

Simulation-Based Fault Detection and Diagnosis for Electric Servomotor Control Rod Drives in BWRX-300

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ABSTRACT

GE-Hitachi's BWRX-300 Small Modular Reactor design adopts innovations from the Advanced Boiling Water Reactor (ABWR), including the use of servomotor-driven fine motion control rod drives (FMC RDs) instead of the hydraulically-driven locking piston control rod drives (LPC RDs) commonly used in current boiling water reactors (BWRs). The FMC RDs provide more precise power control during normal operation and functional backup to the hydraulic SCRAM (rapid reactor shutdown) system during emergency scenarios. To address the challenge of monitoring the novel servomotor-driven FMC RDs in the BWRX-300, for which no operational data exist, this paper develops and evaluates a simulation-based, two-stage diagnostic framework. A model of the FMC RD servomotor and ball-screw drivetrain was created and verified in MATLAB/Simulink to generate comprehensive datasets for healthy operation and key fault modes, including stator short circuits and mechanical load faults. From these simulations, diagnostic features were extracted from motor currents and control-response signals. The proposed framework first uses Auto-Associative Kernel Regression (AAKR) and a Sequential Probability Ratio Test (SPRT) for anomaly detection, achieving an 85.9% true positive rate (TPR) with a 2.15% false positive rate (FPR). At similar FPR,

the Stage 1 AAKR-SPRT configuration achieved higher detection rates than Mahalanobis monitoring, Principal Component Analysis (PCA) T^2/Q , and One-Class Support Vector Machine (OCSVM). Upon detection, a second-stage multi-channel SPRT classifier diagnoses the specific fault type, successfully identifying 100% of Load faults and 75% of Short faults. Compared with a two-channel OCSVM, it produced the same fault recall but reduced cross-fault alarms from 14 to one. This study demonstrates that a simulation-driven approach can establish an interpretable health-monitoring framework for critical reactor components before they enter operation, supporting the development of condition-based maintenance from the outset.

1. INTRODUCTION

Nuclear power currently supplies about 20% of U.S. electricity and more than half of the nation's carbon-free generation (U.S. Energy Information Administration, 2023). Its economic competitiveness is constrained, however, by operations and maintenance (O&M) costs, which account for more than 60% of the levelized cost of electricity (LCOE) in operating plants (World Nuclear Association, 2020). Efforts to maintain the role of nuclear in a decarbonized energy mix therefore increasingly focus on reducing O&M costs while maintaining safety. Advanced reactor designs such as Small Modular Reactors (SMRs) target lower capital expenditures through design simplification, but their long-term viability also depends on efficient O&M (OECD Nuclear Energy Agency, 2021).

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Control rod drive mechanisms (CRDMs) are essential components in light-water reactors, regulating reactivity during routine operation and facilitating rapid shutdown capability during transients. In pressurized water reactors (PWRs), electromagnetic latch mechanisms hold control rods in position against gravity; in a scram, the rods fall freely into the core. In conventional boiling water reactors (BWRs), CRDMs use hydraulic pressure from the bottom head to move rods upward against gravity, with scram achieved by depressurizing the hydraulic lines (Knief, 2008; International Atomic Energy Agency, 2009). The Advanced Boiling Water Reactor (ABWR) retained hydraulic drives but also introduced fine motion control rod drives (FMCRDs) for power shaping, combining stepper motor actuation with hydraulic scram (International Atomic Energy Agency, 2020). The BWRX-300 builds on this lineage but eliminates large hydraulic systems by adopting permanent magnet synchronous servomotor-driven FMCRDs, while retaining accumulator-based hydraulic scram capability (GE Hitachi Nuclear Energy, 2023). This innovation reduces system complexity and plant footprint, but it also introduces a novel actuator technology into nuclear service. Failure of a control rod servomotor in this context could result in reactivity control errors or trigger a scram, with direct implications for both plant safety and economic performance. Servomotors are widely applied in aerospace, robotics, and manufacturing for their controllability and precision (Lee et al., 2023), but no empirical reliability or degradation data exist for their use in nuclear CRDMs under reactor operating conditions.

A large body of research exists on prognostics and health management (PHM) of servomotors and electrical drives in other industries. PHM shifts maintenance from reactive and time-based schedules to condition-based and predictive strategies (Jardine et al., 2006; Coble et al., 2015). Failure modes relevant to servomotors, such as stator inter-turn short circuits, bearing wear, misalignment, demagnetization, and drivetrain degradation, are well documented (Nandi et al., 2005; Chen et al., 2019). Condition monitoring is typically based on non-intrusive electrical and kinematic signals, such as phase currents and encoder speed, which are also the most accessible signals in FMCRD control systems. Motor current signature analysis (MCSA) remains a standard tool for detecting both electrical and mechanical faults (Miljković, 2015; Yang et al., 2021), and vibration or pressure monitoring is used when accessible (Randall, 2011). Numerous studies demonstrate fault detection from speed signals under variable-speed conditions (Pei et al., 2023) and the effectiveness of combining multi-source heterogeneous data (Ji et al., 2021; Han et al., 2024). Time-frequency analysis techniques such as the Short-Time Fourier Transform (STFT), Continuous Wavelet Transform (CWT), and Empirical Mode Decomposition (EMD) are widely applied to capture transient features in non-stationary

signals (Cocconcelli et al., 2012; Randall, 2011). More recently, deep learning models (e.g., Convolutional Neural Networks (CNNs), Residual Networks (ResNets), and Long Short-Term Memory networks (LSTMs)) have been used for automatic feature extraction (Li et al., 2019). To address cases where only healthy data are available, hybrid methods couple these deep features with one-class anomaly detection, such as GA-SVDD, where a Genetic Algorithm (GA) optimizes Support Vector Data Description (SVDD) for robust detection without requiring labeled fault data (Yang et al., 2024). In this approach, SVDD learns the boundary that encloses normal data in feature space, and the GA tunes kernel parameters to minimize errors. Any data point falling outside this learned boundary is flagged as anomalous, making the method well suited to situations where fault examples are scarce or absent. In nuclear applications, PHM frameworks must also minimize both false positives, which waste component life through unnecessary maintenance, and false negatives, which risk unplanned outages and scrams (Coble et al., 2015).

Condition-monitoring approaches for safety-relevant electromechanical systems can be broadly viewed as simulation-driven, data-driven, or hybrid. Simulation-driven approaches are particularly useful when representative operational fault data are unavailable because fault conditions can be generated and studied in a controlled model environment. This paradigm has been demonstrated for rotating machinery (Sobie et al., 2018) and applied to simulated FMCRD operation (Ifeyanyi et al., 2024). Its principal limitation is that the resulting diagnostic conclusions remain dependent on the fidelity of the underlying physical model. Supervised data-driven fault-classification methods can capture complex relationships directly from measured signals but generally require representative labeled examples of the fault classes of interest (Hu et al., 2021; Kumar et al., 2022). Similar diagnostic challenges have been studied for aerospace electromechanical actuators, which likewise combine electric motors with mechanical transmission elements such as ball screws (Yin et al., 2022). In this context, diagnostic studies have addressed failure modes including ball-screw jamming and motor winding faults (Balaban et al., 2015). Hybrid approaches provide another direction by combining physical modeling with data-driven learning (Ji et al., 2025). For example, model-based predictions can provide a physically grounded reference for normal or faulty behavior, while a data-driven model learns residual patterns or discrepancies between the predicted and measured responses. This can reduce reliance on either a perfectly accurate physical model or a large labeled fault dataset alone.

Despite this maturity, direct transfer of these methods to nuclear FMCRDs faces several constraints. First, no operational data, whether healthy or faulty, exist for BWRX-

300 FMCRDs, limiting the applicability of data-hungry supervised deep learning approaches that require large labeled datasets (Qi et al., 2023; Hu et al., 2021). Second, the bottom-mounted drive configuration favors non-intrusive monitoring using signals already associated with motor and position control, such as phase current and rod-position feedback (GE Hitachi Nuclear Energy, 2023). Vibration and other sensing modalities remain potentially complementary, particularly for mechanical faults, but would require an additional sensing channel. Third, safety-critical applications require interpretability: diagnostic indicators must be transparently linked to physical mechanisms to be credible to operators and regulators (Reddy et al., 2024; Hu et al., 2021). Together, these constraints motivate approaches that make use of physics-based modeling to generate representative datasets, extract physically interpretable features, and apply established monitoring techniques such as Fourier Transform and Wavelet Transform, consistent with engineering practice (Ji et al., 2025; Kim et al., 2008).

This study addresses these challenges by developing a diagnostic methodology for the BWRX-300 FMCRD servomotor system using simulation-based analysis. A permanent magnet synchronous motor (PMSM) model coupled with a ball-screw mechanism was implemented in MATLAB/Simulink to generate data for both nominal operation and representative fault conditions, including stator winding short circuits and increased load torque. Diagnostic features were extracted from motor currents, control responses, and mechanical outputs, and analyzed using Auto-Associative Kernel Regression (AAKR) for healthy state prediction and residual generation followed by Sequential Probability Ratio Testing (SPRT) for anomaly detection and fault isolation (Hines et al., 2006; Li et al., 2017; Jung et al., 2025).

The contribution of this work is not the development of AAKR or SPRT themselves. AAKR is an established nonparametric method for healthy-state reconstruction and condition monitoring (Baraldi et al., 2015), while SPRT has been widely used for statistical change and anomaly detection (Hines et al., 2006; Li et al., 2017). Rather, the contribution lies in their application-specific integration within a two-stage FMCRD diagnostic architecture that combines simulation-generated fault cases, physically interpretable motor and control-response features, healthy-reference anomaly detection, and fault-specific diagnostic channels.

Consistent with the standard PHM workflow (i.e., data generation, feature extraction, anomaly detection, and diagnosis), this approach adapts proven techniques from industrial servomotors (Kelley and Hagan, 2020) to the unique constraints of nuclear CRDMs. This work demonstrates how an interpretable, data-efficient, simulation-

based diagnostic baseline can be developed for reactor components that are not yet in operation.

The primary objectives are, therefore, to: (1) develop and verify a physics-based Simulink model of the FMCRD capable of simulating both healthy operation and specific electrical and mechanical fault modes; (2) generate a comprehensive dataset from this model to serve as the basis for health monitoring method development; (3) design a two-stage diagnostic framework that first detects anomalies and then classifies the specific fault type; and (4) evaluate the framework using detection, false alarm, and fault isolation performance measures. The remainder of this paper is organized as follows: Section 2 describes the full methodology including the development of the FMCRD model in Simulink, feature extraction considerations, and two-stage diagnostic methodology; Section 3 presents the results and discussion of the framework's performance; and concluding remarks are given in Section 4.

2. METHODOLOGY

2.1. Overview of Methodology

The diagnostic methodology developed in this study is implemented as a two-stage fault detection and diagnosis framework tailored to the BWRX-300 fine motion control rod drive (FMCRD) servomotor system. The framework (Figure 1) reflects best practices in safety-critical monitoring: (i) fault detection for anomaly screening, and (ii) fault diagnosis for isolating the root cause (Isermann, 2011).

Stage 1 – Fault Detection: Auto-Associative Kernel Regression (AAKR) is trained on healthy operational data to learn a baseline model of system behavior. Sequential Probability Ratio Testing (SPRT) is then applied to residuals for statistically rigorous anomaly detection (Hines et al., 2006; Di Maio et al., 2013). This stage functions as a gatekeeper so that the diagnostic stage is only activated when a statistically significant departure from normal operation is confirmed. This approach is intended to limit unnecessary false alarms, which is important in nuclear settings where unplanned maintenance carries high cost and availability consequences.

