Spacecraft 3-axis Controlled Attitude Determination and Control System Reaction Wheels Fault Detection, Isolation and Identification using Machine Learning Techniques

Tamer Sayed Abdel Aziz[1], Sherif Hussein[2], Mohammed Sobhy [3], and Gouda Ismail Salama[4]

[1] *Sector of Assembly, Integration and Test, Space Technology Center, Cairo, Egypt*
tilki101@gmail.com

[2,3,4] *Department of Computer Engineering and Artificial Intelligence, MTC,Cairo, Egypt*
s.hussein@mtc.edu.eg
mohamedms@mtc.edu.eg
gisalama@mtc.edu.eg

Abstract

Spacecraft attitude control systems rely on reaction wheels (RW) as the primary means of precise three-axis attitude control. Faults in these RWs might lead to system instability and, in severe cases, mission failure. This paper presents advanced machine learning-based techniques for the detection, isolation, and identification of RW faults in spacecraft. The proposed approach leverages advanced data analytics and machine learning algorithms to analyze sensor data from the RWs, enabling early detection of faults and effective isolation of the faulty component, and identifying the types of faults detected, specifically, voltage, current, and temperature faults. Three-axis controlled satellite high-fidelity models are simulated to generate data for both nominal and faulty states of RW. The simulated data is employed with the Fault Detection, Identification, and Isolation (FDII) approach. The generated data is passed into five different machine learning classifiers, and the isolation and identification results are verified via cross-validation. The proposed techniques are tested on three defined datasets using the three-orthogonal RW configuration to verify their robustness. The results show that the system has higher isolation and identification accuracy when compared to other studies that used various methodologies.

1. Introduction

Spacecraft is considered one of the most expensive control systems created in recent decades. It consists of a group of integrated systems, such as the power supply system (PSS), the attitude determination and control subsystem (ADCS) , thermal control system (TCS), and communication system(CS). The attitude determination and control subsystem (ADCS), which uses reaction wheels (RWs) as actuators, is one of the most vital components of a spacecraft. By speeding up or slowing down the flywheels attached to an electric motor, RWs adjust the satellite's orientation or perform maneuvers under disturbances (Rahimi et al. (2017)).

The complexity of a single RW results in a highly nonlinear dynamic system. More RWs can be added to the assembly, combined with the satellite's attitude and dynamics in orbit. The minimum number of RWs required for a spacecraft to achieve three-axis attitude control is three (Ni et al. (2021)). Each RW is typically aligned along a different axis (X, Y, and Z) to allow the spacecraft to rotate in any direction. However, for redundancy and increased reliability, spacecraft often use four RWs arranged in a tetrahedral configuration (Nomura et al. (2016)). Spacecraft rely heavily on RWs for attitude control. Reaction wheels store momentum and can be rotated to counteract unwanted torques, keeping the spacecraft pointed in the desired direction, as shown in Figure (1).

When a spacecraft changes the speed of one RW, such as by increasing its spin rate, it affects the system's overall angular momentum. To conserve angular momentum, the other two wheels must adjust to compensate for this change. This cross-coupling effect means the operation of one wheel directly influences the behavior of the others (Ismail & Varatharajoo (2010)). Accordingly, RW faults can significantly impact spacecraft performance and mission success. Therefore, ensuring the reliability and mission success of these systems is essential, leading to the advancement of fault detection, isolation, and identification (FDII) techniques for ADCS. Detecting faults and isolating their root causes becomes difficult if the parameters of interest are non-measurable to the FDII

https://doi.org/10.36001/IJPHM.2025.v16i2.4395

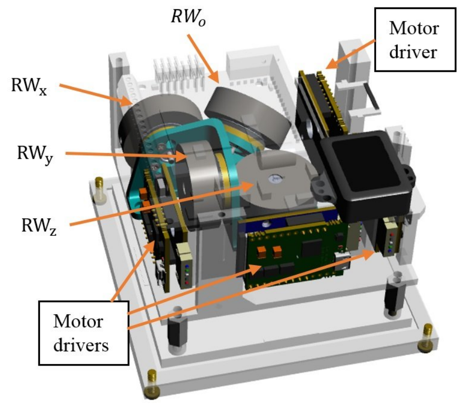

Figure 1. Reaction Wheels within Spacecraft.

scheme.

FDII approaches are mainly divided into model-based and data-driven categories. Model-based approaches continuously compare the actual system state with the nominal state to generate residuals using a mathematical model of ideal system behavior. This method describes the system's dynamic behavior and physical understanding. Data-driven approaches analyze system outputs and rely on large amounts of data, performing well with large-scale and complex systems while reducing time and costs by eliminating the need for model development. These approaches are beneficial when no mathematical model or expert knowledge is available (Tidriri et al. (2016)).

Model-based FDII techniques leveraging machine learning (ML) offer significant advantages over traditional methods, especially in complex systems like spacecraft RWs. ML-based techniques learn directly from operational data, reducing complexity and computational demands. They excel at recognizing patterns and subtle relationships in data, improving accuracy and robustness in fault detection under diverse conditions. These techniques are highly scalable and flexible, and easier to implement. They also facilitate predictive maintenance by identifying faults early, reducing downtime, and extending component lifespan. Additionally, ML-based FDII systems continuously improve with more data, enhancing operational efficiency and adaptability. Overall, integrating ML with model-based FDII techniques provides a powerful, efficient, and adaptable solution for modern aerospace applications.

A robust FDII technique that can accurately detect when a fault occurs, isolate which specific reaction wheel is affected, and identify the type of fault, whether transient, abrupt, or permanent. Figure(2) is a primary objective. ML techniques offer promising solutions by leveraging patterns in sensor data to differentiate between normal operation and various fault conditions.

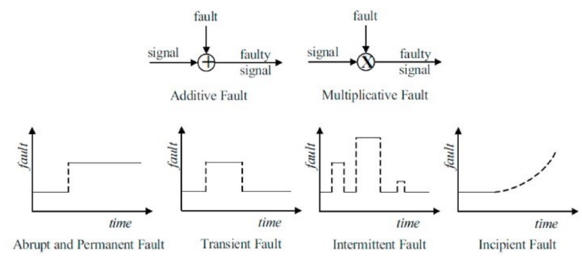

Figure 2. types of Faults.

Faults in ADCS RWs, can be categorized as abrupt and transient time-varying faults, along with a generalized fault case, which are introduced into the RW components via bus voltage and torque gain variations. Abrupt faults lead to immediate system shutdown, while transient faults are temporary and may resolve over time. Consequently, multi-fault detection in spacecraft RW is critical for monitoring and identifying potential faults within these ADCS components. Spacecraft RWs can experience various fault combinations, including temperature and voltage variations, torque changes, and current fluctuations in motor axis windings. Hybrid faults, involving over-voltage, under-voltage, current loss, and temperature elevation, may occur simultaneously, impacting RW performance. Time-varying faults, evolving due to wear, component degradation, or other factors, can also occur alongside other fault types, creating intricate fault scenarios.

2. BACKGROUND

Several studies have explored the use of ML for RW FDII. Some researchers implemented FDII with only one axis RW; on the other hand, other researchers implemented it using other configurations of multiple RW.

J. Vaz Carneiro's study (Vaz Carneiro et al. (2022)) provides a comprehensive overview of various ML algorithms applied to RW FDII, including Support Vector Machines (SVMs), Artificial Neural Networks (ANNs), Decision Trees (DT), Random Forests (RF), Kernel Methods (KM), and Deep Learning (DL) techniques. Both supervised and unsupervised algorithms are shown to perform effectively, even when faults produce subtle effects in telemetry data.

Building on such insights, Ehab A. Omran (Omran & Murtada (2019)) introduces an efficient anomaly classification method specifically for 1-axis spacecraft RW, Figure(3). This method employs the Prony method for feature extraction and a feed-forward neural network with backpropagation for anomaly detection. Complementing this, J.R. Mansell (Mansell (2020)) explores the application of DL to spacecraft Fault Detection, Isolation, and Recovery (FDIR) through transfer learning. His approach utilizes One-Class Support Vector Machines (OCSVMs) and Long Short-Term Memory (LSTM) networks to diagnose faults in RW, enabling the transfer of learning from simula-

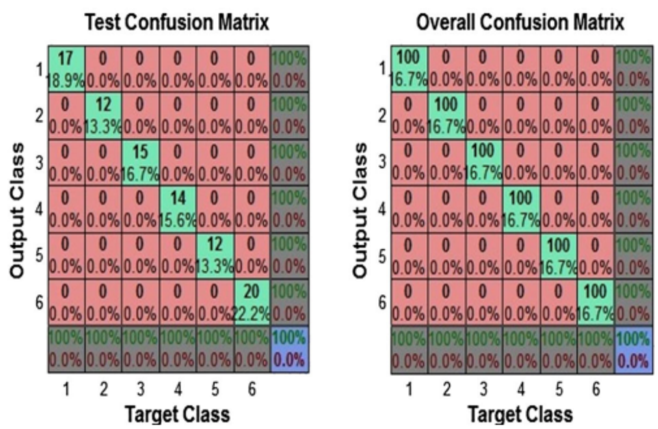

Figure 3. Prony Method FDII Confusion Matrix (Omran & Murtada (2019)).

tion data to real satellite data.

