ASEAN FAW ACTION PLAN
Supporting IPM Across Southeast Asia

Drones and Digital IPM

Webinar Series
Part 2: 28 November 2024

Supported by
Australian Government
Department of Foreign Affairs and Trade

The session will be recorded.
A copy will be shared 1 week after this session.

Technical issues?

- **Audio**
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    (if using a mobile phone) and make sure it is on
  - Check connection to speaker
    (if using a desktop/laptop)
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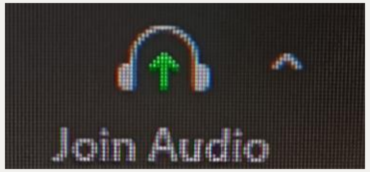
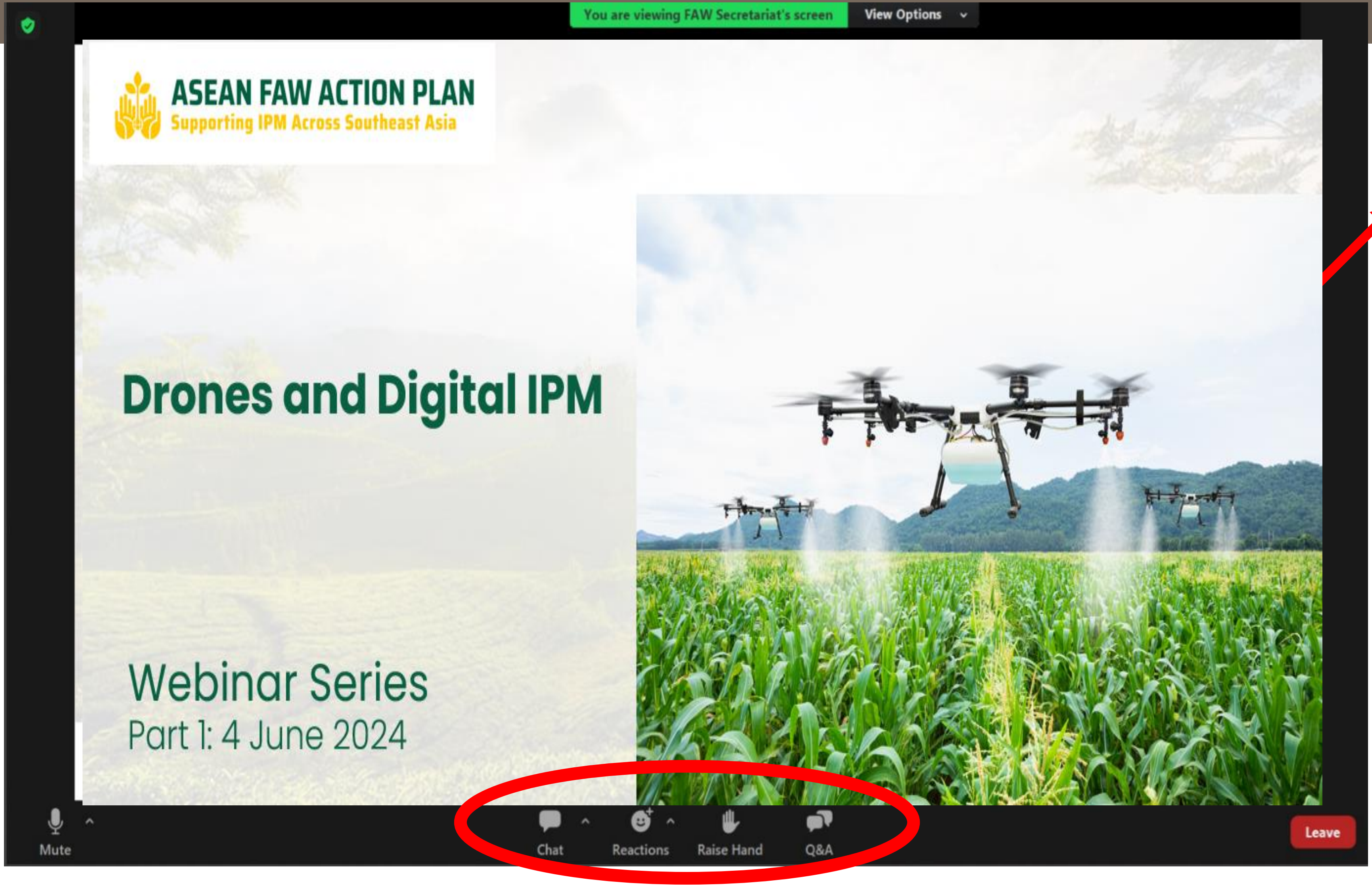


A recording of the webinar will be made and be distributed
See www.aseanfawaction.org/drones-and-digital-ipm



1. Use the **Q&A box** to ask questions to the speakers

2. Use **Chat** to make a comment to everyone (e.g. thank a speaker, share a link, highlight an important point)

3. Use **Reactions** if you want to share a reaction quickly – thumbs up, congratulations, etc.

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Agenda

Time (SGT)	Agenda	Speaker
10:00	**Welcome & Remarks**	ASEAN Action Plan – Dr Alison Watson
10:10	**Drones for Climate-Resilient Rice Production in the Mekong Delta**	**Dr Nguyen The Cuong** | Mekong Delta Rice Research Institute (CLRRI), Vietnam
10:30	**Q & A Session**	
10:45	**Swarm Technology and Autonomous Drone Innovation**	**Dr Richard Han** | Macquarie University, Australia.

Time (SGT)	Agenda	Speaker
11:05	**Q & A Session**	
11:25	**Closing**	ASEAN Action Plan – Dr Alison Watson
11:30	**End**	

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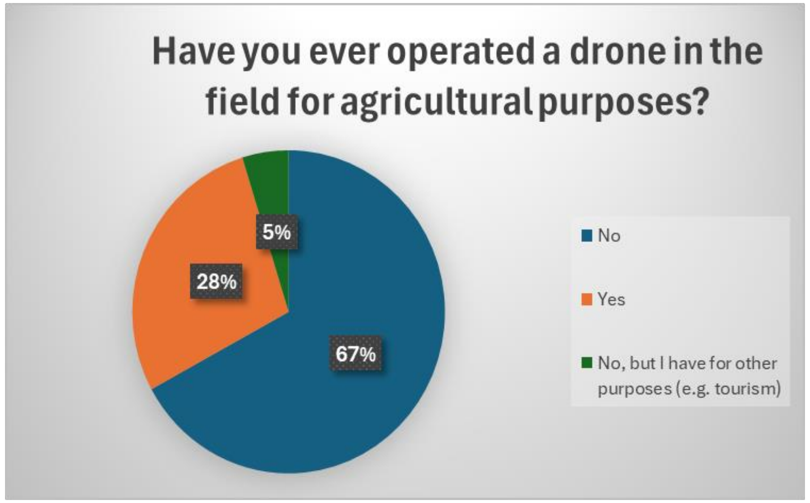
Poll

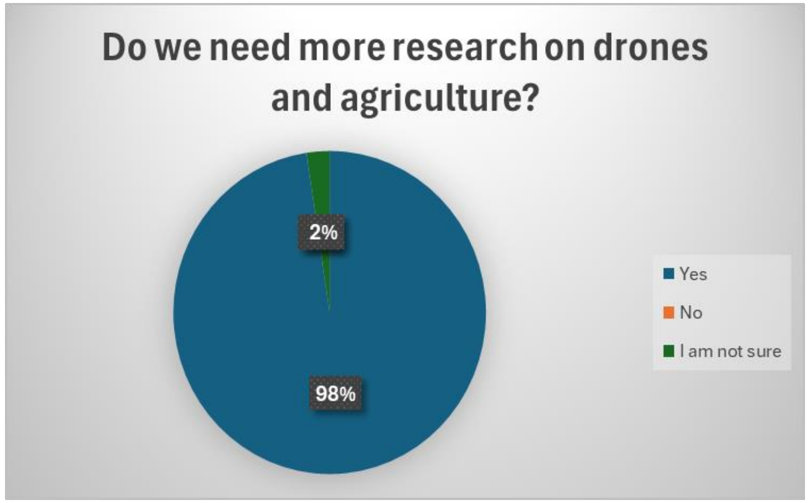
1. Who has operated a drone in the field for agricultural purposes?

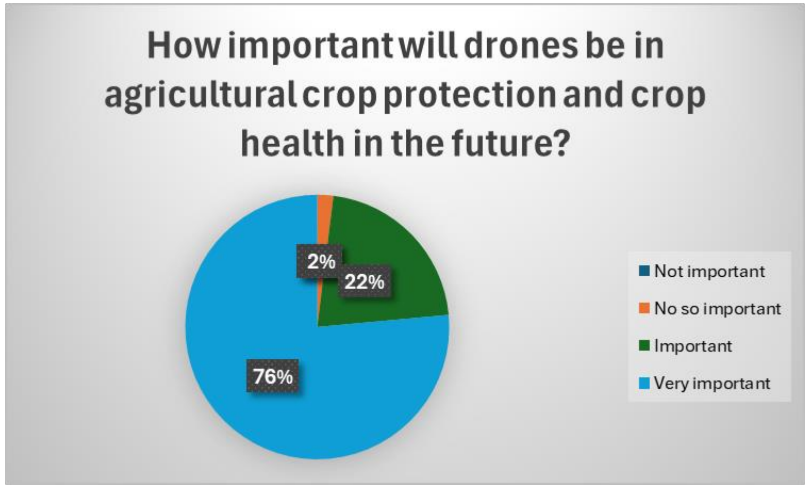
2. How important will drones **be** in agricultural crop protection and crop health in the future?

3. Do we need more research on drones and agriculture?

4. Do we need more standards around drone use for agricultural practices in the field?







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Poll

1. Who has operated a drone in the field for agricultural purposes?

2. How important do you think proper training is for people to fly drones for agricultural purposes?

3. Should agricultural drone pilots be registered?

4. Should pesticide application by drones be regulated? (e.g. rules around who can apply pesticides by drones, standards that must be applied and safety rules that have to be followed)

Session 2: Thursday 28h November from 10:00 to 11:30

Drones for Climate-Resilient Rice Production in the Mekong Delta

Our Speaker:

Dr Nguyen The Cuong | Mekong Delta Rice Research Institute (CLRRI), Vietnam

Swarm Technology and Autonomous Drone Innovation

Our speaker

Dr Richard Han | Macquarie University, Australia.

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Drones and IPM Webinar Series 2024

Drones for Climate-Resilient Rice Production in the Mekong Delta

Nguyen The Cuong
Cuu Long Delta Rice Research Institute
Can Tho City, Vietnam

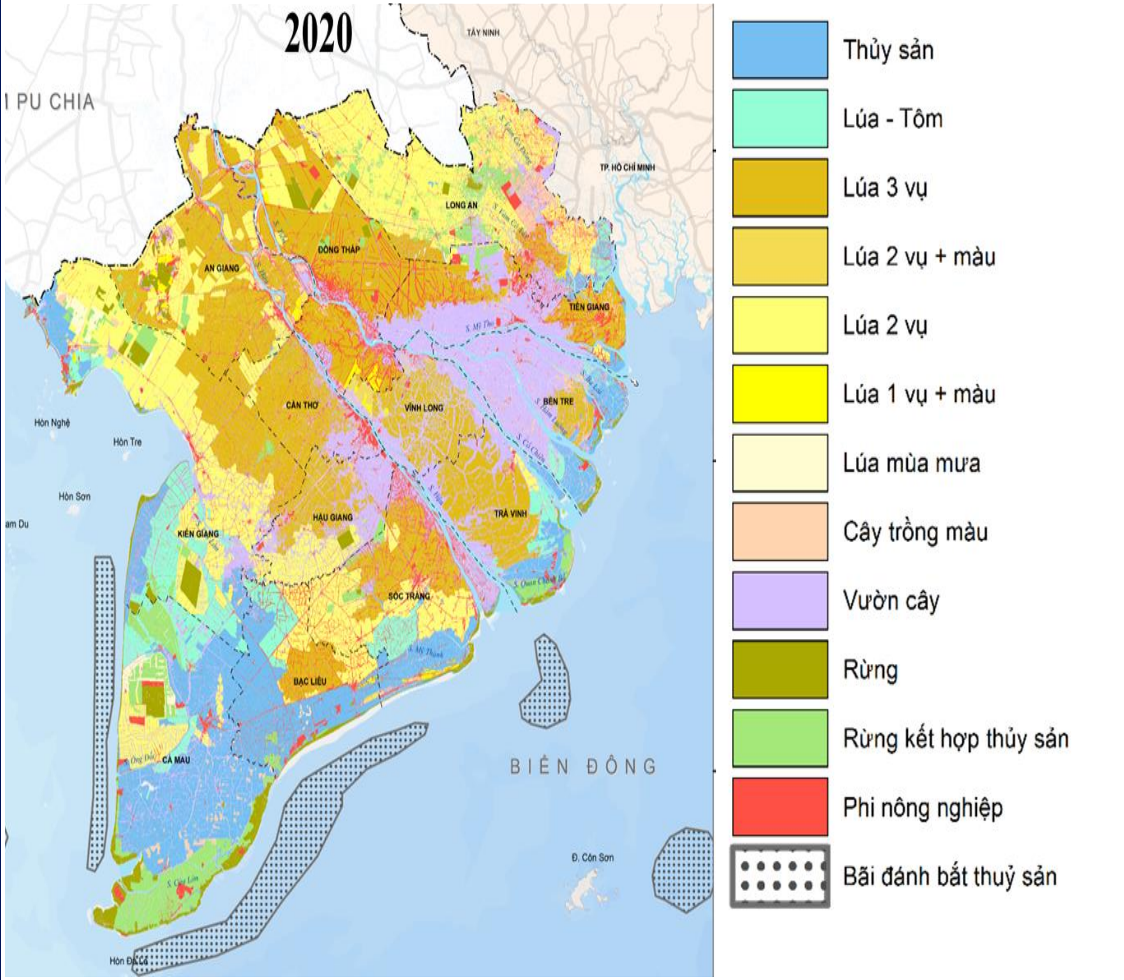
28 November 2024

Content




https://phuongtindrone.vn/

The Mekong Delta – The Rice Bowl of Vietnam



Source: Ministry of Planning and Investment, 2020

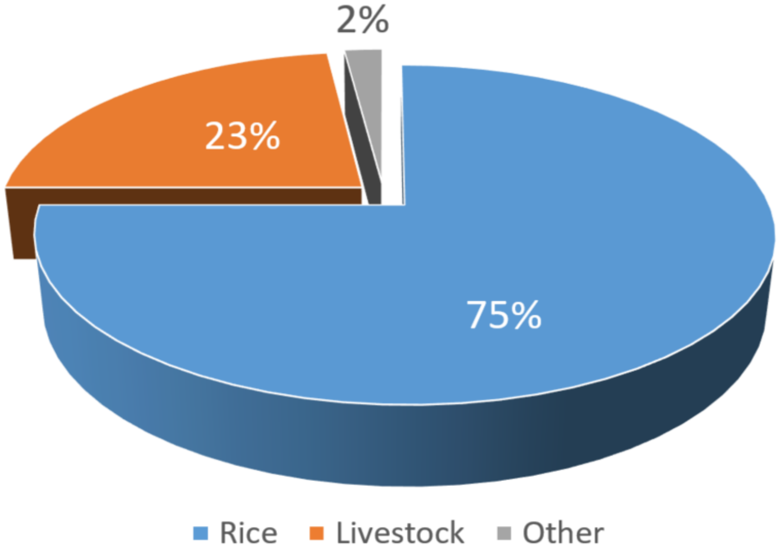
Rice Production in the Mekong Delta

Rice land:	1.7 million ha
Sowing area:	3.9 million ha/ year
Triple rice/year area:	700.000 ha
Total production:	23.8 million tons
	56% of VN rice production
	90% of total export volume
Average yield:	6.1 ton/ha
Rice ecosystem:	Diverse environments

VIỆN LÚA ĐỒNG BẰNG SÔNG CỬU LONG 1977 CLRRI

Major Challenges in Rice Production

- Climate change impacts
- Soil and water degradation
- High GHG emission
- Pest and disease outbreaks
- Inefficient resource use
- Market volatility
- Labor shortages
- High input costs



Methane emission in Agriculture (Source: MONRE. 2020)

Drone Application in Rice Production

Direct Field Operations

- ❑ Seeding
- ❑ Fertilizer application
- ❑ Pesticide spraying

Monitoring and Analysis

- ❑ Crop monitoring
- ❑ Water management
- ❑ Disease detection
- ❑ Yield estimation
- ❑ Field mapping
- ❑ Soil analysis
- ❑ Assist GHG measurement

Benefits of Drone in Rice Production

- ❑ Increasing efficiency
- ❑ Reducing labor dependency.
- ❑ Precision application
- ❑ Reducing water and chemical waste.
- ❑ Reduce health risk for workers

Align with Climate Goals

- ❑ Minimizing GHG emissions
- ❑ Promoting sustainable practices: Precision agriculture, Enhancing soil health, Monitoring and early detection; Reduce health risk for workers
- ❑ Supporting climate-resilient practices: Data-driven decisions, small holder inclusive

VN Drone Market & Application in the Mekong Delta Rice Production

Vietnam agricultural drones market (AgriTechDigest, 2024)

- USD 4.84 million in 2021
- USD 18.11 million by 2028
- Annual Growth Rate 21.1%
- Estimated number of agri. drones 6,000 (rice, fruit trees, banana, coffees …)

Trend of drone application in the Mekong Delta rice sector

2018

Plant protection
Foliar fertilizing

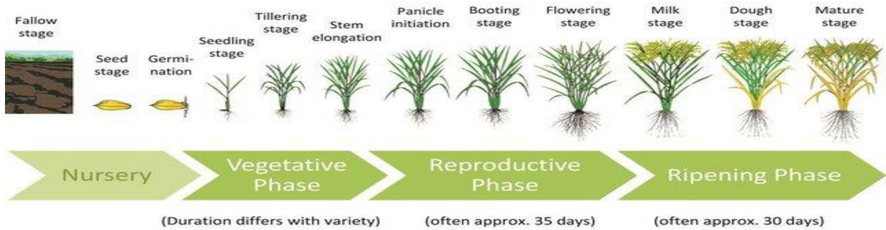
2023

Plant protection
Seeding
Fertilizing

Now -> Future

- Direct application
- Crop, soil and water monitoring & analysis
- GHG monitoring & analysis
- Assist development of new varieties (phenotyping)

Drone Application in the MD Rice Production



Drone Application

- Golden snail

- Fertilization (NPK-granule)
- Foliar fertilizers (liquid)

Land preparation → Crop establishment → Fertilization → Plant protection → Harvesting

