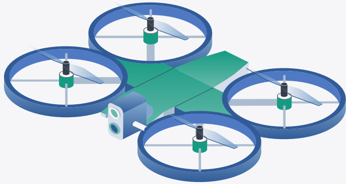
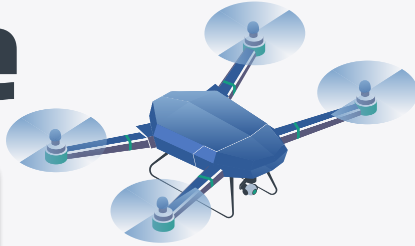
Simulation Driven Approach to Evaluate a Reinforcement Learning based Navigation System for Last Mile Drone Logistics



Zakaria Benali | Supervisor: Dr Amina Hamoud

Presentation Outline



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Introduction

Why Drone Delivery Is Inevitable for Sustainable and Cost-effective Urban Logistics ?

Exponential Growth: The value of goods delivered to consumers by drones worldwide will grow by 74% on an annual basis, from $251 million in 2024 to $65,177 million in 2034 [1].

Significant Emission Reductions: drones produce up to **94% fewer greenhouse gas emissions** per package compared to diesel trucks, making them a cleaner alternative for last-mile deliveries [2].

Enhanced Energy Efficiency: Drones consume up to **94% less energy per parcel** than traditional delivery vehicles, contributing to lower operational costs and environmental impact [3].

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Problem Statement

Risks Posed by Drone Navigation to Manned Aviation Safety

The Federal Aviation Administration (FAA) received a concerning 2,596 pilot reports of drone sightings near manned aircraft in 2021 , more than twice the 1,210 reports recorded in 2015, the first full year such incidents were tracked [4].

In the UK, 174 near-midair collisions between manned aircrafts and drones throughout the last three years have been recorded, including 61 in 2022, 55 in 2023, 58 in 2024 [5].

Autonomous drones struggle to reliably navigate urban environments with dynamic obstacles (e.g., helicopters) and adverse weather [6].

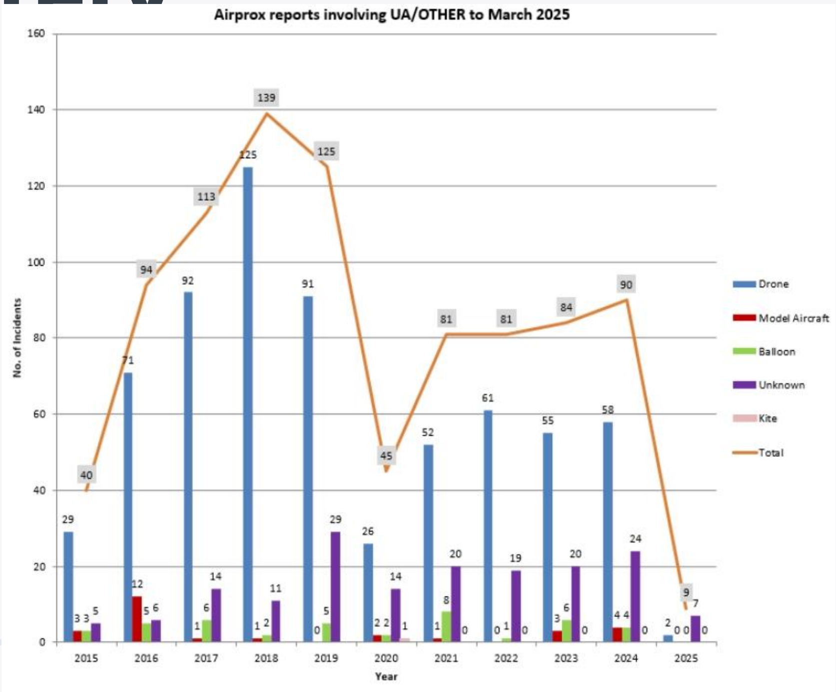

Figure 1: Commercial Manned Aircrafts and Drone Encounters in the UK over the last decade [5]

