Summary Report

Integrated Proactive Multi-Fault Detection for Predictive Maintenance Applications

Ph.D. in Aerospace Engineering
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Francesco Marino

Supervisors:
Prof. Giorgio Guglieri, Supervisor
Prof. Paolo Maggiore, Co-Supervisor

1 Introduction and Research Objectives

This thesis addresses a critical challenge in modern aerospace engineering: developing robust and reliable methods for predictive maintenance of complex electromechanical systems. The research focuses on fault detection and identification (FDI) techniques that can identify multiple coexisting degradation modes while providing well-calibrated uncertainty estimates. The work is motivated by the significant economic benefits of prognostics and health management (PHM) in aviation, including reduced unscheduled maintenance, enhanced aircraft availability, optimized spare parts inventory, and mitigation of ”No Fault Found” cases.

Modern aircraft systems integrate increasingly complex components that interact in ways that complicate fault detection and isolation. Traditionally, maintenance interventions have been predetermined based on fixed schedules established during the design phase, leading to inefficiencies where still-functional components might be replaced or, conversely, damaged components might continue to operate. PHM strategies aim to continuously monitor the actual health status of components, enabling more informed maintenance decisions and improved remaining useful life (RUL) predictions.

The research focuses on electromechanical actuators (EMAs), which represent a promising technology in flight control systems, potentially eliminating the need for traditional hydraulic systems and reducing aircraft weight, fuel consumption, and maintenance costs. However, their widespread adoption in primary flight controls is limited by concerns regarding reliability and the risk of mechanical jamming. Implementing effective PHM for these systems requires addressing four key challenges:

1. The indirect nature of sensor measurements, which do not directly correlate with component degradation states
2. The scarcity of labeled failure data in aerospace applications
3. The complexity of detecting multiple concurrent faults
4. The need for reliable uncertainty quantification in degradation estimates

To address these challenges, this research develops and evaluates two novel model architectures: the Integrated Fault Detection and Isolation (IFDI) model and the Multi-Model Residual FDI (MMR-FDI). Both architectures incorporate deep learning techniques to extract meaningful features from time-series data and provide probabilistic estimates of degradation parameters. The methodology employs stimulus signals to identify multiple failures and implements end-to-end data-driven architectures that integrate prior information with observational data.

2 Research Methodology and Approach

The research methodology follows a systematic approach that integrates physics-based modeling with advanced machine learning techniques. The core of this approach involves three primary steps:

1. Development of a high-fidelity physics-based model of an electromechanical actuator

2. Collection and processing of simulated data representing various degradation scenarios

3. Design and implementation of machine learning models for fault detection and isolation

2.1 High-Fidelity Electromechanical Actuator Model

A comprehensive high-fidelity model of an electromechanical actuator was developed to provide a reliable simulation environment for generating training and validation data. This model captures the complex dynamics of the EMA, including electromagnetic interactions, mechanical transmission, and control electronics. The model incorporates three critical degradation modes:

1. **Friction Degradation (FDTx)**: Manifests through increased static and dynamic friction in mechanical transmission elements, particularly affecting gear teeth surfaces and bearing components.

2. **Backlash Development (BLK)**: Represents mechanical play between transmission components, implemented through a hysteresis-based approach centered on the user shaft position.

3. **Static Rotor Eccentricity (Zeta)**: Occurs when the rotor's axis of rotation becomes offset from the stator's axis of symmetry, resulting in magnetic field asymmetry.

The model was validated through a dedicated test bench campaign, ensuring its accuracy in replicating the behavior of real EMAs under various operating conditions and degradation scenarios. This validation established the model's reliability as a foundation for generating comprehensive datasets to train the fault detection algorithms.

2.2 Data Collection and Processing

The dataset generation process involved three thousand simulations using the high-fidelity model with different operating conditions (degradation parameters and external loads). To ensure comprehensive coverage of potential operating conditions, four key parameters were varied parametrically:

- Friction degradation (FDTx): ranging from nominal conditions to severe degradation
- Backlash (BLK): variations from 0 to critical values typical of mechanical wear
- Static eccentricity coefficient (Zeta): parameter indicating the static eccentricity of the rotor
- External loads: simulating various aerodynamic conditions encountered during cruise

The research focused on the cruise phase of flight, where the actuator experiences relatively steady-state conditions, making it ideal for fault detection analysis. A simplified stimulus signal was developed to extract relevant portions of the actuator response during cruise conditions, enabling multiple detection points per flight.

Mueen's Algorithm for Similarity Search (MASS) was employed to identify patterns of interest within the response recorded during the cruise. This approach ensured robust detection of fault signatures, even at different rates or with slight temporal distortions. The extracted time series segments, each corresponding to the stimulus signal pattern, formed the foundational dataset for training the FDI models.