Further enhancing ML-based fault diagnosis, Z. Zhu et al. (Zhu et al. (2022)) propose the Particle Swarm Optimization Extreme Learning Machine (PSO-ELM) algorithm to overcome the limitations of the Extreme Learning Machine (ELM) in diagnosing faults in satellite RW. This approach improves both the accuracy and generalization of fault classification. Additionally, S. Voss (Voss (2019)) investigates the application of DL for fault detection and isolation within the ADCS, focusing on generating useful telemetry through simulations.

To address time-varying faults, AER Abd-Elhay (Abd-Elhay et al. (2022)) presents a DL method combining a 1D Convolutional Neural Network (1D-CNN) with an LSTM network for fast and accurate fault identification in spacecraft RWs. Finally, T.S. Abdel Aziz (Abdel Aziz et al. (2024)) introduces advanced ML-based FDII techniques that enhance the Prony method for both single and multiple fault management, leading to significant improvements in fault detection accuracy, isolation time, and memory efficiency in critical spacecraft subsystems like ADCS.

These studies collectively advance the field of spacecraft RW FDII by utilizing various ML algorithms and techniques. This results in more accurate fault detection, improved fault isolation, and overall greater system reliability. However, previous studies often assumed that only one axis of the RW was faulty while the other axes operated normally, which may potentially lead to inaccurate fault detection. Consequently, researchers have started to explore the possibility of faults occurring in different 3-axis RW, as described below.

M.O. Folami (Folami (2021)) explores an ML approach using an enhanced RF classifier, which incorporates features from multiple domains: temporal, statistical, and spectral for isolating faults in 3-axis reaction wheels (RWs). The proposed method improves the accuracy and reliability of fault isolation, successfully detecting and isolating multiple fault scenarios with robust performance, even in the presence of noisy data, missing sensors, and missing values.

B. Akbarinia (Akbarinia & Shahmohamadi Ousaloo (2023)) advances this field by presenting an improved Extreme Learning Machine (ELM)-based approach for multi-sensor RW fault diagnosis. ELMs, known for their rapid training speed, are enhanced in this study through a novel feature selection method that significantly boosts their effectiveness in detecting and diagnosing faults in onboard 3-axis RWs.

Building on the robustness of ensemble methods, Afshin Rahimi (Rahimi & Saadat (2019)) investigates the application of RF and DT algorithms for fault isolation in RWs onboard 3-axis controlled satellites. Rahimi's work proposes an ML-based approach that leverages an enhanced RF classifier with features extracted from multiple domains, such as temporal, statistical, and spectral data, to achieve effective RW fault isolation, Three datasets, each representing permanent, abrupt, and transient faults, were used in the process, the setup of the technique as shown in Figure(4).

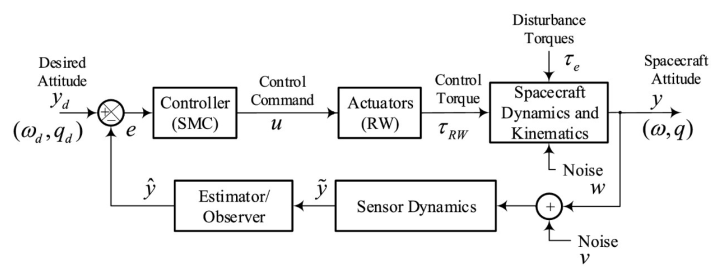

Figure 4. Ensemble ML Proposed Setup (Rahimi & Saadat (2019))
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Most research involves generating residuals through analytical models, which do not effectively explain detected faults. Mixed learning models are constrained by the performance of the best classifier in the ensemble, and many methods focus solely on a single RW, overlooking multiple faults or different RW assemblies. Therefore, the objective of this study is to design and develop an ML-based FDII technique capable of autonomously detecting, isolating, and identifying faults within a nonlinear system, specifically for an in-orbit closed-loop controlled satellite with three-axis RWs as actuators.

For validation, two approaches will be discussed: one applying the proposed ML-based technique and Prony method on three-axis RWs (as Prony is typically used only with single-axis RW (Omran & Murtada (2019, 2016)), and the other applying the proposed technique on a separate dataset of three main fault types for three-axis RWs to compare performance with an ensemble ML-based FDII technique (Rahimi & Saadat (2019)).

Due to the unavailability of datasets published for previous research, a simulation model of the "ITHACOT Type A" by

Goodrich (Bill (1998)) 3-axis Orthogonal configuration RWs was developed using MATLAB Simulink will be discussed later used to generate three different datasets. This simulation model encompasses accurate representations of RW behaviors under normal operation and diverse fault scenarios. It includes mechanisms to inject simulated faults into the RWs, generating sensor data that reflects realistic operational conditions. This technique aims to apply to other systems but is designed for this specific application, and this will be discussed further.

3. PROBLEM DEFINITION

The occurrence of faults in a spacecraft's three-axis RWs poses a critical challenge in aerospace engineering (Rahimi & Saadat (2020); Folami (2021); Castaldi et al. (2022); Abbasi Nozari et al. (2024)). RWs are fundamental to maintaining the spacecraft's precise orientation, each aligned along different orthogonal axes. When faults arise, they can severely disrupt mission objectives and compromise the stability of the spacecraft. The challenge lies in detecting and identifying these faults with acceptable accuracy swiftly while contending with the spacecraft's constrained resources, minimal memory, and time.

Furthermore, the problem is compounded by the need to manage voltage and current faults, but also includes those related to temperature, across all three axes. Addressing these faults comprehensively is essential for ensuring the stability and success of spacecraft missions, highlighting the complexity and significance of this engineering challenge.

4. PROPOSED ML-BASED FDII TECHNIQUE

4.1. Methodology

The proposed FDII technique employs five distinct ML algorithms, each applied to a custom orthogonal RW configuration model to address the complexity of fault diagnosis in spacecraft. The selected ML algorithms are SVM, Artificial Neural Networks (ANN), Ensemble Subspace Discriminant (ESD), DT, and RF. DT and RF fall within ensemble ML techniques and are included here for comparison with previous work (Rahimi & Saadat (2019)). Due to the lack of readily available datasets specific to ensemble ML for RWs, a simulated dataset was developed for this study, ensuring comprehensive coverage of various fault conditions. Each model was specifically tuned to detect, isolate, and classify three main types of faults: transient, abrupt, and permanent, leveraging the orthogonal RW configuration model to achieve precise fault location and type identification.

The study's three datasets are tailored to represent each fault type and capture the unique characteristics of each failure mode. SVMs are effective for distinguishing between normal and fault conditions in complex, high-dimensional feature spaces, making them suitable for nuanced fault separation. ANNs excel in detecting subtle fault patterns within large datasets, while ESD methods, though less effective alone, become robust when integrated with other models, enhancing resilience to complex, high-dimensional fault data. DTs and RFs perform well in feature selection and segmentation, contributing to reliable fault classification. Given the dynamic space environment, robustness to noise is essential, and these models provide inherent resilience critical for practical fault detection.

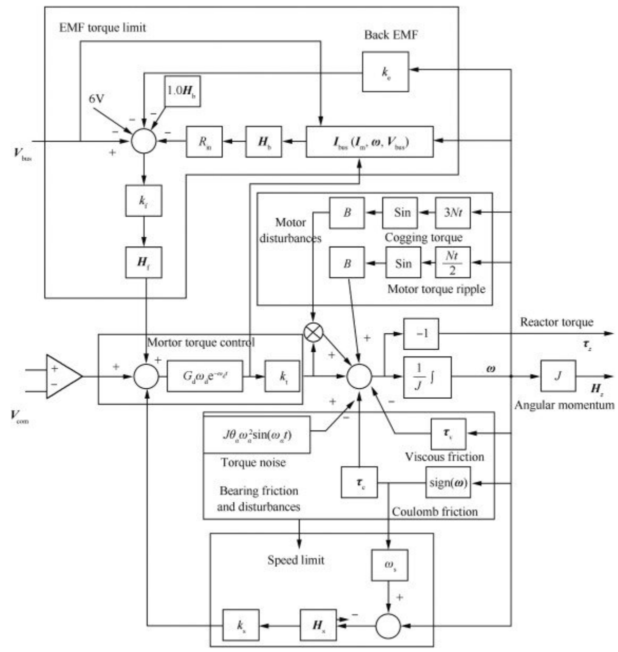


Figure 5. ITHACOT Type A Reaction Wheel Mathematical Model (Wang et al. (2015))

The FDII process starts with generating and pre-processing simulated data. Using a detailed mathematical model based on the "ITHACOT Type A" three-axis orthogonal configuration by Goodrich (Bill (1998)), As shown in Figure (5). The model captures accurate RW behaviors under both nominal and faulty conditions. The simulation includes mechanisms for injecting specific voltage, current, and temperature faults, generating sensor data that reflects realistic operational environments for each fault type.

