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Optimal shortest path selection using an evolutionary algorithm in wireless sensor networks

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ABSTRACT

A wireless sensor network comprises of distributed independent devices, called sensors that monitor the physical conditions of the environment for various applications, such as tracking and observing environmental changes. Sensors have the ability to detect information, process it, and forward it to neighboring sensor nodes. Wireless sensor networks are facing many issues in terms of scalability, which necessitates numerous nodes and network range. The route chosen between the source node and the destination node with the shortest distance determines how well the network performs. In this paper, evolutionary algorithm based shortest path selection provides high end accessibility of path nodes for data transmission among source and destination. It employs the best fitness function methodology, which involves the replication of input, mutation, crossover, and mutation methods, to produce efficient outcomes that align with the best fitness function, thereby determining the shortest path. This is a probabilistic technique that receives input from learning models and provides the best results. The execution results are presented well compared with earlier methodologies in terms of path cost, function values, throughput, packet delivery ratio, and computation time.

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1. INTRODUCTION

In wireless sensor network (WSN), the system is managed by nodes that have built in central processing units (CPUs). These nodes establish connections with each other, the base station, and the internet [1]. The base station (BS) is responsible for gathering, analyzing, and delivering data to the end user for decision-making, while the nodes handle sensing, data processing, and transmission. A WSN is a transient network made up of a group of wireless sensor nodes that may be anywhere necessary with previous centralized or infrastructure nodes [2]. We now use them to observe environmental events, human activity, and natural calamities [3]. WSN's known for its dynamic nature and mobility. Hence, the secure dispatch of data requires a lot of energy. The real investigation of mobile nodes lies in their limited battery life. Every node in the network has a permanent communication range; therefore, a starting node requires the help of intermediate nodes along the way to an ending node. In the WSN, protocols utilizing cluster-based communication play a critical role in decreasing energy utilization [4].

To reduce latency and increase throughput when running real-time applications on mobile ad hoc networks, this study has proposed a route stability-based multi-path quality-of-service (QoS) routing protocol for a reduction in latency and an increase in throughput when running real time networks. The author has integrated hop-by-hop admission control and resource reservation techniques into a path discovery procedure [5]. Most clustering techniques organize nodes into groups. Each cluster selects a cluster head (CH) based on the energy between the cluster's former nodes within a specific time frame. CH gathers data from cluster nodes and sends it either directly to the sink node or via CH to different clusters in the network [6]. In the past, there have been several routing protocols discussed in relation to WSN security and energy efficiency. In any case, it is crucial to provide a superior resolution for security and energy efficiency in WSN, given that military workers operating in accessible areas need additional energy for safe communication [7]. The following related work area examines the variety of protection concerns and their value: attacks such as Sybil and Sinkhole suspend the regular nodes in the route and destroy the data for the duration of the broadcast process, reducing the network's throughput [8]. Recent years have witnessed the emergence of several key pre-distribution methods, which have established common keys essential for symmetric cryptosystems, adding significant interest to symmetric cryptography, energy effectiveness and throughput has been seen each with the confirmation of bounces based brief method determination [9]. One unique advantage of WSN is that it makes it possible to continuously monitor and supervise industrial operations, which increases efficiency, effectiveness, and safety. WSNs are useful for energy optimization and routing strategies that help the environment while saving money. We should develop an efficient routing protocol solution for WSNs to balance power usage and prevent access, data manipulation, and disclosures by malicious nodes on the network [10]. The recommended method offers benefits like enhanced dependability, reduced power usage, and better security. Secure routing protocols can prevent unauthorized users from connecting to the network and protect sensitive data from attacks. The protocol can improve system reliability by reducing the possibility of network congestion and packet loss, as well as by using less energy, which increases system life and lowers operating costs [11].

The most important contribution of this paper is evolutionary algorithm based shortest path selection in WSN. Each Sensor node's routing is created by the evolutionary algorithm (EA), which then finds a group of neighbor nodes. Because of its functionality, EA creates products of higher quality than other existing algorithms. Increase in throughput and energy efficiency was enabled with the evaluation done by this optimal node based shortest path identification for every pair of hops along the path from source to destination. This method contributes to the network's maximum stability by reducing delay and energy usage [12].

