

Hybrid Power Drones for Multipurpose Applications

Maryam Aldhanhani

MSc. Thesis

May 2025

Thesis submitted to Khalifa University of Science and Technology in accordance with the requirements of the degree of MSc in Electrical Engineering the Department of Electrical Engineering.

Hybrid Power Drones for Multipurpose Applications

By

Maryam Aldhanhani

A thesis submitted in partial fulfillment of the requirements for the degree of

MSc in Electrical Engineering

at

Khalifa University

Thesis Committee

Dr. Reyad El-Khazali (Main Advisor),
Khalifa University

Prof. Yahya Zweiri (Co-Advisor),
Khalifa University

Dr. Khalifa Al Hosani (RSC Member 1),
Khalifa University

Dr. Jorge Dias (RSC Member 2)
Khalifa University

May 2025

Abstract

Maryam M. AlDhanhani, "**Hybrid Power Drones for Multipurpose Applications**", M.Sc. Thesis, MSc in Electrical Engineering, Department of Electrical Engineering, Khalifa University of Science and Technology, United Arab Emirates, May 2025.

The purpose of this research is to provide details on the process of designing and implementing a hybrid power drone for multipurpose applications. This innovative design combines the internal combustion engine (ICE) and battery power sources to drive the hybrid drone, ensuring its ability to maintain a stable and controlled flight. Such drones are valuable in fields like agriculture, firefighting, and police surveillance, where long flight time and high payload capacities are crucial. Typically, electric drones are powered by lithium batteries. However, the challenge lies in their limited effective flight times, which hardly exceed 10 to 30 minutes, especially when dealing with high payloads. This constraint presents a significant challenge for applications that require long operational endurance. Addressing this issue, this research explores innovative strategies to push the boundaries of Unmanned Aerial Vehicle (UAV) performance. The main objective is to not only extend the flight durations but also significantly increase the payload capacity of these aerial platforms and optimize the power supplied to the UAV.

This work also presents the problem statement, outlining the key challenges addressed by the project. The objectives are defined to guide the development of the hybrid power UAV, ensuring efficient energy management, optimizing power distribution, and enhancing flight endurance. Additionally, the study focuses on the optimization of the power management system (PMS) using advanced techniques to minimize fuel consumption and maximize efficiency. Demonstrating its effectiveness in extending flight time and improving operational performance.

Indexing Terms: Unmanned Aerial Vehicle, Hybrid Power sources, Controller Design, Internal Combustion Engine, Batteries.

Acknowledgment

﴿وَآخِرُ دَعْوَاهُمْ أَنِ الْحَمْدُ لِلَّهِ رَبِّ الْعَالَمِينَ﴾

The author wishes to acknowledge the invaluable guidance of Dr. Reyad El-Khazali, Prof. Yahya Zweiri, and the rest of the committee for their invaluable guidance and support throughout this research journey. Their expertise, insightful feedback, and unwavering encouragement have been instrumental in the completion of this work. The author would also like to acknowledge the contribution of Khalifa University's research facilities to the results of this research.

To the greatest man, my beloved father, whom I lost at the beginning of this journey. Although he is no longer here to witness this achievement, his presence has remained with me in every step along the way. This accomplishment is a reflection of his lasting influence on my life. This is not my achievement, but his.

To my first and everlasting supporter, my dear friend Sara. Your unwavering faith in me, your constant encouragement, and your continuous support have been a pillar of strength throughout my journey. Without your presence, belief, and kindness, none of these achievements would have been possible. I owe every step of this path, every challenge overcome, and every success I now celebrate to you. I am truly grateful to have you in my life.

I would like to express my deepest gratitude to my mother and siblings— Shamsa, Moza, Noura, and Hamad— for their continuous support and encouragement throughout my journey. Their unwavering pride in my achievements has been an endless source of motivation, and their strong belief in my abilities has given me the strength to overcome even the most challenging moments. This accomplishment is as much theirs as it is mine.

To Halcon EECE team, my friends, and all those who supported me. Those who shared in my challenges, celebrated my achievements, and whose encouragement sustained me throughout this entire journey, I extend my deepest gratitude for your unwavering support and meaningful presence.

Declaration and Copyright

Declaration

I declare that the work in this thesis was carried out in accordance with the regulations of Khalifa University of Science and Technology. The work is entirely my own except where indicated by special reference in the text. Any views expressed in the thesis are those of the author and in no way represent those of Khalifa University of Science and Technology. No part of the thesis has been presented to any other university for any degree.

Author Name: Maryam Aldhanhani

Author Signature: 

Date: 16-May-2025

Copyright ©

No part of this thesis may be reproduced, stored in a retrieval system, or transmitted, in any form or by any means, electronic, mechanical, photocopying, recording, scanning or otherwise, without prior written permission of the author. The thesis may be made available for consultation in Khalifa University of Science and Technology Library and for inter-library lending for use in another library and may be copied in full or in part for any bona fide library or research worker, on the understanding that users are made aware of their obligations under copyright, i.e. that no quotation and no information derived from it may be published without the author's prior consent.

Table of Contents

Abstract I
Acknowledgment II
Declaration and Copyright III
Table of Contents IV
List of Figures VI
List of Tables VII
Chapter 1 . Introduction 1
1.1 Background And Motivation 1
1.2 Problem Statement 3
1.3 Thesis Objectives 3
1.4 Scope and Limitations 4
Chapter 2 . Literature Review 5
2.1 Unmanned Aerial Systems (UAS) 5
2.1.1. Unmanned Aerial Vehicle 5
2.2.2. Ground Control Station 8
2.2.3. Communication Systems 9
2.2 UAV Power Sources 12
2.2.1 Battery-Powered UAV 12
2.2.2 Tethering 15
2.2.3 ICE -Powered UAVs 16
2.2.4 Fuel Cell-Powered UAVs 16
2.2.5 Solar Cells- Powered UAVs 17
2.2.6 Supercapacitors 17
2.2.7 Hybrid Power UAVs 20
2.3 Power Management System (PMS) 21
2.3.1 Rule-Based Strategy 22
2.3.2 Fuzzy Logic Strategy 22
2.6 Relevant Research and Development 23
2.7 Design Limitations and Constrains 26
Chapter 3 . System Requirements 27
3.1 Methodology 28
3.2 Power System Analysis 28
3.2.1 Weight and Thrust Requirements 29
3.2.2 Power Requirements 30
3.2.3 Battery Analysis 32
3.2.4 ICE Analysis 33
3.2.5 Hybrid Power Analysis 33
Chapter 4 . Power Management Optimization 35

4.1 Input Data Filtering 36
4.2 Problem formulation 36
4.2.1 Objective Function 37
4.2.2 Decision Variables 37
4.2.3 Battery Constraints 37
4.2.4 SoC Constraints 38
4.2.5 ICE Constraints 38
4.2.6 Fuel Tank Constraints 39
4.3 Optimization Techniques 40
4.3.1 Linear Programming Optimization 40
4.3.2 Dynamic Programming Optimization 41
4.4 Results 41
4.4.1 Linear Programming 42
4.4.2 Dynamic Programming 44
Chapter 5 . Application of Hybrid Power Drone 47
5.1 Car Plate Detection 47
5.3 Methodology 49
5.3.1 Dataset 50
5.3.2 Yol0v8 Model and Performance Evaluation 51
5.4 Results and Discussion 53
5.5 Conclusion 58
Chapter 6 . Research Schedule 59
Chapter 7 . Conclusion 60
7.1 Critical Appraisal 61
7.2 Future Work 61

List of Figures

Figure 2.1: Block diagram of a typical UAS [5] 5
Figure 2.2: (a) Fixed-wing aircraft, (b) Rotary-wing aircraft. 6
Figure 2.3: Ragone plot [4] 13
Figure 2.4:Swapping vs hot swapping techniques 13
Figure 2.5: Swapping and hot swapping algorithms 14
Figure 2.6: Laser-powered UAVs 14
Figure 2.7:Tethered UAVs 15
Figure 2.8: Hybrid power drone 21
Figure 3.1: Flow chart of the research methodology 28
Figure 3.2: Flight time using Battery vs Hybrid Power system 34
Figure 4.1: Actual load/demand power 35
Figure 4.2: Actual and filtered load/demand power 36
Figure 4.3: Power generation and load profiles- LP Method 42
Figure 4.4: LP Battery Profile 43
Figure 4.5: SoC- LP Method 43
Figure 4.6: Fuel Tank Capacity- LP Method 43
Figure 4.7: Power generation and load profiles- DP Method 44
Figure 4.8: DP Battery Power 45
Figure 4.9: SoC- DP Method 45
Figure 4.10: Hydrogen Tank Capacity- DP Method 45
Figure 5.1: Example of plate numbers 47
Figure 5.2: Plate detection system 50
Figure 5.3: Training loss curves 53
Figure 5.4: Class instance distribution across the categories 56
Figure 5.5: Example of YOLOv8 results on the testing images 56
Figure 5.6: Low detection confidence (A letter and old_Umalq classes) 57
Figure 6.1: Research Schedule 59

List of Tables

Table 2.1: Comparison between rotary-wings UAV 7
Table 2.2: Comparison among UranusLink, UAVCan, and MAVLink protocols 11
Table 2.3: The advantages and limitations of power sources [5], [14], [16],[4] 18
Table 2.4: Comparison of the different characteristics of various power sources. [16] 19
Table 2.5: Comparison of power source ratios 19
Table 3.1: Components Specifications 29
Table 3.2: Thrust-to-weight ratio 30
Table 3.3: Required power from the motor at each phase 30
Table 3.4: Subsystems power needed 31
Table 3.5: Total power for 3 phases 31
Table 3.6: Li-po Battery Specifications 32
Table 3.7: Total flight time using battery only 32
Table 3.8: ICE Specifications 33
Table 3.9: Extra flight time using a hybrid power source 34
Table 5.1: Yolov8 parameters 51
Table 5.2: Performance metrics 54

Chapter 1 . Introduction

1.1 Background And Motivation

The UAVs have emerged as revolutionary technologies, transforming various industries. Initially developed for military use, drones seamlessly integrated into civilian purposes, reshaping tasks that are limited by human capabilities. Their smaller sizes, novel applications, and improvements in technology drive their development from experimental prototypes to complex, widely available technology. The roots of drone technology trace back to the early 20th century, with initial experiments in remote-controlled aircraft. However, it was in the latter half of the century that drones gained strategic importance in military contexts, particularly in exploration and surveillance [1]. In the following years, UAV technology became accessible to the public, moving from military applications to being widely used by civilians. Advances in propulsion, navigation, and communication technologies have made drones cutting-edge innovations. Equipped with a variety of technological components, including GPS systems, cameras, sensors, and advanced features like lidar or radar. Drones come in various shapes and sizes designed for specific purposes, quadcopters, hexacopters, octocopters, and fixed-wing drones serve diverse functions from leisure activities to mapping and surveying. Developments in drone technology continually push boundaries, integrating artificial intelligence and machine learning for enhanced autonomous capabilities. Swarming technology, where multiple drones collaborate in a coordinated manner, is actively researched for applications in surveillance and emergency response operations [2].

Drones have become essential across various industries. In the infrastructure sector, they contribute significantly to investment monitoring, maintenance, and asset inventory. Agriculture utilizes drones for soil analysis, drainage assessment, crop health monitoring, yield prediction, and targeted application of pesticides and fertilizers. The transport industry allocates drones for the delivery of goods and medical logistics, while drones play a necessary role in the security sector, monitoring lines and sites, and implementing proactive response measures. In the entertainment and media industries, drones find applications in advertising, aerial photography, shows, and special effects. The insurance industry uses drones to help with settling claims and finding fraud.

Telecommunication utilizes drones for tower maintenance and signal broadcasting, and the mining industry uses drones for planning, exploration, and environmental impact assessment. Additionally, drones capture aerial photography, transform agriculture with precise farming techniques, aid environmental monitoring, and play a crucial role in search and rescue operations. Infrastructure inspection benefits from drones' access to hard-to-reach areas, ensuring safer evaluations. In surveillance and security, drones enhance situational awareness, and their potential use in delivery services promises to revolutionize logistics. In disaster response, drones offer rapid assessments, aiding emergency responders in evaluating damage. Mapping and surveying applications benefit from drones' speed and precision, creating detailed maps and 3D models. Scientific research across fields like meteorology, archaeology, and oceanography relies on drones as adaptable platforms for data collection in challenging environments [3]. The diverse range of drone applications underscores their transformative impact on traditional processes and their potential contribution to advancements in numerous fields.

The main power source for conventional electric drones has been lithium-polymer (LiPo) batteries. Despite having advantages such as high energy density and rechargeability, LiPo batteries have intrinsic limitations, especially in terms of charging time, long flying time, and heavy payload capacity. Unfortunately, due to constraints related to weight and space, simply increasing the number of batteries is not a viable solution. The use of additional power sources is then necessary to balance the limitations of the batteries while remaining compliant with weight and space constraints to increase the endurance of UAVs [4]. The emergence of hybrid power drones represents a significant advancement in the field of UAVs, offering an interesting solution to address some of the key challenges faced by traditional electric drones. With the increasing demand for UAVs in diverse sectors, hybrid power setups have captured interest due to their capacity to improve performance, versatility, and sustainability [5]. Combining batteries with additional energy sources, such as fuel cells, solar cells, and supercapacitors, enables the system to take advantage of each source's benefits and address its limitations [6]. The motivation for this research stems from the need for innovative advancements in unmanned aviation, particularly in extending UAV flight endurance through efficient power management. Over the years, drones have evolved from experimental devices to essential tools in various applications, including environmental monitoring, disaster response, surveillance, and logistics. However, a major limitation remains their restricted flight duration due to battery constraints.

1.2 Problem Statement

This study focuses on the development and optimization of a hybrid PMS for UAVs, integrating a battery system with an ICE. Unlike previous works that primarily focus on the structural design of hybrid drones, this research aims to enhance energy efficiency, extend operational range, and ensure optimal power distribution across different flight phases (takeoff, cruising, and maneuvering). A PMS is implemented to regulate energy flow, optimize source switching, and improve power allocation between the battery and ICE. Beyond power management, this research also explores AI-based detection as an onboard application for the hybrid drone, specifically focusing on automatic license plate recognition (ALPR) in the UAE. By integrating deep learning-based object detection models, the drone can be utilized for real-time vehicle identification, offering enhanced surveillance and traffic monitoring capabilities. Through a comprehensive analysis of the hybrid power system's performance and optimization techniques, this study demonstrates how effective power distribution and management can overcome traditional endurance limitations, making UAVs more reliable and versatile for extended missions.

1.3 Thesis Objectives

The objectives of this research are focused on optimizing power management and efficiency in a hybrid-powered drone by focusing on its fundamental aspects and integrating AI-based applications. The key objectives are:

- Conduct a detailed power system analysis, evaluating energy requirements across different flight phases (takeoff, gliding, and maneuvering) to optimize power distribution and extend flight time.
- Develop and optimize a hybrid power management system, ensuring efficient energy flow regulation between a lithium-polymer battery and an ICE to improve endurance and operational efficiency.
- Implement and test energy optimization techniques such as Linear Programming (LP) and Dynamic Programming (DP) to enhance energy efficiency, minimize fuel consumption, and maximize the drone endurance.

- Integrate AI-based detection as an onboard application, specifically developing an ALPR system using deep learning-based object detection to enhance UAV surveillance and traffic monitoring capabilities.
- Validate the hybrid UAV's performance through simulations, ensuring improved endurance, power efficiency, and payload capacity for extended operational applications.

1.4 Scope and Limitations

This study explores hybrid power management and AI-based detection in UAVs, aiming to enhance endurance and operational efficiency. However, several challenges must be considered:

- Power Management Complexity: Regulating energy distribution between the battery and ICE generator requires advanced optimization techniques, but real-world factors such as variable loads and dynamic flight conditions may introduce uncertainties.
- Limited Environmental Representation: Simulations may not fully replicate real-world conditions, affecting the accuracy of performance predictions.
- Simplified Assumptions: Certain modeling simplifications may lead to differences between simulated and actual UAV behavior.
- AI-Based Detection Limitations: The ALPR system may struggle with varying lighting, motion blur, and diverse license plate formats, and available data for training is limited, affecting accuracy. Additional dataset augmentation and fine-tuning may be needed.
- Hardware Constraints: The ICE's fixed power output is insufficient for peak loads during takeoff, requiring efficient battery support and energy balancing.