This simulation process is essential for creating a robust training dataset that enables ML models to learn and classify fault patterns accurately. The simulation framework illustrates the 3-axis RW structure and the mathematical model for fault injection, designed with flexibility to adapt to other systems but optimized for this specific application. By utilizing realistic fault data, it ensures that the ML algorithms are well-suited for real-world spacecraft operations, enhancing the reliability and performance of attitude control systems.

Once deployed, the trained models continuously monitor sensor data, detecting any deviations that indicate a fault. They isolate the faulty RW and classify the fault type in real time based on known fault signatures. A rigorous validation phase ensures that the models generalize well to new fault scenarios, providing consistent reliability in operational conditions. The block diagram for the proposed technique is shown in Figure (6)

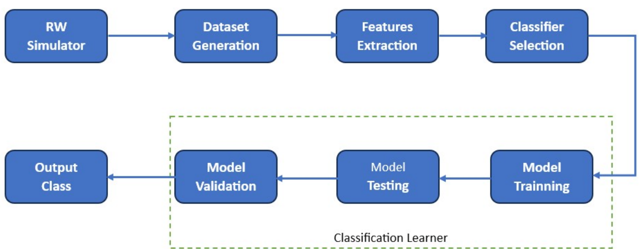


Figure 6. Proposed technique Block Diagram

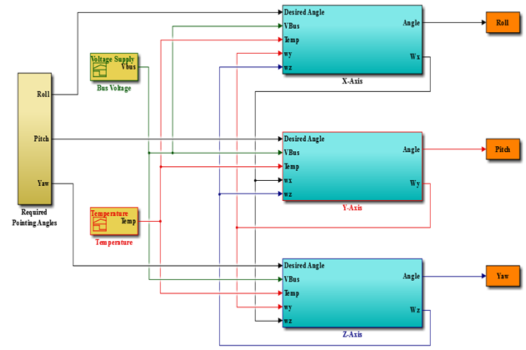
For validation, two primary approaches are presented. First, the proposed ML-based FDII technique is compared against the Prony method, adapted here for three-axis RWs even though it has traditionally been applied only to single-axis RW configurations (Omran & Murtada (2019, 2016)). Second, performance is evaluated by applying the technique to a separate dataset that includes the three main fault types, with results benchmarked against state-of-the-art ensemble ML-based FDII techniques (Rahimi & Saadat (2019)). This comparative analysis assesses accuracy, isolation time, and model robustness, providing a comprehensive evaluation of the proposed technique's efficacy relative to established methods. The integrated approach of ML models combined with a comprehensive simulation model aims to significantly improve spacecraft reliability by enabling proactive fault management.

4.2. Mathematical Simulator

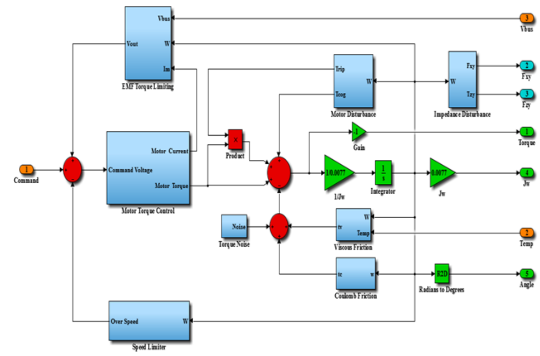
A detailed simulation model of the "ITHACOT Type A" by Goodrich Bill (1998) for 3-axis orthogonal RWs was developed using MATLAB Simulink, as shown in Figures (7).

This simulation model is designed to accurately replicate both normal and faulty operation scenarios, serving as a critical tool for generating datasets essential for training and evaluating ML algorithms within MATLAB's Classification Learner.

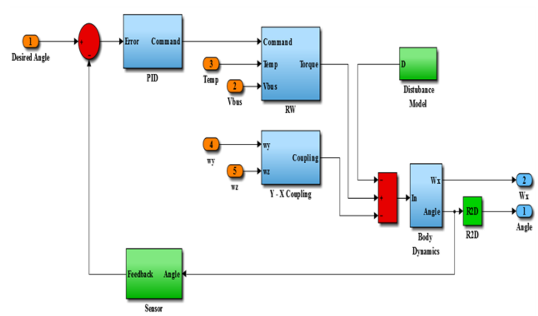
The simulation model captures the dynamics and behaviors of the RWs under varying operational conditions, including both normal operation and fault scenarios. The system simulates spacecraft maneuvers in nominal conditions and integrates fault injections to simulate real-world challenges that might impact spacecraft stability. We incorporated environmental uncertainties by adding spacecraft dynamics and space environment blocks into our simulator, guided by the MATLAB



(a) 3-axis RW Simulation Model



(b) RW Detailed Simulation Model



(c) RW Control Commands Simulation Model

Figure 7. ITHACOT Type A RW Simulink Simulation Model.

Aerospace Blockset. This allowed us to model effects such as radiation and thermal fluctuations on sensor readings, ensuring realistic fault patterns in the simulated data. These faults are categorized into three primary types: - Transient Faults: These are short-lived disturbances, such as momentary power fluctuations or brief mechanical anomalies, which can cause temporary degradation in performance. - Abrupt faults: These faults occur intermittently and can be due to components that periodically malfunction, such as electrical shorts or sensor misreadings that resolve after a period. - Permanent Faults: These represent long-lasting or irreversible failures, such as a complete loss of functionality in a reaction wheel due to physical damage or system wear.

By replicating these fault types, the simulation model introduces realistic fault scenarios, which are critical for training ML models to detect, isolate, and identify faults in real-time spacecraft operations. The fault injection process is implemented through carefully controlled blocks within Simulink that modify parameters like voltage, current, and temperature to simulate each fault type. This approach ensures that the generated datasets closely resemble operational conditions, reflecting the dynamic response of RWs under fault conditions.

The model records a wide range of operational parameters, such as sensor readings (e.g., voltage, current, and temperature), RW speeds, and other relevant spacecraft performance metrics. These datasets are then preprocessed to fit the required input format for MATLAB's Classification Learner, where various ML algorithms are used. The generated datasets were divided into fault categories for each model. The performance of each model is rigorously evaluated using cross-validation techniques to ensure that the trained algorithms can generalize well across unseen data.

4.3. Features Extractions

To effectively detect and classify reaction wheel faults, we extracted features from the time, frequency, and shape domains of the measured signals. These features provide complementary insights into the dynamic behavior of the system and capture fault-related patterns across electrical and thermal domains.

Time-domain features such as Peak-to-Peak Amplitude, Root Mean Square (RMS), and Zero-Crossing Rate quantify amplitude variations, signal energy, and oscillation frequency. RMS and Peak-to-Peak are particularly sensitive to excessive current draw, which may arise from bearing degradation or mechanical imbalance. Similarly, Zero-Crossing Rate can reveal abnormal oscillations induced by voltage instability in the power electronics driving the reaction wheel motor.

Frequency-domain features such as Fourier Transform, Spectral Centroid, Power Spectral Density (PSD), and Short-Time Fourier Transform (STFT) capture spectral energy distributions and transient frequency variations. These features are critical for identifying voltage ripple effects, where periodic disturbances in the supply voltage manifest as distinct spectral peaks. Likewise, harmonic distortions in the frequency spectrum often correspond to current fluctuations caused by winding degradation, torque ripple, or partial short-circuits in the motor drive.

Shape-based features, such as Slope and Curvature, describe the local geometric properties of the signal waveform. The slope can reveal abrupt transients in voltage or current, while curvature highlights nonlinearities and sudden waveform deviations that often accompany torque disturbances or rapid dynamic responses. These shape-based indicators are also correlated with temperature-related faults, as thermal fluctuations modify the resistive and inductive characteristics of motor windings, leading to nonlinear current–voltage relationships that appear as changes in curvature.

By combining these domains, the extracted features provide a physically grounded diagnostic representation of reaction wheel behavior. Time-domain features are effective for capturing amplitude-driven current faults, frequency-domain features are suited for detecting spectral patterns of voltage instabilities, and shape-based features are sensitive to nonlinear behaviors linked to temperature-induced degradations. This multimodal approach ensures that both gradual degradations and abrupt disturbances are captured, enabling the robust detection and isolation of reaction wheel faults, as shown in Table (1).

