

Enhancing the Quality of Service by GBSO Splay Tree Routing Framework in Wireless Sensor Network

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Abstract

Quality of Service (QoS) is a critical feature of Wireless Sensor Networks (WSNs) with routing algorithms. Data packets are moved between cluster heads with QoS using a number of energy-efficient routing techniques. However, sustaining high scalability while increasing the life of a WSN's networks scenario remains a challenging task. Thus, this research aims to develop an energy-balancing component that ensures equal energy consumption for all network sensors while offering flexible routing without congestion, even at peak hours. This research work proposes a Gravitational Blackhole Search Optimised splay tree routing framework. Based on the splay tree topology, the routing procedure is carried out by the suggested method using three distinct steps. Initially, the proposed GBSO decides the optimal route at initiation phases by choosing the root node with optimum energy in the splay tree. In the selection stage, the steps for energy update and trust update are completed by evaluating a novel reliance function utilising the Parent Reliance (PR) and Grand Parent Reliance (GPR). Finally, in the routing phase, using the fitness measure and the minimal distance, the GBSO algorithm determines the best route for data broadcast. The model results demonstrated the efficacy of the suggested technique with 99.52% packet delivery ratio, a minimum delay of 0.19 s, and a network lifetime of 1750 rounds with 200 nodes. Also, the comparative analysis ensured that the suggested algorithm surpasses the effectiveness of the existing algorithm in all aspects and guaranteed end-to-end delivery of packets.

Keywords: Wireless Sensor Networks; Quality of Service; energy balancing; energy-efficient routing; splay tree; network lifetime; packet delivery ratio; delay.

1. Introduction

A wireless sensor network (WSN) is a group of several sensor nodes, that were often installed in remote locations to track environmental variables including temperature, humidity, and wetness. Climate, force, heat, visual, audio, movement, image, and chemical & the sensor nodes also contain additional sensors [1]. Due to the variety of sensor nodes, WSNs have several possibilities in various fields, from agriculture to daily life, including healthcare, the military, and defence. It's a complicated task to devise various algorithms for various purposes. Data aggregation, clustering, routing, localisation, defect detection, job scheduling, and remote monitoring are a few of the concerns that the designer of WSNs must consider [2]. Also, energy is restricted in WSNs, most investigations have found that trust acquisition and dissemination consume a lot of energy, which has a negative impact on network longevity [31].

Routing is one of the most crucial responsibilities since a large portion of the energy is used to move data packets from the sender to the receiver, whether using a single hop or several hops. The sensor network designer must carefully consider every issue with the sensor node's energy usage when routing the data if they want to keep the sensor network operational for a very long period [3]. Based on the applications and network architecture, every routing protocol has certain characteristics and requirements. Additionally, by ensuring that the network makes effective routing decisions in any given situation, the network's throughput could be boosted [4]. By permitting both global and local routing of reasoning and information, as well as other cutting-edge features, knowledge plans can help knowledge-based networks. There may be ways to boost network throughput using this innovative feature while the routing effectiveness increases [5]. An individual's cognitive system receives the proper instructions to recognise the notion in previously given hypotheses. The system comprehends the node cognitive properties for network efficiency evaluation and control over a different network parts. A thorough grasp of the network environment is necessary to get better results [6].

The excellence of the service and network-wide performance enhancement have been credited with the longevity and popularity of these algorithms. Because of the intelligence behaviour, these algorithms can adapt to continually changing and complicated wireless surroundings [7]. Self-optimisation & self-healing were implemented by upgrading automation features to wireless networks. Several data-driven techniques have been examined over the past few years in the context of cellular networks, cognitive radio networks, wireless body area networks, wireless sensor networks, and mobile ad hoc networks [8]. These methods are used to handle a variety of concerns, including spectrum sensing, energy-harvesting communication, localisation, data clustering and aggregation, routing, medium access control & others. Algorithms for machine learning are used to address problems in anomaly detection, grouping, classification, and regression [9].

Three routing techniques have been specifically suggested for WSNs: horizontal, geographical, and hierarchical. When flat routing, which makes use of the multi-hop approach, is applied, each sensor node completes the same tasks [10]. Sensing function completion is made possible by the sensor nodes' mutual collaboration. Instead of distributing data over the whole network, location-based routing uses sensor node position data to target a specific area. [11]. In hierarchical routing, the network region is divided into clusters, and sensor nodes with higher energy are in charge of processing and transmitting data. The least amount of energy is used by hierarchical routing systems [12]. Moreover, due to the fact sensor nodes are powered by stochastic renewable energy, analysing and optimising network lifespan under continuous and fluctuating energy supply is extremely challenging [32].

This research examines current routing protocols and identifies flaws that may require improvement to create an effective and ideal routing system for next-generation networks. Energy efficiency is more significant than other reported WSN routing difficulties because of its connection to the complete computing process of the sensor nodes. This research improvises the existing routing protocol to perform an energy-efficient routing protocol. The proposed research on the optimized splay tree routing framework contributes to the advancement of WSNs as a whole, providing domain-independent solutions to challenges in routing efficiency, scalability, energy efficiency, adaptability, and customization. These advances have the potential to benefit various industries and domains, promoting the adoption and utilization of WSN technology across different applications.

The organisation of this manuscript: the summary of the paper is provided in the abstract, section 1 comprises the introduction part with the background of the research, section 2 provides the summary of existing literature works on the same topic, section 3 explains the research method in detail with three subsections, section 4 analyses the simulation of the suggested method and depicts the findings of the research, the conclusion summarises the research done and its significance, and finally the references of the sources cited in the paper are listed.

2. Literature Survey

To deliver the data packets to the receiver, Suresh Kumar et al. [13] used Exponentially-Ant Lion Whale Optimization (E-ALWO) algorithm to construct an energy-efficient and trust-based routing paradigm. To determine the routing path, the network's efficiency and longevity must be increased more than with other meta-heuristic optimisation techniques. Yun et al. [14] selected a node that had to select a routing path utilising a novel approach, it took into account the levels of possible data aggregation of surrounding nodes. The suggested method makes advantage of reinforcement learning to find the best path by maximising incentives at each sensor node. The QoS-aware energy balancing secure routing (QEBSR) solution for WSNs is suggested suggested by Rathee et al. [15]. The routing path's nodes' trustworthiness as well as updated procedures for computing end-to-end transmission delay are offered. Furthermore, considering the packet loss and creation rates was suggested as a simpler but equally effective trust computation technique. By using an environment-fusion multi-path routing protocol (EFMRP), Fu et al. [16] provided a reliable message-forwarding service in challenging situations. EFMRP bases routing choices on a mixed potential field considering depth, remaining energy, and environment. Built-in routes may avoid passing through risk zones to maintain the paths safe when the environmental field is created and updated, utilising the sensing capabilities of WSN itself. The final route is designed to fulfil the three virtual potential fields simultaneously. In this study, Khot et al. [17] created Particle-Water Wave Optimization (P-WWO) to route data packets in a safe manner. Particle Swarm Optimisation (PSO) and Water Wave Optimisation are combined to create the proposed P-WWO method . The recommended optimisation can decide if packets can be communicated along the specified route or whether data has to be diverted due to the route maintenance operation. Efati et al. [18], considered the node distance, remaining energy, and free buffer to optimize the CH selection. Ant colony optimisation (ACO) technique determines the route between sender CH and sink. When developing routing protocols for WSNs, minimising the power consumption of network nodes is one of the primary considerations. However, it could not meet expectations in smaller networks and faster timeframes. Xue et al [19], introduces the cross-layer-based Harris-hawks-optimization-algorithm (CL-HHO) routing protocol for WSN and k-medoids

