Chapter 11
Advanced Condition Monitoring framework for CFRP Gear Drivetrains Using Machine Learning and Multibody Dynamics Simulations

G. Karyofyllas, J. Koutsoupakis, and P. Giagopoulos

Abstract The advancements in key industry sectors such as automotive, wind turbines, oil, and gas have led to the increased use of Carbon-Fiber Reinforced Polymer (CFRP) materials in constructing shafts and gears with metal connectors for transmission drivetrain applications. Monitoring the health of these drivetrain components can prevent failures and enable effective maintenance schedules, ensuring high availability, reliability, and maintainability. Real-time condition monitoring (CM) via vibration measurements allows for fault detection and predictive maintenance. The accuracy and robustness of a CM application depend significantly on the availability of data for various health states, which typically necessitates comprehensive experimental measurements. In this work, an innovative condition monitoring (CM) framework for detecting and localizing damage in a lab-scale gear drivetrain system is presented. The framework leverages Machine Learning (ML) models that are trained on data produced through numerical simulations based on an Optimal Multibody Dynamics (MBD) model of the physical system. The experimental drivetrain is a single-stage system using CFRP shafts and gears, necessitating a high-fidelity MBD model to accurately represent the nonlinear material properties and layup of the CFRP shaft, as well as the 3D-printed gear set. The system, comprising shafts and gears, is mounted in four support bearings included in the MBD model. The model's precision is improved by thoroughly modeling the contact mechanics involved in gear meshing. This includes the development of an innovative contact force model that considers the influences of variable mesh stiffness, transmission error, and backlash. The objective is to perform damage identification across different health states using simulated responses for supervised health state classification, rather than relying solely on experimental data. Damage scenarios considered include cracks and delamination in the composite shaft and surface roughness, spalls, or missing teeth in the gear pair. The robustness and accuracy of the ML models are validated by accurately classifying faults in the physical system, demonstrating the proposed damage detection method's generalization capabilities and potential.

Keywords Carbon-Fiber Reinforced Polymer (CFRP) · Condition Monitoring (CM) · Multibody Dynamics (MBD) · Machine Learning (ML) · Gear Drivetrain · Damage Detection · Contact Mechanics

Introduction

In recent years, the increasing adoption of advanced materials like Carbon-Fiber Reinforced Polymer (CFRP) in key industry sectors, including automotive, wind turbines, and oil and gas, has sparked a transformation in the design and manufacturing of critical drivetrain components such as shafts and gears. The superior mechanical properties of CFRP, including a high strength-to-weight ratio, fatigue resistance, and corrosion resistance, make it an ideal choice for applications requiring high-performance, lightweight components [1]. These materials are particularly suited for transmission drivetrain systems, where energy efficiency, durability, and reliability are paramount. However, as CFRP components are integrated more widely into complex mechanical systems, the need for effective monitoring and maintenance strategies becomes increasingly important to prevent unexpected failures and optimize operational performance [2].

A crucial aspect of ensuring the reliability and performance of drivetrain systems is the ability to monitor the health of components in real time. Condition monitoring (CM) plays a vital role in detecting early signs of wear, damage, or faults in

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drivetrain components, enabling predictive maintenance and reducing the risk of costly breakdowns [3]. Among the various CM techniques, vibration-based monitoring is a well-established method for identifying faults in rotating machinery [4]. By analyzing the vibrational response of components, it is possible to detect deviations from normal operating conditions that may indicate the presence of damage, such as cracks, surface roughness, or gear tooth wear [5]. This approach provides a non-invasive and efficient means of assessing the health of drivetrain systems [6].

Despite the advantages of vibration-based condition monitoring, one of the key challenges is the requirement for a comprehensive dataset that accurately represents various health states of the system. In traditional CM approaches, this dataset is typically generated through extensive experimental measurements, which can be time-consuming, costly, and sometimes impractical, especially when dealing with novel materials like CFRP [7]. Moreover, obtaining experimental data for different damage scenarios and fault types may be difficult due to the complexity and diversity of possible failure modes in drivetrain systems. Therefore, there is a need for innovative methods to complement or replace experimental data collection for the development of robust condition monitoring frameworks [8].

In this work, is proposed an innovative condition monitoring framework that addresses these challenges by leveraging numerical simulations to generate training data for machine learning (ML) models. The proposed framework focuses on the detection and localization of damage in a lab-scale gear drivetrain system that incorporates CFRP shafts and gears. Rather than relying solely on experimental data, a high-fidelity multibody dynamics (MBD) model of the drivetrain system to simulate is utilized the vibrational responses under various health states [9]. The MBD model incorporates the nonlinear material properties and layup of CFRP shafts, as well as the intricate contact mechanics involved in gear meshing, including variable mesh stiffness, transmission error, and backlash [10]. These factors are essential for accurately simulating the physical behavior of the drivetrain components, particularly under different damage conditions [11].