Chapter 2 . Literature Review

2.1 Unmanned Aerial Systems (UAS)

The block diagram of powered aerial vehicles is shown in Figure 2.1, it can operate autonomously without a human operator from the ground stations. These devices can fly independently or with remote control and produce lift using aerodynamic forces. UAS technology has grown quickly in recent years, gaining traction in different industries due to its diverse applications [7].

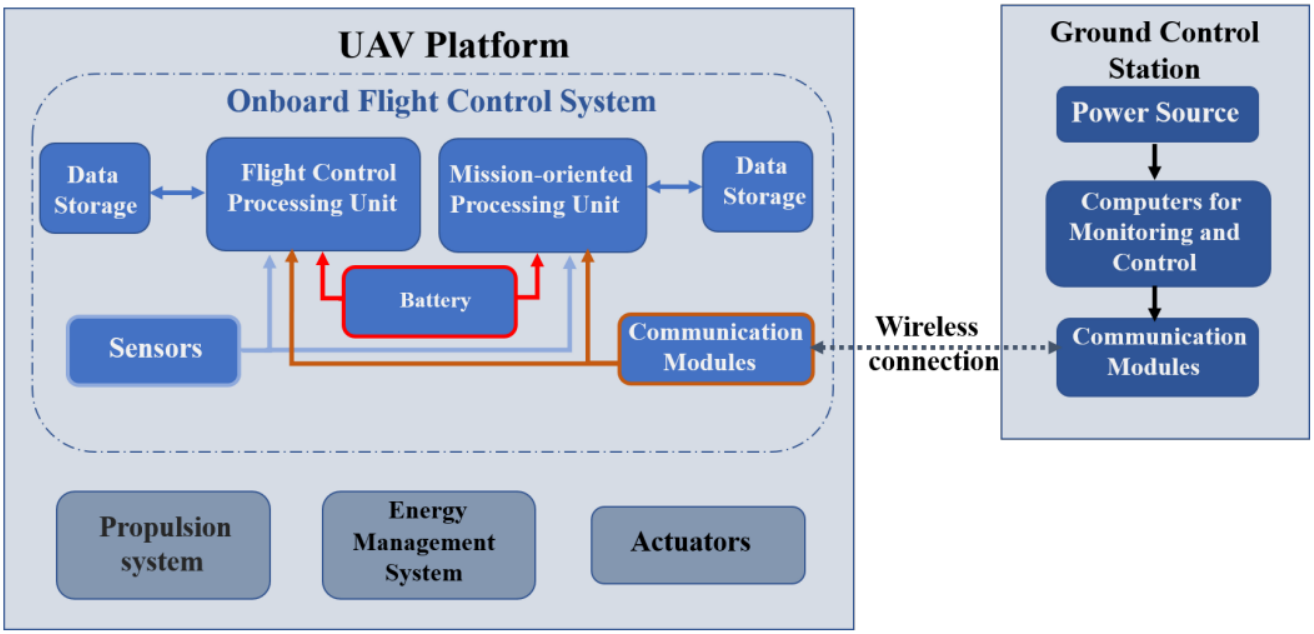


Figure 2.1: Block diagram of a typical UAS [5]

2.1.1. Unmanned Aerial Vehicle

The UAV is the core of the UAS, which represents the unmanned aircraft itself. The UAV structure comprises the flight control system, propulsion system, sensors, and payload equipment. The propulsion system holds significant importance as it facilitates the movement of the UAV by transforming electrical energy into mechanical force [8]. UAVs can be classified based on various parameters, and this depends on the specific mission requirements, such as range, endurance, payload capacity, and flexibility. In terms of size, the UAVs can be further categorized as mini,

micro, and nano UAVs [5]. In terms of aerodynamic flight principles, they can be categorized as fixed-wing or rotary-wing aircraft as shown in Figure 2.2 [7].

When comparing fixed-wing and rotary-wing UAVs, several key factors come into consideration. Fixed-wing Mini UAS, for instance, exhibits a notable advantage in endurance, boasting an average flight time of nearly 11 hours, surpassing rotary-wing counterparts by 40% [9]. However, in situations where adaptability and manoeuverability within limited spaces are of importance, rotary-wing UAVs demonstrate exceptional performance. The hover capability and precision manoeuvering make them ideal for missions such as continuous surveillance. Yet, they do consume more energy for sustained flight, resulting in reduced endurance and slower speeds, which may lead to extended flight time. On the other side, fixed-wing UAVs are more effective in speed and efficiency, covering longer distances rapidly. While rotary-wing UAVs offer advantages with their compact configurations, fixed-wing may present challenges in terms of heavier launch and recovery mechanisms. Payload capacity aligns rotary-wing UASs, allowing for the carriage of heavier payloads, suitable for tasks like infrastructure inspection and field monitoring. Finally, the application focus varies, with fixed-wing UASs often deployed for monitoring extensive areas like large fields or forests, while rotary-wing UASs find their specialized roles in applications such as inspecting infrastructure like bridges, dams, windmills, as well as monitoring smaller fields and performing spraying operations[7], [9]



(a) (b)

Figure 2.2: (a) Fixed-wing aircraft, (b) Rotary-wing

A quadcopter is a multi-rotor helicopter that is powered and lifted by four rotors, defining it as a rotorcraft due to the rotor-driven lift generation. Quadcopters, unlike traditional helicopters, have two sets of fixed-pitch propellers, two clockwise and two counterclockwise. The quadcopter manages its lift and torque by modifying the RPM of its motors, which can be achieved by varying the rotation rate of one or more motor, hence changing torque load and thrust/lift characteristics [10]. By adjusting the motors speed, each motor contributes to lift, allowing position, altitude, and orientation variations. Control of thrust from individual motor allows for precise movements such as forward, backward, side shifts, and vertical axis rotation. A self-control algorithm controls motors thrust to achieve desired flight patterns and stability, allowing for stable hovering. Quadcopters are designed and controlled utilizing a variety of techniques that incorporate both horizontal and vertical movement [11]. Table 2.1 compares different rotary-wing UAVs.

Table 2.1: Comparison between rotary-wings UAV

	Advantages	**Limitations**
Quadcopter	o Simple mechanical structure and control system. o Lower cost o Easy to maneuver o Opposite forces stays balanced.	o Light lifting capacity. o Less stability compared to higher rotor configurations.
Hexacopter	o Higher stability o Increased payload capacity and redundancy.	o Insufficient performance and battery capacity. o More complex control system. o Higher cost o Limited manoeuverability in tight spaces.
Octocopter	o Very high stability. o Greater lifting capacity and redundancy.	o Several components to keep track of.

Multicopter:	o Enhanced stability and payload capacity. o Increased redundancy. o Greater manoeuverability.	o Maintenance can be more challenging due to more components and systems. o Increased complexity and cost.

One example of a multicopter design is the Volocopter flying taxi, created by Volocopter, which provides a practical and sustainable type of transportation in crowded urban areas like Dubai. Modern transportation problems can be effectively solved with the Volocopter flying taxi, which has the potential to improve urban mobility. It can do forward and vertical flight, and landing due to its 18 electric motor-powered rotors. Stable and accurate flight control is provided by advanced flight control systems, which include gyroscopes and sensors. It is designed for short- to medium-range flights in urban areas. It is capable of traveling at speeds of up to 100 km/h and has a range of up to 35 kilometers on a single charge with a maximum payload of 200kg. The Volocopter flying taxi offers environmentally friendly and efficient transportation, aligning with Dubai's commitment to embracing innovation and technology for urban development [12].

2.2.2. Ground Control Station

A ground control station (GCS) is critical in the operation of UAS, working as the nerve system for managing and controlling the UAV. Essential components include a central processing unit, telemetry/telecommand module, user control module, wireless datalink subsystem, and either a graphical user interface or command-line interface. The wireless datalink subsystem is set up for remote connection with the UAS, allowing the GCS and the UAV to exchange critical information and commands. The GCS's telemetry/telecommand module serves two functions: 1) Downloads onboard data from the UAV, guaranteeing that operators have current data. 2) Uploads commands from the ground station to the UAV, ensuring smooth command communication. This bidirectional data sharing is critical to the efficiency and security of UAS flights [9]. The graphical user interface component, which includes a display module, is intended to give operators a visual representation of the data acquired from the UAV. It also plays an important function in keeping communication and data connections between the UAV and the ground station functional. This interface is required for users to keep track of the UAV's status, receive telemetry data, and send commands, all of

which are required for the UAS to operate successfully. Communicating effectively between the GSC and the UAV is critical to achieving reliable and secure operation. To send out commands as well as receive real-time data, UAS mainly relies on communication via wireless systems like radio frequency (RF) communication or satellite communication. This technology ensures that operators can keep control of the aircraft and check its status even when it is out of sight. In essence, the GCS and its communication subsystem are important connections that allow operators to realize the full potential of UAS technology while maintaining mission safety and efficiency [8].

2.2.3. Communication Systems

UAVs are controlled by the controller or GCS using several communication protocols, such as MAVLink, UranusLink, and UAVCAN. Messages are transferred using these communication protocols. These messages include a variety of information about the UAV as well as specific control directives delivered from GCS to the UAV or the UAV to GCS. Effective communication between the GSC and the UAV is crucial for safe and reliable operation. UAS relies on wireless communication systems, such as radio frequency (RF) links or satellite communication, to transmit commands and receive real-time data. UAVs can communicate using a variety of different protocols [13]. The most common are briefly discussed.

A) Uranuslink Protocol

A lightweight communication protocol designed for radio systems to facilitate both reliable and unreliable packet-oriented transmission. It uses a packet structure consisting of several fields, such as start bit, sequence number, message identification, data length, and data itself [8], allowing for robust data transmission while maintaining a balance between overhead and efficiency [13].

B) UAVCAN Protocol

An open-source protocol designed for secure connectivity in UAVs. It operates on a publish-subscribe architecture and is suitable for resource-constrained and real-time systems like UAVs. The protocol eliminates the need for a master node, to ensure no single point of failure in the communication network. UAVCAN supports multiple nodes and multiple interfaces, making it ideal for safety concerns in applications. Every UAVCAN node has its own ID, and ID 1 is a

commonly used value for a UAVCAN node. The MAVLink Component ID (COMPID) number and the UAVCAN Node ID must match for proper communication between units [8].

C) MAVLINK Protocol

An open-source and lightweight protocol primarily used for bidirectional communication between GCSs and UAVs [9]. It was first published by Lorenz Meier in early 2009. The current recommended version is MAVLink 2.0, which was published in early 2017. MAVLink protocol has two message types: messages from the GCS to the UAV and UAV messages to the GCS. In MAVLink 1.0, the protocol headers include the following fields: STX (start of the frame), LEN (payload size), SEQ (sequence of the packet), SYS ID (unmanned system ID), COMP ID (system element sender), Message ID (type of message), Payload (actual message information), and Checksum (CRC, ensures message integrity). MAVLink 2.0 includes all the fields of MAVLink 1.0 and adds new fields while increasing the size of some existing fields. The additional fields are INCFLAG and CMPFLAG (flags for incompatibility and compatibility), SIGNATURE (for message authentication), LinkID (representation of the link/channel), and Timestamp (encodes the scheme of timestamp to avoid replay attacks). The MAVLink 2.0 protocol offers enhanced security elements through message authentication and tamper-proofing features. The message signature ensures the authenticity of the message and prevents unauthorized tampering. The authenticated messages are discarded if they are earlier than the previous packet from the same source, the calculated signature differs from the message signature, or the timestamp is greater than one minute compared to the local system time [8], [13].

Table 2.2: Comparison among UranusLink, UAVCan, and MAVLink protocols

Protocol	**Advantages**	**Limitations**
Uranuslink	○ Open-source ○ Lightweight ○ Designed for aerospace and robotic applications. ○ Supports dual and triple modular redundant transports.	○ Less empirical evidence ○ UranusLink has recently been proposed and its first stable version is not yet available. ○ No support for multiple programming languages. ○ No support for concurrent systems. ○ Not scalable
UAVCAN	○ Open-source ○ Lightweight ○ Low latency ○ Ability to detect and overcome data loss.	○ Less empirical evidence ○ Not widely used ○ No support for multiple programming languages. ○ No support for concurrent systems. ○ Not scalable ○ Designed for UAVs with small overhead. ○ Limited encryption ability ○ Designed for only small data flow.
MAVLink	○ Widely accepted ○ Scalable ○ Support for multiple languages. ○ Support for concurrent systems. ○ Large empirical evidence ○ Lightweight ○ Open-source ○ Low latency	○ No security mechanism

2.2 UAV Power Sources

There are a variety of power sources on the market at present, many of which have applications in the drone industry. These include batteries, solar power, fuel cells, ICE, and more. Some power sources have been abandoned over time because their disadvantages have been found to exceed their benefits in some situations. These disadvantages could include being either large or heavy, having trouble moving, or having a low energy density. Most power sources are categorized according to their individual energy and power densities [14].

2.2.1 Battery-Powered UAV

The UAVs rely on batteries as their main power source due to their portability and simplicity [15]. Battery-powered platforms offer improved flexibility and are cost-effective, making them suitable for hobbyist applications. The selection of an optimal battery type is dependent upon a comprehensive assessment of various factors, including power density, energy density, weight, volume, cycle life, cost, safety, and maintenance, among other criteria. These considerations influence different aspects of drone performance. Power density, for instance, directly impacts acceleration capabilities, while energy density plays an important role in determining the operational range. Cycle life considerations inform the frequency of battery replacements. Additionally, weight and volume considerations significantly influence the overall range of the drone system, and cost considerations impact resource availability. Lithium Polymer (LiPo) batteries are commonly used in small UAVs due to their superior energy density as shown in Figure 2.3, power-to-energy balance and long cycle life, enabling longer flight times [16]. It is estimated that almost 90% of micro aerial vehicles on the market, weighing less than 2 kg and under 100 cm in length, are powered by LiPo batteries. However, these smaller UAVs may have limitations in endurance due to weight restrictions on the battery packs. With LiPo batteries, the maximum flight time of these small-scale UAVs is around 90 minutes on a single charge [2], [5]. To address these limitations, various techniques have been proposed to recharge or replace depleted batteries during flight to increase the endurance and range of battery-based drones and allow for longer and more persistent missions.

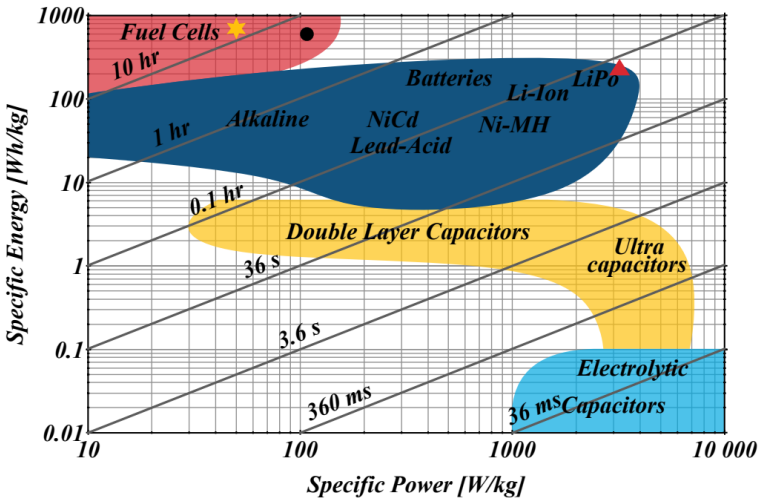
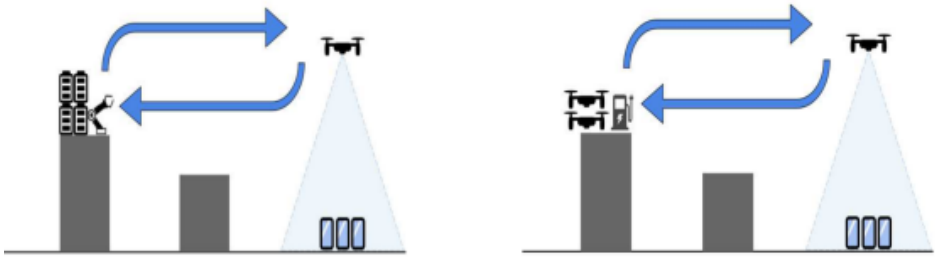


Figure 2.3: Ragone plot [4]

A) Battery Swapping

Swapping is a method by which depleted batteries in a UAV are replaced with fully charged ones during the mission. It can be done autonomously or with human intervention, as shown in Figures 2.4 and 2.5. The concept of hot swapping involves replacing the depleted battery while the UAV is still running, allowing it to continue operating without interruption. The swapping technique extends the UAV's operating time by using a ground station where UAVs can land for charging or changing batteries. UAV swarms are used for persistent applications, ensuring continuous service by seamlessly transferring a hotspot from one unit to another. A reliable management system is required to facilitate UAV cooperation in the swapping process [2], [5].



