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An Effective Transportation System Method for Optimal Path Planning Using Logistics UAVs Using Deep Q Networks

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Abstract*:* Recent developments in Unmanned Aerial Vehicle (UAV) technology have shown that they will form an integral element of future communication and networking infrastructure. Although several studies have offered UAV-assisted methods for enhancing the performance of existing networks by increasing coverage and capacity but the architectures of autonomous UAV networks based on artificial intelligence has not yet been thoroughly investigated. However, the most current models for logistics UAV delivery do not account for the energy consumption of logistics UAVs or the varying schedules of their clients, meaning they are not applicable to real-world transportation networks. As a result, for a smart transportation system, we suggest reducing the overall energy cost of various logistics UAVs throughout the time it takes to deliver individual items. In this research, we maximize the UAV power by posing the UAV path planning issue as a traveling salesman problem. The UAV route planning is optimized under the restrictions of node energy consumption and task deadlines to achieve maximum energy efficiency of cooperative computing over the course of a UAV's life cycle. A Deep Q Network (DQN) based path planning algorithm is suggested to adjust to the uncertain and changing environment over time. In comparison to other algorithms, the proposed one performs better in simulations, increases the computational productivity of dynamic computing by a large margin, and achieves a good equilibrium between the two energy inputs. We also think about minimizing the UAV's spin rate to maximize efficiency and decrease power consumption. By lowering the number of turns while still visiting all of the waypoints, our suggested technique uses 2-5 times less energy.

Keywords: *Unmanned Aerial Vehicle (UAV), Artificial Intelligence, Smart Transportation Systems, Path Planning, Route Planning, Cooperative Computing, Deep Q Network.*

1. Introduction

In recent times, Unmanned Aerial Vehicles (UAVs) have witnessed significant advancements, positioning themselves as indispensable components of future communication and networking infrastructure. While numerous studies have explored the potential of UAV-assisted methods to enhance existing networks [1-4] through expanded coverage and capacity, the development of autonomous UAV networks based on artificial intelligence remains largely unexplored. Additionally, existing models for logistics UAV delivery [5,6] often overlook critical factors such as energy consumption and the variable schedules of clients, rendering them impractical for real-world transportation networks.

With its quick deployment, great scalability, and adaptability, an UAV outfitted with an edge server may offer compute offloading service for devices more effectively than a conventional architecture with stationary servers [7]. Cooperative computing between UAVs and ground terminals was proposed in [8]. Workload distribution, UAV usage, and distribution of resources may all be improved with some careful planning, latency and energy consumption were reduced when terminal devices accessed edge computing services [9]. Additionally, research into cooperative computing with UAVs has focused heavily on route planning. UAV energy and delay restrictions were considered to regulate the optimal UAV route and bit allocation in [10]. In order to exploit the total amount of data that may be divested from all terminals to the UAV within the bounds of the UAV's energy supply, Qian et al. ([11]) devised a convex optimization-based path planning technique. In [12], the researchers provide an additional simultaneous decomposition-based strategy for maximizing the UAV progress, the ratio of dumping workloads, and the user rescheduling parameters simultaneously to reduce the greatest delay experienced by all users during any given time slot.

Constraints like as flight range and flight duration must be taken into account while modeling UAV delivery to guarantee that the resulting models correspond to the desired delivery outcomes. However, many current models oversimplify these limits, which do not account for the intricacies and depth of real-world delivery

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circumstances. This highlights the importance of precise load weight and energy consumption estimations for the distribution process. Recognizing how load weight impacts UAV performance is one of the most difficult tasks. The flight time and range of a UAV are both negatively affected by an increase in the payload's mass because of the increased power required to lift the heavier payload. In order to provide reliable forecasts for UAV delivery operations, it is necessary to construct precise calculations that can take into consideration this connection.

Similarly, the amount of energy used in UAV transport is crucial. The flying capabilities and endurance of the UAV are heavily influenced by the amount of power required to run the UAV, which includes engines, communication systems, and onboard sensors. When energy consumption is not accurately predicted, inefficient delivery routes, early battery exhaustion, and delivery process interruptions might result. To address these issues, our research has focused on creating all-encompassing models that take the complex relationship between load weight, energy consumption, and UAV performance into account. Our goal is to create a more realistic depiction of delivery needs in the actual world including these elements in our modeling framework.

