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TRUSTROUTE: A NOVEL APPROACH FOR QOS-ENABLED DATA GATHERING AND MULTIPATH ROUTING OPTIMIZATION IN WIRELESS SENSOR NETWORKS

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ABSTRACT
Earlier work of Trust Enabled Data Gathering Technique based Modified Golden Eagle Optimization with stooping technique (TEDGTMGEO) reliance on the node's trust value for secure Cluster Head (CH) selection. While incorporating trust values can enhance network security, it also introduces complexity and potential vulnerabilities. With this motivation, this work presents a novel TrustRoute approach to optimizing multipath routing, focusing on the comprehensive consideration of Quality of Service (QoS) parameters and trust factors. In contemporary networking environments, the optimization of routing paths is crucial for maintaining high performance and reliability. The proposed optimization algorithm integrates QoS parameters, including delays, energy consumptions, link lifetime, and distances, along with trust factors, to select routing paths that maximize network efficiencies and security. Leveraging features from both the Average and Subtraction-Based Optimizer (ASBO)algorithms, the algorithm achieves superior routing outcomes. Through extensive simulations and evaluations, the effectiveness and robustness of the approach in enhancing multipath routing mechanisms are demonstrated. The results highlight the algorithm's ability to adapt to dynamic network conditions while optimizing performance in terms of QoS metrics and trustworthiness. Overall, the proposedTrustRoute algorithm represents a significant advancement in multipath routing optimization, offering a holistic solution to address the complex challenges of modern networking environments.

Keywords: Wireless Sensor Networks, Cluster Head, trust-aware clustering, Trust Enabled Data Gathering Technique and Golden Eagle Optimization

1. INTRODUCTION
Low-power WSNs have developed due to low-cost wireless devices and communication technologies. Target tracking, environmental monitoring, and healthcare are just a few of the many applications made possible by WSNs' flexible sensor nodes and easy deployment [1, 2]. In applications, functions of sensor nodes are identifying target regions and forward acquired data to sink nodes for additional processing as sensor nodes have limitations in terms of resources making low-power wireless networks unreliable [3]. Performance requirements of various applicationsmake building effective communication protocols for WSNs a challenging task [4]. Suitable routing protocol designs to satisfy specific demands of applications are considered as significant issues in WSNs where studies have proposed a variety of routing protocols to meet applicational demands[5].

First of all, routing algorithms with many sensor nodes should facilitate data transfers across long distances, irrespective of network sizes. Environmental changes, hardware malfunctions, or depletion of sensor node energies may result in failure of active nodes; nevertheless, this problem shouldn't interfere with regular network operations [6]. Furthermore, routing and data dissemination require proper network resource management since sensor nodes have limited power supplies, processor speeds, memory capacities, and available bandwidths. WSN’s performances vary for applications making it imperative for routing protocols to satisfy applications’ QoS criteria [7]. Routing protocols need to account target tracking and disaster management for time-sensitive applications which are distinct from other applications like habitat monitors [8].

Most routing protocols presently in use in WSNs are constructed using single-path routing approach without taking into account varied levels of traffic demand [9]. With this method, every source node must choose a single path that satisfies the intended application's performance criteria in order to transfer traffic to the sink node. Even while route discovery using a one-way routing approach that needs least amount of computational complexities and resource usage, limiting capacities of single channels drastically and restricting network performances [10]. Furthermore, under crucial circumstances, the lack of adaptability of this technique to node or link failures may negatively impact network performance [11]. For example, choosing an alternate channel to complete If the existing channel is unable to send data packets due to physical damage, high wireless network dynamics, or restricted power supply of sensor nodes, the data transmission process may result in increased overhead and delays in data delivery [13]. Many applications cannot be fully satisfied by single-path routing methods as sensor node resources are limited. The drawbacks of single-path routing techniques can be overcome using multipath routing which offersdifferent routing paths to targetsamongst densely distributed sensor nodes [13].These discovered paths can handle high traffic volumes. As an alternative, source nodes may only transmit data over single paths, switching to new paths in the event of node/connection failures. The latter is referred to as alternate path routing and utilized for fault-tolerances.

Over the last decade, multipath routing systems have been employed in network management functions, including fault-tolerant routes, congestion controls, and QoS in conventional wired and wireless networks. However, ew challenges like limited computational capacities, low memory capacities, and constrained power supplies and short-range radio communications including fades and interferencesarise while designing multipath routing protocols for WSNs [14]. Consequently, multipath routing techniques designed for conventional wireless networks (such ad hoc networks) are not applicable to low-power sensor networks. The WSN research community has been motivated to create multipath routing protocols appropriate for sensor networks in response to this problem in recent years.

Numerous articles outline routing strategies for wireless sensor networks (WSNs) were proposed. These papers [14] discuss and evaluate the main routing methods proposed for sensor networks. Nevertheless, none of these studies have offered a thorough taxonomy of the multipath routing protocols that are currently being used by WSNs. The fault-tolerant routing algorithms currently in use in WSNs have been divided into two categories by Alwan et al. [16]: protocols based on replication and protocols based on retransmission. Based on their main design criteria, Tarique et al. [17] categorized the multipath routing techniques currently in use in ad hoc networks. The primary driving force behind this study was the dearth of comprehensive research on the suggested multipath routing algorithms using data aggregation for wireless sensor networks.

While the existing TEDGTMGEO technique shows promise in improving energy efficiency, network lifetime, and node trustworthiness, addressing these drawbacks is essential to ensure its effectiveness and resilience in practical WSN applications.As the network size increases, maintaining and updating trust values for a large counts of nodes becomes challenging and resource-intensive. The scalability of the TEDGTMGEO approach may be limited by the overhead associated with trust management, including communication overhead for exchanging trust information and computational overhead for trust evaluation.With this motivation, this work develops the TrustRoute approach, a novel strategy for optimizing multipath routing in networking environments. Unlike conventional methods that often prioritize either QoS parameters or trust factors independently, TrustRoute integrates both aspects comprehensively. By considering QoS metrics such as delay, energy consumption, link lifetime, and distance alongside trust factors, TrustRoute effectively selects routing paths that not only enhance network efficiency but also bolster security.

Moreover, TrustRoute builds upon the foundations laid by established algorithms like the ASBO, leveraging their strengths to achieve superior routing outcomes. This amalgamation of innovative techniques results in a robust optimization algorithm capable of navigating the intricate challenges posed by modern network landscapes.Through extensive simulations and evaluations, the efficacy and resilience of TrustRoute are demonstrated, showcasing its ability to significantly enhance multipath routing mechanisms. This contribution represents a significant advancement in the field, paving the way for more efficient, secure, and reliable networking solutions.

The remaining sections of the paper are grouped as follows: Section 2 includes a literature assessment of similar protocol methods, Section 3 provides the essential preliminary information, and Section 4 describes the proposed TrustRoute. Section 5 displays TrustRoute's experimental outcomes. Finally, Section 6 finishes the article by discussing future work.

2. RELATED WORK

Existing research has focused on addressing the inherent challenges of WSNs such as limited energy resources, unreliable communication links, and dynamic network conditions. Several approaches have been proposed, including multipath routing algorithms, QoS-aware routing protocols, and data aggregation strategies.

