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Research Article

Optimise Energy Consumption of Wireless Sensor Networks by using modified Ant Colony Optimization

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Abstract: Routing represents a pivotal concern in the context of Wireless Sensor Networks (WSN) owing to its divergence from traditional network routing paradigms. The inherent dynamism of the WSN environment, coupled with the scarcity of available resources, engenders considerable challenges for industry and academia alike in devising efficient routing strategies. Addressing these challenges, a viable recourse is applying heuristic search methodologies to ascertain the best path in WSNs. Ant Colony Optimization (ACO) is a well-established heuristic algorithm that has demonstrated notable advancements in routing contexts. This paper presents an altered routing protocol that is based on ant colony optimization. In this protocol, we incorporate the inverse of the distance between nodes and their neighbours in the probability equations of ACO, along with considering pheromone levels and residual energy. These formulation modifications facilitate the selection of the most suitable candidate for the subsequent hop, effectively minimising the average energy consumption across all nodes in each iteration. Furthermore, in this protocol, we iteratively fine-tune ACO's parameter values based on the outcomes of several experimental trials. The experimental analysis is conducted through a diverse set of network topologies, and the results are compared against well-established ACO algorithms and routing protocols. The efficacy of the proposed protocol is assessed based on various performance metrics, encompassing throughput, energy consumption, network lifetime, energy consumption, the extent of data transferred over the network, and the length of paths traversed by packets. These metrics collectively provide a comprehensive evaluation of the performance attainments of the routing protocols.

Keywords: WSN; Energy consumption; Optimization; ACO

I. INTRODUCTION

Wireless Sensor Networks (WSNs) encompass a set of miniature sensors designed to gather data from the observed environment and transmit it to a central base station known as the Sink [1]. Based on the specific application or purpose, these sensors can collect diverse data types, including temperature, noise, and pressure. The Sink processes the received data and may forward it to remote users or cloud platforms, facilitating integration with the Internet of Things (IoT). The IoT finds extensive applications in various domains, such as forest and ocean monitoring, nuclear reactor area management, and healthcare [2]. **Fig. 1** depicts the integration of WSN with IoT. Each sensor comprises three principal components: the sensing unit responsible for data acquisition, the processing unit housing storage memory, and the communication unit for data transmission and reception. Additional elements, such as GPS and mobilisers for mobility management in the case of mobile sensors, may also be incorporated, albeit at the expense of higher energy consumption [3]. Solar cells can be integrated as an auxiliary power source to address energy constraints [4]. However, the primary power source for sensors remains batteries, posing a significant challenge in WSNs, as these batteries are typically non-rechargeable and non-replaceable due to the sensors' remote and hazardous deployment locations, their small size and low cost [5]. The communication phase incurs the highest energy consumption, surpassing that of sensing and processing. Given the extensive deployment of sensors over vast geographical areas, manual management becomes impractical, necessitating dynamic routing techniques in WSNs to minimize energy consumption during communication. Achieving this objective involves leveraging artificial intelligence techniques and distributed algorithms to learn the network topology and determine energy-efficient paths [6][7]. This study proposes enhancing flat routing protocols for WSNs by modifying the traditional ACO algorithm.

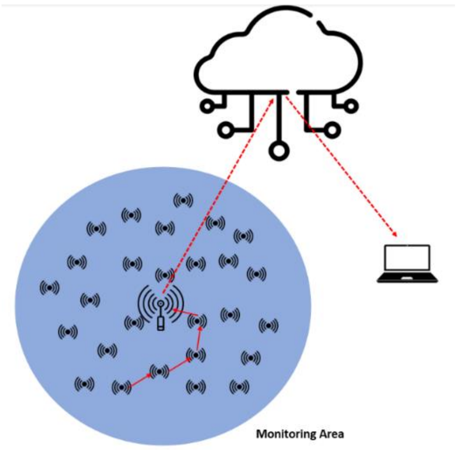

Figure 1. *Wireless Sensor Network components and their integration with IoT [4]*

Routing in Wireless Sensor Networks (WSNs) presents several formidable challenges, including those about energy consumption, communication range, and the establishment of peer-to-peer (P2P) communications. In P2P networks, all devices are interconnected with equal permissions and shared responsibilities for data processing. Unlike client and server networks, no specific devices in P2P networks are designated solely for sending or receiving data [8]. Each device possesses the same rights as its peers and can fulfil analogous functions. Consequently, in WSNs, each sensor must judiciously select the most suitable neighbour within its communication range, facilitating the formation of efficient multi-hop paths leading to the sink node. The goal is to minimize the distance traversed and, thus, conserve energy during data transmission. **Fig. 2** visually depicts the sensing and communication ranges of the sensors.