(a) Swapping (b) Hot Swapping

Figure 2.4:Swapping vs hot swapping techniques

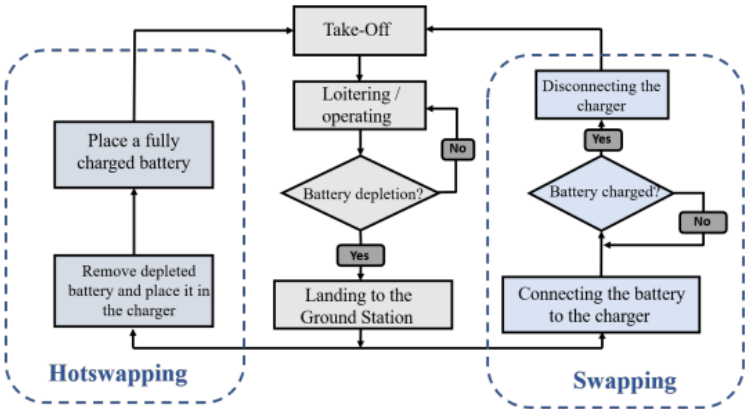


Figure 2.5: Swapping and hot swapping algorithms

B) Laser-Beam Inflight Recharging

Laser-beam inflight recharging is an alternative approach to extend the operating time of battery-based UAVs without the need to land and recharge. In this technique, a ground station with a prime power source supplies a laser generator that transmits a light beam to the UAV while it is airborne as shown in Figure 2.6. The UAV is equipped with an embedded optical receiver that converts the light into electricity, which powers the UAV. This technology enables UAVs to stay in flight for a long time, eliminating the risks associated with take-off and landing. Laser transmitters can be deployed on high rooftops or mobile stations to establish a radiative link between the UAV and the nearest energy source for fast power transfer. LaserMotive company has developed a working prototype that enables the transfer of hundreds of watts of power. The experiments have shown the feasibility of the technique with more than 12 hours of flight time for a quadcopter [2], [5].

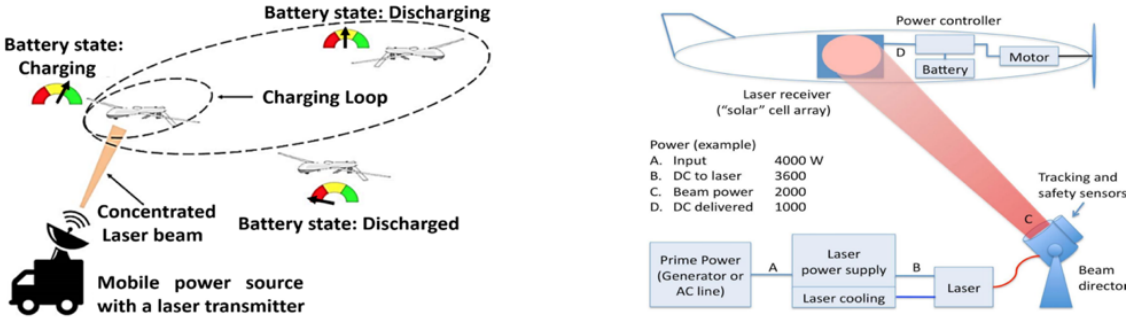


Figure 2.6: Laser-powered UAVs

It is important to note that battery-based drones still face challenges in terms of limited autonomy and the specific energy of batteries, which restricts their usage to commercial purposes [6]. Although battery technology has improved over the years, increasing the number or size of batteries is not a practical solution due to weight constraints. To overcome this limitation and extend the endurance of battery-based drones, alternative power sources have been explored.

2.2.2 Tethering

Tethering is another method used for power management on UAVs. It involves keeping the UAV connected to a power source via a tether while it is in flight as shown in Figure 2.7. This allows the UAV to have unlimited operating time without the need to land and recharge. The power is transferred through the tether, ensuring a safe and effective data transfer between the UAV and the ground station. However, tethering has limitations, including the necessity of a ground station and limited operating area. In case of tethering loss, there is a risk of UAV damage. Despite these limitations, tethered UAVs can be used for persistent operations that require long-duration flight [5].

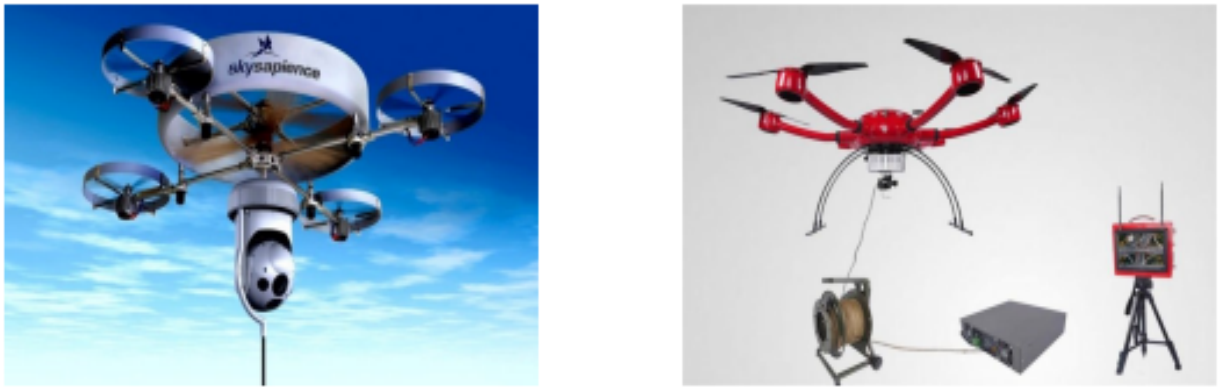


Figure 2.7:Tethered UAVs

2.2.3 ICE -Powered UAVs

The ICE, encompassing both petrol and diesel variants, shares fundamental components such as a combustion chamber, pistons, and fuel injectors. While petrol engines rely on spark plugs for ignition, diesel engines self-ignite under pressure, sometimes assisted by glow plugs during cold conditions. Variations like Kerosene, Methanol, Ethanol, and LPG Propane offer diverse performance benefits, with gasoline-powered solutions showcasing flight times exceeding 20 hours in fixed-wing UAVs. Diesel engines, renowned for their efficiency and fuel adaptability, operate on various fuels with higher energy densities. However, their robustness often translates to increased weight and bulkiness, which presents challenges for drone integration. Despite their advantages, including extended flight times and robustness, ICEs require careful maintenance ,heavier compared to battery-powered counterparts and cause more vibration that should be considerd when sesigning a control algorithm [17].

2.2.4 Fuel Cell-Powered UAVs

Fuel cell-powered UAVs, designed to enhance endurance and performance over battery-powered systems, provide high energy density and instant refueling without memory effects. Fuel cells offer advantages such as low noise and thermal footprint, minimal vibration, ease of operational support, and physical robustness when compared to traditional ICE. However, they exhibit slower response times to power demands, necessitate auxiliary equipment like compressors and regulators, and face challenges regarding hydrogen storage, distribution, and safety [4], [11].

As indicated in Figure 2.3, fuel cell typically has a lower specific power in comparison to batteries and supercapacitors, affecting their ability to deliver power per unit weight and consequently impacting the UAV performance and manoeuverability. While batteries and supercapacitors boast significantly higher specific power, their use is constrained to shorter durations due to lower energy density. Therefore, hybrid systems that combine fuel cells with batteries or supercapacitors aim to achieve optimal overall performance. These hybrid configurations leverage the high specific power of batteries or supercapacitors while taking advantage of the long endurance, and fuel cell's low weight and high specific energy. However, this introduces complexity and additional weight to the system [3].

2.2.5 Solar Cells- Powered UAVs

Photovoltaic cells can be used to directly convert sunlight into electrical energy, which is then used to power the UAV's various systems. The primary advantage of solar power in UAVs is its potential for unlimited and renewable energy and free sunlight as a reliable energy source, especially for long-endurance missions. Solar power is also eco-friendly, producing no harmful emissions or pollutants. Nevertheless, it has limitations such as dependence on sunlight, leading to reduced power generation during cloudy or nighttime conditions, affecting flight capabilities and endurance. To address this limitation, hybrid power systems that combine solar power with other sources like fuel cells or batteries are employed. These systems serve as backup power sources during periods of low solar energy availability.However, they may require larger wings, making them less suitable for rotary-wing UAVs. Additionally, they involve energy storage devices and necessitate BMS and maximum power point tracking techniques to optimize performance[5],[6], [18]

2.2.6 Supercapacitors

Supercapacitors are being investigated as auxiliary power sources for UAVs due to their unique advantages. They can mitigate the limitations of batteries, such as slow power dynamics and extended charging times, making them suitable for UAV take-off and sudden manoeuvers. By integrating supercapacitors into hybrid power supply systems, UAVs can achieve increased power density and rapid power response, enhancing overall performance. In hybrid UAV propulsion systems where fuel cells are the primary power source, supercapacitors serve as auxiliaries, ensuring optimal fuel cell operation for steady-state power delivery and extended lifetime. Moreover, supercapacitors are efficient at load smoothing and dynamic response, stabilizing DC bus voltage, and addressing power fluctuations during dynamic flights. Their high-power density and quick response are valuable for rapid power delivery during manoeuvers or high-demand situations. These characteristics are coupled with a broad temperature. However, they require BMS and voltage regulation [2, [5], [6].

A critical comparative analysis of UAV power supply configurations is proposed in Table 2.3 while, Tables 4 and 5 summarize the characteristics between different power sources at same amount of payload, excluding the solar power as it’s not commonly used for rotary wing UAVs.

Table 2.3: The advantages and limitations of power sources [5], [14], [16],[4]

Power source	**Advantages**	**limitations**
ICE	- Very high specific power and energy - Large autonomy and payload range.	- Heavy weight - large size - noisy - Complex maintenance
Battery	- High stored energy - Portable and simple - long cycle life	- Low specific power - Reduced flight time - Slow recharging - More batteries, more weight and cost
Fuel cell	- High specific power, rapid refuelling without ‘’memory effect”, to extend endurance. - Weight saved. - Low noise and infrared signature, minimal vibration, and physical robustness.	- Long response time - Needs compressors, regulators, etc. - Large Size - Lower energy efficiency compared to batteries. - Hydrogen extraction process increases refuel time and cost.
Solar cell	- Energy and power density are increased. - improvements in endurance and response time, rapid refuelling, and energy storage. - Clean, available power	- Only for fixed wings drones - Large wings are needed. - Energy management system (EMS) is needed. - MPPT algorithm is needed. - Sunlight is needed.

Table 2.4: Comparison of the different characteristics of various power sources. [16]

Power Source / ***product name***	***Li − Po Battery*** / ***DJI Matrice 600***	***Hydrogen FC*** / ***BMPower 1 kW***	***ICE*** / ***Yeair!***
Specific energy (Wh/kg)	9.99	646	**2600**
Flight time (min)	20	**250**	120
Weight (kg)	10	6.5	**4.9**
Payload (kg)	5	5	5
Recharge/discharge time (min)	92	Refuel time	Refuel time
Cost (USD)	5,699	13,410	**1,550**

Table 2.5: Comparison of power source ratios

Power source	$\frac{Payload(kg}{Weight(kg)}$	$\frac{Flight\ Time(min)}{Cost(USD)}$	$\frac{Flight\ Time(min)}{Weight(kg)}$	$\frac{Payload(kg)}{Flight\ Time(min)}$	$\frac{Flight\ Time(min)}{Recharge\ time(min)}$
ICE	**1.020408**	**0.077419**	24.4898	0.041667	<120
Battery	0.5	0.003509	2	**0.25**	0.217391
Hydrogen Fuel Cell	0.769231	0.018643	**38.46154**	0.02	**<250**

Based on the reported information and analysis of three distinct drone power sources: Li-Po Battery (DJI Matrice 600), Hydrogen Fuel Cell (BMPower 1 kW) and ICE (Yeair!) where several remarkable observations emerge [16]. Tables 2.4 and 2.5 show the compression between the three power sources exhibit equal payload capacities of 5 kg, ensuring consistent carrying capabilities. The ICE emerges as the optimal choice among the power sources, exhibiting superior performance metrics as it offers a higher payload-to-weight ratio and flight times-to-cost ratio compared to both the battery and hydrogen fuel cell at the same amount of payload. In terms of specific energy, gasoline demonstrates the highest value at 2600 Wh/kg, followed by hydrogen fuel cell at 646 Wh/kg and Li-Po battery at 9.99 Wh/kg, indicating gasoline's superior energy storage per unit weight. Gasoline proves to be the lightest at 4.9 kg, enhancing manoeuverability and flight duration, followed by the hydrogen fuel cell at 6.5 kg and the Li-Po battery at 10 kg. In terms of cost-effectiveness, gasoline stands out as the most economical option at $1,550, followed by Li-Po battery at $5,699 and hydrogen fuel cell at $13,410. The hydrogen fuel cell has the longest

flight time at 250 minutes, exceeding gasoline at 120 minutes and Li-Po battery at 20 minutes. Extended flight durations are advantageous for long missions [16].

While fuel cell power offers potential advantages, it also presents several disadvantages in comparison to traditional ICEs and battery-powered systems. Fuel cells typically exhibit lower efficiency rates (around 45%) compared to batteries (over 70%) and ICEs (approximately 40%), resulting in higher overall costs and complexity. Issues surrounding hydrogen storage and refuelling, particularly in military applications, create logistical challenges, while factors like flight altitude and oxygen concentration affect fuel cell functionality, especially in high-altitude long-endurance (HALE) UAVs. Moreover, fuel cell systems require careful temperature management, with high working temperatures being necessary for efficient operation, adding complexity to their integration into drone propulsion systems. Despite its potential, the limitations still prevent fuel cell technology from being fully integrated into drones, highlighting the necessity of continuous innovation and improvement in this field [17].

2.2.7 Hybrid Power UAVs

Hybrid power sources refer to the combination of multiple power sources in a power supply system. They enable UAVs to benefit from the advantages of multiple power sources while compensating for their limitations, increasing endurance, and optimizing performance. The use of hybrid power supply systems in UAVs offers several advantages because it allows UAVs to benefit from the different power sources while compensating for their limitations [5], [6], [19].

Considering the findings above, gasoline emerges as a promising drone power source due to its high specific energy, extended flight time, lightweight design, and cost efficiency. Integrating gasoline with a battery as a hybrid power system has the potential to further enhance performance metrics such as weight, payload capacity, and cost-efficiency. By leveraging gasoline's high energy density and quick refueling capabilities alongside the battery's storage efficiency, the hybrid power drone can achieve superior overall performance compared to using either power source individually.



Figure 2.8: Hybrid power drone

2.3 Power Management System (PMS)

Power management strategies are an important aspect of drone delivery systems. To achieve efficient energy usage and extend the lifespan of power sources, power needs to be split optimally between various sources. This can be accomplished through active power management, where the energy management unit controls the power outputs through converters. Additionally, passive methods can be used for small UAVs to directly connect the power sources to the propulsion system without the need for additional converters and controllers. Several control methods, such as rule-based control, fuzzy logic strategies, and dynamic programming, can be employed for energy management. These strategies consider factors such as power requirements, battery state of charge (SoC), fuel consumption, and the contribution of each power source to the supply process. The selection of an energy management system should be based on optimal and accurate modeling techniques[2].

2.3.1 Rule-Based Strategy

Rule-based strategies involve the use of predefined rules to control and manage the energy supply and distribution in drone systems. These strategies are known for their simplicity and robustness in management. They can be implemented online with low computing costs, making them practical for real-time energy management. Rule-based control methods assign output power to power sources based on power requirements and battery lifetime. They often rely on parameters such as power demand, SoC, and battery capacity to make decisions on power allocation. A study by Lee et al. used a rule-based control system to manage a UAV powered by a fuel cell, battery, and solar cells. The system assigned priority to solar cells as the primary power source and used DC-DC converters to control the terminal voltage of each source. Rule-based strategies are advantageous due to their simplicity and low computational requirements, but they may not fully optimize the energy management process [2], [5], [15].

