Enhancing the Lifetime of WSN Using a Modified Ant Colony Optimization Algorithm

Belal K. Elfarra [1*], Mamoun A. Salha [2*], Raed S. Rasheed [3*], Jehad Aldahdooh [4*], and Aiman Ahmed AbuSamra [5]

[1*] Islamic University of Gaza, P.O. Box 108, Gaza Strip, Palestine. fbelal@iugaza.edu.ps, Orcid: https://orcid.org/0009-0008-8187-598X

[2*] Islamic University of Gaza, P.O. Box 108, Gaza Strip, Palestine. masalha@iugaza.edu.ps, Orcid: https://orcid.org/0009-0001-3870-3225

[3*] Islamic University of Gaza, P.O. Box 108, Gaza Strip, Palestine. rrasheed@iugaza.edu.ps, Orcid: https://orcid.org/0000-0002-0553-949X

[4*] University of Helsinki, Helsinki, Finland. jehad.aldahdooh@helsinki.fi, Orcid: https://orcid.org/0000-0002-9947-4067

[5] Islamic University of Gaza, P.O. Box 108, Gaza Strip, Palestine. aasamra@iugaza.edu.ps, Orcid: https://orcid.org/0000-0003-4652-3993

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Abstract

Wireless sensor networks (WSNs) have been extensively used in various fields, such as health, defense, education, and industrial applications, to collect and transmit environmental data to the base station. However, energy efficiency is a significant challenge in WSNs, as data transmission is typically limited to a single route, leading to excessive energy consumption by the nodes along that route. This can lead to a decrease in the network's overall efficiency and effectiveness. To address this issue, this study aims to extend the lifespan of WSNs by optimizing route selection based on three variables: residual node energy, distance to the base station, and number of shared neighbors. In this paper, the authors propose three systematic approaches, namely Energy-Aware ACO Routing (EACO), Cost-Effective ACO Routing (CEACO), and Cost-Efficient Node Replacement Strategies ACO (CERACO), to enhance the lifetime of WSNs. These approaches consider various factors such as cost, energy consumption, replacement, and reliability. The paper provides a practical guide for researchers and practitioners to overcome the challenges related to energy efficiency and cost-effectiveness in WSNs. Experimental results demonstrate that the first dead node occurs later with the proposed methods than with the traditional Ant Colony Optimization (ACO) algorithm.

Keywords: Wireless Sensor Network, Network Aspects, Performance, Evaluation, Ant Colony Optimization, Energy Consumption.

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*Corresponding author: [1,2,3]Islamic University of Gaza, P.O. Box 108, Gaza Strip, Palestine, [4] University of Helsinki, Helsinki, Finland.

1 Introduction

WSNs have gained significant attention in recent years due to their wide range of applications in various fields such as military, healthcare, and environmental monitoring. However, one major challenge in WSNs is the limited lifetime of the sensor nodes due to their limited energy resources. Moreover, it has limited memory, processing capabilities and narrow bandwidth (Lewis, F.L., 2004) (Serwadda, A., 2016) (Chong, C.Y., 2003). Traditional network load balancing and routing methods are ineffective in WSNs, where crowded and complicated situations are often the case. Therefore, in this research, we went for routing protocols that utilize Swarm Intelligence (SI) are being developed to achieve efficient routing and minimize energy consumption. SI is a collective behavior exhibited by decentralized, self-organized systems composed of many individuals that interact with each other. It is inspired by the behavior of social insects such as ants, bees, and termites, which exhibit sophisticated collective behaviors even though each individual insect follows simple rules (Keerthi, S., 2015).

One popular such technique is the use of ant colony optimization (ACO) algorithm, ACO is a heuristic optimization algorithm inspired by the foraging behavior of ants. It has been successfully applied to various optimization problems, including routing in WSNs because of its heuristic nature and ability to adapt to distributed and dynamic contexts.

The primary objectives of ACO are to maximize throughput and reduce delay and energy consumption (Nasir, H.J.A., 2017).