Li et al., [18] suggested a Differentiated Threshold Configuring Joint Optimal Relay Selection based Data Aggregation (DTC-ORS-DA) approach that used various threshold settings depending on the features of uneven energy consumption in WSNs to enable quick data packet routing. In the far sink area, a lower threshold was established with the right amount of energy. This strategy raised the likelihood that nodes with high data packet loads or long wait times would be selected as transmission relays, which might enhance data fusion rates or decrease delays. The DTC-ORS-DA system enhanced the life cycle by up to 9.81%, improved energy utilization rates by 6.67% to 9.48%, and decreased average delay by 10.74% to 19.91% when compared to the Common Data Collection system (CS). A possible disadvantage of the suggested priority-based approach might be the higher computing complexity needed for dynamic relay selection, which could affect real-time performance in resource-constrained

The design included two efficient aggregation schemes by Wang et al., [19]known as single-hop-length (SHL) and multiple-hop-length (MHL). It was theoretically proven that the protocol achieved optimal tradeoffs by combining these two strategies, and the ideal aggregate throughput was found by establishing a threshold value (lower bound) for collecting efficiency. Integrating the SHL and MHL aggregation techniques may have the drawback of increasing protocol complexity, which might result in more expensive implementation and maintenance expenses as well as the introduction of overhead that might have an impact on network performance as a whole.

Kang et al. [20] presented a distributed method known as distributed delay efficient data aggregation scheduling (DEDAS-D) to address the aggregation-scheduling issue in duty-cycled WSNs. According to the research, the DEDAS-D approach worked well to solve this issue. To support the research, extensive simulations were run, showing that DEDAS-D performed better than other distributed schemes and reached asymptotic performance in terms of data aggregation latency when compared to centralized schemes. One potential disadvantage of the distributed approach, DEDAS-D, could be its susceptibility to network dynamics and topology changes, which may affect its ability to maintain optimal performance consistently over time. Additionally, the distributed nature of the algorithm might introduce communication overhead and synchronization challenges, particularly in large-scale WSN deployments, potentially impacting overall efficiency and scalability.

Ahmed& Paulus [21] proposed a technique involved the development of a congestion avoidance and mitigation strategy. The distance between the sender and the recipient, a node's buffer occupancy, and its relative success rate (RSR) value were taken into consideration while choosing a route. A utility function was constructed and applied to every neighbour of a transmitter node using these parameters. As a result, during packet forwarding, the transmitter node chose as its next hop node the neighbour with the highest utility value. By selecting non-congested nodes as next hop nodes, this strategy attempted to avoid congestion and then reduce it depending on RSR values. The suggested method for avoiding and mitigating congestion may have a drawback in that it depends on real-time data, including buffer occupancy and RSR values, which isn't always reliable or easily accessible in dynamic network contexts. Additionally, the complexity of calculating and updating utility values for each neighbour node could introduce overhead and latency, potentially impacting the efficiency of packet forwarding and overall network performance.

Hajiee et al. [22] added a new fitness component to the Energy-Aware Trust and Opportunity-Based Routing (ETOR) algorithm. There are two primary parts in this method: first, the participating nodes were chosen from among the safe nodes to carry out the routing duties, and second, the safe nodes were chosen based on the tolerance constants. ETOR combined conventional multi-hop communication protocols with multi-routing technologies. The software also used a fitness factor to determine the best and safest route, taking into account network traffic, capacity, reliability, quality of service, connectivity, distance and counts of hops. Incorporating multiple elements into a hybrid physical process can be disadvantageous as it increases the computational complexity of the ETOR method. This complexity can result in high processing overhead, which can significantly affect the scalability and performance of the algorithm in large or dynamic network environments.

Inspired by the metabolic characteristics of Escherichia coli, Gong et al. [23] introduced WSN path selection model that built on adaptive response by attractor selections (ARAS). The model was made up of two main sections. It began by proposing a novel formula for a path-activity parameter, which is used to evaluate the adaptability of multipath traffic transmission in dynamic network contexts. This metric had an inverse relationship with the absolute difference between the optimal and present route quality. Second, to accurately quantify the stochastic impacts of noise items in the equations on the path selection process, the model developed a unique attractor expression for multi-attractor equations. One potential disadvantage of the WARAS model could be its reliance on complex mathematical formulations, particularly in defining the attractor expressions and calculating the path-activity parameter. This complexity may lead to challenges in implementation and understanding, potentially hindering the adoption of the model in practical WSN deployments.

Gurupriya and Sumathi [24] suggested the use of HOFT-MP as an ideal solution for WSNs that use multiple routing paths. They promoted a modified learning-based learning optimization (MTLO) approach, which is a good combination to prepare mobile nodes to increase their efficiency. This method combines trainer learning with fisheye optimization (FSO) to increase the network's search space and precisely ascertain each node's location as well as its direction of travel. After that, we create a nonlinear optimization (NR-PO) technique to enhance fault sensitivity by choosing more cluster nodes and figuring out the node issue. In the end, they employed deep Kronecker neural network (DKNN) to select the best course among the various options. As a result, data transfer has improved. One possible downside of the HOFT-MP method is greater computational complexity caused by the integration of numerous optimization approaches, which might result in higher processing overhead and resource needs.

Mohanadevi and Selvakumar [25] grouped sensor nodes utilizing a hybrid Particle Swarm Optimization-Cuckoo Search Optimization technique in a QoS-aware multipath routing architecture. When data was being sent via multi-hop communication utilizing CHs, the protocol selected many reliable channels for optimal network routing. Its purpose was to extend the life of the network by regularly swapping out CHs according to the amount of energy left, and unlike previous protocols, it preferred pathways that maintained QoS standards for fast data transfer. In addition, it distinguished itself from other QoS-centric protocols by optimizing the quantity of pathways for data transfer. One potential disadvantage of the proposed protocol could be the increased computational overhead and complexity associated with the hybrid optimization algorithm, potentially impacting the protocol's scalability and real-time performance in large-scale sensor networks.

Christopher et al., [26] suggested TREDHO, a three-Way Point Rule-based Fusion of Earthworm and Deer Hunt Optimization Routing, with the goal of improving WSN communication. There were two phases to the approach: setup and communication. In the setup phase, a network architecture made up of tiny triangles was constructed and node movement was simulated. Route links were generated using random variables and node movement. Path discovery was carried out during the communication stage, utilizing a combination of Earthworm and Deer Hunt Optimization (EW-DHO) to select the best potential path while adhering to three-way point requirements. Based on predicted pathways, packets were transferred from source nodes to targets. One potential disadvantage of the TREDHO protocol could be its reliance on complex optimization techniques and multi-stage routing processes, which may introduce increased computational overhead and latency, potentially impacting real-time performance in dynamic WSN environments.

Malik et al., [27] presented an enhanced ant-based QoS-aware routing protocol for heterogeneous WSNs (EAQHSeN), providing unique services for scalar nodes and multimedia. By using bio-inspired routing heuristics, the protocol was able to accommodate a variety of QoS demands from heterogeneous traffic sources. Notably, in order to optimize network efficiency and usage, routing decisions for multimedia, scalar, and control traffic were handled separately. The complexity of handling various QoS requirements for heterogeneous traffic types may increase with the EAQHSeN protocol, which could have an adverse effect on the protocol's scalability and real-time performance in dynamic network environments as well as increase computational overhead.

