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OPTIMIZING ENERGY EFFICIENCY AND FAULT TOLERANCE IN WIRELESS SENSOR NETWORKS THROUGH NOVEL CLUSTERING APPROACH

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Abstract
Developing cutting-edge technologies has enhanced confidence in planning significant wireless networks of low-power devices. When designing and deploying wireless sensor networks (WSNs), energy consumption and fault tolerance are the two most important considerations—not keeping up with technical advancements. To demonstrate both energy-efficient clustering and cluster heads' (CHs') fault-tolerant operation, we proposed Adaptive Grey Wolf Optimized Ant Colony Optimization (AGWO-ACO) to obtain efficient energy consumption and find the shortest path in WSNs,. The suggested technique integrates AGWO with ACO to obtain the best value of the ρ factor for ACO using GWO. The fuzzy inference process used by the grouping approach dynamically generates CHs while accounting for various node characteristics and network conditions. We used a cluster-based fault-tolerant routing protocol (CFTR) that allows high-energy nodes to perform as CHs and execute multiple rounds of operations, hence minimizing the requirement for periodic re-clustering. The reliability of the WSN is improved by a fault tolerance mechanism that reduces communication failures and assures reliable data flow throughout the network. The suggested clustering technique aims to cluster the sensor nodes, lowering energy consumption during data transmission and facilitating effective failure detection and recovery. The proposed technique integrates AGWO with ACO to obtain the best value of the ρ factor for ACO using GWO with a novel clustering approach. We demonstrated that 3312 packets were forwarded, and the best route remained 1, demonstrating constant optimization. These findings show that the suggested AGWO-ACO method outperforms contrasted to other traditional methods, making it convenient for crucial and resource-constrained WSN scenarios.

Keywords:
Adaptive Grey Wolf Optimized Ant Colony Optimization (AGWO-ACO) Cluster Head, Fault-Tolerant, Fuzzy Inference Mechanism and Routing Protocol, Wireless Sensor Networks (WSNs)

1. INTRODUCTION

WSNs have developed an essential methodology in the region of universal computing, permissive a distributed structure of enforced sensor nodes to monitor and gather information from the physical setting [1]. These networks are utilized in numerous fields including environmental observation, healthcare, industrial automation, and smart cities. A WSN consists of compact, self-governing sensor nodes that are regulated with the capacity to sense, process, and communicate [2]. This allows them to perform together in associating and authorization data to a central base station or other nodes in the network. WSNs are used to delight the necessity for obtaining and measuring real-time data in dynamic and distanced situations [3].

WSNs are greatly useful for situations where a conventional wired framework is impracticable or economically expensive because of their resilience and scalability [4]. Although WSNs have various benefits they also endure difficulties, with energy performance being a substantial challenge. Sensor nodes frequently have limited energy resources, generally susceptible to battery power [5]. The endurance of a WSN has a powerful association with the energy consumption of every individual node. Maximizing the operating time of these networks is essential for their sustainable use in various applications.

The aspiration for higher energy development in WSNs is a multidimensional development that commits to network design, communication protocols, and node hardware [6]. Advancements in energy productivity not only enhance the operating consist of individual nodes but also compute the total validity and efficacy of the network. The purpose of improving energy efficiency in WSNs encompasses optimizing communication protocols to decrease the energy used through data transmission and response [7]. This consolidates the development of effective routing computations, data aggregation strategies, and protocols for the dynamic reconfiguration of networks [8]. Furthermore, developments in sensor node hardware, like low-power features and energy-collection approaches, are compelling in perfecting energy efficiency.

Investigating sleep/awake methods and power administration approaches performs a crucial role in conserving energy in WSNs [9]. By strategically controlling the power states of individual nodes, it is achievable to accomplish a harmonious equilibrium among the operational requirements of the network and the commitment to preserving energy, ultimately resulting in a protracted network generation.

The broad addition of WSN has regularly modified the field of data gathering and monitoring in numerous fields [10]. Yet, the effective implementation of WSNs depends on effectively addressing the issue of energy efficiency. The achievement of enhanced energy efficiency entails a comprehensive strategy that encompasses progress in communication protocols, network design, and sensor node hardware [11]. The collaborative efforts are focused on advancing WSNs to enhance their resilience, dependability, and environmental sustainability, therefore ensuring their contribution to the development of intelligent and integrated systems.

The remainder of this research is divided into subsequent sections. The literature review conducted in various WSN models is presented in Section 2. The suggested procedure is presented in section 3. Section 4 contains the experimental findings of the proposed AGWO-ACO, while Section 5 presents the conclusion of the research.

