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Graph Attention Network and Mountain Gazelle Optimizer-Based Resource Allocation for RIs Assisted UAV Wireless Powered Sensor Networks

Ebby Darney P[2]

[2]Professor, Department of Electrical and Electronics Engineering,
Rajarajeswari College of Engineering, Bangalore, India – 560074.

Corresponding Author E-mail

ABSTRACT: Wireless sensor networks (WSNs) are limited by energy availability, unreliable communication and inefficient resource allocation especially in remote and disaster prone environments. To tackle these issues, this work proposes a resource allocation framework for reconfigurable intelligent surface (RIS)-assisted unmanned aerial vehicle (UAV) wireless-powered sensor networks based on Graph Attention Network (GAT) and Mountain Gazelle Optimizer (MGO). The GAT model predicts the effective communication paths by analysing the network connectivity and the link quality, while MGO optimizes the power allocation, bandwidth allocation, time-slot assignment and UAV scheduling. Furthermore, the RIS controller switches the reflection configuration to increase the signal strength and cancel the interference. The proposed approach achieves an energy consumption of 0.02, a throughput of 3.4 and an end-to-end delay of 0.01. The comparative results show the better energy efficiency, throughput and communication performance than the reported ACO, ABC, WOA and GWO results.

Keywords: GAT, MGO, UAV, RIS, WSN.

1. Introduction

Unmanned Aerial Vehicles (UAV) have attracted substantial attention from the wireless communication networks because of the mobility, quick response, and cost savings [1-2]. The UAVs are extensively used for environmental surveillance, disaster management, emergency response, and gathering information from distant places [3]. Within the wireless sensor networks, the UAVs help establish communication in those regions where there is no availability of any infrastructure. Nevertheless, low energy available, short flight time, and processing limitations impact the performance of UAVs while undertaking complex operations [4-5].

Reconfigurable intelligent surface (RIS) technology has been introduced recently as an effective technique to enhance the performance of wireless communication through control of signal reflection and improvement in received signal strength with reduction in interference. Incorporation of RIS technology along with UAV-assisted WSN increase the connectivity of network and reliability of communication with energy efficiency [6-7]. Moreover, UAVs facilitate wireless power transfer to energy-depleted sensor nodes, and thereby, energy harvesting take place at the sensor node to transmit the collected information. This process carried out in two steps including wireless power transfer in which energy is harvested from UAV to the sensor nodes and subsequent wireless information transfer in which energy collected is used to transmit information to the UAV or base station [8].

There are several approaches that are adopted to classify network conditions and provide resource allocation in RIS-enabled UAV wireless-powered sensor networks. Graph Neural Network (GNN) model relations between the connected sensors, but it prone to over smoothing. K-Nearest Neighbours (KNN) classify the network conditions based on the similarity of the features but it becomes computationally inefficient when dealing with large-scale datasets. Deep Neural Network (DNNs) learn nonlinear correlations between the residual energy, channel gain, UAV position, and the traffic load, but it requires sufficient training dataset. Graph Convolutional Network (GCN) use both the features of the sensors and the network topology, but it is prone to over smoothing [9-12]. To solve these problems, the novel GAT is adopted that uses attention coefficients to neighboring nodes and earn the network relations efficiently. Moreover, the MGO the power and bandwidth of the UAVs and schedules them depending on the network state. The combination of GAT and MGO leads to better utilization of resources and better performance in the RIS-assisted UAV wireless-powered sensor networks. The main contributions of this work are summarized below.

- This paper proposes a framework of RIS-assisted UAV wireless-powered sensor networks based on GAT-MGO. The GAT model is used to predict efficient communication routes and the MGO algorithm is used to optimize the power allocation, bandwidth distribution, time-slot assignment and UAV scheduling.
- The RIS reflection setting is optimized to improve the signal strength and reduce the interference, resulting in improved communication reliability and efficient use of resources.
- The proposed framework achieves an energy consumption of 0.02, throughput of 3.4 and end-to-end delay of 0.01, which shows improved network performance.

