



CHENGWEI WANG

DIGITAL TWIN OF AIRCRAFT ELECTRICAL ACTUATOR TO
GENERATE DATA FOR HEALTH MANAGEMENT RESEARCH

SCHOOL OF AEROSPACE, TRANSPORT AND
MANUFACTURING
PHD IN TRANSPORT

DOCTORATE OF PHILOSOPHY
Academic Year: 2020 - 2024

Supervisor: DR IP-SHING FAN
Associate Supervisor: DR STEPHEN KING
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This thesis is submitted in partial fulfilment of the requirements for
the degree of DOCTORATE OF PHILOSOPHY

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Abstract

Electric-powered actuators play an important role in the new generations of commercial aircraft systems. They are used in Flight Control, Propulsion, Landing Gear and even seat actuation. As they are “Power-by-Wire” and connected to the aircraft control system, it is easy to acquire their operations and health data. Electro-Mechanical Actuator (EMA) is increasingly used to replace traditional hydraulic actuators in the future All/More Electric Aircraft.

However, lack of historical operational data makes complicated the risk analysis of EMA into aircraft systems. This research aims to develop an approach of Digital Twin design to support data generation for Aircraft Health Management algorithm development. The Digital Twin is designed to represent flight control EMA. The data generator is developed combining the Digital Twin EMA and a fault injection module, controlled by MATLAB scripts, to simulate operations in multiple scenarios, including nominal operations, degradation, and fault. EMA faults represented include unstable power supply, mechanical backlash, and power cable wear. The combination of simultaneous faults is explored by introducing multiple faults as part of the case analysis. This research indicates data could be generated to enable failure features detection in early or mid-stage failures. The research tackles the challenge to monitor, trigger and locate faults at subsystem/component level of an EMA. The framework could generate datasets to accelerate diagnostic and prognostic research in the early detection of EMA failures and enhance performance, thus facilitating timely maintenance actions that can prevent costly downtimes and extend the operational life of aircraft components.

The framework extends the concept of Digital Twin as a tool to support engineering design and operations to a tool for data generation.

Keywords:

ELECTRICAL ACTUATOR, DIGITAL TWIN, HEALTH MANAGEMENT, DATA TRAINING

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Finally, I would like to thank myself. I have been confused, lost, panicked, and depressed, but in the end, I overcame these negative emotions and reached the end of the journey slowly, firmly, and cheerfully.

春风得意马蹄疾，一日看尽长安花。

——孟郊[唐]《登科后》

I gallop calmly like putting a spring in my step in the pleasing vernal breeze, as
if I can appreciate the blooming flowers throughout Chang'an in one day.

--- Meng Jiao [Tang Dynasty] ***After Advancing to the Award***

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List of Nomenclature

e	base of the natural logarithm
Σ	Covariance matrix computed from standardised features
i	current
I_a	current input to motor
k	constant that represents the rate of temperature increase
K_e	back-EMF constant
L	phase inductance
L_c	length of conductor
L_{hinge}	actuator connected from flap hinge point
N	angular velocity in rpm
P	leadscrew pitch
P_o	power output of the motor
r	Actuator-to-flap transmission ratio
R	phase resistance
$\mathbb{R}$	Number of retained principal components used for projection
R_e	equivalent resistance
r_{gb}	gearbox ratio
r_{wg}	worm gear ratio
S	cross-sectional area
S_{arc}	arc length
t	time
T	Transpose operator for vectors or matrices
$T(t)$	temperature of the motor at time t
T_0	initial temperature of the motor at $t = 0$
T_g	torque through gearbox
T_w	torque through worm
V	motor terminal voltage

$\mathbb{V}$	Matrix of eigenvectors of the covariance matrix
V_c	equivalent generator voltage
V_a	voltage input
x	linear displacement
X	Original feature matrix, with N samples and D features
X_{std}	Standardised feature matrix after mean and variance normalisation
Z	Projected data in the PCA space
ω	shaft angular velocity
ω_m	motor angular velocity
θ_{def}	maximum flap deflection
θ_m	motor rotation
η	motor efficiency
ρ	resistivity of the cable material
μ	Feature-wise mean vector of the original dataset
σ	Feature-wise standard deviation vector
Λ	Diagonal matrix of eigenvalues indicating variance explained by each PC

List of Abbreviations

AC	Alternating Current
ADHF	Adaptive Dropped Hinge Flap
AE	Aircraft Electrification
AI	Artificial Intelligence
ALS	Active Load-Sensitive
AOG	Aircraft On Ground
APU	Auxiliary Power Unit
AVG	Average
BLDC	Brushless Direct-Current
CO ₂	Carbon Dioxide
C-MAPSS	Commercial Modular Aero-Propulsion System Simulation
DC	Direct Current
DT	Digital Twin
DDDT	Data-Driven Digital Twin
EA	Electrical Actuation
EBHA	Electric-Backup Hydraulic Actuator
ECS	Environmental Control Systems
ECU	Electronic Control Unit
EHA	Electro-Hydraulic Actuator
EHSA	Electro-Hydro-Static Actuator
EM	Electric Motor
EMA	Electro-Mechanical Actuator
EMF	Electro-Motive Forces
EPU	Electronic Power Unit
ESM	Electrically Excited Synchronous Machine
eVTOL	Electric Vertical Take-Off and Landing aircraft
EU	European Union
FbW	Fly-by-Wire

FC	Flight Control
FFT	Fast Fourier Transform
FMECA	Failure Mode, Effects, and Criticality Analysis
FPVM	Fixed-displacement Pump and Variable-speed Motor
GAN	Generative Adversarial Network
HSA	Hydraulic Servo Actuator
IEEE	Institute of Electrical and Electronics Engineers
IM	Induction Machine
IVHM	Integrated Vehicle Health Management
LR	Logistic Regression
MBDT	Model-Driven Digital Twin
MD	Mechanical Drive
MEA	More Electrical Aircraft
MTBF	Mean Time Between Failures
MTOW	Maximum Take-Off Weight
NASA	National Aeronautics and Space Administration
OEM	Original Equipment Manufacturer
OOB	Out-of-Bag
PbW	Power-by-Wire
PCA	Principal Component Analysis
PdM	Predictive Maintenance
PHM	Prognostics Health Management
PID	Proportional-Integral-Derivative
PLM	Product Lifecycle Management
PMSM	Permanent Magnet Synchronous Motor
RF	Random Forest
RFR	Random Forest Regression
RUL	Remaining Useful Life
SAE	Society of Automotive Engineers

SHM	System Health Monitoring
SOTA	State-Of-The-Art
SRM	Switched Reluctance Motor
SVM	Support-Vector Machine
UMAP	Uniform Manifold Approximation and Projection
USA	United States of America
VAE	Variational Auto-Encoders
VPFM	Variable-displacement Pump and Fixed-speed Motor
VPVM	Variable-displacement Pump and Variable-speed Motor
XWB	Extra Wide Body

List of Publications

C Wang, I.S. Fan, S. King (2022). Failure Mapping for Aircraft Electrical Actuation System Health Management, *7th European Conference of the PHM Society (PHME 2022)*, 6-8 July 2022, Turin, Italy.

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1 INTRODUCTION

1.1 Background and Motivation

1.1.1 Aircraft Electrification

The aerospace industry has seen an escalation in system complexity, driven by the demand for more range, speed, and control in modern aircraft. The complexity has led to a notable increase in the maintenance costs associated with hydraulic and pneumatic systems. The concern on higher jet fuel prices and operational cost, together with the need of aviation sustainability and greenhouse emission reduction have been driving aircraft development [1][2][3]. Sustainable Aviation Fuels (SAFs) was developed and used partially in the aviation industry with an advantage of 80% emission reduction during its full lifecycle. With the development of high output density power supply [4][5], another development is the Aircraft Electrification (AE) approach towards the More Electric Aircraft (MEA). Supported by significant industrial and research investments MEA has pushed the practical readiness of electric system technologies. MEA uses mainly electrical and electric-hybrid systems instead of combinations of secondary power sources to realise operations by avoiding many of the fundamental drawbacks of their hydraulic, pneumatic, and mechanical counterparts. They are notably more flexible, lightweight, environmentally friendly, and efficient.

AE provides greater flexibility in design at the same time improving safety, allowing for interchangeability and re-configurability [4]. It also brings benefits in aircraft weight reduction and power efficiency. Lower carbon emission is another significant advantage of AE. The development and extension of commercial aviation continue to raise the industry's contribution to global emissions [6], which reached to 915 million tons of CO₂ in 2019, an increase of 29% since 2013 [7][8]. According to the EU's Flightpath 2050 Program [9], it sets a goal of decreasing 75% CO₂ emissions per passenger kilometre and a 90% reduction in NO_x emissions. With the use of fuel cell, it is expected to reduce fuel consumption by 1 to 5% and increase its efficiency by 1 to 3%.

AE can be a driver for increasing the sustainability of connectivity within cities. It is also believed to generate lower perceived noise emission, quieter during operation and benefits urban areas to meet the target of 65% noise reduction in Flightpath 2050 program [10]. There are several electric aircrafts that took to the sky. The Finnish Pipistrel Alpha Electro, a two-seat electric plane, took off in August 2018 [11]. This is believed to be a milestone for the Finnish aviation to enter a more nature-friendly future. In September 2020, Cranfield University supported ZeroAvia to successfully deliver the world's first hydrogen fuel cell powered aircraft, which is a big move towards zero-emission aviation [12]. AutoFlight, an eVTOL startup, conducted the first inter-city electric taxi trip between Zhuhai and Shenzhen [13], two major cities within Guangdong-Hong Kong-Macao Greater Bay Area of Southern China on 1st March 2024. The one-way trial flight dramatically cut the travel duration from a 3 hours' drive to 20 minutes in the air.

Table 1.1-1 Examples of Electric aircraft and eVTOL prototypes

OEM	Model	Category	Range (km)	MTOW (Ton)	Seat	Noise Emission (dB)
Pipistreal [11]	Alpha Electro	E-aircraft	~600	0.55	2	N/A
Pipistreal [14]	Velis Electro	E-aircraft	~700	0.6	2	~60
ZeroAvia [12]	PA-46-350P	E-aircraft	N/A	1.969	6	N/A
AutoFlight [15]	Prosperity-CN	eVTOL	~250	2	5	~65
Joby Aviation [16]	Tiltrotor	eVTOL	~160	2.177	4	~45.2

1.1.2 Role and Demand of Electric-Activated Equipment Health Management

(This Section draws partly on previously published work by the author in PHM Society 2022.)

While the adoption of electric-activated equipment presents multiple advantages, it also requires robust monitoring and management mechanisms. As the use of electric-activated equipment in aircraft becomes more frequent, the reduction in local redundancy has raised concerns regarding the need for revisions in the generic maintenance protocols to accommodate these new systems:

- Inspections of electrical components must be incorporated as specific tasks within maintenance operations.
- An increase in enhanced testing, e.g., high current test is necessary to validate the adaptability of junction installations.
- Safety procedures for operators must be updated to ensure their protection during the dismantling and fitting of components.

The approach to maintenance planning will require adjustments, particularly in the context of implementing preventive or scheduled maintenance routines.

In this regard, the development of smart systems for electric-activated equipment health management arises as a crucial need. The term 'smart' involves a range of technologies, including sensors, data analytics, machine learning, and predictive maintenance algorithms. These elements converge to create an ecosystem that continuously monitors the operational parameters of electrical actuators, identifies anomalies, and predicts potential malfunctions. The implementation of such systems offers benefits, involving enhanced safety, operational efficiency, and cost-effectiveness. The need for smart electric-activated equipment health management arises from the complexity and criticality of modern aircraft operations. Any malfunction or failure in these components could have severe consequences. Traditional maintenance practices, which often rely on routine checks and scheduled replacements, may not be sufficient to address the dynamic operational environment of modern aviation. The

unpredictable nature of wear and tear, coupled with the growing demands placed on aircraft systems, necessitates a more proactive and data-driven approach to maintenance. Smart systems for electric-activated equipment health management bridge this gap by providing real-time insights into the condition of these critical components.

1.1.3 Electrical Actuator

A key element in realising the goals of the MEA initiative and a typical example of electric-activated equipment is the adoption of electrically powered actuation systems. Electric Actuators (EAs), which convert electrical energy into mechanical motion, are increasingly substituting traditional hydraulic and pneumatic actuators across an aircraft, due to their reliability, precision, reduced maintenance requirements and lightweight. In the aerospace industry, weight is a critical factor. Traditional hydraulic systems are not only heavy but also require extensive infrastructure, including hydraulic fluid storage and distribution mechanisms. Electrical actuators, on the other hand, are inherently lightweight and compact. This reduction in weight has a cascading effect on the aircraft's overall efficiency. In an era where airlines are constantly seeking ways to optimise operational costs, the weight reduction offered by electrical actuators becomes a substantial value proposition.

Two dominant kinds of EAs, Electro-Hydraulic Actuator (EHA) and Electro-Mechanical Actuator (EMA) systems, have been considered mature and found in service on multiple recent large passenger aircraft types. EAs offer precise control and can operate under severe environmental conditions, improving safety

while reducing weight and maintenance costs. Employed in flight control surface [17], landing gear, brakes [18], and engine control systems.

Table 1.1-2 EAs in flight control on Boeing 787 and Airbus 350 XWB

Flight Control	Panel	Aircraft Model	
		Airbus 350 XWB	Boeing 787
Primary	Aileron	<ul style="list-style-type: none"> Hydraulics EHSA 	EHA
	Elevator	EHSA	<ul style="list-style-type: none"> EHA
	Rudder		<ul style="list-style-type: none"> Redundant EMA
Secondary	Flap	<ul style="list-style-type: none"> Hydraulics EHA 	EHA
	Slat		
	Spoiler	<ul style="list-style-type: none"> Hydraulics EBHA 	<ul style="list-style-type: none"> EHA
	Trimmer	<ul style="list-style-type: none"> EMA EHSA 	<ul style="list-style-type: none"> Simplex EMA

EAs facilitate accurate control over aircraft dynamics, such as lift and drag, particularly beneficial in “Fly-by-Wire” (FbW) aircraft that use electronic signals for flight surface control, as exemplified in Table 1.1-2. Compared to fully hydraulic primary and secondary flight control system used in the older Boeing 737s, EMAs and EHAs replace some of the hydraulic actuators in the newer Boeing 787 as shown in Figure 1.1-1 [19]. EMAs are used for driving mid-spoiler surfaces of the Boeing 787, and trimmable horizontal stabilisers of the Airbus 380 (no longer in production). On the new Airbus 350 XWB, Electro-Hydro-Static Actuators

(EHSAs) are used for driving both primary (aileron, elevator, and rudder) and secondary flight control panels (spoiler and trimmer) shown in Figure 1.1-2

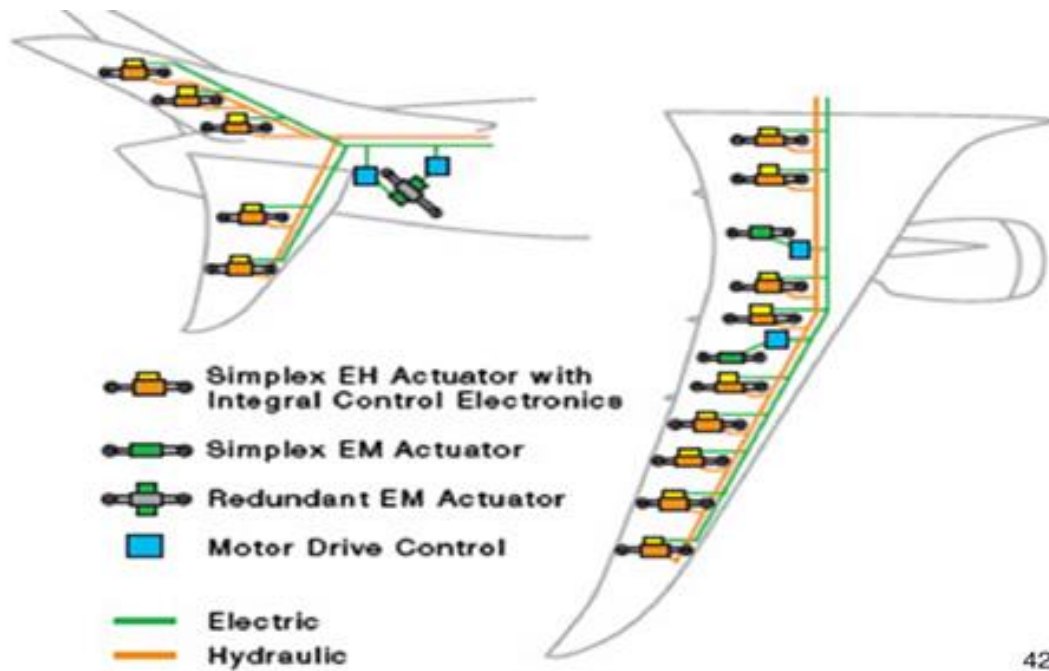


Figure 1.1-1 Boeing 787 primary flight control system [19]

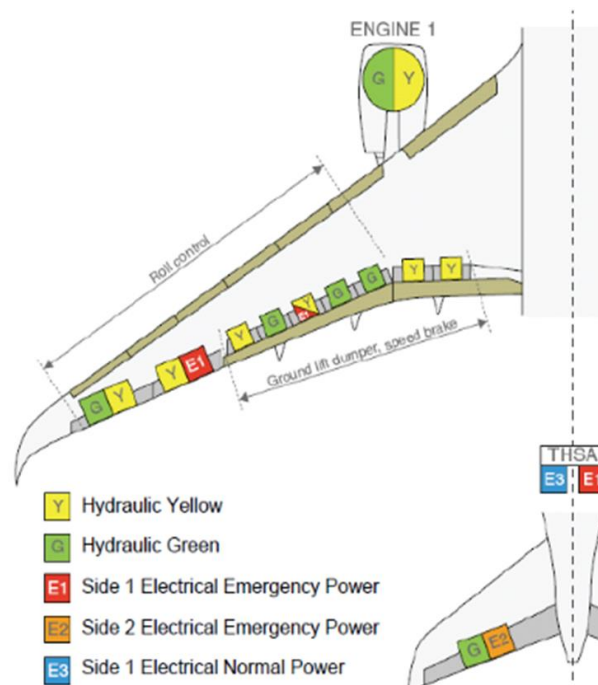


Figure 1.1-2 Airbus 350 XWB actuator and power source distribution on left wing, engine, and elevator [20]

1.1.4 Difficulty of Flight Control EA Health Management

This section discusses general factors delaying research and development and commercialisation of EA health management technologies. Applying health management techniques to flight control electronic drive systems presents a number of challenges and complexities. The system is critical to the safety and performance of the aircraft, so its reliable operation is a top priority.

- **Complexity of the system** [21]. The flight control electrical execution system is complex, integrating mechanical, electrical, and software components. This complexity makes it challenging to effectively monitor and manage the health of the entire system only from the status data of each component.
- **Real-time monitoring and analysis** [22]. Real-time data collection, processing, and analysis are required to detect anomalies or predict failures before they occur. This requires advanced algorithms and significant computational resources, especially when dealing with the large amount of data generated by the system.
- **Data Security and Privacy** [22][23]. The collection and transmission of operational data for health management purposes raises concerns about data security and privacy. Securing this data against cyber threats is critical.
- **Data Availability** [23][24]. The access of historical operational data is always a concern in terms of reliable data fed into training smart algorithms. As for the EMA, which is currently not involved in critical subsystems in flight control, it is impossible to get sufficient data with both quality and quantity.
- **Interoperability** [23]. Ensuring that health management technologies are interoperable with the different systems and platforms used throughout the aviation industry is a challenge. Standardisation is under way but is not yet fully realised.
- **Expertise and training** [23]. To use health management techniques effectively, expertise and training of personnel are required. This includes not only operators but also maintenance and engineering personnel.

- **False positives and false negatives** [23]. It is a significant challenge for operators to strike a balance between sensitivity and specificity to avoid false positives or missing critical signals when detecting potential problems.
- **Environmental factors** [21][22][24]. The system operates under harsh environmental conditions, including high altitude, extreme temperatures, and vibrations, which may affect the overall reliability of sensor readings and health monitoring technology.
- **Safety and Certification Standards** [24][25]. Any health management technology applied to a flight control system must meet stringent safety and certification standards. Ensuring that innovative technologies meet these standards is both time and money consuming.
- **Integration with existing systems** [24]. Integrating health management technology with existing the flight control system without compromising performance or safety is a significant challenge. This requires a well-planned testing and validation.
- **Cost** [22][24]. Developing, implementing, and maintaining advanced health management technologies can be costly. The cost must be matched by the benefits in terms of increased safety, reliability, and reduced maintenance costs, and a balance between both should be achieved.

Addressing these challenges requires a multidisciplinary approach that includes technological advances, testing and validation, collaboration from the aviation industry, and compliance with regulatory standards. Despite these difficulties, the integration of health management techniques into flight control EA systems promises to improve safety, reliability, and efficiency in the aviation industry.

1.2 Research Gap

The EMA represents a compact and efficient solution for motion actuation, delivering specified torque output and meeting control system requirements. However, the integration of EMAs into safety-critical primary flight control systems or high-lift surface control mechanisms faces significant challenges due to the

lack of historical operational data or specific features and restricted access to current performance data.

Access to sufficient volume of quality data is an ongoing challenge in system health management research and development. While the notion of using real time information to assess the health status of systems or components is good, to obtain sufficient data to establish reliable patterns for diagnosis of health state and prediction of remaining useful life is a common problem for health management research [25][26][27].

The data challenge is especially difficult at a system level when multiple mechanisms work together to deliver a system function. The degradation of one mechanism could be compensated by others to achieve the required performance, hiding information that may indicate failures. Flight control systems powered by EMAs is a good representative of this type of systems.

1.3 Research Aim

This research aims to address this gap by proposing an approach to generate high-fidelity data for health management research. The EMA powered flight control system is the use case example. The research proposes and develops a framework that simulates scenarios of different operations and multiple failures with a Digital Twin (DT) that represents a flight control system powered by EMA and generate fault and performance data to support system health management research.

This approach is a foundation for future developments in the integration of EMAs into critical aerospace systems; and could be extended to model other complex systems for health management research.

1.4 Research Approach

The approach used DT concepts to build physical-representative simulation model based on engineering principle and product specification. The DT model closely mirrors the operational characteristics of EMAs. The model is developed with open-access software. The model was then combined with software

modules including scenario demonstrator, event injector, control script as a data generator. The simulation of scenarios focuses on capturing the complex interplay under different operational statuses between electrical, mechanical, and thermal management components within the actuator, as well as the interactions and dependencies between the electrical, mechanical circuits, and control circuit.

Once evaluated, the approach to develop the EMA model could be the framework of other health management researchers.

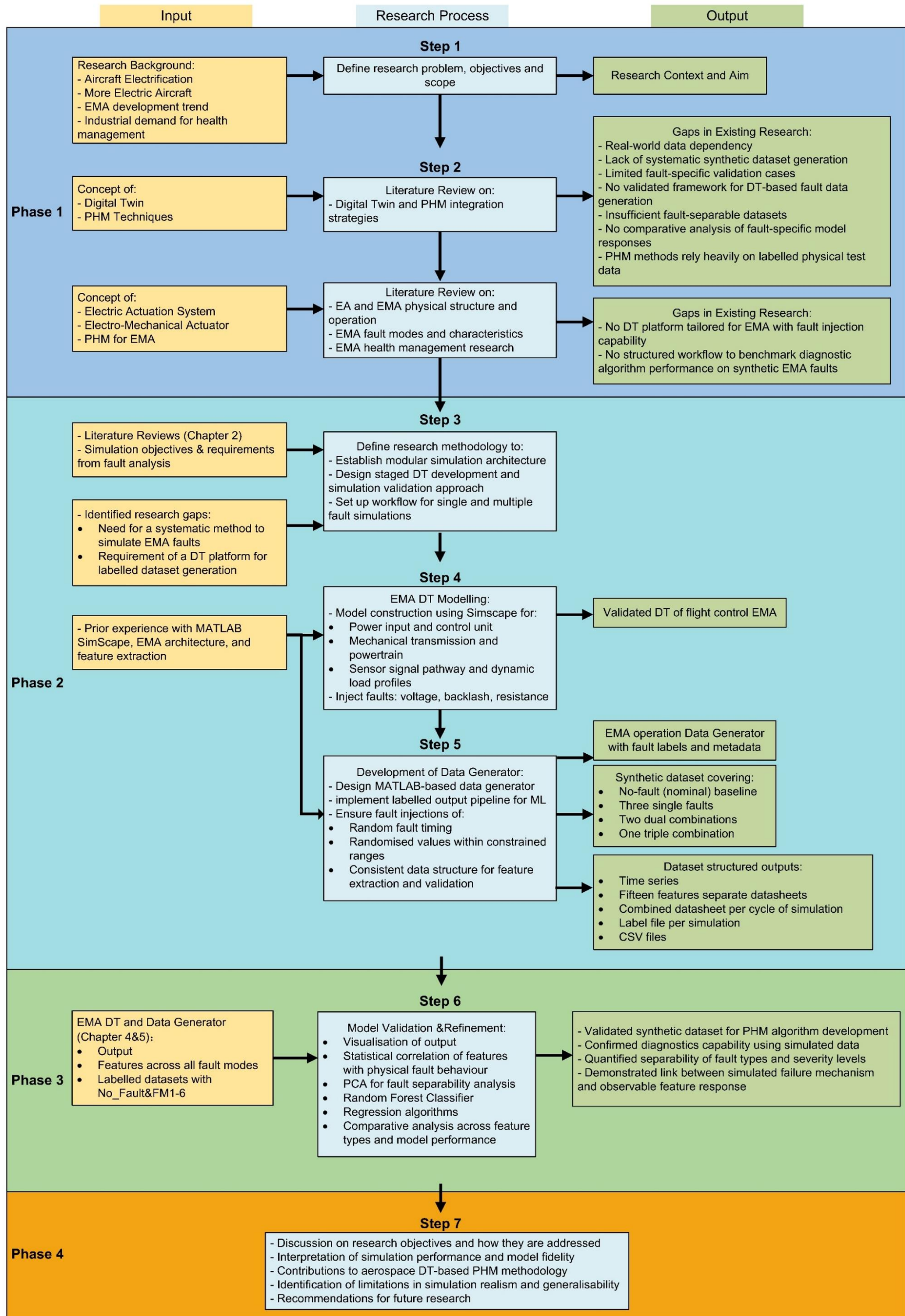


Figure 1.4-1 Research approach of this work

1.5 Research Objectives

To achieve the research aim, this thesis sets out the following five specific objectives:

Objective 1:

A Literature Review to understand the existing knowledge and define gaps between:

- a) DT principle and application in industries.
- b) DT in system health management research.
- c) EMA fault diagnostics and prognostics research approaches.
- d) fundamentals of different types of EAs at component and system level.
- e) failure characteristics of EMA at component and system level.

Objective 2:

To define simulation environment and scenarios with sufficient complexity to:

- a) represent EMA operations in different stages during a flight.
- b) choose key failure characteristics to represent fault situations.

Objective 3:

To develop a flexible data generation framework that integrates the EMA model, scenario control, fault injection, and automated labelling, producing machine learning-ready datasets for PHM research.

Objective 4:

To extract, analyse, and evaluate key health-related features from the generated data, identifying which signals and combinations are most effective for fault detection and diagnosis.

Objective 5:

To validate the usefulness of the synthetic datasets through engineering reasoning and machine learning methods, and to demonstrate the generalisability of the framework for future extensions.

1.6 Research Scope

The research case study is an EMA used in the inner flap of an Airbus 350 XWB. No proprietary data is used in this work. Publicly available data from EMA suppliers, engineering handbooks, literature and domain experts are the knowledge sources. The research studies and simulates the nominal, degradation, and fault operations of EMA at subsystem/component level.

Assumption: A singular EMA can provide equivalent torque/force as the EHA to drive the inner flap. In the nominal situation, the operation of full extension and retraction can be satisfied.

1.7 Thesis Structure

This thesis is structured into nine chapters. The first chapter introduces the general background, aim, objectives, scope, and potential contributions of the research.

Chapter 2 provides a Literature Review of relevant domains, including the principles and applications of DT technology, the evolution from hydraulic to EA systems, EMA components and failure modes, and current approaches to EMA health management and simulation. This Chapter identifies the research gap that the thesis addresses.

Chapter 3 presents the methodology used for developing a modular EMA DT and simulation framework using MATLAB SimScape. It describes the design of fault scenarios, feature extraction strategies, and the logic for data generation and labelling, including both single and multiple fault cases.

Chapter 4 details the development of the EMA DT model. It explains the design of electrical, mechanical, and control subsystems and how they are integrated into a fault-injectable, data-generating simulation environment. Subsystem specifications and modelling assumptions are also discussed.

Chapter 5 describes the architecture and implementation of the data generation framework. It outlines the role of supporting MATLAB scripts for random fault injection, scenario definition, simulation automation, and structured data export for machine learning applications.

Chapter 6 presents the results of fault simulations. The effects of each fault mode on system performance are analysed, and key features are evaluated for their ability to distinguish nominal, degraded, and fault conditions. Examples of output data, fault labels, and computational time consumption are presented.

Chapter 7 evaluates the diagnostics usefulness of the generated data. It explores feature trends, fault separability, and the performance of supervised learning models trained on synthetic datasets. These experiments validate the framework's effectiveness in supporting health monitoring and diagnostics.

Chapter 8 discusses key findings, research contributions, and the fulfilment of the stated objectives. It highlights the scientific and engineering implications of the developed framework and compares it to existing approaches. The Chapter also reflects on limitations and generalisability.

Finally, recommendations for future work are provided in chapters 9 and 10.

2 LITERATURE REVIEW

(This Section draws partly on previously published work by the author in PHM Society 2022, SAE AeroTech 2023, and IEEE WCNC 2025)

This chapter presents the collation of knowledge to establish the state-of-the-art in the use of Digital Twin, aircraft health management and the data challenge, and the engineering focus of this work in EA systems.

Section 2.1 reviews DT technology, including its principle, pros, and cons. The review provides a particular focus on the use of digital solutions and DT in operation and health monitoring of complex engineering systems that are directly relevant to the design of the EMA-represented model and data-generation framework developed in this thesis.

Section 2.2 discusses the advantages and limitations of EA systems in aircraft compared to traditional Hydraulic Servo System (HSA).

Section 2.3 introduces the working principle and variants of EHA. This section highlights the transferable knowledge from HAS to EHA, emphasising advantages such as reduced weight and improved distribution, which support the growing role of EMA.

Section 2.4 introduces the working principle and structure of EMA, forming the foundation for following model design chapters.

Section 2.5 introduces and discusses in detail the failure characteristics and potential features that may have strong correlations or indications from perspective of data.

Section 2.6 evaluates and reviews the development progress of EMA simulation, modelling, and digital transformation methods towards health monitoring. The outcome summarises key features for focusing and simulating, as well as concerns raised for further development and implementation with new technologies.

Section 2.7 addresses the research gap and research focus.

2.1 Digital Twin

2.1.1 Principle and motivation

2.1.1.1 Origin

The NASA's Apollo space program was the first program to use the "Twin" concept [29]. Two identical space vehicles were built in the program, so that the space vehicle on earth can mirror, simulate, and predict the conditions of the other one in space. The vehicle remained on earth was the twin of the vehicle that executed missions in the space.

The concept and model of the DT was first publicly introduced in 2002 by Michael Grieves [28] as a technique for Product Lifecycle Management (PLM) [29]. Initially, DTs are recognised as an information system. The motivation of creating DTs is to develop a life-long asset information visualising technique for asset-intensive industries. This is why a DT is described, in many research articles, as the virtual information integration of a physical asset. In 2012, the concept of DTs was revisited and further defined by the NASA as a multi-physics, multiscale, probabilistic, ultra-fidelity simulation that reflects, in a timely manner, the state of a corresponding twin based on the historical data, real-time sensor data, and physical model [29]. According to Gabor [30][31], DTs can be multi-scaled simulations built based on the expert knowledge and real data collected from existing system, to realise a more accurate simulation and representation of the system. The DT integrates sensor data from the vehicle's on-board IVHM system, maintenance history and all available historical and fleet data. By combining this information, the DT continuously forecasts the health of the vehicle or system, the remaining useful life, and the probability of mission success.

The need for an accurate and efficient health management system has become important in safety-critical and mission-critical aerospace systems [32]. The most important goal of health management is to constantly monitor the performance of these aerospace systems, identify faults (diagnosis), predict possible failures in the near future, and quantify remaining useful life (RUL, prognosis) in order to aid online decision-making. These component-level mathematical models can be

constructed either using laws of physics (physical-based models) or using data collected through component-level testing (data-driven models) and are used for both system-level diagnostics and prognostics.

Based on above discussion, DTs have been applied in the context of the Prognostics Health Management (PHM) techniques. However, traditional DT mainly focuses on the geometric modelling and physical modelling, while it rarely considers the behaviour modelling and rules modelling.

2.1.1.2 Model-Based Digital Twin

A Model-Based Digital Twin (MBDT) is a digital representation of a real-world system or process that is based on a mathematical or computational model [28]. It is a virtual replica of the real-world system that is built using principles of physics, engineering, or other scientific disciplines. The goal of a MBDT is to simulate and predict the behaviour of the real-world system in order to optimise its performance, improve efficiency, and reduce costs. By building a virtual model of the real-world system, organisations can evaluate and optimise different scenarios and configurations to identify the best course of action. This can help organisations make more informed and accurate decisions and improve the efficiency and performance of their operations.

2.1.1.3 Data-Driven Digital Twin

Data-Driven Digital Twin (DDDT) extends the concept of a digital representation of a real-world system, process, or product to one that is powered by data and analytics [28][30]. It is a virtual model of a physical entity that is constantly updated with real-time data from sensors and other sources. By constantly updating the DDDT with real-time data, organisations can gain a better understanding of the performance and behaviour of their systems and use this information to make real time decisions and improvements.

2.1.2 DT Applications

2.1.2.1 Smart Manufacturing

Modern manufacturing requires physical and digital interaction in a closed-loop manner and the digitalisation of manufacturing systems consolidate the basis of

smart manufacturing [34]. Manufacturing is one of the industries where the DTs are successfully used in terms of maintenance and operations monitoring and optimisation. As discussed by Kritzinger *et al.* [35], the DT can help simulate and optimise the production system, from single components to whole assembly. In detail, DTs support production planning, control, and maintenance, as well as manufacturing platform layout planning to gain increased competitiveness, productivity, and efficiency.

At the product level, process monitoring, and virtual modelling are aspects attracting researchers' attention. Zheng *et al.* [36] established a three-layer DT model for geometric feature inspection of car body-in-white. The model consists of a DT workshop layout as data object and source controller, a DT real-time mapping module as data collector and simulator, and a DT pattern recognition module as data transformer and demonstrator. Botkina *et al.* [37] developed a DT of a cutting tool by collecting data throughout the production lifecycle. The data format and structure, information flows between physical tool object and the DT assets are main aspects the authors focused on. Zhang *et al.* [38] applied a DT-based solution to the hollow glass production line by merging, transforming, and distributing real-time data to generate an authoritative DT model.

At the level of manufacturing platform, Tao and Zhang [39] proposed a virtual shop-floor concept by establishing a DT expanding its four key components: physical shopfloor, virtual shopfloor, shop-floor service system, and shop-floor DT data.

2.1.2.2 Aviation

DT application for aircraft can be split into different categories by application scenarios.

For aircraft maintenance, DT-based predictive maintenance can significantly add value to condition-based maintenance as part of Integrated Vehicle Health Management (IVHM) by offering data supporting normal, degradation and abnormal operations [40].

For aircraft system operation DTs, Li *et al.* [41] proposed a concept developing a prognostics DT based a dynamic Bayesian network to monitor health status of aircraft wings. Seshadri and Krishnamurthy [42] focused on structure status monitoring and health assessment management and developed a DT-based structural health management tools, which enables accurate detection. It also provides a foundation to employ on-board and in-flight condition monitoring and prognostics. Tuegel [43] assessed an Airframe DT in assisting of designing and maintaining airframes. Xu *et al.* [44] proposed a DT-driven analysis framework for optimising gas exchange system of 2-stroke heavy fuel aircraft engine. Within this DT framework, multiple modules interact with their targeted physical entities of engines and work collaboratively within the group.

2.1.3 Benefits of DT in Aviation

The use of DTs brings benefits across various aspects of aviation, notably in decision-making, maintenance, safety, operations, and customer experience.

Decision-making and optimisation [29][34]. One main advantage of DTs is that it allows organisations to make more informed and accurate decisions. By constantly updating the DT with real-time data from sensors and other sources, organisations can gain a better understanding of the performance and behaviour of their systems, processes, and products. This rich data stream enables more precise and informed decisions, optimising operations, pinpointing inefficiencies, and enhancing the overall functionality of the physical entity. As a virtual test platform, DTs significantly expedite the verification and validation processes, thus shortening development cycles.

Improved maintenance and repair [31]. In terms of maintenance and repair, DTs stand as a critical solution in predictive maintenance techniques. They allow for continuous monitoring of aircraft systems and components, enabling organisations like OEMs, airlines, or third-party operators to proactively address potential issues, scheduling maintenance before problems appear. This proactive approach not only minimises downtime but also strengthens aircraft reliability, which in turn elevates customer satisfaction and reduces operational costs. For

instance, monitoring the wear and tear of aircraft engines via DTs can forestall engine failures and enhance overall aircraft reliability.

Enhanced safety and risk management. By continually tracking the performance and condition of aircraft systems, operators can pre-emptively identify and address safety concerns, thereby averting accidents and incidents. DTs further contribute to risk management by anticipating and mitigating the impacts of disruptions like adverse weather or equipment failures.

Optimised flight operations [31]. The role of DTs extends to optimising aircraft and fleet operations. By analysing data on flight routes, fuel consumption, and weather patterns, DTs help in identifying cost reduction and efficiency enhancement opportunities. They also hold potential in refining aspects like crew scheduling, aircraft utilisation, and passenger experience.

Improved customer experience [39]. DTs significantly uplift the customer experience by providing real-time information that can be used to enhance the front-end passenger experience. They enable a deeper understanding of customer preferences from pre-flight to post-flight, allowing airlines to customise their offerings to individual customer needs. This personalisation of services and products marks a significant leap in tailoring the aviation experience to individual preferences.

2.1.4 DT Adoption Challenges

Data quality and accuracy [30][45]. A significant challenge in the application of DTs for predictive maintenance is the quality and accuracy of data. Effective DTs rely on high-quality data that mirrors the actual performance and condition of the real-world system. If the data is flawed or unreliable, the DT might offer incorrect predictions, leading to poor maintenance decisions with severe consequences like component failures or system downtime. Ensuring data quality and accuracy is thus vital for the efficacy of DTs. The vast amount of data generated by aircraft, as highlighted by Badea et al. [45], indicates the need for further research in big data management, particularly considering that an average Boeing 737 generates 40 terabytes of information per hour on a six-hour flight.

Data standards to facilitate collaborative interaction and association [39]. A perennial issue in data-related technology is the lack of standardisation across various systems and equipment. A DT must integrate and analyse data from diverse sources, but this is complicated when the data from different systems are structured differently. Overcoming this challenge may require investments in data standardisation and integration technologies. Abdallah and Fan's [46] proposition of an ontology knowledge management concept for supporting full digitisation in aircraft operations and maintenance underlines this need.

High upfront cost [22]. The high upfront costs of building and maintaining a DT pose a significant challenge, especially for large and complex systems such as Environmental Control Systems (ECS) and propulsion systems. This investment in hardware, software, and data analytics capabilities can be a substantial burden for organisations with limited resources and often necessitates a long-term commitment to realise a return on investment. Moreover, the complexity of the real-world systems represented by DTs and the intricacies of data sources and analytics tools add to the challenge of effectively implementing and maintaining a DT for predictive maintenance.

Beyond these general technical and economic challenges, the aviation sector faces an additional layer of complexity: the requirement for system redundancy and certification compliance. This aspect is fundamental to aircraft system design and imposes further constraints on DT adoption.

Aircraft safety and certification plays a crucial role in the design, development, and implementation of aircraft systems, and it poses significant challenges when new techniques, such as DTs, are employed. The representation of an aircraft subsystem by DTs and the compatibility between DTs and predictive maintenance techniques are areas that have not been extensively addressed in the literature.

2.1.5 DT in System Health Management

Current System Health Management (SHM) research mainly emphasises feature extraction and threshold-based diagnostics. By constructing virtual replicas of physical systems, DTs facilitate real-time monitoring, diagnostics, and decision-making. Despite their potential, the application of DTs in SHM remains underdeveloped. The challenges for effective use of DTs for SHM include real-time adaptability, multi-physics integration, advanced prognostic and prescriptive capabilities, data accessibility and quality, scalability, human-system interaction, uncertainty quantification, cybersecurity, and cost considerations. Addressing these limitations necessitates an integrated approach that leverages advanced Artificial Intelligence (AI), multi-domain modelling, and robust data frameworks [47][48][49].

One of the most critical challenges in DT-based SHM is the lack of real-time adaptability and dynamic learning capabilities. Effective SHM requires continuous monitoring and adaptation to evolving system states, environmental conditions, and operational contexts. However, many DT implementations rely on static models or predefined thresholds, which are inadequate for capturing the dynamic nature of real-world degradation processes and failure modes. To overcome this limitation, DTs must integrate real-time data streams, self-learning algorithms, and feedback mechanisms [49]. Advanced ML techniques, such as transfer learning, and reinforcement learning, can significantly enhance the predictive accuracy and adaptability of DTs. By incorporating these capabilities, DTs can transition from reactive tools to proactive enablers of SHM [50].

Another significant gap lies in the insufficient integration of multi-physics and multi-scale models within DT frameworks. SHM necessitates a comprehensive understanding of interactions between mechanical, electrical, thermal, and other domains, as well as the interplay between component-level and system-level behaviours. However, many DTs focus on single-domain simulations, which fail to capture the holistic nature of complex systems [51]. Developing multi-physics and multi-scale models is computationally intensive and requires substantial domain expertise. Hybrid modelling approaches, which combine physics-based

simulations with data-driven techniques, offer a promising solution by leveraging the strengths of both theories [48]. Additionally, scalable computing architectures, such as cloud-based platforms and edge computing, can support the integration of multi-domain models into DT frameworks [52].

While DTs work in diagnostics, their prognostic and prescriptive capabilities remain limited. SHM requires not only the identification of current issues but also the prediction of future failures and the provision of actionable intervention recommendations [49]. Prognostics involves modelling degradation processes and quantifying uncertainties, which are often absent in current DT implementations. Prescriptive analytics, on the other hand, requires seamless integration with decision-support systems to translate insights into meaningful actions. Enhancing DTs with advanced prognostic algorithms, such as Bayesian networks and deep learning for time-series forecasting, can improve their ability to predict system health trends [50]. Furthermore, integrating DTs with decision-making frameworks can enable prescriptive actions, such as optimised maintenance schedules and operational adjustments, thereby bridging the gap between diagnostics, prognostics, and prescriptive analytics.

Data quality, availability, and integration pose fundamental challenges for DT-based SHM. High-quality, high-frequency data from sensors, historical records, and operational logs are essential for accurate health monitoring. However, data silos, missing data, and noise often limit the effectiveness of DTs [49][53]. Integrating heterogeneous data sources, such as IoT sensors, maintenance logs, and environmental data, into a unified DT framework is a non-trivial task. Data preprocessing pipelines and data fusion techniques are necessary to ensure that DTs have access to reliable and comprehensive data. Moreover, edge computing can be leveraged to process data closer to the source, reducing latency and improving real-time capabilities. By addressing these data challenges, DTs can provide more accurate and timely insights for SHM [47]. Recent literature recognises this challenge and supports the use of simulation-generated data as a legitimate and valuable foundation for DT development. Glaessgen and Stargel anticipated that high-fidelity simulation could complement real asset data in future

DTs [29]. Rasheed et al. [54][55] advocated for hybrid DT architectures, where simulated data supports training, validation, and exploration of rare fault modes. Wu and Li [56] proposed a Dynamic DDDT entirely based on synthetic data for aero-engine degradation modelling, demonstrating comparable diagnostic performance. Zio further emphasises the use of simulation in contexts lacking historical failure records, especially for prognostic model development [49].

Table 2.1-1 Compare between data source: historical data and data generators

Factor	Historical Data	Data Generators
Reliability	High (if available)	Moderate (depends on accuracy)
Coverage	May not all failure modes have captured	Can simulate rare failure cases
Adaptability	Limited to past conditions	Can generate new scenarios
Realism	Captures real-world variability	May miss unforeseen failure patterns
Computational Cost	Low (once collected)	High (if using complex simulations)

The feasibility of training DTs depends significantly on the availability of historical data or alternative data-generation methods. Historical data is critical for accurately modelling system behaviour, detecting degradation trends, and predicting failures [58]. It provides real-world insights into past system performance and failure modes, making it indispensable for developing dependable SHM algorithms. However, in many industries, historical failure data is scarce due to high system reliability, sensor limitations, or data privacy restrictions. When historical data is insufficient, data generation techniques can serve as a viable alternative. Physics-based simulations, such as computational fluid dynamics (CFD) and finite element analysis (FEA), can generate synthetic operational and failure data. These methods are particularly useful for modelling complex failure scenarios that are rarely observed in real operations. Additionally, generative AI, such as generative adversarial networks (GANs) and variational autoencoders (VAEs), can create realistic failure patterns for training predictive models. Data augmentation techniques, including noise injection and interpolation, can also expand limited datasets, improving model robustness [59].

Both approaches, historical data and data generation, have strengths and limitations. Historical data provides real-world variability but may be incomplete or inaccessible, whereas generated data can supplement missing cases but requires validation against real-world conditions [50][60]. A hybrid approach, combining historical data with physics-based simulations and AI-generated data, could be an effective strategy. Validating synthetic data against real-world observations ensures credibility, and combining physics-based models with machine learning enhances DT adaptability. By leveraging both real and synthetic data, DTs can achieve higher accuracy, robustness, and generalisability in SHM applications [57].

Scalability and interoperability are additional barriers to the widespread adoption of DTs for SHM [47]. Many DTs are designed for specific systems or components, making it difficult to scale them across larger systems or integrate them with other digital tools. Adopting open standards, such as ISO 23247 for DT frameworks, and modular DT designs can help ensure scalability and interoperability. By enabling seamless integration with existing systems and tools, DTs can become more accessible and effective for SHM applications.

In conclusion, while DT technology holds potential for system health management, several gaps must be addressed to fully realise its capabilities. These include the need for real-time adaptability, multi-physics integration, advanced prognostic and prescriptive capabilities, improved data quality and integration, scalability and interoperability, human-centric design, uncertainty quantification, cybersecurity, and cost-effectiveness. Addressing these challenges requires a multidisciplinary approach, combining advancements in AI, IoT, and human factors engineering. Additionally, an effective data strategy, balancing historical data with synthetic data generation, is crucial for training DT models that can support robust health management decisions. By bridging these gaps, DTs can evolve from passive monitoring tools to proactive, predictive enablers of system health management, ultimately improving system reliability, safety, and operational efficiency.