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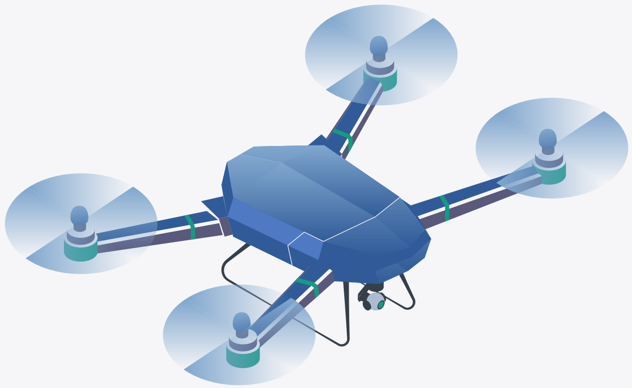
Gaps in the Literature Review



Gap Identified	Description
Limited realism in simulations	❑ Urban simulations often lack dynamic elements like manned aircraft (e.g., helicopters) and environmental factors (e.g., rain, lighting), reducing real-world applicability [7]. ❑ Most environments lack **adaptive feedback loops** to correct simulation deficiencies based on performance [8].
Weak handling of dynamic obstacles	❑ RL models struggle with fast-moving obstacles and sensor noise, reducing decision accuracy in urban airspace [9]. ❑ **Sparse reward structures** slow learning and reduce model generalisation to unseen scenarios [10].
Regulatory gaps in modelling	Airspace constraints (e.g., UK CAA altitude <120m) or unscheduled traffic (e.g., emergency helicopters) have not been tested in a rainy weather condition [11,12].

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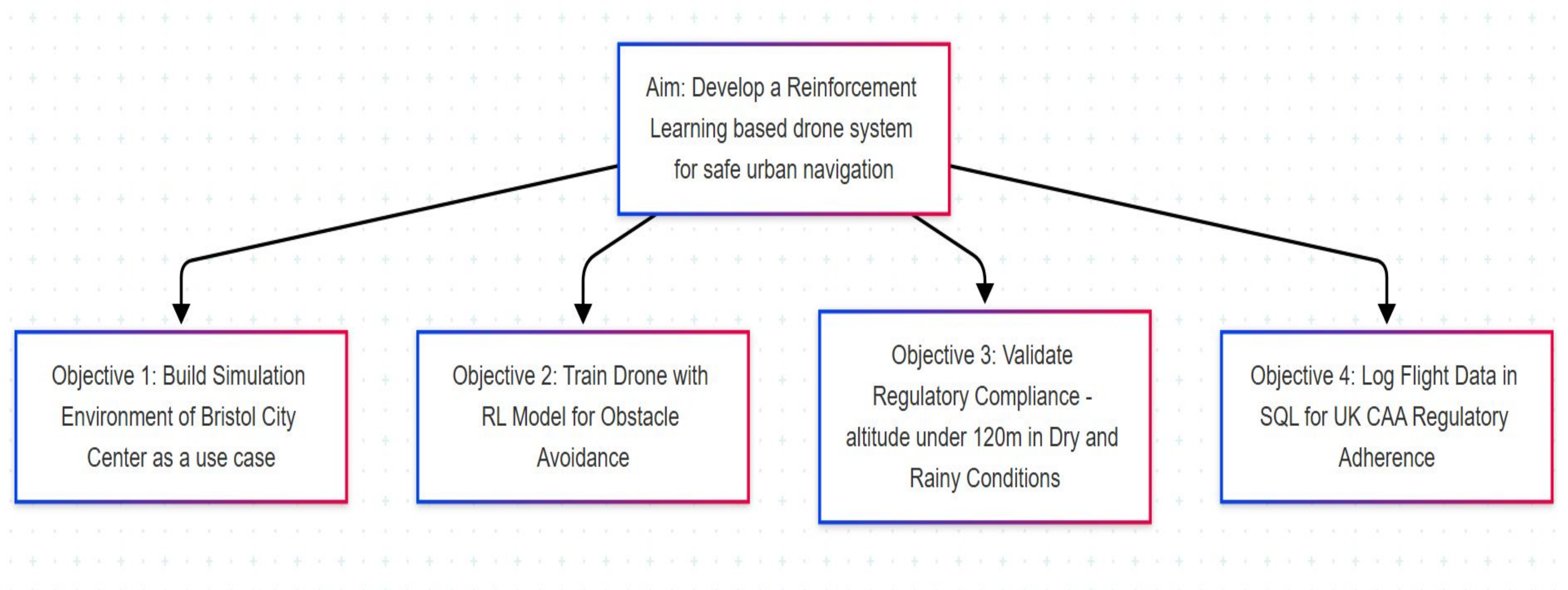
Aims & Objectives