with improved artificial bee colony (K-IABC)-based energy-efficient clustering to achieve higher quality-of-service (QoS) performance. Least-Square Policy Iteration (LSPI), an effective model-free RL-based approach, is suggested by obi et al [20], to optimise network lifespan and energy usage in WSNs. A Centralised Routing Protocol for Lifetime and Energy Optimisation with a Genetic Algorithm (GA) and LSPI (CRPLEOGALSPI) is the designed protocol that was produced, which was not affected by the learning rate, selects a routing path in a given state after taking into account all feasible routing pathways. Barnwal et al [21], provided the MHCRTTEWSN approach which primarily focuses on increasing the WSN's energy efficiency and longevity through the clustering and routing procedure. The MHCRTTEWSN model uses the whale moth flame optimisation (WMFO) approach to effectively cluster data. This technique uses fitness functions that take into account intra-cluster distance, inter-cluster distance, energy, and balancing factor. In order to decrease the number of working nodes and conserve energy, a novel clustering model known as DCCM that is based on the duty cycle approach has been presented by Liu et al [22]. This model provides a new designed coverage relationship matrix (CRM) and cover sets (CSs) that allow nodes to operate alternately to reduce energy depletion.

Table 1. The related articles with there objective, significance and limitation

Ref No	Author	Technique/ Objective	Significance	Limitation/ Future Scope
[13]	Suresh Kumar	Exponentially-Ant Lion Whale Optimization (E-ALWO) based routing.	energy-efficient and trust-based routing architecture for sending data packets in minimal delay.	The inclusion of another meta-heuristic optimization technique.
[14]	Wan-Kyu Yun	An original, data-aggregation-aware, energy-efficient routing method.	Neighbouring nodes' data were combined when a node needs to choose a routing path.	Message delivery is inefficient in challenging conditions.
[15]	Manisha Rathee	QoS-aware energy balancing secure routing (QEBSR) algorithm	Solves the trade-off between network longevity, QoS, and security.	To operate in situations where weight estimation is impossible
[16]	Xiuwen Fu	The environment-fusion multipath routing protocol (EFMRP)	Increases the packet delivery ratio and network longevity	Workability with multi-sink WSNs.
[17]	Pradeep Sadashiv Khot	Particle-Water Wave Optimization (P-WWO) safe routing method	Routing data packets in an optimum and secure manner.	Lowering the packet loss ratio and boosting productivity to fend against harmful assaults.
[18]	Seyedsalar Sefati	The optimized black hole method based CH selection.	The distance, residual energy, and free buffer of nodes all work together to optimize the CH selection.	To optimize deployment of nodes and routing for data transmission.

[19]	Xingsi Xue	A cross-layer-based optimal-routing approach	CL-HHO addresses the power imbalance issue in wireless sensor networks	To optimize CL routing protocol.
[20]	Elvis Obi	Least-Square Policy Iteration (LSPI).	The network lifespan and energy consumption in WSNs are proposed to be optimized	prioritizing strategies for sensor nodes providing more data packets.
[21]	Sweta Kumari Barnwal	MHCRT-EEWSN	The design of the metaheuristic cluster-based routing approach for energy-efficient WSN	Data aggregation and data compression techniques at the network's CHs.
[22]	Yang Liu	DCCM clustering model	to lower the number of working nodes in order to conserve energy based on the duty cycle approach.	Complexity due to different energy levels and communication radii.

Even more, work has been done for better communication. Still, the network's effectiveness and lifespan must be improved with an equally effective trust computation technique as described in **Table 1**. The network should also avoid creating risk zones via congestion to maintain the paths safe and provide QoS. Thus, the proposed method provides an efficient topology to avoid congestion, a practical trust computation to improve the reliability and optimum routing with a high packet delivery ratio and extends the network lifetime with proper energy balancing.

3. GBSO Splay Tree Routing Framework

In WSN, conventional approach in a fixed network with only one sink node never address the issue of overusing few sensors, particularly. The sensor nodes nearest the sink nodes overtier of energy, while the nodes farthest from the sink node may still have 90% of their starting energy. Thus this research aims to develop an energy-balancing component which ensures equivalent energy consumption for each and every networked sensor at the same time and offers a flexible routing without any congestion, even at peak hours. The emphasis of this field's study has moved from energy consumption reduction to energy consumption balancing techniques to solve the issue of unequal energy consumption in WSNs & maximise the longevity of the network. Developing an energy-balancing algorithmic component is required to guarantee that each sensor uses roughly the same amount of energy, extending the network's lifetime. Therefore the proposed research in this work employs a Gravitational Black hole search optimised splay tree routing framework, as shown in **Fig. 1**, which integrates the splay tree routing algorithm to eliminate the drawbacks in the existing standard with proposed Gravitational Black hole search optimisation. Most prominently, traffic congestion is caused by the massive data transmission on the network lines during peak hours. The conventional methodology generally provides various congestion control methods, although it faces a local convergence problem when the routing nodes are not updated simultaneously. Therefore, it is necessary to create a routing algorithm that operates effectively, has a long lifespan, reduces congestion, and provides excellent quality of service (QoS).

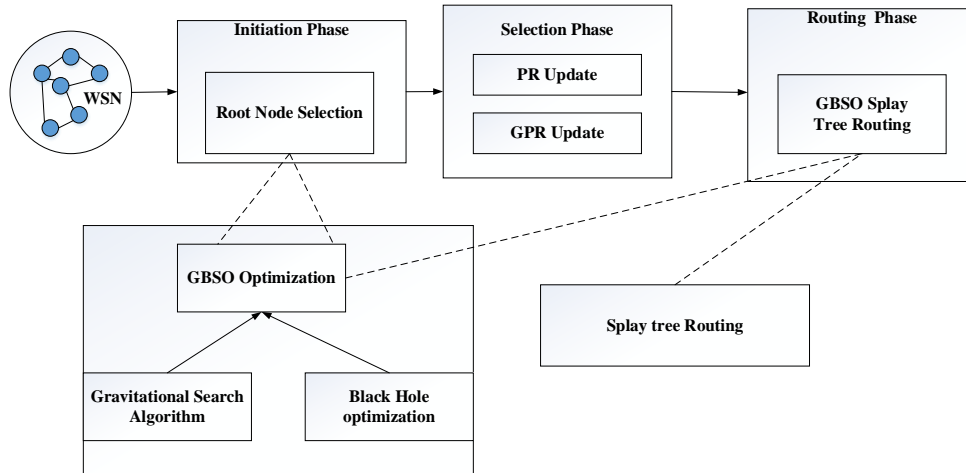


Fig. 1. Architecture flow diagram of the proposed routing model

3.1 Initiation

The proposed GBSO algorithm builds a routing table by the protocol formed via the splay tree data framework. The splay tree routing utilises self-adjusting Binary Search Tree (BST) with the normal functions of a BST for insert, search and delete. In addition, it includes a splaying behaviour where the recently added node is splayed to the root. In the splay tree network, Three steps are used by the proposed method to carry out the routing process: initiation, selection and routing. Gravitational Black hole search optimisation, an efficient and ideal secure routing technique, is created to carry out the routing operation in the sensor network.