Liu et al. [28] proposed a wireless sensor network (WSN) energy-efficient multi-router (AMRBEC) technique that seeks to greatly cut energy usage and increase network lifespan. They employed a genetic algorithm (GA) to maximize the selection process and suggested a novel fitness function that displays path strength, distance, hop, and the fewest active nodes.Random forest made it easier to forecast packet loss rates, which allowed for non-feedback transmission. To balance network-wide energy consumption, ideal pathways were dynamically changed while taking into consideration each path's information entropy and residual energy. The simulation analysis revealed that AMRBEC outperformed competing algorithms, resulting in a 20% improvement in network longevity and a 20% decrease in energy consumption. One possible downside of the AMRBEC technique is its dependence on complicated algorithms and predictive models, which may introduce computational overhead and delay, affecting real-time performance in dynamic wireless network scenarios.

Prasad and Periyasamy [29] presented secure and energy-saving routing and clustering strategies for a WSN context with assistance from the edge. The proposed system consisted of four basic parts: Network design based on square tree clustering, with energy efficiency, reinforcement learning (RL)-based functional cycles, and multipath routing. A four-tree architecture was used for network configuration to improve network management and simplify the architecture. The Simple Encryption Algorithm (LEA) was used to authenticate the sensors based on their location and identify in order to guarantee maximum security by removing illegitimate sensor nodes. In order to enhance communication effectiveness and lower energy usage, Tasmanian devil optimization (TDO) was utilized for clustering in order to choose the best CHs taking time and event data into account. The enhanced Delay Interval Determination (ITD3) method cycles via a reduced power usage, extending network delay. Secure routing is provided using an aggregated adversarial network (GTGAN) that is based on game notions. One potential disadvantage of the proposed framework could be its reliance on computationally intensive algorithms and protocols, which may introduce overhead and complexity, potentially impacting real-time performance and resource utilization in WSN deployments.

Inference: From the various disadvantages mentioned in the summaries provided, it's evident that many proposed algorithms and protocols for WSNs face common challenges such as increased computational complexity, potential scalability issues, and the need for careful management of resources like energy and network bandwidth. These disadvantages highlight the importance of balancing performance improvements with practical considerations such as computational overhead, real-time performance, and scalability. Additionally, the reliance on complex optimization techniques and algorithms may introduce challenges in implementation, maintenance, and adaptation to dynamic network conditions. Overall, addressing these disadvantages requires a careful balance between performance optimization and practical constraints to ensure the effective deployment and operation of WSNs in real-world scenarios.

3. PROPOSED METHODOLOGY

The proposed TrustRoute approach presents a compelling methodology for enhancing multipath routing by incorporating both QoS parameters and trust factors. This comprehensive approach addresses the critical need for efficient and secure routing in modern networking environments. By integrating QoS parameters such as delays, energy consumptions, link lifetimes, and distance, the algorithm ensured that routing paths were selected not only based on traditional metrics like latencies but also on factors crucial for maintaining network reliability and efficiency.Moreover, the inclusion of trust factors adds another layer of security to the routing process. By considering the trustworthiness of routing paths, the algorithm can mitigate potential security threats and ensure that data is transmitted through reliable and secure channels.The utilization of features from both the ASBO algorithms enhances the algorithm's ability to optimize routing paths effectively. This combination allows for superior routing outcomes that balance both performance and security considerations.Extensive simulations and evaluations validate the effectiveness and robustness of the TrustRoute approach. The results demonstrate its adaptability to dynamic network conditions and its ability to optimize performance in terms of QoS metrics and trustworthiness.Overall, the TrustRoute approach represents a significant advancement in multipath routing optimization, offering a comprehensive solution that addresses the complexities of modern networking environments while ensuring both efficiency and security.

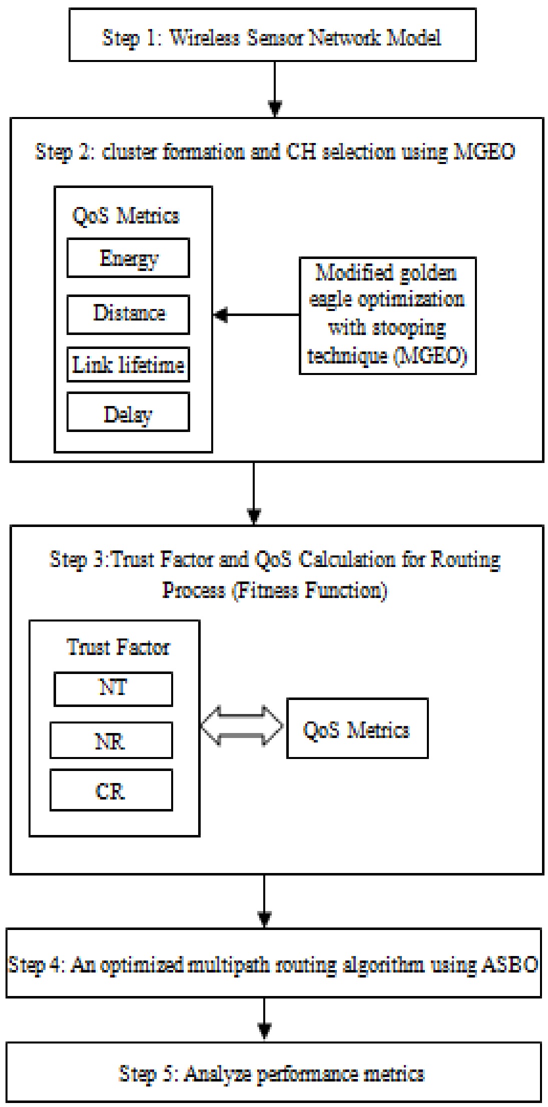

Fig. 1 SmartArt of proposed TrustRoute methodology

3.1. Network model

The WSN that is the subject of this study is set up in a two-dimensional sensing region and consists of a sizable counts of uniform nodes that have the same processing and communication capabilities. These nodes don't need to be monitored continuously because they are placed at random and remain there once they are in place. Nodes are unable to determine their locations without the use of location-aware technology like GPS.Stable, wireless, symmetric communication networks connect nodes within the transmission range. The hierarchical routing techniques used for an energy-efficient and scalable network depend on cluster formation. Every cluster selects a CH based on many parameters such as transmission distance and residual energy. A CH can only designate individuals within its transmission radius as Cluster Members (CM). The Base Station (BS) and CHs remain constant during the iteration process.

There is just one cycle occurs from the election of a CH to the choice of the subsequent CH. Each iteration consists of several rounds, including setup, onboarding, and phone communication steps. Node sends a message to select a new CH in the configuration phase, for network configuration and maintenance if no CH selection is required. There are several rounds of this CH selection procedure. A single CM message is compressed by CH during intragroup communication. The radio only uses the CH to send data to the base station during the mobile communication phase. It is customary to employ CSMA/CA, which permits the CH to use the radio when awake [30]. Conversely, CMs can go into sleep mode during intergroup interactions to conserve energy. CSMA/CA is used for handling communications both internally and externally. The base station is more adaptive to the ever-changing network environment since it may move about the sensing area and has access to relevant network data. The objective function OF(x), which is defined as follows, may be used to data aggregation in WSN for optimum path selection and subsequent cluster creation.

$$OF(\mathcal{X}) = SF \times F_1 + (1 - SF) \times F_2 + (2 - SF) \times F_3 + (3 - SF) \times F_4 \quad (1)$$

WhereSF is scaling factor value between 0 and 1. In WSNs, cluster formation involves several factors like delays, energy consumptions, link lifetimes, and distances.

