hosseinzadeh et al. [21] implemented a Cluster-based Trusted Routing approach through the Fire Hawk Optimization approach (CTRF) for network security enhancement through the consideration of

energy nodes in WSN. The significant characteristics of the trust function were defined using exponential constants trust parameters, which included weighted redundancy rate, energy state, and weighted reception rate. Furthermore, an implemented approach designed the fire hawk optimization-assisted clustering approach for CH selection from an individual group. Eventually, the CTRF approach decided on an inter-cluster routing way by a trusted routing approach for data transmission in CH to BS.

Kumar and Srimanchari [22] introduced the energy- and security-aware data aggregation as well as an efficient routing approach for WSNs. The introduced approach was based on Quantum Behavior and Gaussian Mutation-assisted Archimedes Optimization Algorithm (QGAOA). The introduced method comprised various parts, such as the formation of the cluster, CH selection, and optimal routing. Primarily, the clusters were formed through a Voronoi-included K-means clustering algorithm. After the selection of CH, the optimal routing was determined through the QGAOA approach.

Shivakumaraswamy et al. [23] presented the Trust-assisted Modified Moth Flame Optimization (T-MMFO) approach for secure cluster-assisted routing in WSN. The presented T-MMFO approach was leveraged for CH selection and routing for the acquisition of secure communication across the network. The presented T-MMFOA offered an improved security over malevolent attacks through an enhanced energy efficiency. The significant target of T-MMFOA was acquired to secure data transmission and enhance the life expectancy of WSN.

Babu and Geethanjali [24] developed a trust-assisted and energy-efficient optimized cluster routing approach through the Trust Index Optimized CH Routing (TIOCHR) approach. CH selection was inclined through energy backup, Packet Delivery Ratio (PDR), and packet consistency were examined as important security metrics. To ensure both consistency and trustworthiness, the most reliable path was selected from all possible routes.

Soltani et al. [25] implemented the Trust-aware and Energy-effective Data Gathering (TEDG) approach to sufficiently collect the information from sensor nodes. An implemented approach involved diverse steps such as clustering, model development, and watchdog selection. These steps were modeled as optimization issues and addressed through Particle Swarm Optimization (PSO). A watchdog selection phase was involved in varying distances because the number of watchdog nodes was unknown. Unknown particle depiction and starting mechanisms were designed to maintain and manage these particles effectively.

Vinitha et al. [26] developed a combination of Taylor series and Cat Salp Swarm Approach named as Taylor C-SSA

for energy-effective multi-hop routing in WSN. The developed method tolerated various phases that included CH selection and data communication. Primarily, the Low Energy Adaptive Clustering Hierarchy (LEACH) protocol leveraged the energy-efficient CH selection for effective data communication through a greater energy. Additionally, the communicated data across CH was forwarded to BS through the chosen optimal hop. Moreover, the trust-based multi-hop routing was performed by an expansion of the trust approach. Although the Taylor series ensured a precise estimation of the basic unit, a developed method was ineffective in optimizing the selection of efficient paths.

Renuga Devi and Sethukarasi [27] implemented the Trust-Based Energy-Based Routing (TBEBR) method for energy utilization reduction, which improved the network sustainability as well as security measures. The implemented method was proposed to determine an energy-effective minimum path routing selection, which was designed to simplify communication through less energy tiredness. The Mixed Integer Linear Programming (MILP) method was selected to design the least energy utilization in the WSN method. A TBEBR-assisted WSN routing that involved less resource consumption, incomplete communication, and fewer energy restrictions.

2.1. Research Gap

The existing optimization-based clustering protocols primarily focus on either energy conservation or trust management, but rarely succeed in achieving both simultaneously. Algorithms such as FFO and RDA lack diversity maintenance and often get trapped in local minima during CH selection. Furthermore, most existing trust mechanisms rely solely on static node behaviors without dynamic adaptability, which leads to unreliable data transmission in hostile environments. However, the conventional Elephant Herding Optimization (EHO) algorithm suffers from slow convergence and poor exploitation in the later stages. Therefore, a significant gap still exists in designing a chaos-enhanced, trust-driven metaheuristic that dynamically balances exploration and exploitation while optimizing energy and trust for secure, long-lasting WSN operations.

3. Proposed Method

In this research, the trust-aware, energy-effective clustering and routing in WSN is performed. This research comprises various significant steps, such as network model, energy model, trust mechanism, clustering, and routing using the proposed EHO approach and data transmission. Figure 1 outlines the schematic flow of the proposed approach.

