

Machine Learning-Based Fault Detection And Health Monitoring Of Brushless DC Motors For Electric Propulsion In Civil Aviation Using Experimental Data

Aria Nazarpour¹

¹ Flight Faculty, Georgian Aviation University, Tbilisi, Georgia , <https://orcid.org/0009-0009-5315-0348>

*Corresponding Author: Aria Nazarpour

Abstract - The increasing adoption of electric propulsion in civil aviation introduces new challenges for the reliable assessment of propulsion system health. Data-driven approaches provide effective tools for identifying deviations in electrical and mechanical behaviour prior to functional failure. This study presents a custom-developed experimental test stand representing a scaled light electric propulsion system, instrumented to measure brushless DC (BLDC) motor parameters including voltage, current, rotational speed, thrust, temperature, and acoustic noise under controlled operating conditions. Motor performance was validated under healthy no-load and propeller-loaded configurations using manufacturer-recommended components. Predefined non-destructive fault scenarios, including battery degradation and propeller damage, were then introduced to generate representative faulty operating states. A supervised Support Vector Machine (SVM) classifier was employed to distinguish between healthy and faulty conditions using multi-sensor experimental data. The proposed approach achieved an overall classification accuracy of approximately 97%, with a fault detection recall of about 98%, demonstrating strong discriminative capability using physically interpretable features. Scenario-based validation under previously unseen operating conditions further indicates the model's ability to generalize beyond training cases. The developed framework provides a lightweight and experimentally grounded solution for condition monitoring of electric propulsion systems and establishes a foundation for future extensions toward unsupervised learning and predictive maintenance.

Keywords - Civil aviation, aircraft maintenance, brushless DC motor, electric propulsion, fault detection, SVM, machine learning.

1. INTRODUCTION

The aviation industry is under increasing pressure to reduce greenhouse gas emissions and environmental impact, in line with global climate objectives extending toward 2050. In response to these challenges, electric and hybrid-electric propulsion systems have emerged as promising solutions for reducing carbon emissions, lowering noise levels, and improving energy efficiency in civil aviation applications [1], [2]. These propulsion concepts are particularly attractive for light aircraft and emerging urban air mobility platforms, where electric powertrains can offer operational and environmental advantages over conventional combustion engines.

Brushless DC (BLDC) motors play a central role in electric and hybrid-electric propulsion systems due to their high efficiency, favourable power-to-weight ratio, and relatively low maintenance requirements. Despite these advantages, BLDC motors remain susceptible to faults arising from propeller-related mechanical degradation and power-source-related electrical disturbances. In safety-critical civil aviation applications, even minor degradations in motor performance can adversely affect system reliability and operational safety. Consequently, reliable fault detection and continuous health monitoring are essential requirements for the widespread adoption of electric propulsion technologies [3], [4].

Traditional aviation maintenance strategies are typically classified as reactive or preventive. Reactive maintenance addresses failures after they occur, while preventive

maintenance replaces components at predefined intervals. Although these approaches are well established, they can be inefficient or overly conservative for electric propulsion systems, where component degradation does not always follow predictable time-based patterns. As a result, condition-based maintenance and health monitoring strategies have gained increasing attention, leveraging operational data to assess the actual condition of components and to support informed maintenance decisions [5]. Fault detection represents a fundamental first step toward such data-driven maintenance frameworks. Recent research has demonstrated the potential of machine learning (ML) techniques for fault detection and diagnosis in electrical machines, including BLDC motors. Both supervised and unsupervised approaches have been investigated using electrical, acoustic, and vibration-based measurements [6]-[9]. However, many existing studies rely on complex sensor configurations, long-term degradation datasets, or deep learning architectures, which may be impractical for early-stage experimental validation or simplified laboratory environments.

In contrast, this study presents a practical and experimentally validated fault detection framework for BLDC motors used in civil aviation electric propulsion systems. A supervised Support Vector Machine (SVM) classifier was employed to distinguish between healthy and faulty operating conditions using short-term steady-state measurements. Experimental data were collected on a custom laboratory test stand using standard motor analysis instrumentation, thrust measurement, and environmental sensors. Motor operation was first validated under no-load conditions and subsequently under propeller-loaded conditions using a manufacturer-recommended propeller. Artificial fault scenarios, including propeller damage and power-source abnormalities, were introduced to evaluate the effectiveness of the SVM-based classification approach.