Table 2.1-2 Key gaps in DT for SHM from Ref. [47] to [53] and [57] to [60] and their corresponding solutions with remark of Data Generator proposed in the thesis

Aspect	Key Challenges	Potential Solutions	Data Generator
Real-time adaptability	Static models struggle to capture evolving system conditions.	Integration of real-time data streams, self-learning AI, and feedback loops (e.g., transfer learning, reinforcement learning).	Real-time command, simulate, signal acquisition. Near-time data storage.
Multi-Physics & Multi-Scale Modelling	Single-domain DTs fail to capture holistic system interactions.	Hybrid modelling combining physics-based and data-driven approaches, cloud and edge computing for scalability.	Physical-referred & multi-scale simulation
Diagnostics, Prognostics & Prescriptive Capabilities	DTs work in diagnostics but lack predictive and intervention abilities.	Bayesian networks, deep learning for failure prediction, integration with decision-support systems for maintenance optimisation.	Open-port provided to interact with the simulator.
Data Availability & Integration	Limited access to high-quality, high-frequency operational and failure data.	Data fusion techniques, edge computing, preprocessing pipelines to improve reliability and accessibility.	Real-time command, simulate, signal acquisition. Near-time data storage.
Historical Data vs. Data Generation	Historical failure data is scarce and incomplete.	Hybrid approach combining historical data, physics-based simulations, generative AI, and data augmentation for robust model training.	Real-time command, simulate, signal acquisition. Near-time data storage.
Scalability & Interoperability	DTs are often system-specific and difficult to integrate with existing tools.	Adoption of open standards (e.g., ISO 23247), modular DT designs, seamless integration with CMMS and ERP systems.	Open-port provided for flexible modification.
Human-System Interaction	DT insights are often not easily interpretable for operators and managers.	Intuitive visualisation tools, decision-support dashboards, and training programs for end-users.	Open-port provided for interactions and flexible modification. Platform-based data scope provides easy access.
Uncertainty Quantification	Lack of confidence in DT predictions due to unquantified uncertainties.	Monte Carlo simulations, Bayesian inference to provide confidence intervals and risk assessments.	Secure and flexible data access for validation, quality check and verification
Cybersecurity & Data Privacy	DTs are vulnerable to cyberattacks due to constant data exchange.	Encryption, secure communication protocols, compliance with regulations (e.g., GDPR, CCPA).	Secure and flexible data access for validation, quality check and verification
Cost & Resource Constraints	High costs limit DT adoption, especially for SMEs.	Cloud-based platforms, open-source tools, modular architectures to reduce costs and improve accessibility.	Platform-based provides cost-effect access and training expense. Accelerates R&D and evaluation processes.

2.2 Replacing Hydraulic Actuation with Electrical Systems

This section discusses the advantages and limitations of EA system compared to traditional centralised hydraulic actuation system.

The conventional centralised hydraulic actuation is a reliable and established solution, with its operational characteristics thoroughly understood from years of experience and application in the field of aviation, from the first ever hydraulic-boosted Lockheed Constellation [61], or the Connie, to modern aircraft such as Airbus 350 XWB [62] and Boeing 777X [63]. There is extensive background knowledge regarding the centralised hydraulic actuation system. Due to civil regulations demanding flight control redundancy, there is a need to include separate hydraulic lines or systems. While this increases both weight and complexity, it also remains vulnerable to failures that can affect all systems simultaneously.

2.2.1 Electrical Actuation Advantage

Electrical actuation system presents design advantages, such as decreased weight and operational vulnerability, alongside enhanced efficiency and so forth. The improvement in efficiency is apparent when comparing traditional centralised systems, which need to stay powered throughout the whole duration of the flight. In contrast, “Power-by-Wire” (PBW) system delivers the precise function required without the issue of supplying excess or reduced power, significantly reducing the continuous losses seen in hydraulic circuits. This approach was first adopted in commercial aviation with the Airbus A380, evolving from the “Fly-by-Wire” (FbW) technology initially used in the Boeing 777. Adopting a similar electric method has been shown to result in a 3% reduction in lifecycle costs and a 6% decrease in gross take-off weight. This shift has accelerated the adoption of more sophisticated controllers, which were previously constrained by the limitations of early-stage hydro-mechanical architecture development [64].

Notable reductions in weight were achieved by using Fly-by-Wire systems, as detailed in Table 2.2-1. Specific examples include the A380, where using electrical signalling has facilitated a 10% reduction in the trim horizontal stabiliser

area. On the A350, electrical signalling enhances aerodynamic efficiency through differential flap setting and adaptive dropped hinged flaps. The decrease in the aircraft's empty weight directly leads to lower ownership and operational costs.

Table 2.2-1 Weight reduction and implementation of Airbus aircraft products [64]

	Model				
	A300-B4	A310	A320	A340	
				A340-200	A340-500/600
Weight reduction	0	-300kg	-200kg	N/A	-50kg*
Implementation	0			-45% of rudder actuator weight**	

*50kg mass reduction is compared to A340-200

**A 45% mass reduction was achieved in A340 series compared to A300.

2.2.2 Electrical Actuation Limitations

Regarding the weakness of EA, the thermal dynamics of the actuator units is a crucial factor since EAs function as localised sources of heat [65]. The requirement for higher electrical quality and the nature of electrical power consumption necessitates a more sophisticated approach to power quality management and the mitigation of electromagnetic interference. Owing to the machine's high torque and the necessity for low mass, thermal management emerges as a principal challenge [65]. With the removal of the hydraulic network, hydraulic fluid, which once serves as a handy method for transporting and dissipating heat produced by the actuation system, is no longer available [66]. From a design perspective, there is a noticeable gap in historical knowledge between hydraulic actuators and electrical ones.

When comparing Electro-Hydraulic Actuator (EHA) with Electro-Mechanical Actuator (EMA), although EHAs are heavier and more complex, they are more compatible for integration alongside centralised hydraulic systems, e.g. a typical example is illustrated in the following Section 2.3.3. Additionally, some of the knowledge from previous component use can be adapted to EHA design. On the other hand, EMAs offer a simpler and lighter alternative but come with own

challenges, including the potential for mechanical backlash and overheating issues. The comparison is summarised in Table 2.2-2.

Table 2.2-2 Comparison between HSA and EA systems.

	Advantage	Limitation
HSA	Stable, mature	Technology saturation
	Time-tested and proven solution	Essentially redundance
	High-amount historical experience	Added weight, complex system
EA	Weight reduction	Thermal dynamics issue
	Operation vulnerability	Increased electrical power requirement
	Improved efficiency	Power quality concern
	Losses largely eliminated by PBW	Electromagnetic interference
	Transferable historical experience	Mechanical Backlash
	Simpler, lighter	

2.3 Electric-Hydraulic/Hydrostatic Actuators

This subsection reviews Electro-Hydraulic Actuator (EHA) and Electro-Hydrostatic Actuators (EHSA), which represent key transitional technologies in the shift from conventional hydraulics to fully electric architectures. Understanding these systems helps clarify the technical evolution leading to their adoption, as mentioned in Section 2.2 the transferrable knowledge benefit. Their principles, configurations, and limitations also provide useful reference points for highlighting the characteristics of EMA.

2.3.1 Electro-Hydraulic Actuation servo system

The EHA system has electric and hydraulic circuits collaborating to drive a hydraulic actuator. According to MOOG, a typical EHA consists of six major

elements (shown as Figure 2.3-1): (1) control electronics (for example, control computer in the cockpit, or guidance system) to create command input signals; (2) servo-amplifier to provide a low power actuating signal, differentiating input signal from feedback signal generated by feedback transducer; (3) servo-valve which responds to actuating signal and controls the flow within the hydraulic circuits to the (4) actuator's piston or cylinder; (5) power supply, normally an electric motor and pump, delivering high-pressure flow of hydraulic fluid within circuits; (6) a feedback transducer measures the position of the actuator (fully extended or retrieve or in progress) and converts this measurement into a proportional signal. The signal will be fed back to the servo-amplifier.

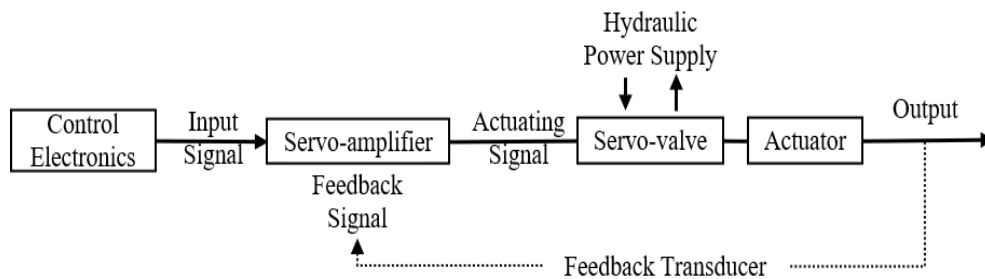


Figure 2.3-1 Schematic of a typical EHA [67]

2.3.2 Electro-Hydro-Static Actuation system

The EHSA employs an electric motor to drive a bidirectional hydraulic pump of typically fixed displacement by adjusting its steering and flow output. This completely self-contained system combines electric and electrohydraulic actuation elements. It receives power from an electric source and command signal input (controls from cockpit via PbW) to effect motion. A typical EHSA includes a servomotor, hydraulic pump, accumulator, and servo-actuator, shown as Figure 2.3-2.

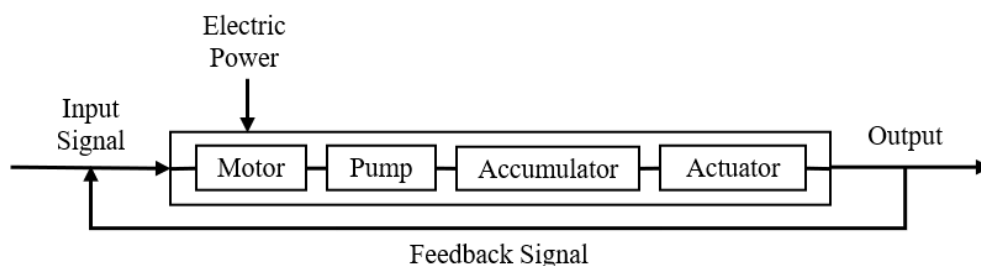
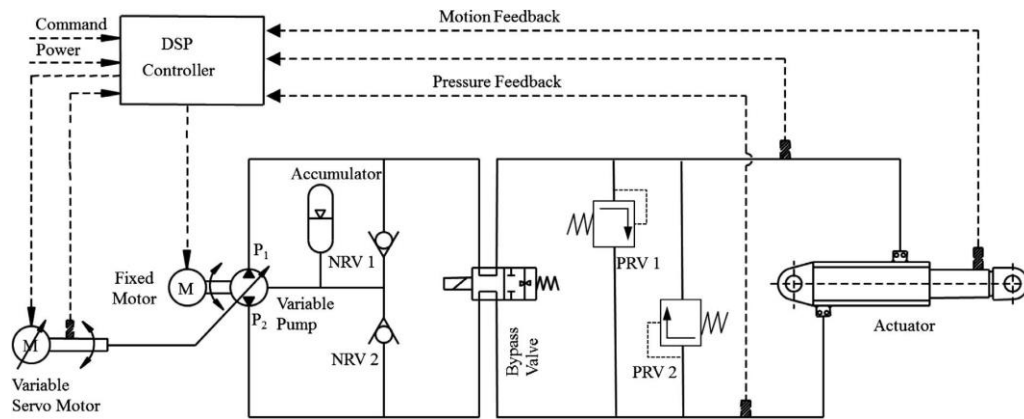


Figure 2.3-2 Schematic of a typical EHSA [67]

Compared with EHA, the servo motor, or a stepping motor, is controlled by the input signal (target command signal) and feedback signal, suitably power amplified.

2.3.2.1 EHSA-VPFM

The EHSA-VPFM (Variable-displacement Pump and Fixed-speed Motor) (shown as Figure 2.3-3) employs a fixed-speed motor and a servo motor to control the swash plate angle of the axial piston pump and pump displacement [68].



DSP - Digital Signal Processing; NRV – Non Return Valve; PRV – Pressure Relief Valve;

Figure 2.3-3 Schematic of an EHSA-VPFM [68]

2.3.2.2 EHSA-FPVM

The EHSA-FPVM (Fixed-displacement Pump and Variable-speed Motor) (shown as Figure 2.3-4) has slower dynamic response than EHSA-VPFM, whilst the efficiency is relatively higher [69], and benefits from simple structure. In this system, a bi-directional pump rotates at variable speeds and directions driven by an electric motor. As a result, the oil flow and supply pressure are variable to drive the symmetrical actuator.

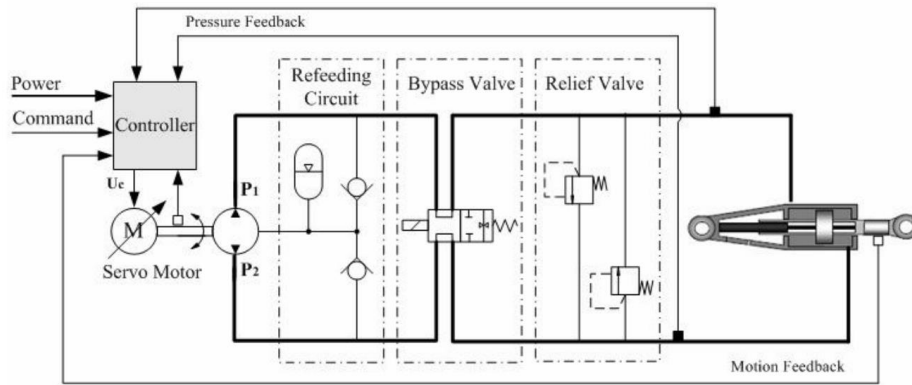


Figure 2.3-4 Schematic of an EHSA-FPVM [69]

Kang et al. [70] proposed a block diagram modelling method of the EHSA-FPVM to address concerns mentioned in Section 2.2.2. A nonlinear accuracy model is established by block diagrams, which contains more information than the conventional linear model. The feedback comparison analysis controls the effect of EHSA refueling circuit to reduce the pressure ripple. A gain variable PID controller is introduced and efficiently compensates the friction. Huang et al. [71] researched on a novel configuration, Active Load-Sensitive Electro-Hydrostatic Actuator (ALS-EHSA), by adding an active load sensing circuit, which consists of a pressure following servo valve and a shuttle valve, on the EHSA-FPVM system. The proposed ALS-EHSA can reduce motor heating. Thanks to higher impedance, it reaches smaller displacement tracking error, near zero speed.

2.3.2.3 EHSA-VPVM

The structure of an EHSA-VPVM(Variable-displacement Pump and Variable-speed Motor) is shown as Figure 2.3-5 [68]. It consists of bi-directional variable pump, controller sensors, hydraulic system, and two servo motors that adjust the displacement of pump and the rotational speed of the pump, respectively.

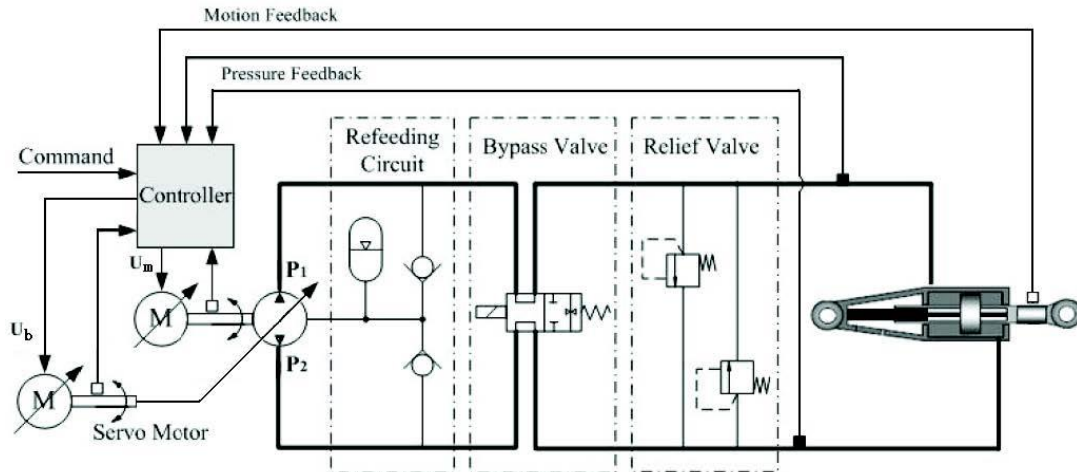


Figure 2.3-5 Schematic of an EHSA-VPVM [68]

2.3.3 Electrical-Backup Hydraulic Actuation system

The Electrical-Backup Hydraulic Actuation system (EBHA) is already used in some aircraft as backup system. It is totally segregated from the normal flight control system and is a combination of a conventional servocontrol and an EHA. In normal mode, it operates as conventional actuator. If there is a hydraulic failure, it operates as EHA.

2.4 Electro-Mechanical Actuator

The EMA system is a distinct category within the domain of motion control technologies, characterised by its ability to convert electrical energy into mechanical force to execute a variety of work. This conversion process is facilitated through the integration of an electric motor with a mechanical transmission mechanism, such as a reduction gearbox or a worm screwdriver, enabling the system to regulate the speed and/or the position of its operational endpoint [72]. EMAs entirely eliminate the need for hydraulic power, reducing the environmental impact, as well as the weight and space required for installation. Table 2.4-1 shows two examples of components' mass reduction of EMAs in the flight control and landing gear systems. Fu et al. [73] introduced a compact gear box-free EMA AMESim model, shown in Figure 2.4-2, which actuates direct driven linear motion, saving weight and claim to offer high potential in geometrical integration. The results show the EMA can benefit aileron actuation for single-

aisle commercial aircraft with effective management of issues like backlash, heat loss and thermal management.

Table 2.4-1 Contributions of different components to the EMA mass in spoiler and nose-wheel steering [74]

Component	Spoiler*	Nose-wheel steering*
Motor	34%	18%
Brake	6%	14%
Reducer	9%	6%
Bearing	13%	-
Screw mechanism	16%	40%
Housing	22%	-
Rack	-	10%
Power electronics	-	12%

*Note: spoiler is in the Secondary flight control and nose-wheel steering is in the Nose Landing Gear system.

In general, an EMA is comprised of an Electronic Control Unit (ECU), an Electronic Power Unit (EPU), an Electric Motor (EM), a Mechanical Drive (MD) and a position sensor [74].

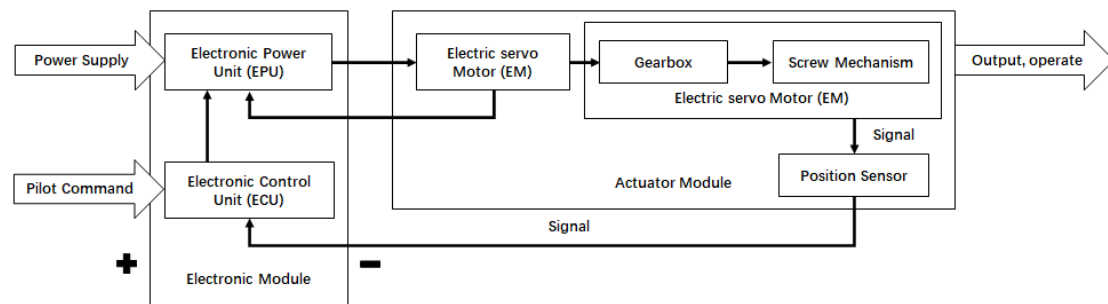


Figure 2.4-1 Schematic of a gear-driven EMA.

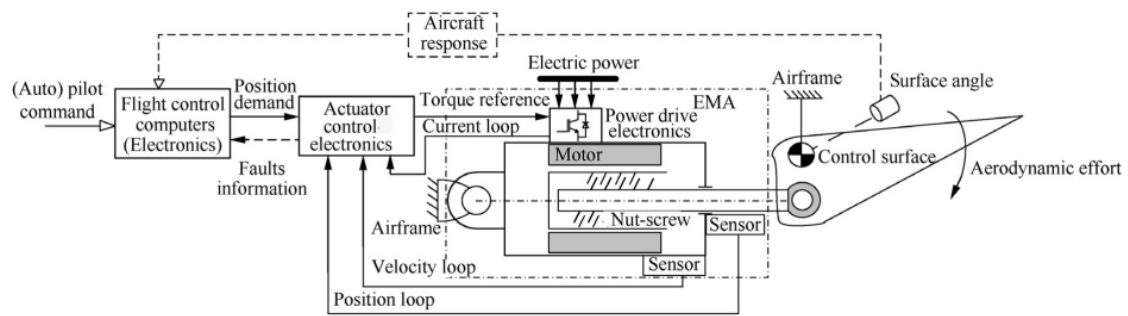


Figure 2.4-2 Schematic of a flight control EMA aileron actuation [74]

Currently, the use of EMAs is confined to secondary flight control on large aircraft. They are used as primary flight control actuators only on small Unmanned Aerial Vehicles (UAVs) and broadly in scenarios where the failure of the actuation system is not critical to the mission or would not lead to the loss of life or loss of expensive flying systems. This situation is partly attributed to the fact that EMA is still a relatively new technology in the aerospace sector: their combined fault modes have not been thoroughly understood, and they generally lack established prognostic methodologies.

A crucial challenge in developing aircraft EMAs is managing the system's fail-safe mode. Historically, hydraulic actuation systems efficiently managed safety through hydraulic components redundancy. However, fault tolerant EMA function must be delivered by a combination of mechanical, electromagnetic, or electrical devices. System robustness requires fault management across various actuator components including power electronics, motors, and transmission mechanisms.

2.4.1 Components of EMA

Figure 2.4-3 shows the major components of and differences between linear and rotary EMAs. Linear EMA is used in flight control is mainly considered in this research.

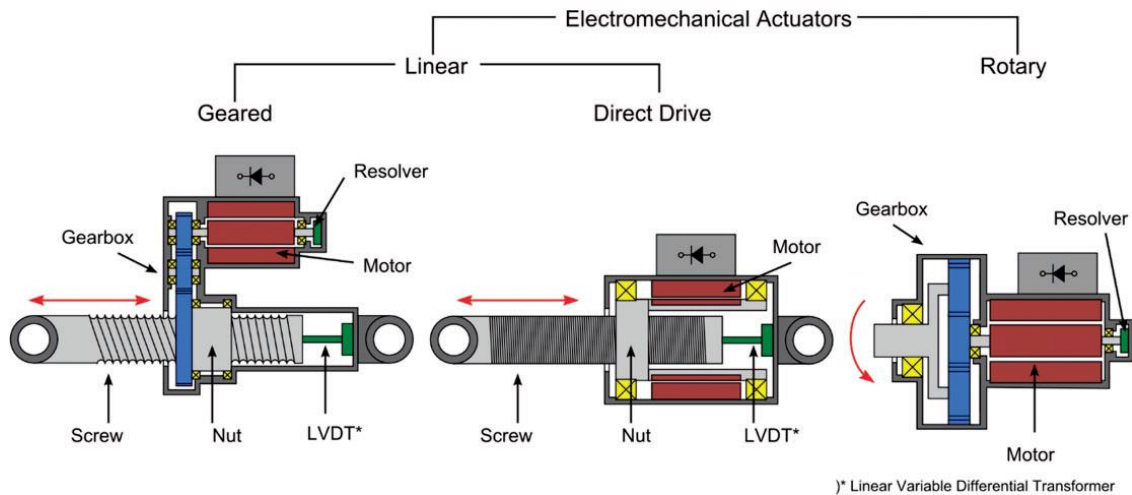


Figure 2.4-3 Classification of different EMA types [75].

2.4.1.1 Electronic Control Unit ECU

Each EMA has a suitable ECU controller, working at 28 Vdc power from external power supply. The ECU receives input command signal from cockpit and transfer to the next processes, including servo motors and EPU. For example, specific voltage input and torque output will be requested by the ECU and transferred to the motor. Additional temperature sensors are usually installed on the controller housing close to the connectors for flight conditions with high external load. This aims at recording the external temperature changes and trigger alarm at high temperature [74].

2.4.1.2 Electronic Power Unit EPU

An Electronic Power Unit (EPU) is a crucial component in the systems, serving as the backbone for power management and distribution. It is designed to convert and control electrical power from one form to another, ensuring that the connected electronic devices and systems receive the correct voltage, current, and type of power they require to operate efficiently and safely. The EPU plays a pivotal role in regulating power supply, protecting systems from power surges, and optimising performance by providing stable and reliable energy.

2.4.1.3 Electrical Motor

Considering the overall volume and mass, as well as long in-flight operation, a compact motor with high reliability and high-power density is required in flight

control. In an electric aircraft, the speed of the motor would be in the range of 16000-24000 rpm or sometimes even higher in order to increase the power density. The choice of motors normally depends on the power supply. Common motor options are Permanent Magnet Synchronous Motor (PMSM), brushless DC (BLDC) motor (a variant of PMSM) and Switched Reluctance Motor (SRM). Excited Synchronous Machines (ESMs) are also considered in some applications.

The BLDC motor can be a suitable choice for flight control, with its advantages in high performance, higher power density than induction motors in same ratings range, and fast acceleration and deceleration. When compared to brushed DC motor, the initial cost of BLDC motor is higher, but it is more economical in the long run owing to their minimal maintenance requirements and high efficiency. The need of complex control, e.g. converting DC to AC to feed the motor, brings in the ECU.

Table 2.4-2 Component of key characteristics for different electrical machine concepts. (-- unfavourable; - disadvantageous; o neutral; + beneficial; ++ very beneficial) [76]

Key Characteristic	ESM	IM	SRM	PMSM/BLDC
Rotor losses	--	O	O	++
Stator losses	++	O	O	O
Windage losses	-	O	--	++
Rotor thermal limitations	O	+	++	O
Colling options	--	O	O	++
Rotor mechanical limitations	--	O	+	++
Torque-to-inertia ratio	O	O	O	++
Compatibility with bearings	-	O	O	++
High-speed capability	--	O	+	++
Short-circuit behaviour	--	++	++	-
Machine complexity	O	+	++	+
Current density	--	+	+	+

Power density	--	+	+	+
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Table 2.4-2 shows the different key characteristics of the electrical machine concepts. Compared with the other machine concepts, the PMSMs are characterised by higher efficiency, higher power density, lower heat production in the rotor, and are capable of sensor-less control, although the magnets are comparatively expensive. Different rotor designs are present for PMSM, i.e., V-shaped buried magnets, beam-like buried magnets, surface-mounted magnets, or multilayer buried magnets. Each rotor design has its benefits concerning flux density, flux distribution, mechanical stability, or weight, and the solution to be addressed depends on the control application. As an example, buried solutions are preferable for obtaining sinusoidal back-electromotive forces (back-EMF), while surface-mounted solutions are suitable for trapezoidal outputs.

The suitability of a motor is often addressed by the power-to-weight ratio. The whole package weight includes the housing, bearings and the related materials. As these can considerably differ depending on the application, the power-to-volume ratio of the motor is considered in some cases, as it is not material dependent.

2.4.1.4 **Gearbox**

If the output of an EMA is rotary, the last component of the kinematic chain will be a gearbox, which is interposed between the motor and the screw providing speed reduction. The main purpose of the gearbox is to decelerate the low-torque servo motor and drive a screw mechanism to reach low speed and high torque. Harmonic gear reducers or cycloidal reducers is commonly used due to its compact structure, ease to achieve zero backlash, high reduction ratio and efficiency.

2.4.1.5 **Screw Mechanism**

If the output of an EMA is linear the last component of the kinematic chain will be a power screw, most often featuring rolling elements. The motor shaft is directly connected to the screw. This mechanism is employed to transform the rotary motion to linear motion with a defined force. The overall weight of the actuator

tends to reduce when the transmission ratio increases (Liscouët et al., 2008) [77]. Higher transmission ratio can cause a decrease in efficiency and imply a higher rotating input speed. Therefore, the balance between the reducer transmission ratio and the lead of the screw mechanism needs to be considered.

2.5 EMA Failure Characteristics of Components

This section focuses on different failures that may occur during operations and the consequent impact the subsystems.

In an EMA, multiple components collaboratively operate to realise certain required commands from the pilot, e.g., the extension and retraction of flaps. Proper operation of these functions depends on stable performance of the components. Random faults happening in one of components could cause failure of the whole system.

2.5.1 Unstable Power Supply

Power generation breakdown is a hidden danger. In the circumstance that one or more of the aircraft's power source fails, and the remaining sources cannot provide sufficient power to maintain the whole system in normal operation until emergency landing would lead to a catastrophe [75]. The constraint frequently imposed by the power supply is the maximum current or kilovolt-amperes which may be drawn during starting. At the design stage, this condition may be addressed either by choosing a lower starting current motor or by use of some form of soft-start device to reduce the current drawn during starting. When considering the power supply constraints, the source impedance must also be considered to ensure that there is sufficient voltage at the machine terminals to overcome the load torque, leaving sufficient torque in hand to accelerate the motor against load.

2.5.2 Overheating

Operating temperature is always a concern on mechanism operation [66]. Considering the transmission mechanism responds to commands and only operates for a short period, mechanical overheating is not a significant risk as the

heat generated from the mechanical interaction , e.g., gear meshing, does not accumulate. Overheating is mainly generated within the electrical servo motor.

There are several reasons for overheating:

Voltage unbalance can produce serious overheating in motors due to the high negative sequence current which flows with a relatively small out-of-balance component. Normally, the motor operates with rated voltage applied and provide rated power. When the voltage applied exceeds its rating, it may generate transient response to pilot's commands and induce emergency. Excessive voltage causes sharp increase in the core magnetic flux density and iron loss and causes the motor to overheat.

Overload is caused by an increase in the load driven by the motor or mechanical backlash in the driven mechanism. Also, mechanical failure happens when rotor and stator are rubbed together, and the rotor is stuck in position.

The lack of lubricating oil or grease causes sleeve bearing damage. Electric motors use either rolling or sleeve bearings of lubricated inner and outer ring metal surfaces to reduce friction. These balls or rollers hold the load and support the motor shaft so that the rotor can rotate smoothly and stably. It is normal to choose bearings which will give a life of 50,000-100,000h running, or even 200,000h on the larger motors. Hence, it is essential to ensure minimum wear in normal operation and achieve sufficient use life. Worn shaft collars could fail to isolate the inner bearing from the outside air. Therefore, air will be absorbed in and deteriorate the lubricant grease, corrode balls or rollers. This issue leads to power fluctuation, and uneven and unstable rotor operation as a result, with excessive heat generated.

The temperature rise of a motor following an exponential function suggests that the rate of temperature increase becomes more rapid over time, assuming no other cooling or limiting factors are introduced. This can be represented mathematically by an exponential growth function, which is typically of the form:

$$T(t) = T_0 \cdot e^{kt} \quad \text{(2-1 Motor Temp Rise)}$$

, where:

- $T(t)$ is the temperature of the motor at time t ,
- T_0 is the initial temperature of the motor at $t = 0$
- e is the base of the natural logarithm (approximately equal to 2.71828),
- k is a constant that represents the rate of temperature increase,
- t is the time.

The constant k is crucial as it determines how quickly the temperature rises. If $k > 0$, the temperature increases over time. The larger the value of k , the faster the temperature rises.

This model assumes that the motor's temperature increases continuously and exponentially due to factors like electrical resistance, friction, or other inefficiencies converting electrical energy into thermal energy. In real-world applications, this exponential growth cannot continue indefinitely as it will eventually be curbed by cooling mechanisms, the motor's thermal capacity, or safety features designed to prevent overheating.

This exponential model is a simplification and might not capture all the nuances of how a motor's temperature changes in operation, especially under varying loads, ambient temperatures, or with different cooling systems in place. However, it provides a useful framework for understanding the potential for rapid temperature increases if not properly managed.

2.5.3 Mechanical Backlash

For HSAs or EHAs, should a fault occur, the hydraulic pressure will be dissipated, and the actuator will automatically switch to a damping mode. In this state, actuators connected in parallel can manipulate the control surface in response to commands from the cockpit without encountering significant problems [78].

However, this scenario does not apply to EMAs, as the backlash of an EMA, for instance, due to a failure of the mechanical screw, could cause the control surface

to become immovable, even if another EMA connected in parallel is functioning correctly. Thus, the issue of mechanical backlash is of paramount importance and requires meticulous attention, as it has the potential to lead to catastrophic outcomes, even in systems designed with redundancy.

The main reason for the failure of flap catching hysteresis is that the maximum driving torque provided by the slewing actuator is unable to overcome the aerodynamic load and the coupling resistance of each component under the condition of satisfying the law of motion [79]. From the kinetic analysis, it can be seen that the sticking reliability of the flap mechanism under different friction coefficients reaches the maximum when the flap deflection angle is in the range of $8^{\circ}\sim 12^{\circ}$, and the results are shown in Table 2.5-1.

Table 2.5-1 Reliability of flap stuck ($[T]=9\text{N/m}$) [80]

Total wear	Coefficient of Friction	Reliability
$\Delta=0.012$	0.14	1
	0.16	0.99456
	0.18	0.81690
	0.20	0.25962
	0.22	0.01658
	0.24	0.00014
	0.26	0

2.5.4 Electric Cable Wear

The extreme environment these devices operating in, e.g., temperature variation and variable pressure levels, can accelerate cable wear in an electric circuit. This may lead to short circuit, higher resistance, overheating or fracture, and loss control in the end [81][82].

The control cables in the wing and nacelle area are near high temperature sources. Contamination or deterioration of insulation material due to environmental exposure will occur at a faster rate than on other control cables.

2.6 Health Management for EMA

The aircraft industry employs electric actuators in multiple systems, including flight control surfaces, landing gear, brakes, and engine control systems. For instance, electric actuators can control the flaps and slats on the wings of an aircraft, providing precise control over the aircraft's lift and drag during take-off and landing. Additionally, electric actuators are ideal for use in modern "Fly-by-Wire" aircraft, which rely on electronic signals to control flight surfaces instead of traditional mechanical linkages. The precise and reliable control provided by electric actuators improves safety and reduces weight and maintenance costs.

Prognostics and Health Management (PHM), refers to the systematic process of monitoring the condition of systems, detecting faults, predicting future degradation, and supporting maintenance decisions [75]. It involves three core tasks: diagnostics (identifying faults), prognostics (predicting future states), and decision support (suggesting actions). This is crucial in various industries to ensure the safety, efficiency, and longevity of machinery and systems [78]. For critical systems like aircraft actuators, PHM enables condition-based maintenance and predictive maintenance, helping to improve reliability, reduce downtime, and lower operational costs.

The four prominent methods used in PHM research include Test Rig, Simulation [83][84], Hardware-In-Loop (HIL), and DT. Each of these methods offers unique advantages and challenges, and they are often used in conjunction to provide a comprehensive understanding of system health and performance.

A test rig is a physical setup designed to replicate the operational conditions of a system or component under study. It allows for the direct measurement and observation of performance under controlled conditions, making it possible to identify potential failure modes and assess the system's reliability. Test rigs are particularly useful for conducting fatigue tests, stress tests, and other forms of durability testing. The primary advantage of using a test rig is the ability to observe real-world behaviours and failures, providing empirical data that is invaluable for validating models and simulations. However, constructing and

operating a test rig can be expensive and time-consuming, and it may not be feasible to replicate all operational conditions.

Simulation involves the use of computer models to predict the behaviour of a system under various conditions. This method allows researchers to conduct experiments that might be impractical or impossible in the real world due to cost, time, or safety constraints. Simulations can range from simple analytical models to complex finite element models that account for detailed material properties and physics. The key advantage of simulation is its flexibility and the ability to quickly evaluate a wide range of scenarios. However, the accuracy of simulations heavily depends on the quality of the models and assumptions made, requiring thorough validation against experimental data [84].

HIL testing integrates physical components with simulated environments, allowing for real-time interaction between the hardware and a computer model simulating the rest of the system. This approach is particularly valuable for testing components of larger systems, such as electronic control units in vehicles, where the component's performance in the context of the entire system is critical. HIL provides a balance between the realism of test rigs and the flexibility of simulation, enabling detailed analysis of hardware behaviour under simulated operational conditions. While HIL can offer more realistic testing scenarios without the full expense of building complete systems, it requires sophisticated simulation models and integration techniques.

A DT is a virtual model of a physical system that is updated with real-time data from sensors and other sources. This approach allows for the continuous monitoring and analysis of a system throughout its lifecycle, providing insights into its current health and future performance. DTs can be used to predict failures, optimise maintenance schedules, and improve system design by incorporating real-world performance data into the model. The primary challenge with DTs lies in the complexity of creating accurate models and integrating real-time data, but the potential benefits for proactive PHM are significant.

Table 2.6-1 Comparison between four methods widely used in PHM

Method	Advantages	Challenges	Preferred Use
Test rig	Direct data	Cost	Durability tests
	Real-world behaviour	Set limitations	
Simulation	Flexibility	Model accuracy	Early design
	Multiple scenarios	Validation required	Theoretical analysis
HIL	Realistic	Sophisticated model	Component testing within system context
	Real-time interaction	Integration complexity	
DT	Continuous monitoring	Model complexity.	CBM, PdM
		Data integration	System optimisation

In practice, a combination of these methods is often used to leverage the strengths of each and provide a more complete picture of system health and performance. By choosing the appropriate method or combination of methods, it is promising that the health of systems can be effectively predicted and managed, ensuring their reliability, safety, and efficiency.

2.6.1 Health Management

Health management begins with the acquisition of physical and control signals that reflect the system's internal state and behaviour. Diagnostic methods analyse these signals to identify anomalies in variables such as current, displacement, torque, and temperature. Characteristic features, including steady-state-deviations, peaks, oscillations, or delays, can indicate faults such as voltage disturbance, mechanical backlash, and abnormal resistance.

Various models and algorithms have been developed to support diagnostics, including statistical classifiers [85][86], frequency-domain transform (e.g., FFT) [86][87][88], entropy measures [88], and machine learning-based decision

boundaries [85][86][87]. These techniques rely on labelled data that correlates specific signal patterns with known fault conditions.

A typical data-driven PHM flow involves the stages is shown in Figure 2.6-1. Common evaluation metrics including P-value analysis and confusion matrices, which are widely used to assess model generalisability and classification performance in multi-fault conditions [85][86].

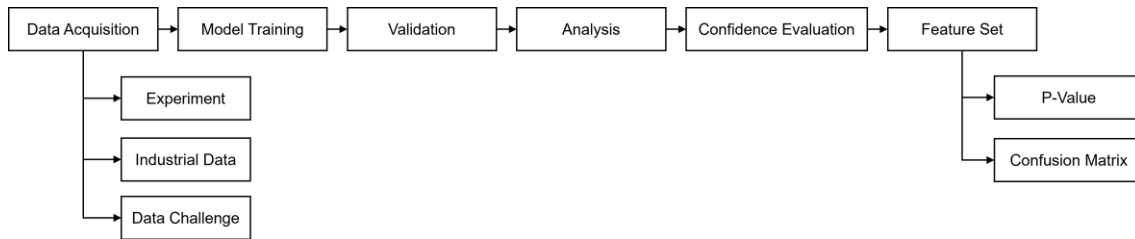


Figure 2.6-1 Typical data-driven PHM workflow [85][87]

While prognostics methods, such as degradation modelling and remaining useful life estimation, are commonly discussed in the context of PHM [89], industrial implementations remain focused on diagnostics. Prognostics typically requires long-term degradation trajectories, which are often unavailable due to limited failure data or high system reliability. Therefore, fault diagnostics continues to serve as a primary focus of health management in many aerospace systems.

For PHM techniques to work well in practice, having good algorithms alone is not enough. The algorithms also need to be trained on suitable data. However, for systems like EMAs, which are still relatively new, historical records of real faults and operational wear are often hard to come by. One way to address this challenge is by generating the needed data through simulation.

To support algorithm development properly, the data needs to follow a clear and consistent structure, usually time-series signals with labels showing what type of fault occurred and when [90]. The data also contain physically meaningful variables that reflect actuator behaviour under different conditions.

It is also important that the data covers different kinds of faults and operating conditions, so that the resulting models are more robust and useful in real applications. This is the reason behind building the DT-based data generator in

this research. The design, the structure of its outputs, and how it is used in later analysis will be explained in Chapters 4, 5, 6 and 7.

2.6.2 Review of EMA Simulation

EMAs have become increasingly significant in the shift toward more electric aircraft architectures, offering advantages such as weight reduction, simplified maintenance, and improved efficiency [73]. As a replacement for traditional hydraulic actuators, the adoption of EMAs necessitates rigorous evaluation of their performance and reliability, particularly under faulty or uncertain operating conditions. Despite the clear advantages in weight reduction, system simplicity, and energy efficiency, EMAs introduce new challenges related to failure modes such as mechanical backlash, electrical resistance drift, overheating, and control system faults. Accordingly, modelling these faults based on features becomes essential for both predictive maintenance and SHM, in which features capture electrical, mechanical, and kinetic responses as studied in Section 2.5. These features serve as diagnostic indicators in both time and frequency domains and are selected based on domain relevance and fault observability. Simulation plays a significant role in this context, providing a safe, flexible, and cost-effective means to explore the behaviour of EMA systems during both nominal and degraded operations.

The simulation of EMAs has evolved through several phases. In the early stages, efforts primarily focused on replicating actuator dynamics under ideal conditions, with limited attention paid to mechanical non-idealities or fault responses. For instance, hybrid actuation concepts incorporating hydraulic backup were explored as early as the mid-1980s. The introduction of modelling platforms such as MATLAB/Simulink and FEA tools in the 2000s enabled the development of more refined EMA simulation models. These models began to incorporate electrical motor dynamics, ballscrew transmission behaviour, and load interactions [93][94][95]. With growing demands for safety assurance and system intelligence, the field gradually shifted toward simulation models that could also support fault diagnostics and health prognostics. Later studies like [96] proposed

hierarchical modelling approaches that linked physical faults with system-level responses, especially in the context of ballscrew jamming.

The current research landscape reveals several focal areas within EMA simulation. A major area of emphasis is the modelling of mechanical jamming phenomena, particularly in the ballscrew assembly. Numerous studies have simulated jamming through abrupt torque spikes, blocked motion paths, or particulate contamination, aiming to replicate both static and dynamic seizure conditions [96]. Another active area concerns the modelling of friction and backlash, both of which contribute to degraded control accuracy and long-term wear. Although friction is widely recognised as a dominant nonlinear effect, its accurate representation remains challenging due to its dependence on temperature, speed, and surface condition [99].

Additionally, researchers have increasingly incorporated control strategies directly within the simulation loop, allowing for closed-loop evaluation of actuator performance under disturbed conditions. These simulations are critical for analysing tracking deviations and transient instability that may arise from control-electromechanical interaction. A smaller but emerging focus has been the inclusion of thermal effects, particularly ballscrew expansion due to internal heating, which can alter load paths and clearance tolerances. However, thermal-mechanical coupling remains relatively underexplored compared to electrical and mechanical domains. In terms of verification and validation, while some models have been supported by laboratory test bench experiments or hardware-in-the-loop simulations, fully validated models under real fault conditions are still scarce. Most validation efforts rely on artificially seeded faults, raising concerns about representativeness and generalisability [99].

Despite these advancements, several challenges remain unresolved. Many simulation models continue to simplify the complex electromechanical coupling inherent in EMA systems, often neglecting nonlinearities or treating fault dynamics in isolation. Such simplifications hinder the ability of these models to represent real-world failure behaviours such as voltage fluctuation, resistance drift, or sensor degradation [77]. Moreover, the lack of access to high-quality

operational and failure data limits the ability to calibrate and validate models, especially for prognostic applications [93]. Another barrier is the high computational cost associated with multi-domain simulations. Incorporating electrical, mechanical, and thermal domains often leads to large-scale, numerically intensive models that are unsuitable for real-time or large-sample analysis [93]. Finally, most studies focus on single-fault scenarios, whereas in practice, multiple fault modes, such as mechanical jamming combined with voltage drops or sensor offsets, may co-exist and interact nonlinearly [99].

Table 2.6-2 Summary of Literature in EMA modelling, simulation and diagnostics

Ref	year	Object	Tech	Application	R&D Subtypes	Gaps	Studied Failure	Failure Scope
[93]	2004	FC EMA	Review	Simulation	EMA Config Design	Model Fidelity	General discussion	N/A
				Modelling		Scalability/Deployment		
[94]	2007	FC EMA	Review	Review	Control Panel	Environment Sensitivity	Friction	Jamming
					Review		Jamming	Wear/Friction
							Stall/overload	
[95]	2008	FC EMA	Analysis	Simulation	EMA Config Design	Environment Sensitivity	Jamming	General Mechanical
					Review		Resistance Change	Fault
							Stall/overload	Jamming
							Thermal Expansion	Resistance Change
[24]	2009	FC EMA	FEA	Simulation	Prototype Establish	Environment Sensitivity	Jamming	General Mechanical
					Applied Validation		Resistance Change	Fault
							Stall/overload	Jamming
							Thermal Expansion	Resistance Change
[97]	2011	Aircraft EMA	Review	Modelling	EMA Config Design	Validation Limitation	General discussion	N/A
				Diagnostics	Control Panel	Hybrid method needed		
					Applied Validation			
[78]	2011	Propulsion EMA	C-MAPSS	Simulation	Prototype Establish	Data Access	Backlash	Backlash
				Modelling	Control Panel	Environment Sensitivity	Jamming	Electrical Fault
				Diagnostics	Applied Validation	Hybrid method needed	Sensor Fault	General Mechanical
				Prognostics	Review		Stall/overload	Fault
							Thermal Expansion	Sensor Fault
								Wear/Friction
[77]	2011	FC EMA	Test rig	Simulation	Prototype Establish	Data Access	Jamming	General Mechanical
			Simulink	Modelling	Control Panel	Environment Sensitivity	Thermal Expansion	Fault
				Diagnostics	Applied Validation	Scalability/Deployment		Jamming
				Prognostics				Wear/Friction
[75]	2011	FC EMA	Review	Applied	Applied Validation	Validation Limitation	General discussion	N/A
				Validation		Data Access		
[98]	2012	General EMA	Review	Modelling	Soft Actuator	Environment Sensitivity	General discussion	N/A
					Review	Hybrid method needed		
[99]	2014	FC EMA	Review	Modelling	EMA Config Design	Validation Limitation	General discussion	N/A
					Applied Validation	Scalability/Deployment		
[84]	2015	FC EMA	Review	Modelling	EMA Config Design	Validation Limitation	General discussion	N/A
					Applied Validation	Scalability/Deployment		
[100]	2016	FC EMA	Review	Review	Applied Validation	Hybrid method needed	Stall/overload	N/A
					Review			
[101]	2017	Robotics EMA	Analysis	Review	Prototype Establish	Environment Sensitivity	Stall/overload	N/A
					Soft Actuator			
					Review			
[96]	2017	FC EMA	Analysis	Simulation	Prototype Establish	Environment Sensitivity	Jamming	Jamming
				Modelling	Applied Validation	Hybrid method needed		
				Diagnostics	Review			
				Prognostics				
[73]	2017	FC EMA	FEA	Simulation	Prototype Establish	Environment Sensitivity	Jamming	Jamming
				Modelling	Applied Validation	Hybrid method needed		
				Diagnostics	Review			
				Prognostics				
[102]	2018	Aircraft EMA	Analysis	Modelling	Prototype Establish	Data Access	Friction	General Mechanical
					Control Panel	Environment Sensitivity	Stall/overload	Fault
					Review			Wear/Friction

[103]	2019	Robotics EMA	Review	Review	Prototype Establish Soft Actuator Review	Hybrid method needed	Stall/overload Voltage Disturbance	Voltage Disturbance
[104]	2019	Robotics EMA	Review	Modelling	EMA Config Design Soft Actuator Review	Environment Sensitivity Scalability/Deployment	Thermal Expansion	N/A
[105]	2021	Aircraft EMA	Neural network Machine Learning	Simulation Modelling Diagnostics Prognostics	Estimation	Hybrid method needed	Control deviation Friction Jamming	General Mechanical Fault Jamming Wear/Friction
[106]	2021	Aircraft EMA	Review/Book	Review	N/A	N/A	General discussion	N/A
[107]	2022	Robotics EMA	Analysis	Review	Soft Actuator Review	Environment Sensitivity	General discussion	Wear/Friction
[108]	2023	FC EMA	Review	Review	Review	N/A	Friction Stall/overload	Wear/Friction

2.7 Research Gap

The development of EMA troubleshooting and remaining useful life prediction needs to use volumes of data of the normal, degradation and failure cases of the components and systems. In engineering domains such as gas turbines, PHM researchers have benefitted from publicly available datasets like NASA's C-MAPSS [78], which provide time-series sensor readings and labels [109].

