

DATA-DRIVEN ENERGY MANAGEMENT FOR FUEL CELL HYBRID
UAV BASED ON MACHINE LEARNING AND MULTI-OBJECTIVE
OPTIMIZATION

BY

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In

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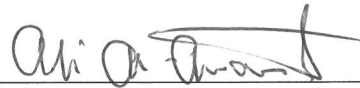
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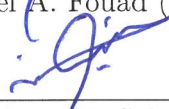
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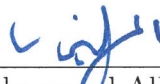
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*To my parents, whose love and support over the years have made me
who I am today.*

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LIST OF SYMBOLS

a	SOC deviation weight
Ah	Ampere-hour
B	Time constant
b	Fuel cell power deviation weight
C	Capacitance
D	Duty cycle
F	Farad
g	Gram
ga	Gravitational acceleration
h	Hour
kg	Kilogram
mm	Millimeter
Q	Battery's capacity
V	Volt
W	Watt

LIST OF ABBREVIATIONS

CBR	Case-Based Reasoning
DMFC	Direct Methanol Fuel Cell
ECM	Equivalent Consumption Minimization
EMS	Energy Management System
FC	Fuel Cell
FL	Fuzzy Logic
HDM	Highly Dynamics Modulation
Li-ion	Lithium-ion
LiPo	Lithium Polymer
MLP	Multi-Layer Perceptron
NN	Neural Network
NSGA-II	Non-dominated Sorting Genetic Algorithm
ORB	Optimized Rule-based
PEMFC	Proton exchange membrane fuel cell
SDM	Smoothly Dynamics Modulation
SOC	State of charge

SOFC	Solid Oxide Fuel Cell
UAV	Unmanned Aerial Vehicle

THESIS ABSTRACT

NAME: Mohammad Alzyod

TITLE OF STUDY: Data-driven Energy Management for Fuel Cell Hybrid UAV based on Machine Learning and Multi-Objective Optimization

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The power supply system hybridization, by combining two or more power sources, is one of the best options to insure a large endurance for a drone. The power supply system structure choice is however crucial. Indeed, it depends not only on the power sources characteristics, but also on the drone mission requirements. In this context, an Energy Management System (EMS) is mandatory to optimally control the power splitting between the onboard power sources to achieve the targeted mission with high performance and high efficiency. An EMS typically includes current and voltage sensors to track the power flow, converters to control power sources outputs, and a processing unit handling the adopted power management strategy. Energy management strategies in drone applications face critical challenges in dynamically changing envi-

ronments. Previous studies have explored online optimization techniques, but they end up with challenges in computational efficiency. This thesis addresses this research gap by proposing two highly adaptable energy management strategies. It proposes Neural Network (NN), multi-objective optimization, data mining, and Case-Based Reasoning (CBR) methods; emphasizing real-time adaptability to dynamic load profiles with low computational demands. To comprehensively prepare the required load data by the proposed strategies, diverse load profile scenarios are generated using three proposed methods: payload modulation, highly dynamics modulation, and smoothly dynamics modulation. Two different penalty factors related to battery State of charge (SOC) deviation and fuel cell power deviation from filtered load are introduced within the objective function of the Equivalent Consumption Minimization (ECM) strategy to be optimized with NSGA-II method for each load scenario to enhance the dynamic response over different loading dynamics. For each load scenario with its corresponding optimized penalty factors, rigorous evaluations are conducted using the improved ECM. Then, these data are investigated once by NN and CBR. In practical scenarios, the proposed techniques demonstrate promising outcomes, achieving optimal hydrogen consumption while maintaining battery State of charge (SOC) within the desired range. Comparative analyses with existing strategies emphasize the robustness and efficiency of these proposed strategies in responding to dynamic load scenarios that have never been experienced. This thesis contributes valuable insights into the delicate balance between energy management adaptability and computational demands for hybrid drones, opening pathways for further research and setting the stage for new developments.

ملخص الرسالة

الاسم:

محمد نايل الزيد

عنوان الدراسة:

إدارة الطاقة المبنية على البيانات للطائرات بدون طيار الهجين التي تعمل بخلايا الوقود استناداً إلى التعلم الآلي الأمثلة

متعددة الأهداف

التخصص:

الهندسة الكهربائية

تاريخ الدرجة العلمية: كانون الأول 2023

تواجه استراتيجيات إدارة الطاقة في تطبيقات الطائرات دون طيار الهجينة تحديات حرجية في بيئات متغيرة ديناميكياً. قامت الدراسات السابقة باستكشاف الكثير من هذه التقنيات، ولكنها واجهت تحد بالخاصة لكمية كبيرة من الحسابات بشكل مستمر. تعالج هذه الأطروحة هذه المشكلة من خلال اقتراح استراتيجيتين قابلتين للتكيف مع التغيرات الديناميكية، من خلال استغلال ميزات عدة طرق بشكل متداخل والتي تشمل استراتيجية الخلايا العصبية الصناعية واستراتيجية الاستدلال المبني على الحالة والعديد من تقنيات الذكاء الاصطناعي والطرق الإحصائية. تركز هذه الأطروحة بشكل رئيسي على تحسين تفاعل واستجابة خلايا الوقود المستخدمة في نظام الطاقة الهجين مع تغيرات الحمل الديناميكية دون الحاجة إلى حسابات معقدة. لإعداد البيانات المطلوبة للاستراتيجيات المقترحة، تم إنشاء سيناريوهات متنوعة لتوفير هذه البيانات باستخدام ثلاثة طرق مقترحة. يتم إدراج معاملات جديدة تتعلق باستجابة بعض مكونات نظام تزويد الطاقة الهجين ضمن القانون المستخدم لاستراتيجية تقليل الاستهلاك المكافئ، ليتم تحسينها فيما بعد بطرق معينة لتحسين الاستجابة مع مختلف الاحمال الديناميكية. يتم لاحقاً الاستفادة من هذه التحسينات مع البيانات التي تم توفيرها باستخدام الطرق الثلاث لتوفير البيانات بشكلها النهائي لكل من استراتيجية الخلايا العصبية الصناعية واستراتيجية الاستدلال المبني على الحالة. أظهر التقييم العملي لهذه الطرق نتائج واعدة، حيث تحقق استهلاك الهيدروجين الأمثل مع الحفاظ على شحن البطارية عند النسبة المطلوبة. كما يسلط هذا التقييم لهذه الطرق بالمقارنة مع الاستراتيجيات الأخرى المستخدمة في أبحاث أخرى الضوء على قوة وكفاءة هذه الاستراتيجيات المقترحة

في التعامل مع سيناريوهات الحمل الديناميكية التي لم تُشَهِد من قبل. كما تقدم هذه الأطروحة رؤى في التوازن الدقيق بين التكيف مع تغيرات الحمل الديناميكية وتقليل الحسابات المطلوبة لذلك، في الطائرات دون طيار الهجينة، مما يفتح المجال للبحث الإضافي ويضع الطريق لتطورات بحثية جديدة.

CHAPTER 1

INTRODUCTION

1.1 General Overview

Research in energy management systems for hybrid Unmanned Aerial Vehicle (UAV) is critical to ensure efficient and optimal usage of energy resources. Energy management is crucial in the success of any hybrid UAV mission, and it could extend missions duration and the longevity of the hybrid components. Therefore, it is essential to continue researching and developing new energy management approaches for hybrid UAV applications that are able to ensure optimal performance.

As the demand for UAV continues to grow, there is an urgent need to develop energy-efficient systems that can support long-duration and high-altitude missions. Energy management systems play a crucial role in this regard, as they can help to reduce energy consumption and improve the overall efficiency of UAV. As such, there is a pressing need for research in this area to develop innovative solutions that can address the energy-related challenges facing UAV. Another important reason to continue researching energy management systems for UAV is the need to reduce the environ-

mental impact of these vehicles. As UAV become increasingly popular and their usage grows, their environmental impact is becoming a significant concern. By developing energy-efficient systems, researchers can help reduce the environmental impact of UAV and promote sustainable aviation practices.

Proton exchange membrane fuel cell (PEMFC) has been identified as a promising alternative to traditional energy sources for UAV [1]. With the increasing demand for UAV applications in various fields, there is a growing need for efficient and sustainable energy management systems to extend their endurance and range. Several research studies have been conducted on energy management strategies for reducing hydrogen consumption. However, vast majority of energy management studies on fuel cell powered hybrid system in mobility applications are on hybrid electric vehicles but those implemented methods are not being able to be applied in drones due to several limitations including:

1. **Weight Constraints:** Drones have strict weight limitations. Adding the necessary components for EMS might exceed the weight limitations, affecting the drone's performance and flight time.
2. **Space Limitations:** Drones have limited space for additional components. Integrating a complex EMS might be challenging due to spatial constraints.
3. **Real-Time Processing:** EMS in hybrid vehicles often rely on sophisticated algorithms and computing power to optimize energy usage. Implementing real-time processing for drones might be difficult due to their size and power constraints.
4. **Dynamic Flight Conditions:** Drones experience highly dynamic flight conditions,

including sudden changes in altitude, wind, and weather.

The challenges faced in implementing EMS for drones, as outlined, underscore the critical need for focused research to overcome these challenges. But developing specialized algorithms capable of real-time processing, adapted to the size and power constraints of drones, remains an uncharted yet crucial area of exploration. Based on that, creating adaptive EMS solutions capable of adjusting within the dynamic flight conditions—rapid altitude changes, varying winds, and unpredictable weather— is highly essential research specifically suited for drones that can enhance the performance and capabilities of UAV.

1.2 Problem Statement

Energy management strategies in drone applications encounter significant challenges due to the dynamic nature of their operating environments where energy demands fluctuate rapidly due to shifting mission requirements and unpredictable environmental conditions. The existing strategies struggle to adapt with these dynamic changes, creating a critical gap in effective energy management solutions for drones. While previous studies have explored online optimization techniques to resolve these issues, these approaches often struggle with computational efficiency issues. The demand for real-time adaptability to dynamic load profiles with low computational requirements remains a critical gap in existing research.

1.3 Research Aim and Objectives

This thesis aims to address the identified research gap by introducing a highly adaptable energy management strategy tailored for drone applications. The specific objectives are to:

1. To propose and develop novel strategies capable of real-time adaptability to dynamic load profiles, implementing neural networks and Case-Based Reasoning. Additionally, generate diverse load profile scenarios using three distinct methods to comprehensively prepare the required load data for the proposed strategy.
2. Assess and demonstrate the remarkable adaptability of the proposed strategies across various load profiles through comparisons with existing energy management strategies.
3. Showcase the proposed strategies ability to closely emulate real-time optimization strategies behavior while significantly reducing computational demands, ensuring robust and efficient responses to dynamic load scenarios, and generalizing responses to unforeseen situations.

1.4 Thesis Organization

The structure of this thesis is outlined as follows: Chapter 2 presents the literature review; the focus is on synthesizing existing knowledge related to the topic. This chapter serves as a foundation for the research by examining previous studies, theories, and empirical evidence. It not only highlights the gaps in the current understanding

but also contextualizes the significance of the research problem or question being addressed. Chapter 3 delves into the research methodology; it details the methodology employed in conducting the research. It elucidates the approach, design, data collection methods, sample selection, and any tools or instruments used for data gathering and analysis. This section offers transparency and insight into the steps taken to ensure the validity, reliability, and ethical considerations of the research. Chapter 4 focuses on results and discussion; this chapter showcases the data obtained from the research methods outlined in Chapter 3. Results are interpreted, analyzed, and contextualized within the broader framework. This chapter is where the significance of the findings is emphasized, relationships between variables are explored, and any unexpected or notable outcomes are discussed. Finally, Chapter 5 encapsulates the entirety of the thesis by summarizing the key findings, reiterating their significance in relation to the research questions or objectives, and discussing their broader implications. Additionally, this chapter suggests avenues for future research, offering a holistic perspective on the subject matter.

CHAPTER 2

LITERATURE REVIEW

Fuel cell-powered research and industrial UAVs have become increasingly popular in recent years as a more sustainable alternative to traditional fossil fuel-powered drones. Fuel cells use hydrogen or other fuels to produce electricity, with only water and heat as byproducts, making them much cleaner and more efficient. Here are some examples of fuel cell-powered research and industrial UAVs and they are summarized in Table 2.1 [2]. These examples demonstrate the potential for fuel cell-powered UAVs in a variety of applications, including military and civilian use. As technology continues to advance, it is likely that we will see even more innovative uses of fuel cell-powered drones in the future.

2.1 UAV Energy System

Energy systems used in drone applications can be categorized into two main types: systems with a single source and hybrid systems. Single-source energy systems for drones typically rely on batteries as the primary energy storage medium. Lithium-ion

Table 2.1: Some examples of fuel cell-powered research and industrial UAVs.

Organization	UAV name	UAV type	Fuel cell type	Hydrogen storage type	Endurance
EnergyOr (2011)	FAUCON H2	Fixed wing	PEM	Compressed H2	10 h04 min
U.S. Naval Research Laboratory (2013)	Ion Tiger	Fixed wing	PEM (550 W)	Cryogenic liquid H2	48 h
EnergyOr (2016)	H2Qauad 1000	Multirotor	PEM (900 W)	Compressed H2	2 h
SKYCORP (2018)	e-Drone Zero	Multirotor	PEM (800 W)	Compressed H2 (3 l, 300 bar)	2 h
BATCAM (2019)	/	Multirotor	PEM	Compressed H2 (6l)	70 min (with 5 kg payload)
MetaVista (2019)	/	Multirotor	PEM (800 W)	Liquide H2 (6l)	12 h07 min

batteries are commonly used due to their high energy density and lightweight nature, allowing drones to achieve longer flight times. However, the limited energy capacity of batteries can restrict the operational range and flight duration of drones, making them suitable for shorter missions or small-scale applications.

Hybrid energy systems, on the other hand, offer an alternative approach for drone operations that require extended flight times or increased payload capacities. These systems integrate multiple energy sources, such as fuel cells, gasoline engines, or solar panels, with batteries to provide a more versatile and efficient power solution. For instance, hybrid drones can combine the long-range capabilities of combustion engines or fuel cells with the high power density and instant response of batteries during peak energy demand, resulting in extended flight durations and improved performance. Hybrid energy systems for drones have the potential to enhance operational flexibility, enabling a broader range of applications, including aerial inspections, surveillance, lo-

gistics, and delivery services. By leveraging the advantages of different energy sources, these systems can optimize power utilization, extend mission durations, and improve overall drone performance while minimizing environmental impact. Continued research and development in hybrid energy systems hold great promise for advancing the capabilities and sustainability of drone applications in various industries. The following are a brief descriptions with summary in Table 2.2 for many drone energy systems that depend on one source architecture or hybrid architecture including the advantages and the limitations of each one that was mentioned or concluded within many previous research studies.

Table 2.2: Energy systems used in drones

Energy sources	Architecture	Advantages	Limitations and drawbacks	Related papers
One electrical source	Battery	Quick responsiveness to power demand due to high energy density and energy storage rather than generation.	Low power density, short endurance, lengthy recharge times with "memory effect" for some battery types, and increased weight and cost due to the addition of additional batteries to boost autonomy	[3]
One electrical source	Fuel cell	High energy density, immediate refilling without the "memory effect," and use more fuel in the same stack (thus reducing weight) to maximize autonomy.	Slow response to power demand, need for auxiliary equipment (compressors, regulators, etc.), lack of infrastructure for hydrogen distribution, storage problems, safety concerns, and high cost of hydrogen production	[4], [5], [6]
Hybrid power supply	Fuel cell and Battery	High energy and power densities improve endurance and response time, as well as energy generation and storage.	Complexity in system integration, potential high costs, and challenges in maintaining balance between power output and efficiency across varying operational conditions.	[6], [7], [8], [9]
Hybrid power supply	Fuel cell, Battery, and solar cells	Increased endurance, pure, free, and accessible energy, lower energy costs, and hydrogen savings are all possible with an additional energy source.	The requirement for big UAV wings, which cannot be employed in rotary-wing UAVs, necessitates the employment of an energy storage device, as well as EMS and MPPT.	[10], [11], [12], [13]
Hybrid power supply	Fuel cell, Battery, and supercapacitor	Very high power density, rapid charging, light weight, and low dc bus fluctuations; very long lifetime, minimal heat loss due to low internal resistance.	Supercapacitor voltage control is required, as well as EMS.	[14], [15]

2.1.1 Battery

Drones powered by batteries commonly utilize Lithium Polymer (LiPo) or Lithium-ion (Li-ion) batteries, where the energy capacity is determined by their chemistry and physical dimensions, allowing for extended flight times with larger batteries. These battery-driven drones boast portability, lightweight design, and simple maintenance; nevertheless, they have limited flight times and require recharging or battery replace-

ment after use.

2.1.2 Fuel Cell

A drone powered by a fuel cell uses hydrogen gas as fuel to generate electricity. Fuel cell-powered drones can provide longer flight times and higher power density than battery-powered drones. They are also more environmentally friendly, emitting only water and heat as by-products. However, they are more expensive and require special infrastructure for hydrogen refueling.

2.1.3 Fuel Cell, Battery, and Solar Cells

This hybrid system combines a fuel cell, battery, and solar cells to power a drone. The fuel cell provides continuous power, while the battery and solar cells provide additional power during peak demand. This system can provide longer flight times and greater flexibility than a battery or fuel cell alone. However, it is more complex and expensive than using a single power source.

2.1.4 Fuel Cell, Battery, and Supercapacitor

This hybrid system combines a fuel cell, battery, and supercapacitor to power a drone. The fuel cell provides continuous power, while the battery and supercapacitor provide additional power during high demand situations. This system can provide higher power density and faster response times than a battery or fuel cell alone. However, it is more complex and expensive than using a single power source.

Table 2.3: Power supply systems that were used in UAV applications

Ref.	Year	Power supply system	Experiments/ Simulations	Contribution	Limitations
[10]	2014	FC/ Battery/ Solar cells	Experiments	An implemented rule-based PMS in a 200 W class UAV was tested in flight for 3.8 hours.	Nighttime operation has not been tested.
[16]	2018	FC/ Battery	Both	State machine approach was examined under various SOC situations.	Only ground test.
[11]	2018	FC/ Battery/ Solar cells	Experiments	Technique for switching between a solar and a fuel cell system	Strategy algorithm missed.
[17]	2009	Battery/ Solar cells	Experiments	Battery management in a solar system to supply power to the electrical circuits of a constructed UAV.	Power for propulsion system neglected.
[9]	2018	FC/ Battery	Experiments	One programmable DC/DC converter is used for online fuzzy rule-based EMS.	No flight test.
[8], [18]	2010 2009	FC/ Battery	Simulations	ANFIS-based controller is used for intelligent EMS and PMS.	Strategy not tested with <u>UAV</u> profile mission.
[19]	2012	FC/ Battery/ Solar cells	Simulations	Constrained thermostat control (CTC) approach.	The proposed architecture may make the system heavy.
[12]	2018	FC/ Battery/ Solar cells	Simulations	Fuzzy logic and state machine methods are combined.	No experimental validations.
[20]	2016	FC/ Battery	Both	Simulating a basic rule-based algorithm in HIL.	No flight test, endurance not discussed.
[21]	2018	Solar cell/ Battery	Simulations	Solar-powered UAV with a three-stage EMS	High dependence on solar energy.
[22]	2009	FC/ Battery	Simulations	Dynamic programming is used to achieve optimal EMS.	Optimization high computational cost.

An additional comprehensive comparative review about the power supply systems that were used in UAV applications including: system topology, contributions, and limitations of each study are listed in Table 2.3. The research in UAV power supply systems from 2009 to 2018 encompasses a range of configurations involving Fuel Cell (FC), batteries, and solar cells. Lee et al. [10] tested a rule-based PMS in a 200 W class UAV, achieving a 3.8-hour flight time, but without validation for operation. Yang et al. [16] examined a state machine approach under diverse state-of-charge (SOC) conditions, constrained to ground tests. Gang et al. [11] introduced a technique for transitioning between solar and fuel cell systems, yet with a missed strategy algorithm. Shiau et al. [17] focused on battery management within solar systems for UAV electrical circuits, omitting power considerations for propulsion. Zhang et al. [9] utilized a programmable DC/DC converter for online fuzzy rule-based energy management but lacked flight testing. Karunarathne et al. [8], [18] implemented ANFIS-based controllers for EMS, untested with UAV profile missions. Lee [19] proposed a constrained thermostat control (CTC) approach through simulations, potentially increasing system weight. Zhang et al. [12] combined fuzzy logic and state machine methods in simulations without experimental validation. Savvaris et al. [20] simulated a rule-based algorithm in hardware-in-the-loop (HIL) setups, lacking flight tests or endurance discussions. Galkin et al. [21] simulated a solar-powered UAV with a three-stage EMS, highlighting high solar energy dependence. Bradley [22] utilized dynamic programming for optimal EMS, facing computational cost challenges.

These studies offer a varied perspective on power supply systems and management strategies for UAVs. However, the absence of validations and computational

complexities underlines the necessity for further research. Enhancing the practicality and robustness of these systems across diverse operational scenarios remains a critical goal.

2.2 Powertrain Topologies

In the context of UAVs, the powertrain is the system that generates power and propels the drone through the air. A hybrid powertrain for a UAV combines two or more energy sources to provide the necessary power for flight. This typically involves a combination of an electric motor powered by batteries and a small internal combustion engine or a fuel cell that can either provide direct propulsion or charge the batteries during flight.

2.2.1 Advantages of Hybrid Powertrains

The advantages of a hybrid powertrain for UAVs are significant. By combining electric and internal combustion or fuel cell power, hybrid UAVs can achieve longer flight times, greater efficiency, and reduced emissions compared to traditional gasoline-powered UAVs. This allows for longer mission durations and increased payload capacity, which can be crucial in applications such as aerial surveillance, delivery, and agriculture. In addition to the benefits of hybrid powertrains, there are also challenges that must be addressed. For example, the integration of multiple energy sources and the associated control systems can be complex and require careful management. Battery technology and charging infrastructure are also critical components of hybrid

UAV powertrains and must be optimized for the specific application.

Despite these challenges, the development of hybrid powertrains for UAVs is a rapidly evolving field, and there are many exciting opportunities for innovation and growth in this area. As the demand for UAVs continues to increase in both commercial and military applications, the development of efficient and sustainable powertrains will be essential to the growth of the industry.

2.2.2 Hybrid Powertrains Architectures

The effectiveness of hybrid power systems is dependent on their proper design. Nine hybrid architectures for power hybrid propulsion systems are shown in Figure 2.1 [23]. Since every power source has a DC-DC converter, all power sources can be actively regulated thanks to the fully active construction. The price of the system will rise, though, as more DC-DC converters are added. Additionally, the DC-DC has a large mass and volume, which hinders the power system's ability to operate more efficiently and save fuel. In this instance, a semi-active structure is used, powered directly by the battery rather than a bidirectional DC-DC converter. Direct hybrid structures and indirect hybrid structures are the two categories in which hybrid structures are typically different. They are split specifically into nine different structures. The nine major hybrid constructions for UAVs based on fuel cell types are listed below, where the letters *a, b, c, d, e, f, g, h, and i* correspond to the corresponding letters in Figure 2.1 [23] with further details later. The lifespan of each PEM fuel cell and Li-ion battery is significantly shorter than that of supercapacitors, which decreases the overall durability of the hybrid power system. Therefore, it is important to consider the PEM

fuel cell and Li-ion batteries ageing performance. Four different influencing factors, which include dynamic load cycling, heavy load cycling, start-stopping, and idling, have an impact on the PEMFC's lifespan. The fuel cell degradation equation in [24] and the relevant parameters of performance degradation rates of the four influencing factors could be achieved in [25].

- (a) Fuel cell/ battery hybrid structure without converters [26];
- (b) Fuel cell/battery /solar cell hybrid structure without converters [27], [28];
- (c) Semi-active fuel cell/battery hybrid structure [27];
- (d) Semi-active battery/ fuel cell hybrid structure [29];
- (e) Fully active battery/ fuel cell hybrid structure [30];
- (f) Fully active fuel cell /supercapacitor/ battery hybrid structure [15], [31];
- (g) Semi-active fuel cell /supercapacitor/ battery hybrid structure [14];
- (h) Semi-active fuel cell/battery /solar cell hybrid structure [19], [32].

2.3 Hydrogen Fuel Cell

Proton exchange membrane fuel cell, direct methanol fuel cell, and solid oxide fuel cell are all types of fuel cells that convert chemical energy from a fuel source directly into electrical energy. However, they differ in terms of the type of fuel they use, the operating temperature, and the application for which they are best suited.

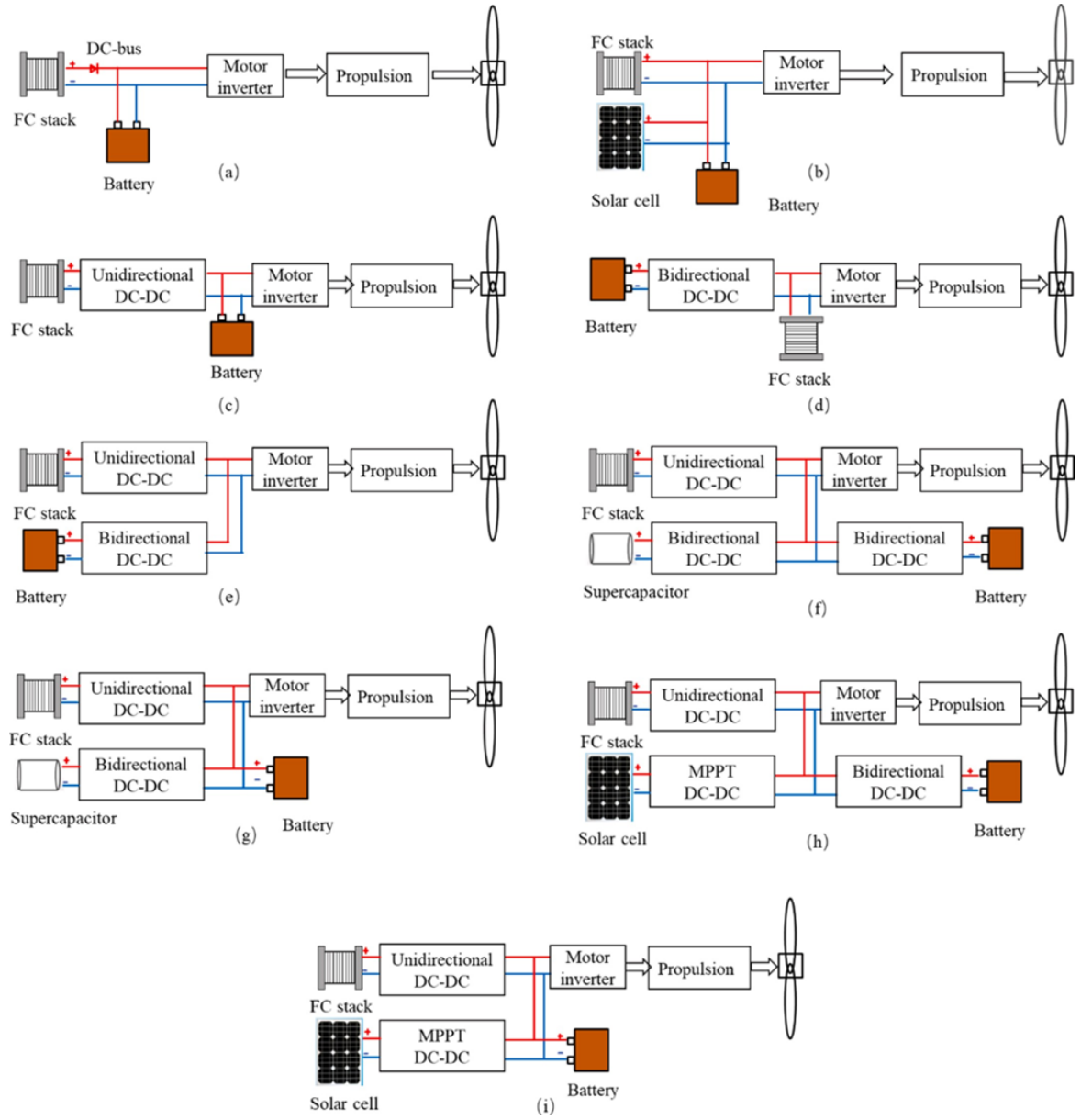


Figure 2.1: The major hybrid constructions for UAVs based on fuel cell

2.3.1 Proton Exchange Membrane Fuel Cell (PEMFC)

PEMFC uses hydrogen gas as the fuel source and operates at a relatively low temperature of around 80°C. PEMFCs are commonly used in transportation applications, such as powering fuel cell vehicles, because they are lightweight, efficient, and produce only water as a byproduct.

2.3.2 Direct Methanol Fuel Cell (DMFC)

DMFC uses methanol as the fuel source instead of hydrogen gas. DMFCs operate at a lower temperature than PEMFCs and are best suited for small portable devices, such as smartphones and laptops, due to their compact size and relatively low power output.

2.3.3 Solid Oxide Fuel Cell (SOFC)

SOFC uses a solid oxide electrolyte instead of a liquid or polymer electrolyte. It can use a variety of fuels, including hydrogen, natural gas, and biogas, and operates at a much higher temperature of around 800°C. SOFCs are commonly used in stationary power applications, such as in large-scale electricity generation for commercial and industrial use, due to their high efficiency and ability to generate heat as well as electricity.

2.3.4 Comparison between PEMFC, DMFC, and SOFC

The major differences between PEMFC, DMFC, and SOFC are listed in Table 2.4 [2]. In summary, the main differences between PEMFC, DMFC, and SOFC are the

Table 2.4: Major characteristics of the most commonly used fuel cell types in UAVs.

FC Type	Fuel	Efficiency (%)	Temp. (C°)	Stack specific power (W/kgs)	System specific power (W/kg)
PEMFC	Hydrogen	40 – 60	30 – 100	> 500	> 150
DMFC	Methanol	20 – 30	20 – 90	> 70	> 50
SOFC	Hydrocarbon	30 – 50	500–1000	> 800	> 100

type of fuel they use, the operating temperature, and the application for which they are best suited. PEMFCs are best for transportation applications using hydrogen gas, DMFCs are best for small portable devices using methanol, and SOFCs are best for stationary power applications using a variety of fuels.

2.4 Hybrid Energy Storage System

Hybrid energy storage systems combine two or more energy storage technologies to overcome the limitations of each individual technology and create a system that is more reliable, efficient, and cost effective. However, there are several key issues that must be considered when designing and operating a hybrid energy storage system.

2.4.1 Compatibility

The different energy storage technologies used in a hybrid system must be compatible with each other to ensure optimal performance and safety. For example, the charge and

discharge rates, operating temperatures, and voltage levels of the different technologies must be compatible to prevent damage and ensure efficient operation.

2.4.2 Control and Management

Hybrid energy storage systems require sophisticated control and management systems to optimize the operation of each storage technology and balance the power flow between them. This can be challenging, especially when the system includes multiple technologies with different response times and capacities.