2. RELATED WORK

The study [12] focused on understanding probable operational disruptions in WSNs to improve the network's robustness and self-healing capacities. When WSNs operate in a resource-constrained and challenging installation environment, many problems might arise, requiring fault tolerance and preventative measures. The study [13] had deployed WSNs to gather a variety of data from the application space for Internet of Things (IoT). Those WSNs included sensor nodes with various capabilities, including data aggregation and power operations. It was essential to transmit data efficiently, accomplished by cluster-based routing.

The “partitioned-based energy-efficient – LEACH (PE-LEACH) protocol was a low energy adaptive clustering hierarchy (LEACH)” variant clustering convention that the authors suggested in the study [14]. Additionally, they provided a taxonomy of LEACH variations. PE-LEACH’s implementation was evaluated. They determined that PE-LEACH functioned more effectively than LEACH.

The study [15] enhanced “Wireless Body Area Networks (WBAN)” reliability, the study offered a renewable, fault-tolerant technique. The system reduced the impacts of channel degradation and body fading while lowering errors, bit error rates, and energy consumption which was done by using cooperative communication and network coding. In terms of remote septic evaluation, the system leverages cooperative connectivity to identify tracking metrics that have improved due to lower values of error rate, better energy consumption, and reduced latency.

The study [16] evaluated that Strong security and dependability measures were required to integrate wireless technology with industrial domains. “Industrial wireless sensor networks (IWSNs)” were prone to security issues because of their challenging deployment environments, open design, and unreliable routing protocols. Adversaries were drawn to targets with low processing power, energy, and resource-constrained communication range. The shortcoming indicated that privacy had to be enhanced for WSNs to be used reliably in industrial applications.

The "fuzzy attribute-based joint integrated scheduling and tree formation (FAJIT)" methodology was a strategy proposed by the investigators [17] for fuzzy logic-based tree generation and parent node recognition in heterogeneous systems. The candidate nodes with the shortest dynamic neighbors were used to choose which parent nodes to choose from. Fuzzy logic was the approach that was used for WSN. On some factors, the outcomes of FAJIT and the "distributed algorithm for Integrated tree Construction and data Aggregation (DICA)" were compared. The findings showed that the suggested method had superior energy consumption.

The work [18] highlighted the scope of transportable WSNs and their evolution. The article examined “Advanced Metering Infrastructure (AMI)”, an automated system for monitoring energy use, concentrating on their use in information sensing, collection, and transmission applications for smart cities. The study [19] demonstrated an innovative energy-efficient, reliable routing method with delay limitations. The technique minimized end-to-end latency while building clusters. Compared to the concurrence, rule-based clustering for the routing model outperformed it, particularly in extending the lifetime of the network while using less energy between cluster building and route finding.

3. PROPOSED METHOD: NETWORK MODELLING PERSPECTIVES

This section includes the model of the network and the pattern of the distribution of nodes in the network. Section 3.1 defines the hierarchical connection among nodes, including the networks themselves. Besides that, a discussion is conducted on the suggested method’s energy consumption model.

3.1 NETWORK MODEL

A network model is a framework that forms the basis for comprehending how the sensor nodes in the network are organized, communicated, and behave. WSNs are networks of small, resource-constrained sensors dispersed over a region and work together to gather and transmit data. The network model determines the regulation, protocols, and integrity that classify how these sensors combine, plan their behavior, and employ accessible resources better. The network’s structure addresses patterns, data routing systems, and processes for retailing with issues, along with data aggregation, energy conservation, and fault tolerance. For wireless sensor networks to accomplish their purposed activities, which may contain ecological monitoring, surveillance, industrial automation, and more, they require designing, managing, and optimizing, and this model is crucial for doing so. The adaptability and performance of the entire method are sustained by an elemental idea known as the network model in WSN, as shown in Fig.1, the general system model for clustered WSN.

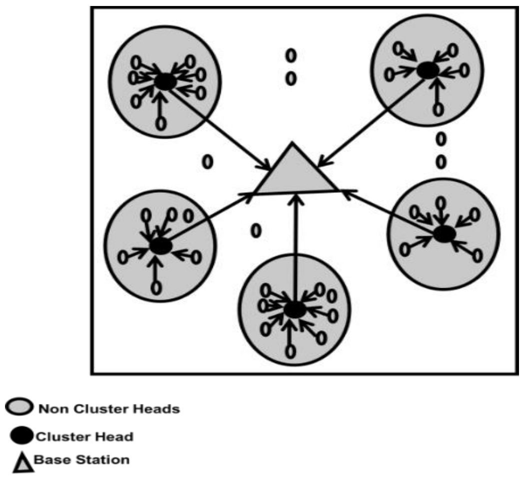

Fig.1. General architecture for clustered WSN

3.2 CLUSTER HEAD (CH)

A CH is a fundamental element. It performs an imperative role as the central node in a group of sensor nodes. The CH’s main responsibility is facilitating effective data management and communication inside the cluster. Data gathering, routing, and transmitting information from the sensor nodes to a centralized base station or sink node are the responsibilities of member nodes. By arranging and coordinating data transmission, they provide a bridge between many sensors in their cluster and the interconnected wide-area network, which helps lower energy usage and improve network scalability.