Table 1. List of equations for feature extraction

Feature	Equation
Peak-to-Peak Amplitude	$A_{\mathrm{p2p}} = \max(x(t)) - \min(x(t))$ Karlöf et al. (2005)
Zero-Crossing Rate	$ZCR = \times \frac{1}{N-1} \sum_{n=1}^{N-1} \mathbf{1}(x(n) \cdot x(n-1) < 0)$ Barnett (2001)
Root Mean Square (RMS)	$\mathrm{RMS} = \sqrt{\frac{1}{N} \sum_{n=1}^{N} x(n)^2}$ Chaurasia & Pal (2020)
Fourier Transform	$X(f) = \int_{-\infty}^{\infty} x(t) e^{-j2\pi ft}\, dt$ Dhurandhar (2024)
Spectral Centroid	$C = \frac{\sum_{k=0}^{N-1} k \cdot \lvert X[k]\rvert^2}{\sum_{k=0}^{N-1} \lvert X[k]\rvert^2}$ Müller (2015)
Power Spectral Density (PSD)	$S_x(f) = \lim_{T \to \infty} \frac{1}{T} \left\lvert \int_{-T/2}^{T/2} x(t) e^{-j2\pi ft}\, dt \right\rvert^2$ Lopez-Villalobos et al. (2021)
Wavelet Transform Coefficients	$W(a,b) = \int_{-\infty}^{\infty} x(t) \psi^* \left(\frac{t-b}{a}\right)\, dt$ Pachori (2023)
Short-Time Fourier Transform (STFT)	$X(t,f) = \int_{-\infty}^{\infty} x(\tau)\, w(t-\tau)\, e^{-j2\pi f\tau}\, d\tau$ Pachori (2023)
Slope	$\mathrm{Slope} = \frac{x(t_2)-x(t_1)}{t_2-t_1}$ Ramanathapuram Anand (2021)
Curvature	$\kappa(t) = \frac{\lvert x''(t)\rvert}{\left(1+(x'(t))^2\right)^{3/2}}$ Douc et al. (2014)

where: x(t) is the time-series signal, N is the total number of samples in the time-series signal, x(n) is the signal value at the n-th sample, N is the total number of samples in the time-series signal, x(n) is the signal value at the n-th sample, f is the frequency variable, x(t) is the time-domain signal, $e^{-j2\pi ft}$ is the complex exponential function, j is the imaginary unit, N is the total number of frequency bins, k is the frequency index, X[k] is the Discrete Fourier Transform of the signal x[n], $X[k]^2$ represents the power spectrum, f is the frequency, $\psi(t)$ is the mother wavelet, a is the scaling parameter (dilation or compression), b is the translation (shift in time), $\psi^*()$ is the complex conjugate of the mother wavelet, t is the time index (center of the window), $w(t-\tau)$ is the window function centered at, $\exp(-j2\pi f\tau)$ is the complex exponential function, x(t1) is the signal value at time t1, x(t2) is the signal value at time t2, $(t2 - t1)$ is the time interval, $d^2x(t)/dt^2$ is the second derivative of x(t) (the acceleration), $dx(t)/dt$ is the first derivative of x(t) (the velocity).

4.4. Dataset

Using the simulation model, three distinct separated datasets were generated to represent three fault categories: permanent, abrupt, and transient. Each dataset is formatted as a 101 by 9000 array, capturing detailed sensor readings and operational states for each fault type. These datasets are combined for comprehensive fault analysis, resulting in a total array size of 808 by 9000 for each RW to cover different combinations scenarios of faulty RWs as shown in table (2), There are eight possible scenarios: three where only one RW is faulty and the others are functioning normally, three where two RWs are faulty and one is functioning, one where all RWs are faulty, and one where all RWs are functioning normally, ensuring that the ML models have sufficient information to accurately detect and isolate which RW or combination of RWs is faulty.

Table 2. Combinations Of Faulty RWs

Scenario	1	2	3	4	5	6	7	8
RW1		×			×	×		×
RW2			×		×		×	×
RW3				×		×	×	×

For identifying the types of faults detected in any RW, initially, we assumed that each of the three fault types—permanent, abrupt, or transient—could have three states: over-voltage, under-voltage, and current loss. For a spacecraft with three RWs, each capable of being in one of these states or being fault-free, the total number of fault combinations was calculated as $n \times n \times n = n^3$ where n is the number of fault combinations which results in this case $10 \times 10 \times 10 = 1000$ faulty combinations.

However, a more detailed analysis introduced the importance of adding temperature errors to the fault types. This revised assumption included five specific states for each fault type: over-voltage, under-voltage, current-loss, over-temperature, and under-temperature. Each RW could now be in one of sixteen states: one of the fifteen fault states or fault-free, leading to a more complex scenario. The total number of possible fault combinations was recalculated as $16 \times 16 \times 16 = 4096$ faulty combinations.

This comprehensive analysis, considering both the initial and the revised assumptions, ensures that ML models for FDII can handle all potential fault scenarios in spacecraft RWs, thereby enhancing reliability and supporting mission success in complex space environments.

5. Results and Discussion

The classifiers used, including SVM, ANN, and ESD, with RF, and DT from the ensemble ML technique Rahimi & Saadat (2019), were implemented via MATLAB's Classification Learner to detect and identify faults within the dataset, with performance evaluated based on accuracy and computational complexity(time and memory).

Two distinct approaches are compared: the first involves applying the Prony-based FDII technique, traditionally used for single-axis RW, to three-axis RWs and comparing its performance with the proposed ML-based FDII technique. The second approach involves applying ensemble ML-based techniques (Rahimi & Saadat (2019)) to the three-axis RWs and comparing their performance with the proposed technique.

5.1. First Case study

The proposed ML-based FDII technique integrates advanced ML classifiers to detect, isolate, and identify faults in a three-axis RW system, focusing on improving real-time applicability and computational efficiency. Unlike traditional approaches like the Prony-based method, which relies on feature extraction and the identification of fault-specific signatures, the proposed technique directly applies machine learning classifiers to sensor data, ensuring high accuracy with lower computational cost.

In this case study, five fault types over-voltage, under-voltage, over-temperature, under-temperature, and current loss—were identified in a three-axis RW configuration using the proposed ML models. Samples of the models' configuration parameters and confusion matrix are shown in Figure (8) and Table (3)

Table 3. ANN Model Configuration Parameters

Preset	Artificial Neural Network
Accuracy (Validation)	98.5 %
Total cost (Validation)	Not applicable
Prediction speed	67 obs/sec
Training time	57.978 sec
Number connected layers	1
First layer size	25
Activation	ReLU
Iteration limit	1000
Lambda	0
Standardize data	Yes

The proposed technique demonstrated significant improvements in fault detection accuracy compared to the Prony-based method, which, despite achieving 100% accuracy in a single-axis RW configuration, dropped to an accuracy of 87.8% when applied to the more complex three-axis system.

In contrast, the proposed ML-based methods maintained an accuracy range of 97% to 99%, as shown in Table (4).

Table (4) provides a comparison of the classification performance between the Prony-based and ML-based techniques. While the Prony method showed a moderate F1-score of 80.5 % with an accuracy of 87.8%, the ML models, especially the ANN, achieved significantly higher performance with an accuracy of 98.5% and an F1-score of 98.8%, outperforming the traditional technique.

The proposed ML-based FDII technique outperforms the Prony method, providing higher accuracy and better handling of

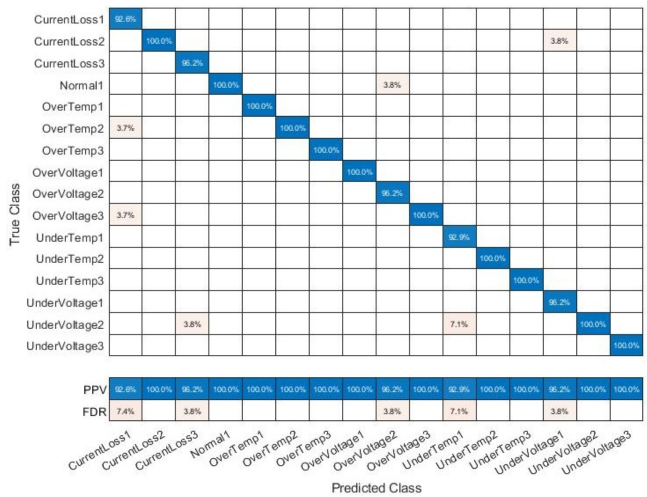


Figure 8. ESD Model Confusion Matrix

Table 4. Accuracy of Prony-based technique versus proposed ML-based technique

Classification Method	Accuracy	precision	Recall	F1-scores(%)
Prony Method	87.8	67.3	50.5	80.5
DT	97.52	98.47	98.47	98.47
RF	98	96.2	96	98
SVM	95	93.34	93.34	93.34
ANN	98.5	98.8	98.5	98.8
ESD	98	98.2	97.3	97.3

complex fault scenarios in three-axis RW systems. The new approach offers superior fault detection, making it a more efficient and reliable solution for spacecraft ADCS applications. Although the results are sufficient for FDII in an ADCS, the Prony method was only applied to permanent faults. Other fault types, such as abrupt and transient faults, were not tested, leading us to discuss the second case.