2.4.3 Maintenance and Replacement

Hybrid energy storage systems require regular maintenance and replacement of components, including batteries, capacitors, and other energy storage devices. This can be complex and costly, especially when the system includes multiple technologies with different lifespans and maintenance requirements.

2.4.4 Safety and Reliability

Hybrid energy storage systems must be designed and operated with safety and reliability in mind. The different storage technologies used in the system can have different safety and reliability characteristics, and must be carefully integrated and monitored to prevent system failures and ensure safe operation.

2.4.5 Cost-Effectiveness

Hybrid energy storage systems can be expensive to design, build, and operate, especially when multiple technologies are used. The cost-effectiveness of the system depends on factors such as the initial cost, operating costs, and expected lifespan of the system.

2.4.6 Design and Optimization of Structures

Finding the best battery and supercapacitor configuration is the focus of this type of research, which also examines how the capacity matching and energy management algorithms can be optimized together. It takes into account how the two issues interact during system operation. The methods that are frequently employed are the integrated optimization method and the multi-objective optimization method.

2.4.7 Energy Management Systems

This kind of research focuses on creating effective and smart control strategies to increase the hybrid energy storage system's durability and stability as well as its capacity to respond to changing operating conditions. Dynamic programming, fuzzy control, and predictive control are some of the methods that are frequently utilized. EMS has been extensively studied in various applications, including drones. An EMS is a system that manages the energy consumption and storage of a device or system.

In summary, hybrid energy storage systems offer a promising solution for overcoming the limitations of individual energy storage technologies. However, key issues such

as compatibility, control and management, maintenance and replacement, safety and reliability, and cost-effectiveness must be considered and addressed to ensure optimal performance and long-term viability of the system.

2.5 Typical Designs for Hybrid Systems

In the realm of hybrid systems for drones, several combinations of energy storage technologies have emerged as promising solutions. One prevalent design integrates fuel cells with batteries, a fusion that has garnered significant attention in recent research [33], [34], [35], [9], [36], [37], [38], [39], [40], [41], [42], [43], [44]. This hybrid system strikes a balance between the high energy density of batteries and the steady power supply from fuel cells. By harnessing immediate power from batteries during peak demands and relying on sustained, efficient energy output from fuel cells during longer missions, this configuration offers a favorable compromise between energy capacity and power output for extended flight durations.

Another emerging design pairs fuel cells with supercapacitors [45]. This configuration emphasizes the rapid energy storage and discharge capabilities of supercapacitors, complementing the continuous energy generation of fuel cells. Supercapacitors excel in swift energy delivery, instrumental in scenarios demanding sudden bursts of power, such as during take-offs or rapid maneuvers. The integration of these technologies aims to enhance the responsiveness and agility of drones without compromising overall energy efficiency.

The most comprehensive approach involves the synergy of fuel cells, batteries,

and supercapacitors [46], [47], [48]. This tribrid system capitalizes on the collective strengths of all three energy storage technologies. By combining the high energy density of batteries, the continuous power output of fuel cells, and the rapid energy transfer capabilities of supercapacitors, drones equipped with this setup can optimize their performance across a spectrum of flight requirements. This design offers versatility and adaptability, enabling drones to efficiently handle varying operational demands.

These different hybrid system designs highlight diverse approaches in leveraging energy storage technologies for drone applications. Understanding their distinct advantages is crucial in selecting the most suitable configuration based on specific mission requirements, balancing energy capacity, power output, and responsiveness.

2.5.1 Fuel Cell and Battery Hybrid System

In this hybrid system, both a fuel cell and a battery are used as energy storage technologies. The fuel cell acts as the main power source, generating electricity through the electrochemical reaction of hydrogen and oxygen. The battery complements the fuel cell by providing additional power during high-demand situations or quick accelerations. This hybrid system offers a balance between sustained power delivery and high-power bursts, optimizing energy management for improved flight duration and responsiveness. It provides extended flight times and the ability to handle dynamic power demands, making it suitable for applications requiring longer missions, increased endurance, and versatility in power delivery.

2.5.2 Fuel cell and Supercapacitor Hybrid System

This hybrid system combines a fuel cell with a supercapacitor as energy storage technologies. The fuel cell serves as the primary power source, producing continuous and efficient power for sustained flight. Supercapacitors act as high-power density storage devices that can quickly store and release energy during high-energy-demand situations or maneuvers. The combination of a fuel cell and supercapacitor allows for optimized power distribution and improved responsiveness, especially during rapid acceleration or maneuvers. This hybrid system is well-suited for applications that require high-power bursts, rapid response times, and enhanced agility.

2.5.3 Fuel cell and Battery and Supercapacitor Hybrid System

This hybrid system integrates all three energy storage technologies: fuel cell, battery, and supercapacitor. The fuel cell serves as the primary power source, providing sustained power for extended flight durations. The battery complements the fuel cell by offering additional energy storage for longer missions or when energy demands exceed the fuel cell's capacity. Supercapacitors provide high-power bursts during acceleration or high-energy-demand maneuvers, ensuring responsive and agile flight capabilities. This comprehensive hybrid system combines the benefits of all three energy storage technologies, offering extended flight times, increased payload capacity, improved power management, and rapid response capabilities. It is particularly useful for applications that require a combination of sustained power delivery, high-power bursts, and

long mission durations, such as aerial photography, surveillance, or scientific research.

Each hybrid system offers unique advantages, and the choice depends on the specific requirements of the drone application, such as flight time, power demand, payload capacity, and mission characteristics. The selection of the appropriate hybrid system ensures optimal energy management and performance for the intended drone application.

2.6 Energy Management System

A comprehensive overview that outlines and contrasts a wide range of energy management approaches developed for different mobility applications is provided in Table 2.5. Followed by detailed discussions of several selected research studies within this domain. The compiled table offers a comprehensive synthesis of contemporary research in energy management across diverse mobility applications. Each study, highlighted within [49], [50], [40], [51], [9], [36] contributes distinct insights into optimizing energy consumption, enhancing endurance, and refining overall operational efficiency across various vehicular domains, including UAVs, drones, hybrid electric vehicles, among others.

In exploring energy management for various mobility applications, multiple research endeavors have surfaced, each contributing distinct methodologies and insights into optimizing energy consumption, enhancing endurance, and refining operational efficiency. These studies span domains from UAVs to heavy-duty vehicles, offering varied approaches and strategies.

Table 2.5: Energy management studies in mobility applications

Ref.	Year	Power Supply System	Application	EMS Technique	Experiments/ Simulations	Contributions
[45]	2021	FC/SC	Tram	Online extremum seeking-based optimization	Simulation Only	It takes into account the fuel cell degradation
[33]	2020	FC/Battery	Vehicles	Dynamic programming and convex programming	Simulation Only	Battery size optimization while doing energy management
[34]	2015	FC/Battery	Vehicles	Weighted improved dynamic programming	Simulation Only	Considering life-cycle cost of the system components and operational cost
[52]	2017	ICE/Battery	Vehicles	Pontryagin's minimum principle	Simulation Only	Formally checking the convexity assumptions for using Pontryagin's minimum principle
[49]	2020	FC/PV	UAV	Pontryagin's minimum principle	Simulation Only	Optimally using the finite energy stored in the hydrogen fuel cell and routing the aircraft through the dynamic energy fields of solar irradiance and wind
[50]	2022	PEMFC/single-stage turbocharged engine	UAV	NSGA-II algorithm	Simulation Only	Maximize the generated thrust of the propulsion system while minimizing fuel consumption rate
[53]	2018	Engine/Battery	Aircraft	NSGA	Both	Proposal of a new non-dominated sorting algorithm; Benchmark based Non-Dominated Sort (BNDs) for the NSGA
[54]	2018	Engine/Battery	Vehicles	Dynamic particle swarm optimization	Simulation Only	Developing optimal strategies for two-variable energy management and gear-shifting in hybrid electric vehicles
[35]	2021	FC/ Battery	Vehicles	Optimization-oriented AECM	Simulation Only	Updating the optimal equivalent factor periodically via local optimization process according to the predicted power to converge the state of charge (SOC) and guarantee fuel economy
[46]	2018	FC/SC/ Battery	Vehicles	SQP based ECMS	Simulation Only	Considering hydrogen consumption of the of three power sources into objective function to solve this problem
[9]	2018	FC/ Battery	UAV	Online fuzzy technique	Both	Experiments with three types of missions are carried out using the hybrid power system test-bench
[36]	2021	FC/Battery	Heavy-duty vehicle	I-OEMS	Simulation Only	Combines a predictive soft-loading method to enhance the load state of sub-stacks
[47]	2021	FC/SC/ Battery	Aircraft	SSA & MBO	Simulation Only	Comparison of various energy management strategies
[37]	2022	FC/Battery	Mobile welding robots	MPPT & ECMS	Both	Inner layer realizes power distribution and energy optimization, outer layer uses state machine control to switch the control strategy according to the operating state of the system
[38]	2021	FC/Battery	Vehicles	IM-PMP	Both	Limit frequent power fluctuations and improve fuel cell durability
[39]	2021	FC/Battery	Drones	Frequency separation rule-based	Simulation Only	Extended endurance, reduced hydrogen consumption
[40]	2018	FC/Battery	Vehicles	Optimized fuzzy logic controller	Both	Experimental 3D mapping is performed to relate the PEMFC's operating temperature and current to the requested power
[48]	2019	FC/SC/ Battery	UAV	An electronic control	Simulation Only	Evaluation under various flight scenarios and different payloads
[41]	2022	FC/Battery	Vehicles	DQN & PER-DQN	Simulation Only	Reducing fuel cell degradation while slightly reducing fuel economy
[42]	2021	FC/Battery	Vehicles and coastal ships	Deep reinforcement learning	Simulation Only	Addressing the limitations of tabular reinforcement learning agents in dealing with large-scale real-world stochastic load profiles
[51]	2019	Engine/Battery	Tracked vehicles	Fast Q-learning based online updating strategy	Experimental Work	Implementing cloud computation to handle the computational burden and achieve real-time performance
[43]	2020	FC/ Battery	Vehicles	ILF	Both	Addressing the issue of time-phase mismatch in predicting the short-term power demand
[44]	2020	FC/Battery	Vehicles	I3D-LSTM	Both	Short-term speed prediction in intelligent fuel cell vehicles (IFCVs) and analyzes future energy consumption based on the predicted speed

Some studies, like Li et al. (2021) [45], Dobrokhodov et al. (2020) [49], and Zhang et al. (2018) [9], delve into optimizing trajectory planning or power flow control in UAVs. Li et al. introduced an extremum seeking-based optimization for tram systems, while Dobrokhodov et al.'s trajectory planning approach significantly boosted

endurance. Zhang et al.’s proposed fuzzy technique effectively regulated power output, enhancing UAV endurance.

Contrastingly, research like Xie et al. (2018) [53], Bahari et al. (2022) [50], and Zhang et al. (2021) [36] focuses on propulsion systems and optimization in vehicles. Xie et al.’s study showcased retrofitting aircraft with hybrid systems, emphasizing fuel efficiency, while Bahari et al. aimed to balance thrust generation and fuel consumption in a novel UAV propulsion system. Zhang et al.’s I-OEMS strategy outperformed conventional methods, significantly improving efficiency and fuel economy in heavy-duty vehicles.

Studies by Kandidayeni et al. (2018) [40], Lu et al. (2022) [37], and Rezk et al. (2021) [47] delve into efficiency enhancements and control strategies. Kandidayeni et al.’s focus on PEMFC’s thermal management improved system efficiency, while Lu et al.’s hierarchical approach optimized power distribution in welding robots. Rezk et al.’s comparative analysis identified the SSA strategy as optimal for hybrid systems, achieving superior hydrogen fuel economy.

Further, studies such as Li et al. (2018) [46], Delprat et al. (2017) [52], and Du et al. (2019) [51] emphasized strategies tailored for specific vehicle types. Li et al.’s work on quadratic programming-based strategies for hybrid electric vehicles accounted for hydrogen consumption from different power sources. Delprat et al.’s application of Pontryagin’s principle was specific to ICE/battery vehicles, while Du et al.’s online updating strategy showcased computational speed improvement in hybrid electric tracked vehicles.

These diverse approaches collectively underline the evolving landscape of energy

management strategies, highlighting the need for specialized solutions across varied vehicular applications. While some studies target specific vehicles or propulsion systems, others concentrate on trajectory planning, power flow control, or efficiency enhancement, showcasing the interdisciplinary nature of optimizing energy management in mobility applications.

2.7 Efficient EMS Issues and Considerations

In the case of drones, an efficient EMS is necessary to ensure the drone’s stability and autonomy while performing its tasks. However, the vast majority of energy management research that are related to the mobility applications were conducted for hybrid vehicles[33], [34], [52], [54], [35], [46], [36], [38], [40], [41], [43], [44]. Indeed, computational resources play a significant role in the application of energy management techniques, and it is a relevant consideration when applying hybrid vehicle energy management techniques to drones. Here’s an expanded explanation:

2.7.1 Processing Power

Hybrid vehicle energy management systems often rely on complex algorithms and real-time data analysis to optimize power distribution and usage. Implementing these techniques in drones would require sufficient computational power to process the necessary data, make decisions, and control the powertrain effectively. Drones, particularly small and lightweight ones, may have limited onboard computing resources, making it challenging to execute complex energy management algorithms in real-time.

2.7.2 Sensor Requirements

Energy management techniques used in hybrid vehicles often rely on various sensors to gather data on factors like vehicle speed, load, and environmental conditions. While drones do have sensors for flight control and navigation, they may not have the same array of sensors as hybrid vehicles. Additional sensors might be needed to provide the necessary data for accurate energy management, which could impose constraints on the size, weight, and cost of the drone.

2.7.3 Real-Time Constraints

Drones operate in dynamic environments and often require real-time decision-making to ensure safe and efficient flight. Applying energy management techniques in realtime to optimize power usage and distribution would require fast computational processing and quick response times. Limited computational resources on drones may pose challenges in meeting these real-time requirements.

2.7.4 Energy Efficiency and Computational Complexity

Energy management techniques in hybrid vehicles involve optimizing power usage based on various factors, including vehicle speed, load, and operating conditions. Achieving such optimization may require computationally intensive algorithms, which, in turn, consume more energy. For drones, where energy efficiency is crucial for extending flight time, striking the right balance between computational complexity and energy consumption becomes a challenge.

2.7.5 Addressing The Limitations

To address these limitations, researchers are exploring energy management techniques that strike a balance between computational complexity and the available computational resources on drones. This may involve developing lightweight algorithms, leveraging onboard sensors efficiently, and considering trade-offs between computational complexity and energy efficiency. Furthermore, advancements in edge computing and the miniaturization of processing units may contribute to improving computational capabilities on drones in future researches.

2.8 Artificial Neural Networks

Biologically inspired, these AI systems typically consist of layers of nodes with non-linear activation functions and a bias term, which are connected by weights. Here, we distinguish between traditional neural networks of the multilayer perceptron (MLP), and deep neural networks (DNNs) which include a wide variety of techniques; such as, recurrent neural networks (RNNs), convolutional neural networks (CNNs) and generative adversarial networks (GANs) [55], [56], [57], [58]. MLPs typically consist of three layers, an input feature layer, a hidden layer, and an output layer. At their simplest, these networks learn an input-output mapping over a training set, so that when a test-case is presented, its features are used to accurately predict/classify at the MLP output layer. Significantly, the model's learning of an input-output mapping depends on modifying the weights connecting the nodes in these layers and the bias terms within the nodes. MLPs should be favored for real-time energy management

in applications like hybrid drones due to their low computational demands. This efficiency makes them a practical choice for systems with limited computing resources. However, the efficacy of MLPs hinges on the quality and quantity of the data used for training. To ensure reliable performance, it’s crucial to gather a comprehensive and representative dataset that captures diverse states and scenarios the system may encounter during operation. This step is pivotal in enhancing the accuracy and effectiveness of MLP-based energy management strategies in real-world applications like hybrid drones.

2.9 Case-Based Reasoning

These systems perform a type of reasoning from examples or cases using a retrieval, reuse, revise, and re-train cycle [59], [60], [61], [62]. At its simplest, in Case-Based Reasoning (CBR), when a query-case is presented the most similar cases to it are retrieved before being adapted (or used directly) to make a prediction/classification. Typically, the retrieval step finds cases by matching the features of the query-case and cases in the case base using k-nearest neighbor (k-NN). Retrieval accuracy (and, hence, the success of the system) can depend heavily on the weights given to these features, weights that reflect their importance in the domain. Notably, CBR is claimed to have a “natural” transparency as its reasoning-from-precedent or reasoning-from-example parallels what human experts sometimes do [63], kolodner2014case; though these claims have not always been extensively user-tested [64]. Accordingly, CBR has a substantial literature on explanation [64], [65], [66], as does its sister area of

recommender systems [67], [68].

To the best of the author’s knowledge, CBR has never been explored for optimizing power allocation as energy management strategy over diverse stationary and mobility hybrid energy system applications.

CBR works by learning from past examples or cases to make decisions. For energy management, it means finding similar situations from a database when faced with a new problem. These past cases are then used to predict or solve energy-related issues. Usually, it finds these similar cases by comparing the features of the current problem with ones in its memory. What is interesting about CBR is that it’s supposed to be transparent, kind of like how human experts learn from past experiences. However, it is not entirely sure how true this is until doing more testing with real situation and interacting with experimental-based load scenarios like what will be explained in the following chapters. That is why diving into explanations within CBR and similar systems that recommend things based on past data. The goal here is to represent the techniques of CBR as energy management strategy. Hopefully, by doing this to find new ways to make our use of energy more efficient in various real-world application, especially for drone application.

2.10 Literature Gap

UAVs which are typically known as drones, have become increasingly common in both military and civilian applications in recent years [69]. The percentage of UAVs used in civilian applications has been rising, and by 2025, non-military drone sales are

predicted to approximately reach 11 billion US dollars [70]. These UAVs offer indispensable capabilities across a range of industries, spanning agriculture, meteorological research, firefighting, and military reconnaissance.

Currently, due to the weight and size constraints on UAVs, batteries and fuel cells have emerged as the most popular choices for power sources. The majority of UAVs nowadays run on batteries, yet long-duration drone flight is impeded by the low energy density of batteries [71]. Although fuel cells provide a high energy density, their slow response time makes them unsuitable for UAV flight in highly dynamic working environments [72], [73], [74]. As a means of compensation, lithium batteries offer superior power density and reduced weight, leading to the rise of hybrid drones [75]. Supercapacitors, known for their high power density and rapid response capabilities, play a crucial role in meeting quick bursts of power during dynamic flight phases, such as take-off and climbing, so integrating it into the powertrain has become a crucial approach to overcome fuel cell/battery fluctuated responses and stabilizing dc bus voltage [15]. Kang K et. al. [76] a compact unmanned aerial vehicle integrating a hybrid system that combined fuel cell and lithium battery technologies, was subjected to a range of operational conditions, and diverse mission scenarios. Additionally, Renau J et. al. [77] explored a hybrid drone equipped with a fuel cell and conducted performance evaluations, notably at a high elevation.

Endurance stands as a crucial performance measure for drones, with electric drones facing the particular challenge of limited flight time. As a result, many drone developers and industrial investors are actively working to overcome this challenge and extend the flight duration. Various research studies have focused on addressing the

issues related to long-range fuel cell-based drones, including optimizing the weight of fuel tanks [78], conducting thermal analyses [79], developing energy-efficient designs [80], and creating embedded hydrogen generators [81]. The hydrogen economy is considered an applicable solution for enhancing the range of fuel cell-based mobile systems, such as aircraft applications [82] and hybrid electric vehicles [83]. Recent studies have also delved into real-time improvements in fueling regulation to reduce hydrogen consumption [84], yet there remains a noticeable gap in this research area. The UAV's Energy Management System (EMS) plays a crucial role within the hybrid UAV technology by efficiently allocating power from its hybrid energy sources. This allocation leads to enhancements in overall performance, including increased efficiency, endurance, and fuel economy [85]. The available literature categorizes EMSs into three distinct groups: rule-based EMSs, optimization-based EMSs, and learning-based EMSs [86], [85].

Rule-based EMSs offer simplicity, ease of implementation, and minimal computational demands [39], [87], but their effectiveness depends heavily on experiential knowledge, lacking a guarantee of optimal control. In pursuit of optimal control, researchers have increasingly turned their attention to exploration of optimization-based EMSs. These systems typically involve the formulation of an objective function with constraints, with the goal of minimizing this function to optimize control objectives. Broadly, optimization-based EMSs can be categorized into global optimization and instantaneous optimization. Global optimization [88] in EMS considers the entire mission, offering guaranteed optimal solutions but with increased computational complexity. It requires prior knowledge of load data and, due to its demanding com-

putational requirements, is generally not feasible for real-time implementation. In contrast, instantaneous optimization [89] focuses on real-time adaptability, making control decisions incrementally for quicker responses, albeit without guaranteed global optimality.

In the realm of real-time or online EMSs, there has been extensive research on various instantaneous optimization-based EMSs, including Pontryagin’s minimum principle (PMP) [89], equivalent consumption minimization strategy (ECMS) [46], and model predictive control (MPC) [90].

A recent study [39] has taken steps to tackle this issue, demonstrating an improvement in hydrogen consumption for a fuel cell/battery-powered drone through ECMS. However, it’s worth noting that ECMS is an online optimization method, which necessitates in-flight calculations to manage power distribution. Unfortunately, online optimization techniques, typically employed in hybrid electric vehicles, are not suitable for drone applications due to their intricate nature and computational demands. The complexity associated with such methods requires the inclusion of powerful calculators, resulting in additional weight and energy consumption, ultimately affecting the maneuverability of the drone.

As dynamic load profiles constantly shift in response to varying mission requirements and environmental conditions, the adaptability of energy management strategies becomes substantial. These dynamic load profiles represent the continuously changing power requirements and energy consumption patterns that a drone must accommodate [91]. When a drone transitions between tasks or operates in different scenarios, it faces a diverse patterns of load profiles. To effectively manage these shifts,

the energy management system must be adaptable by being capable of adjusting the power allocations among the fuel cell, battery, and supercapacitor in real-time [92].

However, adaptability comes at a computational cost by incorporating an efficient calculator which introduces extra weight and increases energy usage, thereby impacting the maneuverability of the drone [93]. More adaptable methods, like on-line optimization algorithms, have the capability to accommodate a wide range of dynamic load profiles, making them suitable for unpredictable mission scenarios. On the other hand, less adaptable methods, such as rule-based methods, are computationally lighter as they rely on predefined sets of rules. While they are well-suited for relatively stable load profiles and known mission scenarios, they may struggle when faced with rapidly changing and unpredictable load profiles. The complex interplay between adaptability and computational demands in energy management for hybrid drones confirms the critical need for further research in this domain.

This thesis introduces a Highly Adaptable Energy Management Strategy for a fuel cell/battery/supercapacitor-powered drone, exploring diverse load profile scenarios produced with different proposed methods and optimizing an improved Consumption Minimization (ECM) strategy using NSGA-II for each load scenario. Leveraging this data, a proposed neural network-based strategy as well as case-based reasoning-based strategy were developed. Their behaviour were compared with various popular energy management strategies.

CHAPTER 3

RESEARCH METHODOLOGY

Energy management strategies in drones applications face critical challenges in dynamically changing environments. Previous studies have explored online optimization techniques but they come up with challenges in computational efficiency. The methodology in this chapter addresses this research gap by proposing a highly adaptable energy management strategy, emphasizing realtime adaptability to dynamic load profiles. To comprehensively prepare the required load data by neural network and case-based reasoning method, diverse load profile scenarios are generated using three proposed methods. They demonstrate remarkable adaptability across different load profiles, and they were compared with various energy management strategies. They stand out for their ability to closely emulate ECM behavior with significantly reduced computational demands, ensuring robustness and efficiency in responding to dynamic load scenarios, showcasing their ability to generalize responses to unseen scenarios.

3.1 Hybrid Drone Powertrain Topology

The hybrid UAV system incorporates several key components, including a fuel cell, battery, supercapacitor, power converter elements, and load profile which represents the power consumption by electronic control units and motors, as illustrated in Fig. 3.1. To efficiently satisfy the power requirements, the sizing of these components are chosen by meticulous computation. The fuel cell, which dominates the system's total weight, serves as the main energy source for the UAV in this hybrid topology.

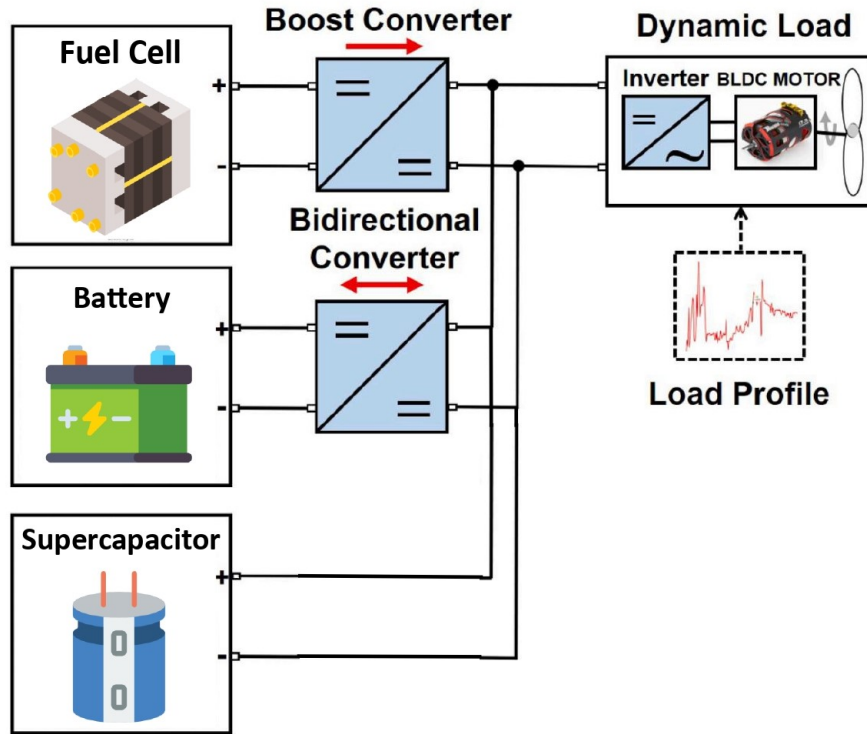


Figure 3.1: Hybrid drone power train topology

To ensure the hybrid UAV system meets its power requirements for various flight tasks, three distinct energy sources, PEM fuel cell, Li-ion battery, and supercapacitor, are employed. Each serves a specific purpose: PEM fuel cell excels at low power applications, while Li-ion battery and supercapacitor technologies are crucial for sud-

den bursts of high power. While the Li-ion battery supplies extra power for longer endurance flights, the supercapacitor offers fast high power output and quick recharging. Specific characteristics of these components, selected based on UAV dynamics, are detailed in Table 3.1.

Table 3.1: Hybrid drone powertrain components specifications

Fuel cell	Maximum peak power	1000 W
	Maximum continuous power	650 W
	Output voltage	19.6 – 25.2 V
	Weight	810 gs
	Size	196 × 88 × 140 mms
Battery	Capacity	1300m Ahs
	Nominal voltage	22.2 Vs
	Weight	230 g
	Size	140 × 30 × 20 mm
Supercapacitor	Capacitance	0.64 Fs
	Voltage	65 V
	Weight	
	Size	53 × 79 × 27 mm
Hydrogen regulator	Weight	250 g
	Output pressure	0.5 ± 0.25 bar
	Tank max. weight	10 kg

Well-designed power converters and methodically energy management strategy are necessary for efficient power allocation between these sources. These power converters are integrated on the DC-bus and improve the output of every energy source. An appropriate DC-bus voltage control method is required for coordinating the regulation of currents and voltages on the DC bus. The UAV’s electric motors receive changing power delivery with time represented by load profile.

3.2 Drone Load Profile Scenarios

To ensure the reliability and adaptability of the energy management system in dynamic environments, it is essential to have a diverse set of load profiles for testing [92]. In this research, three methods are proposed for obtaining new load profile scenarios, each designed to simulate varying degrees of dynamic load fluctuations. These methods include Payload Modulation, Highly Dynamics Modulation (HDM), and Smoothly Dynamics Modulation (SDM). By exploring these methods, we aim to comprehensively evaluate the performance of energy management strategies across a wide range of dynamic scenarios. These scenarios are primarily meant to investigate the ways in which various dynamic conditions impact energy management strategies. The behavior of energy management can be significantly impacted by the unique characteristics of load profiles, including fluctuations, gradual changes, and sudden spikes [94]. Thus, investigating these characteristics will be part of our proposed criterion for creating new scenarios, which will enable us to assess the flexibility and effectiveness of energy management techniques in a range of real-world environments. The load profile, obtained from [95] through experimental work, which includes takeoff and hovering operations. By applying a scaling factor of 0.67 which is based on the relationship between load power and drone weight, to this load profile, one can estimate power demand curves for the newly developed hybrid drone with all of its components [96]. Then, it serves as a reference or normal load profile to be investigated by the three methods mentioned earlier for generating new scenarios. The utilization of a well-established load profile as the basis for our analysis provides a solid foundation

for practically evaluating our proposed energy management system.

There are a total of 40 scenarios generated as follows: Scenario 1 represents the normal load profile. Scenarios 2 to 13 are generated using the HDM method, starting from a 25W offset and increasing in increments of 25W, ranging from 25W to 300W. Scenarios 14 to 25 are generated using the SDM method, following the same pattern of a 25W offset and 25W increments, within the 25W to 300W range. Finally, scenarios 26 to 40 are generated by varying the payload weight, starting from 100g and increasing in 100g increments, with a range from 100g to 1500g.

3.2.1 Highly Dynamics Modulation (HDM)

This method introduces extreme load variations by employing a pulse generator to create offsets X_{offset} above and below the normal load profile over specific time intervals as depicted in Fig. 3.2a. The amplitude for the pulse generator is twice the offset value with 50% pulse width over 50 seconds time period. In this method, we systematically modulate the load profile with different offset values, ranging from 25W to 300W in steps of 25W. The purpose is to replicate severe and sudden load changes that can occur in dynamic environments. HDM method enables us to evaluate how the energy management strategy responds and adapts with highly dynamic fluctuations. The provided data by this method helps us assess EMS strategy's robustness under undesirable conditions.

3.2.2 Smoothly Dynamics Modulation (SDM)

This method is built upon the HDM method by introducing a filtering mechanism to create gradual and smoother load profile variations as depicted in Fig. 3.2a. It aims to simulate more gradual and continuous changes in the load profile. By adding a filter to the configuration, SDM method generates a set of scenarios that provide insights into EMS strategy's performance under varying degrees of dynamic fluctuations. It ensures that energy management is tested not only in extreme scenarios but also in cases where load changes are more predictable and gradual, thereby offering a more comprehensive evaluation of EMS strategy's adaptability.