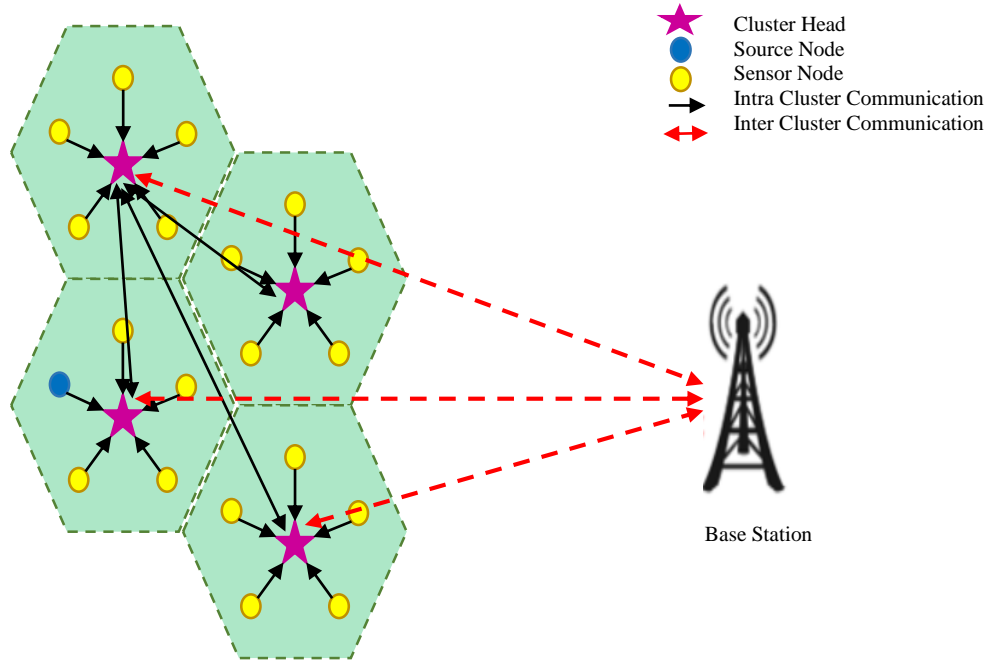


Fig. 1 Diagrammatic flow of the network model of WSN

3.1. Network Model

During deployment of the network, each SN ($sn_1, sn_2, \dots, sn_i, \dots, sn_N$) is designated as either a Cluster Head (CH) or a Cluster Member (CM). The CMs collect environmental data and transmit the acquired information to the respective CH. Therefore, the CH employs a data

aggregation task and transmits to the Base Station (BS) or sinks by a particular route. After an aggregation of data collected by the sink, the sink node estimates the data and delivers appropriate guidelines according to network restrictions [28]. The consideration of a network is concise as trails:

- The BS is fixed, and its position is prearranged in a network.
- The BS involves unconstrained energy as well as greater processing power.
- Each node is made aware of the BS position within the network.
- Each node is homogeneous, and it is identified by a particular ID, such as ID_{SN_i} .
- The nodes are immobile and are arbitrarily dispersed on a network.
- The placement system is deployed on each node for position identification.

3.2. Energy Model

In WSN, the major challenge is to minimize the energy consumption of nodes because they are powered by small batteries that are difficult to recharge and replace. An energy model is the most crucial standard, which needs to be understood and optimized to minimize the power consumption of each node in a network [29]. Each node employs diverse tasks such as sensing, processing, storing the data, and transmitting. The transmission task is an energy-overwhelming task in SN. Based on the energy system, the utilized energy replaces each k -bit frame among SN_i (receiver) and SN_j (sender), which is estimated in Equation (1).

$$E_{TX}(k, d) = \begin{cases} E_{elec} \times k + E_{fs} \times k + d^2, & d < d_0 \\ E_{elec} \times k + E_{mp} \times k + d^4, & d \geq d_0 \end{cases} \quad (1)$$

Furthermore, the energy is produced through SN_j , which is provided in Equation (2) as follows.

$$E_{RX}(k, d) = E_{elec} \times k \quad (2)$$

Here, E_{fs} , E_{mp} and E_{elec} demonstrates that the energies are consumed through the amplifier in free space, the amplifier in the multi-path model, and the electrical board individually. d_0 illustrates a distance threshold.

3.3. Cluster Formation

In the proposed trust- and energy-based CH selection, the routing approach uses the EHO algorithm in which optimization is performed based on parameters such as the node's residual energy, trust score, and distance from the node to the BS. The optimization results in the CH selection into multiple phases, which include too large, large, medium, small, and too small, representing various levels of suitability. This strategy aims to reduce the energy utilization of Sensor Nodes (SNs) while significantly enhancing the overall lifetime and stability of the WSN.

3.4. Trust Computation

In practice, a trust approach is integrated through an optimization approach for selecting the CH to eliminate

impostors from diverse malevolent outbreaks. In an introduced model, the intra-cluster transmission and SN communicate the sensitive data to CH through a greater trust value. A trust is estimated through various trusts, such as direct, indirect, and total.

3.4.1. Direct trust

The SN i directly communicates with various node j , by estimating a direct trust using Equations (3) to (5), which integrates the node trust as well as packet drop influence in the time interval t .

$$DT = (1 - \alpha)NT_{(i,j)}(t) + PDF_{(i,j)}(t) \quad (3)$$

$$NT_{(i,j)}(t) = \frac{P_{rv}(i)}{P_{fd}(j)} \quad (4)$$

$$PDF_{(i,j)}(t) = \frac{R_X(t)}{T_X(t)} \quad (5)$$

Where DT stands for Direct Trust; NT illustrates Node Trust; $P_{rv}(i)$ means node j , which obtains the packets from node i ; $P_{fd}(j)$ denotes node y transmitting the packets to another node. The packet drop occurs during the communication procedure, resulting in data loss. $R_X(t)$ demonstrates the number of packets obtained through each SN in time t . $T_X(t)$ illustrates the number of packets communicated through each SN in time t , which lies in the range between 0 and 1.

