Dynamic path planning and computation offloading in Wireless Powered UAV-IoT Network

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Abstract: Unmanned Aerial Vehicles (UAVs) played an important role with distributed processing and performing computing tasks for Internet of Things (IoT). Wireless power transfer from UAVs to IoT devices is crucial as it enables continuous and efficient operation of IoT devices without the need for physical connections or frequent battery replacements. This technology ensures uninterrupted data collection, monitoring, and communication, ultimately enhancing productivity, connectivity, and the overall functionality of IoT applications in various fields such as agriculture, environmental monitoring, smart cities, healthcare and military applications. UAVs are often used for tasks such as surveillance, inspection, and delivery. These tasks often require UAVs to fly complex trajectories in dynamic environments. Path planning can help UAVs to plan and execute their trajectories more efficiently and to help the IoT nodes with the on-borad computing resources of UAVs acting as edge servers. However, with the varying depletion of energy in IoT nodes, the path planning decisions have to be dynamic and suitable for the changed IoT scenario. In this work, we plan to design a dynamic trajectory while considering the computation and energy demands of the IoT devices.

Keywords: Unmanned Aerial Vehicles (UAVs); Internet of Things (IoT); Trajectory planning; Wirelessly Powered Networks; Edge computing.

1. Introduction

The increase in UAVs usage has resulted in an increased research focus on these aerial platforms used for dynamic path planning and computing offload in Wireless Powered UAV-IoT Networks. Therefore, in the world of IoT and in particular UAVs, navigation is one of the main research directions as these UAVs have to be able to quickly move across complex terrain in the limited time. Unmanned Aerial Vehicle and Internet of Things Integration has created new ways to gather information and interact. However, the optimization of the path of the UAV into Wireless Powered UAV-IoT Networks also faces a major challenge in deciding the computation offloading. Thus, this research paper seeks to investigate the dynamic path planning and computation offloading strategies that can be applied in such networks to enhance efficiency and effectiveness at the intersection of UAV communications and IoT technology.

Many recent studies have highlighted the importance of optimal trajectory tuning and offloading techniques for UAV-IoT network efficiency. Significantly, the research done in [1] was aimed at reducing the average AoI, with UAV trajectory, energy transfer time, and data collection time being optimized together. Also, [3] and [4] dealt with path planning for UAVs within the edge computing network environments focusing on the importance of trajectory optimization in order to enable successful computation offloading from IoT devices. In addition, [5] and [8] indicate that energy-efficient trajectory optimization and real-time path planning are essential for UAVs in saving energy while improving data collection efficiency. These studies were fundamental in understanding ways to effectively utilize renewable energy sources such that less energy is required by IoT in order to support UAVs.

Additionally, new reinforcement learning and optimisation techniques were presented in [6], [9] and [10] to deal with collision avoidance, energy optimization, and cooperative path planning for several UAVs. These strategies are vital for the creation of complex algorithms that will support effective UAV path planning and computing off loads in many challenging scenarios.

In line with these advancements, this research paper aims to present a comprehensive framework for dynamic path planning and computation offloading in Wireless Powered UAV-IoT Networks. By synthesizing and extending the findings from the aforementioned studies, we propose an integrated approach that optimizes UAV trajectories while facilitating effective computation offloading strategies. Leveraging the insights gleaned from the diverse perspectives presented in the literature, this research seeks to address the intricate challenges associated with dynamic path planning and computation offloading, thereby paving the way for enhanced performance and efficiency in UAV-IoT networks.

2. Related Works

In the existing literature, the problem of UAV's path planning was considered in the context of IoT Networks. Most of these works focused only on the aspect of planning the UAV path considering different features such as trajectory optimization, energy efficiency, minimizing flying time, age of information and coverage. However, these works did not consider the joint problem of computation offloading and path planning in the context of wirelessly powered IoT.