In study [13], an efficient meta-heuristic in the form of a genetic algorithm is discussed, that overcomes a number of faults of previous meta-heuristics, along with an accurate method for calculating the fitness function. Jain *et al.* [14] conducted an investigation into energy management from the perspective of wireless sensor networks. In study [15], the energy-aware routing (EAR) protocol estimates the connection quality of sensor nodes, aiming to cut down on energy consumption and choose a preferred next hop. In study [16], the effectiveness is quantified for dynamic scaling and modulation scheme. Each node in [17] energy efficient wireless sensor network has only the ability to transmit directly as strict restricted number of the nodes. The limited transmission range is implied by the scarce resources for getting the traffic requires routing utilizing intermediary nodes, forming a multi-hop route for getting the data to its final location when the nodes are designed properly. This study presents a novel error aware data clustering algorithm at the cluster heads in [18] for a decrease in data inside a network. A routing method based on energy awareness and throughput, known as the greedy forwarding technique strategy, has been provided in this study [19], [20]. It offers both packet loss and end to end packet delivery. This paper presents a novel approach in [21] benefits WSN applications by offering appropriate management at a reasonable cost in the absence of cross channel traffic. As wireless sensor networks gain reputation, the focus of the researchers is on a variety of challenging concern that considerably lower total concert, such as energy hole improvement and connection asymmetry minimization. Swarm intelligence is a technique used in [22] for identification eavesdroppers in the location of setting of agent-based technique. Artificial bee colony attack identification can help recognition of the difference between the eavesdropper and the node IDs listed in the rule set [23]. Dhamodharan *et al.* [24] analyses have recently presented research on intrusion detection systems (IDS) in WSNs, providing through categorization of various IDS approaches based on the detection methods used by them. Dhamodharan *et al.* [25] created a mixed integer programming (MIP) structure to identify how the reverse path hop length affects the WSN period and to perform wide numerical analysis to improve the impact on the WSN life time.

2. METHOD

This study presents the, best optimal path for transmission of data in a predetermined network with a careful selection of the best optimal path in terms of distance, trust values and energy. The preceding sections have explained. The proposed network model is illustrated in Figure 1.

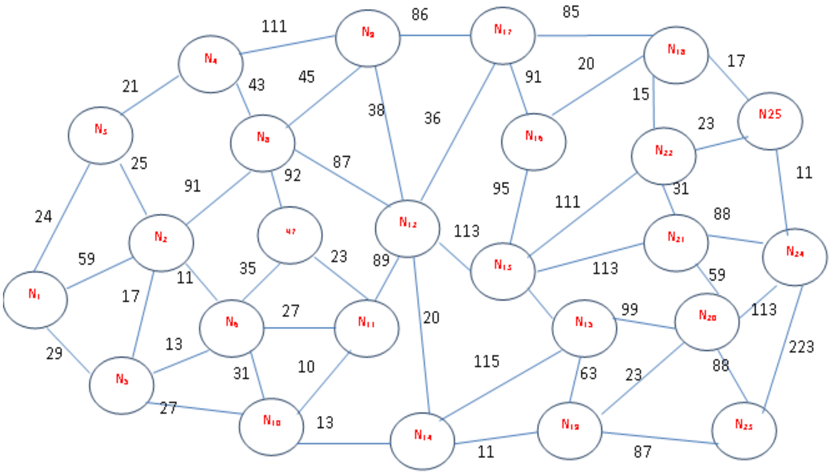

Figure 1. Proposed network model for shortest path

2.1. Network assumptions

The network is depicted as network representationG standing for as a graph G(V, E), were

$$V = \{Node_1, Node_2, \dots, Node_N\} \tag{1}$$

$$E = GI_{Xy} = Link\left(node_x, node_y\right) \forall x, y \in V. \tag{2}$$

The network utilized in this study has definite characteristics, whose ideals are described below for a clear realization of the anticipated methods.

- η : the network has the form $\eta = R \times W$
- R : the size of the network η
- W : the network height η
- N : stands for the overall numerous of nodes presented in the network η.
- E : quantity of edges/edges
- $\eta = [C_{xy}]$: is the price of weight matrix
- The source node and destination node are denoted by S, D
- (EA_{xy}) is used to represent the link.
- $EA_{xy} = \begin{cases} 1, & \text{if link exists} \\ 0, & \text{else} \end{cases}$
- (Xi, Yi) : position index for every node-i
- ITV : every node initially i's trust value is considered to be 100. *// Trust value*
- M : the overall number of routes best feasible from $S1$ to $D1$
- K : numerous of best shortest path from $S1$ to $D1$
- $Dist - 1$: raw distance from $S1$ to $D1$
- $\{h_1, h_2, \dots, h_m\}$: intermediately nodes among $S1$ and $D1$

The existence of the initial node S and the final destination node D is also known. Each node is given a starting energy value (IE) of 100. Node I use m joules of energy for transport of each data packet from IE. For getting the data packet, Node I use l joules of energy from IE. Each node makes periodical changes in its state, including alive, sleep, wake up, T_x, R_x and idle.