3.2.3 Payload Modulation

It was investigated here how changes in payload affect the power consumption of a multirotor drone. The power consumption is modeled as a function of the take-off mass, and we will vary the payload from 100g to 1500g in increments of 100g to explore different scenarios. The propulsion power as a function of take-off mass, considering the many factors for propeller configurations, is given by [97]:

$$P_{\text{TOM}} (m_{\text{TOM}}) = \kappa_{\text{int}} \frac{(m_{\text{TOM}} \cdot ga)^{3/2}}{2\sqrt{2 \cdot \rho_{\text{air}} \cdot A_{\text{prop}}}} \quad (3.1)$$

Where: P_{TOM} is the power consumption as a function of the take-off mass. m_{TOM} is the total take-off mass of the drone. κ_{int} is the inefficiency factor for the specific propeller configuration [98]. ga represents the acceleration due to gravity. ρ_{air} is the density of air. A_{prop} is the propeller disc area. This method introduces consistent

load shift to the average load of the normal load profile L_{avg} throughout the entire load profile proportional to the difference between extra weight added W_{extra} and drone weight W_{drone} by employing eq.3.1 as depicted in Fig. 3.2b. By varying the payload while keeping other parameters constant, we aim to understand how payload values from 100g to 1500g impact the power requirements of our drone.

Fig. 3.3 presents different load profile scenarios, resulting from applying payload modulation, HDM and SDM methods.

3.3 Modeling

Within various studies, the models presented in [99] and incorporated into the Specialized Power Systems (SPS) Simulink toolbox, were used [100]. This integration uses a method that combines models based on electric circuits with curve-fitting properties. These models are suitable for simulations, and their parameters can be easily obtained from datasheets. When it comes to DC/DC converters, average value models have been applied.

3.3.1 PEM Fuel Cell Model

PEM fuel cells are used extensively in the development of drones because of their useful characteristics, which include quick startup and a low operating temperature that lowers warm-up times and allows for rapid response. The particular model that is being examined is detailed in [99]. The voltage output of the fuel cell, denoted as

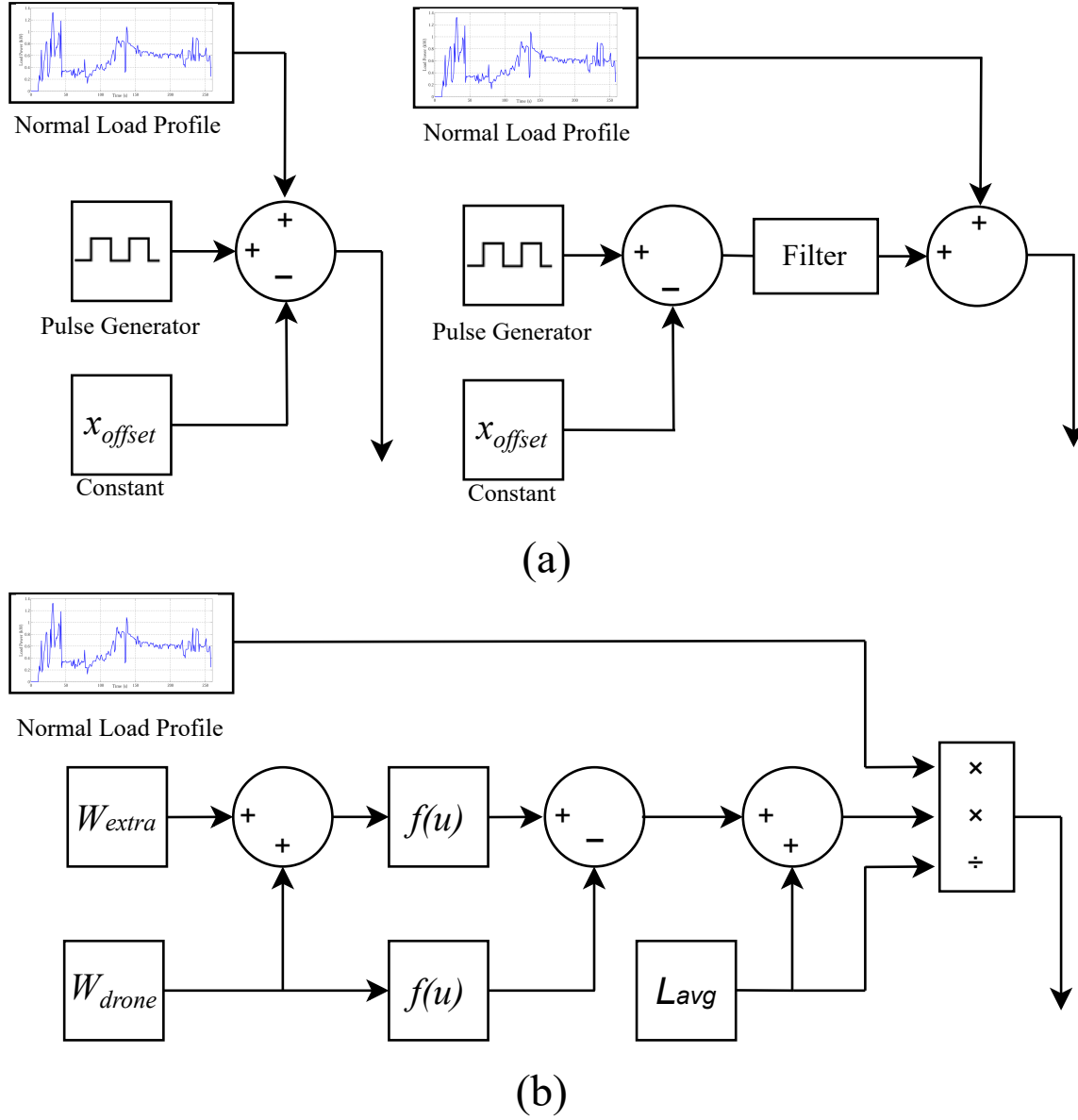
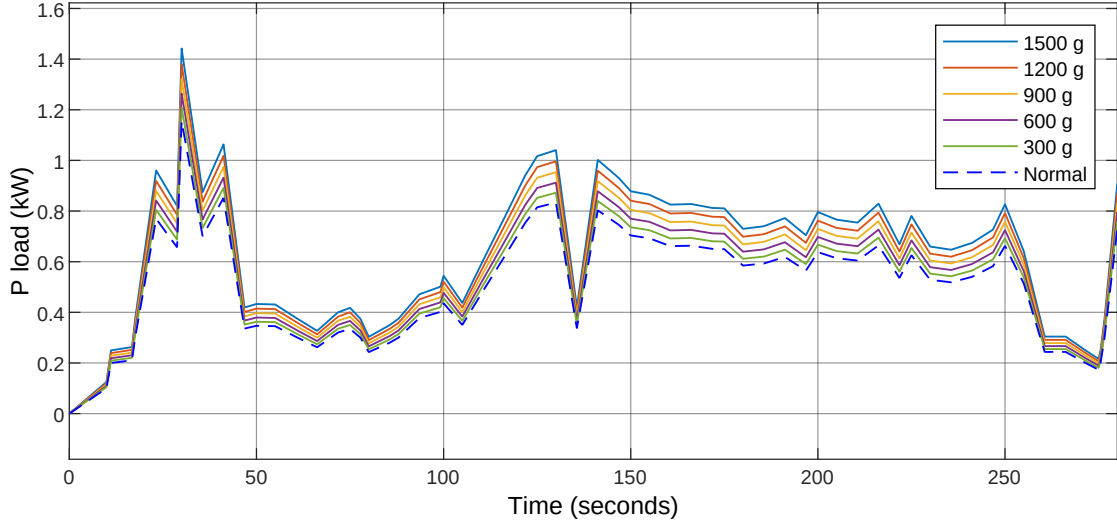


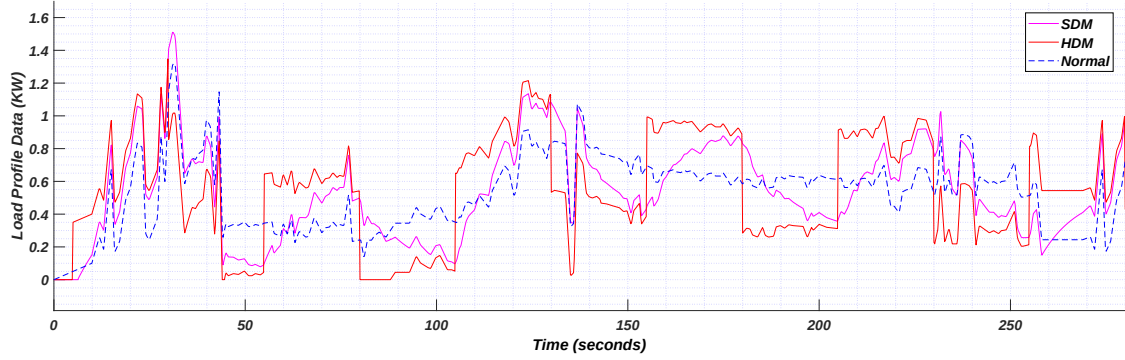
Figure 3.2: Schematic diagrams for (a) HDM to the left and SDM to the right (b) Payload modulation

V_{fc} , is expressed as follows:

$$\begin{cases} V_{fc} = E_{OC} - V_{act} - V_{Ohm} \\ V_{act} = A \cdot \ln(i_{fc}/i_0) \cdot \frac{1}{1+s \cdot T_d/3} \\ V_{Ohm} = r_{Ohm} \cdot i_{fc} \end{cases} \quad (3.2)$$



(a)



(b)

Figure 3.3: Some load profile scenarios (a) Payload variation effect, (b) HDM & SDM with 300W offset.

In this context, E_{OC} signifies the open circuit voltage in volts, which identified from the overall cell reaction chemical thermodynamics. V_{act} stands for the activation voltage drop resulting from the reactions' slowness on the electrode surface. Meanwhile, V_{Ohm} corresponds to the ohmic drop that arises as a result of the electrically conductive components' resistance. Additionally, the parameter A is termed the Tafel slope (V) which represents the relationship between the overpotential (difference between

the cell potential and the thermodynamic equilibrium potential) and the logarithm of the current density, and i_0 represents the exchange current (A). It's important to note that the cell voltage cannot instantaneously adapt to changes in current. The voltage response delay to a current variation, caused by the charge double layer phenomenon, is characterized by T_d as illustrated in Fig. 3.4a. A diode is employed to prevent any potential reverse current flow, typically fulfilled by the boost converter when connected to the stack.

3.3.2 Battery Model

In this research, a Li-ion battery type is selected due to its properties including its high energy density and efficiency when compared to alternative battery technologies. Consequently, it stands as an ideal choice for powering drones in various applications. The model we have employed is based on an updated Shepherd curve fitting model, which incorporates a voltage polarization term to account for the battery's state of charge (SOC) effect. Furthermore, to ensure the stability of the simulation, a filtered battery current is employed, denoted as i^* , to compute the polarization resistance, Pol_{res} . The battery voltage can be expressed as follows [101]:

$$V_{bat} = E_0 - R_{int} \cdot i - K \frac{Q}{Q - it} \cdot it - K \frac{Q}{Q - it} \cdot i^* + A \cdot \exp(-B \cdot it) \quad (3.3)$$

Here, E_0 signifies the battery's constant voltage (in Volts), and R_{int} represents the internal resistance. The terms Q and ' it ' correspond to the battery's capacity and actual charge (in Ampere-hours), respectively. The polarization constant is denoted as K (in

Volts per Ampere-hour), and B is the time constant for the exponential component (in reciprocal Ampere-hours). The polarization resistance, Pol_{res} , is represented by the term $K \frac{Q}{Q-it}$, while the polarization voltage is depicted by $K \frac{Q}{Q-it} \cdot it$.

Much like the approach used in fuel cell modeling, the model parameters can be established either by referencing the manufacturer's datasheet or by conducting a polarization test. The equivalent circuit of this battery model is illustrated in Fig. 3.4b below.

3.3.3 Supercapacitor Model

Supercapacitors share similarities with traditional electrostatic or electrolytic capacitors, but their distinct advantage lies in their ability to store or release a greater amount of energy, thanks to their elevated capacitance [102]. The supercapacitor model integrated into the specialized power systems (SPS) toolbox relies on the Stern model, which merges the Helmholtz and Gouy–Chapman models [103]. The formula for the capacitance of a supercapacitor (SC) is given by:

$$C = \left[\frac{d}{N_e \epsilon \epsilon_0 A_i} + \frac{2N_e RT}{F Q_c \sinh \left(\frac{Q_c}{N_e^2 A_i \sqrt{8RT \epsilon_0 c}} \right)} \right]^{-1} \quad (3.4)$$

Here, N_e signifies the number of layers in the electrode. ϵ_0 and ϵ represent the permittivities of free space and the electrolyte material (in Farads per meter), respectively. A_i denotes the area shared between electrodes and electrolyte (in square meters). d is the Helmholtz layer length (or molecular radius) (in meters). Q_c indicates the cell electric charge (in Coulombs), and c represents the molar concentration (in moles per

cubic meter). R is the ideal gas constant, and T is the operating temperature (in kelvin). The total capacitance, C_T , and the output voltage can be computed as:

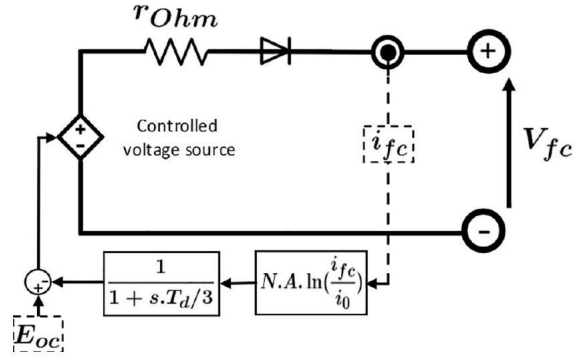
$$\begin{cases} C_T = \frac{N_p}{N_s} C \\ V_{SC} = \frac{N_p Q_C}{C_T} - R_{SC} \cdot i_{SC} \end{cases} \quad (3.5)$$

Here, N_s and N_p refer to the series and parallel cells of the supercapacitor module, respectively. R_{SC} and i_{SC} denote the resistance (in Ohms) and current (in Amperes) of the supercapacitor module, respectively. The equivalent circuit of this supercapacitor model is illustrated in Fig. 3.4c below.

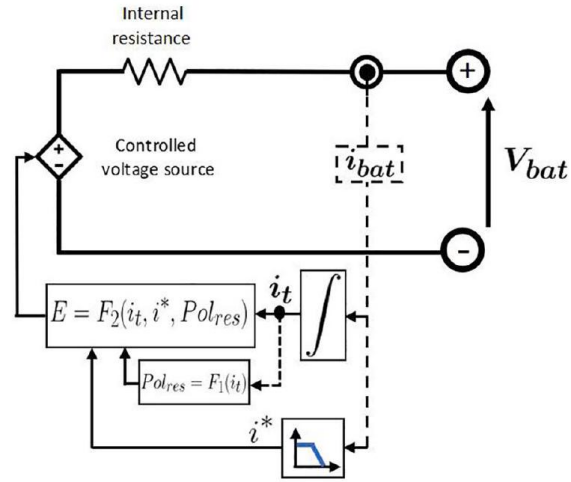
3.3.4 DC/DC Converters Models

When it comes to DC/DC converters, various topologies are proposed in the existing body of literature. These converters can be classified into two categories: isolated and non-isolated converters. Isolated converters are mostly utilized in medium and low-power applications, known for their galvanic isolation and high voltage ratio [104]. In contrast, non-isolated converters are characterized by their compactness and simple architecture, except that they offer a lower voltage ratio. In a study presented in [105], many architectures for DC/DC converter are compared and assessed based on several criteria, including efficiency, reliability, cost, and losses.

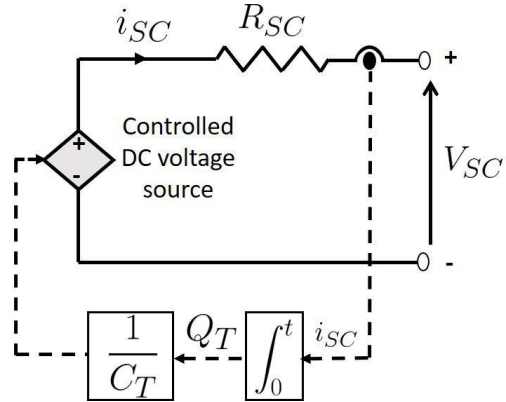
It is possible to implement DC/DC converters through two modeling approaches: average value models or switching models. The latter approach allows for the de-



(a)



(b)



(c)

Figure 3.4: The equivalent circuits for (a) Fuel Cell, (b) Battery, (c) Supercapacitor.

tailed observation of all switching phenomena, but it takes a long simulation time because of the high sampling frequency. Such models are typically employed for design-focused studies. In contrast, average value models are adopted, utilizing controlled voltage/current sources to substitute switches. These models maintain the conversion dynamics while significantly reducing simulation times. Fig. 3.5 shows the average value models that were implemented. Here, D is the duty cycle, η is the converter efficiency, and the high voltage side V_H to the low voltage side V_L are from the DC bus side.

The boost converter output-input voltage relationship is proportional to the duty cycle in the sense that higher D will yield higher output voltages for a given input voltage. In the following two equations, the voltage and current relationship between these two side are presented:

$$V_L = (1 - D) \cdot V_H \quad (3.6)$$

$$I_H = \eta(1 - D) \cdot I_L \quad (3.7)$$

In a bidirectional buck-boost converter, the current flowing through the converter depends on the mode of operation, either in buck mode (stepping down voltage) or boost mode (stepping up voltage). These two equations describe the relationship between input and output currents and voltages in a bidirectional buck-boost converter,

$$I_L = D \cdot I_H \quad (3.8)$$

$$V_H = D \cdot V_L \quad (3.9)$$

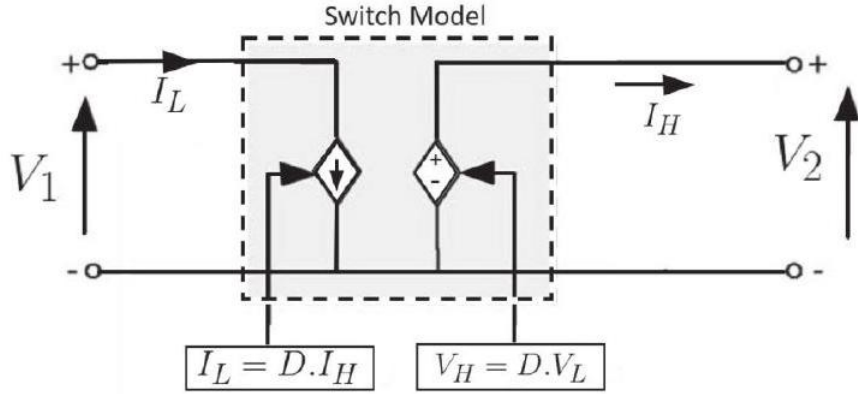
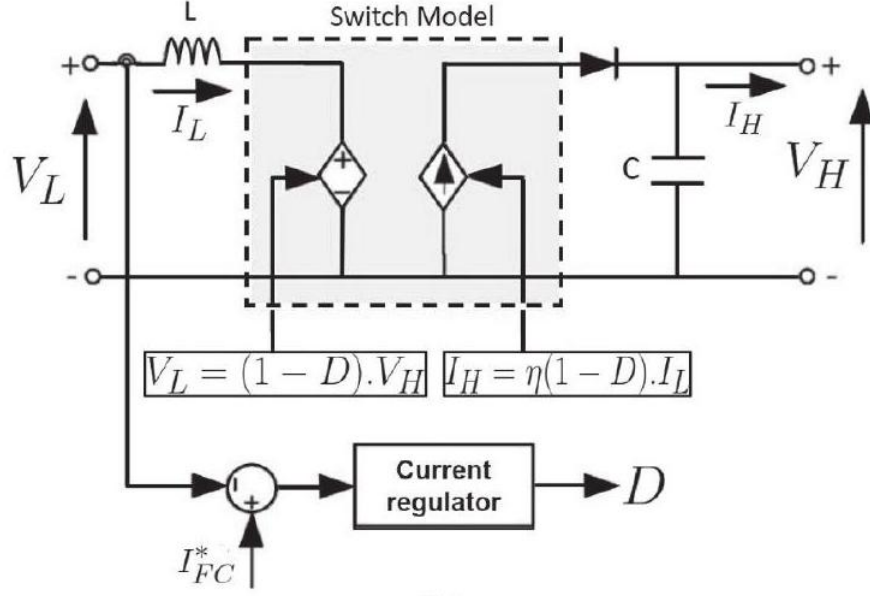


Figure 3.5: DC/DC average model converters. (a) Boost converter, (b) Bidirectional converter.

3.4 DC-Bus Voltage Control

In the context of the system described, DC bus voltage control plays a critical role in maintaining the stability and efficiency of the overall power supply. The fuel cell's output power reference (P_{FC}) is calculated and supplied via the DC/DC boost converter. The energy storage system meets any additional power requirements. The DC

bus voltage regulation scheme depicted in Fig. 3.6, where the reference voltage is set to VDC_{ref} , uses the duty cycle (D) to control the bi-directional DC/DC converter. In addition, the supercapacitor's direct connection to the DC bus plays a crucial role in minimizing DC bus voltage deviations, particularly in situations where the load experiences rapid and significant changes.

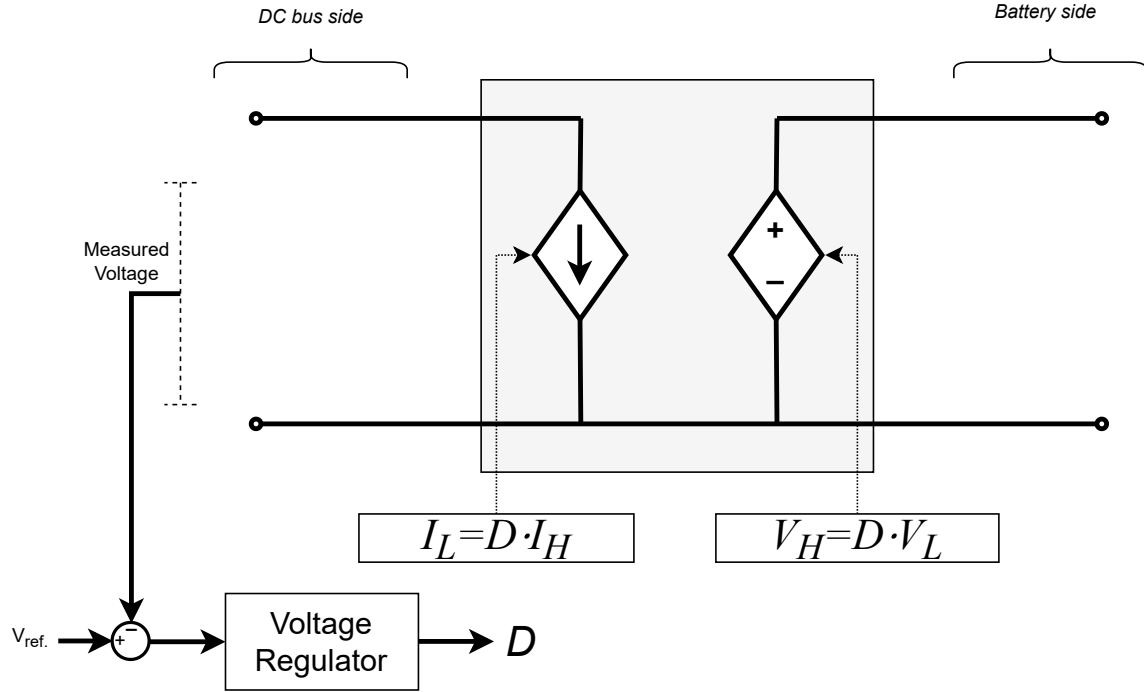


Figure 3.6: The DC bus voltage regulation scheme.

3.5 Energy Management Strategies

Implementing real-time optimization-based energy management algorithms on drones requires a more advanced hardware platform, which, in turn, results in increased energy consumption and added weight, ultimately reducing the drone's endurance. This study introduces a novel energy management approaches to tackle this issue. These

strategies are developed through multi-objective optimization of the basic Equivalent Consumption Minimization (ECM) approach, addressing diverse load profile scenarios with distinct dynamic load characteristics to create an efficient and representative dataset for neural network training. Many EMS strategies were developed for comparative evaluation including Optimized Rule-based (ORB), Fuzzy Logic (FL), and Equivalent Consumption Minimization (ECM), followed by a comprehensive explanation of the proposed methods.

3.5.1 Optimized Rule-based Strategy

The approach described in reference [106] integrates a combination of rule-based techniques and a multiobjective genetic algorithm. Control rules are applied to compute the desired power output for fuel cell and the remaining power from the battery and/or supercapacitor. Subsequently, a genetic algorithm optimization process is employed to enhance drone endurance and performance. This optimization revolves around fine-tuning these control rules to identify the most suitable parameter values, with the dual goals of minimizing hydrogen consumption and minimizing battery SOC deviation. The optimized parameters include the battery charging power denoted as P_{char} , the limits for both of fuel cell power denoted as P_{FC-min} and P_{FC-max} , and battery SOC denoted as SOC_{min} and SOC_{max} . Fig. 3.7 provides a concise summary of the integrated control rules. Optimized Rule-based (ORB) was applied in quite similar way to what was called "Charge Sustaining Mode" in [106] with almost same multiobjective genetic parameters but load profile, powertrain and sizing are different.

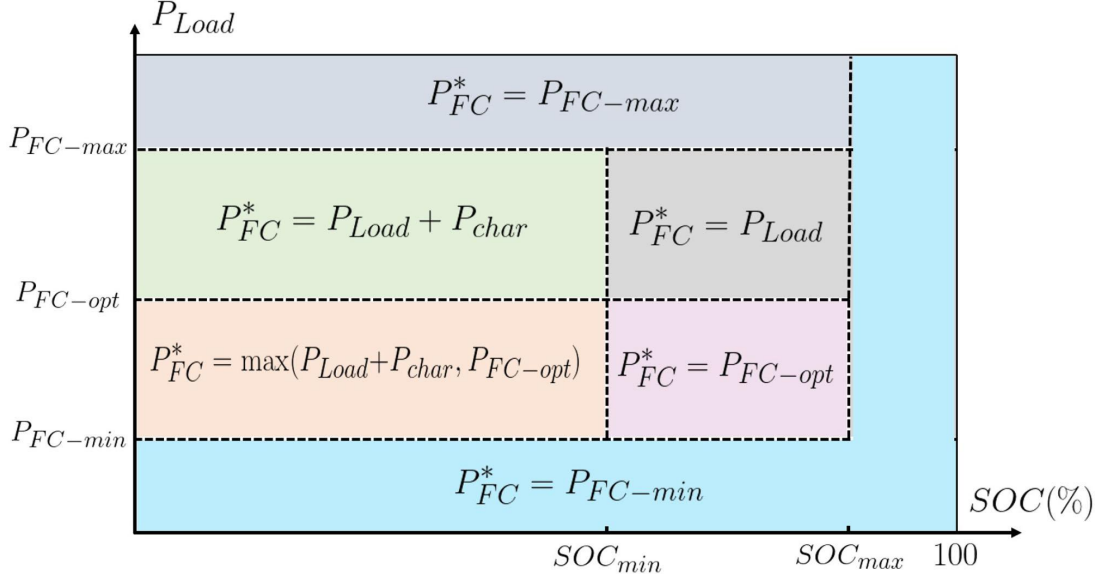


Figure 3.7: The control rules integrated into the optimized rule-based EMS.

3.5.2 Fuzzy Logic Strategy

Fuzzy Logic (FL) has seen widespread use in energy management systems, notably in electric vehicle applications, due to its robustness in handling measurement inaccuracies and its rapid response to load variations [107]. Its ease of implementation with low computational requirements makes it a suitable choice for drone applications, where in-flight computational resources are limited, in contrast to electric vehicles or microgrids. In our study, it is applied in similar way to [106] as a benchmark to calculate the fuel cell reference power based on battery SOC and P_{Load} using membership functions, as depicted in Fig. 3.8, and control decisions are derived from state machine rules outlined in Table 3.2. Mamdani's fuzzy inference technique, coupled with the centroid approach for defuzzification, is employed, as shown in Fig. 3.9.

Table 3.2: FL implemented rules.

P_{FC}	P_{Load}				
		VL	L	M	H
SOC	L	L	M	H	H
	M	VL	L	M	H
	H	VL	L	M	H

VL $\rightarrow$ Very Low, L $\rightarrow$ Low, M $\rightarrow$ Medium, H $\rightarrow$ High.

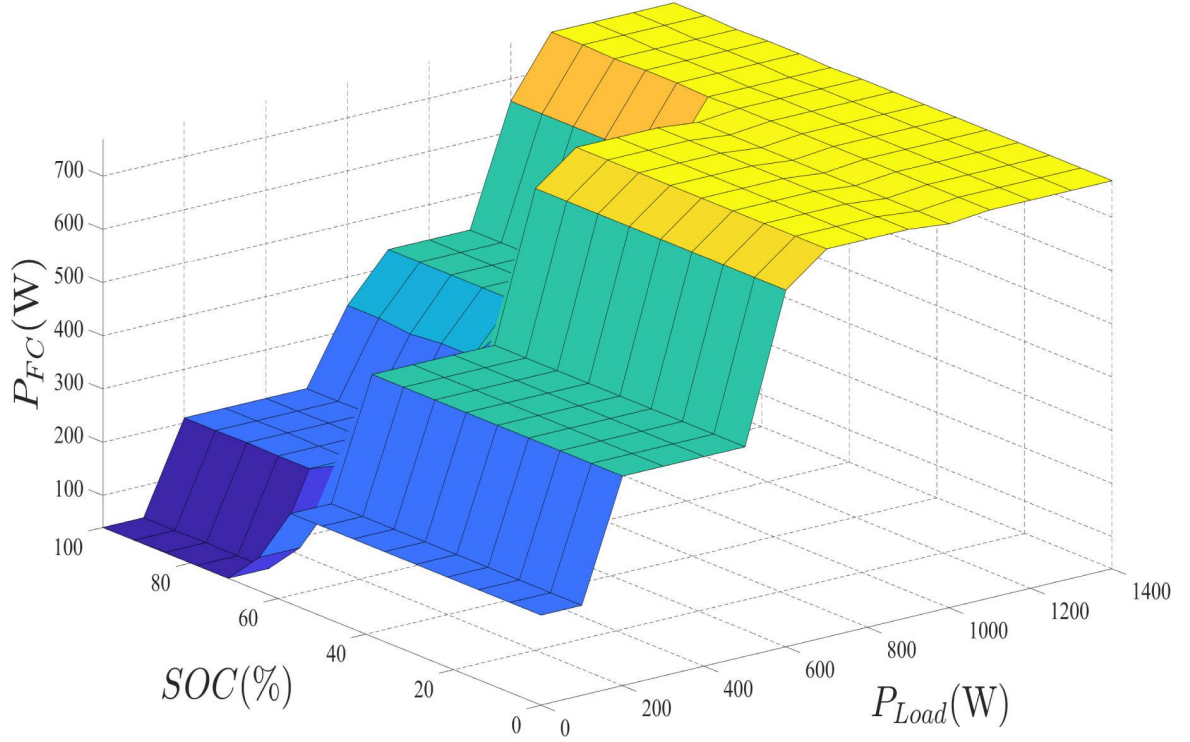


Figure 3.8: Fuzzy rules surface.