Routing in Wireless Sensor Networks (WSNs) determines network lifetime and overall performance. Given the reliance of sensors on battery power and the significant energy consumption in communication, efficient routing management is essential to reduce energy consumption while maintaining high throughput. This study proposes leveraging Artificial Intelligence (AI) algorithms to determine the next hop or candidate neighbour for packet transmission, a key distinction of WSN routing from other network types. Each sensor possesses limited knowledge of its immediate neighbours within its communication range rather than the entire network, necessitating novel approaches for flat routing protocols that do not rely on central nodes. In order to tackle this problem, we are presenting smart routing protocols. This protocol uses a modified (ACO) algorithm to select the next node while searching for the sink (destination). The modification involves performing thorough testing and analysis of various network topologies to determine the optimal parameter values (α, β, ρ, γ, and Q) for ACO in the flat routing protocol within WSNs. To mitigate energy consumption, we propose reducing the communication range of the sensors to prevent packets from being transmitted across long distances, a strategy based on the energy model discussed later. Additionally, we aim to minimise the Time-to-Live (TTL) value (number of hops) based on the network size. Furthermore, to address the issue of fast node depletion in flat protocols, we propose using super sensors near the sink to handle high loads efficiently, mitigating the risk of nodes dying prematurely. These suggested strategies are expected to improve the efficiency and performance of flat routing protocols in WSNs, leading to prolonged network lifetime and enhanced overall operation.

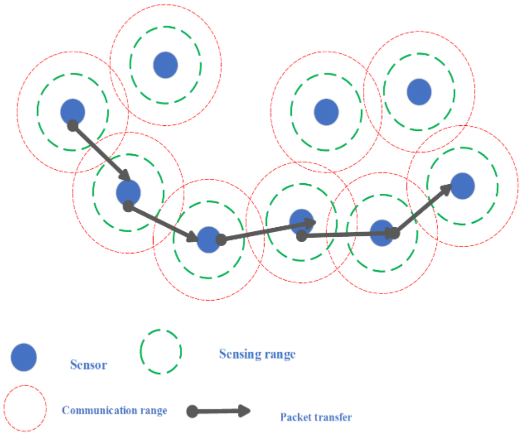

Figure 2. *Shows the packet routing in WSN based on the communication range*

This paper is organised as follows: Section Two presents the related work, and Section Three presents the materials and proposed models of this work, followed by a result analysis illustrated in Section Four. Section five concludes all the concepts and the future direction in this research field.

II. RELATED WORK

This section reviews various research studies focused on reducing energy consumption in Wireless Sensor Networks (WSN) through hierarchical and flat routing approaches. In one study [8], the researchers employed Capsule Neural Network to develop a learning model for identifying suitable cluster heads within the cluster based on identity records. They also utilized shortest path selection to identify forward nodes outside the clusters, reducing energy consumption. In another research effort [9], gravitational force and fuzzy rules were integrated to construct clusters and manage routing, improving network lifetime. Where the fuzzy logic has been used to select appropriate nodes as cluster heads, on the other hand, the Energy-efficient Scalable Clustering Protocol [10] addressed distances between and within clusters to generate equiponderant clusters. The Particle Swarm Optimization technology based on Dragonfly's algorithm (DA–PSO) was employed to select a cluster head, along with a new energy-efficient fitness function for optimal CH selection. However, hierarchical routing protocols suffer from inefficiencies in cluster head selection and frequent cluster head changes during the network's lifetime, along with the rapid depletion of cluster heads due to their dual roles of collecting sensing data and forwarding it to the sink.

In another study [11], the researcher proposed an intelligent opportunistic routing protocol (IOP) using a machine learning technique to select the next hop based on residual energy.

It is important to note that the heuristic function based solely on save the residual energy in [12][13] did not guarantee to reach the sink in fewer hops, resulting in decreased throughput despite high energy consumption. One significant limitation of flat routing protocols is the rapid energy depletion of sensors near the sink due to the heavy load of transmitting sensing data from other sensors. In contrast, the proposed protocol addresses this limitation by utilizing solar cells as a power supply for the sensors near the sink and leveraging methods based on artificial intelligence to find the minimum length of the success path, thereby enhancing energy efficiency.