This paper presents three systematic approaches - EACO, CEACO, and CERACO - to improve the lifetime of wireless sensor networks (Kang, J., 2019). These approaches consider several factors, such as energy consumption, distance, and replacement, to identify the most efficient path for transmitting data.

The rest of this paper is organized as follows: section II describes the background of this research. Section III describes the statement of the problem. Section IV provides a literature review of related works. Section V presents the proposed idea. Section VI describes the methodology. Section VII describes the experimental results. Finally, section VIII presents the conclusion.

2 Background

The traditional ACO algorithm, also known as the Ant System (AS), was developed to solve the Traveling Salesman Problem (TSP). The TSP involves finding the shortest closed path, or tour, that connects multiple places and visits each one just once. This problem can be represented as an undirected graph, G = (V, E), where V represents nodes or cities and E represents the undirected edges that connect them. The weights of the edges represent the distances between the nodes, and the objective is to discover the quickest route that visits each city and returns to the origin. The ACO algorithm uses a SI approach, where a group of artificial ants are used to find an approximate solution to the TSP by simulating the behavior of real ants. Each ant generates a tour by moving through the graph and updating the pheromone levels on the edges, which are used to guide the movement of the next ant. The ACO algorithm is known for its ability to find the shortest path quickly (Dorigo, M., 1996), but it may not always find the optimal solution, for example, in a WSN, the shortest path may pass through a node that has no other neighboring nodes as options to pass through. If this path were to be used, the node will quickly exhaust its energy and die, resulting in a severed link between two sections of the network.

The search space S for the problem, represented by the undirected graph in Figure 1, is composed of all possible tours. The objective function's value for a certain tour, represented by $\boldsymbol{f(s)}$, where $\boldsymbol{s \in S}$, calculated as the total of the weights of the tour's edges. The TSP is equivalent to a discrete optimization problem, and the ACO algorithm assigns a pheromone value to the edges of the graph as solution components., $\boldsymbol{\tau}_{i,j}$, to each edge $\mathbf{e}_{i,j}$.

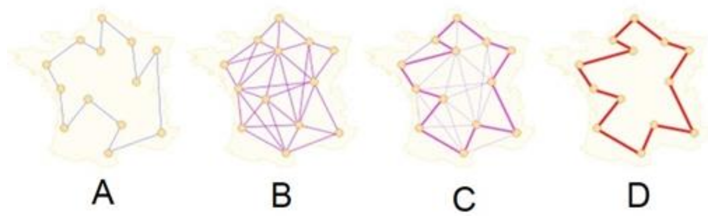

Figure 1: Illustration of an Undirected Graph that Displays the Cities and the Connections between them. (The Sequence of Steps Used in the ACO Algorithm to Find the Most Efficient Closed Path)

The algorithm is based on a group of artificial ants, each constructing a potential tour or round-trip through the nodes. Each tour is considered as a solution, s, in the search space S, and the goal function, f(s), is the total of the weights of each edge. The objective is to find the tour with the highest value of the pheromone and the lowest f(s). Constructing a solution, the ant visits all the nodes, then goes back to the starting node

The traversed edge is selected with a probability determined by $p(ci \mid s)$..

$$p(c_i \mid s) = \frac{\tau_i^{\alpha}}{\sum_{c_{j \in N(s)}} (\tau_j^{\alpha})} \qquad (1)$$

The edge that the ant traversed is included in the constructed solution (Alhanjouri, M., 2011).

The ant leaves an additional amount of pheromones on all the edges it traversed, the release of pheromones is:

$$\tau_i^{\alpha} \leftarrow \tau_i^{\alpha} + \frac{Q}{f(s)} \qquad (2)$$

Following each cycle, pheromone trails are evaporated as follows:

$$\tau_i^{\alpha} \leftarrow (1 - \mathrm{p}).\, \tau_i^{\alpha} \qquad (3)$$

The preceding procedures are used to design a single route, and they can be repeated indefinitely to find the optimal solution. The likelihood of an edge being chosen increases in proportion to the intensity of the pheromone trail that is laid out between two cities on each visit. The stronger the pheromone trail, the higher the chance that the edge will be selected for the path (Alhanjouri, M., 2011).