2.3.2 Fuzzy Logic Strategy

On the other hand, fuzzy logic strategies utilize fuzzy control algorithms to allocate power in drone systems based on inputs such as SoC, power demand, and photovoltaic power. Fuzzy logic considers multiple inputs and generates control commands based on predefined fuzzy rules, establishing priorities and constraints to determine an appropriate management strategy. Fuzzy control algorithms can manage uncertainty and inaccurate data, making them suitable for managing energy from various sources in drone systems. The fuzzy EMS used the battery's SoC and power demand as input variables to calculate fuel cell power output. Fuzzy logic strategies perform well in power allocation and optimization, especially when dealing with multiple power sources in UAV systems [2], [18].

2.6 Relevant Research and Development

Multirotor drones have become essential in various industries, performing tasks such as aerial photography, surveillance, mapping, and delivery services. However, the limited flight time of traditional electric-powered multirotor drones has remained a significant challenge, limiting their effectiveness in long-duration missions. In response, researchers and engineers have turned their attention to hybrid propulsion systems as a promising solution to extend flight times while maintaining operational efficiency and versatility [20].

Nagorny et al. [21] discussed UAVs operation based on different propulsion systems, specifically electric, ICE, and hybrid systems. An experiment has been conducted to highlight the advantages and limitations of each propulsion type. However, the study reveals that relatively small and medium-sized UAVs (weighing around 50 kilograms) could benefit from a hybrid propulsion system, while for heavy UAVs hybrid propulsion results in a 25% shorter flight range and flight time compared to ICE UAVs.

Jarrah et al. [22] proposed novel hybrid designs that integrate two gasoline engines with electric motors to optimize thrust-to-weight ratios and energy efficiency. taking the advantages offered from both types of propulsion, gasoline engines for high energy density and electric motors for precise control. Optimization techniques have been developed, including thrust distribution algorithms and energy management strategies. By carefully balancing the contribution of each propulsion system and optimizing operational parameters, researchers achieve remarkable improvements in endurance and mission capability. This approach results in a 50-minute flight time on a controlled test stand, with 75% of the lift provided by the gas system and 25% by the electric system.

Cardone et al. [20] developed numerical models of HEPS using energy methods to simulate the interaction between various components, including ICEs, electric motors, lithium batteries, and aircraft propellers. Experimental setups have been employed to validate the accuracy and reliability of these numerical models, especially in the presence of abnormal operating conditions, ensuring their robustness and applicability across a range of scenarios.

Carreno et al. demonstrated successful application of control systems integrating fuzzy logic and PID controllers to manage energy usage and optimize propulsion performance in UAVs. Using MATLAB-Simulink and the Simscape library, they accurately modelled the dynamics of hybrid propulsion systems and propeller dynamics. The design and tuning of PID controllers,

employing methodologies like root locus analysis, ensured precise control over electric motors, engine speed, and energy distribution within the hybrid propulsion system. These advancements facilitate enhanced energy management [23], improved flight performance, and expanded capabilities across various UAV missions.

Lucena et al. proposed a novel architectural design for hybrid UAVs consisting of flying wings with pusher configurations equipped with ICE propellers, combined with multirotors featuring electric motor-powered propeller sets. This design has been validated through comprehensive testing methods, including takeoff, horizontal flight, transition, and autonomy tests, demonstrating the functionality and effectiveness of the hybrid prototypes [24].

Krznar et al. explored configurations combining ICEs with electricity generators and LiPo batteries. By connecting these components in parallel and developing dedicated control systems, experimental validation of hybrid power unit control systems was conducted using custom-built prototypes. The results show that hybrid propulsion systems can achieve a two-fold increase in energy density compared to battery-only systems, leading to higher flight autonomy for multirotor UAVs [25].

Machado et al. conducted experimental evaluations of parallel hybrid propulsion systems customized for small UAVs. By integrated all components of the hybrid electric propulsion system (HEPS) into modular test benches to accurately characterize system performance. Employing rule-based controllers based on the ideal operating line concept, the objective was to optimize the torque of ICEs and electric motors to minimize fuel consumption effectively. The results indicate successful supplementation of ICE power by electric motors, resulting in reduced fuel consumption. Additionally, the electric motors demonstrated the ability to function as generators, recharging batteries using power from the ICEs [26].

Another recent study by Lu et al. highlighted the advantages of combining the capabilities of multi-rotor drones with those of fixed-wing UAVs. This integration offers enhanced maneuverability, operational flexibility, and endurance, making VTOL UAVs suitable for a wide range of missions. A novel propulsion scheme is proposed, including gasoline-electric hybrid systems, aiming to optimize power distribution and energy utilization while meeting operational requirements. Flight experiments and real-time testing have been conducted to validate the performance and reliability of prototype VTOL UAVs [27].

Refrence [28]explores an optimal fuzzy logic-based energy management strategy to enhance the efficiency and reliability of hybrid power systems in UAVs. By integrating fuel cells and batteries, the proposed system dynamically balances power demands and energy availability, demonstrating improved performance in various flight scenarios.

Refrence [29] discusses real-time energy management strategies integrated with digital twin technologies for hybrid electric UAVs. It emphasizes the potential of fuzzy logic systems to adapt to dynamic environmental conditions, ensuring optimal power utilization and enhanced flight efficiency.

Refrence [30]investigates a fuzzy logic-based approach for energy management in hybrid fuel cell propulsion systems. The study highlights the adaptability of fuzzy logic in handling uncertain and dynamic energy demands, showcasing its suitability for UAV applications.

Refrence[31] provides a practical approach to managing energy in hybrid propulsion drones, demonstrating the importance of rule-based strategies for real-time power optimization. The findings support the design of more reliable and efficient energy systems for drones used in demanding applications like surveillance, delivery, and environmental monitoring.

Refrence [15] presents the rule-based EMS methodology effectively integrates real flight data to enhance the energy efficiency and performance of hybrid drones. By balancing power between the fuel cell and battery and conserving hydrogen, the approach ensures reliability and sustainability in drone operations.

2.7 Design Limitations and Constrains

The limitations identified encompass the restricted flight duration and payload capacity of electric drones utilizing lithium batteries, limiting their effectiveness to short durations with low payloads. This constraint presents challenges for applications requiring extended flight durations and increased payload capacity. The necessity comes for a hybrid power drone, merging electric batteries with a gasoline power generator to extend flying time and enhance payload capacity. A gap exists in the absence of a comparative study between electric batteries and a hybrid power solution, preventing a comprehensive understanding of their effectiveness in improving drone duration and efficiency. Additionally, power management optimization techniques are required to efficiently regulate energy flow between the two power sources, ensuring optimal power distribution, extended flight duration, and improved energy efficiency without relying on traditional power management strategies. The adaptation to specific applications, such as firefighting or agricultural tasks, lacks detailed plans for determining the maximum payload based on the chosen power generator and incorporating features like obstacle avoidance and specialized cameras.

Chapter 3 . System Requirements

The System Requirements for the hybrid power UAV encompass essential hardware, software, and operational components necessary for efficient power management optimization and AI-based detection. The project requirements are focusing on various aspects of drone design and performance, with a strong emphasis on efficiency. The hybrid system, combining a gasoline generator and lithium-polymer batteries, is designed to extend flight time and enhance drone efficiency through optimized power distribution. The power system includes a Li-Po 6S, 44.4V, 22Ah battery, an ICE (P500, 5.5kW output), and a BMS for energy regulation. The UAV structure consists of a carbon fiber frame, eight brushless DC motors (each consuming up to 1554W), optimized propellers, and a Pixhawk-based flight controller for stability and navigation as listed in Table 3.1. The AI-based detection system integrates a high-resolution camera and an NVIDIA Jetson board to implement ALPR using YOLOv8-L. The software requirements include Python-based power optimization algorithms (LP and DP), MATLAB/Python for power analysis, PyTorch for deep learning, OpenCV for image processing, and ArduPilot/PX4 for flight control and telemetry management. Operational requirements involve a reliable power source, an open test environment, compliance with UAV regulations, and real-time data collection from the BMS, flight controller, and AI system. These specifications ensure the UAV is optimized for hybrid energy management, extended endurance, and AI-powered surveillance applications while meeting the efficiency demands of a hybrid power system.

3.1 Methodology

The methodology of this thesis shown in Figure 3.1, follows a structured approach to developing and optimizing a hybrid power UAV, focusing on power system analysis, energy management optimization, and AI-based detection. The process begins with defining the UAV's design requirements, considering total mass, power system components, and integrated technologies. A detailed power system analysis evaluates energy consumption across different flight phases (takeoff, gliding, and maneuvering), including weight impact, thrust-to-weight ratio, and power requirements for motors and onboard subsystems (flight controller, telemetry, etc.). To enhance flight endurance and energy efficiency, a hybrid power system is implemented, integrating a gasoline generator and Li-Po battery for power distribution and peak load management. A PMS is developed using LP and DP to optimize energy allocation, minimize fuel consumption, and ensure reliable power delivery across all flight phases. This methodology ensures the UAV achieves long endurance and energy efficiency.

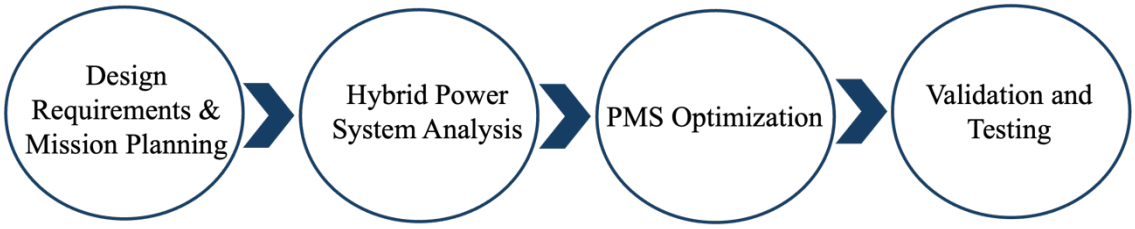


Figure 3.1: Flow chart of the research methodology

3.2 Power System Analysis

This section of the report presents a detailed power analysis of the drone shown in Figure 2.8, focusing on the energy requirements and the performance of the hybrid power system across different flight phases, including takeoff, gliding, and maneuvering. The objective is to ensure that the system can reliably meet the load power of each phase while optimizing energy efficiency and flight time. The analysis begins by analyzing the drone's total weight and its influence on thrust and power requirements. This is followed by an evaluation of the power consumption of the subsystems, such as the motors, flight controller, and telemetry system, during each flight phase. A detailed evaluation of the energy contributions from the battery and generator is also conducted to determine their sufficiency and runtime capabilities. By integrating a hybrid power system, the

drone combines the strengths of a gasoline generator and a Li-Po battery to manage peak loads and enhance endurance. This analysis helps optimize power distribution, improve efficiency, and ensure reliable performance under various flight conditions. By optimizing power distribution and integrating the hybrid configuration effectively, this drone achieves greater operational range and energy efficiency, making it well-suited for extended missions in diverse applications. This section demonstrates the potential of hybrid power systems to overcome traditional energy limitations and enhance the performance of drones in demanding scenarios.

3.2.1 Weight and Thrust Requirements

The drone's components are listed below in Table 3.1 with their individual weights, quantities, and total contributions to the All-Up Weight (AUW):

Table 3.1: Components Specifications

No.	Name	Weight kg)	Quantity	Total weight (kg)
1	Taxi support back	2.3	1	2.3
2	Taxi support front	0.553	2	1.106
3	Battery	2.5	2	5
4	Generator	7	1	7
5	Carbon fiber base	5	1	5
6	Carbon fiber rods	0.33	4	1.32
7	Motor clamps	0.068	8	0.544
8	3D Rod clamps	0.018	8	0.144
9	Steel clamps	0.2	4	0.8
10	Bolts for 3D rod clamps	0.046	16	0.736
11	Shell	2	1	2
12	Motors	0.325	8	2.6
13	Propellers	0.094	8	0.752
14	Controllers and sensors	2	1	2
15	Small steel clamps	0.013	30	0.39
16	Other electrical components	2	1	2
17	Other mechanical components	1	1	1
18	Fuel	1.925	2.5L	1.925
19	Payload		6.5	
Total weight				42

The drone's All-Up Weight (AUW) is **42 kg**, requiring sufficient thrust to achieve stable flight. The thrust-to-weight ratio is designed at **2:1** as shown in Table 3.2, providing the necessary lift and stability, especially under payload conditions.

Table 3.2: Thrust-to-weight ratio

Auw	Thrust: Weight	Total Thrust	Thrust/Motor (8)
42Kg	2:1	84Kg	10.5Kg

3.2.2 Power Requirements

A) Motors

The power usage of the 8 motors changes with the demands of each flight phase summarized in Table 8. During takeoff, the motors use 80% of their maximum capacity, consuming 9,945.6 W to lift the drone. In the gliding phase, which requires less thrust to maintain altitude, the motors operate at only 15% capacity, using 1,864.8 W. For maneuvering, which involves moderat

e thrust for directional changes, the motors use 40% of their capacity, consuming 4,972.8 W. These calculations include all eight motors, showing their critical role in meeting the drone's power needs. Efficient power distribution is essential to ensure the motors perform effectively without wasting energy. The max power of the motor is calculated as follows;

$$44.4V * 35A = 1554W \quad (1)$$

Table 3.3: Required power from the motor at each phase

Flight Phase	Power Usage (% Of Max)	Total Power (W)
Takeoff	80%	9,945.6
Gliding	15%	1,864.8
Maneuvering	40%	4,972.8

B) Subsystems

The subsystems of the drone, including the flight controller and telemetry system, contribute a consistent and essential power demand throughout all flight phases. The flight controller operates at 5V and consumes a current of 2.8A, resulting in a power consumption of 14W. This system is responsible for maintaining stability and executing flight commands, making it a critical component for the drone's operation. The telemetry system, which transmits real-time data between the drone and the ground station, operates at 12V and consumes 5A, resulting in a power consumption of 60W. This subsystem is vital for monitoring flight parameters and ensuring safe and efficient operations. The total power requirement of the subsystems is 74W, which is a consistent baseline energy demand across all flight phases. These systems, while not as energy-intensive as the motors, play an essential role in the overall power requirements of the drone. Managing their power efficiently is key to maximizing the drone's operational time and ensuring reliability.

Table 3.4: Subsystems power needed

Subsystem	Voltage (V)	Current (A)	Power (W)
Flight Controller	5	2.8	14
Telemetry	12	5	60

C) Total Power

The total power requirements for the drone during each flight phase are determined by combining the power consumed by the motors and subsystems. The subsystems, including the flight controller and telemetry, have a consistent power demand of 74W across all phases. The motor power varies significantly based on the operational requirements of each phase:

Table 3.5: Total power for 3 phases

Flight Phase	Subsystems Power (W)	Motors Power (W)	Total Power (W)
Takeoff	74	9,945.6	10,019.6
Gliding	74	1,864.8	1,938.8
Maneuvering	74	4,972.8	5,046.8

3.2.3 Battery Analysis

The drone utilizes Li-Po battery with the following specifications:

Table 3.6: Li-po Battery Specifications

Battery Type	Current Capacity	Voltage	Discharge Rate	Cell Configuration	Max Current Draw	Weight
Li-Po	22Ah	44.4V	25C	2x6s	550A	5Kg

$$\text{Battery Capacity } = 22 * 44.4 = 976.8\, Wh \quad (2)$$

The battery is responsible for powering the motors and subsystems across all flight phases, including takeoff, gliding, and maneuvering. The energy consumption for each phase is detailed below:

Table 3.7: Total flight time using battery only

Flight phases	Takeoff	Gliding	Maneuvering	Total
Energy (Wh)	83.5	646.3	84.133	813.878
Time(minutes)	0.5	20	1	21.5

The total energy requirement for all phases is 813.878 Wh, which is below the maximum battery capacity of 976.8 Wh. A 12% safety margin is included in the calculations to ensure reliable operation and account for unforeseen power demands or inefficiencies. Even with this margin applied, the battery can comfortably handle the total energy requirement, confirming its suitability for the drone's flight. This analysis demonstrates that the battery has sufficient capacity to meet the power demands of the drone while maintaining a safety buffer, ensuring efficient and reliable operation throughout the flight.