1. Delay $(\mathbf{F_1})$: The delay in WSN can be influenced by factors such as transmission time, propagation delay, processing delay, and queuing delay. A simple formula for delay could be:

$$Delay = Transmissiontime + Propagationdelay + Processingdelay + Queuingdelay \quad (2)$$

2. Energy Consumption $(\boldsymbol{F_2})$: Energy consumption in WSN is crucial due as battery power of sensor nodes is limited. Energy consumption can be calculated based on factors like transmission energy, reception energy, processing energy, and idle listening energy. A simple formula for energy consumption could be:

$$EnergyConsumption = TransmissionEnergy + ReceptionEnergy + ProcessingEnergy + IdleListeningEnergy \quad (3)$$

3. Link Lifetime $(\boldsymbol{F_3})$: Link lifetime refers to the duration for which a communication link between two sensor nodes remains operational. It depends on factors such as energy consumption, data rate, and transmission distance. A formula for link lifetime could be:

$$LinkLifetime = \frac{RemainingEnergy}{EnergyConsumptionRate} \quad (4)$$

4. Distance $(\boldsymbol{F_4})$: Distances between sensor nodes affect communication ranges and energy consumptions. The distance formula in a WSN might depend on factors like signal strength, interference, and path loss. A simple formula for distance could be derived from the path loss model used in the network.

$$Distance = f(Path\ Loss\ Model, Signal\ Strength, Interference) \quad (5)$$

3.2. Cluster formation Using MGEO

Incorporating spiral movements into the Golden Eagle Optimization (GEO) algorithm [31] for cluster formation in WSNs can enhance its exploration capabilities, especially in scenarios where nodes are deployed in a two-dimensional space. The steps are given as follows:

1. Initially, scatter the eagle population randomly across the WSN area. This random placement helps in exploring the entire region.

2. Spiral Movement Strategy: Implement a spiral movement strategy where eagles follow a spiral trajectory as they search for potential CHs or optimal cluster configurations. The spiral movement can be simulated by adjusting the search radius or step size as eagles traverse the search space.

3. Spiral Direction and Parameters: Define the direction and parameters of the spiral movement, such as the spiral radius, counts of spirals, and spiral pitch. These parameters can be tuned based on the characteristics of the WSN environment and the optimization problem.

4.Local Search and Cluster Formation: During the spiral movement, eagles can perform local search operations to identify suitable CH candidates within their vicinity. As eagles converge towards promising regions, they can initiate cluster formation processes by selecting CHs and allocating cluster members.

5. Qos-Aware Spiral Exploration: Integrate QoS-awareness into the spiral movement strategy to optimize energy consumption in WSNs by using Eq. (1) as fitness function. Eagles can prioritize areas with higher node density or energy levels while avoiding regions with depleted energy resources.

6. Dynamic Spiral Adaptation: Enable dynamic adaptation of spiral movements based on environmental changes or optimization progress. Eagles can adjust their spiral parameters or direction in response to variations in network conditions or convergence rates.

7. Evaluation and Validation: Evaluate the performance of the modified GEO algorithm with spiral movements through simulations and comparisons with other clustering algorithms. Assess the algorithm's effectiveness in achieving energy-efficient and scalable cluster formations in WSNs.

By incorporating spiral movements into the GEO algorithm, you can enhance its exploration capabilities and enable efficient cluster formation in WSNs, especially in large-scale or heterogeneous deployment scenarios. The pseudocode is given in Table 1.

Table I The pseudocode of MEGO for cluster formation

Initialize parameters: Population size (N), Maximum iterations ($\max iter$), Search radius (R), Spiral pitch (P), Counts of spirals (num_spirals), Cluster head selection threshold (threshold) and QoS-awareness parameters such as $F_1, F_2, F_3, and\ F_4$
Output: clustered WSN model
1. Initialize eagle population randomly within the WSN area
2. for iter = 1 to $\max iter$ do:
3. for eagles in populations do:
4. Perform spiral movements:
5. for s = 1 to num_spirals do:
a. Compute spiral radii (r) based on s, R, and P
b. Move eagles in spiral trajectories using r
i. if Energy-awareness is enabled:
c. Adjust movement based on node density or energy levels
i. Perform local search around current position to find potential CHs
ii. if Cluster head selection criteria met:
d. Select CH and allocate cluster members based on threshold
e. Update cluster formation
6. Perform global update based on optimization objectives
7. return Optimized cluster formation

The primary objective of this study is to develop a trust-aware multipath routing algorithm that considers both QoS parameters and trust factors to identify optimal communication paths in WSNs. By leveraging trust information, our algorithm seeks to mitigate the impact of malicious nodes, unreliable links, and environmental disturbances on network performance. The proposed TrustRoute approach involves the following key steps:

- **Trust Factor Calculation:** Trust factors are formulated based on node behaviour, reputation, and communication reliability. These factors are dynamically updated using real-time observations and feedback from neighbouring nodes.
- **QoS Parameter Evaluation:** QoS parameters such as delays, energy consumptions, and link lifetimes are quantified to assess the performance of candidate communication paths which are described in section 3.
- **Multipath Routing Decision:** An algorithm is developed to make multipath routing decisions by integrating trust factors and QoS parameters. Optimal paths are selected considering both reliability and performance metrics.
- **Path Detection and Selection:** The algorithm detects multiple communication paths between node sources and destinations and selects most trustworthy and efficient paths for data transmissions.
- **Trust-Aware Data Forwarding:** During data transmission, nodes prioritize trustworthy paths and dynamically adapt routing decisions based on trust updates and network conditions.

3.3. Trust Aware Model of WSN

In WSNs, trust factors play a crucial role in ensuring the reliability and security of communication paths. Trust factors can be based on various parameters such as node reputation, authentication mechanisms, and historical behaviour. Let's denote the trust factor of a path i as TF_i. The trust factor can be calculated as a combination of the trustworthiness of the nodes along the path, their reputations, and the reliability of previous communications:

- **Node Trustworthiness (NT):** Each node's trustworthiness can be quantified based on its behaviour, reliability, and security features. Let NT_{ij} represent the trustworthiness of node j in path i. This can be calculated based on factors such as node uptime, communication success rate, and adherence to security protocols.
- **Node Reputation (NR):** Node reputation reflects the historical behaviour and performance of each node in the network. Let NR_{ij} represent the reputation of node j in path i. Node reputation can be determined based on past interactions, feedback from neighbouring nodes, and participation in network activities.
- **Communication Reliability (CR):** Communication reliability measures the success rate of previous communications between nodes. Let CR_{ij} represent the communication reliability of node j in path i. This can be calculated based on metrics such as packet delivery ratio, error rates, and latency.