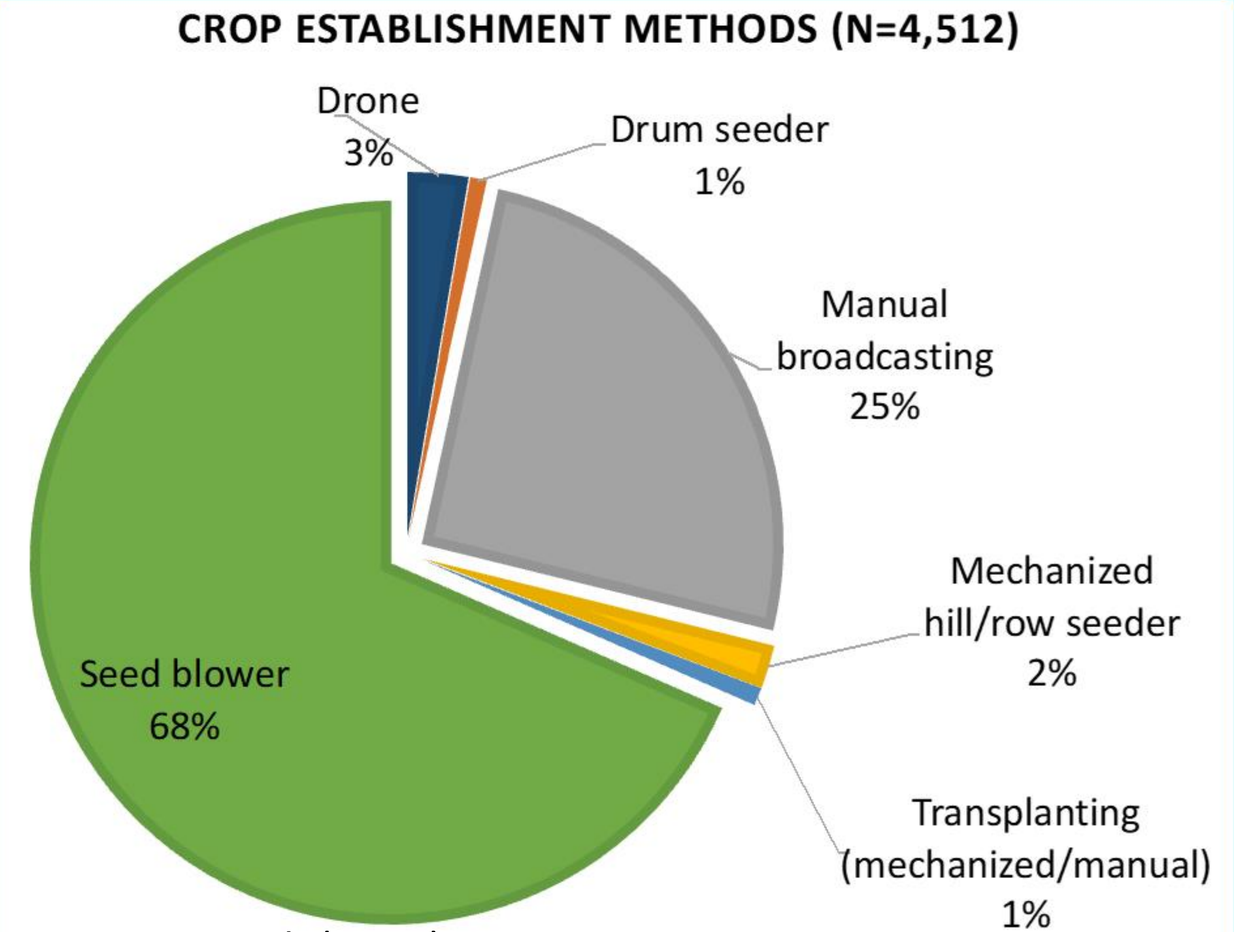
Crop establishment:
- Seeding
- Pre-emergent herbicide
- Post-emergent herbicide

Plant protection:
- Pesticides
- Fungicides

Advantages of Drones in Rice Production in the MD Context:

- Effectively address labor shortages, particularly during peak periods
- Suitability for challenge areas: muddy and water logged areas in MD, which is difficult for large machines
- Enable uniform, concentrated and synchronized sowing across large areas quickly to avoid bad weather, improve water management, optimize input use, enhance pest control, and ultimately improve rice quality for whole sale or export.
- Reduce rice yield loss by 150 - 200 kg/ha compared to conventional spraying methods, as drones eliminate the need for trampling rice plants while walking through the fields.

Drone for Direct Application in Rice Production in the MD



An. Hung. et al. (2024)

Early 2024 - Survey

- Seeding: 3% area ~ 117.000 ha

Estimation:

- Fertilizing: 3 x 3% area ~ 351.000 ha
- Spraying: at least 5 x 3% area ~ 585.000 ha
- Old spraying drones: > 600.000 ha

Drone for Direct Application in Rice Production in the MD: Case Study at Cuu Long Delta Rice Research Institute

Treatment	Seeding rate	Fertilizer
T1 (DRONE)	60 kg/ha	**Fertilizer rate 80 N – 40 P_2O_5 – 30 K_2O (kg/ha):** First application (7-10 DAS): 40% N + 50% P_2O_5 + 50% K_2O; Second application (22-25 DAS): 30% N + 50% P_2O_5; Third application (42-45 DAS): 30% N + 50% K_2O
T2 (DRONE)	60 kg/ha	**Fertilizer rate 80 N – 40 P_2O_5 – 30 K_2O (kg/ha):** First application (basal application): 70% N + 100% P_2O_5 + 50% K_2O; Second application (42-45 DAS): 30% N + 50% K_2O
T3 (DRONE)	80 kg/ha	**Fertilizer rate 80 N – 40 P_2O_5 – 30 K_2O (kg/ha):** First application (7-10 DAS): 40% N + 50% P_2O_5 + 50% K_2O; Second application (22-25 DAS): 30% N + 50% P_2O_5; Third application (42-45 DAS): 30% N + 50% K_2O
T4 (Regular practice)	150 kg/ha	**Fertilizer rate 100 N – 90 P_2O_5 – 50 K_2O (kg/ha) (blower backpack machine):** First application (3-4 DAS): 10% N; Second application (10-12 DAS): 35% N + 40% P_2O_5; Third application (22-25 DAS): 45% N + 60% P_2O_5; Fourth application (42-45 DAS): 10% N + 100% K_2O
T5 (Cluster seeding machine)	60 kg/ha Row 20cm x cluster 13 cm	***Application of cluster seeding machines combined with deep fertilizer incorporation.*** **Fertilizer rate 80 N – 40 P_2O_5 – 30 K_2O (kg/ha):** First application: seeding time. 70% N + 100%P + 50% kali; Second application: 37- 42DAS 30% N + 50% K. blower backpack machine. Fertilizer incorporate depth: ~5cm

(CLRRI - Thach Tran et al. 2024)

Drone for Direct Application in Rice Production in the MD: Case Study at Cuu Long Delta Rice Research Institute

Seeding by Drone

Seeding by Cluster Seeding Machine
Incorporated with fertilizer deep placement

(CLRRI - Thach Tran et al. 2024)

Drone for Direct Application in Rice Production in the MD: Case Study at Cuu Long Delta Rice Research Institute

T1 (Drone)
60 kg/ha

T2 (Drone)
60 kg/ha
Fertilizer deep placement

T3 (Drone)
80 kg/ha

T4 (Seed Blower)
150 kg/ha

T5
60 kg/ha
Cluster seeding
Fertilizer deep placement

(CLRRI - Thach Tran et al. 2024)

Drone for Direct Application in Rice Production in the MD: Case Study at Cuu Long Delta Rice Research Institute

(CLRRI - Thach Tran et al. 2024)

Drone for Direct Application in Rice Production in the MD: Case Study at Cuu Long Delta Rice Research Institute

T1 (Drone)
60 kg/ha

T2 (Drone):
60 kg/ha
Fertilizer deep placement

T3 (Drone)
80 kg/ha

T4
150 kg/ha
(Seed Blower Machine)

T5: 60 kg/ha
Cluster seeding
Fertilizer deep placement

(CLRRI - Thach Tran et al. 2024)

Table. Yield components and yield across treatments

TreatmeT	No. of panicle /m^2	No. filled grains/panicle	Predicted yield (t/ha)	Actual yield (t/ha)
T1	371	84.6	7.53	5.64
T2	379	86.5	7.85	**5.89**
T3	407	81.0	7.56	5.67
T4	365	77.5	7.09	5.32
T5	420	74.1	7.46	5.59

(CLRRI - Thach Tran et al. 2024)

Table. Cost and benefit calculation across the treatments

(CLRRI - Thach Tran et al. 2024)

Categories	T1	T2	T3	T4	T5
I. Total cost (VN đ/ha)	**28.475.300**	**28.173.300**	**29.035.300**	**33.974.600**	**28.081.321**
1. Input (VN đ/ha)	*9.610.500*	*9.468.500*	*10.120.500*	*13.764.500*	*9.520.582*
- Rice seed	1.080.000	1.080.000	1.440.000	1.440.000	1.080.000
+ Seeding rate (kg/ha)	60	60	80	150	60
+ Seed cost (VN đ/kg)	18.000	18.000	18.000	18.000	18.000
- Fertilizers	4.281.000	4.281.000	4.281.000	7.705.000	4.281.000
- Pesticides	4.249.500	4.107.500	4.399.500	4.619.500	4.159.582
2. Labor (VN đ/ha)	*18.864.800*	*18.704.800*	*18.914.800*	*20.210.100*	*18.560.739*
II. Total income	**50.805.000**	**52.983.000**	**51.039.000**	**47.853.000**	**50.319.000**
- Yield (kg/ha)	5.645	5.887	5.671	5.317	5.591
- Rice price (VN đ/kg)	9.000	9.000	9.000	9.000	9.000
III. Net income (VN dong)	**22.329.700**	**24.809.700**	**22.003.700**	**13.878.400**	**22.237.679**
VI. Investment efficiency	**1.78**	**1.88**	**1.76**	**1.41**	**1.79**

Drone Capacity and Service Costs by Activities

No	Activities	Unit	Drone capacity (ha/day)	Price (VN dong)		Difference (VN dong)
				Drone	Labor	
1	Seeding	ha	50	500,000	550,000	50,000 ~ 2USD/ha
2	Pesticide spraying	ha	50	150,000	270,000	120,000 ~ 4.8USD/ha
3	Fertilizing	kg	60	2,000	2,500	500 ~ 0.02USD/kg

(CLRRI - Thach Tran et al. 2024)

Costs of Seeding, Fertilizing, and Spraying Services

No	Activities	Unit	Drone		Labor		Different
			Price	Cost	Price	Cost	
1	Seeding	dong/ha	500.000	500.000	550.000	550.000	-50.000
2	Spraying (7 times/season)	dong/ha	150.000	1.050.000	270.000	1.890.000	-840.000
3	Fertilizing (500 kg/ season)	dong/kg	2.000	1.000.000	2.500	1.250.000	-250.000
Total save by Drone (per ha):							-1.140.000 ~ 46USD (-30.1%)

(CLRRI - Thach Tran et al. 2024)

Challenges in Implementation of Drones in Rice Production

- **Economic constraints**: High costs for purchase, maintenance, and lack of financing options.
- **Technical challenges**: Complex operation and repair, limited battery life, and weather dependence.
- **Regulatory barriers**: Unclear policies and lack of standardization for agricultural drones.
- **Social resistance**: Hesitation to adopt new technologies and limited awareness among farmers.
- **Environmental issues**: Flooded fields, small fragmented farms, and disposal of drone components (e.g. battery).
- **Data limitations**: Lack of expertise for data analysis and poor internet connectivity in rural areas.
- **Sustainability concerns**: Dependence on imported technology and lack of local expertise.

Addressing Drone Implementation Challenges in the Mekong Delta

- **Capacity building**: Train farmers and technicians in drone use and maintenance, especially safety.
- **Financial support**: Provide subsidies, loans, and cooperative cost-sharing models.
- **Regulatory support**: Develop clear policies (regulation, insurance etc.) and operational guidelines for drones.
- **Localized solutions**: Design drones tailored to Delta's environmental conditions.
- **Infrastructure development**: Establish local repair centers and improve connectivity.
- **Awareness campaigns**: Educate farmers on benefits and ease of drone adoption.
- **Public-Private Partnerships**: Collaborate with tech companies and NGOs for scaling.

SOCIETY classical weather Vietnam sport Miss International Queen

Drone entangled in power transmission line causes massive blackout in southern Vietnam

Tuesday, October 15, 2024, 15:36 GMT+7

A drone crashed into a 110kV power transmission line in Long An Province, southern Vietnam, causing a power blackout for 76,000 households and units in the province. Photo: Long An Power Company

A drone that a local resident used to spray pesticides crashed into a 110kV power transmission line in Long An Province, located in southern Vietnam, causing a power blackout for 76,000 households and units in five districts across the province on Sunday.

Highlights

In Vietnam, Buddhist 'phenomenon' Thich Minh Tue says will halt alms-receiving activities


CLRRI
THANK YOU FOR LISTENING

MQ DrONE Lab.

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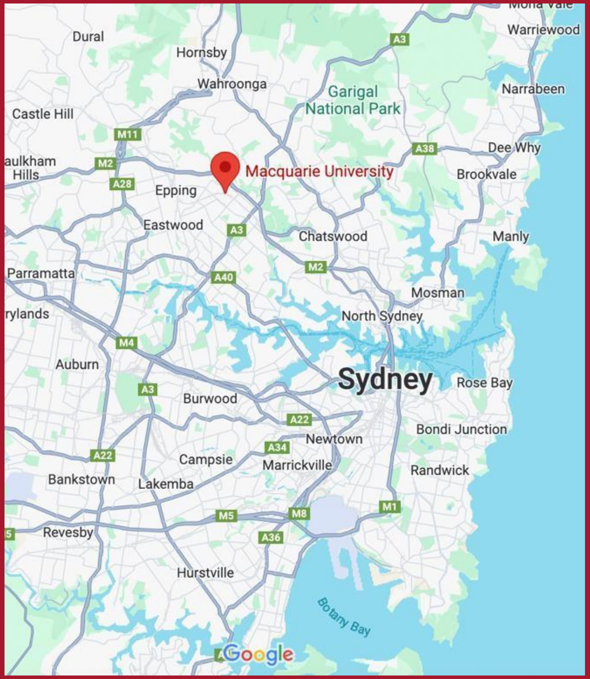
Projects in Autonomous Drone Systems

Professor Richard (Rick) Han

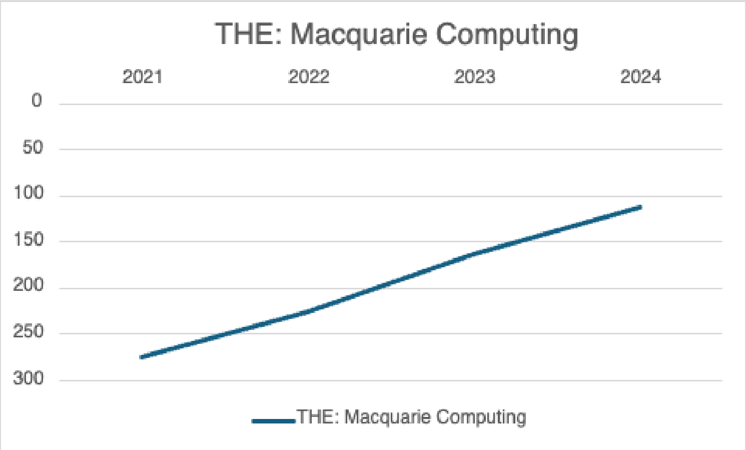
Macquarie University, School of Computing



Macquarie University School of Computing

MACQUARIE University SYDNEY·AUSTRALIA

- ❑ THE (Times Higher Education) World University Rankings, Computer Science



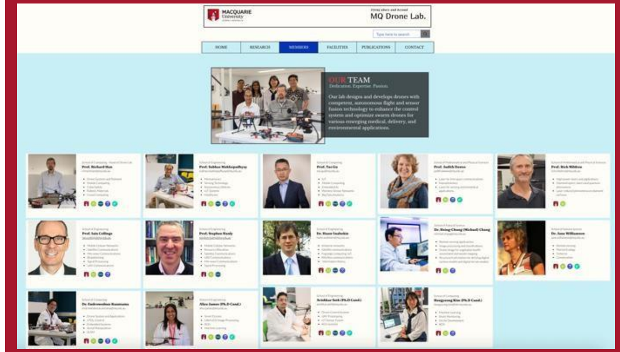
- ❑ many hires, strong in AI/ML, Data Science, NLP, security, & mobile computing
  - ❑ Tao Gu Mobicom chair 2022, Sydney, IEEE Fellow
  - ❑ Mobile Computing CS rankings.org #48 world/#1 Australia

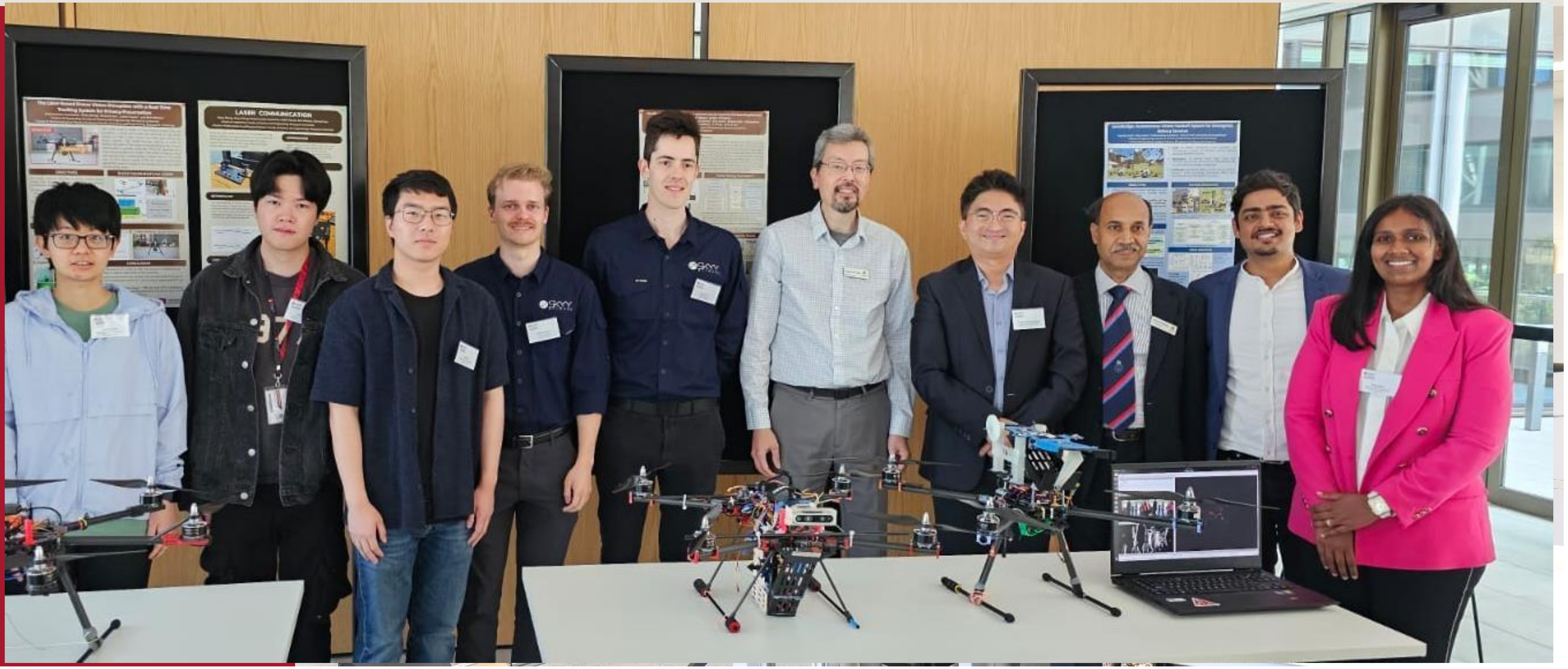
Introduction to MQ Drone Lab

Professors Richard Han, Endrowedness Kuantama, Subhas Mukhopadhyay (IEEE Fellow)

