



OPEN ACCESS

EDITED BY

Andrew Wileman,
Loughborough University,
United Kingdom

REVIEWED BY

Ron S. Kenett,
Samuel Neaman Institute for National
Policy Research, Israel
Paul Arévalo-Cordero,
University of Cuenca, Ecuador

*CORRESPONDENCE

Chengwei Wang,
✉ chengwei.wang@cranfield.ac.uk

RECEIVED 18 September 2025

REVISED 23 February 2026

ACCEPTED 05 March 2026

PUBLISHED 10 April 2026

CITATION

Wang C, Fan I-S and King SP (2026) A
digital twin-based fault simulation
framework for aircraft electromechanical
actuators: method and demonstration.
Front. Aerosp. Eng. 5:1708392.
doi: 10.3389/fpace.2026.1708392

COPYRIGHT

© 2026 Wang, Fan and King. This is an
open-access article distributed under the
terms of the [Creative Commons
Attribution License \(CC BY\)](#). The use,
distribution or reproduction in other
forums is permitted, provided the original
author(s) and the copyright owner(s) are
credited and that the original publication
in this journal is cited, in accordance with
accepted academic practice. No use,
distribution or reproduction is permitted
which does not comply with these terms.

A digital twin-based fault simulation framework for aircraft electromechanical actuators: method and demonstration

Chengwei Wang*, Ip-Shing Fan and Stephen P. King

Integrated Vehicle Health Management Centre, Faculty of Engineering and Applied Science, Cranfield University, Cranfield, United Kingdom

Electromechanical actuators have become key components in next-generation aircraft architectures, particularly under More Electric Aircraft and Power-by-Wire paradigms. However, their operational complexity, compounded by mechanical-electrical interactions, introduces failure modes that are both difficult to detect and insufficiently represented in existing datasets. This paper presents a comprehensive digital twin-based framework developed to simulate and analyse EMA behaviour under both nominal and faulty conditions. Implemented using MATLAB Simulink and Simscape, the framework comprises modular voltage and load profiles, structured fault injection mechanisms, and labelled data generation tools. This work investigates the signal responses to various fault types, including mechanical backlash, voltage drop, and electrical resistance anomalies, both in isolation and combination. The simulation output enables systematic feature extraction and evaluation for diagnostics and health indicator development. The framework generated a high-fidelity dataset of 70,000 labelled samples, which demonstrated excellent feature separability for both single and compound faults under Principal Component Analysis. This research addresses the aerospace industry's pressing need for synthetic, fault-labelled data to train and validate diagnostic algorithms and offers a scalable methodology applicable to diverse actuator configurations. The resulting openable, labelled dataset and modular scripts enable reproducible benchmarking for EMA health monitoring and will be extended to physics-informed prognostics in subsequent work.

KEYWORDS

digital twin, electromechanical actuator, health monitoring, prognostics, synthetic dataset

1 Introduction

The aviation industry is undergoing a significant transformation driven by the pursuit of greater efficiency, reduced emissions, and enhanced operational reliability. This transition is particularly visible in the migration from traditional hydraulic systems to electromechanical actuators (EMAs) within the framework of More Electric Aircraft (MEA) and Power-by-Wire (PbW) architectures (Zaporozhets, 2020; Emmanouil, 2020; Janson et al., 2017). EMAs offer several advantages: they eliminate the need for hydraulic lines, reduce system weight, simplify maintenance procedures, and integrate seamlessly with digital control systems (MOOG, 2020).

Despite these advantages, EMAs present unique diagnostic challenges. Their failure modes span both electrical and mechanical domains, with interactions between motor

characteristics, load dynamics, gear backlash, thermal effects, and sensor degradation (Fu et al., 2017; Wang et al., 2022). Detecting and isolating such faults requires multidomain sensing, cross-signal interpretation, and often, predictive insights into degradation patterns. Traditional data collection methods, dependent on physical testing or operational incident logging, struggle to produce the volume and variety of labelled fault data required to train modern diagnostic and prognostic algorithms.

The Digital Twin (DT) paradigm has emerged as a promising solution to this challenge. A DT is a virtual representation of a physical asset that mirrors its structure, behaviour, and performance (Glaessgen and Stargel, 2012). When applied to aircraft actuators, DTs enable engineers to simulate operational behaviour under nominal and faulty conditions, generate synthetic datasets, evaluate fault progression, and test health management strategies before deployment.

The increasing electrification of aerospace systems parallels broader trends observed in large-scale renewable energy integration, where accurate demand modelling and predictive frameworks are essential for system reliability and planning (Arévalo et al., 2024). As aircraft actuation architectures transition toward fully electric configurations, DT models provide a structured foundation for managing electrical load complexity and supporting predictive health management.

This paper presents a DT-based fault simulation framework specifically designed for aircraft EMAs. The system supports a wide range of simulation scenarios, including multiple fault types and durations, offering a scalable and reproducible method for synthetic health data generation.

2 Failure modes and system-level impacts

2.1 The role of DTs in system health management

The concept of a “twin” originated with NASA’s Apollo program (Glaessgen and Stargel, 2012), where an identical vehicle on Earth was used to mirror and troubleshoot the spacecraft in orbit. The modern DT, first conceptualised by Grieves in 2002 (Grieves, 2016; Grieves, 2023), has evolved into a multi-physics, multi-scale, probabilistic simulation that is continuously updated with data from its physical counterpart. In the context of PHM (Liu et al., 2018), DTs serve two primary roles: as a real-time mirror for operational monitoring and as a simulation platform for data generation. While real-time monitoring is a long-term goal, the immediate challenge for many new systems like EMAs is the lack of historical data needed to build diagnostic models in the first place. Recent literature (Quattrocchi et al., 2021; Cole and Tang, 2022; Wang et al., 2023; Annaz and Kaluarachchi, 2023) recognises this challenge and supports the use of simulation-generated data as a legitimate foundation for DT development following a multiple cycle framework as shown in Figure 1, especially for exploring rare fault modes or for systems where historical failure records are non-existent.

2.2 Evolution of aircraft actuation systems

For decades, centralised hydraulic systems were the standard for aircraft flight control, valued for their reliability and power density (Maré and Fu, 2017). However, they suffer from drawbacks including high weight, complex maintenance, and vulnerability to single-point failures in hydraulic lines. The MEA initiative has driven the adoption of electrically powered actuators, which are categorised into two main types: Electro-Hydraulic Actuators (EHAs) and Electro-Mechanical Actuators (EMAs). EHAs are self-contained hydraulic systems driven by an electric motor, offering a bridge between legacy and fully electric architectures. EMAs, however, completely eliminate hydraulic fluid, converting electrical energy directly into mechanical motion via motors and gear trains. This offers the greatest benefits in weight reduction and efficiency but introduces new failure modes and thermal management challenges (Lawson and Pointon, 2008; Wager et al., 2011; Xu et al., 2014).

2.3 EMA components and failure characteristics

EMAs are composed of tightly integrated electrical and mechanical components. The primary subsystems include the electric motor, gear transmission (often screw–nut or planetary mechanisms), electronic control unit (ECU), and position feedback sensors. These subsystems are jointly responsible for converting electrical energy into controlled mechanical motion.

Failure in EMAs may originate from electrical disturbances, mechanical degradation, or sensor anomalies. A systematic understanding of failure modes is essential for simulation, diagnosis, and eventual health management. The dominant failure types are categorised into three representative single-fault modes and their combinations.

- **Voltage disturbance (FM1):** Sudden voltage drops, often caused by transient supply conditions or degraded motor driver circuits, lead to torque underproduction. This results in slowed actuator response, incomplete positioning, and tracking delays.
- **Mechanical backlash (FM2):** Excess clearance in the mechanical transmission, whether through gear wear, thread loosening, or poor assembly, introduces non-linear and oscillatory displacement behaviour. This is particularly noticeable during direction changes or under variable loads.
- **Resistance change (FM3):** Corrosion, connector degradation, or wire fatigue may increase electrical resistance in the circuit, altering current drawing and heating patterns. This leads to increased power consumption and may obscure fault boundaries.

The combined effect of multiple fault modes is both realistic and diagnostically challenging. In scenarios such as FM6 (backlash + resistance + undervoltage), overlapping symptoms can mask the individual fault signatures, requiring multi-feature fusion for accurate classification.