5.2. Second Case study

In this case study, the proposed ML-based techniques are compared with the ensemble ML technique (Rahimi & Saadat (2019)), which aims to explore data-driven ML Models for isolating nonlinear systems of an in-orbit closed-loop controlled satellite with RWs, utilizing high-fidelity models and ensemble techniques like RF, DT. The output results for the ensemble ML technique were sufficient for three types of faults as shown in Table (5)(Rahimi & Saadat (2019)).

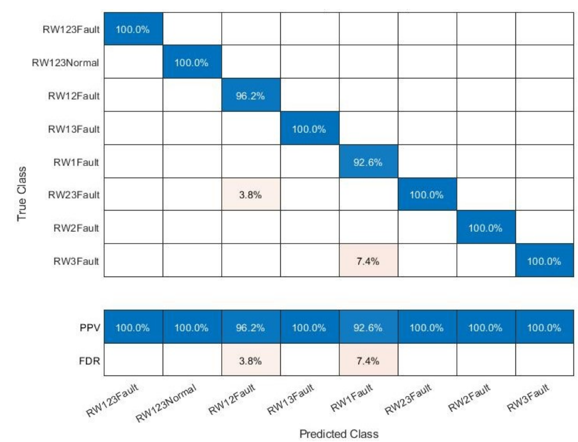
Table 5. Ensemble ML-based FDII accuracy (Rahimi & Saadat (2019))

Classification Method	abrupt Score (%)	Transient Score (%)	Permanent Score (%)
Ensemble (RF)	97.65	88.5	35.64
Ensemble (DT)	94.18	83.20	29.77

Both ensemble ML techniques and the proposed ML technique were applied to the same dataset to compare their effectiveness in isolating faulty RWs. These techniques were tested on three different separated datasets, each representing a distinct type of fault: transient, permanent, and abrupt. This comprehensive comparison aimed to evaluate the performance of each method across various faulty RW scenarios.

5.2.1. Permanent Fault Case

A permanent fault in a spacecraft's RW is a malfunction that makes the wheel non-operational and irreparable. This type of fault prevents the RW from controlling the spacecraft's orientation. Using the RW model simulator, the permanent fault is simulated and introduced into the model. The inception time for the faults is set to a random value $t \in (0, 10)$ seconds, and the duration of these faults is defined as the time from inception to the end of the simulation. Ensemble ML-based techniques, DT, and RF with the proposed ML-based techniques SVM, ESD, and ANN, were applied on the resulting faulty datasets. Samples of the models' configuration parameters and confusion matrix are shown in Figure (9)



(a) SVM Model Confusion Matrix

Preset	ESD
Accuracy (Validation)	98.0
Total cost (Validation)	0
Prediction speed	23 obs/sec
Ensemble method	Subspacec
Learner type	Discriminant
Training time	162.05 sec
Covariance structure	Full

Table 6. ESD model configuration and results

Figure 9. Permanent Fault Case confusion Matrix and Model Configuration Parameters

The proposed ML-based techniques show enhanced results in detection accuracy over the ensemble ML technique, as shown in Table (7).

The table clearly illustrates the superior performance of the proposed ML-based techniques, SVM, ANN, and ESD, compared to ensemble ML-based techniques, DT and RF, partic-

Table 7. Proposed technique with ensemble ML technique Permanent Fault case

Classification Method	Accuracy	precision	Recall	F1-scores(%)
Ensemble (DT)	88.5	N/A	N/A	N/A
Ensemble (RF)	83.2	N/A	N/A	N/A
DT	98	98.1	96.2	97.1
RF	97.52	98.1	97.9	97.9
SVM	98.5	98.4	99.2	98.75
ANN	98.5	99.6	98	98.4
ESD	98	98.1	95.6	95.4

ularly in the context of Permanent fault. SVM and ANN both achieve an impressive accuracy of 98.5%, highlighting their effectiveness. SVM is particularly strong in recall (99.2%), making it ideal for situations where minimizing false negatives is essential.

Its balanced precision (98.4%) and F1-score (98.75%) further emphasize its robustness in fault detection. While ANN matches SVM in accuracy, it stands out with the highest precision (99.6%), making it highly reliable for minimizing false positives, although its recall (98%) and F1-score (98.4%) are slightly lower than SVM's, indicating a subtle trade-off between the two models.

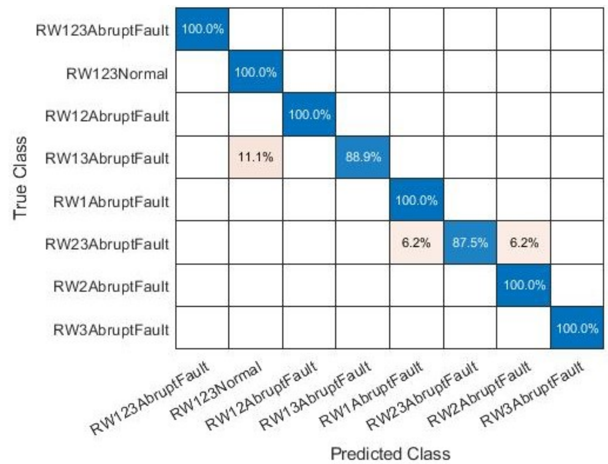
The results suggest that SVM and ANN are particularly well-suited for permanent fault cases due to their high accuracy and well-balanced trade-offs between precision and recall. While ensemble methods like ESD are effective, their complexity should be carefully considered against simpler models like DT, especially when computational efficiency, model interpretability, and minimizing false negatives are crucial.

5.2.2. Abrupt Fault case

Abrupt faults can be viewed as instantaneous faults within the system that can lead to a complete shutdown and failure of the system. Using RW model simulator the permanent fault is simulated and introduced into the model, the fault inception time is set at a random value $V_{\text{in}} \in (5, 55)$ seconds, and the duration of each fault is randomly determined to not exceed the total simulation time of 100 seconds.

Ensemble ML-based techniques with the proposed techniques were applied to the resulting faulty datasets. Samples of the models' configuration parameters and confusion matrix are shown in Figure (10).

The proposed techniques show enhanced results in detection accuracy over the ensemble ML technique, as shown in Table (9). ESD, SVM, and ANN, which achieved accuracies of 96%, 95%, and 95.5%, respectively. While RF demonstrates the highest overall accuracy, SVM and ANN offer robust and balanced performance across precision, recall, and F1-score, making them viable alternatives in scenarios where slight trade-offs in accuracy are acceptable. The ESD technique excels with a remarkable precision of 98.6%, indicating its effectiveness in minimizing false positives—a crucial factor in fault detection scenarios where incorrect identification could lead to unnecessary interventions. ESD's highest F1-score of 96.3% highlights its balanced performance, making it particularly suitable for applications where both precision and recall are vital.



(a) RF Model Confusion Matrix

Preset	SVM
Accuracy (Validation)	95.0 %
Total cost (Validation)	11
Prediction speed	5.1 obs/sec
Training time	177.99 sec
Kernel scale	Automatic
Multiclass method	One-vs-One
Standardize data	Yes

Table 8. SVM model configuration and results

Figure 10. Abrupt Fault Case confusion Matrix and Model Configuration Parameters

Table 9. Proposed technique Vs ensemble ML abrupt Fault case

Classification Method	Accuracy	precision	Recall	F1-scores(%)
Ensemble (DT)	35.64	N/A	N/A	N/A
Ensemble (RF)	29.77	N/A	N/A	N/A
DT	92	92.1	89.4	89.7
RF	96.89	96.38	95.14	95.75
SVM	95	96.3	93.6	94.9
ANN	95.5	95.7	92.2	93.9
ESD	96	98.6	94.1	96.3

In contrast, the Ensemble ML-based techniques DT and RF significantly underperform, with accuracies of 35.64% and 29.77%, respectively.

These results suggest that these techniques, particularly when applied to abrupt fault cases, may not be as effective as the proposed methods. ESD offers exceptional precision and a balanced F1-score, suggesting it is better suited for situations where minimizing false positives is a priority. SVM and ANN remain strong contenders, especially when computational efficiency and fault tolerance are essential considerations.

5.2.3. Transient Fault case

Transient faults are more temporary and may return to normal parameter conditions given enough time. Inception time for faults is set at a random value $\in (0, 10)$ seconds, and the duration of these faults is set randomly. Using the RW model simulator, the transient fault is simulated and introduced into the model, and ensemble ML-based techniques with the proposed techniques were applied to the resulting faulty datasets. Samples of the models' confusion matrix are shown in Figure (11). The proposed techniques show enhanced results in detection accuracy over the ensemble ML technique, as shown in Table (10).