3.1.1 Network model

The proposed WSN consists of S sink nodes and N sensor nodes. The wireless connections serve as a representation of the direct communication between sensor nodes. Each node in the network is uniformly spread and has its unique ID, allowing the nodes to be divided into clusters. The sink node is positioned as closely as possible to where it would receive data bytes from other network nodes that are typically linked. Each sensor node sends data to the base station via a routing strategy based on a selected root node (RN). Let N represents the overall number of sensor nodes and GN represent the collection of nodes belonging to cluster group G . According to the standard, the network is split into G clusters. After cluster groups have formed in the network, data packets can be delivered from each node N to the appropriate RN so that RN can collect data packets from cluster members. RN sends data packets, which base station S receives.

3.1.2 Energy model

Assuming that the nodes in the network cannot replenish their energy, each sensor node has a starting energy of J_0 . The free space network relies on the range between the transmitter and receiver, the multi-path fading model, on the other hand, investigates the energy loss experienced when transferring data from the k th node to the l th CH. Though the transmitter has radio circuitry and a power amplifier for emitting energy, radio devices at the receiver end dissipate energy. Thus the amount of energy lost by each data packet is measured in units of U and depends on the nature of the node.

As a result, in this research, the energy used by the node to deliver U bytes of data is represented as,

$$J_{dis}(x^k) = J_{elc} * U + J_{amp} * U * \|x^k - G^l\|^4; \text{if } \|x^k - G^l\| \geq s_0 \quad (1)$$

$$J_{dis}(x^k) = J_{elc} * U + J_w * U * \|x^k - G^l\|^2; \text{if } \|x^k - G^l\| < s_0 \quad (2)$$

$$V_{s0} = \sqrt{\frac{J_w}{J_{amp}}} \quad (3)$$

J_{elc} stands for electronic energy, which is determined by evaluating scattering, filtering, amplifying, modulating, and digital coding.

$$J_{elc} = J_{trans} + J_{agg} \quad (4)$$

Where, J_{trans} indicates the energy of the transmitter, and J_{agg} , indicates the energy of data aggregation. Moreover, J_{amp} signifies the energy variable for the transmitter's power amplifier, and $\|x^k - G^l\|$, defines the separation between the typical member nodes and CH.

Indeed, the energy lost by the receiver upon the receiving U bytes of data from CH can be observed as,

$$J_{dis}(G^l) = J_{elc} * U \quad (5)$$

Each node J_a 's energy value is upgraded after transmitting or receiving U bytes of data.

$$J_{a+1}(x^k) = J_a(x^k) - J_{dis}(x^k) \quad (6)$$

$$J_{a+1}(G^l) = J_a(G^l) - J_{dis}(G^l) \quad (7)$$

Most of the network's nodes are meant to be dead nodes. Thus the data transmission procedure mentioned above continues. The node is considered dead when the energy is lower than zero.

3.1.3 Root Node Optimisation

At the commencement phase, the interface between the sensor nodes and the base station (BS) is created. This stage is essential since it establishes the framework for WSNs' overall communication process. The sensor nodes build a network during the commencement phase by locating them, synchronising them, selecting the optimal cluster head (CH), and establishing contact with the base station. Choosing one or more nodes to act as the CH is the first step in building the network. The coordinating node must control communication between the sensor nodes and the BS.

Especially in peak hours, the data transmission will be more, causing congestion; hence the selected CH must be responsible enough to handle the traffic and maintain proper energy consumption throughout the network. Thus this study suggests a splay tree topology for the node deployment and based on that topology, the optimum node is elected to play the role of CH.

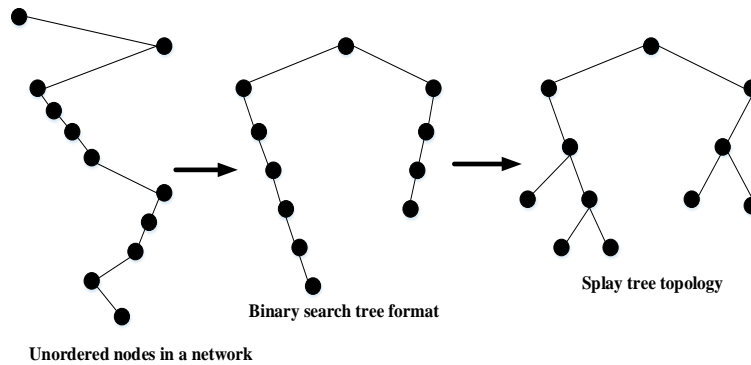


Fig. 2. Node deployment based on Splay tree topology

The normal insert, search, and delete operations of a binary search tree are included in a self-adjusting binary search tree called a splay tree (BST). In addition, it includes splaying behaviour where the newly inserted node is splayed to the root. That is performed to access the recently accessed node easily. The nodes in a binary tree with two nodes are sorted in the order that they appear. In a Binary Search Tree (BST), the nodes in the left subtree have a lesser value than the nodes in the right subtree. The root is chosen to be the first node, the node with lesser value is placed on the left, and a node with a higher value is kept on the right, as shown in Fig. 2. The process and the condition continue for the nodes to be added. The operations to be performed are insertion, search and deletion. The existing splay tree algorithm is implemented in the WSN nodes to form the underlay topology. It occurs whenever a search occurs to find the next hop node for a path in the network.

N sensor nodes are taken into consideration and all nodes are taken as a member of the splay tree topology and re-arranged as and when the routes are calculated and the structure of the routing path changes. Sleator and Tarjan created the data structure known as the Splay Tree [23]. An element in the left sub-tree of every node x is $\leq x$, and every node in the right sub-tree if every node of x is $\geq x$, making it an ordered binary tree. All of the common search tree operations on an N-node splay tree have an amortised time constraint of $O(\log(n))$ per operation. By "amortised time," we mean the time spent on each operation on average throughout the worst-case set of operations. To relocate a node to the root when we access it, we may perform a single rotation or a sequence of rotations. The most intriguing feature of this structure is that it does not require explicit rebalancing of the tree after each operation, unlike balanced tree systems like 2-3 trees or AVL trees. Splaying rotations are used to cause it automatically. It is made up of the zig-zag, zig-zig, and zig sub-operations.

RN plays a vital role in the sub-operation performed by the splay tree. The proposed GBSO initially selects the root node using a black hole optimisation technique to identify the best path. Based on a fitness metric that considers latency and energy, the black hole algorithm chooses the node as the root node. Based on the node's fitness with the least latency and energy, the root node is selected. The best path must then be chosen to complete the routing.