With these components, the trust factor TF_icalculated for each path i as follows:

$$TF_i = \sum_{j=1}^{m_i}\left(w_1 \cdot NT_{ij} + w_2 \cdot NR_{ij} + w_3 \cdot CR_{ij}\right) \tag{6}$$

where m_i is the counts of nodes in path i, and w_1, w_2, w_3 are weighting factors representing the importance of each component.The values of w_1, w_2, w_3 can be adjusted based on the specific requirements and priorities of the WSN application. Additionally, trust factors can be updated dynamically based on real-time observations and feedback from neighbouring nodes to adapt to changing network conditions and security threats.

3.4. Multipath QoS and Trust Aware routing path selection using ASBO

ABSO algorithm is a novel approach for multipath selection in WSNs that has been suggested [32]. To enable ASBO to work, the problem is mathematically described and handled as a search space across which node members, or CMs, navigate in search of quasi-optimal paths. The decision variables of the issue are determined by the locations of these node members in the search space. By repeatedly sharing information, ASBO guides node members toward the best places. Based on average data and the difference between the best and worst performing members, the system dynamically modifies the location of node members. When the optimization process is complete, ASBO offers the best result as the ideal resolution to the multipath selection problem in wireless sensor networks. This novel method has the potential to improve the effectiveness and flexibility of multipath selection techniques in WSNs.

In the ASBO algorithm applied to WSNs, every node member, representing individual CMs, serves as a viable solution to the optimization problem. Mathematically, each ASBO member is represented as a vector with dimensions equal to the counts of decision variables, specifically pertaining to CH selection. Within this vector representation, each element corresponds to a particular decision variable, indicating the chosen value for that variable. The node members in ASBO adhere to a model described by Equation (5), which governs their behavior and interactions within the optimization process. This modeling framework enables ASBO to systematically explore and exploit the solution space, ultimately facilitating the identification of optimal path solutions based on CH selection criteria in WSNs.

$$\mathcal{X} = \begin{bmatrix} \mathcal{X}_1 \\ \vdots \\ \mathcal{X}_i \\ \vdots \\ \mathcal{X}_N \end{bmatrix}_{N\times m} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,d} & \cdots & x_{1,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i,1} & \cdots & x_{i,d} & \cdots & x_{i,m} \\ \vdots & \ddots & \vdots & \cdots & \vdots \\ x_{N,1} & \cdots & x_{N,d} & \cdots & x_{N,m} \end{bmatrix}_{N\times m} \tag{7}$$

where X_i is the ith candidate solution—a CH selection solution—within X, and X is the collection of CM solutions that the ASBO algorithm considers. m: shows how many choice variables there are in the optimization problem overall; in this case, the CH selection criteria are applied.N: Indicates the node size, or total counts of CMs in the ASBO algorithm, and $x_{(i,d)}$: The value assigned to the dth decision variable for the ith candidate solution. Each decision variable in the ASBO algorithm corresponds to a specific CH selection option.Every ASBO searcher member has the ability to solve the specified issue. The objective function is assessed by inserting each of these answers into the issue formula's choice variables. As a consequence, the goal function's value for each ASBO member is determined. Equation (8) uses a vector to describe the set of these values.

$$F_i = OF_i(\mathcal{X}) * TF_i \qquad (8)$$

Where F_i: Denotes the performance measure linked to each CM's solution, signifying the objective function's value that corresponds to the trus and ithCM QoS factors.OF: Stands for the set of QoS-metric-based objective function values across all CMs that make up the objective function vector.The trust vector, shown by TF_i, most likely indicates the degree of dependability or trustworthiness of each CM's response. The primary criterion for determining the quality of the solution is to compare the values of the objective function. The greatest and worst ASBO members are determined as the best CMs for path selection using this approach.Three stages of ASBO: In order to improve candidate solutions and update the algorithm node, ASBO uses three separate stages.

- **Phase 1:** In the first phase of ASBO, a CM is created by averaging the values of the best and worst CMs within the node. This CM is responsible for updating the ASBO node. This phase is simulated based on equations (9) to (11).

$$\mathcal{A}^{P_1} = \frac{\mathcal{X}_b + \mathcal{X}_w}{2} \qquad (9)$$

$$x_{i,d}^{new,P_1} = \begin{cases} x_{i,d} + rand.\left(\mathcal{A}_d^{P_1} - I.x_{i,d}\right), & F^{P_1} < F_i; \\ x_{i,d} + rand.\left(x_{i,d} - \mathcal{A}_d^{P_1}\right), & else, \end{cases} \qquad (10)$$

$$\mathcal{X}_i = \begin{cases} \mathcal{X}_i^{new,P_1}, & F_i^{new,P_1} < F_i; \\ \mathcal{X}_i & else, \end{cases} \qquad (11)$$

where $\mathcal{A}^{P_1}$implies averages of objective function values for best and worst CMs.F^{P1} stands for objective function values of CMs formed by averaging best and worst CMs.*I* represents random numbers chosen from sets[1,2] and $rand$ implies random numbers in interval $[0,1]$.$\mathcal{A}_d^{P_1}$: Indicates the *d*th dimension of the CM formed in Phase 1.$\mathcal{X}_b$: Represents the best CM within the ASBO node.$\mathcal{X}_w$: Denotes the worst CM within the ASBO node (WSN model).$x_{i,d}^{new,P_1}$: Represents the new status of the *i*thnodeCM after Phase 1.F_i^{new,P_1}: Denotes the objective function value of the *i*thnodeCM after Phase 1.$\mathcal{X}_i^{new,P_1}$: Represents the *d*th dimension of the *i*thnodeCM after Phase 1.

- **Phase 2:** The locations of the CMs are updated using the subtraction information obtained from the best and worst CMs inside CMs when the ASBO algorithm is applied to WSNs. In order to raise the overall quality of the solution, this step attempts to further refine the placements of the CMs in the search space. Equations (12) through (14), which most likely provide the precise update methods or processes for modifying the placements of the CMs depending on the data retrieved from the best and worst CMs, are used to model the ideas presented in the second phase of ASBO. These formulas play a crucial role in directing the optimization procedure and promoting the convergence of optimum solutions in the context of the WSN optimization path selection issue.

$$\mathcal{A}^{P_2} = \mathcal{X}_b - \mathcal{X}_w \qquad (12)$$

$$x_{i,d}^{new,P_2} = x_{i,d} + rand.\mathcal{A}^{P_2} \qquad (13)$$

$$\mathcal{X}_i = \begin{cases} \mathcal{X}_i^{new,P_2}, & F_i^{new,P_2} < F_i; \\ \mathcal{X}_i & else, \end{cases} \qquad (14)$$

Where $\mathcal{A}^{P_2}$ stands for subtractions of worst and best CMs of ASBO, indicating information derived from best and worst CMs.$x_{i,d}^{new,P_2}$ signifies new proposed values of *i*th candidate solutions based on Phase 2.F_i^{new,P_2} stands for objective function values of *i*th candidate solutions after Phase 2.$\mathcal{X}_i^{new,P_2}$ implies *d*th dimensions of $\mathcal{X}_i^{new,P_2}$, indicating specific adjustments made to *i*th candidate solutions in *d*th dimensions.