3 Statement of the Problem

One of the primary challenges in deploying and operating Wireless Sensor Networks (WSNs) is the limited lifetime of sensor nodes due to constraints on their energy resources. The problem addressed in this study is to enhance the lifetime of sensor nodes in WSNs while maintaining efficient data transmission. Diverse strategies for extending the lifespan of wireless sensor networks (WSNs) have been developed to combat this limitation. The proposed approaches EACO, CEACO, and CERACO take energy consumption, distance, and replacement into account to find the optimal path for data transmission in order to improve the lifetime of the WSN. We have assessed the performance of the proposed methods through the use of simulation experiments and compared them to the traditional ACO algorithm.

4 Related Works

Extending the lifespan of the wireless sensor network (WSN) and reducing energy consumption by the nodes during data transfer were among the primary research goals in WSNs.

Some researchers have employed a hybrid technique to enhance energy efficiency. For instance, the authors in (Younus, H.A., 2022) (Aroba, O.J., 2021) (Yuste-Delgado, A.J., 2020) (Chen, H., 2017) (Wang, J., 2015) used different clustering strategies. In contrast, (GhasemAghaei, R., 2007) combined reinforcement learning with the ant colony optimization technique to create a novel algorithm that utilizes the data packet routing behavior of ants as a model. The algorithm adapts to network changes by adjusting its parameters based on the feedback received.

Using Wmba and Qoga, the authors of (Gupta, S.C., 2021) provide a channel selection and routing technique that considers energy consumption for wireless sensor networks. Combining Weighted Maximum Betweenness Technique (Wmba) and Quality of Gradient Algorithm (Qoga), the suggested algorithm determines the appropriate sensor nodes for data collection and transmission. The program also employs an energy-aware channel selection technique to preserve energy and increase the network's lifetime.

The authors of (Adumbabu, I., 2022) utilized the Improved Coyote Optimization Algorithm which comprises three phases: setup, transmission, and measurement phase along with the Improved Jaya Optimization with Levy Flight (IJO-LF) to establish the optimal route between the base station (BS) and the CH.

Effective Hybrid Routing Protocol (EHRP) proposed in (Moussa, N., 2022) is a protocol that combines single-hop and multi-hop routing with ACO algorithm to eliminate delay time. By utilizing the Received Signal Strength Indicator (RSSI) and energy consumption statistics, EHRP maintains energy and reduces the likelihood of transmission failure. EHRP is able to reduce energy usage and delay while improving packet delivery ratio.

A new method for calculating the transition probability of ants based on the energy consumption of the nodes and a new mechanism for adjusting the pheromone trail strength depending on the energy consumption of the nodes are employed by the authors of (Kulkarni, P.H., 2017). The suggested routing protocol includes a brand-new mechanism that modifies the strength of the pheromone trail. This mechanism is dependent on the amount of energy that the nodes consume.

The paper (GhasemAghaei, R., 2008) suggests a new ant-based routing algorithm for wireless sensor networks that uses the behavior of ants as a model for sending data packets from multiple sources to a single sink.

Ants also serve as the inspiration for the Quality of Service (QoS) conscious routing system for the authors of (Malik, S.K., 2017) (Zhang, Y., 2004) (Camilo, T., 2006) (Cai, W., 2006) (Sharma, S., 2017). Their suggested routing protocols are based on algorithms, that search for the most energy-efficient routes.

The authors of (Wang, X., 2008) propose a location-aware algorithm for routing data packets in wireless sensor networks. This algorithm considers the location information of sensor nodes to find efficient routes for data packets, which improves routing performance compared to location-unaware algorithms. Simulation results are presented to demonstrate the effectiveness of the proposed algorithm.

