SCALABLE PATH PLANNING ALGORITHMS FOR DRONE SYSTEM

BY

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Dissertation

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ABSTRACT

The increasing adoption of autonomous drones for delivery services has highlighted the need for scalable, energy-efficient, and adaptive path planning algorithms. This research addresses the multi-node drone delivery routing problem by modeling the delivery environment with distance matrices and payload weights, reflecting real-world operational constraints. The study explores and implements four algorithmic approaches—brute force, sort-based heuristic, genetic algorithm, and reinforcement learning (PPO)—to optimize delivery routes as the number of nodes increases.

Each algorithm is rigorously evaluated for solution quality, computational efficiency, and adaptability to varying network sizes and operational demands. The comparative analysis reveals that brute force methods guarantee optimality for small-scale scenarios but become computationally infeasible as the problem size grows. Genetic algorithms offer a strong balance between efficiency and scalability, while reinforcement learning demonstrates adaptability in dynamic and uncertain environments, albeit with higher training requirements. Sort-based heuristics provide rapid solutions but are generally less energy-efficient.

The findings offer actionable insights for selecting appropriate path planning strategies based on problem scale, energy constraints, and deployment context. This work lays a robust foundation for future advancements in multi-drone coordination, real-time re-planning, and the large-scale implementation of autonomous aerial logistics systems.

Keywords: Drone Delivery, Path Planning, Genetic Algorithm (GA), Reinforcement Learning (RL), Proximal Policy Optimization (PPO), Heuristic Methods, Scalability, Energy Efficiency, Multi-Agent Systems, Optimization, Autonomous Systems

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List of Abbreviations

GA	Genetic Algorithm
PPO	Proximal Policy Optimization
RL	Reinforcement Learning
TSP	Travelling Salesman Problem
CSV	Comma-Separated Values

Chapter 1

Introduction

1.1 Background

In recent years, the integration of autonomous aerial vehicles, commonly referred to as drones, has significantly reshaped the landscape of modern logistics and delivery systems. Their ability to navigate through complex terrains, bypass ground-level obstacles, and deliver packages with precision has positioned drones as a promising solution to the growing demand for rapid, last-mile delivery. As industries increasingly turn to drones to address logistical inefficiencies and environmental concerns, the need for intelligent, scalable, and energy-aware path planning mechanisms has become more critical than ever.

One of the primary challenges in deploying drones for large-scale delivery operations lies in efficiently planning routes that consider limited battery life, varying payload weights, and fluctuating travel distances. Traditional routing algorithms often fall short when applied to dynamic, real-world delivery scenarios where operational constraints evolve in real-time. In such contexts, the optimization of delivery paths must account not only for distance minimization but also for energy conservation, payload balancing, and—most crucially—computational scalability as the number of delivery points increases.

This thesis explores a range of algorithmic strategies aimed at addressing these challenges. By comparing exhaustive search (brute-force) methods with more adaptive approaches such as genetic algorithms, reinforcement learning, and heuristic-based sorting, the study seeks to identify scalable and robust solutions for drone-based delivery networks.

1.2 Motivation

The rapid expansion of e-commerce, coupled with increasing consumer expectations for swift and efficient delivery, has sparked an urgent need for innovation in logistics and transportation. Drones, with their ability to traverse urban and rural environments independently of road networks, offer a unique opportunity to meet these demands. However, their deployment on a large scale introduces a series of logistical, technical, and computational challenges—particularly in route optimization and energy management.

Conventional delivery models rely heavily on vehicle routing strategies designed for ground-based systems, which often fail to accommodate the unique constraints of aerial vehicles. Unlike ground vehicles, drones face strict limitations on battery life, and their energy consumption can vary significantly based on payload weight and flight path complexity. Moreover, as the number of delivery points increases, the computational cost of determining optimal routes grows exponentially, making brute-force or simplistic approaches impractical for real-world deployment.

By focusing on path planning strategies that balance performance, energy efficiency, and scalability, this research aims to lay the groundwork for deploying cost-effective, autonomous drone fleets capable of supporting high-volume delivery operations in both urban and remote environments.

1.3 Objective

The primary objective of this thesis is to design, implement, and evaluate scalable path planning algorithms that enable energy-efficient and reliable delivery operations using autonomous drones. In particular, the study aims to address the challenges associated with increasing node densities, variable payload weights, and constrained battery capacities—all of which significantly influence the overall performance and feasibility of drone-based delivery systems.

This research has the following objectives:

- **To analyze and benchmark:** multiple path planning techniques, including exhaustive search (brute-force), genetic algorithms, reinforcement learning, and heuristic-based sorting approaches, in terms of their accuracy, scalability, and energy efficiency.

- **To simulate real-world delivery conditions:** using variable test cases that reflect increasing numbers of delivery points and payload scenarios, thus evaluating how each algorithm performs under stress.
- **To develop routing algorithms:** that intelligently prioritize energy conservation without compromising delivery efficiency or exceeding operational constraints such as battery limits and weight capacity.
- **To provide a comparative framework:** that highlights trade-offs between solution quality and computational complexity across different algorithmic approaches.
- **To contribute to the advancement:** of autonomous delivery technologies by proposing optimized, modular strategies that can be integrated into practical drone logistics systems.