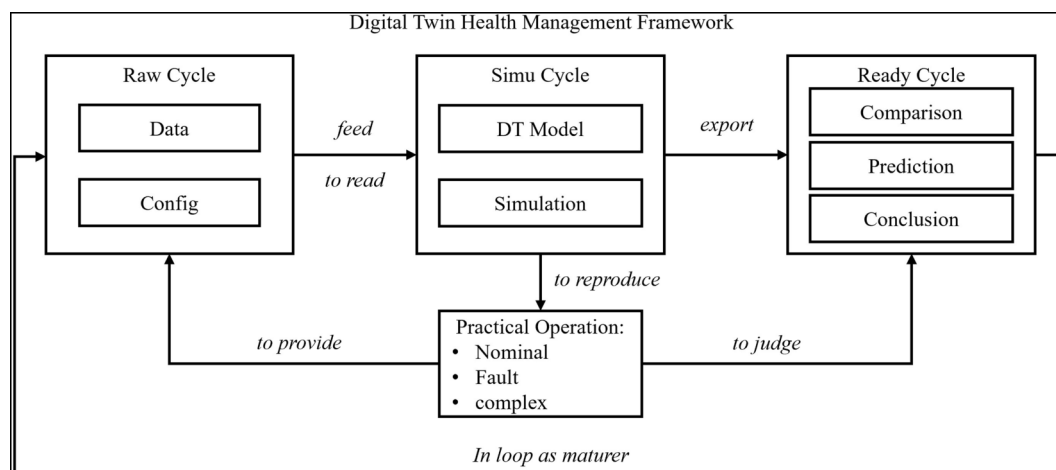


FIGURE 1
DT Framework structure with three key cycles (reprinted with permission from Wang et al., 2025).

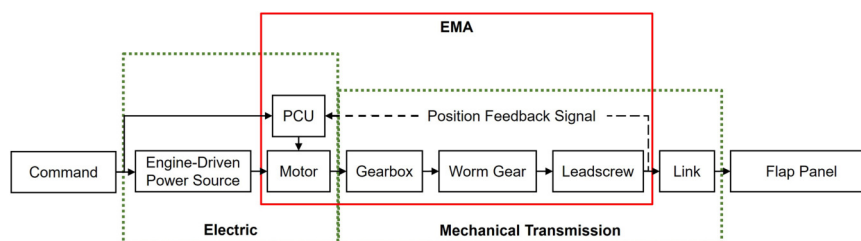


FIGURE 2
System operation of the EMA-driven inboard flap extension.

To simulate these conditions faithfully, it is essential to model both the physical fault mechanisms and their time-dependent injection profiles. The next sections introduce the DT design, and the configurable simulation environment used to replicate these effects.

3 DT framework design

The methodology follows a structured engineering approach to systematically develop, operate, and validate the DT for data generation. The methodology follows a structured engineering approach, with the framework implemented in the MATLAB/Simulink and Simscape environment for its multi-domain modelling capabilities and flexibility in script-based automation.

3.1 Case study: A350XWB inboard flap actuator

This work emulates an inboard flap-like duty cycle with A350XWB-inspired loading assumptions for demonstration (AIRBUS, 2017). While the actual aircraft uses a mix of hydraulic

and electro-hydraulic systems, its advanced fly-by-wire architecture provides a suitable context for exploring a fully electromechanical solution. Figure 2 shows detailed system structure and energy transmission powertrain of a typical EMA referring to Figure 3. The simulation models a 30-s flap extension cycle, which is representative of a pre-flight check. To ensure fault signatures are observable, the applied mechanical loads of 8, 10, and 12 kN are derived from estimated aerodynamic forces during in-flight deployment, creating a challenging test scenario for the actuator.

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

Flight speed during descending:

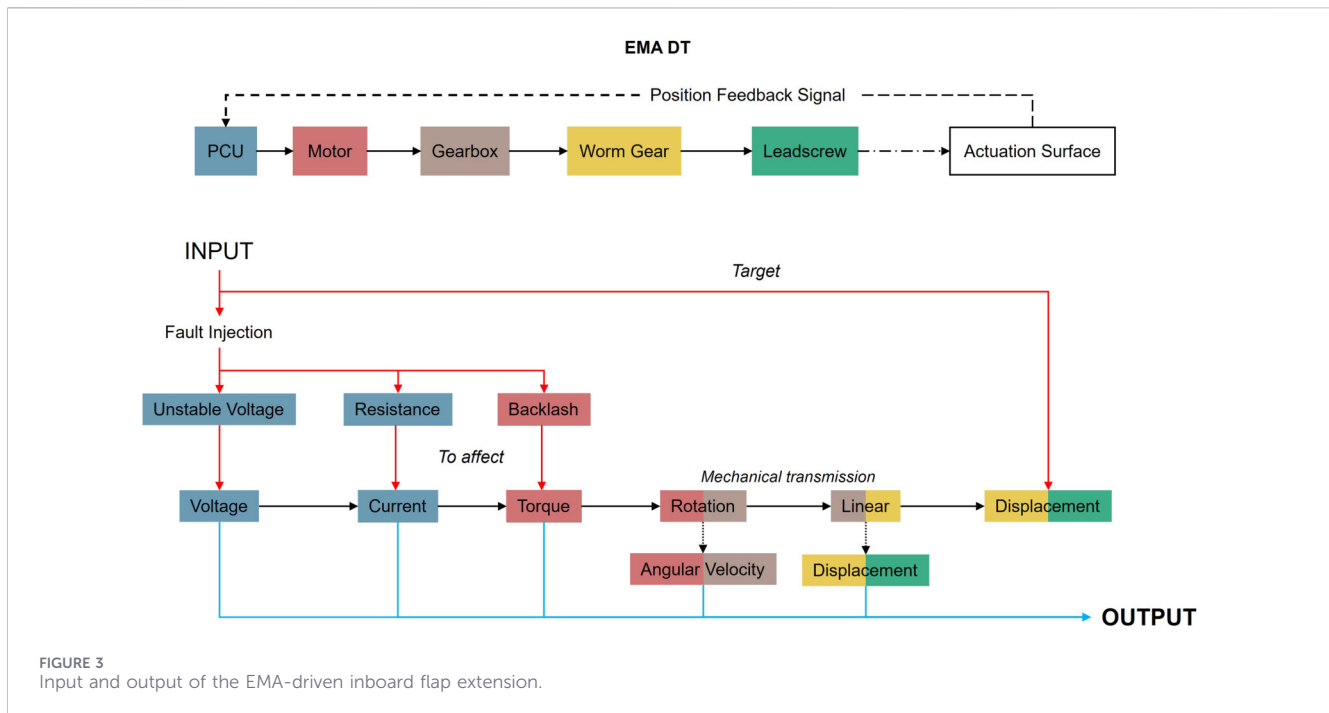
$$V_{\text{descend}} = 129 \text{ m/s} \approx 250 \text{ knots}$$

Flight speed during approaching:

$$V_{\text{approach}} = 77 \text{ m/s} \approx 150 \text{ knots}$$

Flight speed at FULL EXTENSION:

$$V_{\text{pre-landing}} = 72 \text{ m/s} \approx 140 \text{ knots}$$



Air density $\rho = 1.225 \text{ kg/m}^3$, Flap area during IDLE and Stage 1 $A_{flap_1} = 0.32 \text{ m}^2$, Flap area during Stage 2 and Stage 2 $A_{flap_2} = 0.48 \text{ m}^2$, Flap area during Stage 3 and FULL EXTENSION $A_{flap_FULL} = 1.28 \text{ m}^2$, Flap lift coefficient $C_{L_flap} = 2.5$, Then,

Dynamic pressures

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

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

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

Aerodynamic force during IDLE to Stage 1:

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

Aerodynamic force during Stage 1 to Stage 2:

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

Aerodynamic force during Stage 2 to Stage 3:

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

Aerodynamic force during Stage 3 to FULL EXTENSION:

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

Therefore, in this study, approximate values of 8kN, 10kN, and 12 kN were selected for different load phases in the simulation.

3.2 DT model development in Simscape

The DT developed in this study is a model-based, high-fidelity simulation framework. It represents a virtual replica of an aircraft

EMA, incorporating both electrical and mechanical domains to emulate system-level behaviours under varying operational and fault conditions. The objective of the model is not to replicate a specific certified actuator configuration, but to construct a physics-consistent and diagnostically representative digital twin framework suitable for health management research. The framework is modular, allowing for extensibility and fault injection, and supports the generation of labelled time-series datasets Suitability.