Table 10. Proposed technique Vs ensemble ML transient Fault case

Classification Method	Accuracy	precision	Recall	F1-scores(%)
Ensemble (DT)	94.18	N/A	N/A	N/A
Ensemble (RF)	97.65	N/A	N/A	N/A
DT	97.97	98.4	96.4	97.4
RF	97.1	98.2	97.1	97.6
SVM	95	98.1	95.2	96.6
ANN	98.5	99.3	97.5	98.4
ESD	99.5	99.8	99.2	99.6

Results indicate that the ESD technique leads with an impressive accuracy of 99.5%, surpassing all other techniques in the detection and management of transient faults. ESD also excels in precision (99.8%), recall (99.2%), and F1-score (99.6%), demonstrating its superior ability to balance both false positives and false negatives. This makes ESD the most reliable technique for scenarios where high accuracy and a balanced precision-recall trade-off are critical. ANN also performs exceptionally well, achieving 98.5% accuracy, just 1% lower than ESD but still higher than the other models. ANN's precision (99.3%), recall (97.5%), and F1-score (98.4%) reflect its strong performance, particularly in situations where slightly lower computational complexity is desirable without significantly compromising detection quality.SVM achieves 95% accuracy, which, while lower than the other techniques, still reflects solid performance. SVM's precision (98.1%) and F1-score (96.6%) highlight its effectiveness, though its lower recall (95.2%) suggests it may miss some faults compared to the top-performing models.

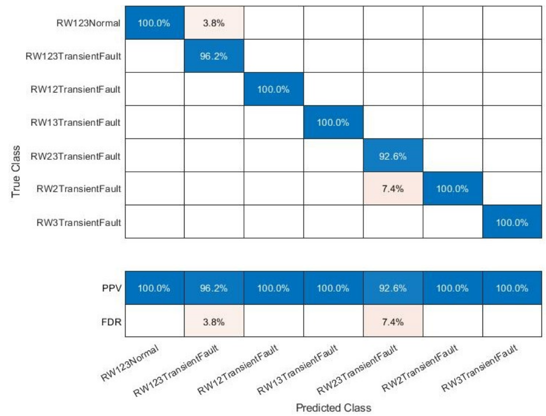
ESD stands out as the most effective technique under transient fault conditions, offering the highest accuracy and the best balance of precision and recall. ANN also provides strong performance, making it a viable alternative when a slightly simpler model is preferred.

5.2.4. Results Analysis

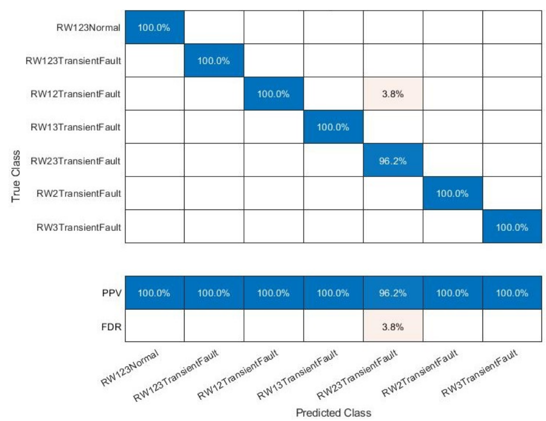
The analysis of ML-based FDII techniques for ADCS RWs across different fault types reveals distinct strengths among the techniques, as shown in Table (11).

For permanent faults, SVM and ANN stand out with a high accuracy of 98.5%, with SVM slightly ahead in precision, recall, and F1-score, making it particularly effective in minimizing false positives. DT also performs well with 98% accuracy, surpassing RF at 97.52%. ESD matches DT's accuracy but doesn't significantly improve upon these simpler models.

In the case of abrupt faults, RF leads with an accuracy of 96.89%, outperforming DT by 5.32% and slightly surpassing SVM and ANN, which achieve 95% and 95.5% accuracy, respectively. While RF is ideal for comprehensive fault detection, ESD, though slightly less accurate (94%), excels in precision (98.6%) and F1-score (96.3%), making it the best choice where minimizing false positives is crucial.



(a) ANN Model Confusion Matrix



(b) ESD Model Confusion Matrix

Figure 11. Transient Fault Case confusion Matrix

Table 11. Proposed ML-based FDII Techniques

Classification Method	abrupt Score (%)	Transient Score (%)	Permanent Score (%)
RF	96.89	97.1	97.52
DT	92	97.97	98
SVM	95	95	98.5
ESD	96	99.5	98
ANN	95.5	98.5	98.5

For transient faults, ESD is the top performer, achieving 99.5$ accuracy with excellent precision (99.8%), recall (99.2%), and F1-score (99.6%). ANN follows closely with 98.5% accuracy, while RF and DT also deliver strong results, with DT having a slight edge in precision and RF in recall. SVM, though slightly behind with 95% accuracy, still demonstrates solid performance.

Results from the previous three cases demonstrated that the proposed ML-based technique outperforms the ensemble ML technique in enhancing fault detection accuracy. However, while both the proposed and ensemble ML techniques are sufficiently accurate in detecting faulty RWs, they are unable to identify the specific type of fault. Additionally, they do not account for temperature faults, which are a critical cause of RW malfunctions. The next section will explore using the proposed technique not only to detect the faulty RW but also to identify the type of fault and detect temperature faults.

5.3. ML-based FDII Techniques without temperature faults

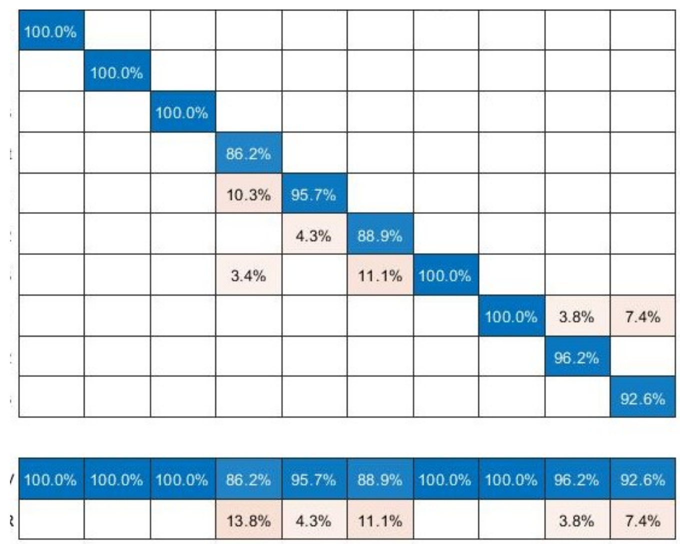
For each of the three types of faults—permanent, abrupt, and transient—various combinations of over-voltage, under-voltage, and current loss faults were generated. This process resulted in about 1,000 labeled combination faults for each fault type, creating a diverse and comprehensive dataset. These datasets underwent extensive preprocessing to ensure high data quality and consistency with the MATLAB classification learner format. Also, steps for feature extraction are applied to prepare the data for machine learning applications.

The ML-based FDII technique was then applied to the three separated preprocessed datasets. This approach was designed to cover all possible fault combinations, providing a robust mechanism for detecting, isolating, and identifying each specific fault scenario. The FDII technique aimed to enhance the reliability and accuracy of fault management in reaction wheels, effectively addressing all potential fault combinations. Samples of the models' confusion matrix are shown in Figure (12)

The results showed that the FDII technique achieved accuracy rates between 97% and 98% in detecting faults in RWs. The lowest accuracy observed for certain fault combinations are shown in table(12).

The results from table(12) indicate that, Without Temperature Faults, SVM and ANN are the top performers for permanent faults, each achieving 98.5% accuracy, with SVM showing a slight edge. ESD also performs strongly, especially in transient faults with 98.5% accuracy. This robust performance highlights the effectiveness of the FDII technique in managing complex fault scenarios in RWs.