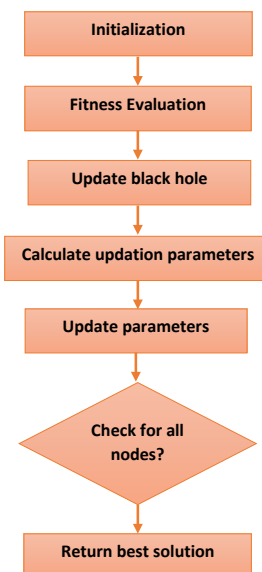


Fig. 3. Root note selection using the GBSO algorithm

A meta-heuristic algorithm based on population is called the black hole algorithm. This algorithm, like other meta-heuristic ones, draws its inspiration from nature. The best candidate is selected to be the black hole during each iteration of the process, and once it starts to attract more candidates, known as stars, around it, it really becomes the black hole. A star will be sucked up by the black hole and vanish ever if it approaches the black hole too closely. In this situation, a new star (candidate solution) is unsystematically formed, enhanced the search area and a fresh search is initiated.

In this work, nodes were placed in the domains using the black hole method in accordance with the flow depicted in Fig. 3. In terms of data transfer, the following approach was used. The graphic illustrates how the GBSO technique will be used to send data when a domain's CH is distant from the sink. Following the investigation of each node's fitness function and selection of the node with the best fitness function as the CH, based on the position of the CH, a new position for each node is determined (black hole node) and any node that is within the black hole node's event radius would be swallowed. However before the network can function, nodes should be randomly dispersed throughout the domains, with one node chosen at random to serve as the CH. This way, the data transmission stage should start once nodes have been installed and developed a network. Thus the overall initiation phase is completed for establishing a reliable and efficient communication network in WSNs. Once the connection is established, the sensor nodes must be selected based on their reliability for ensuring the lossless transmission of data to the base station.

3.2. Selection Phase

To continue the process of the initiation phase, the reliance functions, such as parent reliance (PR) and grandparent reliance (GPR), are determined for every node. The reliance function determines the node's reliability in routing the data bytes. The dependence function defines competency, dependability, constructive feedback or interactions, and reliability on the data transmission procedure to all adjacent nodes. Each node gained the PR value from its linked neighbours directly, but the GPR indirectly obtained the trust value from the neighbouring nodes.

3.2.1. Parent Reliance (PR)

In the splay topology, the node directly connected to its neighbours in relation to capability and dependability for handling the actual request is considered PR. Directly linked nodes have a network connectivity interface established with their neighbours. The probability function of effective interactions between nodes, which determines how nodes connected to the selected RN behave in the topology and send packets to their intended recipients, makes up the PR of a node.

$R(x_k, x_d)$, represents the response of an effective encounter

$$R(x_k, x_d) = \frac{FP_{dk}(y)}{FP_{dk}(y) + \alpha[SP_{kd}(y) - FP_{dk}(y)]} \quad (8)$$

Where α stands for the penalty weight applied to the misbehaving node, x^d , stands for the node that is next to x^k , $SP_{kd}(y)$ stands for the amount of data bytes sent by x^k to x^d , $FP_{dk}(y)$, indicate the amount of data bytes forwarded by x^d through x^d , and y stands for the passage of time.

3.2.2. Grand Parent Reliance (GPR)

The node is dependent on GPR for two-hop data transfer, which indicates that the node indirectly depends on its neighbour's neighbour nodes. GPR examines the capacity of each node to judge its reliability and consistency inside the trusted class. The GPR is determined by,

$$Q(x_k, x_c) = R(x_k, x_d) * R(x_d, x_c) \quad (9)$$

Where c provides the PR of nodes x_k and x_d , and $R(x_d, x_c)$ represents the DT of nodes x_d and node x_c , respectively, and $Q(x_k, x_c)$ signifies the RT value of the node x_k towards node x_d .

3.3. Routing Phase

When the selection step is over, the routing phase starts to determine the best path to choose to transfer the data packets to Base Station through splaying. The suggested routing protocol known as the GBSO algorithm, however, uses fitness criteria to choose the best path. As a result, BHA and GSA were included into the architecture of the planned GBSO. The estimated solution vector is used to choose the most efficient path for sending packets from source to recipient. Finding the best route p among the several multi-path in a wireless network is essential.

The optimal route for transmitting data via RN from sender to receiver is chosen by taking reasons like energy, time, distance and reliance into account. The optimal approach is based on maximum fitness, which is said to be determined by least latency, least distance, most ideal trust value and most energy. The maximal fitness function is calculated as,

$$B = \frac{1}{4} [b + (1 - h) + (1 - \beta) + \mu] \quad (10)$$

$$b = \frac{1}{a} \sum_{K=1}^a b_k \quad (11)$$

$$h = \frac{a}{m} \quad (12)$$

$$\beta = \frac{1}{a^2 \times \eta} \sum_{K=1}^a \sum_{T=K+1}^a \beta(K, T) \quad (13)$$

$$\mu = \frac{1}{3a^2 \times \eta} \sum_{K=1}^a \sum_{T=K+1}^a [GP + GPR] \quad (14)$$

Where B indicates fitness function, b specifies energy, h represents delay, β is the distance, μ denotes trust, and η signifies normalisation factor.

3.3.1. Gravitational Search Algorithm

A colony of swarm entities in GSA seeks out the most optimal result cohesively. There is a gravitational attraction between one search agent and the other search agent. Before concentrating in the region with the global optimum, a sizeable number of search agents are initially used to interact with one another and explore the whole search space. A Kbest function monitors the progress of the search process. If a search space has to be examined, the Kbest value is maintained higher; else a smaller Kbest value is measured for exploitation. There is a mass value assigned to each search agent. The preferred choice is thought to be the more effective mass search agent. It suggests that when compared to rival search agents, the greater mass search agent has better fitness values. According to the principles of gravity and motion, all other search agents attempt to go toward the mass with the most significant weight. For the present iteration, the solution with the highest mass is thought to be the best choice.

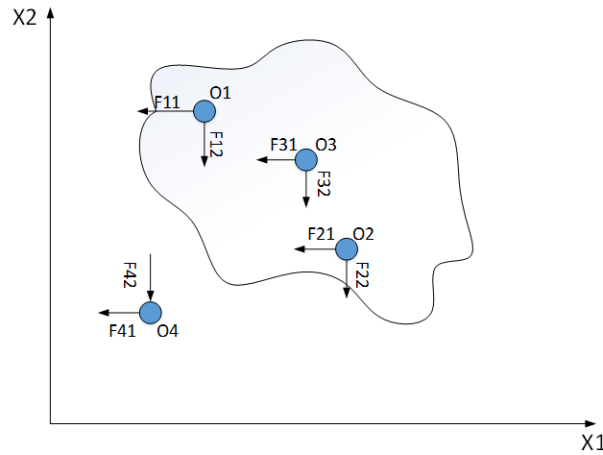


Fig. 4. illustrates a vector-based representation of the GSA's force and motion mechanism.