3.2.4 ICE Analysis

The drone is equipped with a P500 Hybrid Generator, which is a lightweight and efficient power source with the following specifications:

$$\text{Operation Time: } \frac{5}{2.5} = 0.5h. \quad (3)$$

$$\text{Generator Capacity} = 5{,}500 \times 0.5 = 2{,}750\ Wh \quad (4)$$

Table 3.8: ICE Specifications

Max Power	Output Power	Voltage	Max Current	Fuel Rate	Fuel Tank	Weight
6,000W	5,000W (Cont)	50-60V	120A	5 L/h	2.5L	7kg

While the generator is effective in providing a continuous and sustainable power source during most phases of the flight, it cannot supply sufficient power during **takeoff**. During takeoff, the total load power reaches **10,000W**, far exceeding the generator's maximum continuous power output of **5,000W**. Even at its peak output of **6,000 W**, the generator cannot provide enough power, requiring an additional power source.

3.2.5 Hybrid Power Analysis

To address this limitation, a hybrid power system is implemented as shown in Table 3.9, by combining the generator with a Li-Po battery. This hybrid configuration ensures that the drone can meet power demands efficiently throughout the flight. During takeoff, the battery complements the generator by providing the extra power required to meet the total load power. During gliding and maneuvering phases, the generator alone is sufficient, with excess capacity used to enhance overall efficiency and extend flight duration.

Table 3.9: Extra flight time using a hybrid power source

	Takeoff	Gliding	Maneuvering	Total
Flight Time(min)	0.5	28	1	29.5
Total power (W)	10019.6	1938.8	5046.8	17005
Total energy (Wh)	83.49	904.77	84.11	1072
Energy from ice (Wh)	50	2333.33	91.667	2475
Gasoline power sufficiency	Not sufficient	Sufficient	Sufficient	-
Needed from Battery (Wh)	33.49	-	-	33.49
Extra Energy from ICE (Wh)	-	1428.56	7.5533	1436.1
Remaining battery capacity (Wh)		943.3		
Extra Flight Time (min)	-	24.952	9.64	**34.6**
Total Flight Time (min)	0.5	52.95	10.64	**64.09**

The hybrid power system effectively overcomes the generator's limitations during high-demand phases such as takeoff. By utilizing extra energy from the generator, the hybrid system provides an additional 41.59 minutes of flight time, resulting in a **198%** increase compared to battery-only operation as shown in Figure 3.2. This improvement significantly enhances the drone's operational range and flexibility for extended missions.

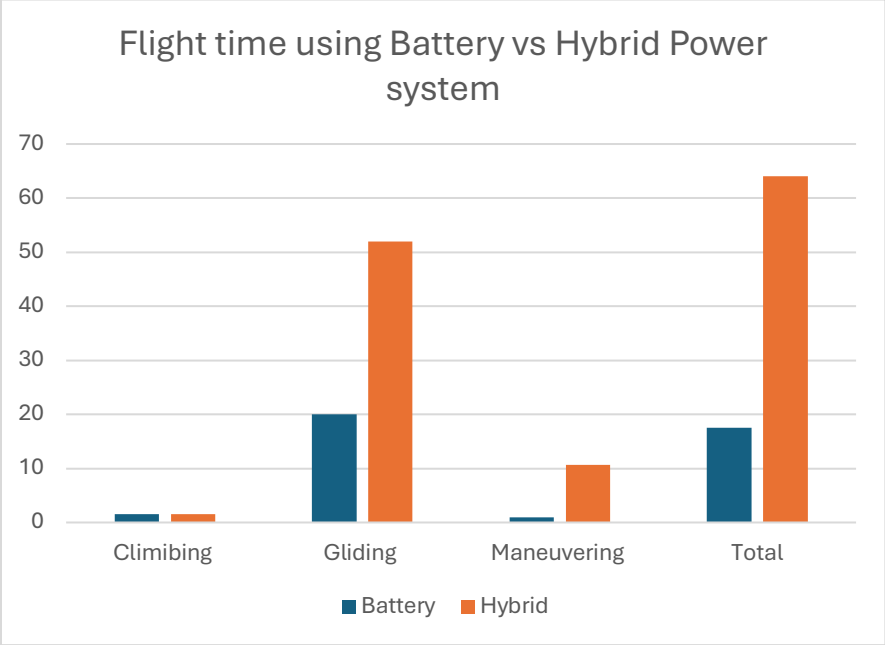


Figure 3.2: Flight time using Battery vs Hybrid Power system

Chapter 4 . Power Management Optimization

Power management plays an important role in ensuring the efficiency and reliability of drone systems, particularly for delivery applications and systems requiring extended power source lifespans. Optimal power distribution can be achieved through active management, where converters regulate energy flow, or passive methods, such as directly connecting power sources to propulsion systems in small UAVs. In this work, the power demand from the load fluctuates significantly over time, as seen in Figure 4.1, where power consumption varies between 0 kW and approximately 30 kW over a period of 743 seconds. The high variability in power demand highlights the importance of applying filtering techniques to smooth out fluctuations. The input data used in this analysis is randomly generated, as real-world testing could not be performed using both the battery and the generator. However, this dataset provides an approximation of expected power consumption trends, allowing for preliminary validation of power management strategies. Effective strategies including LP and DP aim to optimize energy usage by accounting for factors such as power demand, battery SoC, and fuel consumption. Accurate modeling and optimization techniques remain essential for designing robust energy management systems.

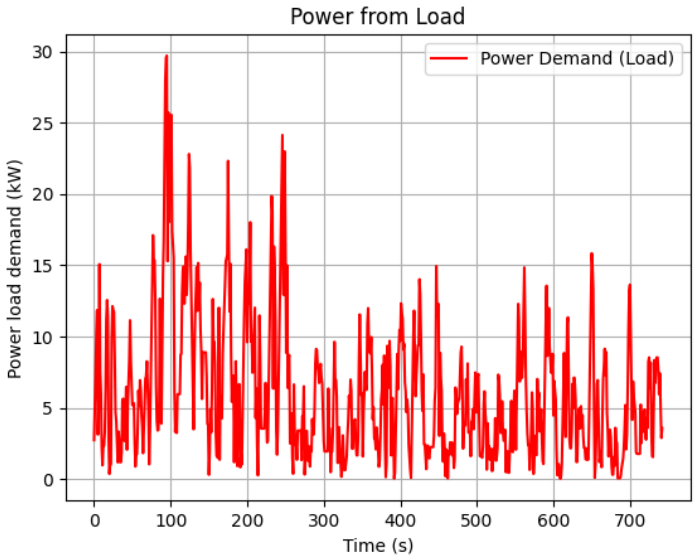


Figure 4.1: Actual load/demand power

4.1 Input Data Filtering

To ensure accurate and reliable power management, it is important to clean the input data by removing unwanted noise and fluctuations. Power data often includes errors caused by sensor inaccuracies, sudden changes, and measurement issues. Using filtering methods helps smooth the data, making it easier to identify power consumption trends. Cleaning the data improves its quality for optimization methods. By reducing noise and removing unusual data points, the processed data can be used effectively for modeling and predictions. Figure 4.2 shows the difference between actual power demand data and the data after applying the moving average filter, demonstrating the benefits of data filtering.

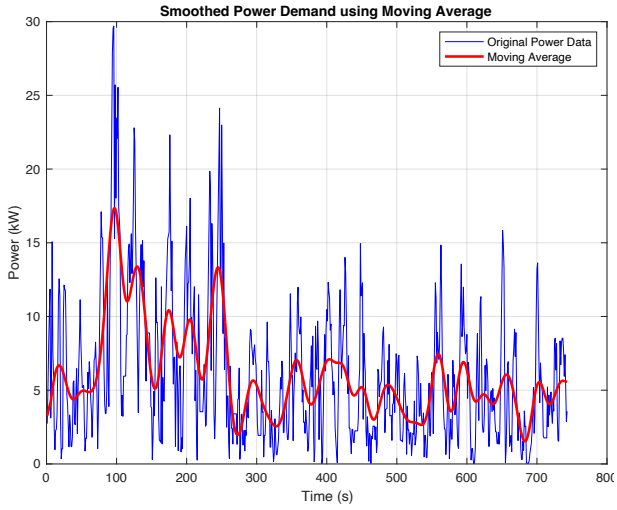


Figure 4.2: Actual and filtered load/demand power

4.2 Problem formulation

The hybrid drone features a hybrid power system comprising an ICE and a battery system, designed to meet the thrust requirements effectively. The configuration specifies a maximum engine output of 6 kW and a battery output of 24.42 kW as shown in Equation 7. It is equipped with a total battery capacity of 0.9768 kWh, achieved by connecting two batteries in series. Additionally, the drone's fuel tank has a maximum capacity of 2.5 liters.

4.2.1 Objective Function

The primary goal of this optimization is to efficiently manage the power distribution between the ICE and the battery system, ensuring dynamic thrust requirements are met under varying operational conditions. The objective function is defined as:

$$\min P_T(t) = \sum_{i=1}^{N} \eta_{ICE} P_1(t) + P_2(t) \quad (5)$$

Where $P_T(t)$ is the total power, $P_1(t)$ is the ICE power and $P_2(t)$ is the battery power. This formula minimizes the combined power output from the ICE and the battery, serving as a measure to reduce fuel consumption while satisfying the ICE energy efficiency (η) over a time vector of length N which is equal to 743. The approach guarantees that power demands are met while adhering to fuel efficiency and battery SoC constraints.

4.2.2 Decision Variables

In the proposed PMS, the ICE is crucial in balancing the power flow. It is specifically used to meet the demand when it exceeds the energy produced by the battery. The power output from the ICE at any given time t is calculated using the power balance equation as shown in Equation 5

$$P_1(t) = P_T(t) - \mathrm{P}_2(t) \quad (6)$$

The load power, $P_T(t)$ is considered input data to the system. This equation ensures that the ICE fills any gap between the demand and what the battery can supply, helping to keep the system running smoothly.

4.2.3 Battery Constraints

The power output from the battery is constrained to ensure it does not exceed its maximum capacity, which is critical for maintaining safe operation within its performance limits. The constraint is mathematically expressed as:

$$0 \leq P_2(t) \leq 24.42 \ kW \quad (7)$$

Where the maximum battery power of 24.42 kW is derived from the configuration of two batteries connected in series. Each battery operates at a voltage of 22.2 V and can deliver up to 550 A of

current. When connected in series, the total available current is the sum of the voltage from each battery, P_2, is calculated by multiplying the current by the total voltage of the batteries:

$$total\ P_2 = 22.2 * 2\,V \times 550A = 24.420\ \ kW \tag{8}$$

4.2.4 SoC Constraints

The battery SoC is a critical parameter that must be carefully managed to ensure safe and efficient operation. The SoC represents the remaining capacity of the battery as a percentage of its total capacity. To prevent damaging the battery, the SoC is constrained to remain within the following bounds:

$$20\% \leq SoC(t) \leq 100\% \tag{9}$$

This range ensures that the battery does not enter a state of deep discharge, which can significantly reduce its lifespan and efficiency, nor does it overcharge, which can lead to safety risks and degrade battery health. The SoC is dynamically updated based on the battery's usage, which is calculated each time step as the battery discharges to meet the power demand. The battery SoC at the next timestep $(n+1)T_s$ is calculated using the following equation:

$$SoC\left((n+1)T_s\right) = SoC\ (nT_s) - \frac{P_2(nT_s) \times \left(\frac{T_s}{3600}\right)}{Q_2} \tag{10}$$

Where $P_2(nT_s)$ represents the power drawn from the battery at the current timestep nT_s (in watts), T_s is the length of the timestep in seconds, and Q_2 is the total battery capacity equal to 976.8 Wh for two batteries connected in series. This equation computes the reduction in battery SoC by accounting for the fraction of energy consumed during the timestep, relative to the total battery capacity.

4.2.5 ICE Constraints

the output power of the ICE is limited to ensure it operates within safe mechanical limits and optimal efficiency. The engine can produce from 0 to 5500 watts of power continuously. This constraint prevents the engine from overloading and ensures it matches the power demands without exceeding its design specifications as follows:

$$0 \leq P_1(t) \leq 5.5kW \tag{11}$$

4.2.6 Fuel Tank Constraints

The tank level is a critical operational parameter that needs to be managed to ensure the continuous functioning of the ICE. The fuel level expressed as *F(t)* is constrained to stay within the specified following limit:

$$0.25\,L \leq F(t) \leq 2.5\,L \tag{12}$$

This range ensures that the fuel tank does not deplete below 10% of the total tank capacity (0.25 liters), which would stop engine operation, nor exceed its maximum capacity of 2.5 liters, which corresponds to the physical limitations of the tank size and prevents overfilling. The fuel tank level is dynamically adjusted based on the engine's fuel consumption, which is determined by the engine's operational power and efficiency at each time step. The fuel tank level at the next timestep $(n+1)Ts$ is calculated using the following equation:

$$Tank\big((n+1)T_s\big) = Tank(T_s) - \Delta Tank \tag{13}$$

$$Tank\big((n+1)T_s\big) = Tank(nT_s) - \left(C_{fuel} \times P_1(nT_s) \times \left(\frac{T_s}{3600}\right)\right) \tag{14}$$

where $P_1(nT_s)$ represents the power output from the ICE at time nT_s (in watts), $T_s$is the timestep in seconds, and $C_{fuel}$is the fuel consumption coefficient, indicating the amount of fuel consumed per unit of electricity generated, which is equal to:

$$C_{fuel} = \frac{5L/h}{5500W} = 0.9L/Wh \tag{15}$$

4.3 Optimization Techniques

This study evaluates two optimization algorithms, LP and DP to manage power flow in a hybrid drone system. Both methods aim to minimize fuel consumption, maintain the SoC of the battery, and meet the load demand while adhering to operational constraints. The input data include the filtered load profile shown in Figure 4.1, ICE and battery constraints, and system parameters. The output of the optimization process includes:

- Power outputs from the battery.
- Power outputs from the battery.
- The SoC of the battery over time,
- The fuel capacity in the tank

4.3.1 Linear Programming Optimization

The LP approach employs a linear optimization algorithm to manage the distribution of power between the ICE and the battery, aiming to minimize fuel consumption while ensuring efficient energy utilization. The algorithm is developed in Python using the *scipy.optimize* library's *linprog* function. It optimizes power outputs from the ICE and battery under defined operational constraints. The input to the LP algorithm is the power demand data (P_T), representing the load profile that the system must satisfy. Predefined parameters, including maximum power outputs for the ICE and battery, battery capacity, and fuel tank capacity, are integrated into the model to establish operational boundaries. A key assumption in this approach is that the efficiency of the ICE and battery remains constant throughout the simulation. While this simplifies the problem and reduces computational complexity, it does not account for variations due to factors such as temperature fluctuations or dynamic load conditions, potentially limiting accuracy in real-world applications.

4.3.2 Dynamic Programming Optimization

The DP approach, on the other hand, explicitly models the characteristics of ICE efficiency, offering a more precise and realistic representation of energy management. By incorporating a polynomial efficiency function and dynamic state transitions, DP captures the effects of varying efficiency on fuel consumption. This method uses a backward iteration process, beginning from the final time step and working back to the initial step. At each time step, the algorithm evaluates all possible battery power levels (P_2) for every SoC level within a discretized SoC grid. For each combination of SoC and battery power, the corresponding ICE power output ($P_1=P_T - P_2$) is calculated, along with the associated cost-to-go (c2g), which reflects the ICE's efficiency. The algorithm dynamically updates the SoC based on battery discharge or charge and interpolates the value function for the next time step using the future c2g. Through this iterative process, DP minimizes the total cost, which includes the c2g and future value, to determine the optimal control action (battery power) at each time step. The results are stored in a policy array for each SoC level and time step, ensuring the algorithm adheres to operational constraints, such as SoC limits and power bounds. Although DP provides a more accurate solution by accounting for efficiency variations and dynamic conditions, it is computationally intensive compared to LP, making it less suitable for real-time applications.

The following equation represents the ICE efficiency assuming it decreases linearly over time:

$$\eta_{ICE}(P_1(t)) = \eta_{ICE_0} - k \cdot P_1(t) \tag{16}$$

Here, k represents the constant rate of efficiency loss per unit of time

4.4 Results

The results of the optimization algorithms demonstrate the effectiveness of the power management strategy in the hybrid drone system. The filtered load data provided as input guided the allocation of power between the ICE and the battery, ensuring operational constraints were satisfied. Both LP and DP approaches successfully managed the power flow, maintaining system efficiency and reliability under varying load conditions.

