Dynamic Energy and Cost-Efficient Multi-UAV Routing Problem Using Enhanced Genetic Algorithm

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Abstract

In this study we propose a novel method for capacitating multi-UAV multi- visit routing problem. Our main focus is on achieving energy and cost effectiveness by using an enhanced genetic algorithm. We delve into the adjustment of UAV speeds based on payloads and study how it impacts energy consumption and operational expenses. Our comprehensive model takes into account the relationships between payload mass, UAV velocity and power usage providing a roadmap for modern UAV delivery networks. Through testing we have demonstrated that our approach can handle the challenges posed by real world delivery scenarios showcasing its adaptability in managing various payload sizes and navigating complex routes. Our research not only confirms that our algorithm is flexible and capable of optimizing UAV delivery operations but also fills a research gap by incorporating speed variability and payload differences in the optimization process. The findings show that UAV-1 achieved optimal delivery efficiency with an initial high speed of 35.555 m/s and strategic speed adjustments based on payload weight, leading to significant energy savings. These enhancements underscore the real-world usefulness and reliability of our suggested technique. Our method provides a scalable solution for enhancing UAV operations, making it well suited for a range of uses.

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1. INTRODUCTION

The logistics and delivery industry has a transformation with the advent of UAV technology. UAVs provide alternative to ground transportation methods by navigating through terrains without being limited by road infrastructure. This presents an opportunity to expedite deliveries to improve efficiency and reduce impact. However, there are challenges associated with using UAVs for delivery purposes.

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These challenges include optimizing payload capacities for energy efficiency addressing safety concerns and developing routing algorithms that can adapt to real time variables. To fully harness the potential of UAV based delivery systems conducting research is crucial. The growing interest in drones for logistics and delivery systems from the demand for more effective delivery options in urban areas where traffic congestion and restricted access can impede traditional delivery methods. Drones offer a way to bypass these challenges by utilizing airspace resulting in more deliveries. Furthermore, the capability of drones to reach challenging locations makes them invaluable for deliveries like medical supplies in disaster affected regions. Despite these benefits there are operational obstacles that must be addressed to establish drone delivery systems on a broad scale.

Key challenges include ensuring the safety and dependability of drone operations in populated areas. Drones need to be equipped with navigation and collision avoidance systems to prevent accidents. Additionally, the regulatory landscape for drones is still evolving, with countries imposing rules on drone flights, particularly those conducted beyond visual line of sight (BVLOS). These regulations must be carefully taken into account when developing drone delivery systems. Another significant challenge is the battery life of drones, which limits their range and payload capacity. Research into energy management and battery technologies is crucial to expand operational reach and improve overall efficiency of drone delivery systems.

In our study we have made contributions to addressing these challenges outlined in existing literature. Here are the key aspects:

- We have developed an algorithm specifically designed to solve the capacitated multi-UAV multi visit routing problem. This approach allows us to optimize both routing efficiency and energy consumption in UAV delivery systems.
- Unlike current studies, we have thoroughly investigated how adjusting UAV speeds based on varying payloads can affect energy efficiency and operational costs. This factor, which has been largely overlooked in the literature far is carefully considered in our research as we are taking an approach, towards modeling delivery systems.
- We have tackled the problem of linear energy consumption associated with the dynamics of UAV payload and speed by introducing a model that accurately represents their complex relationship. This model does not enhance the realism of our simulations, Also enables us to optimize UAV operations in various conditions more effectively.
- To validate our proposed algorithm, we conducted computational experiments that closely resemble real world delivery challenges. These experiments showcase algorithms adaptability, payloads, route complexities and operational requirements showing its potential to enhance the efficiency of UAV based delivery services.

Through these contributions our research fills gaps in existing literature by creating a framework for optimizing UAV delivery systems. This framework ensures adjustment to needs while simultaneously minimizing energy usage and costs. The sections of the paper are structured as follows; In Section II a thorough review of existing literature is presented to establish an understanding of the status of UAV assisted delivery systems. Section III introduces the problem formulation, including decision variables, constraints and our chosen approach. It also provides an explanation of the function and calculations, for various aspects such as segment capacity and energy constraints. In Section IV we delve into the methodology by elaborating on the steps involved in the Genetic Algorithm (GA) process. We also discussed how we integrated K Means Clustering and the 2 Opt Algorithm within the GA framework to adapt it specifically for UAV delivery purposes. Moving on to Section V we present results that encompass simulation setup details along with an analysis and discussion of these results. Lastly in Section VI we conclude this paper by summarizing our contributions highlighting real world applications and benefits suggesting areas for research and proposing improvements.

2. LITERATURE REVIEW

Dorling and colleagues (Dorling et al., 2017) used the realm of UAV delivery by focusing on vehicle routing problems. They provide insights into the derivation of an energy consumption model for multirotor UAVs highlighting the correlation between energy usage, payload capacity and battery weight. (Otto et al., 2018) conduct a literature survey on optimization approaches for aerial vehicles (UAVs) in civil applications. Their research offers an overview of optimization strategies specifically tailored to UAVs and their applications in remote sensing. There have been studies focusing on UAV routing taking into consideration factors like linear energy consumption (Bruni et al., 2023), wind effects for energy saving in a truck UAV delivery system (Sorbelli et al., 2023) and power consumption rate and wind effects in the vehicle routing problem involving UAVs (Kim & Kim, 2022). These studies have made contributions to developing operational models and mathematical optimization techniques, for achieving energy efficient UAV routing. The field of UAV routing has seen advancements in algorithmic approaches. For instance (Zudio et al., 2021) developed a key genetic algorithm to tackle the hybrid vehicle UAV routing problem, for pickup and delivery. (G. Wu et al., 2022) proposed a coordinated vehicle UAV arc routing approach that leverages improved neighborhood search techniques. These studies have primarily focused on devising optimization techniques and heuristic algorithms to address complex UAV routing problems.

(Khan et al., 2022) presented a Dynamic UAV approach tailored for disaster scenarios offering energy efficiency through event/weather prediction and efficient path planning strategies. (Melo et al., 2021) tackled the challenge of achieving optimality in UAV path planning by emphasizing factors such as time, cost and energy efficiency. (J. Li et al., 2022) highlighted the nature of dynamic path planning and its potential to enhance UAV flight efficiency.

Recent research has focused on optimizing drone scheduling through multi-objective mixed integer programming models. A study by (Nikolić et al., 2023) proposed a mixed integer linear programming formulation aimed at minimizing total delays in servicing tasks and the total flying time of all drones, taking into account task duration and significance. The study's results, obtained using CPLEX to solve the generated MILPs, indicate that task assignments on a fleet of drones depend significantly on drone speed and the number of drones analyzed. (Meng et al., 2023) propose a novel two-stage heuristic algorithm in which a maximum payload method is developed to construct the initial solutions, followed by an improved simulated annealing algorithm with problem-specific neighborhood operators and tailored acceleration strategies. According to (C. Huang et al., 2018) the importance of dynamic path planning, for UAVs, in accomplishing missions was highlighted. Similarly, (Pachayappan & Sudhakar, 2021) proposed a solution to address UAV routing challenges by implementing docking stations for pickup and delivery services. Specifically, their approach aims to optimize both energy efficiency and cost effectiveness. Consequently, these studies collectively provide insights into the development of approaches, optimization algorithms and energy aware routing strategies for UAVs in dynamic path planning scenarios. The capacitated UAV routing problem (CDRP) entails assigning UAVs with carrying capacity to cater to a group of customers while minimizing operational costs. For instance, (Q. Wu et al., 2018) proposed a UAV wireless communication system, where multiple UAVs are utilized to serve users on the ground within a specified 2D region. Their study underscores the collaborative nature of systems. (Sacramento et al., 2019) proposed a neighborhood search metaheuristic specifically designed for solving the vehicle routing problem with UAVs. Notably, they emphasized the significance of route planning and resource allocation in optimizing delivery operations.

Efficiently managing energy and costs while routing is crucial, for optimizing the efficiency of multi-UAV systems. According to (Dorling et al., 2017), developing vehicle routing problems (VRPs) for UAV delivery scenarios is significant, therefore highlighting the importance of path planning for UAV operations. In the context of UAV systems, the multi visit routing problem plays a critical role especially when considering the vehicle routing problem with UAVs (Nuryanti, 2023). Nuryanti also emphasizes the importance of optimizing multi visit path planning by using the Tabu search algorithm and Analytical Hierarchy Process. These approaches address challenges through mapping and mathematical optimization techniques. Furthermore (Poikonen & Campbell, 2020) highlighted those new contributions, in UAV research should focus on models of UAV types and new UAV applications. (Claro et al., 2023) emphasized the significance of factoring in characteristics of UAVs such as weight when planning energy paths highlighting the necessity for dynamic adjustments to accommodate variations in payload weight. In a publication by (Y. Huang et al., 2022), it was highlighted that existing coverage path planning algorithms often make assumptions about constant UAV speed. The authors stressed the significance of incorporating dynamic speed adjustments to account for factors such as turns, including deceleration, turning and acceleration. (Y. Li et al., 2022) proposed an extension to the Q learning mechanism to address exploration exploitation dilemma by introducing an exploration factor. It is possible to extend this approach to facilitate dynamic path adjustments based on variations in payload.