The main contributions of this work are summarized as follows:

- Development of an experimental framework suitable for fault detection studies in electric propulsion systems using readily available instrumentation.
- Validation of a binary SVM-based fault detection method achieving reliable fault detection using experimentally measured electrical, mechanical, thermal, and acoustic features, without requiring long-duration testing or complex sensing architectures.
- Establishment of a foundation for future research toward continuous health monitoring and predictive maintenance of electric propulsion systems.

II. BACKGROUND AND LITERATURE REVIEW

A. Maintenance Strategies and Health Monitoring

Aviation maintenance strategies have traditionally been classified as reactive or preventive. Reactive maintenance addresses failures after occurrence, leading to unplanned downtime and potential safety risks, while preventive maintenance replaces components at fixed intervals regardless of their actual condition. Although preventive approaches improve safety, they often result in unnecessary replacements and increased operational costs, particularly for systems with variable operating profiles [5].

With the increasing adoption of electric propulsion systems, these traditional strategies are becoming less effective. Electric motors, power electronics, and energy storage systems exhibit degradation mechanisms that are not strictly time-dependent. Consequently, condition-based maintenance (CBM) and health monitoring approaches have gained significant attention. These strategies rely on operational measurements to

assess component health and support maintenance decisions based on actual operating conditions rather than predefined schedules.

Health monitoring systems aim to identify deviations from normal behavior at an early stage, enabling corrective actions before faults evolve into failures. Fault detection represents the fundamental first layer of such systems and is particularly critical for safety-critical applications such as civil aviation, where reliability and availability are essential.

B. Fault Detection in Brushless DC Motors

Brushless DC (BLDC) motors are widely used in electric propulsion systems due to their high efficiency and compact design; however, they remain vulnerable to various fault types. Common faults include electrical degradation in windings, propeller-related mechanical imbalance, and power-source disturbances such as battery voltage instability. These faults can manifest as changes in electrical signals, mechanical output, thermal behavior, and acoustic emissions.

Machine learning techniques have been increasingly applied to fault detection in electrical machines. Supervised learning methods, particularly Support Vector Machines (SVM), have demonstrated strong performance in classifying healthy and faulty operating states using measured features. Prior studies have successfully applied SVM-based approaches using vibration, acoustic, and electrical measurements, including applications in small unmanned aerial vehicle motors [6], [7].

Unsupervised learning methods have also been explored for scenarios where labeled fault data are limited. Clustering and anomaly detection techniques can identify deviations from normal behavior without explicit fault labels [8]. However, these approaches often require large datasets and careful parameter tuning to minimize false alarms, which can limit their practicality in early experimental studies or small-scale laboratory environments.

C. Research Gap and Motivation

Despite substantial progress in ML-based fault detection for BLDC motors, several limitations remain in the existing literature. Many studies focus on long-term degradation analysis, deep learning architectures, or complex sensing systems that are not well suited to early-stage experimental validation or simplified laboratory setups. Furthermore, experimental investigations targeting BLDC motors for civil aviation electric propulsion, particularly those incorporating thrust measurements and environmental effects, remain limited.

This study addresses these gaps by proposing a simple and experimentally grounded fault detection framework based on supervised SVM classification. The approach integrates electrical, mechanical, thermal, acoustic, and environmental measurements. By relying on short-term steady-state measurements, fault detection is achieved without long-duration testing, reducing experimental complexity and hardware risk.

Focusing on binary classification between healthy and faulty operating conditions, this work establishes a clear and interpretable baseline for fault detection in electric propulsion systems. The proposed methodology is designed to be extensible, providing a foundation for future research on unsupervised learning, degradation analysis, and predictive maintenance using the same experimental platform.

III. EXPERIMENTAL SETUP

A. Brushless DC Motor and Propeller Selection

The experimental investigations were conducted using a commercially available brushless DC (BLDC) outrunner motor, model A2217-2300 KV (4T), which is widely used in small-scale electric propulsion applications and for which manufacturer reference data are publicly available. The motor specifications, including rated voltage range, KV constant, maximum current capability, efficiency characteristics, and recommended propeller sizes, were obtained from manufacturer datasheets and distributor technical documentation [10].

According to the manufacturer specifications, the A2217-2300 KV motor, shown in Fig. 1, is designed to operate within a recommended voltage range of 7.4 V to 11.1 V, corresponding to 2S-3S LiPo battery configurations. In this study, a 7.4 V (2S) power supply was deliberately selected to ensure compatibility with all measurement instruments, power electronics, and safety constraints of the experimental stand. This choice maintains operation well within the motor's nominal design envelope and avoids unnecessary thermal or mechanical stress during repeated experimental runs.

Fig. 1. A2217-2300 KV brushless DC outrunner motor.