3.3 CLUSTER-BASED FAULT-TOLERANT ROUTING PROTOCOLS (CFTR)

The suggested process is divided into five stages: start, clustering, neighbors CHs selection, information routing, and tolerating faults, Fig.2 demonstrates the network structure.

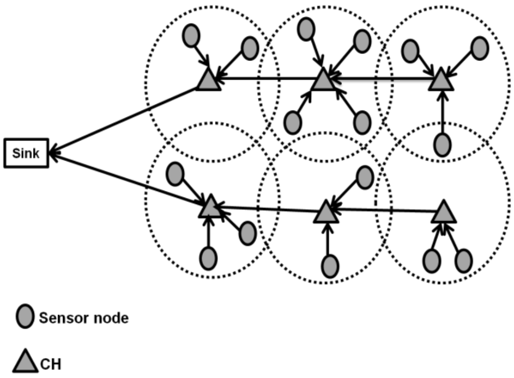

Fig.2. Network structure

3.3.1 Starting stage:

Each node in this stage is responsive to its closeness to the central sink node. A saturation phase is started by the sink, which transmits HELLO messages at regular intervals across the network. Each node determines its distance to the sink by using the intensity of signal as an indication after receiving the HELLO message. Then, a critical stage that includes information routing and cluster development follows. The distance data from the first exchange is essential for creating effective clusters and routing paths, which support the network's methodical structure and functioning.

3.3.2 Clustering phase:

A CFTR protocol focus on energy savings and load balancing. During the clustering phase of this technique, CHs and the accompanying cluster members are identified. A preference is given to nodes with greater energy levels to act as cluster heads in the future CH selection step. These nodes allow the cluster to function for several rounds without the requirement for re-clustering overhead, pending the identification of another cluster member with the same cluster with greater energy than the current CH. Based on crucial energy efficiency and load-balancing characteristics, cluster members interact with CHs throughout the cluster creation process. It is conceivable for specific sensor nodes to be placed outside of any CH's communication range in higher network installations. For CH functions, nodes with greater energy levels are given priority. Unless a cluster member with greater energy is located inside the same cluster, these high-energy CHs allow clusters to function for many rounds without incurring re-clustering expenses. Depending on vital energy efficiency and load-balancing characteristics, cluster members establish links with CHs during the cluster formation phase. It is feasible for certain sensor nodes in big networks to be located beyond any CH's communication range. To solve this issue, CFTR uses a multi-hop mode to link these nodes to a CH. A proportion of CHs is chosen in the first round using a technique similar to that used in earlier research approximately 5%. When a CH sends out an ADV_MSG message, sensor nodes that receive it, add the CH to their list of potential CHs (C and CH) and cease to be CH nodes for that round. When a CH sends out an ADV_MSG message, sensor nodes that receive it add the CH to their list of potential CHs (C and CH) and cease to be CH nodes for that round. The suggested method uses a route that uses less energy.

$$AV_{(G_j,Y_j)} = \frac{MA_{(G_j,Y_j)}}{KA_{G_j}} \text{ and } AV_{(G_j,Sink)} = \frac{MA_{(G_j,Sink)}}{KA_{G_j}} \tag{1}$$

$$CHCost(Y_j,G_j) \propto \frac{1}{AV_{(G_j,Y_j)}}$$

$$CHCost(Y_j,G_j) \propto \frac{1}{AV_{(Y_j,Sink)}} \tag{2}$$

Eq.(1) determines the Availability Value (AV) in CFTR for a particular node's communication with a sensor node or the sink, taking into consideration the Message Amount (MA) and Knowledge Amount (KA). Based on these variables, AV assigns the path an appropriateness assessment. The total cost of communication among a Cluster Head (CH) and a sensor node or the sink is expressed in Eq.(2) as CHCost. In the wireless sensor network, routes with greater reliability and less consumption of energy are preferred because of the cost's inverse relationship to AV.