4.4.1 Linear Programming

The LP algorithm effectively managed power distribution between the battery and the ICE. During peak demand (17.3 kW), the battery supplied 11.8 kW, covering 68.2% of the load, while the ICE provided the remaining 5.5 kW (31.79%) as shown in Figure 4.3. This balance demonstrates the algorithm's ability to efficiently utilize both power sources to meet demand. The battery's SoC shown in Figure 4.5 was maintained within safe limits throughout the simulation. Starting at 90%, the SoC gradually decreased as the battery supplied power to the load, reaching 0.58%. This steady decline reflects efficient battery usage without risking deep discharge. The fuel tank capacity shown in Figure 4.6 shows the ICE's supplementary role in power management. Starting with a full tank of 2.5 liters, fuel usage was linear over time as the ICE supported the battery. By the end of the simulation, approximately 1.7 liters of fuel remained, confirming minimized fuel consumption and efficient ICE operation.

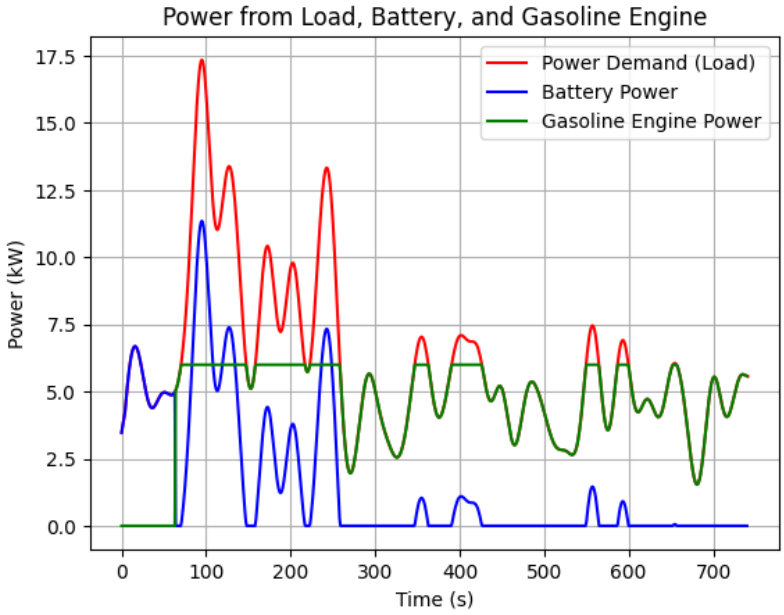


Figure 4.3: Power generation and load profiles- LP Method

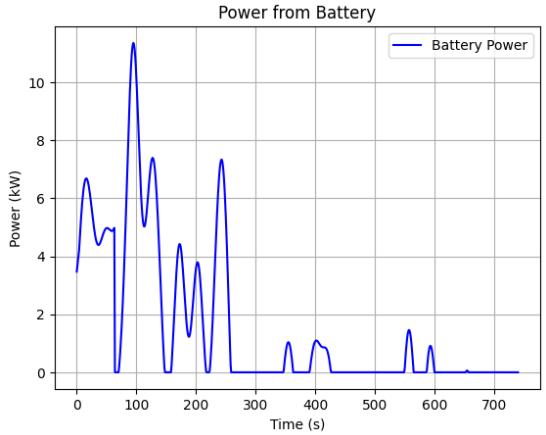


Figure 4.4: LP Battery Profile

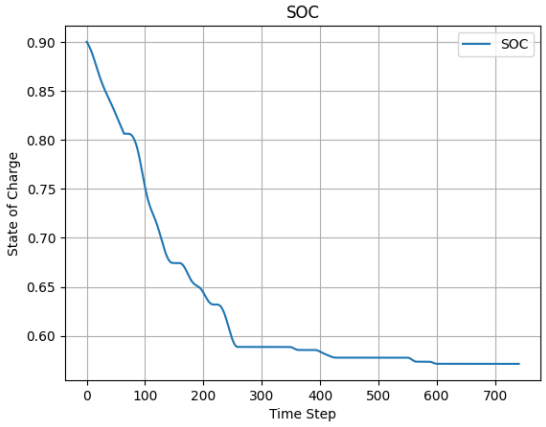


Figure 4.5: SoC- LP Method

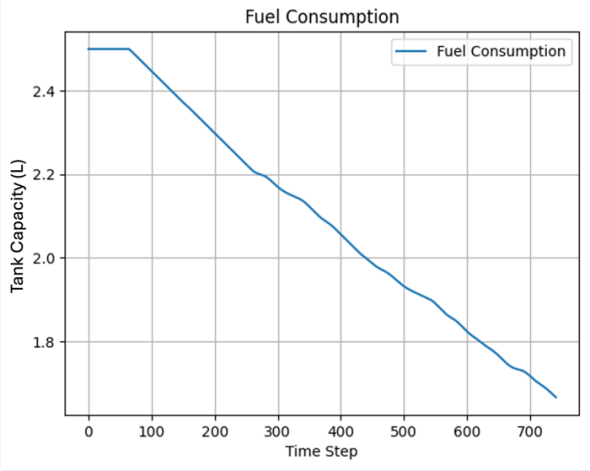


Figure 4.6: Fuel Tank Capacity- LP Method

4.4.2 Dynamic Programming

The DP algorithm provided a more detailed and dynamic representation of power management by accounting for the changing efficiency of the ICE over time. During periods of high load, the battery contributed up to 68.2% of the required power (11.8 kW at 17.3 kW peak demand), while the ICE maintained a stable output of 5.5 kW to ensure power balance as shown in Figure 4.7. The algorithm effectively prioritized battery usage, minimizing reliance on the ICE during non-peak periods. Moreover, SoC shown in Figure 4.9 shows that higher initial SoC levels (e.g., 90%) allowed for extended battery discharge, reducing ICE usage and improving overall efficiency. Conversely, lower initial SoC levels (e.g., 50%) led to faster battery depletion, requiring greater ICE support and increasing fuel consumption. In all cases, the SoC remained above the critical 20% threshold, demonstrating the algorithm's ability to manage battery usage effectively. Fuel consumption results further highlight the benefits of higher initial SoC levels. With more battery capacity available at the start, the ICE operated less frequently, resulting in reduced cumulative fuel usage as shown in Figure 4.10. These results confirm the DP algorithm's ability to optimize fuel consumption by dynamically adapting to load variations and prioritizing battery utilization.

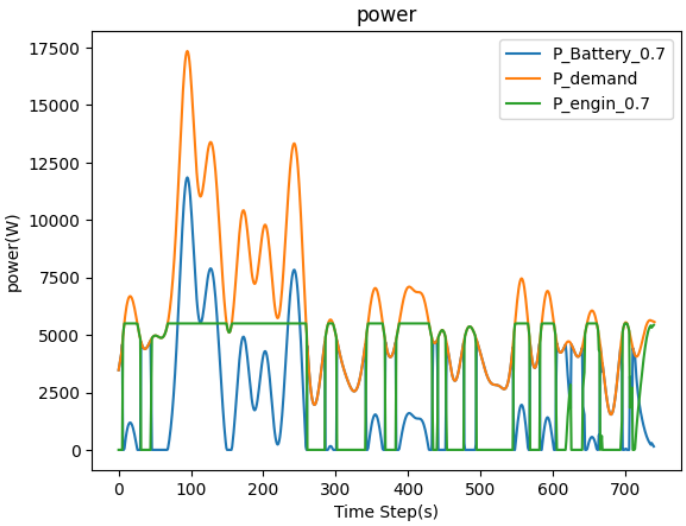


Figure 4.7: Power generation and load profiles- DP Method

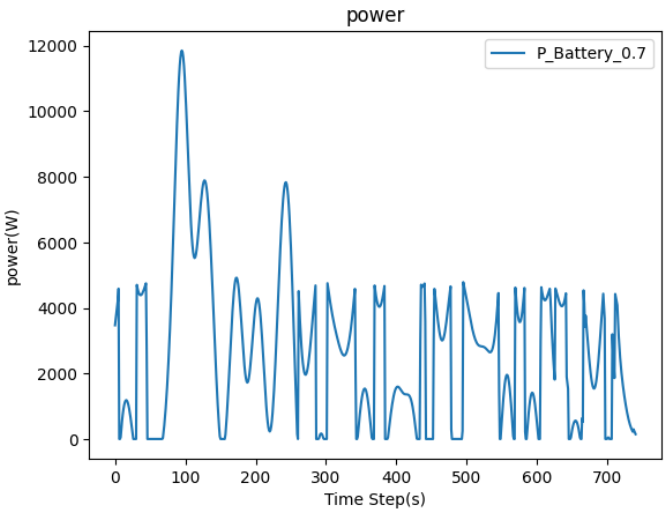


Figure 4.8: DP Battery Power

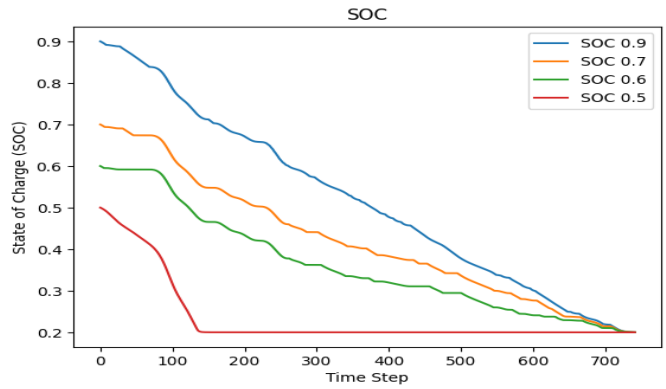


Figure 4.9: SoC- DP Method

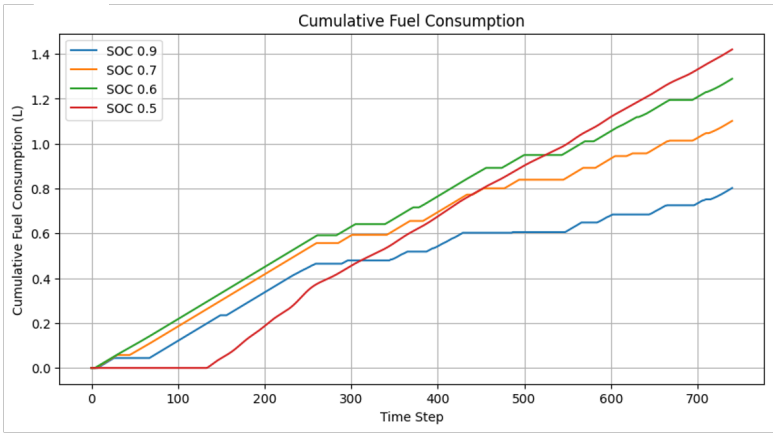


Figure 4.10: Hydrogen Tank Capacity- DP Method

Both approaches successfully minimize fuel consumption, optimize energy utilization, and extend flight time by dynamically balancing power contributions between the ICE and the battery while adhering to operational constraints. During peak load demand (approximately 17.3 kW), the battery contributes up to 11.8 kW (68.2%) of the load, while the ICE provides a stable 5.5 kW (31.7%) to maintain balance and prevent excessive battery discharge. Both algorithms ensure that the SoC remains above the critical 20% threshold and limit fuel usage to approximately 1.7 liters out of the 2.5-liter tank capacity. While DP adapts dynamically to real-time load fluctuations, providing more granular control, LP offers consistent SoC management and delivers comparable power values with lower computational complexity. This makes LP a practical and attractive choice for many real-world applications where efficiency and simplicity are prioritized. It is notable that, in this case, the battery contributes more overall using the DP method compared to the LP method. The SoC shows different initial battery conditions, and we observe that the battery reaches its minimum level earlier in the DP approach. This behavior confirms the higher contribution and heavier utilization of the battery when using DP. These results confirm that both algorithms effectively manage power flow, meet load requirements, and contribute to key operational benefits:

- **Energy Efficiency:** Optimal switching between the ICE and the battery reduces fuel consumption and extends battery life.
- **System Reliability:** Ensuring smooth transitions prevents sudden voltage drops or power losses, which are critical in drone applications.
- **Operational Cost Reduction:** Lower fuel consumption and reduced strain on battery components translate to a longer lifespan and lower maintenance costs.

By leveraging these optimizations, hybrid drone systems can achieve better performance, increased endurance, and more sustainable energy use.

Chapter 5 . Application of Hybrid Power Drone

5.1 Car Plate Detection

The increasing number of private and public vehicles has led to a growing demand for advanced vehicle monitoring, security enforcement, and intelligent transportation systems (ITS). ALPR has become an essential tool in modern traffic management, offering solutions for law enforcement, toll collection, parking management, and access control [32]. By automating the process of license plate identification, ALPR systems minimize the need for human involvement while significantly enhancing the effectiveness of regulatory enforcement and security operations [33]. In the United Arab Emirates (UAE), ALPR systems face unique challenges due to the diversity of license plate formats, the incorporation of Arabic and English characters, and varying font styles across different emirates as shown in Figure 5.1. These differences reduce the effectiveness of traditional Optical Character Recognition (OCR) methods, requiring more advanced object detection and classification models. Additionally, factors like lighting conditions, vehicle speed, and plate obstructions create further challenges in achieving accurate detection [34].



Figure 5.1: Example of plate numbers

Recent advancements in deep learning and computer vision have significantly transformed the field of object detection, enabling real-time and highly accurate recognition of objects in various applications. Object detection (OD) is a fundamental task in computer vision that involves identifying and localizing objects within an image or video. Traditional OD techniques rely on handcrafted features and classical machine learning approaches, which were often limited by their dependency on predefined rules and heuristics. However, the emergence of deep learning has revolutionized OD by introducing neural network-based models that learn feature representations directly from data, eliminating the need for manual feature engineering. Among the most impactful deep learning models for OD are convolutional neural networks (CNNs), which extract hierarchical feature maps from images, enabling robust detection of objects in diverse scenarios [35]. The evolution of OD has led to the development of several state-of-the-art architectures,

including Region-based Convolutional Neural Networks (R-CNN), Single Shot MultiBox Detector (SSD), and the You Only Look Once (YOLO) family of models. These architectures offer varying trade-offs between detection speed and accuracy, making them suitable for applications ranging from autonomous driving to security surveillance. The YOLO series, in particular, has gained widespread adoption due to its ability to achieve real-time OD with high accuracy. Unlike traditional two-stage detectors that require multiple processing steps, YOLO employs a single-stage detection mechanism, making it highly efficient for real-time scenarios. The latest iterations, such as YOLOv8, incorporate advanced feature extraction techniques, anchor-free detection, and improved loss functions, further enhancing detection performance across various domains [36].

Additionally, integrating deep learning-based clustering algorithms, such as Density-Based Spatial Clustering of Applications with Noise (DBSCAN), has further improved object detection pipelines[37]. By grouping closely related detections, these techniques enhance multi-object recognition, particularly in applications like license plate recognition and character grouping. This approach improves license plate reconstruction by organizing detected characters into meaningful sequences, ensuring higher accuracy in recognizing alphanumeric patterns. The combination of OD with clustering methods has facilitated significant advancements in intelligent transportation systems, smart city applications, and automated security monitoring.

5.3 Methodology

This section presents a structured explanation of the detection and recognition methodology, detailing the approach employed for vehicle and license plate identification using YOLOv8-L. It begins with an overview of the dataset utilized for training and evaluation, followed by the data augmentation techniques implemented to enhance model generalization. Subsequently, the feature extraction process is examined, emphasizing the role of YOLOv8-L in detecting vehicles, license plates, license plate numbers, and issuing emirates. A detailed discussion is provided on the model selection, including the configuration of YOLOv8-L, which was chosen due to its high accuracy and efficiency in object detection. The dataset was labeled with 54 distinct classes, covering vehicles, license plates, characters, numbers, and emirate names. The dataset was then splitted into training (70%), validation (20%), and testing (10%) to ensure robust model evaluation.

The implementation process involved configuring YOLOv8-L using PyTorch, training the model with a dataset, and fine-tuning it for optimal detection accuracy. After training, the system performed inference using the trained weights to generate predictions. Unlike traditional OCR-based recognition, YOLOv8-L was used directly to detect both the license plate number and the issuing emirate, eliminating the need for an additional text recognition model.