However, no such datasets exist for EMAs in aircraft applications. The available public datasets either focus on unrelated systems (e.g., turbofan engines) or lack structured fault annotations and domain-relevant features. Moreover, these datasets seldom reflect the electromechanical characteristics unique to EMA systems. This limits their direct applicability to EMA-specific fault diagnosis and remaining useful life prediction, as observed in reviews that emphasise the importance of domain-representative simulation or hybrid models when real-world failure data is rare [49][54].

This lack of application-specific, labelled, and machine learning-ready datasets, represents a major barrier to advancing EMA health management research. Therefore, there is a clear need for a data generation platform that can simulate realistic EMA behaviours under both nominal and faulty conditions, and export structured, labelled, time-series datasets aligned with PHM research practices.

2.8 Chapter Summary

This chapter reviews key concepts in DT technologies and establishes the foundation for modelling and simulating the operation of the EMA in this research. The exploration into the advancements in EA systems, specifically focusing on EMAs within the aviation sector. It outlines the benefits and operational efficiencies of EMAs and contrasts them with different types of EHAs. A significant portion of the chapter is dedicated to discussing PHM techniques for EMAs, and the importance of accurately estimating remaining useful life for maintenance optimisation. The chapter concludes by highlighting the gap in current research, especially in the missing data needed for PHM research for EMA monitoring and maintenance prediction.

3 METHODOLOGY

This chapter presents a two-layered methodology developed for simulating the operation and failure behaviour of aircraft EMAs. The first is to build a representative DT of an EMA used in aircraft. The EMA model, based on SimScape in MATLAB/Simulink, captures the electromechanical dynamics relevant to aircraft flight control applications, with particular focus on flap actuation mechanisms. This model reflects the key physical parts of the actuator and shows how it behaves during both normal and faulty conditions. The second layer uses this DT as a basis to create an efficient data generator. This generator can run different scenarios, inject fault values, and record structured outputs that can be used to train algorithms for system health monitoring. Together, these two layers provide a practical way to create realistic, labelled data in situations where real-world data is not available.

Section 3.1 introduces the overall methodological framework, highlighting the steps from problem definition to data validation.

Section 3.2 outlines the development of the EMA model in SimScape, including its architecture, interfacing strategy, and fault injection mechanisms.

Section 3.3 describes the case study focused on the inboard flap actuator of the Airbus A350XWB and details the physical architecture and operational assumptions.

Section 3.4 summarises the methodology and key contributions of the chapter.

3.1 Methodological Approach

The purpose of the simulation framework developed in this study is to function as a data generator tailored for PHM applications, capable of producing realistic, structured datasets with full fault labelling. The data output format is inspired by leading PHM datasets such as C-MAPSS and PHM Society benchmarks,

enabling easy adaptation to supervised learning, RUL prediction, and fault diagnosis pipelines.

The methodology adopted in this thesis followed a structured engineering approach to systematically develop, operate, and validate the DT used for data generation for health management research. As illustrated in Figure 3.1-1, the process is organised into the following stages:

- **Problem Definition:** The operational objective is to simulate actuator behaviours under both nominal and faulted conditions across multiple flight scenarios. This requires defining target outputs (e.g., current, displacement, voltage) and inputs (e.g., control commands, external disturbances) that the DT must support.
- **Model Design and Platform Selection:** A modular DT architecture was designed to accommodate physical accuracy and computational flexibility. MATLAB/Simulink and SimScape were chosen for their compatibility with mathematic-based module library, multi-domain modelling and automated data export capabilities.
- **Scenario Configuration:** Representative flight phases and fault injection sequences were developed, ensuring realistic operational coverage. The input configurations include load profiles, flight condition timelines, and defined actuator failure modes.
- **Model Development and Integration:** The DT model was implemented by integrating electrical, mechanical, and control subsystems. These MATLAB/Simulink and SimScape components were validated individually and collectively to ensure dynamic coherence.
- **Data Generation:** Simulations were executed to produce structured signal outputs. Each run was labelled according to scenario identifiers and fault

conditions. The output data was formatted and managed to support PHM algorithm ingestion.

- **Validation and Testing:** The generated data was assessed against expected behavioural trends (e.g., signal saturation under jamming). The completeness and correctness of data were verified through both internal checks and comparison with known system responses.

This staged methodology ensures both transparency and scalability, allowing fault coverage to be expanded and diagnostic models to be trained with consistent input-output mappings.

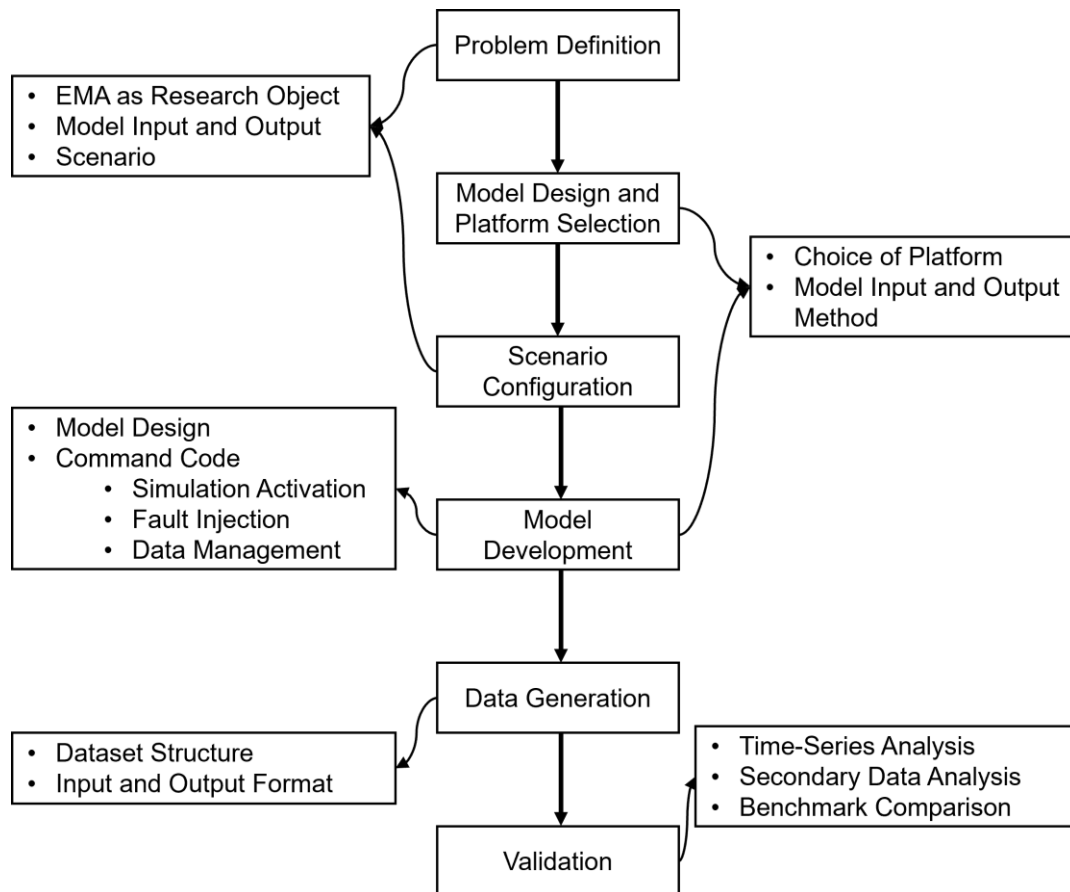


Figure 3.1-1 Overview of methodology in this research

3.2 MATLAB SimScape

SimScape, part of MATLAB's Simulink environment, is a simulation software developed by MathWorks. It provides a modelling and simulation platform for

systems engineering. SimScape enables users to simulate real-world physical systems within the Simulink environment. It extends Simulink's capabilities by offering an intuitive and flexible platform for modelling physical systems across multiple domains such as mechanical, electrical, hydraulic, and thermal systems. Also, it seamlessly integrates with Simulink, providing a powerful environment for combining physical models with control systems and signal processing algorithms.

The physical network approach simplifies the modelling process, making it more accessible to users. By providing a unified environment for multi-domain system simulation, SimScape can significantly reduce development and testing time. The ability to model physical interactions explicitly and handle units and conversions accurately leads to more reliable simulations and predictions. It also enables the exploration of a wide range of design alternatives quickly and efficiently, helping to optimise performance and identify potential issues early in the design process.

SimScape offers a powerful and flexible platform for the modelling and simulation of physical systems, contributing to more efficient and effective engineering processes. Its integration with MATLAB and Simulink further enhances its capabilities, making it a valuable tool for engineers and researchers working on complex systems across a variety of domains.

3.3 Case Study

The case study developed a DT model of an EMA that can provide the equivalent performance of the actuator to drive the inboard flaps of an Airbus 350XWB. The Airbus 350XWB is a modern aircraft with advanced avionics system. With the beneficial design of the Adaptive Dropped Hinge Flap (Figure 3.3-1 [110]) in the flight control system, it enables simplification of the flap kinematics illustrated in Figure 3.3-4 and achieves wing weight reduction [110]. While the current flight control actuation is a combination of conventional hydraulics, EHSA, and EBHA as shown in Figure 3.3-2 [20]. The control avionics architecture as explained in Section 3.3.2 is ready for EHSA, providing the platform for further electric actuators adoption. The inboard flap is the larger control surface and experience the higher mechanical stress and wear amongst the flight control

surfaces. Possible future modifications adopting EMA with precision position control would contribute to further wing and system & structures weight reduction.

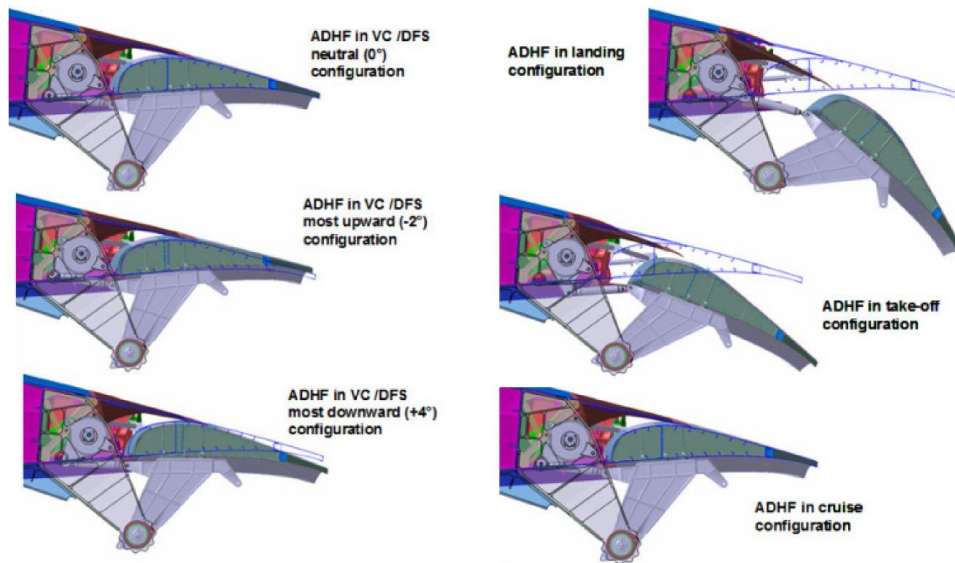
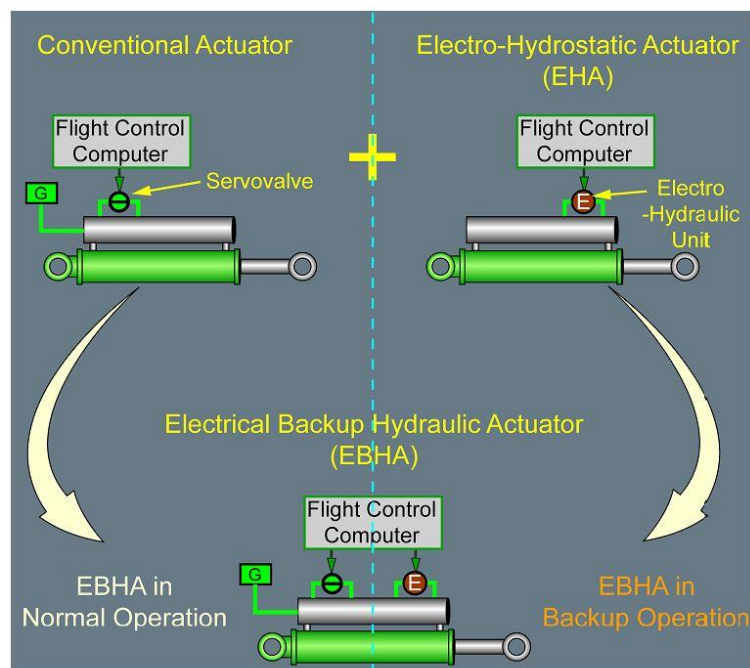


Figure 3.3-1 The A350XWB Adaptive Dropped Hinge Flap (ADHF) on ground, in cruise and high-lift settings with hydraulic actuation [110]



*Note: The **YELLOW** or the **GREEN** hydraulic circuit supplies the actuators (refer to [next page](#)).*

Figure 3.3-2 A350 XWB flight control actuator collections [20]

3.3.1 Flap Operation Scenarios

The modelling work in this thesis centres on an EMA system deployed on the flap control surface of a modern commercial aircraft. As stated in Objective 2a, the DT framework aims to reproduce realistic actuator behaviour under both nominal and degraded conditions across representative flight phases. The following four segments were selected: Pre-Flight, Taxiing, Take-off, In-Cruise, and Landing.

These flight phases were chosen based on three criteria:

- Mechanical load variability: Each phase imposes different force profiles on the flap surface, affecting actuator torque and energy consumption.
- Control activity frequency: Control surface movements (e.g., flap extension/retraction) occur in predictable patterns during each flight phase.
- Failure criticality: Different failure modes (e.g., mechanical backlash or voltage drop) may have varying levels of impact depending on the phase.

This scenario design follows standard flap control procedures outlined in [20], which includes typical deployment sequences during take-off and landing, and confirms that the flap actuator is usually inactive during in-cruise except under abnormal conditions. The load profiles used in the simulations are derived from these procedures and simplified into stepwise sequences for computational tractability. A simplified version of the flap deployment configuration is used, and multi-step scenarios were designed to represent the three stages, as shown in Figure 3.3-3. This abstraction captures the major transitions in flap angle, which correspond to changes in aerodynamic load and actuator displacement referring to Figure 4.1-1 and Figure 3.3-4, where:

- a) PFC stands for Pre-Flight Check, represents nominal operations on ground, changing from 0 to 15 degrees, with displacement up to 80 mm.
- b) TF means take-off procedure, changing from 0 to 15 to 20 degrees, with displacement reaching 110 mm and 140 mm, respectively.
- c) LD means landing procedure, in which flap will extend to FULL position with a displacement of 300 mm, changing from 0 to 15 to 20 to 25 to 45.

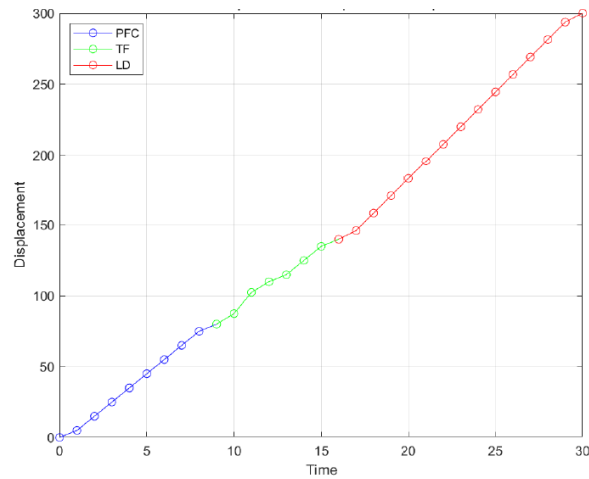


Figure 3.3-3 Leadscrew displacement through flap extension operations

FLAPS Lever Position	Configuration on ECAM	Maximum Speed	Flight Phase
0		VMO/MMO	Cruise
1		255 kt	Holding
		220 kt	Takeoff/ Approach
2		212 kt	Takeoff/ Approach
3		195 kt	Takeoff/ Approach/ Landing
		190 kt	Landing
FULL		186 kt	Landing

Figure 3.3-4 Slats and flaps configuration on Airbus A350 XWB [20]

The three stages of flap deflection during system operations are discussed and reference values are discussed in this subsection.

3.3.1.1 Pre-flight Check

PFC is a basic and essential check prior to each flight. In general situation, ground maintenance staff walks around the aircraft and visually observe if

sensors, fuselage, engines, fairings, panels are in good condition. At the same time, pilots run functional checks including the flight control system, checking if ailerons, spoilers, flaps, rudder, and trimmer are responding to command. The aircraft will be pushed out by pushback tug and start taxiing to the runway. During this period, the flaps will extend to 15 degrees, or Position 1-2 in Figure 3.3-4.

Under this circumstance, the load profile against flaps is set at zero. The load to EMA is the weight of flap mechanism and is assumed at a static value of 8kN at neutral position and 12kN at Position 1-2.

3.3.1.2 Take-off

Compared to PFC and taxiing, flaps deflect to Position 2 and 3-1 at 20 and 25 degrees for more lift. Static loads of 8kN and 12kN respectively are added to represent this stage.

3.3.1.3 Landing

Flaps continue to extend to FULL at 45 degrees during approaching to achieve a maximum lift and drag at landing as well as lower landing speed. A static load of 10kN is added to represent this stage.

Table 3.3-1 Reference Value for flap extension operations [20]

Stage	Position	Deflection Angle	Displacement (mm)	Load Profile (kN)	Time (s)
PFC	1-2	15	80	8	9
TF	2	20	110	12	12
	3	25	140	8	16
LD	FULL	45	300	10	30

3.3.2 A350XWB Flight Control

Aircraft flight control systems enable the pilot to command and regulate the aircraft's motion by actuating surfaces such as flaps, ailerons, rudders and elevators. These surfaces must respond reliably and promptly to varying aerodynamic loads throughout the flight envelope. Increasingly, EMAs are being

integrated into flight control system due to their reduced weight, improved maintainability, and compatibility with more-electric aircraft architectures. To ensure operational safety and reliability, it is essential to understand how different EMA components interact during flap operations and how various faults can affect their performance. To demonstrate this, the flight control system of the Airbus A350 XWB is used as a representative example. Although it primarily employs hydraulic and hybrid actuation, the signal and actuation flow illustrated in Figure 3.3-5 and Figure 3.3-6 helps demonstrate the command-execute relationship in flap operations.

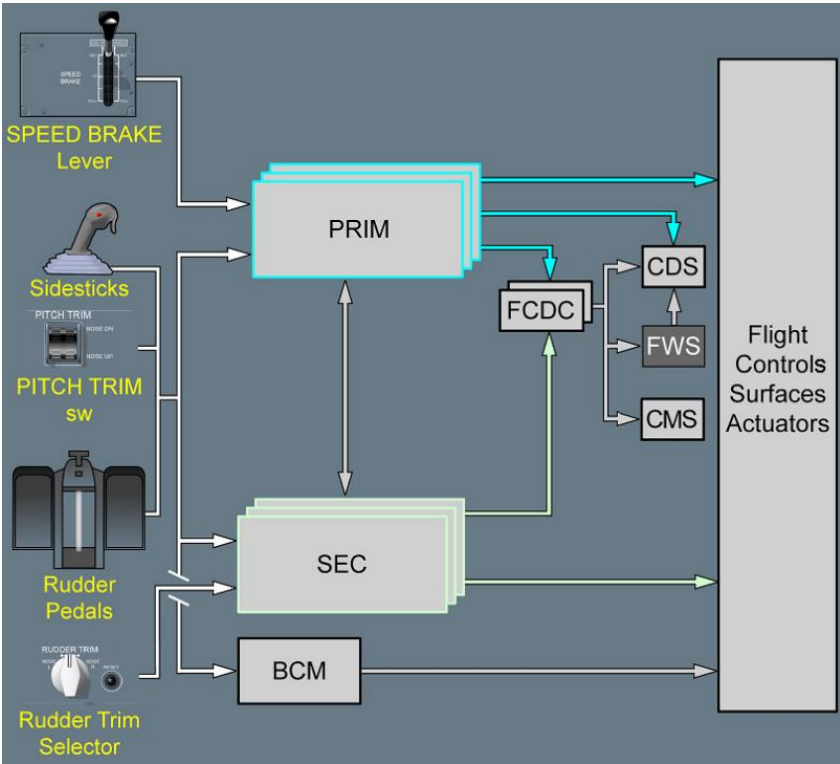


Figure 3.3-5 A350 flight control Architecture [20]

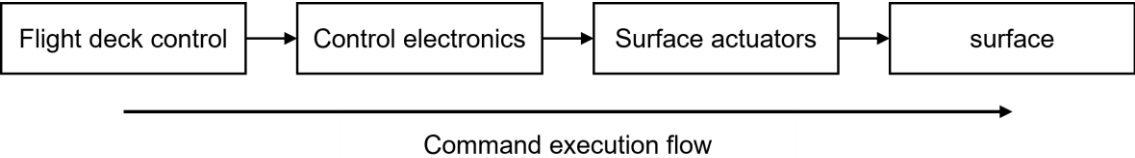


Figure 3.3-6 A simplified illustration of A350 flight control system

In the control electronics, Primary Flight Computers (PRIMs) control the aircraft under normal, direct, or alternate laws. It a) performs the control of flight controls;

b) deliver Flight Guidance (FG), Autothrust (A/THR, to control power setting of the engine), and AP/FD (AutoPilot/Flight Director TCAS, to avoid mid-air traffic collisions); and c) operate Flight Envelope (FE) function. Secondary Flight Computers (SECs) provide complete aircraft control in direct law only. It transfers pilot command to surface actuators. Flight Control Data Concentrators (FCDCs) gather data from PRIMs and SECs and deliver them to subsystems including Control and Display System (CDS), Flight Warning System (FWS), and Centralised Maintenance System (CMS). An Electrical Backup Control Module (BCM) is employed to control the aircraft under the circumstance that PRIMs and SECs fail.

In the operation cycle, position transducer keeps tracking the current flap position. The transducer will be triggered and activated once flap lever position change. The signal is then received by PRIM and transmit to surface actuator. Central hydraulic system received the signal and then open hydraulic valves to drive the hydraulic motor of a power drive unit and torque tubes, transferring signals to mechanical transmission. Transmission assemblies holding nuts and drive bar execute mechanisms driving the flap.

If the hydraulic system fails during flap deflection, the PRIM will command the power drive unit electric motor to operate the flaps.

If the PRIM fails, SEC or BCM will take control of the aircraft. Signal will be sent from cockpit to power drive unit electric motor to retract the flaps.

3.4 Chapter Summary

This chapter has outlined a structured methodology for developing a simulation framework to support health monitoring research for EMAs. A DT of an EMA is designed to emulate the actuation of inboard flaps on the Airbus A350XWB. The model incorporates electrical, mechanical, and control subsystems, enabling the injection of faults via modular inputs. The Airbus A350XWB flight control was presented to explain the scenario setup and fault injection.

Chapters 4, 5, 6 and 7 reports the execution of the methodology steps.

4 EMA DIGITAL TWIN DEVELOPMENT

This chapter presents the SimScape realisation of the case study EMA model described in the previous chapter. As mentioned in Section 3.2, SimScape provides a rich selection of element bricks representing ideal functions and operations of practical components. The high freedom of adjusting configurations of parameters of each block allows prompt modifications and switching between scenarios as well as simulating real-world problems.

Section 4.1 details the selection and employment of elements used in the EMA model. A summary of elements and default settings (for nominal operation as target) is provided at the end of this section.

Section 4.2 describes the construction of each subsystem. The modelling decisions and simplifications made for each domain are explained with justification based on literature and simulation requirements.

Section 4.3 demonstrates the overall schematic of the model. Illustrations and explanations of each circuit follows.

Section 4.4 presents the preliminary testing and validation of the DT EMA. Several nominal and single-fault simulations are conducted to ensure system response consistency and to verify the effectiveness of subsystem integration.

Section 4.5 summarises the model development process and discusses its readiness for integration into the data generation framework introduced in Chapter 5.

4.1 EMA Model

To accurately replicate the EMA's behaviour in the DT model, it is essential to understand the mechanical structure and loading conditions of the inboard flap system. This system operation analysis guides the structure and development of the DT modelling. The EMA model was constructed using information from:

- Aircraft Maintenance Manuals (AMM), which specify actuator operating profiles and load timelines. The Cranfield Boeing 737 Ground

Demonstrator documentation was used as reference and scaled to approximate the Airbus A350XWB.

- Academic literature and engineering texts for component-level modelling of electrical machines and mechanical linkages (e.g., [73][74][100][108]).
- Public datasheets from EMA suppliers such as MOOG, which inform the parameter ranges (e.g., torque capacity, gear ratios, stroke lengths) [113].

The EMA does not act in isolation. It operates within a multi-body mechanical assembly, converting electrical energy into mechanical motion and ultimately generating force to deflect the flap surface. The force generated by the EMA is transmitted through a series of mechanical components that define the actuator's driving structure as shown in Figure 4.1-1.

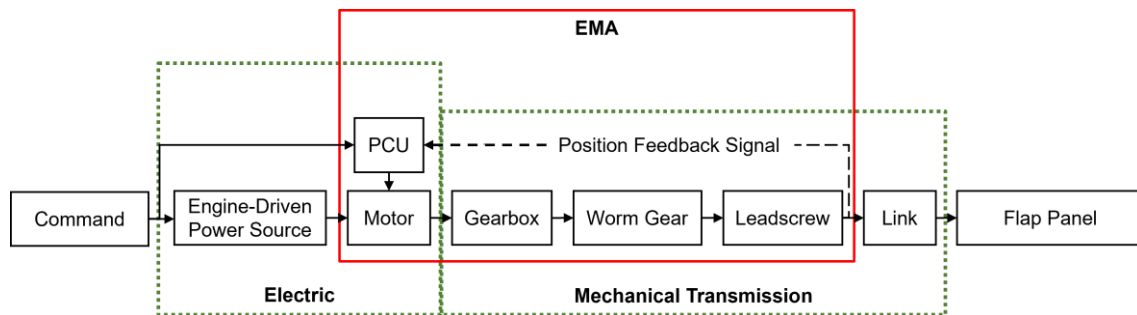


Figure 4.1-1 System operation of the EMA-driven inboard flap extension

In this configuration, the motor operates as the kinetic energy source and is directly connected to a gearbox, which adjusts the torque-speed characteristics of the drive. The gearbox output is coupled to a worm gear, which redirects the rotational motion and enables conversion into linear displacement through a leadscrew. The leadscrew terminates at a fixed end that is rigidly connected to a bearing-supported interface on the flap surface. This mechanical chain provides the structural pathway from the motor output to the flap attachment point and forms the basis for force and displacement transmission in the model.

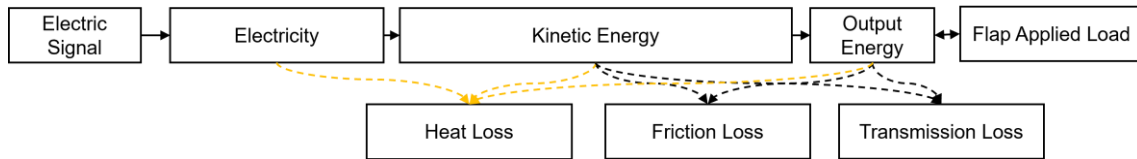


Figure 4.1-2 Energy transformation of the EMA-driven inboard flap extension

From the systems perspective, the EMA is driven by electrical power supplied through the onboard avionics system. The energy pathway can be decomposed into a powertrain structure, starting from electrical energy input, passing through the motor and transmission stages, and resulting in mechanical work at the flap surface. Losses such as heat dissipation in the motor windings and friction within the mechanical transmission happened during energy transmission. This is illustrated in the functional energy flowchart in Figure 4.1-2.

The design of a DT as a PHM data generator purposefully injects inputs that represent the faults a PHM researcher intends to study and collect output relevant for PHM algorithms development. In this EMA model, the faults being studied are Unstable Power Supply, Mechanical Backlash and Electric Cable Wear as reviewed in Section 2.5. The model is designed as a modular representation of the EMA and adding other faults are relatively easy to do.

To clarify the signal pathway within the EMA model, Figure provides a conceptual flow diagram illustrating how the major variables interact through the simulation.

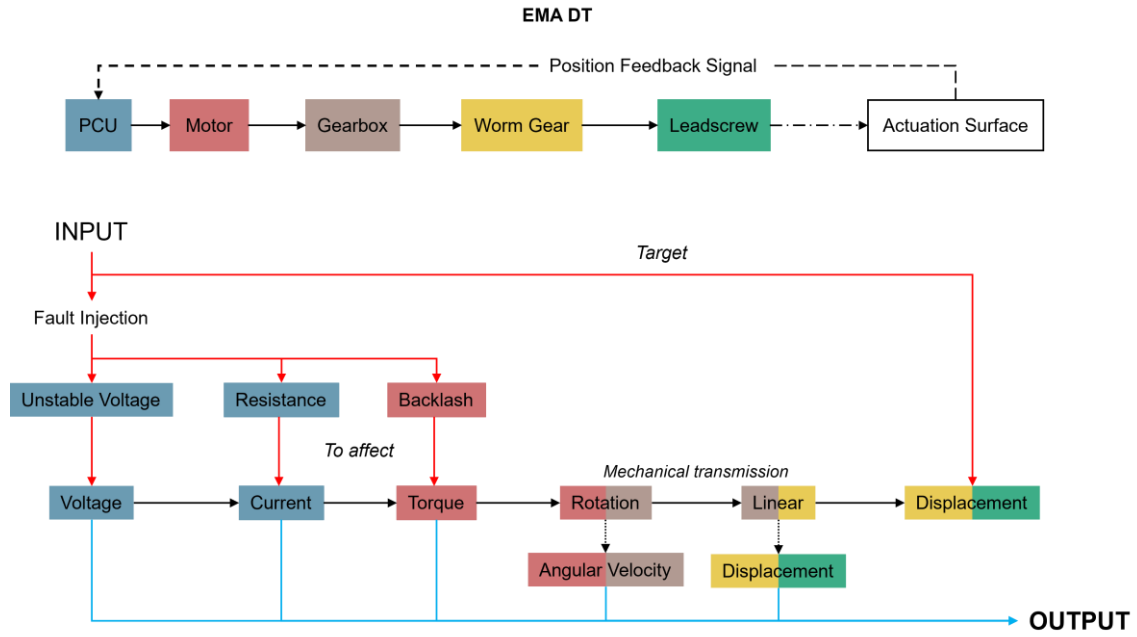


Figure 4.1-3 Input/Output of the EMA-driven inboard flap extension

The control signal initiates voltage supply (V_{input}), which drives the BLDC motor to generate torque. The torque is transmitted through a gearbox and a leadscrew, resulting in translational displacement and actuation force at the output. Meanwhile, the system continuously monitors electrical feedback (I_{motor}), mechanical motion (x_{disp} , ω_{out}), and thermal state for each simulation instance. This control-to-response chain enables a traceable and interpretable mapping between inputs and generated features, as required for PHM algorithm training. shows the signal flow and fault propagation paths through the EMA DT align with Table 5.2 1. The blue arrows represent the nominal control-to-response signal chain, while red arrows illustrate fault injection paths and their influence on key observable features. Three fault types as discussed in Section 4.2.6 impact the system at distinct locations, propagating through the EMA and ultimately affecting the displacement output.

The Output of the models represent the placement of sensors in the EMA components and subsystems to measure detection signals of interest. This EMA model has 15 output parameters with data for PHM researcher to carry out diagnostic and prognostic analysis. The choice of the 15 parameters is explained in the following section.

4.2 Subsystem Specifications

The EMA model discussed in Figure 4.1-1 consists of three circuits, control unit, electric circuit, and mechanical circuit. SimScape blocks are selected to represent practical components and circuits in an EMA.

4.2.1 Control Unit

The Control Unit consists of the PCU box, feedback signal receiver and motor control unit in Figure 4.1-1. Section 2.4.1.3 explains the choice of BLDC motors in EMA systems. The standard method for regulating the BLDC involves using a cascade structure consisting of three interconnected loops: the current loop, the velocity loop, and the position loop [73]. The position and speed control units were developed to input values, defined according to the scenarios, into the ECU. Feedback signal is collected at the transmission end of the mechanical circuit and is sent back to control panel. A six-step control law, Figure 4.2-1, is implemented to perform electronic commutation by switching the DC supply across the motor phases in a timed sequence.

A solver configuration is an essential block in SimScape model, and it helps define solver settings for the simulation. The ode23t solver is used in the model primarily because it is well-suited for stiff systems with algebraic constraints, which aligns closely with the characteristics of the EMA DT model.

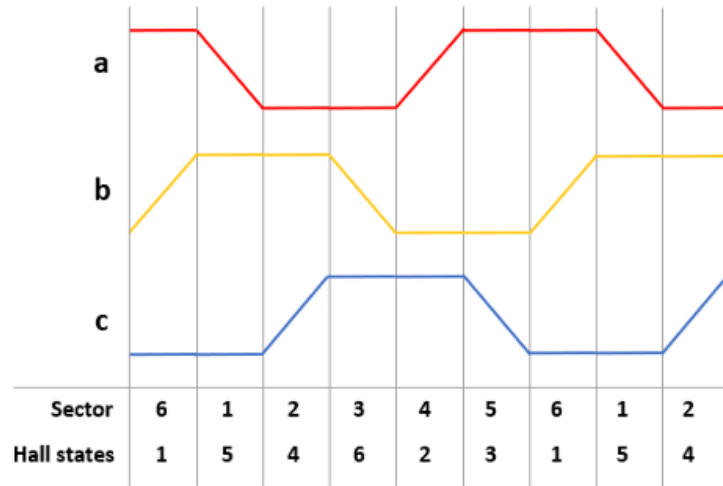


Figure 4.2-1 Six-step control law of BLDC motor with Phase a, b, and c represent stator windings [114][115]

4.2.2 Electric Circuit

The electric circuit is the left green box in Figure 4.1-1. A controlled DC voltage source is used to provide stable and constant voltage fed to the BLDC motor. It is designed to be powerful enough to maintain the specified voltage at its output regardless of the current passing through it. The default value is set at 28Vdc. A current sensor is inserted into the circuit to measure the current in the electric circuit. As in the nature of BLDC motor, voltage supply is a constant value, current changes responding to changes in the BLDC motor output end, or rotor end. The simplified trapezoidal back-EMF BLDC motor model is used:

$$V = R \cdot i + L \cdot \frac{di}{dt} + K_e \cdot \omega \quad \text{(4-1 simplified trapezoidal back-EMF BLDC)}$$

, where: V is the motor terminal voltage, i is the current, R, L are phase resistance and inductance, ω is the shaft angular velocity, and K_e back-EMF constant.

When simulating mechanical backlash failure, a rotational electromechanical converter was used to represent the torque-speed relationship of a simplified DC motor. This modelling abstraction bypasses the need for detailed commutation or control electronics, thereby simplifying the motor representation while retaining

the essential electromechanical characteristics. Such an approach is suitable for fault injection studies focused on mechanical phenomena, as it enables accurate analysis of fault effects without the added complexity of full motor dynamics [116][117].

4.2.3 Mechanical Circuit

The mechanical circuit is the right green box in Figure 4.1-1. It starts from the rotor shaft of the BLDC motor. Energy and motion flows through:

- a) A reduction gearbox with default gear ratio at 5, transfer high rotary speed to high torque.
- b) A worm screw, originally giving high ratio speed reduction, employed in the model for mechanical backlash injection purpose.
- c) A leadscrew, converting rotational motion into translational motion.

For this mechanical transmission chain:

- r_{gb} : gearbox ratio,
- r_{wg} : worm gear ratio,
- P : leadscrew pitch (mm/rev),
- θ_m : motor rotation (rad),
- ω_m : motor angular velocity,
- T_g, T_w : torque through gearbox/worm,
- x : linear displacement (mm),

Then gearbox output:

$$\theta_g = \frac{1}{r_{gb}} \cdot \theta_m \quad \text{(4-2 gearbox rotation)}$$

$$\omega_g = \frac{1}{r_{gb}} \cdot \theta \cdot \omega_m \quad \text{(4-3 gearbox angular velocity)}$$

Worm Gear Output:

$$\theta_w = \frac{1}{r_{wg}} \cdot \theta_g = \frac{1}{r_{gb} \cdot r_{wg}} \cdot \theta_m \quad (4-4 \text{ Worm Gear Rotation})$$

$$T_w = r_{wg} \cdot T_g \quad (4-5 \text{ Worm Gear Torque})$$

Leadscrew Displacement:

$$x = \frac{\theta_w}{2\pi} \cdot p = \frac{\theta_m}{2\pi \cdot r_{gb} \cdot r_{wg}} \cdot p \quad (4-6 \text{ Leadscrew Displacement})$$

These equations define how electrical energy is converted into linear mechanical motion, which is used both for system actuation and feature generation for SHM algorithms.

Different motion sensors are inserted in the circuits to measure data, including rotational sensors, translational sensors, and position hard stop. Two separate signal inputs are used to import fault data to represent load profile and mechanical backlash reverse torque, respectively.

4.2.4 PHM Features at Component Level

Correlating components in Section 2.4.1 and failure characteristics in Section 2.5, failure features are linked and correlated, as shown in Table 4.2-1.

For example, bearings in mechanical mechanisms that are corroded or lack lubrication cannot support rotors rotating in a stable condition, irregular vibration could be detected. The frequency of vibration and the vibration of the rotor or the motor can be set as feature references. The two values of frequency and amplitude of normal operational condition can be used as thresholds. When abnormal conditions occur, the feature signals activate the trigger, which can be a clue of failure in bearings and the specific components involved.

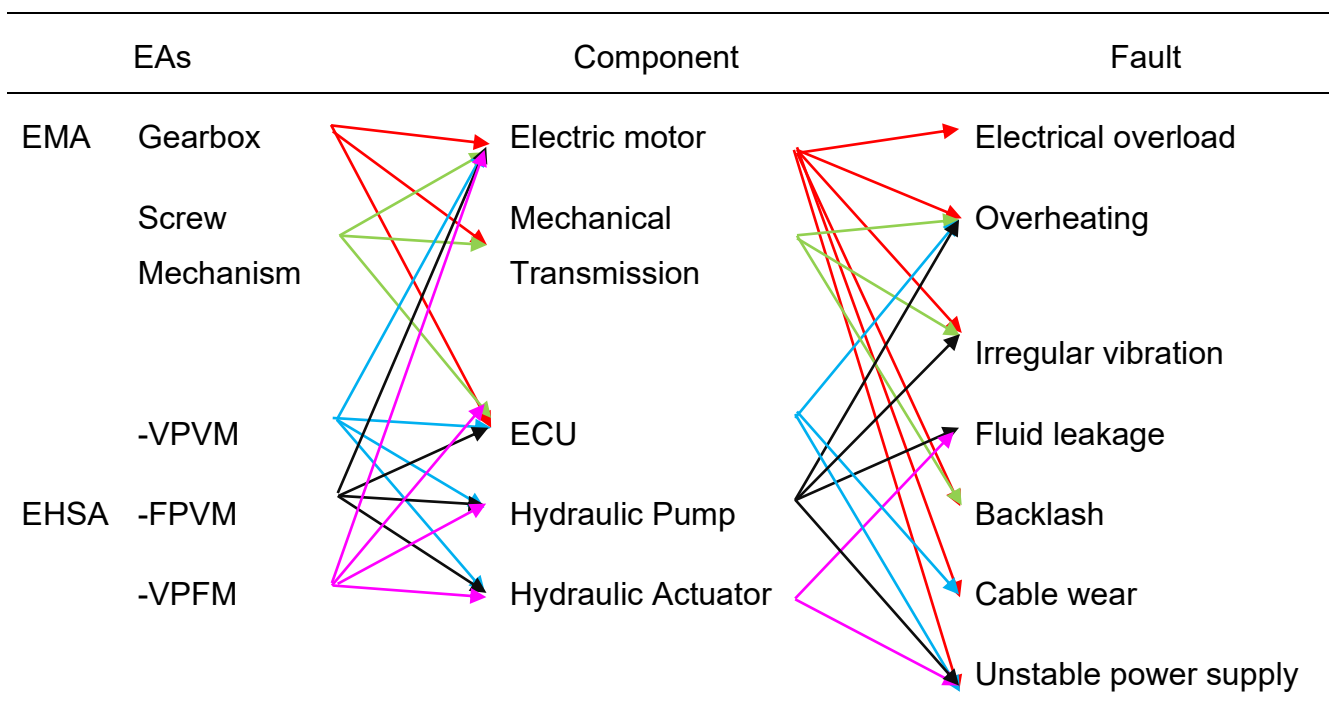
Table 4.2-1 A summary of fault, related features, and measurement reference of components of EA systems

Subsystems/Components	Fault	Feature	Unit
Electric Motor	Electrical overload	Excessive voltage input	+ΔV
		Excessive torque output	+ΔN·m
Mechanism Transmission (Gearbox, screw mechanism)	Overheating	Temperature	+Δ°C
		Irregular vibration	Frequency (times)
	ECU	Fluid leakage	Amplitude
Pressure drops			+ΔPa
Hydraulic Pump	Backlash	Shortened displacement	-Δx
		Delayed response	+Δt
	Hydraulic Actuator	Cable wear	Irregular torque output
Excessive voltage			+ΔV
Hydraulic Actuator	Unstable power supply	Short circuit (Excessive amplitude)	+ΔA
		Excessive resistance	+ΔΩ
		Voltage input drop	-ΔV
Hydraulic Actuator	Unstable power supply	Amplitude input drop	-ΔA
		Insufficient torque output	-ΔN·m

4.2.5 Failure Effects at Subsystem Level

Table 4.2-2 shows the complex relationship between fault indication and the component that causes the fault. When a fault alarm shows up in EMA, indicating an abnormal operation, it may be caused by electric overload, overheating, irregular vibration (normally caused by worn bearings), gear backlash or unstable power supply, or even worn electric cable.

Table 4.2-2 A summary of interconnection from system level to component level and their fault characteristics



If a temperature rise is reported in the flight control system, the good diagnostic troubleshooting guides the trace back to the component level and help to distinguish whether the cause is the motor or the ECU, or either mechanism or hydraulic mechanisms.

The EMA DT model is designed to represent the system behaviour correctly and generate simulation data to support PMH research to develop algorithms for effective fault diagnosis.

4.2.6 EMA PHM Features

In a complex EMA, the correct execution of commanded functions, such as flap extension and retraction, relies on the coordinated operation of multiple components. Faults occurring at the component level can propagate through the system, exhibiting as degraded or failed performance at the subsystem level. To support effective condition monitoring and fault diagnosis, a structured set of features could be identified to represent the physical behaviour of the EMA across its electrical, mechanical, and kinetic domains. These features capture key operational variables which reflect both nominal and faulty system behaviour.

Based on Sections 2.5, 4.2.4 and 4.2.5, fifteen primary features are identified PHM interest, covering the motor, transmission elements (gearbox, worm gear, leadscrew), and load responses. These features are selected to reflect changes due to electrical anomalies, mechanical faults, and compound degradation effects. In fault scenarios involving PID compensation or injected disturbances, additional control-related signals such as adjusted voltage and amplitude are also captured.

The complete feature set is summarised in Table 4.2-3, which maps each feature to its physical domain, measurement point, and relevance for fault detection. This structured approach ensures that feature extraction aligns with the failure characteristics discussed in Section 2.5.

Table 4.2-3 Summary of monitored features for EMA fault detection

Feature Name	Physical Domain	Measurement Point	Relevance for Fault
Voltage	Electrical	Motor terminal input	<ul style="list-style-type: none"> • Detects power instability • control system compensation indicator
Amplitude		Motor input current peak	Sensitive to current surges under load changes or faults
Resistance		Electric circuit	<ul style="list-style-type: none"> • Indicates cable wear • Corrosion • Partial breaks
Rotor Torque Output	Mechanical	Motor shaft	<ul style="list-style-type: none"> • Responds to load variations • Drops under voltage/resistance faults
Rotor Angular Velocity			<ul style="list-style-type: none"> • Decreases under load or with backlash • Inverse to torque
Gearbox Torque Input			<ul style="list-style-type: none"> • Affected by motor performance • Changes under electrical faults
Gearbox Angular Velocity		Gearbox input shaft	Reflects dynamic response to motor speed and load
Gearbox Torque Output			<ul style="list-style-type: none"> • Sensitive to load transmission • Disturbances reflect transmission faults
Worm Torque Input			<ul style="list-style-type: none"> • Indicates transmission of motor effort • Drop may indicate slippage
Worm Angular Velocity		Worm input shaft	<ul style="list-style-type: none"> • Slows under resistance/backlash • Useful for dynamic diagnostics
Worm Torque Output			Drop or instability may suggest backlash or torque losses
Leadscrew Torque Input			<ul style="list-style-type: none"> • Reacts to downstream jamming/backlash • May rise sharply under load
Leadscrew Angular Velocity		Leadscrew	<ul style="list-style-type: none"> • Flattened under torque resistance • Useful for progression tracking
Leadscrew Torque Output			<ul style="list-style-type: none"> • Represents final torque transfer • Deviation indicates system stress
Leadscrew Displacement	Kinematic	Linear actuator output	<ul style="list-style-type: none"> • Key indicator of flap position • Deviation reveals motion failure

4.2.7 Failure Values in Simulation

Building upon the previously defined set of fifteen simulation features in Section 4.2.6, which capture electrical, mechanical, and motion-domain responses of the EMA system, this section outlines the parameter values used for simulating representative failure modes. These simulation features serve as the observable indicators through which the presence and severity of faults can be assessed. Among them, variables such as voltage amplitude, current response, torque fluctuations, and axial displacement are particularly sensitive to disturbances caused by system degradation.

Three failures are selected based on their practical relevance and observable impact across the defined features: (1) unstable voltage supply; (2) mechanical backlash; (3) cable wear induced electrical resistance change. These were injected as input disturbances during EMA operation to evaluate their effects on the system.

4.2.7.1 Unstable voltage

For this case study, a standard BLDC motor is selected. A -7% to +5% variation from the rated voltage is considered as specified in the FAA Standard for Power Inverters [111]. In the simulation, a 7% voltage drop is assumed as the operational safety limit to evaluate EMA performance in degraded power input conditions, the acceptable lower limit to be simulated is at 26.04Vdc. Therefore, a range of voltage values will be input to the model, as from **[24Vdc to 29.4Vdc]**. The range **[28Vdc to 29.4Vdc]** are fault values representing the power supply operating above rated output and **[26.04Vdc to ~28Vdc]** are fault values under, and **[24Vdc to 26.04Vdc]** outside acceptable tolerance. This fault mode shall be referred to as FM1.

4.2.7.2 Mechanical Backlash

For EMA output, discrete reverse torque input is employed to represent mechanical backlash to the mechanical transmission system. This approach is chosen for its ability to approximate the sudden engagement and disengagement behaviour typically observed in systems affected by backlash. Mechanical

backlash does not exhibit as a gradual force but rather as a distinct and intermittent resistance when the direction of motion reverses and the clearance between mating components is taken up. By applying torque in **[50Nm, 100Nm and 150Nm]**, the simulation can reproduce different severities of backlash while maintaining a controlled input. The backlash load is injected at any time and randomly between [2.4s, 3.6s] based on uniform distribution [112]. This method contrasts with the approach of Fu et al. [73] who implemented backlash through a pre-loaded Coulomb friction model that freezes displacement upon engagement.