www.mqdronelab.com

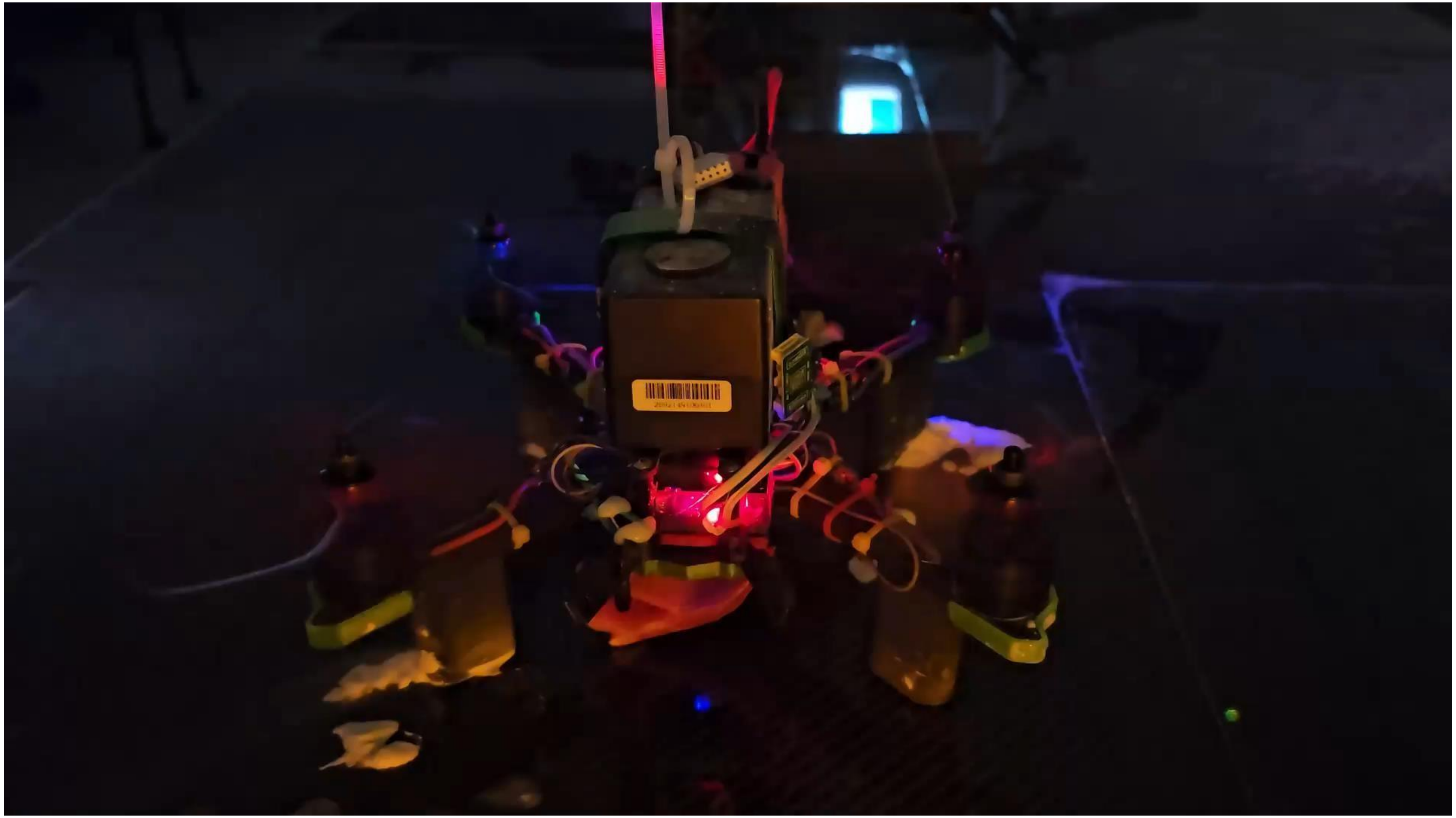
@ our Drone Industry Workshop





MQ Drone Lab Facilities

www.mqdronelab.com



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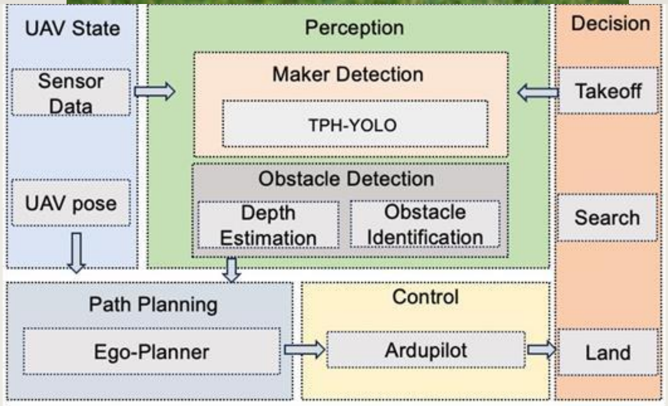
Macquarie Drone Lab Research Projects

mqdronelab.com

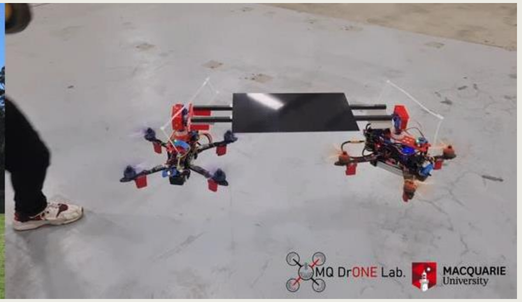
Performance

Safety



Autonomous

Cooperative Swarms



Collaborative Drone Swarm Lift & Transport

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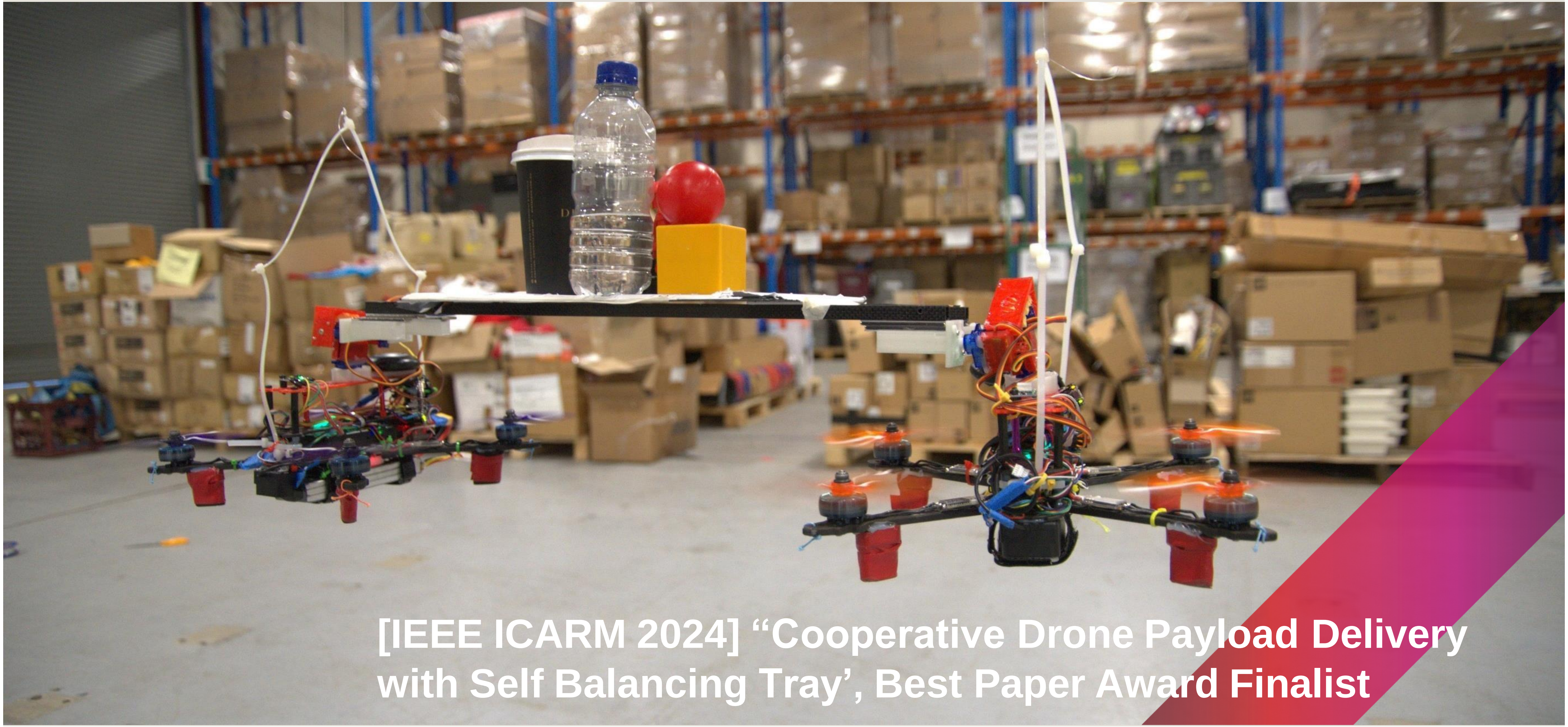
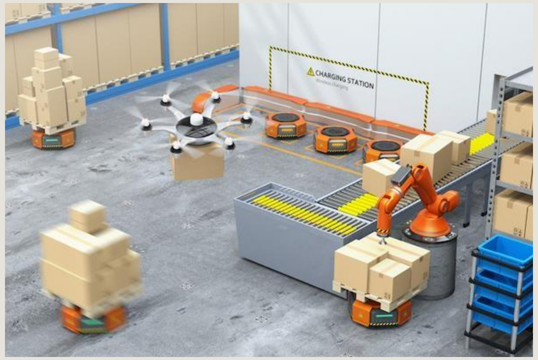


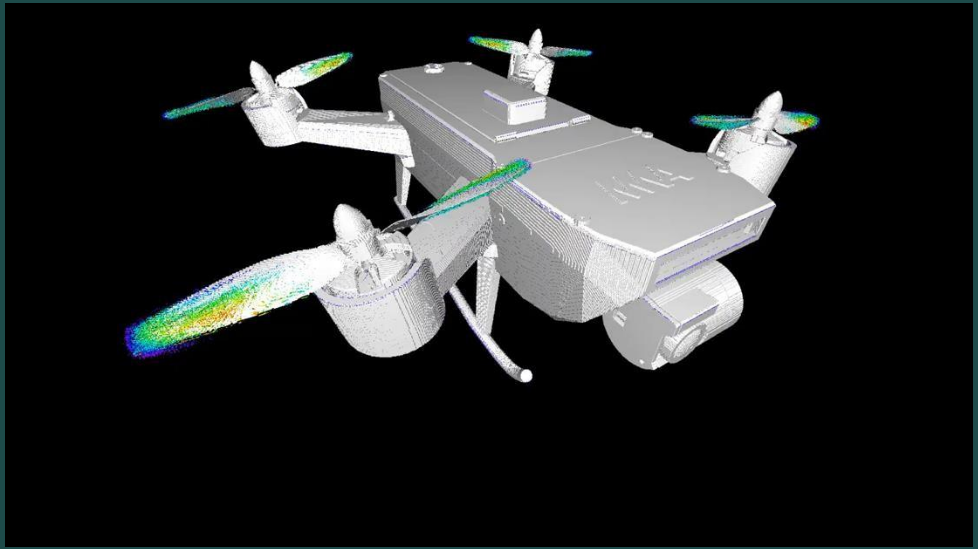
[IEEE ICARM 2024] "Cooperative Drone Payload Delivery with Self Balancing Tray', Best Paper Award Finalist

Limitations of Lift Mechanisms



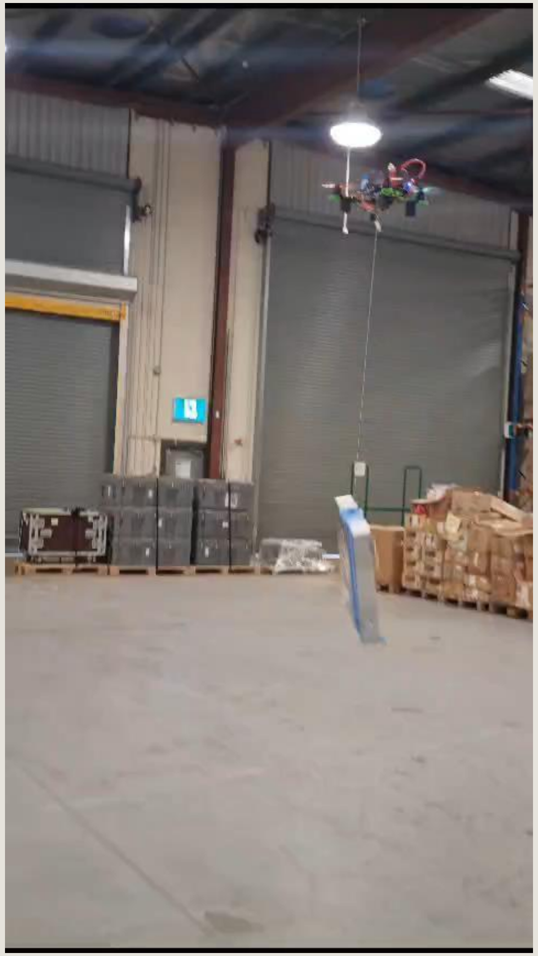
DRONE CHALLENGE:

- LIMITED DRONE PAYLOAD
- SMALL SPACE FOR PAYLOAD [CENTRE OF GRAVITY & AIRFLOW]

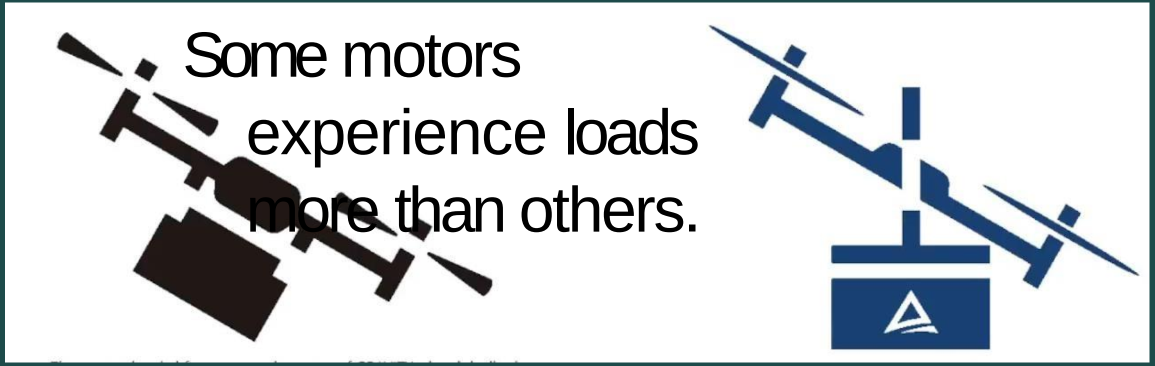


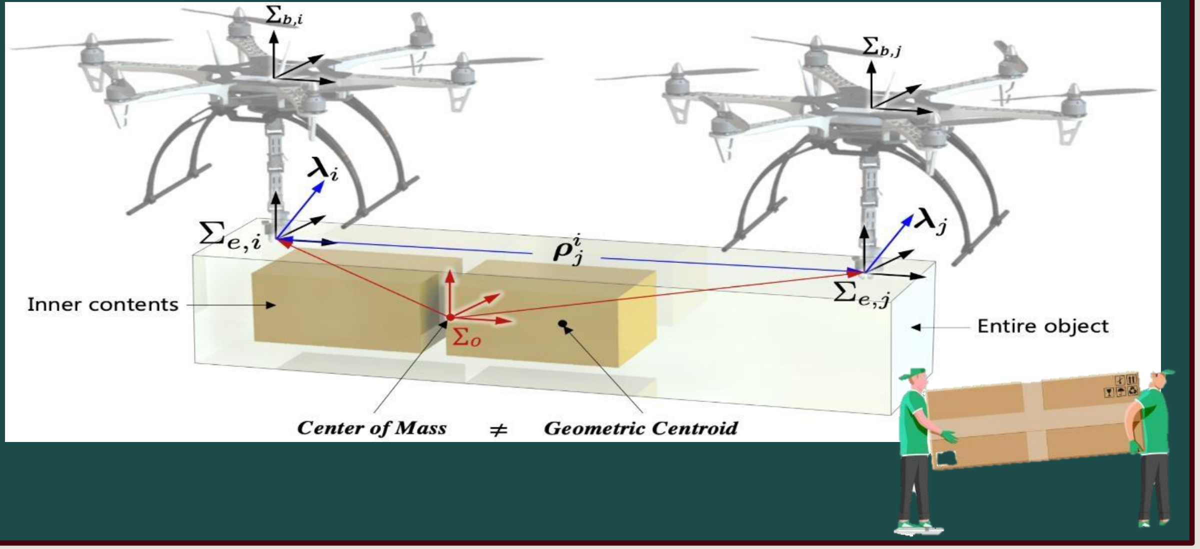
Challenges of Drone Lift

PROBLEM - CENTRE OF GRAVITY & AIRFLOW



BALANCE LIFT





Drone Swarm Lift Design

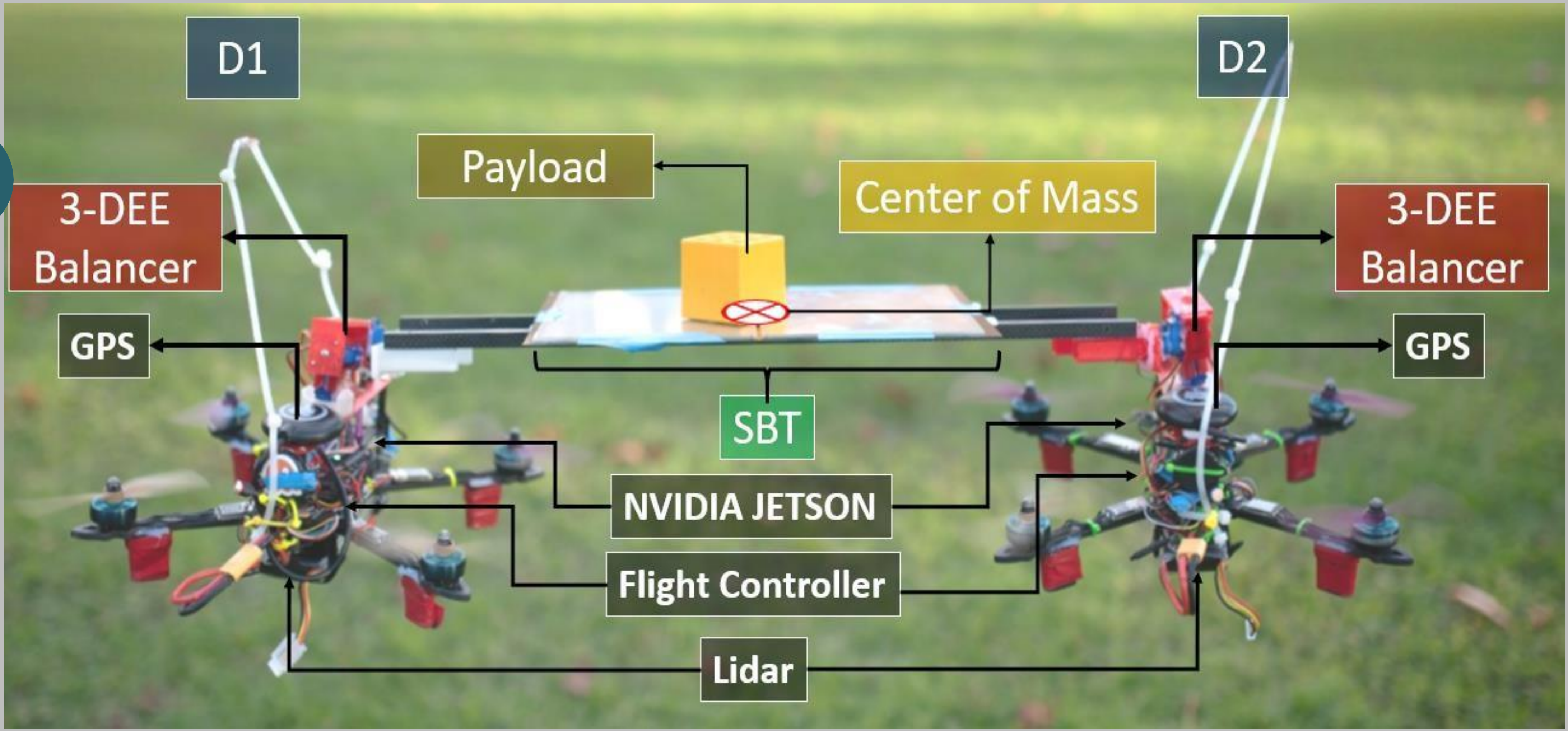
Pull-based Lift

Our approach: Push-based Lift

Challenges:

- ❖ Pendulum, airflow, and wind effects
- ❖ Hierarchical control strategy
- ❖ Manipulation for payload parameter
- ❖ Load distribution based on trajectory planning

DRONE SWARM LIFT SYSTEM



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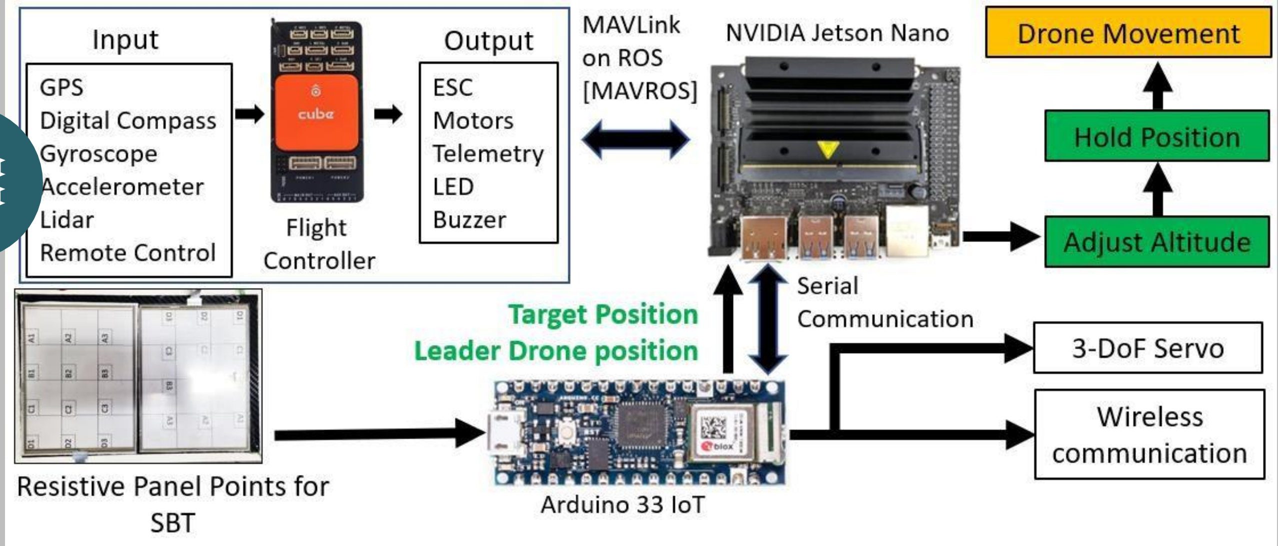
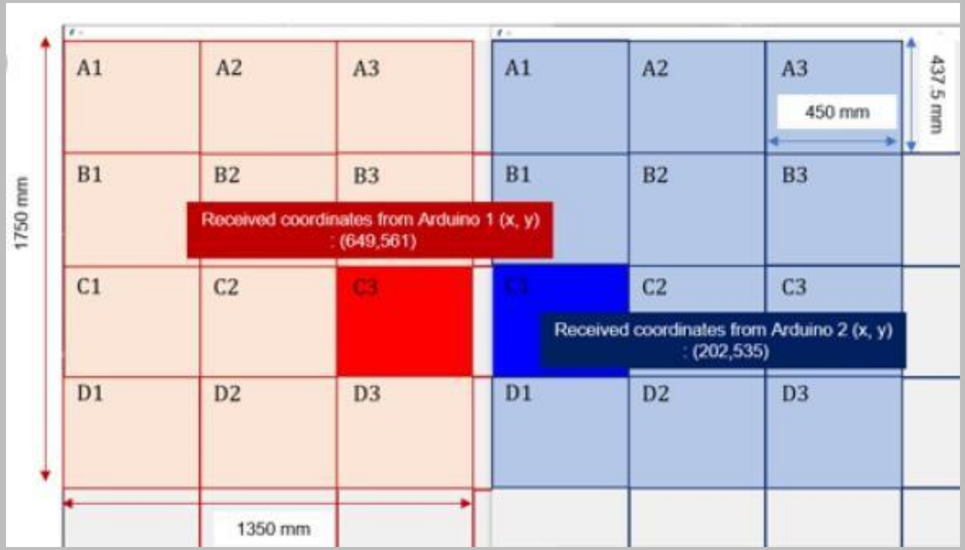
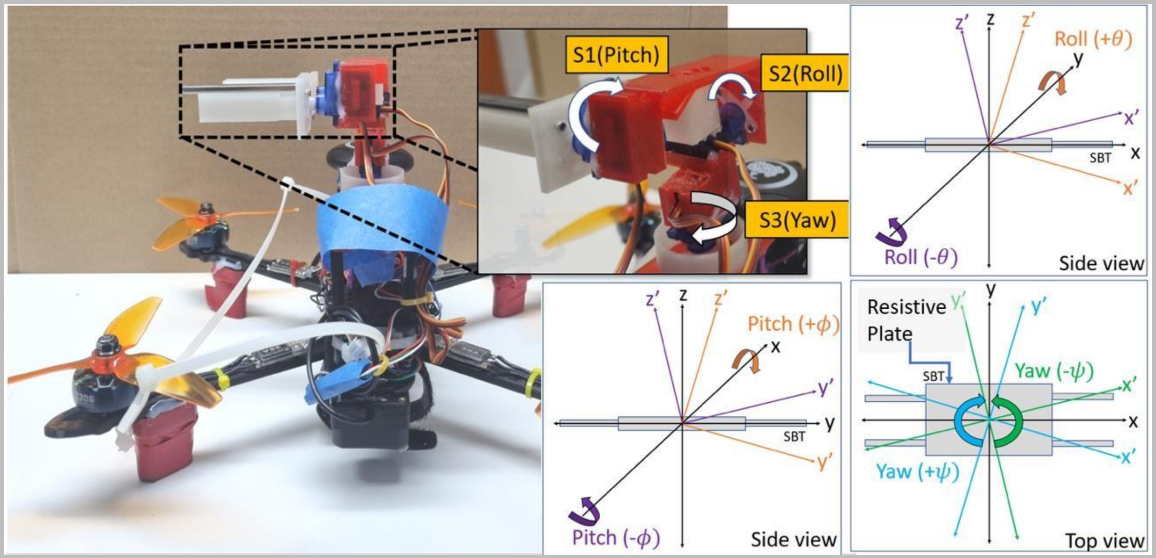
SWARM LIFT ARCHITECTURE AND METHOD

BLOCK DIAGRAM



LOAD SENSING PARAMETER





SBT – SERVO ANGLE

Servo	Angle
S1	0 - 30°
S2	0 - 40°
S3	0 - 30 °

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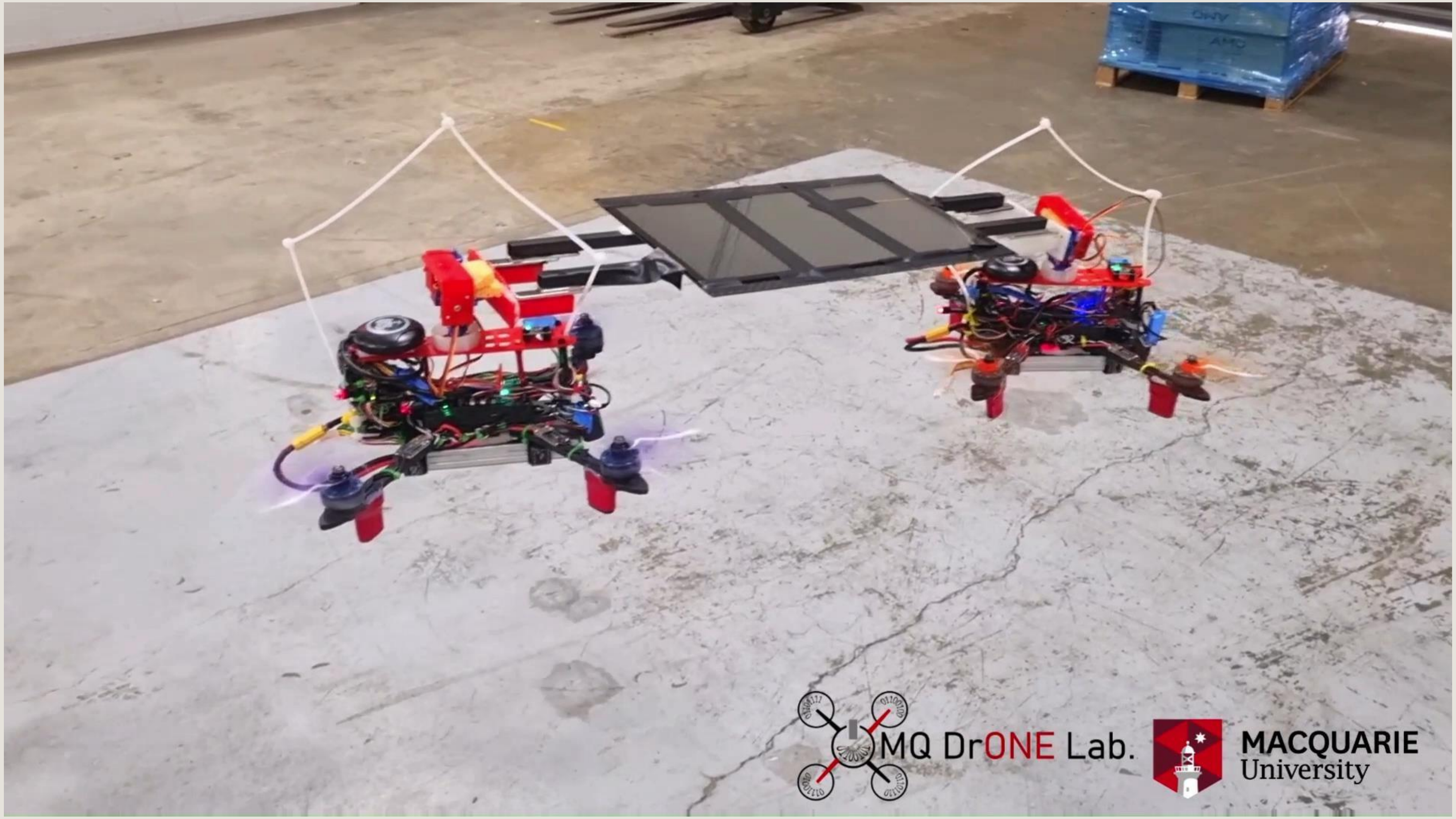
Drone Swarm Lift Demonstration



- Patented
- Next-gen: autonomous & more drones [under submission]

AeroBridge: Autonomous Drone Handoff System for Emergency Battery Services

[MobiCom 2024]

Avishkar Seth, Alice James, Endrowednes Kuantama, Subhas Mukhopadhyay, Richard Han*

Macquarie University Drone Lab
Faculty of Science and Engineering
Sydney, Australia

MQ DrONE Lab.

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Association for Computing Machinery

MobiCom 2024
The 30th Annual International Conference On Mobile Computing And Networking
Nov. 18-22, 2024, Washington, D.C., USA

Critical Applications of Drones

1. Aerial Survey

2. Emergency Medical Delivery

3. Marine Monitoring

4. Powerline Maintenance

5. Bushfire Control

6. Agriculture Drones

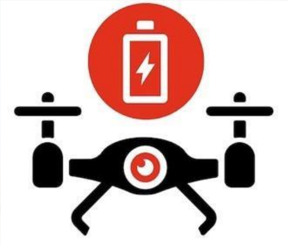
Problem: Limited Battery Life for Continuous Flights

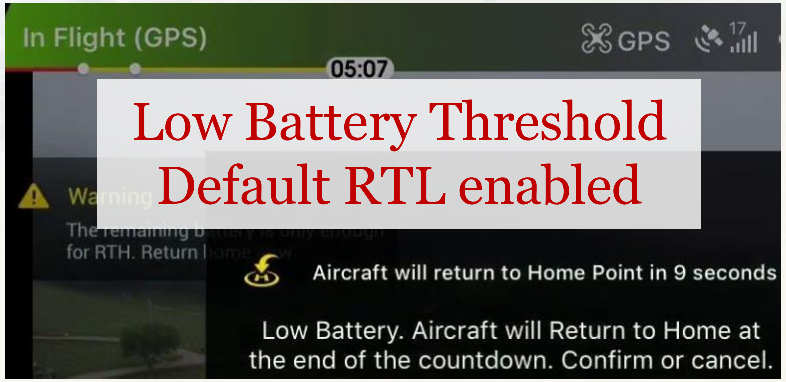
Example LiPo battery solutions

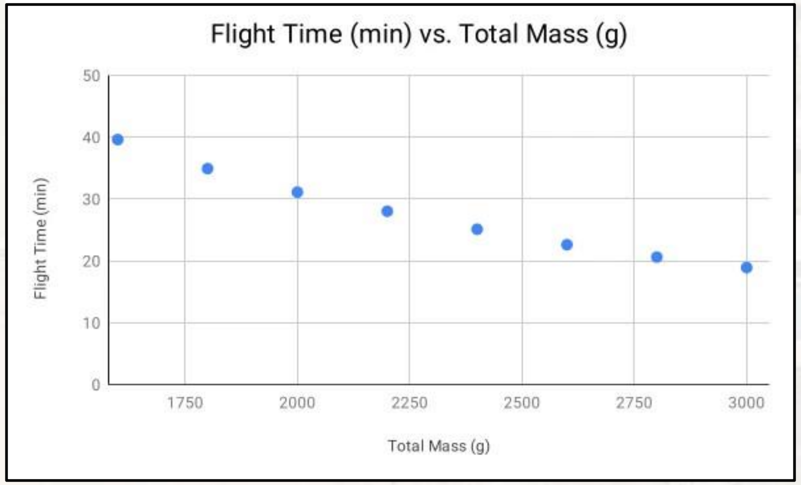
Excess weight

	A	B	C
Mass	6900g	7100g	6450g
Capacity	22,000mAh	20,000mAh	22,000mAh
C Rating	25C	65C	25C
Flight time	32 mins	29 mins	33 mins

~45-60 mins average flight time







Limited Battery Capacity with increasing weight

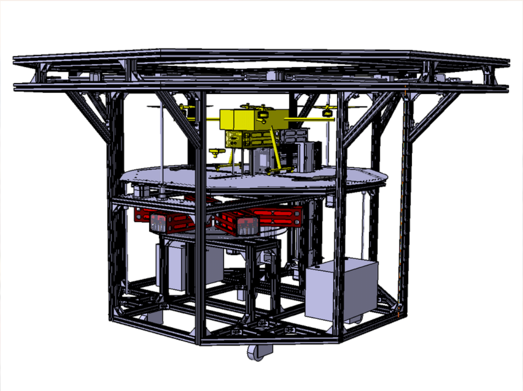
System Constraints

1. Heavy battery systems
2. Battery power must be conserved for RTL, further reducing flight time
3. Disruption of service (tracking/delivery)

1. https://www.tytorobotics.com/blogs/articles/a-guide-to-lithium-polymer-batteries-for-drones

Current Solutions

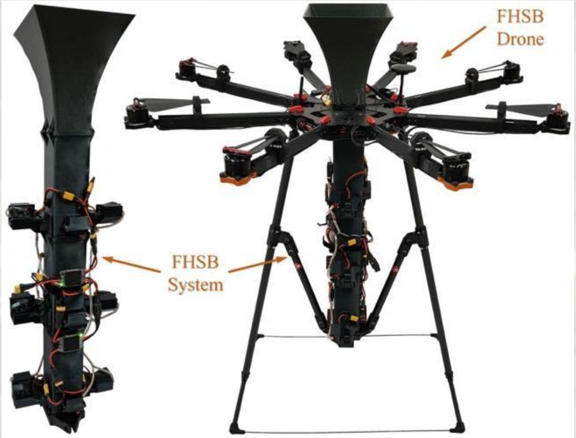
Bulkier Batteries



Ground-based battery swap

Wireless Charging

Replace the operating drone with a new drone

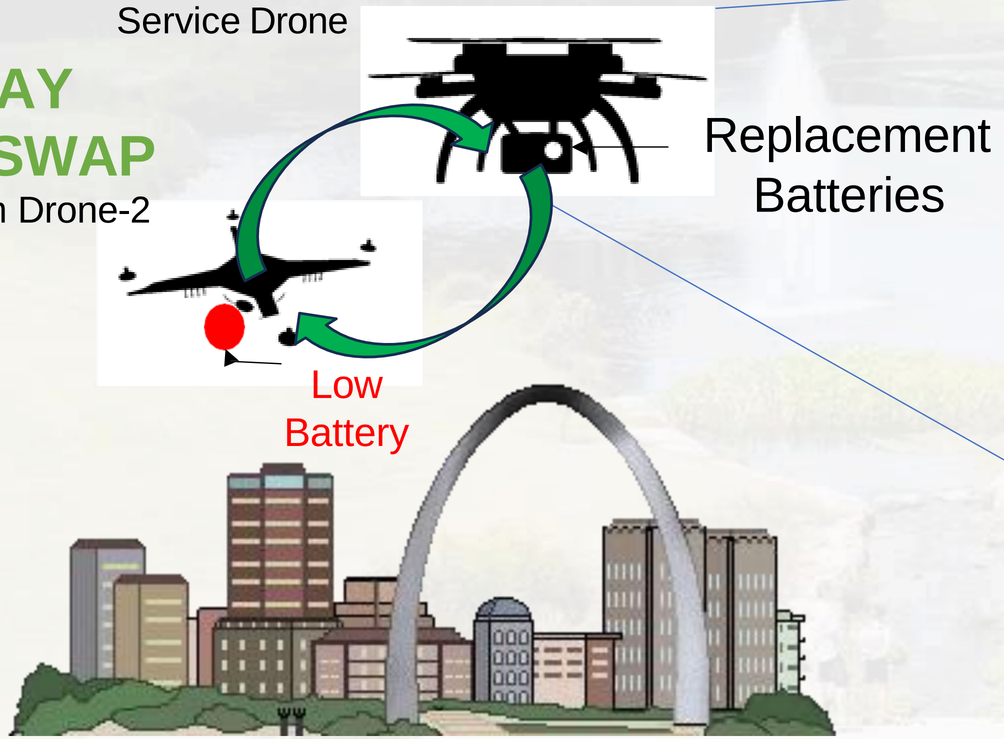


Bulky on-board replacement system

AeroBridge: Towards Mid-Air Battery Swap

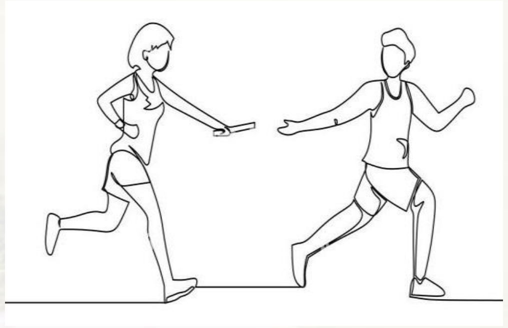
Emergency Battery Services (EBS)