To enhance the accuracy of license plate reconstruction, the methodology also integrates Density-Based Spatial Clustering of Applications with Noise (DBSCAN) to cluster detected characters and group them into complete license plate numbers. The clustering process involves identifying spatially related detections and ensuring that characters belonging to the same plate are grouped. This approach significantly improves plate number reconstruction, especially in scenarios where multiple license plates are present within the same image. The DBSCAN clustering algorithm enables the model to correctly associate detected digits, letters, and emirate names into a structured and readable format, mitigating errors in plate reconstruction. Finally, testing was conducted to validate the model's performance in practical applications. The evaluation metrics included precision, recall, mAP (mean Average Precision), and inference speed, ensuring the system's reliability. Figure 5.2 provides an overview of the methodology, serving as a roadmap for the subsequent sections where each component will be discussed in detail.

The implementation was carried out in Python 3.9.18, utilizing key libraries such as Ultralytics (YOLOv8) for object detection, PyTorch for deep learning, OpenCV for image

processing, NumPy and Pandas for data handling, Matplotlib for visualization, Supervision for bounding box annotation, and Scikit-learn (DBSCAN) for clustering license plate elements. The overall methodology ensures a robust, efficient, and scalable solution for automated license plate recognition using deep learning-based object detection.

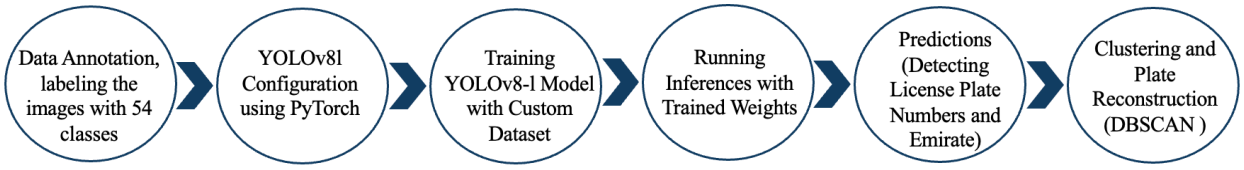


Figure 5.2: Plate detection system

5.3.1 Dataset

A United Arab Emirates (UAE) Car dataset of 8,190 images is considered for vehicle detection and ALPR. It contains annotated images of cars and various license plate categories used in the UAE.

To ensure balanced training and evaluation, the dataset is divided into:

- **Training Set**: 5,194 images (~70%)
- **Validation Set**: 1,473 images (~20%)
- **Test Set**: 748 images (~10%)

Each image in the dataset has been carefully annotated using Roboflow, with bounding boxes drawn around vehicles, license plates, license plate numbers, and the issuing emirate. Each annotation includes class index, bounding box center coordinates (x, y), width, and height, all normalized between 0 and 1 to maintain consistency across different image resolutions. The dataset includes 54 classes, categorized into two main groups:

A. Vehicle Views
    - back_car
    - front_car

B. License Plate Categories by Emirate

The dataset categorizes license plates based on the emirate of issuance, distinguishing between new and old designs of each emirate:

- Dubai: *new_DUBAI, old_DUBAI*
- Abu Dhabi: *new_Abudhabi, old_Abudhabi*

- Ajman: *new_Ajman, old_Ajman*
- Fujairah: *new_Fujairah, old_Fujairah*
- Ras Al Khaimah (RAK): *new_RAK, old_RAk*
- Sharjah: *new_Sharjah, old_Sharjah*
- Umm Al Quwain: *new_Umalq, old_Umalq*

Additionally, the dataset includes digits (0-9) and letters (A-Z) to facilitate recognition of license plate numbers and characters.

To enhance model robustness, the dataset employs augmentation techniques, including:

- **Exposure Adjustment**: Brightness variation of ±4% to simulate different lighting conditions.
- **Noise Addition**: Random noise affecting up to 2% of pixels to improve generalization.

5.3.2 Yol0v8 Model and Performance Evaluation

The parameters in Table 5.1 were chosen to balance training performance and generalization. The AdamW optimizer was selected for its improved weight decay regularization, while the initial and final learning rates were fine-tuned to ensure effective convergence of the model.

Table 5.1: Yolov8 parameters

Hyperparameter	Value
Model	YOLOv8-L
Epochs	100
Image Size	1280
Batch Size	10
Optimizer	AdamW
Initial Learning Rate (lr0)	0.0005
Final Learning Rate (lrf)	0.3

To assess the performance of the YOLOv8-L model, several key evaluation metrics are used, including Precision (P), Recall (R), Mean Average Precision (mAP@50), and Mean Average

Precision (mAP@50-95). These metrics provide insights into the model's accuracy, reliability, and effectiveness in detecting and recognizing objects.

A. Precision (P)

Precision measures the proportion of correctly predicted positive detections (true positives) out of all predicted positive detections (true positives + false positives). It is defined as [38]:

$$P = \frac{TP}{TP+FP} \tag{17}$$

Where:

- TP (True Positives): Correctly detected objects.
- FP (False Positives): Incorrectly detected objects.

A high precision indicates that the model produces fewer false positives, meaning it is reliable in making predictions.

B. Recall (R)

Recall measures the proportion of correctly predicted positive detections (true positives) out of all actual positive instances (true positives + false negatives). It is defined as [38]:

$$R = \frac{TP}{TP+FN} \tag{18}$$

Where:

- FN (False Negatives): Objects that were present in the image but not detected by the model.

A high recall indicates that the model detects most of the actual objects, even if some predictions are incorrect.

C. Mean Average Precision

Mean Average Precision (mAP@50) evaluates the model's accuracy by computing the Average Precision (AP) for each class and averaging it across all classes. It considers a detection correct if the Intersection over Union (IoU) ≥ 0.5. It is defined as [39]

$$mAP@50 = \frac{1}{N}\sum_{1}^{N} AP_i \tag{19}$$

Where:

- N is the total number of object classes.

- AP_i is the average precision for class i.

A higher mAP@50 value indicates better detection accuracy.

D. Mean Average Precision

The mAP@50-95 extends mAP evaluation by computing the average mAP across multiple IoU thresholds ranging from 0.5 to 0.95 in steps of 0.05. It is calculated as [40]:

$$mAP@50-95 = \frac{1}{10}\sum_{t=o.5}^{0.95} mAP@t \quad (20)$$

It requires higher IoU thresholds for a prediction to be considered correct. It provides a more comprehensive measure of the model's localization accuracy.

5.4 Results and Discussion

This section presents the evaluation results of the YOLOv8-L model on the UAE Car dataset. The model was assessed based on precision, recall, and mean Average Precision (mAP) at different IoU thresholds, and performance trends were analyzed using training loss curves and evaluation plots.

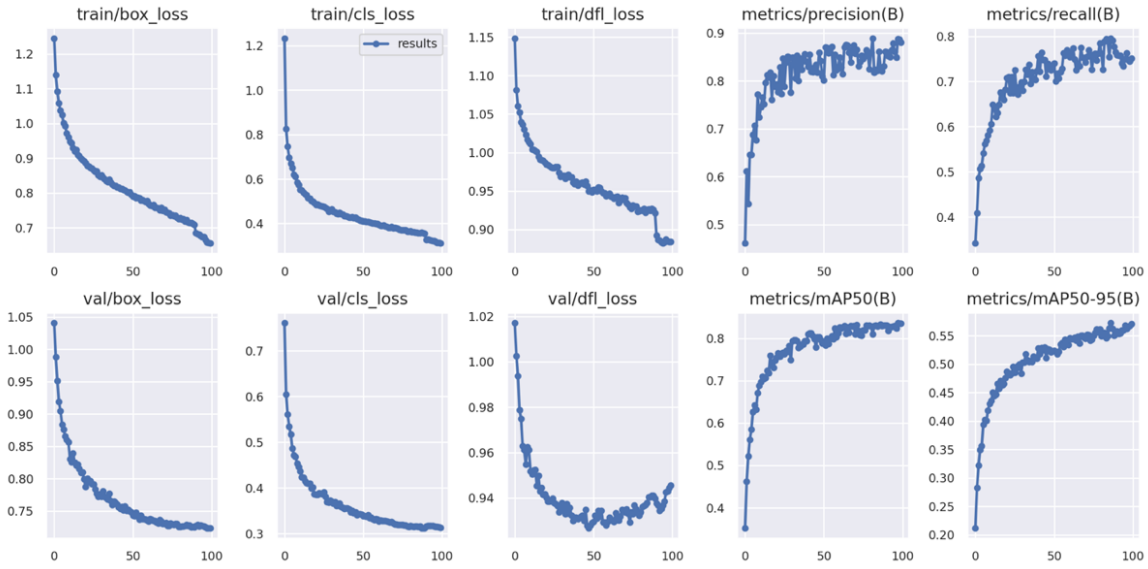


Figure 5.3: Training loss curves

The training loss curves shown in Figure 5.3 indicate that the model's box loss, classification loss, and objectness loss consistently decreased over 100 epochs, signifying stable convergence.

- The **precision and recall curves** show an upward trend, stabilizing after **60 epochs**, demonstrating effective learning.

- The **mAP@50 and mAP@50-95 curves** indicate a consistent increase in detection accuracy, reaching a near-optimal value by the end of training.

Table 5.2 summarizes the performance metrics for the testing images including license plate numbers, emirate names, and vehicle detection. The key performance indicators include Precision (P), Recall (R), mAP@50, and mAP@50-95.

The model outcome:

- High precision values for most classes, especially numbers (0-9), emirate names, and the plate, demonstrating low false positive rates.
- Recall scores above 0.8 for most categories, indicating that the model effectively identifies actual objects with minimal false negatives.
- An overall mAP@50 of 0.995 for the plate shows high detection accuracy.
- A slightly lower mAP@50-95 for imbalanced classes such as old_Ajman (0.203) and old_Umalq (0.597) due to limited data samples as shown in Figure 5.4

Table 5.2: Performance metrics

Class	Total Samples	Detected Samples	Precision (P)	Recall (R)	mAP@50	mAP@50-95
0	748	300	0.952	0.827	0.88	0.637
1	748	521	0.985	0.757	0.892	0.644
2	748	446	0.976	0.832	0.907	0.659
3	748	357	0.973	0.805	0.889	0.618
4	748	294	0.959	0.787	0.877	0.618
5	748	442	0.968	0.873	0.924	0.713
6	748	490	0.971	0.815	0.896	0.706
7	748	434	0.97	0.824	0.908	0.676
8	748	290	0.957	0.774	0.854	0.616
9	748	430	0.965	0.856	0.926	0.672
A	748	5	0	0	0	0
B	748	6	1	0.818	0.955	0.578
C	748	95	0.956	0.923	0.975	0.626
D	748	13	0.576	0.769	0.688	0.451
E	748	21	0.946	0.619	0.764	0.521

F	748	28	0.957	0.821	0.9	0.67
G	748	15	0.853	0.777	0.897	0.615
H	748	30	0.959	0.779	0.875	0.557
I	748	19	0.92	0.605	0.821	0.531
J	748	21	0.996	0.857	0.917	0.588
K	748	25	0.936	0.88	0.977	0.673
L	748	22	1	0.953	0.995	0.711
M	748	12	0.827	0.917	0.885	0.664
N	748	25	0.847	0.68	0.804	0.525
O	748	10	0.72	0.8	0.821	0.522
P	748	25	0.931	0.8	0.914	0.633
Q	748	24	0.946	0.731	0.911	0.607
R	748	40	0.863	0.775	0.856	0.619
S	748	31	1	0.871	0.958	0.695
T	748	21	0.942	0.773	0.885	0.581
U	748	24	0.87	0.835	0.921	0.67
V	748	20	0.929	0.9	0.937	0.652
W	748	23	0.86	0.957	0.972	0.695
X	748	22	0.913	0.636	0.734	0.421
Y	748	14	0.957	0.857	0.904	0.521
Z	748	43	0.999	1	0.995	0.677
back_car	748	134	0.964	0.992	0.985	0.742
front_car	748	813	0.978	1	0.995	0.814
new_DUBAI	748	495	0.986	0.935	0.983	0.784
old_DUBAI	748	143	0.964	0.934	0.979	0.773
old_abudabi	748	103	0.961	0.97	0.989	0.773
old_ajman	748	2	0.437	0.5	0.507	0.203
old_Umalq	748	1	1	0	0.995	0.597
old_sharjah	748	14	0.927	0.909	0.879	0.588
plate	748	1037	0.976	0.995	0.995	0.932

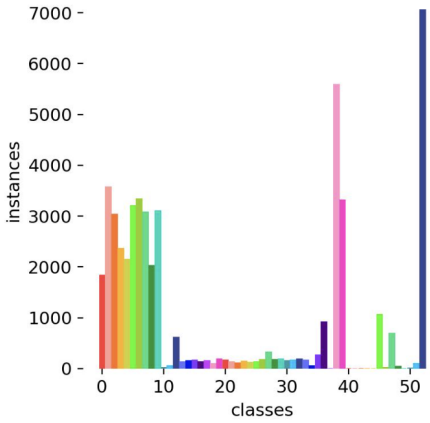


Figure 5.4: Class instance distribution across the categories

Figure 5.5 presents the results of the YOLOv8-L model applied to testing images. The model accurately detects and localizes license plates, vehicle numbers, and issuing emirates under various lighting conditions, including low-light and indoor parking environments. Additionally, the model demonstrates robust performance in handling headlight glare and reflections, successfully detecting and recognizing license plate numbers even in high-glare nighttime scenarios. However, rare license plate categories (e.g., old_ajman, old_am) had lower detection confidence due to dataset imbalance as Figure 5.6 shows, where the detected region is *old_Fujairah* while the ground truth is *old_Umalq* .



Figure 5.5: Example of YOLOv8 results on the testing images



Figure 5.6: Low detection confidence (A letter and old_Umalq classes)

Despite achieving high accuracy, the YOLOv8-L model exhibits certain limitations, primarily due to class imbalance and generalization challenges. Some license plate categories have significantly fewer training samples, resulting in lower recall values for underrepresented classes such as *old_ajman, old_Umalq, and letter A*, which leads the model to prioritize more frequently occurring classes while struggling with rare ones. Additionally, while the model performs well on common UAE license plates, its ability to generalize to unseen plate designs in real-world scenarios may be limited, necessitating further fine-tuning to ensure consistent detection across diverse plate formats and varying environmental conditions. To address these limitations, dataset augmentation is recommended to generate synthetic samples for underrepresented license plate categories through techniques such as geometric transformations, exposure adjustments, and synthetic overlays. Furthermore, incorporating additional real-world traffic footage and diverse plate formats for fine-tuning would enhance the model's capacity to generalize across various lighting conditions, plate designs, and regional variations. By implementing these improvements, the YOLOv8-L model can achieve higher recall for rare classes and greater robustness in real-world ALPR applications.

5.5 Conclusion

The YOLOv8-L model demonstrated high precision and detection accuracy for vehicle and license plate recognition tasks, making it well-suited for real-time applications such as traffic monitoring, smart parking, and law enforcement. The model achieved an overall **mAP@50 of 0.995** for license plate detection, highlighting its robustness in recognizing license plates under various environmental conditions, including low-light and high-glare scenarios.

However, performance analysis revealed challenges associated with class imbalance, particularly for rare license plate categories such as *old_Ajman* and *old_Umalq*, which exhibited lower detection confidence due to the limited number of training samples. Similarly, certain letter categories, such as *A*, had detection difficulties, suggesting that the model prioritizes more frequently occurring classes. Despite its limitations, the model's strong detection performance across common UAE license plate formats suggests its practical applicability in real-time ALPR systems. With further refinements, the YOLOv8-L model can achieve even greater robustness, ensuring reliable license plate detection across various deployment scenarios.

Chapter 6 . Research Schedule

The research started on September, 2023 and is planned to finish by the 17th of March, 2025. Figure 6.1 shows the Gantt chart with a breakdown of the tasks.