Table 4.2-4 A comparison between methods used in the research and literature

	Model Design	
	This study	Fu MPT Model
Simulation platform	SimScape	AMESim
Backlash representative	Reverse torque input	Coulomb
Injection period	5 seconds	Instantaneous point
After injection	Decrease speed	Freeze the position
Backlash released	Return to function	Freeze at the position

While the Fu method captures the abrupt locking effect of severe backlash, the stepped torque input proposed here provides a more flexible framework for simulating earlier-stage or milder backlash phenomena. As outlined in Table 4.2-4, this enables the DT to reflect a broader range of practical conditions, particularly those encountered during early fault development where performance degradation is subtle yet detectable. This fault mode shall be referred to as FM2.

4.2.7.3 Electrical cable wear

To emulate electrical resistance faults in a physically meaningful and numerically stable manner, fault values were designed to symmetrically deviate from the nominal resistance within a moderate range as shown in Table 4.2-5 [81][82].

This strategy ensures that the simulated deviations are sufficient to induce observable changes in system-level responses while avoiding perturbations that are either too subtle to be detected or too extreme to maintain solver stability.

Table 4.2-5 Selected Resistance Fault Levels with Relative Deviations and Associated Failure Mechanisms [81][82]

Fault Value (ohm)	Offset	Type
0.3	~-52%	Severe contamination
		Conductive fluid exposure
		Shorted resistance
0.45	~-28%	Mild contact degradation
		Solder joint cracking
0.8	~+29%	Cable aging
		Loose connections
		Elevated temperature
1	~+61%	Severe aging
		Corrosion
		Partial conductor breakage

4.3 SimScape Model for EMA

The development of the EMA SimScape model was guided by the need to replicate components functionalities discussed in Section 2.4, to represent the fundamental physical principles and multi-domain interactions described in Section 3.2. This subsection presents the reasoning behind the key design

choices and the connections between the components and circuits used in the simulation.

4.3.1 Architecture

The model architecture reflects the multi-domain nature of a real-world EMA, which integrates electrical, mechanical, control and thermal domains. Each component and module were selected to mirror a specific function of the physical system and to enable traceable cause-effect methods for health management applications.

Figure 4.3-1 is a schematic overview of the EMA SimScape model, where:

- a) **Blue** lines and elements represent electric circuits. The electric circuit in the model is designed to reflect the power supply and motor drive structure of a BLDC motor, which is the preferred motor type for aircraft EMAs due to its high power density and efficiency (Section 2.4.1.3). A controlled voltage source, combined with a three-phase inverter and BLDC motor block, enables dynamic simulation of power supply fluctuations and motor response. This configuration supports fault injection at the power input level (unstable voltage supply, FM1), directly linking system input to thermal and mechanical outcomes.
- b) **Bright green** and elements represent rotational motion and sensing as part of the mechanical circuits, and **Deep green** and elements represent translational motion and sensing as part of mechanical circuits. From the rotor output of the BLDC motor, mechanical energy flows through a reduction gearbox, a worm gear, and a leadscrew, components identified in Section 2.4.1.4 and 2.4.1.5 in transforming high-speed rotation into low-speed, high-torque linear motion for flap actuation. This cascade reflects actual EMA load paths in aircraft flight control surfaces (Section 3.3.1) and enables simulation of torque loss or mechanical backlash (FM2) by injecting counter-torque at critical points in the drivetrain.
- c) **Orange** lines and elements represent the thermal sensing module to monitor temperature change in BLDC motor windings. Thermal behaviour, while not actively influencing system feedback in the current model, is

- included via thermal sensing modules (Figure 4.3-8 and Figure 4.3-9) to assess long-term degradation potential and validate safety thresholds, as excessive winding temperature is a critical failure precursor (Section 2.5.2). This sets the groundwork for extended prognostics in future work.
- d) **Black** line (outer circle) is a speed and position signal transmission loop connecting command, ECU, feedback modules, aligning with the mid and outer loop in control mentioned in Section 3.2. The control loop employs a nested PID architecture, position (displacement), velocity, and voltage-supply loops, mimicking real-world EMA control strategies. This structure not only maintains the actuator's position fidelity (Figure 4.3-11) but also allows for observation of compensatory behaviours under fault, such as increased current to offset torque loss or degraded resistance.
 - e) **Red rectangle** highlights the fault injection elements in the model. These include From Workspace blocks that allow faults to be introduced by calling fault data generated and saved in the Workspace (to be discussed in Section 5.3.1). The design enables time-controlled and value-adjustable injection of single or multiple faults, either deterministically or through MATLAB-generated random input datasets. This modular injection setup allows researchers to flexibly simulate a wide range of fault scenarios across different domains, ensuring the model can support both controlled experiments and large-scale data generation for algorithm training, system diagnostics, and health indicator sensitivity analysis.
 - f) **Orange rectangle** highlights the data acquisition ports integrated throughout the model. These include Scope blocks for real-time signal visualisation and To Workspace blocks for structured data export. Positioned at key points across the electrical, mechanical, and thermal domains, these ports allow continuous monitoring and recording of essential signals listed in Figure 4.1-2. This setup ensures that data can be captured from any subsystem or component under any simulated scenario. By supporting both interactive visualisation and systematic data logging, the model enables in-depth interaction analysis and facilitates

downstream tasks such as feature extraction, fault effect evaluation, and machine learning model development for health management research.

A detailed discussion on each circuit will be covered in the next subsection.

A selection of functional elements from the SimScape library are listed in Table 4.3-1. The selection is based on analysis in Section 4.1. Besides the elements, Simulink-based mathematical elements are also used in the model for control purposes, e.g., PID, Unit Delay, Sum, etc.

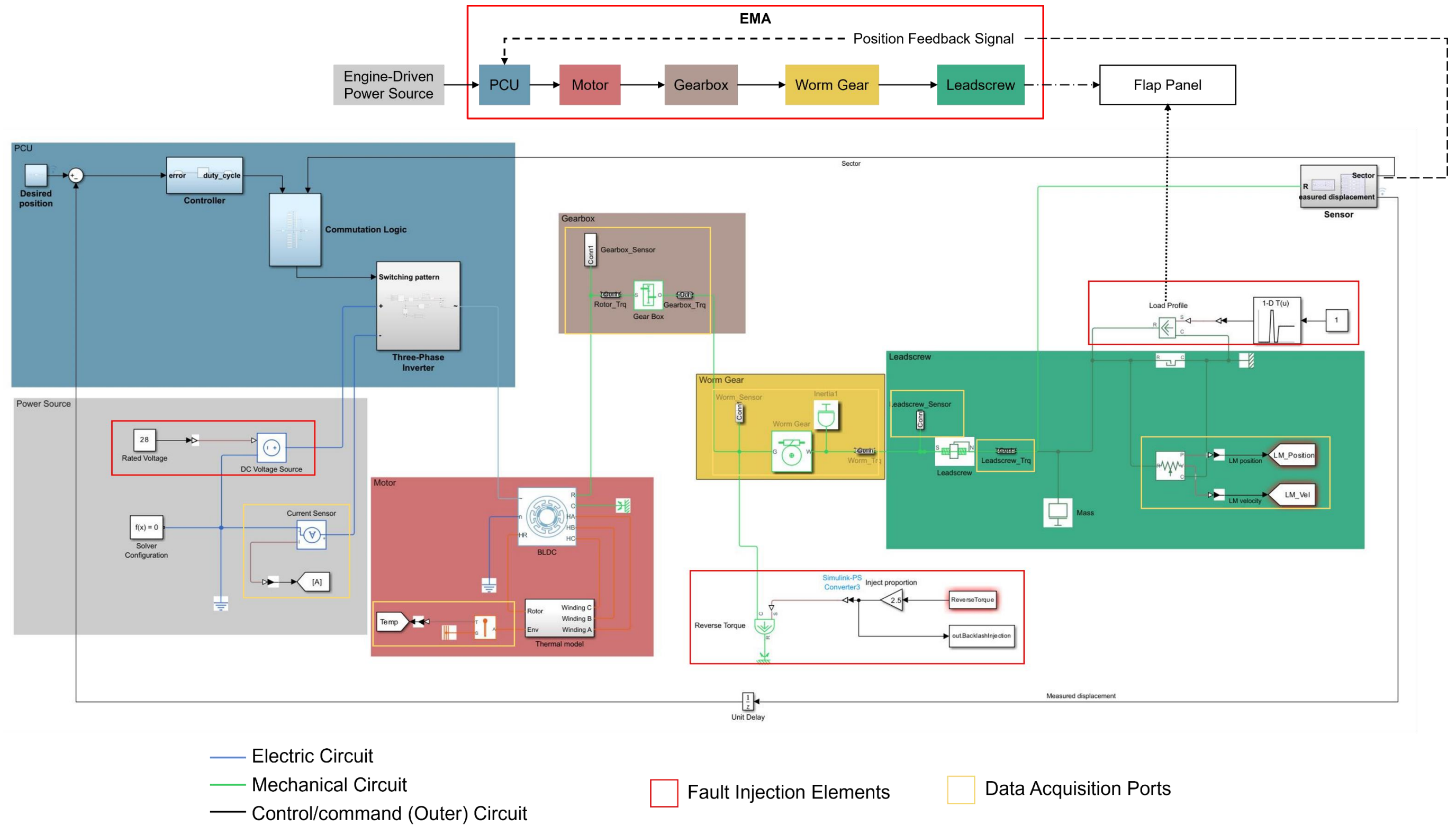
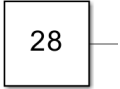
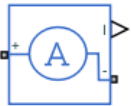
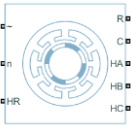
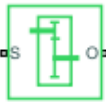
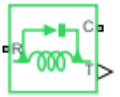
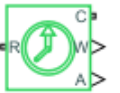
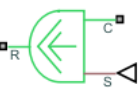
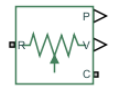
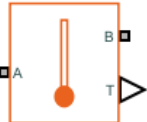


Figure 4.3-1 An overview of the schematic EMA model

Table 4.3-1 Key elements and nominal parameters in the model

NO.	Element	Name	Parameter
1		Constant value	28 Vdc
2		Controlled Voltage Source	Receive input from NO.1
3		Current Sensor	Read current value through electric circuit
4		BLDC motor	Three-winding BLDC motor, default four pole pairs, control law refer to Figure 4.2-1.
5		Rotational electromechanical converter	Simplified DC motor
6		Gear box	Gear ratio at 5
7		Worm gear	Gear ratio at 2 Thread type is left-hand
8		Leadscrew	Rotational to translational motion, 10 mm per revolution
9		Ideal torque sensor	Read torque through mech transmission
10		Ideal rotational motion sensor	Read angular velocity and angular acceleration
11		Ideal torque source	Generate reverse torque to mech transmission to represent backlash failure
12		Translational hard stop	Control the whole displacement, set at 300 mm
13		Ideal force source	Work as load profile to EMA, referring to Table 3.3-1.
14		Ideal translational motion sensor	Read translational displacement, velocity, and acceleration
15		Temperature sensor	Ideal no-heat-flow-through sensor, read temperature changes.

4.3.2 Module Design

Figure 4.3-2 shows the schematic of the electric circuit in the EMA, modelling the electric block in Figure 4.3-1. The voltage source provides constant source at a defined value of 28 Vdc. In the failure of unstable power supply, the constant reference value will be replaced with an input dataset with faults.

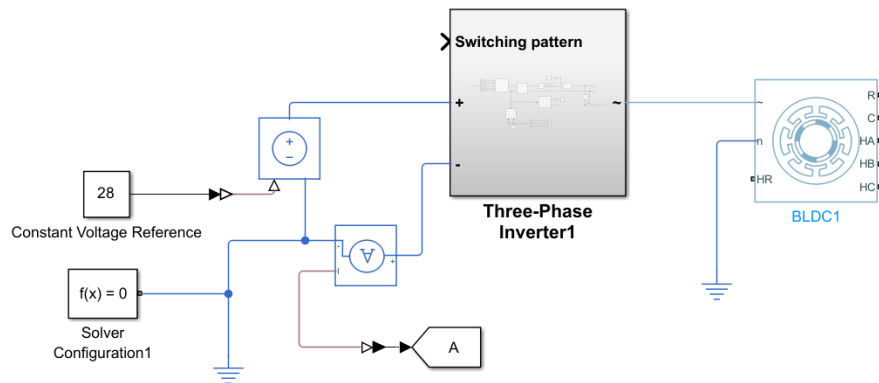


Figure 4.3-2 Electric circuit in the model

Figure 4.3-3 shows the structure of a three-phase inverter in the model that converts direct current into alternating current to actuate the BLDC motor. In this module, it receives commands from the communication block in the control panel to change pattern referring to Figure 4.3-1.

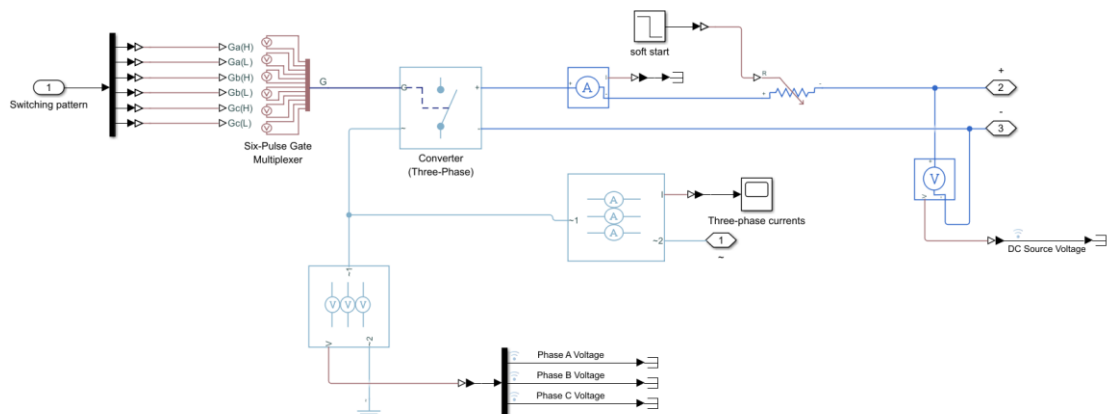


Figure 4.3-3 Schematic of three-phase inverter

Figure 4.3-4 demonstrates the structure of the mechanical circuit, or mechanical transmission, to represent the mechanism operations in the EMA, modelling the mechanical block without link in Figure 4.1-1. The mechanical motion, including rotation and torque, is provided from the rotor shaft end of BLDC motor. The energy then passes through two rotational mechanisms, a gear box, and a worm screw, to decrease rotational speed and achieve proportional torque output. The worm screw is connected by a leadscrew, which transfer rotational motion into translational movement to represent the nut attached to flaps. An inertia and mass block are used to represent basic specifications of the leadscrew. Several sensors are used for data acquisition in 1) angular velocity; 2) torque output from BLDC motor; 3), torque by gear box and reverse torque injected into the transmission train; 4) representative load profile applied to the circuit; 5) displacement of nut moving against worm mechanism in the leadscrew.

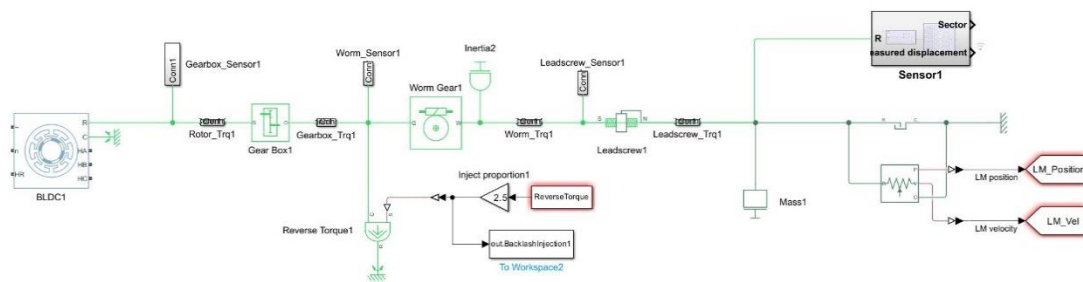


Figure 4.3-4 Mechanical circuit in the model

Figure 4.3-5 shows the load profile module with a defined load input for different stages of flap deflections referring to Table 3.3-1. The signal is applied through S-signal port of the ideal force source element. In the element, positive torque will be recorded if the signal passes port R to C. In this case, the signal is input as a continuous load passing port C to R, as against the transmission train.

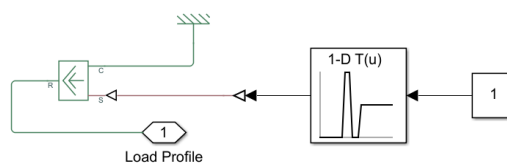


Figure 4.3-5 Load profile module

Figure 4.3-6 shows the equivalent mechanical backlash (Fault Mode FM2) module, the grey block in Figure 4.3-1. In this module, a defined backlash torque referring to Section 3.3.2 is injected into the ideal torque source element through the S-signal port. Similarly, the signal is input as a negative torque passing port C to R, hence this can be treated as a reverse torque input against the transmission train.

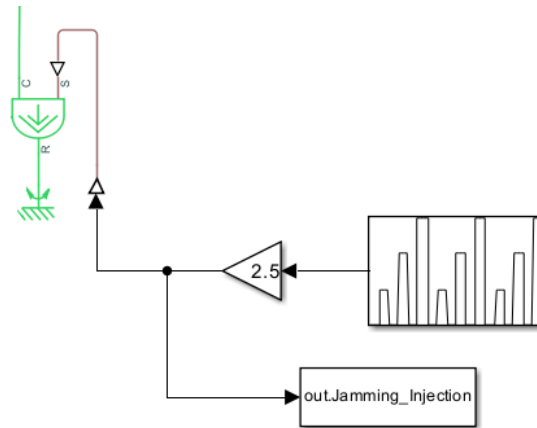


Figure 4.3-6 Equivalent mechanical backlash module with proportional adjustment

Figure 4.3-7 shows an example of sensing module which is linked to the rotor shaft. Both angular acceleration and angular velocity are acquired for analysis. Similarly, positive signals will be recorded if pass through port R to C. The A port can output position signal while it is not involved in the study. A data reservoir can be connected to save the dataset.

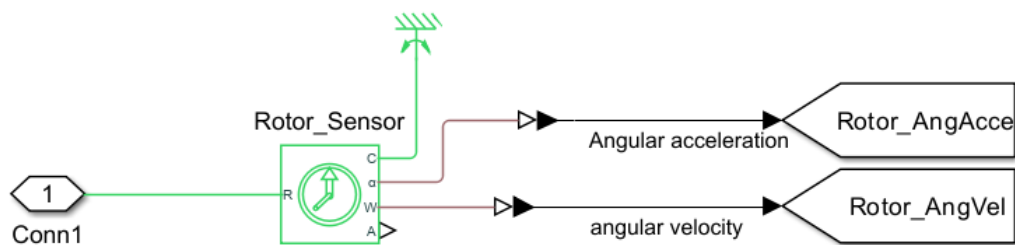


Figure 4.3-7 Sensing module, using rotational motion sensor as an example

Figure 4.3-8 and Figure 4.3-9 show structures of the thermal module monitoring the BLDC motor winding temperature change against room temperature (288K) throughout simulations. Iron loss, heat loss are not considered and investigated. Temperature is a potential indicator of failure.

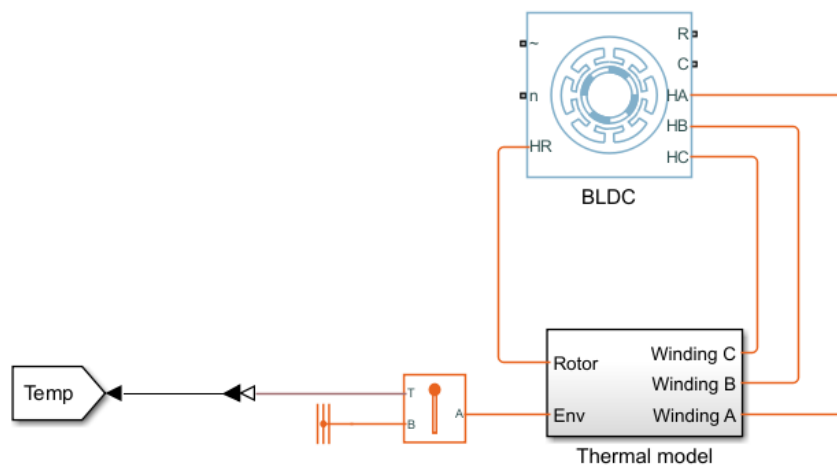


Figure 4.3-8 Thermal module in the model

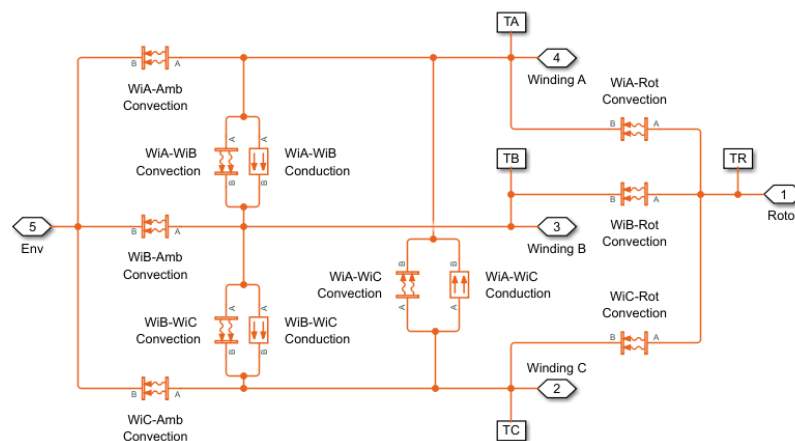


Figure 4.3-9 Thermal sensing for windings in the BLDC motor

Figure 4.3-10 shows a virtual multiple-way oscilloscope element that provides real-time data reading function. Here, several 'From' function elements are used to receive data from 'Goto' elements in circuits.

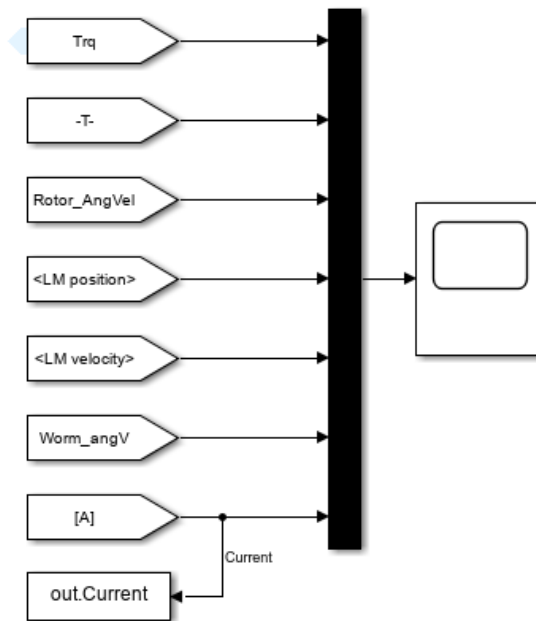


Figure 4.3-10 Virtual oscilloscope to read real-time data in simulation

Figure 4.3-11 shows the outer control loop that realise commanding, signal acquisition, and feedback displacement of nut against leadscrew (position) to the controller.

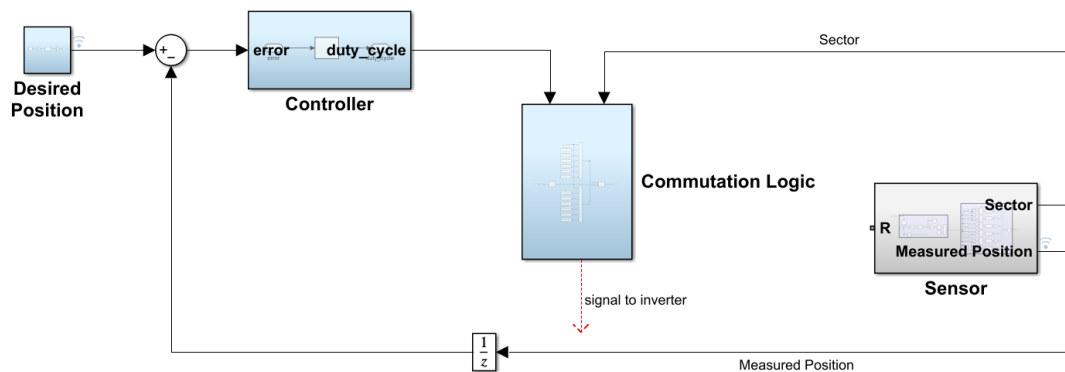


Figure 4.3-11 Position control unit (loop)

The connection of these modules through SimScape physical ports ensures conservation of energy and continuity of signal flow across domains, supporting a high-fidelity replication of real actuator dynamics. The modular approach also

mirrors the physical modularity of EMA systems as described in Section 2.4.1 and facilitates scenario-specific simulation.

In summary, the model design choices and interconnections are rooted in physical workability and health monitoring relevance. The careful mapping between subsystem components and failure characteristics (elaborated in Section 3.4) enables meaningful feature extraction and system response analysis, thereby fulfilling the methodological aims set out in Section 3.1.

4.3.3 Model Input/Output Configuration and Port Design

While the EMA model structure was described in Section 4.1, this section details how the model is configured for scalable batch simulations. Specifically, the model architecture is interfaced for automated fault injection, signal capture, and metadata tracking.

The EMA system model used in this study is implemented in MATLAB Simulink with SimScape Multibody and Electrical libraries. The model adopts a modular structure that reflects key physical and control subsystems: electrical motor, mechanical transmission, sensor feedback, and outer-loop control. Design values including nominal torque, voltage, displacement range, and fault thresholds from catalogue-level datasheets are used as modelling parameters. The initial model data range for the variables are extracted from literature and engineering handbooks.

Table 4.3-2 listed the key input and output variables of the EMA model, including their physical meanings, units, and simulation roles as referred to Figure 4.1-1. This table complements the simulation feature list in Table 4.2-3 by focusing specifically on the physical variables interfaced through model ports, which serve either as input signals for fault injection or output signals for performance monitoring and data export. The simulation step size is fixed at 1e-3s to ensure consistent resolution for dataset generation.

Table 4.3-2 Key input and output variables of the EMA model

Variable	Description	Unit	Role
----------	-------------	------	------

V_input	Supply voltage to the BLDC motor	Volt	Primary input; fault injection (FM1)
R_motor	Motor circuit resistance	Ohm	Adjustable to simulate cable degradation (FM3)
T_reverse	Reverse load torque on leadscrew	Nm	Injected to emulate backlash fault (FM2)
T_out	Leadscrew output torque	Nm	Output for performance tracking
ω_{out}	Rotational speed of motor/shaft	rad/s	Used in degradation feature analysis
x_disp	Leadscrew linear displacement	mm	Position output for control validation
I_motor	Motor phase current	Amp	Input to electrical condition monitoring

4.4 Model Test

This section reports on the simulation runs using a nominal flight operation to compare results of a nominal good condition with fault injections to test the behaviour of the SimScape model.

The simulation was designed to represent the flight controls functional check before taxing. The pilot commands the flap extension to move stage by stage to full extension to ensure freedom of movement. The simulation duration is 30s from start to full flap extension.

Each nominal or fault scenario has a dataset of 10,000 simulations. The input value of the scenario is used to seed a random number generator to create a controlled set of 10,000 simulation runs. This creates statistically meaningful range of injection parameters (e.g., input magnitude and onset time) and the corresponding system responses. This creates a solution space to enable robust training of machine learning models with stable performance, while also supporting train-test splits, k-fold cross-validation, and sub-class analysis (e.g., low versus high amplitude fault conditions). Such a dataset scale is aligned with common practices in PHM applications, where sufficient variation is required to capture fault progression patterns, support classification and regression tasks (e.g., RUL prediction), and evaluate generalisation across fault types and dynamic stages. The design ensures that the dataset is not only statistically

balanced but also structurally representative of real-world diagnostic and prognostic challenges.

4.4.1 Nominal Condition

From Figure 4.1-3 the Input to the model are the Voltage and the target leadscrew displacement, representing the correct flap position. The flight control system receives feedback from the displacement as a load force.

4.4.1.1 Independent feature values

The nominal load profile is defined referring to Table 3.3-1 to represent stepped load change to flap surface during its deflection.

Voltage input is expected to be constant and is an independent variable for fault injection in following scenarios. The default value is 28 Vdc and is as shown in Figure 4.4-1. Due to the nature of BLDC motor, the DC voltage should be constant, and it is neither affected by excessive load nor triggered by insufficient power output. Though the latter will trigger the control unit to apply higher current to make up to the sufficient power, the additional heat generated can bring in iron loss and heat losses.

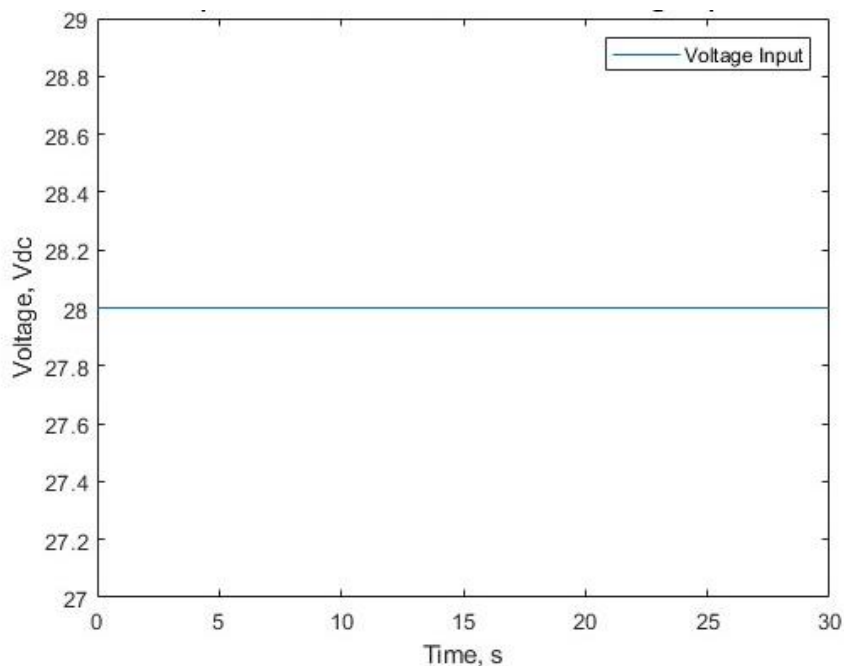


Figure 4.4-1 Voltage input

Figure 4.4-2 shows the defined load profile as input. The first 9 seconds is the flap moving to position 1, with a low load of 8kN. Movement from position 1 to 2 is a greater deflection angle at a higher speed, resulting in the higher load of 12kN. Moving from position 2 to 3 drops back to the normal movement load of 8kN. Extension to full flap is the longest displacement and requires a higher load of 10kN. The calculation to estimate the load profile is in Appendix B.3.

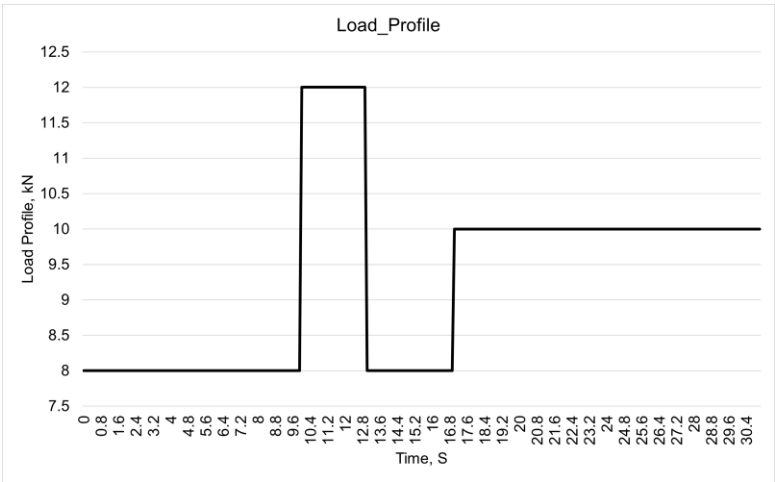


Figure 4.4-2 Defined load profile as input

Figure 4.4-3 is the output signal from the model. This corresponds well with the load profile in Figure 4.4-2, confirming the model performs as designed.

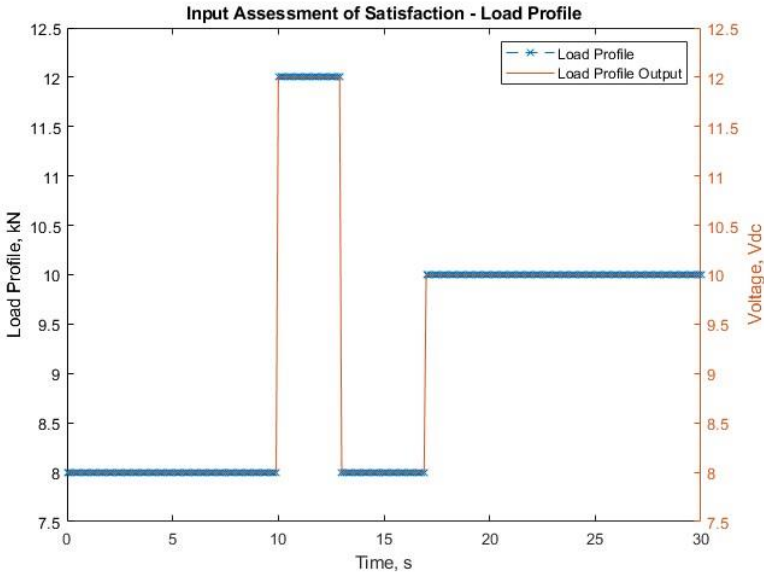


Figure 4.4-3 Load profile output against input

The nominal leadscrew displacement is an independent variable which must be satisfied at all scenarios. A comparison between displacement target and output is shown in Figure 4.4-4. The strong correlation demonstrates that the model can represent the function of receiving flight control commands from the cockpit and extend flaps to the designated deflection position accordingly.

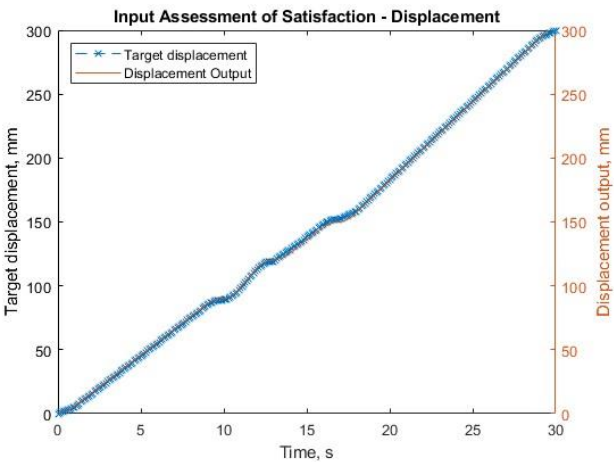


Figure 4.4-4 Good overlapping between target and actual displacement

4.4.1.2 Dependent features response

Out of the 15 features in the model, the behaviours of the current, angular velocity and displacement are used to illustrate the test of the nominal condition.

Figure 4.4-5. shows a current overshoot, similar to the overshoot phenomenon mentioned in [64].

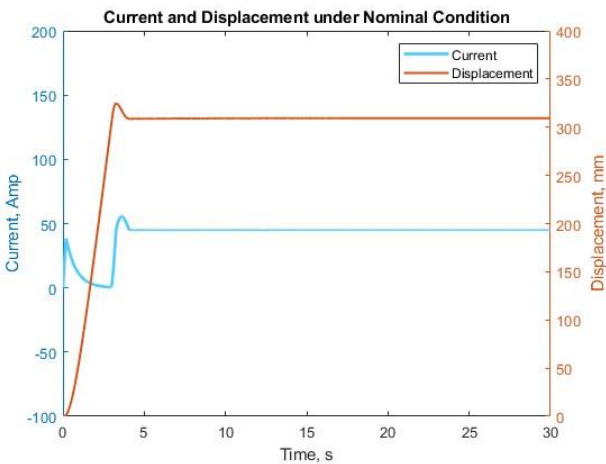


Figure 4.4-5 Current and displacement in free actuation condition

Figure 4.4-6 shows the current and angular velocity changes during the nominal operations. As the pilot pulled the flap lever to different positions, the command is transferred to the actuator via PRIM, and the nut moves accordingly. When approaching the target position, the flap deflects to the target angle, the displacement rate slows down, vice versa.

A strong correlation between current and angular velocity changes can be observed. The angular velocity is inversely proportional to current when a static load is applied to the system, obeying the relationship proven as shown in Figure 4.4-7. The calculation:

$$V_a = I_a \times R + V_c \quad (4-7 \text{ Voltage Input})$$

, and

$$V_c = K_e \times N \quad (4-8 \text{ Equivalent Generator Voltage})$$

, hence

$$V_a = I_a \times R + K_e \times N \quad (4-9 \text{ Calculated Voltage Input})$$

$$N = \frac{V_a}{K_e} - \frac{R}{V_e} \times I_a \quad (4-10 \text{ Calculated Angular Velocity})$$

, where V_a is voltage input, I_a is current input to motor, R is equivalent resistance, V_c is equivalent generator voltage, K_e is back-EMF constant, and N is angular velocity in rpm. With the increase of I_a , N decreases accordingly.

When the simulation sequence starts, higher current than steady value is drawn to activate the motor. This returns to steady value after the output torque reaches the required value, and angular velocity reaches the rated state.

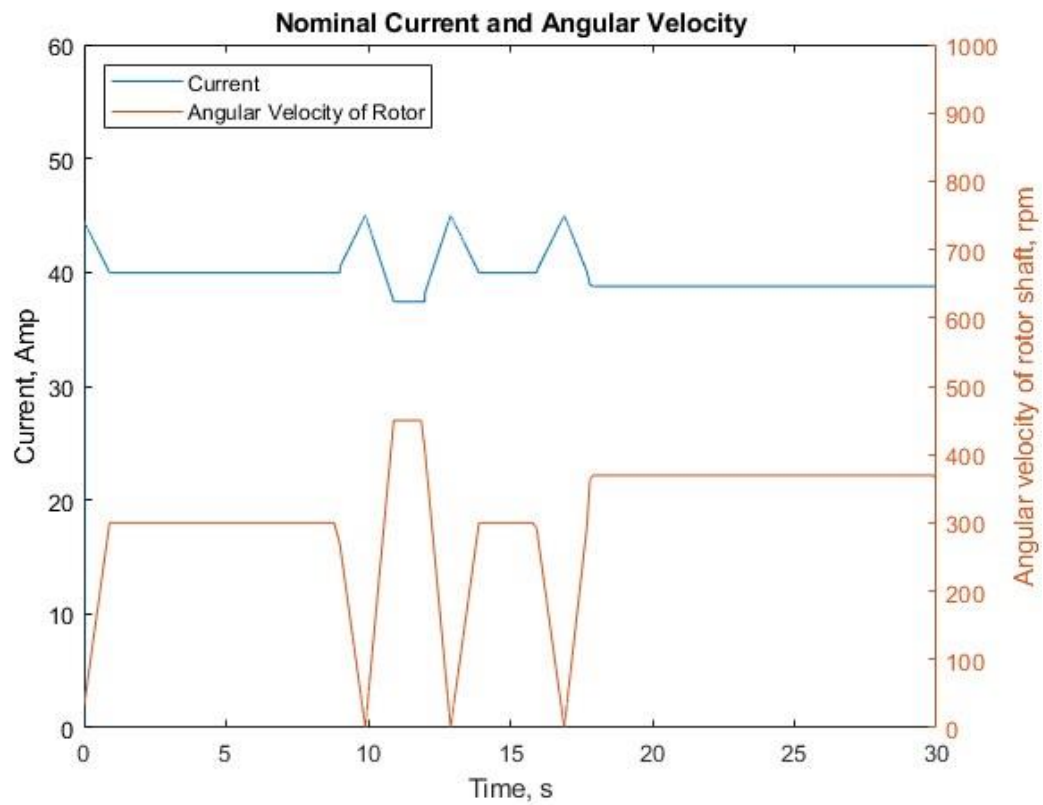


Figure 4.4-6 Current and angular velocity in nominal operation

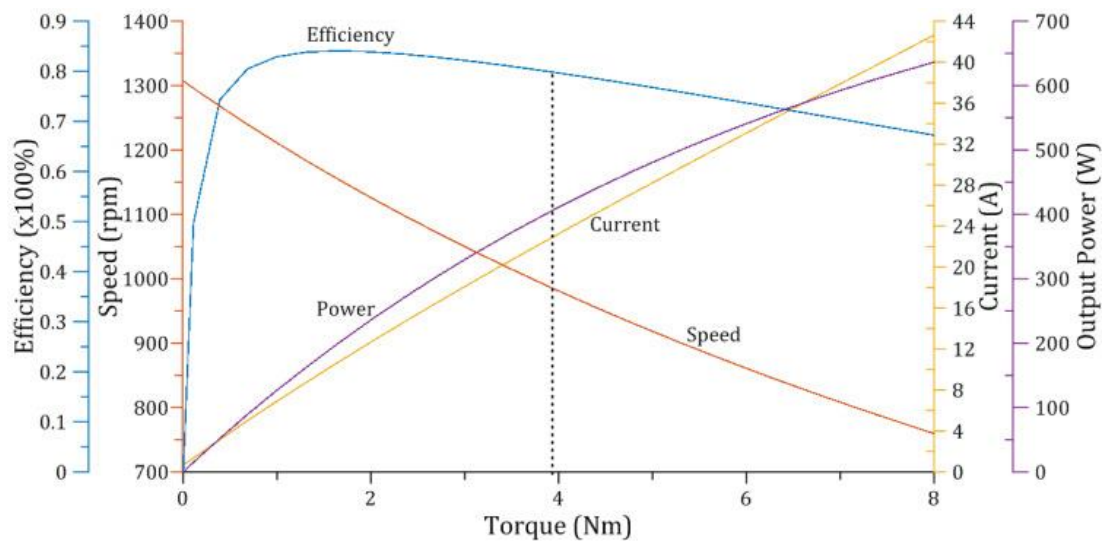


Figure 4.4-7 Typical characteristic curves of a BLDC motor [115]

Figure 4.4-8 shows displacement and translational velocity of nut in leadscrew under nominal operation. A clear correlation can be observed as it represents a FULL extension operation.

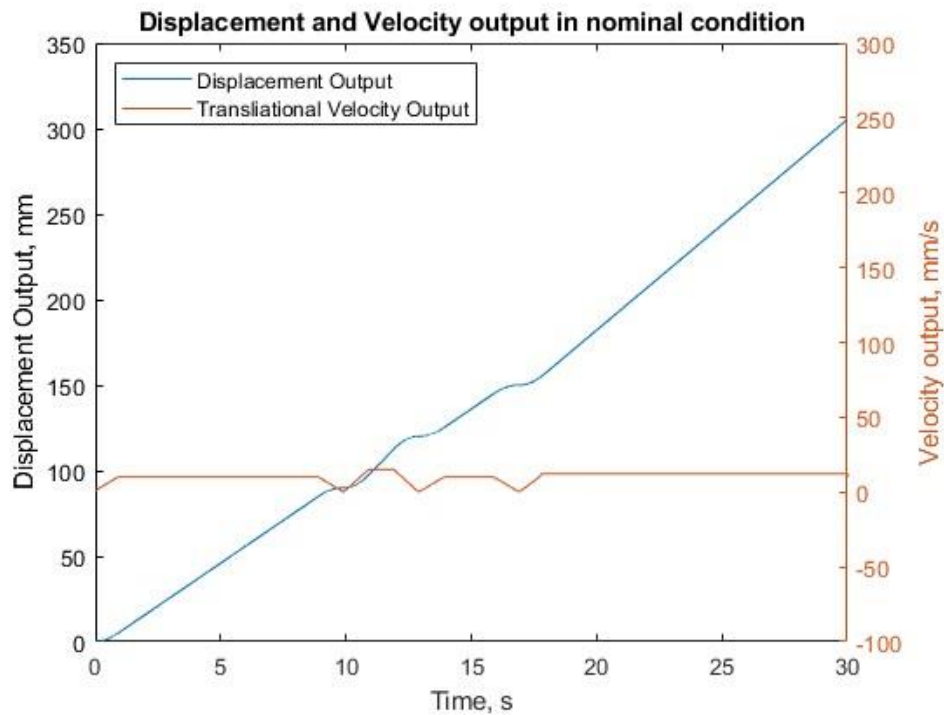


Figure 4.4-8 Displacement and translational velocity in nominal operation

These will be used as reference and threshold values in comparisons with the failure scenarios.

4.4.2 Single Fault Injections

The three independent faults selected to be simulated are unstable voltage, mechanical backlash and electric cable wear resistance. The simulation definition of each fault is the fault type, the time the fault starts in the 30s simulation, the fault duration and the related value.

4.4.2.1 Independent feature input

For Fault Mode FM1 Unstable Voltage Supply, Figure 4.4-9 illustrates the injection control of three simulations with injected values of 24Vdc, 26.04Vdc and 29.4Vdc, respectively. Voltage supply faults all have a duration of 10s. Thus, the injection start time can be in the range between 0s and 20s. The start time and the fault value can be used as seed values for random number generators to create a population of simulation input values to create datasets of controlled fault variations, further explained in Chapter 5.

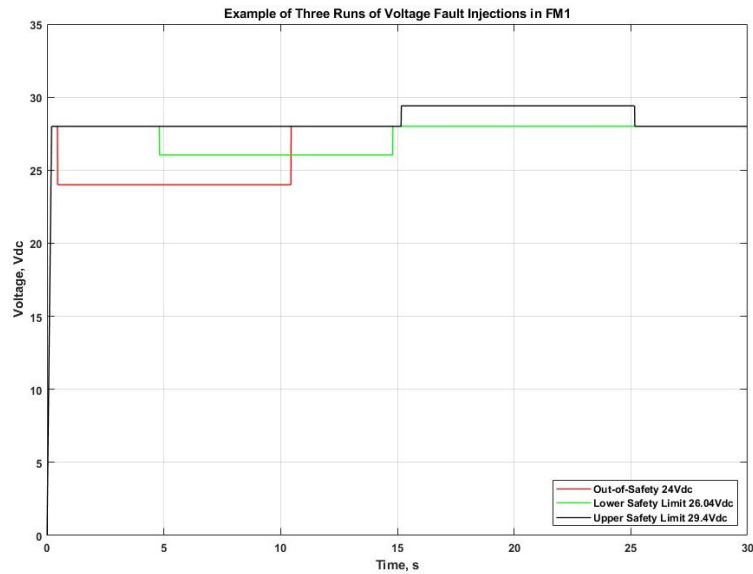


Figure 4.4-9 Three examples of injected fault value in Fault Mode FM1

Fault Mode FM2 Mechanical Backlash is realised as reverse torque in the simulation. It is an independent input variable in failure scenarios as explained in Section 2.5.3 and Section 3.2. A demonstration of three example simulation runs is shown in Figure 4.4-10. The result shows that the model can respond to abnormal load input, which can be used to indirectly simulate mechanical backlash.