Stage 2 – Fault Diagnosis: Once an anomaly is flagged, a second layer of SPRT classifiers evaluates fault-sensitive features derived from current, speed, and position signals. This stage discriminates between electrical and mechanical degradation modes, providing interpretable indicators directly linked to their characteristic responses. By layering anomaly detection and diagnosis, the framework combines sensitivity to incipient faults with specificity in classification, complementing the strengths of both systems.

This layered design not only separates the tasks of general detection and specific diagnosis but also aligns with the

practical lifecycle of data in a new system: Stage 1 can be developed primarily from healthy-reference data, while the Stage 2 diagnostic models are refined as more fault-specific data become available.

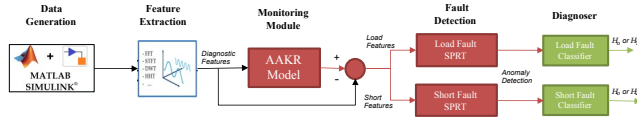


Figure 1. FMCRD Multi-Fault Health Monitoring System

2.2. FMCRD System and Failure Context

The FMCRD (Figure 2) couples a PMSM to a ball screw mechanism that translates rotational motion into vertical rod displacement. This electromechanical drive allows fine, incremental positioning of control rods during normal operations, while hydraulic scram capability ensures rapid rod insertion during transients (GE Hitachi Nuclear Energy, 2023; U.S. Nuclear Regulatory Commission, 2021). Because this design replaces the large hydraulic-based control systems used in legacy BWRs, servomotor integrity is essential for reliable reactivity control (International Atomic Energy Agency, 1997).

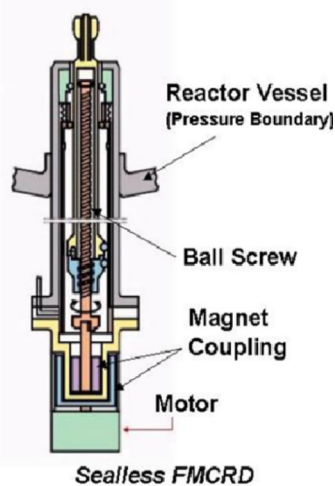


Figure 2. GE's Fine Motion Control Rod Drive (FMCRD) Design in the ABWR (International Atomic Energy Agency, 1997)

Across industrial applications, servomotor faults fall into two broad classes: electrical and mechanical, with stator insulation failures and bearing degradation accounting for the majority of motor downtime (Nandi et al., 2005; Chen et al., 2019). Fault statistics from high-voltage PMSMs show that stator faults dominate ($\approx 66\%$), followed by bearing and rotor faults ($\approx 13\%$ each), with other mechanisms

less common ($\approx 8\%$) (Figure 3) (Pietrzak and Wolkiewicz, 2021). This distribution motivates prioritizing stator short circuits and mechanical load faults in the FMCRD diagnostic framework.

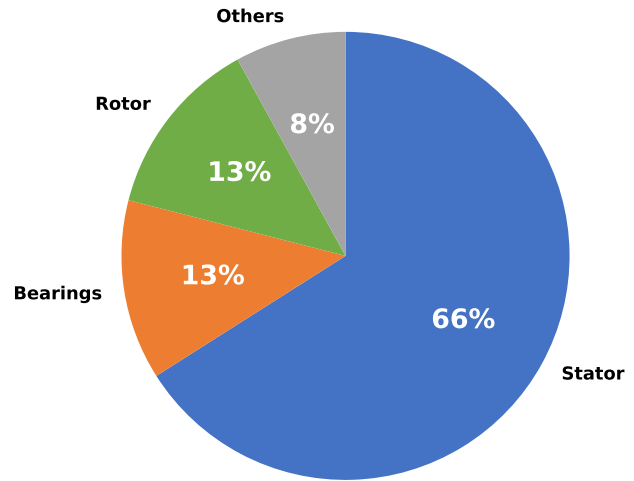


Figure 3. Major Faults of High-Voltage Electrical Machines. Adapted from (Pietrzak and Wolkiewicz, 2021)

2.2.1. Electrical Faults: Stator Inter-Turn Short Circuit (ITSC)

Stator winding insulation breakdown is among the most frequent and destructive failure modes in alternating-current (AC) servomotors, responsible for roughly 30–40% of induction motor failures in industrial settings (Nandi et al., 2005; Kumar et al., 2022). In PMSMs, which are favored for FMCRD applications, the proportion of electrical failures can be even higher, reported in some studies to approach two-thirds of total failures, owing to high voltage stress and thermal loading (Milfont et al., 2024; Pietrzak and Wolkiewicz, 2021).

An inter-turn short circuit (ITSC) arises when insulation degrades between adjacent turns in a coil, creating a low-impedance circulating current that produces intense localized heating (Chen et al., 2022). If left unchecked, ITSC faults escalate rapidly into phase-to-phase or ground faults, potentially destroying the motor (Cusidó et al., 2011; Almounajjed et al., 2022).

The primary diagnostic signature is the distortion of the air-gap magnetic field, which introduces additional spatial harmonics into the stator magnetomotive force. These distortions manifest as characteristic sideband components around the supply frequency and its multiples in the stator

current spectrum. The exact locations and amplitudes of these harmonics depend on the winding distribution, pole-pair count, and severity of the short, and therefore no single closed-form expression universally describes ITSC fault frequencies (Chen et al., 2019; Nandi et al., 2005). Nevertheless, several studies report that ITSC conditions often strengthen lower-order sidebands and can produce notable increases in specific harmonics, particularly the third one, which has been shown to be a sensitive early indicator of shorted turns (Nandi et al., 2005).

These harmonic signatures can be effectively extracted using Fourier-transform-based spectral analysis or time–frequency techniques such as the STFT and wavelet transforms, making them suitable for non-intrusive condition monitoring of PMSMs (Roura and Romeral Martínez, 2011; Pietrzak and Wolkiewicz, 2022).

ITSC was selected as the representative electrical fault for three main reasons. First, its high prevalence and severity make it one of the most safety-significant electrical failures in motors, especially in critical applications. Second, it typically progresses from an incipient stage, offering a limited but exploitable detection window before catastrophic escalation (Almounajjed et al., 2022). Third, ITSC signatures are observable in readily available electrical measurements (e.g., phase currents and voltages), which aligns with the monitoring constraints of bottom-mounted BWRX-300 FMCRD drives.

In the Simulink FMCRD model developed in this work, ITSC faults are emulated by introducing a resistive single-phase short in the PMSM stator winding at a specified time and severity level. This produces characteristic changes in current signatures while the position profile remains largely unaffected during early ITSC progression, highlighting the need for multi-signal monitoring and feature extraction.

2.2.2. Mechanical Faults: Bearings and Drivetrain (Ball Screw)

Although stator faults dominate the overall fault distribution in high-voltage machines (Figure 3), mechanical failures remain a major contributor to servomotor downtime, accounting for roughly 25–30% of total cases, with bearings alone responsible for about 13% (Pietrzak and Wolkiewicz, 2021). Rolling element bearings are particularly vulnerable due to fatigue, contamination, or lubrication breakdown. Localized defects on the inner race, outer race, or rolling elements generate periodic impacts, which modulate vibration, current, and speed signals (Randall, 2011). These impacts produce characteristic bearing fault frequencies tied to shaft geometry and rotational speed, detectable via current signature analysis, vibration monitoring, or instantaneous angular speed (IAS) methods (Moustafa et al., 2014; Zhang et al., 2014; Huang et al., 2025).

In FMCRDs, bearing-related degradation is especially relevant because these actuators often operate at low speeds, with intermittent operation, and under variable loads—conditions that obscure classical spectral signatures (Subramanian et al., 2023). Advanced techniques such as speed signature analysis (Huang et al., 2025) and deep-learning-based feature extraction (Raouf et al., 2024; Sun et al., 2018) have been shown to improve detection sensitivity under these nonstationary conditions.

Beyond bearings, the ball screw drive that translates motor rotation into linear control rod motion represents a second critical failure point. Unlike industrial applications where ball screw degradation primarily reduces positioning accuracy, failures in FMCRDs can compromise reactivity control and scram reliability, directly impacting nuclear safety. Two principal degradation modes are emphasized:

- **Progressive wear and friction increase:** Lubrication breakdown, surface fatigue, or guide track damage gradually increase resistive torque. This manifests as rising average current demand, slower actuator response, and increased thermal stress (Xie et al., 2022; Cocconcelli et al., 2012).
- **Abrupt obstruction or jamming:** Foreign debris or rod-binding produces a sudden torque spike, forcing large transient currents and significant position tracking errors (Yang et al., 2021; Huang et al., 2025).

Recent work has demonstrated that ball-screw degradation can be detected using continuous wavelet transform (CWT) coupled with convolutional neural networks (Xie et al., 2022) and deep feature aggregation techniques (Shao et al., 2017). Importantly, these methods rely on electrical and kinematic signals such as phase currents, rotor speed, and position error which are already available in FMCRD systems without additional instrumentation. These advanced methods can be explored for FMCRD in the future, while here we focus on well-established methods for the purpose of interpretability and transparency.

Mechanical faults, while statistically less frequent than stator faults, have a disproportionate safety impact in FMCRD applications. Bearing degradation represents a well-documented failure mode that challenges low-speed detection (Moustafa et al., 2014). Ball screw faults, meanwhile, uniquely affect precise control rod positioning. While the primary scram function is hydraulically driven, ball screw integrity is essential for fine motion reactivity regulation and the electromechanical backup insertion capability. Together with the ITSC case, these mechanical modes provide fault scenarios for evaluating diagnostic methodologies under both incipient and abrupt conditions.

2.2.3. Fault Scenarios Injected in the FMCRD Model

Based on expert knowledge, literature review, and relevance to nuclear safety, three representative fault scenarios were selected for the FMCRD MATLAB/Simulink model (Table 1) (Almounajjed et al., 2022; Chen et al., 2019; Huang et al., 2025; Cocconcelli et al., 2012; Xie et al., 2022; Yang et al., 2021). These span electrical and mechanical categories as well as abrupt and progressive degradation modes, providing a tractable but realistic set of challenges for the diagnostic framework.

Fault	Key Characteristics
Stator Inter-Turn Short Circuit (ITSC)	Electrical insulation failure modeled as a resistive path between turns. Produces characteristic current harmonics, increased third-harmonic amplitude, and local heating.
Ball Screw Jam (Step Torque)	Abrupt obstruction modeled as a step change in load torque. Results in sharp current spike, large transient position error, and sudden control instability.
Ball Screw Wear (Ramp Torque)	Progressive degradation modeled as a ramping load torque. Leads to gradual rise in motor current, longer rise/settling times, and higher thermal stress.

Table 1. Injected FMCRD Fault Scenarios in Simulink

The fault conditions were introduced through Simulink input parameters. For each simulation, the fault type, activation time, and magnitude were specified before execution. The electrical short-circuit case was activated through the stator fault block at the prescribed switching time, whereas the Step and Ramp load cases were applied through the mechanical-load path using step and ramp input profiles, respectively. The corresponding numerical fault-injection settings are reported in Table 2 together with the principal model parameters. The Step-load and Ramp-load cases represent abrupt and progressively increasing mechanical loading conditions for diagnostic evaluation.