Four search agents O_1 to O_4) are depicted in the image in varying sizes. A bigger agent is thought to be a heavier mass search agent and has a higher fitness value. So, for a certain iteration, O_3 is the best solution (gBest) and O_4 is the worst option (gWorst) in the Fig 4. The force that other search agents (F_{12}, F_{13} and F_{14}) are exerting on the search agent O_1 causes it to update its location value. The heavy force component that O_1 delivered, however, causes the resulting movement vector (L_1) to point in the direction of O_3 . Here is also an explanation of the GSA method's mathematical formulations. Consider a universe with P search agents, each of which has d dimensions. It is possible to express the i th search agent (S_i) as (16).

$$S_i = (s_i^1, s_i^2, \dots, s_i^d), i = 1, 2, \dots, P \quad (15)$$

During iteration $t + 1$, the informed position of search agent S_i is provided by the

$$S_i(t + 1) = S_i(t) + V_i(t + 1) \quad (16)$$

Where $V_i(t+1)$ is the updated velocity of the i^{th} search agent as provided by and $S_i(t)$ is the search agent at iteration t .

$$V_i(t + 1) = rand \times V_i(t) + a_i(t), \quad (17)$$

Thus, $a_i(t)$ is determined as the acceleration of search agent i at the t^{th} iteration.

$$a_i(t) = \frac{Force_i(t)}{Mass_i(t)} \quad (18)$$

Here, $Force_i(t)$ and $Mass_i(t)$, with regard to the overall force and mass of the i^{th} item at the t^{th} repetition.

The two different forms of search agent masses are gravitational mass and inertial mass. These masses were viewed as being equal by the GSA's writers. Therefore, the mass $Mass_i(t)$, i th search agent at t th iteration is calculated as (19).

$$Mass_i(t) = \frac{m_i(t)}{\sum_{j=1}^P m_j(t)}, \quad (19)$$

$$m_i(t) = \frac{f_i(t) - bad(t)}{good(t) - bad(t)}, \quad (20)$$

$$good(t) = \min_{j \in \{1, \dots, P\}} f_j(t) \quad (21)$$

$$bad(t) = \max_{j \in \{1, \dots, P\}} f_j(t) \quad (22)$$

Where, $f_i(t)$ is the i^{th} , search agent fitness value, $good(t)$ and $bad(t)$, is considered by (21) and (22), correspondingly, for the minimisation issue.

Also, the total force $Force_i(t)$ is the weighted sum of the force applied by K best randomly selected search agents on i^{th} search agent, and it is given in (23).

$$\text{Force}_i(t) = \sum_{j=1, j \neq i}^{K_{\text{best}}} \text{rand} F_{ij}(t), \quad (23)$$

Where, rand is a chance value between 0 and 1. F_{ij} is the force of j^{th} search agent on i^{th} search agent and is calculated by(24).

$$F_{ij}^r(t) = G(t) \frac{\text{Mass}_i(t) \times \text{Mass}_j(t)}{R_{ij}(t) + \epsilon} (s_j(t) - s_i(t)) \quad (24)$$

In (9), K best is given as (25) at t^{th} iteration.

$$K_{\text{best}}(t) = \text{final_per} + \left(\frac{1-t}{\text{maxit}} \right) \times (100 - \text{final_per}) \quad (25)$$

where final-per is the proportion of search representatives chosen to use energy, and maxit is the number of iterations. The behaviour of K_{best} with increasing iterations is shown by the fact that K_{best} drops linearly over iterations, as seen in [Fig. 5](#).

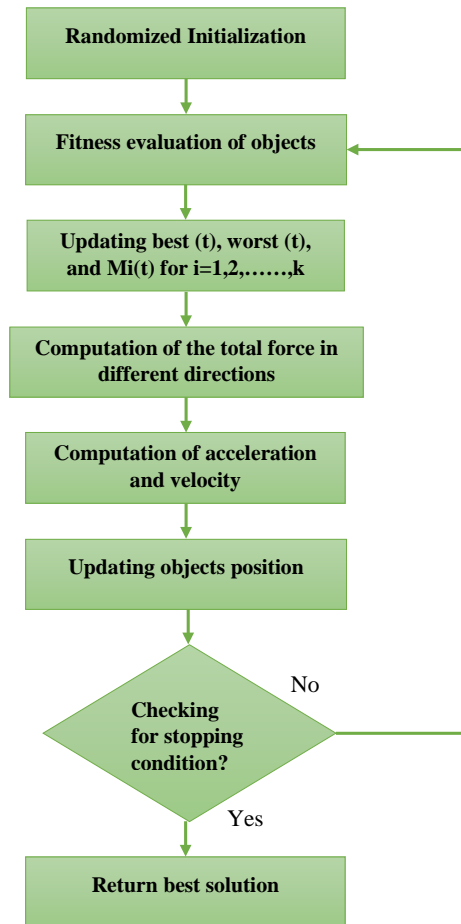


Fig. 5. Routing with GBSO algorithm

The proposed method was simulated to prove the working of the GBSO in improvising the QoS of the WSN communication. GBSO algorithm performs a global optimisation, which finds the best possible routing within a given search space. It avoids getting stuck in local optima and finds the optimal path between nodes. Thus the proposed GBSO method performs a optimized routing lowering the network complexity with lower computational time.

4. Result and Discussion

In addition to providing a comparison of the proposed approach with the current one, this part elaborates on the findings and analysis of the created GBSO algorithm by taking numerous parameters such as network lifetime, throughput, number of packets sent, the number of alive and dead nodes into account.

4.1 Experimental setup

The suggested technique is tested using the MATLAB tool 2021a and the following hardware and software: Windows 10 OS, Intel CPU, and 8GB Memory. **Table 2** displays the simulation parameters taken into account for the experiment.

Table 2. Simulation parameters

Parameters	Value
Energy Parameters	
Energy of free space	0.00000000001 J
Energy of transmitter	0.00000005 J
Energy spend in receiver	0.00000005 J
Energy spent for data transfer	0.000000005 J
Dimension of area	
Length of area	100
Width of area	100
Total number of nodes	200
Optimisation parameter	
Search agent number	10
Maximum iterations	100
Lower boundary	0
Upper boundary	1
Network topology	Splay tree

To simulate the proposed GBSO method's impact on the QoS of WSN communication, this research used MATLAB 2021a software. The simulation involved the utilization of a splay tree-based routing algorithm. Firstly, the simulation environment was setup by defining the parameters as given in table 2, based on which the splay tree-based routing algorithm was implemented. This routing in the WSN was optimized by determining the next hop for the required source and destination. The behaviour of each node in the WSN was specified for message generation, decision-making based on the GBSO routing algorithm, and the data was transmitted. Then the network topology was created, initializing the nodes based on the defined behaviour, and running the simulation loop. The simulation loop was iterated with varying values, allowing the nodes to perform their operations, exchange messages, and update the routing information based on proposed GBSO routing algorithm. Then the performance metrics such as computational time, packet delivery ratio, latenc for ensuring QoS measures of interest was analyzed to assess the effectiveness of the GBSO method in improving the QoS of WSN communication.

4.2. Performance Metrics

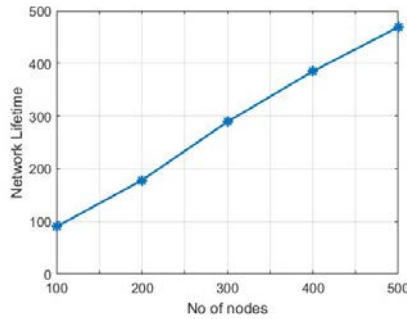


Fig. 6. Performance of the proposed method based on network lifetime

Each node in a WSN typically has a limited battery life, and when the quantity of nodes rises, the network's energy consumption also increases. This means that the battery life of each node may be reduced, leading to a shorter overall network lifetime. But if the nodes are well-distributed and can balance their energy consumption, then the network's life tends to increase the number of nodes. In our proposed GBSO method, a proper energy balance increases the network lifetime. **Fig. 6** demonstrates that the network life grows linearly from 90 to 480 from 100 to 500 nodes. This demonstrates how the suggested solution lowers energy usage and routing overhead thereby reduces the complexity.