The core structure of the DT, illustrated in Figure 4 and detailed in the schematic in Figure 5, follows a four-layer hierarchy.

- **Input Definition Layer:** This layer includes two primary inputs—voltage profile and load profile. The voltage profile includes both nominal conditions and fault-injected disturbances (e.g., undervoltage events). The load profile simulates realistic flight control actuator demand, segmented into four operational phases, mimicking pitch, or flap deflection sequences.
- **Electromechanical System Layer:** This is the heart of the DT model, comprising subsystems for the DC motor, gear transmission, inertia model, and backlash logic. The motor is modelled using physical parameters such as internal resistance, inductance, back-EMF constant, and torque constant. The screw-nut mechanism is implemented using Simscape Multibody elements, capturing nonlinear stiffness, backlash gaps, and damping.
- **Fault Injection Layer:** Faults are introduced using controllable blocks that modify parameters dynamically. For example, mechanical backlash is simulated using an effect-based approach. Instead of modelling the micro-physics of gear wear, a reverse torque is injected into the drivetrain to replicate the sudden resistive force experienced when mechanical clearance is taken up. This method faithfully

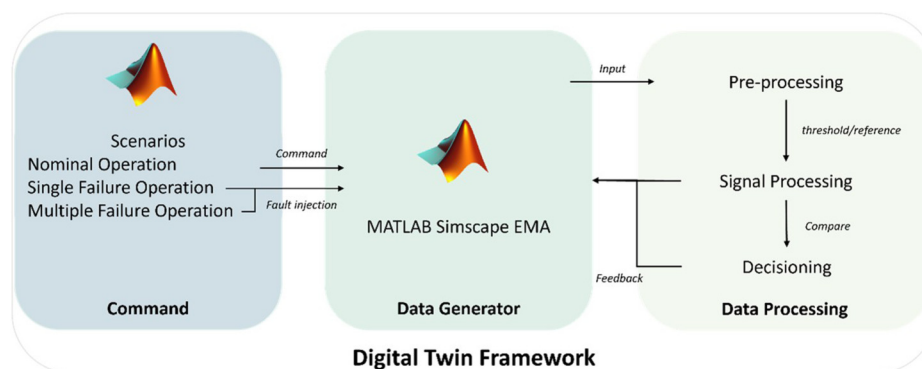


FIGURE 4
Structure of DDDT Framework as further expansion of approach.

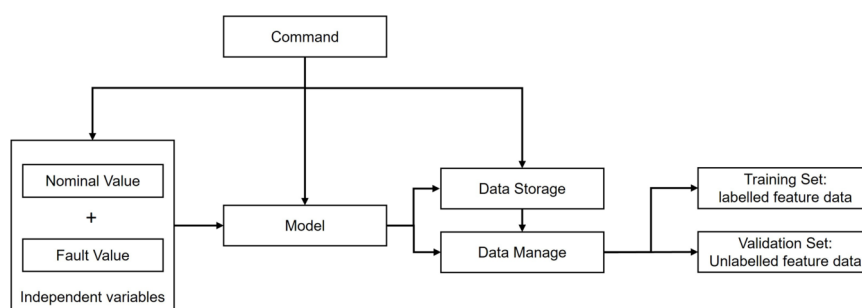


FIGURE 5
Schematic of simulation framework.

reproduces the key diagnostic signatures (e.g., current spikes and velocity dips) while maintaining high computational efficiency. Voltage disturbances are imposed through switch blocks that reduce supply voltage in specific time windows. Resistance faults are realised by dynamically changing the internal resistance of the power circuit.

- **Data Acquisition Layer:** All outputs, including voltage, current, power, displacement, velocity, and fault flags, are recorded at a sampling frequency of 100 Hz. Each simulation outputs 3,000 data points per signal per scenario, making the dataset suitable for deep learning, signal analysis, and statistical feature engineering.

The electrical architecture follows a 28 Vdc aerospace power bus configuration, which is standard for commercial aircraft actuation systems and consistent with publicly available information from industrial manufacturers (MOOG, 2018). This ensures that the electrical operating envelope reflects realistic aerospace practice. The electromechanical topology, including the motor–gear–leadscrew transmission chain, aligns with validated EMA architectures reported in the literature (Fu et al., 2017; Balaban et al., 2015; Mazzoleni et al., 2021). These prior works provide experimentally and analytically supported modelling frameworks for flight-control

EMAs, forming the structural basis of the present digital twin implementation.

The parameter magnitudes listed in Table 1 were selected to remain within the order-of-magnitude ranges reported for aerospace electromechanical actuators. While exact proprietary actuator specifications are not publicly disclosed, the selected voltage level, transmission ratios, and stroke length remain within the typical ranges reported in aerospace EMA literature and industrial documentation (MOOG, 2018; Fu et al., 2017; Balaban et al., 2015; Mazzoleni et al., 2021; Quattrocchi et al., 2021; Annaz and Kaluarachchi, 2023; Wan et al., 2024).

Importantly, behavioural validation is demonstrated through transient electromechanical responses. Under backlash injection, the simulated current surge and corresponding rotor speed dip reproduce the characteristic “current spike–velocity drop” signature observed in experimental PHM testbeds (Balaban et al., 2011). This behavioural consistency provides engineering-level validation of the model’s dynamic response to mechanical disturbances.

The DT architecture is also designed for scalability. Users can adjust fault severity (e.g., magnitude of voltage drop), duration (e.g., transient vs. sustained fault), and onset time (early-stage or end-of-cycle fault) via simulation parameters or script inputs. This capability supports batch generation of scenario-rich datasets with ground-truth labels.

TABLE 1 Key elements and nominal parameters in the model.

Element	Parameter	Nominal
Controlled voltage source	Voltage	28 Vdc
BLDC motor	Pole pairs	4
Gearbox	Gear ratio	5:1
Worm gear	Gear ratio	2:1
Leadscrew	Pitch	10 mm/rev
Translational hard stop	Displacement	300 mm

TABLE 2 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	FM1+FM2	Voltage + backlash
FM5	FM2+FM3	Backlash + resistance
FM6	FM1+FM2+FM3	Voltage + backlash + resistance

3.3 Fault injection and simulation campaign

The fault injection strategy follows a structured campaign approach. A total of seven fault modes (FM1–FM6&Nominal) are defined, including both single-fault and compound-fault scenarios, as summarised in Table 2. The selected magnitude intervals were chosen to represent mild, moderate, and severe degradation levels observed in aerospace maintenance reports and experimental EMA studies (Balaban et al., 2011; Fu et al., 2017). These ranges were bounded to ensure observable but non-catastrophic actuator behaviour within a single operational cycle.

- **FM1 (Unstable Voltage):** A 10-s voltage deviation is injected at a random start time. The fault voltage is drawn from a uniform distribution between 24.0 Vdc and 29.4 Vdc. The supply voltage profile is then defined as:

$$V(t) = \begin{cases} V_{nom}, & t < t_0 \\ V_f, & t_0 \leq t \leq t_0 + T_f \\ V_{nom}, & t > t_0 + T_f \end{cases}$$

where:

$$\begin{aligned} V_{nom} &= 28 \text{ Vdc} \\ T_f &= 10 \text{ s} \\ t_0 &\sim U(5, 25) \\ V_f &\sim U(24.0, 29.4) \end{aligned}$$

Figure 6 provides a visual example of this process, illustrating three separate simulation runs where both the timing and severity of the injected voltage fault are varied to ensure a diverse and representative dataset.