In [1] the researchers formulated an optimization problem with the objective of minimizing the average Age of Information (AoI) in a UAV-assisted wireless powered Internet-of-Things (IoT) system. This problem involves the joint optimization of the UAVs trajectory, energy transfer time, and data collection time.

Peng et al. [3], defined the problem of path planning in a UAV-assisted edge computing network for IoT applications. The core challenge was to find an efficient path for a UAV equipped with an edge server to offload and process computing tasks from multiple IoT devices. The researchers considered the mobility of IoT devices. Their main objectives were to maximize the amount of data bits offloaded by IoT devices and, simultaneously, minimize the energy consumption of the UAV. In [4] the researchers defined the problem of efficient trajectory planning for unmanned aerial vehicles (UAVs) in the context of collecting data from Internet of Things (IoT) devices in an urban environment. The core challenge was to optimize UAV flight paths while considering factors such as limited flying time and obstacle avoidance.

Zhang et al. [5] aimed to design a trajectory for the UAV that allowed it to operate efficiently, taking into account its power source, which includes both solar energy and charging stations (CSs). This approach ensures sustainable communication services while avoiding energy depletion. It also addresses the complex problem of energy-efficient trajectory optimization for UAVs in IoT networks.

A reinforcement learning approach was proposed by Hsu et al. [6] for UAVs in communication networks to learn collision avoidance strategies. This approach allows UAVs to make decisions on avoiding collisions with other UAVs without prior knowledge of their trajectories. It includes the proposal of a reinforcement learning approach, employing optimization techniques, solving the traveling salesman problem (to find a shortened route). In [7] the researchers addressed the challenge of optimizing trajectory planning for unmanned aerial vehicles (UAVs) in the context of communication networks. They focused on optimizing trajectory planning for UAVs in urban environments to collect data from IoT devices.

The researchers in [8] aimed to minimize two critical objectives: Completion Time: To minimize the time it takes for UAVs to complete their data collection tasks, and Total Energy Consumption:To minimize the overall energy consumption of UAVs during data collection. Whereas, in [9], the authors aimed at solving the energy optimization and coverage path planning challenges in UAV-enabled edge computing networks. They applied a Q-learning approach and demonstrated the algorithm's convergence and its effectiveness in reducing energy consumption compared to existing solutions. Q-learning is a reinforcement learning technique used to make sequential decisions in uncertain environments.

[10] addresses the problem of energy-efficient collaborative path planning for multiple UAVs to maximize data collection from distributed sensors while considering energy constraints and the total covered area. This approach is designed to address the collaborative path planning of UAVs, and aims to maximize data collection while avoiding collisions among UAVs. In [11], the researchers identified the need for an efficient UAV-assisted wireless powered communication system for an IoT network. They recognized the challenge of managing IoT devices with limited data storage and battery capacity while optimizing data collection and energy broadcasting. They proposed a solution based on a multi-objective optimization problem.