3.5.3 Equivalent Consumption Minimization (ECM) Strategy

In the domain of mobility applications, the literature has delved into the investigation of ECMS [108], [109], [110], [111]. It aims to reduce the overall consumption of hydrogen in fuel cells directly by the fuel cell itself and indirectly related to the energy

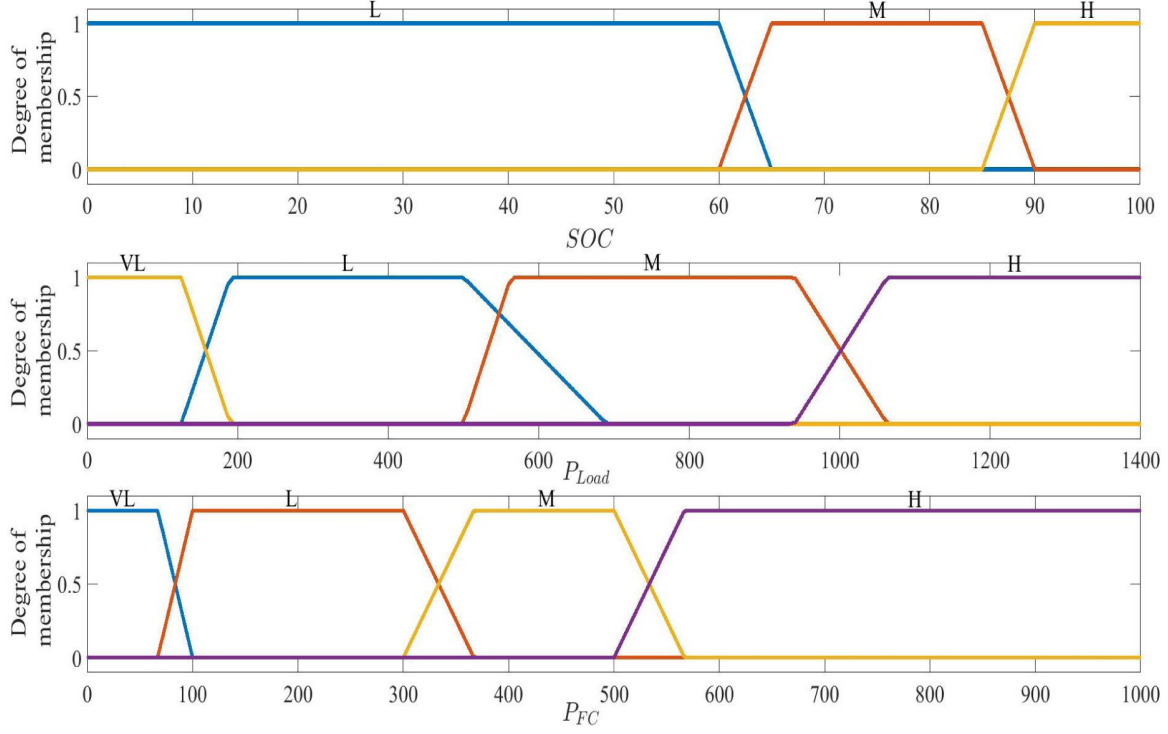


Figure 3.9: Centroid defuzzification approach.

storage sources, all within each sampling time. The strategy ensures efficient operation of each energy source without requiring advanced prediction or prior data about the planned mission. The vehicle's battery SOC gradually decreases when supplying energy, requiring the fuel cell to consume hydrogen for recharging. Conversely, a high battery SOC preserves energy for future maneuvers, ultimately reducing hydrogen consumption [112]. The battery's energy is translated into an equivalent hydrogen consumption to streamline the optimization process into a single objective, this virtual hydrogen consumption is proportional to the energy it provides and is governed by an equivalence factor denoted as λ . The relationship between the battery's SOC

and this equivalence factor is expressed by [110]:

$$\lambda = 1 - 2\beta \left[\frac{SOC - 0.5 (SOC_{\max} + SOC_{\min})}{SOC_{\max} + SOC_{\min}} \right] \quad (3.10)$$

The parameter β serves as a coefficient for SOC balance to accurately modeling the charge and discharge processes. In previous studies, this coefficient was set to 0.6 [82]. The equivalence factor, λ , significantly influences the system's dynamics; a larger λ increases the penalty on the battery's energy, demanding more hydrogen for recharging, while a smaller λ penalizes the fuel cell, prompting the algorithm to rely more on the battery to restore its desired SOC. The algorithm's dependence on β is mitigated by including λ in the cost function. The problem formulated as follows:

$$\min. F = [P_{FC} + \lambda \cdot P_{Bat}] \cdot \Delta T \quad (3.11)$$

Constrained by

$$\left\{ \begin{array}{l} P_{\text{Load}} = P_{FC} + P_{\text{Bat}} \\ P_{FC-\min} \leq P_{FC} \leq P_{FC-\max} \\ P_{\text{Bat-ch}} \leq P_{\text{Bat}} \leq P_{\text{Bat-max}} \\ 0 \leq \lambda \leq 2 \end{array} \right. \quad (3.12)$$

This problem was addressed within the Matlab/Simulink using the "fmincon" function by employing the SQP approach, it involves limits on each variable. The function call $y = \text{fmincon}(F, y_0, A, B, A_{eq}, B_{eq}, LB, UB)$, was investigated to minimize F . Here, A and B handle linear inequalities (set as empty matrices in this case), while A_{eq} and

B_{eq} manage linear equalities, and UB and LB set solution bounds within constraints ($LB \leq y \leq UB$). Based on previous studies [82] and the technical specification of powertrain components, the selected parameters values are: $SOC_{\min} = 50$, $SOC_{\max} = 90$, $P_{FC-\min} = 100$, $P_{FC-\max} = 800$, $P_{\text{Bat-ch}} = 100$, and $P_{\text{Bat-max}} = 500$.

$$\left\{ \begin{array}{l} y_0 = [P_{FC-\min}, 0, 0] \\ \\ A_{eq} = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \\ \\ B_{eq} = \begin{bmatrix} 1 - 2\beta \left[\frac{SOC - 0.5(SOC_{\max} + SOC_{\min})}{SOC_{\max} + SOC_{\min}} \right] \\ P_{\text{Load}} \end{bmatrix} \\ \\ UB = \begin{bmatrix} P_{FC-\max} \\ 2 \\ P_{\text{Bat-max}} \end{bmatrix} \\ \\ LB = \begin{bmatrix} P_{FC-\min} \\ 0 \\ P_{\text{Bat-min}} \end{bmatrix} \end{array} \right. \quad (3.13)$$

3.5.4 Improved ECM with Neural Network (NN)

In the context of energy management for drones, we introduce an innovative approach which was built upon the foundation of ECM, this proposed strategy addresses the research gap by enhancing adaptability and computational efficiency. To achieve this, two key penalty factors were introduced, 'a' and 'b,' within objective function of ECM. These penalty factors are crucial in adjusting the weight of P_{Bat} and P_{FC} during real-time optimization. The parameter 'a' represents the consideration for the battery's SOC deviation within the objective function. In dynamic load scenarios, it is essential to ensure that the battery's SOC remains within an acceptable range to support the drone's operations. Setting an appropriate value for 'a' allows to control the penalty on SOC deviation and, therefore, maintaining the battery SOC within acceptable range. The parameter 'b' reflects the concern for the difference between P_{FC} and P_L . In dynamic load scenarios, the drone's power demand can fluctuate rapidly. By adjusting 'b,' we can control the penalty on the deviation between the power generated by the fuel cell and the power needed to meet the load requirements. This ensures that the fuel cell's contribution aligns with the actual power needs. The objective function is modified to be as follows:

$$F = [(\alpha - a \cdot H_1/k_1) \cdot P_B + (b \cdot H_2/k_2) \cdot P_{FC}] \cdot \Delta T \quad (3.14)$$

Where H_1 and H_2 are penalty functions that consider SOC deviation and power deviation, respectively. k_1 and k_2 are constants related to these penalty functions. To ensure that the penalty functions (H_1 and H_2) respond appropriately to varying

conditions, we define them as piecewise functions:

$$H_1 = \begin{cases} x_1 & h_1 \leq x_1 \\ h_1 & -x_1 \leq h_1 \leq x_1 \\ -x_1 & -x_1 \leq h_1 \end{cases} \quad (3.15)$$

$$H_2 = \begin{cases} x_2 & h_2 \leq x_2 \\ h_2 & -x_2 \leq h_2 \leq x_2 \\ -x_2 & x_2 \leq h_2 \end{cases} \quad (3.16)$$

Where h_1 represents the SOC deviation, h_2 represents the power deviation. x_1 and x_2 are threshold values for the penalty functions. After a thorough analysis with a trial-and-error method to obtain the desired outcome, the selected values for x_1 , x_2 , k_1 and k_2 were 5, 500, 100, 10,000 respectively. The work is divided into three stages as illustrated in Fig. 3.10. In the first stage of our proposed work, we conducted an extensive study in which we examined a total of 40 diverse load profile scenarios, each undergoing multi-objective optimization. The optimization process involved the fine-tuning of penalty factors 'a' and 'b' for each load profile scenario. To achieve this optimization, we employed the Non-dominated Sorting Genetic Algorithm (NSGA-II) as implemented based on the methodology described in [113]. The optimization approach has two objectives: reducing the hydrogen consumption and the second one is related to the battery SOC behavior which is reducing SOC deviation to keep battery energy for emergency cases while contributing in the power supply during the

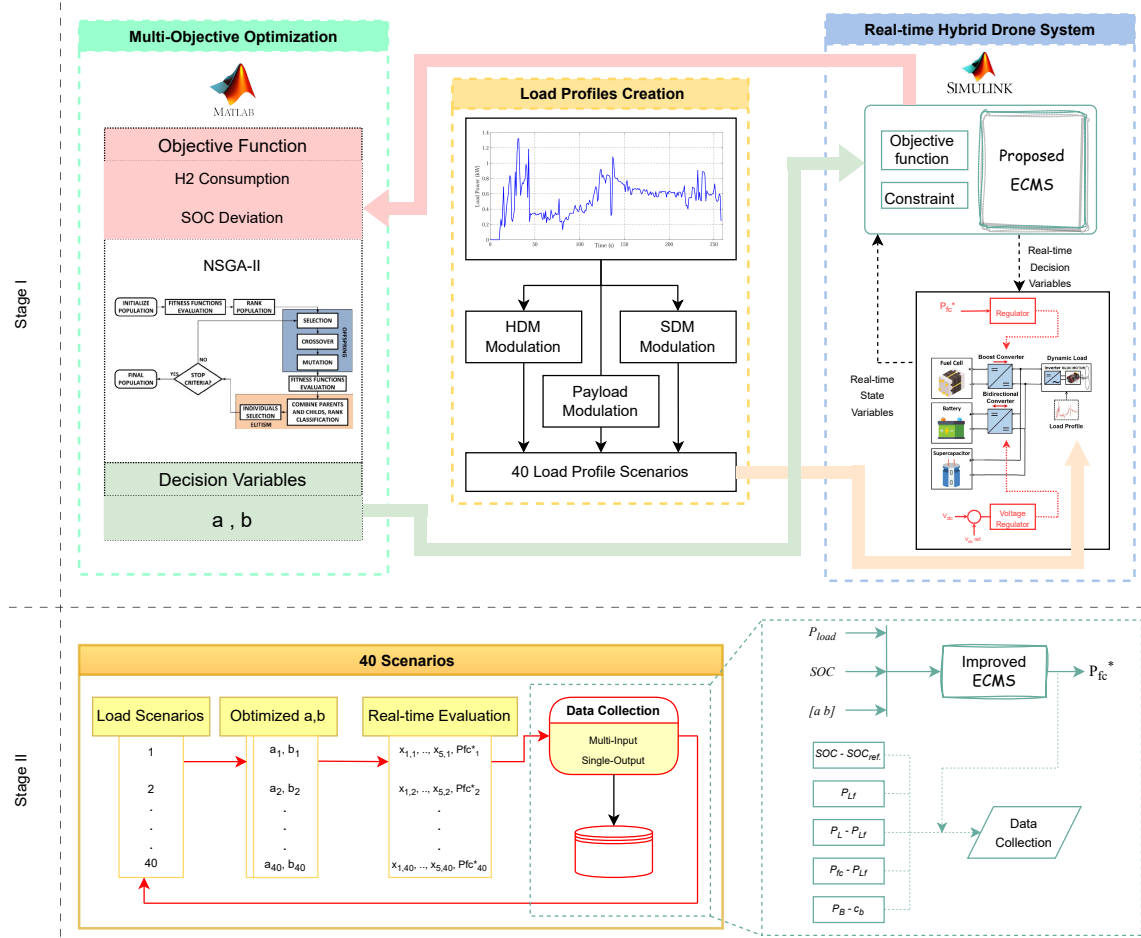


Figure 3.10: The first stage includes creating load profile scenarios with NSGA-II optimization for each by real-time implementation for each run, the second stage includes evaluating each scenario with its corresponding optimized 'a' and 'b'.

mission. It allows the drone to keep the battery energy in emergency situations while supplying the dynamic load not being met by fuel cell. These emergency situations include returning back to the fueling station and having enough energy reservoir to complete the mission in case of empty hydrogen cylinder. Minimized cost-function is represented by SOC deviation, which is the difference between the final SOC (SOC_{fin}) and the initial one (SOC₀). Thus, the battery service life can be saved reducing the number of charge-discharge cycles. The NSGA-II parameters selected for this study are outlined in Table 3.3. Upon a thorough analysis, the decision variable boundaries are defined as follows:

Table 3.3: NSGA-II setting parameters

Parameter	Value
Population size	50
Generation number	50
Crossover fraction	0.7
Mutation fraction	0.4
Mutation rate	0.02

$$\begin{cases} -1 \leq a \leq 1 \\ 0.5 \leq b \leq 2.5 \end{cases} \quad (3.17)$$

In the second stage, each load profile scenario with its selected penalty factors values as a result of NSGA-II implementation will go to further real-time evaluation to prepare and collect the necessarily input data for neural network training with their corresponding optimal fuel cell power. The data should carefully reflect the real-time changes in the load characteristics as well as the dynamic behavior each hybrid sources in order to ensure a fine prediction of the improved ECM behavior. Five different time-series state variables were collected over the evaluation time horizon

which are: the SOC deviation ($SOC - SOC_{opt}$), the filtered load (P_{Lf}), the deviation between load and filtered load ($P_L - P_{Lf}$), the deviation between fuel cell power and filtered load ($P_{fc} - P_{Lf}$), and the deviation between battery power and its preferable charging power ($P_b - c_b$) which selected to be 100W based on the battery technical characteristics.

In the third stage, NN is trained on the collected data in the previous stage. Thus, NN imitates the improved ECM framework by dynamically adjusting the fuel cell reference power. By doing so, this approach ensures that the energy management strategy adapts effectively to dynamic load profiles, striking a balance between adaptability and computational efficiency. This approach addresses the challenges posed by real-time optimization in drone applications. To simplify this, Fig. 3.11 shows the difference between the implementation of the second stage "Improved ECMS" and the third stage "NN".

The precision of the output from this NN-based strategy depends on the quality of its training data. Thus, (6×212040) input-output datasets consist of five different representative time-series state variables mentioned previously with a sampling time of 0.2 seconds were collected with their corresponding resulted fuel cell reference power throughout the simulation time horizon for each scenario. Through multiple thousands of epochs for iteratively refining the training process, errors were minimized until reaching a threshold of $1e-4$. An error below 0.0001 indicates that the NN-based strategy aligns closely with the desired training values.

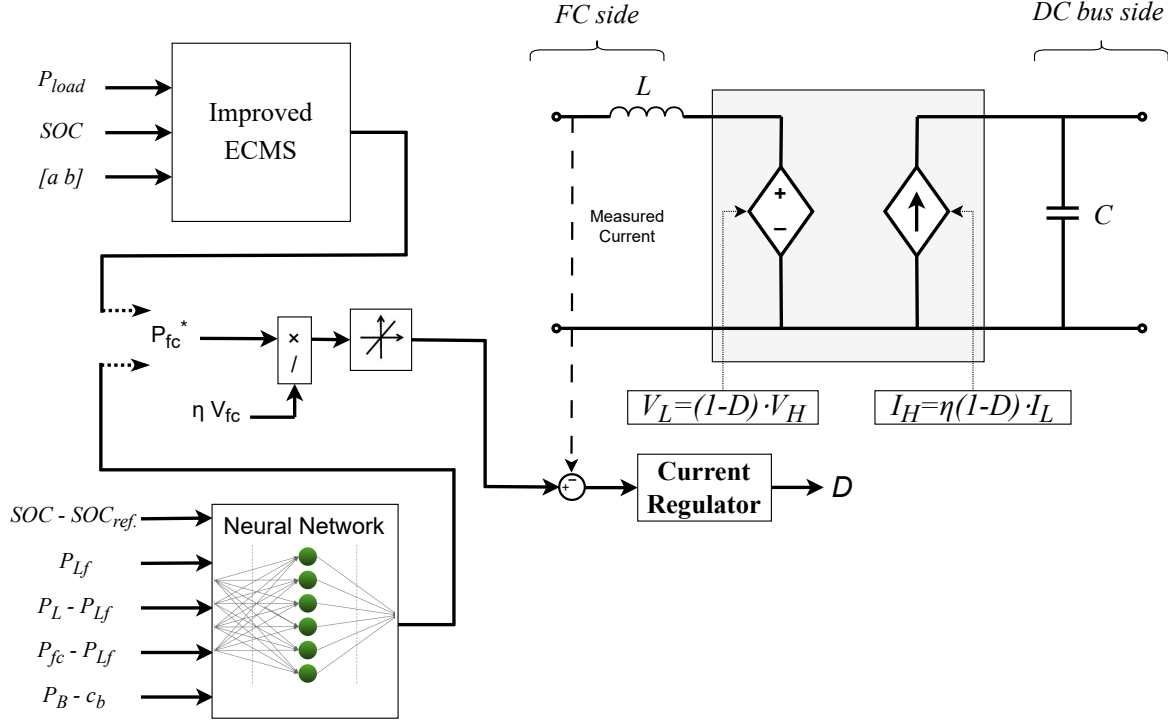


Figure 3.11: The difference between the implementation of the second stage "Improved ECMS" and the third stage "NN".

3.5.5 Improved ECM with Case-Based Reasoning (CBR)

Case-Based Reasoning (CBR) is an AI problem-solving methodology that involves solving new problems by leveraging solutions from past similar cases. This iterative process comprises retrieval, reuse, revision, and retention as shown in 3.12. The core idea is to utilize the knowledge stored in historical cases to solve new problems, making it particularly suitable for domains where explicit rule-based systems are difficult to develop or where large volumes of historical data exist.

The data used in the Neural Network (NN) model, as described in the previous section, consists of (6×212040) input-output pairs. This extensive dataset undergoes a crucial offline step known as Data Reduction. By implementing K-Means Clustering,

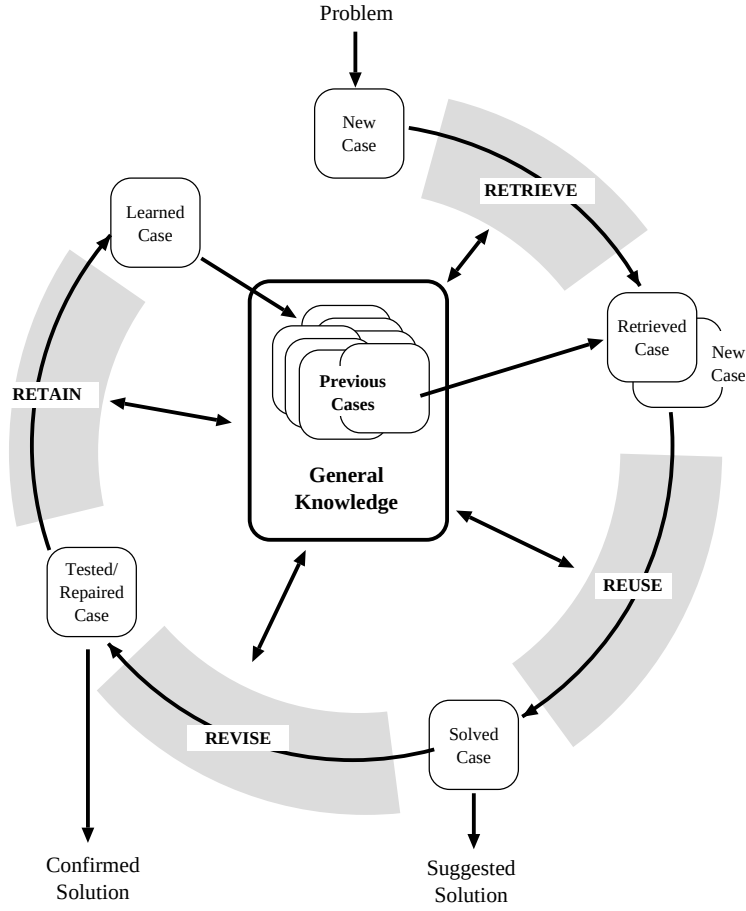


Figure 3.12: The CBR process cycle.

which reduces the data dimensionality from (6×212040) to a representative dataset of the size $(6 \times K)$ as illustrated in Fig. 3.13. This reduction aims to minimize real-time computations during the retrieval process. However, K-Means Clustering partitions the data into K clusters, thereby identifying representative data points that capture essential information from the original dataset. These representative data points will be used to represent the entire dataset efficiently, reducing computational complexity in real-time similarity calculations for retrieving relevant information.

In the context of the CBR cycle, retrieval phase involves finding historical cases similar to the current problem case. It typically includes two steps: similarity mea-

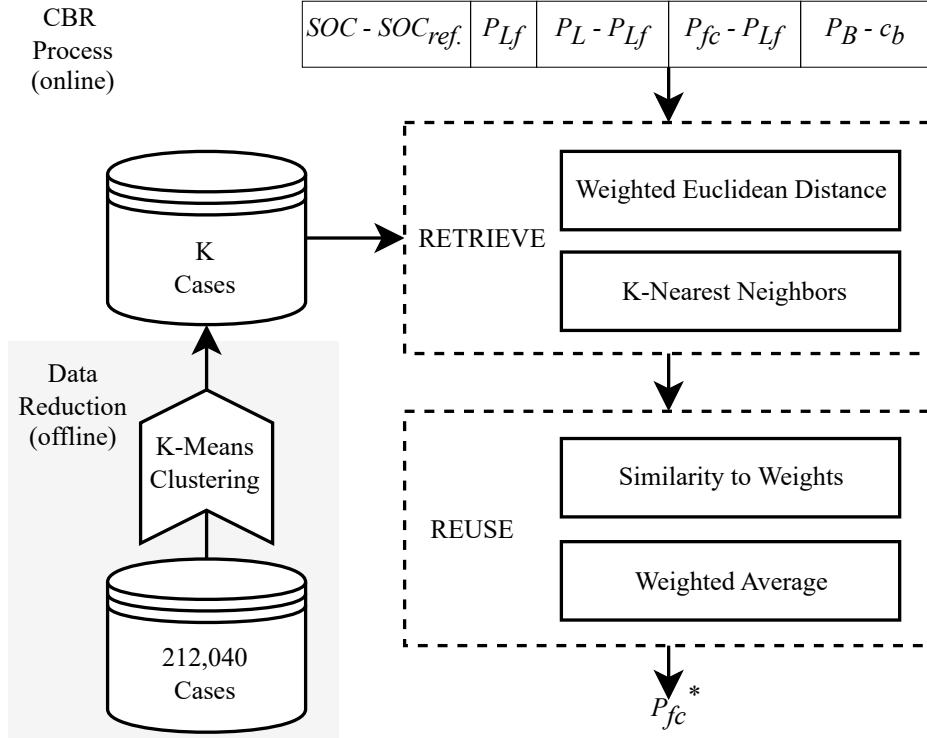


Figure 3.13: The different phases of the proposed CBR energy management strategy including offline phase for data reduction, and online phase for real-time CBR implementation.

surement and K-Nearest Neighbors (KNN). Then reuse phase comes after that, once similar cases are identified, the reuse phase adapts these cases to solve the new problem. This phase includes: weight calculation and weighted average estimation.

- **1st Step: Normalization:** As CBR relies on historical data, it is important to perform data preprocessing to obtain high-quality of base cases. Normalization preprocessing gives all attributes standard scores so that they can be compared to prevent domination by larger scale features during distance calculations. Min-Max normalization, also known as feature scaling, is a technique used to rescale a dataset's values to a specific range, usually between 0 and 1. The formula for

Min-Max normalization is:

$$X_{\text{normalized}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (3.18)$$

Where X is the original value you want to normalize. $X_{\min}$ and $X_{\max}$ are the minimum and maximum values in the dataset, respectively. $X_{\text{normalized}}$ is the normalized value of X within the range $[0, 1]$.

The result of this normalization process ensures that all values in the dataset are proportionally scaled to fit within the specified range. It's particularly useful in scenarios where different features in a dataset have different scales and need to be standardized for fair comparison or for machine learning algorithms that perform better with standardized input values.

- **2nd Step: Similarity Measurement:** Similarity measurement is crucial for comparing the features of the new case with historical cases in a case base to find the most similar cases to a new problem or query. The weighted Euclidean distance is a method used for this purpose, especially when different attributes or inputs of cases hold varying degrees of importance or relevance.

The weighted Euclidean distance formula incorporates weights for each input attribute to emphasize their significance in the similarity calculation. The five inputs in the dataset will have five weights, w_1 , w_2 , w_3 , w_4 , and w_5 , representing different attributes. These weights will be optimized using NSGA-II to minimize battery SOC deviation as well as hydrogen consumption.

The formula for the weighted Euclidean distance between two cases A and B with n attributes is:

$$D_{\text{weighted}}(A, B) = \sqrt{\sum_{i=1}^n w_i \cdot (A_i - B_i)^2} \quad (3.19)$$

where $D_{\text{weighted}}(A, B)$ represents the weighted Euclidean distance between the new case A and historical cases B . A_i and B_i are the values of attribute i in cases A and B respectively. w_i represents the weight assigned to attribute i . n is the total number of attributes or inputs in the cases.

- **3rd Step: K-Nearest Neighbors (KNN):** After computing distances, KNN identifies the 'k' most similar historical cases. This 'k' value affects the model's complexity and generalization.

1. **Setting the value of k :** k is a hyperparameter representing the number of nearest neighbors to consider. The choice of k impacts the model's performance, complexity, and generalization ability. Smaller values of k might lead to overfitting since the model might become too sensitive to local variations in the data. On the other hand, larger values of k may oversimplify the model and potentially ignore local patterns or nuances in the data.

2. **Sorting the obtained distances:** After computing distances between the new problem case and historical cases, these distances are sorted in ascending order. This sorting step helps in identifying the closest or most

similar cases to the new problem case.

3. **Picking up k nearest cases to the problem case:** Once the distances are sorted, the algorithm selects the k cases with the smallest distances.

These k nearest cases are considered as the most similar historical cases to the new problem case.

- **4th Step: Similarity to Weights:** Assigning weights (w_n^d) based on the inverse of distances. Closer cases receive higher weights, implying a greater influence on the estimation.

1. **Calculating the weights of each case:** For each of the picked up cases (from the previous step), calculate the weight (w_n^d) based on the inverse of the distance. The weight assigned to each case is the reciprocal of the distance:

$$w_n^d = \frac{1}{d_n} \quad (3.20)$$

Where d_n is the distance of the n th case from the problem case. Closer cases will have higher weights due to their smaller distances, implying they will have a greater influence on the estimation or decision-making process.

2. **Calculating the total weight:** After calculating the weights for all picked up cases, calculate the total weight by summing up all these individual weights. The total weight can be computed as:

$$\sum_{n=1}^{kn} w_n^d \quad (3.21)$$

where kn represents the k nearest cases selected. This total weight represents the overall influence or importance of the selected cases in the estimation or decision-making process.

- **5th Step: Weighted Average Estimation:** Using the calculated weights in a weighted average formula to estimate the target value P_{fc}^* . This method accounts for varying degrees of importance of the selected similar cases. Taking into account the varying degrees of importance of the cases

$$X_j = \frac{\sum_{n=1}^{kn} w_n^d \cdot x_{jn}}{\sum_{n=1}^{kn} w_i^d} \quad (3.22)$$

Where $i = \{1, 2, \dots, K\}$, $j = \{1, 2, \dots, 5\}$, and $n = \{1, 2, \dots, kn\}$.