Aim: Develop a Reinforcement Learning based drone system for safe urban navigation
Objective 1: Build Simulation Environment of Bristol City Center as a use case
Objective 2: Train Drone with RL Model for Obstacle Avoidance
Objective 3: Validate Regulatory Compliance - altitude under 120m in Dry and Rainy Conditions
Objective 4: Log Flight Data in SQL for UK CAA Regulatory Adherence

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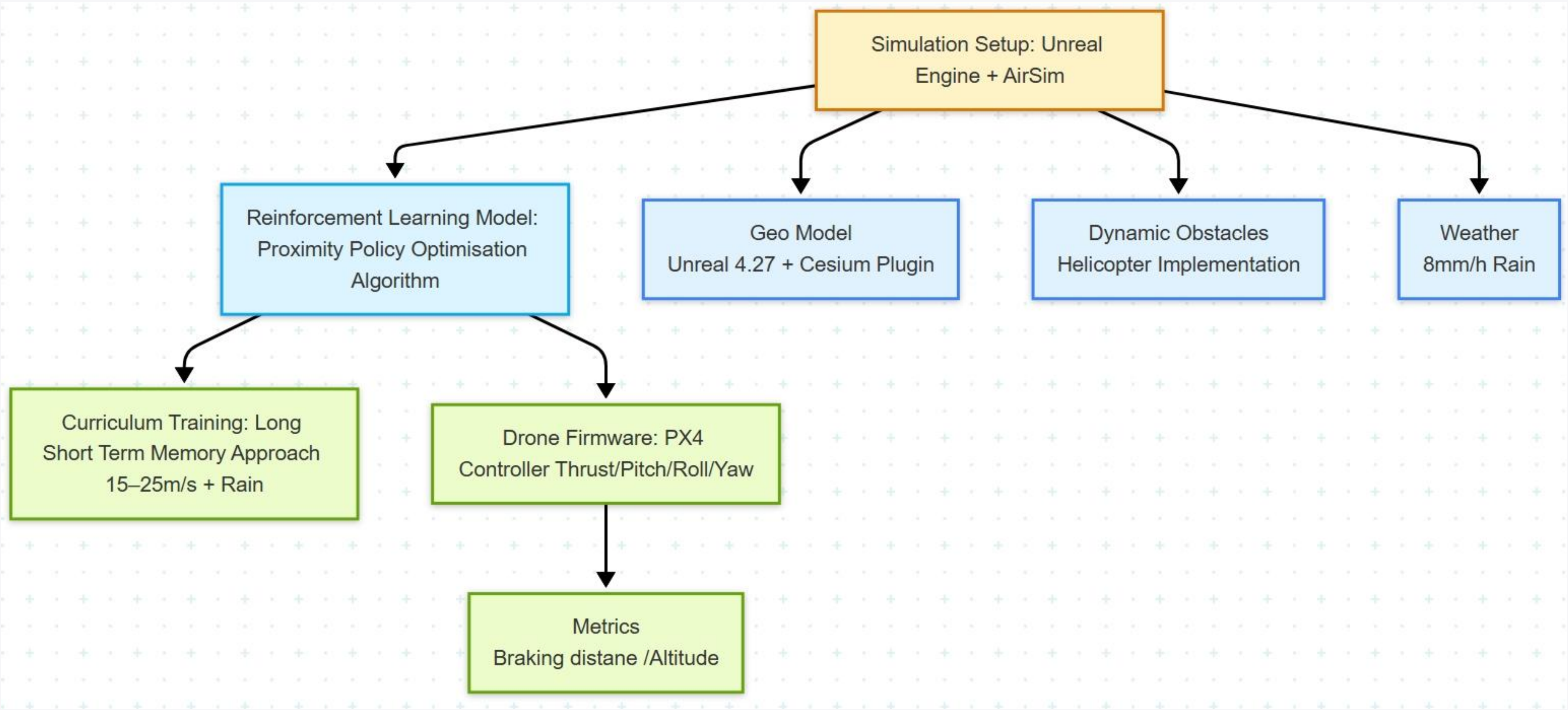
Methodology