TWO-WAY BATTERY SWAP



Mid-Air Refuelling

Relay - Baton Handoff



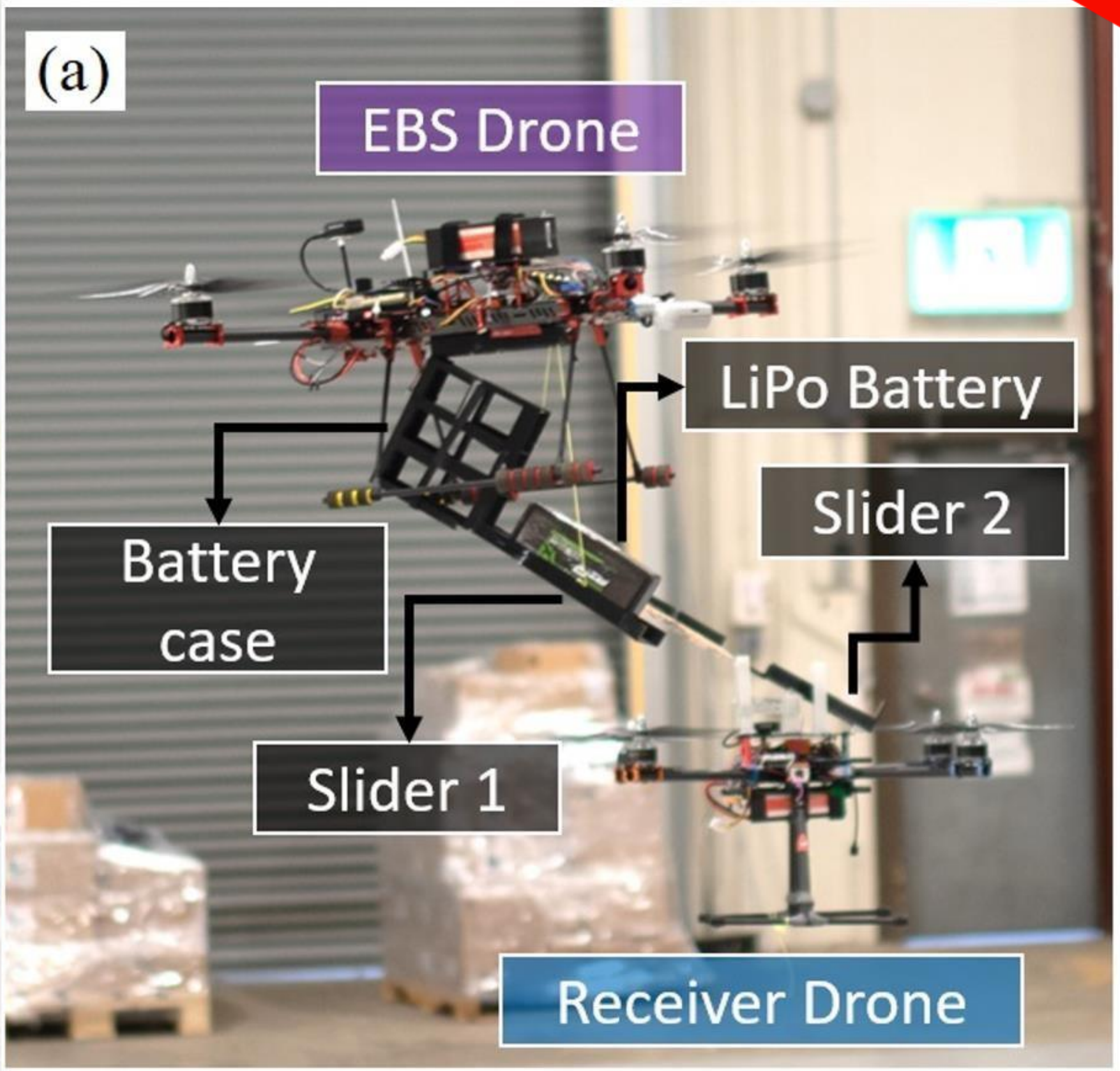
System Advantages

1. Extend Flight time almost indefinitely
2. Drone can remain at service location, uninterrupted
3. No additional weights due to the swapping
4. We can build **Emergency Battery Services (EBS)**

AeroBridge: Design Goals

Design Goals

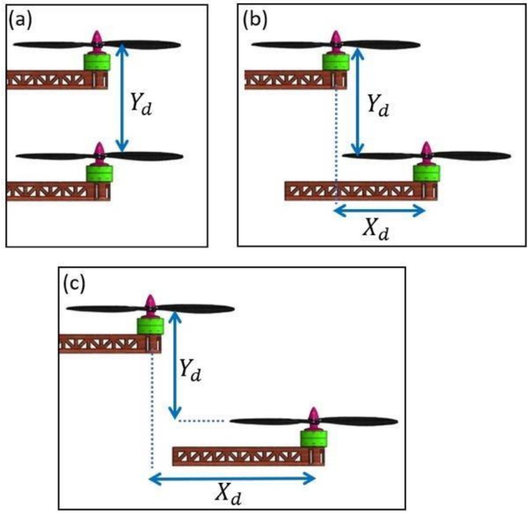
1. Accurate
2. Smooth and Quick Transfer
3. Light-Weight
4. Robust
5. Low cost



The battery transfer mechanism
- EBS and Receiver Drones

Contributions

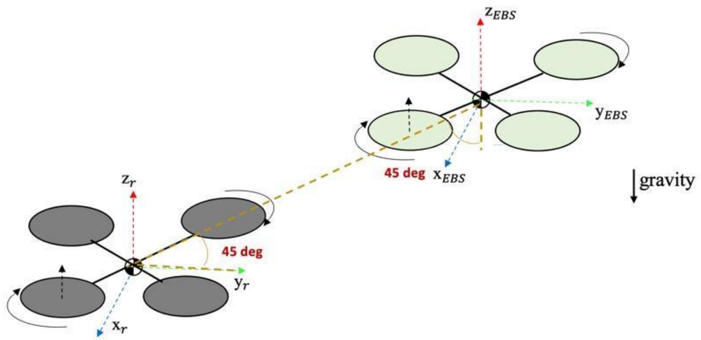
Proximity Flight



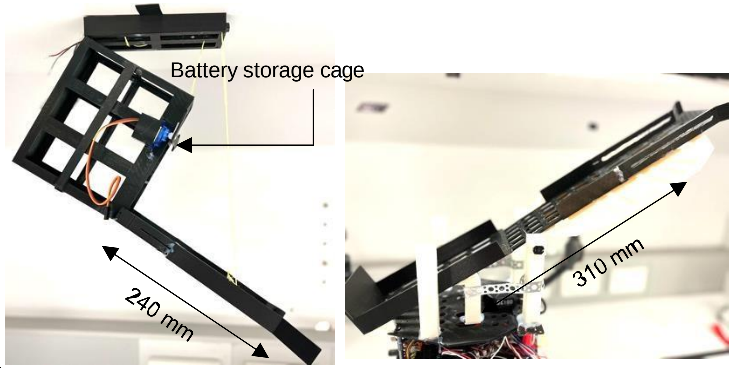
The drone position model based on airflow position (a) $X_d = 0$ cm (b) $X_d = 16$ cm (c) $X_d = 32$ cm.

- Use Quadcopters for analysing Proximity Flight
- Analyse the precise position and distance

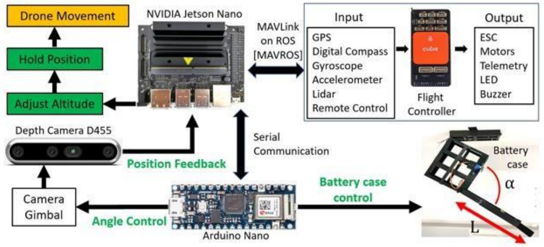
Mid-Air Docking System



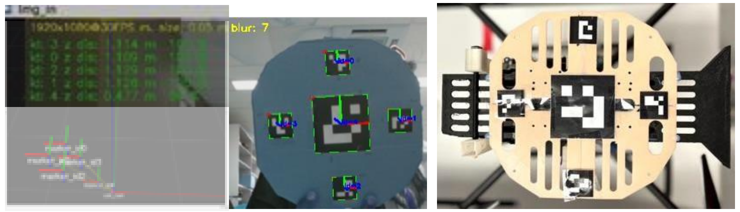
Design a mechatronic mid-air docking system for item transfer.



Visual Inertial Approach



- Improve the last cm positioning challenge of GPS.



- Use a novel visual inertial approach that uses a ArUco marker design configured with pose information.

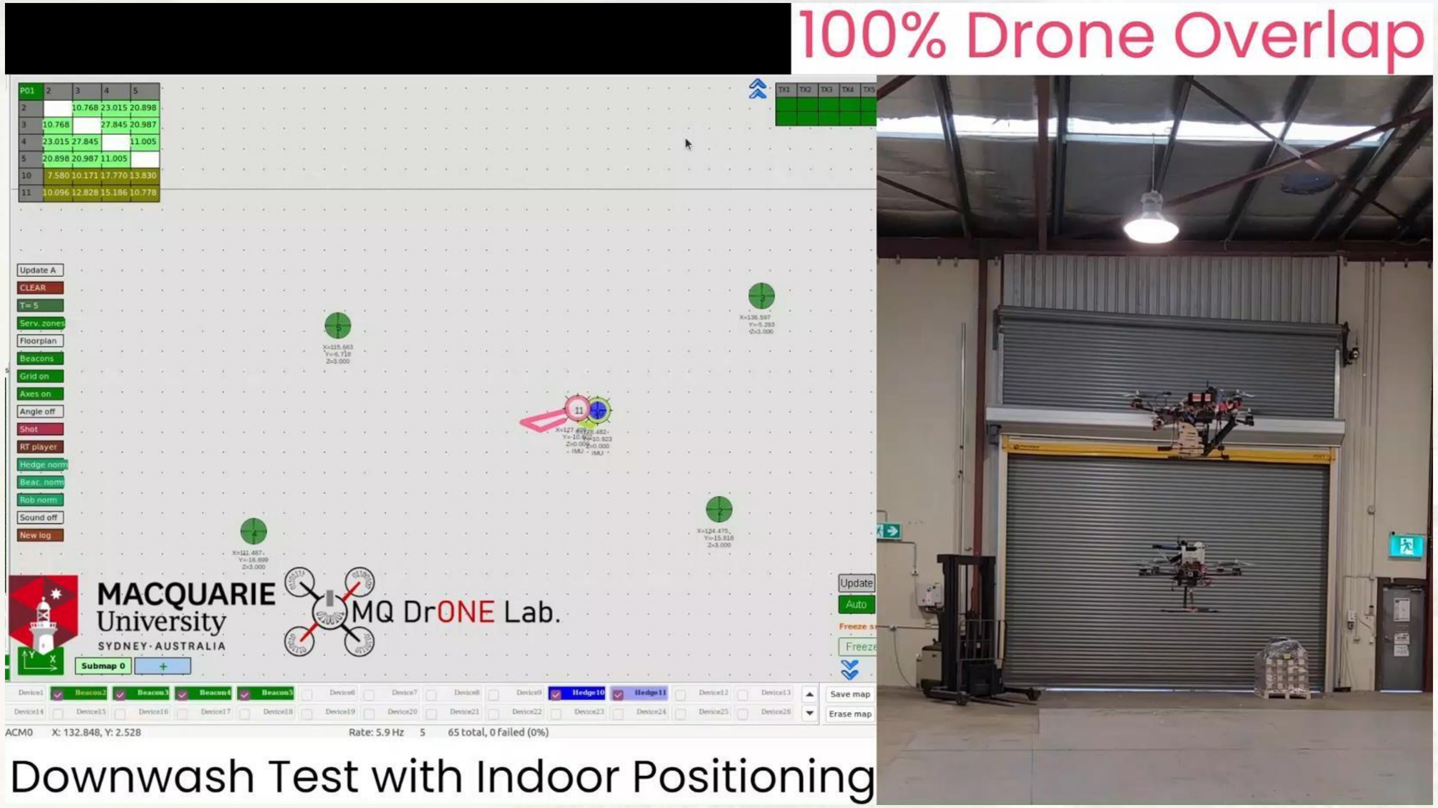
Contributions: ***0.5 m*** proximity transfer, mid-air ***docking*** system, ***visual inertial*** approach for improving positioning

Currently no such system exists!

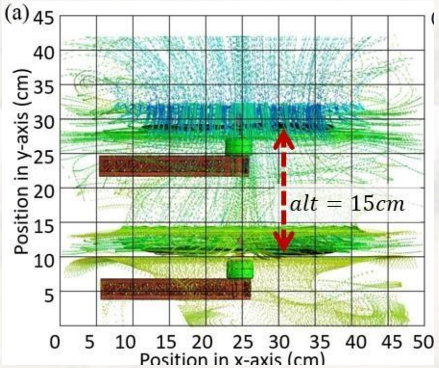
Downwash Turbulence Tests

Downwash Proximity 100%

Due to the downwash turbulence, the receiver drone below is destabilized and can drift across the x or y axes. The horizontal displacement **is ~2.4m**.



Example of airflow disturbance below the drone's propellers



The airflow between two propellers with X_d = 0 cm

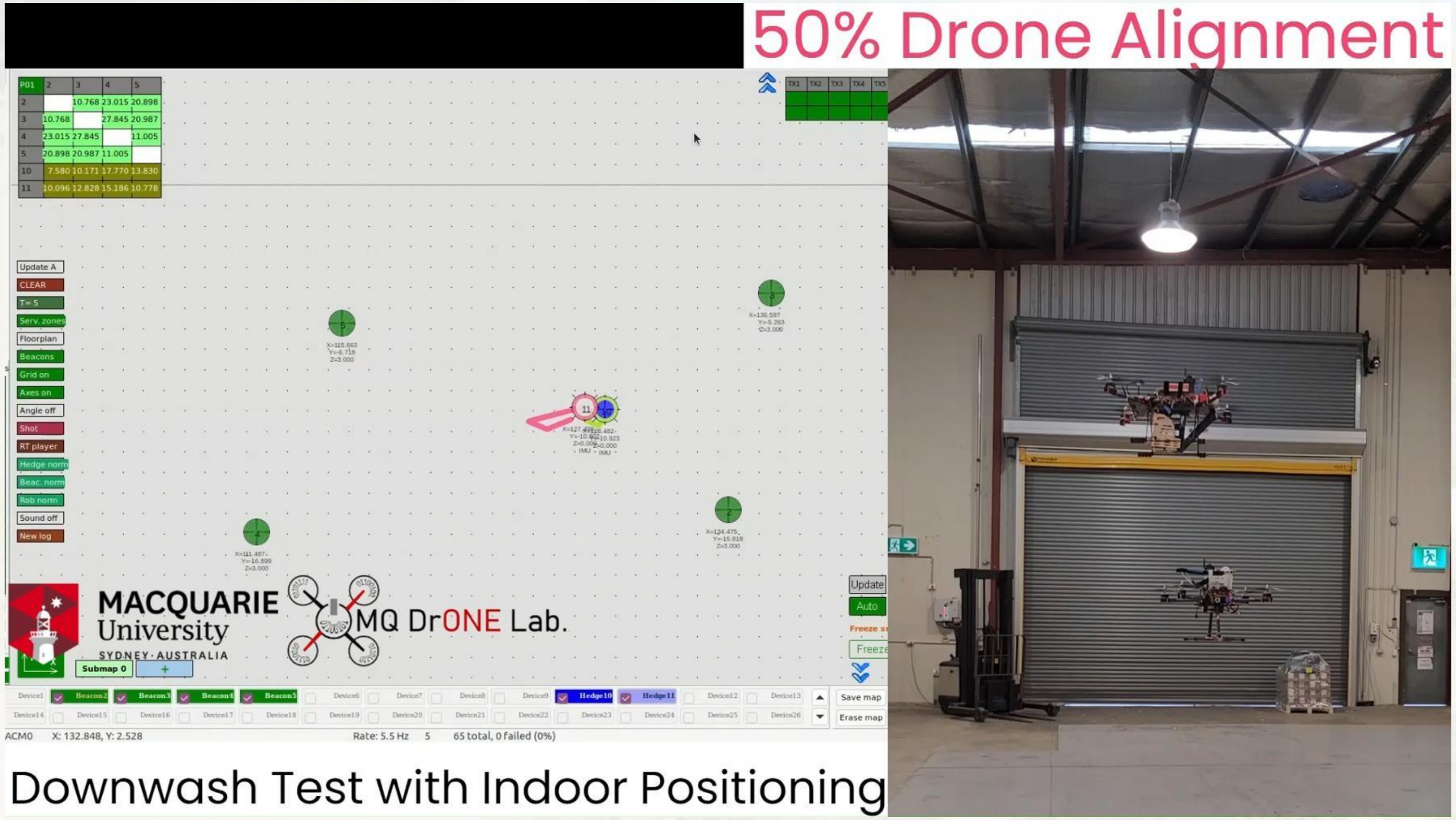
Airflow Analysis CFD

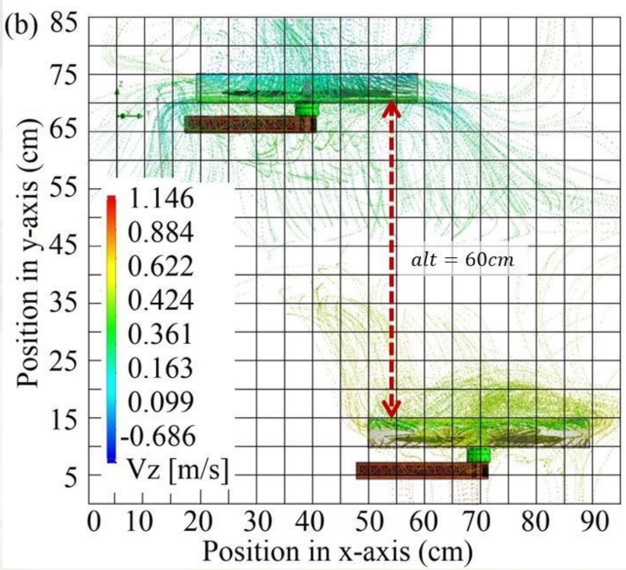
The CFD simulation outcome portrays harsh airflow interactions between two propellers aligned perpendicularly.

Drone Proximity Alignment – Partial Overlap

Downwash Proximity 50%

Diagonal placement, corresponding to **50 percent overlap** between the drones further reduces downwash impact.





The airflow between two propellers with alt = 60 cm.