The use of CFRP in shafts and gears presents unique challenges for condition monitoring due to the material's anisotropic behavior and complex damage mechanisms, such as delamination and cracking [12]. Additionally, the gear pair, constructed using 3D-printed materials, introduces further complexity due to the possibility of defects such as surface roughness, spalling, or missing teeth [13]. To address these challenges, an innovative contact force model that captures the dynamic interactions between the gear teeth is developed, enabling accurate simulation of the vibrational response under healthy and damaged conditions. The simulated responses generated from the MBD model serve as the training data for the machine learning models, which are then used to classify the health state of the drivetrain system. Supervised learning algorithms are employed to differentiate between normal operation and various damage scenarios, including cracks and delamination in the composite shaft and gear defects such as surface roughness and missing teeth. By training the ML models on numerically simulated data, we can bypass the need for exhaustive experimental measurements while still achieving high levels of accuracy and robustness in fault detection and classification.

The key contributions of this research are twofold. First, is presented a comprehensive MBD model of a drivetrain system with CFRP components that accurately simulates the complex dynamics of the system under different health conditions. This model includes detailed representations of the material properties, contact mechanics, and gear meshing behavior, providing a realistic basis for generating training data [14]. Second, is demonstrated the effectiveness of machine learning techniques in classifying faults based on the simulated data, showcasing the potential for integrating numerical simulations and data-driven methods in condition monitoring frameworks [15]. The proposed approach not only reduces the reliance on experimental data but also improves the generalization capabilities of the CM system, making it applicable to a wide range of drivetrain applications [16].

The remainder of this paper is organized as follows: First, the **Background** section outlines the theoretical foundation, including the multibody dynamics (MBD) model and the associated theoretical equations. This section also covers the modeling of contact forces between the gears and bushings, as well as the data mining process used to train the machine learning (ML) model. Additionally, the basic formulation for identifying the drivetrain's condition through the ML model is presented. Next, the **Analysis** section provides a detailed description of the drivetrain system under investigation, focusing on the CFRP shafts and 3D-printed gears, as well as the development of the MBD model to simulate the system's dynamics. This section also discusses the model updating process, in which the MBD model is refined using experimental datasets from the drivetrain's healthy state. Simulated damage scenarios are introduced as part of this section. In this section, the results of the fault classification experiments are also presented, accompanied by an analysis of the model's accuracy and its ability to generalize across different conditions. Finally, the paper concludes with a **Conclusion** section, summarizing the findings and providing recommendations for future research directions in condition monitoring for CFRP-based drivetrain systems.

Background

Multibody Dynamics (MBD) is a framework used to describe the dynamic interactions between interconnected bodies in a system. These bodies are connected through kinematic constraints and are influenced by both internal and external forces. When a system consists of components with varying degrees of stiffness or flexibility, its equations of motion can be expressed generally as:

$$\begin{cases} M\underline{\ddot{q}} + C\underline{\dot{q}} + K\underline{q} = \underline{f}\,(t) + A^T\underline{\lambda} \\ \underline{\Phi}(\underline{q}, t) = \underline{0} \end{cases} \tag{1}$$

In this formulation, M, C, and K represent the system's mass, damping, and stiffness matrices, respectively. The terms $\underline{\ddot{q}}$, $\underline{\dot{q}}$, and $\underline{q}$ denote the acceleration, velocity, and displacement vectors of the system's generalized coordinates. $\underline{f}$ refers to external forces acting on the system, while $A^T\underline{\lambda}$ accounts for the constraints imposed by Lagrange multipliers. The constraint equations $\underline{\Phi}(\underline{q}, t) = \underline{0}$ ensure that the kinematic constraints defined by the system's ideal joints are satisfied, allowing an accurate depiction of the dynamics of both rigid and flexible components [17].

In the drivetrain MBD model, bushings are introduced to act as both supports and flexible connectors between components. Bushings allow relative motion between parts while providing resistance to specific degrees of freedom, adding flexibility compared to rigid connections. They are typically characterized by their stiffness and damping properties, and their force-displacement behavior is often modeled using a spring-damper system. The equation governing the forces exerted by a bushing is typically:

$$F = -k * \delta - c * \dot{\delta} \tag{2}$$

In this equation, F represents the force exerted by the bushing, k is the stiffness, c is the damping coefficient, δ is the deformation of the bushing, and $\dot{\delta}$ is the rate of deformation (velocity). This model effectively captures the compliance and damping behavior of the bushing, which plays a crucial role in the dynamics of the system by allowing controlled flexibility.