3.3.3 Phase of Determining Neighboring CH:

The CH starts the dissemination of a message requesting a SEARCH across network to find its nearby CHs. The SEARCH message contains relevant data about the CH, including its ID, estimated distance from that field, and a sink node. NLAST is the default value for the status field, suggesting this message isn't among the last to be delivered. Receiving the SEARCH message, an ACK message is returned by a CH that is farther away from to sink. The ACK message also includes the NCCR and NBPR, distance, and energy cost source. The number of backward CHs is used to update the NBPR, initially set to 1 for the first CH selection. In comparison to other CHs, the sink node has a greater priority. As a consequence, when a CH receives an ACK message from the sink, it immediately transmits data to it. In the best-case and worst-case situations, respectively, each CH demands both lower and higher-level CHs, this method creates a network of CHs that are directed toward the sink.

3.3.4 Data routing phase:

Communication between clusters, both intra- and inter-cluster is covered in this section.

- ***Intra-cluster data forward***: Following clustering, CH gives the members with its time division multiple access (TDMA) schedule. According to this, each participant has designated slots when they can send data while the others go into sleep mode. The CH compiles and transmits the data it receives to the sink in the inter-cluster communication protocol.
- ***Inter-cluster data forward***: The process of inter-cluster data forwarding in network communication involves sending or relaying data across several clusters or groups of nodes, as shown in Fig.3, the structure of a routing algorithm. This happens when data gathered by CHs or nodes inside one cluster must be transmitted to another cluster or a central data sink, such as in hierarchical or multi-hop networks. Inter-cluster data forwarding entails sending the data in a

system of intermediary nodes to make sure it reaches the cluster or sink it is meant for taking network topology, routing protocols, and data aggregation strategies into account. Inter-cluster data forwarding's main objectives are to provide effective data routing from several clusters to a single place for processing or storage and to allow smooth and dependable communication across various network components.

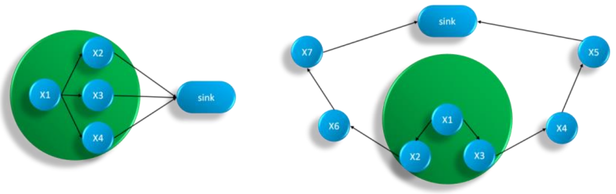

Fig.3. Structure of a routing algorithm

3.3.5 Fault tolerance stage:

Despite the case of a CH collapse, our CFTR's fault-tolerant system can keep the network running normally. Fault recovery and fault detection are the two sections of the approach. The absence of ACK signals to cluster members from their CHs for transmitted data packets indicates a CH failure. After detecting a failure, each member of the cluster Si verifies a C and CH(Si) for recovery. A relay node capable of connecting to a far-off CH is chosen if C and CH(Si) are empty by looking at its BackUp(Si). Data are routed via alternate CHs in the event of failure detection, with lower-level CHs preferred over higher-level CHs.

4. ADAPTIVE GREY WOLF OPTIMIZED ANT COLONY OPTIMIZATION (AGWO-ACO)

4.1 ADAPTIVE GRAY WOLF OPTIMIZATION (AGWO)

The leadership structure and hunting behavior of grey wolves served as the basis for the Adaptive Grey Wolf Optimization. As mentioned, the wolves' vector representation is provided in Eq.(3, and the method starts with the population's organic development of wolves arbitrarily, aiming to get the optimal 3 solutions in the first 3 locations (QB_1, QB_2, QB_3).

$$\vec{E} = \vec{e}_1 + \vec{e}_2 + \cdots + \vec{e}_n \tag{3}$$

The three primary phases of wolves in the wolf hunting technique were surrounding, pursuing, and stalking, and with n = search space dimension, the 3 optimal solutions move in the direction of the intention while the equilibrium of the pack (RP) tracks their path. To compute the prey's encirclement, the prey's positions are subtracted from the estimated distance, and the wolves multiply the result by the coefficient vectors. The hunt is conducted when the 3 optimal solutions have examined the location of the food and the RP has updated its positions by the optimal solutions. The location of the associated ideal solution is subtracted from the RP in the aggressive processing, where the grey wolves split from one another while searching for prey and combine while attacking the prey to estimate the distance for each optimal solution. In this sense, the equations below are constructed. On the circular hunting stage, distance is calculated as follows:

$$\overrightarrow{dist} = |\, \vec{v} \cdot \left(\overrightarrow{position}_{prey}(d) - \overrightarrow{position}_{wolf}(ed) \right) | \tag{4}$$

The distance vector is computed during the circular hunting stage using Eq.(4). It calculates the absolute difference between the prey's current location and the coefficient-vector-weighted prey position. This represents the distance the wolf pack keeps from the prey as they collaborate to surround it. Where v is the coefficient vector.