Airflow Analysis CFD

Maximum displacement **observed is ~0.1m**

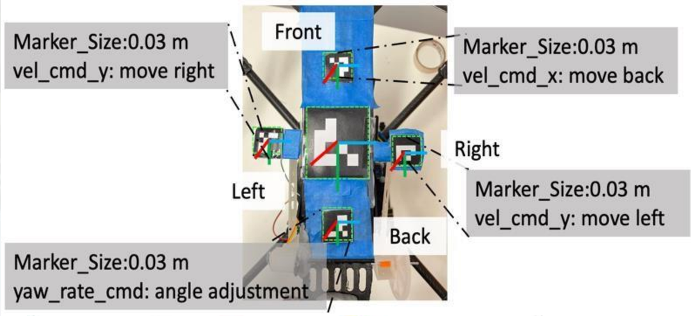
Thus, we conclude the optimal **closest distance of 0.5m** to position two drones for stable and quick item transfer

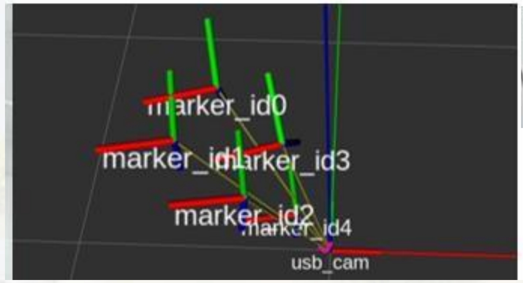
Cross Marker Positioning Tracking

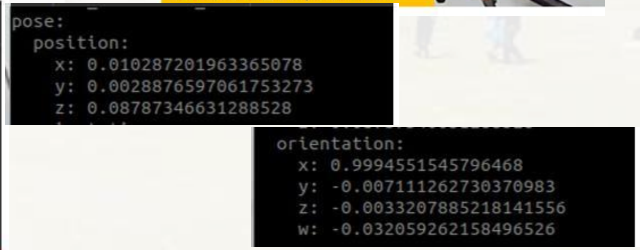
CMP Design

The CMP design with the central marker (70x70 mm). The EBS can detect this marker on the receiver drone from a **3 m distance**.

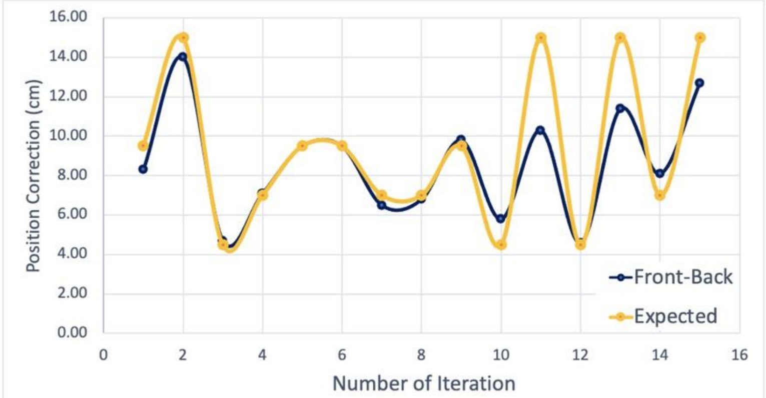
The remainder four markers (30x30 mm) in CMP **detected from 0.7 m distance**; provide position reference to the EBS drone **with 'cm' accuracy** of the receiver drone's position.



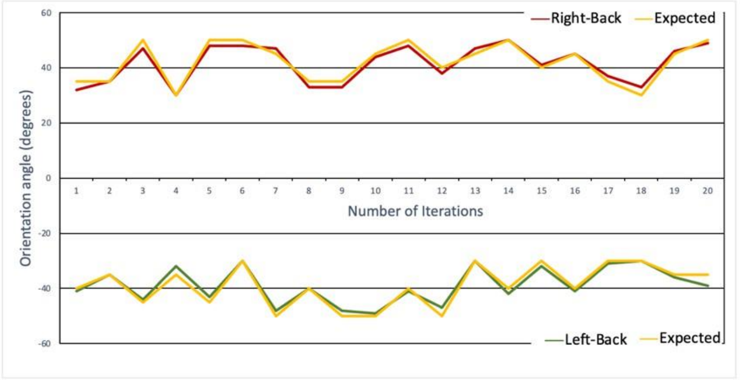




Unique marker position estimate for receiver drones with ROS 'tf' reference for each marker.



Position correction for the Front position for 15 iterations.



Orientation angle correction for Right and Left position for 20 iterations.

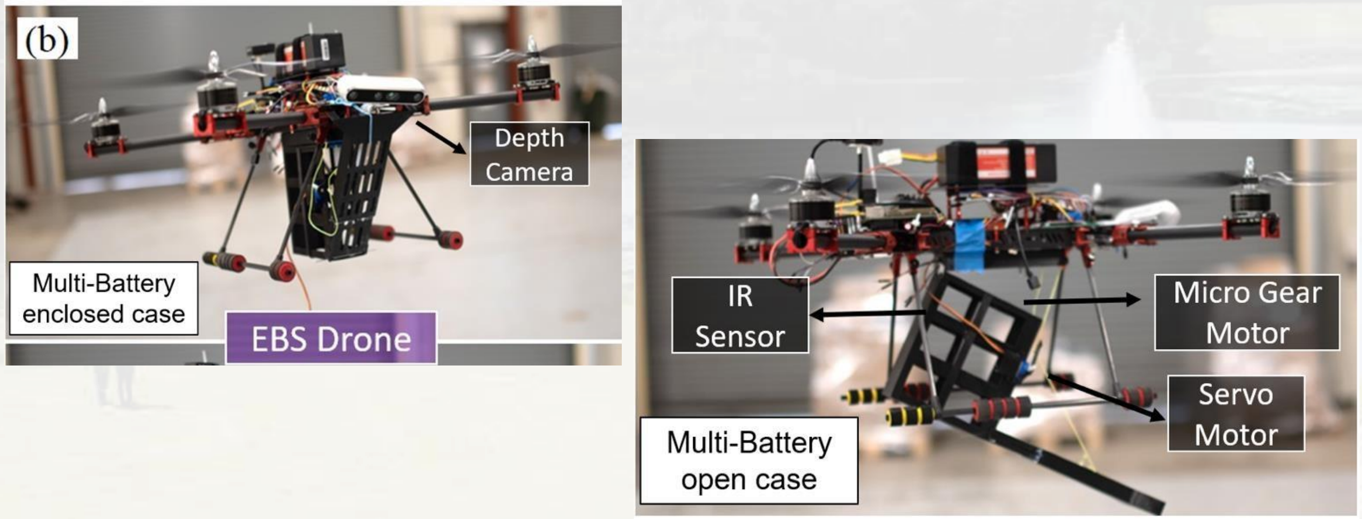
Experimental Analysis

The CMP detection and distance accuracy is validated both indoors and outdoors.

The average **position offset is ~2 cm** during front and back corrections over 15 iterations.

The average **orientation offset is ~4 deg** during yaw adjustments ranging between 30 to 50 deg for 20 iterations.

AeroBridge: System Implementation



The battery transfer mechanism Two-stage flight of EBS drone.

EBS Drone Configuration

EBS Drone mechatronic slide system is **3D printed and light weight**.

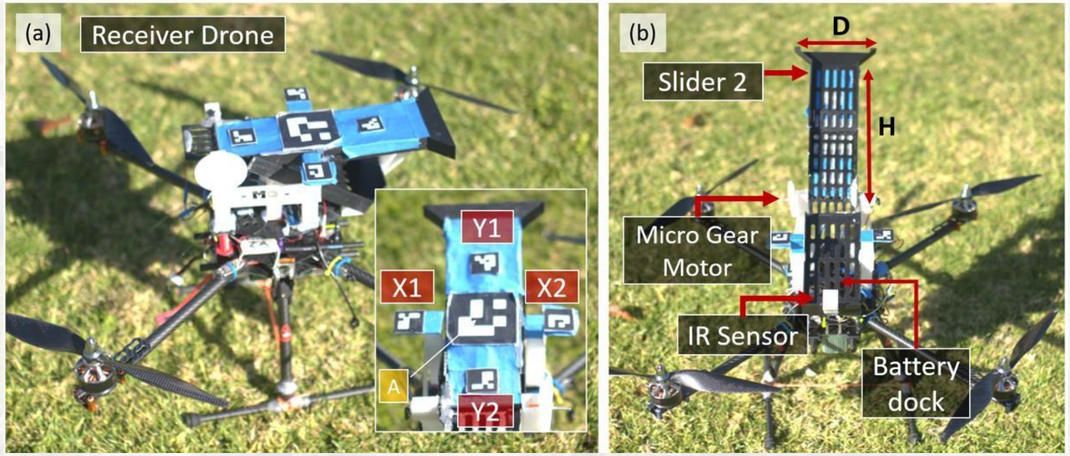
Multi-battery case to power a fleet of drones

Equipped with **downward facing depth camera**.

Receiver Drone Configuration

The receiver drone is equipped with a similar **automated mechatronic slide system**

The top surface is equipped with a **custom marker localization** for accurate docking.



Receiving drone mechanism (a) CMP design (b) Drone design for the receiver.

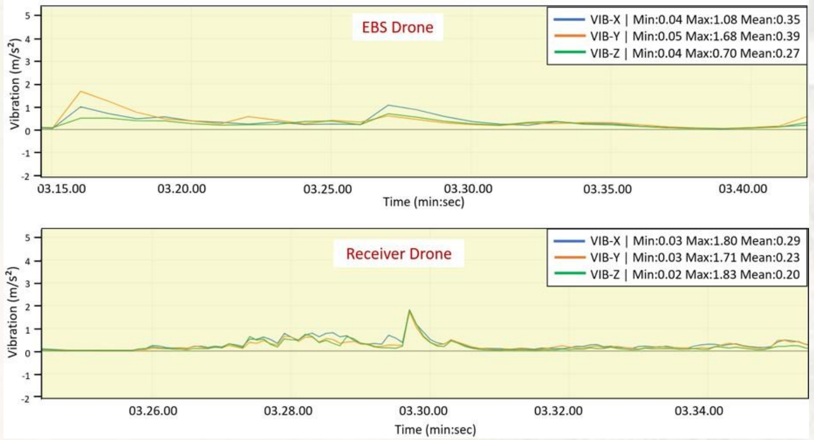
AeroBridge Handoff Demonstration

AeroBridge transfer outdoor test 1

We present **real-world validation** for the handoff during outdoor flights.

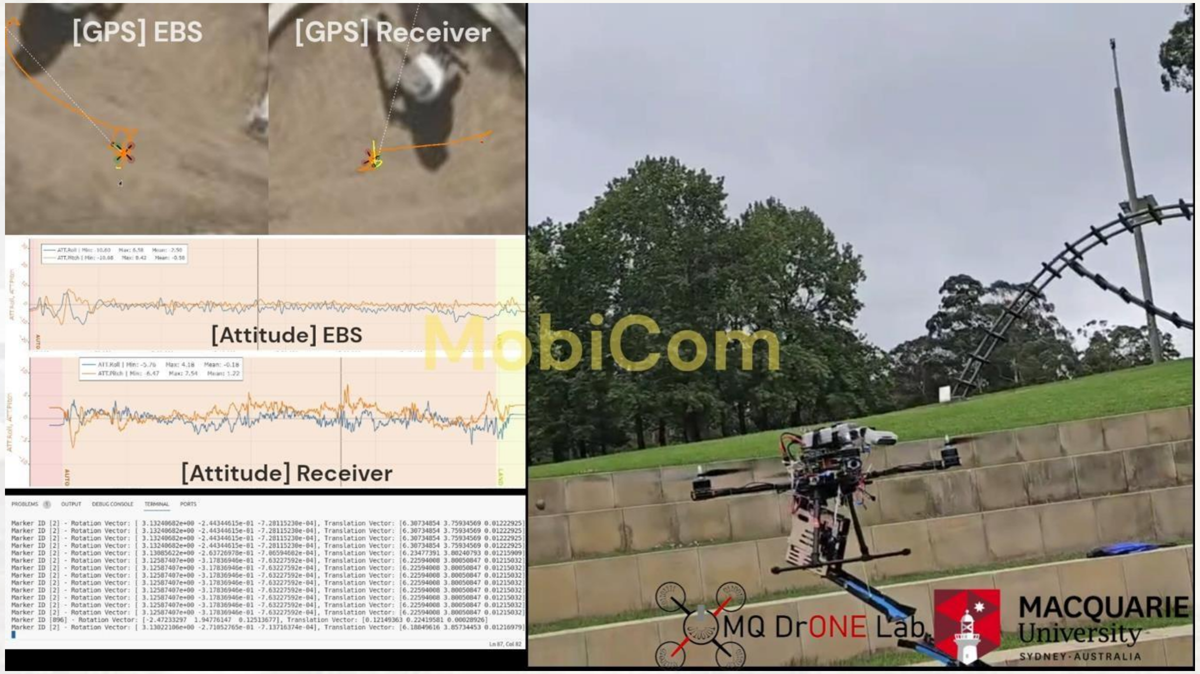
An **integrated sensor feedback** from GPS and Visual Inertial approach is used to improve cm level precision for docking.

The system allows for a smooth transfer up to **+2 cm offset** while docking



Vibration across all axes for EBS and Receiver drone during transfer.

The **low vibration across all axes** results prove the system is stable at **0.5 m** proximity while making the transfer.

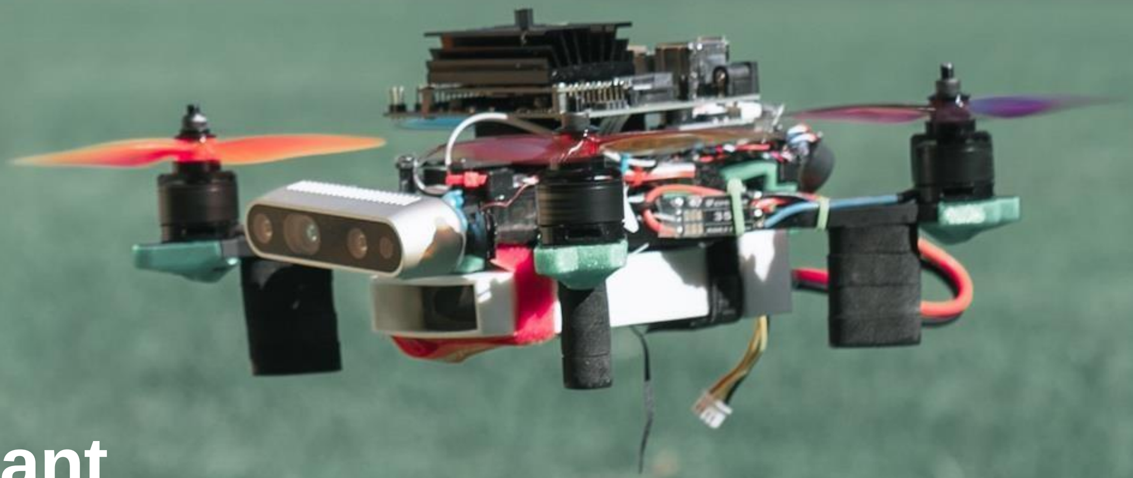


AeroBridge transfer outdoor test 2

Autonomous Drone Landing

MACQUARIE University SYDNEY·AUSTRALIA

[ICSE 2025] “GARL: Genetic Algorithm-Augmented Reinforcement Learning to Detect Violations in Marker-Based Autonomous Landing Systems”



ARC Linkage Grant

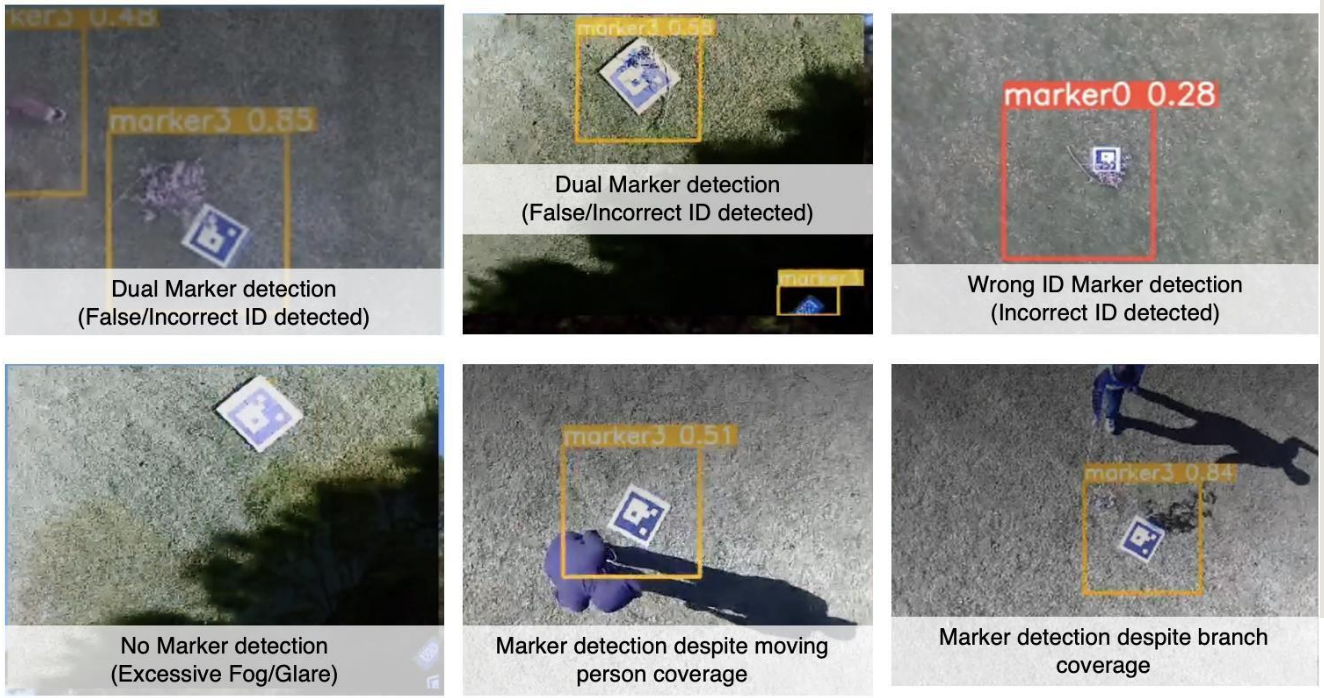
- ❑ $450K
- ❑ Collaboration with industry partner Skyy Network

Autonomous Drone Landing

Last Meter Problem

- *Where is a safe place to land?*
- Teach AI/ML to learn from computer vision and multimodal sensors
- Not even Google or Amazon have solved this
- Guided landing with human-placed markers
- Autonomous landing

Human-assisted Autonomous Drone Landing



Dual Marker detection (False/Incorrect ID detected)
Dual Marker detection (False/Incorrect ID detected)
Wrong ID Marker detection (Incorrect ID detected)
No Marker detection (Excessive Fog/Glare)
Marker detection despite moving person coverage
Marker detection despite branch coverage

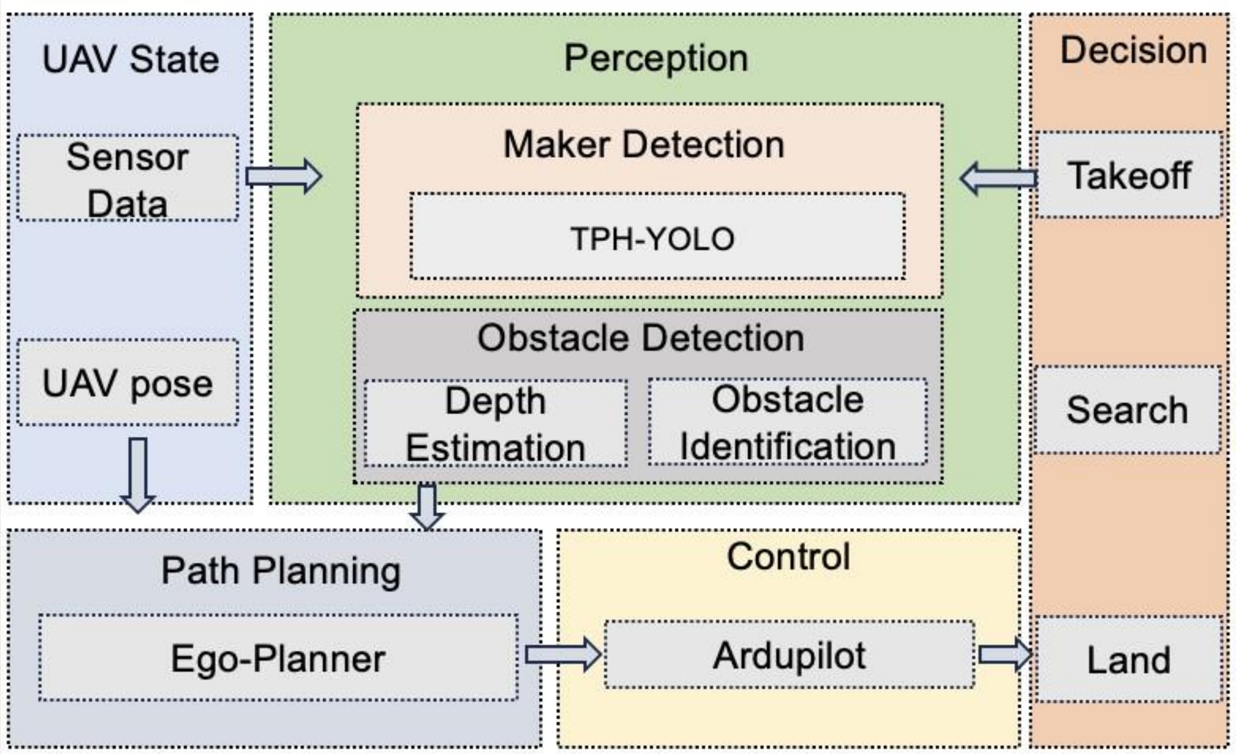
- ❑ Human lays out marker to tell drone where to land

Guided Landing Issues

- ❑ Training computer vision to recognize the right marker
- ❑ False positives
- ❑ False negatives
- ❑ Robustness to shadows, obstructions, glare, etc.