(b) ANN Model Confusion Matrix

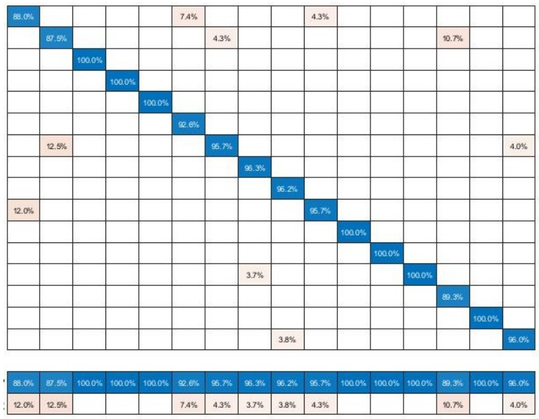


(b) SVM Model Confusion Matrix

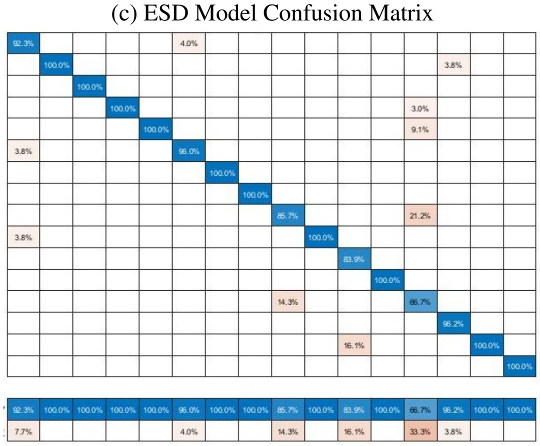
Figure 12. ML-Based FDII Without temperature Faults Case confusion Matrix

5.4. ML-based FDII Techniques with temperature faults

Injecting over-temperature and under-temperature conditions into the RW model simulator for the three main categories of faults, permanent, abrupt, and transient, resulted in approximately 4,000 combined faults. Each of these faults was meticulously labeled, and the datasets underwent comprehensive preprocessing. This preprocessing included formatting and feature extraction to ensure high-quality and consistent data suitable for machine learning applications. The ML-based FDII technique was then applied to these processed datasets. The FDII technique aimed to detect and identify the various combinations of faults accurately. Samples of the models' confusion matrix are shown in Figure (13).



(c) ESD Model Confusion Matrix



(d) SVM Model Confusion Matrix

Figure 13. ML-Based FDII With temperature Faults Case confusion Matrix

The results demonstrated a high accuracy in identifying and detecting the combined faults, with detailed analysis showing the minimum accuracy achieved for the most challenging fault combinations shown in Table (12).

With Temperature Faults, ANN and ESD achieved the highest accuracy for permanent faults at 98%. For transient faults at 96% and ANN at 97%. abrupt faults but remains competitive with 95.5% and 96% accuracy.

5.5. Complexity Analysis

A comprehensive evaluation will compare newly proposed ML-based FDII techniques with existing state-of-the-art techniques, focusing on time and memory complexity. The objective is to demonstrate the superior performance of the proposed techniques in accurately and efficiently detecting and identifying faults in RW, compared to established techniques such as the Prony-based technique and ensemble ML-Based technique (Rahimi & Saadat (2019)).

Type	Method	Abrupt Score (%)	Transient Score (%)	Permanent Score (%)
Without Temp Fault	RF	97.2	98.3	98.52
	DT	97	96	97.5
	SVM	95	98	98.5
	ESD	96	98.5	98
	ANN	95	98	98.5
With Temp Fault	RF	96	97.3	97
	DT	92	98	98
	SVM	94.3	95	96.5
	ESD	96	97	98
	ANN	95.5	96	98

Table 12. Proposed ML-based FDII with and Without temperature faults

The comparison, detailed in Table (13), examines time and memory complexities, revealing that while all techniques achieve acceptable accuracy in fault detection, computational burden disparities underscore each FDII technique's efficiency and practicality.

Model	Accuracy	Time Complexity	Memory Complexity	Remarks
Prony technique	87.8%	$O(n^3)$ (Prony) + $O(N)$ (FFNN)	$O(N)$ (Prony) + $O(1)$ (FFNN)	(n):Length of signal segment (N):Number of data points
Ensemble ML RF	97.65%	$O(n^2 pn_{trees})$	$O(n^2 pn_{trees})$	(n) :number of training sample (p):number of features n_{trees}: number of trees
Ensemble ML DT	94.18%	$O(n^2 p)$	$O(n^2 p)$	(n) :number of training sample (p):number of features
DT	98%	$O(n + \log(n) * d)$	$O(n)$	(n):Number of set points (d):Dimension of data
ESD	98%	$O(M)$	$O(mn + mt + nt)$	(M):Number of features (m):Number of samples (n):Number of features $(r) = \min(m, n)$
SVM	98.5%	$O(n^2)$	$O(n^2)$	(n):Number of trainning samples
ANN	98.5%	$O(N)$	$O(N)$	(N):Number of network connections

Table 13. Comparison of Different Models (Rahimi & Saadat (2019); Abdel Aziz et al. (2024); Rahimi & Saadat (2020); Lee & CHEN (2020); Nalepa & Kawulok (2019); Podgorelec & Zorman (2012); Cai et al. (2007, 2008))

The results depicted in Table (13) evaluating the techniques based on the comparison table, SVM and ANN demonstrate the highest accuracy at 98.5%, making them ideal for tasks where precision is critical. However, ANN stands out due to its superior computational efficiency with a time and memory complexity of $(O(N))$ (Lee & CHEN (2020)), where N is the number of network connections. This makes it highly scalable, particularly in large datasets, while SVM, despite its accuracy, suffers from high computational costs with $O(n^2)$ time and memory complexity (Nalepa & Kawulok (2019)), limiting its practicality for larger data. DT and ESD also offer strong accuracy at 98%, but DT excels with efficient time complexity $(O(n + \log(n) * d)$ (Rahimi & Saadat (2020)) and moderate memory usage $(O(n))$ (Podgorelec & Zorman (2012)), making it a balanced choice for many applications. ESD is similarly efficient in time complexity but may require more memory depending on the dataset's dimensions (Cai et al. (2007, 2008)). The Ensemble ML techniques (Random Forest and Decision Tree ensembles) deliver high accuracy (up to 97.65% for RF), but their quadratic complexity $(O(n^2 pn_{trees})$ makes them computationally expensive, especially in large-scale scenarios. For applications constrained by memory, the Prony technique is the most efficient with

$O(N)$ (Abdel Aziz et al. (2024)) memory complexity for the core algorithm and $O(1)$ (Abdel Aziz et al. (2024)) for the feedforward neural network. However, its lower accuracy of 87.8% might be a drawback in tasks requiring higher precision.

In contrast, the comparison in Table (13) highlights that while all FDII techniques achieve strong detection accuracy, their computational demands vary significantly, directly affecting suitability for on-orbit spacecraft deployment. In resource-constrained environments, several factors are critical. Onboard processing power is limited to radiation-hardened CPUs (e.g., RAD750, LEON3) operating at a few hundred MHz to low GHz (Berger et al. (2001); Kraja & Acher (2011))), making lightweight ML models such as ANN, DT, and SVM each with polynomial or near-linear complexity more feasible than deep learning or ensemble methods requiring high-performance GPUs or TPUs. Memory availability is similarly restricted, often to a few hundred MB, where models with quadratic memory requirements (e.g., SVM: $O(n^2)$ may encounter scalability issues, while ANN and DT remain more efficient O(n), respectively). Real-time responsiveness is essential, with fault detection required within seconds to protect spacecraft actuators. In this context, ANN offers a great balance of high accuracy (98.5%) and computational efficiency, making it the optimal choice for most practical FDII applications, especially where time, memory, and accuracy requirements must be simultaneously addressed, while DT provides a slightly less accurate but computationally efficient alternative.

6. CONCLUSION

The study presents a machine learning-based Fault Detection, Isolation, and Identification (FDII) system for spacecraft reaction wheels (RWs), addressing critical issues in spacecraft attitude control. By simulating high-fidelity models of a three-axis controlled satellite, the research explores various faults (voltage, current, temperature) using classifiers such as SVM, ANN, RF, DT, and ESD. Results show that machine learning techniques outperform traditional methods like Prony's technique in both detection accuracy and computational efficiency. Among the classifiers, SVM and ANN achieve the highest accuracy for permanent faults (98.5%), while ESD excels in transient fault detection (99.5%). The analysis emphasizes the balance between fault detection accuracy and computational complexity, recommending ANN for most practical applications due to its scalability and efficiency. The study concludes that the proposed machine learning techniques are robust and significantly improve fault detection, though further refinement is needed for identifying specific fault types and temperature faults.

REFERENCES

Abbasi Nozari, H., Sadati Rostami, S., Castaldi, P., & Simani, S. (2024). Hybrid robust fault detection and isolation of satellite reaction wheel actuators. *Journal of Control and Decision*, *11*(1), 117–131.

Abdel Aziz, T., Salama, G., Mohamed, M., & Hussein, S. (2024). Efficient machine learning based techniques for fault detection and identification in spacecraft reaction wheel. *Aerospace Systems*, 1–14.

Abd-Elhay, A.-E. R., Murtada, W. A., & Youssef, M. I. (2022). A reliable deep learning approach for time-varying faults identification: Spacecraft reaction wheel case study. *IEEE Access*, *10*, 75495-75512. doi: 10.1109/ACCESS.2022.3191331

Akbarinia, B., & Shahmohamadi Ousaloo, H. (2023). Sensor fault-tolerant attitude determination system based on the nonlinear interacting-multiple-model approach. *Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering*, *237*(5), 1041–1059.