- **FM2 (Mechanical Backlash):** Backlash is simulated using an “effect-based” approach. Instead of modelling micro-physics, a reverse torque is injected into the drivetrain to replicate the resistive force experience. This approach reproduces the characteristic electromechanical transient response without modelling micro-geometry wear. Between one and three backlash events are injected per cycle, with magnitudes of 50, 100, or 150 Nm and randomised timing and duration:

$$T_{inj}(t) = \sum_{k=1}^N T_b^{(k)} \cdot H(t-t_k)$$

where:

$$N \in \{1, 2, 3\}$$

$$T_b^{(k)} \in \{50, 100, 150\} \text{ Nm}$$

t_k randomly distributed within actuator load phases

$$H(\cdot) = \text{Heaviside step function}$$

- **FM3 (Resistance Change):** A 10-s resistance change is injected at a random start time, with the fault value selected from {0.3, 0.45, 0.8, 1.0} Ohm to represent different levels of cable degradation. It is then defined as:

$$R(t) = R_{nom} + \Delta R(t)$$

where:

$$\Delta R(t) = \begin{cases} 0, & t < t_0 \\ R_f, & t_0 < t < t_0 + T_f \end{cases}$$

With $R_f = \{0.3, 0.45, 0.8, 1.0\} \text{ Ohm}$

- **Compound Faults (FM4-FM6):** Dual-fault (FM4, FM5) and triple-fault (FM6) scenarios are constructed by independently generating FM1, FM2, and FM3 parameter perturbations and applying them simultaneously to the system model:

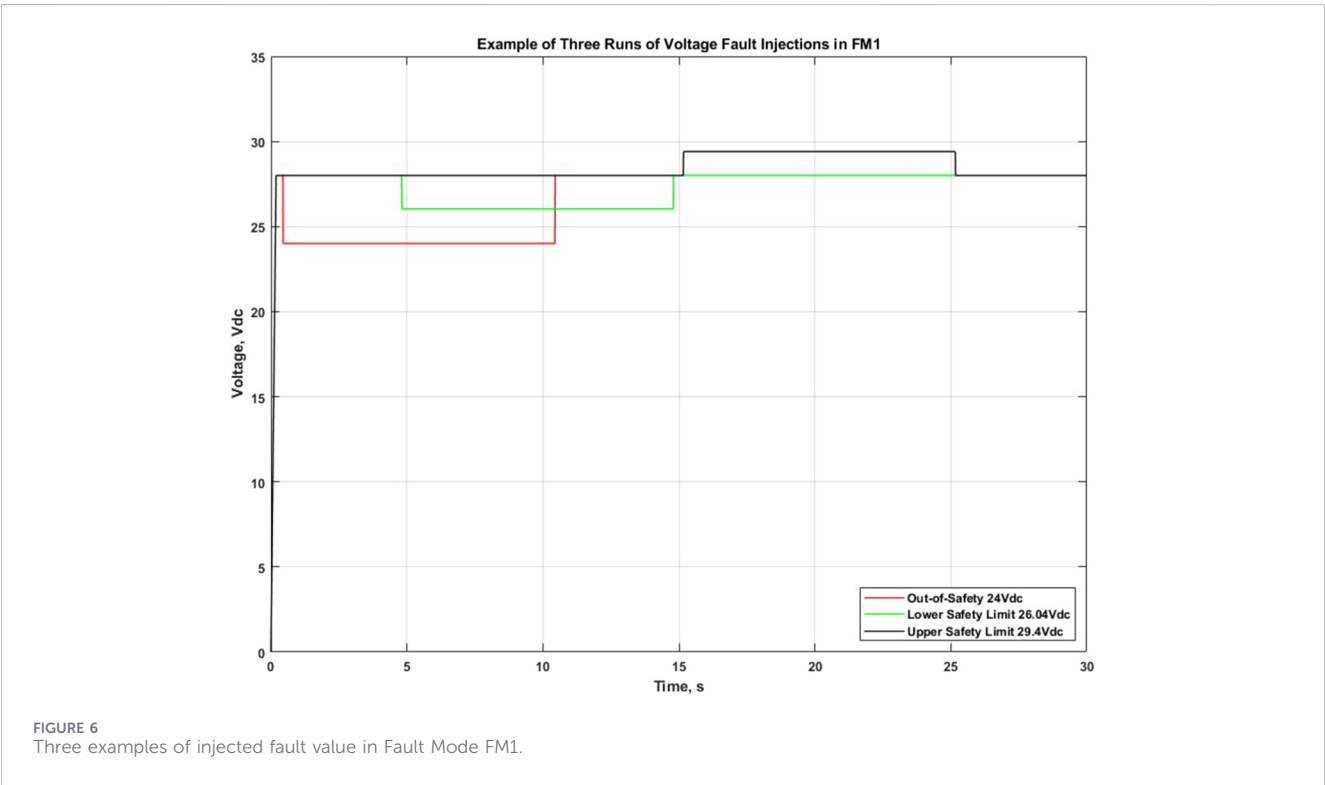
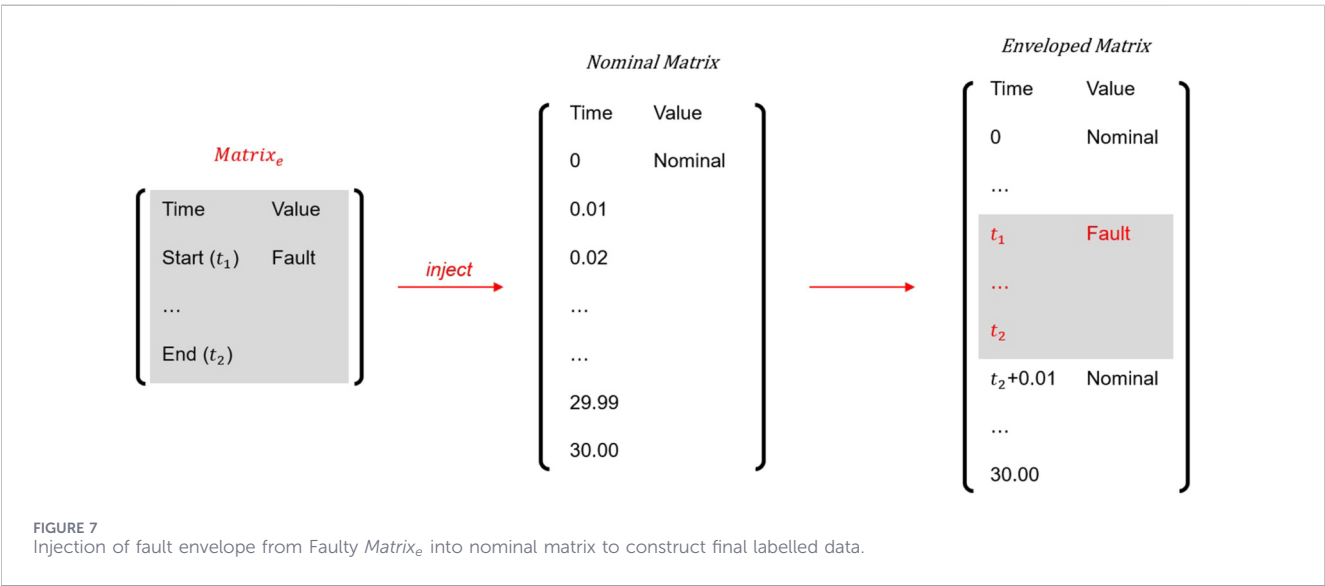
$$\{V(t), T_{inj}(t), R(t)\}$$

The interaction occurs naturally through the system’s multi-domain dynamics rather than artificial signal mixing. This preserves physical causality and avoids synthetic feature superposition. The perturbation functions modify model parameters directly within the Simscape multi-domain dynamic equations, allowing the resulting electrical–mechanical interaction to emerge naturally from system coupling.

Crucially, this study moves beyond simple hard faults by simulating a range of fault severities for each mode. For instance, voltage deviations were drawn from a continuous uniform distribution, while backlash and resistance faults were injected at multiple discrete levels to represent varying degrees of degradation.

Each simulation runs for 30 s, covering a full actuator cycle under a predefined load profile. The profile consists of four segments, progressively applying force and displacement as follows: (1) moderate extension, (2) sharp increase in resistance, (3) return under lower load, and (4) final long-travel operation. This structure allows for fault visibility across different loading conditions and speeds.

The timing of fault injection is randomised within controlled intervals. Faults may occur between 5s and 25s of the simulation as



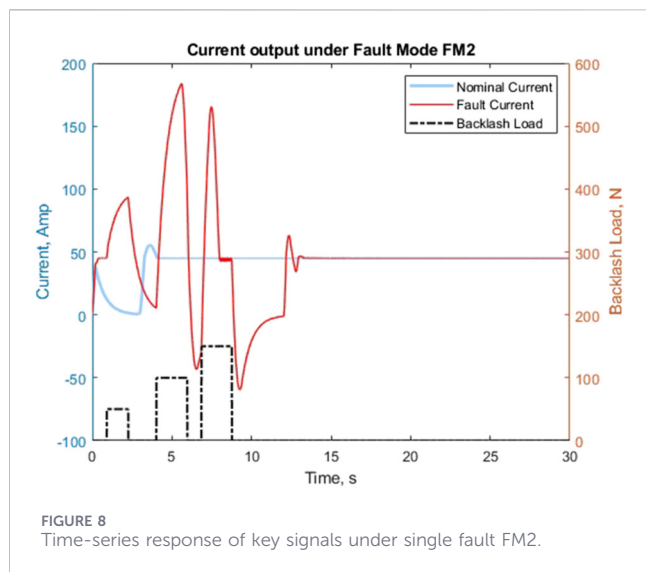
shown in [Figure 7](#) to ensure the actuator is under meaningful load. Each run includes metadata: fault type, injection window, magnitude, and expected physical manifestation. For example, in FM3, resistance increases from 0.6Ω to 1.0Ω over a 4-s window, resulting in increased current draw and thermal dissipation.