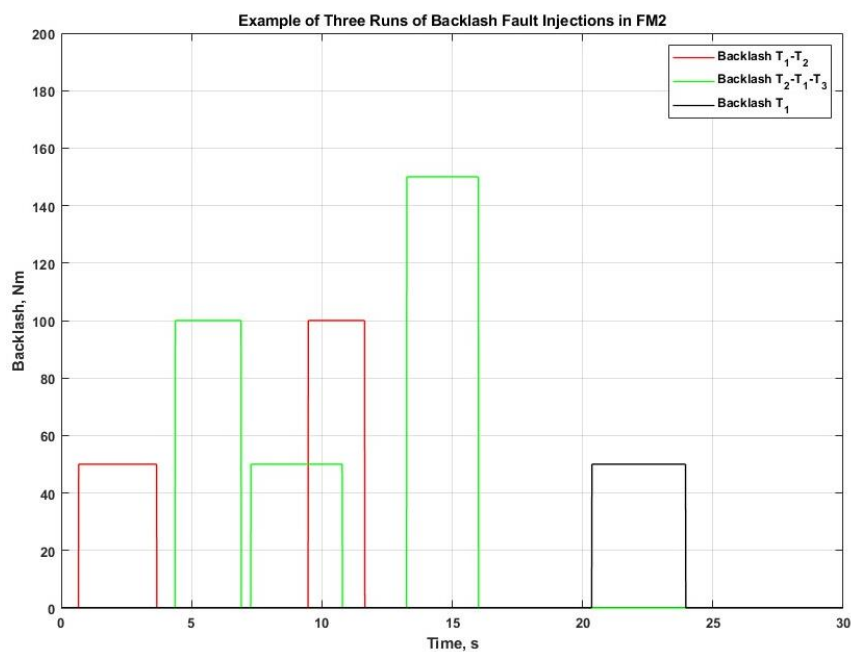


Figure 4.4-10 Good overlapping between defined and actual reverse torque

In all the defined fault modes, the fault values can be manipulated to represent different severities of degradation. This design of the values generates fault data that encompasses a range of behaviours, capturing both early-stage and more severe degradation patterns. The used of seeded random numbers also mirrors real-world variability in fault appearance and supports the generation of richer, more generalisable datasets for health monitoring applications. The injection values and timing for each run are defined by algorithms presented in Section 4.2.7, and the exact parameters used are recorded in the simulation label file in Section 6.2.3.

4.4.2.2 Single fault demonstrations

This subsection demonstrates simulation results under single failure injection.

4.4.2.2.1 Fault Mode 1 unstable voltage

Figure 4.4-11 presents the distribution of the 10,000 voltage fault injection values and their associated timepoints within the simulation environment. The figure illustrates a scatter plot highlighting the stochastic and uniformly distributed nature of the injected fault voltages, which range from 24 Vdc to 29.4Vdc. These faults are introduced across a broad temporal span, starting from 0 seconds up to 20 seconds to cover the overall 30-second into the simulation run.

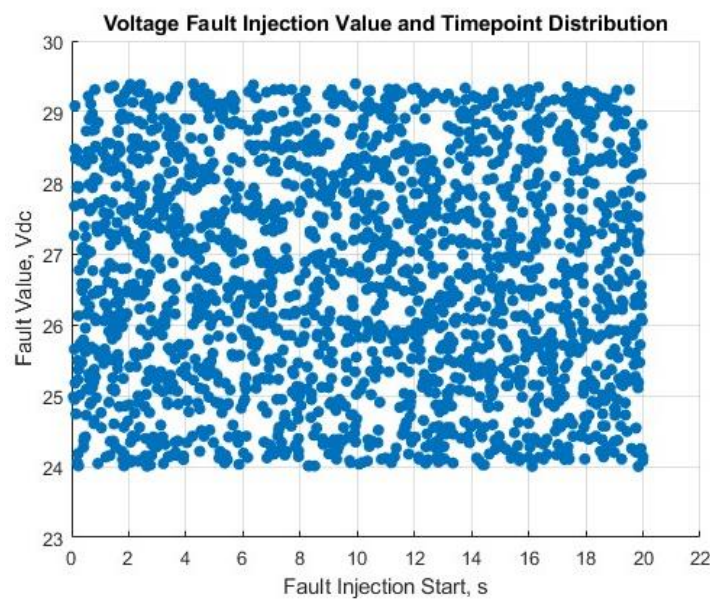


Figure 4.4-11 Voltage fault injection and timepoint distribution in FM1

Figure 4.4-12 shows current output with fault voltage input against nominal current. This is one simulation cycle used as the example in Table 4.4-1. The lowered voltage triggered the control unit to supply a higher current can be seen at both the beginning and the end of the failure window. The elevated current observed in response to a voltage drop aligns with the back-EMF equation and torque generation principle discussed in Sections 2.5.1. This reflects how the control system compensates for under-voltage by increasing current, a well-known behaviour in BLDC motors (Section 2.4.1.3).

According to Equ. (4-11 Motor Power Output)

$$P_o = \eta \times V_a \times I_a \quad (4-11 \text{ Motor Power Output})$$

, where P_o represents power output of the motor, η is motor efficiency.

$$P_{o_1} = P_{o_2} \quad (4-12 \text{ Power Consistency})$$

$$V_A \times I_A = V_B \times I_B \quad (4-13 \text{ Calculated Power Consistency})$$

, where point A and B are captured of values in Table 4.4-1 and it satisfies the Equ. (4-13):

Table 4.4-1 Sampled current values under Fault Mode 1

Point	Voltage (Vdc)	Current (A)
A	26	48.46
B	28	45

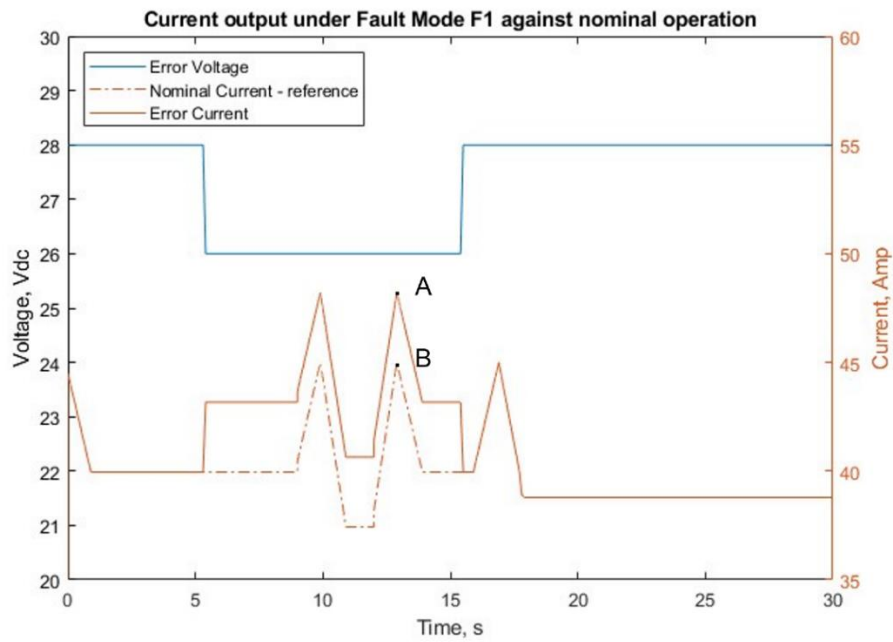


Figure 4.4-12 Current output compared with nominal under FM1

In real-world EMA operation, such compensation may lead to overheating or accelerated wear of motor windings, especially under sustained undervoltage conditions, which is consistent with practical motor degradation scenarios in avionics applications. The heat is unlikely to be significant in a 30s pre-flight check. It may be a more interesting feature during a 20-minute descent.

Beyond current and heat, unstable voltage may also exhibit other effects. This scenario discussion illustrates the type of PHM correlations that the EMA model can support.

4.4.2.2.2 Fault Mode 2 mechanical backlash

Mechanical backlash can happen as a series of resistance events in the same flap extension operation. To represent the injection patterns of mechanical backlash faults, a statistical distribution of different magnitudes of reverse torque injections is used. Three discrete levels of backlash faults (50Nm, 100Nm, and 150Nm) were selected and randomly injected into each of the 10,000 simulation cycles. The percentage of cycles containing faults injected once, twice, or three times was statistically illustrated in Figure 4.4-13.

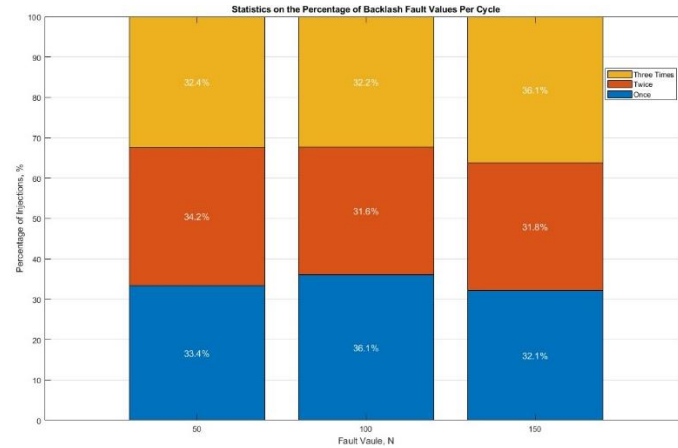


Figure 4.4-13 Statistics on the percentage of backlash fault values per cycle in FM2

In Figure 4.4-14, when an additional torque applied against the transmission train, higher current is provided to maintain the motor torque output. After the reverse torque is removed, the current dropped accordingly, with a tiny gap as fake free-load period, and then remain at steady stage. The correlation between current and angular velocity is shown in Figure 4.4-15. Though the backlash value does not cause a stall, other features should be analysed to identify possible degradation to pre-empt failure. The delayed current rise and angular velocity fluctuations observed during backlash phases directly map to the mechanical resistance and clearance-induced instability outlined in Sections 2.5.3 and 4.2.4.

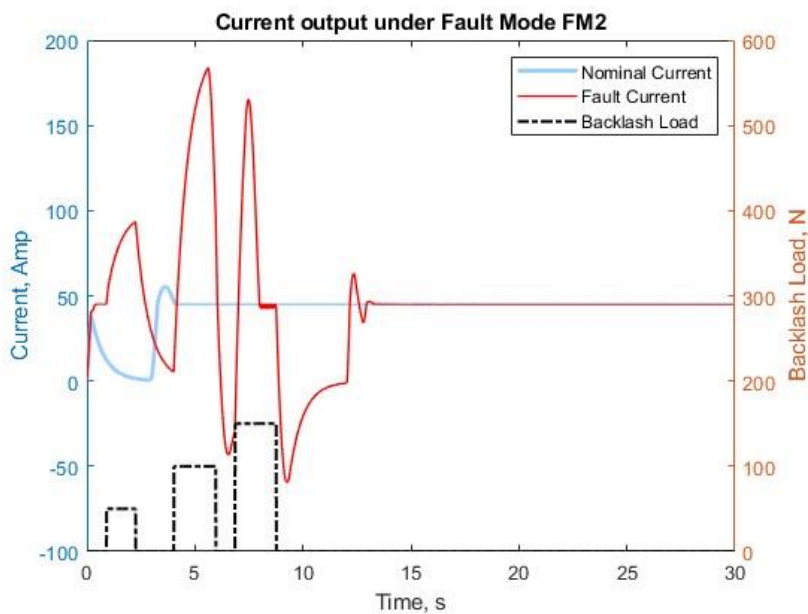


Figure 4.4-14 Current output under FM2

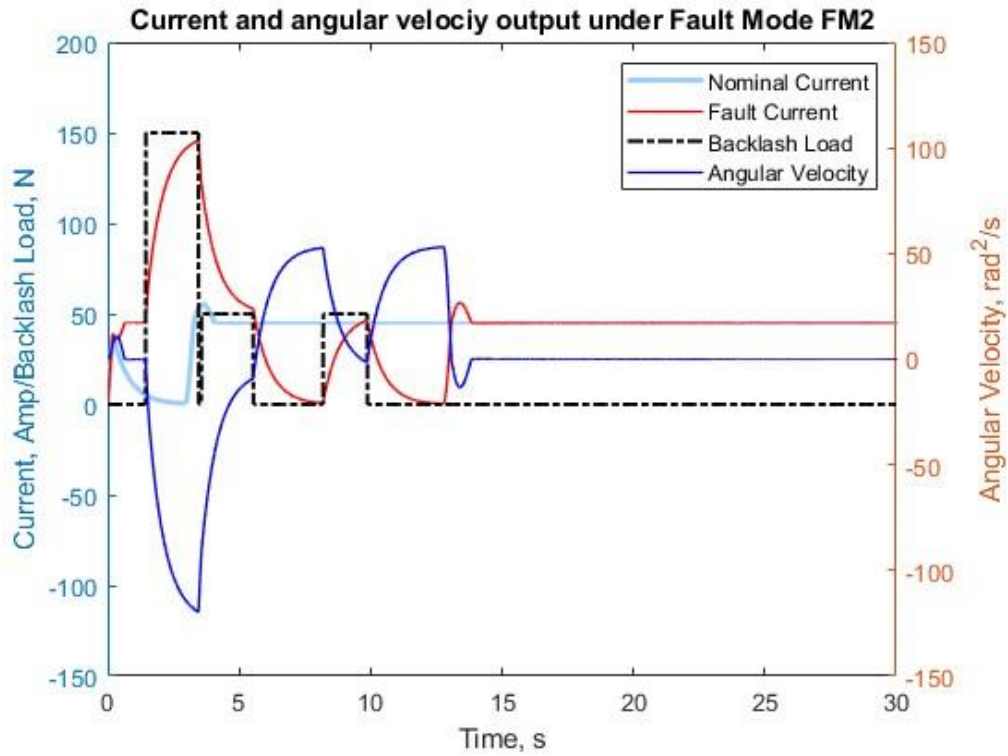


Figure 4.4-15 Current and angular velocity output under FM2

In practice, backlash in transmission systems leads to oscillatory behaviours and loss of control fidelity, especially during direction reversal or transient loads. The wave in torque response supports prior literature noting [64] that mild backlash can remain undetected by displacement-based features, emphasising the value of dynamic features like torque deviation and rotational acceleration.

4.4.2.2.3 Fault Mode 3 electric cable wear

Figure 4.4-16 presents the distribution of resistance fault injection values of 0.3, 0.45, 0.8 and 1 as defined in Section 4.4.2.2.3 and their corresponding start time in the simulation. The fault injections were uniformly distributed with injection start times spanning from 0 seconds to 20 seconds to cover the 30-second operation time.

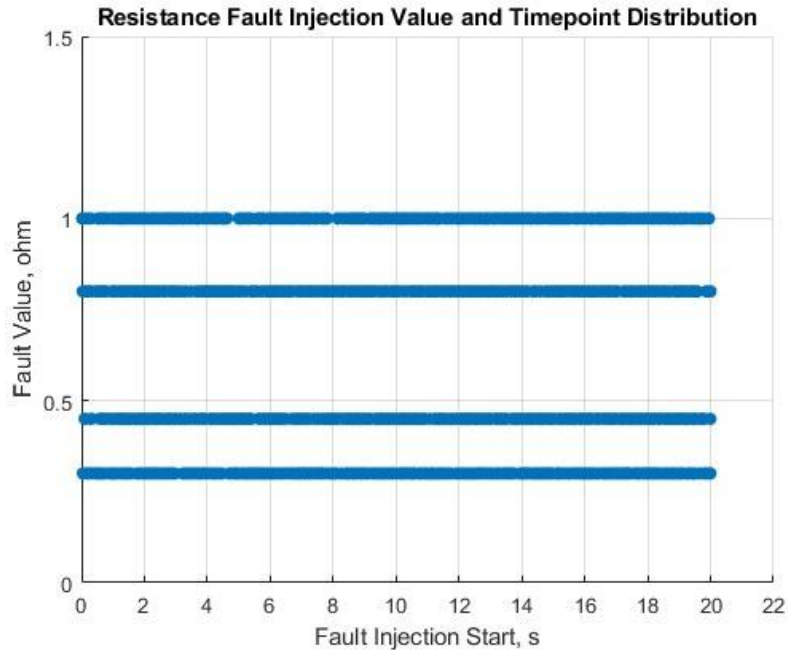


Figure 4.4-16 Resistance fault injection value and timepoint distribution

According to Equ. (4-14 Cable Resistance), the resistance R of a conductor is inversely proportional to its cross-sectional area S .

$$R = \frac{\rho \times L_c}{S} \quad (4-14 \text{ Cable Resistance})$$

, where ρ represent resistivity of the cable material, L_c is the length of conductor.

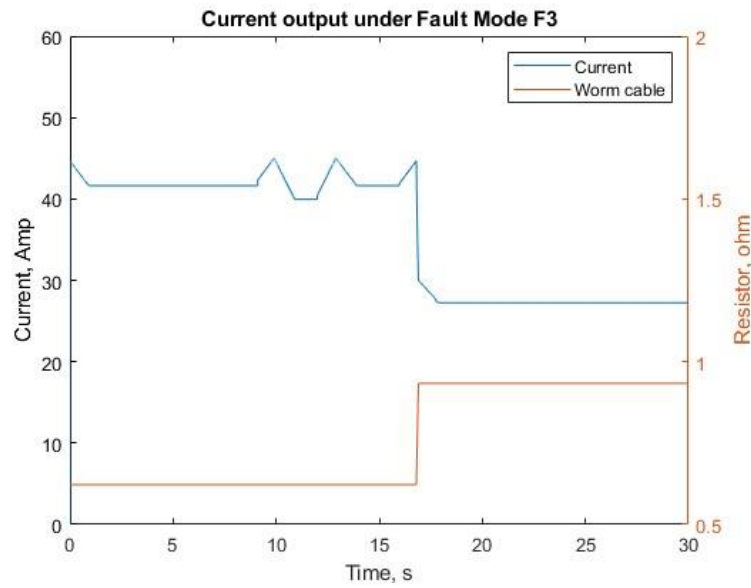


Figure 4.4-17 Current output under Fault Mode FM3

Figure 4.4-17 shows the effect of injected higher resistance, which satisfies the Equ. (4-15 Calculated Voltage Consistency).

$$V_a = I_A \times R_A = I_B \times R_B \quad (4-15 \text{ Calculated Voltage Consistency})$$

The increased resistance severely affects the motor power output, resulting in unsuccessful flap deflection, as shown in Figure 4.4-18. The unsatisfied displacement can trigger position sensor in the outer loop and this failure can then be fed back to the warning system in the cockpit. In this case, fault between practical displacement and designed position can be a feature to identify Fault Mode FM3.

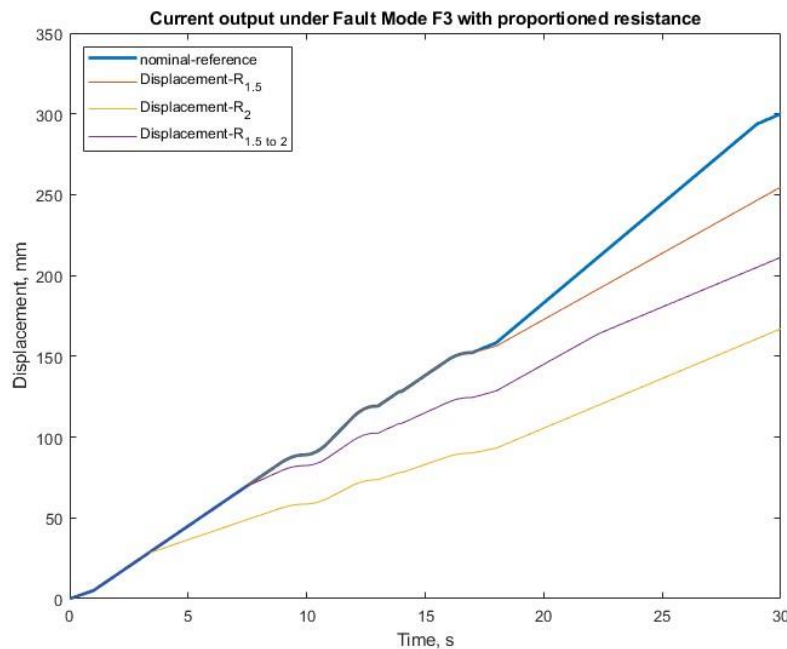


Figure 4.4-18 Displacement output under Fault Mode FM3 with proportioned resistance

The observed power degradation, lowered current, and displacement shortfall correspond well with electrical cable wear and insulation damage, as outlined in Section 2.5.4. Resistance increases leads to excessive voltage drop across the circuit, and as shown in Figure 4.4-18, this results in insufficient actuation force. In the real-world system, this may exhibit as a sluggish or stalled actuator despite normal command signals. The model effectively captures these dynamics and

supports the use of displacement error and resistance-current trends as practical features for early-stage electrical degradation.

4.5 Chapter Summary

This chapter presented the implementation of a DT model for an EMA using MATLAB SimScape. The model captures the physical behaviour of the inboard flap actuation system, incorporating interconnected electrical, mechanical, and control subsystems. Subsystem specifications were derived from maintenance documentation, literature, and supplier datasheets, ensuring a balance between realism and computational efficiency.

The model integrates a cascaded control loop architecture, a trapezoidal back-EMF BLDC motor representation, and a mechanical transmission chain comprising gearbox, worm gear, and leadscrew. A set of sensors and diagnostic interfaces were embedded to enable signal monitoring across domains. Fault injection points were incorporated at key interfaces, allowing controlled introduction of voltage disturbances, mechanical backlash, and resistance anomalies.

The model validation comparing nominal and single-fault conditions confirmed consistent system behaviour with theoretical expectations, including dynamic current response, torque propagation, and displacement tracking. The developed model serves as the foundation for batch simulation and labelled data generation, which is the focus of the following chapter.

5 DATA GENERATOR DEVELOPMENT

This chapter presents the architecture and implementation of the simulation-based data generation system designed to support health monitoring research. The system adopts a two-level structure, developed to maximise flexibility, modularity, and future scalability:

- a) At the top level is the data generator, which manages the overall running of the simulations, loading input conditions, injecting faults, collecting outputs, and saving data with proper labels. It acts like the main controller, making sure each simulation is consistent and that all results are stored in a clear and useful format.
- b) Underneath this sits the DT of the EMA introduced in Chapter 4. This model is built in SimScape, and it represents how the actuator works: including its electrical parts, mechanical drive, control system, and how it reacts when faults happen.

Separating into these two layers enables use adaptability. The EMA DT can be updated or replaced without requiring modifications to the control logic, while the data generator framework itself can be reused to simulate other actuator systems or failure modes in future applications.

Section 5.1 describes all elements in the data generating framework, including input, command, simulation, output, data configuration setup.

Section 5.2 introduces the integrated simulation flow and interfacing strategy, detailing how model inputs, outputs, and fault signals are synchronised.

Section 5.3 describes the input setup and supporting MATLAB algorithms used to drive the simulation runs.

Section 5.4 details the structure of the generated datasets, including labelling and computational performance.

Section 5.5 presents validation strategies, encompassing physics-based reasoning, benchmarking against prior work, and regression-based data

consistency checks, and Section 5.6 lists the computing resources setup used to run the simulations.

5.1 Digital Twin

In addition to replicating the physical behaviour of the EMA, the EMA DT is also designed as a data generator with structured input and output capabilities. From the early stages of model construction, particular attention was given to ensuring that the simulation outputs align with the data format expected in PHM applications.

Specifically, the DT is configured to export time-series feature matrices containing key physical variables (e.g., voltage, current, force, displacement), structured to support machine learning workflows. These outputs are supplemented by fault label information and can be directed to either the MATLAB workspace or external files such as .csv or .xlsx, depending on downstream usage scenarios. The modular architecture, fault injection capability, and output logging components are developed in a way that directly supports dataset construction for fault classification, prognostics, and health index tracking. A complete example of the structured output dataset is provided in Chapter 6.1.

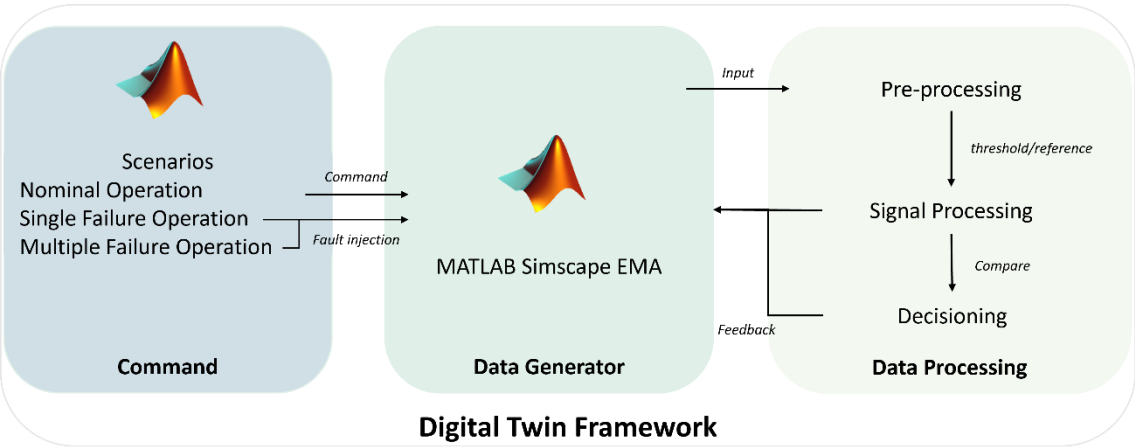


Figure 5.1-1 Structure of DDDT Framework as further expansion of approach

Figure 5.1-1 shows the structure of the DT framework developed. The input commands are the operation scenarios defined in Section 4.4. The scenarios are coupled with relevant fault dataset to inject faults into the EMA model. Each

scenario definition is a data table that enumerates the simulation parameters of the 10000 simulation runs. The datasets generated by the model can be specified to either output to MATLAB Workspace or exported to Excel file as data records.

5.2 Simulation Dataflow and Model Interfacing

The EMA DT, developed in Chapter 4, is interfaced and controlled through a simulation management framework that enables structured data generation for PHM research. This section reports the control flow for running batch simulations with the corresponding model configuration and interface design, detailing how simulation commands, input faults, and structured outputs are synchronised across the system.

5.2.1 Data Generation Control Flow

This subsection describes all the elements in the data generating framework, including input, command, simulation, output, data configuration setup. Figure 5.2-1 illustrates the overall data generation framework. Each simulation cycle follows these four core steps:

1. Command to activate the simulation, importing the nominal datasheet and injecting randomly generated fault values to selected independent variables.
2. Feeding the modified datasheet to the model via **FromWorkspace** ports.
3. Extracting simulation outputs from the model and exporting feature data to the designated storage format (.csv/.xlsx).
4. Collecting metadata from the fault injector (e.g., fault value, start time) and writing it to a structured label file (Simulation_Label_Table.csv) for supervised learning tasks.

As a result, for each completed simulation cycle, following data files can be generated:

- A full time-series feature dataset (Simulation_"n"_Result.csv)
- A corresponding feature name table (Simulation_"n"_Feature.csv)

- A metadata label file with scenario information (Simulation_Label_Table.csv)

This control scheme allows automated execution of simulation cases while preserving traceability and structural clarity of all data components.

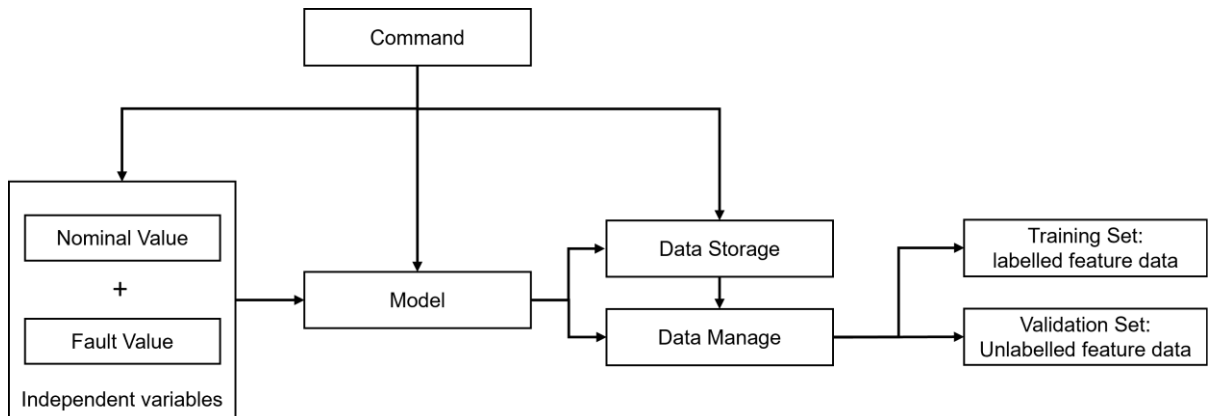


Figure 5.2-1 Schematic of simulation framework

The SimScape model includes designated open ports for three types of interaction:

1. **Fault control ports:** parameters like voltage, resistance, and reverse load are externally set via signal blocks.
2. **Data export ports:** selected variables are routed to a workspace-saving function and linked to the data generation pipeline.
3. **Metadata tagging:** Scenario ID and timestamping: metadata for each simulation is embedded through ported constants, allowing linkage to dataset labels.

This interface structure allows batch simulation with controlled variation and supports integration into the broader architecture. Each simulation scenario is traceable via scenario ID and can be indexed in the dataset matrix.

5.3 Simulation Scenarios

Each simulation cycle was designed with a duration of 30 seconds to ensure sufficient temporal coverage across multiple operational phases of the flap actuation process. This period aligns with the representative actuation timeline

observed in the Airbus A350XWB inboard flap system and allows for steady-state behaviours to emerge following command inputs:

- a) Within each cycle, fault injection is constrained to a 10-second window. This duration is chosen to span at least two out of three functional stages of flap movement, initial acceleration, transitional motion, and final deceleration, as defined in the nominal load profile in Table 3.3-1. Capturing system response across multiple movement stages improves the robustness of extracted features and enhances the realism of the generated dataset for health monitoring studies. This timing setup also balances model responsiveness with computational efficiency, enabling high-throughput simulations to be conducted within feasible runtime constraints.
 - b) The start time of each fault injection of unstable voltage FM1 and electric cable wear FM3 is randomly selected within the first 20 seconds of the 30-second simulation. The start time and duration of mechanical backlash FM2 injection is randomly selected within the first 26.4s of the 30-second simulation. This introduces temporal variability across simulations, ensuring that faults occur under diverse dynamic conditions and system loads. Randomising the fault onset prevents overfitting to specific time-aligned patterns and enhances the generalisability of any machine learning model trained on this dataset. It also better reflects real-world scenarios where failures do not occur at fixed, predictable times.
- The default sampling frequency is 100Hz.

5.3.1 Input

The simulation input is a MATLAB Workspace data sheet with two columns and 3001 rows. The first column is time from 0s to 30s stepped at 0.01s, representing 100Hz data sampling frequency. The second column is the value of the injected variable, i.e. voltage, backlash and resistance. In a nominal good condition, the 3001 values are exactly the same, for example voltage would be 28Vdc.

5.3.1.1 Fault Data Generation

Mechanical systems degradation and failure are generally governed by deterministic physical laws, such as wear, fatigue, or thermal stress. While these processes are not truly random, they may exhibit stochastic characteristics due to variations in operating conditions, manufacturing tolerances, and external influences. Considering the complex and partially unpredictable nature of degradation and failure processes in electromechanical systems, a random number generator was used to add variability into the input data that represents a fault condition.

The start time of the fault is also stochastic. The fault can happen at any time within the 30 seconds flap extension. Fault like backlash may exhibit as more than once during the 30 seconds.

The use of randomised synthetic data in this context is therefore a controlled approximation aimed at broadening the range of observed behaviours during model evaluation [118][119]. The random value generator is designed to produce values following a specific statistical distribution, with parameters that can be adjusted accordingly, referring to Table 5.3-1.

The generation of $Matrix_e$ follows the logic chain shown as Figure 5.3-1. The left-hand side of the Figure generates the fault input value. The right-hand side generates the start time of the fault condition. Only faults that completes its run within the 30s simulation are considered.

The random value generator is initialised by setting the seed of MATLAB's random number generator to ensure reproducibility of results. This is accomplished using the `rng` function with a specific seed value or the `shuffle` option for a seed based on the current time.

A statistical uniform distribution and relevant parameters such as mean, variance, minimum and maximum values, or probabilities are specified. For a uniform distribution, the `rand` function is used, optionally scaled, and shifted to match the specified range.

The generated values are formatted according to the specifications, which involves rounding, converting to integers, or arranging into matrices, arrays, and vectors. The values are exported through **ToWorkspace** function for recording.

The code includes a validation step to ensure the generated values adhere to the specified distribution, using statistical tests or visual inspection (e.g., histogram plotting). Three random value generators and injectors codes can be found in Appendix C, Appendix D, and Appendix E.

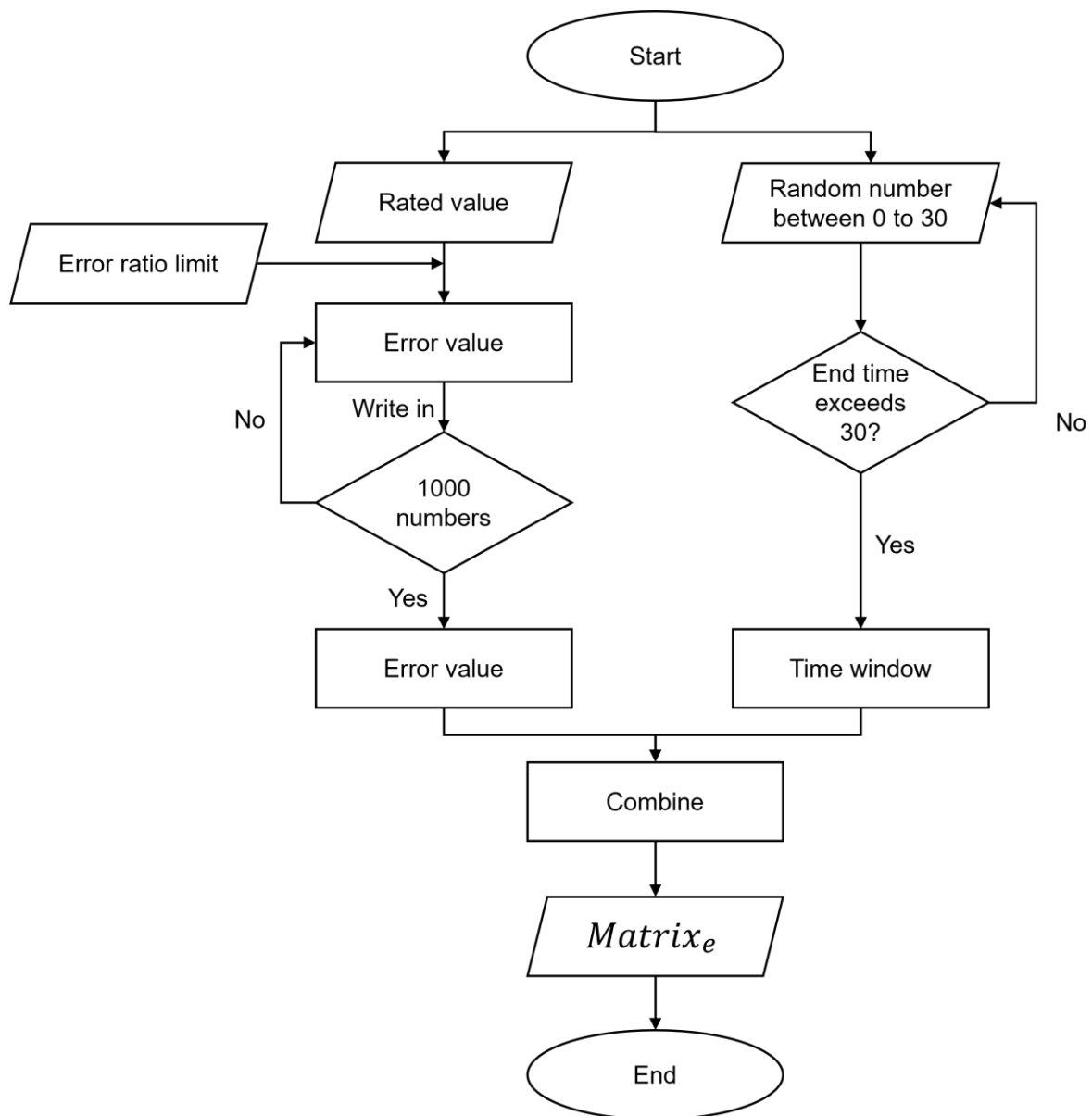


Figure 5.3-1 Flow chart of random data generator and injector for *Matrix_e*

Table 5.3-1 Random value generator specifications

Parameter	Value	Comment
Input	Nominal value	e.g., 28Vdc
	Error ratio	e.g., -7% to +5%
Sampling step	0.01 second	
Output	Fault value	10-sec-step*matrix
	Inject time point	

The $Matrix_e$ is in format of a 1000*2 matrix with two columns containing the start time and fault data, respectively.

As illustrated in Figure 5.3-2, the nominal matrix is initially filled with nominal operation values. The fault in $Matrix_e$ (left) is injected to the nominal at the time that corresponding to the time at the first row of in $Matrix_e$ (t_1 to t_2 , uniformly random selected start time), producing the final enveloped matrix (right).

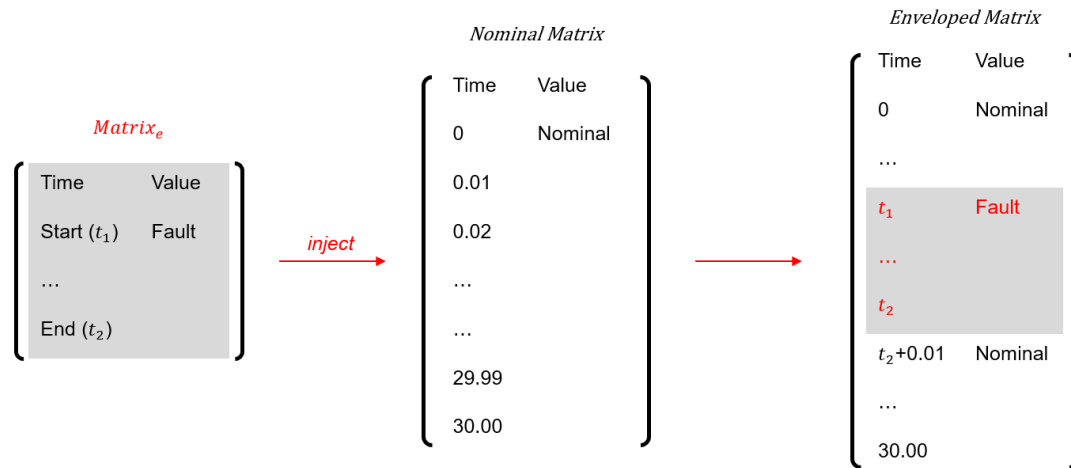


Figure 5.3-2 Injection of fault envelope from $Matrix_e$ into nominal matrix to construct final labelled data.

5.3.1.2 Fault Injection blocks

The final matrices for voltage as independent feature explained in Section 4.4.2.1 and failure characteristics explained in Section 4.2.7 containing the faulty $Matrix_e$ is injected into the model from the beginning of the simulation by using **FromWorkspace** elements shown as an example in Figure 5.3-3.

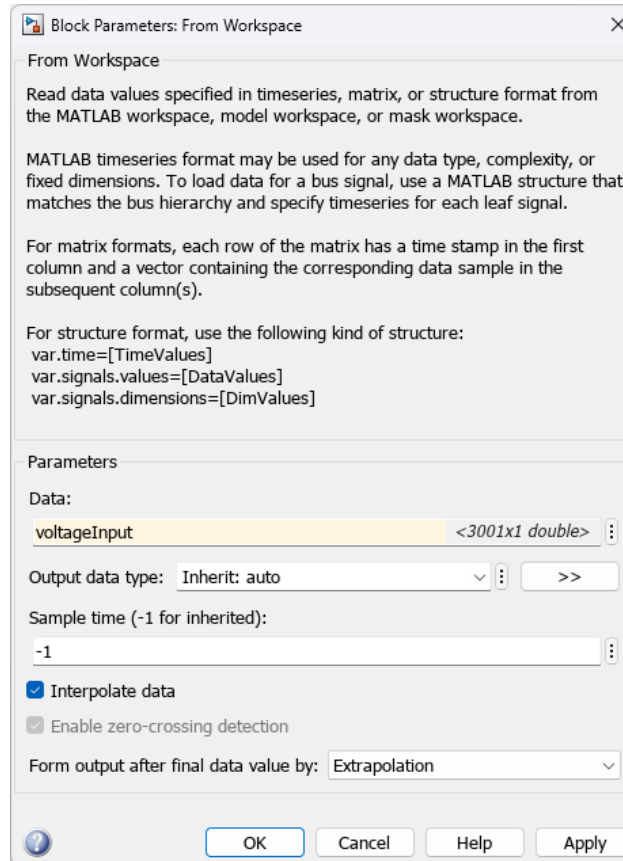


Figure 5.3-3 Example of From Workspace with 3001*1 ‘VoltageInput’ data matrix input containing $Matrix_e$

This design ensures that faults are introduced across the phases of actuator motion, thereby capturing a broad range of system responses. The reasoning behind this randomisation is twofold. First, it prevents systematic bias in the dataset, ensuring that no specific time window is overrepresented. Second, it mirrors the uncertainty of real-world failure occurrences, where faults can happen under varying load and dynamic conditions. By uniformly distributing the injection start time, the framework creates diversity in feature expression, which is essential for robust training of data-driven diagnostic algorithms.

5.3.2 Single Fault Modes: FM1-FM3

This subsection presents examples of $Matrix_e$ for single fault modes FM1, FM2, and FM3, and enveloped final input matrices for voltage as independent feature explained in Section 4.4.2.1 and failure characteristics explained in Section 4.2.7. Single fault injection has been presented and discussed in Section 4.4.2.2.

5.3.2.1 Fault Mode 1 unstable voltage

An example of a final enveloped matrix containing $Matrix_e$ with fault voltage value used for FM1 is shown in Table 5.3-2. If the random number is 11.96, which means the time point to inject $Matrix_e$ is at 11.96 second since the start of the simulation, the failure will happen during the period from 11.96 second to 21.95 seconds; after which the model should run in nominal condition if this is in single failure scenario. The fault start time is uniformly randomly generated as explained in Section 4.2.7 and generated by MATLAB script in Appendix C.

Table 5.3-2 Example a $Matrix_e$ of in FM1 Unstable Voltage Supply with fault value 27.33215 Vdc injected between 11.96s to 21.95s

Time	Voltage Value	Comment
0	0	Initiate and motor activation
...	...	
...	28	
11.95	28	
11.96	27.33215	Fault voltage injected
...	...	
21.95	27.33215	
21.96	28	Back to nominal
...	28	
30.00	28	

5.3.2.2 Fault mode 2 mechanical backlash

An example of a final enveloped matrix containing $Matrix_e$ with fault backlash reverse torque of FM2 is shown in Table 5.3-3. The simulation comprises three backlash fault injections. The simulation started in nominal condition and when reached 0.83 seconds, the first randomly selected 150Nm reverse torque was injected to the model and last until 3.79 seconds. It then returned to nominal condition, representing the release of backlash by applying additional torque output from servo motor. Similar patterns happened during 6.44 seconds to 10.17 seconds, and 15.99 seconds to 19.50 seconds with backlash load of 150Nm and 100Nm, respectively. The three durations and loads are uniformly randomly generated as explained in Section 4.2.7 and generated by MATLAB script in Appendix D.

Table 5.3-3 Example of a $Matrix_e$ in FM2 Mechanical Backlash with fault value 150Nm injected between 0.83s to 3.79s and 15.99s to 19.60s, and 100Nm between 6.44s and 10.17s.

Time	Backlash Value	Comment
0	0	Initiate and motor activation
0.01	0	
...	0	
0.83	150	Backlash injected
...	150	
3.79	150	
3.80	0	Back to nominal
...	0	
6.44	100	Second Injection ($Matrix_e$)
...	100	

10.17	100	
10.18	0	Back to nominal
...	0	
15.99	150	Third Injection ($Matrix_e$)
...	150	
19.60	150	
19.61	0	Back to nominal
...	0	
30.00	0	

5.3.2.3 Fault Mode 3 electric cable wear

Table 5.3-4 shows an example of a final enveloped matrix containing $Matrix_e$ with fault FM3 resistance change. The random number in this simulation is 5.62, which means the time point to inject $Matrix_e$ is at 5.62 second since the start of the simulation, the failure happened during the period from 5.62 second to 15.61 seconds, after which the model returned to nominal condition. The fault start time is uniformly randomly generated as explained in Section 4.2.7 and generated by MATLAB script in Appendix E.

Table 5.3-4 Example of a $Matrix_e$ in FM3 Electric Cable Wear with fault value 1ohm injected between 5.62s to 15.61s.

Time	Resistance Value	Comment
0	0.6222	Initiate and motor activation
0.01	0.6222	
0.02	0.6222	

...	0.6222	
5.62	1	Fault resistance injected
5.63	1	
...	...	
15.61	1	
15.62	0.6222	Back to nominal
...	0.6222	
30.00	0.6222	

5.3.3 Combined Fault Modes: FM4–FM6

To simulate more complex and diagnostically challenging fault scenarios, the fault injection framework is extended to include combinations of fault modes. Three compound fault types are introduced as FM4 to FM6:

- a) FM4 merges unstable voltage supply FM1 and mechanical backlash FM2.
- b) FM5 merges backlash FM2 with resistance change FM3.
- c) FM6 incorporates all three fault types simultaneously.

These combinations are constructed by covering individual $Matrix_e$ inputs for each mode, with independently sampled start times and amplitudes for example in Table 5.3-5.

Table 5.3-5 Example of a summary of three *Matrix_{es}* in FM6 Multiple Faults

Time	Voltage	Backlash	Resistance	Comment
0	0	0	0.6222	Initiate and motor activation
0.01	1.473684	0	0.6222	
...	28	0	0.6222	
2.00	28	50	0.6222	Backlash injected
...	28	50	0.6222	
4.89	28	50	0.6222	
4.90	28	0	0.6222	Backlash released
...	28	0	0.6222	
5.17	28	0	0.45	Fault resistance injected
...	28	0	0.45	
5.89	28	100	0.45	Backlash injected
...	28	100	0.45	
7.58	27.13	100	0.45	Fault voltage injected
...	27.13	100	0.45	
9.32	27.13	100	0.45	
9.33	27.13	0	0.45	Backlash released
...	27.13	0	0.45	
13.77	27.13	100	0.45	Backlash injected
...	27.13	100	0.45	
15.17	27.13	100	0.45	
15.18	27.13	100	0.6222	Resistance back to nominal
...	27.13	100	0.6222	
17.58	27.13	100	0.6222	
17.59	28	100	0.6222	Voltage back to nominal
...	28	100	0.6222	
17.72	28	100	0.6222	
17.73	28	0	0.6222	Backlash released
...	28	0	0.6222	Back to nominal
30.00	28	0	0.6222	

Table 5.3-6 Summary of Fault Modes FM1–FM6 and Their Physical Interpretation

Fault Mode	Description	Fault Types Included
FM1	Voltage disturbance	Unstable voltage supply
FM2	Mechanical backlash	Transmission clearance
FM3	Resistance change	Electrical resistance anomaly
FM4	Combined FM1+FM2	Voltage + Backlash
FM5	Combined FM2+FM3	Backlash + Resistance
FM6	Combined FM1+FM2+FM3	All three fault types

The combined injection structure is designed to reflect potential multiple degradation in EMA, such as contact oxidation and mechanical wear occurring simultaneously. It also supports the evaluation of classifier robustness under overlapping fault symptoms. Details of the resulting dataset structure and feature impact are analysed in Section 6.1.