III. MATERIALS AND METHODS

1. Network setting

Two distinct models govern the distribution of sensors within the monitoring area: the pre-planned mode, wherein the monitoring area is readily accessible for manual sensor deployment and management, resulting in efficient coverage with a reduced number of sensors, and the ad-hoc mode, which assumes greater significance in challenging or distant environments where manual access is impractical. In the ad-hoc mode, a larger number of sensors are deployed randomly to achieve the required coverage [14][15][16]. The latter distribution model was adopted during the network's construction phase, randomly deploying N sensors within a square area. The network configurations encompassed three setups, each varying in the number of nodes and network area: 80 nodes in a 100x100-meter region, 160 nodes in a 200x200-meter region, and 240 nodes in a 300x300-meter region.

During the network operation, each sensor initiates communication by sending a hello packet to its neighbouring sensors, conveying essential information such as ID, location, and energy status. Data transfer within the network was categorized into three modes: event-driven, where data transmission commences upon specific events; time-driven, wherein sensed data is transmitted to the sink at predetermined intervals; and query-driven, where data transmission is triggered in response to sensor requests [6]. In the proposed model, the first type, i.e., event-driven data transfer, was adopted to enable a specific group of sensors to transmit their sensing data during each operational round. To simulate this behaviour, the set of sensors responsible for data transmission during each round was randomly selected.

2. Energy model

This study assumes that all sensors initially possess equal energy levels. However, over time, each sensor's energy varies due to energy depletion during the sensor operations (sensing, data processing, and communication). The energy expended on sensing and processing is minimal compared to the energy used for communication [17].

Every sensor keeps an information table about neighbouring nodes: their IDs, remaining energy levels, and positions. The Euclidean distance formula calculates the distance between nodes, and any changes in energy levels are promptly updated in the table. We utilize the equations specified in reference [18] to evaluate energy consumption during communication. Specifically, one of two equations is applied depending on the distance between sender and receiver sensors. When the distance is below a predefined threshold "d0," the free space model is employed. On the other hand, if the distance surpasses this threshold, the multipath fading model calculates the energy needed for transmitting a 1-bit packet.

$$E_T(l,d) = \begin{cases} lE_{elec} + \mathcal{E}_{fs} d^2 & if \;\; d < d_o \\ lE_{elec} + \mathcal{E}_{mp} d^4 & if \; d \geq d_o \end{cases} \tag{1}$$

where E_{elec} is the energy of the electronic circuit, while $\mathcal{E}_{fs}$ and $\mathcal{E}_{mp}$ are the energy consumed. In the receiver sensor, energy lost in receiving *l* bits is:

$$ER(l) = lE_{elec} \tag{2}$$

3. Ant colony optimization

Ant Colony Optimization (ACO) Wireless Sensor Networks (WSNs) use pheromone information to help sensor nodes select suitable neighbors. In this study, we propose enhancement of Ant Colony Optimization for flat routing protocol, an intelligent protocol based on ACO. Initially, all connections between sensors are assigned uniform initial pheromone values. Consequently, during the first hop, sensor nodes make their next-hop selections without being influenced by pheromone concentration. However, the pheromone values are updated with each successive round, impacting the subsequent next-hop selections.

To enhance the heuristic function in the probability equation, we suggest two methods in the proposed Modified ACO. Firstly, we employ the inverse of the distance between nodes i and j to establish the heuristic function η_{ij}, favouring a higher probability for shorter distances, thereby encouraging the selection of closer sensors. Secondly, we incorporate two additional heuristic functions, along with the pheromone value, by incorporating the distance between nodes i and j and the residual energy of the neighbour sensor. Consequently, the probability equation takes the form of equation (3):

$$parentp_{ij}^{m}(t) = \frac{[\tau_{ij}(t)]^{\alpha} \quad . \ [n_{ij}\,(t)]^{\beta}}{\sum_{m\in N_i^k}[\,\tau_{im}\,(t)]^{\alpha} . \quad [n_{im}\,(t)]^{\beta}}, \qquad if\ j \in N_i^k \tag{3}$$

where η_{ij} represents the inverse of the distance between nodes i and j, and δ_j denotes the difference between the initial and residual energy of node j.

To perform pheromone updates, we utilized equations 4 and 5.

$$\tau_{ij}(t+\Delta t) = (1-\rho).\tau_{ij}(t) \tag{4}$$

for all edge in the network, and

$$\tau_{ij}(t+\Delta t) = \tau_{ij}(t) + \Delta\tau_{ij}(t) \tag{5}$$

for all success paths.