Barnett, J. T. (2001). Zero-crossings of random processes with application to estimation and detection. In F. Marvasti (Ed.), *Nonuniform sampling: Theory and practice* (pp. 393–437). Boston, MA: Springer US. doi: 10.1007/978-1-4615-1229-5_9

Berger, R. W., Bayles, D., Brown, R., Doyle, S., Kazemzadeh, A., Knowles, K., … others (2001). The rad750/sup tm/-a radiation hardened powerpc/sup tm/processor for high performance spaceborne applications. In *2001 ieee aerospace conference proceedings (cat. no. 01th8542)* (Vol. 5, pp. 2263–2272).

Bill, B. (1998). High fidelity mathematical modeling of reaction wheel performance. In *21st annual american astronautical society guidance and control conference.*

Cai, D., He, X., & Han, J. (2007). Srda: An efficient algorithm for large-scale discriminant analysis. *IEEE transactions on knowledge and data engineering*, *20*(1), 1–12.

Cai, D., He, X., & Han, J. (2008). Training linear discriminant analysis in linear time. In *2008 ieee 24th international conference on data engineering* (pp. 209–217).

Castaldi, P., Nozari, H., Sadati-Rostami, J., Banadaki, H., & Simani, S. (2022). Intelligent hybrid robust fault detection and isolation of reaction wheels in satellite attitude control system. In *2022 ieee 9th international workshop on metrology for aerospace (metroaerospace)* (pp. 441–446).

Chaurasia, V., & Pal, S. (2020). Application of machine learning time series analysis for prediction covid-19 pandemic. *Research on Biomedical Engineering*, 1–13.

Dhurandhar, S. (2024). Fourier analysis. In *Understanding mathematical concepts in physics: Insights from geometrical and numerical approaches* (pp. 53–86). Springer.

Douc, R., Moulines, E., & Stoffer, D. (2014). *Nonlinear time series: Theory, methods and applications with r examples*. CRC press.

Folami, M. O. (2021). *Reaction wheels fault isolation onboard 3-axis controlled satellite using enhanced random forest with multidomain features* (Unpublished master's thesis). University of Windsor (Canada).

Ismail, Z., & Varatharajoo, R. (2010). A study of reaction wheel configurations for a 3-axis satellite attitude control. *Advances in Space Research*, *45*(6), 750-759. doi: https://doi.org/10.1016/j.asr.2009.11.004

Karlöf, L., Ølgård, T., Godtliebsen, F., Kaczmarska, M., & Fischer, H. (2005). Statistical techniques to select detection thresholds for peak signals in ice-core data. *Journal of Glaciology*, *51*(175), 655–662. doi: 10.3189/172756505781829115

Kraja, F., & Acher, G. (2011). Using many-core processors to improve the performance of space computing platforms. In *2011 aerospace conference* (pp. 1–17).

Lee, R., & CHEN, I.-Y. (2020). The time complexity analysis of neural network model configurations. In *2020 international conference on mathematics and computers in science and engineering (macise)* (pp. 178–183).

Lopez-Villalobos, C. A., Rodriguez-Hernandez, O., Martinez-Alvarado, O., & Hernandez-Yepes, J. (2021). Effects of wind power spectrum analysis over resource assessment. *Renewable Energy*, *167*, 761–773.

Mansell, J. R. (2020). *Deep learning fault protection applied to spacecraft attitude determination and control* (Unpublished doctoral dissertation). Purdue University.

Müller, M. (2015). *Fundamentals of music processing: Audio, analysis, algorithms, applications* (Vol. 5). Springer.

Nalepa, J., & Kawulok, M. (2019). Selecting training sets for support vector machines: a review. *Artificial Intelligence Review*, *52*(2), 857–900.

Ni, S., Chen, S., Liao, Y., & Cheng, N. (2021). Design and verification of attitude control system for a small satellite. In *Proceedings of the 2021 2nd international conference on control, robotics and intelligent system* (p. 88–92). New York, NY, USA: Association for Computing Machinery. Retrieved from https://doi.org/10.1145/3483845.3483861 doi: $10.1145/3483845.3483861$

Nomura, S., Ikari, S., & Nakasuka, S. (2016). Three-axis attitude maneuver of spacecraft by reaction wheels with rotation speed constraints. *IFAC-PapersOnLine*, *49*(17), 130-134. (20th IFAC Symposium on Automatic Control in AerospaceACA 2016) doi: https://doi.org/10.1016/j.ifacol.2016.09.023

Omran, E. A., & Murtada, W. A. (2016). Fault detection and identification of spacecraft reaction wheels using autoregressive moving average model and neural networks. In *2016 12th international computer engineering conference (icenco)* (pp. 77–82).

Omran, E. A., & Murtada, W. A. (2019). Efficient anomaly classification for spacecraft reaction wheels. *Neural Computing and Applications*, *31*, 2741–2747.

Pachori, R. B. (2023). *Time-frequency analysis techniques and their applications*. CRC Press.

Podgorelec, V., & Zorman, M. (2012). Decision treesdecision tree. In R. A. Meyers (Ed.), *Computational complexity: Theory, techniques, and applications* (pp. 827–845). New York, NY: Springer New York.

Rahimi, A., Datta, S., Kleyko, D., Frady, E. P., Olshausen, B., Kanerva, P., & Rabaey, J. M. (2017). High-dimensional computing as a nanoscalable paradigm. *IEEE Transactions on Circuits and Systems I: Regular Papers*, *64*(9), 2508–2521.

Rahimi, A., & Saadat, A. (2019). Fault isolation of reaction wheels onboard 3-axis controlled in-orbit satellite using ensemble machine learning techniques. In *The international conference on aerospace system science and engineering.*

Rahimi, A., & Saadat, A. (2020). Fault isolation of reaction wheels onboard three-axis controlled in-orbit satellite using ensemble machine learning. *Aerospace Systems*, *3*(2), 119–126.

Ramanathapuram Anand, A. (2021). *Demand forecasting based on short univariate time series: A comparative study* (Unpublished master's thesis). NTNU.

Tidriri, K., Chatti, N., Verron, S., & Tiplica, T. (2016). Bridging data-driven and model-based approaches for process fault diagnosis and health monitoring: A review of researches and future challenges. *Annual Reviews in Control*, *42*, 63-81. doi: https://doi.org/10.1016/j.arcontrol.2016.09.008

Vaz Carneiro, J., Schaub, H., Lahijanian, M., Lang, K., & Borozdin, K. (2022). Machine learning for reaction wheel fault detection using simulated telemetry data. In *Aiaa scitech 2022 forum* (p. 2507).

Voss, S. (2019). Application of deep learning for spacecraft fault detection and isolation.

Wang, R., Gong, X., Xu, M., & Li, Y. (2015). Fault detection of flywheel system based on clustering and principal component analysis. *Chinese Journal of Aeronautics*, *28*(6), 1676–1688.

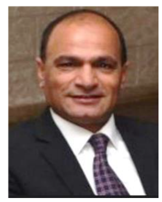
Zhu, Z., Pang, Y., & Chen, Y. (2022). A fault diagnosis method for satellite reaction wheel based on pso-elm. In *2022 41st chinese control conference (ccc)* (pp. 4002–4007).

BIOGRAPHIES

T S Abdel Aziz Tamer earned his B.Sc. and M.Sc. degrees from the Military Technical College, Cairo, Egypt, in 2005 and 2019, respectively. He specializes in spacecraft design, assembly, integration, and testing. Currently, he serves as the Chief of Spacecraft Electrical Testing at the Space Technology Center in Cairo. His work focuses on developing and evaluating advanced spacecraft technologies to ensure their readiness for mission deployment.

S Hussein Sherif received the B.Sc. and M.Sc. degrees from the Computer Eng. and AI department in the Military Technical College, Cairo, Egypt, in 2005 and 2012. He received his Ph.D. degree from the Computer Science Department at the University of Idaho. Sherif does research in Vehicular Ad-Hoc Network (VANET). He is interested in the fault tolerance and reliability of safety applications in VANET subjected to malicious attacks. He is also interested in Embedded computer systems and biomedical image processing. He can be contacted at email: s.hussein@mtc.edu.eg.

Mohamed S. Mohamed Mohamed S. Mohamed received his M.S. degree (2011) and B.S (2004) in Computer Engineering from Military Technical College, Egypt (MTC). He also received his Ph.D. degree (2018) in electrical and computer engineering from the University of Idaho, USA (UI). He is currently a faculty member at the Computer Eng and AI department in MTC. His researches focus on cybersecurity, malicious acts, variability issues related to connected vehicles, survivable systems, and networks. He can be contacted at email: mohamedms@mtc.edu.eg.



Gouda I. Salama Gouda I. Salama received the Bachelor engineering and Master's engineering degrees from MTC, Cairo, Egypt, in 1988 and 1994, respectively. As well, he received a Ph.D. degree in Electrical and Computer Engineering from Virginia Tech. University, U.S.A., in 1999. He is currently a faculty member with the Department of Computer Eng and AI, MTC. His research interests are in image and video processing, pattern recognition, and information security. He can be contacted at email: gisalama@mtc.edu.eg..