5.4 Output Data Structure Description

The simulation framework representing EMA behaviour under various operating and fault conditions act as a structured data generator for machine learning–based PHM as addressed in Section 2.7. The design of the data structure follows conventions widely adopted in the PHM community like database format for NASA's C-MAPSS and PHM Society Data Challenge datasets. Each simulation run produces output in a standardised format consisting of two core components:

- **Feature Dataset:** A multivariate time series comprising physical variables such as voltage, current, displacement, velocity, force, and power. The data is sampled at a fixed frequency (100 Hz) and organised into matrices where each row represents a time step, and each column corresponds to a sensor or state variable.
- **Label File:** A structured annotation file indicating simulation ID, fault type, injection parameters, and fault onset/offset times. This enables supervised

learning workflows and facilitates performance benchmarking for classification or regression models.

In addition to aligning the output structure with PHM standards, particular emphasis is placed on the traceability and determinism of label generation. Each label entry is generated at the time of simulation, solely based on the injected fault parameters defined in the input matrix. The label file, exported as `Simulation_Label_Table.csv`, includes key metadata fields such as Simulation ID, Fault Mode (FM1–FM6 summarised in Table 5.4-1), Fault Value, Injection start time, and end time. These fields provide complete context for each simulation run and support a wide range of supervised learning tasks. Table 5.4-1 summarises the structure and meaning of each field in the label file.

Table 5.4-1 Structure and meaning of fields in the label file

Field Name	Description
RunID	Unique identifier for each run
FaultMode	Fault class (FM1-FM6)
FaultValue	Injected fault magnitude
FaultStart (s)	Time when fault begins
FaultEnd (s)	Time when fault ends

A complete example of the label file structure is illustrated in Table 6.1-3, while the field definitions and naming conventions are summarised in Table 5.4-1 for clarity and documentation purposes.

5.5 Data Analysis and Validation

To ensure consistency between simulation inputs and the generated outputs, a mapping structure is implemented between the input command tables and the resulting data files. Each simulation run is governed by a predefined input datasheet, which specifies the operational scenario, fault values, and injection timing. These parameters are read into the simulation model through

FromWorkspace blocks and directly affect physical components within the EMA DT.

During the simulation, the outputs are collected via **ToWorkspace** blocks and exported to structured files. These include: (1) time-series sensor measurements, (2) a feature name table indicating the variable names and units, and (3) a label file that records metadata such as fault value(s), injection start time(s), and fault mode type.

The validity of the developed simulation models is assessed through a combination of engineering-based reasoning, comparative analysis with prior research, and preliminary machine learning evaluation. Three complementary strategies are employed:

1. Engineering-theoretical consistency

All simulated fault mechanisms and system responses are constructed to align with fundamental physical principles governing electro-mechanical actuators. Relationships between voltage, current, resistance, mechanical load, and displacement are evaluated using established laws such as Ohm's law and Newton's second law. Fault effects are examined to ensure physical plausibility and dynamic realism. Additionally, simulated signals are inspected to confirm consistency with the expected temporal and functional profiles for each injected fault mode.

2. Comparative benchmarking against prior research

Output signals and fault responses are qualitatively compared with results reported in related modelling and simulation studies in the domains of fault diagnosis, actuator modelling, and DT systems. This includes comparisons with known failure signatures, system-level degradation behaviours, and dynamic responses under perturbation. The modelling framework is implemented using established tools (MATLAB/Simulink and SimScape), allowing for alignment with widely accepted simulation practices and solver configurations.

3. Data-driven regression-based assessment

To further validate the internal consistency and discriminability of the simulated dataset, three classical machine learning regression models, Linear Regression (LR), Support Vector Machine (SVM), and Random Forest Regression (RFR), are trained to predict system states (e.g., displacement or power input) based on selected input variables (e.g., voltage, current, resistance). These models are used to assess the learnability and noise level of the generated data, as well as to confirm the presence of strong input–output relationships under both nominal and fault conditions. Evaluation metrics such as Mean Squared Error (MSE) and R^2 scores are reported across training and validation splits to demonstrate the utility of the dataset for downstream tasks such as fault classification, system identification, and DT refinement. This is presented in Chapter 6.

Together, these validation strategies provide a comprehensive basis for assessing the fidelity, relevance, and generalisability of the simulation framework, as well as its suitability for supporting data-driven health monitoring applications.

5.6 Simulation Platform Specification

The simulations were run on a computer with the following specifications as shown in Table 5.6-1.

Table 5.6-1 Simulation platform specification

Part	Model
CPU Model	AMD Ryzen 9 3900X
CPU Speed	3.8GHz
RAM	64GB
OS	Windows 11 23H2
Graphics card	ROG STRIX GeForce RTX 4080 SUPER 16GB GDDR6X OC
MATLAB	R2023B Update 6

5.7 Chapter Summary

This chapter has described the development of the DT–based data generator used in this research. The system is built in two levels: a top-level framework that

manages inputs, fault injection, and data export, and a bottom-level EMA model that simulates detailed electromechanical behaviour. Input values, including fault parameters, are generated through MATLAB algorithms and injected into the model in a controlled way.

The outputs are structured as labelled time-series datasets, designed to match formats commonly used in PHM research. Multiple validation strategies have been used to confirm the consistency and physical realism of the simulation results, including basic machine learning checks. The data generator has been designed for flexibility, scalability, and compatibility with algorithm training needs, and is able to produce large datasets efficiently using typical desktop hardware.

6 FAULT SIMULATION OUTPUT

This chapter presents the output covering the multiple fault modes and scenarios. These simulations aim to evaluate the system's behavioural response under nominal, single-fault, dual-fault, and multiple-fault scenarios. The outputs are analysed to assess whether the key features captured by the simulation are effective in identifying and differentiating failure modes.

Section 6.1 explains the structure of the generated datasets, their format, and computational characteristics. It also demonstrates sample outputs and simulation label files that support downstream data processing.

Section 6.2 evaluates the input and output of the SimScape EMA model under the multiple fault conditions, illustrating how the DT accurately reflects the influence of various failure types on system dynamics.

6.1 Data Structure

The structure of the generated dataset follows the time-series conventions in PHM research, with consistent sampling intervals, multi-sensor outputs, and structured labels, making the outputs directly usable in ML pipelines. For each completed simulation, the following data files in the structure mentioned in Section 5.4 are generated:

- 1*cycle-number Dataset 1 consisting of all features.
- 1*cycle-number Dataset 2 with feature name for all features, respectively.
- 1*label file.

The three sampled data files to show the structure are in Table 6.1-1, Table 6.1-2, Table 6.1-3.

Table 6.1-1 Example of part of all feature datasheet specification from 6.66s for a 0.17s duration of FM2

Time	Voltage	Current	PowerInput	Displacement	RTorOut	RAngVel	GearTorIn	GearTorOut	GearAngVel	WormTorIn	WormTorOut
6.66	28	-34.5196	-966.549	92.85233	4724.883	4724.883	4724.883	-0.12923	944.9767	-0.12923	-0.12923
6.67	28	-33.9777	-951.375	94.41656	4692.684	4692.684	4692.684	-0.12923	938.5368	-0.12923	-0.12923
6.68	28	-33.4443	-936.442	95.97023	4660.994	4660.994	4660.994	-0.12923	932.1987	-0.12923	-0.12923
6.69	28	-32.9194	-921.744	97.51349	4629.805	4629.805	4629.805	-0.12923	925.9609	-0.12923	-0.12923
6.7	28	-32.4028	-907.279	99.04653	4599.109	4599.109	4599.109	-0.12923	919.8218	-0.12923	-0.12923
6.71	28	-31.8944	-893.043	100.5695	4568.899	4568.899	4568.899	-0.12923	913.7798	-0.12923	-0.12923
6.72	28	-31.394	-879.032	102.0826	4539.167	4539.167	4539.167	-0.12923	907.8334	-0.12923	-0.12923
6.73	28	-30.9015	-865.243	103.5859	4509.905	4509.905	4509.905	-0.12923	901.981	-0.12923	-0.12923
6.74	28	-30.4168	-851.671	105.0796	4481.106	4481.106	4481.106	-0.12923	896.2211	-0.12923	-0.12923
6.75	28	-29.9398	-838.315	106.5638	4452.762	4452.762	4452.762	-0.12923	890.5524	-0.12923	-0.12923
6.76	28	-29.4703	-825.169	108.0388	4424.867	4424.867	4424.867	-0.12923	884.9734	-0.12923	-0.12923
6.77	28	-29.0083	-812.232	109.5046	4397.413	4397.413	4397.413	-0.12923	879.4825	-0.12923	-0.12923
6.78	28	-28.5535	-799.499	110.9614	4370.393	4370.393	4370.393	-0.12923	874.0786	-0.12923	-0.12923
6.79	28	-28.106	-786.968	112.4093	4343.8	4343.8	4343.8	-0.12923	868.7601	-0.12923	-0.12923
6.8	28	-27.6655	-774.635	113.8485	4317.629	4317.629	4317.629	-0.12923	863.5257	-0.12923	-0.12923
6.81	28	-27.232	-762.496	115.2791	4291.871	4291.871	4291.871	-0.12923	858.3742	-0.12923	-0.12923

Table 6.1-2 Example of single feature datasheet specification from 0 to 1.19 second of FM2

Time	Current	Time	Current	Time	Current	Time	Current	Time	Current	Time	Current
0	-1.51E-06	0.2	40.95258	0.4	45.11806	0.6	44.98112	0.8	44.94509	1	45.17712
0.01	2.331453	0.21	40.86386	0.41	44.95797	0.61	45.33111	0.81	45.26852	1.01	44.9803
0.02	4.627501	0.22	40.83217	0.42	45.33694	0.62	45.14988	0.82	45.07506	1.02	45.28879
0.03	6.890118	0.23	40.85626	0.43	45.16996	0.63	44.97172	0.83	44.88546	1.03	45.08766
0.04	9.121661	0.24	40.9342	0.44	45.00558	0.64	45.31602	0.84	45.20759	1.04	44.89046
0.05	11.32483	0.25	41.06342	0.45	44.84487	0.65	45.13219	0.85	45.01438	1.05	45.19803
0.06	13.50262	0.26	41.24073	0.46	45.2224	0.66	44.95162	0.86	44.82542	1.06	44.99776
0.07	15.65828	0.27	41.4624	0.47	45.05637	0.67	45.29123	0.87	45.14866	1.07	45.29965
0.08	17.79525	0.28	41.72425	0.48	44.89368	0.68	45.10545	0.88	44.95685	1.08	45.0951
0.09	19.91711	0.29	42.02164	0.49	45.26753	0.69	44.92314	0.89	45.27491	1.09	44.89451
0.1	22.02754	0.3	42.34966	0.5	45.09902	0.7	45.25937	0.9	45.07871	1.1	45.19558
0.11	24.13028	0.31	42.70308	0.51	44.93364	0.71	45.07237	0.91	44.88639	1.11	44.99212
0.12	26.22904	0.32	43.07653	0.52	45.30238	0.72	44.8891	0.92	45.20333	1.12	45.2879
0.13	28.32749	0.33	43.4645	0.53	45.13084	0.73	45.2234	0.93	45.00761	1.13	45.0805
0.14	30.42919	0.34	43.86148	0.54	44.96228	0.74	45.03598	0.94	44.81624	1.14	44.87721
0.15	32.53756	0.35	44.26197	0.55	45.32499	0.75	44.85253	0.95	45.13484	1.15	45.17308
0.16	34.65583	0.36	44.6606	0.56	45.15014	0.76	45.18642	0.96	44.94094	1.16	44.96738
0.17	36.78701	0.37	45.05218	0.57	44.97822	0.77	44.99932	0.97	45.25494	1.17	45.25879
0.18	38.93385	0.38	44.89555	0.58	45.3345	0.78	45.32652	0.98	45.05703	1.18	45.04964
0.19	41.0988	0.39	45.28102	0.59	45.15633	0.79	45.13409	0.99	44.86318	1.19	44.84487

Table 6.1-3 Example of label file specification from 20 cycles of FM2

RunID	Label	AnomalyType	Backlash1	StartTime1	EndTime1	Backlash2	StartTime2	EndTime2	Backlash3	StartTime3	EndTime3
1	2	Mechanical Backlash	150	3.59	5.53	NaN	NaN	NaN	NaN	NaN	NaN
2	2	Mechanical Backlash	50	4.11	5.77	150	6.57	8.37	NaN	NaN	NaN
3	2	Mechanical Backlash	150	2.64	3.64	NaN	NaN	NaN	NaN	NaN	NaN
4	2	Mechanical Backlash	150	2.17	3.47	100	3.75	5.74	NaN	NaN	NaN
5	2	Mechanical Backlash	150	2.24	4.19	NaN	NaN	NaN	NaN	NaN	NaN
6	2	Mechanical Backlash	50	2.92	3.93	150	7.44	8.95	NaN	NaN	NaN
7	2	Mechanical Backlash	50	6.5	7.97	NaN	NaN	NaN	NaN	NaN	NaN
8	2	Mechanical Backlash	100	4.03	5.96	150	6.86	8.76	50	0.91	2.25
9	2	Mechanical Backlash	100	0.85	2.75	50	8.37	9.44	NaN	NaN	NaN
10	2	Mechanical Backlash	50	3.57	5.53	50	8.2	9.87	150	1.45	3.45
101	2	Mechanical Backlash	100	4.94	6.9	100	7.94	9.49	50	2.7	4.26
102	2	Mechanical Backlash	150	3.39	4.97	NaN	NaN	NaN	NaN	NaN	NaN
103	2	Mechanical Backlash	150	6.51	8.12	100	4.7	5.93	150	2.43	4.35
104	2	Mechanical Backlash	150	3.59	5.18	NaN	NaN	NaN	NaN	NaN	NaN
105	2	Mechanical Backlash	150	6.66	8.41	150	3.29	4.74	100	1.16	2.34
106	2	Mechanical Backlash	50	4.74	6.46	NaN	NaN	NaN	NaN	NaN	NaN
107	2	Mechanical Backlash	150	2.25	4.22	150	7.7	9.12	100	0.15	1.31
108	2	Mechanical Backlash	50	1.2	2.77	100	7.64	8.73	NaN	NaN	NaN
109	2	Mechanical Backlash	150	5.72	7.42	NaN	NaN	NaN	NaN	NaN	NaN
110	2	Mechanical Backlash	50	3.92	5.42	NaN	NaN	NaN	NaN	NaN	NaN

The computational time is also measured by using `tic`, `toc` function. The result for running 10000 simulation cycles on each fault scenario is summaries in the following Table 6.1-4.

Table 6.1-4 Summary of dataset and computational time

Fault Mode	Cycle Number	Computational Time (s)	Per Cycle (s)
No_Fault		18964.08	1.90
FM1 (Voltage)		20516.81	2.06
FM2 (Backlash)		19364.05	1.94
FM3 (Resistance)	10000	30419.46	3.05
FM4 (Vol+Backlash)		22717.79	2.28
FM5 (Backlash+Res)		21059.26	2.11
FM6 (Vol+Backlash+Res)		29961.87	3.00

6.2 Fault Data Examples

6.2.1 Dual Fault Modes

6.2.1.1 Fault Mode 4 Power Supply and Backlash

Fault Mode FM1 and FM2 are injected to the model. Figure 6.2-1 and Figure 6.2-2 present the statistical distribution of the 10000 simulation runs for the combined Voltage and Mechanical Backlash fault mode (FM4) as defined in Section 5.3.3. Figure 6.2-1 illustrates the distribution of voltage fault injection values and their respective timepoints. Figure 6.2-2 shows the percentage distribution of backlash fault injections across different values.

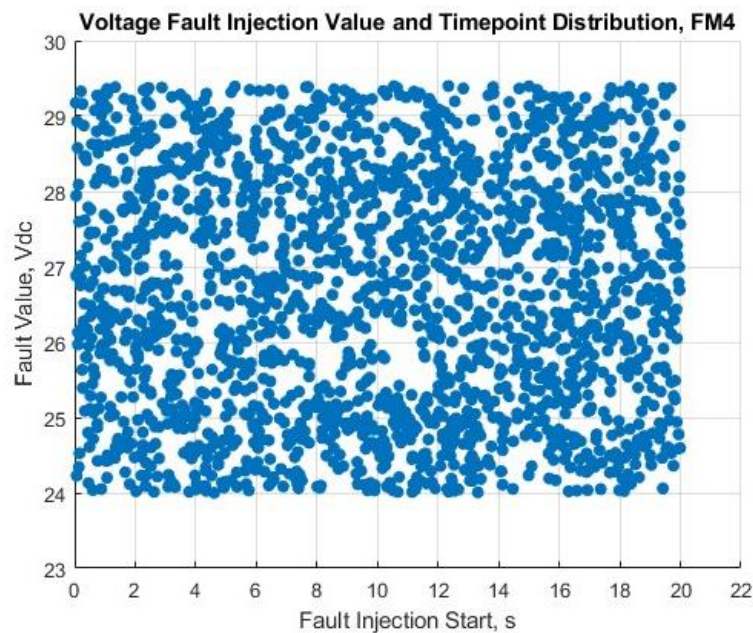


Figure 6.2-1 Voltage fault injection value and timepoint distribution in FM4

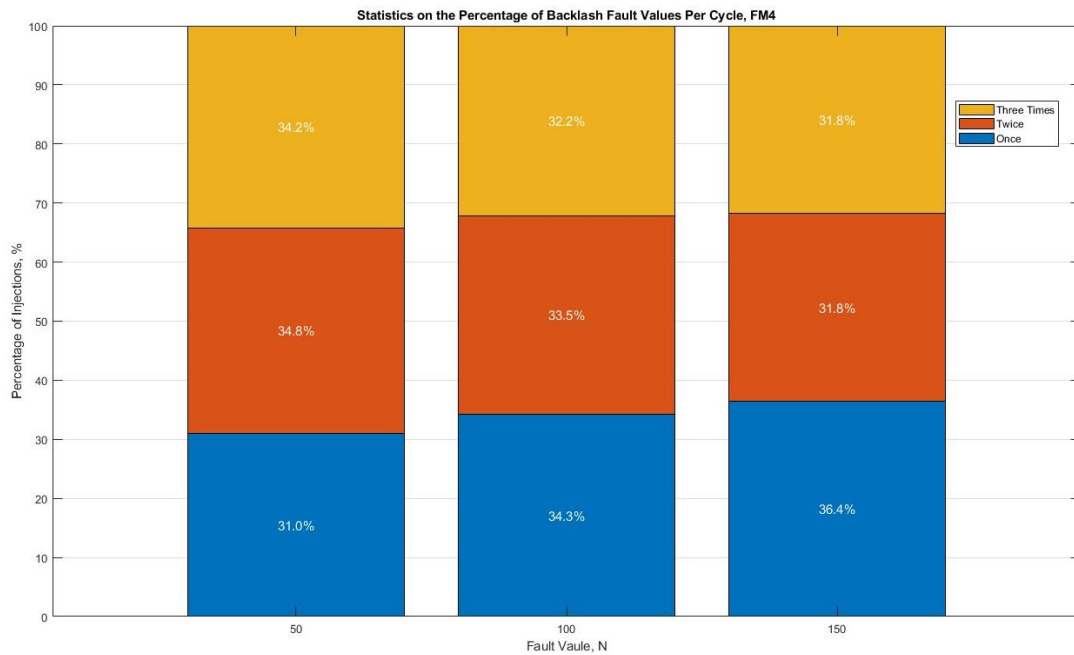


Figure 6.2-2 Statistics on the percentage of backlash fault values per cycle in FM4

Figure 6.2-3 illustrates the current output under the dual-fault condition for one of the simulation runs with Fault Mode FM1 (voltage disturbance) (green line) and Fault Mode FM2 (mechanical backlash) (black dash-dot line) simultaneously injected into the system model. The supply voltage is reduced to 27 V and backlash load shows as abrupt variations in the load profile.

The plot presents a comparison between nominal current (blue line) and fault current (red line). The nominal current is presented earlier in Figure 4.4-5. The simultaneous presence of compensatory current spikes (due to low voltage) and load-induced ripples (due to backlash) reflect fault compounding, where faults from two different domains introduce coupled responses. The fault current exhibits oscillations and sharp spikes in magnitude, particularly during transitions in the backlash load or voltage steps.

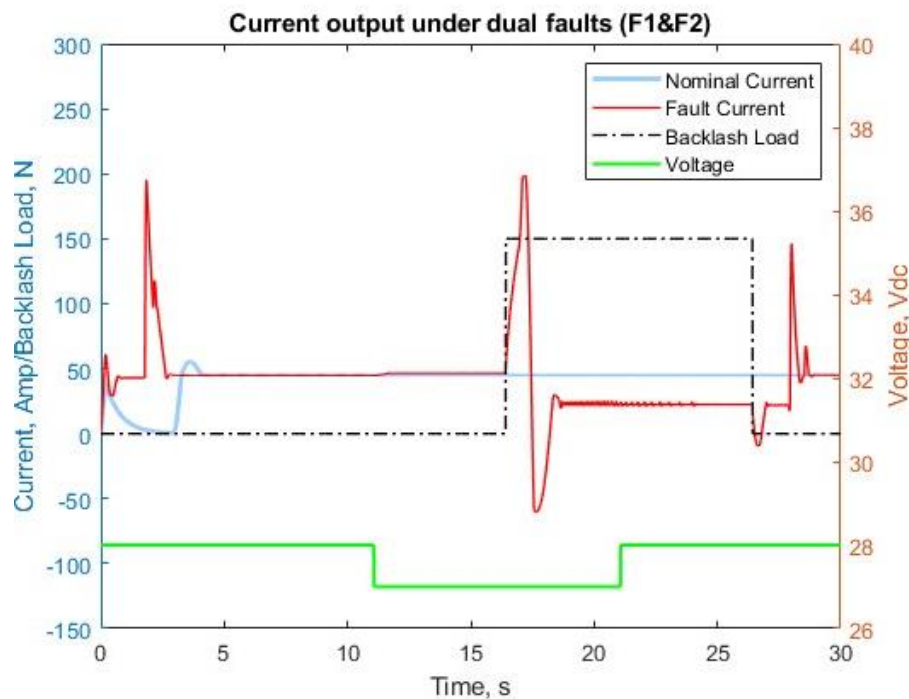


Figure 6.2-3 Current output under FM4

After the voltage drop to 27V at 11.33s, there is a slight elevation of the fault current, indicating increased electrical effort required to maintain actuator performance under reduced voltage. When the backlash happens, the current spiked to sustain the extension. A similar effect was previously observed in Figure 4.4-14, affirming the strong influence of reverse torque and voltage deficiencies on the current.

Such scenarios are difficult to isolate in real aircraft systems and have been reported as leading contributors to intermittent flight control surface delays [120]. This demonstrates the multi-domain simulation approach and confirms that dual-fault interactions cannot be diagnosed by any single signal in isolation.

6.2.1.2 Fault Mode 5 Cable Wear and Backlash

Figure 6.2-4 and Figure 6.2-5 illustrate the input distribution of the 10,000 combined Mechanical Backlash and Resistance Change fault injections for Fault Mode 5 (FM5).

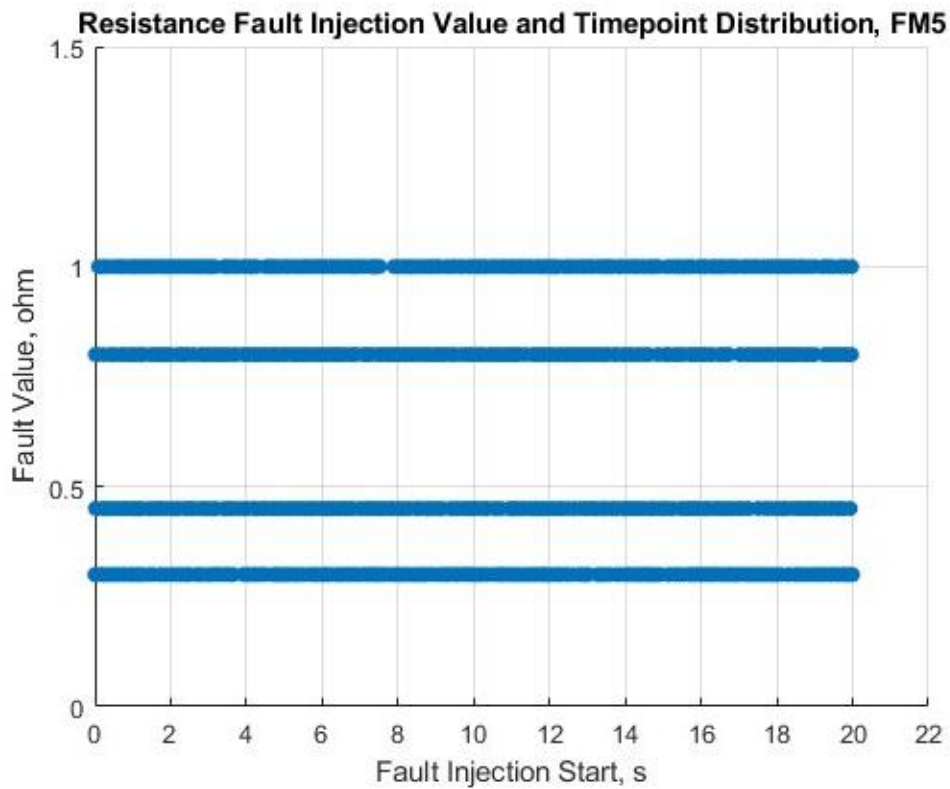


Figure 6.2-4 Resistance fault injection value and timepoint distribution in FM5

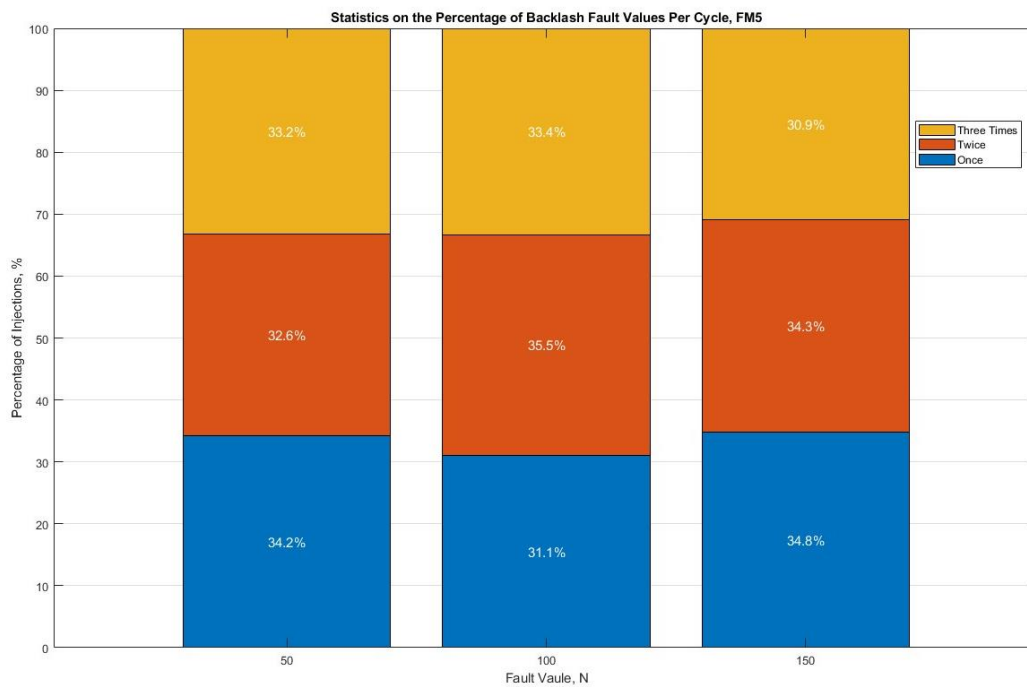


Figure 6.2-5 Statistics on the percentage of backlash fault values per cycle in FM5

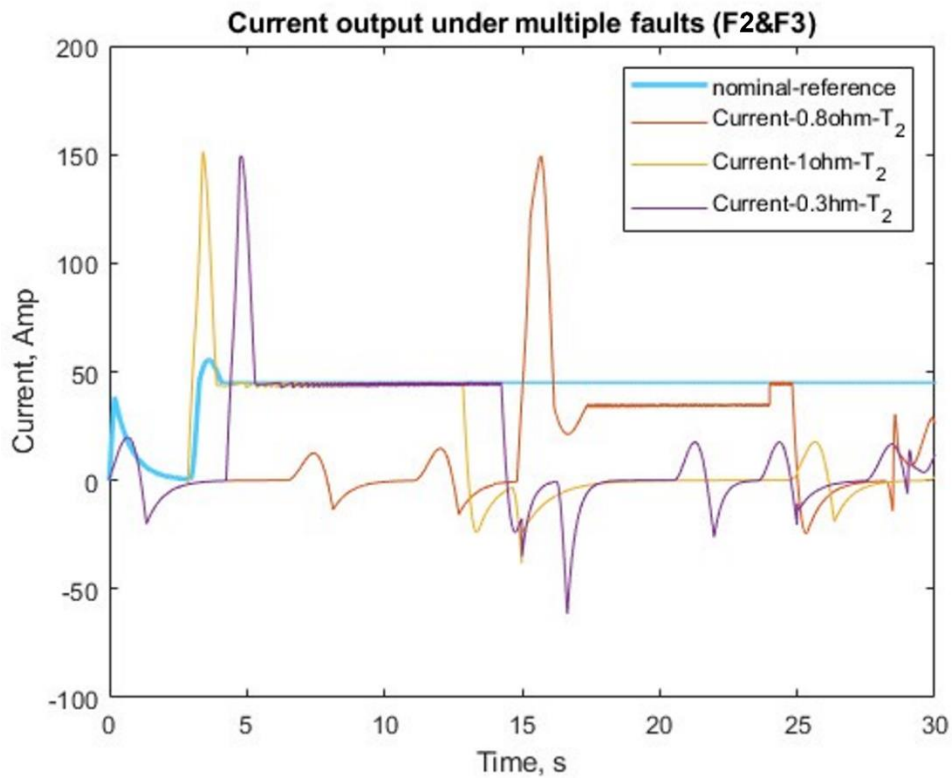


Figure 6.2-6 Current output under FM5

Figure 6.2-6 illustrates the current output of three simulation runs under the effect of dual faults FM5: mechanical backlash and electrical resistance variation (FM2 & FM3). The three fault cases compared are: resistance values of 0.8ohm, 1.0ohm, and 0.3ohm, while voltage remains nominal.

The 0.8ohm case (orange line) shows moderate instability, with current peaking around 150 A early on and another spike near 15 seconds. The waveform includes intermittent fluctuations and reduces current plateaus, suggesting intermittent loss in torque response or oscillatory control. In the 1.0ohm case (gold line), the current behaviour is even more erratic. This severe deviation from the nominal resistance induces substantial drops in current, with visible suppression below zero amps across several intervals, which shows evidence of overcompensation or actuator performance collapse due to excessive resistance.

In contrast, the scenario with reduced resistance (0.3ohm, purple line) exhibits a distinct profile. Though it also displays sharp current deviations during early and mid-cycle, the magnitude is generally more contained, and the waveform

eventually stabilises more quickly. However, around 16 seconds, a sharp negative peak occurs, likely triggered by backlash reversal or a transient overload. Compared to the high-resistance cases, the 0.3ohm scenario shows better energy flow continuity and faster recovery, highlighting that lowering resistance under constant mechanical load can alleviate the electrical burden on the system. Overall, the results confirm that while mechanical load phase (T_2) stays fixed, current output is highly sensitive to resistance deviation. Increased resistance leads to unstable or inadequate current supply, while moderate reductions can improve control stability, albeit at the cost of brief overshoots during transitions.

This case reflects the practical challenge of simultaneous electrical degradation and mechanical fault. The simulation results in Figure 6.2-6 repeat findings from aircraft maintenance reports where loose or aging cable insulation (raising resistance) coincided with increased drivetrain friction [22][83][84]. The model's ability to reproduce both undercurrent and torque fluctuation behaviours confirms its usefulness for data generation in failure co-dependence studies as discussed in Section 6.2.1.2.

6.2.2 Multiple Fault Mode 6

Figure 6.2-7, Figure 6.2-8 and Figure 6.2-9 presents the fault injection statistics of the 10000 simulations for Fault Mode 6 (FM6), which integrates voltage disturbance, mechanical backlash, and resistance change within a single simulation cycle.

The three fault variables were uniformly distributed both in terms of their value range and their temporal occurrence as defined in Section 5.3.3.

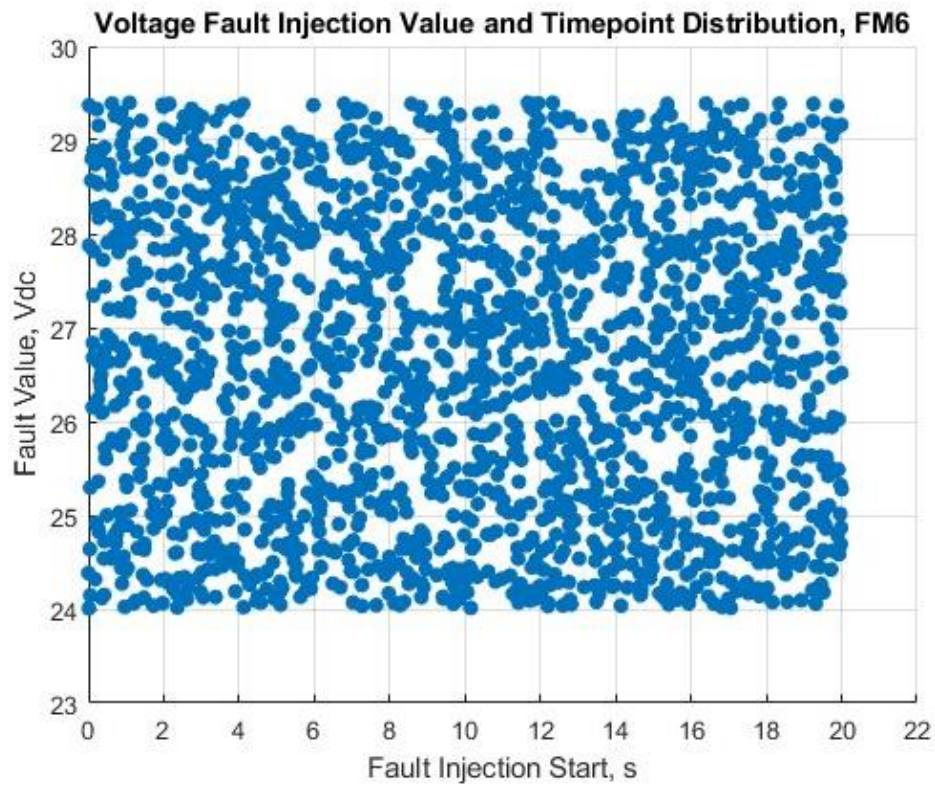


Figure 6.2-7 Voltage fault injection value and timepoint distribution in FM6

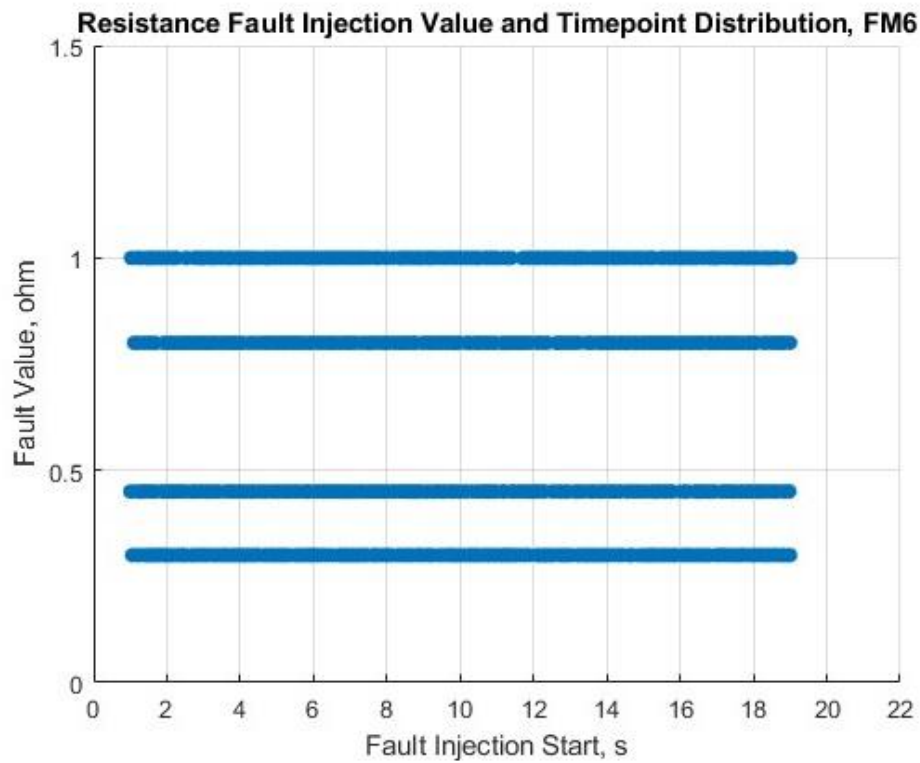


Figure 6.2-8 Resistance fault injection value and timepoint distribution in FM6

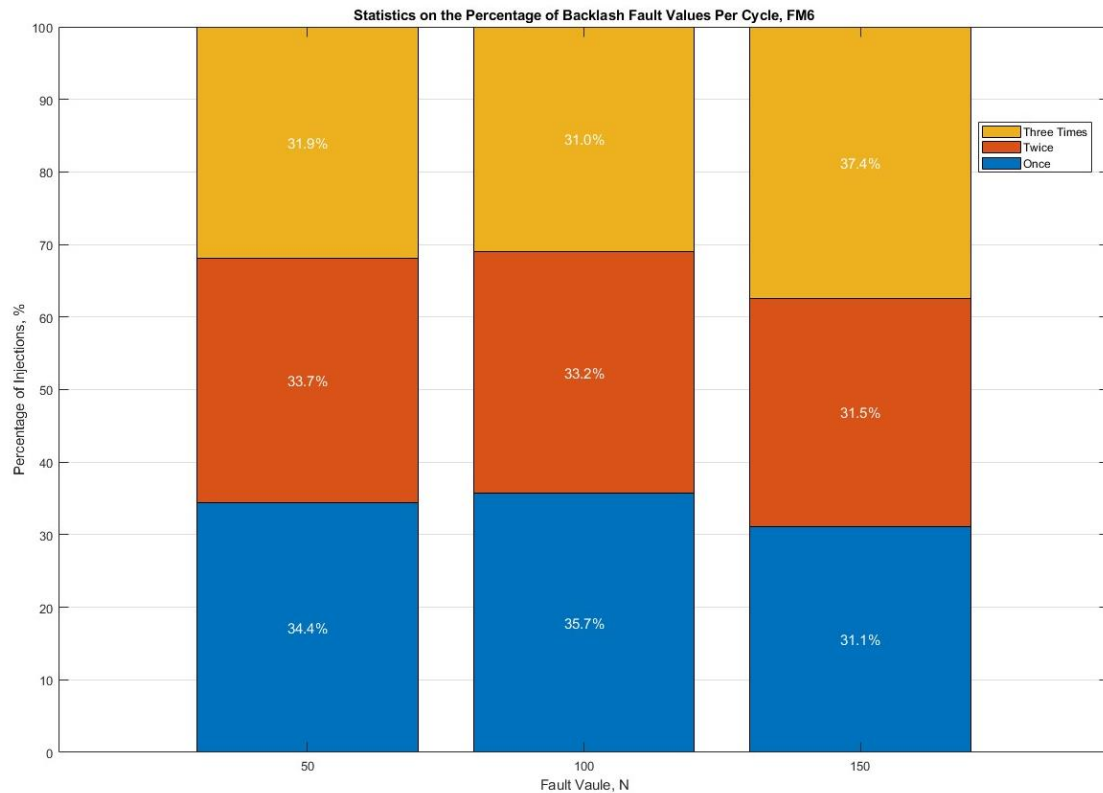


Figure 6.2-9 Statistic on the percentage of backlash fault values per cycle in FM6

Three examples of FM6 simulation runs were selected to demonstrate the outcomes of the data generator as listed in Table 6.2-1. The selection was based on both voltage tolerance (-7%~+5%) mentioned in Section 4.2.7.1. Example 1 (RunID: 55):

- Injected voltage 24.33Vdc, which is below the -7% lower safety limit of the nominal 28Vdc, simulating an unsafe undervoltage condition.
- Resistance: 0.3ohm, representing a clean but possibly loosely connected circuit.
- Backlash: 1 time during the cycle, reflecting a mild and isolated mechanical disturbance.
- Engineering scenario: Representative of a pre-flight flap test during Auxiliary Power Unit (APU)-only operation, where temporary voltage sag may occur due to multiple subsystems drawing current simultaneously. The actuation circuit remains largely intact, but the

actuator experiences a brief backlash during high-load extension due to cold-start mechanical stiffness.

- Example 2 (RunID: 5156):
 - Injected voltage 29.40Vdc, positioned at the +5% upper safety limit, mimicking a system operating at high electrical potential.
 - Resistance: 1ohm, indicating significant cable aging or insulation wear.
 - Backlash: 2 times, stressing the system's ability to recover from repeated minor torque gaps.
 - Engineering scenario: Representative of over-voltage combines with aged wiring and sticky control surface mechanism, leading to variable current delivery and unstable compensation.
- Example 3 (RunID: 8455):
 - Injected voltage 26.09Vdc, close to the lower safe limit.
 - Resistance: 0.8ohm, indicating moderate internal degradation.
 - Backlash: 3 times, imposing multiple high-load torque reversals.
 - Engineering scenario: Representative of lowered-voltage combined with partial harness contamination, and a jamming hinge.

Table 6.2-1 Label of three samples of FM6 simulation runs with No.55, 5156 and 8455

RunID	Voltage	StartTime	Resistance	StartTime	Backlash1	StartTime1	EndTime1	Backlash2	StartTime2	EndTime2	Backlash3	StartTime3	EndTime3
55	24.33	9.93	0.3	17.86	100	6.22	9.02	NaN	NaN	NaN	NaN	NaN	NaN
5156	29.40	1.09	1	10.46	100	4.99	8.27	100	13.58	17.5	NaN	NaN	NaN
8455	26.09	0.35	0.8	9.15	150	1.47	4.18	150	11.88	14.64	150	6.04	8.9

The output file captures 15 simulation features. The current diagram is the focus of the following illustrations as it represents a simple data point from the ECU. All the other features are evaluated to develop the discussion.

6.2.2.1 FM6 Case 1

In the first example run, shown in Figure 6.2-10, the system experiences a backlash event followed by a low voltage event, and a cable resistance drop during the voltage event during which the voltage recovered.

Compared to the nominal current reference (blue line), the fault current (red line) exhibits an evident spike following the backlash event. The spike indicates the PCU calls for compensatory effort to maintain torque output by feeding higher current, reaching roughly 100A. The current drops down to 0 after the backlash frees. The current recovery pattern Figure 4.4 14 overlaps with the low voltage event and recovers to a level below the expected nominal value. The beginning of resistance drop event is at the later stage of low voltage event, and the current surges higher to provide sufficient power input and torque to meet displacement target. The actuator returns to nominal extension status after all faults release.

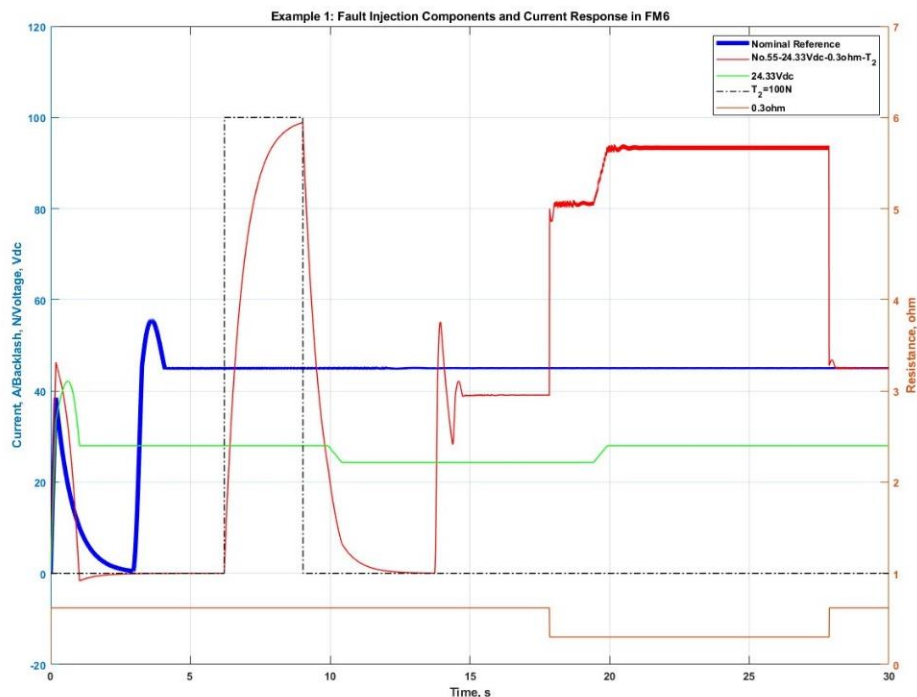


Figure 6.2-10 Example 1 of FM6, 24.33Vdc, 0.3Ohm, 100Nm backlash one time

The current plot clearly shows the identifiable features associated with the backlash event. The resistance event is prominent in the plot. However, the voltage event is not so clearly identifiable. This is an example of the complexity of the interactions between the causes of faults and challenge the PHM research to classify fault features and correlate them to engineering events.

6.2.2.2 FM6 Case 2

In the second example run as shown in Figure 6.2-11, the system experiences two backlash events, the second backlash overlapped with resistance increase and partially with voltage increase.

The fault current response shows strong fluctuations and notable instability. In the early stage where the injected voltage is at upper safety limit, it has minor effect on current. The higher current and voltage are triggered by the PCU to compensate excessive load during backlash event, which is similar to the phenomenon in Figure 6.2-10. In the middle-to-late stage, with compensation voltage reaches near 60Vdc, the elevated resistance continuously hampers control stability, and the current reaches 120A and fails to recover to a smooth profile. It then takes a sharp drop and return to nominal after all the faults are cleared, indicating potential overcompensation and control saturation. These dynamics are consistent with the findings in Section 6.2.1.2, where high-resistance wiring faults disrupted the control loop.