CHAPTER 4

RESULTS DISCUSSION

4.1 NSGA-II Optimization

In this extensive study, a total of 40 diverse scenarios were examined, each undergoing multi-objective optimization. In Fig. 4.1, some of the comprehensive multi-objective optimization results across different drone load profile scenarios are presented. The Fig. displays Pareto fronts for both HDM and SDM methods under varying offset values. It's clear that as the offset value increases, more hydrogen is needed to keep the battery at a specific SOC level. At a low offset like 50W, the two methods look have very identical pareto fronts, but as the offset goes up, the difference between them becomes more significant, especially at 300W. This happens due to the fact that the average load exceeds that of the typical load profile, and the battery has to handle most of the rapid load changes, which means it needs more frequent recharging. Consequently, this leads to increased losses due to charging and discharging inefficiencies. Additionally, when applying HDM with a 300W offset, the the minimum achievable SOC deviation is around 7%, indicating that beyond a certain level of load dynamics

that must be supplied by the hybrid system, the system struggles to maintain the battery SOC at its desired level due to several limitations, such as the fuel cell's ramping limit, the maximum allowable charging power for the battery, and the limited super-capacitor capacity. The curve on the pareto fronts shows the possible combinations

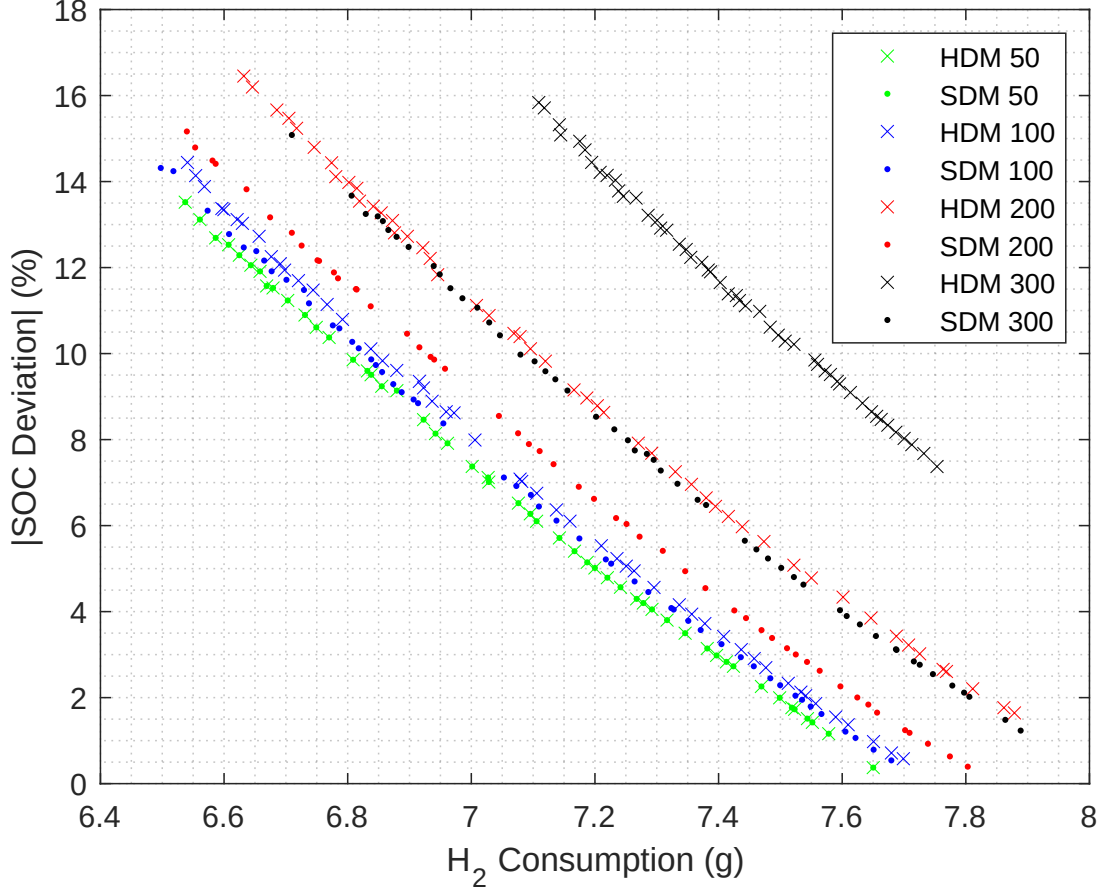


Figure 4.1: Pareto fronts for both HDM and SDM methods under different offsets.

of SOC deviation and hydrogen consumption for different sets of variables. The criteria for selecting variables from the Pareto front are primarily based on the trade-off between inversely related objectives; State of Charge (SOC) deviation and hydrogen consumption. However, for longer and more persistent missions, variables leading to minimal SOC deviation as closer as 0% are preferred in our work to ensure the drone's

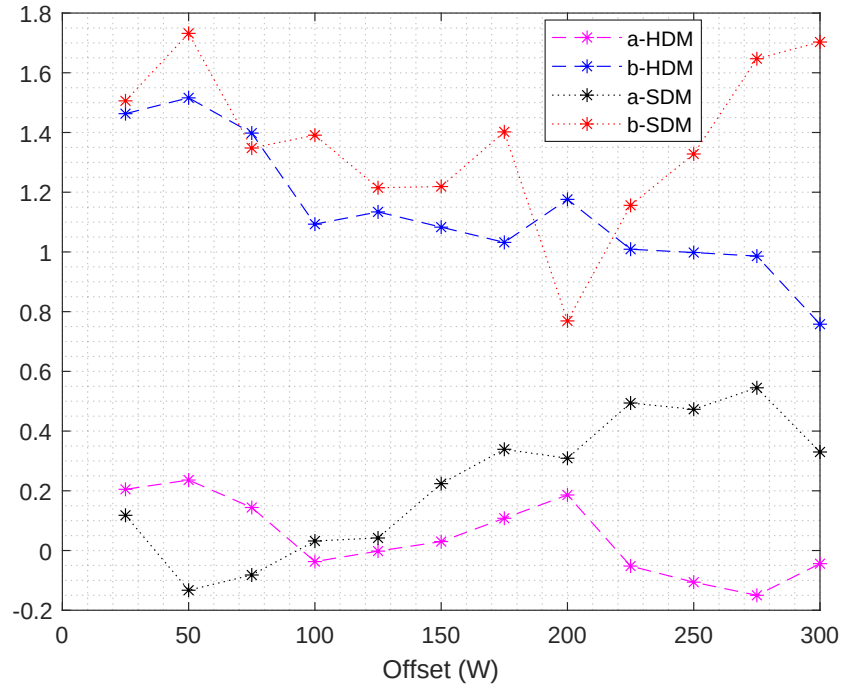


Figure 4.2: 'a' and 'b' values over different load profile scenarios.

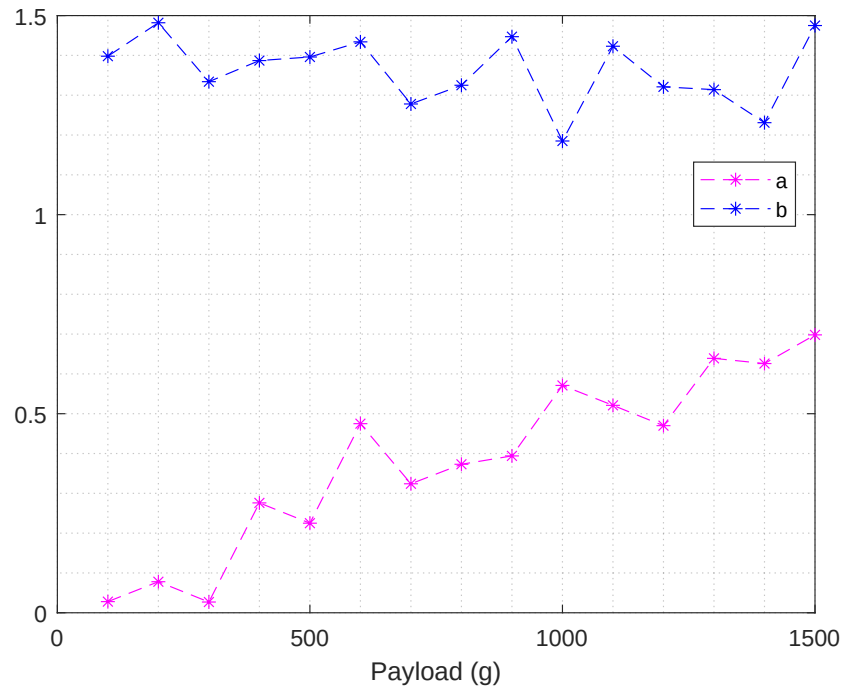


Figure 4.3: 'a' and 'b' values over different payload scenarios.

battery stays within a specific SOC range.

In Fig. 4.2, we're looking at two optimized important factors, 'a' and 'b,' when trying to adjust fuel cell power wight within ECM objective function over different load profile scenarios using HDM and SDM methods. 'a' represents how much we care about the battery's SOC deviation in the objective, while 'b' reflects how much we care about the difference between fuel cell power and load power.

For HDM, 'a' values don't seem to have a clear pattern as they scattered around zero, but in SDM, they show a clear increase. This suggests that SOC deviation weight matters more when the load changes smoothly. In cases with rapid load changes, the system is already working hard to maximize fuel cell power to keep the battery SOC where it should be. 'b' values for HDM follow a decreasing trend as the offset increases over a range from 1.5 to 0.7, but for SDM, they don't show a consistent trend as they decrease almost 1.7 until the offset reaches about 200W as it was about 0.7, where they start to increase to reach the starting point. This shows that the weight for the difference between fuel cell power and load power matters more when dealing with rapid load changes.

In Fig. 4.3, we're looking at similar optimized factors but in the context of payload variations. Here, 'a' values clearly increase as payload increases from almost 0 to 0.7, while 'b' doesn't follow a clear pattern as its values were scattered around 1.4. When payload increases, the average load also somehow goes up, but the load rapid dynamic variations stay similar to the normal load. This explains why 'b' doesn't change over all scenarios. 'a' values increase because they help prevent SOC deviation when the average load increases due to extra weight.

4.2 CBR Implementation

The selection of values for the weights in the weighted euclidean distance and the ' K_m ' parameter in k-means clustering as well as ' K_n ' parameter in k-nearest neighbors, is a critical decision that significantly influences the performance and outcomes of CBR algorithms. The selection of ' K_n ' directly impacts the algorithm's bias-variance trade-off. There is no structured method for the selection of ' K_n ' in K-nearest neighbors. Smaller ' K_n ' values introduce noise and will have a higher influence on the result, while larger ' K_n ' values lead to smoother decision boundaries, which means a lower variance but increased bias. In general practice, choosing the value of ' K_n ' is ' $K_n = \sqrt{N}$ '. Additionally, the value of ' K_n ' should be odd in order to avoid confusion between two classes of data. Therefore, as the number of clusters preferred is not too large, accepted around 10 in order to minimize the computations, the selected value for ' K_n ' is 3 in this work. For the weighted Euclidean distance, determining the optimal weights involves assessing the relative importance of each of the five inputs. To fine-tune these weights, an optimization approach using NSGA-II will be employed. NSGA-II will be applied for each value of ' K_m ' beginning from 3 and progressively moving forward. Among these different clustering numbers, each with its corresponding optimized weights, the emphasis and selection from the Pareto front will be on the case that is more conservative about minimizing SOC deviation while considering other objectives. In k-means clustering, the optimal value for ' K_n ' necessitates a delicate balance between model complexity and the ability to accurately capture the underlying structure within the dataset. Based on that, after implementing NSGA-II for several

consecutive values of ' K_m ', the least value that has SOC deviation almost near zero will be selected. As seen in table 4.1 and figure 4.4, the selected value for ' K_m ' is 6 where the weights are 0.58, 0.47, 0.51, 0.94, 0.28 respectively. Refer to Appendix A about more resulted details from implementing k-means clustering and NSGA-II optimization including the pareto fronts as well as visualizing the normalized clustering centers.

Table 4.1: Weights values as a result of implementing NSGA-II for different K values.

K	3	4	5	6	7	8	9	10
SOC dev.	7.44	2.87	0.23	0.11	0.04	0.01	0.34	0.30
H2 con.	7.91	8.31	8.62	8.64	8.62	8.64	8.58	8.59
W1	0.08	0.66	0.81	0.58	0.78	0.61	0.85	0.81
W2	0.39	0.45	0.41	0.47	0.19	0.31	0.49	0.67
W3	0.47	0.15	0.17	0.51	0.41	0.49	0.78	0.72
W4	0.07	0.78	0.95	0.94	0.52	0.85	0.27	0.34
W5	0.83	0.53	0.24	0.28	0.83	0.40	0.97	0.78

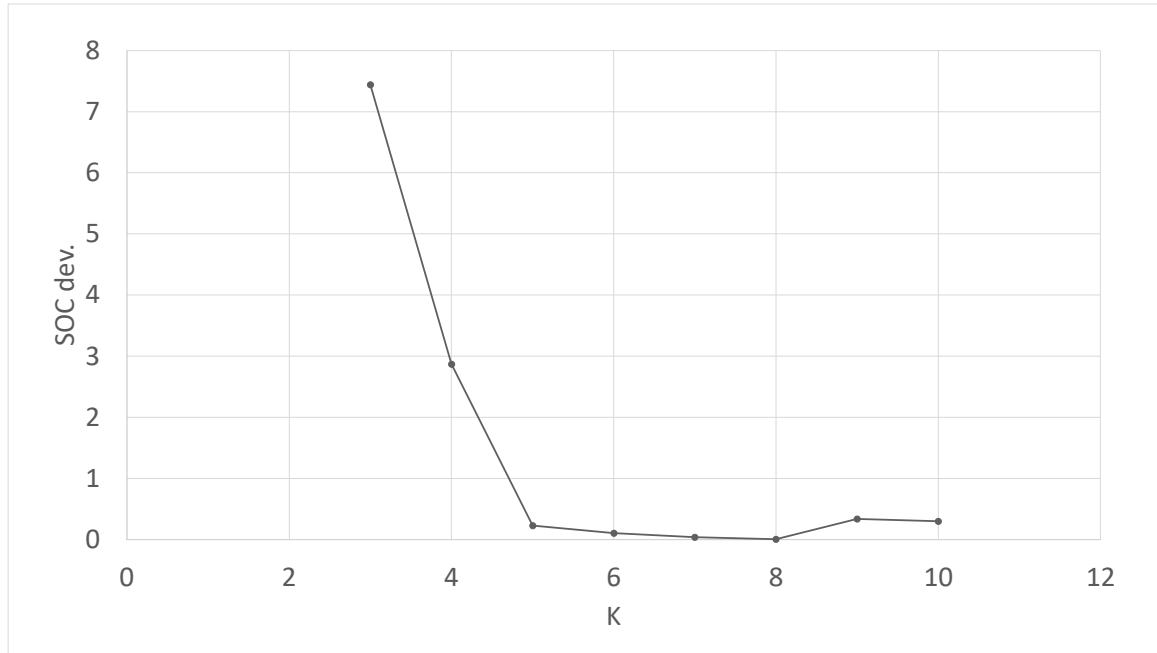


Figure 4.4: Variation of minimum SOC deviation with K values.

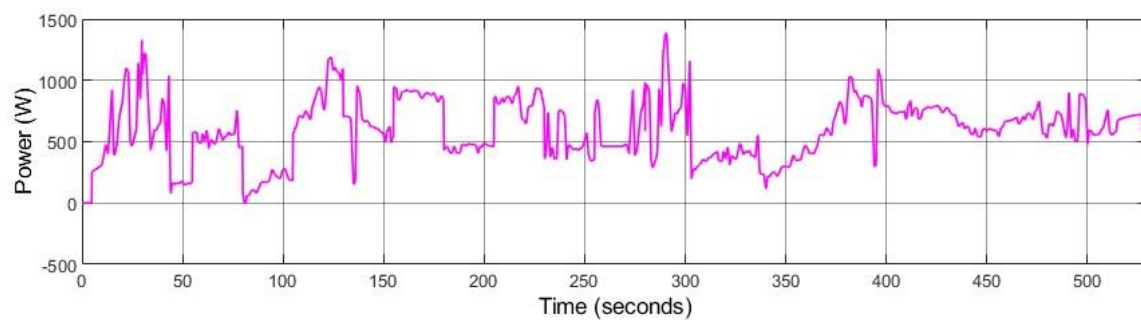
4.3 Power Distribution

A new load profile, distinct from the training dataset, is essential to practically evaluate the proposed method. In this study, three distinct load profiles were developed as shown in Fig. 4.5, each with unique characteristics. They serve as a basis for comparative evaluations between the NN, CBR, and other energy management strategies. This approach allows us to thoroughly evaluate the effectiveness and performance of the proposed methods in handling diverse load scenarios.

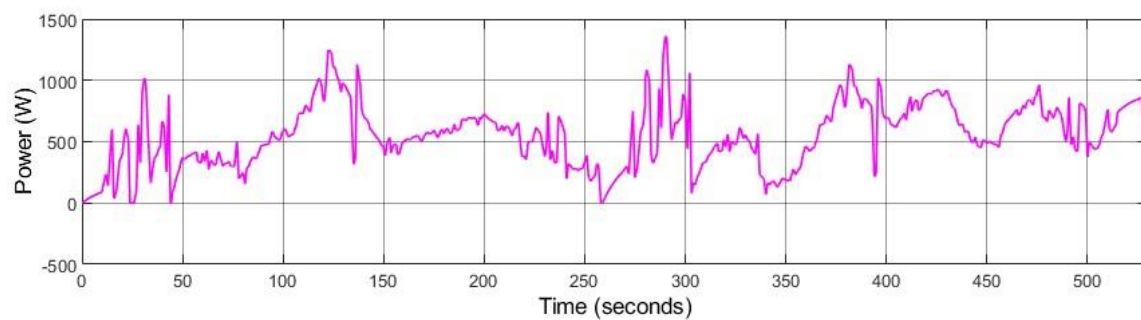
For each of these load profile, the power distribution among different hybrid sources for each energy management strategy are illustrated in Fig. 4.6, 4.7, and 4.8. The hybrid system which includes fuel cell, battery, and supercapacitor, each component plays a distinct role. The fuel cell consistently delivers almost constant power, while the battery provides extra power, especially during peak demand, to match the desired load power. When the load power is less than that of the fuel cell, the battery starts charging to increase its SOC. Additionally, the supercapacitor, with its rapid response time, acts as a power buffer and can assist during transient power demands, enhancing the overall performance and efficiency of the hybrid system.

The power distribution for ORB-EMS is shown in Fig. 4.6a, 4.7a, and 4.8a, the fuel cell power has almost flat pattern near 500W with some variation when the load exceeds this value. So, it is clear that there is not a high degree of interaction between fuel cell reference power and load variation which will be reflected the ability of this method to maintain the battery SOC close to its reference value.

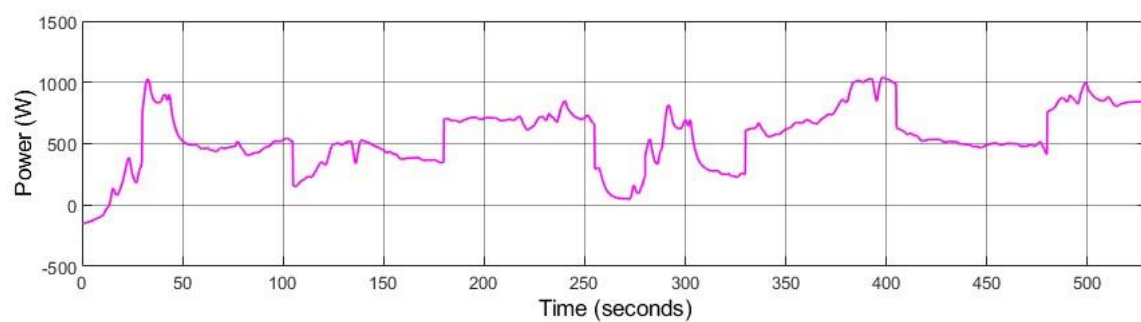
The behavior of FL-EMS is illustrated In Fig. 4.6b, 4.7b, and 4.8b, the fuel



(a)



(b)



(c)

Figure 4.5: The three distinct load profiles used for evaluation.

cell demonstrates a quick reaction in delivering power to match changes in the load, leading to a somewhat rough power profile. Over a long period, these variations can impact the durability of the fuel cell, it is advisable to control the fuel cell current ramping limit and rely on the battery and supercapacitor to provide power during such fluctuations.

For the ECM-EMS power distribution depicted in Fig. 4.6c, 4.7c, and 4.8c, the fuel cell power pattern exhibits a bit more fluctuating compared to the ORB-EMS, primarily because of the optimization algorithm's attempt to determine the fuel cell power reference value that minimizes hydrogen consumption for each sampling time. Nevertheless, it remains considerably more stable than the power profile of FL-EMS, which serves as a valuable indicator of the fuel cell's overall health.

In Fig. 4.6d, 4.7d, and 4.8d, it's worth noting that the fuel cell power profile for NN-EMS was nearly identical to that of ECM-EMS among all the testing loads, even though the testing load profiles employed were not part of the training dataset. This remarkable similarity between the power profiles of NN-EMS and ECM-EMS underline the robustness and adaptability of the neural network-based proposed EMS, as it managed to generalize its fuel cell power managements effectively to an unseen load profile, resulting in a nearly identical power profile to that for optimization-based EMS without high computation resources requirements. Additionally, that confirms the effectiveness of the three proposed load profile scenarios creation methods. These methods provide a means to generate diverse and representative load profiles, thereby providing a substantial dataset for handling a wide range of dynamic load scenarios for drone applications. This dataset, in turn, significantly enhances the adaptability

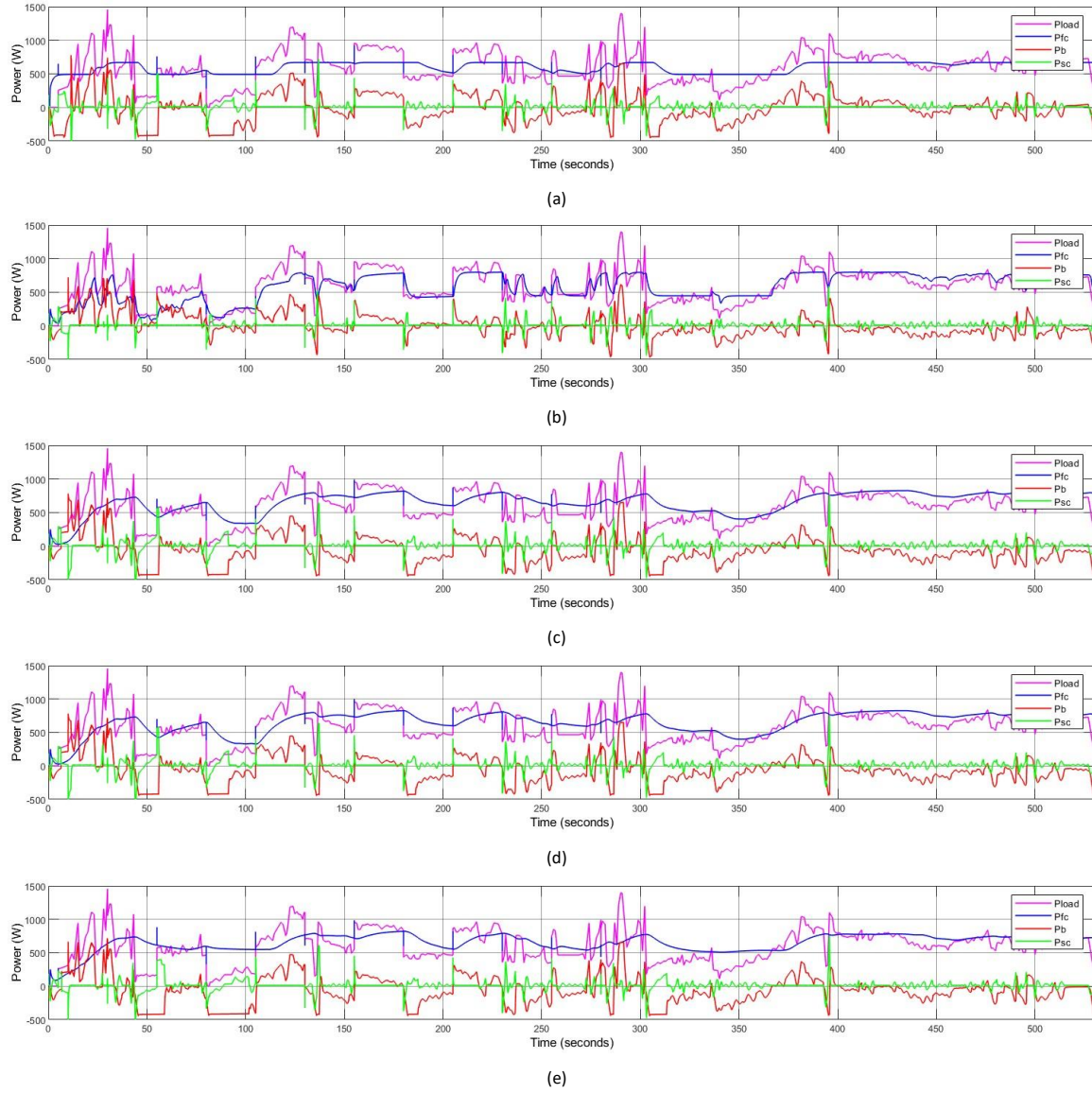


Figure 4.6: Power distribution for different EMS with the first load profile (a) ORB (b) FL (c) ECM (d) NN (e) CBR.

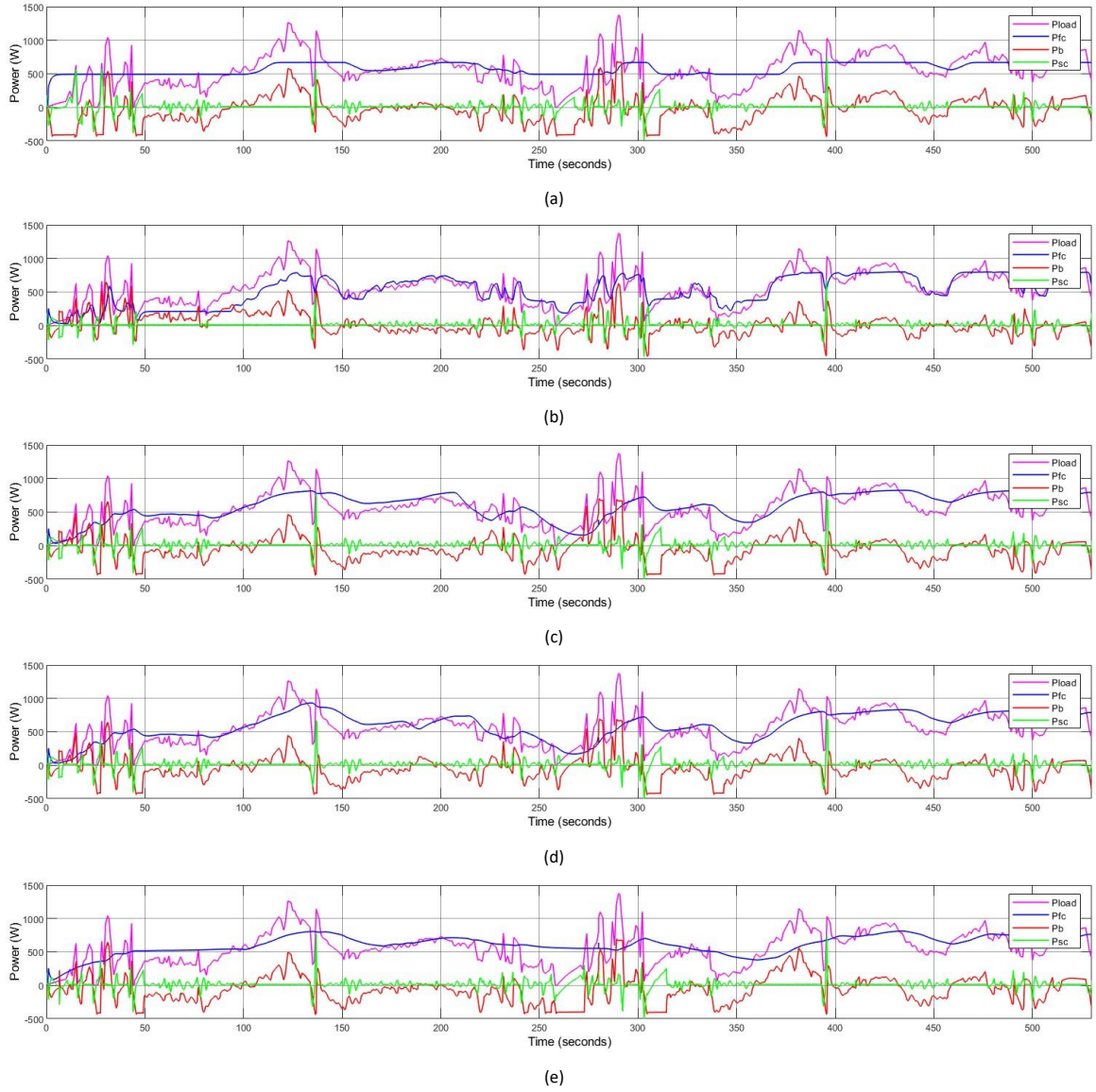


Figure 4.7: Power distribution for different EMS with the second load profile (a) ORB (b) FL (c) ECM (d) NN (e) CBR.

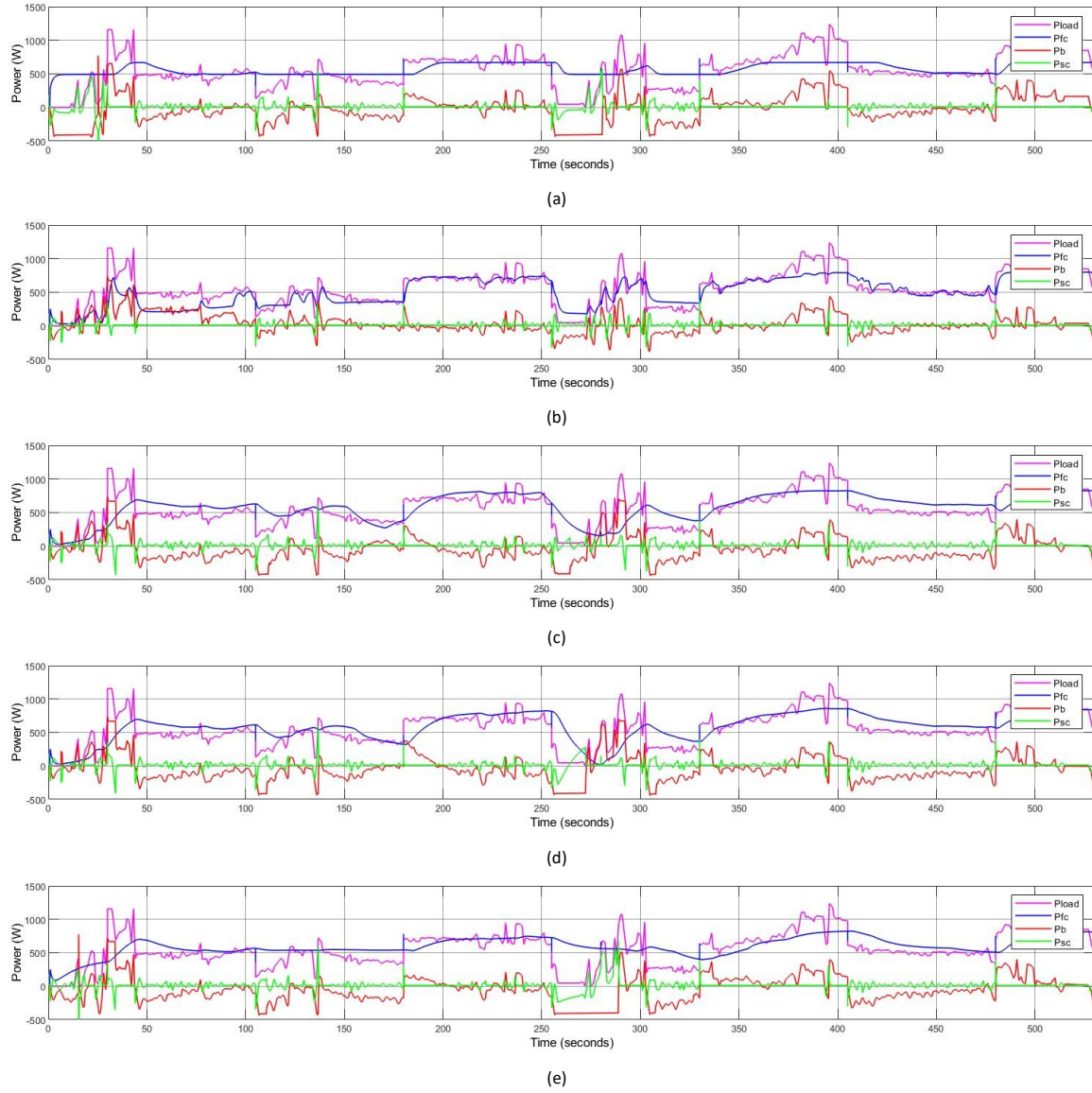


Figure 4.8: Power distribution for different EMS with the third load profile (a) ORB (b) FL (c) ECM (d) NN (e) CBR.

and robustness of the proposed EMS, enabling it to respond effectively to new and challenging load profiles.