The theoretical no-load rotational speed of a BLDC motor can be approximated by formula shown (1):

$$RPM_0 = K_V \times V \quad (1)$$

Where K_V is the motor velocity constant (rpm/V), V is the applied voltage, and RPM_0 is the no-load rotational speed in revolutions per minute. For the tested motor operating at 7.4 V, this relationship yields a theoretical no-load speed of approximately 17000 rpm, which is used as a reference for validating experimentally measured rotational speed values.

For loaded operation, the motor was equipped with a manufacturer-recommended 6×4E propeller [11], shown in Fig. 2. The first value (6 inches) denotes the propeller diameter, while the second value (4 inches) represents the geometric pitch. This propeller selection follows established motor-propeller matching principles, whereby high-KV motors are paired with relatively small-diameter and moderate-pitch propellers to limit current draw and maintain acceptable efficiency. This configuration represents a realistic operating condition for small electric propulsion systems while avoiding motor overloading.

Fig. 2. 6×4E two-blade propeller.



B. Thrust Measurement and Mechanical Configuration

Thrust measurements were obtained using a Mayatech MT10 Pro thrust test stand, which measures axial thrust through a calibrated load-cell mechanism. The thrust stand provides real-time thrust readings displayed in grams and ounces, enabling direct comparison with manufacturer performance data. For analysis and reporting, thrust values are converted to SI units where required.

The thrust stand was mounted on a rigid base positioned at the edge of the experimental table. The distance between the propeller plane and the downstream thrust measurement reference point was approximately 10 cm, ensuring consistent airflow conditions and repeatable force transmission during testing. A two-axis spirit level indicator was used to verify that the thrust stand remained level throughout all experiments, minimizing measurement bias due to unintended gravitational components.

C. Electrical Power Supply and Battery System

Electrical power was supplied using a 2S lithium-polymer (LiPo) battery with a nominal voltage of 7.4 V, which provides controlled charging current, cell balancing, and voltage monitoring prior to each experimental run.

To ensure stable electrical conditions, the experimental setup included a dedicated battery power station supplying the thrust stand and motor analyzer. A separate power distribution unit was used to supply auxiliary equipment, including environmental sensors, display monitors, and data recording devices. This separation minimized electrical interference and improved measurement repeatability.

D. Instrumentation and Sensor Configuration

Motor electrical and rotational parameters were measured using a SkyRC BMA-01 motor analyzer, which provides real-time measurements of voltage, current, electrical power, and rotational speed. The analyzer was configured according to the motor pole count to ensure accurate RPM readings.

Thermal and environmental conditions were monitored using two independent sensors: a combined air intake temperature and relative humidity sensor positioned upstream of the propeller, and

a contact temperature sensor attached directly to the motor stator casing.

The sensor configuration, enables correlation between electrical loading, thermal response, and environmental conditions without introducing destructive stress to the motor.

E. Data Acquisition and Visual Recording

All experimental runs were visually recorded using a fixed camera mounted on a rigid metal stand, ensuring a constant viewing angle and repeatable framing across all tests. The camera simultaneously captured the displays of all measurement devices and the mechanical behavior of the propulsion system, as shown in Fig. 3.

A laptop workstation was used for monitoring and data storage, supported by an external 15-inch ASUS monitor configured as a secondary display. This dual-screen configuration enabled real-time observation of experimental parameters on one screen while recording and validating data on the other.

Fig. 3. Full experimental table showing motor, propeller, sensors, power distribution, laptop, and external monitor.



F. Experimental Scope and Relevance to General Aviation

The experimental setup enables controlled investigation of BLDC motor behavior under both no-load and propeller-loaded conditions using manufacturer-recommended components and operating limits. Fault scenarios are introduced in a non-destructive manner, allowing repeated measurements without compromising motor integrity.

Although the test stand represents a small-scale laboratory system, this work is not focused on unmanned aerial vehicles or drone-specific applications. Instead, the setup serves as a representative experimental platform for studying electric motor behavior, fault characteristics, and maintenance-relevant indicators applicable to light general aviation aircraft. The emphasis is placed on identifying performance deviations, abnormal operating patterns, and health monitoring strategies relevant to reliable operation of electric propulsion systems in manned light aircraft.

IV. TEST PROCEDURE AND DATA ACQUISITION

A. Test Strategy and Operating Conditions

The experimental campaign was designed to evaluate BLDC motor behaviour and fault detectability under controlled and repeatable conditions. All tests were conducted at eight discrete throttle levels (1-8) using the SkyRC BMA-01 motor analyser. At each throttle level, the motor was operated until quasi-steady-state conditions were reached prior to data recording.