2.2. Network model

Consider the Figure 1 the network model, which creates a multi hop network illustration of links and nodes known as edges. Every node in the network is connected to the other nodes by a cost matrix. Facilitating from the originating node, in-between nodes and ending node has a cost weighted value. The Evolutionary algorithm that creates a connection between the nodes is referred to as $EA_{(xy)}$. When connections among the nodes live, the cost is retrieved; otherwise, no link is supplied. The EA matrix is a diagonal zero matrix, which the link considers as 1 and 0. Chromosomes and the fitness function, an evolutionary illustration, make up the evolutionary algorithm. Here, 50 links and 25 nodes are measured with 25 chromosomes and 50 links arbitrarily hit the algorithm to offer the subsequent cost matrix.

a. The steps involved
- Select the type of encoding
- Choose population size
- Randomly choose initial population
- Select partial chromosomes
- Crossover and mutation
- Off spring
- Recombination

Based on the present possessions related to the probabilistic model the best solution is obtained. The selection property will examine the fundamental based on fitness. This will cause offspring to appear in Table 1 for reproduction, a higher fitness value is regularly measured. Cross over research relevant approach among the sets taken in to consideration. If more than one attribute contributes to the frequent character, then the attribute will be tested for crossover property and taken into consideration.

Table 1. Crossover

Node N_5	Node N_{12}	Offspring	Offspring
00101	01100		
		Node N_4	$Node_{13}$
Crossover random generation		00100	01101

Every node in a measured network organize figure is randomly positioned, and the dynamic optimum path is examined using the current methodology. The algorithm generates both the worst and best outcomes in each cycle with the poorest results being discarded. Every round of algorithm provides the entire worst and best results, the worst results is called off. The most excellent ones for each node element examined in Table 2 is now applied to a random sample of nodes.

Table 2. Cost estimation

Node	1	3	4	8	9	12	17	18	22	25
BCE	00001	00011	00100	01000	01001	01100	10001	10010	10110	11001
Cost		24	21	43	45	38	36	85	15	23

b. Fitness function

An evolutionary illustration technique utilized to acquire the objective function with arbitrary variables of numerals. Based on these persons are calculate and agreed for optimization. Below is a representation of the optimal fitness function used for estimate, best fitness function.

$$F = \frac{1}{\sum_{i=1}^{N-1} \eta_i(\xi_i, \xi_{i+1})} \tag{3}$$

At first, there is no legitimate flow. In the following iterative creation along with objective functions, where i stands for arbitrary creation numbers.

$$Q(S \cdot g) = O(s) + Pi \tag{4}$$

where $O(s)$ is objective function and P_i is penalty. This is the main step while primary population is created.

2.3. Generalizing decision model

The fundamentals of an objective function are designed to optimize for the best possible. The optimization itself has characteristics like mutation and cross over in the selection roulette wheel. The nodes in this network, which are distributed at random, are regarded as a population. The goal function is actualized to provide assessed route finding in light of the heuristic models. It will go through N iterations until either the route is found or every conceivable input is linked to the probabilistic approach, whichever comes first. Based on the random input, every creative outcome the best result in Figure 2. Illustrates how the worst options are eliminated from consideration while the greatest outcome is simplified and widely accepted.

Assume that the first-generation candidate solution for node N_5 is represented as 00101 and node N_{12} can be represented as 01100. The probabilistic models receive information from each generation that has been born in order to provide the result. Here after the offspring, it was N_5 is converted in to N_4 represented as 00100 and N_{12} has N_{13} represented as 01101 the crossover detail is depicted in Table 1.

The chromosomal output is adjusted when considering the path after random generation, where the beginning population is taken into account with a minor value of 1 to an utmost value of 25. Mutation limits the solutions that are setting for local optimal. The BCD value of node 1 is considered as 00001, node 3 as 00011 and cost weight is 24 like that for node 25 the cost weight is 23 that is displayed in Table 2.

Theorem-1: Let G represent the position of generations. If generation G' depends on $\{G\}$ in such a way that every node in G states 'γ' then we can decompose in G, such $|\gamma| \geq G'$, we can split 'γ′' into:

a. $\gamma \neq Null\ node\ (or) |\gamma| > 0$ (or) $|\gamma| \geq 1$.
b. $|\alpha\beta| \leq G'$
c. Total $j \geq 0$, the network node $\alpha\beta_z^j$

where, α and β represent the nodes in the network, z is the best path between j possible routes among α and β. The cost matrix that was taken into account for the population. Each node in the network has a weight that connects it to the other nodes. Every node uniqueness is run through the fitness function technique for each point to get an accurate estimation. The size L probability vector is specified as, $P_i \Rightarrow \mathrm{Prob}(P_i, L)$, win $= \frac{1}{L_e}$ and Lose $= \frac{1}{L_P}$. The solution is presented in Table 3, which is compact genetic algorithm. From Table 3 based on random generation the actual count value having zero are eliminated (i.e.) string 1 to string 5 are having zero value. After eliminating the string, we go for cross over mutation by electing the highest string value (i.e.) 3 strings no 10. This is presented in Table 4.