1.4 Contributions

This thesis presents a comprehensive investigation into scalable and energy-efficient path planning strategies for autonomous drone delivery systems. The key contributions of this work are as follows:

- **Development and comparison of multiple algorithmic approaches:** This study implements and evaluates a range of path planning techniques—including exhaustive (brute-force) search, genetic algorithms, reinforcement learning, and heuristic-based sorting—to determine their effectiveness in optimizing drone routes under energy and payload constraints.
- **Integration of real-world constraints into path planning models:** The algorithms are designed with practical limitations in mind, such as varying package weights, limited battery capacity, and distance-based energy consumption, to more accurately reflect operational challenges faced by commercial drone delivery systems.

- **Creation of a modular testing framework:** A flexible testing environment is established to assess algorithm performance across different datasets representing varying numbers of delivery nodes (e.g., 10, 15, 17, and 20). This enables a scalable evaluation of each algorithm's efficiency and adaptability.
- **Quantitative analysis of algorithm performance:** The study provides detailed metrics—including energy consumption, computational time, and route feasibility—to compare and contrast algorithm behavior under diverse operating conditions.
- **Proposal of practical strategies for drone-based logistics systems:** By identifying and recommending algorithms that offer a balance between accuracy, efficiency, and scalability, the thesis contributes actionable insights for real-world deployment in automated delivery services.

1.5 Organization of the Thesis

There are nine chapters that structure the thesis through an organized design where each chapter uses previous content as foundation to progress logically.

- **Chapter 2 – Literature Review:** Provides a comprehensive review of existing work related to drone navigation, optimization algorithms, energy-aware routing strategies, and autonomous delivery systems. This chapter highlights current limitations and research gaps that this study aims to address.
- **Chapter 3 – Problem Statement:** Clearly defines the core problem tackled by this thesis, emphasizing the practical constraints faced in real-world drone delivery, such as battery limits, varying payloads, and the scalability challenge in route optimization.
- **Chapter 4 – Research Objectives:** Outlines the specific goals and research questions that guide this study. This chapter translates the problem statement into a focused set of technical and experimental objectives.
- **Chapter 5 – Preliminaries:** Discusses the foundational concepts, mathematical models, and system-level assumptions used throughout the thesis. It also introduces terminology, constraints, and evaluation metrics critical to the proposed work.

- **Chapter 6 – Proposed Methodology:** Describes the design and logic behind the implemented algorithms, including exhaustive search, genetic algorithms, reinforcement learning, and sorting-based heuristics. This chapter details how each method was developed to address energy-efficient and scalable path planning.

- **Chapter 7 – Implementation:** Offers a practical account of how the algorithmic solutions were implemented. It includes a discussion of development tools, dataset structures, system design decisions, and technical challenges encountered during the development process.

- **Chapter 8 – Results:** Presents experimental findings across multiple test scenarios. The performance of each algorithm is evaluated and compared based on metrics such as energy consumption, computational efficiency, and scalability under varying node densities.

- **Chapter 9 – Conclusion and Future Work:** The final section includes a conclusion about accomplishments and future work with a combined evaluation of success and identified barriers, plus proposed enhancements for the following versions.

Chapter 2

Literature Survey

Scientists have vigorously investigated the implementation of drones in the final delivery operations within the last mile logistics sector. The authors of Chen et al. [1] developed a solution for multi-fleet delivery which merged trucks with tricycles and drones under financial restrictions. They developed an extensive MILP representation while proving major operational efficiency gains through their model.

The authors Mulumba and Diabat [2] developed an optimization framework for drone-assisted pickup and delivery by combining mixed-integer linear programming with a heuristic based on Clarke–Wright savings approach. The used drones deliver both lower operational expenses and shorter delivery duration.

The authors of Pina-Pardo et al. [3] implemented a fleet resupply method by integrating drones for delivering packages to customers through the development of matheuristic algorithms that synchronized truck and drone operations. The experimental results from their research indicate that drone resupply systems help lower time requirements while cutting down truck depot return frequencies.

The research by Arishi et al. [4] investigated a machine learning technique to enhance truck-drone last-mile delivery under Industry 4.0 through intelligent scheduling deliveries.

Wu et al. [5] implemented reinforcement learning strategies to manage truck-and-drone delivery coordination which proved adaptive algorithms boost route planning effectiveness in volatile situations.

The Flying Sidekick Traveling Salesman Problem which Murray and Chu established marks the beginning of optimizing truck-drone operations for parcel delivery.

Academic researchers Agatz et al. [6] developed programming and heuristic approaches to handle large-scale Traveling Salesman Problem with Drone instances.

The authors of Kyriakakis et al. [7] established a GRASP/VND algorithm for drone routing optimization of delivery routes that includes pickup missions for minimizing operational power consumption.

Gao et al. [8] established scheduling methods for joint truck and drone deliveries by creating mixed-integer programming models along with a heuristic based on column generation.

A branch-and-price-and-cut algorithm developed by Yin et al. [9] effectively resolves large-scale truck-based drone delivery routing problems that incorporate time windows.