Electrical, mechanical, thermal, acoustic, and environmental parameters were recorded simultaneously. Although data extraction is currently performed from recorded video frames, a Python-based optical character recognition (OCR) framework using Tesseract is

integrated into the methodology to enable automated numerical extraction and future real-time monitoring. These data extraction is double checked with manual video analysis (frame by frame) to ensure no error is captured in data readings.

B. Environmental Conditions

Experiments were conducted under three ambient temperature conditions (T1-T3) and three relative humidity levels (RH1-RH3). Temperature variation was achieved by conducting experiments in different indoor environments, while relative humidity was adjusted using a laboratory humidifier. Exact temperature and humidity values were measured during each experiment and recorded as part of the dataset.

Environmental variations were included to evaluate the robustness of the fault detection method under realistic operating conditions without exceeding safe motor limits.

C. Operating Scenarios and Dataset Structure

Two operating categories were defined: healthy and faulty. Healthy operation included nominal battery condition, an intact manufacturer-recommended 6×4E propeller, all throttle levels, and all environmental combinations.

Faulty operation included degraded or unstable battery behaviour and a chipped propeller introducing rotor imbalance. Internal motor faults were intentionally excluded to avoid irreversible damage. Data were organized into four subsets:

- Validate0: No-load motor operation (no propeller)
- Validate1: Propeller-loaded validation at maximum throttle
- Normal operation: Healthy configuration across all conditions
- Fault scenarios: Battery and propeller faults across all conditions

This structure ensured consistency, repeatability, and traceability across the dataset.

D. Data Recording and Visual Monitoring

All experimental runs were visually recorded using a fixed camera capturing the displays of all instruments and the mechanical behaviour of the propulsion system. Regions of interest (ROI) were defined for each display to enable synchronized extraction of electrical, mechanical, thermal, and environmental parameters (Fig. 4).

Fig. 4. Camera view showing OCR regions of interest for automated data extraction.



TABLE IV SUMMARIZES THE MEASURED FEATURES USED FOR FAULT DETECTION, ALONG WITH THEIR PHYSICAL UNITS AND DESCRIPTION.

Feature	Symbol	Unit	Description
Supply voltage	(V)	V	Battery voltage
Current	(I)	A	Current draw
Rotational speed	RPM	rpm	Rotational speed
Thrust	(T)	g	Axial thrust
Motor temperature	(T_m)	°C	Stator/casing temperature
Ambient temperature	(T_a)	°C	Intake air temperature
Relative humidity	RH	%	Ambient relative humidity
Acoustic noise	(N)	dB	Sound level near the motor
Velocity constant	(K_V)	rpm/V	Motor velocity constant

V. FAULT DEFINITIONS AND SCENARIO CLASSIFICATION

This section defines the fault types considered in the study and the structure of the experimental scenarios used for supervised learning. Clear and physically meaningful fault definitions are required to ensure that the classifier learns abnormal behaviour rather than normal operational variability.

A. Healthy Operating Condition

A healthy operating condition is defined as operation within manufacturer-recommended limits without intentional degradation. This includes a functional BLDC motor, a healthy 2S LiPo battery, an intact 6×4E propeller, all throttle levels, and varying environmental conditions. Temperature and humidity variations are treated as operating conditions rather than faults.

B. Battery Fault Definition

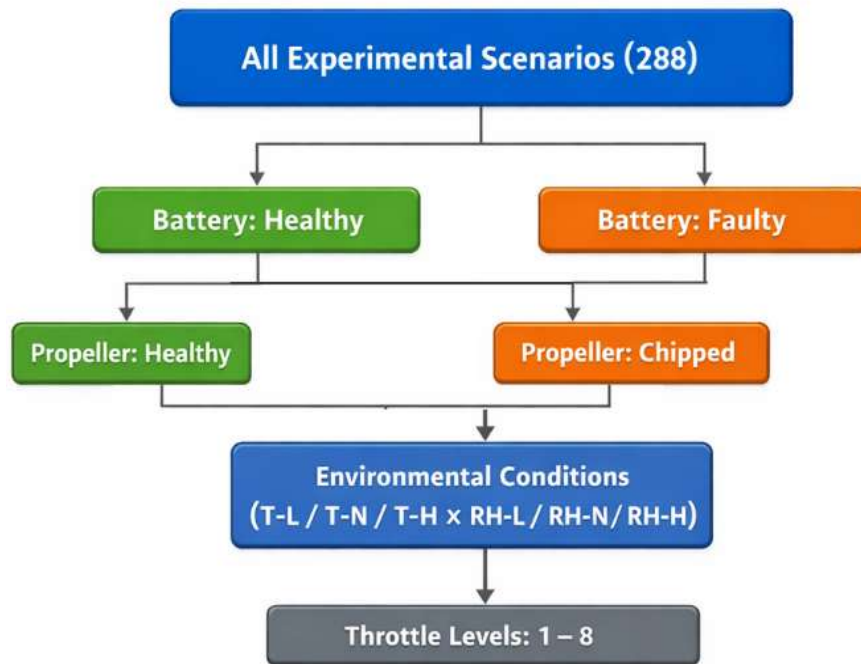
Battery faults are defined as abnormal electrical behaviour originating from the power source, including increased internal resistance, voltage sag under load, and unstable voltage response during throttle changes. These effects directly influence current, rotational speed, thrust, and thermal behaviour, making them observable through multi-sensor measurements without physically modifying the motor.