1.1 Research Gap

While traditional techniques like GNN, KNN, DNN, and GCN have been employed for performing analysis and allocating resources for networks, these algorithms pose some challenges due to over-smoothing, high computation cost, and the need for more training data. In addition, simultaneous optimization for communication path prediction, power allocation, bandwidth distribution, time-slot allocation, UAV scheduling, and RIS reflection configuration has proved to be a difficult problem in RIS-assisted UAV wireless-powered sensor networks. This has resulted in the necessity for designing a hybrid model that uses GAT and MGO.

2. Recent Works

S. No	Tittle/ author name/year	Methodology used	Advantages	Disadvantages
1.	Chen et al (2026) [13]	The method integrates ACO for dynamic route planning and MILP for routing and energy optimization. It determines efficient transmission paths considering node energy and sink mobility.	The method optimizes path selection to improve routing efficiency and minimize energy consumption. It supports load balancing and prolongs network lifetime.	ACO and MILP require high computational resources with increase in the size of network. Frequent mobility of the sink also raises the routing complexity and overhead.
2.	Dinesh et al (2025) [14]	This method employs Artificial Bee Colony (ABC) optimization for choosing energy efficient routing paths in wireless body area networks (WBANs. It takes into account the energy of the nodes, communication distance	The method reduces the energy consumption and improves the routing efficiency. It helps to balance the load of network and prolong the lifetime of network.	The algorithm need more computation and parameter tuning. Its performance might degrade in highly dynamic network conditions.

		and routing conditions to enhance the data transmission.		
3.	Nabavi et al (2021) [15]	This method utilizes a Multi-Objective Whale Optimization Algorithm (MOWOA) for optimal routing path selection in wireless sensor networks. It takes into account energy consumption, delay and network lifetime to enhance routing performance	The method enhances routing efficiency and balances energy consumption of sensor nodes. It provides a longer network lifetime and reliable data communication.	The algorithm computationally intensive and require careful parameter tuning. However, It not perform well on large networks or on highly dynamic networks.
4.	Rami Reddy et al (2023) [16]	It employs an improved Gray Wolf Optimization (GWO) algorithm to select the optimal cluster heads depending on the residual energy, communication distance, and node distribution. Its goal is to balance energy consumption and improve routing efficiency	The method reduces the energy consumption and balances the network load among the sensor nodes. It is helpful to extend the lifetime of the network and improve the efficiency of the data transmission.	It also need more computational resources and parameter tuning. Its performance reduced in large-scale or highly dynamic networks. .

2.1 Objectives

- To develop a RIS-assisted UAV wireless-powered sensor network aiming for reliable communication and efficient energy extraction.
- To Collect data on environmental, industry, agriculture, and disaster monitoring, and monitor energy levels of the sensors and network conditions.
- To utilize the MGO for optimal power allocation, bandwidth allocation, time-slot assignment and UAV scheduling.
- To use GAT for effective network state analysis, link quality evaluation and communication route prediction
- To optimize the RIS reflection beams to improve the signals and decrease the interference, and enhance the throughput, PDR, energy efficiency, network lifetime and utilization of resources

3. Proposed Work Explanation

The proposed RIS-assisted UAV wireless-powered WSN is intended to enhance energy efficiency, resource allocation, and reliable communication. The first layer is the sensor data generation layer which collects the environmental, industrial, agriculture, and disaster monitoring data. The wireless energy harvesting process allows UAVs to help in energy transfer to sensor nodes and monitors their energy levels. The network state information module collects important parameters, including residual energy, channel gain, UAV position, sensor traffic load, and RIS reflection status. Based on the above parameters, the MGO allocates resources and optimizes UAV schedules. The resource allocation framework distributes power, bandwidth, time slots and UAV tasks to enhance the utilization of network resources is denoted in Figure 1.