2.3 Fault Detection and Isolation Model Architectures

Two complementary model architectures were developed for fault detection and isolation:

2.3.1 Integrated Fault Detection and Isolation (IFDI) Model

The IFDI model architecture leverages the feature extraction capabilities of convolutional neural networks to minimize direct manipulation of the original time series. The model processes two input sequences from simulation results: θ_m (motor angular velocity) and I_{3eq} (three-phase equivalent current). This dual-input approach enables comprehensive fault detection by simultaneously analyzing mechanical and electrical signatures.

The architecture consists of three main components:

- One-dimensional convolutional layers (1D CNN) that serve as feature extractors from the temporal sequences
- Pooling layers that reduce feature map dimensionality

- Fully connected layers that process the flattened feature maps

To prevent overfitting and enable uncertainty estimation, dropout with a 0.3 rate is applied between the dense layers. The model outputs estimates for three degradation parameters (FDTx, BLK, and Zeta) along with their associated uncertainties.

2.3.2 Multi-Model Residual FDI (MMR-FDI)

The MMR-FDI architecture addresses the limitations of the IFDI model, particularly focusing on the output layer configuration constraints and complex degradation scenarios. This advanced approach maintains the CNN-based feature extraction foundation while implementing specialized model architectures for subsequent processing.

The MMR-FDI follows a four-phase process:

1. **Base Model Training**: Multiple models leverage the robust CNN feature extractor before specializing in different degradation patterns

2. **Model Selection using Conditional Mutual Information (CMI)**: Systematically identifies models that contribute unique information while minimizing redundancy

3. **Weight Optimization**: Determines optimal model contribution weights

4. **Prediction and Uncertainty Estimation**: Combines model outputs to generate final degradation estimates with confidence intervals

The MMR-FDI architecture incorporates both parametric and non-parametric models, creating a complementary system where each model's strengths compensate for others' limitations. This hybrid approach proves more robust than the IFDI model, particularly in handling edge cases and anomalous behavior patterns.

3 Uncertainty Quantification and Estimation

A critical aspect of the research is the development of robust uncertainty estimation in the fault detection process. Both model architectures incorporate mechanisms for quantifying uncertainties in their predictions, providing essential information for risk-aware decision-making in maintenance planning.

3.1 Dropout for Bayesian Approximation

The research implements Monte Carlo dropout as a Bayesian approximation mechanism to provide uncertainty estimates for the degradation parameters. Dropout serves a dual purpose in the models:

1. As a regularization method to prevent overfitting

2. As a means for uncertainty quantification

During inference, multiple forward passes are executed with different dropout masks, generating a distribution of predictions for each degradation parameter. The variance in these predictions serves as a measure of epistemic uncertainty (model uncertainty), while the mean provides the best estimate of the degradation level.

3.2 Uncertainty Integration in MMR-FDI

The MMR-FDI architecture implements a more sophisticated uncertainty estimation framework that combines individual model uncertainties with ensemble diversity. Each model in the ensemble provides uncertainty estimates through different mechanisms:

- Neural Network Models (FNN, IFDI): Employ Monte Carlo dropout for Bayesian approximation

- Density-Based Cluster Regression (DBCR): Derives uncertainty from density measurements and distance to cluster centroids

- Random Forest (RF): Extracts prediction intervals directly from the distribution of individual tree outputs

These heterogeneous uncertainty estimates are combined using a Gaussian mixture approach that accounts for both individual model uncertainties and inter-model disagreement. This comprehensive approach enables the MMR-FDI to provide well-calibrated uncertainty estimates that appropriately reflect the confidence in its predictions across different operating conditions.

4 Results and Performance Evaluation

The performance of both model architectures was evaluated using a comprehensive test dataset generated through the high-fidelity simulation model. The evaluation focused on the accuracy of degradation parameter estimation and the calibration of uncertainty estimates.

4.1 IFDI Model Performance

The IFDI model demonstrated strong predictive capabilities for the FDTx (friction coefficient) and Zeta (eccentricity) parameters throughout the normalized damage range. For these parameters, the model maintained an error margin of approximately $\pm 5\%$ across the full degradation spectrum, with appropriately calibrated uncertainty bounds.

However, the model exhibited limitations in accurately estimating the BLK (backlash) parameter, particularly in the high degradation range (0.4-1.0). The model systematically underestimated backlash in this range while maintaining accuracy in the low range (0.0-0.4). This limitation was attributed to the non-linear dynamics of backlash, where beyond a certain threshold, its impact on actuator response diminishes, creating a saturation effect that complicates the learning process.

A key feature of the IFDI model was its ability to express appropriate epistemic uncertainty, with uncertainty bounds widening in regions where training data was sparse. This heteroscedasticity demonstrated how the model calibrated prediction confidence, appropriately expressing reduced confidence when predicting beyond well-represented regions of the training data.