The authors of (Kannan, M., 2017) presented a brand novel routing technique for industrial wireless sensor networks called Ant Star Fuzzy Routing (ASFR) (IWSNs). The Ant Star algorithm and fuzzy logic are both incorporated into the ASFR protocol in order to achieve the overarching goal of improving the routing performance in industrial settings. The Ant Star approach is utilized for the purpose of path selection, while fuzzy logic is used for the purpose of node selection. The results of the simulation show that ASFR works better than traditional routing protocols like AODV and DSR in industrial settings in terms of the ratio of packets delivered, the latency from beginning to finish, and the amount of energy that is used.

The research (Wen, Y.F., 2008) provides an adaptive ant-based routing method for wireless sensor networks that employs a combination of energy and latency parameters to select the optimal data packet routes. The program routes packets using ant behavior as a model and adjusts to network changes by altering the weight of the energy and latency metrics.

The authors of (Sun, Y., 2017) proposed a novel approach to change the strength of a pheromone trail and determine the probability of ant movement based on energy consumption.

However, the vast majority of the algorithms proposed by researchers rely on the distance heuristic, which is impractical in real world scenarios and fails to account for crucial energy metrics.

5 Methodology

Matching packets and sensor nodes are a crucial process in WSN, as forwarding packets must be matched with available sensor nodes based on packet characteristics such as length and priority, as well as sensor node capacity such as residual energy and current load.

Without this matching, the dissemination of packets across all available sensor nodes may not be equitable. A good routing algorithm should be able to identify one or more optimal paths for sending submitted packets from the source node to the destination node with the fewest hops.

Selecting one ideal path increases the likelihood of nodes along that path passing away, as their energy is depleted much faster than other nodes in the network. As a result of the intensive packet transmission; this, in turn, affects the network's lifetime.

In order to demonstrate the effectiveness of our concept, we adapt a MATLAB program (Cesar silva., 2023) for a specific 9-nodes wireless sensor network covering a 1000m × 1000m region within a 500m neighboring range. In this network, nodes 1 and 2 are designated as the source and sink nodes, respectively. Using the ACO-Based Routing algorithm with the Euclidean Distance parameter, we were able to identify the optimal path for data transmission between node1 and node2 as shown in Figure 2. Additionally, we observed that after transmitting 5,680 packets the optimal path was found to be though nodes 1, 8, 4, 2, and node 8 was no longer functional and considered a dead node.

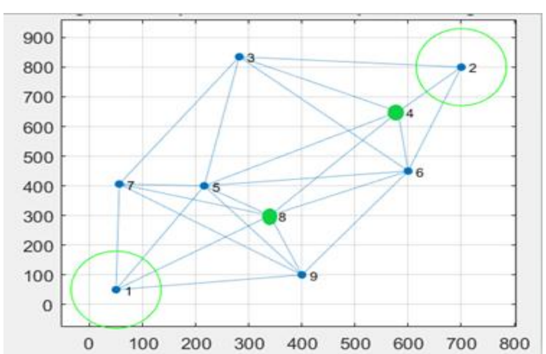

Figure 2: Topology 1: A Representation of the Network's First Topology, Depicting the Shortest Path (Highlighted in Green) Between Node1 and Node2

The following algorithm is used to describe ACO meta-heuristic:

Algorithm 1: Ant colony optimization (ACO)

init pheromone τ_i=const for each component c_i
while** termination conditions not met **do
***for** all ants i*
init s={ }
while** s is not a solution **do
choose c_j with probability = $p(c_i \mid s)$
expand s by c_j
end loop
***for** all ants i*
***for** all c_j in the solution s*
increase pheromone: $\tau_j=\tau_j+ const / f(s)$
end loop
***for** all pheromones i*
evaporate: $\tau_i=(1-\rho)\cdot\tau_i$
end loop
end loop

Choosing next hop cj is done randomly using Roulette-Wheel method with probability $p(c_i|s)$.

In the majority of ACO algorithms, the probabilities, also known as the transition probabilities, are specified as follows:

$$p(c_i \mid s) = \tau_i^{\alpha} / \sum_{Cj \in N(s)} \tau_j^{\alpha} \qquad (4)$$

The values of the parameter α determine the interaction between pheromone data and heuristics. N(s) is the set of all solution components that are practicable. Probabilities based on the concentration of pheromone caused packets to travel through one optimal route, which will rapidly deplete the energy of the route's nodes, and the first dead node will soon appear.