3. PROBLEM FORMULATION

In this section, we explained our model that will optimize the process from the central warehouse to the delivery points by UAVs to predetermined delivery points, under capacity, energy and time constraints. The main purpose of our study is to optimize the total flight time, energy consumption and total subtour distance of each segment separately while delivering UAVs to multiple points. In this context, it is aimed to make the overall delivery task operationally sustainable by minimizing resources such as energy efficiency and total cost minimization.

Table 1. Notations

Symbol	Description
N	Number of delivery points including the depot
D	Number of drones in the system
M_p	Maximum payload capacity of a drone (kg)
W_b	Base weight of a drone (kg)
ρ	Air density (kg/m^3)
C_d	Drag coefficient
A	Wing area of drones (m^2)
g	Gravitational acceleration (m/s^2)
h	Height for takeoff and landing (m)
P	Size of the population in the genetic algorithm
G	Maximum number of generations in the genetic algorithm
μ	Mutation rate in the genetic algorithm
T	Tournament size in the genetic algorithm
ϵ	Acceleration coefficient during takeoff
$V_{b_{min}}$	Base minimum speed for drone movement (m/s)
$V_{b_{max}}$	Base maximum speed for drone movement (m/s)
I	Set of drone indices
C	Set of clusters for delivery points
R	Set of routes for each drone
S	Set of segments in a drone's route

3.1. Decision Variables

The decision variables we used in the formulation of our model are explained below:

- Route Assignment $R_{\{d,p\}}$: It is a binary variable indicating whether the delivery point p is on the UAV d subtour route $R_{\{d,p\}} = 1$, it will take the value 1 if the UAV d is assigned to the delivery point p, and 0 otherwise $R_{\{d,p\}} = 0$.
- Load Distribution $L_{\{d,p\}}$: It is a type of continuous variable that represents the weight of the payload carried by the UAV d to the delivery point p.
- Energy Consumption $_{s\}}$: It is a continuous type of variable that calculates energy consumed by the UAV d during the flight segment s. It takes into account the total payload, speed and total segment flight distance of the UAV in that flight segment s.
- Flight Speed $V_{\{d,s\}}$: It is a continuous type of variable that represents the flight speed of the UAV d in the flight segment s. It aims at energy efficiency by dynamically determining the speed of the UAV according to its weight at the beginning of the flight segment s.

The decision variables described above are elements of the optimization process that forms the basis of our research. Through these variables, the assignment of delivery points to UAVs, payload distribution according to UAV capacity, and dynamic adjustment of UAV speeds within the subtour allow energy efficiency to be achieved. By ensuring optimal adjustment of these variables, operationally efficient and effective resource use of the UAV overall mission will be ensured. In this way, it will offer sustainable and applicable solutions in all application areas where last-mile delivery is made.

This research sets itself apart from studies by incorporating dynamic speed adjustments based on payload weight, which is a relatively unexplored aspect within UAV routing problems. While past research has mainly focused on fixed speeds and linear models for energy consumption our method presents a comprehensive model that considers the complex relationship between UAV speed, payload mass and energy usage. This improvement does not enhance efficiency but also ensures that the proposed solution can adapt to real world delivery scenarios where payloads and routes may vary significantly. Through experiments that replicate real world conditions we validate our model and showcase its practical applicability and reliability, in optimizing UAV operations for a range of logistical tasks.

3.2. Methodological Approach

To achieve these goals, we have implemented an Enhanced Genetic Algorithm (EGA) combined with K Means clustering for grouping of delivery points providing a dual optimization strategy.
Initial Clustering: We utilize K Means clustering to group delivery points based on their proximity. This step forms the foundation for assigning routes to UAVs aiming to minimize the initial distances covered. Genetic Algorithm Optimization: The EGA explores potential routing solutions, where each solution represents a set of delivery routes covering all designated points. The effectiveness or "fitness" of each solution is evaluated using our function prioritizing solutions that minimize overall delivery costs. The solutions in the Genetic Algorithm (GA) go through a series of refining steps, including selection, crossover and mutation processes. These steps help the GA converge towards a set of delivery routes that're either optimal or very close to optimal. Moreover, we also take into account adjustments in speed and payload to enhance energy efficiency. We consider the dynamic relationship between UAV speed, payload weight and energy consumption to ensure optimization.

This framework represents the challenges faced by real world UAV delivery systems taking into account practical limitations such as energy capacity and payload restrictions. Our customized approach aims to provide a efficient and scalable solution for autonomous UAV-based delivery systems. We emphasize the importance of adaptability to operational scenarios and environmental conditions.

3.3. Objective Function

The goal of our UAV delivery system is to minimize the total flight duration for all UAVs involved in the mission. Considering the variability in UAV speeds and the significance of energy consumption we formulate the function as follows.

$$min_z = \sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{N} t_{ijk} \cdot x_{ijk} \tag{1}$$

Where:

- Z represents the total flight duration that we aim to minimize.
- K denotes the number of UAVs being used.
- N corresponds to the number of delivery points, includ- ing the depot.
- t_{ijk} indicates the time taken for UAV k to travel directly from point i to point j, considering variable speeds.
- x_{ijk} is a binary variable that equals 1 if UAV k travels directly from point i to point j, and 0 otherwise.

3.4. Constraints

Our model addresses several key operational constraints to ensure realistic and viable delivery route optimization:

Payload Capacity: Each UAV is designed with a maximum payload capacity to ensure that it doesn't carry more than its safe and optimal load. This helps maintain safety standards and compliance with regulations.

Energy Consumption: It is crucial to optimize the battery life of UAVs. Our model takes into account factors such as payload, flight speed and travel distance to minimize energy consumption. This does not extend the operational range of the UAVs but also enhances overall efficiency.

Delivery Point Servicing: Ensuring that each package reaches its designated delivery point is of importance. Our model guarantees coverage of all delivery points leaving no destination overlooked or unattended.

1.1.1. Capacity Constraint

The capacity constraint plays a role in the UAV delivery system ensuring that each UAV is not overloaded beyond its maximum payload capacity. This constraint is vital for the feasibility and safety of the UAV routes.

Mathematically we can express the capacity constraint for each UAV as follows;

$$\sum_{p \in \mathrm{route}_d} \mathrm{weight}(p) \leq \mathrm{max\_payload}, \quad \forall \in D \tag{2}$$

Where,

- $\sum_{p \in \mathrm{route}_d} \mathrm{weight}(p)$, calculates the weight of all packages in the route of UAV d.
- max $\_payload$, represents the weight that a UAV can carry.
- $\forall d \ \in D$, indicates that this constraint applies to every UAV in the set *D*.

1.1.2. Energy Constraint

When it comes to our UAV delivery system, one of the factors we consider is how to effectively manage our energy resources. We have implemented a mechanism known as the energy constraint to ensure that our UAVs can complete their delivery tasks successfully without draining their batteries.

The energy constraint plays a role in determining which delivery tasks are assigned to each UAV and helps with planning the route. We only assign a task to a UAV if it meets the energy constraint criteria. If a specific subtask requires than 80% of the UAV's battery capacity, we consider the UAV unsuitable for that particular task. In cases our system. Selects another UAV with enough battery capacity or adjusts the route to reduce energy demands. This approach guarantees that our UAVs won't run out of power midway through their routes ensuring both efficiency and safety.

The following notations used for formulation:

- $E_{\text{segment}}(m, h, d)$: Represents the energy consumption of a segment, which depends on the UAV's mass m, height h, and distance d.
- E_{total}: Denotes the energy consumption for subtour of the UAV's route.
- B_{current}: Refers to the battery capacity of the UAV.
- route: represents the collection of segments, in the UAV's path.

To calculate the energy for a part of the route we add up all individual segment energies:

$$E_{\text{total}} = \sum_{s \in \text{route}} E_{\text{segment}}(s) \tag{3}$$

The energy constraint is then expressed as follows:

$$E_{\text{total}} \leq 0.8 \times B_{\text{current}} \tag{4}$$

1.1.3. Routing Constraints

The routing constraints guarantee that every delivery point is visited once by a UAV and that each UAV's route begins and ends at the depot.

Constraint for Visiting Delivery Points This constraint ensures that each delivery point is visited by one UAV. It can be expressed as follows;

$$\sum_{k=1}^{K} \sum_{\substack{i=1 \\ i \neq j}}^{N} x_{ijk} = 1, \forall j = 1,2, \dots, N \tag{5}$$

According to this equation for every delivery point j there should be one route from a different point
i taken by any UAV k.

Constraint for Depot Start- End This constraint ensures that each UAV's route starts and ends at the depot. It can be formulated as two equations;

$$\sum_{i=1}^{N} x_{0ik} = 1, \forall k = 1,2, \dots, K \tag{6}$$

$$\sum_{j=1}^{N} x_{0jk} = 1, \forall k = 1,2, \dots, K \tag{7}$$

These equations ensure that for each UAV k there is one route starting from the depot (represented as point '0') to a delivery point j and one route returning from a delivery point i

back, to the depot.