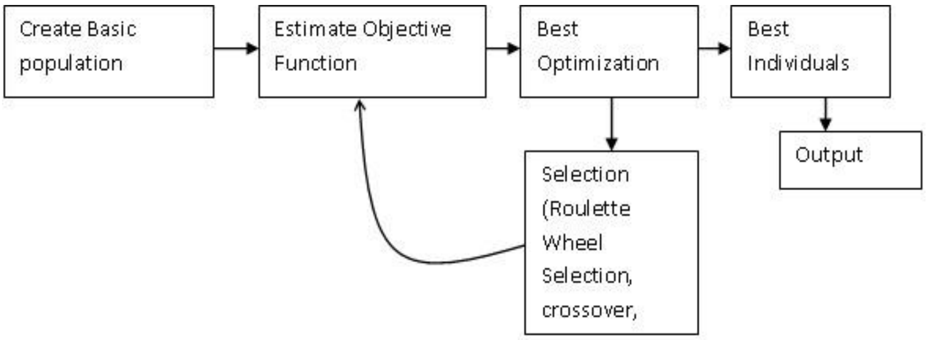

Figure 2. Evolutionary algorithm for refining individuals

Table 3. Step 1 calculation of evolutionary algorithm

String No	Position x	Binary node value	F(x)=x^2	Probability count	Expected count	Actual count
1	1	00001	1	0.0004	0.004	0
2	3	00011	9	0.0044	0.044	0
3	4	00100	16	0.0078	0.079	0
4	8	01000	64	0.0314	0.314	0
5	9	01001	81	0.0397	0.398	0
6	12	01100	144	0.0706	0.707	1
7	17	10001	289	0.1418	1.419	1
8	18	10010	324	0.159	1.591	2
9	22	10110	484	0.238	2.376	2
10	25	11001	625	0.307	3.070	3
		Total	2037	1.0001	10.00	
		AVG	203.7			

The marginal distribution of the set being examined for distribution in the previous table is given as follows, $\mathrm{N} \sum_k \mathrm{entropy}\ (\mathrm{M_i})$. Where, $\mathrm{M_i}$ is the marginal distribution of the k^{th} subset of genes. Entropy $=$ Randomness of distribution $\sum \mathrm{P_i} \log_2 \mathrm{P_i}$ based on this from these six values we are eliminating the string count after that we can get the expected count.

Table 4. Step 2 calculation of evolutionary algorithm

String NO	Position X	Random cross over	$F(x)=x^2$	Probability count	Expected count	Actual count
1	24	11000	576	0.222	1.33	1
2	13	01101	169	0.065	0.390	0
3	25	11001	625	0.241	1.444	1
4	17	10001	289	0.111	0.668	1
5	24	11000	576	0.222	1.33	1
6	19	10011	361	0.139	0.834	1
			2596	1	5.996	
			432.7			

3. RESULTS AND DISCUSSION

The shortest path algorithm clearly demonstrates using 25 nodes and 50 links are taken into account. The implementation is carried out using a NS2 and the results are comparing with previous shortest path methods with proposed evolutionary algorithm and parameters used. Numerous of creations measured now is 50 utmost and single estimates comprise every node in all illustration is shown in Figure 3. Table 5 compares individual generation cost and route cost. Results are compared against the vector size's winning probability. The computing time is the amount of time required for each data transfer after path investigation. The Proposed method is compared with existing method 25 nodes are taken into consideration. Each iteration of the route discovery process is tested for fewer than 50 generations, with a direct link between 25 nodes 50 edges. The two ways for finding the best and worst path are compared and it is discovered that the compact Evolutionary algorithm approach produces the best result. Figures 3 and 4 show the comparison of computational time. For 5 nodes, the time taken to process the data in Dijkstra's algorithm can take 6 ms, in the genetic algorithm, it can take 5 ms; and in the proposed evolutionary algorithm, it can take 2 ms. likewise, we can compare with 10, 15, 20, and 25 nodes. The computational time for 25 nodes was 10 ms in the proposed method, whereas existing methods it takes 19 and 25 ms, respectively. In Figure 4, the computational time for 50 nodes was 15 ms in the proposed method, whereas in the existing method, can take 22 and 18 ms. For 250 nodes, the evolutionary algorithm can take 36 ms, a significantly shorter time than existing methods 48 and 42 ms. The graph below illustrates the comparison of route failures.