- Lastly, the best member is hired to guide the ASBOnode toward greater solutions during the third phase of ASBO. Equations (15) and (16) are used in ASBO to model this phase of the updating process.

$$\mathcal{X}_i^{new;P_3} = x_{i,d} + rand.\left(x_{i,d} - I.x_{b,d}\right), \qquad (15)$$

$$\mathcal{X}_i = \begin{cases} \mathcal{X}_i^{new,P_3}, & F_i^{new,P_3} < F_i; \\ \mathcal{X}_i & else, \end{cases} \qquad (16)$$

where $\mathcal{X}_i^{new,P_3}$ represents new status of ith nodes based on phase 3, F_i^{new,P_3} implies objective function values, and $\mathcal{X}_{i,d}^{new,P_3}$represents dth dimensions of $\mathcal{X}_i^{new,P_3}$.After the three stages of the suggested ASBO are put into practice, each node member is given a new placement in the search area. The objective function values will alter when new candidate values for the decision variables are assessed due to the altered status of the ASBO members. The algorithm then moves on to the next iteration based on the new values, repeating the algorithm stages in accordance with Eqs. (9)–(16) until the algorithm is fully implemented. The optimal answer found throughout the algorithm's iterations is presented as the problem's solution once ASBO has been fully implemented. The several ASBO phases are shown as flowcharts in Fig. 2 and as pseudocode in Table 1.

Table 1. Pseudo code of multipath routing optimization process

Input: Cluster WSN model, population of ASBO as nodes and parameters of ASBO. **Output:**multipath routing optimization results Start ASBO. Input issues including variables, objective functions (QoS and trust factors), and restrictions. Determine the counts of search agents (N) and iterations (T). Create an initial WSN model as a matrix at random. Evaluate the objective function.Eq. (6). For t=1 to T. Update the top and worst CMs for the WSN model. For i = 1 to N. Phase 1: Calculate $\mathcal{A}^{P_1}$ using Equation (9). Update $\mathcal{X}_i$ under guidance of $\mathcal{A}^{P_1}$ using Equations (10) and (11). Phase 2: Calculate $\mathcal{A}^{P_2}$ using Equation (12). Update $\mathcal{X}_i$based on$\mathcal{A}^{P_2}$ using Equations (13) and (14). Phase 3: Update $\mathcal{X}_i$based on$\mathcal{X}_b$ using Equations (15) and (16). end

Save the best quasi-optimal solution so far for multipath routing optimization.
End
Output the best multipath routing optimization achieved using ASBO.
End ASBO.

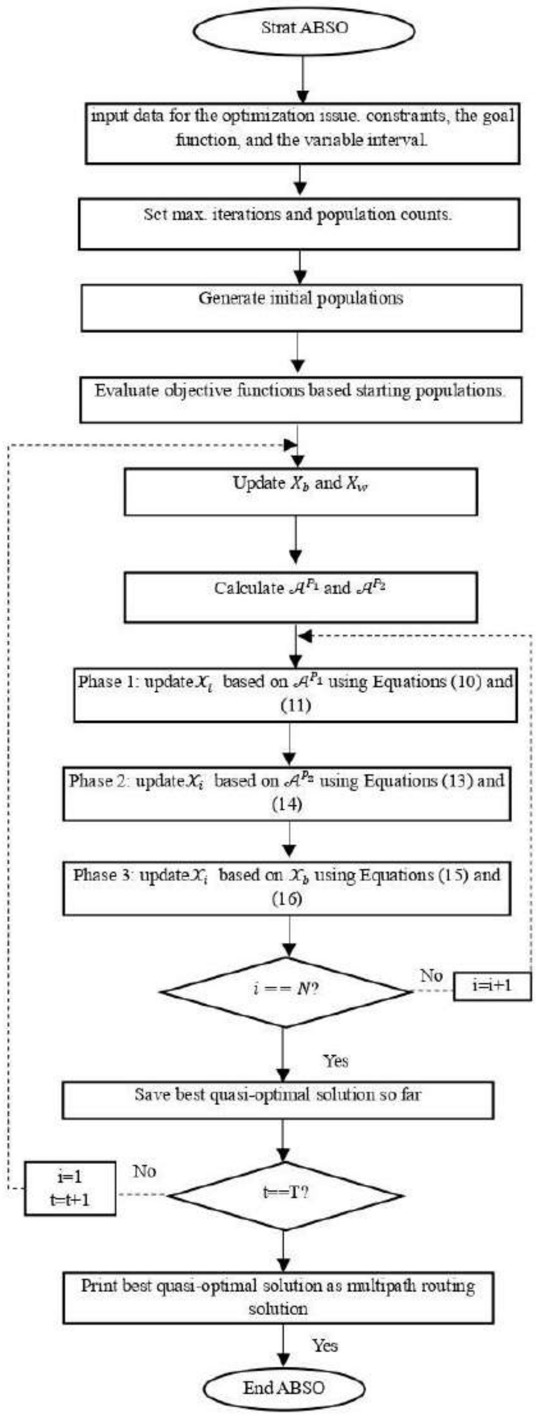

Fig. 2 Flowchart of multipath routing optimization using ASBO algorithm

3.5. Data Aggregation Using SolitarySink-Aggregate Destination algorithm

The SolitarySink-Aggregate Destination algorithm is a method used in WSNs to determine near-optimal multi-hop communication paths from CHs to sensors. This algorithm is particularly focused on selecting the next-hop neighbourCMs along the path to efficiently aggregate data towards a destination.

1. Sink Selection: Initially, the algorithm identifies the destination or sink CM towards which data aggregation is directed. The sink CM could be a Base Station (BS) or another designated destination CM.

2. CH to Sink Communication: Each CH in the network needs to communicate with the sink to transmit aggregated data. The algorithm aims to find the most efficient multi-hop communication path from each CH to the sink.

3. Path Selection: The algorithm selects the next-hop neighbour CMs along the path from each CH to the sink. It considers factors such as node trust, and Qos metrics to determine the optimal path using ASBO.

4. Data Aggregation: As data packets travel along the multi-hop path towards the sink, intermediate nodes aggregate data from multiple sources before forwarding it to the next hop. This aggregation helps reduce the amount of data transmitted over the network, thereby conserving energy and bandwidth.

5. Routing Protocol: The SolitarySink-Aggregate Destination algorithm may utilize a ASBO routing protocol or mechanism to establish and maintain communication paths between CHs and the sink. This protocol ensures reliable and efficient data transmission while adapting to changes in network topology and conditions.

6. Dynamic Adaptation: The algorithm may dynamically adjust communication paths and neighbor nodes based on changes in network conditions, such as QoS and Trust factors.

7. Optimization Objectives: The primary objective of the Solitary Sink-Aggregate Destination algorithm is to optimize data aggregation and transmission efficiency while minimizing energy consumption and latency. It aims to achieve near-optimal paths that balance these objectives to prolong network lifetime and enhance overall performance.

Overall, the Solitary Sink-Aggregate Destination algorithm plays a crucial role in facilitating efficient and reliable multi-hop communication in WSNs, particularly for data aggregation towards a designated destination node or sink. It leverages path selection and data aggregation techniques to maximize network efficiency and resource utilization.