Simulation Setup: Unreal Engine + AirSim
Reinforcement Learning Model: Proximity Policy Optimisation Algorithm
Geo Model
Unreal 4.27 + Cesium Plugin
Dynamic Obstacles
Helicopter Implementation
Weather
8mm/h Rain
Curriculum Training: Long Short Term Memory Approach 15–25m/s + Rain
Drone Firmware: PX4
Controller Thrust/Pitch/Roll/Yaw
Metrics
Braking distane /Altitude

Modelling of the Simulation Environment

Simulation Environment
❑ Created using **Cesium for Unreal Engine 4.27** with **AirSim** integration, allowing geo-accurate photogrammetry and high-resolution 3D urban modelling.   ❑ Featured **dynamic level-of-detail (LOD)** rendering and real-time geospatial streaming for performance and realism.   ❑ Included weather effects (rain), and regulatory constraints (altitude limits) to simulate real-world drone operations.

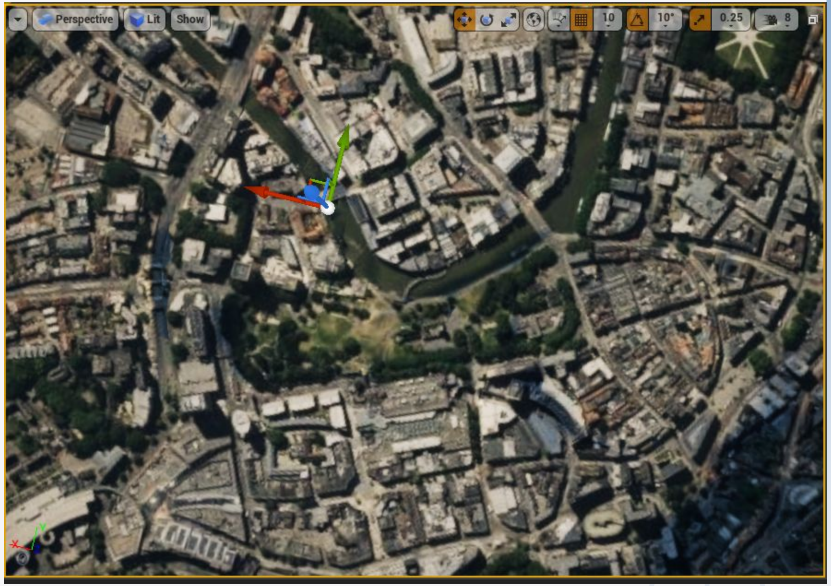


Figure 2: Modelled Environment in AirSim

Modelling the Dynamic Obstacle: Helicopter

Helicopter Implementation
❑ Imported as a **3D asset** with realistic **rotor dynamics** and **collision boundaries.** ❑ Followed a **preset flight path** below 120m using Unreal Engine’s waypoint system and behaviour trees, with a non-reactive AI controller. ❑ Used **asynchronous processing** to enhance simulation efficiency and maintain stable interaction between the helicopter AI and the simulation framework.