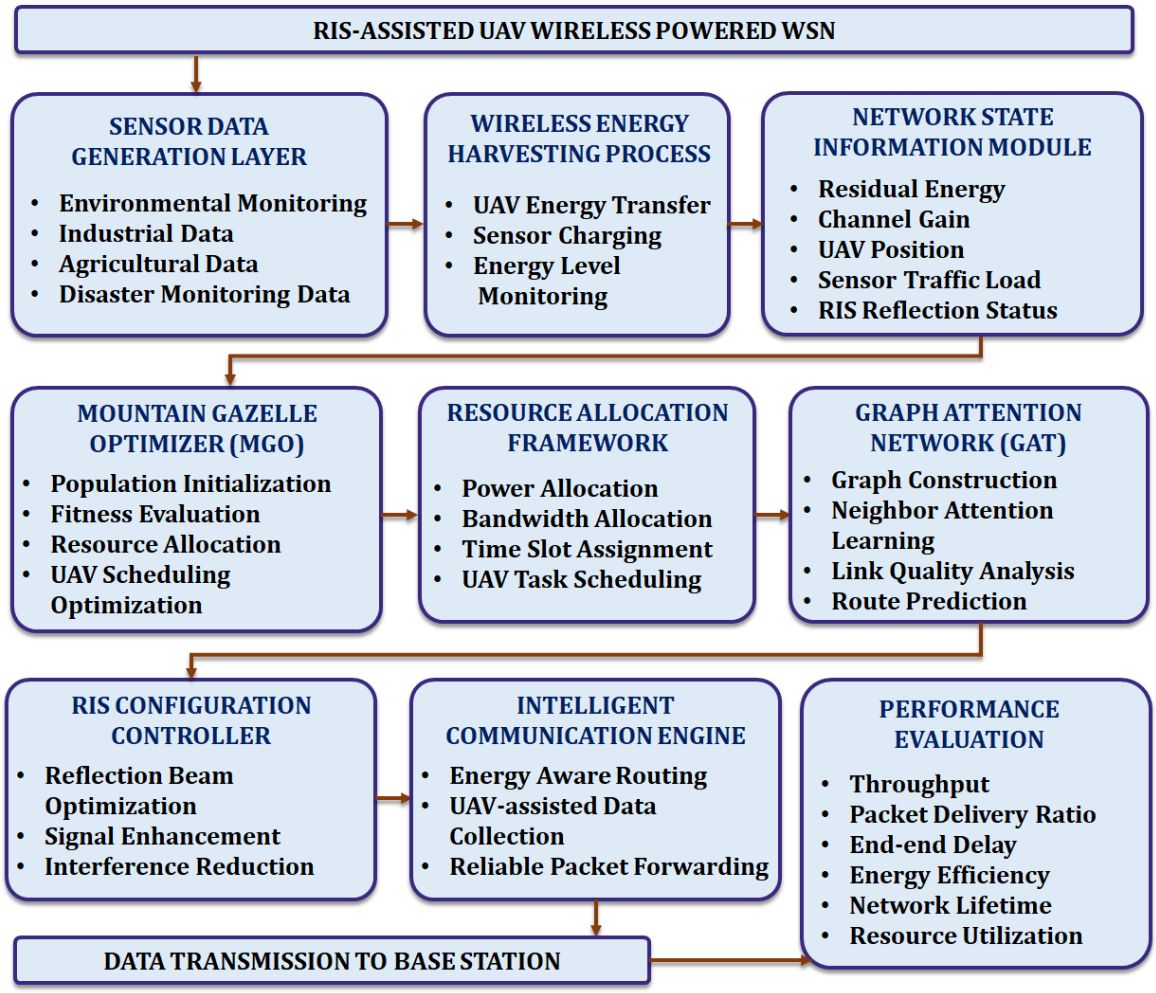


Figure 1: *Proposed System Architecture*

Furthermore, the GAT module builds the network graph, learns the relationship of neighboring nodes, analyses the link quality, and predicts the appropriate communication routes. The RIS configuration controller optimizes the reflection beams to improve the communication reliability by improving the signal strength and reducing the interference. Then, the intelligence communication engine executes energy-aware routing, UAV-assisted data gathering and reliable packet transmission. The gathered data are transmitted to the base station for further processing. The overall communication performance of the proposed framework is analysed considering key performance indicators including throughput, packet delivery ratio, end-to-end delay, energy efficiency, network lifetime.

4. Proposed system modelling

4.1 MGO

The proposed system applies MGO to optimize power allocation, bandwidth distribution, time-slot assignment, and UAV scheduling based on the network-state information, including residual energy, channel gain, UAV position, traffic load, and RIS status. The optimization process is to improve throughput and energy efficiency, and decrease energy consumption and communication delay

The initial population of candidate solutions is given by:

$$X = \begin{bmatrix} X_{11} & \cdots & X_{1d} \\ X_{21} & \cdots & X_{2d} \\ \vdots & \ddots & \vdots \\ X_{N1} & \cdots & X_{Nd} \end{bmatrix}$$

Where N is the number of candidate solutions and d is the number of decision variables.