The simulation framework is controlled by MATLAB scripts that automate the entire data generation process. The overall dataset size and construction protocol are detailed in [Section 4.3](#). For each run, the framework generates a time-series data file and a

corresponding label file containing the ground truth for the fault type, magnitude, and timing. This automated pipeline ensures the creation of a large-scale, structured, and fully labelled dataset ready for machine learning applications.

4 Results and feature response analysis

The DT model was used to generate multivariate time-series data under each of the seven fault scenarios. The output signals include



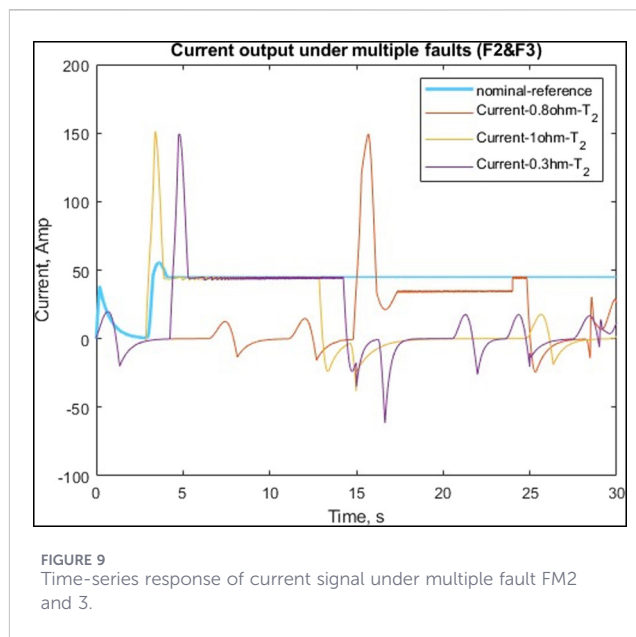
voltage, current, displacement, velocity, and power. Diagnostic features were extracted from both time and frequency domains to assess their sensitivity and robustness across fault modes.

4.1 Signal trends under individual faults

Each single-fault scenario exhibits characteristic deviations in signal behaviour.

- FM1 (voltage disturbance) results in significant underperformance during high-load segments. Displacement tracking fails to reach its intended final value, particularly in Phase IV. The rise time of velocity is also notably delayed, leading to a higher rise delay index (RDI).
- In FM2 (mechanical backlash), the displacement trace displays a stair-stepped lag in response to changing loads, especially during reversal points in Phase II and IV. These are accompanied by oscillatory velocity patterns with increased peak-to-peak variation.
- FM3 (resistance increase) induces elevated RMS current and average power during all load segments. Notably, power spikes and phase delay between voltage and current were observed during sharp load changes, reflecting impaired energy transmission efficiency.

As illustrated in Figure 8, the injection of a backlash load (black dashed line) into the drivetrain elicits an immediate and sharp response from the system. The motor current (red line) spikes dramatically to over 150 Amps to overcome the sudden mechanical resistance, a stark contrast to the smooth nominal current (light blue). Simultaneously, the angular velocity (dark blue line) experiences a corresponding sharp dip, visualising the classic “current spike, velocity dip” signature that is a symbol of mechanical backlash, jamming or binding events. This provides a clear physical validation that the model accurately captures the electromechanical response to a mechanical fault.



4.2 Combined fault responses

Real-world failures often involve multiple interacting faults. The framework’s ability to simulate these is a key strength.

- FM4 (Voltage + Backlash): In this scenario, the current signal exhibits both the sustained elevation due to voltage compensation and the sharp spikes caused by backlash events. The signatures are superimposed, creating a complex waveform that is more challenging to diagnose than either fault in isolation.
- FM5 (Backlash + Resistance): The combination of increased resistance and backlash leads to highly erratic current behavior. The overall current is suppressed due to the resistance, but the backlash events still trigger sharp, albeit smaller, spikes. This reflects a system struggling with both power delivery and mechanical integrity.
- FM6 (Voltage + Backlash + Resistance): This triple-fault scenario produces the most complex and unstable responses. The current signal shows extreme fluctuations, with the controller’s attempts to compensate for one fault often being disrupted by the effects of another. This highlights the non-linear interactions that can occur and underscores the need for multi-signal fusion in advanced diagnostics, as relying on a single signal could easily lead to misclassification.

Figure 9 demonstrates this by plotting the current response for FM5 under three different levels of resistance. When resistance is high (1.0 Ω , yellow line), the current is generally suppressed and unstable. In contrast, with lower resistance (0.3 Ω , purple line), the current spikes caused by backlash are much sharper and more pronounced. This addresses the issue of fault severity, showing that the diagnostic signature is not static, but changes based on the underlying condition of the components.

The FM6 produces the most complex responses, as it combines disturbances from all three domains. Figure 10 deconstructs a single

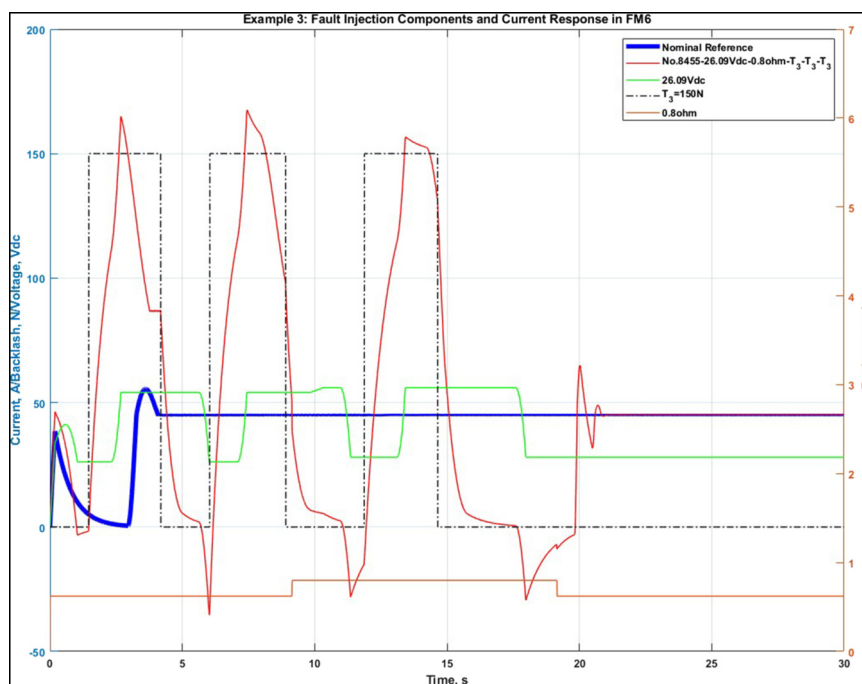


FIGURE 10
Example three of FM6, 26.09Vdc, 0.8Ω, 150Nm backlash three times.

run of an FM6 fault, plotting the individual injected fault components, a voltage drop, a resistance increase, and multiple backlash loads, on the same timeline as the resulting current response. The final current waveform (red line) is a complex superposition of the system's reactions to each of these stimuli. The large spikes are driven by the backlash events, while the overall shape and magnitude of the current are modulated by the concurrent voltage and resistance faults. This provides a compelling illustration of the diagnostic challenge posed by compound faults, underscoring the need for multi-signal fusion to deconstruct such complex signatures.

4.3 Dataset construction and reproducibility

The dataset was constructed through a fully automated simulation campaign to ensure statistical robustness, class balance, and reproducibility. For each of the seven defined operating conditions (Nominal and FM1–FM6), 10,000 independent simulation cycles were executed, resulting in a total of 70,000 labelled samples. Each condition therefore contains an equal number of samples, ensuring strict class balance across all fault categories and preventing bias toward any specific mode during multi-class evaluation.