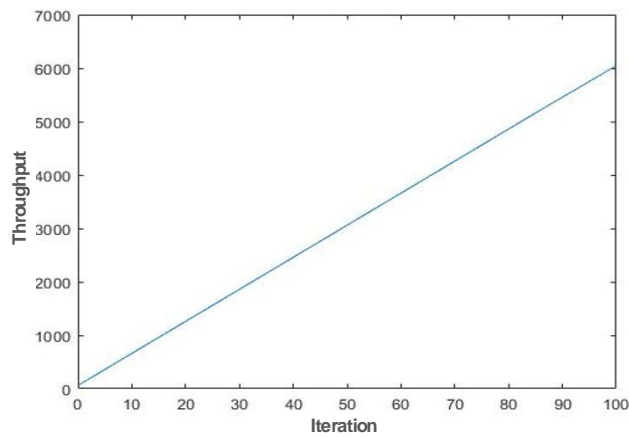


Fig. 7. Performance of the proposed method based on throughput

Throughput describes the speed at which data may be successfully sent from the sender node to the receiver node in WSN. Iteration refers to the number of times a particular task or operation is repeated in the network. The relationship between throughput and iteration in a WSN depends on several factors, including the network topology, the routing protocol used, the data transmission rate, and the channel conditions. As the number of iterations increases, the network may become more congested, leading to longer delays and higher packet loss rates, which can reduce the overall throughput. However, based on the GBSO method, since the network is well-organised and can balance the traffic load, the latency increases to 6000 for 100 iterations as shown in **Fig. 7** which indicates that the complexity of the method is very low. Hence this shows that there is no congestion, and all the packets are transferred without any loss.

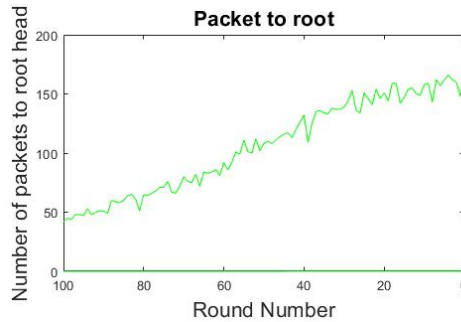


Fig. 8. Performance of the proposed method based on the number of packets sent to the root node at different rounds

The root head is typically the node that serves as the sink for the network. During each round of communication in the network, all nodes send one or more packets to the root head. The number of packets each node sends depends on the sensing frequency, the data aggregation technique, and the routing protocol employed. According to the features of the network's root node, **Fig. 8** clearly demonstrates that the nodes' ability to transmit packets declines as the round number increases. Since the charge of the root node is high initially, more packets are generated by each node, increasing the total quantity of packets transmitted to the root head. Similarly, the GBSO technique used involves merging data from multiple nodes. Thereby the packets need to be sent to the root head to transmit the aggregated data get lowered to 40.

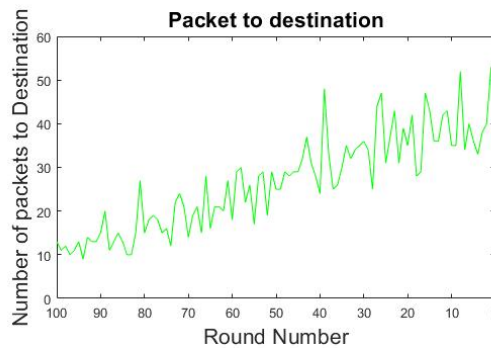


Fig. 9. Performance of the proposed method based on the number of packets sent to the destination at different rounds.

Depending on the network topology, and routing protocol, the nodes' packet output may vary from one round to the next. This proposal proposes a GBSO routing protocol to minimise the quantity of packets transmitted to the target node. The number of packets transmitted to the target node declines as the round number rises, depending on the optimisation characteristics of the network as shown in **Fig. 9**. When the energy is high, more packets may be generated by each node, increasing the amount of packets delivered to the target node. When the quantity of rounds rises, the energy of the RN decreases, and the number of packets gets reduced. Similarly, the GBSO technique involves merging data from multiple nodes when more packets must be sent to the receiver node to transmit the aggregated data.

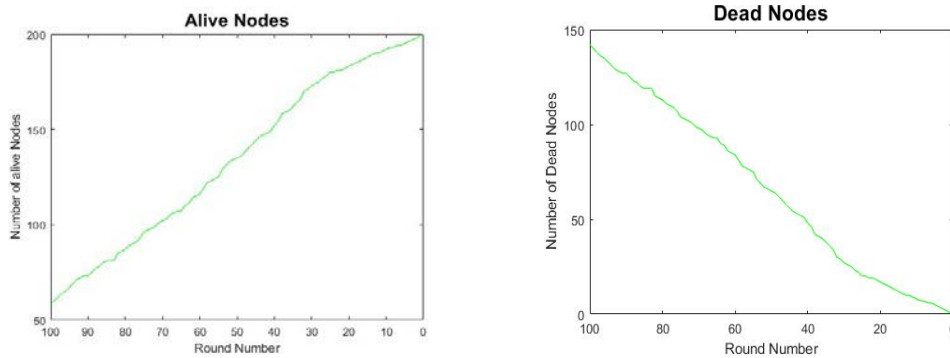


Fig. 10. Shows the number of alive and dead nodes in the proposed routing varying from round to round

Every node in the network sends data to the sink node once a round. As a result, depending on the node's availability, the number of active nodes in a WSN may vary from round to round. Thus, the above graph analyses the relationship between the number of alive or dead nodes with round numbers, which can be related to the network performance and resilience to node failures. In the proposed method total of 200 nodes were selected initially, and at the end of the 100th iteration still, 50 nodes have energy as shown in Fig. 10, which replicates that the network lifetime is improvised by proper energy balance using the GBSO algorithm.

4.3 Comparative Analysis

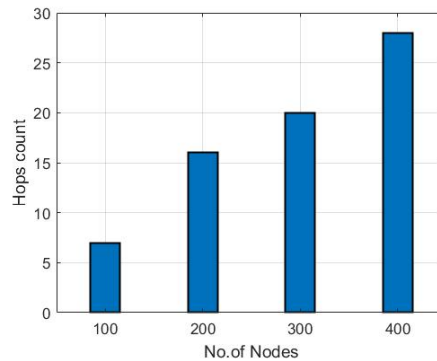


Fig. 11. Comparing the hop count based on the increasing number of nodes

The network architecture and the chosen routing protocol determine the correlation between the hop count and the quantity of nodes in a WSN. The average hop count increases along with the node count in a WSN because of the expanding distance between nodes and the opportunity for more sophisticated routing methods. In this research method, the hop count is maintained to be minimum using the gravitational search algorithm to optimise the routing path. Fig. 11 depicts that the hop count is increased only up to 28 even while considering 400 no of nodes. The proposed method utilises 200 nodes for which only 17 hops were required, which reduces the overall energy consumption.