In the hunting stage, the distance for each ideal solution is provided as Eq.(5), Eq.(6), and Eq.(7):

$$\overrightarrow{dist}_{QB1} = |\, \vec{v}_1 \cdot \overrightarrow{position}_{QB1} - \overrightarrow{position}_{wolf} \,| \tag{5}$$

$$\overrightarrow{dist}_{QB2} = |\, \vec{v}_2 \cdot \overrightarrow{position}_{QB2} - \overrightarrow{position}_{wolf} \,| \tag{6}$$

$$\overrightarrow{dist}_{QB3} = |\, \vec{v}_3 \cdot \overrightarrow{position}_{QB3} - \overrightarrow{position}_{wolf} \,| \tag{7}$$

The distances between each optimum solution (QB_1, QB_2, QB_3) and the current wolf location during the hunting phase are calculated using Eq.(5), Eq.(6), and Eq.(7). This illustrates how the technique employs the closeness of each optimum solution to steer the pack's movement during cooperative hunting, assisting in the search space's integration toward optimum alternatives.

4.2 ANT COLONY OPTIMIZATION (ACO)

It is a probabilistic metaheuristic approach utilized to solve issues involving combinatorial optimization. The approach aims to replicate the hunting habits of ants to identify more efficient routes from colonies to food sources. Ants release pheromones while they are in motion, which helps them communicate with other ants. The selection of a route is influenced by the concentration of pheromone, with larger concentrations being more suitable for following ant selections. Shorter pathways accumulate pheromones more rapidly, strengthening their electability over time. The process of pheromone condensation makes it more difficult to recognize less favorable courses, consequently promoting the identification of alternate routes. The ACO algorithm functions by using global modifying principles, local updating, and state transition, which replicate the probabilistic, and adaption characteristics of ant activity. The algorithm's stochastic nature and adaptable techniques allow it to effectively navigate around barriers, giving it a resilient solution for intricate optimization tasks.

Ants relocate among nodes employing the state transition method described in Eq.(8).

$$t = \begin{cases} \arg\max\limits_{v \in I_l(q)} \left[\tau(q,v)\right]^{\alpha} \left[\eta(q,v)\right]^{\beta}, & \text{if } r \le r_0 \\ T, & \text{otherwise} \end{cases} \tag{8}$$

In the state transitioning rule, $\tau(q,v)$ represents the opposite side of the distance among nodes q and v. The expression $I_l(q)$ represents the collection of nodes that an ant located at node q might potentially visit in the subsequent time step. The variables α and β define the appropriate significance of pheromone and proximity of nodes.

Each time ants go to their nodes using the state transitioning rule, the pheromone is modified according to the local updating method and communicated.

$$\tau(q,t) \leftarrow (1-\rho)\tau(q,t) + \rho\Delta\tau(q,t) \tag{9}$$

The pheromone dispersion coefficient ρ is a decimal value that occurs within the range of 0 to 1. The function $\tau(q,t)$ represents the change in pheromone level, denoted as τ_0, which is equal to the product of m and K_{mm} raised to a value of -1, indicating the starting quantity of pheromone. In this context, m represents the total number of cities, whereas K_{mm} is the cost generated by the closest neighbor heuristic. Once all ants have traveled to all cities, the global updating rule is executed.

$$\Delta\tau(q,t)=\begin{cases}K_{ha}^{-1}, & \text{if}(q,t)\in \text{GlobalBestTour}\\ 0, & \text{otherwise}\end{cases} \tag{10}$$

where ρ is constant and K_{ha} represents the optimal tour found globally.