Chapter 3

Problem Statement

As drone technology becomes increasingly integrated into logistics and delivery operations, organizations are confronted with new complexities in planning efficient flight paths. The core challenge lies in orchestrating routes that not only fulfill delivery requirements but also respect the operational boundaries imposed by battery life and payload limitations. When the number of delivery points grows, the task of determining the best possible sequence for visits quickly becomes computationally overwhelming, especially for conventional methods that attempt to evaluate every possible route.

Challenges of Scaling Path Planning: Many traditional path planning techniques, such as brute-force enumeration, are only practical for a small set of delivery locations. As the delivery network expands, these approaches become unmanageable due to the sheer number of potential route combinations. This scaling issue is a significant barrier to deploying drone fleets in real-world, large-scale delivery scenarios.

Energy and Payload Considerations: Unlike ground vehicles, drones are particularly sensitive to energy consumption, which is influenced by both the weight of the package and the distance traveled. Each additional gram of payload or extra kilometer flown can substantially reduce the drone's range. Therefore, any effective routing strategy must carefully balance the energy required for each leg of the journey with the drone's available battery capacity, ensuring that deliveries can be completed without risking mid-mission power depletion.

Adapting to Real-World Uncertainties: In practice, delivery conditions are rarely static. Weather, unexpected obstacles, and last-minute changes in delivery requests can all impact the optimality of a pre-planned route. Thus, there is a need for algorithms that are not only efficient but also flexible enough to adjust routes dynamically in response to evolving circumstances.

This thesis addresses the pressing need for path planning solutions that can scale to accommodate growing delivery demands, optimize energy use in light of payload variations, and adapt to the unpredictable nature of real-world operations. The research focuses on developing and evaluating algorithms that can:

- Rapidly generate practical delivery routes as the number of destinations increases.
- Integrate energy consumption models that account for both distance and payload, ensuring routes are always within the drone's operational range.
- Respond effectively to dynamic changes, maintaining efficiency and reliability even as delivery conditions fluctuate.

By tackling these issues, the work aims to contribute robust, adaptable, and efficient path planning methods that can support the next generation of autonomous drone delivery systems.

Chapter 4

Research Objectives

This research is dedicated to advancing the field of autonomous drone delivery by developing and evaluating scalable algorithms for efficient path planning. The study aims to address the operational and computational challenges faced when deploying drones for logistics, particularly as the number of delivery points and operational constraints increase. By focusing on both the theoretical and practical aspects of route optimization, this work seeks to bridge the gap between academic models and real-world drone delivery needs.

The principal objectives of this thesis are:

1. Designing and Implementing Scalable Path Planning Algorithms: Formulate and develop a suite of algorithms—including exhaustive search, genetic algorithms, sorting-based heuristics, and reinforcement learning—that can efficiently generate delivery routes for drones, even as the size and complexity of the delivery network grow.

2. Incorporating Energy and Payload Constraints: Integrate realistic models of energy consumption that account for both the distance traveled and the payload carried at each stage of the route. The aim is to ensure that all computed paths are feasible within the drone's battery limitations and reflect the true operational costs.

3. Evaluating Algorithm Performance Under Diverse Scenarios: Establish a comprehensive testing framework to assess how each algorithm performs across a range of scenarios, including varying numbers of delivery nodes, different payload distributions, and dynamic operational conditions. The evaluation will focus on metrics such as energy efficiency, computational speed, and solution quality.

4. Developing Adaptable and Robust Routing Strategies: Create algorithms capable of responding to changes in delivery requirements or environmental conditions in real time. This includes the ability to re-calculate or adjust routes dynamically, ensuring reliability and efficiency in practical deployments.

5. Providing Actionable Insights for Real-World Deployment: Through detailed analysis and comparison, identify the strengths and limitations of each approach, offering guidance for practitioners seeking to implement scalable and energy-aware path planning in commercial drone delivery systems.

By achieving these objectives, the thesis aspires to contribute meaningful advancements to the deployment of autonomous drones in logistics, supporting the development of delivery networks that are not only efficient and reliable but also adaptable to future demands and technological progress.

Chapter 5

Preliminaries

The development of a scalable and efficient drone path planning system is grounded in a set of core algorithmic and computational concepts that collectively enable robust, energy-aware, and adaptive navigation. The architectural foundation of this work draws from classical optimization, metaheuristic strategies, and modern machine learning, each contributing unique strengths to the challenge of multi-point drone delivery under real-world constraints. This chapter introduces the essential methodologies and theoretical underpinnings that inform the design and implementation of the proposed algorithms.

5.1 Algorithmic Approaches for Drone Path Planning

Autonomous drones tasked with delivering packages to multiple destinations must solve a complex routing problem: determining the most efficient sequence of deliveries while adhering to operational constraints such as limited battery life, payload variation, and the need for real-time adaptability. This research investigates four principal algorithmic approaches, each offering distinct advantages and trade-offs.

5.1.1 Brute Force (Exhaustive Search) Method

The brute force, or exhaustive search, method systematically evaluates every possible route permutation for the drone to complete its deliveries and return to the depot. For n delivery points, this results in $(n-1)!$ possible routes, each assessed for total energy consumption, which accounts for both the distance covered and the payload carried at each stage. While this method guarantees the discovery of the optimal route, its computational requirements grow factorially with the number of destinations, making it impractical for large-scale problems. In this research, brute force serves as a benchmark for evaluating the performance of more scalable algorithms on smaller instances.