These injected scenarios do not exhaustively cover all possible FMCRD faults (e.g., open circuits, phase-to-phase shorts, bearing spalls), but they represent credible initiating conditions with distinct spectral and time-domain features. More importantly, they allow systematic evaluation of the proposed two-stage diagnostic workflow under relevant operating constraints, where abrupt failures (jam, ITSC) pose immediate safety risks and progressive wear threatens long-term reliability. Additionally, the user can inject any number of electric faults into the motor. An open circuit is a break in one or multiple phase currents yet results in a trivial scenario (zero phase current) from a detection perspective.

Furthermore, the three-phase short can be prevented by identifying the single-phase short circuit before it spreads to adjacent phases in the stator windings. For these reasons, these two particular faults were precluded from the analysis.

2.3. FMCRD Modeling Using Simulink Simscape

A physics-based model of the Fine Motion Control Rod Drive (FMCRD) was developed in Simulink's Simscape environment to emulate the electromechanical behavior of the servomotor–ball screw assembly (Ifeyanyi et al., 2024; MathWorks, 2023b; Sun et al., 2007). This virtual representation allows for systematic injection of electrical and mechanical faults under controlled conditions, generating datasets that capture both healthy and degraded behavior. Such simulation-based data are especially important in the nuclear context, where direct experimentation with safety components is often impractical and undesirable.

The FMCRD is a critical subsystem that converts electrical command signals into precise linear displacement of control rods within the reactor core. It consists of three tightly coupled functional blocks:

- Servomotor subsystem: a PMSM with three-phase excitation, stator current regulation, and speed feedback;
- Ball screw subsystem: converting rotary shaft motion into linear displacement of the control rod load and representing the associated shaft and load dynamics; and
- Control and protection subsystem: cascaded feedback controllers for current, speed, and position regulation, along with braking logic to secure the rod after the commanded motion.

2.3.1. Model Architecture and Control Strategy

The PMSM model is adapted from the MathWorks' AC6 PMSM drive template, configured for a three-phase 220 V, 60 Hz supply (MathWorks, 2023a). The stator dynamics are represented in the rotating dq reference frame, where electromagnetic torque arises from the interaction between stator currents and rotor permanent magnets.

The FMCRD servo system operates on a cascaded control principle, translating a desired *Position Reference* into precise linear motion of the control rod (Figure 4). The process begins in the outer position loop, where the target displacement is compared against the measured rod position, producing a *Speed Reference*. This command is passed to the speed loop, where a proportional-integral-derivative (PID) controller compares it with the measured rotor speed and computes the torque demand.

This torque requirement is decomposed into two current commands:

- $i_{q,ref}$, which directly controls torque production, and

Subsystem	Parameter	Value
Simulation	Solver	Fixed-step
	Effective simulation step	2×10^{-5} s
Electrical Supply	Supply voltage	220 V
	Supply frequency	60 Hz
	Source resistance	0.02Ω
	Source inductance	0.05 mH
PMSM	Stator resistance, R_s	0.20Ω
	Stator leakage inductance, L_{ls}	8.5×10^{-3} H
	Magnetizing inductance, L_{ms}	8.5×10^{-3} H
	Rotor inertia, J	0.089 kg m ²
	Viscous-friction coefficient	0.005 N m s
	Permanent-magnet flux linkage	0.175 V s
Drivetrain	Shaft inertia	0.01 kg m ²
	Ball-screw lead	20 mm
	Minimum control-rod mass	185 kg
Control	Position-controller proportional gain	100
	Position-controller integral gain	-0.04
	Position-controller derivative gain	-50
	Position-controller filter coefficient	100
	Controller output limits	± 180
Noise	Band-limited white-noise power	1×10^{-16}
	Noise scaling factor	1
Fault Injection	Single-phase short circuit	$R_f \approx 10^{-5}$ -3 Ω ; $t_f \approx 1.25$ -8 s
	Step-load case	Load value ≈ 185 -1000 kg; $t_f \approx 1.25$ -8 s
	Ramp-load case	Ramp slope ≈ 185 -1000 kg/s; start time ≈ 1.25 -8 s

Table 2. **Principal Parameters of the FMC RD Simulink Model.** Parameters used in the FMC RD simulation model for dataset generation.

3. Current-based features: harmonic amplitudes and Discrete Wavelet Transform (DWT) band powers from three-phase stator currents, sensitive to both electrical and electromechanical faults.

Because detection and diagnosis have distinct objectives, features are organized into two diagnostic matrices corresponding to the two stages of the framework.

Stage 1's objective is broad anomaly detection. Table 3 contains a global feature set (25 variables) spanning all categories. The feature selection process for this method involved an initial screening based on linear correlation analysis to reduce redundancy and a subsequent exclusion of features that demonstrated low sensitivity or were irrelevant to the primary operational phases (e.g., features from the braking period were removed). The final set of 25 features is used as input to the Stage 1 AAKR model, and the resulting residuals are evaluated by a single SPRT channel. Unlike the method employed in Stage 2, this approach does not pre-assign features to specific faults; instead, it relies on the model to learn the complex relationships between the combined feature set and the different fault modes. The cost is interpretability, which is acceptable since Stage 1 outputs only a binary anomaly alarm.

For Stage 2, the feature selection logic was refined to support fault isolation. A diagnostic matrix (Table 4) was generated by analyzing the sensitivity of 24 distinct features to short faults and mechanical load faults using a ternary directional logic: positive shift (+1), negative shift (−1), or negligible sensitivity (0). Features with no sensitivity to either fault type ([0, 0]) were discarded to avoid injecting noise into the classifier.

This analysis revealed three groups of features. First, several fault-specific features respond predominantly to only one fault type and therefore act as discriminators. Rise time, control rod speed, startup residual slope, startup/steady-state peak frequency and power, and DWT D8 power (IDs 1, 6, 7, 12, 15, 16, 20) are consistently sensitive to ITSC but not to load faults. Conversely, transient time, settling time, and startup peak amplitude and power (IDs 2, 3, 11, 13) are selectively sensitive to load faults. These short-only and load-only responses provide directional evidence that biases the multi-channel SPRT toward the corresponding fault hypothesis.

Second, a set of common-mode features (e.g., overshoot percentage and down residual slope) exhibit similar positive shifts for both fault types, reflecting the fact that both ITSC and increased load torque stress the servo loop and drive currents in a broadly similar way. These features are informative for detection but ambiguous for diagnosis.

The distinctive outlier is Feature 19 (Deceleration Peak Power), which is the only feature with a physically robust

Feature Type	Current	ID	Feature Name
Control System Based		1	Rise Time
		2	Transient Time
		3	Settling Time
		4	Overshoot Percentage
Mechanical Features		5	SS Residual Slope
3-Phase Current Features	Phase A	6	Startup Peak Frequency
		7	SS Peak Power
		8	Down Peak Frequency
		9	DWT D8 Power
		10	SS Avg Power
	Phase B	11	Down Peak Frequency
		12	SS Peak Power
		13	Down Peak Frequency
		14	DWT D8 Power
		15	SS Avg Power
	Phase C	16	Down Peak Frequency
		17	SS Peak Power
		18	Down Peak Frequency
		19	DWT D8 Power
		20	SS Avg Power
	Stator Current	21	Down Peak Frequency
		22	SS Peak Power
		23	Down Peak Frequency
		24	DWT D8 Power
		25	SS Avg Power

Table 3. Stage 1 (Fault Detection) Global Feature Set.
Correlation-screened, broad feature pool used in a single-channel SPRT to maximize sensitivity to anomalies across operating conditions. Classification is deferred to Stage 2.

bidirectional response: it increases for short faults, where current spikes lead to higher active electrical braking, but decreases for load faults, where additional mechanical friction assists the deceleration. While Table 4 presents binary sensitivities for clarity, Feature 19 provides the only consistent sign reversal across operating conditions, and is therefore used as the primary discriminator in the multi-channel SPRT logic.

Feature Type	ID	Feature Name	Short Fault	Load Fault
Control System Based	1	Rise Time	1	0
	2	Transient Time	0	1
	3	Settling Time	0	1
	4	Overshoot Percentage	1	1
	5	Undershoot Percentage	0	0
Mechanical Features	6	Control Rod Speed	1	0
	7	Startup Residual Slope	1	0
	8	SS Residual Slope	0	0
	9	Down Residual Slope	1	1
	10	Break Residual Slope	0	0
3-Phase Current Features	11	Startup Peak Amplitude	0	1
	12	Startup Peak Frequency	1	0
	13	Startup Peak Power	0	1
	14	SS Peak Amplitude	1	1
	15	SS Peak Frequency	1	0
	16	SS Peak Power	1	0
	17	Down Peak Amplitude	1	1
	18	Down Peak Frequency	0	0
	19	Down Peak Power	1	1
	20	DWT D8 Power	1	0
	21	DWT D9 Power	0	0
	22	DWT D10 Power	0	0
	23	DWT D11 Power	0	0
	24	DWT Approx. Power	0	0

Table 4. **Stage 2 (Fault Diagnosis) Diagnostic Feature Matrix.** Binary entries indicate feature sensitivity to fault type (1 = strong effect, 0 = negligible). This fault-specific map supports multi-channel SPRT by grouping features according to relevance for **ITSC** and **Load (Jam/Wear)** modes.

The fault-response analysis described above identifies features that are relevant for diagnosis, but it may still retain redundant features that reflect the same underlying behavior. To address this, correlation-guided pruning was applied to

the final Stage 2 set. The pruning path was based on the absolute feature correlations calculated using only the 499 healthy training observations. Fault labels and diagnostic performance were not used to select or rank features for removal. Instead, diagnostic performance was evaluated after each successive reduction along the predefined pruning path to assess whether a smaller feature set could retain the performance of the original Stage 2 model.

2.4. Feature Extraction Methods for Servomotor Condition Monitoring

Effective fault detection and diagnosis depend on extracting meaningful features from available sensor data. This section details the methods used to process raw simulation outputs, specifically, control rod position and three-phase stator currents, into a set of diagnostic indicators. These features are designed to be sensitive to the electrical and mechanical fault modes described in Section 2.2 and serve as the direct inputs for the health monitoring system outlined in Section 2.5. The methodology prioritizes non-intrusive monitoring techniques, such as Motor Current Signature Analysis (MCSA), which are practical for the BWRX-300's bottom-mounted drive configuration and have been widely validated for diagnosing mechanical faults in rotating systems (Thomson and Fenger, 2001; Krichen et al., 2020; Messaoudi and Sbita, 2010).

The process involves two primary categories of feature extraction: (1) analysis of the system's dynamic control response and mechanical outputs, and (2) time-frequency analysis of the stator currents. While a stator fault is electrical in origin, its effects can propagate through the electromechanical system, affecting speed, torque, and ultimately the control rod's position profile (Pietrzak and Wolkiewicz, 2021). Similarly, mechanical load faults require a compensatory response from the motor's electrical system. Therefore, combining features from both domains provides a more comprehensive and robust diagnostic capability, a strategy supported by research on multi-source heterogeneous data (Qiu et al., 2021).

2.4.1. Control and Mechanical Based Features

Fundamentally, the FMCRD's performance is characterized by its ability to follow a commanded position trajectory. Deviations from the nominal response can indicate underlying degradation. As illustrated in Figure 6, the position profile of the control rod in response to a step command resembles a classic dynamic system response. From this profile, several key performance metrics are extracted to serve as diagnostic features. These include:

- **Rise time:** The time taken for the position to rise from 10% to 90% of its final value, which can be affected by increased friction or reduced motor torque.
- **Overshoot/Undershoot:** The percentage by which the

peak position exceeds the final value. Variations in this metric serve as a proxy for the system's damping ratio, which changes as mechanical degradation (such as wear or lubrication breakdown) alters the effective friction in the drivetrain (Armstrong-Hélouvy et al., 1994).