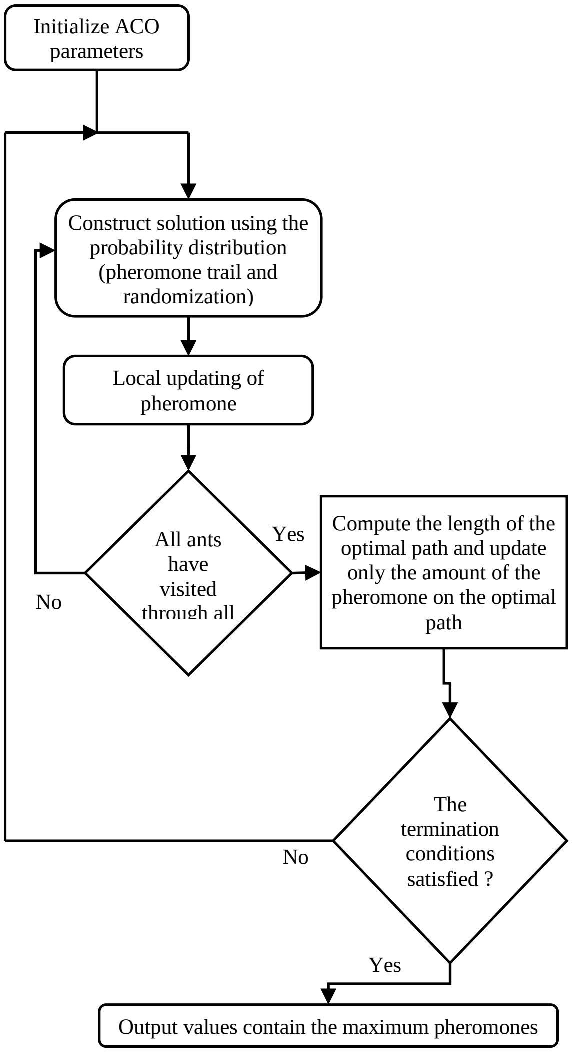

Fig.4. Process of ACO

The ACO algorithm works by executing a sequence of iterative procedures as mentioned in Fig.4. At first, the pheromone table and ACO characteristics are set up. The assignment of ants to nodes is done randomly, where each ant selects its next location based on a distribution of probabilities. Following the implementation of local pheromone updates, the procedure iterates until all ants have traversed each city. Afterwards, the most efficient route is calculated, and a global pheromone update takes place. The technique proceeds through these phases until the specified halting requirements are satisfied. This repeated process provides continual development of routes depending on pheromone data and, lastly dominant to a greatly efficient solution within the search area.

The approach combines AGWO and ACO, two optimization approaches. While ACO seeks food by imitating ants, AGWO is renowned for its ability to identify suitable solutions. The primary objective of this combined technique is to determine the optimal value for a crucial ACO parameter, ρ. This parameter assists in achieving a balance between the algorithm's exploration of new locations and its concentration on well-established areas. AGWO assists in locating the optimal ρ value for the ACO. The objective is to use the complementary qualities of AGWO and ACO to improve energy efficiency and fault tolerance of wireless sensor networks. The goal of this novel combination is to enhance the grouping of wireless sensor networks, increasing their robustness and practicality.

5. RESULTS AND DISCUSSION

5.1 EXPERIMENTAL SETUP

We established a wireless sensor network scenario with different node densities using a MATLAB model-based experimental setup. The AGWO-ACO hybrid algorithm was used to maximize clustering by taking into consideration randomly given parameters. We evaluated the efficiency and resilience of the system by analyzing its energy consumption and ability to handle faults. We compared the findings with those of conventional clustering methods. By using a randomized strategy, we were able to verify the efficacy of our hybrid algorithm over a wide range of network topologies.

5.2 SIMULATION FINDINGS

During the evaluation phase, a total of 9 nodes were selected for simulation. The simulation consisted of 5 neighboring nodes for every chosen node, with a spatial interval of 500 electron distances between them. Nodes with energy levels beyond 100mV are categorized as active (favorable), whilst those falling below 100mV are deemed inactive (unfavorable). The purpose of this configuration was to evaluate the performance and efficiency of the proposed system, with a specific emphasis on energy metrics and the interaction dynamics between surrounding nodes. The selected parameters and node selection are intentionally designed to capture the complicated details of energy usage and communication patterns inside the wireless sensor network. The results derived from this simulation will provide essential information on the effectiveness of the clustering technique in enhancing energy efficiency and fault tolerance in wireless sensor networks.

The proposed technique integrates AGWO with ACO to obtain the best value of the ρ factor for ACO using GWO. The primary objective is to decrease energy consumption and determine the most efficient path with the least amount of distance. Without optimization, simulated operations enabled the node's energy to be fully utilized, leading to node failure. Nevertheless, the suggested Adaptive Optimization significantly improves energy use efficiency.

The findings demonstrate the efficacy of the Adaptive GWO-ACO method in addressing significant concerns pertaining to energy use in wireless sensor networks, providing an optimistic approach for sustainable and robust network functionality. During the initial stage, our wireless sensor network consisted of 9 specifically chosen nodes for transmitting packets. During this time. After examination, we found that nodes become inactive (dead) throughout the transmission process. The difficulties encountered in this suboptimal situation emphasizing the significant problems faced, such as the inability to establish efficient communication routes and the subsequent failures of nodes. This underscores the importance of optimization in improving the overall performance and dependability of the wireless sensor network. The Fig.5 demonstrates the issues faced in this phase, demonstrating the significant effect of not optimized configurations on packet transmission and node availability.