1.2. Time Calculation for Each Segment

We calculate each segments time t_{ijk} based on factors such as distance, between points and variable speed of the UAV. Calculation is presented in the way;

$$t_{ijk} = \frac{d_{ij}}{v_{ijk}} \tag{8}$$

Where:

- d_{ij} denotes the Euclidean distance between points i and j.
- v_{ijk} represent the speed of UAV k when traveling from point i to point j.

1.2.1. Calculation of Distance

The distance denoted as d_{ij} between two points (x_1, y_1) and (x_2, y_2) can be determined by using the following formula:

$$d_{ij} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{9}$$

where (x_1, y_1) and (x_2, y_2) are the coordinates of points i and j, respectively.

1.2.2. Calculation of Speed

The optimal speed v_{ijk} of UAV k for the segment from point i to point j is calculated considering various factors such as the total mass of the UAV including its payload, aerodynamic characteristics, and environmental conditions. Formula used is:

$$v_{ijk} = V_{opt}(m_k + \text{payload}(i,j), A, C_d, \rho) \tag{10}$$

where V_{opt} represents a function that calculates the optimal speed for minimizing energy consumption while maintaining aerodynamic efficiency. In this context:

- m_k is the base weight of the UAV.
- payload (i, j) is the weight of the payload being carried from point i to point j.
- A is the cross-sectional area exposed to airflow.
- C_d is the drag coefficient, which quantifies the UAV's resistance to motion through air.
- ρ is the air density, which affects the aerodynamic forces experienced by the UAV.

The function V_{opt} is derived from standard principles of aerodynamics, balancing the need for speed with energy efficiency to optimize the UAV's performance across varying payloads and environmental conditions. This relationship is fundamental in UAV operations, particularly when efficient route completion is critical under dynamic conditions.

1.3. Calculating Optimal Speed

Finding the speed for a UAV is essential to ensure flight, where energy consumption and aerodynamic efficiency are balanced. In this section we will outline the approach used to determine the speed of a UAV taking into account factors such as its weight, aerodynamic properties and environmental conditions.

Algorithm 1 Calculate Optimal Speed

```
Input: Drone mass m, wing area A, drag coefficient C_d, air density ρ, base minimum speed, base maximum speed
Output: Optimal speed for the drone
procedure CalculateOptimalSpeed(m, A, C_d, ρ, base_min_speed = 40, base_max_speed = 60)
    Calculate weight_factor based on m
    min_speed ← base_min_speed · weight_factor
    max_speed ← base_max_speed · weight_factor
    Initialize optimal_speed calculation process
    for each speed in a range from min_speed to max_speed do
        Compute power_required for speed
    end for
    optimal_speed ← speed minimizing power_required
    return optimal_speed
end procedure
```

Figure 1. Optimal speed algorithm

Weight factor: To start off we calculate the weight factor W_f by considering the base weight of the UAV W_b. Its maximum payload M_p. This weight factor helps adjust the speed range based on the weight of the UAV.

$$W_f = \frac{m}{W_b + M_p} \tag{11}$$

Determining Minimum and Maximum Speeds: we determine both theV_{min} and V_{max} speeds that our UAV can achieve. We also take into account base minimum V_{bmin}. Maximum V_{bmax} speeds in this calculation.

$$V_{min} = V_{b_{min}} \times W_f \tag{12}$$

$$V_{max} = V_{b_{max}} \times W_f \tag{13}$$

Power Required at a Given Speed: The power required at a given speed, P_r (s), is crucial for understanding the energy demands of UAV flight operations. This power is the sum of the forces needed to overcome aerodynamic drag and gravitational forces, particularly when changing altitude. The required power at speed s is calculated as follows:

$$P_r(s) = D_f(s) + m \times g \times s \quad (14)$$

$$D_f(s) = 0.5 \times \rho \times C_d \times A \times s^2 \quad (15)$$

where:

- $D_f(s)$ represents the drag force acting on the UAV at speed s.
- m is the total mass of the UAV, including its payload.
- g is the acceleration due to gravity, relevant for vertical movement components.
- s is the speed of the UAV.
- ρ is the air density.
- C_d is the drag coefficient.
- A is the effective cross-sectional area facing the airflow.

The first equation integrates the drag force, derived from the basic drag equation in fluid dynamics, with the gravitational force component when ascending or descending. This comprehensive approach to calculating power requirements ensures that the UAV's battery and motor capabilities are adequately specified to handle various flight conditions efficiently.

1.4. Calculating Energy Consumption for UAV Flight Segment

In this section, we calculated the process of determining the energy needs for each segment of a UAVs flight. This calculation is essential for optimizing flight paths maximizing energy efficiency and extending the range of UAVs. The section begins by outlining an approach that outlines the inputs and outputs for calculating segment energy. This algorithm serves as a foundation for calculations and theoretical explanations of the UAVs flight dynamics.

The section breaks down the energy calculation into components each addressing a specific aspect of the UAVs flight. It starts by calculating takeoff time, which's crucial in understanding the phase of the UAVs journey. Then it focuses on determining the acceleration required to reach the desired altitude, which significantly impacts energy consumption during ascent. Next it provides an analysis of takeoff dynamics covering both positive and negative acceleration phases to ensure a transition from ground to hover. The section also delves into power requirements during takeoff, cruising and landing stages to give an encompassing view of energy dynamics throughout the flight. Ultimately these calculations culminate in determining segment energy expressed in Watt hours measure, for real world applications. The careful method of calculating energy segments highlights the significance of accuracy in planning UAV flights. Emphasizes the necessity for algorithms to improve operational efficiency.

Algorithm 2 Calculate Segment Energy

Input: Drone mass m, height h, distance d, air density ρ, wing area A, drag coefficient C_d, gravitational acceleration g

Output: Energy consumption for a segment, cruise time, optimal speed, acceleration coefficient ϵ

procedure CalculateSegmentEnergy(m, h, d, ρ, A, C_d, $g = 9.81$)

$\quad$ $optimal\_speed \leftarrow$ calculate_optimal_speed(m, A, C_d, ρ)

$\quad$ $t\_takeoff \leftarrow \frac{h}{optimal\_speed}$

$\quad$ $t\_landing \leftarrow \frac{h}{optimal\_speed}$

$\quad$ $\epsilon \leftarrow \frac{4 \cdot h}{t\_takeoff^2}$

$\quad$ Calculate $P\_takeoff$, $E\_takeoff$, t_cruise, P_hover, P_drag, P_cruise, E_cruise, and $E\_landing$

$\quad$ $E\_segment \leftarrow E\_takeoff + E\_cruise + E\_landing$

$\quad$ $E\_segment\_Wh \leftarrow \frac{E\_segment}{3600}$

$\quad$ **return** $E\_segment\_Wh$, t_cruise, $optimal\_speed$, ϵ

end procedure

Figure 2. UAV segment energy algorithm

1.4.1. Take-off Dynamic

To determine the time needed for takeoff denoted as t_{takeoff}, we use the altitude change h and the optimal speed v_{opt}, in the formula;

$$t_{takeoff} = \frac{h}{v_{opt}} \tag{16}$$

1.4.2. Acceleration Calculation

To understand how a UAV takes off it's important to grasp the significance of the acceleration coefficient ε in achieving flight performance. The acceleration coefficient plays a role in ensuring that the UAV maintains a speed during both takeoff and landing aligning with its constant speed during the cruising phase. This alignment is vital for maintaining efficiency and stability throughout the flight. Determining ε involves calculating a speed denoted as V_{opt} , which is considered ideal for the UAVs operation. Since average speeds differ across flight segments (takeoff and landing versus cruising) separate calculations are made for each segment. This tailored approach allows for management of acceleration to efficiently achieve V_{opt} .

During takeoff acceleration is divided into negative phases; first accelerating to $g + \varepsilon$ to gain altitude up to $h/2$ then decelerating to $g\ \varepsilon$ to reach the desired altitude h. This segmentation optimizes the UAVs performance by calculating ε for each phase. By doing the UAV, we can maintain an average speed that facilitates seamless transitions between different flight modes from takeoff, to cruising and finally landing. The process of taking off and landing with a UAV involves two distinct acceleration phases to reach a specific altitude h.

Take-off Dynamics: During takeoff there are two phases of acceleration;

- Positive Acceleration Phase (Ground to $h/2$): The UAV accelerates by applying a force to g
  $+ \varepsilon$ from the ground to an altitude of $h/2$. This phase ensures altitude gain.

- Negative Acceleration Phase ($h/2$ to h): From an altitude of $h/2$ to h the UAV decelerates by applying a force to g ε, in order to smoothly transition into a state at altitude h.