- **Settling time:** The time required for the response to remain within a specified tolerance band of the final value. For this study, it is formally defined as the time after which the absolute positioning error $|y(t) - y_{\text{final}}|$ remains continuously below 2% of the maximum step magnitude. This feature captures the system's ability to stabilize and is highly sensitive to the stick-slip behavior in mechanical faults.
- **Transient time:** A metric similar to settling time but with a stricter tolerance (e.g., 1% of e_{max}), capturing how quickly the most significant transient dynamics decay.

In addition to these system-level metrics, features are derived from the position residuals, e_i , which represent the instantaneous error between the commanded and actual rod position (as shown in Figure 6). The first-time derivative of these residuals, calculated as in Eq. 1, provides an estimate of the control rod's velocity, v_e .

$$v_e = \frac{e_{i+1} - e_i}{\Delta t} \quad (1)$$

Subsequent derivatives yield the acceleration error, a_e . The slopes of these residual-derived signals during different operational phases (startup, steady-state, deceleration) capture subtle changes in the drivetrain dynamics that may not be apparent in the primary position signal alone.

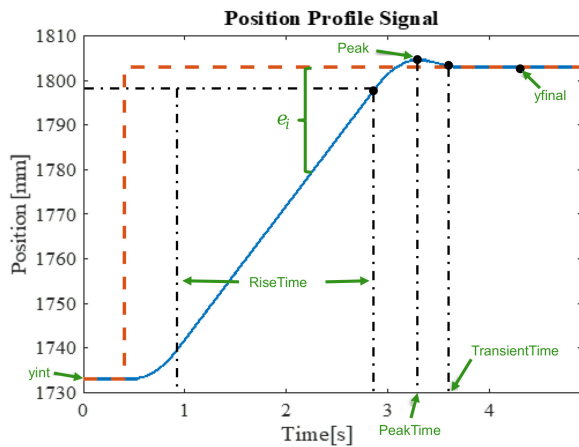


Figure 6. Key Features of a Step-Response to a Dynamic System (derived from MATLAB's dynamic system model)

2.4.2. Method for 3-Phase Current Feature Extraction

Motor Current Signature Analysis (MCSA) is a well-established technique for detecting faults in electrical machines by analyzing the frequency content of the stator current (Miljković, 2015; El Hachemi Benbouzid, 2000; Liu et al., 2022). This approach is founded on the principle that electrical faults, as well as mechanical anomalies, introduce characteristic distortions and harmonics into the stator current signal. Some of these methods are based on the raw current signal, such as calculating statistical features like root-mean-square (RMS), skewness, and kurtosis (Yang et al., 2021), while others rely on the processed signal. These processing techniques involve various mathematical methods, including frequency-domain analysis via the Fast Fourier Transform (FFT) for stationary signals (Zhan and Zhou, 2017), time-frequency decomposition using wavelet transforms (Kim et al., 2008), Short-Time Fourier Transform (STFT) and the Hilbert-Huang Transform (HHT) for non-stationary signals, and vector space transformations like the Park transform, which converts the three-phase system into two components in an orthogonal stationary frame ($i_{\alpha\beta}$). Because FMCRD servomotors will often operate under variable speeds and loads, a combination of analysis techniques is required for robust diagnosis (Lee et al., 2023; Liu et al., 2022). The methods employed in this study include the FFT for stationary signal analysis and the DWT for non-stationary, transient conditions.

For periods of steady-state operation, where the motor runs at a relatively constant speed, FFT serves as an effective and computationally efficient tool for fault diagnosis, forming the basis of modern MCSA (El Hachemi Benbouzid, 2000). The basic principle of this method is to transform the motor's current signal from the time domain, where it appears as a complex waveform, into the frequency domain (Nandi et al., 2005). This transformation decomposes the signal into its constituent sinusoidal frequencies, revealing a spectrum of amplitudes at various frequencies. In a healthy motor, this spectrum is typically dominated by the fundamental supply frequency and its expected harmonics. However, the onset of a fault, such as an ITSC, disrupts the physical symmetry of the stator's magnetic field, which in turn induces new, predictable harmonic components in the current signal that act as clear diagnostic markers (Thomson and Fenger, 2001; Nandi et al., 2005; Chen et al., 2019). This approach has proven effective because electrical and mechanical anomalies each produce unique current signatures that can be isolated and identified through spectral analysis (Kumar et al., 2022).

The process begins with establishing a baseline by identifying the motor's fundamental electrical supply frequency, f_s . This frequency is directly tied to the motor's rotational speed (ω_{nom}) and its number of pole pairs (p), as calculated in Eq. 2. For the FMCRD system simulated in this study, the

nominal operating speed results in a fundamental frequency of approximately 12 Hz.

$$f_s = \frac{\omega_{nom} \cdot p}{60} \quad (2)$$

When an asymmetric fault like an ITSC occurs, the resulting imbalance in the magnetic field creates additional frequencies in the current spectrum. The specific frequencies of these fault-induced harmonics, f_{short} , can be theoretically predicted using Equation 3, where k is an integer representing the harmonic order (Krichen et al., 2020). A notable indicator of an ITSC is a significant increase in the amplitude of the third harmonic ($3f_s$) and the appearance of sideband harmonics around the fundamental frequency (Nandi et al., 2005). Figure 7 clearly illustrates this effect, comparing the FFT spectrum of a healthy motor current with that of a motor under a short-circuit fault. The faulted signal (in red) shows significantly larger amplitudes at specific harmonic frequencies (e.g., ~ 36 Hz, ~ 60 Hz, ~ 156 Hz, and ~ 180 Hz) compared to the healthy signal (in blue). Even at the fundamental frequency (~ 12 Hz), the amplitude of the faulted signal is already significantly higher than the healthy one, indicating that the fault is already causing a substantial increase in current draw even at the primary operating frequency. The presence of these multiple, amplified harmonics provides a robust and reliable signature for diagnosing the short circuit fault. This approach of identifying fault-specific spectral characteristics is a common practice in MCSA-based fault detection (Zhan and Zhou, 2017).

$$f_{short} = \left(1 \pm \frac{2k-1}{p}\right) \cdot f_s \quad (3)$$

However, FFT analysis has important limitations. Its requirement for signal stationarity makes it less effective during the transient phases of motor operation (startup, deceleration) (Lee et al., 2023; Henao et al., 2014). These challenges are amplified in modern PMSMs that use sophisticated closed-loop vector control systems, which are designed to react to and correct irregularities to ensure smooth motor operation (Armstrong-Hélouvy et al., 1994). While this improves performance, it also means the controller can automatically compensate for the effects of a fault, such as an ITSC. By masking the symptoms of the failure, the control system makes it very difficult to detect problems at an early stage. Moreover, the FFT amplitude spectrum can be misleading. It can contain frequency spikes that are a normal part of the motor's operation and are not related to any fault (Thomson and Fenger, 2001; Nandi et al., 2005). For instance, even multiples of the motor's fundamental frequency f_s can appear and change with the load torque and rotor speed (Pietrzak and Wolkiewicz, 2021). This makes

it difficult to isolate the specific frequency changes that are exclusively caused by a winding failure.

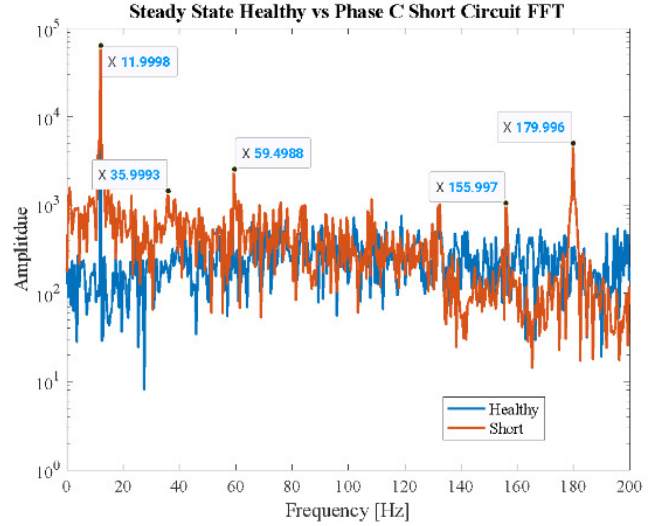


Figure 7. FFT Spectral Analysis Comparison of Healthy vs Steady State Short Circuit Fault

Despite these limitations, FFT remains an indispensable tool for diagnostics due to its high efficiency and effectiveness at characterizing faults during steady-state conditions, which constitute a significant portion of many machines' operating cycles. Coupled with increasing computing power of microcontrollers that allow excellent data resolution, FFT provides a clear, foundational analysis that can be supplemented by other methods to cover the full operational range.

To overcome the limitations of FFT, DWT is used. DWT is particularly well-suited for analyzing non-stationary signals because it provides both time and frequency information, making it an appropriate tool for analyzing signals from systems under variable operating conditions (Roura and Romeral Martínez, 2011; Cusidó et al., 2011; Lee et al., 2023). The DWT performs a multi-resolution analysis by passing the signal through a series of high-pass and low-pass filters, decomposing it into different frequency bands known as "details" (d_i) and "approximations" (Kim et al., 2008). The signals produced from the FMCRD are known to be predominantly nonstationary; therefore, the use of DWT is worth investigating for transient analysis.

A stator winding fault will increase the energy in the specific detail levels that correspond to the characteristic fault frequencies identified by FFT. Table 5 shows the mapping between the DWT detail levels and the frequency bands containing the expected ITSC harmonics. For instance, Detail Level 10 (d_{10}) covers the 24-49 Hz band, which contains the prominent third harmonic ($3f_s \approx 36$ Hz), recognized as the most reliable and often largest indicator of

an ITSC, as discussed previously. To increase the reliability of the diagnosis and reduce false positives, Detail Level 9 (d_9) and 8 (d_8) are analyzed. Level 9 isolates the 49-98 Hz band, containing the fifth harmonic ($5f_s \approx 60$ Hz). An energy increase in this band provides supporting evidence, reinforcing the conclusion drawn from d_{10} and confirming that the anomaly is a structured harmonic fault rather than a random event. Conversely, the remaining detail levels are excluded from the fault-finding logic for different reasons. The high energy observed in details d_{11} and d_{12} is expected, as these bands contain the fundamental supply frequency (f_s) and represent the motor's healthy, baseline operational state, not a fault. Finally, the first seven details (d_1 - d_7) correspond to the highest frequency ranges, which are dominated by the inverter's PWM switching noise and other electromagnetic interference. As they contain no useful diagnostic information, they are disregarded in the analysis.

The energy content, P , of each detail signal is calculated using Eq. 4. The diagnosis can then be made by comparing the estimated energy content of any decomposed detail's healthy and faulty values. A significant increase in the energy of these specific details serves as a fault indicator, a technique validated in multiple studies on motor fault diagnosis (Qiu et al., 2021; Hu et al., 2021).

$$P = \frac{1}{T} \cdot \int_0^T (d_i(t)^2) dt \quad (4)$$

where d_i is the detailed signal.

The choice of the mother wavelet is crucial for the effectiveness of DWT. A higher-order wavelet provides better frequency resolution, which helps to isolate fault signatures from other signal components, though at an increased computational cost. Hence, there is an apparent trade-off between the order of the mother wavelet and the computational cost to separate the different frequency bands. The Daubechies family of wavelets has been shown to be effective for analyzing complex, non-stationary signals in servomotor applications (Roura and Romeral Martínez, 2011; Kim et al., 2008). Following (Pietrzak and Wolkiewicz, 2021), a Daubechies wavelet of order 13 (db13) was selected to reduce frequency crossover between adjacent decomposition bands.