Table 5. Best fitness algorithm for discovery of best path

Route	Best fitness value	Best path
Path-1	0.1095	1-3-4-8-9-12- 17-18-22-25
Path-2	0.7969	1-5-6-11-10-14-19-20-21-22-18-25
Path-3	0.1636	1-2-6-10-11-7-8-9-12-17-18-22-25

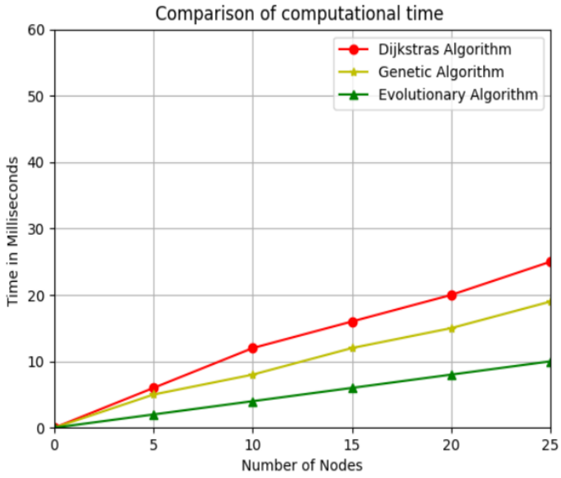

Figure 3. Comparison of computational time with proposed methods using 25 nodes

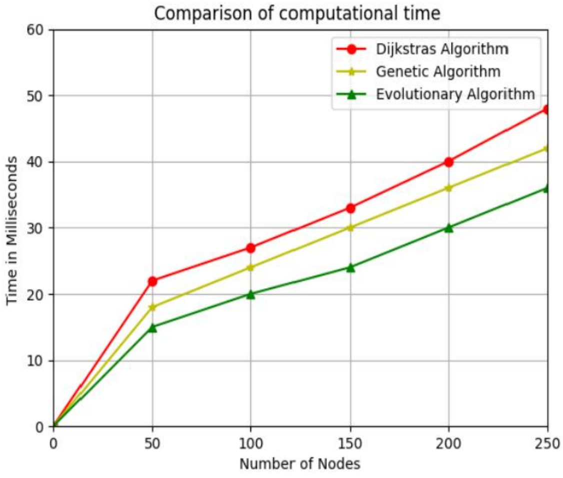

Figure 4. Comparison of computational time with proposed methods using 250 nodes

In Figure 4, the computational time for 50 nodes was 15 ms in the proposed method, whereas in the existing method, can take 22 and 18 ms. For 250 nodes, the evolutionary algorithm can take 36 ms, a significantly shorter time than existing methods 48 and 42 ms. The graph below illustrates the comparison of route failures. in Figures 5 and 6. For 5 nodes, the existing method can take 2%, and 1%, and the proposed evolutionary algorithm can take 0%. Likewise, we can compare with 10, 15, 20, and 25 nodes.

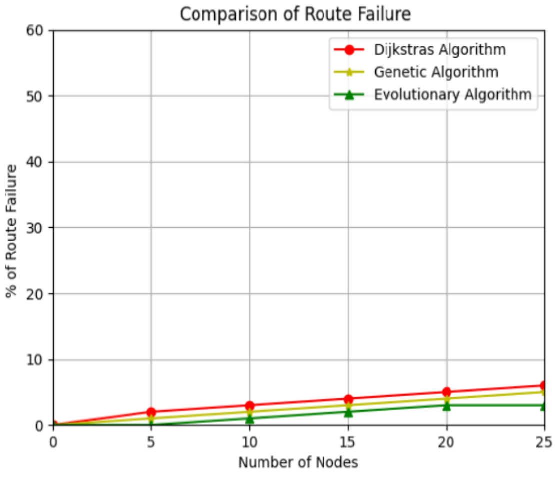

Figure 5. Comparison of route failure ratio with proposed methods using 25 nodes

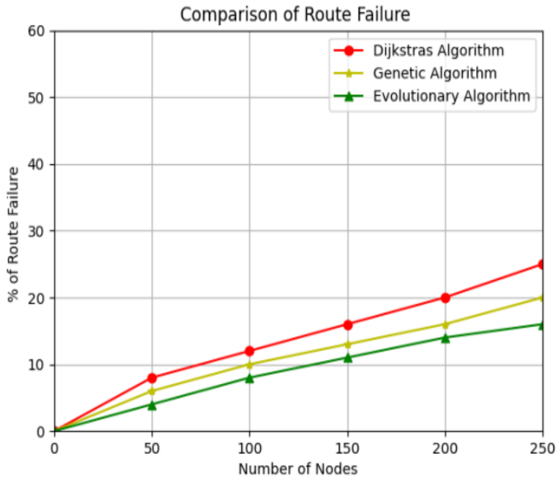

Figure 6. Comparison of route failure ratio with proposed methods using 250 nodes