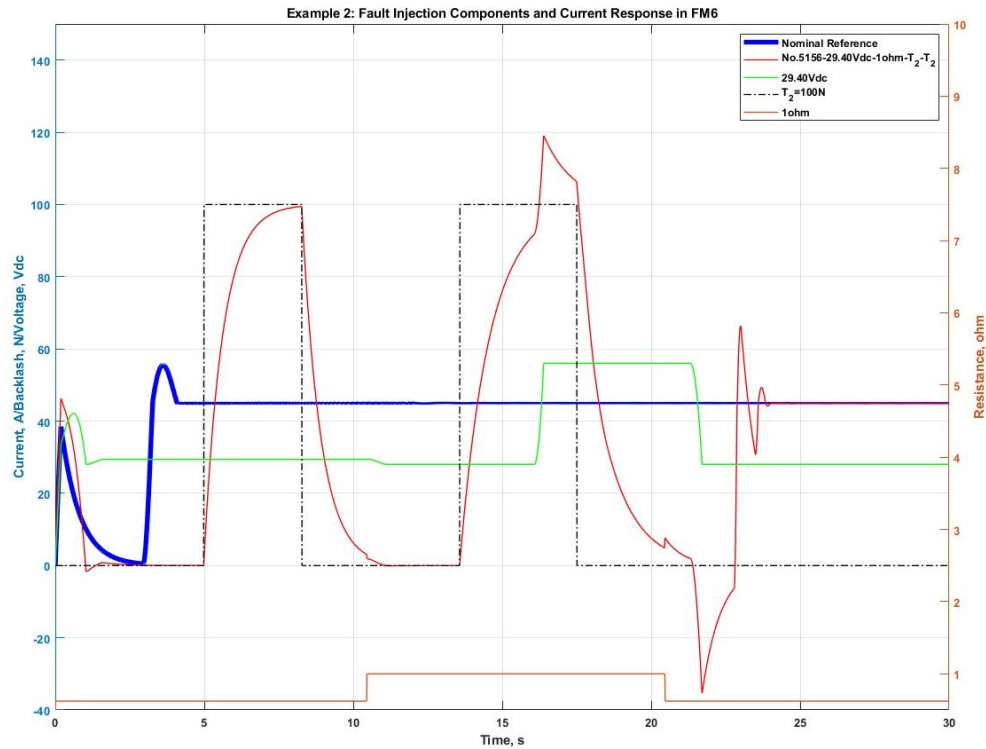


Figure 6.2-11 Example 2 of FM6, 29.40Vdc, 10hm, 100Nm backlash two times

The current plot clearly shows two distinct backlash events. They are not exact replicates as there are the voltage and resistance events interact only with the second backlash. This example illustrates the PHM challenge to classify features although they are not exactly the same.

6.2.2.3 FM6 Case 3

The third example run as shown in Figure 6.2-12 presents a combined fault setting where three backlashes are injected in three separate time periods, and the resistance increase event happens after second backlash happens, enveloping the third backlash. The voltage drop event is not obvious due to the continuous compensation requests triggered by PCU.

The current plot in this configuration displays pronounced peaks, reaching nearly 180 A, following each of the three torque reversal events. The magnitude and frequency of current oscillations are significantly higher than in the previous examples, reflecting the greater effort required to overcome mechanical resistance under partial electrical degradation. Despite these disturbances, the

system remains stable and is able to recover to near-nominal post-transient. This case illustrates the controller's resilience under high-load, moderate-fault conditions, and the importance of balancing mechanical demand with electrical capacity to avoid excessive overdrive.

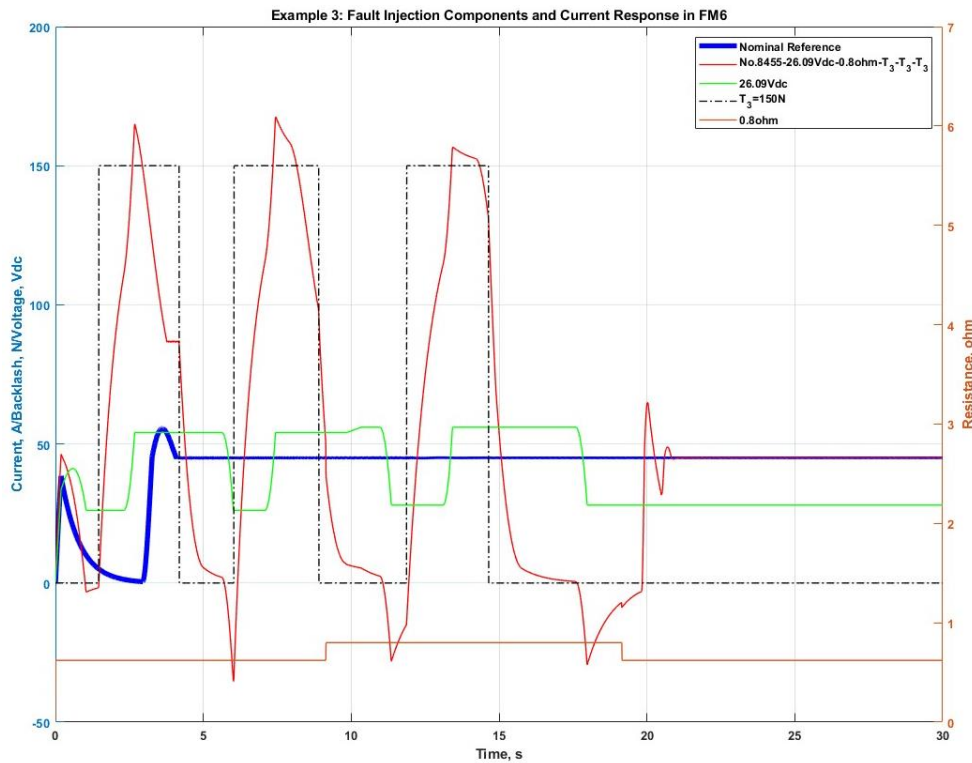


Figure 6.2-12 Example 3 of FM6, 26.09Vdc, 0.8Ohm, 150Nm backlash three times

The current plot clearly shows the three distinct backlash events. They are similar but different as the voltage and resistance events interact differently. This example illustrates the PHM challenge to correlate fault features with the causes of fault.

6.2.2.4 FM6 Cases combination

Figure 6.2-13 compares the fault current profiles of the three FM6 examples against the nominal reference. While these three runs differ in their injected fault combinations, ranging from undervoltage with minimal resistance (example 1), to high voltage with severe resistance (example 2), and moderate voltage with moderate resistance and high mechanical load (example 3), their current

responses during certain periods of the cycle display similar magnitudes and oscillation patterns.

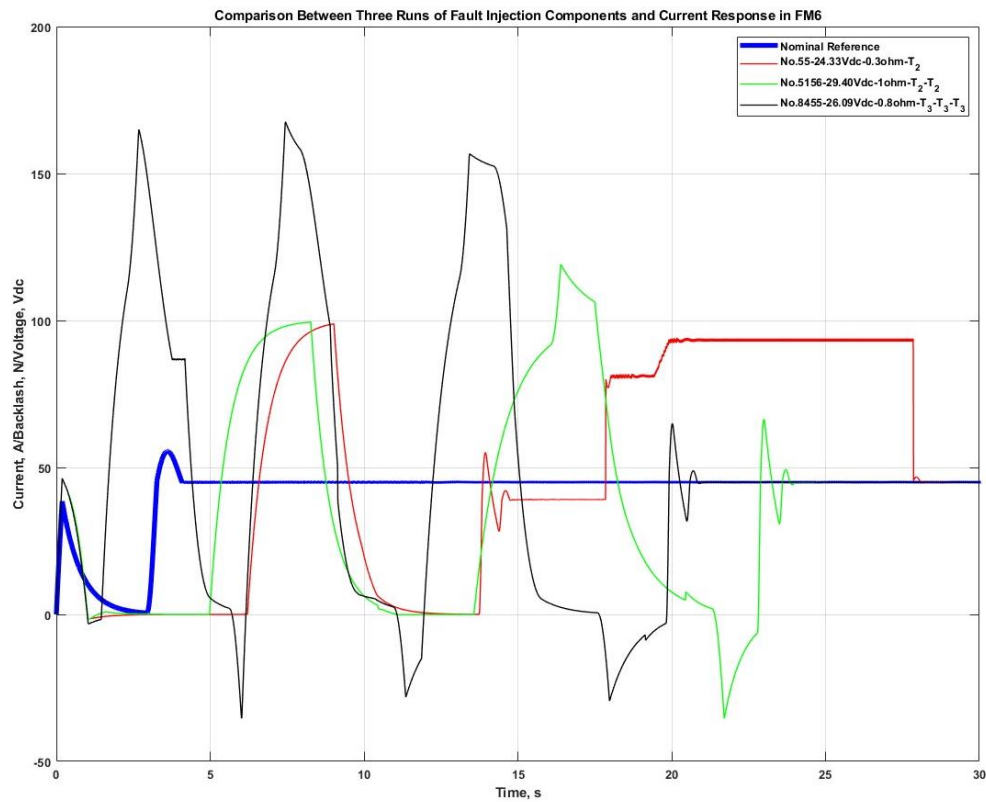


Figure 6.2-13 Comparison between above three simulation runs of FM6

For instance, both example 1 and example 2 present current peaks around 100A to 120 A following backlash events, despite contrasting electrical conditions: example 1 suffers from limited voltage, while example 2 experiences restricted current flow due to high resistance. In example 3, the current reaches the highest peak (~180 A) but later converges toward the envelope of example 2. This indicates that under the combined influence of resistance and PID control compensation, output power may stabilise to a comparable level even when voltage and current regulation differ.

This phenomenon illustrates the non-uniqueness of current forms as indicators of specific fault types under compound degradation conditions. Due to the active role of the PCU and PID controller, the system dynamically adjusts current to maintain actuator performance, which may obscure the root cause of anomalies. For instance, high resistance may suppress current despite high voltage

(example 2), while undervoltage in a low-resistance circuit (example 1) may produce comparable overcurrent events. In both cases, the net mechanical output and displacement behaviour may appear deceptively similar. The resulting feature form similarity underscores the risk of fault misclassification if diagnosis relies solely on current amplitude or shape. This highlights the importance of multi-domain signal fusion and temporal feature extraction for robust fault identification.

The strong oscillations and inconsistent current behaviour in multi-fault scenarios reflect complex fault interaction effects seen in real-world aging EMA systems, where cumulative degradation overwhelms compensation capabilities of the control unit. This reflects the conditions described in Table 4.2-3 and Table 4.2-2 where multiple features, especially current instability and displacement delay, must be jointly monitored. The demonstration of these simulated patterns illustrates the DT's usefulness as a testbed for fault-tolerant control and robust PHM algorithm development.

6.2.3 Simulation Label File

Along with simulation data generated, a label file is generated in the same folder. One label contains cycle number, labelling (0, 1, 2, 3, 4, 5, 6), fault characteristics, injection value, injection start time and end time. Table 6.2-2 shows an example of label of the first 10 cycles of FM1 simulation. By outputting in the format, it helps algorithms to read, analyse, correlate, and learn pattern.

Table 6.2-2 Exemplified 10 Simulation cycles labelling under FM1

RunID	Label	AnomalyType	FaultTimeStart	FaultValue
1	1	Unstable Voltage	14	27.5
2	1	Unstable Voltage	18	26
3	1	Unstable Voltage	11	23
4	1	Unstable Voltage	10	27
5	1	Unstable Voltage	16	26.5
6	1	Unstable Voltage	10	27.5
7	1	Unstable Voltage	19	23
8	1	Unstable Voltage	12	23
9	1	Unstable Voltage	13	25.5
10	1	Unstable Voltage	14	24

6.3 Chapter Summary

This chapter presents the simulation output for evaluating the performance of a digital EMA across various fault modes and scenarios, addressing Objective 4 of the study. The simulations use the SimScape EMA model and include scenarios of nominal operations, single fault modes, dual fault modes and multiple faults.

The model accurately represents the EMA behaviour under nominal conditions, with good correlation observed between input and output signals for load profile, voltage, and leadscrew displacement. This demonstrates the model's ability to simulate the behaviour of EMA in responding to flight control commands accurately.

The behaviour of fault-injected EMA is also studied to help identify related failures:

- a) Fault Mode FM1 (unstable voltage supply) affects the EMA operation by causing higher current inputs to adjust for the lowered voltage, which can be identified by comparing steady-state and peak current values to nominal.
- b) Fault Mode FM2 (mechanical backlash) is shown through the need for higher current to maintain torque output against additional resistance, indicating mechanical backlash can be identified by changes in current and angular velocity.
- c) Fault Mode FM3 (resistance change) impacts the EMA by increasing resistance and affecting motor power output, leading to unsatisfactory flap deflection. This fault can be identified by difference between actual displacement and designed position.
- d) Combining fault modes, the simulation results indicate a significant impact on the performance of EMA, with changes in current values suggesting the presence of faults. Identifying these faults involves comparing steady-state and peak current values against nominal values.

The chapter concludes that the SimScape model, supported by the developed algorithms for random fault injection, can effectively simulate the EMA's

behaviour across a range of operating conditions, including nominal operations and faults.

Overall, the chapter successfully demonstrates the feasibility of using the digital EMA model to simulate and analyse various fault modes, offering a method to evaluate robustness and reliability of EMA in facing different operational challenges. This contributes to enhancing the understanding and diagnostic capabilities for EMAs in practical applications.

7 DATA GENERATION FOR PHM

This chapter aims to demonstrate the quality and diagnostic utility of datasets generated by the data generator, with a focus on their ability to support representative and well-established algorithmic approaches for fault analysis. Rather than seeking to develop novel classifiers or regressors, the intention here is to use classical, widely accepted diagnostic and prognostic algorithms, such as Random Forest, PCA, and regression models, as benchmark tools. These serve as independent validators of the data usability. If these standard algorithms can extract meaningful and separable patterns, then there is high confidence that the generated datasets are sufficiently rich, structured, and realistic for health monitoring research. In this way, the goal of this chapter is not to optimise algorithms, but to demonstrate that the DT-based data generator produces diagnostically informative datasets that can support algorithm development in a consistent and meaningful manner.

The structured time-series records capture actuator signals across multiple operational and fault scenarios as detailed in Table 5.3-6. Each record represents a 30-second simulation with 15 monitored features as listed in Table 4.2-3:

The additional feature data also acquired when PID in action in fault simulations are Voltage and Amplitude.

These signals reflect actuator behaviour under nominal, single fault, dual fault, and compound degradation conditions. Each scenario run produces 10000 datasets (with failure labelled/pre-defined). For algorithms illustration, 7500 are used for training and 2500 for validation.

Section 7.1 introduces and describes the structure of the generated datasets, detailing their organisation, accessibility, and data labelling approach. This ensures full reproducibility and offers other researchers clear understanding on how the datasets can be used to support PHM applications.

Section 7.2 evaluates the separability of the different fault types using both linear (PCA) and non-linear (UMAP) dimensionality reduction techniques to assess how well the generated feature space can distinguish between various fault conditions.

These analyses verify whether the generated data sufficiently preserve discriminative characteristics across different fault conditions, offering an early indication of their diagnostic usefulness.

Section 7.3 demonstrates the use of a Random Forest classifier for fault classification. An out-of-bag (OOB) analysis presents the error rates of the output data across different fault scenarios.

Section 7.4 explores whether the datasets support fault magnitude prediction using three established regression techniques available in MATLAB: Logistic Regression (LR), Support Vector Machine (SVM), and Random Forest Regression (RFR). The aim here is to examine whether the datasets provide sufficiently structured and continuous features for PHM research.

Section 7.5 summarises the chapter's key findings, emphasising the implications of these results for developing and refining diagnostic and prognostic algorithms. The conclusion underlines the importance of multi-domain feature integration and provides recommendations for future research directions, particularly regarding the use of advanced feature extraction methods and more sophisticated algorithmic strategies to enhance fault detection and prediction capabilities.

7.1 Validation Dataset

The datasets generated for validation presented in Chapter 7 can be accessed via:

- CORD - Cranfield University Research Data system at <https://dspace.lib.cranfield.ac.uk/handle/1826/20712>
- Access could be sought from the researcher or the primary supervisor.

The dataset for nominal condition is saved in the folder under the name “No-Fault”, and the six Fault Modes are saved in folders under the name “FM_’n” as shown in Figure 7.1-1;

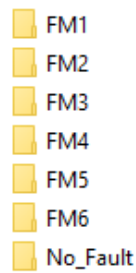


Figure 7.1-1 Fault Mode dataset folders

Under each folder, there are three types of files:

- datasheet exported for per cycle, as shown in Table 6.1-1, under the name Simulation_"n"_Result under the folder Result_All, as shown in Figure 7.1-2.
- separate exported datasheet per cycle for each feature, as shown in Table 6.1-2, under the name Simulation_"n"_Feature", as shown in Figure 7.1-2.
- Label datasheet for the scenario, as shown in Table 6.1-3, under the name Simulation_Label_Table, as shown in Figure 7.1-3.

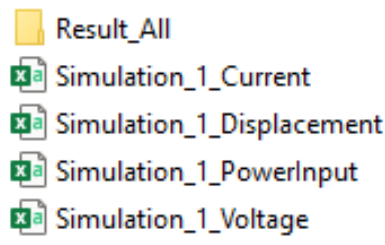


Figure 7.1-2 Feature separate datasheet and scenario result folder



Figure 7.1-3 Label file for scenarios

7.2 Failure Separability and Implications for Diagnosis

To evaluate the potential for classifying different fault types based on the generated simulation data, both linear and non-linear dimensionality reduction techniques were employed to visualise feature space separability. The MATLAB Principal Component Analysis (PCA) and Uniform Manifold Approximation and

Projection (UMAP) analysis are used to develop insights into the structural behaviour of each fault category and its implication for diagnostic. 2000 datasets for each 6 Fault Modes and the nominal are used.

7.2.1 Principal Component Analysis

PCA takes a dataset with many variables and reduce them to a smaller number of unrelated principal components that still retain the information in the dataset. These principal components are linear combinations of the original variables. Each principal component explains part of the variance in the data set.

For this analysis using MATLAB PCA, a raw matrix was created by pulling data from all 15 features based on a 30-dimensional statistical feature space, including standard deviation and mean values. Then the PCA input dimension is limited to 10 rather than using all 30 original signal channels because each signal is summarised through mean and standard deviation, rather than retaining the full time-series data. This dimensionality reduction preserves essential characteristics while improving computational efficiency, interpretability, and class separability. Using all 30 raw channels would introduce redundancy, increase noise sensitivity, and hinder visualisation or classification performance.

To obtain the first and second principal components (PC1 and PC2) through PCA, a standardised matrix $X \in \mathbb{R}^{N \times D}$ is to ensure zero mean and unit variance across all features. This standardisation step is critical to prevent features with larger scales from dominating the analysis and is defined as:

$$X_{std} = \frac{X - \mu}{\sigma} \quad (7-1 \text{ PCA Standardisation})$$

, where $\mu \in \mathbb{R}^D$ and $\sigma \in \mathbb{R}^D$ denote the mean and standard deviation vectors of the original features, computed column-wise.

A covariance matrix Σ is next computed as:

$$\Sigma = \frac{1}{N-1} X_{std}^T X_{std} \quad (7-2 \text{ Covariance Matrix})$$

to captures the linear interdependencies between all pairs of standardised features.

Eigenvalue decomposition is then performed on Σ :

$$\Sigma = \mathbb{V}\Lambda\mathbb{V}^T \quad \textbf{(7-3 Eigenvalue Decomposition)}$$

, where $\mathbb{V} \in \mathbb{R}^{D \times D}$ contains the eigenvectors (principal directions), and $\Lambda \in \mathbb{R}^{D \times D}$ is a diagonal matrix of the corresponding eigenvalues, sorted in descending order. Each eigenvector represents a principal component direction, while the associated eigenvalue indicates the variance captured along that direction.

The first two columns of $\mathbb{V}$, corresponding to the largest two eigenvalues in Λ , defines PC1 and PC2. The standardised data are then projected onto these components:

$$Z = X_{std}\mathbb{V}_{(:,1:2)} \quad \textbf{(7-4 Standardised Data Projection)}$$

yielding a reduced-dimensional representation $Z \in \mathbb{R}^{D \times 2}$, which captures the dominant variance in the dataset. These components facilitate visualisation and help assess the linear separability between fault classes.

Figure 7.2-1 shows that the principal components PC1 and PC2 capture 58.84% and 40.98% of the total variance, respectively, supporting the reliability of this projection. The compound faults (FM5 and FM6) form clear and well-separated clusters, indicating strong feature expression. FM2 and FM4 also have reasonable separation, although with some overlap. In contrast, FM1 and FM3 remain partially embedded within the larger clusters, and while Nominal data (marked in brown) appears isolated, its proximity to certain fault clusters suggests the need for precise thresholds in diagnosis.

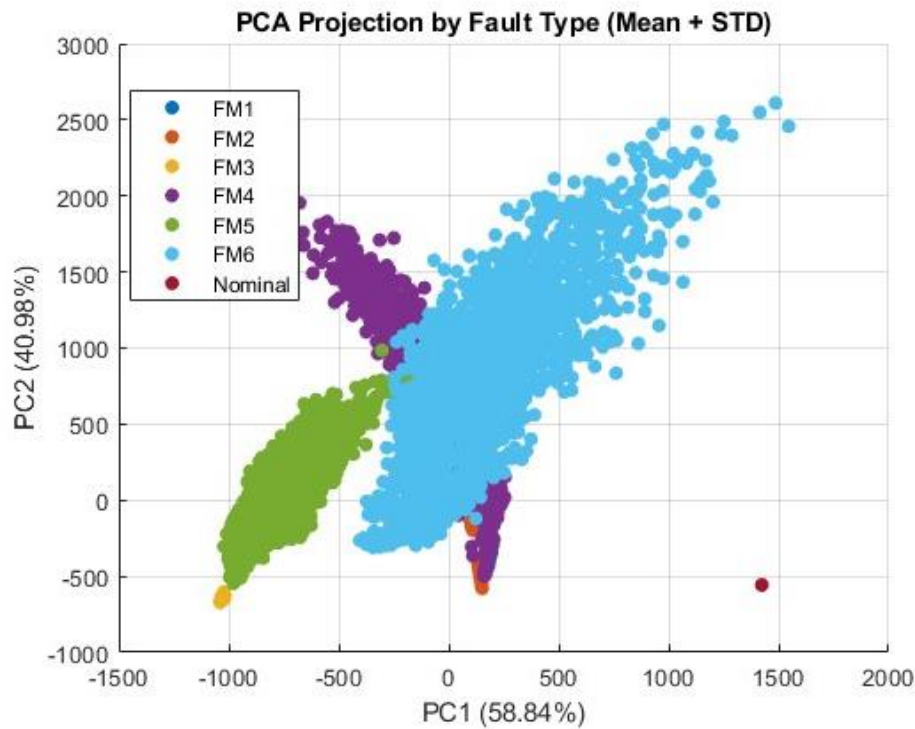


Figure 7.2-1 PCA projection based on mean and standard deviation features

7.2.2 Uniform Manifold Approximation and Projection

Uniform Manifold Approximation and Projection is a further analysis to reduce highly complex data to a simpler expression. While PCA uses a linear representation, UMAP uses multi-dimensional mathematics that better model the second and higher-level relationships between the variables.

Non-linear dimensionality reduction using UMAP based on the same dataset in Section 7.2.1 PCA analysis was carried out, illustrated in Figure 7.2-2. This shows enhanced local clustering structures. The Nominal condition forms a highly compact and isolated cluster, suggesting excellent separability from faulty conditions. FM5 and FM6 maintain distinct, dense groupings, while FM2 and FM4 show partial overlapping but are still distinguishable. FM1 and FM3 display more scattered distributions, reflecting their weaker or less consistent fault signatures. Compared with the PCA, UMAP demonstrates improved discrimination of subtle fault characteristics, particularly for mid-range compound failures.

The combined analysis confirms that compound faults (FM5 and FM6) are highly observable in both linear and non-linear spaces, making them straightforward for machine learning models to classify. Meanwhile, FM1 and FM3 highlight the challenges of detecting low-impact faults, where signal compensation or variable behaviour may obscure diagnostic patterns. These results suggest that multi-domain features, augmented by non-linear feature engineering, is needed to enhance the robustness of diagnostic frameworks.

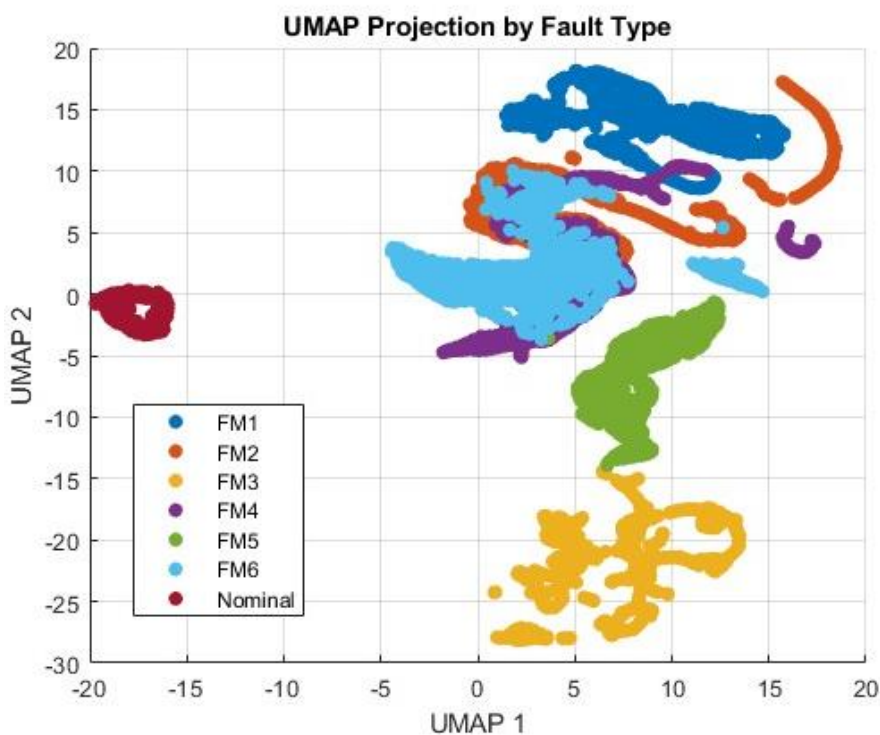


Figure 7.2-2 UMAP 2D embedding showing fault separability with Nominal (No-Fault)

A comparative evaluation across all six fault modes shows two categories of diagnostic difficulty, and a summary is provided in Table 7.2-1.

Among the fault types studied, FM1 (unstable voltage) exhibited the weakest distributional features in both PCA and UMAP projections. The samples clustered densely and overlapped significantly with other fault classes, particularly FM4 and FM6. This suggests that moderate voltage fluctuations, while affecting actuator input signals, may not produce distinct deviations in system-level outputs such as displacement or torque. As such, FM1 constitutes a "low observability" fault

scenario, where traditional statistical features may be inadequate for reliable detection without incorporating transient dynamics or control response behaviour.

FM3 (Resistance Change) exhibited the most irregular distribution under both PCA and UMAP projections. Its samples were widely scattered and failed to form high-density clusters, indicating a high degree of intra-class variability. This suggests that the impact of resistance faults on actuator-level signals is highly context-dependent, and that such faults are inherently more challenging to isolate without incorporating transient or frequency-domain features.

In summary, FM1 and FM3 represent weak or non-consistent fault behaviours, either due to system-level compensation (voltage drop) or irregular impact patterns (resistance variation). In contrast, compound faults such as FM5 and FM6 produce strong, high-density clusters in low-dimensional projections, supporting their high observability and separability. Intermediate faults like FM2 and FM4 demonstrate partial overlap and moderate consistency, underscoring the need for enriched feature spaces or hybrid diagnostic strategies.

Table 7.2-1 Comparative Summary of Fault Types Based on PCA/UMAP Behaviour and Diagnostic Properties

Fault Mode	Physical Mechanism	Distribution Density	Intra-Class Consistency	Inter-Class Separability	Diagnostic Difficulty	Characteristic Summary
FM1	Current compensation by controller, minimal output change	High	High	Low	High	Low-impact, easily masked fault
FM2	Localised mechanical oscillation, low mean variation	Medium	Medium	Moderate	Medium	Mild local disturbance, partially distinguishable
FM3	Nonlinear interaction in power chain, high signal noise	Low	Low	Moderate	High	Unstable effect, highly variable fault
FM4	Combined mild electrical and mechanical disturbance	High	Medium	Moderate	Medium	Intermediate compound fault, more detectable
FM5	Mechanical fluctuation + electrical impedance variation	High	High	High	Low	Clear structural separation, compound fault
FM6	Combined multi-domain disturbance with strongest nonlinearities	Medium	Medium	High	Low	Highly expressive, strong-feature compound fault

7.3 Random Forest Classifier with FFT Feature Performance

To assess whether the generated datasets possess sufficient feature separability for typical classification tasks in PHM, this section uses the Random Forest (RF) classifier. RF is an established and widely adopted method for its robustness against overfitting and its ability to handle high-dimensional, non-linear feature spaces effectively [121]. Its ensemble structure also provides reliable performance across imbalanced datasets, making it well-suited for fault detection using FFT-derived features [122].

The analysis was constructed using the same 10-dimensional statistical feature space used in the PCA/UMAP analysis, comprising the mean and standard deviation. A total of 15000 labelled samples, evenly distributed across six fault categories (FM1–FM6), plus 2500 nominal sets were used. The dataset was randomly partitioned into 80% training and 20% test sets, with the RF model trained using 100 decision trees and out-of-bag (OOB) prediction enabled for feature importance evaluation.

The classification results are summarised in the confusion matrix presented in Figure 7.3-1. The classifier achieved perfect prediction accuracy with all test samples correctly classified into their corresponding fault categories. Each diagonal element of the matrix displays a 100% success rate, and no misclassifications were observed. This highlights the clear separability of the synthetic dataset in the constructed feature space and confirms the suitability of the selected statistical descriptors for supervised classification. The achieved 100% classification accuracy in this study suggests that the fault types in the simulated dataset are easily separable within the extracted feature space, particularly with the combination of mean and standard deviation statistics. However, this result could indicate that the dataset may be too simplistic or does not fully capture the complexities and noise typically present in real-world fault scenarios. To further evaluate the robustness of the model, additional experiments involving data augmentation (e.g., adding noise) should be conducted. Furthermore, cross-validation techniques will be employed in future analyses to ensure that the model

does not overfit to the current data, thereby improving its generalisation capabilities.

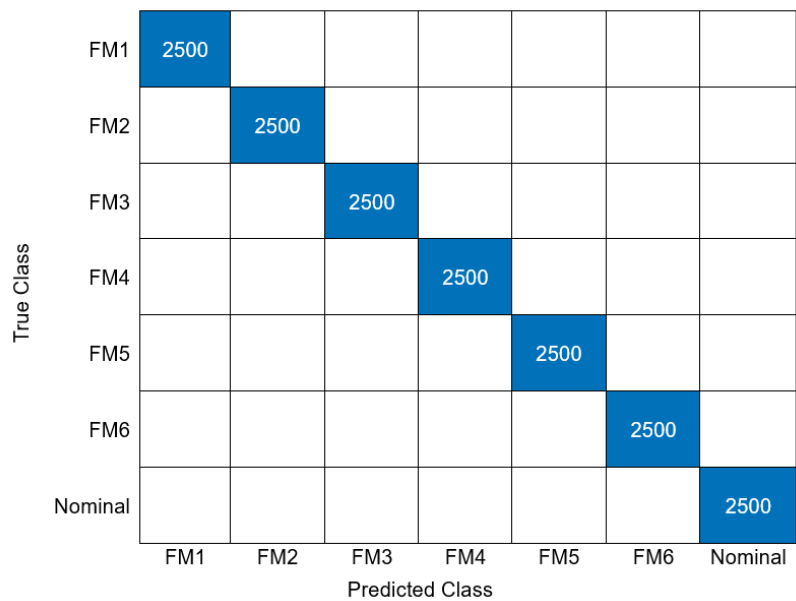


Figure 7.3-1 Confusion matrix showing perfect test set classification

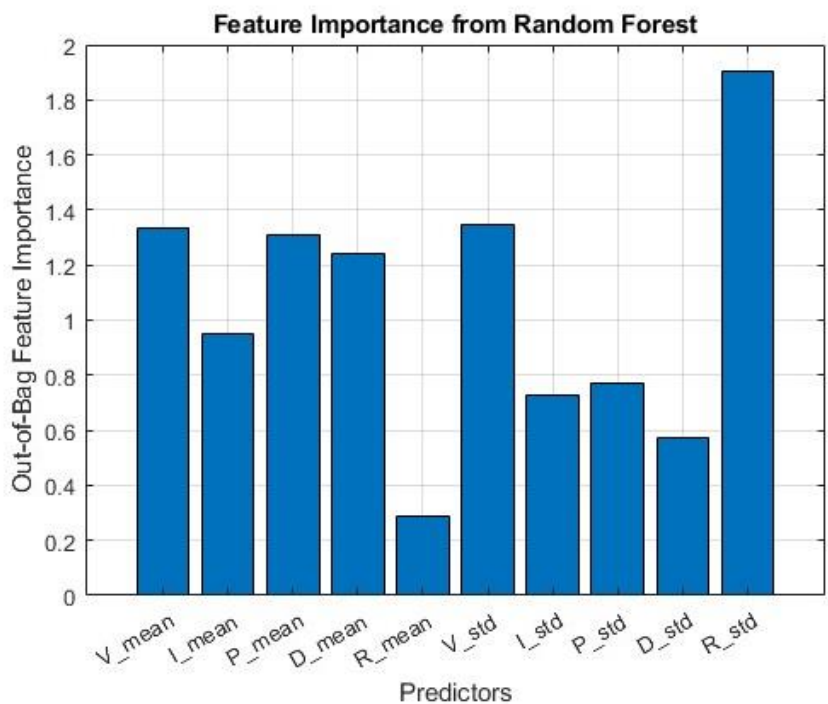


Figure 7.3-2 Predictor importance based on OOB permutation scores

Figure 7.3-2 presents the bar chart of out-of-bag permutation feature importance scores. Among the ten features, the standard deviation of resistance (R_{std}) emerged as the most significant predictor, followed by displacement-related features (D_{std} , D_{mean}) and voltage mean (V_{mean}). These results are consistent with the physical characteristics of the simulated faults. For instance, FM3, FM5, and FM6 involve resistance perturbations, whose effects are more accurately captured by the variability (rather than the mean) of electrical signals. On the other hand, FM2 and FM4 (involving mechanical backlash) show greater reliance on displacement fluctuations, aligning with the observed importance of D_{std} .

The high classification accuracy and the clear ranking of feature importance demonstrate that the extracted feature space provides a highly expressive and discriminative representation of the fault conditions. Furthermore, the results justify the use of standard deviation features in capturing local signal fluctuations that are often indicative of dynamic system degradation.

To further explore features discrimination, a reduced set of three features are used to run RF again: Current, Rotor Angular Velocity, and Worm Torque Output. These features are selected based on their direct physical relevance to electromechanical actuator operation:

- **Current** captures electrical load characteristics and reflects variations in power supply or resistance-related faults.
- **Rotor Angular Velocity Output** represents the mechanical dynamics of the actuator, making it sensitive to mechanical disturbances such as backlash or obstruction.
- **Worm Torque Output** provides insight into the transmitted mechanical load, especially under stress or abnormal torque behaviour, which is critical for detecting load path anomalies.

True Class	FM1	2063			437			
	FM2		2500					
	FM3			2500				
	FM4	338			2162			
	FM5					2463	37	
	FM6					14	2486	
	Nominal							2500
		FM1	FM2	FM3	FM4	FM5	FM6	Nominal
		Predicted Class						

Figure 7.3-3 Confusion matrix gained using three selected features

Figure 7.3-3 shows the confusion matrix for the classifier. The results highlight the following:

- Overall accuracy is 90.56%
- FM2, FM3, FM5, FM6, and Nominal categories achieve near-perfect classification, each showing 100% correct predictions (FM2, FM3, Nominal) or only minor errors (FM5: 2463 correct, 37 misclassified; FM6: 2486 correct, 14 misclassified).
- FM1 and FM4 show significant misclassifications. For FM1, 437 samples are misclassified as FM4; for FM4, 338 samples are predicted as FM1. This indicates notable overlap between these classes in the feature space.
 - In this two scenarios, the PID controller triggers the compensation of higher amplitude to either achieve enough power output to mechanical transmission or power against backlash mode. In certain value ranges of voltage or injection time, the three features may show similar patterns. Therefore, there has a higher misclassification possibilities between FM1 and FM3 based on only three features.

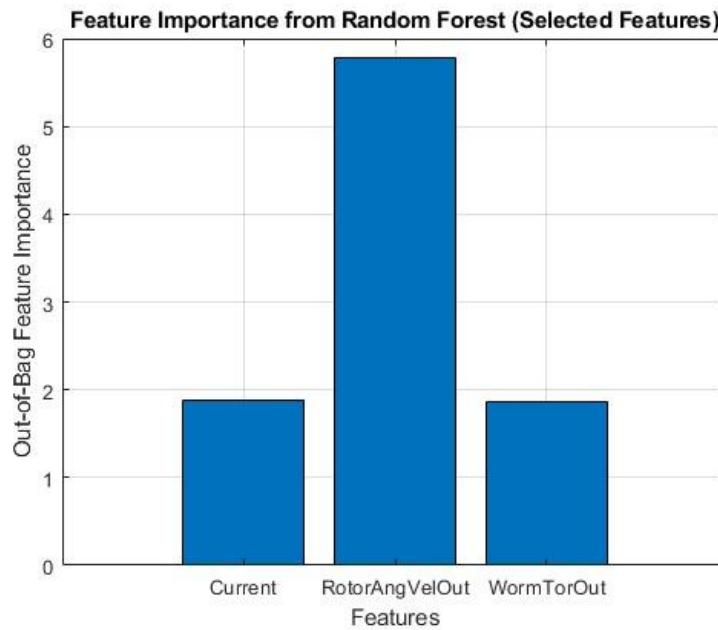


Figure 7.3-4 Feature importance from RF

The overall pattern suggests that Rotor Angular Velocity plays a dominant role in distinguishing mechanical faults (as confirmed in Figure 7.3-4), while Current and Worm Torque Output provide complementary insights into electrical and mechanical interplay. However, FM1 (unstable voltage) and FM4 (combined mild fault) both present challenges because their feature signatures overlap, likely due to both involving subtle changes that do not significantly alter mechanical dynamics.

To further explore the impact of each feature, a further Random Forest experiment was conducted using only Current and Worm Torque Output on the same dataset, intentionally excluding Rotor Angular Velocity Output. The rationale was to assess the classifier's diagnostic capacity relying purely on electrical signals, which is relevant for scenarios where mechanical sensing might be unavailable or impractical.

The feature importance results, shown in Figure 7.3-5, indicate that Current now dominates the feature set, with a noticeably higher out-of-bag importance score than Worm Torque Output. This shift reflects the stronger sensitivity of Current to fault-related variations, especially for electrical anomalies.

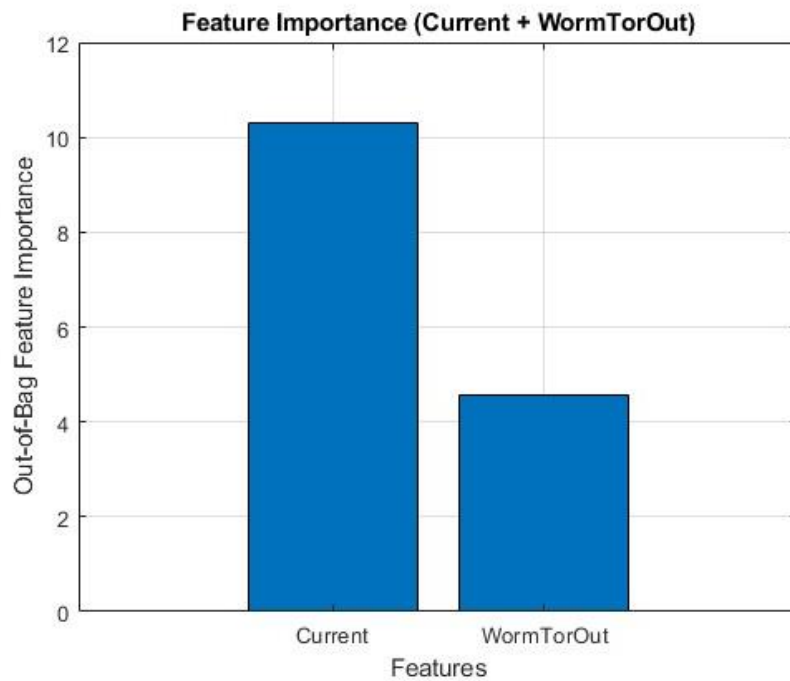


Figure 7.3-5 Feature importance Current vs Worm Torque Output from RF

True Class	FM1	1301	394		539		266	
	FM2	325	1486		506		183	
	FM3			2500				
	FM4	607	751		628		514	
	FM5					2428	72	
	FM6	384	298		443	37	1338	
	Nominal							2500
		FM1	FM2	FM3	FM4	FM5	FM6	Nominal
		Predicted Class						

Figure 7.3-6 Confusion matrix gained using Current and Worm Torque Output

The corresponding confusion matrix (as shown in Figure 7.3-6) highlights a significant decline in classification performance compared with the full feature set. Notably, substantial misclassification occurs primarily among fault modes FM1,

FM2, FM4, and FM6, indicating pronounced overlaps within these categories. Specifically, FM1 and FM4, FM2 and FM4, as well as FM4 and FM6 exhibit extensive confusion.

- For FM1 and FM4, the PID controller compensates for electrical instabilities by adjusting amplitude to ensure sufficient mechanical power output. Due to subtle variations in electrical and mechanical signals within certain voltage and injection time ranges, FM1's electrical instability patterns closely resemble the mild disturbances characterising FM4, resulting in frequent misclassification between these two fault modes.
- FM2's localised mechanical backlash shares signal characteristics with FM4's mild compound disturbances, particularly when analysed solely based on Current and Worm Torque Output. Without direct mechanical dynamic indicators such as Rotor Angular Velocity, the distinctions between mechanical oscillations and mild electrical-mechanical interactions diminish, thereby increasing the likelihood of misclassification.
- The significant overlap between FM4 and FM6 arises due to the inherent complexity of these fault modes. FM6 involves multiple strong nonlinearities across mechanical and electrical domains, producing patterns that partially coincide with the mild compound disturbances represented in FM4. Relying exclusively on electrical signals further limits the model's ability to discriminate clearly between these complex scenarios, resulting in substantial confusion.
- FM3 (resistance changes) and Nominal conditions maintain perfect classification accuracy, underscoring the robustness of purely electrical signals in distinguishing clear-cut electrical faults and normal operational states.

These findings strongly reinforce the conclusion that although Current and Worm Torque Output provide valuable diagnostic information, especially for straightforward electrical anomalies. Their diagnostic capability is markedly insufficient for reliable fault separation in more complex scenarios. Therefore, integrating multi-domain features, particularly mechanical dynamics such as

Rotor Angular Velocity, remains essential to ensure comprehensive and robust fault diagnostics across all operational conditions.

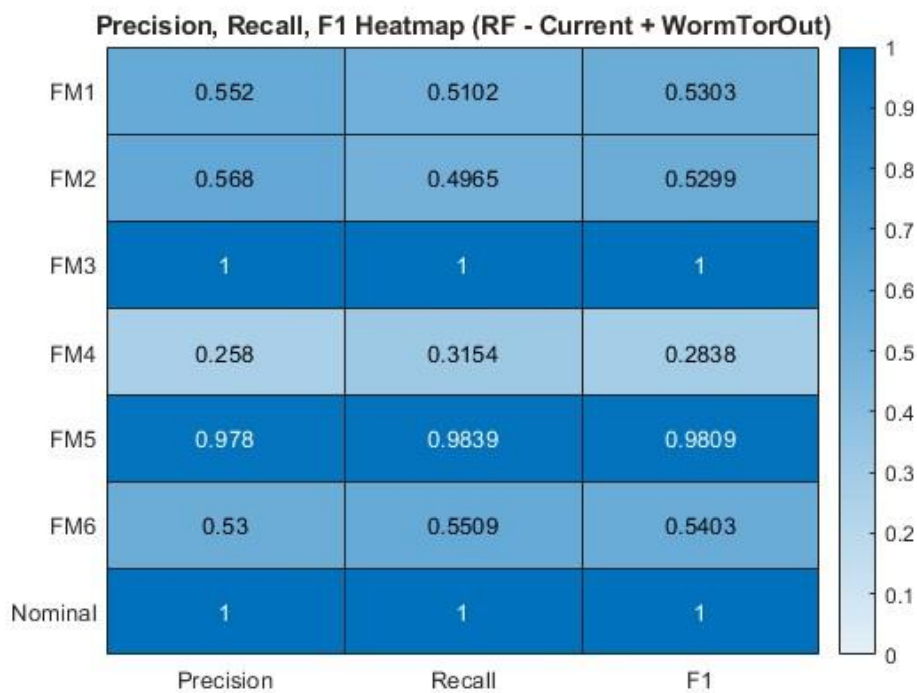


Figure 7.3-7 Precision, recall, and F1 scores for Current and Worm Torque Output

The detailed precision, recall, and F1 scores are presented in Figure 7.3-7, which further quantifies the diagnostic performance. As expected, FM3 and the Nominal condition achieve perfect metrics, while FM5 also demonstrates high precision and recall (~0.98). In contrast, FM1, FM2, FM4, and FM6 exhibit moderate scores, reflecting the challenges noted earlier.

To further isolate the diagnostic capability of a single feature, the experiment was structured into two stages: (1) spectral analysis of the Current signal, and (2) classification performance using Random Forest with FFT-based features.

Figure 7.3-8 illustrates the FFT spectrum of a typical Current signal from FM1 (unstable voltage). The linear-scale plot shows that the signal is dominated by low-frequency components (<5 Hz), with amplitude rapidly decaying at higher frequencies. This indicates that most of the fault-relevant energy resides in the lower frequency bands.

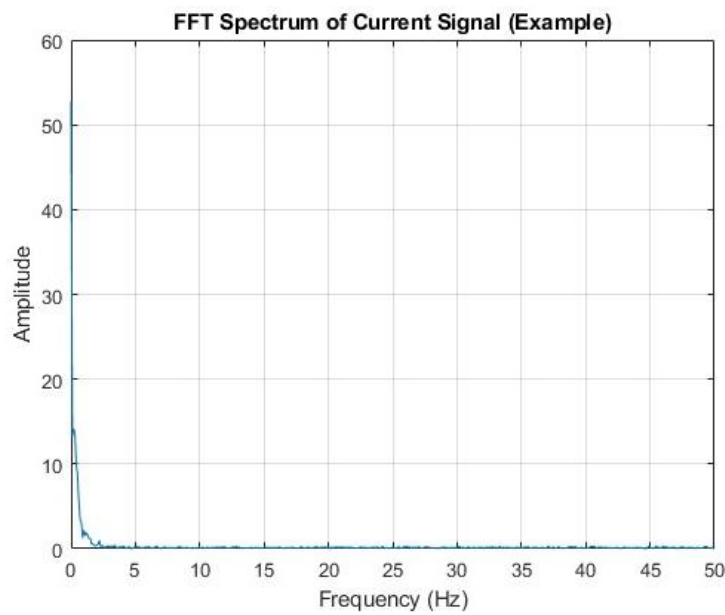


Figure 7.3-8 FFT Spectrum of Current

To reveal finer spectral details, the same signal is plotted on a logarithmic scale in Figure 7.3-9. The plot shows that aside from a dominant peak near 0 Hz, which reflects the DC component and baseline operation, the spectrum remains largely flat, with no distinct peaks across the mid- and high-frequency ranges.