AutoLand Software System

- Marker-based landing system has its own complexity. Below is the Multi-Modules Marker-based landing system (MM-MLS)

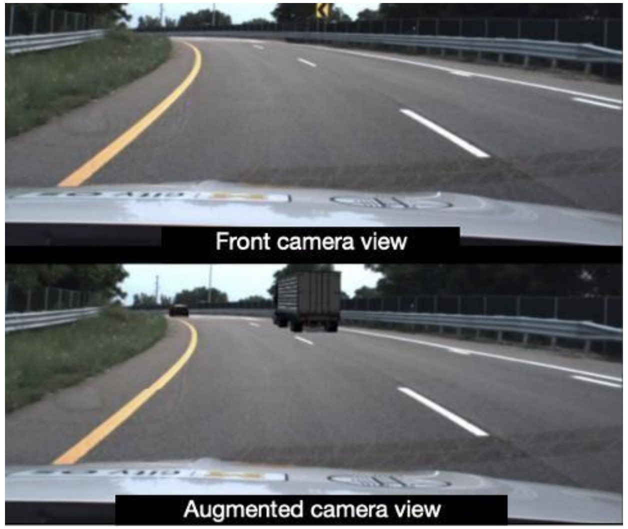


Unsafe due to bugs!

Testing Challenges & Motivations

CHALLENGES – SIMULATION VS REAL WORLD

- Real-world testing: Conduct on actual roads with a physical autonomous vehicle
  - \+ Authentic environment and unpredictable situations
  - +. Provides real sensor data and interactions
  - \- Expensive and time-consuming
  - \- Limited control over test conditions



[1]

[1] Feng, S., Sun, H., Yan, X., Zhu, H., Zou, Z., Shen, S., & Liu, H. X. (2023). Dense reinforcement learning for safety validation of autonomous vehicles. *Nature*, *615*(7953), 620-627.

Testing Challenges & Motivations

CHALLENGES – SIMULATION VS REAL WORLD

- Simulation testing: Use simulator to create virtual environments and scenarios
    - + Cost-effective and scalable
    - +. No safety risks to people or property
  - - Relies on the accuracy and fidelity of the simulation model

- Reproduce findings of simulation-tested failures in the real world

Genetic Algorithms (GA) vs Reinforcement Learning (RL)

- Offline approaches like Genetic Algorithms (GA) rely on pre-defined configurations for variables such as weather and object positions, limiting their ability to explore the dynamic search space and potentially missing critical corner cases [2][3].
- Online methods like RL can adjust test cases in real-time but often struggle to converge within limited time due to the extensive learning space in simulation testing [1] .

1 Feng, S., Sun, H., Yan, X., Zhu, H., Zou, Z., Shen, S., & Liu, H. X. (2023). Dense reinforcement learning for safety validation of autonomous vehicles. *Nature*, *615*(7953), 620-627.

2 Tian, H., Jiang, Y., Wu, G., Yan, J., Wei, J., Chen, W., ... & Ye, D. (2022, November). MOSAT: finding safety violations of autonomous driving systems using multi-objective genetic algorithm. In *Proceedings of the 30th ACM Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering* (pp. 94-106).

3 Li, G., Li, Y., Jha, S., Tsai, T., Sullivan, M., Hari, S. K. S., ... & Iyer, R. (2020, October). Av-fuzzer: Finding safety violations in autonomous driving systems. In *2020 IEEE 31st international symposium on software reliability engineering (ISSRE)* (pp. 25-36). IEEE.

GARL = GA + RL

MOTIVATION

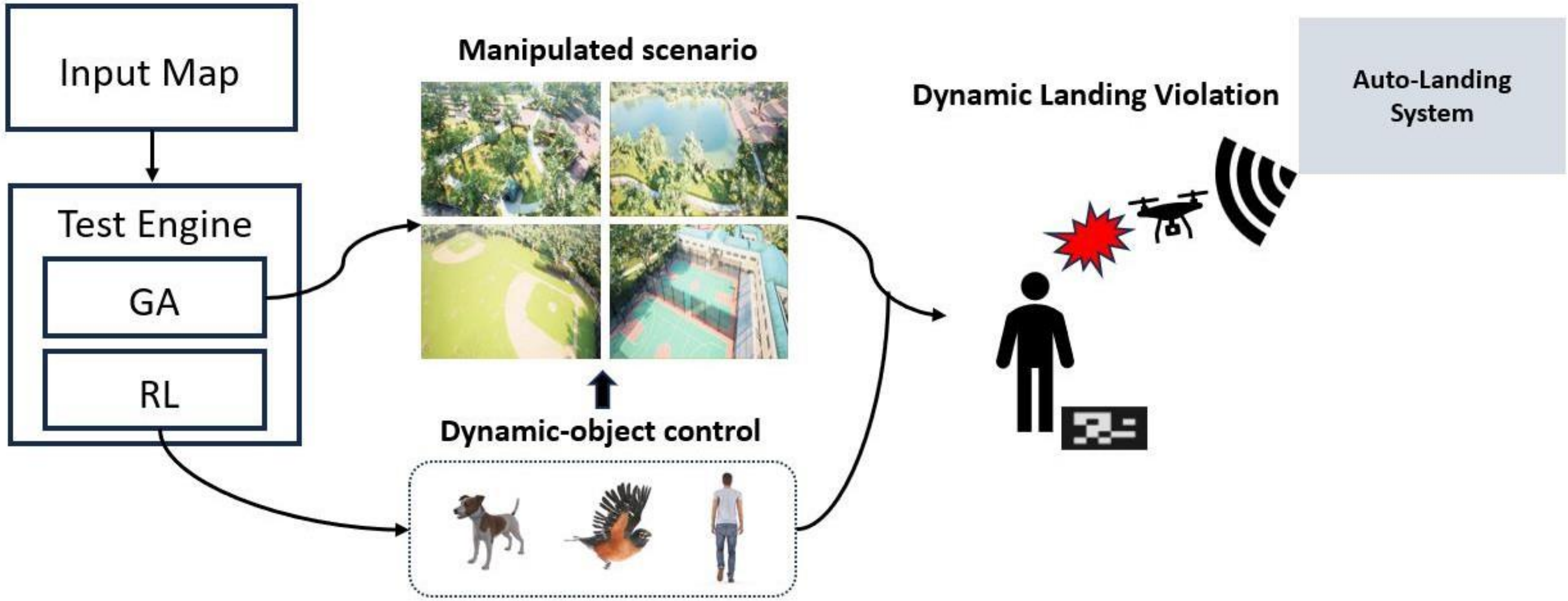
Our motivation is to develop a testing method that can generate dynamic trajectories online while maintaining training efficiency.

Solution insight:

- Using offline genetic algorithms (GA) to reduce the exploration space of online reinforcement learning (RL), enabling faster convergence of RL models.
- Creating a pre-training environment for the RL agent, allowing the trained agent to be seamlessly transferred and applied to any scenario.
- Exploring the complex interplay among dynamic objects and thus generating dynamic trajectories.

GARL

HIGH-LEVEL OVERVIEW



Autonomous Landing System Performance

(a) Court

(b) Lawn

Landing violation percentage

	OpenCV-MLS	*TPHYolo-MLS*	*MM-MLS*
Map Court	71.50%	30.96%	20.60%
Map Lawn	42.75%	38.25%	17.11%

GARL vs Baselines

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Method	Metric	Court	Lawn
GARL	Landing violation %	**20.60%**	**17.11%**
	Top-10	**42**	**76**
	Parameter distance	**0.19**	**0.19**
	3D trajectory coverage%	**11.24%**	**11.94%**
	Time Consumption (hours)	12	12
Multi-Obj GA	Landing violation %	14.25%	9.23%
	Top-10	73	113
	Parameter distance	0.16	0.16
	3D trajectory coverage	4.92%	8.43%
	Time Consumption (hours)	11	11
Random	Landing violation %	9.37%	8.52%
	Top-10	205	112
	Parameter distance	0.13	0.13
	3D trajectory coverage	3.51%	4.92%
	Time Consumption (hours)	11	11
Offline RL Fuzzer	Landing violation %	2.25%	2.13%
	Top-10	cannot find	cannot find
	Parameter distance	0.12	0.12
	3D trajectory coverage	1.41%	3.51%
	Time Consumption (hours)	11	11
Online RL	Landing violation %	12.75%	5.94%
	Top-10	104	141
	Parameter distance	0.13	0.13
	3D trajectory coverage	4.92%	7.03%
	Time Consumption (hours)	11	11
Surrogate trained RL with random scenario	Landing violation %	14.19%	13.53%
	Top-10	67	108
	Parameter distance	0.13	0.13
	3D trajectory coverage	8.43%	8.43%
	Time Consumption (hours)	12	12

Discovered 5 Violation Types:

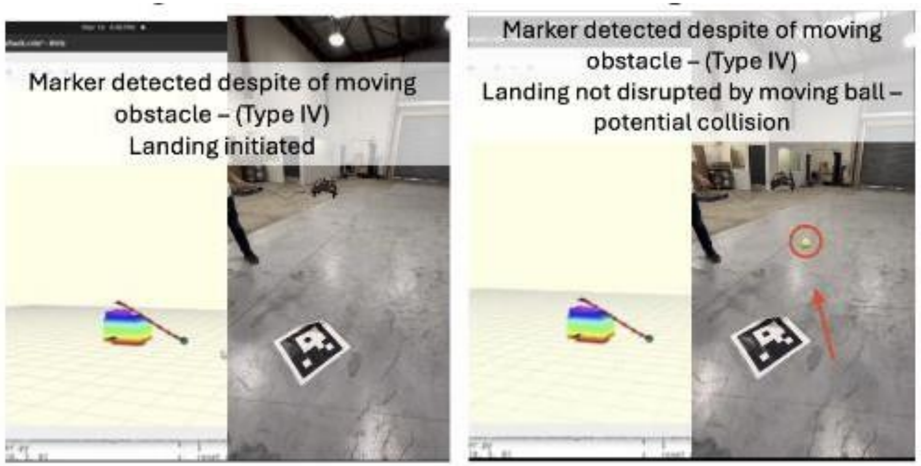
1. False positives
2. False negatives
3. Static object collision
4. Dynamic object collision
5. Planner failure

Real world reproduction of GARL-identified Types I and II violations

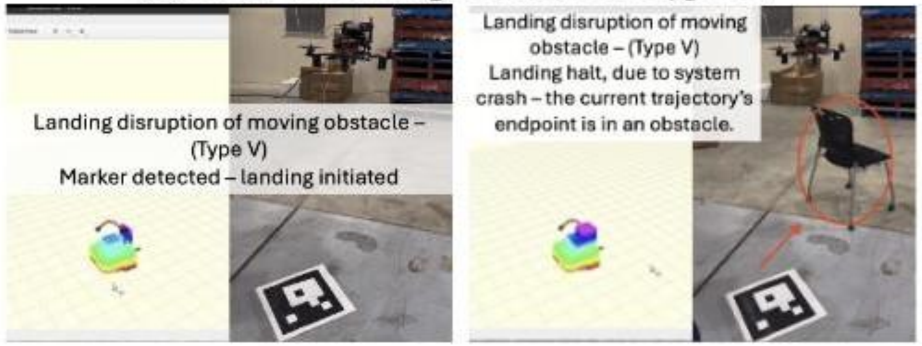
(a) False negative detection

(b) False positive detection

Real world reproduction of GARL-identified Types IV and V violations



(c) Real-world experiment for *Type IV*



(d) Real-world experiment for *Type V*

Summary: 3 Autonomous Drone Projects

Drone Swarm Lift

- ❑ Two drones cooperate to lift and transport a payload on a self-balanced tray

Mid-Air Battery Transfer for Drones

- ❑ Two drones cooperate to rendezvous and transfer a battery from one drone to the other in mid air

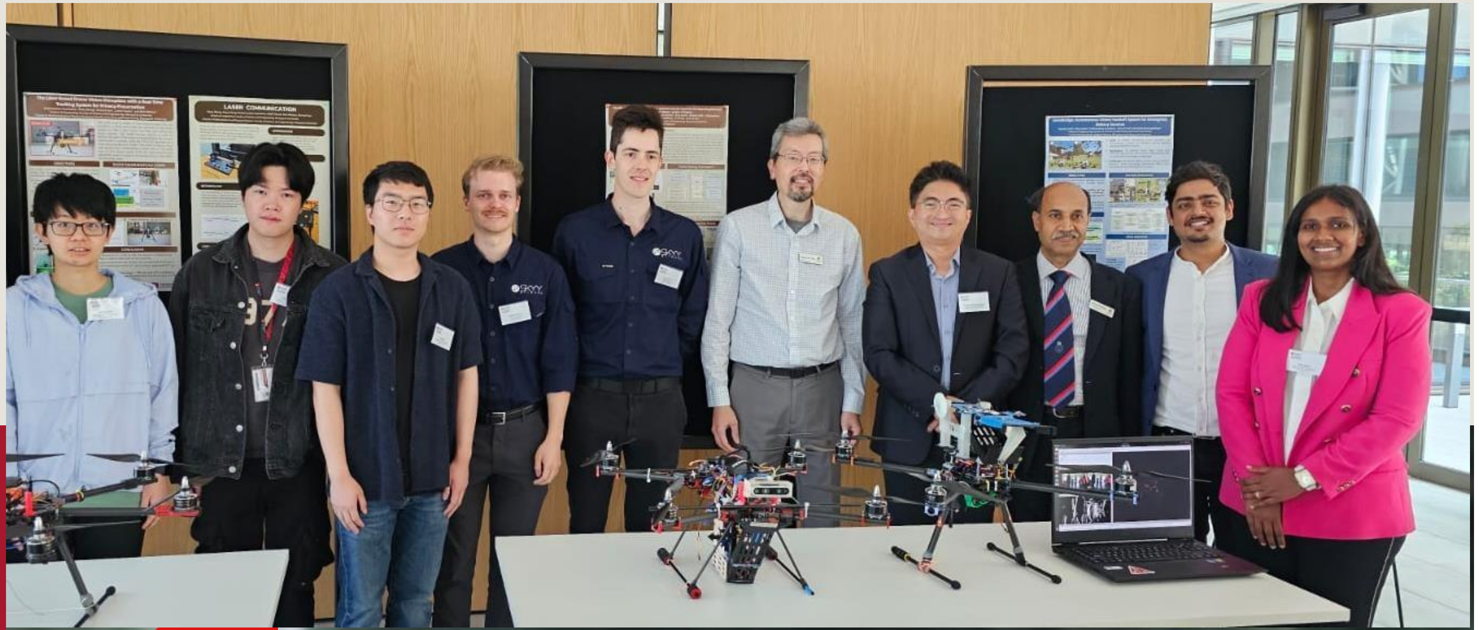
Safe Autonomous Landing

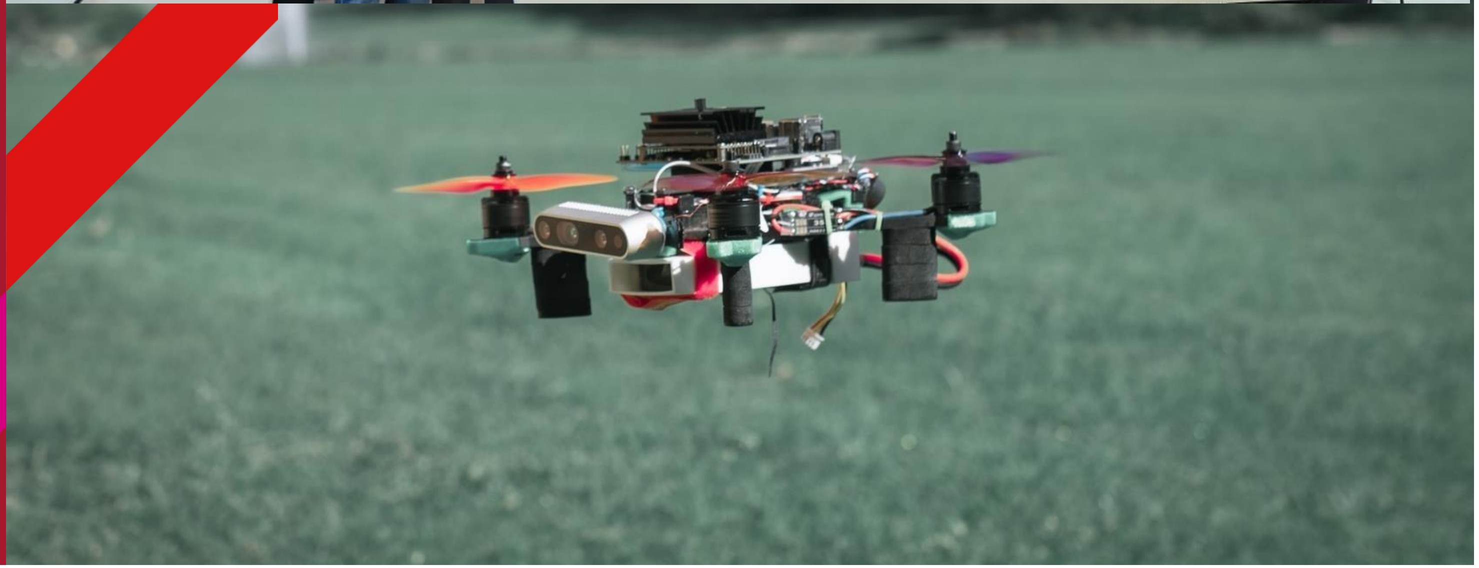
- ❑ An RL-based algorithm was proposed to efficiently find corner cases that cause the Auto Landing system to fail in simulation & real world

MACQUARIE University SYDNEY · AUSTRALIA

Thank you!