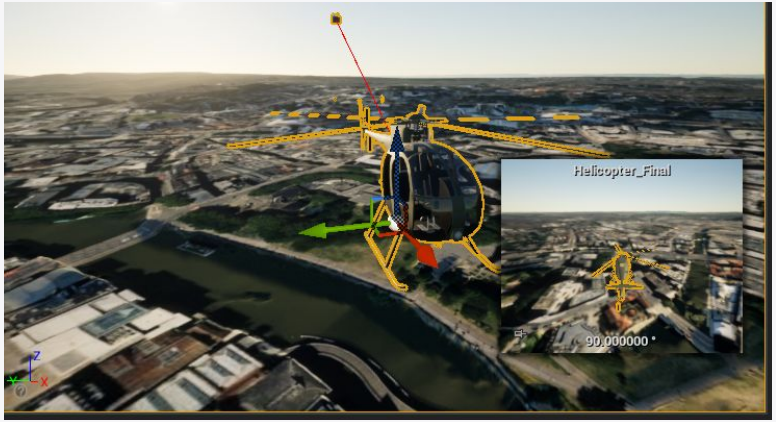


Figure 3: Modelled Helicopter in Unreal Engine

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Results & Analysis

Finetuning the Detection Accuracy through Training Episodes

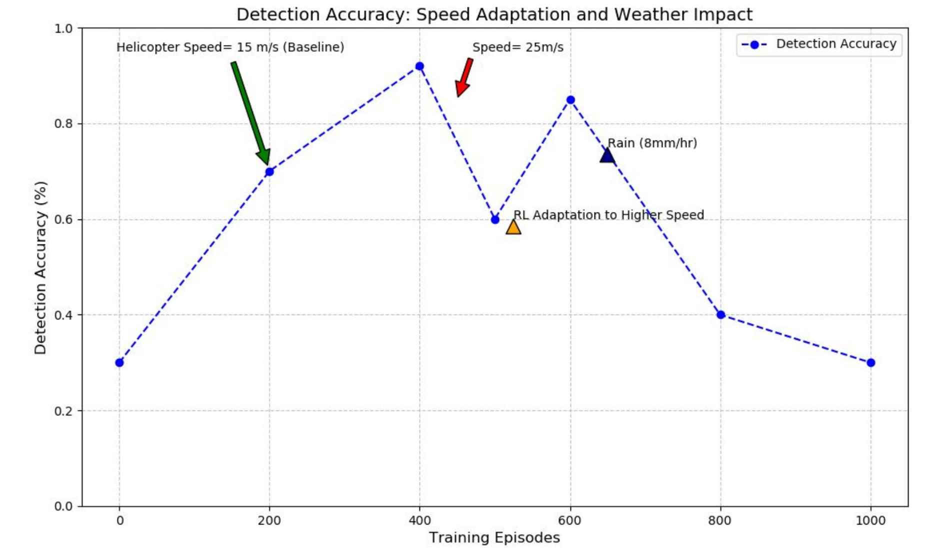


Figure 4: Variation in Reinforcement Learning Detection Accuracy Across Helicopter Speeds and Rain Conditions Over Training Episodes.

- The Proximal Policy Optimisation (PPO) algorithm initially achieved **92% detection accuracy** under **15 m/s** helicopter speed in **dry weather**.
- At a helicopter of a 25 m/s, it caused a **40% drop in accuracy**, falling to 60%, reflecting the RL agent's initial difficulty with rapid motion patterns.
- **Curriculum learning**, as supported by [3], enabled gradual adaptation to higher speeds, allowing the model to recover to 85% accuracy after continued training of approximately 1000 episodes.