To address this issue, we propose three potential solutions. In each solution, we modify the computation of transition probabilities in order to modify the next hop in terms of:

1. Reserved energy in each tour node (E).
2. Number of shared neighbors between hop nodes (N).
3. Total route distance (D).

Energy-Aware ACO Routing (EACO)

In EACO, transition probabilities should be proportionally high for nodes with adequate energy that are healthy. Algorithm 2 shows the mechanism of simulating energy consumption and recharging for nodes within the network of EACO. Recharging for these nodes can be accomplished through either cables orsolar energy.

Algorithm 2: Energy simulation

```
init node energy C_Ne = const for each Node
energy consuming per cycle E_cc=0.85
energy recovery per cycle E_rc=0.2
random energy factor R_ef = 0.02*rand number
for each cycle
    for all c_j in solution s
        C_Ne= C_Ne- Ecc^Ref+Erc^Ref
    end loop
    for all c_j not in solution s
        C_Ne= C_Ne+Erc^Ref
    end loop
end loop
```

Therefore, in order to select the most promising path, we must consider the amount of unused energy stored within the nodes of this path. As a result, we prioritize routes with a higher residual energy by utilizing an exponential decay function, which decreases the probability quickly as residual energy decline. However, a challenge arises when longer routes accumulate more energy, resulting in (Corresponding author) a higher undue priority. To address this, we introduce a variable β, which is determined by trial and error and dependent on the network size. By dividing the energy sum by the total number of nodes multiplied by β, we can mitigate the issue. This solution, presented as equation (5), is the first of three proposed solutions for enhancing energy consumption.

$$p(c_i \mid s) = \frac{\tau_i^{\alpha} * \dfrac{e^{E*(E)}}{h*\beta}}{\sum_{Cj \in N(s)} \left(\tau_j^{\alpha} * \dfrac{e^{E*(E)}}{h*\beta} \right)} \qquad (5)$$

Where h represents the nodes counts in the selected tour.

Cost-Effective ACO Routing (CEACO)

In order to keep expenses to a minimum, it is necessary to select the path to be dependent not only on the amount of energy available, but also on the physical distance that separates each node. The distance traveled is inversely proportional to the probability of making a change.

When we added the distance factor to equation (5), we ran into two problems: first, that the energy should have the highest priority; to address this problem, we used an exponential function for the rout length; second, the distance dimension may differ from network to network; to address this problem, we used the normalization process. Both of these problems were addressed by the proposed equation (6) which was used as a second approach for reducing the amount of energy.

$$p(ci \mid s) = \frac{\tau_i^{\alpha} * \dfrac{e^{E*(E)}}{h*\beta*e^{\frac{D}{d}}}}{\sum_{Cj \in N(s)} \left(\tau_j^{\alpha} * \dfrac{e^{E*(E)}}{h*\beta*e^{\frac{D}{d}}} \right)} \qquad (6)$$

Where D is the tour length and d is the minimum hop length.

Cost-Efficient Node Replacement Strategies ACO (CERACO)

CERACO is employed to ensure that, prior to a node's depletion of energy, there exists a neighboring node capable of performing the same functions is identified and designated to take over its responsibilities. This allows the depleted node to be recharged while its duties are carried out by the backup node.

Therefore, in CERACO we include the number of shared neighbors (N) between hop's nodes to determine the next hop.

$$p(ci \mid s) = \frac{\tau_j^{\alpha} * \frac{e^{E*(E)}}{h * \beta * e^{\frac{D}{d}}} * N}{\sum_{Cj \in N(s)} \left(\tau_j^{\alpha} * \frac{e^{E*(E)}}{h * \beta * e^{\frac{D}{d}}} * N \right)} \tag{7}$$

6 Experimental and Results

The ACO algorithm is a meta-heuristic that, as was already mentioned, optimizes a problem by repeatedly attempting to enhance a candidate solution. This necessitates an accurate assessment of ACO algorithm parameters, such as α, β, the population size (M), the maximum number of iterations, and the pheromone trail degradation coefficient (p), and pheromone amount (Δτ(t)), which have a significant effect on ACO's performance. The selection of parameters relies on the optimization problem at hand. In this article, Q=1, p=0.2, and α=0.1 are utilized.