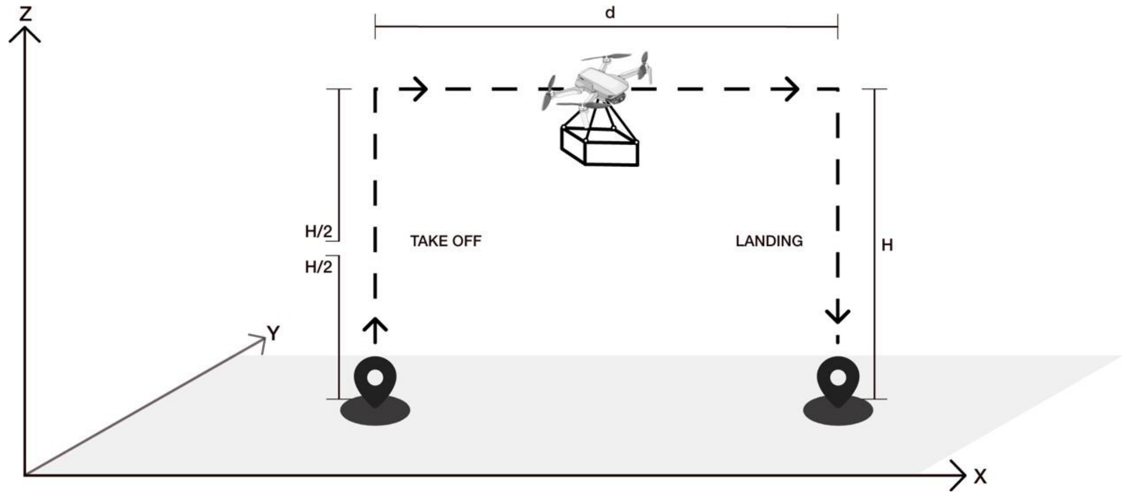

Figure 3. UAV segment

flight Landing Dynamics: During landing there are two phases of acceleration;

- Deceleration Phase (h to $h/2$): To land the UAV gradually descends from an altitude of h by accelerating downwards with a force of $g + \varepsilon$ until it reaches an altitude of $h/2$ effectively controlling its descent rate.

- Final Approach Phase ($h/2$ to Landing): From an altitude of $h/2$ to the landing point the UAV applies a force of g ε to slow down its descent and ensure a controlled and smooth landing.

To ensure an efficient and controlled climb, to a desired height h in a time period t we use a two-step acceleration strategy. This technique is based on the core principles of kinematics of how objects move with acceleration.

The fundamental equation in kinematics, for an object starting from rest and experiencing acceleration is as follows:

$$s = ut + \frac{1}{2}at^2 \tag{17}$$

where:

- s denotes displacement,

- u initial velocity,
- a acceleration,
- t represents time.

To determine the required acceleration ε for the UAV to reach an altitude of h within a time frame t we utilize the position equation during the half of ascent. This two-phase acceleration strategy ensures an efficient climb to the desired altitude.

$$\frac{h}{2} = \frac{1}{2}\varepsilon(\frac{t}{2})^2 \tag{18}$$

Solving for ε, we get:

$$\varepsilon = \frac{4h}{t^2} \tag{19}$$

This two-phase acceleration approach ensures a smooth and efficient ascent to the desired altitude.

1.4.3. Take-off, Cruise, and Landing Power Calculations

Take-off: Building upon the research conducted by (Leishman, 2006) on rotor helicopters and further expanded upon (Dorling et al., 2017), we can calculate the power P necessary for a single rotor helicopter to maintain hover using the aerodynamic principles described.

$$P = \sqrt{\frac{T^{3/2}}{2\rho\sigma}} \tag{20}$$

The thrust T can be determined as follows:

$$T = (W + m)g \tag{21}$$

with W represents the weight of the frame, m is the combined weight of the battery and payload , g denotes acceleration due, to gravity , ρ represents air density and σ refers to the area of the spinning blade disc.

To calculate the power required for takeoff (P_{takeoff}) we need to generate lift to counteract the weight of the UAV and provide acceleration. This can be calculated using:

Lift Force: $F_{\text{lift}} = m \cdot (g + \varepsilon)$ (22)

Power to Lift: $P_{\text{lift}} = \frac{F_{\text{lift}} \cdot v_{\text{air}}}{\eta}$ (23)

Air Velocity by Rotors: $v_{\text{air}} = \sqrt{\frac{F_{\text{lift}}}{2 \cdot \rho \cdot A}}$ (24)

where:

- m is the mass of the UAV,
- g is the acceleration due to gravity,
- ε refers to acceleration,
- ρ denotes air density,
- A represents total rotor area and
- η signifies efficiency of propulsion system.

By combining these calculations, we can accurately deter- mine the power required for takeoff while considering both aerodynamic principles that govern UAV flight.

Cruise: During the cruise phase of a UAVs flight the total power required is a combination of the power needed to maintain hover and the power needed to overcome drag.

The overall power required for cruising denoted as P_{cruise} is the sum of the power to sustain lift and the power needed to parasitic drag when moving forward. According to (Thibbotuwawa et al., 2019), parasitic drag force F_P can be modeled as follows:

$$F_P = \frac{1}{2} C_D A_D \rho v^2 \tag{25}$$

C_D represents the drag coefficient, A_D is the reference area of the UAV, ρ stands for air density and v
denotes the velocity of the UAV, to the air.

As a result, we can calculate the power required to overcome this drag P_{drag} using;

$$P_{\text{drag}} = F_P \times v = \frac{1}{2} C_D A_D \rho v^3 \tag{26}$$

Hover power refers to the energy required for maintaining a stationary position by generating lift equal to that of the UAVs weight. It can be approximated by:

$$P_{\text{hover}} = \frac{(m \cdot g)^{3/2}}{\sqrt{2 \cdot \rho \cdot A}} \tag{27}$$

Combine the power of hovering and dragging, get the power needed for cruising:

$$P_{\text{cruise}} = \left(\frac{(m \cdot g)^{3/2}}{\sqrt{2 \cdot \rho \cdot A}}\right) + \left(\frac{1}{2} \cdot \rho \cdot C_d \cdot A_{\text{front}} \cdot v^3\right) \tag{28}$$

This approach offers an understanding of the power requirements during the cruise phase taking into consideration both lifting and aerodynamic resistance.

Landing: The power necessary for landing P_{landing} is assumed to be equivalent to that required for takeoff.

$$P_{landing} = P_{takeoff} \tag{29}$$

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1.4.4. Total Energy for the Segment

Calculating the energy required for a UAVs route involves adding up the energy used during takeoff, cruising, and landing. This calculation is crucial, for mission planning and resource allocation to ensure that UAVs can complete their tasks efficiently without running out of energy. E_{segment}, is the sum of the energy during takeoff, cruise, and landing:

$$E_{\text{segment}} = E_{\text{takeoff}} + E_{\text{cruise}} + E_{\text{landing}} \tag{30}$$

Calculating flight time and energy plays a role in analyzing our UAV operations. As you can see in Algorithm 3, It focuses on determining how time and energy a UAV needs to complete a specific route. This calculation is vital, for mission planning and resource management ensuring that UAVs can carry out their tasks efficiently without running out of energy.

Algorithm 3 Calculate Flight Time and Energy

```
Input: distances, route, drone_id, package_weights, drone_base_weight, ρ, A, C_d, g = 9.81, h = 50
Output: segment_details, total_time, total_energy
procedure CalculateFlightTimeAndEnergy
    drone_weight ← drone_base_weight
    total_time, total_energy ← 0, 0
    Initialize segment_details as an empty list
    remaining_payload ← sum of package_weights for each point in route[1 : −1]
    for i ← 0 to length(route) − 2 do
        start_point ← route[i]
        end_point ← route[i + 1]
        segment_distance ← distances[start_point][end_point]
        if end_point ≠ 0 then
            payload ← package_weights[end_point]
        else
            payload ← 0
        end if
        drone_weight_with_payload ← drone_weight + remaining_payload
        Calculate optimal_speed using drone_weight_with_payload, A, C_d, ρ
        t_cruise ← segment_distance/optimal_speed
        Calculate energy, t_takeoff, t_landing, and epsilon for the segment
        segment_time ← t_cruise + t_takeoff + t_landing
        Update total_time and total_energy
        Append segment details to segment_details
        if end_point ≠ 0 then
            remaining_payload ← remaining_payload − payload
        end if
    end for
    return segment_details, total_time, total_energy
end procedure
```

Figure 4. UAV flight time and energy algorithm

2. METHODOLOGY

In this section we have applied a framework that combines different techniques to investigate the relationship between payload capacity, flight speed and energy efficiency in UAV logistics. Our approach involves three methods; K Means clustering, an enhanced genetic algorithm and the 2 opt heuristic.

To begin with we used K Means clustering to categorize delivery destinations into clusters.

This allowed us to assign each cluster to UAVs ensuring a distribution of delivery tasks. Once the clusters were established our enhanced genetic algorithm took over. Its main objective was to determine the flight routes by considering factors such as distance between points, payload capacities of the UAVs and their associated energy requirements.

To further optimize these routes, we employed the 2 opt heuristic. This technique carefully rearranged the stops within each route to minimize travel distance and consequently reduce energy consumption. By combining these strategies in a manner, we were able to thoroughly explore how UAV based delivery systems operate and gain valuable insights into improving UAV performance with regards to payload management speed regulation and energy utilization.