3.4.2. Indirect Trust

Node estimates the trustworthiness of a node j with respect to packet size, but it lacks historical communication for node j . In this illustration, node i acquires the trust degree of node j 's from its nearest, which is identified through Equation (6).

$$IT(i) = \frac{1}{K} \sum_{j=1}^K DT(j) \quad (6)$$

Here, $IT(i)$ specifies an indirect trust of the node i , and $DT(j)$ illustrates a direct trust for data j .

3.4.3. Total Trust

In the proposed framework, an entire trust value is estimated through the following Equation (7). A trust score is fixed in a range between 0 and 0.5, which illustrates the minimum trust score from 0.6 to 1, which demonstrates the greatest trust score.

$$TT = \beta DT + \gamma IT \quad (7)$$

In the initial round, each node preserves the path of its energy value as well as allocates it to adjacent nodes. Each initial trust value of a node is one, thereby reflecting a similar level of trust among all nodes.

3.5. Cluster Head and Route Path Selection using EHO

The clustering process is carried out after CHs are selected in the initialized network. An adjacent CH is merged through non-cluster members in this procedure to design a cluster [30].

The metaheuristic approaches are often helpful as well as effective in solving large optimization issues. The significant advantage of meta-heuristics is their capability to perform local and global discoveries with excellent performance, as well as less input required for maintaining restrictions.

Thus, this research considers the EHO [31, 32] approach for selecting energy-efficient clustering and routing. The mathematical depictions of the EHO algorithm are described as follows.

3.5.1. Initialization

Primarily, the Elk Herd (EH) is formed, representing a population-based problem-solving approach that consists of two main groups, such as bulls and harem. The location of each Elk is formulated in Equation (8).

$$x_j^i = lb_j + (ub_j - lb_j) \times rand \tag{8}$$

Where x_j^i illustrates the location of i th Elk in j th dimension; ub_j and lb_j illustrates the upper and lower borders of j th dimension. $rand$ illustrates the equally distributed arbitrary value in a range between 0 and 1. A fitness function for each Elk's problem-solving is identified. The supremacy of Elk in EH is hierarchical, which is based on objective functions.

3.5.2. Rutting Season

At this season, the EH begins family groups according to the bull ratio B_r , where the total count of relations is estimated as $B = \lfloor B_r \times N \rfloor$. In the herd, the bulls are chosen based on the objective function.

Particularly, the greatest B individuals with the highest objective function values in the EH algorithm are chosen as bulls, which is formulated in Equation (9) as follows.

$$B = \arg \min_{j=(1,2,\dots,B)} f(x^j) \tag{9}$$

A roulette wheel selection approach is performed to assign the harems to each bull in a herd, where the harems are dispersed between the assemblies in a number of objective functions, which is formulated in Equation (10) as follows.

$$p_j = \frac{|f(x^j)|}{\sum_{k=1}^B |f(x^k)|} \tag{10}$$

Where p_j illustrates a selection probability of each bull x^i in B , $f(x^k)$ illustrates a complete objective function of the bull x^i ; $\sum_{k=1}^B f(x^k)$, which illustrates the total complete fitness function of each bull, and B means the parameter utilized to estimate the count of intimate assemblies.

3.5.3. Calving Season

In this phase, the calves $x_i^j(t+1)$ in all harems are initially regenerated according to the characteristics of the bull; $x^{h_j}(t)$ as well as mother harem $x_i^j(t)$. If the calf $x_i^j(t+1)$ provides a similar metric i as its bull father in the harem, a calf is regenerated in Equation (11) as follows.

$$x_i^j(t+1) = x_i^j(t) + \beta \left(x_i^{h_j}(t) - x_i^j(t) \right) + \gamma \left(x_i^k(t) - x_i^j(t) \right) \tag{11}$$

Where $x_i^j(t+1)$ illustrates an i th elk in j th dimension at $t+1$ iteration; $x_i^j(t)$ illustrates the arbitrarily chosen Elk from a herd, where $k \in (1, 2, \dots, EHS)$ and α illustrates an arbitrary value in a range between 0 and 1, which identifies a proportion of stochastic elements performing in an unknown calf replica.

Once a calf inherits similar characteristics to its mother, it acquires features from both its father bull and its harem mother. This relationship is expressed in Equation (12) as trails:

$$x_i^j(t+1) = x_i^j(t) + \left(x_i^{h_j}(t) - x_i^j(t) \right) + \gamma \left(x_i^r(t) - x_i^j(t) \right) \tag{12}$$

Where $x_i^{h_j}(t)$ specifies a bull of harem j ; r illustrates a metric of an arbitrarily chosen bull from the present group that is $r \in B$; γ and β illustrate the binary arbitrary values in a range between 0 and 2. Then, the congenital traits from priority produced calves are arbitrarily identified.

3.5.4. Selection Season

During this phase, all members, including bulls, harem, and calves, are integrated into a unified problem-solving space. Particularly, a population matrix EH keeps a present bull's group as well as harems, whereas the unknown problem-solving matrix EH' keeps the calves fused into a provisional matrix EH_temp .

Then, each candidate in EH is sorted in sequential order according to the objective function, and the greatest EHS candidates are chosen as the upcoming generation population to replace the actual population matrix EH . Figure 2 illustrates a flowchart of the proposed EHO approach.