However, DWT is not immune to challenges of frequency resolution. If strong, non-fault-related harmonics exist very close to the diagnostic frequency bands, their energy can leak into the detail levels of interest, potentially complicating the fault detection (Peng et al., 2009).

Ultimately, the strategic combination of FFT for steady-state conditions and DWT for transient analysis provides a holistic view of the motor's health, supporting fault detection across

Detailed Signal	Frequency Band [Hz]	Short Fault FFT Harmonics
Detail Level 8- d_8	98-195	$15f_s=180\text{Hz}$ $13f_s=156\text{Hz}$
Detail Level 9- d_9	49-98	$5f_s=60\text{Hz}$
Detail Level 10- d_{10}	24-49	$3f_s=36\text{Hz}$
Detail Level 11- d_{11}	12-24	f_s
Detail Level 12- d_{12}	0-12	f_s

Table 5. DWT Detail-Level Frequency Bands and Associated Short-Fault Harmonics

both steady-state and transient conditions evaluated in the FMCRD simulations.

2.5. Health Monitoring System Implementation

Following the signal processing and feature extraction steps, we obtain input data for the health monitoring system which consists of two stages, as mentioned in Section 2.1. This section details the technical implementation of this two-stage system, designed to address the challenges of monitoring FMCRD specifically. The core of the system is a hybrid data-driven pipeline that pairs AAKR for generating a healthy operational baseline with SPRT for statistical decision-making. This strategy is recognized for enhancing fault detection, as it allows each component to perform its specialized task: AAKR handles the complex, non-linear modeling, while a secondary method analyzes its output for signs of deviation (Hines et al., 2006; Li et al., 2017). The deliberate choice of a method that relies solely on normal operation data, a common necessity in industrial early warning systems where fault data is scarce or unavailable, is particularly well-suited for applications where interpretability and minimizing false alarms are important (Min et al., 2017).

2.5.1. Auto-Associative Kernel Regression (AAKR) for Signal Reconstruction and Residual Generation

Empirical modeling is the process of fitting a model to historical data to describe a system's behavior. The auto-associative kernel regression (AAKR) was selected as the nonparametric modeling technique for this work due to its proven performance in condition monitoring (Yu et al., 2018; Jung et al., 2025).

The first stage of our pipeline uses AAKR to create an empirical model of normal, fault-free operation. AAKR is a form of non-parametric modeling, which means it does not assume a closed mathematical form for the system. Instead, it operates as a "lazy learning" algorithm by maintaining a library of healthy historical data and making predictions for new observations based on local similarity (Baraldi et al., 2015).

As a lazy learning technique, AAKR does not try to define a single, global function for the system. Instead, it uses a library of historical data, or memory vectors, selected from normal, fault-free operation. For every new motor health observation (a query vector $\mathbf{q}$), the model makes a prediction by finding the most similar past observations in its library. A heavy emphasis is placed on these similar past observations to predict what the current measurements should be if the system were healthy.

This similarity is quantified using the Euclidean distance, shown in Equation 5, which measures how far the new query vector $\mathbf{q}$ is from each historical training vector $\mathbf{x}_i$.

$$d(\mathbf{x}_i, \mathbf{q}) = \sqrt{\sum_j (x_{ij} - q_j)^2} \quad (5)$$

A small distance implies high similarity. A Gaussian kernel is used to translate this distance into a similarity weight, as shown in Equation 6.

$$w_i = \exp\left(-\frac{d(\mathbf{x}_i, \mathbf{q})^2}{H^2}\right) \quad (6)$$

Here, w_i is the weight assigned to each historical vector, d is the Euclidean distance, and H is the bandwidth. The bandwidth is a critical smoothing hyperparameter that controls the model's bias-variance trade-off; a larger bandwidth results in a smoother, more generalized model, while a smaller bandwidth fits the training data more tightly.

The AAKR model then performs a kernel regression by using these weights to calculate a weighted average of the historical data, producing a reconstruction ($\hat{\mathbf{x}}$) of what the query vector $\mathbf{q}$ would look like under healthy conditions. The most important output from this stage is the residual vector, $\mathbf{r} = \mathbf{q} - \hat{\mathbf{x}}$, which represents the difference between the actual measurement and the healthy prediction (Qin, 2003). These residuals are the direct input for the next stage of analysis.

2.5.2. Sequential Probability Ratio Test (SPRT) for Anomaly Detection

While AAKR residuals indicate deviation, relying on a simple magnitude threshold is often insufficient. It can be insensitive to incipient faults and prone to false alarms from random noise. Therefore, there is a need for a different approach specifically designed for residual analysis. The Sequential Probability Ratio Test (SPRT) is one such method that can be used to determine if a significant change has occurred in the residuals generated by the AAKR model (Wald, 1945). It is commonly paired with AAKR for fault detection to utilize different strengths of each method (Li et al., 2017). While AAKR transforms the complex monitoring problem into a simpler one of analyzing residuals,

SPRT provides a robust statistical framework to decide whether these residuals indicate a fault.

SPRT is designed to efficiently distinguish between two competing hypotheses regarding the stochastic behavior of the AAKR residuals. Assuming these residuals follow a Gaussian distribution, the test decides between:

- Null hypothesis (H_0): Represents healthy operation. The residuals are drawn from a normal distribution with a mean of μ_0 (typically near zero) and a variance of σ^2 , denoted as $H_0 : r \sim \mathcal{N}(\mu_0, \sigma^2)$.
- Alternative hypothesis (H_1): Represents a specific fault condition. The mean of the residuals has shifted to a value μ_1 (representing the expected fault signature), while the variance σ^2 is assumed to remain constant, denoted as $H_1 : r \sim \mathcal{N}(\mu_1, \sigma^2)$.

The decision process involves calculating a cumulative test statistic, S_i , which integrates the evidence from the log-likelihood ratio of each new observation as shown in Equation 7.

$$S_i = S_{i-1} + \log \lambda_i \quad (7)$$

This statistic updates the cumulative log-likelihood ratio as each new observation arrives. Because it evaluates the decision boundaries at every step, it can defer a decision until sufficient evidence is obtained, giving it near-optimal sampling efficiency, requiring, on average, the fewest observations to reach a conclusion, and strong robustness to temporary noise (Chetouani, 2014). If S_i crosses a predefined fault threshold, H_0 is rejected, and a "flag" is raised for that feature to indicate a statistically significant deviation.

To further improve the system's robustness against measurement noise and prevent false alarms caused by isolated outliers, a voting scheme was implemented. An alert is generated only if a minimum number of monitored variables support the alternative hypothesis. The practice of fusing evidence from multiple information sources (in this case, feature-level flags) to make a more reliable decision is a common and effective strategy in industrial monitoring systems (Qiu et al., 2021; Han et al., 2024; Shao et al., 2017). The voting threshold is a tunable hyperparameter optimized to balance the system's sensitivity and specificity, detailed in the next section.

2.5.3. Stage-Specific Configurations

The AAKR-SPRT pipeline is configured differently for the two distinct goals of the framework: fault detection and fault diagnosis. To develop and evaluate each stage, dedicated datasets were generated using the physics-based Simulink model. All simulations included normally distributed white noise injected into the position sensor measurement, which

propagated through the Simulink model due to the closed feedback loop of the servomotor's speed PID controller to create a realistic signal environment.

A common principle in the design of both datasets is the intentional imbalance between healthy and faulted observations. In any real-world industrial system, healthy operation is the predominant state. The datasets reflect this reality, providing a large library of normal operational data to ensure the AAKR model can build a robust and accurate baseline of fault-free behavior. As described in Section 2.2, three primary fault types were modeled.

Stage 1 (Fault Detection) is designed for high sensitivity and serves as a first-pass screen. It uses a single model with the broad, global feature set of 25 variables (Table 3). The use of a wide range of features allows the system to create a wider net to catch any statistically significant anomaly. The SPRT voting threshold for this stage was empirically optimized to a cutoff of 3 flags to achieve high detection rates while maintaining a low false alarm rate.

The performance of this detection stage was evaluated on a dataset, summarized in Table 6. This experiment was designed to test performance against variations in fault timing. In the first set of simulations (Set 1), faults were injected at time $t = 0$. In the second, more challenging set (Set 2), fault injection times were varied between $t = 0.5s$ and $t = 1.0s$. This experimental design evaluates the system by first confirming its basic detection capability under ideal conditions (fault at $t = 0$) and then stress-testing its robustness against more challenging faults that occur at unpredictable times.

The data were segmented into discrete observation windows. Each window corresponds to a single control rod movement command, referred to in Table 6 and Table 8 as an observation window.

Dataset Type	Healthy	Short Fault Set 1	Step-load Set 1	Ramp-load Set 1	Short Fault Set 2	Step-load Set 2	Ramp-load Set 2
Total Observation Windows	233	23	24	24	46	48	48

Table 6. Dataset Composition for Stage 1 (Detection) Evaluation

The large number of healthy observations relative to faulted ones establishes a strong, representative baseline for normal operation. The second set of fault scenarios contains approximately double the number of observations as the first. This was done to test the system's robustness when faced with the additional variable of uncertain fault injection timing, which is a more realistic and challenging scenario.

Stage 2 (Fault Diagnosis) is designed for specificity and is

activated only after Stage 1 raises an alarm. As shown in Figure 1, this stage uses a multi-channel architecture of parallel SPRT classifiers, each dedicated to a specific fault class.

Each classifier uses a fault-specific tolerance vector derived from the separation between the healthy and corresponding fault residual distributions. For feature j and fault class F , the tolerance is defined as

$$\tau_{F,j} = \frac{|\mu_{0,j} - \mu_{F,j}|}{\sigma_{0,j}}, \quad (8)$$

where $\mu_{0,j}$ and $\sigma_{0,j}$ are the mean and standard deviation of the healthy residual for feature j , and $\mu_{F,j}$ is the mean residual for the corresponding fault class.

The specific configuration for each diagnostic classifier is detailed in Table 7. Each test monitors a curated subset of features known to be sensitive to its target fault and employs a stricter voting threshold that requires a high level of consensus among features before declaring a diagnosis.

SPRT Test	Alt. Hyp. H_1	Monitored Variables	Fault Alarm Thresholds
Load Fault	$\mu = \mu_1$	2, 3, 11, 13, 19	Load Alarms > 4 (of 5) Diagnostic Features
Short Fault	$\mu = \mu_1$	1, 6, 7, 12, 15, 19, 20	Short Alarms > 5 (of 7) Diagnostic Features

Table 7. SPRT Diagnostic Classifier Parameters for Stage 2

This targeted approach means that a diagnosis is based on a physically meaningful pattern of feature deviations, directly linking the output to the underlying failure mechanism.

The development of these diagnostic classifiers required a dedicated dataset for parameter tuning. To create it, a simulation of 60 control rods was run with randomized motion profiles (varying position, direction, and duration). The analysis was constructed on a "per-position step" basis, resulting in the 196 distinct observation windows detailed in Table 8. A key aspect of this development dataset was the use of a consistent fault magnitude, which provided a stable and controlled environment for calculating the fault-specific tolerances, $\tau_{F,j}$, and optimizing the voting thresholds shown in Table 7.