The population size, mutation rate and maximum generation were carefully selected based on testing to strike a balance, between efficiency and the thoroughness of our genetic algorithms search process. For instance, the population size was chosen to maintain a range of solutions without converging quickly. The mutation rate was adjusted to introduce variation without disrupting progress towards convergence. Limiting the number of generations helped prevent computational time while still allowing the algorithm enough chances to discover nearly optimal solutions. These parameters play a role in how the algorithm performs by influencing how much exploration, versus exploitation occurs in searching for solutions ultimately impacting both speed of convergence and solution quality. Figure 5 shows UAV used in application (DroneEngr, 2024).

Figure 5. UAV

Table 2 and table 3 shows package weights, coordinates, and the UAV specifications.

Table 2. Package weights and coordinates

Point ID	Coordinates (x, y)	Package weight (kg)
0	(342, 598)	0
1	(200, 900)	5
2	(120, 300)	10
3	(250, 990)	15
4	(300, 700)	10
5	(350, 500)	20
6	(400, 400)	5
7	(900, 150)	10
8	(600, 600)	15
9	(900, 100)	5
10	(550, 850)	10

Table 3. UAV specifications

Specification	Value
Number of UAVs (D)	4
Max payload per UAV (M_p)	40 kg
UAV base weight (W_b)	20 kg
Air density (ρ)	1.225 kg/m^3
Drag coefficient (C_d)	1
Wing area (A)	2 m^2
Gravitational acceleration (g)	9.81 m/s^2
Height for takeoff/landing (h)	50 m
Base min/max speed (V_{bmin}, V_{bmax})	Variable based on payload

Genetic Algorithm (GA) that we used in our model is a method that draws inspiration from natural selection and genetics. It proves to be highly effective when it comes to solving optimization problems in the case of dynamic path planning, for multi-UAV systems used in last mile delivery. In our research we employ Genetic Algorithm (GA) to optimize the routes taken by UAVs (Unmanned Aerial Vehicles) with a focus on achieving energy and cost efficiency. This section provides an explanation of how we have adopted GA methodology to tackle the challenges faced by UAV-based delivery systems.

The foundation of our GA methodology lies in Darwin's theory of evolution, which highlights the importance of survival and evolution of the solutions. In our case each potential route configuration for UAVs is considered as a chromosome with individual segments representing genes that make up these routes. The effectiveness of each solution is evaluated based on its efficiency in terms of energy consumption, delivery time and adherence to payload constraints. As you can see in Fig. 6. our approach using GA is characterized by its nature as it maintains and evolves a population of solutions over generations. This method ensures improvement in the search for the efficient routes for UAV deliveries.

2.1. Steps In Genetic Algorithm Process

The parameters for Population Size and Maximum Generations were determined through empirical testing, aimed at balancing the computational efficiency with the depth and diversity of the search process in our genetic algorithm.

The Population Size was established based on iterative trials to identify a size that allows sufficient diversity while avoiding both premature convergence and excessive computational load. This size ensures a robust search across the genetic landscape, enhancing the algorithm’s ability to find near- optimal solutions without getting trapped in local minimal. Maximum Generations were set by observing the point at which improvements in solution quality plateaued over successive runs, indicating convergence of the algorithm. This parameter helps in terminating the algorithm once additional iterations cease to provide significant value, thus optimizing computational resources and time. These parameters were adjusted through a series of preliminary simulations, testing various scenarios to strike an optimal balance that accommodates the complexities of multi- UAV routing problems while maintaining reasonable execution times.

Initial Population: The starting point of our algorithm (GA) is a set of UAV route configurations. Each configuration, called a chromosome consists of routes that represent sequences of delivery points. During initialization we aim to cover a range of solutions to thoroughly explore the search space.

Selection: This process is akin to selection based on evaluating fitness. The fittest solutions, which optimize delivery routes for time and energy efficiency while adhering to payload limits have a chance of being chosen for reproduction. To maintain a balance between exploiting the solutions and exploring possibilities we employ a roulette wheel mechanism to select solutions for the next generation.

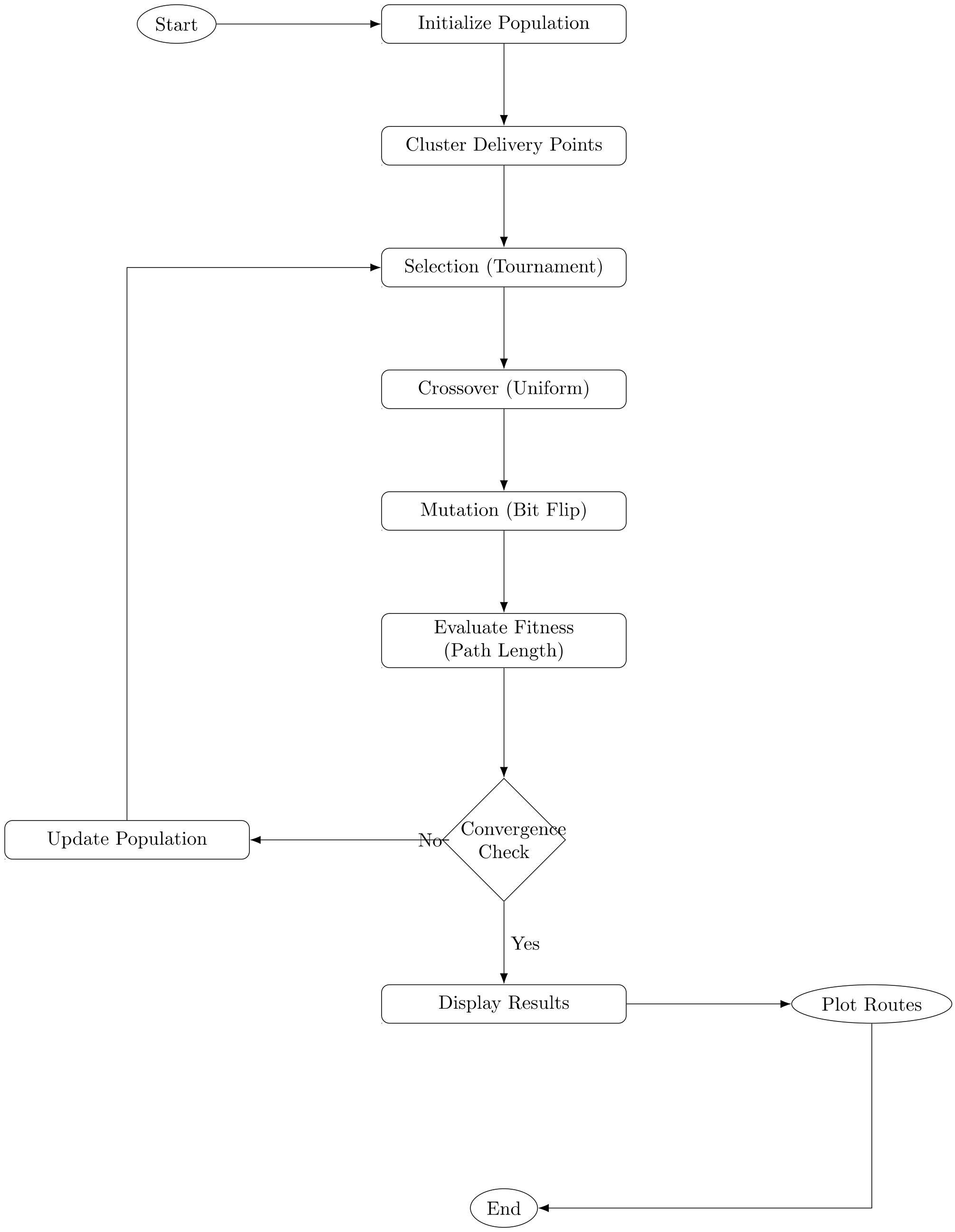

Figure 6. Genetic algorithm process

Crossover: Crossover plays a role in producing solutions (offspring) by combining selected parent solutions. Our GA incorporates techniques like point or multi point crossover, where segments of parent routes are exchanged to create configurations.

Mutation: Mutation introduces changes to the offspring promoting diversity within the population and preventing convergence towards local optima. We carefully control the mutation rate to ensure it contributes to exploration without hindering progress, towards solutions.

2.2. K-Means Clustering in Genetic Algorithm

The K Means clustering technique plays a role in dividing delivery points into clusters each assigned to an Unmanned Aerial Vehicle (UAV). This process is vital for generating the population in Genetic Algorithms (GA).

The goal of the K-Means clustering algorithm is to partition *n* delivery points into *K* clusters ensuring that each point p_i belongs to the cluster with the mean. This creates a partition $S = S_1, S_2, \ldots, S_K$, with the objective of minimizing the sum of squares within each cluster (WCSS):

$$\text{Min} \sum_{i=1}^{K} \sum_{p \in S_i} \|p - \mu_i\|^2 \tag{31}$$

where μ is the mean of points in S_i .

Implementing into Genetic Algortihm

- The K Means technique is employed to assign delivery points to UAVs based on their proximity, which establishes the routes.
- This clustering approach forms the foundation of the population within Genetic Algorithms (GA) guaranteing a set of starting solutions.