3. Proposed Scheme

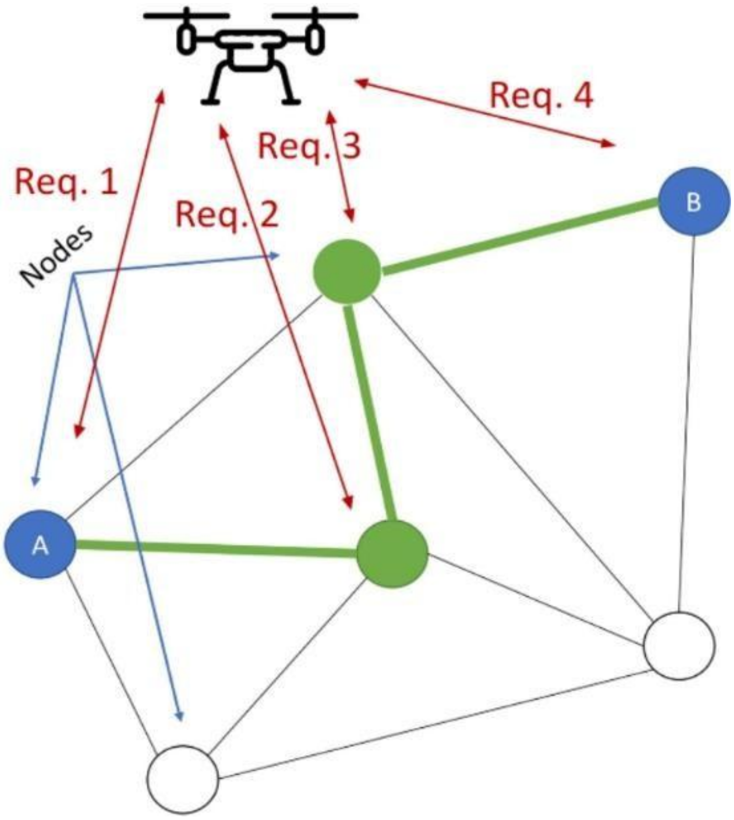

Figure 1 : System Model

In Figure 1 The IoT device i.e drone is connected to different nodes and getting requests from the nodes. It can be used to improve energy efficiency and extend battery life. UAVs and IoT devices often have limited battery life, which can limit their operational capabilities.

In the following, describing about the steps followed in this proposed method.

UAV.py
Step 1 - Initialization:
Initializing UAV properties such as name, start position, range limit, and batterypercentage.
Initialize path, sensors_assigned, battery_values, and distance_travelled_values lists.

Step 2 - Calculate Distance: Defining a method (calculate_distance) to compute the Euclidean distance betweentwo points.
Step 3 - Update Path:

Implementing a method (update_path) to update the UAVs path with a new path.
Step 4 - Find Optimal Path:

Defining a method (find_optimal_path) that calculates the optimal path for the UAV totraverse a set of assigned sensors.
Uses a greedy algorithm to select the nearest sensor at each step until all sensors arevisited.
Step 5 - Display Details:

Implementing a method (display_details) to print details about the UAV, including itsname, start position, range limit, battery percentage, and assigned path.
Step 6 - Navigate:

Implementing a method (navigate) for the UAV to traverse its assigned path. Iteratesthrough the assigned sensors, calculates distances, updates the total distance traveled,and simulates battery consumption. Checks if the battery level is below 10% and returns to the charging point if necessary.
Step 7 - Calculate Total Distance:

Defining a method (calculate_total_distance) to compute the total distance traveled bythe UAV along its assigned path.
Step 8 - Recharge Process:

Simulating a recharge process when the battery is low, by sleeping for 5 seconds and then setting the battery percentage to 100%.

main.py:

Used classes as follows:

Sensor and Event Classes:

The Sensor class represents a sensor with properties such as type, battery percentage,sensor range, location, and a unique ID.
The Event class represents an event with properties such as type, range, duration, timeinterval, start time, end time, location, and a unique ID.
Both classes have methods to generate location, display details, run the event (with asleep simulation for duration), and generate the next event.
UAV Class:
The UAV class represents an Unmanned Aerial Vehicle with properties like name, startposition, range limit, battery percentage, assigned sensors, and path. Methods include initializing the UAV, calculating distance, updating the path, finding the optimal path, displaying details, navigating (simulating movement and battery usage), and calculating the total distance travelled.
Simulation Setup:
Randomly generates sensor and event details based on configuration data from a JSONfile (config.json).
Creates a specified number of UAVs, assigns sensors to UAVs based on distance,calculates optimal paths for UAVs, and starts UAV navigation.
Tkinter GUI:
A Tkinter - based GUI with tabs for displaying Sensor, Event, and UAV details.The UAV Simulation App class manages the GUI components and tables for displaying information about sensors, events, and UAVs.

The GUI includes sub-tabs for each UAV, displaying assigned sensors, battery percentages, and total distance travelled.