The power distribution for CBR proposed strategy in Fig. Fig. 4.6e, 4.7e, and 4.8e shows the smoothest fuel cell power pattern among all implemented methods while interacting effectively with several load variation throughout the time horizon in the three load profiles. It also shows some improvements in term of fuel cell durability. The fuel cell degradation rate is directly proportion to low-power operation (less than 5% of FC maximum power), high-power operation (more than 90% of FC maximum power), and transient load changes [114], [115]. It is clear from the mentioned figures that CBR has the superiority to reduce the degradation caused by transient load changes with the highly smooth fuel cell power curve. Additionally, the fuel cell power curve are varied within narrow range which means reducing the degradation by high and low power power operation.

4.4 SOC Variation and H_2 Consumption

The SOC responses are illustrated in Fig. 4.9, 4.11, and 4.13 during the flight missions for all EMS. It is obvious that only CBR achieves the desired reference SOC by the end of the mission for each of the three load profiles. It leads to almost 0% deviations in the battery SOC by the end of the simulation time horizon. Regarding ECM and NN, their responses almost were similar with 0%, 1%, and 2% SOC deviation during all load profiles which indicates that the methodology of collecting data in the first stage of this work were efficient and sufficient for the neural network to behaves like real-

time optimization techniques but with much lower computations. However, among the efficient response for each of CBR, ECM, and NN by the end of simulation, it is obvious that CBR not only achieve that by the end of simulation time but also during several times of the simulation.

In contrast, ORB-EMS leads to 8%, 4%, and 8% decreases in SOC, and FL-EMS causes 9%, 10%, and 12% decline during the 530-second cycle. Consequently, these two EMS strategies are not suitable for long missions since the SOC continues to deplete over time, unlike CBR, ECM and NN. Thus, it is crucial to adjust the fuel cell output power to account for SOC fluctuations, considering the preferred operational ranges into fuel cell power reference calculations. Furthermore, ORB behaved very efficient when it was applied in [106] where it was called "Charge Sustaining Mode", because it was optimized on that specific load profile, but when it comes to new load scenarios, it shows a lack of adaptability and lack of ability to maintain SOC close to its reference value.

It is obvious from Fig. 4.10, 4.12, and 4.14 that hydrogen consumption were almost similar to each of CBR, ECM, and NN. The hydrogen consumption with CBR was slightly higher in the second and third load profile with not more than 0.15 but this increase was due to maintaining SOC at reference value especially in the second and third load profile where both of ECM and NN had slight deviation. Despite the near-similarity between NN and ECM in terms of hydrogen consumption and SOC deviation, the developed NN achieves this outcome with significantly lower computations, eliminating the necessity for real-time optimization computational requirements.

Furthermore, while ORB and FL exhibit a decrease in hydrogen consumption,

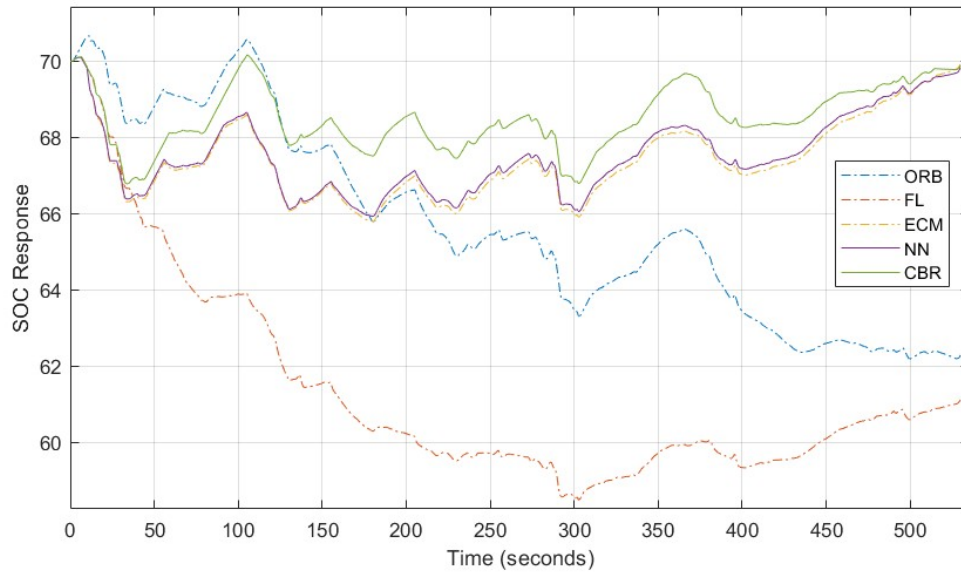


Figure 4.9: SOC response with the first load profile

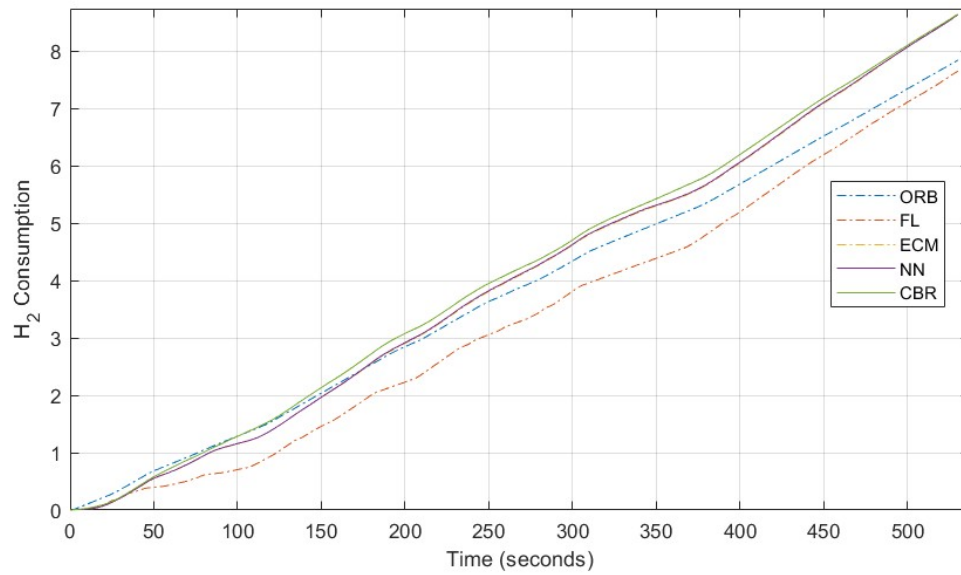


Figure 4.10: H_2 consumption with the first load profile

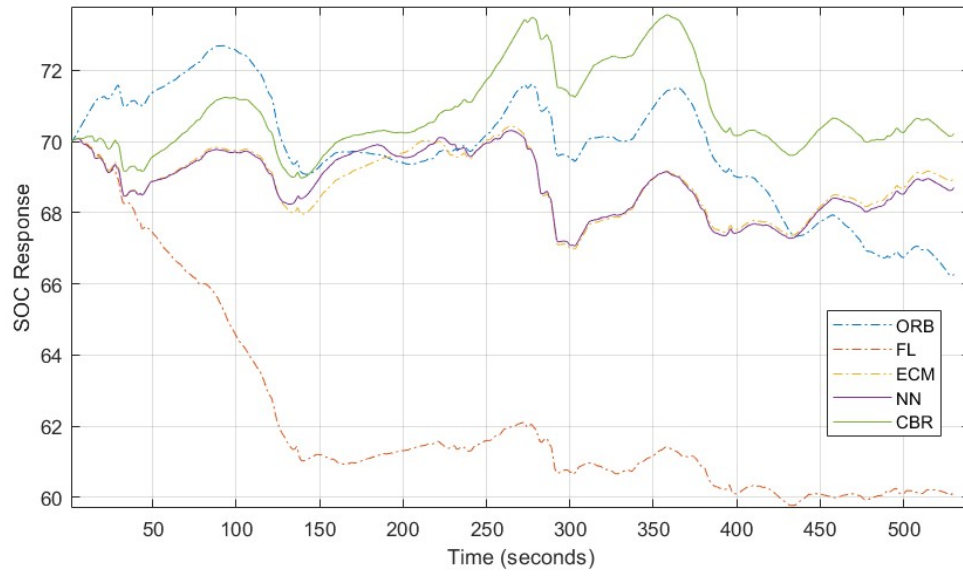


Figure 4.11: SOC response with the second load profile

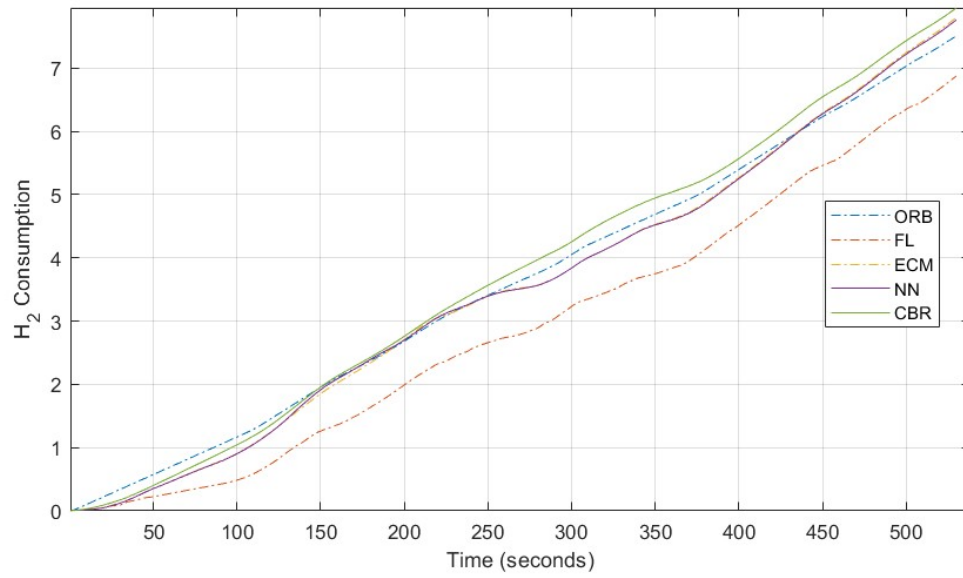


Figure 4.12: H_2 consumption with the second load profile

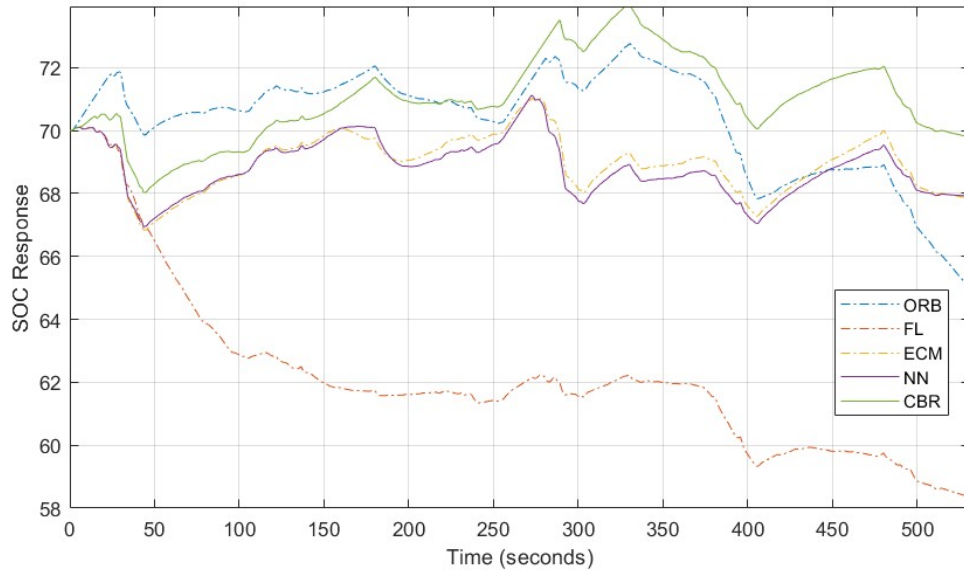


Figure 4.13: SOC response with the third load profile

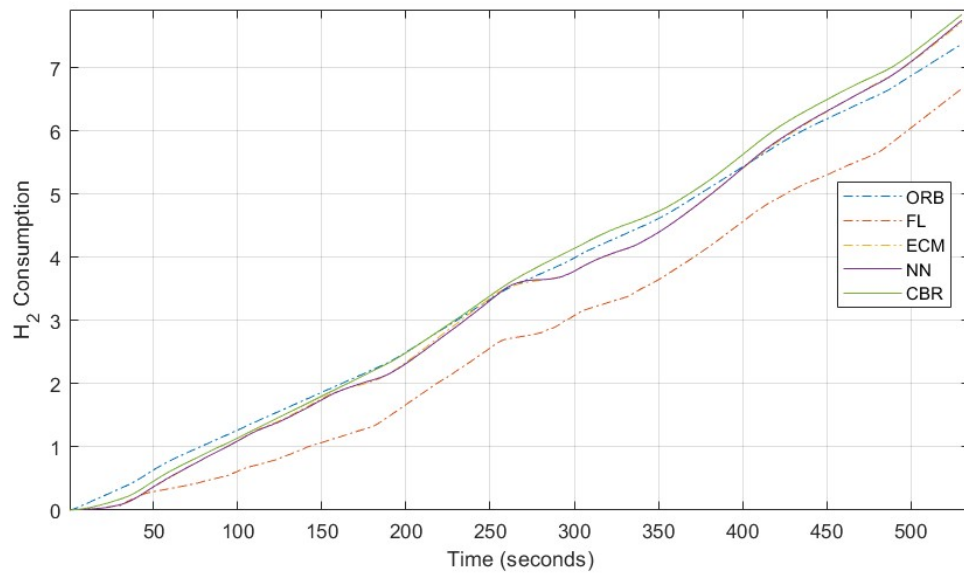


Figure 4.14: H_2 consumption with the third load profile

this reduction is attributed to a notable deviation in SOC. This highlights a lack of adaptability in these methods when faced with unforeseen dynamic load scenarios. In contrast, the proposed methodology including NN which demonstrate a near-similarity to ECM in terms of hydrogen consumption and SOC deviation as well as CBR which demonstrate better response than ECM which is a real-time optimization technique in terms SOC deviation with similar hydrogen consumption, outshines in computational efficiency as it does not require high computations resources to achieve that, making it a more robust solution across varied operational conditions.

To conclude, all these mentioned observations including mainly SOC deviation, hydrogen consumption, and total energy consumption are illustrated in comparative visualization mannerer as shown in Fig. 4.15, 4.16, and 4.17.

It is worth to mention one feature for the propose CBR strategy cannot be found in any other strategies which is the real-time adjustment in case of non-preferred behavior by trying a higher number of clusters data K_m with its corresponding optimized weights until achieving a preferred behavior. However, all these clusters data with different values of K_m with its optimized weights should be prepared as offline stage to be ready to shift between them when it is necessary. For the selected value of K_m which is 6 in our case, it not preferred to move with higher value unless the performance of the energy management system requires to be adjusted as mentioned previously because this come with more computations as the main purpose of this work is to develop effective energy management strategy that does not require high computations while having the ability to adapt to any load dynamics scenarios. A qualitative comparison summary is clarified in Table 4.2.

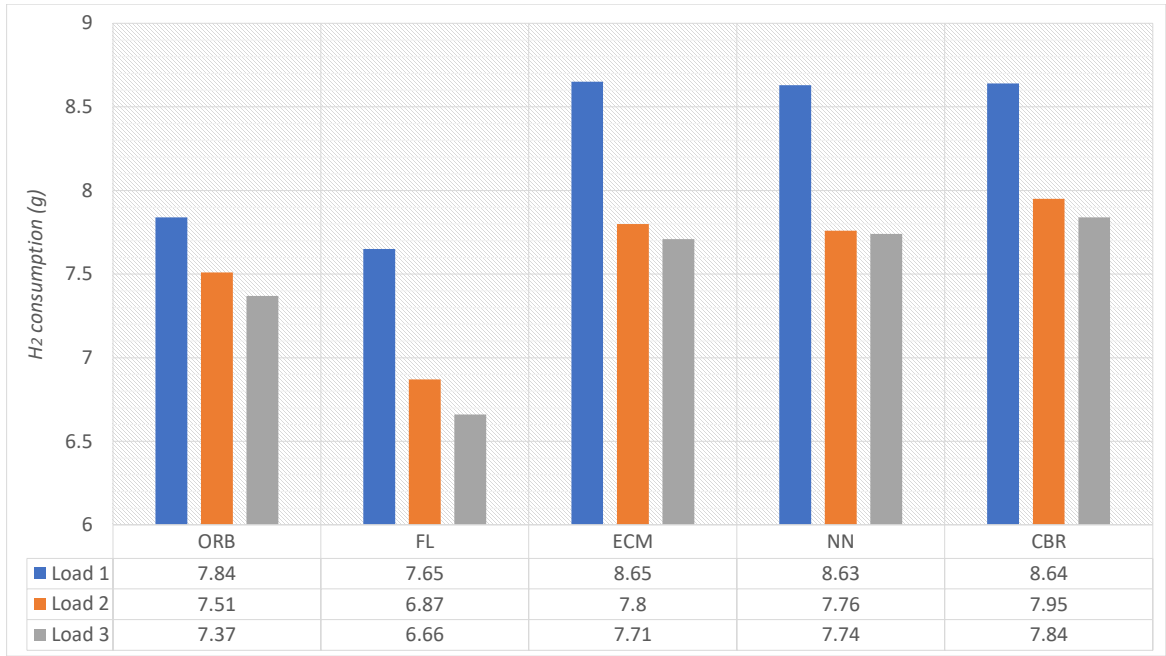


Figure 4.15: H_2 consumption summary for all load profiles

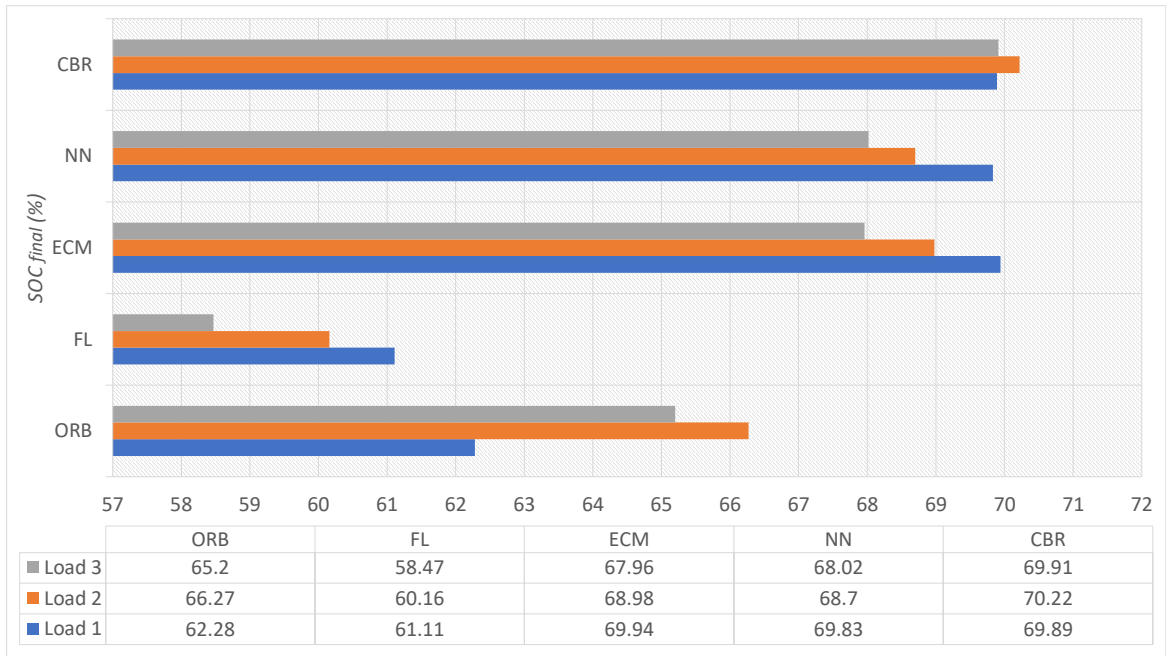


Figure 4.16: SOC final summary for all load profiles

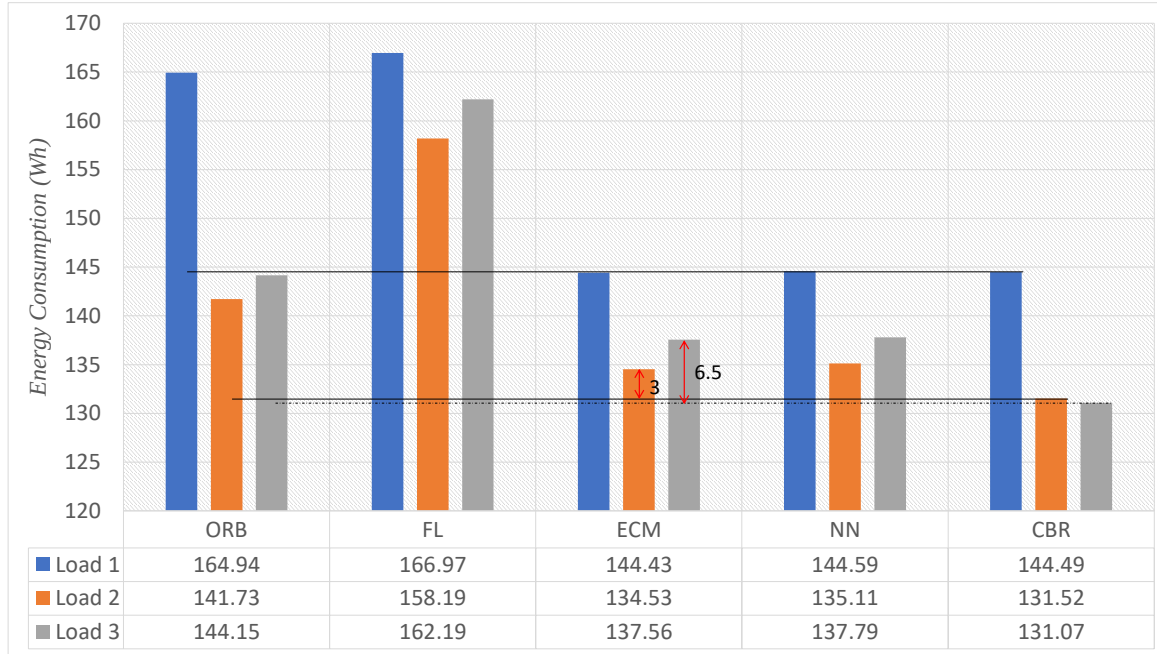


Figure 4.17: Total energy consumption for all load profiles

Table 4.2: qualitative comparison summary

	ORB	FL	ECM	NN	CBR
Computational demand	low	low	high	low	low
Adaptability	low	low	high	high	high
Maintaining SOC	low	low	med	med	high
Reducing FC degradation	med	low	med	med	high
Energy Consumption	high	high	med	med	low
Adjustability (real-time)	×	×	×	×	✓

CHAPTER 5

CONCLUSION

This thesis concludes with an extensive exploration and comparison of various Energy Management Strategies (EMS) for drone applications.

- The study introduces an innovative approach that enhances adaptability and computational efficiency within the context of ECM using neural network (NN) and Case-Based Reasoning (CBR). The proposed ECM strategy, incorporating penalty factors 'a' and 'b' within its objective function, demonstrates a refined approach in managing the battery's State of Charge (SOC) and aligning power generation with dynamic load requirements.
- The optimization process, employing Non-dominated Sorting Genetic Algorithm II (NSGA-II), fine-tunes these penalty factors for diverse load scenarios.
- The subsequent stages involve real-time evaluation and training a neural network on collected data to dynamically adjust fuel cell power, enabling effective adaptation to varying load profiles.

- The results and discussions showcase the comparative analysis of several EMS methods. Notably, the NN-based strategy mirrors the ECM's performance with minimal computations, highlighting its adaptability to unforeseen load profiles.
- Meanwhile, CBR stands out for its ability to maintain SOC at reference values throughout the mission duration, minimizing deviations and demonstrating superior adaptability to dynamic load scenarios compared to ECM and NN. Moreover, the study evaluates power distribution among hybrid sources, revealing nuanced patterns in fuel cell, battery, and supercapacitor usage across different EMS. CBR notably displays a smoother fuel cell power curve, indicating reduced degradation and efficient power management in response to load variations. Conversely, other strategies like ORB-EMS and FL-EMS exhibit fluctuations impacting the fuel cell's durability and SOC maintenance.
- The assessment of SOC variation and hydrogen consumption further substantiates the superiority of CBR, ECM, and NN in maintaining SOC close to reference values with similar hydrogen consumption rates, signifying robust adaptability and efficiency across diverse operational conditions. This is contrasted with ORB-EMS and FL-EMS, which exhibit SOC decline and reduced hydrogen consumption due to limitations in adaptability to new load scenarios.
- The comprehensive comparative visualization encapsulates the key findings, demonstrating the adaptive and efficient nature of CBR, and NN-based strategies in managing SOC deviation and hydrogen consumption across various load profiles.

This thesis contributes a thorough understanding of how different EMS strategies perform in dynamic load scenarios for drone applications. It emphasizes the significance of adaptability and computational efficiency, underlining the potential of NN and CBR-based approaches for effective energy management in real-time drone operations.

Future Research Direction: Energy management for drones is crucial for extended operational capabilities. The thesis's conclusions highlight the potential for each of Neural Network (NN) and Case-Based Reasoning (CBR) methods to optimize energy usage. To further this line of inquiry, future research will focus on refining and implementing a hybrid NN-CBR model for enhanced drone energy management. This research direction includes the following:

- Develop a unified framework that integrates NN and CBR methodologies to optimize drone energy strategies.
- Enhance adaptability by enabling the hybrid model to dynamically adjust energy distribution based on real-time data and changing load profiles.
- Implement an optimization mechanism within the hybrid model to fine-tune decision-making parameters for varied load scenarios.
- Design an onboard system for real-time energy management, allowing drones to autonomously adapt to operational conditions.
- The methodology involves investigating effective ways to merge NN and CBR algorithms seamlessly.

- Continuous learning mechanisms will be designed to facilitate the hybrid model's adaptation to incoming data streams.
- Extensive simulations and real-world tests will validate its performance across diverse scenarios.

Expected outcomes include improved energy management efficiency, real-time adaptability in various mission scenarios, and the potential applicability of the hybrid model to other autonomous systems beyond drones. This research direction seeks to significantly advance drone energy management by introducing a hybrid NN-CBR model. Success in this endeavor would enhance adaptability, efficiency, and autonomy in managing energy resources for drone operations across different environments and mission profiles.