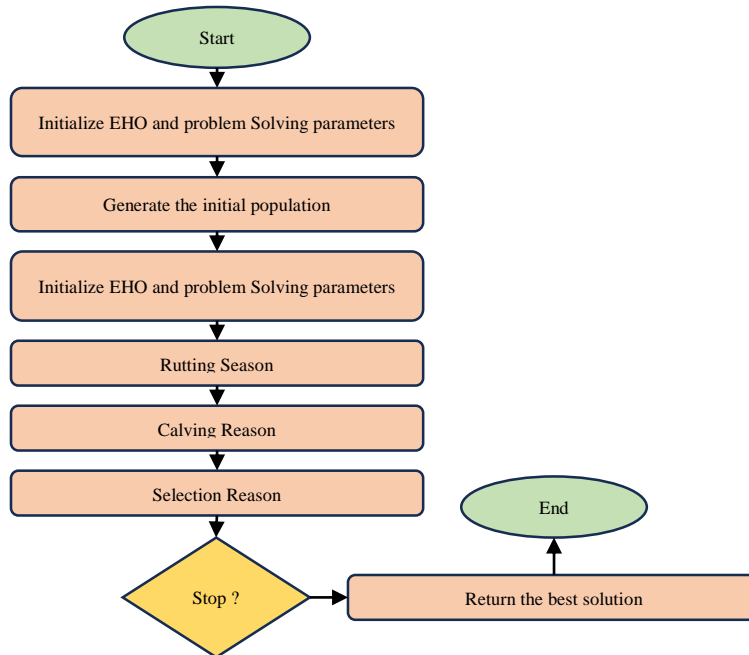


Fig. 2 Flowchart of the proposed method

3.5.5. Tent Mapping Reverse Learning

Because of the tendency of standard EHO to get trapped in local optima, which relatively slows down the convergence rate, this research introduces an enhanced strategy by integrating the TMRL mechanism into EHO. This enhancement aims to achieve optimal trust and energy-effective clustering as well as routing in WSN. Tent mapping is a piecewise linear mathematical mapping characterized by its tent-shaped structure. Its visual depiction resembles a tent, which has been identified as having larger applications over diverse domains. The important characteristics of this mapping lie in its capability to employ linear transformations through various slopes across various numerical intervals; hence, it generates rich and complex dynamic activities.

In swarm intelligence optimization algorithms, population initialization plays a crucial part in determining the excellence and diversity of the search procedure. A well-initialized population enhances solution diversity and accelerates the convergence of the optimization approach. Due to its superior uniformity and ergodicity, relative to other mapping methods, tent mapping is employed in this research to effectively initialize the EH population.

Moreover, to improve the excellence of the initialized population, a reverse learning mechanism is combined. This mechanism refines and filters the initial population to select the most promising candidates, thereby creating a more favorable environment for the following optimization and enhancing the rapid convergence for the proposed approach. The mathematical depictions of tent mapping are provided in Equation (13).

$$X_{n+1} = \begin{cases} 2X_n, & 0 \leq X_n \leq \frac{1}{2} \\ 2(1 - X_n), & \frac{1}{2} \leq X_n \leq 1 \end{cases} \quad (13)$$

Considering the D-dimensional EH population with candidate solutions $\{X_1, X_2, X_3, \dots, X_D\}$, where each $X \in [lb, ub]$. The respective opposite problem-solving is described as $X' = \{X'_1, X'_2, X'_3, \dots, X'_D\}$, each component is estimated as $X' = lb + ub - X_i$. A complete beginning of the EH population through opposition understanding of tent mapping is divided into diverse phases:

Step 1: Utilize a tent mapping for the location initialization of the EH $x_{ij} (i = 1, 2 \dots D, j = 1, 2 \dots N)$, where N illustrates the population extent.

Step 2: Produce opposite candidate locations x_{ij} according to the definition of reverse problem-solving for an initial population location of EH.

Step 3: Arrange the candidate locations produced through the binary approaches based on objective values, then choose one with the greatest objective as male EH and one with the second greatest as female EH.

The proposed TMRL improves conventional TMRL by integrating nonlinear chaotic control and fitness-adaptive reversal strength. Conventional tent mapping suffers from limited diversity when the population gradually converges, leading to repetitive or symmetric exploration patterns. To enhance the diversity and ignore periodic stagnation, the nonlinear distortion term is estimated in Equation (14).

$$T'_{r,\beta}(x) = \begin{cases} rx^\beta, & 0 \leq x \leq 0.5 \\ r(1-x)^\beta, & 0.5 \leq x \leq 1 \end{cases} \quad r \in (1,2], \beta > 0 \quad (14)$$

Where β controls the nonlinearity intensity, rather than a fixed linear opposition, which generates the reverse solution, consider the fitness quality of each candidate, which is calculated in Equation (15).

$$X_d^{ETMRL} = L_d + U_d - X_d + \lambda(T'_{r,\beta}(x_d) - 0.5)(U_d - L_d) \quad (15)$$

Where $\lambda \in [0,1]$ specifies an adaptive weight inversely proportional to the fitness value, which is formulated in Equation (16).

$$\lambda = \frac{f_{\text{worst}} - f_i}{f_{\text{worst}} - f_{\text{best}} + \epsilon} \quad (16)$$

By proposing a nonlinear exponent β in the tent map (Equation 14), TMRL dynamically distorts the chaotic sequence, thereby preventing premature periodicity and producing richer, fine-grained sampling of the search space. Furthermore, Equation (15) fuses the chaos-generated offset with an adaptive scaling factor λ , which depends on the individual's fitness quality.