C. Propeller Fault Definition

A mechanical fault is introduced by creating a controlled chipped-propeller condition, representing rotor imbalance and altered aerodynamic loading. This fault leads to increased vibration and acoustic emissions, as well as changes in thrust and current characteristics, while remaining non-destructive and repeatable.

D. Scenario Classification and Experimental Design

Each experimental scenario is defined by a unique combination of throttle level, temperature, humidity, battery condition, and propeller condition, as illustrated in Fig. 5.

Fig. 5. Hierarchical classification of experimental scenarios.

A full factorial design was adopted:

$$8 \times 3 \times 3 \times 2 \times 2 = 288 \text{ scenarios}$$

Table V, summarizes the environmental classes, fault conditions, and experimental scenario structure used to generate the complete dataset.

TABLE V SUMMARY OF ENVIRONMENTAL CLASSES, FAULT CONDITIONS, AND EXPERIMENTAL SCENARIO STRUCTURE USED FOR SUPERVISED LEARNING.

Category	Class	Symbol	Range
Relative Humidity	Low (Dry)	RH-L	$\leq 40 \%$
	Moderate	RH-N	41 - 60 %
	High (Humid)	RH-H	$\geq 61 \%$
Ambient Temperature	Low (Cold)	T-L	$\leq 15 ^\circ\text{C}$
	Normal	T-N	16 - 25 $^\circ\text{C}$
	High (Hot)	T-H	$\geq 26 ^\circ\text{C}$
Battery Condition	Healthy		
	Faulty		
Propeller Condition	Healthy		
	Faulty		
Throttle Levels	1 - 8		
Total Scenarios	288		

This structure ensures systematic coverage of the operating envelope and fault space, supporting reliable supervised learning and generalization.

VI. FAULT DETECTION METHODOLOGY

This section describes the supervised machine learning framework used for fault detection. The focus is on reliable binary classification of healthy and faulty operating conditions using short-duration steady-state measurements.

A. Feature Vector and Class Labels

Each experimental operating point is represented by a feature vector shown in (2):

$$\mathbf{x}_i = [V_i \quad I_i \quad RPM_i \quad K_{V,i} \quad T_i \quad T_{m,i} \quad RH_i \quad N_i]^T$$

where the features represent electrical, mechanical, thermal, acoustic, and environmental parameters. Each feature vector is assigned a binary class label shown in (3):

$$y_i \in \{0,1\}$$

where “0” denotes healthy operation and “1” denotes faulty operation.

B. Support Vector Machine Formulation

A Support Vector Machine (SVM) classifier is employed to maximize the separation margin between healthy and faulty classes. For linearly separable data, the separating hyperplane is defined as shown in (4):

$$\mathbf{w}^T \mathbf{x} + b = 0$$

For experimental data, a soft margin formulation shown in (5) is used to allow controlled misclassification:

$$\min_{\mathbf{w}, b, \xi} \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{i=1}^N \xi_i$$

subject to (6):

$$y_i(\mathbf{w}^T \mathbf{x}_i + b) \geq 1 - \xi_i, \xi_i \geq 0$$

To preserve physical interpretability and avoid unnecessary model complexity, a linear Support Vector Machine (SVM) formulation was adopted in this study. Preliminary analysis indicated that the selected electrical, mechanical, thermal, acoustic, and environmental features provide sufficient separability between healthy and faulty operating conditions in the original feature space. Consequently, nonlinear kernel mappings were not required at this stage. The use of a linear decision boundary enables direct association between feature variations and underlying physical fault mechanisms, which is desirable for maintenance-oriented fault detection.