2.3. 2-Opt Algorithm in Genetic Algorithm

The 2 Opt algorithm serves as a search method utilized to enhance the routes generated by Genetic Algorithms (GA). It consistently replaces two edges with two edges to decrease the route length.

- Lets consider a route denoted as R, which consists of points $R = (r_1, r_2, \ldots, r_n)$.
- In the 2 Opt technique we removed two edges (r_i, r_{i+1}) and (r_j, r_{j+1}). Then reconnect the paths formed.
- The resulting new route is denoted as R' which follows the order $R' = (r_1, \ldots, r_i, r_j, \ldots, r_{i+1}, r_{j+1}, \ldots, r_n)$.
- We keep this change only if it reduces the distance of

the route. Implementing into Genetic Algorithm

- In a Genetic Algorithm (GA) after performing crossover and mutation steps on each offspring.
- We apply the 2 Opt technique to refine each route individually.
- This step focuses on optimizing the order in which delivery points are visited.
- It helps prevent getting trapped in solutions and enhances the overall fitness of the population.

2.4. Multi-UAV System Implementation

Calculating Distances: To plan the route of each UAV effectively it is essential to determine the distances between delivery points. The distance for each segment of a route can be calculated using the formula:

$$d_{ij} = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2} \tag{32}$$

This formula enables us to compute the straight-line distance between any two points i and j, where (x_i, y_i) and (x_j, y_j) represent their coordinates.

Optimal Speed and Energy Calculation: To maximize efficiency while minimizing energy consumption it is crucial to determine the speed for each segment of a UAVs route. The optimal speed considers factors, like the UAVs weight and aerodynamic properties. It can be calculated as follows;

$$v_{\mathrm{opt}} = \min_{v}\left(P_{\mathrm{drag}}(v) + P_{\mathrm{lift}}(v)\right) \tag{33}$$

Additionally, we need to consider the energy required for completing each segment of the route including takeoff, cruising and landing phases:

$$E_{\mathrm{segment}} = (P_{\mathrm{takeoff}} \times t_{\mathrm{takeoff}}) + (P_{\mathrm{cruise}} \times t_{\mathrm{cruise}}) + \left(P_{\mathrm{landing}} \times t_{\mathrm{landing}}\right) \tag{34}$$

This energy calculation incorporates parameters and aerodynamic principles. The formulate (33) and
(34) contribute to a model that optimizes UAV flight paths by calculating the necessary energy.

3. COMPUTATIONAL RESULTS

Our research delves into the Capacitated UAV Routing Problem (CDRP) using a UAV approach with a focus, on optimizing energy and cost efficiency through a multi visit system. We devised our solution by employing a Genetic Algorithm, which incorporates the 2 Opt technique for route optimization well as the K means Clustering Method to efficiently allocate tasks among UAVs. These methodologies collectively address the nature of routing UAVs while considering capacity limitations, energy efficiency and operational expenses. To implement our solution, we utilized Python programming language in conjunction with the PyCharm Integrated Development Environment (IDE). Additionally, we leveraged the capabilities of Gurobi 11.0 to solve optimization problems. All computations were performed on a MacBook Pro computer equipped with an M3 chip and 8GB of RAM. This setup demonstrates that our approach is applicable on available computing platforms. The solvers parameters were kept at their default settings to ensure that our results can be reproduced reliably. Furthermore, to strike a balance between exploration and practical constraints we imposed a four-hour time limit on each experiment.

By employing this framework, we were able to examine the effectiveness of our proposed methodologies in enhancing operational efficiency within UAV routing systems. Our findings underscore potential for advancements in UAV logistics.

3.1. Simulation Setup

Our simulation environment is carefully designed to add the complexities and limitations, in real world UAV delivery operations. The experimental parameters are as follows:

- Population Size: We have set it at 50 which determines the diversity of route solutions explored by our algorithm striking a balance between exploration and exploitation.
- Maximum Generations: Limited to 100 indicating the depth of search conducted for optimal route configurations.
- Mutation Rate: Kept at a fixed value of 0.1 this rate emphasizes the algorithms' ability to introduce variability and avoid getting stuck in local optima.
- Tournament Size: Set at 5 representing the selection process for breeding within the algorithm framework.
- Battery Capacity: Our UAV fleet operates with a capacity of 300-watt hours determining their range and endurance.
- Number of UAVs: Our delivery fleet consists of four UAVs, which aligns with operational scalability and manageability considerations.

- UAV Specifications: Each UAV has a base weight of 20 kg and a maximum payload capacity of 40 kg. These parameters are crucial for understanding energy consumption and routing dynamics.
- Package Weights and Delivery Coordinates: To simulate delivery scenarios package weights vary from 5 to 20 kg. Additionally, delivery points are strategically dispersed to challenge the routing algorithm.

This configuration does not demonstrate the versatility of our model. Also investigates its boundaries and capacities when faced with diverse logistical limitations.

3.2. Results

In the operations of UAVs, adjustments in speed relative to changes in payload weight are strategically managed to optimize delivery efficiency. For UAV-1, the initial high speed of 35.555 m/s with a payload of 35 kg is employed to quickly cover the longer initial segment of the delivery route. As the UAV makes deliveries and the payload decreases, the speed is systematically reduced. This reduction in speed is not directly due to the decrease in payload but is a strategic decision to conserve energy and enhance flight safety as the UAV becomes lighter and more energy-efficient in its operations.

Table 4. UAV-1 subtour results

Segment	Route	Optimal Speed	Epsilon	Payload	Package Weight	Flight Time	Energy
1	(0, 5)	35.555	1.580	35	20	5.577	49.186
2	(5, 6)	17.777	0.395	15	5	11.913	33.9
3	(6, 2)	13.333	0.222	10	10	29.799	54.026
4	(2, 0)	4.444	0.024	0	0	106.11	36.693
					Total Subtour	153.401	173.807

This adaptive speed management strategy ensures that UAVs operate effectively when carrying loads using an advanced control system to balance the goals of saving time and conserving energy. In the case of UAV-2 we noticed a decrease in the speed and acceleration coefficient (epsilon) as it moves along its delivery route starting at a speed of 17.777 m/s with a 15 kg load and gradually decreasing to 4.444 m/s as the load decreases to zero. This highlights how control mechanisms adjust speed based on payload weight during deliveries with energy consumption (210.667 Wh) heavily impacted by both the weight being carried and the distance traveled, emphasizing the need to optimize these factors for delivery efficiency.

Table 5. UAV-2 subtour results

Segment	Route	Optimal Speed	Epsilon	Payload	Package Weight	Flight Time	Energy
1	(0, 7)	17.777	0.395	15	10	45.876	128.058
2	(7, 9)	8.888	0.098	5	5	16.875	16.645
3	(9, 0)	4.444	0.024	0	0	190.779	65.963
					Total Subtour	253.531	210.667

When we look at the results of UAV-3's subtour, we can see that there is a balance between managing the payload and maximizing energy efficiency. At first the UAV carries a payload of 20 kg and reaches a speed of 22.222 m/s thanks to a higher acceleration coefficient (epsilon) of 0.617; as the payload decreases to 15 kg the speed decreases to 17.777 m/s. Eventually drops to 4.444 m/s with no payload showing significant energy savings. The total duration of this trip is 144.030 seconds, with an energy usage of 148.861 Wh highlighting how important it is to consider payload weight and flight dynamics when planning routes and adjusting speeds to improve the efficiency and performance of UAV delivery systems.

Table 6. UAV-3 subtour results

Segment	Route	Optimal Speed	Epsilon	Payload	Package Weight	Flight Time	Energy
1	(0, 1)	22.222	0.617	20	5	19.517	77.231
2	(1, 3)	17.777	0.395	15	15	11.416	32.521
3	(3, 0)	4.444	0.024	0	0	113.096	39.108
					Total Subtour	144.030	148.861

The UAV-4 begin its route carrying a 35 kg payload reaching a speed of 35.555 m/s and an acceleration factor (epsilon) of 1.58. In the leg of the flight, it consumes 51.834 Wh of energy due to the load and high speed. As the mission progresses, the payload decreases to 25 kg. To 15 kg both the speed and epsilon decrease proportionally to 26.666 m/s and 17.777 m/s respectively allowing for more efficient energy usage. When flying without any payload the UAV maintains a speed of 4.444 m/s resulting in a reduction in energy consumption to only 27.857 Wh for this phase. It completes this part of the journey, in 121.115 seconds by adjusting its flight dynamics and energy consumption based on the changing payload weights.

Table 7. UAV-4 subtour results

Segment	Route	Optimal Speed	Epsilon	Payload	Package Weight	Flight Time	Energy
1	(0, 4)	35.555	1.58	35	10	5.914	51.834
2	(4, 10)	26.666	0.888	25	10	14.683	77.391
3	(10, 8)	17.777	0.395	15	15	19.965	56.224
4	(8, 0)	4.444	0.024	0	0	80.551	27.857
					Total Subtour	121.115	213.307

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Figure 7. UAV mission delivery subtours

Note: The total mission was completed in a time of 253.53 seconds, consuming a total energy of
746.64 Wh.