This allows poorer solutions to explore the search space more aggressively, while elite solutions focus on local exploitation with minimal perturbation. Together, these mechanisms attain a self-balanced population, and the diversity is preserved without compromising convergence precision. In the context of EHO, ETMRL accelerates the discovery of high-quality cluster-head candidates, which mitigates local stagnation and enhances overall robustness as well as stability of convergence over more runs.

3.6. Transmission of Data

Both single- and multi-hop communication approaches utilized in clustering methods often result in energy loss between CMs. This issue occurs at some SN in the network and minimizes the overall network's lifetime. The energy depletion of sensor nodes located closest to the Base Station (BS) is higher than that of the other nodes, leading to a problem known as the hotspot issue in clustering protocols.

3.7. Fitness function

The variety of cluster nodes is identified by leveraging a multi-objective fitness task. This research considers an optimal CH among SN by using a new fitness function, which estimates the distance among nodes, trust, traffic rate, density of the cluster, and remaining energy. By combining these factors, the proposed fitness function offers a holistic balance between energy efficiency, load distribution, and communication reliability.

3.7.1. Distance among Nodes (FF₁)

The sensors in WSNs utilized the energy while broadcasting the data from the transmitter CH and BS. An energy utilization of SN is directly proportional to the distance.

Thus, it is required to choose the CH, which contains the minimum distance from CM and BS. The distance among nodes is formulated in Equation (17).

$$FF_1 = \sum_{i=1}^D \text{dis}(CH_i, BS) \quad (17)$$

Where $\text{dis}(CH_i, BS)$ illustrates the distance between CH and BS of node i .

3.7.2. Trust (FF₂)

The trust is a significant characteristic in an aim function to reinforce the safety against malicious activities in CH selection.

A trust depends on the activity of packet transmission, which represents a relationship among transmitted (TDP_{ij}) and received (RDP_{ij}) data. A trust is used for eliminating the Distributed Denial of Service (DDoS) attacks during data packets, which is estimated in Equation (18).

$$FF_2 = g_i = \frac{TDP_{ij}}{RDP_{ij}} \quad (18)$$

Where g_i means estimated trust value.

3.7.3. Traffic Rate (FF₃)

The traffic rate represents the minimum efficient level of network utilization and is influenced by factors such as traffic density, channel load, buffer utilization, traffic scaling, and packet drop rate. The traffic rate is formulated in Equation (19).

$$FF_3 = \frac{1}{3} [B_{\text{utilization}} + P_{\text{drop}} + C_{\text{load}}] \quad (19)$$

Where $B_{\text{utilization}}$ demonstrates the buffer utilization, P_{drop} is a packet drop and C_{load} is a channel load.

3.7.4. Cluster Density (FF₄)

This is described as a node that illustrates how to transmit the data easily. The density is the proportion of the whole cluster to the whole nodes. The cluster density is formulated in Equation (20).

$$FF_4 = \frac{1}{M} \sum_{i=1}^A |Y_i| \quad (20)$$

Where Y_i is a i th cluster node, M illustrates the total number of nodes in a network, and A demonstrates the total number of CH.

3.7.5. Remaining Energy (FF₅)

The CH is required to collect, receive, and transmit the data to the BS. A sensor energy is considered for the pursuing hop CH, and energy execution is formulated in Equation (21).

$$FF_5 = \sum_{i=1}^D \frac{1}{E_{CH_i}} \tag{21}$$

Where E_{CH_i} is the remaining energy of i th CH. A weight value is applied to each fitness function. An individual objective function is acquired from various objectives and formulated in Equation (22).

$$OF = \delta_1 FF_1 + \delta_2 FF_2 + \delta_3 FF_3 + \delta_4 FF_4 + \delta_5 FF_5 \tag{22}$$

Where OF illustrates the overall fitness function; $\delta_1, \delta_2, \delta_3, \delta_4$ and δ_5 specify the weight values, which are performed for each fitness function.

4. Simulation Results

Here, the simulation analysis, simulation setup, and experimental parameters are presented. The proposed approach is implemented on MATLAB 2020R with a system configuration of an Intel i5 processor, 16GB RAM, and Windows 10OS. The number of nodes, sink location, and network size are multiple significant parameters that affect a network’s lifetime. The placement of the sink plays a critical role in energy usage and network lifetime. Because the sink is positioned at the center of the sensing field in the proposed experiments, transmission distances are reduced, and energy usage is reduced for most nodes. In scenarios where the sink is located far from the clusters, the nodes positioned near the sink deplete the energy more rapidly due to excessive data relaying, leading to the hotspot problem. Considering these three important factors, various WSN conditions are designed to provide a more comprehensive evaluation of the proposed approach.