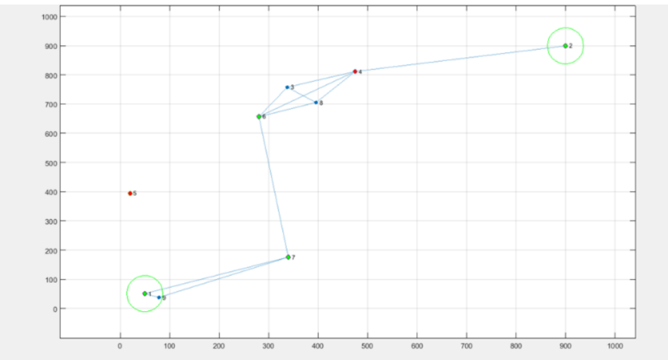

Fig.5. Without optimization

The suggested methodology effectively achieved optimum routing in the implementation of AGWO-ACO, exhibiting efficient energy usage within the wireless sensor network. ACO delivered 3312 packets after completion, identifying the optimum route with routing nodes (3, 4, and 5). Finally, node energy levels dropped to 13.789, 12.6659, and 9.78105, respectively as mentioned in Table 2. Fig.6 shows the comprehensive outcomes.

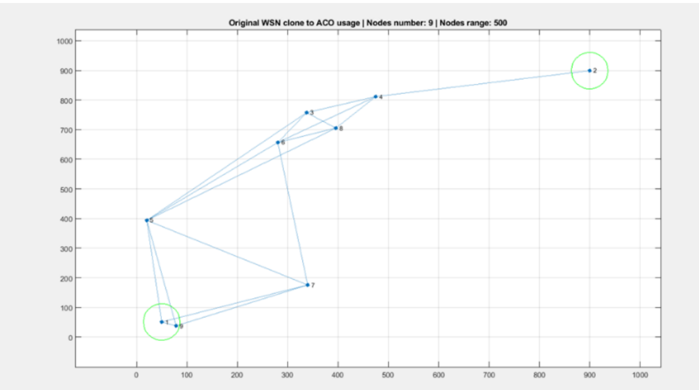

Fig.6. Proposed AGWO-ACO

Our developed AGWO-ACO algorithm revealed significant efficiency benefits while measuring energy usage across different packet transport situations. The energy consumption of the proposed AGWO-ACO is mentioned in Table.1 and Fig.7. These findings demonstrate the algorithm's ability to improve energy efficiency in WSNs.

Table.1. Energy consumption

Packets sent	Best route	Routing nodes	Nodes energy (mV)
500	1	3	82.2634
		4	81.1403
		5	78.2554
1000	1	3	70.088
		4	68.9649
		5	66.0801
1500	1	3	57.9126
		4	56.7895
		5	53.9047
2000	1	3	45.7372
		4	44.6141
		5	41.7293
2500	1	3	33.5618
		4	32.4387
		5	29.5539
3000	1	3	21.3865
		4	20.2633
		5	17.3785
3312	1	3	13.789
		4	12.6659
		5	9.78105

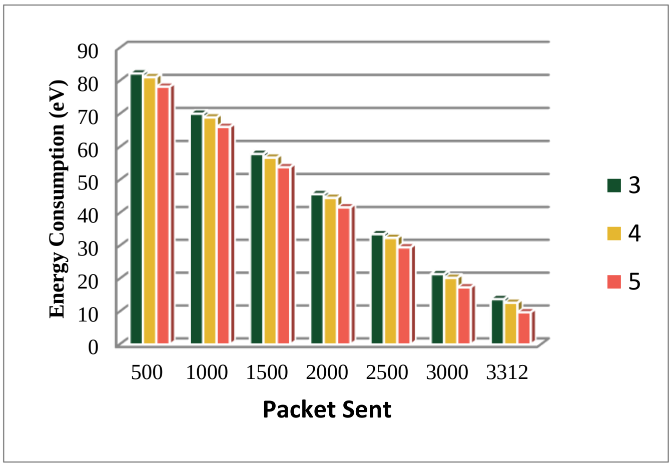

Fig.7. Energy consumption

5.3 COMPARISON ANALYSIS

The comparison phase is done on various parameters including network energy and computational time, with the existing methodologies such as, "Artificial Bee Colony algorithm (ABC) [20], Fractional Artificial Bee Colony algorithm (FABC) [20], and Ant Colony Optimization (ACO) [20]" for evaluate the effectiveness of the suggested method (AGWO-ACO).