Simulation and sampling protocol: All simulations were conducted at a fixed sampling frequency of 100 Hz over a 30-s actuator duty cycle, generating 3,000 data points per signal per run. To prevent models from exploiting deterministic phase timing associated with specific load segments, only a single 15-s segment was extracted from each simulation cycle. The starting point of the

extracted window was uniformly random within a valid time range, ensuring that at least two operational phases were included. Each sample corresponds to one independently executed simulation run. Only one analysis window is extracted per run, and no overlapping segments are generated. Consequently, no temporal overlap exists between samples in the training and validation subsets, eliminating the risk of data leakage through duplicated time-series fragments. Since fault onset time, magnitude, and duration are randomised independently for each run, substantial intra-class variability is preserved.

Train-validation strategy: For diagnostic evaluation, the dataset was partitioned into 75% training and 25% validation subsets using class-preserving random sampling to maintain equal label distribution in both sets. Because each sample originates from an independent simulation run, the train-validation split does not introduce scenario-level leakage. All classification experiments reported in this study were conducted using this fixed partition protocol to ensure comparability across feature configurations.

Script-controlled simulation workflow: The DT framework operates through automated MATLAB scripts that control the entire batch execution process. Each simulation run follows a deterministic pipeline.

- i. Selection of operating condition (Nominal or FM1–FM6)
- ii. Randomised generation of fault parameters within predefined bounds
- iii. Assignment of load profile configuration
- iv. Execution of the 30-s multi-domain Simscape simulation
- v. Export of time-series signals and associated metadata

TABLE 3 List of features/signals recorded in datasheet.

Number	Feature/Signal	Unit
1	Time	s
2	Supply voltage	V
3	Motor current	A
4	Rotor angular velocity	rad/s
5	Worm torque output	Nm
6	Linear displacement	mm
7	Electrical power	W
8	Motor efficiency	%

Fault magnitude, injection timing, duration, load profile identifier, and random seed values are stored alongside signal outputs. This ensures complete traceability between parameter perturbation and observable electromechanical response.

The modular architecture allows independent adjustment of voltage profiles, mechanical load definitions, and fault severity ranges without modifying the core electromechanical model. When identical random seeds and configuration parameters are used, the dataset can be regenerated deterministically.

Dataset schema: Each simulation run produces one structured CSV file corresponding to a single actuator duty cycle. Signals are recorded in consistent column order and physical units as shown in Table 3.

Feature extraction is performed on the defined 15-s window, as described above.

Metadata definition: In addition to signal data, each sample contains structured metadata fields that ensure full parameter traceability.

- `fault_mode` (nominal, FM1-FM6)
- `fault_magnitude`
- `injection_start_time`
- `injection_duration`
- `load_profile_id`
- `random_seed`

This structured schema links each time-series sample to its originating perturbation configuration, enabling reproducible benchmarking of diagnostic algorithms and controlled sensitivity studies.

This structured dataset construction and evaluation protocol ensures statistical balance, prevents artificial performance inflation, and provides a reproducible foundation for benchmarking diagnostic algorithms using the generated synthetic EMA dataset.

4.4 Feature extraction and clustering

A total of twenty statistical and dynamic features were extracted, including.

- Time-domain: RMS, peak, skewness, rise time, fall delay, overshoot, area under curve.

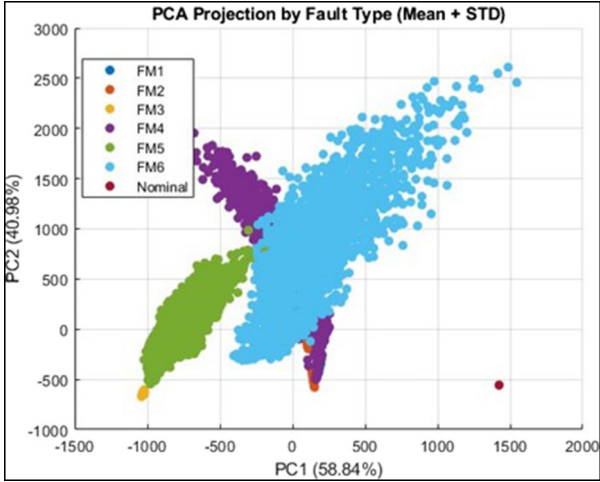


FIGURE 11
PCA projection based on mean and standard deviation features.

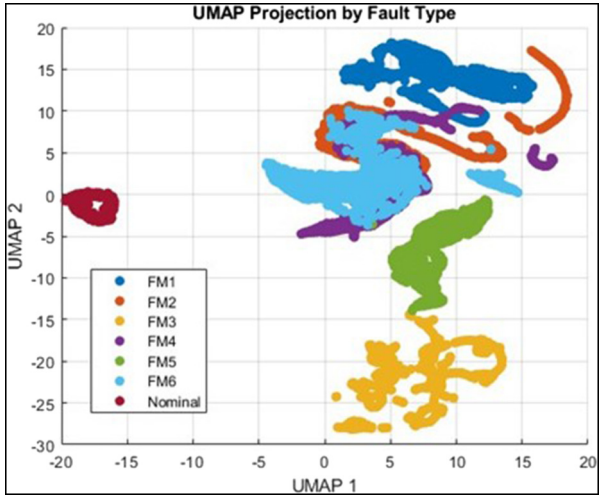
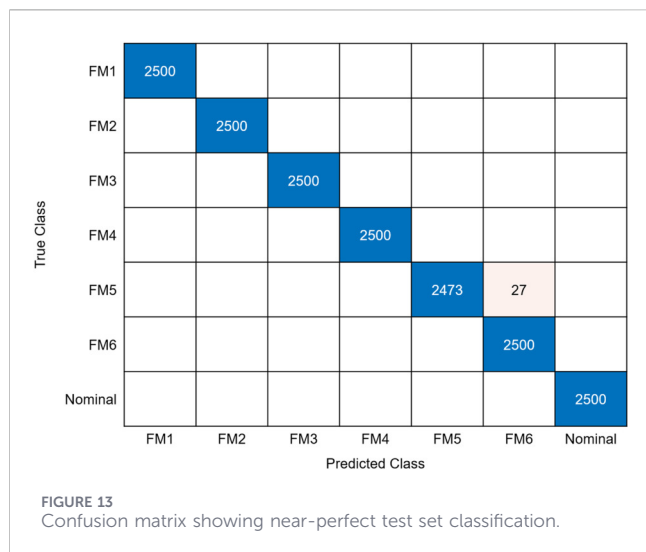
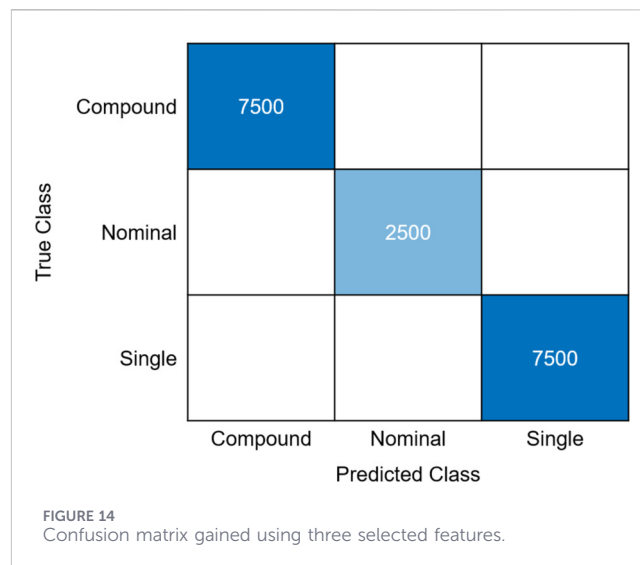


FIGURE 12
UMAP 2D embedding showing fault separability with Nominal (No-Fault).

- Frequency-domain: dominant frequency, spectral centroid, energy entropy.

Figure 11 presents the Principal Component Analysis (PCA) projection of the feature space, which visually confirms the diagnostic separability of the fault modes. The first two principal components capture the majority of the variance, and the distinct, dense clusters for the compound faults (FM5 and FM6) are immediately apparent. FM5–FM6 overlapped partially due to combined signatures but remained distinguishable with higher-order components.

UMAP visualisation as shown in Figure 12 further confirmed class separation, suggesting feasibility of supervised fault classification.