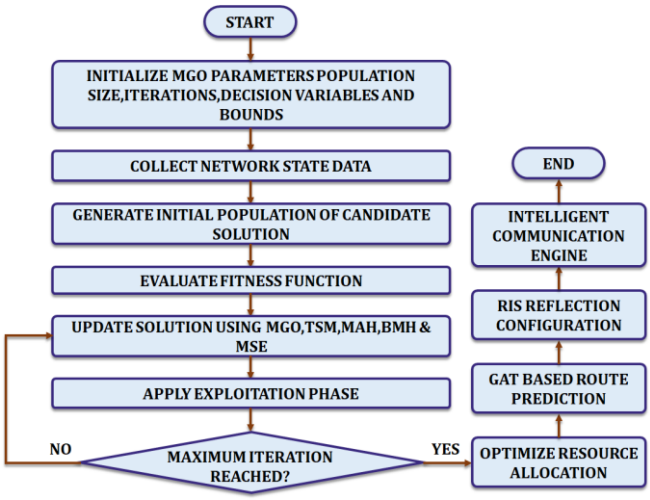


Figure 2: *Flowchart of MGO*

The fitness function is defined as:

$$\min F(x) = w_1 E(X) + w_2 D(X) - w_3 T(X) - w_{4\eta}(X) \quad (1)$$

Where $E(X)$ is the energy consumption, $D(X)$ is the communication delay, $T(X)$ is the throughput, and $\eta(X)$ is the energy efficiency. The weights w_1, w_2, w_3 and w_4 indicate the importance of each metric.

The MGO algorithm uses its search mechanisms to update candidate solutions to determine appropriate resource-allocation parameters. The following equations show these updates.

$$X_i^{TSM} = X_{best} - \left|\left(r_1 BH - r_2 X_i(t)\right)F\right|C \quad (2)$$

$$X_i^{MaH} = (BH + C_2) + (r_3 X_{best} - r_4 X_{rand})C_3 \quad (3)$$

$$X_i^{BMH} = X_i(t) - D + (r_5 X_{best} - r_6 BH)C \quad (4)$$

$$X_i^{MSF} = lb + r_7(ub - lb) \quad (5)$$

Where $X_i(t)$ is the current solution, X_{best} is the best solution, X_{rand} is a randomly selected solution, lb and ub are the lower and upper bounds, and r_1 to r_7 are random numbers. These equations should be checked against the particular MGO formulation used in the implementation.

The optimized resource-allocation parameters are then given to the GAT-based network analysis and RIS reflection controller to enable efficient routing, improved link quality, and reliable communication in the UAV-assisted sensor network.

4.2 GAT

The WSN face the problem of varying connectivity and link-quality. The proposed GAT adaptively incorporates the relationships of neighboring nodes, residual energy and channel quality to predict efficient communication paths, and to address the drawbacks of conventional GCN, which improve the reliability of RIS-assisted UAV wireless-powered sensor networks.

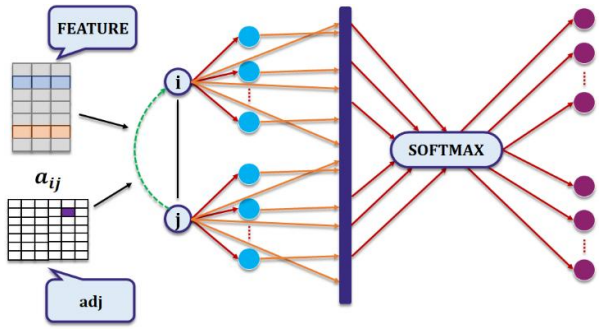


Figure 3: *GAT Architecture*

The GAT evaluates the neighboring sensor nodes using self-attention, as shown in Figure 3. It then applies MGO-based resource allocation to handle residual energy, channel gain, traffic load, UAV position, and link quality, to predict efficient communication routes based on node features and adjacency relationships.

$$H = WX \quad (6)$$

The attention mechanism computes the relationship between connected nodes as a function of their transformed feature vectors. The attention score between nodes i and j is given as:

$$e_{ij} = LeakyReLU\left[a^T\left(Wh_i || Wh_j\right)\right] \quad (7)$$

Where h_i and h_j denote the feature vectors of nodes i and j respectively, a is a learnable attention vector and || denotes concatenation. The

adjacency matrix ensures that attention is only calculated between connected neighboring nodes.