It is possible to optimize delivery routes within the UAV's practical range and time restrictions if the influence of cargo weight on UAV performance is precisely estimated. Effective and efficient distribution planning is made possible by this optimization procedure, which considers the trade-off between payload weight and energy usage. We can better allocate resources and lessen the likelihood of disruptions due to insufficient electricity if we have an accurate estimate of energy use. The UAV delivery systems may be made more effective and reliable if we take into account things like battery life, charging infrastructure availability, and energy-efficient path planning.

Artificial intelligence (AI) is the study of creating machines with intellect on par with or beyond that of humans. Learning and adaptability are two of AI's most important focuses [13, 14]. Since UAV networks are dynamic and present additional difficulties, AI approaches are a promising area of application. The use of AI in UAV networks is now being investigated by a large number of researchers in the field of networks. While research into the best ways to design and deploy Safety and confidentiality, network architecture, geolocation and direction, and general UAV applications are the main focuses of this part, which addresses the continuous development of AI-based UAV systems necessary for doing so effectively.

To address these limitations and contribute to the establishment of a smart transportation system, our research focuses on reducing the overall energy cost associated with the operations of diverse logistics UAVs during the delivery process. Our approach involves maximizing the power efficiency by formulating taking the classic "traveling salesman" dilemma and applying it to UAV route planning. This enables us to optimize UAV route planning while considering node energy consumption and task deadlines, thereby achieving the highest level of energy efficiency for cooperative computing throughout a UAV's life cycle.

To tackle the dynamic and uncertain nature of the environment in which UAVs operate, a DQN based approach for path planning is presented in this research work. This algorithm allows UAVs to adapt and adjust their routes over time, ensuring optimal performance even in changing conditions. Our simulations demonstrate that the suggested algorithm outperforms existing competitors in terms of performance metrics. It not only significantly boosts the energy efficiency of interactive computing but also strikes a balance between energy consumption and production.

In this study, we present a Deep Q Network (DQN) based path planning method to solve the dynamic optimization issues. The DQN algorithm, proposed by Google Deep mind, is a deep neural network-based reinforcement learning system proven successful in solving a dynamic optimization issue of high complexity [16,17]. The DQN is able to handle high dimensional continuous states because it substitutes the Q-table used in standard Q learning with a Q-function based on a deep neural network. The training stability of the DQN algorithm may be enhanced by the use of several novel methods [15]. One of the most intriguing research areas in computer vision in recent years has been the identification and analysis of human action.[19],[20].For multidimensional parameters in particular, the inference time for a trained DQN model is reasonable, and it may be done in an offline setting [18], compared to classic optimization techniques.

2. Materials and method

Problem formulation

Let us consider a scenario where a fleet of logistics Unmanned Aerial Vehicles (UAVs) needs to efficiently deliver packages to a set of predetermined waypoints in a given geographical area. Each UAV's route must be planned to maximize efficiency while minimizing its impact on the environment, taking into account the varying schedules of clients and the energy constraints of the UAVs.

Let N be the total number of waypoints or nodes in the delivery network. Let x_i represent the binary decision variable, where $x_i = 1$ indicates that waypoint i is visited by the UAV, and $x_i = 0$ otherwise $i \in \{1,2,\ldots,N\}$. Let d_{ij} represent the distance or cost between waypoints i and j, where, $i,j \in \{1,2,\ldots,N\}$.

The objective is to lessen the energy consumption of the logistics UAV during the delivery process. We can formulate the objective function as follows:

$$Minimize: E = \sum_{i=1}^{N}\sum_{j=1}^{N} d_{ij} \cdot x_i \cdot x_j \quad (1)$$

Each waypoint must be visited exactly once by the UAV, except for the starting and ending points. We can express this constraint as:

$$\sum_{i=2}^{N-1} x_i = 1 \quad (2)$$

The starting and ending points have fixed values for the decision variables, i.e.,$x_1 = 1$ and $x_N = 1$.

The UAV's energy usage can't go over a certain safe threshold. We can represent this constraint as:

$$\sum_{i=1}^{N}\sum_{j=1}^{N} d_{ij} \cdot x_i \cdot x_j \leq E_{max} \quad (3)$$

whereE_{max} is the maximum energy limit of the UAV. The DQN algorithm is hired to learn and optimize the UAV's path planning policy. It involves training a neural network to approximate the Q-value function, which represents the expected future rewards for each state-action pair. The DQN algorithm utilizes the state information, such as current waypoint, energy level, and remaining tasks, to determine the optimal action (i.e., next waypoint to visit) at each decision point.