Safe Drone Manoeuvring

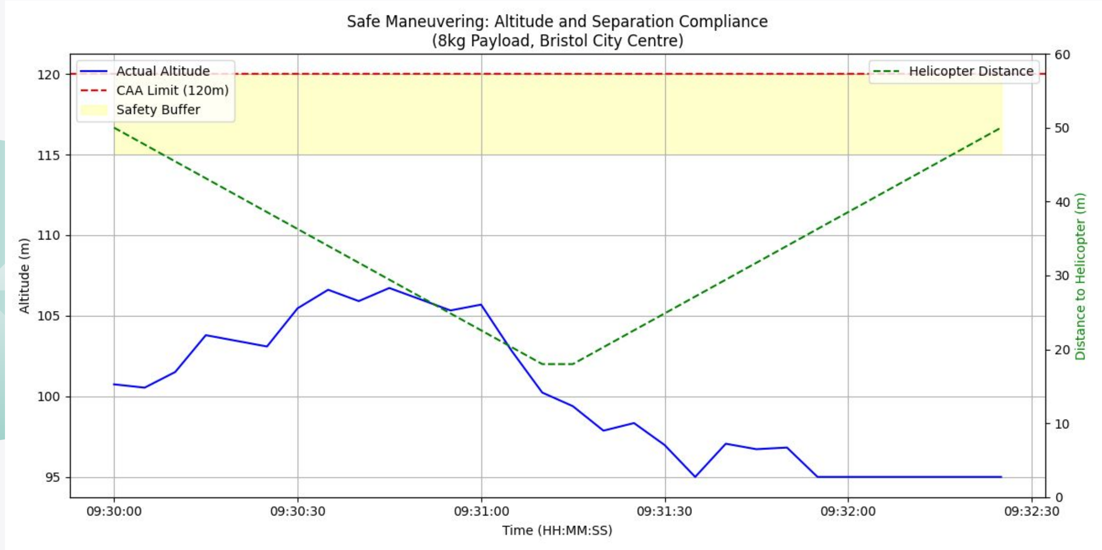


Figure 5: Drone Altitude and Distance from Helicopter when Manoeuvring in a clear weather with an 8 Kg Payload.

Altitude Compliance:

Drone maintained altitude between **95 m and 110 m**, safely above tallest building (90 m).

Stayed well below the **CAA legal limit of 120 m**, with an added safety buffer.

Separation from Helicopter:

Minimum separation distance reached ~20 m during maneuver.

Drone adjusted altitude downward in response, maintaining safe operation.

Regulatory & Operational Safety:

Demonstrated **adherence to UK airspace regulations**.

Drone Behaviour in a rainy Weather

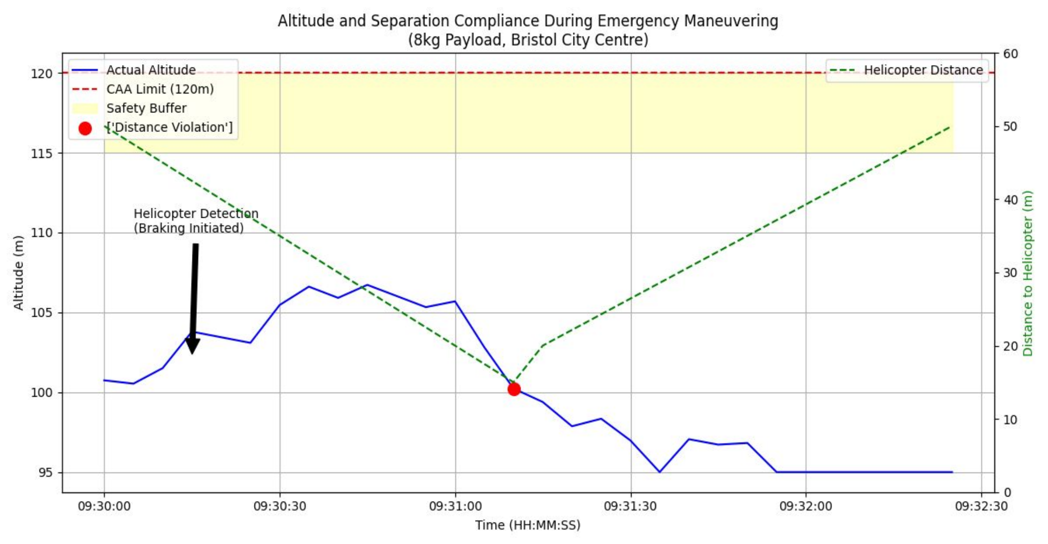


Figure 6: Drone Altitude and Distance from Helicopter when Manoeuvring in an 8mm/hr rainy weather.