4.5 Diagnostic performance evaluation

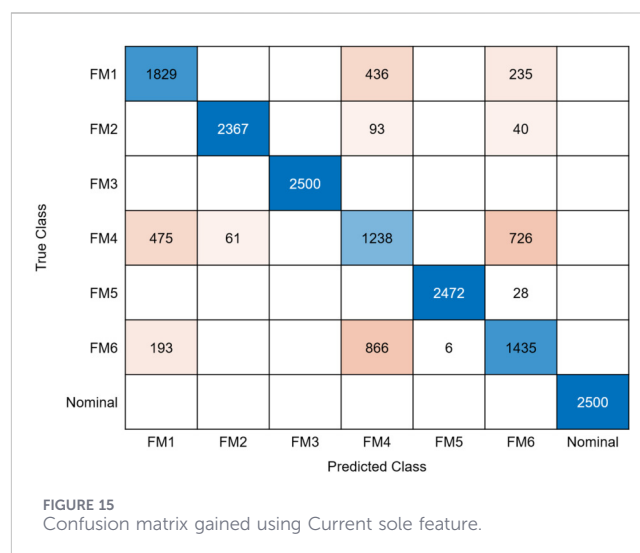
The study considers a fixed, task-specific load profile corresponding to the aerodynamic loading during flap deployment. This design choice reflects a mission-oriented diagnostic setting where the actuator operates under a consistent operational envelope for a given function. Consequently, the present evaluation does not aim to demonstrate cross-task generalisation across fundamentally different load profiles. Instead, practical diagnostic value is assessed via measurement-noise robustness, which directly reflects sensor uncertainty expected in operational monitoring.

To quantitatively assess the diagnostic utility of the DT-generated dataset, supervised classification experiments were conducted using a Random Forest (RF) classifier under additive Gaussian measurement noise ranging from 0% to 5% (0%, 1%, 3%, and 5%) applied to all measured signals. This noise magnitude represents a conservative estimate of sensor uncertainty in operational monitoring environments.

A structured feature-ablation strategy was adopted to examine the extent to which diagnostic information emerges from electromechanical coupling rather than from a single dominant variable.

First, the feature set was limited to three physically meaningful electromechanical variables: mean Current, Rotor Angular Velocity, and Worm Torque Output. These variables directly capture electrical excitation, rotational dynamics, and mechanical load transmission, respectively. The corresponding confusion matrix, shown in Figure 13, exhibits near-perfect classification performance under the same 5% noise condition. Only minor residual confusion remains between closely related compound fault modes. The substantial improvement relative to the single-feature case confirms that diagnostic separability arises from multi-domain physical interactions rather than from isolated signal deviations.

To further evaluate engineering-level interpretability, fault modes were grouped into three categories: Nominal, Single Fault (FM1–FM3), and Compound Fault (FM4–FM6). The grouped confusion matrix in Figure 14 demonstrates good separation under the three-feature configuration. This result indicates that,



even when individual compound faults may exhibit partial overlap in high-dimensional space, the dataset robustly preserves higher-level diagnostic distinctions relevant to maintenance decision-making.

Subsequently, a minimal-sensor scenario was evaluated using only the mean stator current as the input feature. The resulting seven-class confusion matrix is shown in Figure 15.

Under this highly constrained configuration, overall accuracy decreases to approximately 83%, with notable misclassification between compound fault modes (FM4–FM6) and certain electrically dominated faults. In particular, confusion arises between FM1 and FM4, and between FM4 and FM6, indicating that current alone is insufficient to resolve mechanically coupled degradation effects. This demonstrates that fault separability is non-trivial and cannot be attributed to trivial statistical artefacts in the dataset. The results show.

- The dataset does not exhibit trivial linear separability, as evidenced by the substantial performance degradation in the single-feature scenario.

TABLE 4 Classification accuracy under varying noise level.

Noise level	1 feature		3 feature	
	LDA	RF	LDA	RF
0%	0.7723	0.8323	0.9703	1
1%	0.7740	0.8249	0.9677	0.9998
3%	0.7783	0.8169	0.9669	0.9994
5%	0.7757	0.8195	0.9671	0.9985

- Multi-sensor electromechanical fusion significantly enhances diagnostic robustness, validating the physical consistency of the digital twin framework.
- Separability remains stable under realistic measurement noise, demonstrating the practical utility of the generated data for benchmarking PHM algorithms.

After evaluating the RF classifier, a linear discriminant analysis (LDA) model was also implemented as a simpler linear benchmark. The quantitative accuracy results across varying noise levels are summarised in Table 4. Two key trends are observed. First, the single-feature configuration exhibits limited separability ($\approx 80\%$), confirming that diagnostic discrimination is non-trivial. Second, the three-feature configuration maintains consistently high accuracy ($>96\%$ for LDA and $\approx 100\%$ for RF) across all tested noise levels, demonstrating robustness against measurement uncertainty. The marginal improvement of RF over LDA indicates that while class boundaries are largely well-separated, non-linear ensemble learning provides additional robustness in resolving compound faults.

This structured analysis provides a clear, data-driven narrative on the diagnostic value of different sensor combinations and validates that the DT-generated data can be used to rigorously evaluate and compare PHM algorithms.

5 Discussion and implications

The results confirm the validity and utility of the developed DT framework in simulating fault behaviours of EMAs. The observed signal responses align with expected degradation pathways reported in previous literature and failure analysis studies. The framework successfully replicates realistic fault onset, progression, and signal interactions across diverse operational phases.

5.1 Implications for system health management

The presented DT framework offers significant advantages over traditional physical test benches and analytical models. First, it enables exhaustive scenario testing without the cost and risk associated with hardware degradation. Second, it supports fault-specific data synthesis at a scale suitable for machine learning workflows. Finally, it allows the investigation of

rarely occurring or mission-critical failure cases under controlled conditions.

Such capabilities are especially valuable for training prognostics models, evaluating health indicators like Remaining Useful Life (RUL), and testing onboard fault-tolerant control strategies. The availability of labelled, high-resolution signal data across fault types strengthens the development of explainable AI for aerospace diagnostics.

5.2 Limitations and model extensibility

While the DT framework demonstrates strong capability in simulating multidomain fault behaviours, several modelling boundaries must be acknowledged.

First, the present model focuses on electromechanical dynamic behaviour under predefined load and voltage profiles. Thermal dynamics, including motor winding heating, gearbox temperature rise, and thermal-mechanical coupling, are not modelled. In practical aerospace systems, temperature variation significantly influences resistance, lubrication properties, and degradation rates. The absence of thermal modelling therefore limits the framework's ability to simulate temperature-driven fault progression or thermal runaway phenomena.

Second, the implemented fault models represent effect-level perturbations rather than physics-based degradation laws. For example, backlash is introduced as an equivalent reverse torque disturbance, and resistance change is modelled as a discrete parameter shift. While these abstractions preserve physical causality at the system level, they do not capture progressive wear mechanisms such as gradual clearance enlargement, material fatigue accumulation, or corrosion growth over multiple cycles. Incorporating physics-informed degradation evolution laws would enable transition from fault diagnosis toward remaining useful life (RUL) estimation.

Third, parameter uncertainty and manufacturing tolerances are not explicitly considered in the current study. Nominal parameter values were selected within order-of-magnitude ranges reported in aerospace literature; however, no Monte Carlo sensitivity analysis or uncertainty propagation study was conducted. Consequently, the robustness of diagnostic separability under parameter variation remains to be formally quantified.

Finally, the present DT operates as an open-loop simulation framework without real operational data assimilation. In an industrial deployment scenario, the twin could be continuously updated using field measurements through parameter identification techniques, Bayesian updating, or state observers (e.g., Kalman filtering). Such hybrid model-data integration would improve predictive fidelity and enable adaptive recalibration over the actuator lifecycle.

Despite these limitations, the modular structure of the proposed framework allows systematic extension. Thermal sub-models, progressive wear laws, stochastic parameter sampling, and closed-loop control dynamics can be incorporated without restructuring the core architecture. These enhancements will be prioritised in subsequent work to transition the framework from a simulation-driven diagnostic platform toward an operational DT supporting prognostics and lifecycle management.

6 Conclusion

This study presented the development and demonstration of a modular DT framework for simulating faults in aircraft EMAs. By replicating both electrical and mechanical subsystems, the model enables the generation of synthetic datasets for health monitoring research. The fault injection capability covers a broad range of degradation modes, including voltage disturbances, resistance changes, and mechanical backlash—either in isolation or combination.