The ACO's parameters (α, β, ρ, γ, and Q) were systematically adjusted after conducting rigorous testing and analysis across the three network topologies to determine the values that optimise high throughput while minimising energy consumption, rendering ACO suitable for this particular context. Algorithm 1 illustrates the modified ACO algorithm. Ant Colony Optimization 1 and 2 focus on minimum distance and energy, respectively.

IV. EXPERIMENT RESULT AND ANALYSIS

This section provides a comprehensive overview of the networks' attributes, the simulation environment employed, the designated parameters, and the performance evaluation results for the two proposed protocols. Additionally, we present a comparative analysis of the outcomes of these protocols concerning the performance metrics adopted for the evaluation. Furthermore, we juxtapose the results of the proposed protocols against other algorithms, which are utilities in flat routing approaches used in Wireless Sensor Networks (WSNs).

1. Environment simulations

In the simulation of network configuration, implementation of routing protocols, and subsequent result analysis, we utilised the Python programming language, complemented by the NetworkX package. To substantiate the efficacy of our proposed protocols, we conducted simulations on three distinct networks. These networks comprised 80 nodes in a 100x100-meter area, 160 nodes in a 200x200-meter area, and 240 nodes in a 300x300-meter area. **Table 1** shows the network scenarios in our experiment, parameters of the network's scenarios.

Table 1. *Network scenarios*

Parameters	Scenario 1	Scenario 2	Scenario 3
Network Area	100x100 m^2	200x200 m^2	300x300 m^2
Base station location	(50,50)	(100,100)	(150,150)
Number of sensors	80	160	240
Deployment	Random scale free	Random scale free	Random scale free
Communication range	20 m	28 m	35 m

Furthermore, **Table 2** accounts for the parameters employed in the network model, energy model, and the Ant Colony Optimization (ACO) algorithm. We maintained consistent parameters throughout our experimental analysis for all the cases.

Table 2. *Experimental parameters*

Parameters	Value
Initial energy of sensors	5 *J*
Number of sinks	1
Location of sink	Centre of area
Packet size	1024
E_{elec}	50 nJ/bit
$\mathcal{E}_{mp}$	0.0013 pJ/bit/m4
$\mathcal{E}_{fs}$	10 pJ/bit/m2
d_0	50
α	2
β	3
Initial pheromone	1
ρ	0.5 – 1
Q	1

2. Result and analysis

This study comprehensively assessed the simulation outcomes encompassing throughput, energy consumption, network lifetime, and success message ratio travelled by data packets. We have juxtaposed the performance of our proposed ACO-based routing algorithm, outlined in [16], with that of the conventional ACO routing protocol under identical simulation conditions, thus substantiating the efficacy of the algorithms in question. In the subsequent section, we will expose each of the metrics above, delineated to two distinct scales: the count of network operation iterations or rounds and the progressive Time-to-Live (TTL) range. Each TTL value corresponds to the network's performance following 1000 iterations of network operation. Furthermore, these metrics will be illustrated across three distinct network topologies, explained in **Table 1**.

The throughput metric indicates the successful delivery of packets to their intended destinations, with the success ratio employed as an illustrative measure in our calculations. The figures presented above conspicuously demonstrate the notable superiority of the ACO-based routing protocol (**Table 3**) in achieving elevated throughput compared to both the traditional ACO protocol and the energy and randomness-based routing approaches. **Fig. 3** and **4** visually depict the success rates across the three network topologies during varying operational iterations and energy consumption. Additionally, **Fig. 5** showcases the metrics as mentioned above in scenarios involving different TTL values, thereby further substantiating the superior throughput performance of our proposed ACO-based routing protocol. **Fig. 6** shows a final comparison of the Network's lifetime among three scenarios, which is explained in **Table 1**. And it shows the proposed ACO achieved high performance compared to the traditional methods.