Compared to existing methods, the route failure rate for 25 nodes was significantly lower as shown in Figure 5. The computational time for 25 nodes was 3%, whereas with existing methods can take 5 % and 6%, respectively. In Figure 6, the route failure for 50 nodes was 4% in the proposed method, compared to existing methods, it was less. The proposed methods had a route failure rate of 4% for 50 nodes, compared to 8% for existing methods can take 6%. Likewise, for 250 nodes, the route failure is 16%; for 250 nodes, it was significantly shorter than existing methods can take 25% and 20%. The graphs in Figures 7 and 8 illustrate the comparison of throughput. For 5 nodes, existing method achieves 97% and 98% the proposed method achieves 100%. Similar comparisons can be made for 10 to 25 nodes. For the 25 nodes, the throughput ratio in the evolutionary algorithm is 97%; this can be higher compared with existing methods.

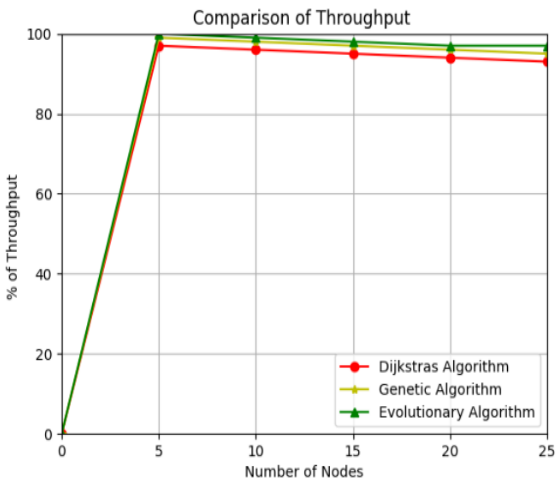

Figure 7. Comparison of throughput using 25 nodes

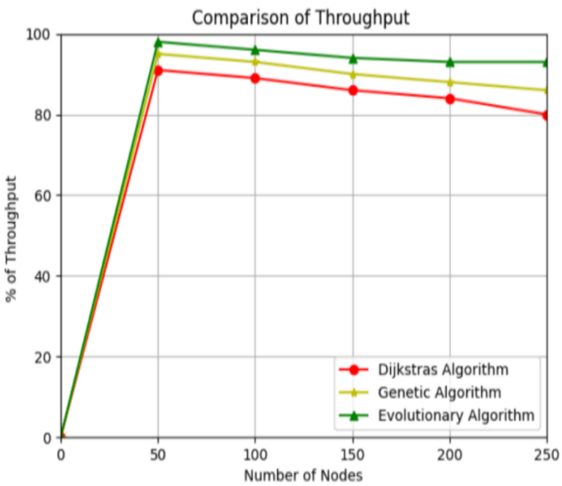

Figure 8. Comparison of throughput using 250 nodes

The graphs as shown in Figures 9 and 10 illustrate the energy comparison. Compared to existing methods energy utilization is very low. During the initial phase of 5 nodes, the energy utilization in the proposed method was 0%, whereas in the existing method, it was 92% and 98%. The graphs below illustrate the energy comparison. Compared to existing methods energy utilization is very low. During the initial phase of 5 nodes, the energy utilization in the proposed method was 0%, whereas in the existing method, it was 92% and 98%. For 50 node execution, the proposed method has a 99% energy level remaining, while the existing method has an energy level of 96 and 92%. In the same case, the energy level of 250 nodes remains at 92% in the proposed method, whereas in the existing method energy level remains at 81% and 77%.