- ❑ In dry conditions, the drone maintains the 15 m safety margin during emergency descent (Fig. 6).
- ❑ Rain causes proximity violation despite altitude compliance: red marker shows <15 m distance.

Impact of Weather on Drone Emergency Braking and Separation Compliance

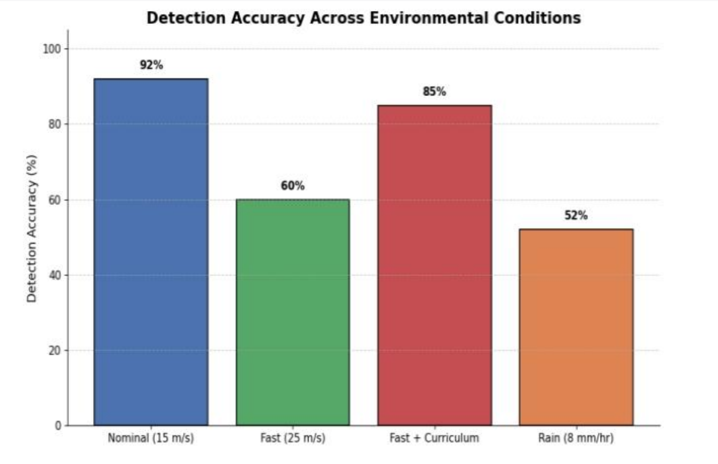
- **Braking distance increases** from 11.6 m (dry) to 19.3 m (rain): a 40% degradation (Table 1).
- Braking performance is independent of helicopter speed across 15–25 m/s.
- Highlights the need for stronger perception technique such as a camera- radar fusion in adverse weather to maintain regulatory safety.

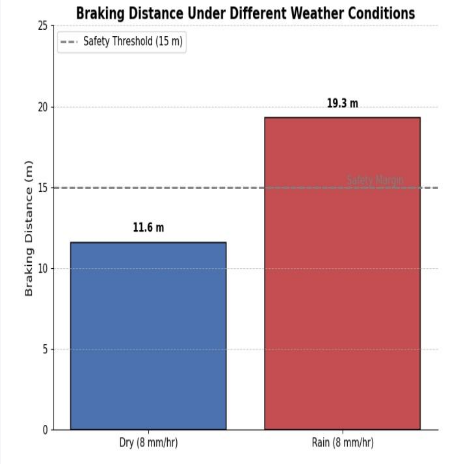
Table 1: Drone Braking Performance Cruising at 30 Km/hr During Helicopter Encounters

Helicopter Speed (m/s)	Scenario	Braking Distance (m)	Braking Time (s)
15	Dry	11.6	2.8
15	Rain (8 mm/hr)	19.3	4.6
20	Dry	11.6	2.8
20	Rain (8 mm/hr)	19.3	4.6
25	Dry	11.6	2.8
25	Rain (8 mm/hr)	19.3	4.6

Summary

Metric	Value/Status
Max Altitude	110 m
Min Altitude	95 m
UK CAA Max Altitude	120 m
N. Safety margin violation	1
Violation Circumstance	Rain (8mm/hr), Helicopter at 25 m/s
Braking distance in Violation	19.3 m
Safety Threshold	15 m
SQL used for	Logging of Drone Altitude and distance to helicopter
Violation Logged in SQL	With Time & Location saved





- ❑ Achieved **92% detection accuracy** under nominal conditions (15 m/s helicopter speed, dry weather).
- ❑ Curriculum learning enabled **85% accuracy recovery** after exposure to high-speed (25 m/s) Helicopter.
- ❑ Demonstrated **regulatory compliance**: altitude (95–110 m) within UK CAA limits and SQL-based flight logging.

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Limitations

Limitations

Category	Description
Perception	Reliance on *camera-only input*; struggles in rain (e.g., 40% braking degradation).
Dynamic Obstacles	Tested only helicopters; excluded UAV swarms, birds, and emergency aircraft.
Weather Scenarios	Rain (8 mm/hr) evaluated; fog, snow, and low-light conditions not tested.
Regulatory Logging	SQL database tracked compliance but lacked *real-time feedback* for adjustments.
Sensor Realism	No modeling of sensor noise, GPS drift, or latency.