The proposed algorithm distributes packets evenly among all available sensor nodes in order to alleviate the strain on heavily utilized nodes. We anticipate a solid routing algorithm that minimizes delay and reduces power consumption, as well as one that keeps nodes alive for as long as feasible and reduces dead nodes, both of which will extend the WSN lifetime

In the first approach-EACO, we must identify the ideal value for the β parameter. According to Figure 3, after 10 rounds, in each round, researchers use different values for β parameter, and as a result: the optimal value is 10000, when trying to use higher values for β parameter, it backfires.

Figure 4 comparing the first dead node between the proposed methods and the conventional ACO algorithm using the topology 1 depicted in Figure 2.

The results demonstrate a substantial improvement for the 10 iterations of the specified methods.

Figure 3: Choose β Value, After 10 Rounds, the Optimal Value is 10000

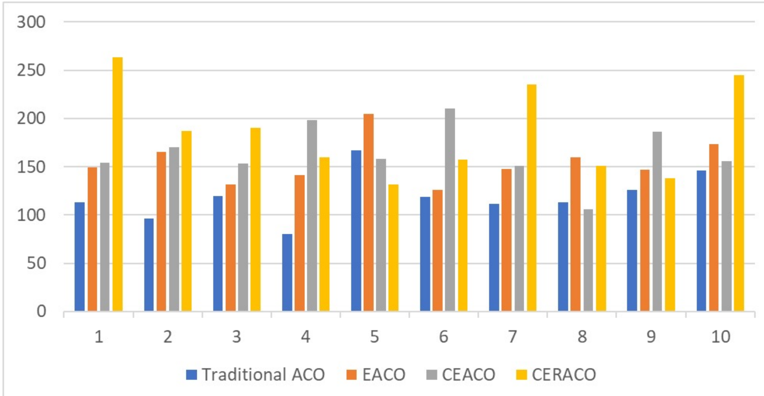

Figure 4: After Implementing the Experiment 10 Times, the Results Showed the Effectiveness of the Proposed Methods Compared to the Traditional ACO

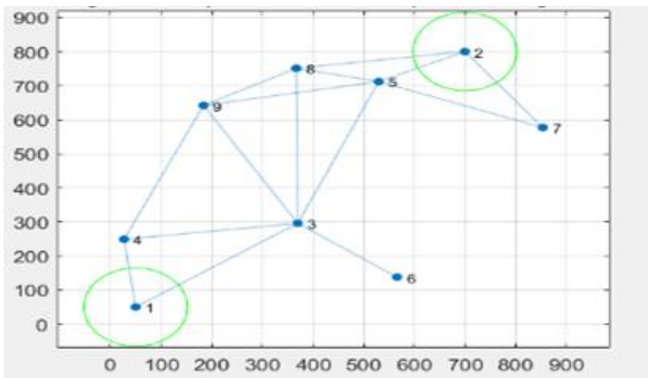

Figure 5: Topology 2, with Two Adjacent Nodes for Source Node, and Three for Destination Node

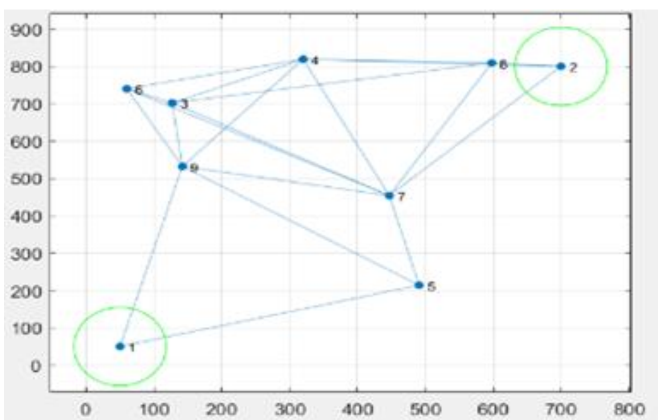

Figure 6: Topology 3, with Two Adjacent Nodes for Source Node, and Two for Destination Node

As shown in Figure 2, 5, 6, 7, and 8, we tried to diverse in topologies to include all possible cases. In the first topology, the source node -node 1- in Figure 2 has four neighbors, which means more routes, while in topology 4 there is only one neighbor.