4.2 MMR-FDI Performance

The MMR-FDI architecture demonstrated significant performance improvements across all three degradation parameters compared to the IFDI model. Quantitatively, the MMR-FDI achieved average relative error reductions of approximately:

- 22% for FDTx (friction coefficient)
- 35% for BLK (backlash)
- 18% for Zeta (eccentricity)

Most notably, the MMR-FDI successfully addressed the high-range BLK estimation limitations present in the IFDI model. While some estimation bias remained visible, the model effectively resolved the severe underestimation at high degradation levels that characterized the IFDI model.

The uncertainty quantification capabilities of the MMR-FDI demonstrated appropriate heteroscedasticity across the prediction range, with well-calibrated confidence intervals that expanded in regions where training data was sparse. This behavior confirmed the model's ability to express appropriate epistemic uncertainty, a critical feature for deployment in safety-critical applications.

4.3 Comparative Analysis

A comprehensive comparison between the IFDI and MMR-FDI models revealed significant performance differentials across the three degradation parameters, with the MMR-FDI consistently demonstrating superior estimation capabilities at the expense of increased architectural complexity.

The superior performance of the MMR-FDI comes with measurable computational costs. The model's architectural complexity introduces approximately 45% increased inference time compared to the IFDI approach, requiring additional computational resources for both training and deployment. Despite these additional costs, the performance improvements justify the increased complexity for applications where degradation parameter estimation accuracy is paramount, particularly in safety-critical systems.

5 Conclusions and Future Developments

The research demonstrated the critical importance of uncertainty estimation in fault detection and isolation processes for electromechanical systems. Through 3,000 simulations using a high-fidelity multi-domain numerical model, the study generated a comprehensive dataset to train and evaluate multiple model architectures for estimating three coexisting degradation parameters: friction coefficients (FDTx), backlash (BLK), and radial eccentricity of the rotor (Zeta).

The IFDI model architecture utilized one-dimensional convolutional layers as the primary feature extractor, demonstrating effective capability to capture significant topological features in sequential data. This architecture successfully controlled overfitting through dimensionality reduction and strategic layer design while maintaining computational efficiency.

The advanced MMR-FDI architecture substantially improved performance across all degradation parameters, delivering average relative error reductions of approximately 22% for FDTx, 35% for BLK, and 18% for Zeta compared to the IFDI model. Most significantly, this enhanced approach successfully addressed the high-range BLK estimation limitations present in the IFDI model.

Both architectures demonstrated robust uncertainty quantification capabilities, with confidence intervals widening in regions where the model needed to extrapolate beyond well-represented training data. This approach demonstrated appropriate uncertainty estimation, providing valuable information for decision-making in safety-critical applications.

5.1 Future Research Directions

Several promising directions for future research emerge from this work:

1. **Transfer Learning**: Implementing transfer learning methodologies could significantly reduce the computational and time requirements for adapting these models to new electromechanical systems with different operating characteristics.

2. **Edge Computing Implementation**: Investigating the implementation of these models on edge computing devices would enable real-time monitoring in resource-constrained environments.

3. **Long-term Prognostics**: Extending the current framework to perform long-term prognostics by forecasting degradation parameter evolution over extended operational periods would transform these diagnostic tools into comprehensive prognostic systems.

6 Summary and Significance

This thesis presents a comprehensive multi-fault detection and isolation framework in electromechanical actuators with robust uncertainty quantification. The developed approaches offer several key advantages over existing methods:

1. **Multi-fault Detection**: The ability to simultaneously estimate multiple degradation parameters, addressing a critical challenge in practical PHM applications.

2. **Uncertainty Quantification**: Well-calibrated uncertainty estimates that appropriately reflect confidence levels across different operating conditions and degradation scenarios.

3. **Architectural Innovation**: Novel model architectures that effectively balance performance, computational efficiency, and generalization capability.

4. **End-to-End Approach**: Integration of feature extraction and parameter estimation in a unified framework, eliminating the need for manual feature engineering.

The research contributes to prognostics and health management by addressing fundamental fault detection and isolation challenges for safety-critical systems. The developed methodologies demonstrate how advanced machine learning techniques can enhance maintenance planning and operational safety in aerospace applications.

The proposed approaches have potential applications beyond electromechanical actuators, extending to various complex industrial systems where accurate degradation estimation and uncertainty quantification are essential for ensuring reliability and safety. By enabling more informed maintenance decisions, these methods can help reduce operating costs, enhance system availability, and improve overall safety in critical applications.

In conclusion, this research establishes a foundation for reliable fault detection in safety-critical systems by analyzing predictive performance across different degradation scenarios. The demonstrated uncertainty estimation capabilities across prediction ranges represent a critical feature for deployment in applications where confidence quantification is as crucial as prediction accuracy.