Fig. 7. provides an analysis of a UAV delivery mission, where UAVs are strategically deployed to balance payload distribution and route efficiency. The goal is to optimize delivery times and energy usage. UAV 1, which initially carried the load started off with speeds but gradually slowed down as deliveries were made. On the hand UAV 4 also started with a payload followed a more energy efficient route. UAV 2s longer flight time indicated that its route might have been longer or less efficient compared to others while UAV 3 maintained parameters throughout the mission. The overall mission was completed in 253.53 seconds consuming around 746.64 Wh of energy. This analysis highlighted the tradeoff between speed, payload capacity and energy consumption in UAV delivery systems. Identified potential areas for future optimization.

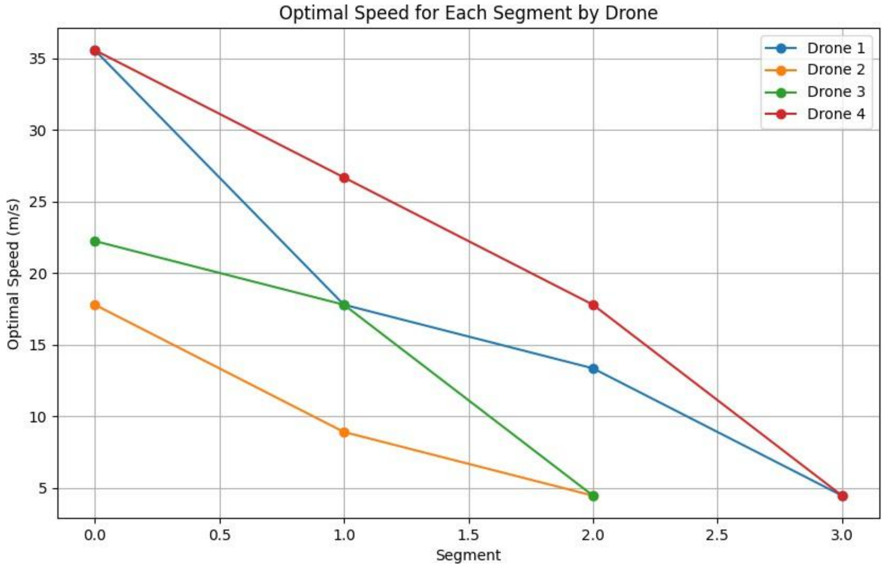

Figure 8. UAV flight segment optimal speeds

Fig. 8 shows how UAVs change their speeds based on changes in payload weight when carrying out deliveries. At the beginning UAVs 1 and 4 begin with speeds of 35 m/s slowing down as their payloads get lighter, which improves efficiency towards the end of the mission. This chart emphasizes the tuning of UAV speeds to save energy and stresses the significance of adjusting speed for payload handling and route planning.

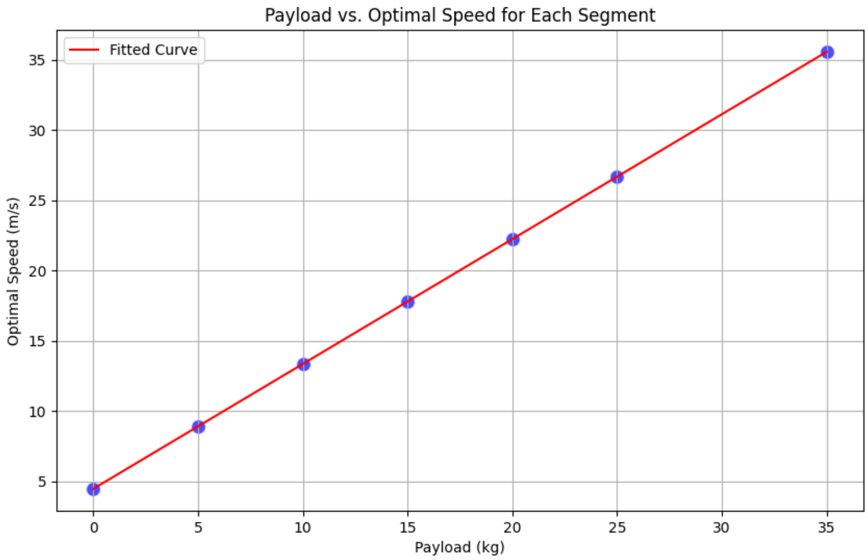

Figure 9. Payload optimal speeds

Figure 8 shows the correlation between UAV payload weights and their optimal speeds, offering analytical perspectives on operational efficiency in UAV delivery systems. The scatter plot, complemented by a curve, demonstrates that as UAVs carry heavier loads, they tend to operate at higher optimal speeds. This relationship is evident through aligned data points and a linear trend line highlighting the increase in speed with payload weight. These optimal speeds were determined using our proposed enhanced genetic algorithm, which dynamically adjusts UAV speeds based on payload weight to optimize energy consumption and operational efficiency. The findings suggest that heavier deliveries require faster travel to maintain optimal flight dynamics and manage energy effectively. The data used for this figure was generated through computational experiments conducted as part of this study, where various payload weights and UAV specifications were tested to observe their impact on optimal speeds.

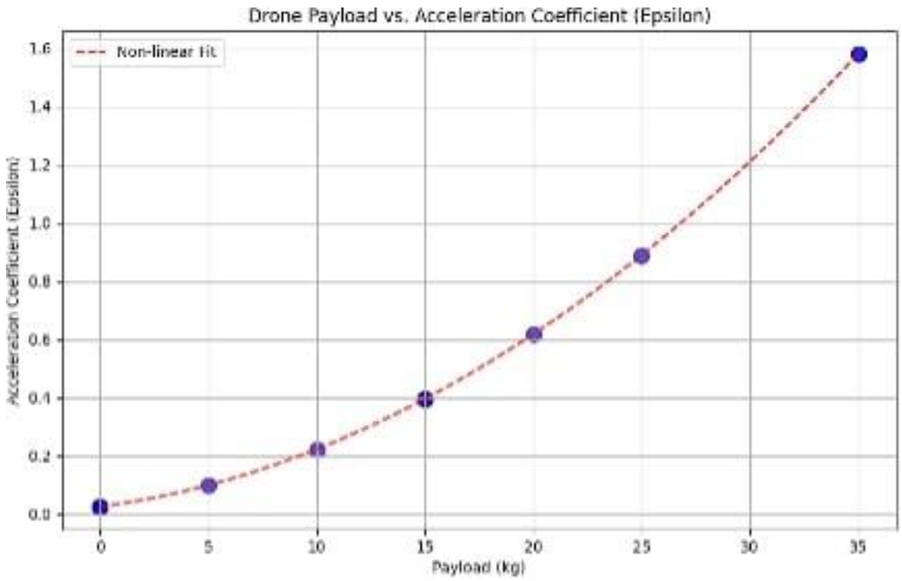

Figure 10. Payload acceleration coefficient

Fig. 10 shows the impact of payload weight, on UAV acceleration indicating that heavier loads demand power for acceleration. This is evident from the rise in the acceleration coefficient (Epsilon) as weight increases. The graph shows that UAVs maintain steady acceleration with payloads but adjustments in flight dynamics and power settings are required for heavier loads. The analysis emphasizes the link between payload weight and operational effectiveness emphasizing the importance of strategic UAV design and mission planning to enhance performance and energy efficiency.

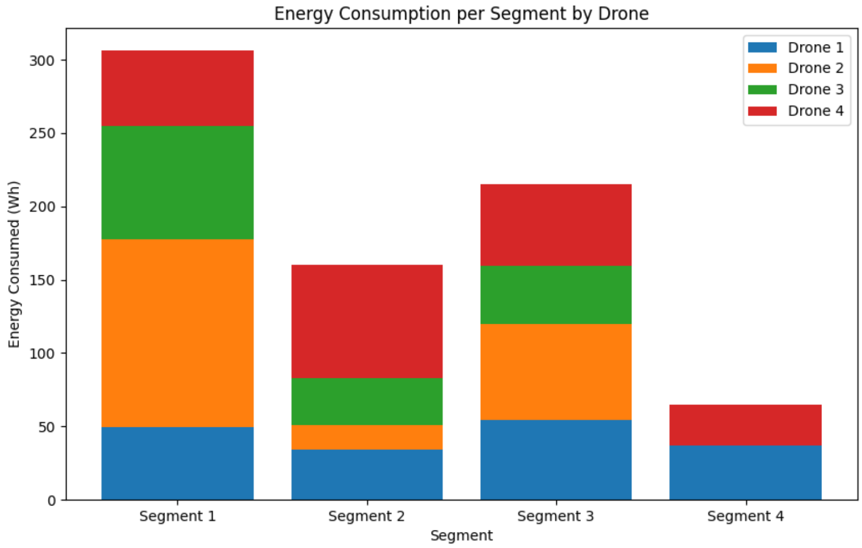

Figure 11. Energy consumptions per segment

In Fig. 11. we can get insights into the energy usage patterns of UAVs during delivery missions. It becomes evident that UAV 2 initially has energy demands, which could be attributed to a load or longer route. On the other hand, UAV 4 demonstrates energy use in the beginning indicating a lighter load or shorter initial segment. As the mission progresses all UAVs show a decrease in energy consumption across segments reflecting payload delivery and reduced energy requirements. Notably UAV 1 consistently consumes energy than the others suggesting its role in covering distances or carrying heavier payloads.