C. Training and Scope

All features are normalized prior to training to ensure equal weighting. This article focuses on demonstrating the fault detection methodology using representative scenarios. The SVM framework provides an interpretable and experimentally robust baseline for

fault detection, with extensions toward unsupervised learning and predictive maintenance identified as future work.

VII. EXPERIMENTAL RESULTS AND DISCUSSION

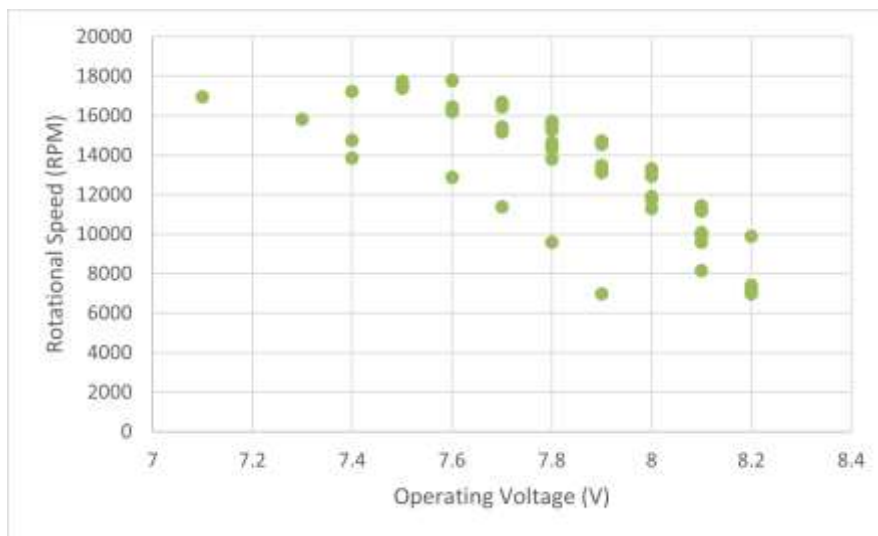
This section presents and discusses the experimental results obtained from the electric motor test bench and the corresponding fault detection outcomes produced by the Support Vector Machine (SVM) classifier. The results are analyzed with respect to physical consistency, repeatability, and classification reliability. Quantitative classification performance is reported using accuracy, fault detection recall, and feature space visualization.

A. Motor Performance Validation Under Healthy Conditions

Prior to fault analysis, the experimental setup was validated under nominal operating conditions using a 2S (7.4 V) LiPo battery and a manufacturer-recommended 6×4E propeller. Measured parameters, including voltage, current, rotational speed, and thrust, exhibited stable and repeatable behavior across identical throttle levels.

The estimated motor velocity constant K_V , derived from experimental measurements, remained consistent with manufacturer reference values within an acceptable error margin, confirming the validity of the experimental setup and measurement chain shown in Fig. 6.

Fig. 6. Measured RPM as a function of operating voltage under healthy conditions, illustrating voltage variation due to normal loading effects.



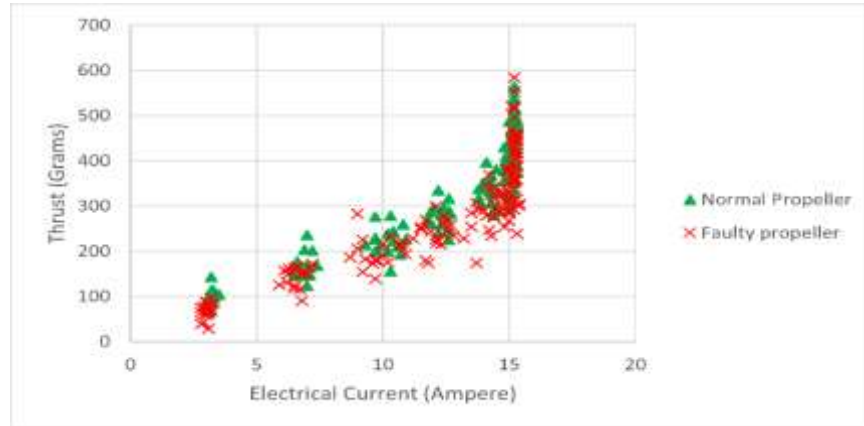
B. Electrical and Mechanical Signatures of Fault Scenarios

Two fault categories were investigated: battery degradation and propeller damage. Battery-related faults resulted in reduced RPM at identical throttle settings, increased current draw for equivalent thrust, and deviations in estimated K_V . These effects are consistent with increased electrical losses and voltage sag.