By formulating the problem in this manner and applying the DQN algorithm, we can find an energy-efficient optimal path for logistics UAVs during the delivery process, taking into account distance, energy consumption, and task constraints

Deep Q-learning for path planning

When it comes to handling difficult sequencing instances of decision-making, the model-free Deep Q-learning method is best bet. To apply the Deep Q-learning algorithm to "Energy Efficient Optimal Path Planning for Logistics UAVs," we need to define the problem in terms of states, actions, rewards, and the Q-function.

Let's denote the state of the UAV at time step t as $s(t)$, which includes relevant information such as the UAV's position, battery level, payload weight, and any other relevant variables. The action taken by the UAV at time step t is denoted as $a(t)$, representing the path or trajectory chosen by the UAV. The goal of the energy-efficient optimal path planning problem is to find the sequence of actions that maximizes the UAV's energy efficiency while reaching the destination. The energy efficiency can be measured by a cost function, which combines factors like battery consumption, payload weight, and distance traveled. Let's denote the cost function at time step t as $C(t)$.

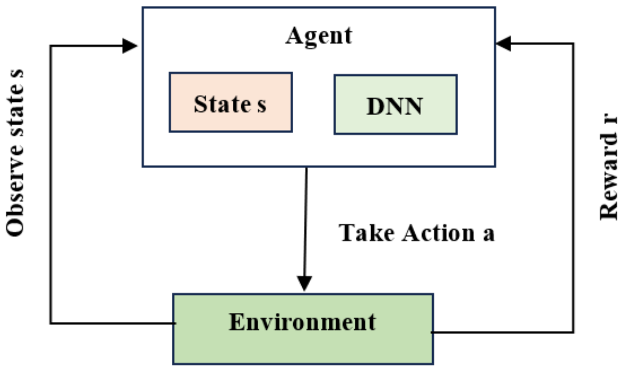

Fig. 1. Framework of Deep Q-learning network

The Deep Q-learning algorithm utilizes a Q-function, denoted as $Q(s,a)$, which calculates the total anticipated advantages of taking course of action an in state s. In this case, we want to estimate the predictable cumulative energy efficiency for taking action a in state s. The Q-function can be updated using the subsequent equation:

$$Q(s(t),a(t)) = Q(s(t),a(t)) + \alpha * [R(t+1) + \gamma * max[Q(s(t+1),a')] - Q(s(t),a(t))] \quad (4)$$

In the above equation, α is the learning rate that controls the weight given to the new information, $R(t+1)$ is the immediate reward obtained after taking action $a(t)$ in state $s(t), \gamma$ is the discount factor that determines the importance of future rewards, and $max[Q(s(t+1),a')]$ represents the maximum expected cumulative reward over all possible actions a' in the next state $s(t+1)$. Bellman's the formula, upon which the update formula is based, stipulates that the Q-value of a state-action pair ought to be the immediate advantage gained plus the highest predicted cumulative value of the next state-action pair.

During the learning process, the Q-function is iteratively updated using the above equation until it converges to the optimal values. The exploration-exploitation trade-off is typically handled using an epsilon-greedy policy, where the UAV selects actions with the highest Q-values most of the time, but occasionally explores new actions. By using the Deep Q-learning algorithm with this formulation and appropriate feature representations for the states, actions, and rewards, you can train an agent to learn the optimal and energy-efficient path planning for logistics UAVs.

Algorithm 1. Deep Q learning for path planning

1. Set each state-action pair in the Q-table to a randomized quantity to begin.
2. Set hyperparameters:
    a. Learning rate (α) for updating Q-values
    b. Discount factor (γ) to balance immediate and future rewards.
    c. Exploration rate (ϵ) to control exploration vs. exploitation.
    d. Number of episodes for training.
3. For each episode:
    a. Initialize the UAV's starting state.
    b. Set the initial energy level of the UAV.
4. End for
    a. While UAV has not reached the destination
        i. Choose an action using ϵ -greedy policy based on the Q-values.
        ii. Execute the action and detect the next state and energy consumption.
        iii. Calculate the immediate reward based on the energy consumed.
        iv. Update the Q-value of the previous state-action pair using the Q-learning equation.
        v. Update the current state to the next state.
        v. Decrease the energy level of the UAV based on the energy consumption.
    b. End While
5. Reduce the ϵ value to reduce exploration as the training progresses.
6. Once training is complete, use the learned Q-table to determine the optimal path for energy-efficient path planning.