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Conclusion

Conclusion

Key Contributions

- **High-Performance RL Navigation**: Achieved **92% detection accuracy** under nominal conditions (15 m/s helicopter, dry weather).
- **Adaptability via Curriculum Learning**: Recovered to **85% accuracy** after exposure to 25 m/s obstacles.
- **Regulatory Compliance**: Maintained altitude (95–110 m) within UK CAA limits and logged flight data via SQL.

Metric	Dry Weather	Rain (8 mm/hr)
Detection Accuracy	92%	60%
Horizontal Separation	~20 m	<15 m (violation)
Braking Distance	11.6 m	19.3 m

Critical Challenges

- **Weather Vulnerability**: Rain caused **40% braking degradation**, violating safety margins.
- **Perception Limits**: Camera-only input struggled in adverse conditions.
- **Dynamic Obstacle Gaps**: Limited to helicopters; excluded UAV swarms, birds.

Implications for Urban Drone Logistics

- Validates RL's potential for safe, regulation-aware navigation in dynamic urban airspace.
- Highlights urgent need for multi-sensor fusion (e.g., radar/camera) and weather-resilient training.

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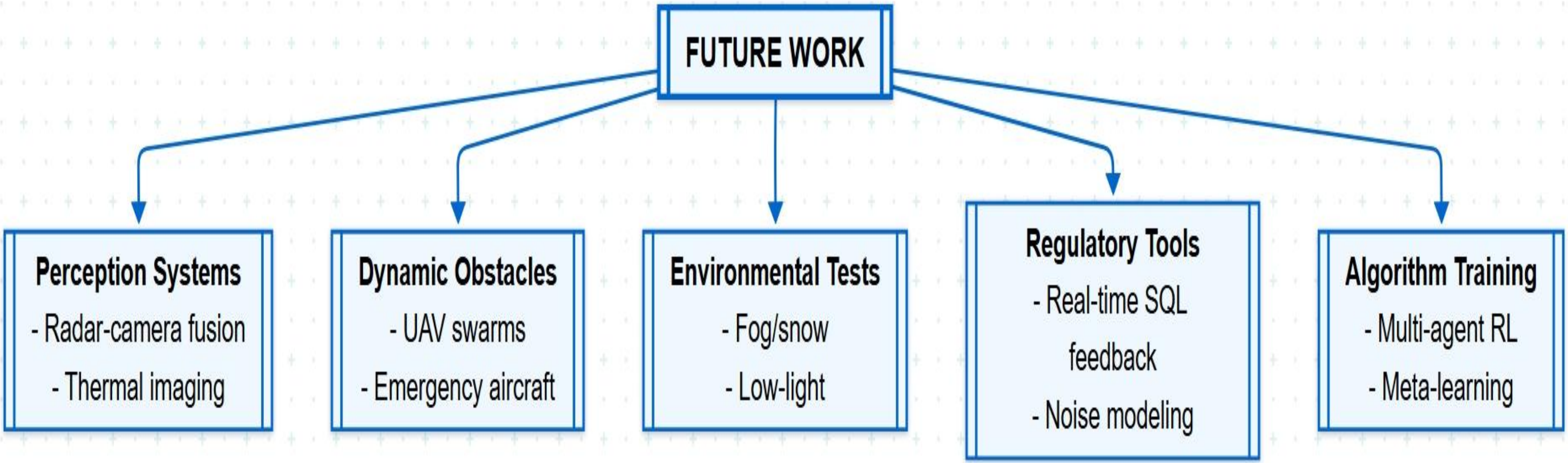
Future Work


FUTURE WORK
Perception Systems
- Radar-camera fusion
- Thermal imaging
Dynamic Obstacles
- UAV swarms
- Emergency aircraft
Environmental Tests
- Fog/snow
- Low-light
Regulatory Tools
- Real-time SQL feedback
- Noise modeling
Algorithm Training
- Multi-agent RL
- Meta-learning

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Thank you