Propeller-related faults produced increased acoustic noise, localized rises in motor stator temperature, and reduced thrust efficiency at comparable electrical input. These

deviations are attributed to aerodynamic imbalance and increased mechanical loading, shown in Fig. 7, under identical throttle settings.

Fig. 7. Comparison of thrust and current for healthy and faulty propeller conditions.

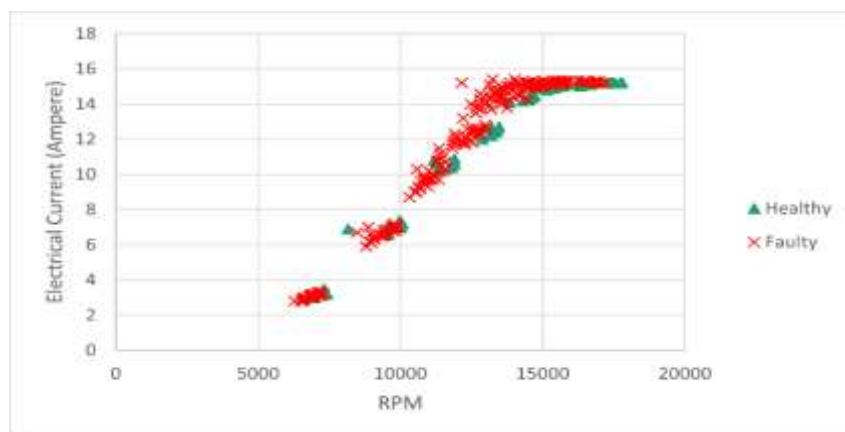


C. Feature Space Separability and Classification Results

An initial linear SVM was trained using an 80/20 stratified train-test split. The classifier achieved an accuracy of 96.6%, with a fault detection recall of 98%, demonstrating strong discriminative capability of the selected features.

In the multidimensional feature space defined by the selected electrical, mechanical, thermal, acoustic, and environmental features, healthy and faulty data points exhibit partial overlap but remain separable using a linear decision boundary in the original feature space. Key contributing features include the current-RPM relationship, thrust-to-power ratio, and motor temperature rise relative to intake airflow conditions, shown in Fig. 8, using directly measured features without additional feature transformation.

Fig. 8. Visualization of experimental data illustrating linear separability between healthy and faulty operating points in the selected feature space.



The trained SVM classifier demonstrated stable classification performance under the considered experimental conditions and robust behavior across the evaluated environmental variations. Misclassifications occurred primarily near transitional operating conditions, which is expected in practical systems.

D. Physical Interpretability and Practical Relevance

A key advantage of the proposed methodology is the physical interpretability of classification outcomes. For example, increased current combined with reduced RPM indicates electrical inefficiency, whereas elevated temperature and acoustic noise at comparable electrical input suggest mechanical imbalance. This interpretability is essential for maintenance-oriented applications in electric propulsion systems.

Although the experiments were conducted at small scale, the observed fault signatures are physics-driven and therefore scalable to light electric propulsion systems for manned aircraft.

E. Limitations and Key Findings

The study is limited to steady-state measurements, binary fault classification, and a representative dataset size; however, these constraints are sufficient to demonstrate reliable fault detection using the proposed framework. These limitations are acceptable for a first-stage fault detection study. The main findings confirm that the test bench produces physically consistent measurements, fault scenarios introduce measurable deviations, and SVM enables reliable binary fault detection using multi-sensor data.

VIII. MODEL GENERALIZATION AND SCENARIO BASED VALIDATION

To assess robustness beyond training conditions, scenario-based validation was performed using operating conditions not included in the training dataset used for SVM model development. These scenarios are designed to provide representative post-training validation cases rather than exhaustive statistical evaluation, demonstrating the model's ability to classify previously unseen operating points

A. Scenario Definitions

Three validation scenarios were defined a conceptual schematic illustrating scenario composition and expected classification outcomes:

- Scenario S1 (Healthy, unseen environment): Healthy battery and propeller under temperature and humidity conditions not included in the training dataset. Expected classification: Healthy.
- Scenario S2 (Single fault, unseen environment): Single fault condition (battery degradation or propeller damage) under temperature and humidity conditions not included in the training dataset. Expected classification: Faulty.
- Scenario S3 (Combined fault): Simultaneous battery degradation and propeller damage under temperature and humidity conditions not included in the training dataset. Expected classification: Faulty.

B. Scenario-Based Evaluation Procedure and Metrics

For each scenario, data were collected across all throttle levels, normalized using the same preprocessing pipeline applied during training, and classified using the trained SVM model. Performance was evaluated using classification accuracy, fault detection behavior, and consistency across throttle levels, defined as stable classification outcomes across all throttle settings within each scenario. Table VIII summarizes the classification outcomes for each validation scenario across all throttle levels.