Table 1 lists the simulation parameters for the proposed approach. In the simulation, a single sink node is deployed at the centre of a $100 \times 100 m^2$ field. Because the CH–sink distance is a part of the fitness function, the sink placement directly influences the energy usage. For the TMRL-EHO implementation, the population size is fixed at 50 candidate solutions, and the greater count of iterations is limited to 500. The TMRL is employed to represent the population through the mean (μ) and standard deviation (σ), which are updated at each iteration to balance exploration and exploitation. The fitness evaluation considered residual energy, node centrality, CH–BS distance, intra-cluster distance, and delay. The optimization process is terminated either when the maximum number of iterations is reached or when the improvement in the best fitness value between successive iterations decreases below the convergence threshold ($\epsilon = 10^{-6}$). Different evaluation metrics, including the total number of rounds for

alive nodes, energy consumption, network lifetime, residual energy, and throughput, are employed to evaluate the significance of the proposed cluster-based routing method.

- Alive node (%): The higher number of active nodes indicates a better network effectiveness and stability.
- Energy Consumption (J): The overall amount of energy utilized through the CH and member nodes.
- Network Lifetime (%): This refers to the duration of the network that remains functional, typically measured until the first node fails or the system can no longer sustain reliable data transmission.
- Remaining/Residual energy (%): At data transmission, the total number of residual energies of nodes is used to estimate the energy consumption.
- Throughput (bps): The count of communicated data packets to the sink.

Table 1. Simulation parameters of the proposed approach

Simulation Parameters	Values
Area Deployment	1500 × 1500m
Initial energy	1 J
Transmission energy	0.01J
Number of nodes	500
Number of Rounds	5000

4.1. Performance Analysis

This portion estimates the effectiveness of the proposed trust, energy-efficient clustering, and routing approach named TMRL-EHO compared with the existing approaches. All the methods analyzed in this section are experimentally based on simulation parameters, which are illustrated in Table 2. The existing optimization approaches, such as Fennec Fox Optimization (FFO), Grey Wolf Optimization (GWO), Red Deer Algorithm (RDA), and conventional EHO, are estimated and compared with the proposed TMRL-EHO based on the same simulation parameters.

Table 2 explains the performance estimation of the proposed approach using the number of rounds. The proposed TMRL-EHO method achieves lower energy consumption and reduced delay, demonstrating its capability to balance load distribution, minimize redundant transmissions, and enhance the overall efficiency of the WSN. The integration of tent mapping ensures population diversity and faster convergence, leading to more energy-optimal CH selection. The adaptive reverse learning improves exploration, which reduces premature convergence. Consequently, the method sustains higher throughput, PDR, and network lifetime by maintaining trusted links and avoiding packet drops, indicating its superior adaptability as well as robustness under varying network densities.

Table 3 provides the performance estimation of throughput according to the number of nodes. As the number of nodes grows, the algorithm dynamically adjusts clustering

configurations using its adaptive fitness evaluation, thereby maintaining consistent energy efficiency and stable delay. The nonlinear chaotic mapping aids in evenly distributing CHs, mitigating congestion, and data redundancy. The observed

balance in PDR and throughput demonstrates the model's capability to maintain data integrity and stable communication, while validating the scalability and robustness of the proposed framework.

Table 2. Performance estimation of the proposed method based on the number of rounds

Performance Metrics	Methods	Number of Nodes				
		100	200	300	400	500
Energy Consumption (J)	FFO	3425.3	3986.7	4472.1	4983.5	5547.4
	GWO	3318.9	3856.2	4376.3	4889.8	5463.7
	RDA	3237.8	3765.3	4281.4	4763.2	5326.5
	EHO	3156.2	3669.8	4183.7	4678.3	5239.4
	TMRL-EHO	2848.4	3293.5	3748.4	4123.1	4648.4
Delay (ms)	FFO	17.3	18.6	19.9	21.4	23.2
	GWO	15.8	17.1	18.4	19.9	21.6
	RDA	14.9	16.3	17.8	19.3	21.1
	EHO	13.7	14.8	16.3	17.7	19.4
	TMRL-EHO	10.4	11.4	13.0	15.4	17.0
Throughput (%)	FFO	91	92	93	93	94
	GWO	92	93	94	94	95
	RDA	93	94	94	95	96
	EHO	95	95	96	96	96
	TMRL-EHO	97	98	96	95	97
Network Lifetime (s)	FFO	756.3	832.4	917.8	985.5	1056.9
	GWO	789.1	864.5	938.7	1008.2	1082.6
	RDA	806.2	889.7	969.4	1037.2	1113.8
	EHO	816.3	901.4	987.6	1068.9	1146.5
	TMRL-EHO	837.8	962.4	1033.2	1139.3	1239.4
PDR (%)	FFO	96.1	95.7	94.9	94.2	93.5
	GWO	97.2	96.6	95.9	95.1	94.3
	RDA	97.9	97.2	96.5	95.7	94.8
	EHO	98.6	98.0	97.4	96.6	95.8
	TMRL-EHO	99.5	99.1	98.2	96.2	95.2

Table 3. Performance estimation of the proposed method based on the number of nodes

Performance Metrics	Methods	Number of Nodes				
		100	200	300	400	500
Energy Consumption (J)	FFO	3621.43	4068.75	4593.62	5078.37	5563.19
	GWO	3493.88	3971.24	4447.86	4933.52	5417.28
	RDA	3369.75	3856.48	4323.19	4787.42	5262.71
	EHO	3248.67	3724.53	4198.31	4673.82	5148.64
	TMRL-EHO	2848.38	3293.48	3748.38	4123.13	4648.36
Delay (ms)	FFO	18.53	19.47	20.62	22.13	23.86
	GWO	17.32	18.28	19.42	20.81	22.49
	RDA	15.89	16.73	17.94	19.38	21.06
	EHO	14.62	15.43	16.88	18.34	19.86
	TMRL-EHO	10.37	11.37	12.97	15.39	17.03
Throughput (%)	FFO	90	91	92	92	93
	GWO	92	93	93	94	94
	RDA	94	95	95	95	96
	EHO	95	96	96	96	96
	TMRL-EHO	97	98	96	95	97
Network Lifetime (s)	FFO	510.83	589.33	789.72	879.64	948.27
	GWO	538.22	698.32	812.38	901.42	978.33
	RDA	693.13	798.82	890.37	967.33	1026.48