APPENDIX A

SUPPLEMENTARY MATERIAL

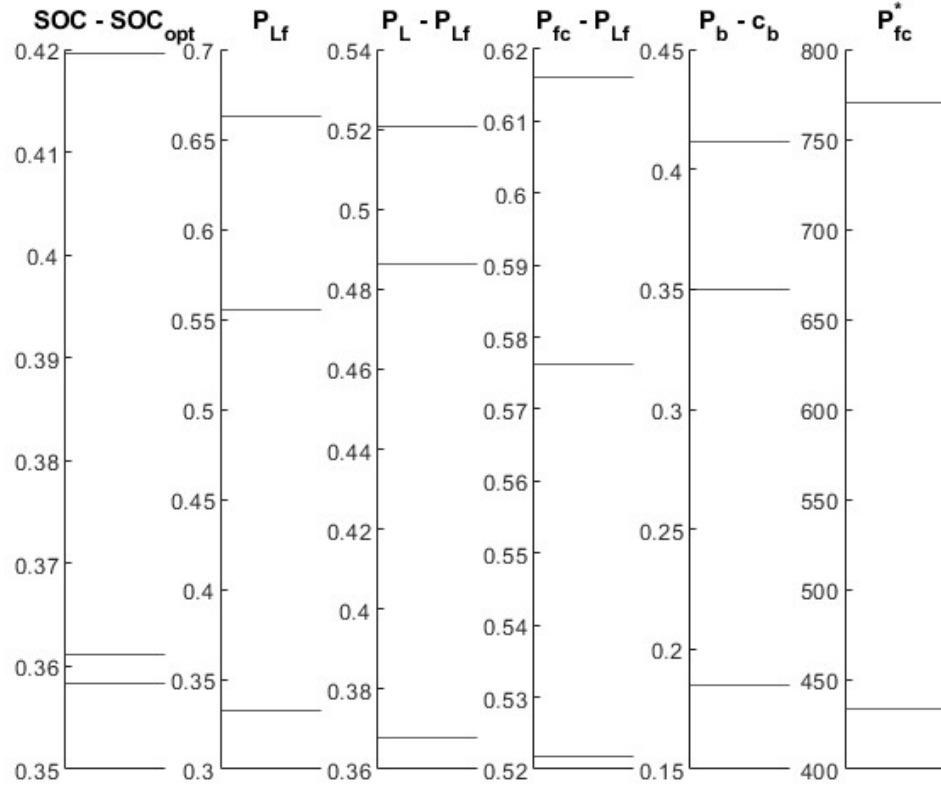


Figure A.1: Visualizing $k=3$ normalized clustering centers of k -means clustering

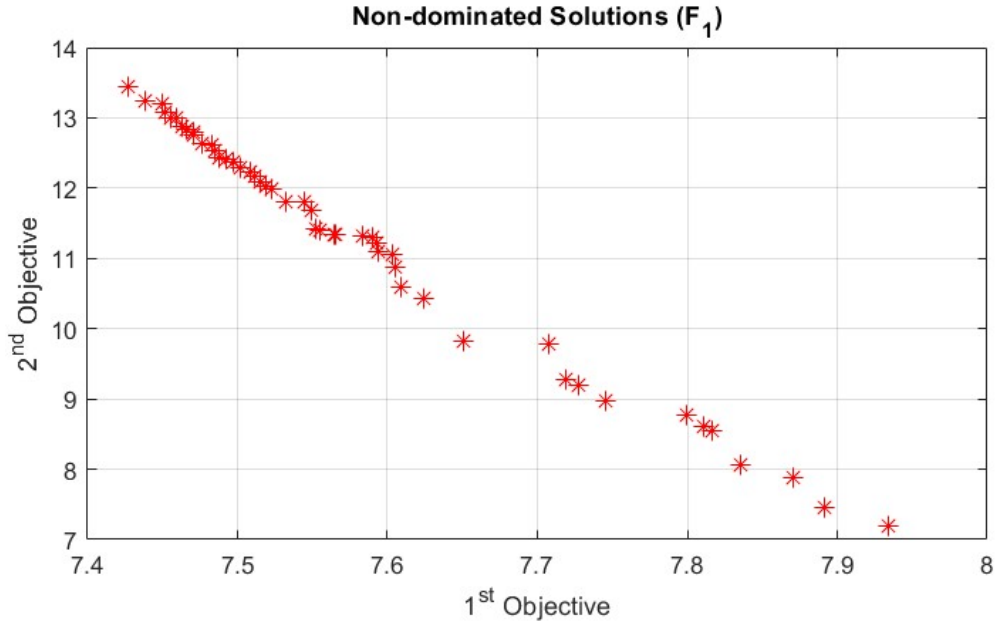


Figure A.2: NSGA-II Pareto front for $k=3$

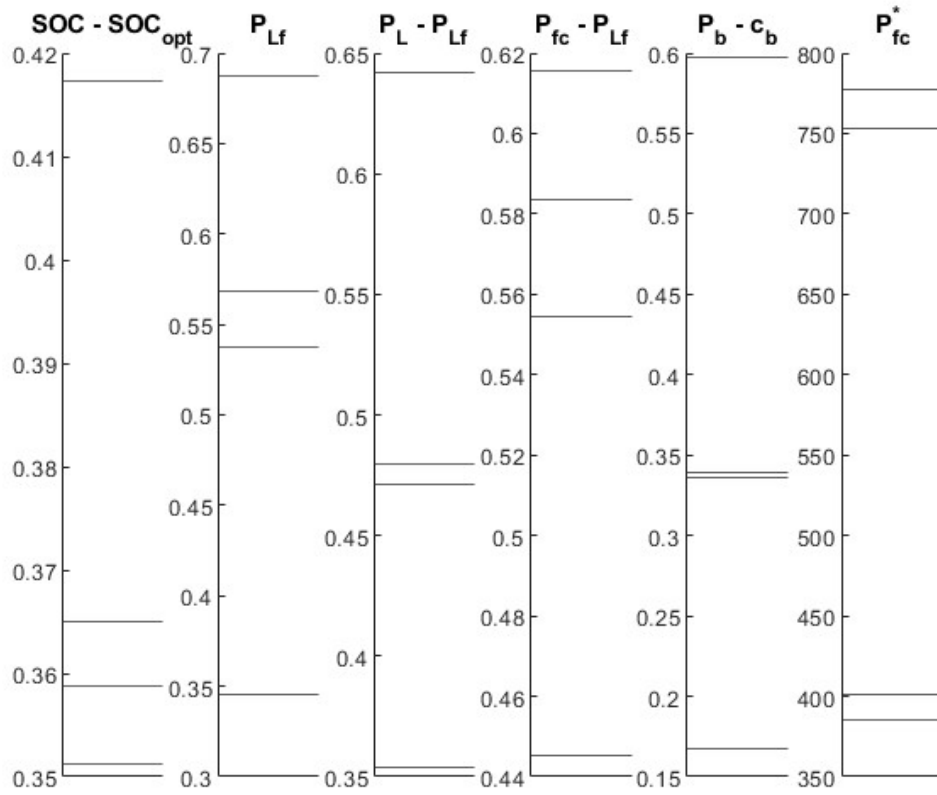


Figure A.3: Visualizing $k=4$ normalized clustering centers of k -means clustering

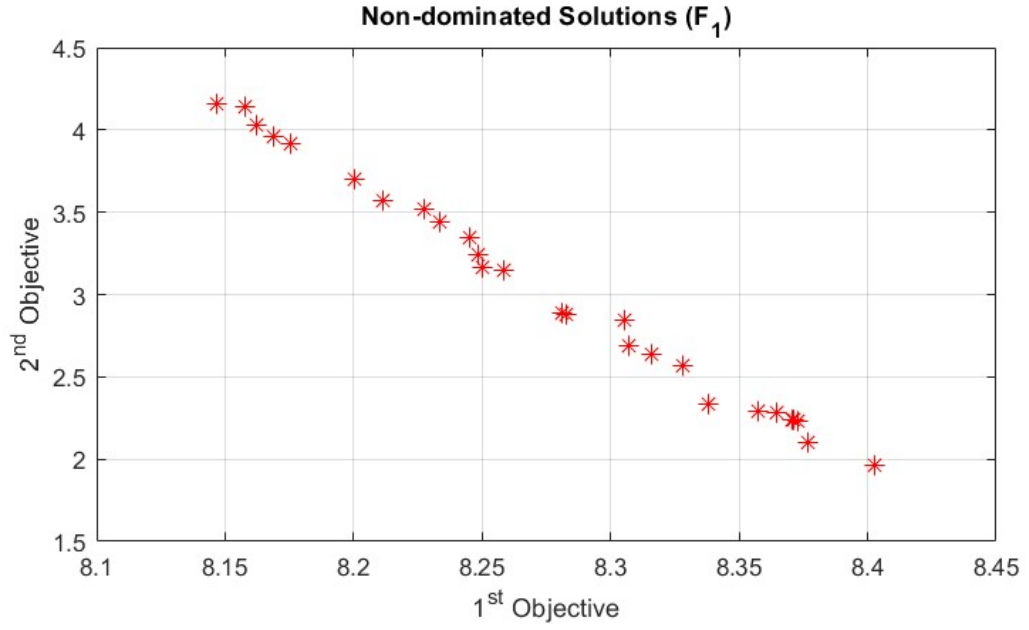


Figure A.4: NSGA-II Pareto front for K=4

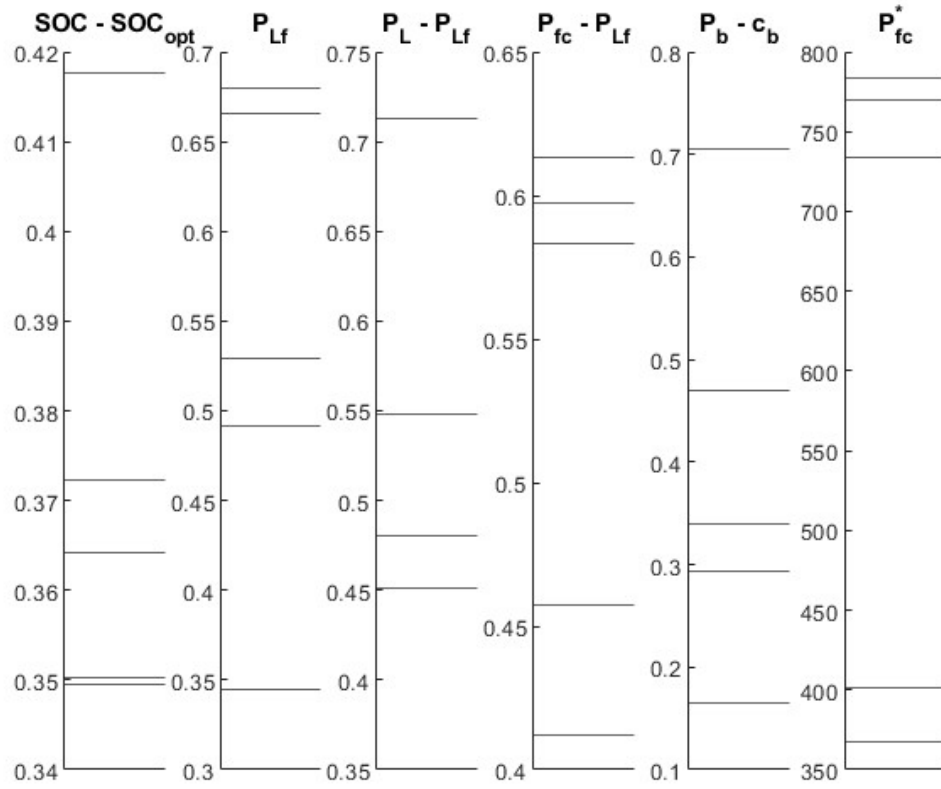


Figure A.5: Visualizing k=5 normalized clustering centers of k-means clustering

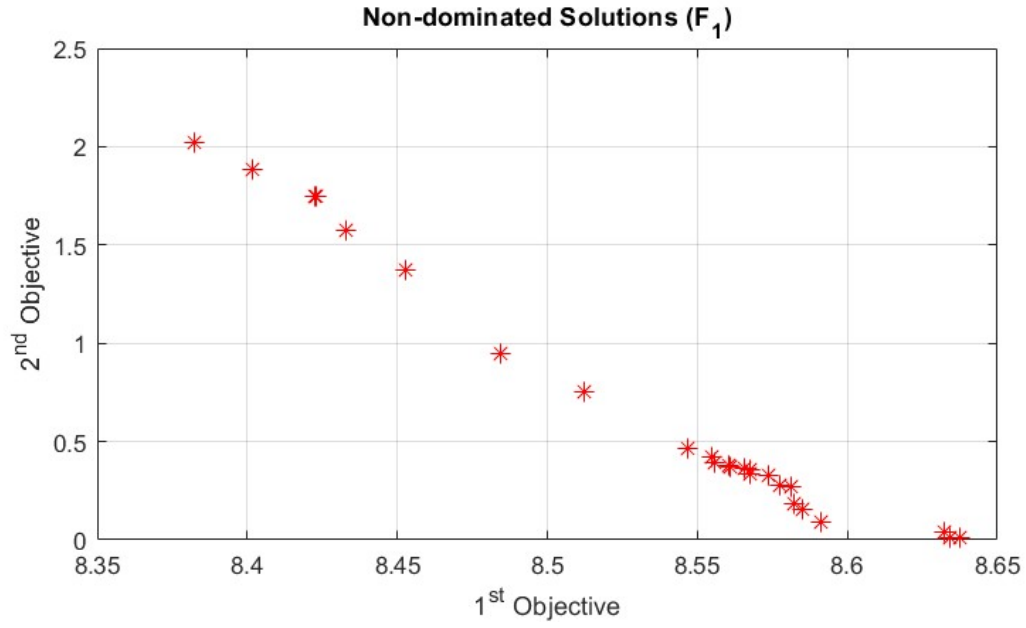


Figure A.6: NSGA-II Pareto front for K=5

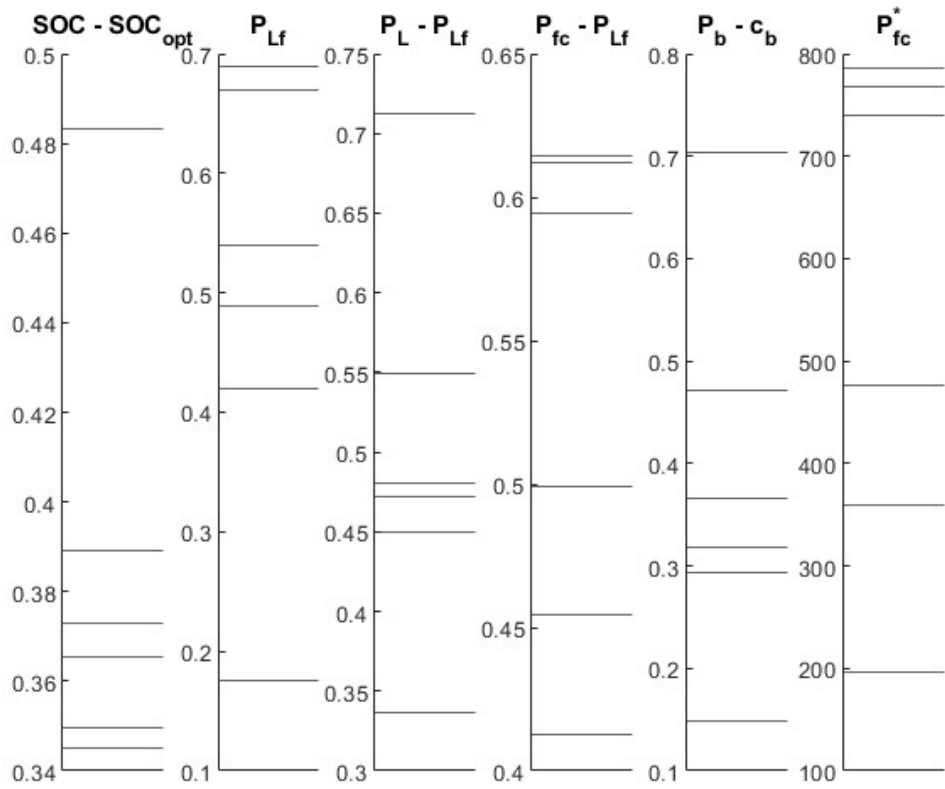


Figure A.7: Visualizing k=6 normalized clustering centers of k-means clustering

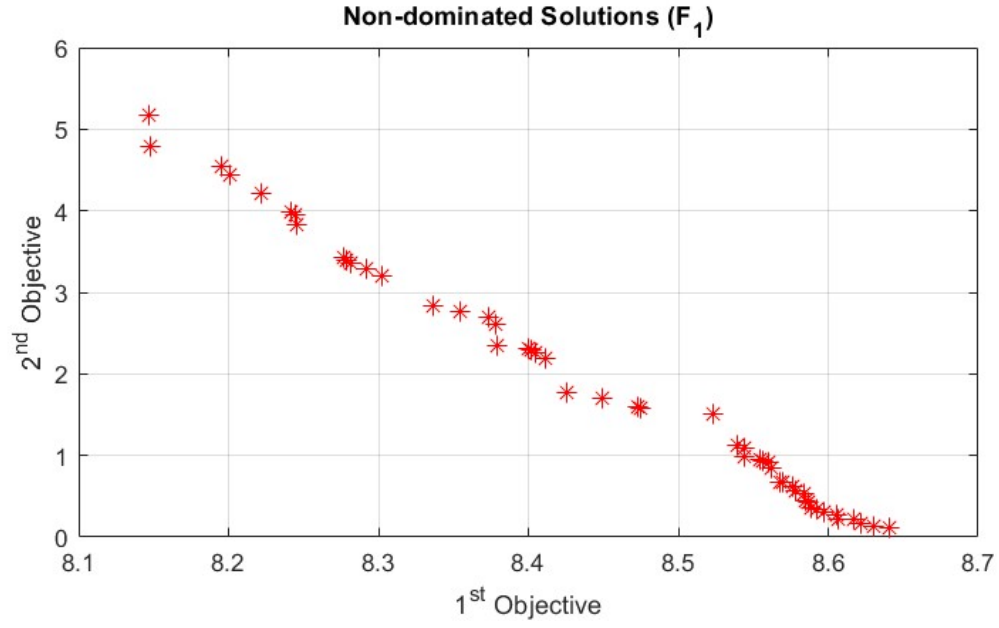


Figure A.8: NSGA-II Pareto front for K=6

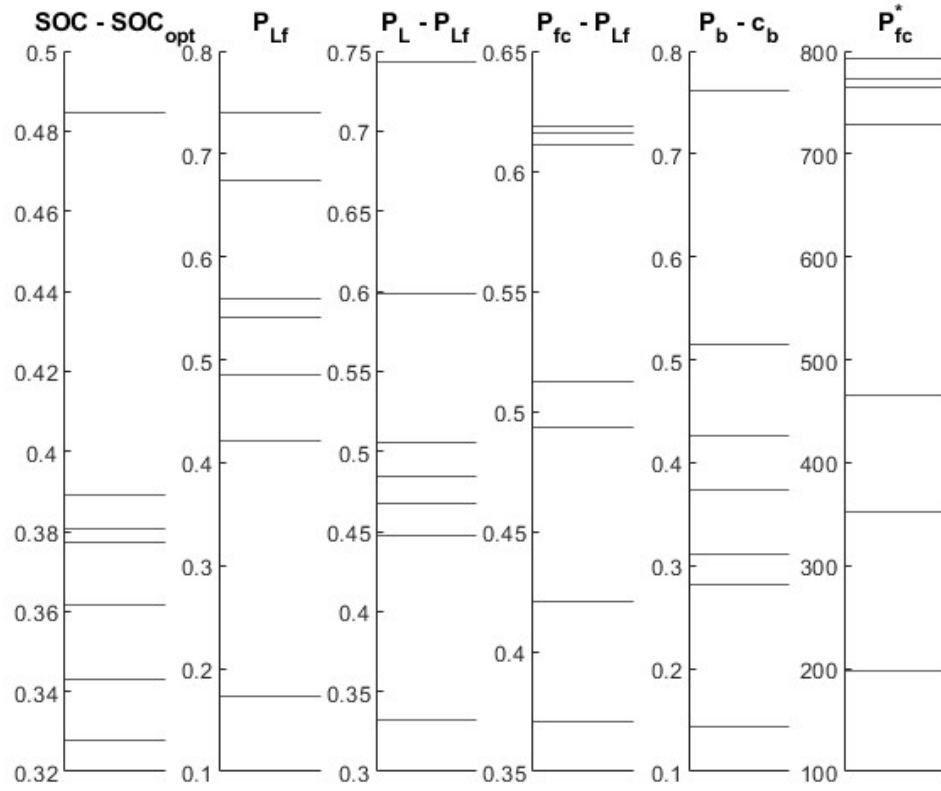


Figure A.9: Visualizing k=7 normalized clustering centers of k-means clustering

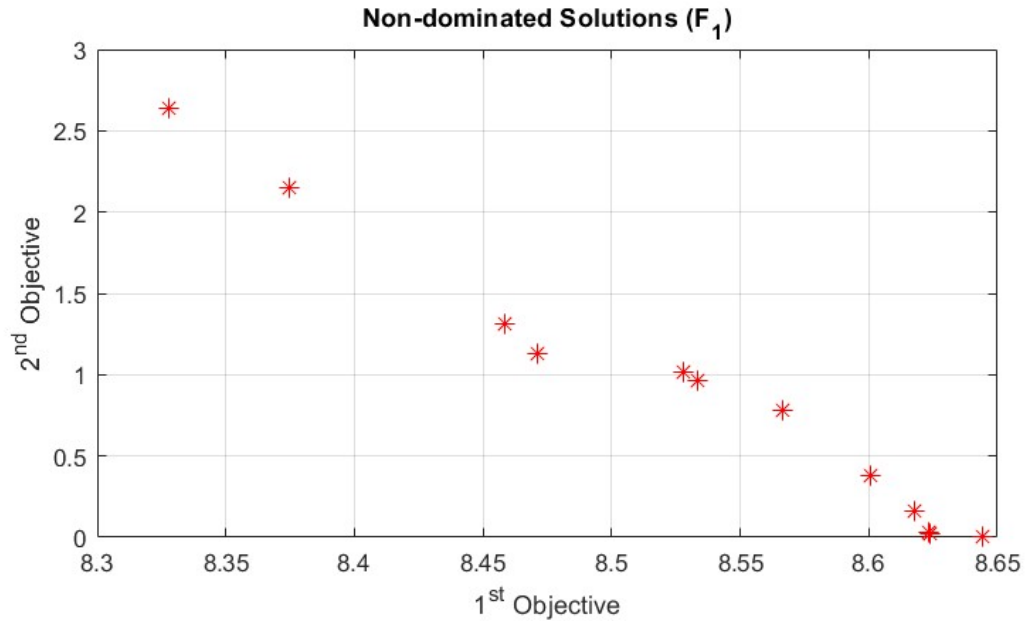


Figure A.10: NSGA-II Pareto front for K=7

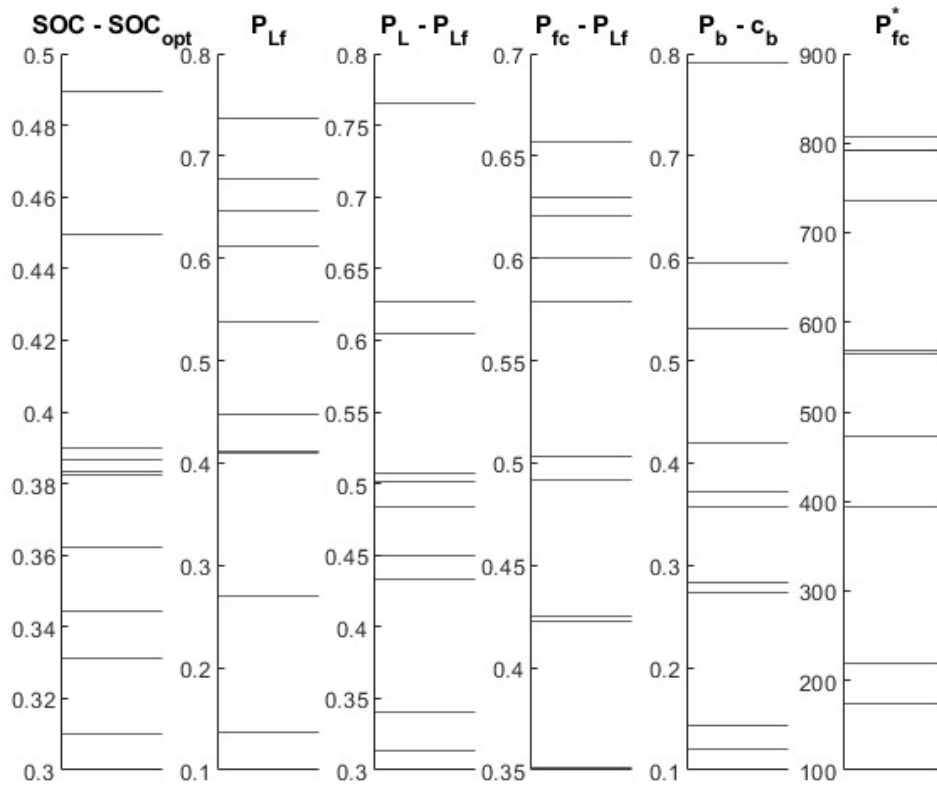


Figure A.11: Visualizing k=8 normalized clustering centers of k-means clustering

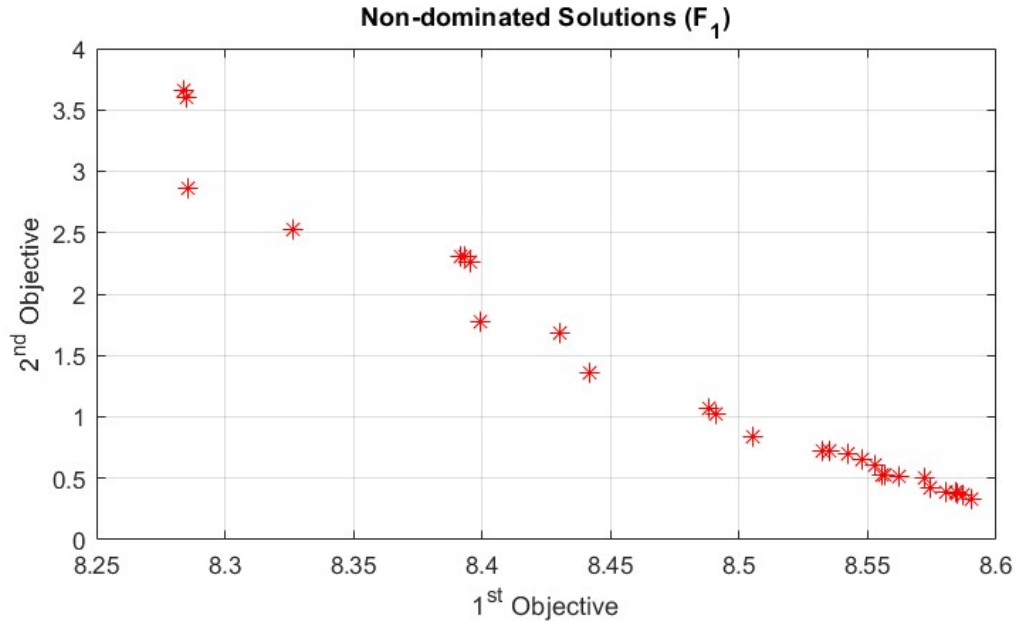


Figure A.12: NSGA-II Pareto front for K=8

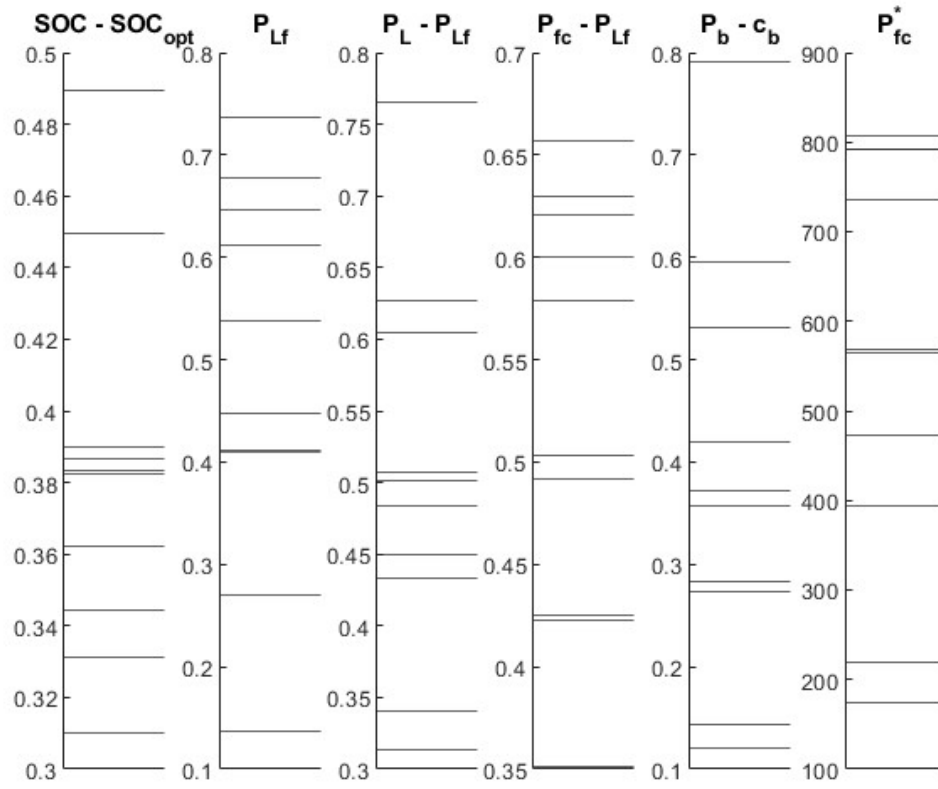


Figure A.13: Visualizing k=9 normalized clustering centers of k-means clustering

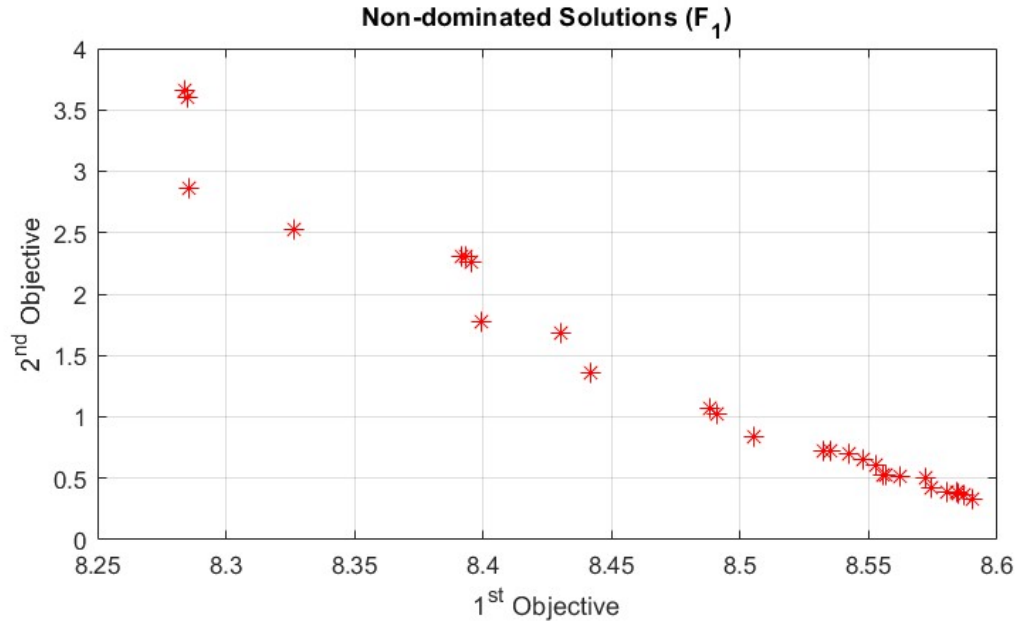


Figure A.14: NSGA-II Pareto front for K=9

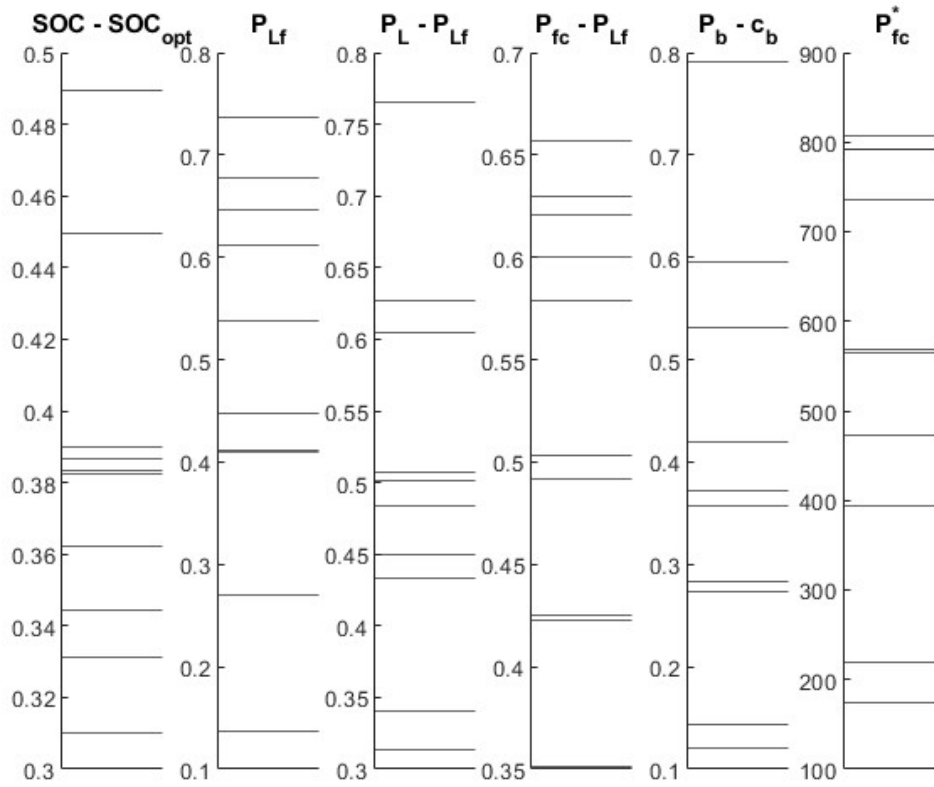


Figure A.15: Visualizing k=10 normalized clustering centers of k-means clustering

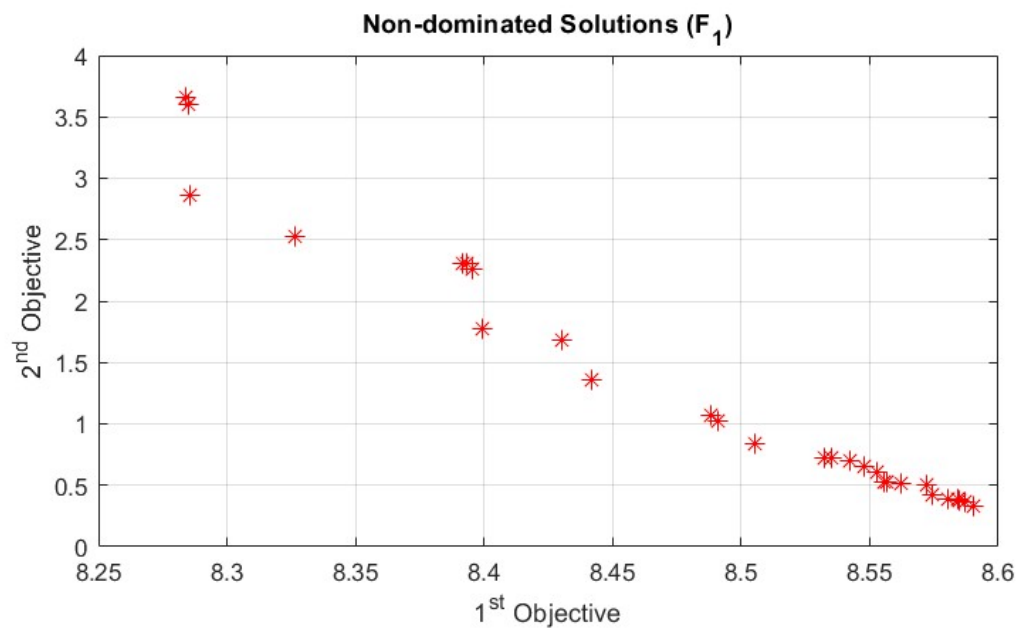


Figure A.16: NSGA-II Pareto front for K=10

REFERENCES

- [1] M. F. Hordeski, *Hydrogen & Fuel Cells: Advances in Transportation and Power*. Crc Press, 2020.
- [2] M. N. Boukoberine, Z. Zhou, and M. Benbouzid, “A critical review on unmanned aerial vehicles power supply and energy management: Solutions, strategies, and prospects,” *Applied Energy*, vol. 255, p. 113823, 2019.
- [3] L. W. Traub, “Range and endurance estimates for battery-powered aircraft,” *Journal of Aircraft*, vol. 48, no. 2, pp. 703–707, 2011.
- [4] K. Swider-Lyons, R. Stroman, G. Page, M. Schuette, J. Mackrell, and J. Rodgers, “Hydrogen fuel cell propulsion for long endurance small uavs,” in *AIAA Centennial of Naval Aviation Forum” 100 Years of Achievement and Progress*, 2011, p. 6975.
- [5] D. Verstraete, K. Lehmkuehler, and K. Wong, “Design of a fuel cell powered blended wing body uav,” in *ASME international mechanical engineering congress and exposition*, vol. 45172. American Society of Mechanical Engineers, 2012, pp. 621–629.