Through realistic simulation of load profiles and signal responses, the DT captures degradation phenomena such as delayed displacement, increased current draw, and amplitude underperformance. These signatures align with reported failure characteristics in operational aircraft systems. Feature extraction and clustering analysis validated that the simulated data preserves diagnostic fidelity and can support training of classification models.

This DT serves as a flexible, scalable tool for research and development in aerospace prognostics. It bridges the gap between physical test rigs and algorithm design, offering a safe and cost-effective environment to evaluate failure signatures and diagnostic metrics. Future work will integrate thermal, environmental, and closed-loop control elements to further enhance realism and extend the twin's application to real-time health management and fault-adaptive control strategies.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

CW: Formal Analysis, Visualization, Data curation, Resources, Project administration, Validation, Methodology, Software, Investigation, Writing – review and editing, Writing – original draft, Conceptualization. I-SF: Project administration, Formal Analysis,

Methodology, Supervision, Conceptualization, Software, Investigation, Writing – review and editing, Resources. SK: Project administration, Conceptualization, Investigation, Writing – review and editing, Software, Resources, Supervision, Methodology, Formal Analysis.

Funding

The author(s) declared that financial support was not received for this work and/or its publication.

Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declared that generative AI was not used in the creation of this manuscript.

Any alternative text (alt text) provided alongside figures in this article has been generated by Frontiers with the support of artificial intelligence and reasonable efforts have been made to ensure accuracy, including review by the authors wherever possible. If you identify any issues, please contact us.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

- AIRBUS (2017). *A350 XWB: flight control, flight deck and systems briefing for pilots*, 8–9. Available online at: <https://www.parlonsaviation.com/wp-content/uploads/2017/12/a350-flight-controls.pdf> (Accessed September 7, 2025).
- Annaz, F. Y., and Kaluarachchi, M. M. (2023). Progress in redundant electromechanical actuators for aerospace applications. *Aerospace* 10, 787. doi:10.3390/aerospace10090787
- Arévalo, P., Cano, A., and Jurado, F. (2024). Large-scale integration of renewable energies by 2050 through demand prediction with ANFIS, Ecuador case study. *Energy* 286, 129446. doi:10.1016/j.energy.2023.129446
- Balaban, E., Saxena, A., Narasimhan, S., Roychoudhury, I., and Goebel, K. (2011). *Experimental validation of a prognostic health management system for electro-mechanical actuators*, infotech@ aerospace, 2011. USA: St. Louis, 29–31. doi:10.2514/6.2011-1518
- Balaban, E., Saxena, A., Narasimhan, S., Roychoudhury, I., Koopmans, M., Ott, C., et al. (2015). Prognostic health-management system development for electromechanical actuators. *J. Aerosp. Inf. Syst.* 12, 2015–2344. doi:10.2514/1.1010171
- Cole, T., and Tang, S. (2022). Liquid metals as soft electromechanical actuators. *Mater. Adv.* 3, 173–185. doi:10.1039/d1ma00885d
- Emmanouil, K. (2020). Reliability in the era of electrification in aviation: a systems approach. *Microelectron. Reliab.* 114 (Nov 2020), 113945. doi:10.1016/j.microrel.2020.113945
- Fu, J., Maré, J., and Fu, Y. (2017). Modelling and simulation of flight control electromechanical actuators with special focus on model architecting, multidisciplinary effects and power flows. *Chin. J. Aeronautics* 30 (1), 47–65. doi:10.1016/j.cja.2016.07.006
- Glaessgen, H., and Stargel, D. S. (2012). "The digital twin paradigm for future NASA and U.S. air force vehicles," in *53rd structure dynamics, and materials conference*, 2012.
- Grieves, M. G. (2016). *Origins of the digital concept*. doi:10.13140/RG.2.2.26367.61609
- Grieves, M. G. (2023). "Digital twins: past, present, and future," in *The digital twin*. N. Crespi, A. T. Drobot, and R. Minerva (Cham: Springer). doi:10.1007/978-3-031-21343-4_4
- Janson, R. H., Bowman, C., Jankovsky, A., Dyson, R., and Felder, J. (2017). "Overview of NASA electrified aircraft propulsion research for large subsonic transports," in *53rd AIAA/SAE/ASEE joint propulsion conference*, July 10–12, 2017, Atlanta, United States. AIAA Propulsion and Energy Forum. doi:10.2514/6.2017-1701
- Lawson, C. P., and Pointon, J. M. (2008). *Thermal management of electromechanical actuator on an all-electric aircraft, 26th international congress of the aeronautical sciences (ICAS), 14–19 September 2008*. USA: Anchorage.
- Liu, R., Yang, B., Zio, E., and Chen, X. (2018). Artificial intelligence for fault diagnosis of rotating machinery: a review. *Mech. Syst. Signal Process.* 108, 33–47. doi:10.1016/j.ymssp.2018.2.016
- Maré, J., and Fu, J. (2017). Review on signal-by-wire and power-by-wire actuation for more electric aircraft. *Chin. J. Aeronautics* 30 (3), 857–870. doi:10.1016/j.cja.2017.03.013

- Mazzoleni, M., Rito, G. D., and Previdi, P. (2021). *Electro-mechanical actuators for the more electric aircraft*. Springer. ISSN, 2193, 1557.
- MOOG (2018). *Modula linear electromechanical actuators*. Available online at: https://www.moog.com/content/dam/moog/literature/sdg/space/actuationmechanisms/SAIS_Modular_EMA_Rev_0315.pdf (Accessed: February 19, 2026)
- MOOG (2020). Primary flight control actuation system for 787. Available online at: <https://www.moog.com/products/actuation-systems/aircraft/primary-flight-control-actuation-system-for-787.html> (Accessed September 7, 2025).
- Quattrocchi, G., Iacono, A., Berri, P. C., Vedova, M. D. L. D., and Maggiore, P. (2021). A new method for friction estimation in EMA transmission. *Actuators* 2021, 10–194. doi:10.3390/act10080194
- Wagner, H., Nikolov, G., Bierig, A., and Spangenberg, H. (2011). Challenges for health monitoring of electromechanical flight control actuation systems. *SAE Int. J. Aerosp.* 4 (2), 1316–1323. doi:10.4271/2011-01-2701
- Wan, Q., Song, C., Zhou, Y., Tong, R., Ma, S., and Liu, G. (2024). Modelling and analysis of the flap actuation system considering the nonlinear factors of EMA, joint clearance and flexibility. *Aerospace* 11. doi:10.3390/aerospace1106044
- Wang, C., Fan, I. S., and King, S. (2022). “Failure mapping for aircraft electrical actuation system health management,” in *7th european conference of the PHM society (PHME 2022)*, 6–8 July 2022, turin, Italy.
- Wang, C., Fan, I. S., and Plastropoulos, A. (2025). “Digital twin-based health management for complex aircraft systems: case studies and applications, 2025 IEEE Wireless Communications and Networking Conference (WCNC), March 24–27, 2025, Milan, Italy, IEEE. 1–6. doi:10.1109/WCNC61545.2025.10978545
- Wang, C., Fan, I. S., and King, S. (2023). *A review of digital twin for vehicle predictive maintenance system*, 2023 AeroTech. Fort Worth, USA.
- Xu, Z., Galea, M., Tighe, C., Hamiti, T., Gerada, C., and Pickering, S. J. (2014). *Mechanical and thermal management design of a motor for an aircraft wheel actuator* in *17th international conference on electrical machines and systems (ICEMS)* (Hangzhou, China), 22–25. doi:10.1109/ICEMS.2014.7014056
- Zaporozhets, V. I., K. S., Isaenko, V., and Synylo, K. (2020). Trends on current and forecasted aircraft hybrid electric architectures and their impact on environment. *Energy* 211 (Nov 2020), 118814. doi:10.1016/j.energy.2020.118814



DSpace

<https://dspace.org/>

A digital twin-based fault simulation framework for aircraft electromechanical actuators: method and demonstration

Wang, Chengwei; Fan, Ip-Shing; King, Stephen

2026-04-10

Frontiers

<https://doi.org/10.3389/fpace.2026.1708392>

Wang C, Fan I-S, King SP. (2026) A digital twin-based fault simulation framework for aircraft electromechanical actuators: method and demonstration. Frontiers in Aerospace Engineering, Volume 5, April 2026, Article number 1708392