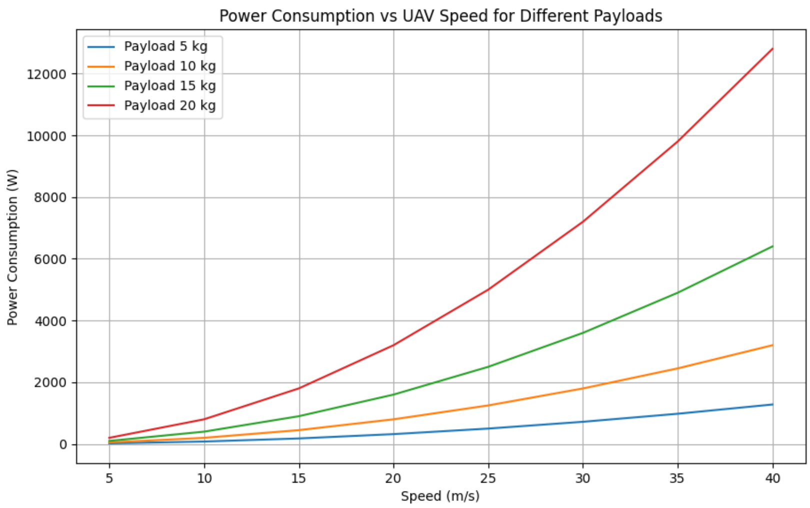

Figure 12. Speed power consumptions

Fig. 12 shows the relationship between UAV's speed, its carried payload, and the consequent power requirements. The data clearly indicate a correlation where power consumption increases with speeds across different payload weights. This highlights the energy demands needed to counteract drag at velocities particularly when dealing with heavier payloads. Such insight is crucial for UAV design as it emphasizes the importance of strategic speed management to enhance energy efficiency and optimize performance.

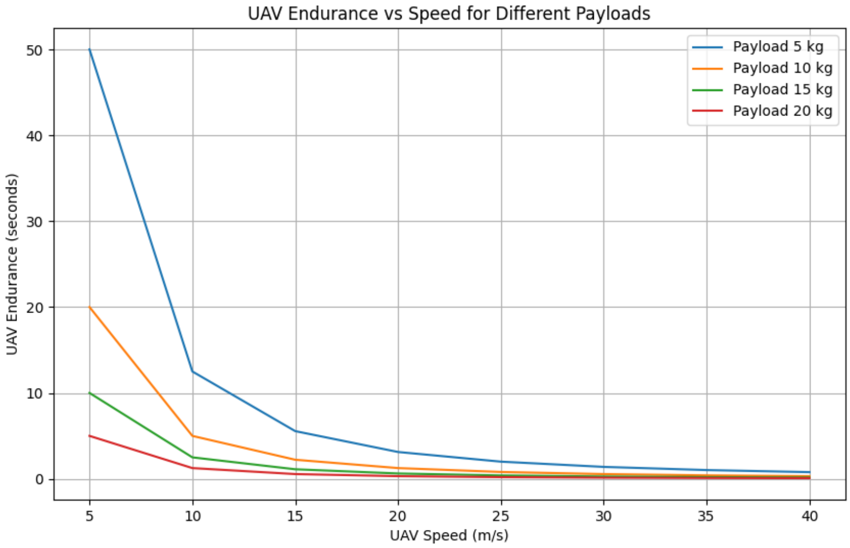

Figure 13. Speed endurance

In Fig. 13, it shows that when the speed of a UAV goes up its endurance goes down with payloads. This emphasizes the importance of flying UAVs, at a speed range to get the most out of their endurance. This evaluation is crucial for planning missions as it enables adjustments in UAV speeds based on payload weight ultimately improving efficiency in tasks, like delivery and surveillance.

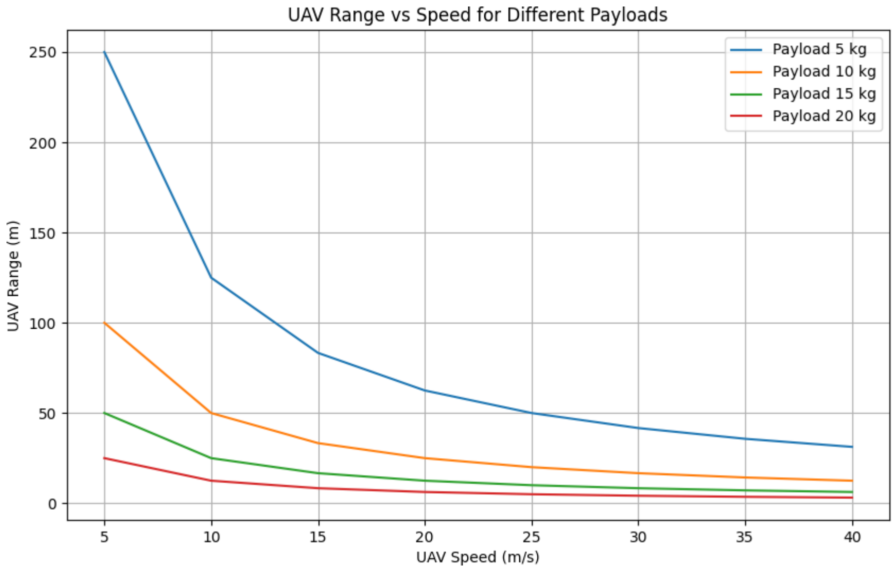

Figure 14. Speed range

Fig. 14. shows that UAVs travel range diminishes as both payload and speed increase. To what was observed in terms of endurance. This indicates an inverse relationship between speed and range across all payloads. Heavier payloads have an impact on the range of UAVs. Much like their effect on endurance. By reducing flight time and distance capabilities when combined with increased speed. Consequently, this underscores the importance of managing speeds, for performance. The values presented in the figure (25 m to 250 m) are derived from specific test scenarios designed to highlight the impact of varying payloads and speeds on UAV range in a controlled environment. These values illustrate the trend rather than representing the maximum possible range of the UAVs. Consequently, this underscores the importance of managing speeds for optimal performance and efficiency in UAV operations.

4. CONCLUSION AND FUTURE WORK

In this study we worked on the performance of four UAVs by exploring aspects such, as speed enhancement, energy conservation, handling of payloads and acceleration features. UAVs 1. 4 demonstrate efficient speed control when carrying loads indicating thrust capabilities, especially UAV 4 which strikes a balance between payload capacity and speed implying a superior power to weight ratio. On the other hand, UAV 3 maintains speeds even with heavy payloads at either energy saving tactics or limitations in thrust compared to UAV 4. Meanwhile UAV 2 demonstrates energy efficiency by utilizing 65.963 Wh even during long flights showcasing effective cruising without any payload onboard. The declining energy usage as payloads are delivered for UAV 4 emphasizes advanced energy management aligned with task completion. This study highlights the importance of managing both the weight and energy consumption of UAVs to optimize delivery routes; it stresses that controlling speed and distributing payloads are factors in improving operational efficiency and cost effectiveness in UAV logistics. Future research should concentrate on creating algorithms that can dynamically adapt routes and speeds based on changing circumstances and testing them in real world settings to enhance their efficacy while also refining energy consumption models to consider impacts for better deployment strategies of UAVs, in diverse delivery scenarios.

Based on our findings, it is advisable for practitioners to implement systems that manage speed and payload dynamically to enhance energy efficiency and operational effectiveness. Policy makers should think about creating rules and regulations that promote the integration of drones into delivery networks emphasizing operation guidelines such as speed restrictions and payload capacities. Moreover, investing in research and development for battery technologies and energy efficient drone designs will play a role in expanding the reach and functionalities of drones. Collaboration between industry stakeholders and regulatory entities can help in establishing procedures for drone operations ensuring scalability and sustainability across logistical settings. These steps will harness the potential of drone technology in improving delivery services while reducing impact and operational expenses.

The experiments conducted involved controlled settings, which may not encompass all factors encountered in real world scenarios like weather conditions, regulatory limitations and unforeseen obstacles. Additionally, the model assumes knowledge about payload weights and delivery locations information that may not always be readily available in situations. Future studies ought to address these uncertainties by exploring algorithms capable of adapting to real time data and dynamic changes in delivery environments. Despite these constraints the proposed model represents an advancement towards optimizing drone-based logistics operations while setting a foundation for research endeavors and practical applications.

5. CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this article.

6. CONTRIBUTION OF AUTHORS

Dr. Alparslan Güzey was responsible for the overall conceptualization, methodology, and preparation of the article. Prof. Dr. Mehmet Hakan Satman, as the Ph.D. supervisor, contributed by reviewing and providing critical feedback on the article.

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