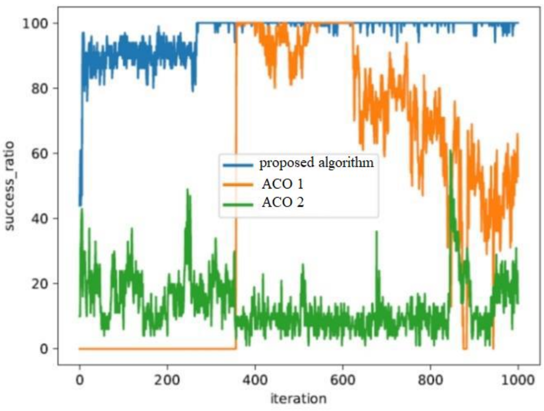

Figure 3. *Success message ratio based on 160 network nodes.*

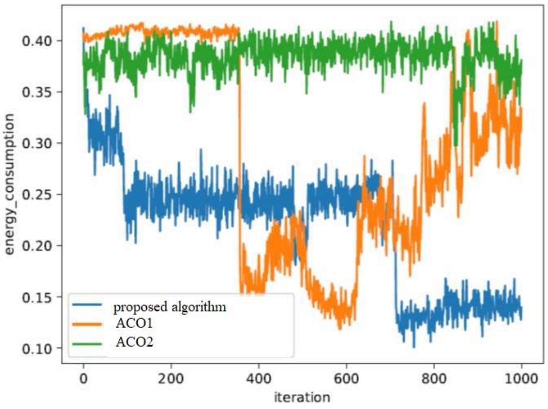

Figure 4. *Energy consumption ratio based on 160 network nodes.*

Table 3. *ACO-based routing protocol algorithm*

```
Input:
    Energy nodes: 5 j
    Set No of hops
    Energy: electronic circuit, amplifier in free space , amplifier in multi path
    Set L: Packet size
Output:
    Successful path
Steps:
Received energy= L* electronic circuit
While no of hops!=0 do:
    Sort the neighbors based on distance and maximum ACO probability using Eq(3)
    Create node list to visit
    If no of hops ==0 then:
        Return (fail)
    Else:
        Visit the nodes list
        Update the success path
```

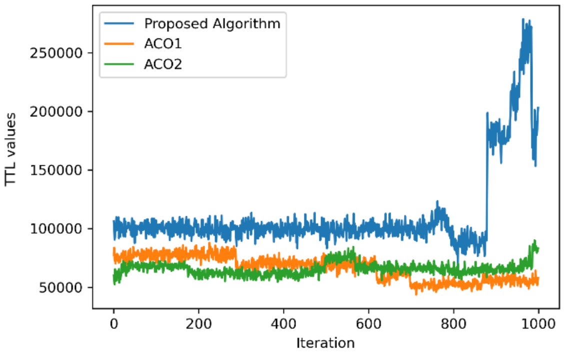

Figure 5. *TTL values over 160 network nodes*

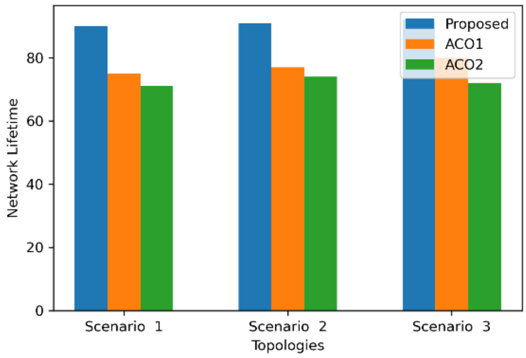

Figure 6. *Comparison of Network's lifetime for three models and three scenarios*

V. CONCLUSION

In this research endeavour, we present a series of intelligent routing protocols designed to enhance the operational longevity of Wireless Sensor Networks (WSNs). Our primary objective revolves around the optimisation of energy utilisation within these networks. To achieve this, we leverage the heuristic search optimisation approach known as Ant Colony Optimization (ACO). Our efforts encompass refining the underlying pheromone concentration equations within the ACO algorithm. Moreover, we meticulously fine-tune the pivotal ACO parameters (α, β, ρ, γ, and Q) based on an iterative process involving comprehensive testing across diverse network topologies. This meticulous parameter calibration is geared towards rendering the ACO algorithm conducive to seamless integration within the framework of flat routing protocols within WSNs. The proposed algorithm's efficacy is examined across three distinct yet controlled network scenarios. These scenarios encapsulate 80 nodes deployed within a 100x100 meter area, 160 nodes spanning a 200x200 meter expanse, and 240 nodes dispersed across a 300x300 meter terrain. Notably, all evaluated scenarios are governed by identical network and energy parameters, ensuring an equitable basis for comparison. The evaluation outcomes compellingly underscore the superior performance of the proposed modified ACO algorithm. This superiority contrasts not only with the conventional ACO algorithm, as documented in [16], but also against a spectrum of alternative protocols. This performance is consistently evident across all dimensions of performance metrics embraced within this comprehensive study.

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AUTHOR CONTRIBUTIONS

Y.Razooqi: Conceptualization, Experiments, Theoretical analysis.

Al-Asfoor: Supervision, Review and editing.

M.Abed: Supervision, Review and editing.

DISCLOSURE STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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