The final Stage 2 implementation was configured as follows. 499 healthy observations were used for AAKR training and 164 healthy observations were retained for evaluation, together with 12 Short, 11 Step-load, and 9 Ramp-load

Dataset Type	Healthy	Short Fault	Step-load	Ramp-load
Total Observation Windows	164	12	11	9

Table 8. Dataset Composition for Stage 2 (Diagnosis) Development

observations. The AAKR model used the 13 retained diagnostic features 1, 2, 3, 6, 7, 11, 12, 13, 14, 15, 16, 19, 20 from Table 4. The Short diagnostic channel used features 1, 6, 7, 12, 15, 19, 20 with a 6-of-7 voting requirement, while the Load channel used features 2, 3, 11, 13, 19 with a 5-of-5 requirement. Optimization using the healthy training data selected $H_{\text{opt}} = 0.16$ for development of the fault-specific tolerances. The final diagnostic operating bandwidth was $H = 0.25$. The SPRT parameters were $\alpha = 0.05$ and $\beta = 0.10$, with prediction clipping enabled.

3. RESULTS AND DISCUSSION

3.1. Simulation Verification and Physical-Parameter Sensitivity

The faults in Table 1 were injected and analyzed within the FMCRD model.

Sun et al. (Sun et al., 2007) modeled the same single-phase open-circuit, single-phase short-circuit, and three-phase short-circuit conditions in an interior PMSM Simulink model. Therefore, the resulting phase-current responses provide a published reference for checking whether the present fault implementation reproduces the expected qualitative post-fault behavior. Figure 8 compares the modeled phase-current responses following fault injection during steady-state operation with the trends reported by Sun et al. This comparison is used as a verification check on the implemented PMSM fault behavior. It is not an experimental validation of the BWRX-300 FMCRD model. Fault injection during steady-state operation also provides a common basis for comparison as injection during startup would interact with the motor-starting behavior and require separate analysis.

Figure 8(a) shows the three-phase currents at steady state and after a single-phase open-circuit fault for the FMCRD Simulink model and the comparison case from the literature. After the fault, the current in the interrupted phase approaches zero. For the wye-connected winding, the remaining two phase currents become approximately equal in magnitude and opposite in polarity. This is the expected circuit response when one phase is opened and current flows through the two remaining phases (Welchko et al., 2002; Sun et al., 2007). The open-circuit fault is not monitored in the health monitoring system; however, it is retained here as

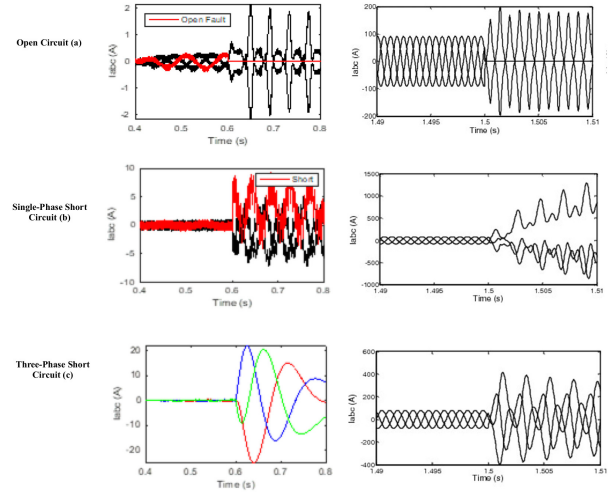


Figure 8. Simulation comparison of stator fault injection: (a) Open Circuit; (b) Single-Phase Short Circuit; (c) Three-Phase Short Circuit

an additional check that the electrical fault implementation behaves as expected.

Figure 8(b) shows the motor performance of a single-phase short-circuit fault at 0.6 s. The fault introduces an asymmetric low-impedance current path and produces a strongly unbalanced phase-current response. The current of the faulted phase (red) becomes more positive compared with the other two phases after fault injection, while the other two phase currents are predominantly negative. This loss of three-phase symmetry is consistent with the expected response of a PMSM to an asymmetrical short-circuit condition (Welchko et al., 2003; Sun et al., 2007).

The increase in current magnitude is smaller in the FMCRD model than in the literature case. The two models use different motor parameters, including a higher stator resistance in the FMCRD model, which can contribute to the difference in current magnitude. As a result, the comparison is focused on the fault-response behavior rather than matching the current magnitude exactly. Finally, Figure 8 c) shows a consequential three-phase short circuit if the short circuit fault is not detected before spreading to adjacent phases.

Although the applied terminal voltage drops to zero after the fault is injected, the rotating permanent-magnet field continues to induce current in the shorted windings. This produces a large transient current and electromagnetic braking as the rotor slows down. The current, speed, and torque responses are consistent with the expected behavior of a three-phase symmetrical short circuit (Welchko et al., 2003; Sun et al., 2007).

The agreement between the modeled responses and the expected PMSM fault behavior provides a qualitative

verification check on the implemented electrical fault responses and supports the use of the model for simulation-based diagnostic development. The comparison does not establish quantitative fidelity to the physical BWRX-300 FMCRD or constitute experimental validation, since operational or hardware-test data are not available.

A local physical-parameter sensitivity analysis was also performed to examine whether changes in the Simulink model parameters would change the final diagnostic result. Four parameter groups were varied one at a time by $\pm 10\%$: stator resistance R_s , stator leakage and magnetizing inductances (L_{ls}, L_{ms}) jointly, rotor inertia J , and motor viscous friction. Four representative cases were evaluated (Healthy, Short, Step-load, and Ramp-load) under the nominal configuration and eight perturbed configurations.

These parameters were selected because they represent key electrical and mechanical properties that directly influence the signals used for diagnosis. The stator resistance R_s affects the phase-current magnitude and voltage drop across the windings, while L_{ls} and L_{ms} govern the inductive current response and therefore influence the transient and frequency-domain behavior of the motor currents. Rotor inertia J affects the motor acceleration and deceleration and consequently the dynamic control response, including quantities such as rise and settling behavior. Motor viscous friction represents the mechanical resistance opposing shaft motion and affects the required motor torque and current during rod movement (Krause et al., 2015; Papananias et al., 2015). Together, these parameters provide representative variations in both the electrical and mechanical dynamics from which the classifier features are extracted.

For the sensitivity analysis, the diagnostic settings were kept fixed at $H = 0.25$, $\alpha = 0.05$, and $\beta = 0.10$, with prediction clipping enabled and voting requirements of 6/7 for Short and 5/5 for Load. No diagnostic settings or thresholds were recalibrated for the perturbed cases. Feature changes from each varied simulation were evaluated relative to its corresponding nominal simulation and applied to the nominal Stage 2 feature baseline.

Parameter	Variation	Max. Feature Change (%)	Max. Vote Change (Short / Load)	Diagnosis Changes
R_s	$\pm 10\%$	5.8	0/0	0
L_{ls}, L_{ms}	$\pm 10\%$	7.9	1/0	0
J	$\pm 10\%$	26.9	5/3	0
Motor friction	$\pm 10\%$	13.2	0/0	0

Table 9. Final Diagnostic Response to Physical Parameter Variations

As shown in Table 9, the parameter perturbations changed the simulated motor response and hence also produced changes in the diagnostic features extracted from the current and control-response signals. The reported maximum feature change represents the largest relative change observed among the Stage 2 diagnostic features for each parameter variation. Rotor inertia produced the largest observed feature change, 26.9%, and also caused the largest changes in the Short and Load voting counts. The maximum feature changes for R_s , (L_{ls}, L_{ms}), and motor friction were 5.8%, 7.9%, and 13.2%, respectively. Despite these changes in the feature values and voting counts, none of the tested perturbations changed the final diagnosis, and the fault-isolation accuracy remained 87.5%.

These results indicate that the diagnostic result was not sensitive to the tested $\pm 10\%$ variations in the individual parameter groups. However, this is only a local one-at-a-time sensitivity check and is not a global uncertainty analysis of the FMCRD model. It does not evaluate simultaneous parameter variations, probability distributions for parameter uncertainty, or structural model uncertainty.

3.2. Hyperparameter Optimization

The performance of the health monitoring framework relies on the interaction between the AAKR signal reconstruction and the SPRT anomaly detection. While the SPRT classifier makes the final decision, its sensitivity is heavily dependent on the quality of the residuals generated by the AAKR model. To optimize the system, the SPRT voting thresholds were fixed based on the logic described in Section 2.5.2 (requiring a minimum of 3 flagged features). A parametric sensitivity study was conducted on the AAKR bandwidth (H), which serves as the primary smoothing parameter of the kernel regression to control variance and bias in the output.

For Stage 1, bandwidths from $H = 0.10$ to 0.25 were evaluated. Increasing the bandwidth reduced the false positive rate (FPR) by smoothing small variations in the AAKR residuals without reducing the observed fault detection rate over the tested range. Among these settings, $H = 0.25$ provided the lowest FPR and was deemed optimal.

Table 10 summarizes the performance of the optimized health monitoring pipeline. Using the optimized AAKR model (Bandwidth $H = 0.25$) to generate residuals for the SPRT classifier, the system achieved a TPR of 85.9% and a FPR of 2.15% across the complete dataset (Set 1 and Set 2). While the SPRT logic successfully detected 100% of electrical faults (69 of 69), it missed several incipient mechanical load faults (detecting 114 of 144), as discussed in greater detail in the subsequent section.

For Stage 2, AAKR bandwidth selection involved two steps. Optimization using the healthy training data gave $H_{\text{opt}} =$

TPR	FPR	Electric Faults Detected	Mech. Faults Detected	Healthy False Alarms
85.9	2.15	69 of 69	114 of 144	5 of 233

Table 10. Stage 1 Performance Metrics of the Best Model
 $H = 0.25$

0.16, which was used to develop the fault-specific SPRT tolerances. The diagnostic bandwidth was then evaluated at $H = 0.10, 0.15, 0.20$, and 0.25 with these tolerances held fixed. Short and Load recall remained 9/12 and 20/20, respectively, while the number of healthy and cross-fault alarms decreased as the bandwidth increased. At $H = 0.25$, there were no healthy false alarms, no Load-to-Short cross-fault alarms, and one Short-to-Load cross-fault alarm. Although bandwidth selection was evaluated separately for the detection and diagnostic stages, $H = 0.25$ emerged as the optimum and was retained as the final operating bandwidth for both.

Because the Stage 2 diagnostic result also depends on the SPRT settings and voting logic, a one-at-a-time sensitivity study was performed around the final diagnostic configuration. In addition to the AAKR bandwidth, the analysis varied α , β , the fault-specific tolerance scale, the Short and Load voting requirements, and prediction clipping. Table 11 summarizes the tested range for each parameter and the resulting diagnostic performance. Here, fault-isolation accuracy represents the percentage of fault cases assigned to the correct diagnostic channel without activation of the other fault channel. The minimum and maximum isolation values are the lowest and highest accuracies observed over the tested values of each parameter. Cross-fault alarms refer to cases in which a Short fault activates the Load diagnostic channel or a Load fault activates the Short diagnostic channel. The final column reports the maximum number of cross-fault alarms observed over the tested values of each parameter.

As shown in Table 11, changes in α from 0.01 to 0.10 and β from 0.05 to 0.20 did not change the diagnostic decisions over the tested ranges. The result was more sensitive to the AAKR bandwidth, fault-specific tolerance scale, and voting thresholds. The extended bandwidth study also showed that $H = 0.25$ was the smallest tested bandwidth to reach the maximum observed isolation accuracy of 87.5%, with the same result obtained at $H = 0.30, 0.40$, and 0.50 .