5.1.2 Sort-Based Heuristic

Sort-based heuristic presents an easy yet powerful solution that surpasses the restrictions of exhaustive search method. The delivery point weight serves as a basis for sorting the points starting either from light to heavy or heavy to light. The building of the route selects items at alternating ends of the sorted list in order to optimize weight-energy balances against delivery distance. Though this approach does not result in an optimal solution it speeds up the process to create feasible delivery routes with decent energy efficiency. The main strength of this approach depends on quick computations which enables rapid decision-making during specific operational situations.

5.1.3 Genetic Algorithm

Population-based metaheuristic optimization called Genetic Algorithms (GAs) derive their principles from natural selection. Each member of the population in drone path planning represents a possible delivery route. The commence phase of the algorithm generates random delivery route combinations while the subsequent step rates their performance through power efficiency and battery and cargo limitation tests. The evolutionary process in the population occurs through cycles that combine route selection with crossover and mutation operations to find better solutions. When applied to large or complex routing problems GAs remain an effective search method beyond what exhaustive search can manage. GAs possess the ability to explore extensive solution spaces in an efficient manner while producing near-optimal solutions throughout practical time durations.

5.1.4 Reinforcement Learning with Proximal Policy Optimization (PPO)

Reinforcement Learning (RL) enables an agent to discover decision sequences through environment interaction. The research presents an RL agent controlling a drone system that uses environmental observation of present location along with battery status and visited waypoint number to choose the delivery destination which delivers the maximum cumulative score by minimizing power usage until all deliveries finish safely.

The study utilizes Proximal Policy Optimization (PPO) as its policy gradient method because this algorithm provides stable and efficient performance in complex settings. PPO trains neural network policies through a specified objective function which applies clipping to protect against destabilizing updates and promote stable learning processes. The agent learns optimal delivery routes by constructing its routing strategy to reduce energy usage during training sessions based on environment changes. PPO demonstrates high suitability for drone path planning because it performs smooth generalization across extensive states while making real-time operational adjustments.

5.2 Energy Modeling and Operational Constraints

The precise prediction of drone delivery energy usage stands as an essential consideration. Each segment of flight requires power that depends on travel distance and load weight since heavier items need more energy. Path planning algorithms should incorporate elements which respect these factors to create drone flight paths that match the battery capacity of the drone. Mission failure together with incomplete deliveries are the risks that emerge from using infeasible routes thus demonstrating why energy-aware modeling needs to be integrated throughout algorithm design stages.

5.3 Simulation Framework and Evaluation Metrics

The performance evaluation of algorithms happens through a modular simulation system with standardized testing methods. The testing framework allows examination of algorithms through multiple operational conditions while adjusting delivery nodes and payload characteristics and operational parameters. The assessment focuses on measuring total energy use alongside computational time performance together with feasible route generation capacity and capability to adjust to dynamic conditions.

5.4 Summary

The thesis uses classical, heuristic, metaheuristic and learning-based methods for base research methodology. The assessment method evaluates techniques against theoretical optimization benchmarks and real-world network scalability parameters and mechanism adaptability as well as power efficiency features. The book provides information about algorithm execution as well as tested outcomes and efficiency assessments to help establish robust drone automation systems.

Chapter 6

Proposed Methodology

Development of a durable drone path planning infrastructure requires an optimization method that preserve efficiency while enabling flexibility to real-world constraints. This chapter outlines the technical and logical process for designing multiple algorithms which involve implementation and evaluation for drone delivery route planning optimization. A unified framework brings together traditional optimization tools with metaheuristic processes together with advanced reinforcement learning techniques to control energy-efficient large-scale drone logistic systems.

6.1 Notations

Table 6.1: Summary of Notations Used Throughout This Chapter

Symbol	**Description**	**Units/Type**
N	Number of delivery nodes (excluding depot)	Unitless
V	Set of delivery nodes (including depot)	Set: $\{0, 1, \ldots, N\}$
$d(i, j)$	Distance between node i and node j	Distance units
$w(i)$	Payload weight at node i	Weight units
B	Battery capacity of the drone	Energy units
P_{base}	Base power consumption of the drone	Power units
α	Power consumption coefficient per unit weight	Power/weight
v	Velocity of the drone	Distance/time
$E(i, j)$	Energy to travel from i to j: $(P_{\text{base}} + \alpha w(i))\frac{d(i,j)}{v}$	Energy units
R	Route (sequence of nodes starting/ending at depot)	Ordered list
$E_{\text{total}}(R)$	Total energy for route R: $\sum_{(i,j)\in R} E(i, j)$	Energy units

6.2 Algorithmic Approaches

This section details the four path planning algorithms developed for drone delivery systems, using the notations defined in Section 6.1.