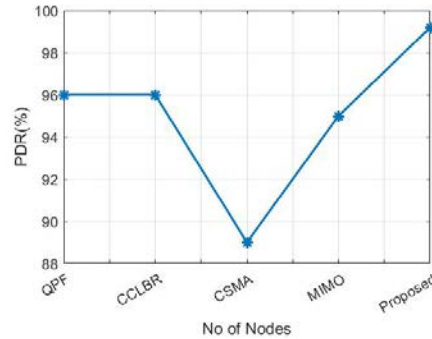


Fig. 12. Comparative analysis of proposed method with conventional methods

Packet Delivery Ratio (PDR) is an important performance metric for evaluating the reliability and effectiveness of communication in WSNs. For the proposed GBSO method, a PDR of 99.52 % was attained as shown in **Fig. 12**, which indicates that the network can deliver a high percentage of the data packets successfully. Thus it can perform an accurate and timely data transmission compared to several conventional techniques. The proposed method gives the highest PDR when compared with QPF [24], CCLBR [25], CSMA [26] and MIMO [27] due to its optimum balance of the transmission energy of the nodes, the optimum routing method.

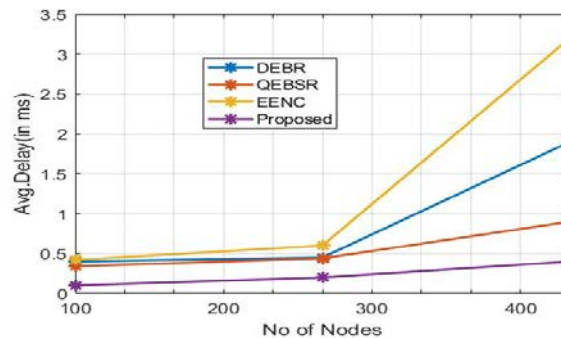


Fig. 13. Comparative analysis of proposed method with conventional methods based on delay

The above graph shows the relationship between the routing algorithm's average delay and the number of nodes for WSNs compared with DEBR [28], QEBSR [29] and EENC [30]. The graph gives important details about the network characteristics & the performance of the suggested GBSO routing technique. Due to the possibility of congestion, as the number of nodes increases, the computational time also increases. The graph in **Fig. 13** shows that as there were 400 nodes instead of 100, the average delay augmented very slightly from 0.19 to 0.47 due to the increased demand for network resources. The graph also shows the comparative analysis with different routing protocols investigating its computational time. It helps to identify that the proposed GBSO method is the most efficient protocol for a given network and application.

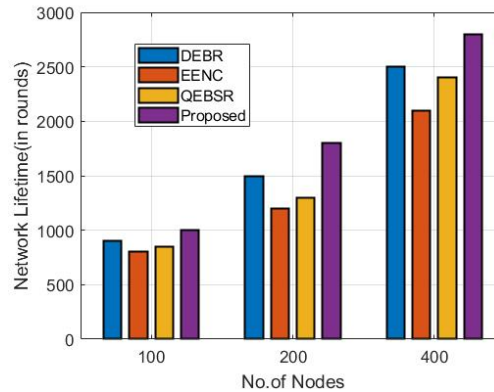


Fig. 14. Comparative analysis of proposed method with conventional methods based on network lifetime

The above graph in **Fig. 14** provides a detailed comparative analysis of a proposed method using network lifetime in WSNs. Comparing the proposed method's performance against DEBR [28], EENC [29], and QESBR [30] regarding network lifetime showed that the suggested method effectively extends the lifespan of the network and accomplishes a improved balancing of energy consumption and network performance. Three phases, initiation, selection and routing, are employed to lower the nodes' energy consumption and increase the network lifespan by up to 1000, 1750 and 2750 rounds for 100, 200 and 400 nodes, respectively, which is far better than the existing method.

5. Conclusion

When the network is overloaded when the data is transmitted, congestion occurs, causing significant packet losses, delay, a lack of available capacity, and jitter. So, it becomes necessary to maintain specific QoS parameters. The proposed method performs energy-efficient routing, extending the network's life and maintaining high scalability. The results clearly demonstrate the designed approach's performance, with a packet delivery ratio of 99.52 percent, a 0.19-second minimum latency, and a network lifetime of 1750 cycles with 200 nodes. Thus this shows that the proposed GBSO method optimizes the routing in WSNs, leading to enhanced QoS metrics such as reduced end-to-end delay, improved packet delivery ratio, and lower energy consumption. The splay tree structure dynamically adapts to changes in the network, ensuring shorter routing paths and reducing the overall network complexity. The GBSO-based splay tree routing framework optimizes the routing paths, reducing the overall energy consumption in the network. By efficiently selecting next hops and minimizing unnecessary data transmissions, the framework helps conserve energy, extending the network's operational lifetime. In future the proposed work can be extended to improve the framework's fault tolerance by including techniques for dealing with node failures and network repair procedures to guarantee the network stays operational and robust in the face of failures.

References

- [1] S. W. Nourildean, M. D. Hassib, and Y. A. Mohammed, "Internet of things based wireless sensor network: a review," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 27, no. 1, pp. 246-261, 2022. [Article \(CrossRef Link\)](#)
- [2] S. Sahu, and S. Silakari, "Analysis of energy, coverage, and fault issues and their impacts on applications of wireless sensor networks: a concise survey," *International Journal of Computer Networks and Applications (IJCNA)*, vol. 8, no. 4, pp. 358-380, 2021. [Article \(CrossRef Link\)](#)
- [3] U. K. Lilhore, O. I. Khalaf, S. Simaiya, C. A. Tavera Romero, G. M. Abdulsahib, and D. Kumar, "A depth-controlled and energy-efficient routing protocol for underwater wireless sensor networks," *International Journal of Distributed Sensor Networks*, vol. 18, no. 9, pp. 15501329221117118, 2022. [Article \(CrossRef Link\)](#)
- [4] A. Rovira-Sugranes, A. Razi, F. Afghah, and J. Chakareski, "A review of AI-enabled routing protocols for UAV networks: Trends, challenges, and future outlook," *Ad Hoc Networks*, vol. 130, pp. 102790, 2022. [Article \(CrossRef Link\)](#)
- [5] I. J. Jacob, and P. E. Darney, "Artificial bee colony optimization algorithm for enhancing routing in wireless networks," *Journal of Artificial Intelligence*, vol. 3, no. 01, pp. 62-71, 2021. [Article \(CrossRef Link\)](#)
- [6] K. Rajnish, V. Bhattacharjee, and V. Chandrabanshi, "Applying Cognitive and Neural Network Approach over Control Flow Graph for Software Defect Prediction," in *Proc. of 2021 Thirteenth International Conference on Contemporary Computing (IC3-2021)*, pp. 13-17, 2021. [Article \(CrossRef Link\)](#)
- [7] A. A. Barakabitze, and R. Walshe, "SDN and NFV for QoE-driven multimedia services delivery: The road towards 6G and beyond networks," *Computer Networks*, vol. 214, pp. 109133, 2022. [Article \(CrossRef Link\)](#)
- [8] T. Omar, T. Ketseoglou, and I. Naffaa, "A novel self-healing model using precoding & big-data based approach for 5G networks," *Pervasive and Mobile Computing*, vol. 73, pp. 101365, 2021. [Article \(CrossRef Link\)](#)
- [9] J. Amutha, S. Sharma, and J. Nagar, "WSN strategies based on sensors, deployment, sensing models, coverage and energy efficiency: Review, approaches and open issues," *Wireless Personal Communications*, vol. 111, pp. 1089-1115, 2020. [Article \(CrossRef Link\)](#)
- [10] A. Mazinani, S. M. Mazinani, and M. Mirzaie, "FMCR-CT: An energy-efficient fuzzy multi cluster-based routing with a constant threshold in wireless sensor network," *Alexandria Engineering Journal*, vol. 58, no. 1, pp. 127-141, 2019. [Article \(CrossRef Link\)](#)
- [11] S. Roychowdhury, and C. Patra, "Geographic adaptive fidelity and geographic energy aware routing in ad hoc routing," *International Journal of Computer and Communication Technology*, vol. 2, no. 2, pp. 91-95, 2011. [Article \(CrossRef Link\)](#)
- [12] R. K. Lenka, M. Kolhar, H. Mohapatra, F. Al-Turjman, and C. Altrjman, "Cluster-based routing protocol with static hub (CRPSH) for WSN-assisted IoT networks," *Sustainability*, vol. 14, no. 12, pp. 7304, 2022. [Article \(CrossRef Link\)](#)
- [13] K. SureshKumar, and P. Vimala, "Energy efficient routing protocol using exponentially-ant lion whale optimization algorithm in wireless sensor networks," *Computer Networks*, vol. 197, pp. 108250, 2021. [Article \(CrossRef Link\)](#)
- [14] W. K. Yun, and S. J. Yoo, "Q-learning-based data-aggregation-aware energy-efficient routing protocol for wireless sensor networks," *IEEE Access*, vol. 9, pp. 10737-10750, 2021. [Article \(CrossRef Link\)](#)
- [15] M. Rathee, S. Kumar, A. H. Gandomi, K. Dilip, B. Balusamy, and R. Patan, "Ant colony optimization based quality of service aware energy balancing secure routing algorithm for wireless sensor networks," *IEEE Transactions on Engineering Management*, vol. 68, no. 1, pp. 170-182, 2021. [Article \(CrossRef Link\)](#)
- [16] X. Fu, G. Fortino, P. Pace, G. Aloï, and W. Li, "Environment-fusion multipath routing protocol for wireless sensor networks," *Information Fusion*, vol. 53, pp. 4-19, 2020. [Article \(CrossRef Link\)](#)