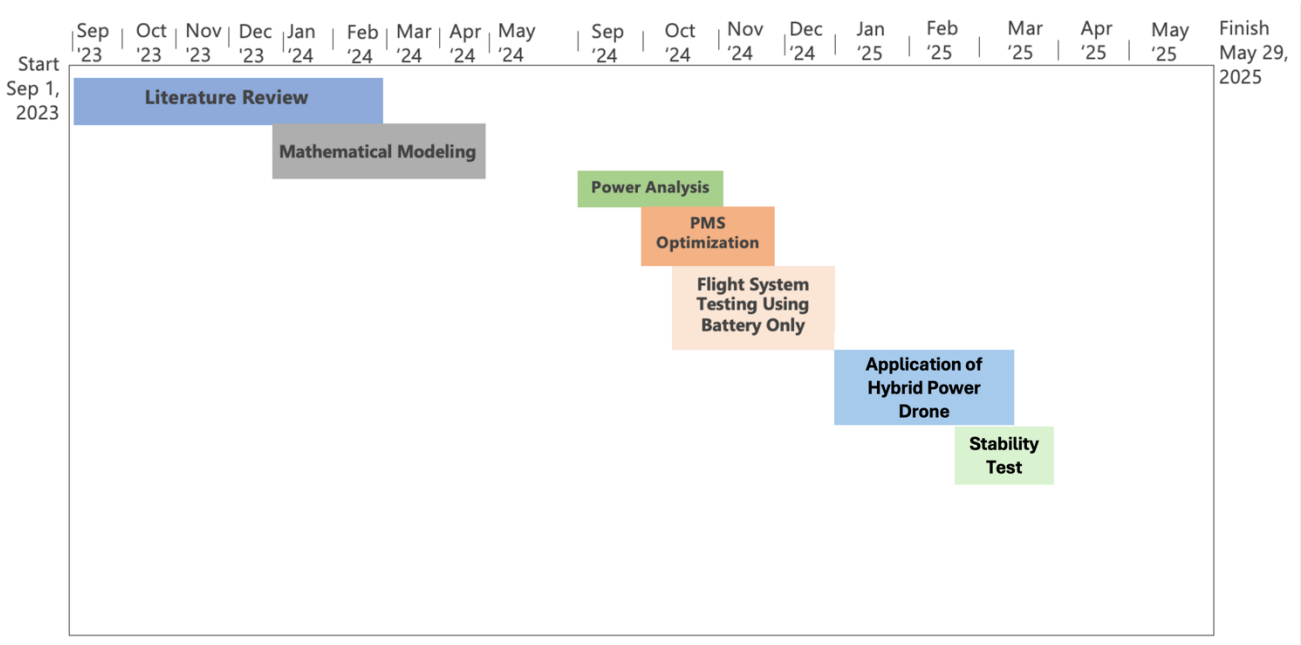


Figure 6.1: Research Schedule

Chapter 7 . Conclusion

Multipurpose drones find utility in agriculture, firefighting, and surveillance, reliant on flight duration and payload capacity. This thesis outlines the implementation process of a hybrid power drone for various applications, merging generator and battery sources to ensure stable flight. While lithium batteries dominate, they can be used for limited flight times and operations. This research seeks innovative strategies to enhance UAV capabilities, focusing on payload capacity and flight duration extension. The research begins with a detailed power system analysis, evaluating energy requirements across different flight phases, including takeoff, gliding, and maneuvering. The hybrid power system is designed to address the limitations of lithium batteries, which, despite their high energy density, offer limited flight times. By strategically combining battery and generator power, the UAV achieves extended operational time while maintaining a stable and reliable power supply. To further optimize energy usage, a PMS was developed using LP and DP. These optimization techniques ensure efficient energy allocation, reducing fuel consumption while maintaining the required power levels for stable flight. Simulation results and real-world tests validate the effectiveness of the hybrid configuration, demonstrating a significant increase in flight duration compared to battery-only UAVs. Additionally, the research explores AI-based detection for license plate recognition, enhancing UAV applications in surveillance and traffic monitoring. The implemented YOLOv8 model demonstrates high precision in detecting vehicles and license plates, making it suitable for real-time enforcement and smart city applications. Despite challenges such as class imbalance and varying environmental conditions, the system performs reliably with the need for further improvements through dataset expansion and fine-tuning.

7.1 Critical Appraisal

- The project scope was initially focused on PMS optimization but was later extended to include an AI-based drone application due to implementation challenges.
- **Part 1: Hybrid Power System Challenges**
    - ICE testing was limited due to technical issues.
    - The ICE efficiency equation used in the DP method can be improved through experimental validation.
    - The larger drone could not be tested due to space constraints.
- **Part 2: AI Implementation and Stability Test Challenges**
    - Limited availability of UAE license plate datasets
    - The original drone batteries were damaged during testing.
    - The battery model is very small and specific, making it difficult to find locally.
    - Integration and real-time testing of the AI model with the drone could not be completed.

7.2 Future Work

- Experimental validation in real-world flight tests
- Integration of machine learning-based detection models
- Explore alternative and efficient power sources (e.g., fuel cells, solar panels, supercapacitors).
- Use AI-driven algorithms to improve power demand forecasting, allowing the system to allocate power in advance and handle sudden peaks more efficiently.
- Use Advanced control algorithms.

References

[1] P. Liu *et al.*, “A review of rotorcraft unmanned aerial vehicle (UAV) developments and applications in civil engineering,” Jun. 01, 2014, *Techno Press*. doi: 10.12989/sss.2014.13.6.1065.

[2] M. S. Rajabi, P. Beigi, and S. Aghakhani, “Drone Delivery Systems and Energy Management: A Review and Future Trends.”

[3] A. Hafeez *et al.*, “Implementation of drone technology for farm monitoring & pesticide spraying: A review,” Jun. 01, 2023, *China Agricultural University*. doi: 10.1016/j.inpa.2022.02.002.

[4] D. Verstraete, … K. L.-A., and undefined 2012, “Design of a fuel cell powered blended wing body UAV,” *asmedigitalcollection.asme.orgD Verstraete, K Lehmkuehler, KC WongASME international mechanical engineering congress and, 2012•asmedigitalcollection.asme.org*, Accessed: Jan. 21, 2024. [Online]. Available: https://asmedigitalcollection.asme.org/IMECE/proceedings-abstract/IMECE2012/621/259669

[5] M. Nadir Boukoberine, Z. Zhou, and M. Benbouzid, “A critical review on unmanned aerial vehicles power supply and energy management: solutions, strategies, and prospects,” 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261919315107

[6] P. IEEE Industrial Electronics Society. Conference (45th : 2019 : Lisbon, Universidade Nova de Lisboa, Institute of Electrical and Electronics Engineers, and IEEE Industrial Electronics Society, *Power Supply Architectures for Drones - A Review*.

[7] H. González-Jorge, J. Martínez-Sánchez, M. Bueno, and P. Arias, “Unmanned aerial systems for civil applications: A review,” Dec. 01, 2017, *MDPI AG*. doi: 10.3390/drones1010002.

[8] N. A. Khan, N. Z. Jhanjhi, S. N. Brohi, and A. Nayyar, “Emerging use of UAV’s: secure communication protocol issues and challenges,” in *Drones in Smart-Cities: Security and Performance*, Elsevier, 2020, pp. 37–55. doi: 10.1016/B978-0-12-819972-5.00003-3.

[9] P. S. Ramesh and J. V. Muruga Lal Jeyan, “Comparative Analysis of Fixed-Wing, Rotary-Wing and Hybrid Mini Unmanned Aircraft Systems (UAS) from the Applications Perspective,” *INCAS Bulletin*, vol. 14, no. 1, pp. 137–151, 2022, doi: 10.13111/2066-8201.2022.14.1.12.

[10] E. G. Prague, “Quadcopter flight mechanics model and control algorithms,” 2016.

[11] W. Ong, S. Srigrarom, and H. Hesse, “Design methodology for heavy-lift unmanned aerial vehicles with coaxial rotors,” in *AIAA Scitech 2019 Forum*, American Institute of Aeronautics and Astronautics Inc, AIAA, 2019. doi: 10.2514/6.2019-2095.

[12] O. A. Marzouk, “Urban air mobility and flying cars: Overview, examples, prospects, drawbacks, and solutions,” *Open Engineering*, vol. 12, no. 1, pp. 662–679, Jan. 2022, doi: 10.1515/ENG-2022-0379.

[13] A. Mohammed *et al.*, “A survey of flight control systems and simulators of aerial robots,” 2021. [Online]. Available: www.ftstjournal.com

[14] B. Lee, P. Park, C. Kim, S. Yang, S. A.-J. of mechanical science and, and undefined 2012, "Power managements of a hybrid electric propulsion system for UAVs," *SpringerB Lee, P Park, C Kim, S Yang, S AhnJournal of mechanical science and technology, 2012•Springer*, vol. 26, no. 8, pp. 2291–2299, Aug. 2012, doi: 10.1007/s12206-012-0601-6.
[15] "Hybrid fuel cell powered drones energy management strategy improvement".
[16] A. Townsend, I. N. Jiya, C. Martinson, D. Bessarabov, and R. Gouws, "A comprehensive review of energy sources for unmanned aerial vehicles, their shortfalls and opportunities for improvements," Nov. 01, 2020, *Elsevier Ltd*. doi: 10.1016/j.heliyon.2020.e05285.
[17] M. Valovi, P. T. Lang, A. Kirk, al -, P. Lang, and J. Dutczak, "Issues related to fuel cells application to small drones propulsion," *iopscience.iop.orgJ DutczakIOP Conference Series: Materials Science and Engineering, 2018•iopscience.iop.org*, doi: 10.1088/1757-899X/421/4/042014.
[18] B. Lee, S. Kwon, P. Park, and K. Kim, "Active power management system for an unmanned aerial vehicle powered by solar cells, a fuel cell, and batteries," *IEEE Trans Aerosp Electron Syst*, vol. 50, no. 4, pp. 3167–3177, Oct. 2014, doi: 10.1109/TAES.2014.130468.
[19] W. B. K. H. R. Gwon, "Development of Hybrid Gasoline-Battery Propulsion System for Multi-Copter Platform," Belo Horizonte, Brazil, 2018. Accessed: Nov. 26, 2024. [Online]. Available: https://www.icas.org/ICAS_ARCHIVE/ICAS2018/data/papers/ICAS2018_0067_paper.pdf
[20] M. Cardone, B. Gargiulo, and E. Fornaro, "Modelling and Experimental Validation of a Hybrid Electric Propulsion System for Light Aircraft and Unmanned Aerial Vehicles," *Energies 2021, Vol. 14, Page 3969*, vol. 14, no. 13, p. 3969, Jul. 2021, doi: 10.3390/EN14133969.
[21] A. S. Nagorny and O. V. Nos, "Unmanned Aerial Vehicles with a Hybrid Propulsion System, as an Analogue of Unmanned Aerial Vehicles with Internal Combustion Engines," *International Conference of Young Specialists on Micro/Nanotechnologies and Electron Devices, EDM*, vol. 2023-June, pp. 1550–1553, 2023, doi: 10.1109/EDM58354.2023.10225225.
[22] K. Jarrah, Y. Alali, A. Lalko, and O. Rawashdeh, "Flight Time Optimization and Modeling of a Hybrid Gasoline–Electric Multirotor Drone: An Experimental Study," *Aerospace 2022, Vol. 9, Page 799*, vol. 9, no. 12, p. 799, Dec. 2022, doi: 10.3390/AEROSPACE9120799.
[23] C. Carreno, E. S. Juan, P. Adasme, L. Canete, F. Seguel, and A. D. Firoozabadi, "Fuzzy-PID controller design for UAV hybrid energy propelled with differential box," *SACVLC 2021 - Proceedings: 2021 3rd South American Colloquium on Visible Light Communications*, 2021, doi: 10.1109/SACVLC53127.2021.9652332.
[24] A. N. Lucena, R. C. S. Freire-Junior, and L. M. G. Goncalves, "Unmanned aerial vehicle with hybrid lift and propulsion," *2021 Latin American Robotics Symposium, 2021 Brazilian Symposium on Robotics, and 2021 Workshop on Robotics in Education, LARS-SBR-WRE 2021*, pp. 36–41, 2021, doi: 10.1109/LARS/SBR/WRE54079.2021.9605409.

[25] M. Krznar, P. Piljek, D. Kotarski, and D. Pavković, “Modeling, control system design and preliminary experimental verification of a hybrid power unit suitable for multirotor uavs,” *Energies 2021, Vol. 14, Page 2669*, vol. 14, no. 9, p. 2669, May 2021, doi: 10.3390/EN14092669.

[26] L. Machado, J. Matlock, and A. Suleman, “Experimental evaluation of a hybrid electric propulsion system for small UAVs,” *Aircraft Engineering and Aerospace Technology*, vol. 92, no. 5, pp. 727–736, May 2020, doi: 10.1108/AEAT-06-2019-0120/FULL/PDF.

[27] W. Lu, D. Zhang, J. Zhang, T. Li, and T. Hu, “Design and implementation of a gasoline-electric hybrid propulsion system for a micro triple tilt-rotor VTOL UAV,” *Proceedings of 2017 IEEE 6th Data Driven Control and Learning Systems Conference, DDCLS 2017*, pp. 433–438, Oct. 2017, doi: 10.1109/DDCLS.2017.8068112.

[28] T. Lei, Y. Wang, X. Jin, Z. Min, X. Zhang, and X. Zhang, “An optimal fuzzy logic-based energy management strategy for a fuel cell/battery hybrid power unmanned aerial vehicle,” *Aerospace 2022, Vol. 9, Page 115*, vol. 9, no. 2, p. 115, Feb. 2022, doi: 10.3390/AEROSPACE9020115.

[29] N. A. Cyrille, N. Jean Calvin, M. M. Ghislain, and S. M. Olivier Thierry, “Critical review on integrated real-time energy management strategy and digital twin applied to hybrid electric UAVs,” *Electrical Engineering 2024*, pp. 1–23, Sep. 2024, doi: 10.1007/S00202-024-02746-5.

[30] E. Nivolianiti, Y. L. Karnavas, and J. F. Charpentier, “Fuzzy logic-based energy management strategy for hybrid fuel cell electric ship power and propulsion system,” *Journal of Marine Science and Engineering 2024, Vol. 12, Page 1813*, vol. 12, no. 10, p. 1813, Oct. 2024, doi: 10.3390/JMSE12101813.

[31] D. Hyun, J. Han, and S. Hong, “Power management strategy of hybrid fuel cell drones for flight performance improvement based on various algorithms,” *Energies 2023, Vol. 16, Page 8001*, vol. 16, no. 24, p. 8001, Dec. 2023, doi: 10.3390/EN16248001.

[32] C. N. E. Anagnostopoulos, I. E. Anagnostopoulos, V. Loumos, and E. Kayafas, “A license plate-recognition algorithm for intelligent transportation system applications,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 7, no. 3, pp. 377–391, Sep. 2006, doi: 10.1109/TITS.2006.880641.

[33] A. A. Quraishi, F. Feyzi, and A. Shahbahrami, “Detection and recognition of vehicle licence plates using deep learning in challenging conditions: a systematic review Detection and recognition of vehicle license plates using deep learning in challenging conditions: a systematic review,” *No. Y, xxxx 1 J. Intelligent Systems Technologies and Applications*, vol. X, no. Y, 2024, doi: 10.1504/IJISTA.2024.139736.

[34] M. A. Sayedelahl, “Enabling Intelligent Traffic Systems: A deep learning method for accurate arabic license plate recognition,” *FMDB Transactions on Sustainable Intelligent Networks*, vol. 1, no. 1, pp. 40–55, 2024, doi: 10.69888/FTSIN.2024.000156.

[35] A. Menon and B. Omman, “Detection and recognition of multiple license plate from still images,” *2018 International Conference on Circuits and Systems in*

Digital Enterprise Technology, ICCSDET 2018, Dec. 2018, doi: 10.1109/ICCSDET.2018.8821138.

[36] V. Agarwal and G. Bansal, "Automatic number plate detection and recognition using YOLO world," *Computers and Electrical Engineering*, vol. 120, p. 109646, Dec. 2024, doi: 10.1016/J.COMPELECENG.2024.109646.

[37] T. Pei *et al.*, "DECODE: A new method for discovering clusters of different densities in spatial data," *Data Min Knowl Disc*, vol. 18, pp. 337–369, 2009, doi: 10.1007/s10618-008-0120-3.

[38] S. Pokhrel, R. Abbas, and B. Aryal, "IoT Security: Botnet detection in IoT using Machine learning".

[39] B. Wang, "A parallel implementation of computing mean average precision", Accessed: Mar. 16, 2025. [Online]. Available: https://github.com/bwangca/fast-map.

[40] M. Şirin Gündüz and G. Işık, "A new YOLO-based method for real-time crowd detection from video and performance analysis of YOLO models," vol. 20, p. 5, 2023, doi: 10.1007/s11554-023-01276-w.