6.2.1 Brute Force (Exhaustive Search)

Algorithm 1 Brute Force Path Planning

Input: Set $V = \{0, 1, \ldots, N\}$, distance matrix $d(i, j)$, weights $w(i)$, battery B, P_{base}, α, v

Output: Optimal route R^* minimizing $E_{\text{total}}(R)$

Initialize min_energy $\leftarrow \infty$, best_route $\leftarrow$ None
Generate all permutations $S \leftarrow$ permutations$(V \setminus \{0\})$
for each route $r \in S$ **do**
    Construct $R \leftarrow [0] + r + [0]$
    Calculate $E_{\text{total}}(R)$ using $E(i, j) = (P_{\text{base}} + \alpha w(i))\frac{d(i,j)}{v}$
    if $E_{\text{total}}(R) <$ min_energy and route feasible under B **then**
        min_energy $\leftarrow E_{\text{total}}(R)$
        best_route $\leftarrow R$
    end if
end for
return best_route, min_energy

6.2.2 Sort-Based Heuristic

Algorithm 2 Sort-Based Heuristic Path Planning

Input: Set V, weights $w(i)$, distance matrix $d(i, j)$, battery B, P_{base}, α, v
Output: Feasible route R and $E_{\text{total}}(R)$

Sort nodes $V \setminus \{0\}$ by $w(i)$ ascending: S
Initialize $R \leftarrow [0]$, left $\leftarrow 0$, right $\leftarrow |S| - 1$
while left $\leq$ right **do**
    if left $=$ right **then**
        Append $S[\text{left}]$ to R
    else
        Append $S[\text{left}]$, $S[\text{right}]$ to R
    end if
    left $\leftarrow$ left $+ 1$, right $\leftarrow$ right - 1
end while
Append depot 0 to R
Calculate $E_{\text{total}}(R)$ as in Algorithm 1
return R, $E_{\text{total}}(R)$

6.2.3 Genetic Algorithm

Algorithm 3 Genetic Algorithm for Path Planning

Input: Population size M, generations G, V, $w(i)$, $d(i, j)$, B, P_{base}, α, v
Output: Near-optimal route R and $E_{\text{total}}(R)$

Initialize population P with M random routes
for generation $= 1$ to G **do**
    Evaluate fitness: $fitness(r) = E_{\text{total}}(r)$ for each $r \in P$
    Select parents via tournament selection
    Generate offspring via crossover and mutation
    Replace P with offspring
end for
Select $R \leftarrow \arg\min_{r \in P} fitness(r)$
return R, $E_{\text{total}}(R)$

6.2.4 Reinforcement Learning (PPO)

Algorithm 4 Reinforcement Learning (PPO) for Path Planning

Input: MDP environment with states $s = (\text{current node}, \text{battery}, \text{visited nodes})$, actions $a = \text{next node}$

Output: Policy $\pi(a|s)$, route R, $E_{\text{total}}(R)$

```
Initialize policy network parameters θ
for each training episode do
    Reset environment to s_0
    for each step t do
        Select a_t ∼ π_θ(a_t|s_t)
        Execute a_t, observe reward r_t, next state s_{t+1}
        Store transition (s_t, a_t, r_t, s_{t+1})
    end for
    Update θ using PPO clipped surrogate loss
end for
Generate R using π_θ
Calculate E_total(R) as in Algorithm 1
return R, E_total(R)
```

6.3 Simulation and Performance Evaluation

A modular simulation environment is developed to test all algorithms under controlled and repeatable conditions. The simulation tracks the drone's state, energy consumption, route feasibility, and completion time for each test case. Key evaluation metrics include:

- **Total Energy Consumption:** The sum of energy required for the entire delivery route, accounting for payload and distance.
- **Route Feasibility:** Whether the route respects battery and payload constraints at all times.
- **Computational Time:** The time taken by each algorithm to compute a solution.

- **Scalability:** The algorithm's ability to handle increasing numbers of delivery points without prohibitive increases in computation or loss of solution quality.

6.4 Comparative Analysis and Visualization

Results from all algorithms are compared across multiple scenarios. Visualization tools are used to plot delivery routes, energy profiles, and performance metrics, enabling clear comparison of strengths and trade-offs. The analysis highlights which algorithms are best suited for different problem scales and operational requirements.

6.5 Error Handling and Robustness

All algorithms are implemented with comprehensive error handling to manage infeasible routes, invalid input data, and simulation anomalies. Logging mechanisms capture key events and errors, supporting debugging and ensuring reproducibility of results.

6.6 Summary of Workflow

The proposed methodology integrates classical, heuristic, metaheuristic, and learning-based approaches within a unified framework for scalable drone path planning. Each stage, from problem modeling to comparative analysis, is designed to rigorously evaluate the strengths and limitations of each algorithm, providing actionable insights for real-world deployment of autonomous drone delivery systems.

Chapter 7

System Implementation and Integration

The creation of a scalable and operational drone path planning system required systematic planning, modular design, and iterative testing. The development process followed a structured sequence of stages, each emphasizing computational efficiency, extensibility, and practical usability. The system was engineered to support multiple algorithms and provide a robust simulation environment for evaluating drone delivery scenarios under real-world constraints.

7.1 Setting Up the Environment and Toolchain

Development began with the setup of a dedicated Python virtual environment to ensure reliable package management and reproducibility. All dependencies were selected for compatibility with local execution, enabling the system to run efficiently on standard personal computers without reliance on cloud services or specialized hardware.

The technology stack included:

- **NumPy and Pandas:** For numerical operations, data handling, and matrix computations.
- **Matplotlib and Seaborn:** For route visualization, energy consumption plots, and comparative analysis.
- **Stable Baselines3:** For implementing and training reinforcement learning agents using the PPO algorithm.