Reducing the Short voting requirement from 6/7 to 5/7 increased Short detection from 9/12 to 10/12, but also produced eight Load-to-Short cross-fault alarms. Increasing the requirement to 7/7 reduced Short detection to 8/12. Reducing the Load voting requirement from 5/5 to 4/5 increased the number of Short-to-Load cross-fault alarms

Parameter	Test Range	Final	Min. Isolation (%)	Max. Isolation (%)	Max. Cross-Fault Alarms
Bandwidth H	0.10–0.50	0.25	31.2	87.5	21
SPRT α	0.01–0.10	0.05	87.5	87.5	1
SPRT β	0.05–0.20	0.10	87.5	87.5	1
Tolerance scale	0.50–1.50	1.00	62.5	87.5	9
Short votes	5–7	6	65.6	87.5	9
Load votes	4–5	5	81.2	87.5	3
Prediction clipping	Off/On	On	81.2	87.5	3

Table 11. Sensitivity of the Stage 2 Diagnostic Result to Selected AAKR–SPRT Parameters

from one to three. Prediction clipping provided a smaller improvement, reducing the total cross-fault alarms from three to one. These results support the selected diagnostic settings mainly through improved fault isolation and reduced cross-fault alarms.

3.3. Model Performance

The performance of the health monitoring framework is presented sequentially, beginning with the Stage 1 fault detection system, followed by the Stage 2 fault diagnosis system.

The primary role of Stage 1 is to function as a sensitive, high-level anomaly detector, providing a binary classification of the system's state as either "Healthy" or "Anomaly." It was evaluated using a dedicated training dataset (Set 1) and a separate, unseen validation dataset (Set 2) to test its robustness against variations in fault injection timing.

Figure 9 illustrates the model's performance on the training data. A clear separation is visible between healthy observations (blue 'x's, all below the cutoff) and all fault types, which are correctly flagged as anomalies by exceeding the threshold of 3 flagged features. This demonstrates the model's ability to learn an effective boundary for normal operation under ideal conditions.

The overall performance of the Stage 1 detector across both datasets is summarized in the confusion matrix in Table 12. The system achieved a TPR, or detection rate, of 85.9% and a FPR, or false alarm rate, of 2.15%. While the false alarm rate is low, the decision to not raise the cutoff threshold to eliminate these false positives was made to avoid further reducing the detection rate for the more subtle load faults.

The confusion matrix provides the high-level metrics, but the missed cases warrant a deeper analysis. The 30 false negatives (missed anomalies) are not random failures; as seen in Figures 9 and 10, they are almost exclusively concentrated

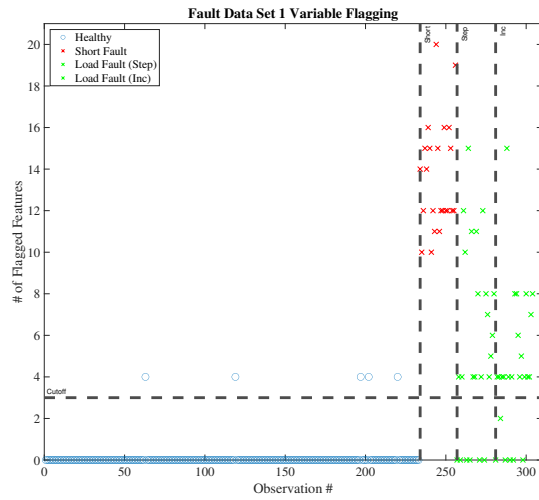


Figure 9. Stage 1 Fault Detection Performance on Training Data (Set 1)

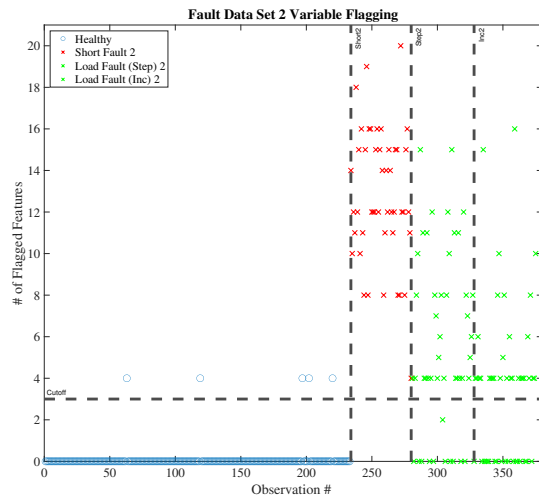


Figure 10. Stage 1 Fault Detection Performance on Validation Data (Set 2)

True Class	Predicted Class		Total
	Healthy	Anomaly	
Healthy	228	5	233
Anomaly	30	183	213

Table 12. Overall Confusion Matrix for Stage 1 Fault Detection

in the initial phases of the Ramp-load faults (labeled “Inc” and “Inc2”). The issue arises because the motor’s closed-loop controller successfully compensates for the small, initial magnitude of the load fault. This compensation masks the fault’s physical effects, leading to a weak signature that fails to cross the detection threshold. This clarifies the nature of the error: it is a problem of detection sensitivity during the fault’s incipient stage, not one of diagnostic misclassification.

Despite this specific challenge with incipient faults, the overall performance of Stage 1 is deemed sufficient for its intended role as a high-level screener. A detection rate of 85.9% demonstrates that the system successfully identifies the majority of anomalous events, particularly severe ones like short circuits. This detection rate was obtained with a FPR of 2.15%, reflecting the selected trade-off between sensitivity and false alarms. This performance reflects a deliberate design trade-off. The reduced sensitivity to low-magnitude, controller-masked faults remains a limitation of the Stage 1 detector. Stage 1’s role is to cost-effectively filter out clearly healthy data and forward any potentially anomalous observation to Stage 2 for fault diagnosis.

To provide a numerical comparison with other fault detection methods, Stage 1’s performance was also compared with a One-Class Support Vector Machine (OCSVM), Principal Component Analysis (PCA) T^2/Q monitoring, and Mahalanobis-distance monitoring. The alternative methods were fitted using healthy training observations only, without using fault labels for model fitting or threshold selection. The comparison, presented in Figure 11, used detection and FPR rather than raw observation counts.

The numerical benchmark was focused on methods that can be developed primarily from healthy-reference data because only a limited number of labeled fault observations are available. Mahalanobis-distance monitoring, PCA T^2/Q , and OCSVM were selected to represent multivariate distance-based, subspace-based statistical, and nonlinear one-class monitoring approaches, respectively. This allows comparison against several different fault-detection strategies without requiring the same limited fault observations to be used for both supervised model training and performance assessment.

As shown in Figure 11, AAKR–SPRT achieved a TPR of 85.9% at a 2.15% FPR. The corresponding TPRs were 60.6% for Mahalanobis monitoring, 56.3% for PCA T^2/Q , and 45.1% for OCSVM, with FPRs between 2.15% and 2.58%. The difference was mainly associated with the mechanical Load faults. All four methods detected the evaluated Short faults, while Load-fault recall was 79.2% for AAKR–SPRT, 41.7% for Mahalanobis monitoring, 35.4% for PCA T^2/Q , and 18.8% for OCSVM. Thus, for the simulated FMCRD data considered here, AAKR–SPRT provided a better balance between fault detection and false alarms, particularly for the Load faults.

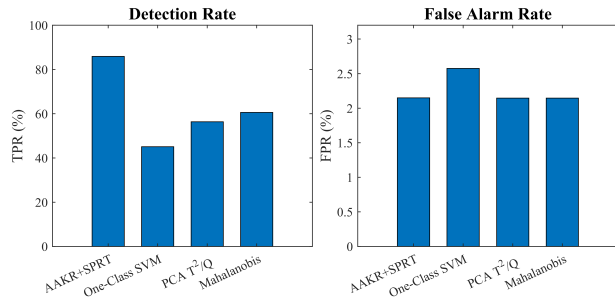


Figure 11. Stage 1 Fault Detection Performance of AAKR-SPRT and Comparable Methods

Once Stage 1 flags an anomaly, Stage 2 is activated to diagnose the specific fault type. This stage employs two parallel SPRT classifiers, one tuned specifically for Load faults and the other for Short faults. Fault isolation is assessed from the outputs of the two diagnostic channels, including whether the non-target channel is also activated. The performance of this diagnostic stage was assessed using its dedicated development dataset, as described in the methodology. This evaluation assesses the tuned classifiers' ability to distinguish between fault types in a controlled environment.

Figure 12 and Figure 13 illustrate the internal workings of the two parallel SPRT classifiers. The Load fault classifier (Figure 12) shows excellent separation, correctly flagging all 20 Load faults while rejecting all healthy data. This performance is quantified in Table 13, which confirms a 100% true positive rate (TPR) for Load faults. However, it incorrectly flags one Short fault, indicating some feature overlap. The Short fault classifier (Figure 13) correctly identifies 9 of the 12 Short faults, with the remaining three falling below its stricter threshold.

The final diagnostic decision is made by combining the outputs of these classifiers. The final diagnostic assessment is based on the outputs of the two channels; if neither channel reaches its voting threshold, no Stage 2 fault class is identified. To clearly assess the performance of each specialized classifier, the system was evaluated based on fault scenarios. Table 13 shows the results focused on identifying load faults, while Table 14 shows the results for identifying Short faults.

Dataset	Amount ID'd			Percent of Total		
	Healthy	Short	Load	Healthy	Short	Load
Healthy	164	0	0	100	0	0
Short Fault	11	0	1	91.67	0	8.33
Load Fault	0	0	20	0	0	100

Table 13. Confusion Matrix for Stage 2 Load Fault Classifier

The diagnostic system identified all 20 evaluated Load faults

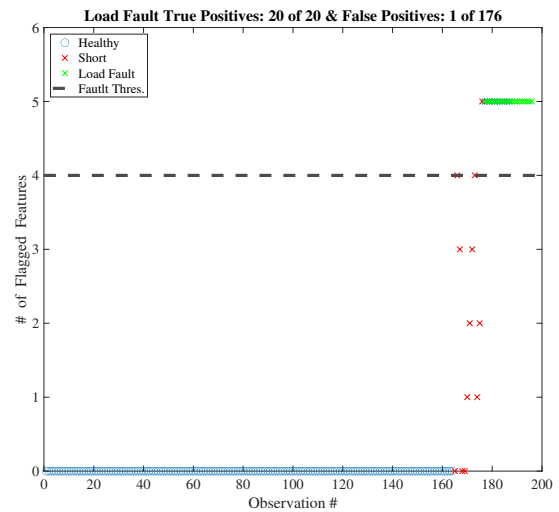


Figure 12. Stage 2 Internal Classifier: Load Fault SPRT Thresholding

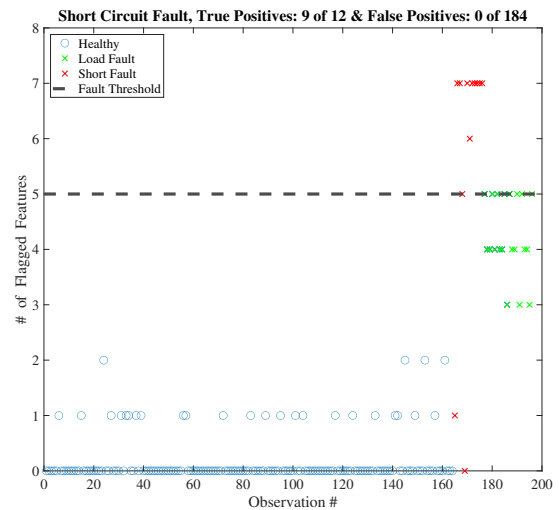


Figure 13. Stage 2 Internal Classifier: Short Fault SPRT Thresholding

Dataset	Amount ID'd			Percent of Total		
	Healthy	Short	Load	Healthy	Short	Load
Healthy	164	0	0	100	0	0
Short Fault	3	9	0	25	75	0
Load Fault	20	0	0	100	0	0

Table 14. Confusion Matrix for Stage 2 Short Fault Classifier

(100% TPR in Table 13) with no misclassification of healthy data. The main challenge is the diagnosis of Short faults. In the Short-fault-focused test (Table 14), the system achieves a 75% TPR (9 of 12), with the three missed faults being classified as healthy.