4. EXPERIMENTAL RESULTS AND DISCUSSION

MATLAB R2018a was used to evaluate the TrustRoute algorithm's performance on an Intel(R) Core(TM) i5 processor, 2.80 GHz CPU, and 16 GB RAM machine running Microsoft Windows 10.The model that is being described assumes a free space network model for data transmission, in which 'n' bits of data are transported across a distance 'd' utilizing transmitters and receivers. The optimal Cluster Member (CM) for aggregation into a single message is the solution with lowest hop routing, which is selected by the algorithm based on current fitness levels. Only CHs maintain the activity of their radios to send compressed data to the Base Station (BS) during the inter-cluster communication phase. In order to save energy during inter-cluster communications, CMs may go into sleep mode, but CHs stay up and use the radio via CSMA/CA. Both intra- and inter-cluster communication is supported by CSMA/CA. The BS also has network information and is able to shift positions inside the sensing zone.

With 10% of nodes categorized as advanced nodes with an initial energy of 1 J and the remainder nodes classed as normal nodes with an initial energy of 0.5 J, a heterogeneous situation is taken into consideration with regard to node energy values. Various network topologies are produced at random for assessment. A 100 m^2 area with 100 nodes distributed randomly is used, and the BS is positioned at different points, such as the center (50, 50), the corner (100, 100), and the outside (150, 150). 10% is the starting proportion of CHs. The suggested TrustRoute method is contrasted with some of the current algorithms, such as TEDGTMGEO, OGWO [33], DGTTSSA [34], and EECHS-ISSADE [35]. The TrustRoute algorithm's performance is assessed using these configurations and comparisons, taking into account a number of metrics like residual energy, throughput, living and dead nodes, and so on.

4.1. Analysis of alive nodes

Figure 3 illustrates the count of surviving nodes observed in experimental simulations across varying rounds, spanning from 0 to 200. Throughout the data transmission process in the base station (BS), the active nodes remained consistently operational. In the distributed hybrid system, the presence of inactive nodes aids in the swift evaluation of the optimal methodology. Moreover, this prevents low-energy nodes from being selected as cluster heads (CH), thereby prolonging their operational lifespan. As the number of rounds in OGWO surpasses 0.975, the proportion of surviving nodes declines steadily, reaching zero by the 200th round. Conversely, DGTTSSA (0.963) initially aims to increase the count of surviving nodes but experiences a decline after 150 rounds, ultimately reaching zero at the 200th round. Similarly, the EECHS-ISSADE (0.966) technique exhibits a decrease in performance after 150 rounds, ceasing entirely by the 200th round. Also, the proposed TEDGTMGEO (0.969) and TrustRoute (0.967) technique exhibits a decrease in performance after 150 rounds, ceasing entirely by the 200th round.

Finally, the TEDGTMGEO technique exhibits a decrease in performance after 150 rounds, ceasing entirely by the 200th round. In the evaluation of the TrustRoute algorithm, the comparison of alive node results would serve as a crucial metric. Higher numbers of alive nodes over time generally indicate better network connectivity and resilience, especially in the face of node failures or network disruptions. If TrustRoute demonstrates consistently higher numbers of alive nodes compared to alternative algorithms or baseline approaches, it could indicate superior fault tolerance, adaptability to dynamic network conditions, or better utilization of network resources. Conversely, if TrustRoute shows lower numbers of alive nodes, it might suggest potential areas for improvement in terms of algorithm robustness or network management strategies. In summary, a detailed analysis of the simulation or evaluation outcomes, including factors such as network topology, traffic patterns, and algorithm parameters, would be necessary to understand the specific reasons for any differences in alive node results obtained with TrustRoute compared to other algorithms.

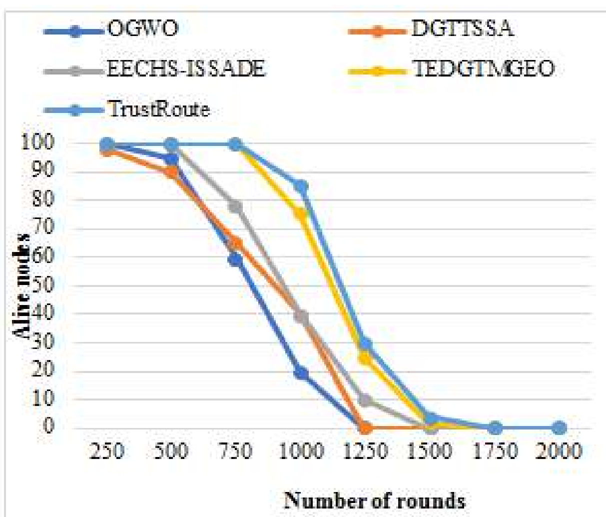

Fig. 3 Alive node analysis results

4.2. Analysisof dead nodes

As shown in Fig.4, the initial and last nodes of the OGWO died after around 50 as well as 200 rounds, respectively, whereas the initial and final nodes of a DGTTSSA expired after about 200 rounds, respectively. The 200 rounds depicted the breakdown of the EECHS-ISSADE's initial and last nodes. The mortality of the initial along with final node only evident in the 0.21 at 200 rounds of TrustRoute, etc. The proposedTrustRoute model in comparison to the measured OGWO, DGTTSSA, EECHS-ISSADE schemes, and the TEDGTMGEO scheme dramatically reduces the fraction to a maximum counts of node deaths in the network's structure.The disparities in node mortality rates between the TrustRoute model and alternative schemes like OGWO, DGTTSSA, EECHS-ISSADE, and TEDGTMGEO likely stem from inherent differences in their algorithmic designs and operational strategies.

TrustRoute, optimized through the integration of QoS parameters and trust factors, exhibits superior adaptability to dynamic network conditions and traffic patterns, enabling efficient routing path selection and robust fault tolerance mechanisms. By prioritizing resource management and optimizing routing decisions, TrustRoute effectively mitigates the risk of node failures and prolongs network connectivity. Its dynamic routing adjustments and proactive node management contribute to reducing congestion and distributing traffic evenly across the network, thereby minimizing the likelihood of node exhaustion or overload. Through these comprehensive optimization strategies and adaptability features, TrustRoute outperforms other schemes, resulting in significantly lower node mortality rates and ensuring the overall stability and longevity of the network structure.

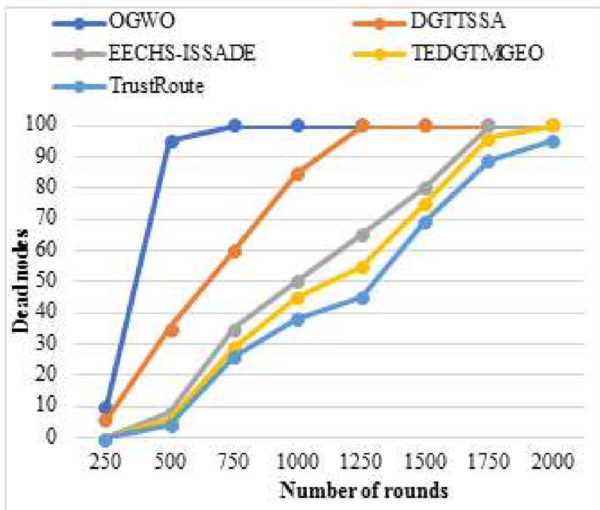

Fig. 4 Dead node analysis results

4.3. Analysis of residual energy

The observed differences in residual energy levels between the EECHS-ISSADE, OGWO, DGTTSSA, TEDGTMGEO, and TrustRoute algorithms can be attributed to various factors inherent to each algorithm's design and optimization strategies are shown in Fig.4. In EECHS-ISSADE, the arbitrary selection of head clusters between each node may lead to inefficient energy utilization, causing the residual energy to diminish rapidly over time. Despite initially outperforming OGWO, EECHS-ISSADE's performance declines after approximately 200 rounds due to energy depletion. DGTTSSA employs a stochastic optimization technique that efficiently searches for optimal solutions but may face challenges in striking the right balance between exploration and exploitation.