CONTACT US AT MQDRONELAB.COM
OR RICHARD.HAN@MQ.EDU.AU

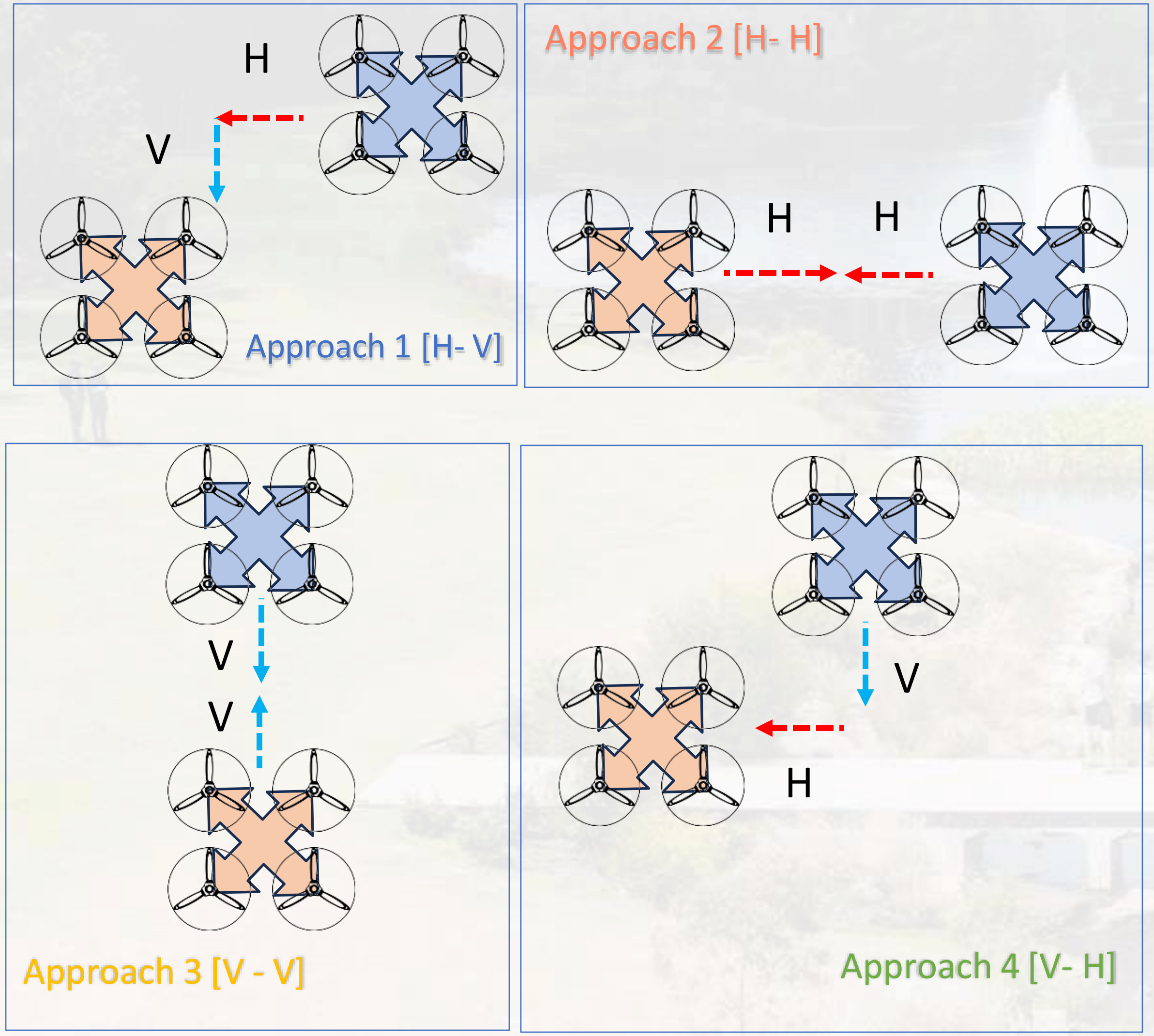




SWARM LIFT CONCLUSIONS

- This research pioneered a novel push-based solution to enhance payload deliveries using cooperative drones.
- Two drones utilize adaptive control with 3-DEE servos for the Self-Balancing Tray (SBT), maintaining an average error rate of less than 1 degree.
- The adaptive SBT control successfully centres the payload with average angle error for yaw, pitch, and roll are 1°, 0.625°, and 2.6°.
- The fine-grain control system ensures precise drone movement control, minimizing vibrations and maintaining object stability at 3 m/s.

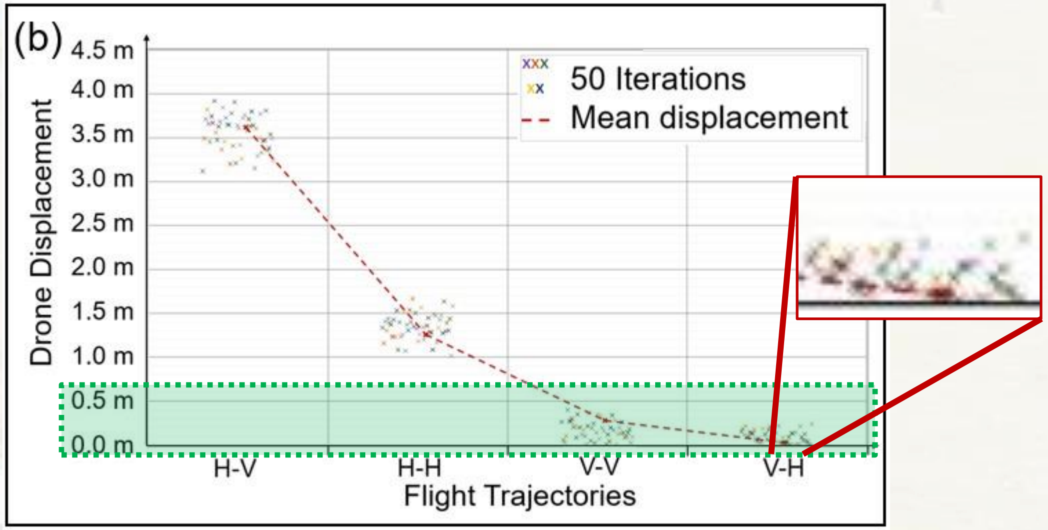
EBS Trajectory Selection



Minimal displacement

Vertical-then-Horizontal

trajectory approach with **~0 m displacement**



Drone Displacement for different trajectories at 1.5 m (50 iterations)

System Flow

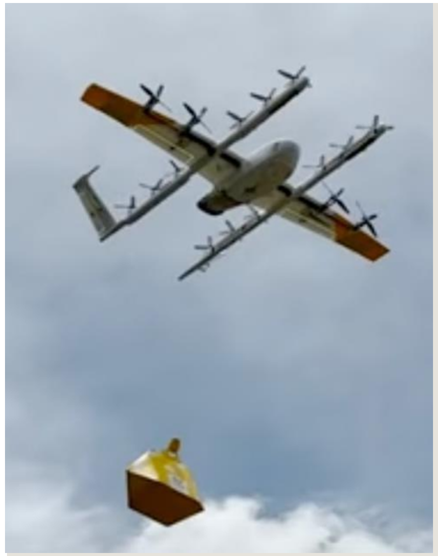
We infer the **best trajectory approach** after **50 iterations** for the EBS drone is to: *descend vertically first* and *then align horizontally*.

AeroBridge Summary

- AeroBridge system one-way battery transfer in under 5 seconds.
- Maintains precise vertical distance of 0.5 meters during transfer.
- CMP model improves positioning with ~1 cm accuracy across all directions.
- Yaw adjustment corrects deviation within 30–50°.
- Diagonal slide mechanism ensures stable mid-air alignment.
- Future research plan will focus on improved localization and robustness and creating a complete two-swap system.

AeroBridge Phase 1 can transfer an item mid-air robustly and accurately

Autonomous Drone Landing

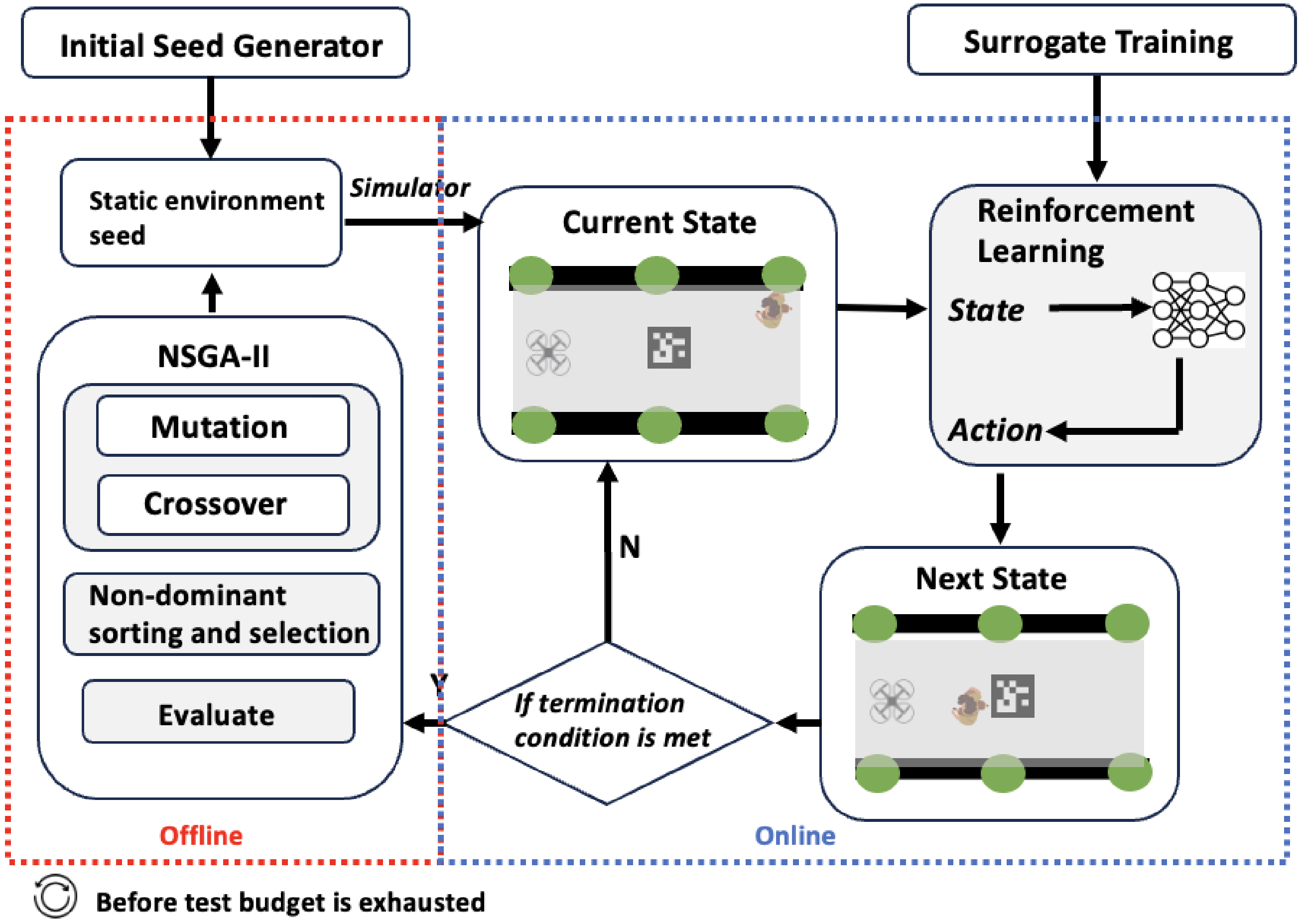


Last Meter "Solutions"

- Not even Google Wing or Amazon have solved this general autonomy landing challenge
- Sling-based solutions lack precision, balance, and safety

GARL

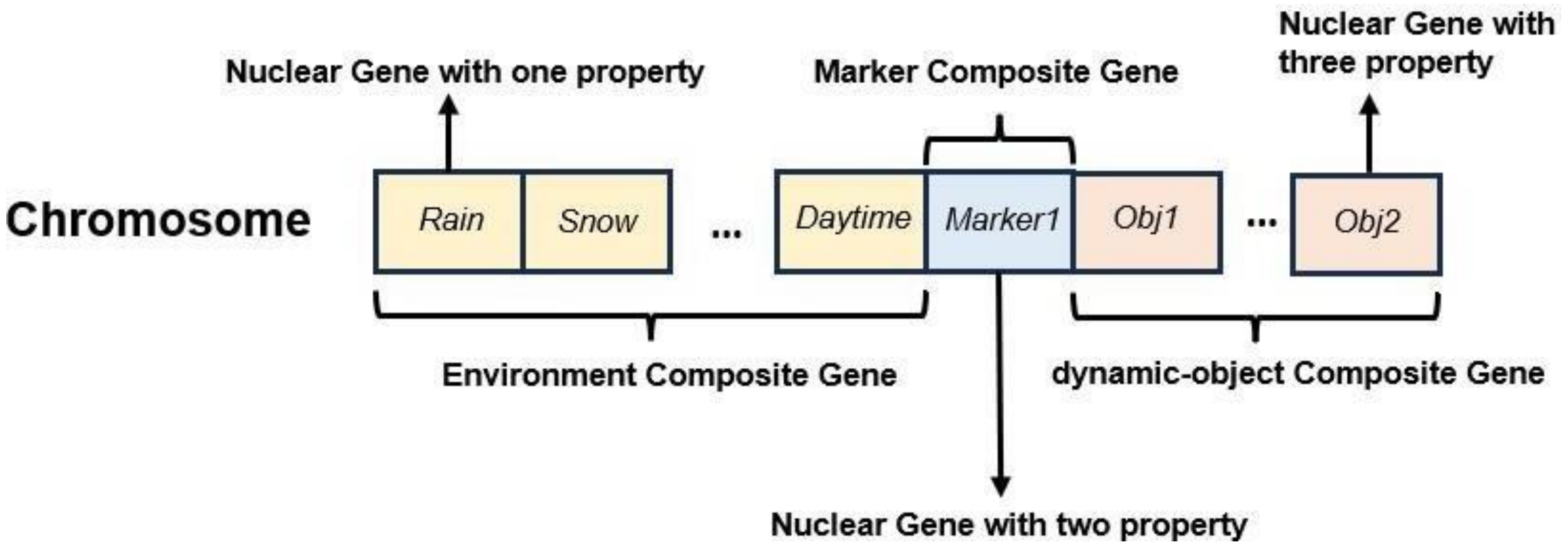
OVERALL WORKFLOW



[4]

GARL

MODELING THE SCENARIO



Multi-objective Fitness function

- Distance-To-Landing (DTL)
- Time-To-Landing (TTL)
- Diversity

$$D_i = \frac{1}{k} \sum_{j=1}^{k} d\left(x_i, x_j\right)$$

current and all others chromosome representation of the test scenario in each generation

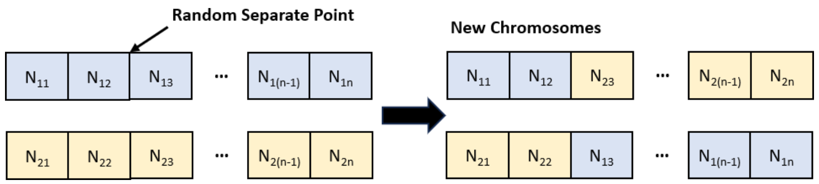
generation size

GARL

OFFLINE GENETIC ALGORITHM

Algorithm 1 The GA chromosome-based suite of variation operators

Input: Parents P_t, Offspring O_t, crossover threshold $threshold_c$, mutation threshold $threshold_m$, number of mutation candidates m
Output: P_{t+1}, O_{t+1}
$P_{t+1} \leftarrow \varnothing$, $O_{t+1} \leftarrow \varnothing$
$R_t \leftarrow P_t \cup O_t$
for i in range(0,$|P_t|$) **do**
  sort and select parent chromosome $x_i \in R_t$
  $P_{t+1} \leftarrow P_{t+1} \cup \{x_i\}$
end for
for each pair of chromosomes $(x_i, x_j) \in P_{t+1}$ **do**
  generate $r \sim U(0, 1)$
  if $r > threshold_c$ **then**
    generate crossover point $s \sim U(0, Len(x_i))$
    $x_i^{'}, x_j^{'} \leftarrow NuclearGeneCrossover(x_i, x_j, s)$
    $O_{t+1} \leftarrow O_{t+1} \cup \{x_i^{'}, x_j^{'}\}$
  else
    $O_{t+1} \leftarrow O_{t+1} \cup \{x_i, x_j\}$
  end if
end for
for each chromosome $x_i \in O_{t+1}$ **do**
  for each nuclear gene $y_i \in x_i$ **do**
    for each property $y_{ij} \in y_i$ **do**
      generate $r \sim U(0, 1)$
      if $r > threshold_m$ **then**
        $M \leftarrow \varnothing$
        for i in range(0,m) **do**
          generate $c \sim$ Property Range
          $M \leftarrow M \cup \{c\}$
        end for
        $y_{ij}^{'} \leftarrow PropertyMutation(y_{ij}, M)$
        $y_{ij} = y_{ij}^{'}$
      end if
    end for
  end for
end for
return P_{t+1}, O_{t+1}



Crossover: swaps genes from good fitness function chromosomes to find new chromosomes with high fitness functions

$$y'_{ij} = m_k, \quad k = \arg\max_{k \in K} \sum_{y \in Y_{ij}} |m_k - y|$$

We intend to find the mutation candidate which are most different from the existing ones

Mutation: nuclear genes mutate at a given rate

GARL

ONLINE REINFORCEMENT LEARNING

State

Dynamic object's position

Marker's position

$$S = (P_{obj,x} - P_{marker,x}, P_{obj,y} - P_{marker,y},$$
$$P_{uav,x} - P_{marker,x}, P_{uav,y} - P_{marker,y})$$

UAV's position

Action

$$A := \{U, D, L, R, S\}$$

Reward

portion of marker obscured by the dynamic object

$$\mathbf{R} = \begin{cases} \frac{S_{gt}}{S_d} + \mathbf{I}, & \text{if } S_d! = 0 \\ \mathbf{I}, & \text{if } S_d = S_{gt} \text{ or } S_d = 0 \end{cases}$$

Collision indicator, the numerical value is 20

RL guides dynamic object dynamically in the direction that increases the probability of violations

Reward dynamic object if it obscures marker or collides with UAV

RL initially trained in simplified surrogate stage before being fully employed in GARL for faster convergence

Even so, 12 hours for RL to converge in surrogate environment

GARL Summary and Future Work

- Novel Hybrid GA + RL algorithm for finding failures in autonomous landing
  - Outperforms baselines in simulation
  - Same violations found in real world flight tests
- Future Work:
  - Moving from single agent to multi-agents RL system.
  - Using GARL in developing and testing learning-enabled autonomous systems, such as autonomous vehicles and humanoid robots.
  - Integrating GARL to devops pipeline of drone system, and achieve fully autonomous testing.

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Closing thoughts

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Part 3: 5 December at:
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A recording of the webinar will be made and be distributed
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