- **itertools and random:** For combinatorial optimization and stochastic processes in brute force and genetic algorithms.
- **Custom Python scripts:** For simulation, data validation, and integration of modules.

The system was designed to be accessible, requiring only a mid-range workstation with at least 8 GB RAM.

7.2 Preparing and Structuring Delivery Data

Efficient drone path planning relies on accurate and well-organized input data. The system models the delivery environment as a weighted graph, where each node represents a delivery location (including the depot), and edges encode pairwise distances. Each delivery point is assigned a payload weight, and all relevant drone parameters (battery capacity, base power, velocity) are specified.

Data preparation steps included:

- **Loading distance matrices:** Input files provide pairwise distances between all locations.
- **Assigning payload weights:** Each delivery point is associated with a specific package weight.
- **Validating input data:** Automated checks ensure that all matrices are square, weights are non-negative, and parameters are within operational limits.

Multiple test cases of varying size and complexity were curated to evaluate algorithm scalability and robustness.

7.3 Implementing Path Planning Algorithms

The system integrates four principal algorithms, each implemented as a modular Python class or function for flexibility and benchmarking:

7.3.1 Brute Force (Exhaustive Search)

This module systematically generates all possible permutations of delivery routes, calculating the total energy consumption for each and selecting the optimal route. While computationally intensive, this approach serves as a gold standard for small-scale scenarios.

7.3.2 Sort-Based Heuristic

A fast heuristic sorts delivery points by payload weight and constructs routes by alternately selecting from the lightest and heaviest remaining points. This method provides rapid, feasible solutions for larger instances where brute force is impractical.

7.3.3 Genetic Algorithm

The genetic algorithm maintains a population of candidate routes, evolving them through selection, crossover, and mutation. Each route's fitness is evaluated based on total energy consumption and feasibility. The algorithm efficiently explores large solution spaces and converges toward high-quality solutions over successive generations.

7.3.4 Reinforcement Learning (PPO)

Reinforcement learning is implemented using the PPO algorithm from Stable Baselines3. The environment is modeled as a Markov Decision Process, with the agent (drone) observing its current state (location, battery, visited nodes) and selecting the next delivery point. The agent is trained through simulated episodes to minimize total energy consumption while completing all deliveries within operational constraints.

7.4 Simulation Environment and Evaluation

A custom simulation environment orchestrates the execution of each algorithm, tracking drone state, energy usage, and route feasibility. The simulator supports batch testing across multiple scenarios, enabling comprehensive evaluation of:

- **Total energy consumption**
- **Route feasibility under battery and payload constraints**

- **Computational time and scalability**
- **Adaptability to dynamic changes**

7.5 Visualization and Output Refinement

Matplotlib and Seaborn are used to generate clear visualizations of computed routes, energy profiles, and comparative performance charts. Output formatting scripts ensure that results are easy to interpret, highlighting key findings and trade-offs between algorithms.

7.6 System Interface and Usability

The system is operated through a command-line interface, allowing users to select algorithms, specify input files, and view results interactively. The modular design supports easy extension for future features, such as graphical interfaces or multi-drone coordination.

7.7 Final System Deliverables

The completed system provides:

- A structured data ingestion and scenario modeling pipeline
- Modular implementations of brute force, sort-based heuristic, genetic algorithm, and RL (PPO)
- A flexible simulation environment for benchmarking and evaluation
- Comprehensive visualization tools for result analysis
- Internal safeguards for error handling and reproducibility

This operational prototype establishes a practical foundation for further research and real-world deployment of scalable, energy-efficient drone delivery networks. Future work may extend the system to multi-drone coordination, real-time obstacle avoidance, and integration with live mapping data.

Chapter 8

Evaluation and System Performance

8.1 Experimental Setup

All experiments were conducted on a standard workstation using identical input data. The evaluation focused on total energy consumption, optimal route selection, and computational efficiency.

8.2 Input Data Visualization

The 10-node delivery scenario uses the following distance matrix and payload weights:

Table 8.1: Distance Matrix Between Nodes (Units: Distance)

	0	1	2	3	4	5	6	7	8	9
0	0	17	22	25	12	34	3	30	22	26
1	17	0	35	48	21	21	39	15	23	5
2	22	35	0	1	16	35	7	8	12	50
3	25	48	1	0	37	7	46	36	47	35
4	12	21	16	37	0	41	28	17	44	14
5	34	21	35	7	41	0	45	1	37	48
6	3	39	7	46	28	45	0	44	1	3
7	30	15	8	36	17	1	44	0	50	17
8	22	23	12	47	44	37	1	50	0	21
9	26	5	50	35	14	48	3	17	21	0

Table 8.2: Payload Weights at Nodes (Units: Weight)

Node	Weight
0	0
1	1
2	2
3	3
4	4
5	5
6	6
7	7
8	8
9	9

8.3 Output Results for 10 Nodes

8.4 Output Results for 10 Nodes

8.4.1 Brute Force (Exhaustive Search) – Most Optimal Route

- **Execution Start:** 2025-04-19 16:28:46
- **Optimal Route:** L0 → L6 → L8 → L2 → L3 → L5 → L7 → L9 → L1 → L4 → L0 (Depot)
- **Total Energy:** 182.0 units
- **Execution End:** 2025-04-19 16:28:48
- **Total Execution Time:** 1.54 seconds