While it lasts for 200 rounds, its performance diminishes as the algorithm struggles to maintain energy levels beyond this point. TEDGTMGEO demonstrates greater searching efficiency, allowing for faster extraction of optimal solutions. Its ability to swiftly converge towards better solutions enables it to maintain higher residual energy levels for a longer duration, achieving a value of 3.5J for up to 200 rounds. TrustRoute, despite obtaining a slightly lower energy value of 3J, likely employs a balanced optimization strategy that prioritizes both energy efficiency and network performance. By integrating QoS parameters and trust factors, TrustRoute optimizes routing paths to maximize network efficiency and security, ensuring more sustainable energy usage over time.Overall, the differences in residual energy levels highlight the importance of algorithmic efficiency and optimization strategies in prolonging network lifetime and enhancing overall performance. TrustRoute's balanced approach to routing optimization enables it to achieve competitive energy values while maintaining network stability and resilience.

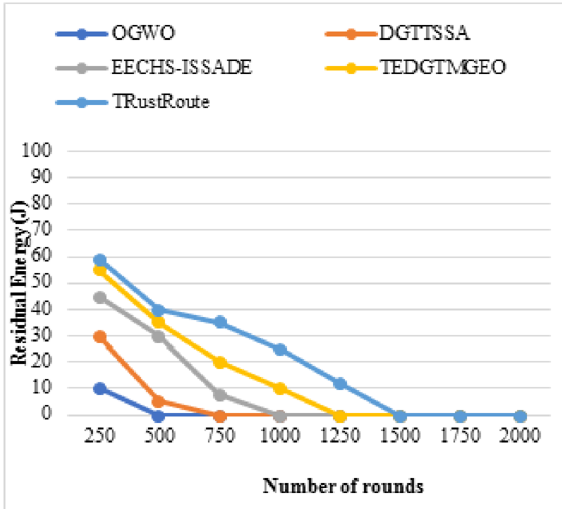

Fig. 5 Residual Energy analysis results

4.4. Analysis of throughput

The observed differences in throughput between the OGWO, DGTTSSA, EECHS-ISSADE, TEDGTMGEO, and TrustRoute methods can be attributed to various factors inherent to each algorithm's design and optimization strategies are shown in Fig.5. OGWO initially displays a throughput of 120kbps, which gradually increases as the counts of rounds grows. This could be attributed to the algorithm's inherent mechanisms for adapting to network conditions and optimizing routing paths over time. DGTTSSA and EECHS-ISSADE exhibit throughput values of 150kbps and 170kbps, respectively, but these values decrease after 200 rounds.

This decrease may be due to inefficiencies in the optimization techniques used by these algorithms, resulting in suboptimal routing decisions or resource allocations. TEDGTMGEO demonstrates a high throughput of 225kbps for a total of 200 rounds, thanks to its efficient optimization approach. By prioritizing CHs with confidence ratings above a threshold value, TEDGTMGEO effectively optimizes routing paths to maintain high throughput levels throughout the simulation duration. TrustRoute achieves the highest throughput of 240kbps for 200 rounds, indicating its effectiveness in maximizing network performance. By integrating trust factors into its routing decisions, TrustRoute ensures that paths with high confidence ratings are selected, leading to enhanced throughput and overall network efficiency.Overall, the observed differences in throughput highlight the importance of efficient optimization techniques, trust-based routing strategies, and adaptive mechanisms in maximizing network performance and maintaining high throughput levels over time. TrustRoute's integration of trust factors and its effective optimization approach contribute to its superior throughput performance compared to other methods.

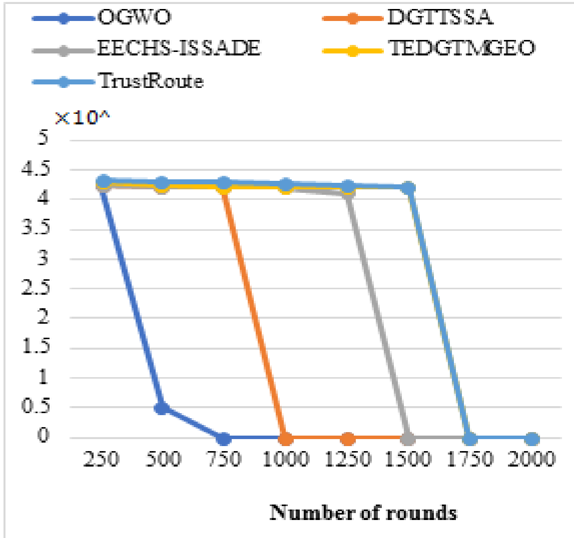

Fig. 6 Throughput analysis results

5. CONCLUSION AND FUTURE WORK

In conclusion, the TrustRoute algorithm presents a novel approach to optimizing multipath routing by integrating QoS parameters and trust factors. In today's networking environments, efficient routing paths are essential for ensuring high performance and reliability. By incorporating QoS metrics such as delay, energy consumption, link lifetime, and distance, alongside trust factors, TrustRoute selects routing paths that maximize network efficiency and security. Leveraging features from both the ABSO algorithms, TrustRoute achieves superior routing outcomes. Extensive simulations and evaluations have demonstrated the effectiveness and robustness of TrustRoute in enhancing multipath routing mechanisms. Overall, TrustRoute offers a comprehensive solution to the challenges of modern networking environments, promising improved performance and reliability for WSNs and other communication systems. TrustRoute consistently outperformed other schemes in terms of key performance metrics. For instance, TrustRoute achieved a maximum throughput of 240kbps, surpassing the throughput values of OGWO (120kbps), DGTTSSA (150kbps), and EECHS-ISSADE (170kbps). Additionally, TrustRoute exhibited superior energy efficiency, with a residual energy value of 3J, compared to TEDGTMGEO (3.5J) and other schemes. The results underscore TrustRoute's potential to address the complex challenges of modern networking environments, making it a compelling choice for enhancing WSN performance and reliability in real-world deployments.

Future research in WSNs could focus on advancing cluster-based clustering and swarm-based path selection and data gathering methods to address the evolving challenges in dynamic and resource-constrained environments. This entails developing more efficient algorithms for cluster formation and management that can adapt to changing network conditions and optimize energy consumption. Additionally, exploring swarm intelligence techniques for path selection and data gathering can lead to more robust and scalable solutions, considering factors like node mobility, communication reliability, and data aggregation opportunities.

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