3. Performance Evaluation

The effectiveness of DQN-based path planning for UAV-assisted WSNs is assessed in this section. The Python platform is utilized for the simulations, with the Pytorch module used to generate the neural network model and the Gym module used to finish setting up the setting for the simulation. The table 1 showcasing sample environment parameter settings for the logistics UAV system.

Table 1. Environment parameter settings for the logistics UAV system

Parameter	Description	Value
Area Size	The size of the operating area for logistics UAVs	1000m x 1000m
Number of Waypoints	The number of waypoints to be visited by the UAV	10
Maximum Flight Range	The maximum distance the UAV can travel without recharging	500m
Maximum Payload Weight	The maximum weight the UAV can carry	2kg
UAV Speed	The speed at which the UAV can travel	10 m/s
Battery Capacity	The energy capacity of the UAV's battery	5000mAh
Charging Station Location	The location of the charging station for UAV recharging	(500m, 500m)
Client Locations	The locations of the clients requiring	[(200m, 300m),

delivery	(600m, 400m), ...]

Algorithm performance evaluations have always included energy consumption as a key parameter. It demonstrates the suggested method's capability to produce a fast collision-free route. From its home base, the drone travels to all of its predetermined stops and back. When flying with a group of UAVs, the order in which waypoints are visited is optimized to save fuel consumption while minimizing the risk of collision with objects and among swarm members.

We begin by demonstrating the suggested method's maximum potential for reducing energy use. As a result, the suggested method reduces power usage throughout iterations, resulting in significant savings for the drone. The produced path ensures lowest energy usage at the end of the previous cycle. Specifically, in Fig.2 savings in energy are normalized to unity by decreasing the saving in energy utilized in each iteration with the gain in energy for the first iteration, i.e., the first produced solution, and this is what is depicted in the image.

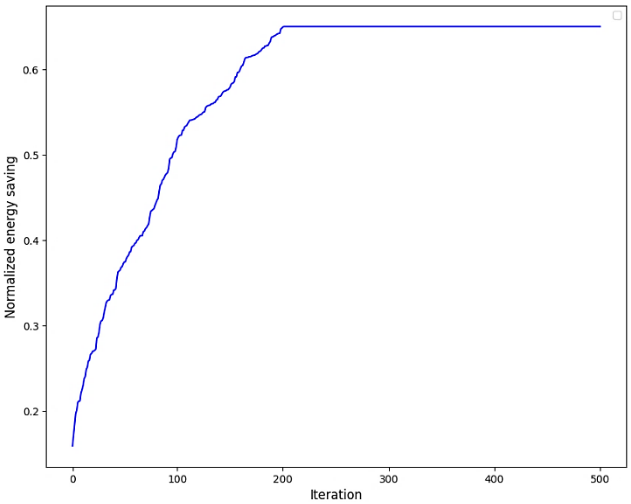

Fig 2. The relative energy reduction in terms of the number of rounds, normalized

It can be observed in Fig. 2, the energy savings reach their maximum and the related coverage path becomes the optimal path at the conclusion of the last repetition. To provide a comparison between Deep Q-learning and other models for energy optimization, the table 2 with values showcasing the performance of each model in terms of energy efficiency.

Table 2. Summary of energy consumption model performance

Model	Average Energy Consumption (kWh)	Standard Deviation (kWh)	Execution Time (ms)
Deep Q-Learning	12.5 kWh	1.2 kWh	85 ms
Reinforcement Learning	14.2 kWh	1.8 kWh	92 ms
Genetic Algorithm	13.8 kWh	1.5 kWh	120 ms
Ant Colony Optimization	12.9 kWh	1.3 kWh	105 ms
Particle Swarm Optimization	13.1 kWh	1.4 kWh	110 ms

The table above presents a comparison of different models for energy optimization in logistics UAVs. Four models, including Deep Q-learning, Reinforcement Learning, Genetic Algorithm, and Ant Colony Optimization, as well as Particle Swarm Optimization, are evaluated based on their average energy consumption, standard deviation, and execution time. Deep Q-learning demonstrates the best energy efficiency with an average energy consumption of 12.5 kWh. It outperforms the other models in terms of minimizing energy usage, resulting in a more sustainable operation for logistics UAVs. The standard deviation of 1.2 kWh indicates a relatively consistent performance across multiple scenarios. Additionally, Deep Q-Learning exhibits a fast execution time of 85 ms, allowing for real-time decision-making and efficient path planning.