TABLE VIII SCENARIO-BASED VALIDATION RESULTS OF THE TRAINED SVM MODEL

Scenario	Fault condition	Environment	Expected class	Observed classification
S1	Healthy	Unseen	Healthy	Healthy
S2	Single fault	Unseen	Faulty	Faulty
S3	Combined fault	Unseen	Faulty	Faulty

C. Discussion on Model Generalization

The results demonstrate that the proposed framework maintains reliable classification under unseen environmental conditions. Scenario S1 confirms low false-positive behavior, while Scenarios S2 and S3 validate sensitivity to both single and compounded fault conditions. These results indicate that the classifier captures physically meaningful fault signatures rather than overfitting to specific experimental configurations, supporting scalability to real operational environments.

IX. CONCLUSIONS AND FUTURE WORK

A This study presented an experimental and data-driven framework for fault detection and health monitoring of a brushless DC motor intended for light electric propulsion applications. A custom test stand was developed to acquire synchronized electrical, mechanical, thermal, acoustic, and environmental data under controlled conditions. Motor operation was validated under no-load and propeller-loaded configurations within the nominal operating envelope.

A supervised SVM classifier was employed to distinguish between healthy and faulty operating states using short-duration steady-state measurements. Non-destructive fault scenarios, including battery degradation and propeller damage, were introduced, and reliable fault detection was demonstrated across multiple throttle levels and environmental conditions. The proposed SVM-based approach achieved an overall classification accuracy of approximately 97%, with a fault detection recall of about 98%, confirming the effectiveness of the selected features and experimental framework.

Scenario-based validation under previously unseen conditions confirmed the generalization capability of the trained model and its robustness to environmental variability. The results indicate that the proposed framework provides a lightweight, interpretable, and experimentally validated solution for condition monitoring of electric propulsion systems relevant to light civil aviation.

Future work will extend the methodology to additional fault types, longer-duration operation, and progressive degradation, enabling predictive maintenance and remaining useful life estimation. Unsupervised learning approaches and scaling toward higher-power propulsion systems will also be investigated.

ACKNOWLEDGEMENT

The author declares that this research was conducted independently and did not receive external funding.

REFERENCES

- [1] I. Moir and A. Seabridge, Aircraft Systems: Mechanical, Electrical, and Avionics Subsystems Integration, 3rd ed. Hoboken, NJ, USA: Wiley, 2008.

- [2] European Commission, Flightpath 2050: Europe's Vision for Aviation. Luxembourg: Publications Office of the European Union, 2011.
- [3] J. R. R. A. Martins and A. Ning, Engineering Design Optimization. Cambridge, U.K.: Cambridge Univ. Press, 2021.
- [4] M. J. Kearns and J. H. Vincent, "Reliability and safety considerations for electric propulsion aircraft," IEEE Aerosp. Electron. Syst. Mag., vol. 35, no. 6, pp. 24-34, Jun. 2020.
- [5] A. Heng, S. Zhang, A. C. C. Tan, and J. Mathew, "Rotating machinery prognostics: State of the art, challenges and opportunities," Mech. Syst. Signal Process., vol. 23, no. 3, pp. 724-739, Apr. 2009.
- [6] M. Dubarry, C. Truchot, and B. Y. Liaw, "Synthesize battery degradation modes via a diagnostic and prognostic model," J. Power Sources, vol. 219, pp. 204-216, Dec. 2012.
- [7] Z. Zhang, S. Li, and Y. Tian, "Fault diagnosis of brushless DC motors based on support vector machines," IEEE Trans. Ind. Electron., vol. 67, no. 5, pp. 3792-3801, May 2020.
- [8] S. Chalapathy and S. Chawla, "Deep learning for anomaly detection: A survey," ACM Comput. Surv., vol. 54, no. 2, pp. 1-38, Mar. 2022.
- [9] A. Bellini, F. Filippetti, C. Tassoni, and G. Capolino, "Advances in diagnostic techniques for induction machines," IEEE Trans. Ind. Electron., vol. 55, no. 12, pp. 4109-4126, Dec. 2008.
- [10] RC Buying, "A2217 Brushless DC Motor Technical Specifications," RC Buying Co., 2023. [Online]. Available: <https://www.rcbuying.com>
- [11] APC Propellers, "Electric Propeller Performance Data," APC Propellers, 2023. [Online]. Available: <https://www.apcprop.com>