Of course, the distribution of nodes varies from one topology to another, with the goal to ensure the effectiveness of proposed methods.

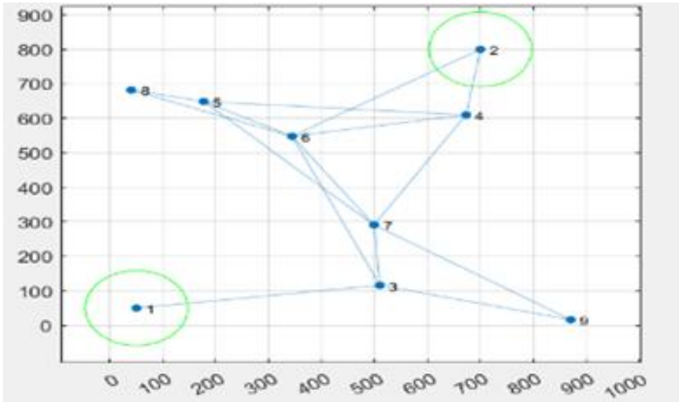

Figure 7: Topology 4, with One Adjacent Node for Source Node, that all Routes will Pass through Node 3

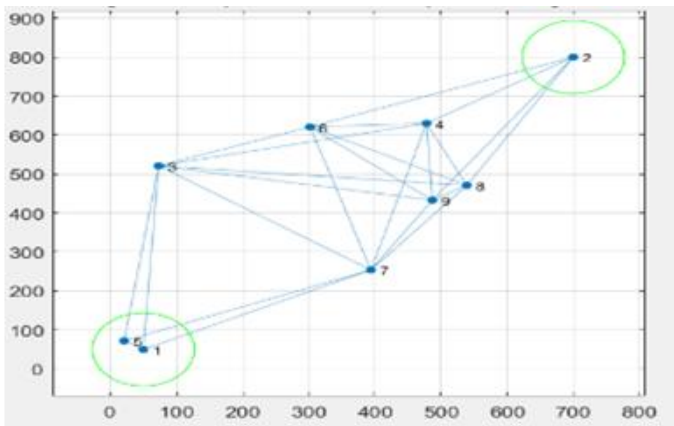

Figure 8: Topology 5, with Three Adjacent Nodes for Source Node, and Four for Destination Node, so Multiple Distinct Routes Between Source and Destination

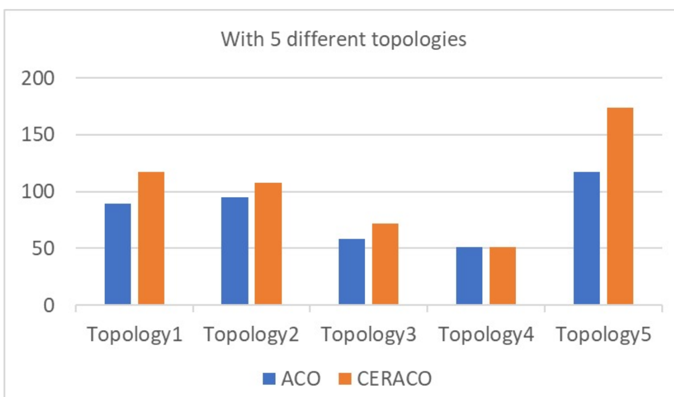

Figure 9: The Results of CERACO and Traditional ACO Using 5 Different Topologies

Figure 9 depicts a comparison between the CERACO and the traditional ACO method. The comparison was carried out using the five different topologies. As demonstrated, when compared to the standard ACO, the proposed technique fares better. But the efficiency is equal in the fourth topology, the reason is that there is just one adjacent neighbor for the source node, that all routes should pass through node 3, which led note 3 to die at equal time for all methods.