- [17] P. S. Khot, and U. Naik, "Particle-water wave optimization for secure routing in wireless sensor network using cluster head selection," *Wireless Personal Communications*, vol. 119, pp. 2405-2429, 2021. [Article \(CrossRef Link\)](#)
- [18] S. Sefati, M. Abdi, and A. Ghaffari, "Cluster-based data transmission scheme in wireless sensor networks using black hole and ant colony algorithms," *International Journal of Communication Systems*, vol. 34, no. 9, pp. e4768, 2021. [Article \(CrossRef Link\)](#).
- [19] X. Xue, R. Shanmugam, S. Palanisamy, O. I. Khalaf, D. Selvaraj, & G. M. Abdulsahib, "A hybrid cross layer with harris-hawk-optimization-based efficient routing for wireless sensor networks," *Symmetry*, vol. 15, no. 2, p. 438, 2023. [Article \(CrossRef Link\)](#).
- [20] E. Obi, Z. Mammeri, & O. E. Ochia, "A Centralized Routing for Lifetime and Energy Optimization in WSNs Using Genetic Algorithm and Least-Square Policy Iteration," *Computers*, vol. 12, no. 2, p. 22, 2023. [Article \(CrossRef Link\)](#).
- [21] S. K. Barnwal, A. Prakash, & D. K. Yadav, "Improved African Buffalo Optimization-Based Energy Efficient Clustering Wireless Sensor Networks using Metaheuristic Routing Technique," *Wireless Personal Communications*, pp. 1-22, 2022. [Article \(CrossRef Link\)](#)
- [22] Y. Liu, C. Li, Y. Zhang, M. Xu, J. Xiao, & J. Zhou, "DCC-IACJS: A novel bio-inspired duty cycle-based clustering approach for energy-efficient wireless sensor networks," *Journal of King Saud University-Computer and Information Sciences*, vol. 35, no. 2, pp. 775-790, 2023. [Article \(CrossRef Link\)](#).
- [23] D. D. Sleator, and R. E. Tarjan, "Self-adjusting binary search trees," *Journal of the ACM (JACM)*, vol. 32, no. 3, pp. 652-686, 1985. [Article \(CrossRef Link\)](#)
- [24] R. K. Verma, K. K. Pattanaik, S. Bharti, D. Saxena, & J. Cao, "A query processing framework for efficient network resource utilization in shared sensor networks," *ACM Transactions on Sensor Networks (TOSN)*, vol. 16, no. 4, pp. 1-28, 2020. [Article \(CrossRef Link\)](#)
- [25] X. J. Shen, Q. Chang, L. Liu, J. Panneerselvam, & Z. J. Zha, "CCLBR: Congestion control-based load balanced routing in unstructured P2P systems," *IEEE Systems Journal*, vol. 12, no. 1, pp. 802-813, 2016. [Article \(CrossRef Link\)](#)
- [26] A. Maatouk, M. Assaad, & A. Ephremides, "Energy efficient and throughput optimal CSMA scheme," *IEEE/ACM Transactions on Networking*, vol. 27, no. 1, pp. 316-329, 2019. [Article \(CrossRef Link\)](#)
- [27] H. He, C. K. Wen, S. Jin, & G. Y. Li, "Deep learning-based channel estimation for beamspace mmWave massive MIMO systems," *IEEE Wireless Communications Letters*, vol. 7, no. 5, pp. 852-855, 2018. [Article \(CrossRef Link\)](#)
- [28] W. Lu, H. Zhao, & H. Zhao, "Distributed energy balancing routing algorithm in wireless sensor networks," *Recent Advances in Computer Science and Information Engineering*, vol. 4, pp. 227-232, 2012. [Article \(CrossRef Link\)](#)
- [29] K. Lin, C. F. Lai, X. Liu, & X. Guan, "Energy efficiency routing with node compromised resistance in wireless sensor networks," *Mobile Networks and Applications*, vol. 17, pp. 75-89, 2012. [Article \(CrossRef Link\)](#)
- [30] M. Rathee, S. Kumar, A. H. Gandomi, K. Dilip, B. Balusamy, & R. Patan, "Ant colony optimization based quality of service aware energy balancing secure routing algorithm for wireless sensor networks," *IEEE Transactions on Engineering Management*, vol. 68, no. 1, pp. 170-182, 2021. [Article \(CrossRef Link\)](#).
- [31] Y. Liu, M. Dong, K. Ota, & A. Liu, "ActiveTrust: Secure and trustable routing in wireless sensor networks," *IEEE Transactions on Information Forensics and Security*, vol. 11, no. 9, pp. 2013-2027, 2016. [Article \(CrossRef Link\)](#)
- [32] J. Ren, Y. Zhang, K. Zhang, A. Liu, J. Chen, and X. S. Shen, "Lifetime and energy hole evolution analysis in data-gathering wireless sensor networks," *IEEE transactions on industrial informatics*, vol. 12, no. 2, pp. 788-800, 2016. [Article \(CrossRef Link\)](#)



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