Plots:

After the Tkinter GUI is displayed and the main loop is started (root.mainloop()), the, plot_battery_remaining, plot_events_vs_time, and plot_total_distance_travelled methods are called to generate plots using Matplotlib.

Simulation Details Printout:

After the GUI is closed, additional details about events and the simulation are printedto the console.

Json:

Config.json

```
{
   “num_sensors”:100,
   “num_events”: 100,
   “num_uavs”: 10
}
```

4. Experimental Study and Result Analysis

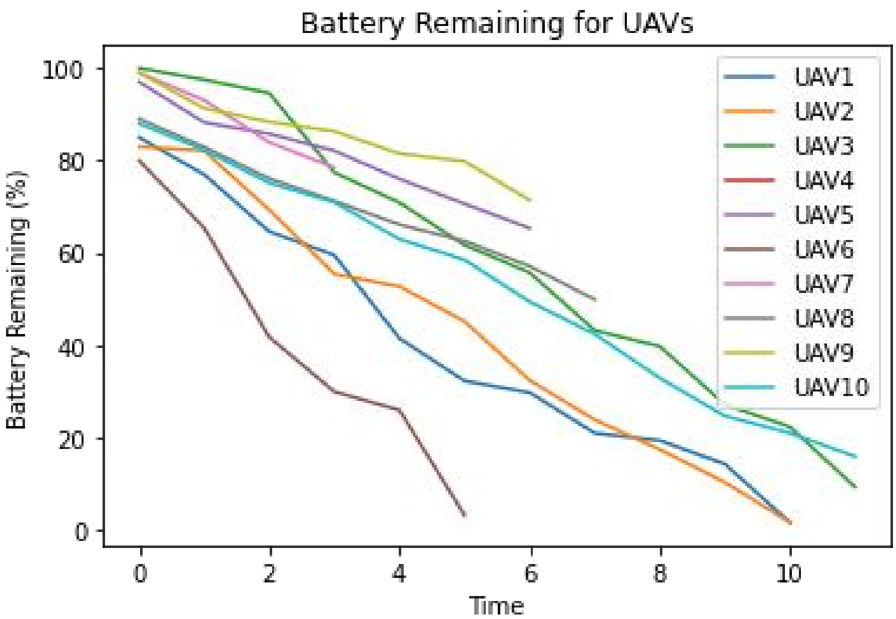

Figure 2 : Remaining Battery % Vs Time

In Figure 2. The graph shows the battery remaining for ten unmanned aerial vehicles (UAVs) over a period of ten hours. The x-axis represents time in hours, and the y-axis represents battery remaining in percentage. Each line represents the battery remaining for one UAV. The battery remaining for all UAVs decreases over time. This is to be expected, as UAVs use battery power to fly. The rate at which the battery remainingdecreases varies from UAV to UAV. Some UAVs have a higher capacity battery andcan fly for longer than others. The graph shows that there is a relationship between the battery remaining and thetime that the UAV has been flying. The longer a

UAV has been flying, the less batteryremaining it has. This relationship is linear, which means that the rate at which the battery remaining decreases is constant.