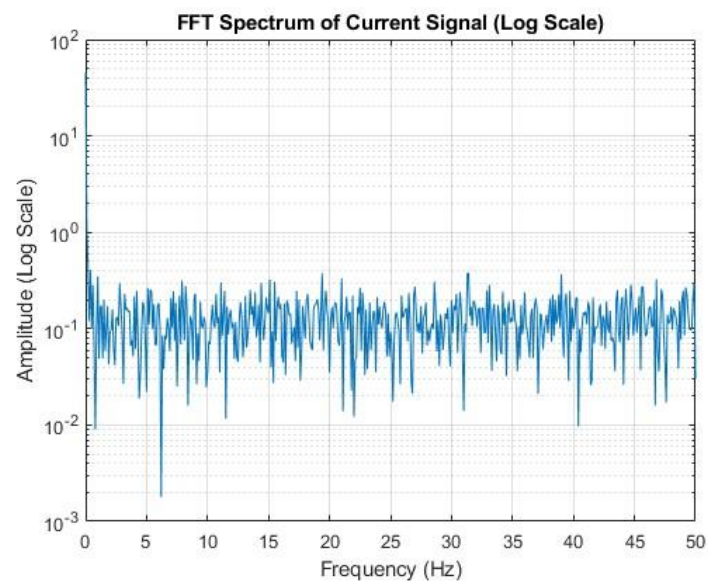


Figure 7.3-9 FFT Spectrum of Current in Log scale

This outcome highlights that while FFT analysis is powerful for weak electrical faults like FM1, the Current signal alone exhibits minimal high-frequency activity.

The lack of pronounced spectral peaks beyond the fundamental frequency means that the diagnostic signature of such faults is inherently subtle in the frequency domain.

True Class	FM1	2477	23					
	FM2	12	2395		27		66	
	FM3			2500				
	FM4				2437		63	
	FM5		51			2361	88	
	FM6		156		26	42	2276	
	Nominal							2500
		FM1	FM2	FM3	FM4	FM5	FM6	Nominal
		Predicted Class						

Figure 7.3-10 Confusion matrix for Current with FFT features using 1000pt windows

The confusion matrix in Figure 7.3-10 shows that even with a single Current feature, the prediction achieves surprisingly high accuracy in several categories. For instance, FM1, FM3, and Nominal maintain near-perfect prediction. FM4 also performs robustly with 94.96% accuracy. However, notable misclassifications occur between FM2 and FM6: 156 FM6 samples are misclassified as FM2, and a few scattered errors persist between FM5 and neighbouring classes.

Despite the simplicity of the input, the classifier attains an overall accuracy of 93.67%, underscoring that the Current signal alone, when transformed into the frequency domain, captures sufficient discriminatory patterns to distinguish most fault types reliably. This highlights the inherent sensitivity of the Current signal to both electrical and mechanical fault signatures, particularly when spectral content is exploited. Nonetheless, residual confusion between FM2 and FM6 indicates that some fault types require richer, multi-modal features to fully resolve their

signatures. This further confirms the advantage of hybrid approaches that integrate mechanical and electrical signals.

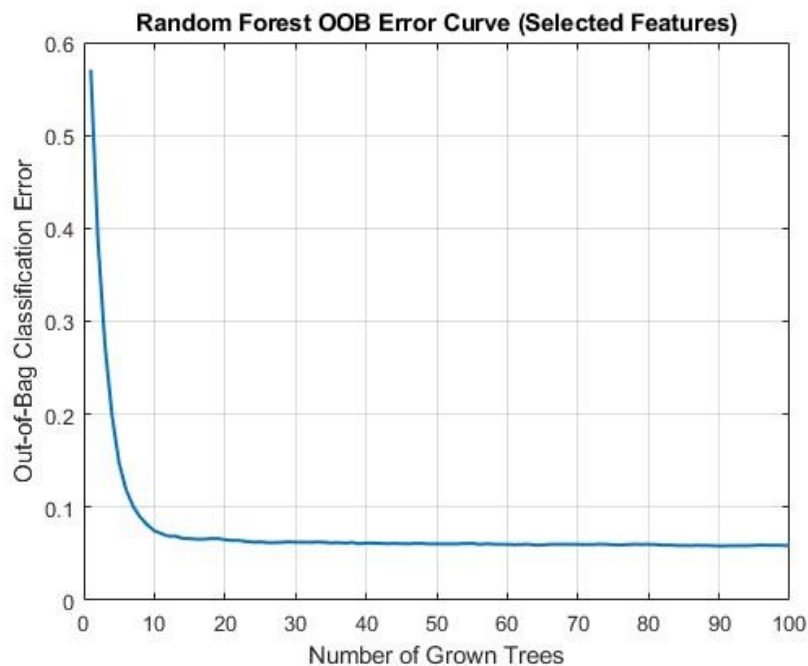


Figure 7.3-11 RF OOB error curve for three selected features

The out-of-bag (OOB) error curves provide insights into the convergence behaviour and generalisation capacity of the Random Forest models under different feature configurations.

Figure 7.3-11 shows the result of classifier using Current, Rotor Angular Velocity Output, and Worm Torque Output. It converges rapidly, with the OOB error stabilising below ~7% after ~20 trees. This indicates strong predictive stability and low generalisation error, thanks to the multi-domain feature set that captures both mechanical and electrical dynamics.

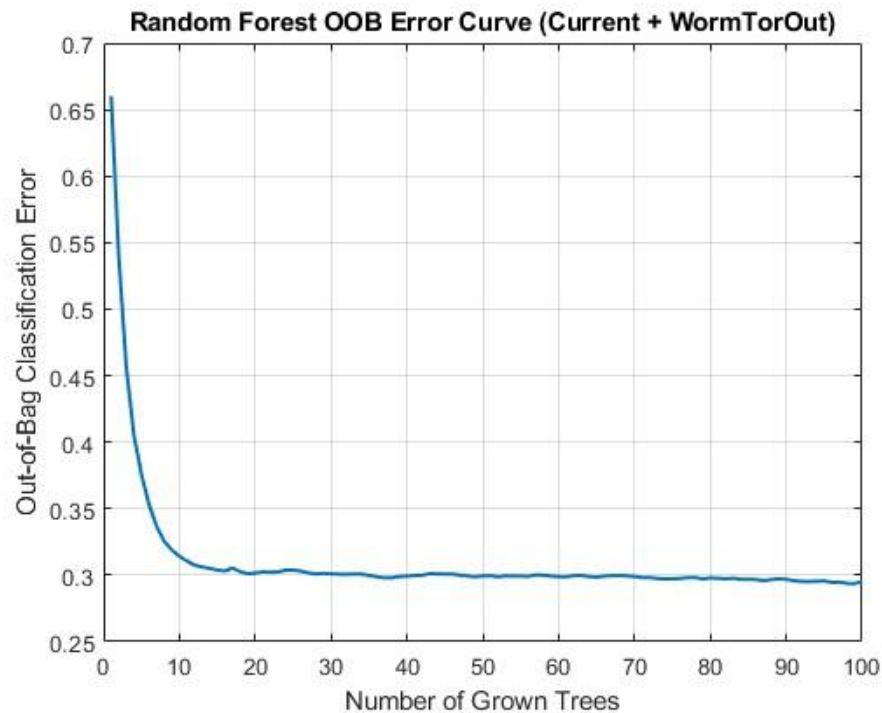


Figure 7.3-12 RF OOB error curve for Current and Worm Torque Output

Figure 7.3-12 shows that when Rotor Angular Velocity Output is removed, the OOB error plateaus at a much higher level (~30%), reflecting weaker model performance and less reliable fault separation. The model still converges quickly (within ~20 trees), but the elevated error suggests significant information loss from excluding mechanical features.

These results reinforce several key points:

- **Convergence Speed:** All models stabilise rapidly (<20 trees), indicating that feature richness mainly affects final accuracy rather than training stability.
- **Feature Power:** Adding Rotor Angular Velocity Output or transforming Current into frequency domain substantially reduces error, confirming the importance of either multi-domain sensing or advanced signal processing.
- **Diagnostic Trade-offs:** While Current + WormTorOut alone is insufficient (30% error), the use of FFT features demonstrates a viable alternative to mechanical sensing for scenarios with limited sensor access.

7.4 Regression Algorithm Performance

This section aims to evaluate whether the DT-generated datasets provide sufficient richness to differentiate the performance of PHM algorithms. Three representative and widely available algorithms in MATLAB, Logistic Regression (LR), Support Vector Machine (SVM), and Random Forest Regression (RFR) are selected to reflect a spectrum of complexity and interpretability with stability comparison shown in Table 7.4-1:

- Logistic Regression (LR): interpretable, fast, but linear-only.
- Support Vector Machine (SVM): effective on small, non-linear datasets.
- Random Forest Regression (RFR): robust in complex, high-dimensional conditions.

Table 7.4-1 Typical stability Comparison of the Three Models

Model	Deterministic	Reason
LR	High	<ul style="list-style-type: none">• Analytical solution or convex optimisation• No randomness involved
SVM	Moderate	<ul style="list-style-type: none">• Convex optimisation• Some implementations involve heuristics or slight randomness
RFR	Low	<ul style="list-style-type: none">• Involves exploration• Random initialisation• Sampling-highly sensitive to seeds and runs

To represent the potential of random event detection, only portions of the 30s simulation run are used to remove the clue about the flap extension sequence structure. From each of the simulation runs, a 15-second (at 100Hz) duration is used so the period covers at least two stages of actuator operation. The start time to extract the 15s period is uniformly-randomly selected. Both the mean and standard deviation of all the 15 features are used in the dataset. The resultant dataset is a 70000*1500*30 matrix, combining the 7 scenarios with 10000 simulation runs each. The combined dataset is split into 75% training and 25% validation.

The MATLAB execution uses `fitlm()`, `fitrsvm()`, and `fitrensemble('Method','Bag')` respectively. P-value is the accepted measure to establish statistical confidence and is a direct output for LR. SVM and RFR (Non-parametric learning algorithms) do not generate P-values. Instead, independent two-sample T-test is used to obtain P-value approximation with `[h, p] = ttest2(Linear_Regression, group2)`.

The confusion matrices shown in Figure 7.4-1 confirmed previous observations shown in Section 7.2, while highlighting variations under data augmentation. A summary of three regression algorithms performance is in Table 7.4-2

```

=== Data Summary ===
Training Set: 52500 samples x 30 features
Test Set: 17500 samples x 30 features

=== Logistic Regression (Multiclass) ===
Accuracy: 97.66%
Confusion Matrix:
2500    0    0    0    0    0    0
  0   2500    0    0    0    0    0
  0    0   2438    0    0    62    0
  0    0    0   2500    0    0    0
  0    0    0    0   2500    0    0
  0    0    67    0    0   2265   168
  0    0    0    0    0    113   2387

=== SVM (Multiclass) ===
Accuracy: 98.14%
Confusion Matrix:
2500    0    0    0    0    0    0
  0   2500    0    0    0    0    0
  0    0   2185    0    0   315    0
  0    0    0   2500    0    0    0
  0    0    0    0   2500    0    0
  0    0    43    0    0   2452    5
  0    0    0    0    0    12   2488

=== Random Forest (Multiclass) ===
Accuracy: 99.83%
Confusion Matrix:
2500    0    0    0    0    0    0
  0   2500    0    0    0    0    0
  0    0   2500    0    0    0    0
  0    0    0   2500    0    0    0
  0    0    0    0   2500    0    0
  0    0    10    0    0   2488    2
  0    0    0    0    11    7   2482

```

Figure 7.4-1 Example confusion matrix of regression algorithms results based on 15 features and 15-second window

LR achieve an overall accuracy of 97.66%, yet misclassifications occurred between FM2, FM5, and FM6. Specifically, 62 samples in the test set(17500) of FM2 were misclassified as FM5, and 113 from FM5 as FM6. This is similar to the results in Figure 7.2-1. These patterns reflect the limitations of linear decision boundaries in resolving complex inter-class overlaps.

SVM demonstrate better overall accuracy at 98.14%. It exhibits significant misclassification of 315 samples from FM2 as FM5. This suggests that, despite its non-linear decision surface, the model still has difficulty distinguishing between certain feature clusters, possibly due to incomplete separation in the high-dimensional space.

RFR delivers the best results, achieving 99.83% accuracy with only minimal misclassifications. The errors are concentrated in FM5 and FM6, totalling fewer than 10 instances. The model's ability to capture hierarchical and nonlinear relationships through ensemble learning proved particularly effective in high-volume, balanced multiclass contexts.

To complement the regression accuracy metrics and model stability observations, Table 7.4-3 presents a comparative analysis of statistical significance for each regression model type across the fault modes. The p-values for LR reflect variable-level significance, whereas the T-statistics and associated inferences for SVM and RFR were obtained through two-sample T-tests on prediction residuals.

Under the No_Fault condition, all three models achieve perfect or near-perfect alignment, with LR and RFR yielding accuracy scores of 1.000 and SVM achieving 0.99. The absence of variability results in undefined p-values and T-statistics under these baseline conditions.

For single-fault (SF) modes FM1 to FM3, LR consistently produces statistically significant p-values ($p < 0.001$), with the highest average accuracy observed in FM1 and FM3. FM2, which involves random backlash, shows slightly lower LR accuracy and a weaker but still significant p-value ($p < 0.05$). This is mirrored by SVM, which shows a drop in average accuracy to 0.3756 in FM2, coupled with a T-statistic of 0.6032, indicating substantial variation and weaker model alignment.

In contrast, RFR maintains high stability and accuracy (average > 0.99) across all SF modes, with T-statistics consistently close to zero, suggesting excellent distributional matching.

In dual-fault (DF) modes FM4 and FM5, LR performance declines moderately, with p-values still indicating statistical significance but at a reduced level. SVM and RFR show slightly degraded alignment (T values drift away from zero), particularly in FM5, where SVM's T-statistic turns negative (-0.0219), hinting at mild systematic bias. Nevertheless, all models still demonstrate acceptable average-level behaviour.

The multi-fault case (FM6) and the Mixture mode present the most challenging analysis. Here, SVM and RFR both exhibit elevated T-statistics (0.1634 and -0.0537 respectively), suggesting increased divergence between predicted and actual values. The corresponding standard deviations for SVM's accuracy and RFR's T-statistics are also the highest across all conditions, indicating that the predictive consistency deteriorates under composite fault conditions.

Overall, LR provides strong baseline interpretability and variable-level statistical confidence, while RFR emerges as the most robust non-parametric approach in terms of prediction fidelity. SVM, though slightly more variable, remains statistically aligned in most fault scenarios. The dual use of p-values and T-statistics offers complementary insights into the regression models' reliability and failure mode sensitivity.

Table 7.4-2 Summary of regression algorithms performance and callback to stability

Model	Accuracy	Main Misclassification	Characteristics & Recommendation	
LR	97.66%	Bidirectional confusion among FM2, 5 and 6	<ul style="list-style-type: none">• Linear model• Suitable for quick benchmarking but limited in handling non-linear boundaries	Consistent with results
SVM	98.14%	Severe confusion FM2 to FM5	<ul style="list-style-type: none">• Non-linear decision surface• Stronger than LR but still challenged by overlapping Fault Modes	Aligned
RFR	99.83%	Minor confusion between FM5 and 6	<ul style="list-style-type: none">• Robust to noise• Excellent non-linear modelling	Generally consistent but slightly outperforms

Table 7.4-3 Overview with mean P-Value for LR and mean T-test values for SVM and RFR based on 100 cycles

Scenarios		LR			SVM			RFR		
		AVG	SD	P	AVG	SD	T	AVG	SD	T
NF		1	0	NaN	0.99	0.1	0.017	1	0	NaN
SF	FM1	0.9914	0.00784	P**	0.8931	0.11780	0.0567	0.9986	0.00174	-0.0361
	FM2	0.8842	0.03952	P*	0.3756	0.15160	0.6032	0.9932	0.00374	-0.0351
	FM3	0.9732	0.01573	P**	0.9684	0.06017	0.0138	0.9852	0.00755	-0.0124
DF	FM4	0.8521	0.01648	P**	0.7924	0.13260	0.1907	0.9931	0.00423	-0.0939
	FM5	0.8041	0.03991	P*	0.794	0.08257	-0.0219	0.8743	0.01473	-0.0574
MF	FM6	0.8502	0.03183	P*	0.8164	0.13445	-0.0539	0.9648	0.00823	-0.0324
	Mixture	0.90790	0.07771	P**	0.80423	0.22233	0.16343	0.97277	0.04232	-0.0537

Note: P*<0.05, P**<0.001

7.5 Chapter Summary

The results presented in this chapter demonstrate that different diagnostic and prognostic algorithms exhibit clear performance differences when evaluated against datasets generated by the DT EMA and Data Generator framework. By systematically simulating an extensive range of operational and fault conditions across the electrical, mechanical, and combined domains, the framework offers a comprehensive benchmarking platform for researchers to critically assess and refine their PHM methodologies.

A significant contribution of this research lies in addressing the prevalent limitation within the PHM community, where many studies primarily rely on simplistic and insufficient datasets for algorithm development (e.g., limited access or lack of historical data). This research bridges this gap by providing high-fidelity, structured, and comprehensive datasets that closely replicate realistic failure conditions. Such datasets enable the development and validation of more sophisticated and industrially applicable algorithms, moving beyond simplified scenarios to address complex real-world applications.

The datasets generated allow for robust evaluation and comparative analysis of multiple PHM algorithms, such as LR, SVM, and RFR, highlighting their strengths and limitations in various fault scenarios. As illustrated in Section 7.4, algorithms showed variable sensitivities to fault complexities, with RFR particularly outperforming others in capturing complex interactions within multi-fault conditions.

Another contribution lies in the framework's ability to show the relative importance of different feature domains. The analysis indicates that features derived from current and displacement signals are particularly critical in differentiating between specific fault modes. For instance, steady-state and peak current values consistently emerge as key indicators for detecting early-stage electrical and mechanical faults, while displacement variations significantly inform the detection of progressive degradation. This insight assists algorithm developers in selecting the most informative features, thus improving diagnostic accuracy and reliability.

Moreover, the integration of dimensionality reduction techniques such as PCA and UMAP underscores the value of feature space exploration, enabling a deeper understanding of feature separability and interaction dynamics. These techniques aid researchers in tailoring their PHM models to capture subtle fault signatures, which might otherwise remain indistinct in high-dimensional raw data.

In conclusion, this DT-based data generation framework significantly advances the PHM field by providing a flexible platform for algorithm evaluation, benchmarking, and refinement. Researchers can leverage these understandings to enhance model robustness, diagnostic sensitivity, and predictive accuracy, ultimately driving forward the development of more reliable and effective PHM solutions for complex electromechanical systems.

8 DISCUSSION

This chapter reflects on the research outcomes presented in the previous chapters and discusses their significance in the context of existing literature and engineering practice. It synthesises key observations from the modelling, simulation, and data generation activities, evaluates the degree to which the research objectives have been met, and elaborates on the novel contributions to the field of DT-based health management for EMA. Limitations of the current work are also considered, along with potential extensions and implications for broader applications in aerospace system design and maintenance.

8.1 Key Research Findings and Observations

In the trend towards AE and MEA in the aviation industry, EMA is gradually used in more systems, beyond as non-critical backup systems. The main concern focuses on the safety implications of its inherent critical failure path. If the mechanical transmission mechanism is stuck, the entire system dropped into a self-locked situation, which is not able to be released by using backup systems. In contrast, for EHAs, a backup electrical motor can alternatively operate the deflection and retrieve of flaps if the hydraulic system is down. Also, thanks to massive historical health management research of hydraulic systems, a considerable amount of knowledge can be transferred and referred to in the maintenance of EHAs. In EMA, there are limited resources available as it is only recently used in aircrafts. Due to the similar reason, there is a lack in accessible and available historical operational data of EMA. Without having sufficient good quality data, the research, development, and implementation of EMA using advanced simulation and Machine Learning technologies is heavily limited.

This thesis aimed to explore whether a DT of an EMA could be used as a data generation platform for fault diagnosis and health management in aircraft systems.

8.1.1 Literature Review

A literature review was conducted to identify the gaps in the research methodologies and practical needs. The review explores in depth the progress of EA systems, with particular emphasis on EMA in the aviation industry. It describes the benefits and operational efficiency that EMAs bring and compares them to various types of EHAs. Considerable space in this chapter is devoted to the study of EMA's PHM techniques, including failure modes down to subsystem and component levels, diagnostic and prognostic methods, and the importance of accurate estimation of RUL for optimal maintenance. The discussion on fault diagnosis and prediction laid the foundation for designing models and simulating EMA operation in this study.

The combination of the review led to the proposal of a DT-based approach that can simulate, represent operational conditions of EMA in critical systems, e.g., flight control.

8.1.2 Research Methodology

The research methodology employed in this study is explained in Chapter 3. A major obstacle to the use of EMA for critical aircraft systems is the concern of fail-safe, which in turn creates the dilemma of the missing and difficult access to historical operational data. In order to solve this problem, this study introduces the method of constructing the EMA model, fault value generator and injection model with the A350 trailing-edge flap operation as the target application case study. This method compares and improves the data analysis and validation methods reported in the literature review.

To better reproduce the EMA operational situation, the design includes multi-step scenarios to replicate the typical stages of flap angle and guide screw displacement during flight phases such as pre-flight inspection, take-off and landing. The failure scenarios are divided into single fault injection and multiple fault injection to assess the response of the system and identify key characteristics that indicate failure.

8.1.3 SimScape DT EMA and Data Generator

The work has produced the following key findings:

- The development of a physical-informed, multi-domain EMA DT (as in Chapter 4) is effective as a high-fidelity simulation of electrical, mechanical, and control subsystems.
- The integration of this DT into a flexible, script-controlled data generator (as in Chapter 5) provides a scalable approach to simulate fault conditions and export machine learning-ready datasets.
- The result in Chapter 6 demonstrates the successful injection of various fault types, with realistic signal responses that reflect theoretical and real-world failure characteristics outlined in Section 2.5.
- Feature separability and regression performance analysis in Chapter 7 confirm that the synthetic data produced by the DT is statistically robust and diagnostically relevant.

These findings together validate the feasibility of using a DT for early-stage data-centric health management research.

8.2 Fulfilment of Research Aim & Objectives

This subsection discusses how the overall research aim, and each individual objective have been achieved.

1. Identify failure characteristics on subsystem and component level and assess potential features that has strong correlations with failure.
2. Demonstrate the applicability of EMA in critical aircraft systems, and its necessity to ensure safety redundancy with the employment of EMA by enriching accessible data to feed modelling to reduce research and development time, as well as to feed machine learning algorithm training for remaining useful life estimation and predictive maintenance.
3. Develop the core EMA model and test with simulation runs representing different stages and conditions of flap deflection operations with potential fault injected.

4. Specify key features that can help identify fault modes and determine their preferable values.
5. Evaluate the synthetic data quality through engineering reasoning and commonly used PHM ML method tests; and demonstrate the generalisability potential of supporting advanced ML algorithm development as a framework for future extensions.

8.3 Research Contribution to Knowledge

Several contributions have been achieved by the research in line with fulfilling the aim and objectives throughout the research journey, from the beginning of background investigation and literature view to the end demonstration and assessment of the DT framework.

- a) The data generator and its core DT EMA is the main contribution from the research. The model helps simulate nominal, degradation, and fault operations, and has the potential to provide reliable data for multiple fault-injected operations. This enables diagnostic and prognostic research to develop methods to detect EMA failures early and enhance aircraft performance. The DT has comprehensive probes and data collection points. The framework can be useful for data generation and collection to support future research.
- b) Defining features to correlate with fault is another research contribution. Sets of features are chosen and injected to the model as fault and another set of features are extracted from signals that are sensitive to changes and can be triggered sooner faults occur. Future PHM research can build on the features set for fault identification in early or middle stages.
- c) Expanding the role of DT is also a research contribution. DT has been gaining interest in the last decades. The dominant application of it is as a tool to support engineering design and operations, reducing overall research and development time and cost. This research added a new role as a tool for data generation, providing data with the advantages of labelled purposes, high fidelity and granularity.

8.4 Limitations

The research focuses on the development of data generator and specify key features for strong correlation with fault mode. The study's scope was limited to a specific linear EMA model and operational scenarios, which may not encompass all potential aspects of aircraft operations.

- The load profile is simplified regardless of the changes in flap angle against the lift. The practical load can be dynamic.
- The thermal changes are lightly touched in this study. A wide range of thermal sensors and modules can be implemented to the model to assess the effect of temperature change.
- Outside air temperature (OTA) was set constant at sea level, 15°C. During aircraft take-off, climbing, approaching, and landing, flap operations typically happen between sea level and typically 500 to 3000 feet, with OTA varying from 10°C to 13°C [123]. The dynamic air flow may also cause changes in surrounding operational condition. The OTA change can be included in future simulations.
- Due to time constraint, the study focused on the three typical failure characteristics. Also, only one multiple fault mode was simulated. Other failure modes mentioned in Section 2.5 can be studied and added to the fault mode pool, which helps scheduling more fault mode and scenarios.
- The simulation was purely based on MATLAB Simulink/SimScape to take advantage of its library resources and was validated in line with engineering theories. Other tools, e.g., SimScape Multibody toolbox could be used as a validation method. It also can work as adds-on as it provides interaction in 3D model and can better demonstrate performance, contributing to an accelerated learning curve.

8.5 Scientific and Engineering Implications

The proposed framework presents several implications for engineering practice, particularly within the domain of MEA design and prognostics. Firstly, the framework supports a shift from reliance on empirical data towards simulation-driven fault diagnosis, facilitating the exploration of rare or early-stage failure

modes that are otherwise inaccessible due to the low failure rate and safety constraints in civil aviation systems. The simulation-generated data can serve as a proxy where in-service data is unavailable. This aligns with the current industry trend towards predictive maintenance and digital engineering integration in product lifecycle management. By incorporating multi-domain physics (electrical, mechanical, and thermal) and supporting configurable fault injections, the framework provides a virtual testbed that could be used to inform actuator control design, tolerance analysis, or system certification support under representative but non-destructive fault conditions. This offers considerable cost and time advantages over physical test rigs or HIL setups, particularly during the early design phases of system health management solutions.

Furthermore, the modular structure and algorithmic flexibility of the framework, especially the use of randomised injection and simulation orchestration, positions it as a viable candidate for integration into broader toolchains for developing intelligent maintenance systems. These capabilities may be especially relevant for OEMs and suppliers aiming to build digital evidence bases for new actuator concepts or to verify the robustness of fault detection algorithms before physical prototyping.

8.6 Comparison with Existing Approaches

Compared with established simulation-based studies in the field of actuator fault modelling, the present work advances the state-of-the-art in several important respects. Prior efforts, such as those reported by Fu et al. [73] and Zio [49], have tended to focus on either individual fault mechanisms (e.g. jamming, control loop disturbances) or relatively simple input-output relationships. In contrast, this study introduces a coherent, multi-fault simulation framework that integrates voltage disturbances, mechanical backlash, and cable degradation into a single platform, allowing for combinatorial fault analysis with high granularity and repeatability.

Additionally, while many existing models require proprietary data or extensive manual configuration, the presented approach demonstrates the use of openly defined actuator parameters, fault abstraction methods (e.g. stepped reverse torque inputs), and fully documented simulation workflows using MATLAB

SimScape. This enhances both reproducibility and accessibility for future research.

From a data science perspective, the synthetic datasets generated in this study achieved levels of feature separability and classification accuracy, particularly using Random Forest and Support Vector Regression models, comparable to those obtained in literature studies employing laboratory test rig data (e.g. [77]). This suggests that carefully designed DTs may be capable of producing data with sufficient fidelity to support early-stage algorithm training, thereby reducing the dependency on scarce or costly experimental data in the development of health monitoring solutions.

8.7 Generalisability of the Framework

Although the case study focused on a linear EMA driving an inboard flap on an Airbus A350 XWB, the underlying architecture of the DT framework is intentionally designed for generalisability. The modularity of the SimScape model permits reconfiguration for different actuator topologies, including rotary EMAs, surface-mounted flap systems, or even electromechanical subsystems in UAVs and UAM platforms.

The fault injection logic, based on signal superposition and temporal parameterisation, can be extended to additional failure mechanisms such as sensor drift, soft-stall, or bearing degradation. Likewise, the controller structures, currently implemented as simplified PID and position-tracking modules, can be replaced with more advanced model-based or adaptive controllers, enabling further studies in closed-loop system stability under fault conditions.

Moreover, the data generation pipeline, which includes real-time labelling and structured output formatting, facilitates integration with machine learning platforms. This allows for use beyond EMA systems, including other high-assurance domains such as electric landing gear actuators, brake control modules, or distributed propulsion systems. As such, the framework constitutes a scalable and adaptable foundation for digital health monitoring research across a range of aerospace systems. This generalisability provides a basis for broader

application of the framework across diverse EMA domains within aerospace and beyond.

9 CONCLUSION

The research aimed to develop a DT-based data generator for capable of representing flight control EMA operations under a range of scenarios, with the aim of generating high-quality, fault-representative datasets to support health management research. Through the design, simulation, and evaluation of a structured EMA model in MATLAB SimScape, the study demonstrated the feasibility of using physics-based digital representations to explore fault scenarios and extract diagnostic features that are otherwise inaccessible in real-world flight data.

The DT EMA successfully simulated various operating conditions, including nominal, degradation, and fault scenarios, with emphasis on early-stage failure characteristics. The three fault modes investigated, unstable power supply (FM1), mechanical backlash (FM2), and cable resistance variation (FM3), were modelled using indirect but physically meaningful representations. These include stepped voltage disturbances, injected reverse torque, and modified resistance parameters. Simulation outputs under these fault modes were validated through engineering principles and regression modelling, confirming that the induced behaviours (e.g., current overshoots, displacement faults) align with theoretical expectations and literature-reported trends.

Diagnostic features were extracted from current, angular velocity, and displacement signals. These features were then evaluated through classification and regression models to assess their separability, relevance, and robustness. The analysis demonstrated that steady-state current, displacement fault, and angular velocity trends are promising indicators for fault detection. In the multi-fault cases, Random Forest and Support Vector Regression models exhibited stable diagnostic performance, suggesting that the data generated by this framework can support downstream health monitoring applications.

Key contributions of the research include:

- The development of a configurable DT framework for fault simulation, including a modular EMA model and automated fault injection system.

- The generation of structured, high-fidelity datasets that capture multi-domain fault responses, suitable for algorithm training in diagnostics and prognostics.
- A proposed reinterpretation of the DT not only as an operational mirror of a physical system, but also as a systematic data generator to support predictive maintenance research in contexts where empirical data is unavailable or limited.

In summary, this research demonstrates that a DT can be used not merely as a monitoring tool, but as a simulation-based enabler for health management development. The framework provides a scalable, accessible, and extensible platform for generating synthetic fault data with embedded physical consistency, supporting early-stage algorithm development, and ultimately contributing to safer and more reliable integration of EMAs in future more-electric aircraft.

10 FUTURE WORK

This research demonstrates the feasibility and utility of a DT-based EMA simulator for synthetic health data generation. Building on this foundation, several directions for future research are proposed, grouped into three broad themes:

1. Model Enhancements

- **Thermal and environmental modelling:** The current model includes only basic thermal sensing. Future versions could incorporate dynamic thermal behaviour within the BLDC motor, gear housing, and surrounding structures. Modelling the impact of external air temperature (e.g., from 15°C at sea level to -30°C at altitude [123]) would also improve simulation practicality.
- **Multi-body simulation integration:** Coupling with SimScape Multibody or similar tools would enable 3D kinematic representation of flap motion and actuator linkage dynamics. This would support studies on mechanical hysteresis, vibration, or stress under deflection.
- **Real-time constraints and solver optimisation:** Future work may also address real-time compatibility for potential Hardware-in-the-Loop (HIL) deployment, involving simplification or modular partitioning of the model.

2. Expanded Fault Library

- **Additional failure mechanisms:** The current framework focuses on three representative failure types. Future scenarios could include:
 - Sensor drift or failure (e.g., position or current sensing degradation)
 - Bearing wear or jamming
 - Encoder misalignment
 - Partial detachment or backlash variability under dynamic loads
- **Progressive fault modelling:** Rather than step-change injection, simulating gradual degradation over time (e.g., linear wear-in, increasing backlash gaps) would enhance relevance for Remaining Useful Life (RUL) estimation studies.

- **Multi-modal fault interactions:** Extending from FM6 (triple fault), new permutations could explore complex fault chains, timing overlaps, and competing recovery mechanisms within the control loop.

3. Advanced Use Cases

- **Control algorithm validation:** Embedding adaptive or model-based control strategies within the loop would allow testing of their performance under degraded scenarios. This is particularly relevant for fault-tolerant EMA design.
- **Health monitoring toolchain integration:** The framework could be extended to output structured datasets directly usable by Python or TensorFlow/Keras-based ML pipelines, including sliding window and ensemble-based feature tracking.
- **Application to other systems:** While the current case study focuses on the A350 inboard flap EMA, the simulation structure can be readily adapted to other actuators such as spoiler, rudder, electric landing gear, or UAM flight surface systems.

In the longer term, this framework may also support digital certification and virtual testing of new actuator architectures prior to physical prototyping. It offers a sandbox for exploring hypothetical or edge-case fault scenarios without safety risks or costly test campaigns.

In conclusion, this work lays the foundation for a flexible and extensible research platform. By pursuing these extensions, the DT-based approach may serve not only academic investigation but also practical implementation in the evolving landscape of more-electric, intelligent, and digitally engineered aircraft systems.

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APPENDICES

Appendix A Ethical approval letter



26 April 2024

Dear Mr Wang ,

Reference: CURES/21754/2024

Project ID: 25016

Title: Digital Twin of Aircraft Electrical Actuator to Generate Data for Health Management Research

Thank you for your application to the Cranfield University Research Ethics System (CURES).

We are pleased to inform you your CURES application, reference CURES/21754/2024 has been reviewed. You may now proceed with the research activities you have sought approval for.

If you have any queries, please contact CURES Support.

We wish you every success with your project.

Regards,

CURES Team

Appendix B Load Profile Calculation

This appendix details the engineering analysis and calculations supporting the selection of the actuator load profile mentioned in Table 3.3-1, and throughout the simulation scenarios presented in Chapter 4 and 5.

B.1 Overview of Load Selection Strategy

The simulation framework models the EMA behaviour during a continuous flap extension, lasting 30 seconds. This period corresponds to pre-flight system verification conducted on the ground. However, the applied mechanical loads of 8, 10, and 12kN are derived from estimated aerodynamic forces expected during in-flight flap deployment under high-lift configuration (during approach and landing).

This modelling strategy is adopted to enhance the observability of fault-induced derivations in actuator performance. It aligns with common practices in DT-based health management simulations, where system excitation is purposefully increased to improve signal-to-noise ratio and feature separability under fault conditions.

B.2 Geometric Justification of Actuator Displacement

To ensure that the EMA displacement is consistent with realistic flap movement, a geometric estimation was conducted.

Given:

The maximum flap deflection θ_{def} is 45° .

An L_{hinge} is 0.83 meter [124].

Transmission ratio r is 0.46 [125].

Then,

The arc length S_{arc} travelled at the point of actuation:

$$S_{arc} = L_{hinge} \cdot \theta_{def} = 0.83 \cdot \left(\frac{45 \cdot \pi}{180} \right) = 0.6519m$$

The displacement d

$$d = S_{arc} \cdot r = 0.6519 \cdot 0.46 = 0.2999m \approx 299.87mm$$

This result supports the 300mm actuator displacement used in the simulation.

B.3 Load Estimation Based on Aerodynamic Reference

The selected load levels are justified by estimating the aerodynamic force acting on the inboard flap during typical approach conditions [126]. Given:

Flight speed during descending $V_{descend} = 129m/s \approx 250knots$,

Flight speed during approaching $V_{approach} = 77m/s \approx 150knots$,

Flight speed at FULL EXTENSION $V_{pre-landing} = 72m/s \approx 140knots$

Air density $\rho = 1.225kg/m^3$,

Flap area during IDLE and Stage 1 $A_{flap_1} = 0.32m^2$,

Flap area during Stage 1 and Stage 2 $A_{flap_2} = 0.48m^2$,

Flap area during Stage 2 and Stage 3 $A_{flap_3} = 0.9m^2$,

Flap area during Stage 3 and FULL EXTENSION $A_{flap_FULL} = 1.28m^2$,

Flap lift coefficient $C_{L_flap} = 2.5$,

Then,

Dynamic pressures

$$P_{flap_descend} = 0.5 \cdot \rho \cdot V_{descend}^2 = 10192.6Pa$$

$$P_{flap_approach} = 0.5 \cdot \rho \cdot V_{approach}^2 = 3631.51Pa$$

$$P_{flap_FULL} = 0.5 \cdot \rho \cdot V_{pre-landing}^2 = 3175.2Pa$$

Aerodynamic force during IDLE to Stage 1

$$F_{flap} = P_{flap_descend} \cdot A_{flap_1} \cdot C_L = 10192.6 \cdot 0.32 \cdot 2.5 = 8154.08N$$

Aerodynamic force during Stage 1 to Stage 2

$$F_{flap} = P_{flap_descend} \cdot A_{flap_2} \cdot C_L = 10192.6 \cdot 0.48 \cdot 2.5 = 12152N$$

Aerodynamic force during Stage 2 to Stage 3

$$F_{flap} = P_{flap_approach} \cdot A_{flap_3} \cdot C_L = 3631.51 \cdot 1.25 \cdot 2.5 = 8170.9N$$

Aerodynamic force during Stage 3 to FULL EXTENSION

$$F_{flap} = P_{flap_FULL} \cdot A_{flap_FULL} \cdot C_L = 3175.2 \cdot 1.28 \cdot 2.5 = 10160.64N$$

Therefore, in this study, approximate values of 8kN, 12kN, and 10kN were selected for different load phases in the simulation, as summarised in Table 3.3-1.

Appendix C Fault Injector – Unstable Voltage/Current

```
%% Random_Voltage.m
% This script injects a voltage disturbance based on externally assigned
VoltageFaultValue and VoltageFaultStartTime.

fs = 100;                % Sampling frequency (Hz)
t_end = 30;              % Total simulation duration (s)
t = (0:1/fs:t_end)';    % Time vector

default_voltage = 28;    % Normal operation voltage

try
    voltage_value = evalin('base', 'VoltageFaultValue');
    start_time    = evalin('base', 'VoltageFaultStartTime');
catch
    error('VoltageFaultValue or VoltageFaultStartTime not found in base
workspace.');
```

```
end

% Validate start_time and voltage_value
if isempty(voltage_value) || isempty(start_time)
    error('VoltageFaultValue or VoltageFaultStartTime is empty.');
```

```
end

% Define fault parameters
fault_duration = 10;      % Fault duration (seconds)
fault_steps = fault_duration * fs;

start_idx = round(start_time * fs) + 1;

% Protection against out-of-bounds
if (start_idx + fault_steps - 1) > length(t)
    error('Voltage fault injection exceeds simulation duration.');
```

```
end

% Create fault segment
ramp_steps = round(0.5 * fs); % 0.5 second smooth transition
flat_steps = fault_steps - 2 * ramp_steps;

ramp_up    = linspace(default_voltage, voltage_value, ramp_steps)';
flat       = voltage_value * ones(flat_steps,1);
ramp_down  = linspace(voltage_value, default_voltage, ramp_steps)';

anomaly_segment = [ramp_up; flat; ramp_down];

% Create full voltage profile
voltage_profile = default_voltage * ones(length(t),1);

voltage_profile(start_idx:start_idx+fault_steps-1) = anomaly_segment;

% Smooth startup phase (0-0.2s ramp-up from 0V)
startup_steps = round(0.2 * fs);
voltage_profile(1:startup_steps) = linspace(0,
voltage_profile(startup_steps+1), startup_steps)';
```

```

% Create timeseries object
VoltageInput = timeseries(voltage_profile, t);

% Assign back to base workspace
assignin('base', 'VoltageInput', VoltageInput);

% Update start and end time for labeling
assignin('base', 'VoltageFaultStartTime', t(start_idx));
assignin('base', 'VoltageFaultEndTime', t(start_idx + fault_steps - 1));

% Progress display
fprintf('Voltage Fault Injected: %.2fV from %.2fs to %.2fs\n', ...
        voltage_value, t(start_idx), t(start_idx + fault_steps - 1));

```

Appendix D Fault Injector – Mechanical Backlash

```
%% Random_Backlash.m
fs = 100;                % Sampling frequency (Hz)
t_end = 30;              % Total simulation duration (s)
t = (0:1/fs:t_end)';    % Time vector

% Backlash value pool (N)
force_values = [50, 100, 150];

% Backlash force initiates from 0
backlash_force = zeros(size(t));

% randomly inject (1 ~ 3) times
num_segments = randi([1, 3]);

% initiate record variables
ValList = NaN(1, 3);
StartList = NaN(1, 3);
EndList = NaN(1, 3);

% First injection
dur_range = [2.4, 4];    % injection time
dur_steps = round((dur_range(1) + (dur_range(2) - dur_range(1)) * rand) *
fs);
max_start_idx = round(10 * fs) - dur_steps - 1;
start_idx = randi([2, max_start_idx]);
backlash_force(start_idx:start_idx+dur_steps) =
force_values(randi(numel(force_values)));

ValList(1) = backlash_force(start_idx);
StartList(1) = t(start_idx);
EndList(1) = t(start_idx + dur_steps);

used_idx = false(length(t),1);
used_idx(start_idx:start_idx+dur_steps) = true;

% Following injections
seg_id = 2;
while seg_id <= num_segments
    dur_steps = round((dur_range(1) + (dur_range(2) - dur_range(1)) * rand) *
fs);
    max_start_idx = round(20 * fs) - dur_steps - 1;
    start_idx = randi([2, max_start_idx]);

    attempt = 0;
    while any(used_idx(start_idx:start_idx+dur_steps)) && attempt < 100
        start_idx = randi([2, max_start_idx]);
        attempt = attempt + 1;
    end

    if attempt >= 100
```

```

        break;
    end

    backlash_force(start_idx:start_idx+dur_steps) =
force_values(randi(numel(force_values)));
    used_idx(start_idx:start_idx+dur_steps) = true;

    Vallist(seg_id) = backlash_force(start_idx);
    StartList(seg_id) = t(start_idx);
    EndList(seg_id) = t(start_idx + dur_steps);

    seg_id = seg_id + 1;
end

% create timeseries object
BacklashInjection = timeseries(backlash_force, t);

% Assign back to base workspace
assignin('base', 'BacklashInjection', BacklashInjection);
assignin('base', 'FaultVallist', Vallist);
assignin('base', 't_start_list', StartList);
assignin('base', 't_end_list', EndList);

% Progress display
fprintf("Backlash %d Injected: \n", seg_id-1);
for j = 1:(seg_id-1)
    fprintf("    • %dN [%0.2fs ~ %0.2fs]\n", Vallist(j), StartList(j),
EndList(j));
end

```

Appendix E Fault Injector – Resistance

```
%% Random_Resistance.m

fs = 100;           % Sampling rate (Hz)
t_end = 30;        % Total simulation time (s)
t = (0:1/fs:t_end)'; % Time vector

% Define normal and fault resistance values (in Ohm)
normal_resistance = 0.62222222;
fault_resistances = [0.3, 0.45, 0.8, 1.0];

% Randomly choose fault resistance value
resistance_value = fault_resistances(randi(numel(fault_resistances)));

% Fault duration is fixed at 10 seconds
fault_duration = 10; % seconds
fault_steps = fault_duration * fs;

% Random start time (ensure enough room for 10s fault)
max_start_time = t_end - fault_duration - 1;
start_time = 1 + (max_start_time - 1) * rand(); % Randomly from 1s onwards

start_idx = round(start_time * fs) + 1;

% Create resistance profile
resistance_profile = normal_resistance * ones(length(t),1);
resistance_profile(start_idx:start_idx+fault_steps-1) = resistance_value;

% Create timeseries
Resistance = timeseries(resistance_profile, t);

% Save to base workspace
assignin('base', 'Resistance', Resistance);
assignin('base', 'ResistanceFaultValue', resistance_value);
assignin('base', 'ResistanceFaultStartTime', t(start_idx));

% Progress display
fprintf('Resistance Fault Injected: %.2f Ohm from %.2fs to %.2fs\n', ...
    resistance_value, t(start_idx), t(start_idx + fault_steps - 1));
```

Appendix F Simulation Configuration Summary

Table Appendix F-1 summarises configuration set-up for all elements in the simulation.

Table Appendix F-1 Element configuration list

Element	Config	Value
Solver (ode23t)	Equation formulation	Time
	Index reduction method	Derivate Replacement
	Consistency tolerance	Model AbsTol and RelTol
	Solver Type	Backward Euler
	Sample time	0.01 second
PID (Voltage Monitor)	Controller	PI
	Form	Parallel
	Proportional (P)	0.02
	Integral (I)	1.5
PID (Displacement Monitor)	Controller	PI
	Form	Ideal
	Proportional (P)	100
	Integral (I)	50
	Output Saturation Upper Limit	28
	Output Saturation Lower Limit	0
From Workspace (Voltage_Data_Source)	Sample time	-1
From Workspace (Reverse_Load_Data_Source)	Sample time	-1
From Workspace (Resistance_Data_Source)	Sample time	-1
From Workspace (Load_Profile_Data_Source)	Sample time	-1
Gearbox	Gear ratio	5
Worm screw	Gear ratio	2
	Thread type	Left-handed
Leadscrew	Screw lead	15 mm
	Thread type	Right-hand
Translational Hard Stop	Upper bound	300 mm
	Lower bound	-0.1 mm
	Contact stiffness at upper bound	1e8 N/m
	Contact damping at upper bound	15000N*s/m

Appendix G MOOG EMA Performance Characteristics [113]



ELECTROMECHANICAL ACTUATORS



Moog has flight-proven experience with several types of actuation, including Electromechanical (EM), Electrohydraulic (EH) and Electrohydrostatic (EHA). By building upon heritage experience, Moog delivers high quality, reliable solutions to meet our customers' needs.

Moog's family of flight-proven, heritage electromechanical (EM) actuators have provided thrust vector control (TVC) for several applications, such as:

KEY FEATURES

- Antares
- Delta IV
- Centaur
- Vega



MOOG

ELECTROMECHANICAL ACTUATORS

LINEAR ACTUATORS - PERFORMANCE CHARACTERISTICS

Characteristics



Application	TVC Stage 1	TVC Stage 1	TVC Upper Stage	TVC Stage 1	TVC Upper Stage Redundant	Flight Control Surfaces	TVC Upper Stage
Horsepower (hp)	26.5	20.5	3.4	2.1	0.4	0.94	0.23
Stall Load (lbf)	40,600	21,727	11,800	4,634	3,190	3,000	745
Power Point	5.83 in/sec @ 30,000 lbf	6.78 in/sec @ 20,000 lbf	2.49 in/sec @ 8,892 lbf	20 in/sec @ 4,634 lbf	2.18 in/sec @ 1,100 lbf	3.10 in/sec @ 2,000 lbf	3.0 in/sec @ 500 lbf
Actuator Weight (lbs)	125	57	32	13	18	8	8
Stroke (+/-, Centered) (in)	2.01	1.16	0.85	1.96	0.85	1.35	1.14
Null Length, Centered (in)	20.16	15.24	13.65	15.54	23.25	8.96	9.88
Voltage DC	280	280	140	270	28	150	55

ROTARY ACTUATORS - PERFORMANCE CHARACTERISTICS

Characteristics



Application	Fin Control	Propellant Valve	Redundant Propellant Valve	Redundant Engine Control Valve	Redundant Engine Control Valve	Triplex Rudder Surface	Triplex Body Flap Surface
Horsepower (hp)	1.6	0.2	0.18	0.002	0.05	2.5	7.5
Stall Torque (in/lbf)	3,000	300	350	—	—	235	255,000
Power Point	2,000 in/lbf @ 300 deg/sec	250 in/lbf @ 300 deg/sec	188 in/lbf @ 360 deg/sec	220 in/lbf @ 3.5 deg/sec	60 in/lbf @ 340 deg/sec	168 in/lbf @ 5,643 deg/sec	127,500 in/lbf @ 22 deg/sec
Actuator Weight (lbs)	12.3	5.1	7.7	17.6	16	35	235
Stroke (+/-, Degree)	50	70	60	3	100	10 revs	22.5 revs
Voltage DC	150	150	28	28	28	270	270

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