Investigation revealed these misses occurred because the fault was injected during the motor's braking phase when phase currents are near zero, rendering the fault signatures temporarily unobservable. Under these conditions, the current-based evidence was insufficient to activate the Short diagnostic channel.

Separately, the Load diagnostic-channel result (Table 13) reveals a single instance where a short fault was misclassified as a load fault. This indicates some overlap in the selected diagnostic features. The principal Stage 2 limitation in these cases is its dependence on the operating portion of the evaluated movement window.

A second comparison was performed for Stage 2 using a two-channel OCSVM. The OCSVM was fitted using healthy data with the same Short- and Load-oriented feature groups used by the corresponding AAKR-SPRT diagnostic channels. The purpose of this comparison was to examine both fault recall and the ability of the two diagnostic channels to separate the Short and Load fault classes.

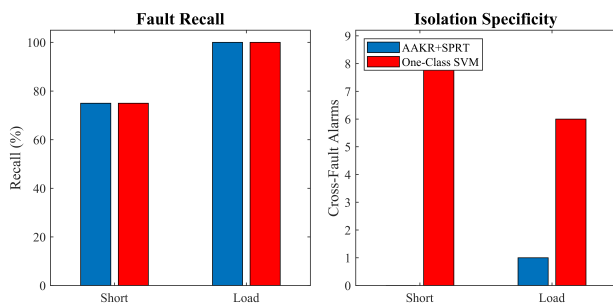


Figure 14. Stage 2 Comparison of AAKR-SPRT and a Two-Channel OCSVM Based on Fault Recall and Cross-Fault Alarms

Figure 14 shows that the two methods produced the same raw fault recall: 75% for Short faults and 100% for Load faults, with no healthy false-positive alarms in either diagnostic channel. The difference was observed in cross-fault alarms. AAKR-SPRT produced no Load-to-Short alarms and one Short-to-Load alarm, whereas the OCSVM produced eight Load-to-Short alarms and six Short-to-Load alarms. Therefore, the main advantage observed for the Stage 2 AAKR-SPRT configuration was better separation between the two fault types rather than higher raw fault recall.

A supervised deep learning model was not used as the primary numerical benchmark because the available labeled Stage 2 fault dataset is limited, containing only 12 Short and

20 Load observations. A separate supervised comparison would require further dividing this already small set among model fitting, hyperparameter selection, and independent evaluation, leaving a very small and strongly split-dependent test set. The numerical comparison was therefore focused on methods that can be implemented within the same healthy-reference setting and evaluated using the same extracted diagnostic features.

A direct deep learning comparison would also change the diagnostic representation as well as the classifier. The present framework operates on physically interpretable features extracted from current, position, and control-response signals, whereas many deep learning approaches are designed to learn representations directly from larger sets of raw or minimally processed signal data. Differences in performance would reflect both the learned representation and the classification method, rather than isolating the diagnostic decision approach examined here. Deep learning and hybrid methods remain relevant alternatives for FMCRD monitoring and should be evaluated in future work when larger simulation datasets and, ultimately, hardware or operational measurements are available.

The choice of sensing modality is another important consideration when interpreting the present results. The framework relies on motor current, position, and control-response features rather than an independent vibration channel. This choice reflects both the signals available in the modeled FMCRD control architecture and the operating characteristics of the application. The BWRX-300 uses an individual FMCRD motor for each control rod (?). Unit-specific vibration monitoring would therefore require dedicated vibration instrumentation across the individual drives, whereas phase current and rod-position feedback are already used by the closed-loop drive controller. The intermittent duty cycle of the FMCRD also favors analysis of these controller signals: each commanded rod movement provides a well-defined transient interval from which position-response and current features can be extracted, while intermittent and low-speed operation can make conventional vibration spectral signatures more difficult to interpret (?). Current-based monitoring therefore provides a non-intrusive diagnostic signal without introducing a separate sensing modality, consistent with the established use of Motor Current Signature Analysis for electrical-machine fault detection (?).

Vibration measurements can nonetheless provide complementary sensitivity to bearing-related impacts and other mechanical responses (Randall, 2011), while instantaneous angular-speed and speed-signature methods provide alternative kinematic indicators (Moustafa et al., 2014; Huang et al., 2025). Combining multiple sensing channels can further improve diagnostic separability by

capturing different manifestations of the same fault (Han et al., 2024; Ji et al., 2025). Because the present simulation does not contain an independent vibration channel, a direct numerical comparison with vibration-based monitoring was not performed. Such a comparison is better suited to future hardware or test-rig studies in which electrical, kinematic, and vibration measurements can be evaluated on the same physical system.

All performance metrics are reported on a segment-by-segment basis. However, in an operational setting, these segment-level flags would be collated and post-processed to establish flag persistence before an alert is raised. Such logic could improve resistance to isolated transient flags, but its effect on detection delay and diagnostic performance would need to be evaluated separately.

Although the system is designed to operate as a pipeline, the two stages were evaluated independently to assess their respective functions separately. Stage 1 was tested on its ability to separate healthy from anomalous data, whereas Stage 2 was tested on its specialized ability to classify different fault types from a dedicated fault dataset. This approach allows for a clear understanding of each stage's capabilities before their integration into a sequential, operational workflow.

The results above use the full 13-feature Stage 2 configuration. The extent to which this feature set can be reduced without changing the diagnostic result is examined next.

3.4. Feature Reduction Analysis

The Stage 2 diagnostic model was initially evaluated using the features retained after the fault-sensitivity screening described in Section 2.3.2. Because several of these features capture related aspects of the motor response, correlation-guided pruning was used to determine whether the feature set could be reduced without affecting the reported fault-isolation performance. Figure 15 shows the diagnostic performance as features were progressively removed along the predefined correlation-based pruning path derived from the healthy training data.

The diagnostic result remained unchanged as the feature set was reduced to five features. The five-feature set consisted of F_3 , F_{12} , F_{13} , F_{15} , and F_{19} , corresponding to: Settling Time, Startup Peak Frequency, Startup Peak Power, Steady-State Peak Frequency, and Down Peak Power, respectively. With this subset, the model retained the original Short recall of 9/12 and Load recall of 20/20, with no healthy false alarms in either diagnostic channel, no Load-to-Short cross-fault alarms, and one Short-to-Load cross-fault alarm. The resulting fault-isolation accuracy remained at 87.5%.

Further reduction to four features decreased diagnostic

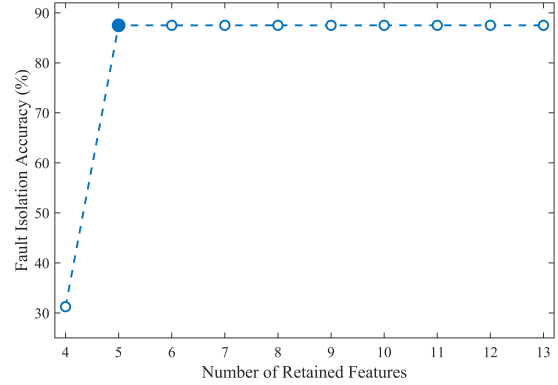


Figure 15. **Stage 2 Performance Along the Correlation-Guided Feature Pruning Path.** The original performance is preserved through a five-feature subset, while further reduction to four features decreases diagnostic performance.

performance. The five-feature configuration is therefore the smallest subset along this pruning path that reproduces the original Stage 2 performance. This result indicates that several features in the original feature set are not required. The diagnostic implementation can potentially be simplified without sacrificing the observed performance. However, the five-feature set should not be interpreted as a globally optimal feature subset because the analysis follows a single correlation-guided removal path rather than an exhaustive search over all possible feature combinations.

The retained features also span different portions of the FMCRD response rather than representing repeated measurements of a single signal characteristic. Settling Time captures the transient control response; the startup and steady-state spectral features characterize changes in the motor-current behavior during different operating phases; and Down Peak Power provides information from the deceleration period.

4. CONCLUSION

In this work, we implemented a two-stage fault detection and diagnosis framework for the BWRX-300 FMCRD servomotor, built on physics-informed features and well-established diagnostic methods. When evaluated using the simulated FMCRD datasets, Stage 1 achieved an 85.9% true positive rate with a 2.15% false positive rate, while Stage 2 identified 100% of the Load faults and 75% of the Short faults.

The contribution lies in the application-specific integration of AAKR-SPRT within a two-stage architecture that combines simulation-based fault generation, physically interpretable motor and control-response features, anomaly detection, and fault isolation. The numerical comparisons further showed higher Stage 1 detection for AAKR-SPRT than for the tested

Mahalanobis, PCA, and OCSVM alternatives at similar FPR. In Stage 2, AAKR–SPRT and the two-channel OCSVM produced the same raw Short and Load recall, but AAKR–SPRT produced substantially fewer cross-fault alarms.

These results show that broad anomaly detection and fault-specific diagnosis can be combined into an interpretable simulation-based diagnostic baseline for FMCRDs before operational fault data become available.

The two stages serve complementary purposes. Stage 1 asks only whether the system is behaving normally, making no assumptions about fault type. This capability is especially important in nuclear applications, where not all failure modes can be foreseen. Stage 2, by contrast, assumes that fault classes are known and uses curated features to identify the mechanism, answering the question of what kind of fault is happening. Notably, the staged approach also aligns with the lifecycle of data. Stage 1 can be developed primarily from healthy-reference data, providing monitoring value before labeled fault data become available. As more data are accumulated over time, Stage 2 can refine fault isolation with additional knowledge, while Stage 1 remains a lightweight front end that prevents classifiers from being overused on clearly normal data.

At the same time, some limitations and directions for improvement remain. In Stage 1, several incipient load faults were missed, likely because the closed-loop controller masked their early response signatures; incorporating additional features tied to control effort could improve sensitivity. In Stage 2, three of the 12 Short observations were not identified by the Short diagnostic channel when the evaluated window coincided with the braking portion of the motor response, where the phase currents approached zero. Additional transient electrical features or operating-state-dependent diagnostic logic could be examined for these conditions.

More fundamentally, the Simulink model of the PMSM drive can itself be refined. Certain diagnostic features increased under multiple fault types, leading to confusion between electrical and mechanical degradations. Improving the physical fidelity of the model, narrowing its scope to a more specific motor–controller configuration, and selecting features with higher independence across fault classes would strengthen fault isolation.

The local physical-parameter sensitivity analysis provides an initial check on this model dependence as none of the tested $\pm 10\%$ one-at-a-time variations in stator resistance, inductance, rotor inertia, or motor viscous friction changed the final Stage 2 diagnosis. However, this result should not be interpreted as global uncertainty quantification because simultaneous parameter uncertainty and structural model uncertainty were not evaluated. The scope of the present work

is fault detection and diagnosis rather than remaining useful life (RUL) prediction. In particular, the Ramp-load case represents a time-varying mechanical loading condition used for diagnostic evaluation; it is not a validated degradation law, and no end-of-life criterion is defined from which RUL could be estimated.

Future work should also explore hybrid physics-informed and data-driven feature design, adaptive thresholding, complementary vibration and multi-signal monitoring, and hardware-in-the-loop validation to evaluate the framework beyond the present simulation study. This study establishes an initial simulation-based fault detection and diagnosis framework for advanced reactor applications as they move from design to operation.

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