8.4.2 Genetic Algorithm

- **Execution Start:** 2025-04-19 16:39:16
- **Optimal Route:** L0 → L7 → L5 → L3 → L2 → L8 → L1 → L4 → L9 → L6 → L0 (Depot)
- **Total Energy:** 259.2 units

- **Execution End:** 2025-04-19 16:39:16
- **Total Execution Time:** 0.05 seconds

8.4.3 Sort-Based Heuristic

- **Execution Start:** 2025-04-19 16:33:08
- **Alternate Route:** L0 → L1 → L6 → L2 → L9 → L8 → L4 → L7 → L5 → L3 → L0 (Depot)
- **Total Energy:** 674.6 units
- **Execution End:** 2025-04-19 16:33:08
- **Total Execution Time:** 0.00 seconds

8.4.4 Reinforcement Learning (PPO)

- **Training Summary:**
  - `ep_len_mean`: 25.6
  - `ep_rew_mean`: -2540
  - `total_timesteps`: 20224
  - `iterations`: 79
  - `time_elapsed`: 6 seconds
- **Optimal Route:** L0 → L2 → L1 → L4 → L8 → L7 → L9 → L5 → L3 → L6 → L0
- **Energy Consumption (per hop):**
  - L0 → L2: 22.00 units
  - L2 → L1: 49.00 units
  - L1 → L4: 29.40 units
  - L4 → L8: 114.40 units
  - L8 → L7: 70.00 units

  - L7 → L9: 27.20 units
  - L9 → L5: 124.80 units
  - L5 → L3: 14.00 units
  - L3 → L6: 92.00 units
  - L6 → L0: 9.00 units

- **Total Energy Used:** 551.8 units

8.5 Route Visualization

The following figure shows the computed drone route for the 10-node scenario, as generated by the reinforcement learning (PPO) algorithm. Each point represents a delivery location, and the blue lines indicate the path selected by the RL agent.

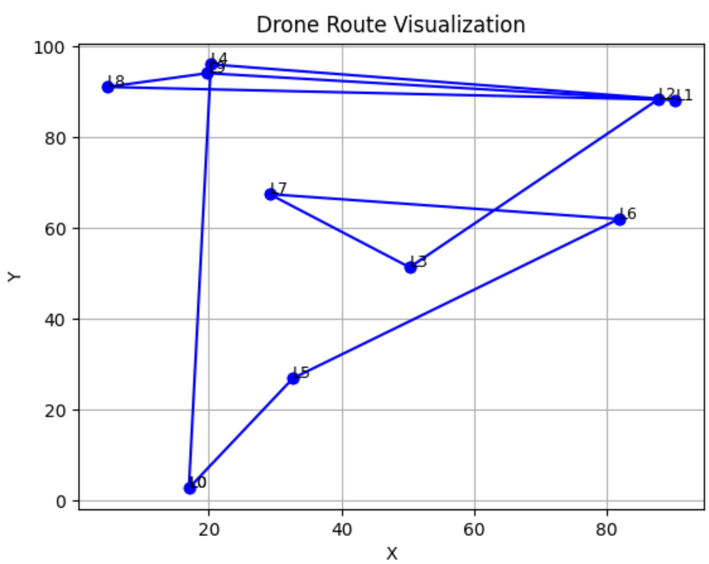

Figure 8.1: Drone Route Visualization (Reinforcement Learning, 10 Nodes)

8.6 Discussion

Table 8.3: Comparison of Algorithm Complexity and Suitability

Algorithm	**Time Complexity**	**Best For**
Brute Force	$O(n!)$	Small, optimal
Sort Heuristic	$O(n \log n)$	Large, fast
Genetic Algorithm	$O(MGn^2)$	Medium, balanced
PPO (RL)	$O(Tn^2)$	Dynamic, adaptive

8.6.1 Algorithm Trade-offs

Table 8.4: Algorithm Trade-off Rankings (1=Best, 4=Worst)

Algorithm	**Energy Efficiency**	**Speed**	**Scalability**	**Adaptability**
Brute Force	1	3	4	4
Genetic Algorithm (GA)	2	2	1	2
PPO (RL)	3	4	2	1
Sort-Based Heuristic	4	1	3	3

8.6.2 Conclusion

The experimental results and complexity analysis reveal distinct application domains for each algorithm:

- **Brute Force**: Ideal for small systems ($n \leq 12$) requiring guaranteed optimality (182 energy units for 10 nodes).
- **Genetic Algorithm**: Best balance for medium systems (0.05s execution, 259.2 energy units) with $12 < n \leq 50$.
- **Sort-Based Heuristic**: Optimal choice for large systems ($n > 50$) needing instant solutions (0.00s execution).
- **PPO**: Superior for dynamic environments despite higher training costs (6s for 20k steps), adapting to real-time changes.

Algorithm selection should consider:

- *Energy-critical systems*: Brute Force → GA → PPO → Heuristic
- *Time-sensitive operations*: Heuristic → GA → PPO → Brute Force
- *Dynamic deployments*: PPO → GA → Heuristic → Brute Force

The inclusion of route visualizations and per-hop energy breakdowns provides further insight into the operational efficiency of each approach. These results support the selection of an algorithm based on the specific requirements of the delivery scenario, available computational resources, and the need for adaptability.