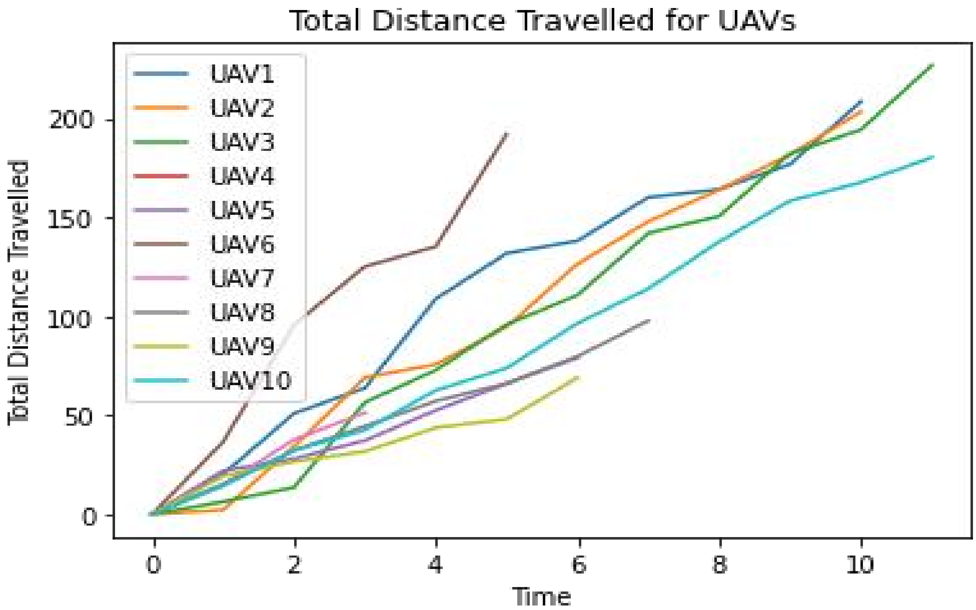

Figure 3: Total Distance Travelled Vs Time

In Figure 3. The graph shows the total distance travelled for ten unmanned aerial vehicles (UAVs) over a period of ten hours. The x-axis represents time in hours, andthe y-axis represents total distance travelled in miles. Each line represents the total distance travelled for one UAV. The total distance travelled for all UAVs increases over time. This is to be expected, as UAVs fly for longer distances. The graph shows that there is a relationship between the total distance travelled and the time that the UAV has been flying. The longer a UAV has been flying, the farther it has travelled. This relationshipis linear, which means that the rate at which the total distance travelled increases is constant.

5. Conclusion

New era of the data collection process, communication, and computation in different aspects has been brought by the introduction of UAVs and IoT. There is no doubt that UAVs play an important part in distributed processing and computing functions for IoT devices. With wireless power transfer, UAVs make IoT devices always functional, solving the problem of connecting cables and battery replacement periodically. This revolutionary technology is the backbone of continuous data collection, real-time performance monitoring, and communication with minimal interruptions, translating into better productivity, connectivity, and overall efficiency of numerous IoT applications across different industries such as agriculture, environmental monitoring, smart cities, healthcare, military operations

Since the employment of UAVs for purposes like monitoring, inspection, and delivery continues to increase, it is apparent that these airborne entities have to traverse intricate paths within tough and volatile environments. Hence, path planning plays a vital role when it comes to proper performance of UAVs' missions. Therefore, integrating UAVs as edge servers using embedded computing resources within IoT nodes will help process data closer to the source, minimize latency, and increase response time. Nevertheless, due to the dynamic character of IoT nodes as well as fluctuating energy level, the optimal path plan should be adaptable enough to adjust itself to the ever evolving IoT environment.

This study aims to contribute to the existing pool of knowledge about Wireless Powered UAV-IoT Networks and focuses on optimizing the path planning process as well as offloading the computation. For UAV data communication to operate with IoT, dynamic strategies are needed as they will evolve and provide data to support IoT equipment. This study seeks to consolidate and extend earlier findings to develop a framework for dynamic path planning and dynamic computation offloading on Wireless Powered UAV-IoT Network. Through this process, we have combined lessons learned from prior research to propose an integrated algorithm which optimizes UAV trajectory and makes calculation of offloading efficient.

In summary, this research paper aims to provide a holistic framework for dynamic path planning and computation offloading in Wireless Powered UAV-IoT Networks. By synthesizing and extending the findings from prior studies, we propose an integrated approach that optimizes UAV trajectories while enabling efficient computation offloading strategies. The insights derived from this multidisciplinary research pave the way for enhanced performance and efficiency in UAV-IoT networks, ultimately contributing to the seamless integration of UAVs and IoT technology in various applications. The research not only advances our understanding of UAV-IoT interactions but also provides a foundation for further innovations in this exciting and rapidly evolving field.

6. References

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