The attention coefficients are computed by normalizing the attention scores via the softmax function:

$$\alpha_{ij} = \frac{exp(e_{ij})}{\sum_{k\epsilon\aleph_i} exp(e_{ik})} \quad (8)$$

Where α_{ij} denotes the importance of neighboring node j to node$i$, and $\aleph_i$ denotes the neighborhood of node i. These coefficients allow the GAT model to focus on relevant neighbor nodes and discover appropriate communication links.

The updated node representation obtained by aggregating the weighted features of neighboring nodes:.

$$h_1' = \sigma\left(\sum_{j\epsilon\aleph_i} \alpha_{ij} W h_j\right) \quad (9)$$

Where σ is the activation function and h_1' is the updated node features. The GAT estimates efficient routes considering network connectivity and link quality. The RIS controller adjusts the reflection coefficients to improve the signal strength and reduce the interference. The intelligent communication engine manages the best resource allocation, route prediction and RIS-assisted signal transmission to improve communication reliability and energy efficiency.

5. Results and Discussion

The proposed GAT-MGO method is compared with the existing optimization techniques using the key network metrics for performance. The results compare the energy consumption, throughput, delay, PDR and network lifetime.

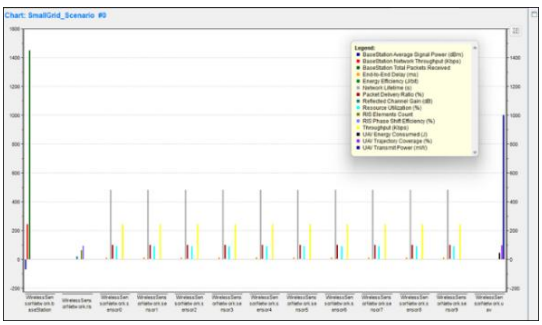


Figure 4: *Network Performance Analysis*

Figure 4 shows the network performance indicators between sensor nodes, base station and UAV. It provides throughput, packet delivery ratio, delay, energy efficiency, utilization of resources, and RIS related performance indicators

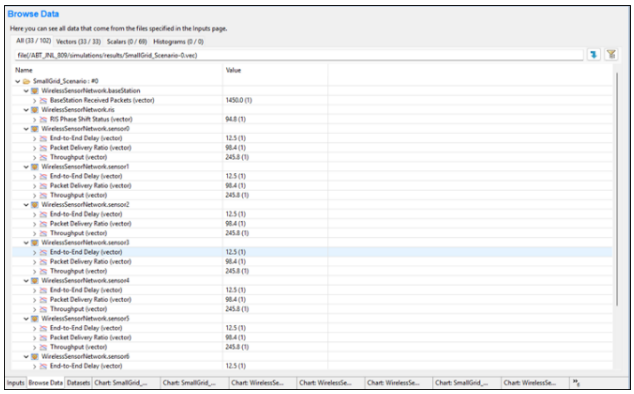


Figure 5: *Simulation data log for RIS-Assisted UAV-WPSN*

Figure 5 Simulation data captured for the base station and for each of the sensor nodes. It provides the main metrics like end-to-end delay, packet delivery ratio, throughput, and RIS phase-shift status.

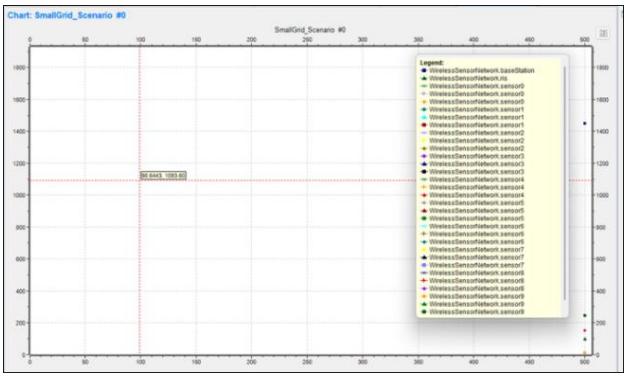


Figure 6: *Network node performance*

Figure 6 illustrates the distribution of the performance of the sensor nodes, the RIS and the base station in the simulation. It presents a comparative view of network-node behaviour for the evaluation of communication performance and resource usage