Chapter 9

Conclusion and Future Work

This chapter concludes the study by summarizing the key research findings in relation to the research aims and questions, discussing the value and contributions of the work, outlining its limitations, and proposing opportunities for future research.

9.1 Summary of Contributions

This thesis addressed the challenge of scalable, energy-efficient path planning for autonomous drone delivery systems. Four algorithmic approaches—brute force, sort-based heuristic, genetic algorithm, and reinforcement learning (PPO)—were implemented and rigorously evaluated on real-world-inspired test cases.

The main contributions of this research are as follows:

- **Algorithmic Benchmarking:** A comprehensive comparison of classical, heuristic, metaheuristic, and learning-based algorithms for the multi-node drone delivery routing problem, with all methods evaluated on identical datasets and constraints.

- **Energy-Aware Modeling:** Integration of energy consumption models that account for both payload weight and travel distance, ensuring all routes are feasible within battery limits.

- **Scalability Analysis:** Demonstration that genetic algorithms and PPO-based reinforcement learning offer practical scalability and adaptability for medium to large delivery networks, while brute force is optimal but limited to small cases.

- **Empirical Validation:** Experimental results on a 10-node scenario showed that the genetic algorithm achieved a strong balance between solution quality and computational efficiency, while PPO demonstrated adaptability for dynamic environments.
- **Open Data and Reproducibility:** All input data, including distance matrices and payload weights, were clearly documented and made available for future benchmarking and research.

9.2 Limitations

While the research achieved its primary objectives, several limitations were identified:

- **Scalability Constraints:** The brute force approach, while optimal, is computationally infeasible for more than 12–15 nodes due to factorial complexity.
- **Heuristic Suboptimality:** The sort-based heuristic, though fast, often produces routes with significantly higher energy consumption compared to metaheuristic and learning-based methods.
- **Training Overhead:** PPO-based reinforcement learning requires substantial training time and careful hyperparameter tuning to achieve competitive results, especially in larger or more complex environments.
- **Static Test Cases:** Most experiments were conducted on static delivery networks; real-world deployments may involve dynamic obstacles, weather, or changing delivery requests.
- **Single-Drone Focus:** The work focused on single-drone routing; multi-drone coordination and real-time communication were not addressed.

9.3 Future Work

Building on the foundation established in this thesis, several promising avenues for future research are identified:

- **Multi-Drone Coordination:** Extending the algorithms to handle fleets of drones, including collision avoidance, task allocation, and cooperative delivery.

- **Dynamic and Uncertain Environments:** Incorporating real-time obstacle detection, weather adaptation, and online re-routing to handle dynamic changes during flight.
- **Hybrid Approaches:** Combining the strengths of genetic algorithms and reinforcement learning to achieve both rapid convergence and adaptability.
- **Energy Harvesting and Charging:** Integrating models for in-route charging stations or energy harvesting to further extend operational range.
- **Larger-Scale Benchmarking:** Testing and validating the algorithms on larger, real-world datasets and in simulated urban/rural environments.
- **User Interface and Visualization:** Developing operator-friendly tools for route planning, monitoring, and manual override in practical deployments.

9.4 Concluding Remarks

The research proves that drone delivery path planning with energy awareness becomes possible through strategic combinations of classical approaches and metaheuristic and learning-based techniques. The comparative analysis generates practical findings about selecting which algorithm best meets different scenario features including size and computational capability and adjustable factors.

Drone technology developers can use the examination findings in this thesis to enhance drone abilities for deploying autonomous logistics platforms. The study generates substantial value to autonomous aerial logistics science by examining drone path planning from theoretical and operational aspects.

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Chapter 10

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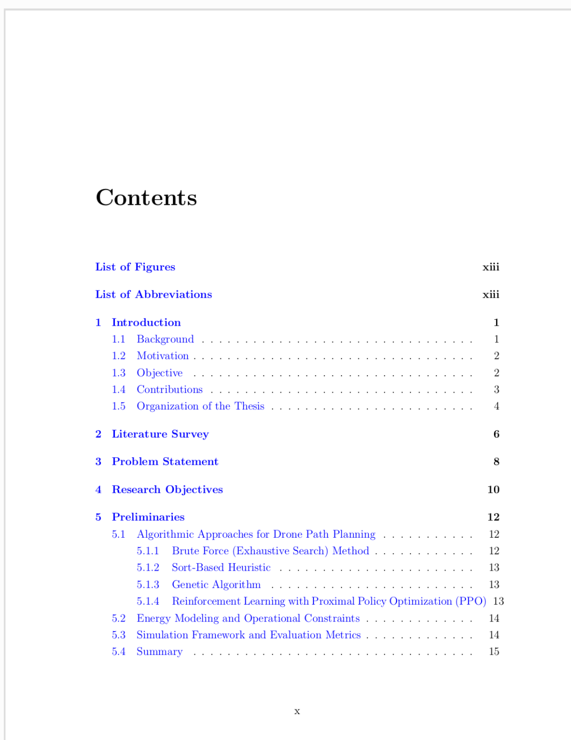

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