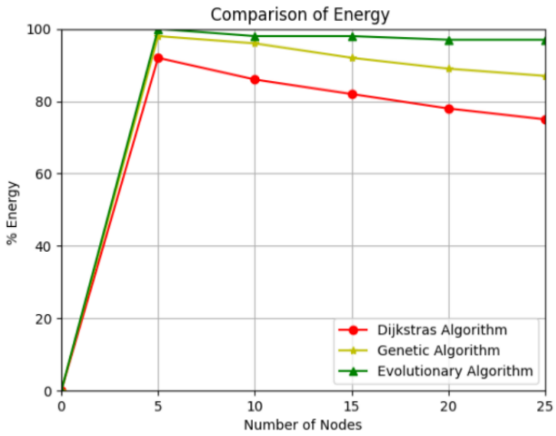

Figure 9. Comparison of energy consumption using 25 nodes

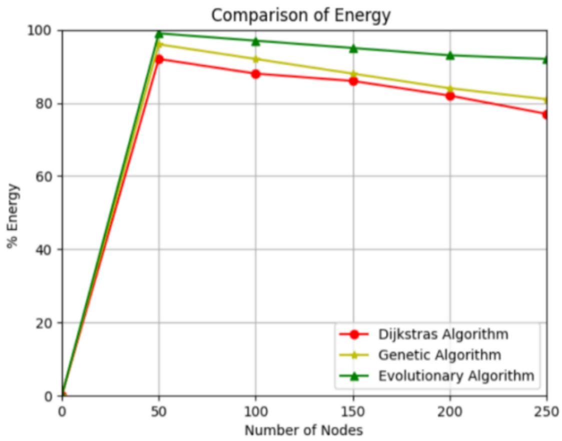

Figure 10. Comparison of energy consumption using 250 nodes

4. CONCLUSION

We construct WSNs from a collection of wireless sensors, each with distinct capacities and constraints, making them suitable for specific uses. This paper provides an evolutionary algorithm for path discovery in wireless sensor networks. The current routing path issue focuses on dynamic discovery, utilizing chromosome detection techniques to generate optimal solutions and provide estimated outcomes for consideration. It examines data transmission path crossover and mutation, both of which have similar properties for takeout data among two genes. The current technique provides elevated convergence instead of focusing on the optimal shortest path. Different approaches are used to investigate the route's failure. In this scenario, irregular efforts in the early population minimally elevate the subspace difficulty. The possible number of attempts to evaluate the target task increases with the number of increments. The precise inputs achieve a 98% rate of progressive route discovery. We note that path discovery fails when certain nodes start a few routes with low energy levels. A number of computations are coordinated with the current calculation, which determines dynamic discovery. Therefore, as node size rises, it may be possible to enhance route finding by using a variety of population generation approaches.

REFERENCES

[1] D. Airehrour, J. A. Gutierrez, and S. K. Ray, "SecTrust-RPL: a secure trust-aware RPL routing protocol for internet of things," *Future Generation Computer Systems*, vol. 93, pp. 860–876, 2019, doi: 10.1016/j.future.2018.03.021.

[2] A. Hamzah, M. Shurman, O. Al-Jarrah, and E. Taqieddin, "Energy-efficient fuzzy-logic-based clustering technique for hierarchical routing protocols in wireless sensor networks," *Sensors (Switzerland)*, vol. 19, no. 3, 2019, doi: 10.3390/s19030561.

[3] T. M. Behera *et al.*, "Energy-efficient routing protocols for wireless sensor networks: architectures, strategies, and performance," *Electronics*, vol. 11, no. 15, Jul. 2022, doi: 10.3390/electronics11152282.

[4] A. Kumar, M. Zhao, K. J. Wong, Y. L. Guan, and P. H. J. Chong, "A comprehensive study of IoT and WSN MAC protocols: research issues, challenges and opportunities," *IEEE Access*, vol. 6, pp. 76228–76262, 2018, doi: 10.1109/ACCESS.2018.2883391.

[5] N. Muruganantham and H. El-Ocla, "Routing using genetic algorithm in wireless sensor networks," *Wireless Personal Communications*, vol. 111, no. 4, pp. 2703–2732, 2020, doi: 10.1007/s11277-019-07011-8.

[6] M. Elshrkawey, S. M. Elsherif, and M. Elsayed Wahed, "An enhancement approach for reducing the energy consumption in wireless sensor networks," *Journal of King Saud University - Computer and Information Sciences*, vol. 30, no. 2, pp. 259–267, 2018, doi: 10.1016/j.jksuci.2017.04.002.

[7] N. T. Hanh, H. T. T. Binh, N. X. Hoai, and M. S. Palaniswami, "An efficient genetic algorithm for maximizing area coverage in wireless sensor networks," *Information Sciences*, vol. 488, pp. 58–75, 2019, doi: 10.1016/j.ins.2019.02.059.