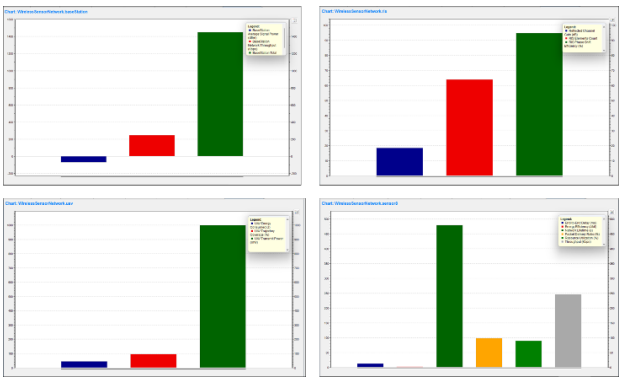


Figure 7: *performance evaluation metrics of base station, RIS, UAV, and sensor node*

Figure 7 shows the key performance metric, including signal power, throughput, packet reception, RIS channel gain, UAV energy consumption and trajectory coverage. It also considers sensor-node delay, energy efficiency, network lifetime, packet delivery ratio, and resource usage to evaluate the overall network performance

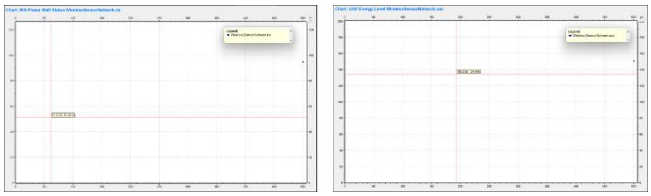


Figure 8: *RIS phase shift and UAV energy analysis*

The RIS phase-shift status and the UAV energy level during the simulation are shown in Figure 8. These parameters help in evaluating the RIS reflection configuration and the energy availability of the UAV to enable reliable communication and wireless power transfer

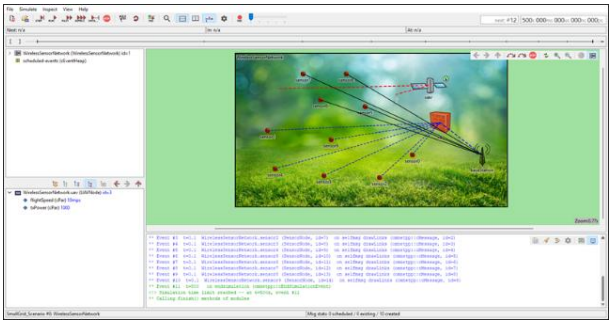


Figure 9: *network simulation model*

Figure 9 illustrates the simulated network with multiple sensor nodes, a UAV and a base station. It displays the network topology and communication links used for data transmission during simulation

Table 2: *Comparative analysis of routing optimization methods*

Method	Energy Consumption	Throughput	End-End Delay
ACO	0.05	2.4	0.2
ABC	0.2	-	-
WOA	-	1.5	-
GWO	0.5	2.2	1.5
Proposed	0.02	3.4	0.01

The proposed method is compared with ACO (0.05, 2.4, 0.2), ABC (0.2), WOA (1.5 throughput), GWO (0.5, 2.2, 1.5) in the table. II. The proposed method has the lowest energy consumption (0.02), highest throughput (3.4) and lowest end-to-end delay (0.01).

6. Conclusion

The proposed GAT-MGO based resource allocation method improves the energy efficiency, throughput and communication reliability of RIS-assisted UAV wireless-powered sensor networks. The GAT predicts the optimal communication routes, and MGO optimizes the allocation of resources and scheduling of UAVs. The RIS reduces interference to improve signal strength and communication reliability. The proposed method also has an energy consumption of 0.02, a throughput of 3.4, and an end-to-end delay of 0.01. The comparative results show that it effectively reduces energy consumption and delay with an increase in throughput which supports reliable and energy efficient network communication. Future work Improve scalability and efficiency Applications Agriculture Industrial monitoring Environmental monitoring Disaster management

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