- [6] T. Kim and S. Kwon, "Design and development of a fuel cell-powered small unmanned aircraft," *International Journal of Hydrogen Energy*, vol. 37, no. 1, pp. 615–622, 2012.
- [7] A. Gong and D. Verstraete, "Role of battery in a hybrid electrical fuel cell uav propulsion system," in *52nd AIAA Aerospace Sciences Meeting*, 2014.
- [8] L. Karunarathne, J. T. Economou, and K. Knowles, "Model based power and energy management system for pem fuel cell/li-ion battery driven propulsion system," 2010.
- [9] X. Zhang, L. Liu, Y. Dai, and T. Lu, "Experimental investigation on the online fuzzy energy management of hybrid fuel cell/battery power system for uavs," *International journal of hydrogen energy*, vol. 43, no. 21, pp. 10 094–10 103, 2018.
- [10] 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 transactions on aerospace and electronic systems*, vol. 50, no. 4, pp. 3167–3177, 2014.
- [11] B. G. Gang and S. Kwon, "Design of an energy management technique for high endurance unmanned aerial vehicles powered by fuel and solar cell systems," *International Journal of Hydrogen Energy*, vol. 43, no. 20, pp. 9787–9796, 2018.
- [12] X. Zhang, L. Liu, and Y. Dai, "Fuzzy state machine energy management strategy for hybrid electric uavs with pv/fuel cell/battery power system," *International Journal of Aerospace Engineering*, vol. 2018, 2018.

- [13] X.-Z. Gao, Z.-X. Hou, Z. Guo, J.-X. Liu, and X.-Q. Chen, “Energy management strategy for solar-powered high-altitude long-endurance aircraft,” *Energy conversion and management*, vol. 70, pp. 20–30, 2013.
- [14] A. Gong, J. L. Palmer, and D. Verstraete, “Flight test of a fuel-cell/battery/supercapacitor triple hybrid uav propulsion system,” in *31st Congress of the International Council of the Aeronautical Sciences*, 2018, p. 11.
- [15] A. Gong, R. MacNeill, D. Verstraete, and J. L. Palmer, “Analysis of a fuel-cell/battery/supercapacitor hybrid propulsion system for a uav using a hardware-in-the-loop flight simulator,” in *2018 AIAA/IEEE Electric Aircraft Technologies Symposium (EATS)*. IEEE, 2018, pp. 1–17.
- [16] Z. Yang, T. Lei, Z. Lin, H. Fu, and X. Zhang, “The testing platform of hybrid electric power system for a fuel cell unmanned aerial vehicle,” in *2018 IEEE International Conference on Electrical Systems for Aircraft, Railway, Ship Propulsion and Road Vehicles & International Transportation Electrification Conference (ESARS-ITEC)*. IEEE, 2018, pp. 1–8.
- [17] J.-K. Shiau, D.-M. Ma, P.-Y. Yang, G.-F. Wang, and J. H. Gong, “Design of a solar power management system for an experimental uav,” *IEEE transactions on aerospace and electronic systems*, vol. 45, no. 4, pp. 1350–1360, 2009.
- [18] L. Karunarathne, J. Economou, and K. Knowles, “Adaptive neuro fuzzy inference system-based intelligent power management strategies for fuel cell/battery driven unmanned electric aerial vehicle,” *Proceedings of the Institution of Me-*

- chanical Engineers, Part G: Journal of Aerospace Engineering*, vol. 224, no. 1, pp. 77–88, 2010.
- [19] B. Lee, P. Park, C. Kim, S. Yang, and S. Ahn, “Power managements of a hybrid electric propulsion system for uavs,” *Journal of mechanical science and technology*, vol. 26, pp. 2291–2299, 2012.
- [20] A. Savvaris, Y. Xie, K. Malandrakis, M. Lopez, and A. Tsourdos, “Development of a fuel cell hybrid-powered unmanned aerial vehicle,” in *2016 24th mediterranean conference on control and automation (MED)*. IEEE, 2016, pp. 1242–1247.
- [21] B. Galkin, J. Kibilda, and L. A. DaSilva, “Uavs as mobile infrastructure: Addressing battery lifetime,” *IEEE Communications Magazine*, vol. 57, no. 6, pp. 132–137, 2019.
- [22] T. Bradley, B. Moffitt, D. Parekh, T. Fuller, and D. Mavris, “Energy management for fuel cell powered hybrid-electric aircraft,” in *7th international energy conversion engineering conference*, 2009, p. 4590.
- [23] C. Zhang, Y. Qiu, J. Chen, Y. Li, Z. Liu, Y. Liu, J. Zhang, and C. S. Hwa, “A comprehensive review of electrochemical hybrid power supply systems and intelligent energy managements for unmanned aerial vehicles in public services,” *Energy and AI*, vol. 9, p. 100175, 2022.

- [24] Z. Song, J. Li, X. Han, L. Xu, L. Lu, M. Ouyang, and H. Hofmann, “Multi-objective optimization of a semi-active battery/supercapacitor energy storage system for electric vehicles,” *Applied Energy*, vol. 135, pp. 212–224, 2014.
- [25] P. Pei, Q. Chang, and T. Tang, “A quick evaluating method for automotive fuel cell lifetime,” *International Journal of Hydrogen Energy*, vol. 33, no. 14, pp. 3829–3836, 2008.
- [26] A. Nishizawa, J. Kallo, O. Garrot, and J. Weiss-Ungethüm, “Fuel cell and li-ion battery direct hybridization system for aircraft applications,” *Journal of Power Sources*, vol. 222, pp. 294–300, 2013.
- [27] B. Lee, P. Park, K. Kim, and S. Kwon, “The flight test and power simulations of an uav powered by solar cells, a fuel cell and batteries,” *Journal of Mechanical Science and Technology*, vol. 28, pp. 399–405, 2014.
- [28] B. G. Gang, H. Kim, and S. Kwon, “Ground simulation of a hybrid power strategy using fuel cells and solar cells for high-endurance unmanned aerial vehicles,” *Energy*, vol. 141, pp. 1547–1554, 2017.
- [29] M. Dudek, P. Tomczyk, P. Wygonik, M. Korkosz, P. Bogusz, and B. Lis, “Hybrid fuel cell–battery system as a main power unit for small unmanned aerial vehicles (uav),” *International Journal of Electrochemical Science*, vol. 8, no. 6, pp. 8442–8463, 2013.

- [30] L. Gao, Z. Jiang, and R. A. Dougal, “An actively controlled fuel cell/battery hybrid to meet pulsed power demands,” *Journal of Power Sources*, vol. 130, no. 1-2, pp. 202–207, 2004.
- [31] G. Ren, G. Ma, and N. Cong, “Review of electrical energy storage system for vehicular applications,” *Renewable and Sustainable Energy Reviews*, vol. 41, pp. 225–236, 2015.
- [32] M. Gadalla and S. Zafar, “Analysis of a hydrogen fuel cell-pv power system for small uav,” *International Journal of Hydrogen Energy*, vol. 41, no. 15, pp. 6422–6432, 2016.
- [33] S. Hou, J. Gao, Y. Zhang, M. Chen, J. Shi, and H. Chen, “A comparison study of battery size optimization and an energy management strategy for fchevs based on dynamic programming and convex programming,” *International journal of hydrogen energy*, vol. 45, no. 41, pp. 21 858–21 872, 2020.
- [34] D. Fares, R. Chedid, F. Panik, S. Karaki, and R. Jabr, “Dynamic programming technique for optimizing fuel cell hybrid vehicles,” *International Journal of Hydrogen Energy*, vol. 40, no. 24, pp. 7777–7790, 2015.
- [35] T. Zeng, C. Zhang, Y. Zhang, C. Deng, D. Hao, Z. Zhu, H. Ran, and D. Cao, “Optimization-oriented adaptive equivalent consumption minimization strategy based on short-term demand power prediction for fuel cell hybrid vehicle,” *Energy*, vol. 227, p. 120305, 2021.

- [36] C. Zhang, T. Zeng, Q. Wu, C. Deng, S. H. Chan, and Z. Liu, “Improved efficiency maximization strategy for vehicular dual-stack fuel cell system considering load state of sub-stacks through predictive soft-loading,” *Renewable Energy*, vol. 179, pp. 929–944, 2021.
- [37] X. Lü, R. Meng, R. Deng, L. Long, and Y. Wu, “Energy economy optimization and comprehensive performance improvement for pemfc/lib hybrid system based on hierarchical optimization,” *Renewable Energy*, vol. 193, pp. 1132–1149, 2022.
- [38] P. Li, Y. Huangfu, C. Tian, S. Quan, Y. Zhang, and J. Wei, “An improved energy management strategy for fuel cell hybrid vehicles based on the pontryagin’s minimum principle,” in *2021 IEEE Industry Applications Society Annual Meeting (IAS)*. IEEE, 2021, pp. 1–6.
- [39] M. N. Boukoberine, M. F. Zia, M. Benbouzid, Z. Zhou, and T. Donato, “Hybrid fuel cell powered drones energy management strategy improvement and hydrogen saving using real flight test data,” *Energy Conversion and Management*, vol. 236, p. 113987, 2021.
- [40] M. Kandidayeni, A. Macias, L. Boulon, and S. Kelouwani, “Efficiency enhancement of an open cathode fuel cell through a systemic management,” *IEEE Transactions on Vehicular Technology*, vol. 68, no. 12, pp. 11 462–11 472, 2019.
- [41] X. Tang, H. Zhou, F. Wang, W. Wang, and X. Lin, “Longevity-conscious energy management strategy of fuel cell hybrid electric vehicle based on deep reinforcement learning,” *Energy*, vol. 238, p. 121593, 2022.

- [42] P. Wu, J. Partridge, E. Anderlini, Y. Liu, and R. Bucknall, “Near-optimal energy management for plug-in hybrid fuel cell and battery propulsion using deep reinforcement learning,” *International Journal of Hydrogen Energy*, vol. 46, no. 80, pp. 40 022–40 040, 2021.
- [43] T. Zeng, C. Zhang, D. Hao, D. Cao, J. Chen, J. Chen, and J. Li, “Data-driven approach for short-term power demand prediction of fuel cell hybrid vehicles,” *Energy*, vol. 208, p. 118319, 2020.
- [44] Y. Zhang, Z. Huang, C. Zhang, C. Lv, C. Deng, D. Hao, J. Chen, and H. Ran, “Improved short-term speed prediction using spatiotemporal-vision-based deep neural network for intelligent fuel cell vehicles,” *IEEE Transactions on Industrial Informatics*, vol. 17, no. 9, pp. 6004–6013, 2020.
- [45] Q. Li, T. Wang, S. Li, W. Chen, H. Liu, E. Breaz, and F. Gao, “Online extremum seeking-based optimized energy management strategy for hybrid electric tram considering fuel cell degradation,” *Applied Energy*, vol. 285, p. 116505, 2021.
- [46] H. Li, A. Ravey, A. N’Diaye, and A. Djerdir, “A novel equivalent consumption minimization strategy for hybrid electric vehicle powered by fuel cell, battery and supercapacitor,” *Journal of Power Sources*, vol. 395, pp. 262–270, 2018.
- [47] H. Rezk, A. M. Nassef, M. A. Abdelkareem, A. H. Alami, and A. Fathy, “Comparison among various energy management strategies for reducing hydrogen consumption in a hybrid fuel cell/supercapacitor/battery system,” *International Journal of Hydrogen Energy*, vol. 46, no. 8, pp. 6110–6126, 2021.

- [48] K. Kaya and Y. Hames, “A study on fuel cell electric unmanned aerial vehicle,” in *2019 4th International Conference on Power Electronics and their Applications (ICPEA)*. Ieee, 2019, pp. 1–6.
- [49] V. Dobrokhodov, K. D. Jones, C. Walton, and I. I. Kaminer, “Energy-optimal trajectory planning of hybrid ultra-long endurance uav in time-varying energy fields,” in *AIAA scitech 2020 forum*, 2020, p. 2299.
- [50] M. Bahari, M. Rostami, A. Entezari, S. Ghahremani, and M. Etminan, “Performance evaluation and multi-objective optimization of a novel uav propulsion system based on pem fuel cell,” *Fuel*, vol. 311, p. 122554, 2022.
- [51] G. Du, Y. Zou, X. Zhang, Z. Kong, J. Wu, and D. He, “Intelligent energy management for hybrid electric tracked vehicles using online reinforcement learning,” *Applied Energy*, vol. 251, p. 113388, 2019.
- [52] S. Delprat, T. Hofman, and S. Paganelli, “Hybrid vehicle energy management: Singular optimal control,” *IEEE Transactions on Vehicular Technology*, vol. 66, no. 11, pp. 9654–9666, 2017.
- [53] Y. Xie, A. Savvaris, and A. Tsourdos, “Sizing of hybrid electric propulsion system for retrofitting a mid-scale aircraft using non-dominated sorting genetic algorithm,” *Aerospace Science and Technology*, vol. 82, pp. 323–333, 2018.
- [54] S.-Y. Chen, C.-H. Wu, Y.-H. Hung, and C.-T. Chung, “Optimal strategies of energy management integrated with transmission control for a hybrid electric

- vehicle using dynamic particle swarm optimization,” *Energy*, vol. 160, pp. 154–170, 2018.
- [55] C. Szegedy, W. Zaremba, I. Sutskever, J. Bruna, D. Erhan, I. Goodfellow, and R. Fergus, “Intriguing properties of neural networks,” *arXiv preprint arXiv:1312.6199*, 2013.
- [56] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet classification with deep convolutional neural networks,” *Advances in neural information processing systems*, vol. 25, 2012.
- [57] I. H. Witten, E. Frank, M. A. Hall, C. J. Pal, and D. Mining, “Practical machine learning tools and techniques,” in *Data Mining*, vol. 2. Morgan Kaufmann, 2016, p. 4.
- [58] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” *nature*, vol. 521, no. 7553, pp. 436–444, 2015.
- [59] J. Kolodner, *Case-based reasoning*. Morgan Kaufmann, 2014.
- [60] A. Aamodt and E. Plaza, “Case-based reasoning: Foundational issues, methodological variations, and system approaches,” *AI communications*, vol. 7, no. 1, pp. 39–59, 1994.
- [61] R. L. De Mantaras, D. McSherry, D. Bridge, D. Leake, B. Smyth, S. Craw, B. Faltings, M. L. Maher, M. T COX, K. Forbus *et al.*, “Retrieval, reuse, revision and retention in case-based reasoning,” *The Knowledge Engineering Review*, vol. 20, no. 3, pp. 215–240, 2005.

- [62] M. T. Keane, “Analogical asides on case-based reasoning,” in *European Workshop on Case-Based Reasoning*. Springer, 1993, pp. 21–32.
- [63] D. B. Leake, “Cbr in context: The present and future,” *Case-based reasoning: Experiences, lessons, and future directions*, pp. 3–30, 1996.
- [64] F. Sørmo, J. Cassens, and A. Aamodt, “Explanation in case-based reasoning—perspectives and goals,” *Artificial Intelligence Review*, vol. 24, pp. 109–143, 2005.
- [65] B. Goodman and S. Flaxman, “European union regulations on algorithmic decision-making and a “right to explanation”,” *AI magazine*, vol. 38, no. 3, pp. 50–57, 2017.
- [66] D. Leake and D. Mcsherry, “Introduction to the special issue on explanation in case-based reasoning,” *The Artificial Intelligence Review*, vol. 24, no. 2, p. 103, 2005.
- [67] N. Tintarev and J. Masthoff, “A survey of explanations in recommender systems,” in *2007 IEEE 23rd international conference on data engineering workshop*. IEEE, 2007, pp. 801–810.
- [68] I. Nunes and D. Jannach, “A systematic review and taxonomy of explanations in decision support and recommender systems,” *User Modeling and User-Adapted Interaction*, vol. 27, pp. 393–444, 2017.
- [69] P. Liu, A. Y. Chen, Y.-N. Huang, J.-Y. Han, J.-S. Lai, S.-C. Kang, T.-H. Wu, M.-C. Wen, M.-H. Tsai *et al.*, “A review of rotorcraft unmanned aerial vehicle

- (uav) developments and applications in civil engineering,” *Smart Struct. Syst*, vol. 13, no. 6, pp. 1065–1094, 2014.
- [70] P. Finnegan, “World civil uas market profile & forecast 2019 edition,” *Teal Group Corporation: Fairfax, VA, USA*, 2019.
- [71] A. Gong and D. Verstraete, “Fuel cell propulsion in small fixed-wing unmanned aerial vehicles: Current status and research needs,” *International journal of hydrogen energy*, vol. 42, no. 33, pp. 21 311–21 333, 2017.
- [72] Y. Tang, W. Yuan, M. Pan, and Z. Wan, “Experimental investigation on the dynamic performance of a hybrid pem fuel cell/battery system for lightweight electric vehicle application,” *Applied Energy*, vol. 88, no. 1, pp. 68–76, 2011.
- [73] D. Verstraete, A. Gong, D. D.-C. Lu, and J. L. Palmer, “Experimental investigation of the role of the battery in the aerostack hybrid, fuel-cell-based propulsion system for small unmanned aircraft systems,” *International Journal of Hydrogen Energy*, vol. 40, no. 3, pp. 1598–1606, 2015.
- [74] D. Verstraete, K. Lehmkuehler, A. Gong, J. R. Harvey, G. Brian, and J. L. Palmer, “Characterisation of a hybrid, fuel-cell-based propulsion system for small unmanned aircraft,” *Journal of power sources*, vol. 250, pp. 204–211, 2014.
- [75] L. Tao, Y. Zhou, L. Zicun, and X. Zhang, “State of art on energy management strategy for hybrid-powered unmanned aerial vehicle,” *Chinese Journal of Aeronautics*, vol. 32, no. 6, pp. 1488–1503, 2019.

- [76] K. Kang, S. Park, S.-O. Cho, K. Choi, and H. Ju, “Development of lightweight 200-w direct methanol fuel cell system for unmanned aerial vehicle applications and flight demonstration,” *Fuel cells*, vol. 14, no. 5, pp. 694–700, 2014.
- [77] J. Renau, F. Sánchez, A. Lozano, J. Barroso, and F. Barreras, “Analysis of the performance of a passive hybrid powerplant to power a lightweight unmanned aerial vehicle for a high altitude mission,” *Journal of Power Sources*, vol. 356, pp. 124–132, 2017.
- [78] Y. Lee, E.-T. Park, J. Jeong, H. Shi, J. Kim, B.-S. Kang, and W. Song, “Weight optimization of hydrogen storage vessels for quadcopter uav using genetic algorithm,” *International Journal of Hydrogen Energy*, vol. 45, no. 58, pp. 33 939–33 947, 2020.
- [79] Z. Ji, J. Qin, K. Cheng, H. Liu, S. Zhang, and P. Dong, “Thermodynamic analysis of a solid oxide fuel cell jet hybrid engine for long-endurance unmanned air vehicles,” *Energy Conversion and Management*, vol. 183, pp. 50–64, 2019.
- [80] T. H. Oh, “Conceptual design of small unmanned aerial vehicle with proton exchange membrane fuel cell system for long endurance mission,” *Energy Conversion and Management*, vol. 176, pp. 349–356, 2018.
- [81] E. Okumus, F. G. B. San, O. Okur, B. E. Turk, E. Cengelci, M. Kilic, C. Karadag, M. Cavdar, A. Turkmen, and M. S. Yazici, “Development of boron-based hydrogen and fuel cell system for small unmanned aerial vehicle,” *international journal of hydrogen energy*, vol. 42, no. 4, pp. 2691–2697, 2017.

- [82] S. N. Motapon, L.-A. Dessaint, and K. Al-Haddad, “A comparative study of energy management schemes for a fuel-cell hybrid emergency power system of more-electric aircraft,” *IEEE transactions on industrial electronics*, vol. 61, no. 3, pp. 1320–1334, 2013.
- [83] Y.-T. Zhang, C. G. Claudel, M.-B. Hu, Y.-H. Yu, and C.-L. Shi, “Develop of a fuel consumption model for hybrid vehicles,” *Energy Conversion and Management*, vol. 207, p. 112546, 2020.
- [84] N. Bizon and I. C. Hoarcă, “Hydrogen saving through optimized control of both fueling flows of the fuel cell hybrid power system under a variable load demand and an unknown renewable power profile,” *Energy conversion and management*, vol. 184, pp. 1–14, 2019.
- [85] L. Xu, Y. Huangfu, R. Ma, R. Xie, Z. Song, D. Zhao, Y. Yang, Y. Wang, and L. Xu, “A comprehensive review on fuel cell uav key technologies: Propulsion system, management strategy and design procedure,” *IEEE Transactions on Transportation Electrification*, 2022.
- [86] T. Liu, X. Tang, H. Wang, H. Yu, and X. Hu, “Adaptive hierarchical energy management design for a plug-in hybrid electric vehicle,” *IEEE Transactions on Vehicular Technology*, vol. 68, no. 12, pp. 11 513–11 522, 2019.
- [87] Y. Shen, P. Cui, X. Wang, X. Han, and Y.-X. Wang, “Variable structure battery-based fuel cell hybrid power system and its incremental fuzzy logic energy man-

- agement strategy,” *International Journal of Hydrogen Energy*, vol. 45, no. 21, pp. 12 130–12 142, 2020.
- [88] H. Wang, P. Li, H. Xiao, X. Zhou, and R. Lei, “Intelligent energy management for solar-powered unmanned aerial vehicle using multi-objective genetic algorithm,” *Energy Conversion and Management*, vol. 280, p. 116805, 2023.
- [89] X. Sun, Y. Zhou, L. Huang, and J. Lian, “A real-time pmp energy management strategy for fuel cell hybrid buses based on driving segment feature recognition,” *International journal of hydrogen energy*, vol. 46, no. 80, pp. 39 983–40 000, 2021.
- [90] C. Sun, X. Hu, S. J. Moura, and F. Sun, “Velocity predictors for predictive energy management in hybrid electric vehicles,” *IEEE Transactions on Control Systems Technology*, vol. 23, no. 3, pp. 1197–1204, 2014.
- [91] C. Muli, S. Park, and M. Liu, “A comparative study on energy consumption models for drones,” in *Global IoT Summit*. Springer, 2022, pp. 199–210.
- [92] Q. Gao, T. Lei, F. Deng, Z. Min, W. Yao, and X. Zhang, “A deep reinforcement learning based energy management strategy for fuel-cell electric uav,” in *2022 International Conference on Power Energy Systems and Applications (ICoPESA)*. IEEE, 2022, pp. 524–530.
- [93] T. Lei, Z. Min, Q. Gao, L. Song, X. Zhang, and X. Zhang, “The architecture optimization and energy management technology of aircraft power systems: A review and future trends,” *Energies*, vol. 15, no. 11, p. 4109, 2022.

- [94] P. Beigi, M. S. Rajabi, and S. Aghakhani, “An overview of drone energy consumption factors and models,” *Handbook of Smart Energy Systems*, pp. 1–20, 2022.
- [95] T. Donato, L. Spedicato, and D. P. Placentino, “Design and performance evaluation of a hybrid electric power system for multicopters,” *Energy Procedia*, vol. 126, pp. 1035–1042, 2017.
- [96] W. Johnson, *Rotorcraft aeromechanics*. Cambridge University Press, 2013, vol. 36.
- [97] J. Apeland, D. Pavlou, and T. Hemmingsen, “Suitability analysis of implementing a fuel cell on a multirotor drone,” *Journal of Aerospace Technology and Management*, vol. 12, 2020.
- [98] J. G. Leishman, “Aerodynamic optimization of a coaxial proprotor,” in *The American Helicopter Society 62nd Annual Forum, Phoenix, USA, 2006*, 2006.
- [99] O. Tremblay, L.-A. Dessaint *et al.*, “A generic fuel cell model for the simulation of fuel cell vehicles,” in *2009 IEEE vehicle power and propulsion conference*. IEEE, 2009, pp. 1722–1729.
- [100] J. Li, H. Wang, H. He, Z. Wei, Q. Yang, and P. Igic, “Battery optimal sizing under a synergistic framework with dqn-based power managements for the fuel cell hybrid powertrain,” *IEEE Transactions on Transportation Electrification*, vol. 8, no. 1, pp. 36–47, 2021.

- [101] O. Tremblay and L.-A. Dessaint, “Experimental validation of a battery dynamic model for ev applications,” *World electric vehicle journal*, vol. 3, no. 2, pp. 289–298, 2009.
- [102] V. Musolino, L. Piegari, and E. Tironi, “New full-frequency-range supercapacitor model with easy identification procedure,” *IEEE transactions on industrial electronics*, vol. 60, no. 1, pp. 112–120, 2012.
- [103] K. B. Oldham, “A gouy–chapman–stern model of the double layer at a (metal)/(ionic liquid) interface,” *Journal of Electroanalytical Chemistry*, vol. 613, no. 2, pp. 131–138, 2008.
- [104] H. Wang, A. Gaillard, and D. Hissel, “A review of dc/dc converter-based electrochemical impedance spectroscopy for fuel cell electric vehicles,” *Renewable Energy*, vol. 141, pp. 124–138, 2019.
- [105] S. Chakraborty, H.-N. Vu, M. M. Hasan, D.-D. Tran, M. E. Baghdadi, and O. Hegazy, “Dc-dc converter topologies for electric vehicles, plug-in hybrid electric vehicles and fast charging stations: State of the art and future trends,” *Energies*, vol. 12, no. 8, p. 1569, 2019.
- [106] M. N. Boukoberine, T. Donato, and M. Benbouzid, “Optimized energy management strategy for hybrid fuel cell powered drones in persistent missions using real flight test data,” *IEEE Transactions on Energy Conversion*, vol. 37, no. 3, pp. 2080–2091, 2022.

- [107] H. Marzougui, A. Kadri, J.-P. Martin, M. Amari, S. Pierfederici, and F. Bacha, "Implementation of energy management strategy of hybrid power source for electrical vehicle," *Energy Conversion and Management*, vol. 195, pp. 830–843, 2019.
- [108] H. Li, A. Ravey, A. N'Diaye, and A. Djerdir, "Online adaptive equivalent consumption minimization strategy for fuel cell hybrid electric vehicle considering power sources degradation," *Energy conversion and management*, vol. 192, pp. 133–149, 2019.
- [109] H. Dong, Z. Zhao, J. Fu, J. Liu, J. Li, K. Liang, and Q. Zhou, "Experiment and simulation investigation on energy management of a gasoline vehicle and hybrid turbocharger optimization based on equivalent consumption minimization strategy," *Energy Conversion and Management*, vol. 226, p. 113518, 2020.
- [110] P. García, J. P. Torreglosa, L. M. Fernández, and F. Jurado, "Viability study of a fc-battery-sc tramway controlled by equivalent consumption minimization strategy," *International journal of hydrogen energy*, vol. 37, no. 11, pp. 9368–9382, 2012.
- [111] W. Zhang, J. Li, L. Xu, and M. Ouyang, "Optimization for a fuel cell/battery/capacity tram with equivalent consumption minimization strategy," *Energy Conversion and Management*, vol. 134, pp. 59–69, 2017.
- [112] J. P. Torreglosa, F. Jurado, P. García, and L. M. Fernández, "Hybrid fuel cell and battery tramway control based on an equivalent consumption minimization

- strategy,” *Control Engineering Practice*, vol. 19, no. 10, pp. 1182–1194, 2011.
- [113] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, “A fast and elitist multiobjective genetic algorithm: Nsga-ii,” *IEEE transactions on evolutionary computation*, vol. 6, no. 2, pp. 182–197, 2002.
- [114] H. Chen, P. Pei, and M. Song, “Lifetime prediction and the economic lifetime of proton exchange membrane fuel cells,” *Applied Energy*, vol. 142, pp. 154–163, 2015.
- [115] K. Song, H. Chen, P. Wen, T. Zhang, B. Zhang, and T. Zhang, “A comprehensive evaluation framework to evaluate energy management strategies of fuel cell electric vehicles,” *Electrochimica Acta*, vol. 292, pp. 960–973, 2018.

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