7 Conclusion

This study proposes three innovative approaches, EACO, CEACO, and CERACO, that utilize the ACO algorithm to identify the best path for data transmission in wireless sensor networks, with the aim of extending the network's lifespan. These methods improve and expand the functionality of the ACO algorithm, with each approach building on the previous one and introducing new criteria. The experimental results indicate that using any of these approaches would significantly enhance the network's overall energy efficiency compared to the traditional ACO algorithm.

The proposed approaches present an improved ACO algorithm that is tailored to the unique characteristics of wireless sensor networks, allowing for the identification of more energy-efficient paths for data transmission.

Our experimental results indicated that the CERACO approach outperformed the other methods in terms of efficiency. However, it was also apparent that the approach had a higher level of complexity compared to the other methods. Consequently, additional effort is required to reassess these circumstances, considering the complexity they pose.

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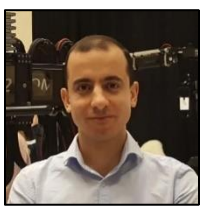
Authors Biography

Belal K. Elfarra is a computer engineer who earned his Master's degree in 2012 from the Islamic University of Gaza in Palestine. With a background in programming and development, he previously worked at PdMAIN Company in Gaza in 1999 as a programming developer. Currently, he is working as a system analyst at the Islamic University and is pursuing his Ph.D. in Computer Engineering at the same university. His research interests include multiagent systems, artificial intelligence, and data clustering analysis, https://orcid.org/0009-0008-8187-598X.

Mamoun A. Salha is an electrical engineer with a Master's degree in electrical engineering with a focus on communication technologies, obtained in 2011 from the Islamic University of Gaza in Palestine. He is currently pursuing a Ph.D. in Computer Engineering.His research interests primarily focuse on fiber optics, wireless communication, speech recognition, and telecommunications technology. Additionally, he is currently focused on data mining, clustering, and ubiquitous computing technologies, https://orcid.org/0009-0001-3870-3225.

Raed S. Rasheed is a scholar who obtained his BSc. degree in Computer Science from Applied Science University (ASU) in Jordan and his MSc. degree in Information Technology from Islamic University of Gaza (IUG) in Palestine. He has published several international research papers in various journals. Raed previously served as a teaching assistant in the faculty of Information Technology at IUG and as a head of Information Technology Affaires at the same institution. Currently, he is lecturer in Multimedia department in thefaculty of Information Technology. His professional research focuses on Blockchain, Multimedia and 3D Web, while his research also includes Computer Vision and Machine Learning, https://orcid.org/0000-0002-0553-949X.



Jehad Aldahdooh is a Ph.D. researcher in Computer Science at the University of Helsinki. He is currently working on natural language processing, using deep learning models to discover drug target interactions. Prior to this, Jehad worked as a researcher at the University of Eastern Finland, where he focused on text mining for Nordic Tweet Stream analysis. Jehad's academic journey began when he earned his Master's degree in computer science from Eötvös Loránd University in Hungary. During his Master's program, Jehad's research was focused on Meta-learning, specifically investigating the importance of meta-features for classification tasks in meta-learning, https://orcid.org/0000-0002-9947-4067.

Aiman Ahmed AbuSamra is a Professor in the Computer Engineering Department at the Islamic University of Gaza. He received his Ph.D. degree from the National Technical University of Ukraine in 1996. Dr. Aiman served as the Assistant Vice President of IT Affairs at IUG between 2011- 2014. He has supervised numerous Master's theses on mobile computer networks, computer security. His research interests include blockchain technology, computer networks and mobile computing. Dr. Aiman is an active member of the Technical Committee of the International Arab Journal of Information Technology (IAJIT) and has been acknowledged as one of its most dedicated reviewers, https://orcid.org/0000-0003-4652-3993.