Network energy is the total amount of energy used inside a system that is connected by a network. It refers to the overall power used by devices, communication modules, and other components that are engaged in the transmission and processing of data. It has a significant influence on factors such as sustainability, operating costs, and environmental consequences. Lower network energy values signify enhanced resource consumption efficiency, leading to greater performance and less environmental impact. The energy consumed values of the proposed method and existing methodologies are mentioned in Table.2 and Fig.8. The proposed model achieved better outcomes in consuming energy.

Table.2. Network energy (mV)

Methods	**Network Energy (mV)**	**Computational Time (s)**
ABC	83.28	3
FABC	70.24	2
ACO	55.45	4.5
AGWO-ACO[Proposed]	52.3611	0.50444

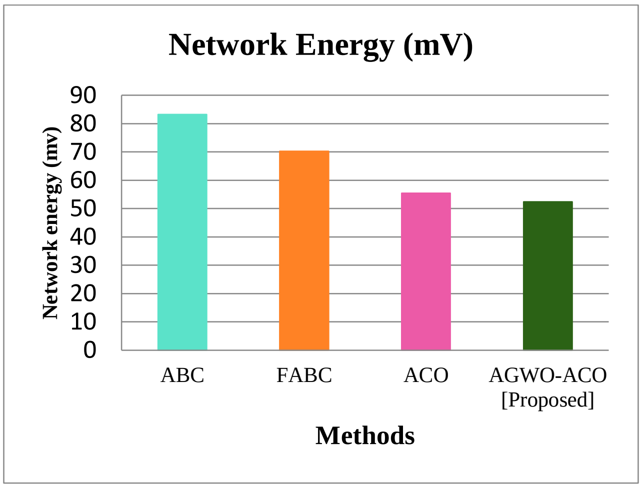

Fig.8. Network energy (mV)

Reduced computational time is commonly preferred, indicating quicker and more efficient execution. The computational time for the suggested method and conventional methodologies is mentioned in Table 3 and Fig.9. The recommended approach demonstrated lower computational time in the evaluation process. Thus the suggested AGWO-ACO algorithm performed better than other established methods.

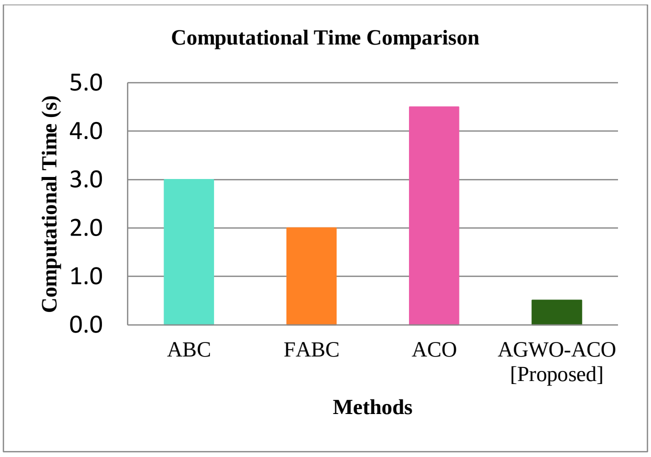

Fig.9. Computational time (Secs)

6. CONCLUSION

The advancement of modern technology has increased confidence in the architecture of extensive wireless networks comprised of energy-efficient devices. Fault tolerance and energy dissipation are the primary considerations when deploying and designing WSNs, rather than depending on technical advancements. In this work, we recommended Adaptive Grey Wolf Optimized Ant Colony Optimization (AGWO-ACO) to obtain efficient energy consumption and find the shortest path in WSNs. The suggested technique integrates AGWO with ACO to obtain the best value of the ρ factor for ACO using GWO with a novel clustering approach. Our findings demonstrated without optimization integration, no suitable path was determined, making the whole network ineffective due to inoperative nodes. Implementing AGWO-ACO technique resulted in optimum routing. ACO packets initiated the process, establishing a suitable path with routing nodes (3, 4, and 5) and demonstrating efficient energy utilization. The network energy and the computational time of our proposed method were evaluated, and compared with the existing methods. The proposed method performed better than other conventional methods. The limitations include the difficulties of scaling up broad networks and the need for further validation in real-world implementations to ensure resilience and flexibility in various contexts. Future studies may investigate the scalability and flexibility of AGWO-ACO in broader WSNs, while also addressing various failure situations and obstacles faced during real-world deployment..

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