	EHO	789.37	893.23	987.22	1059.38	1134.25
	TMRL-EHO	837.83	962.38	1033.23	1139.33	1239.38
PDR (%)	FFO	90.7	93.7	92.5	90.6	87.3
	GWO	92.3	94.7	94.6	92.4	88.2
	RDA	94.2	95.2	95.1	93.6	91.6
	EHO	97.8	97.2	96.3	95.7	93.3
	TMRL-EHO	99.5	99.1	98.2	96.2	95.2

Table 4. Statistical analysis of the average of the proposed method in overall performance metrics

Metric	Mean	Standard deviation	Variance	Coefficients of Variation
Energy Consumption	3732.75	684.25	468198.06	18.33
Delay	13.83	2.54	6.45	18.36
Throughput	96.6	1.14	1.30	1.18
Network Lifetime	1042.83	151.19	22859.8	14.50
PDR	97.64	1.64	2.69	1.68

Table 5. Average performance analysis of the proposed method using different performance metrics

Methods	Performance Metrics				
	Energy Consumption (J)	Delay (ms)	Throughput (%)	Network lifetime (s)	PDR (%)
FFO	4543.2	20.1	93	909.8	94.7
GWO	4375.8	19.0	94	936.6	95.6
RDA	4282.8	18.1	95	963.3	96.2
EHO	4185.5	17.2	96	987.3	97.0
TMRL-EHO	3732.8	13.8	96.6	1042.8	97.6

Table 4 presents a statistical analysis of the proposed method in overall performance metrics. The low standard deviation and variance for throughput as well as PDR demonstrate the proposed model’s consistency across diverse simulation rounds.

The moderate coefficient of variation for delay and energy usage reflects adaptive stability under varying conditions. This statistical uniformity confirms that TMRL-EHO maintains optimal trade-offs between exploitation and exploration, resulting in stable network behaviour and high reliability, regardless of changes in network size or traffic

dynamics. Table 5 presents an average performance analysis of the proposed method using different performance metrics. The comparative analysis reveals that TMRL-EHO consistently outperforms conventional optimization techniques across all performance indicators. The hybridization of chaos-based initialization and adaptive reverse learning ensures minimal communication delay and efficient CH distribution. Energy consumption reduction stems from optimized routing paths that avoid malicious nodes. Moreover, the steady improvement in lifetime and PDR indicates a stable and trustworthy communication environment, thereby confirming the method’s superiority in energy and security trade-offs.

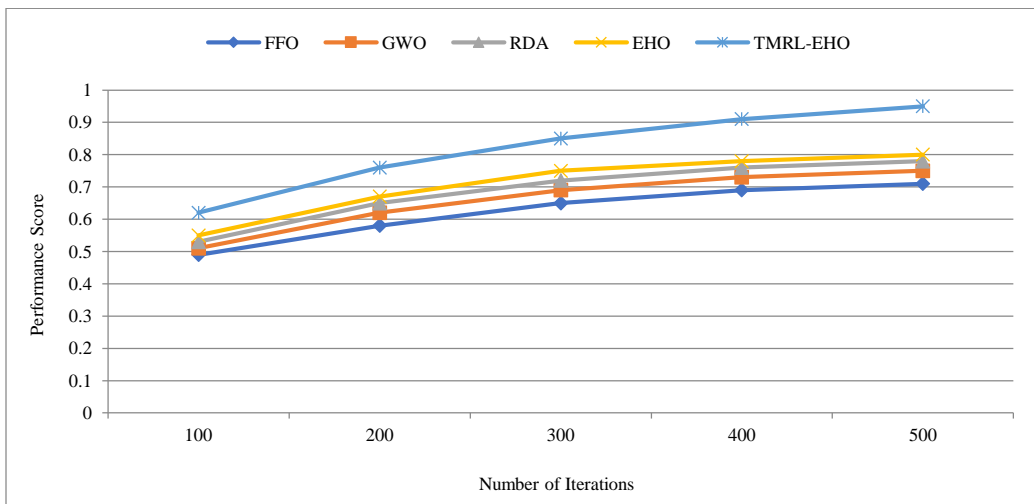


Fig. 3 Convergence analysis of the proposed method with existing methods based on the number of iterations

Figure 3 illustrates the convergence analysis of the proposed method with the existing methods based on the number of iterations. It is confirmed that the proposed TMRL-EHO converges rapidly and attains a greater optimal fitness value within some iterations.

The early step raises fitness, which illustrates an improved exploration because of tent mapping, whereas smooth stabilization in further iterations confirms efficient exploitation allowed through adaptive reverse learning.

Consequently, conventional approaches exhibit slower convergence and premature stagnation. This analysis confirms that the TMRL-EHO offers greater convergence speed,

stability, and solution quality for trust-aware, energy-effective clustering and routing in WSNs.