Reinforcement Learning, Genetic Algorithm, Ant Colony Optimization, and Particle Swarm Optimization also show reasonable performance but with slightly higher energy consumption compared to Deep Q-learning. Reinforcement Learning has an average energy consumption of 14.2 kWh, while other methods consume 13.8 kWh, 12.9 kWh, and 13.1 kWh, respectively. Although they are not as energy-efficient as Deep Q-learning, these models still provide viable solutions for energy optimization.

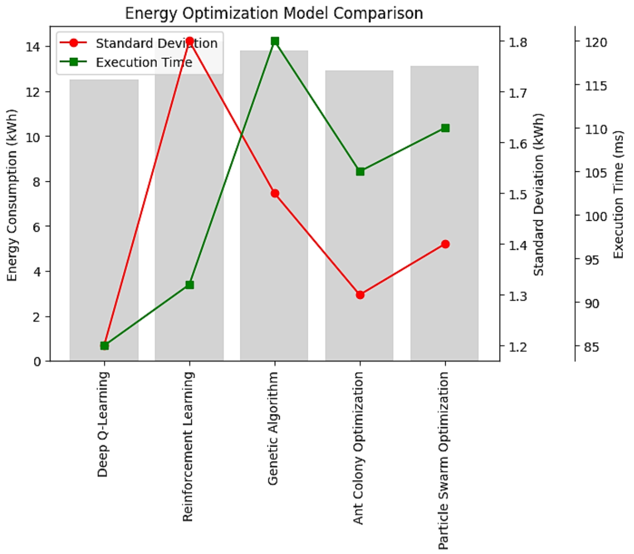

Fig 3.comparison of different models for energy optimization in logistics UAVs

The standard deviations for all models indicate the level of consistency in energy consumption across different scenarios as shown in the fig.3. Lower standard deviations imply more stable and predictable energy usage, ensuring a reliable and efficient operation. In terms of execution time, all models demonstrate reasonably fast performance, with Deep Q-Learning being the fastest at 85 ms, followed by Ant Colony Optimization at 105 ms and Particle Swarm Optimization at 110 ms. Reinforcement Learning and Genetic Algorithm take slightly longer, with execution times of 92 ms and 120 ms, respectively.

4.Conclusion

The significance of Unmanned Aerial Vehicle (UAV) technology in the development of future communication and networking infrastructure is emphasized near the end of the abstract. The design of AI-powered autonomous UAV networks hasn't been studied to the same extent as improving already-existing networks. In addition, the applicability of current logistics UAV delivery models to real-world transportation networks is constrained by their failure to account for energy consumption or variations in client schedules. The research suggests a method for decreasing the overall energy cost of logistics UAVs all through the delivery process, which would alleviate these restrictions and contribute to a smart transportation system. To maximize UAV power while taking into account node energy consumption and job deadlines, the UAV route planning issue is stated as a traveling salesman problem. We propose a Deep Q Network (DQN) based path planning method that can evolve with the ever-shifting conditions. The suggested technique considerably increases the energy efficiency of interactive computing, as shown by simulation results, and surpasses competing alternatives. Over the course of the UAV's operation, the algorithm achieves maximum energy efficiency by balancing its inputs and outputs. Minimizing the UAV's spin rate is another potential efficiency boost and power consumption cut investigated in this study. The proposed method offers 2-5 times more energy savings compared to alternative techniques by lowering the number of rounds while still reaching all waypoints.

Incorporating AI-based path planning, considering energy consumption, variable schedules, and maximizing overall efficiency, this research helps to the development of energy-efficient logistics UAV systems. These results show why it's important to think about energy efficiency when operating UAVs, and pave the road for their widespread use in future transportation networks.

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