[8] K. U. R. Khoumbati, S. A. Solangi, Z. Bhatti, and D. N. Hakro, "Optimal route planning by genetic algorithm for wireless sensor networks," *2020 International Conference on Information Science and Communication Technology (ICISCT)*, Karachi, Pakistan,

2020, pp. 1-4, doi: 10.1109/ICISCT49550.2020.9079944.
[9] D. Goyal and M. R. Tripathy, "Routing protocols for wireless sensor networks: a surveys," in *2012 Second International Conference on Advanced Computing & Communication Technologies*, Jan. 2012, pp. 474–480, doi: 10.1109/ACCT.2012.98.
[10] A. Seyfollahi, T. Taami, and A. Ghaffari, "Towards developing a machine learning-metaheuristic-enhanced energy-sensitive routing framework for the internet of things," *Microprocessors and Microsystems*, vol. 96, 2023, doi: 10.1016/j.micpro.2022.104747.
[11] 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, doi: 10.1109/ACCESS.2021.3051360.
[12] G. S. Binu and B. Shajimohan, "A novel heuristic based energy efficient routing strategy in wireless sensor network," *Peer-to-Peer Networking and Applications*, vol. 13, no. 6, pp. 1853–1871, 2020, doi: 10.1007/s12083-020-00939-w.
[13] S. Duraisamy, G. K. Pugalendhi, and P. Balaji, "Reducing energy consumption of wireless sensor networks using rules and extreme learning machine algorithm," *The Journal of Engineering*, vol. 2019, no. 9, pp. 5443–5448, 2019, doi: 10.1049/joe.2018.5288.
[14] P. Jain, K. Markam, and R. Naik, "An algorithm of the shortest path with fuzzy logic in wireless Sensor networks," *International Research Journal of Engineering and Technology (IRJET)*, pp. 135–141, 2018.
[15] K. N. Qureshi, S. Din, G. Jeon, and F. Piccialli, "Link quality and energy utilization based preferable next hop selection routing for wireless body area networks," *Computer Communications*, vol. 149, pp. 382–392, Jan. 2020, doi: 10.1016/j.comcom.2019.10.030.
[16] S. Khriji, R. Chéour, and O. Kanoun, "Dynamic voltage and frequency scaling and duty-cycling for ultra low-power wireless sensor nodes," *Electronics (Switzerland)*, vol. 11, no. 24, 2022, doi: 10.3390/electronics11244071.
[17] A. Chehri, R. Saadane, N. Hakem, and H. Chaibi, "Enhancing energy efficiency of wireless sensor network for mining industry applications," *Procedia Computer Science*, vol. 176, pp. 261–270, 2020, doi: 10.1016/j.procs.2020.08.028.
[18] M. K. Alam, A. A. Aziz, S. A. Latif, and A. Awang, "Error-aware data clustering for in-network data reduction in wireless sensor networks," *Sensors*, vol. 20, no. 4, Feb. 2020, doi: 10.3390/s20041011.
[19] W. A. Hussein, B. M. Ali, M. F. A. Rasid, and F. Hashim, "Smart geographical routing protocol achieving high QoS and energy efficiency based for wireless multimedia sensor networks," *Egyptian Informatics Journal*, vol. 23, no. 2, pp. 225–238, 2022, doi: 10.1016/j.eij.2021.12.005.
[20] T. Amgoth, P. K. Jana, and S. Thampi, "Energy-aware routing algorithm for wireless sensor networks," *Computers and Electrical Engineering*, vol. 41, no. C, pp. 357–367, 2015, doi: 10.1016/j.compeleceng.2014.07.010.
[21] F. R. Mughal *et al.*, "A new asymmetric link quality routing protocol (ALQR) for heterogeneous WSNs," *Microprocessors and Microsystems*, vol. 93, 2022, doi: 10.1016/j.micpro.2022.104617.
[22] M. M. Hasan, A. Karmaker, M. S. Alam, and A. Craig, "Minimizing the adverse effects of asymmetric links: a novel cooperative asynchronous mac protocol for wireless sensor networks," *Sensors (Switzerland)*, vol. 19, no. 10, 2019, doi: 10.3390/s19102402.
[23] M. Kim, S. Park, and W. Lee, "Energy and distance-aware hopping sensor relocation for wireless sensor networks," *Sensors (Switzerland)*, vol. 19, no. 7, 2019, doi: 10.3390/s19071567.
[24] U. S. R. Dhamodharan, S. Rajendran, R. A. Sundaramoorthy, and M. Thirunavukkarasan, "A centralized mechanism for preventing DDOS attack in wireless sensor networks," *Wireless Personal Communications*, vol. 124, no. 2, pp. 1191–1208, 2022, doi: 10.1007/s11277-021-09401-3.
[25] U. S. R. Dhamodharan, P. S. Gavaskar, F. Al-Turjman, R. Sathiyaraj, and B. Balusamy, "Artificial bee colony method for identifying eavesdropper in terrestrial cellular networks," *Transactions on Emerging Telecommunications Technologies*, vol. 32, no. 7, 2021, doi: 10.1002/ett.3941.

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