4.2. Comparative Analysis

Table 6 demonstrates the simulation parameters of diverse scenarios. Scenarios 1, 2, and 3 are represented by the CTRF method [21], QGAOA [22], and T-MMFOA [23], respectively. The various scenarios are compared using the proposed TMRL-EHO approach to validate the significance of the model. Table 7 explains a comparative analysis of the proposed method through the CTRF method [21]. Table 8 presents a comparative analysis of the proposed method with QGAOA [22]. Table 9 provides the comparative analysis of the proposed approach with T-MMFOA [23].

Table 6. Simulation parameters of the different scenarios.

Parameters	Simulations		
	1	2	3
Initial Energy	1J	1 J	-
Area	100 × 100m ²	1500 × 1500m ²	1000 × 1000m ²
Number of nodes	100	500	100 to 500

Table 7. Comparative Analysis of the proposed TMRL-EHO method with CTRF [21]

Scenario	Methods	Performance Metric	Number of malicious nodes				
			10	20	30	40	50
1	CTRF [21]	Throughput (kbps)	200	197	195	193	190
		Delay (s)	0.004	0.005	0.006	0.007	0.008
	Proposed TMRL-EHO	Throughput (kbps)	203	200	198	195	193
		Delay (s)	0.002	0.003	0.004	0.005	0.006

Table 8. Comparative Analysis of the proposed TMRL-EHO method with QGAOA [22]

Scenario	Method	Performance Metric	Number of nodes			
			100	200	300	500
2	QGAOA [22]	ECP (J)	3897.25	4312.93	4901.32	5921.91
		Delay (ms)	11.34	13.24	14.56	18.86
		Throughput (%)	96	97	94	95
	Proposed TMRL-EHO	ECP (J)	2848.38	3293.48	3748.38	4648.36
		Delay (ms)	10.37	11.37	12.97	17.03
		Throughput (%)	97	98	96	97

Table 9. Comparative Analysis of the proposed TMRL-EHO method with T-MMFOA [23]

Scenario	Method	Performance Metric	Number of nodes			
			100	200	300	500
3	T-MMFOA [23]	PDR (%)	99.1	98.5	96.9	94.3
		Delay (ms)	2.9	3.3	4.5	7.4
		EC (J)	5.3	6.6	7.3	8.9
		Throughput (%)	95.2	96.7	97.4	99.2
	Proposed TMRL-EHO	PDR (%)	99.5	99.1	98.2	96.2
		Delay (ms)	1.6	2.5	3.3	6.2
		EC (J)	4.7	5.4	6.2	7.3
		Throughput (%)	96.2	97.8	98.2	99.6

4.3. Discussion

The findings significantly illustrate that merging TMRL through EHO improves global search diversity and convergence rate. The nonlinear chaotic mapping assists in

neglecting local stagnation and inspires uniform population distribution, resulting in more reliable CH selection. The fitness function’s multi-objective nature optimally balances energy, trust, and communication parameters, while

promoting prolonged stability. The proposed approach not only enhances routing integrity but also mitigates data loss caused by unreliable or malicious nodes. The TMRL-EHO approach illustrates effective resilience under varying traffic conditions, also preserving network connectivity while minimizing packet drops and delay. Its adaptability makes it suitable for dynamic IoT-WSN environments, where scalability and energy constraints are critical. Generally, these discoveries validate the proposed approach significantly, which combines security awareness, energy optimization, and intelligent adaptation in a unified routing mechanism.

The effectiveness of the proposed TMRL-EHO method is mainly because of its improved exploration and balanced optimization strategy. The tent mapping mechanism offers a well-distributed initial population, thereby allowing rapid convergence and avoiding local optima. The reverse learning process further refines solutions by enhancing candidate quality. Moreover, the multi-objective fitness function accounts for both energy efficiency and trust, which ensures reliable and secure routing. As a result, the proposed approach attains minimum energy consumption, minimized delay, and enhanced throughput, and the network lifetime compared to existing state-of-the-art techniques.

5. Conclusion

This research introduced a TMRL-EHO framework for trust-aware and energy-effective clustering as well as routing in WSNs. The approach successfully integrates chaotic initialization and adaptive reverse learning to strengthen

convergence behavior and avoid local minima. By incorporating trust, energy, and density factors into the fitness function, the proposed model effectively enhances reliability, stability, and scalability. The method exhibits consistent energy conservation and robust data delivery while establishing a dependable routing structure. The findings confirm that the TMRL-EHO framework ensures secure communication with optimized power utilization and minimal latency. Its hybrid mechanism improves adaptability in heterogeneous and dynamic WSN deployments. Future work will concentrate on enhancing the trust analysis in dynamic scenarios, which solves the node heterogeneity. This aims to improve an approach's strength and applicability in dynamic WSN settings. Future research focuses on developing lightweight Artificial Intelligence (AI) models and optimized data collection strategies to enhance overall model efficiency and performance. Improving the framework to analyze the computational time during data transmission and combining hybrid approaches to further enhance adaptability.

Conflicts of interest

The authors declare no conflict of interest.

Funding Statement

The authors declare that no external funding was received for the preparation of this manuscript.

Acknowledgments

Authors 1 and 2 contributed equally to this work.

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