In the drivetrain MBD model, contact between the gear pair is defined to accurately capture the interaction forces during meshing. To simulate the energy dissipation within the system, a damping component is introduced alongside the stiffness component of the contact force. This damping is represented using a hysteresis damping factor, which accounts for energy loss due to material deformation and contact mechanics. The hysteresis factor χ is determined using one of several available models, with each model providing a distinct relationship between the hysteresis factor, coefficient of restitution (c_r), and the initial indentation velocity $(\dot{\delta})$ at the moment of contact [18]. The general form of the damping model is given by:

$$F_n = -k * \delta^n - \chi * \delta^n * \dot{\delta} \tag{3}$$

Table 1 provides a summary of different models used to estimate the hysteresis damping factor χ based on the contact force model.

Table 1 Hysteresis damping factor χ with respect to the contact force model.

Gharib & Hurmuzlu	Herbert & McWhannel	Flores et al.	Lee & Wang
$\frac{1}{c_r}\frac{K}{\dot{\delta}^{(-)}}$	$\frac{6(1-c_r)}{(2c_r-1)^2+3}\frac{K}{\dot{\delta}^{(-)}}$	$\frac{8(1-c_r)}{5c_r}\frac{K}{\dot{\delta}^{(-)}}$	$\frac{3(1-c_r)}{4}\frac{K}{\dot{\delta}^{(-)}}$
Hunt & Crossley	**Lankarani & Nikravesh**	**Zhiuing & Qishao**	**Gonthier et al.**
$\frac{3(1-c_r)}{2}\frac{K}{\dot{\delta}^{(-)}}$	$\frac{3(1-c_r^2)}{4}\frac{K}{\dot{\delta}^{(-)}}$	$\frac{3(1-c_r^2)e^{2(1-c_r)}}{4}\frac{K}{\dot{\delta}^{(-)}}$	$\frac{1-c_r^2}{c_r}\frac{K}{\dot{\delta}^{(-)}}$

The contact forces between the gears and the forces in the bushings of the drivetrain model are then optimized for best performance by tuning the model parameters using the Covariance Matrix Adaptation Evolution Strategy (CMA-ES). CMA-ES is particularly effective in handling complex optimization scenarios characterized by discontinuities, noise, local optima, and other challenges [19]. The goal is to optimize a set of model parameters θ by minimizing the error between the experimental dataset and the predicted model's response in the frequency domain, obtained through Fast Fourier Transformation (FFT) of the accelerations at the bearing positions.

The error between the experimental and numerical responses for the $i-th$ predicted model can be minimized using the following cost function:

$$J_i\,(\theta) = \frac{1}{N}\sum_{\iota=1}^{N} \frac{\sum_{j=1}^{m}\left(\hat{a}(\theta)_{ij} - a_{ij}\right)^2}{\sum_{j=1}^{m}\left(a_{ij}\right)^2} \tag{4}$$

In this equation, $\hat{a}\,(\theta)_{ij}$ represents the FFT of the acceleration response at the $j-th$ bearing location for the $i-th$ frequency in the numerical model, and a_{ij} is the FFT of the experimental acceleration data at the same bearing location.

The optimization starts with an initial set of parameters in the vector θ, which represent the parameters for the drivetrain's numerical model.

The CMA-ES algorithm iteratively updates the parameters by calculating the numerical model's response and minimizing the cost function $J(\theta)$, which is based on normalized least squares error. The process continues until the parameter values are refined, aligning the numerical and experimental frequency responses, and ensuring a more accurate representation of the drivetrain's dynamics.

Next, the optimal MBD model is utilized to generate labeled data for training the proposed supervised machine learning framework. This numerical model produces a comprehensive dataset that encompasses various health states in the rotor dynamics model under investigation, providing detailed information about both the health status and specific instances of damage occurring at discrete locations within the structure. To account for the inherent uncertainty in real-world systems, key hyperparameters θ are sampled from a Gaussian distribution. In practical experiments, uncertainty is always present, resulting in discrepancies between experimental responses and those predicted by the model. By sampling the model's hyperparameters, these issues are addressed, mitigating discrepancies observed between numerical and experimental data across different trials.

To facilitate the generation of N labeled datasets, an automated algorithm, as shown in Figure 1, has been developed. This algorithm leverages the numerical model's response to compute Fast Fourier Transforms (FFTs) from the acceleration data in the X and Y directions, which serve as the primary input for the machine learning framework. At the end of the process, the algorithm determines the model's health status and returns both the FFTs and the health label Y. This label, represented as a single integer, indicates the simulated health state, designating whether the corresponding MBD model instance is healthy or exhibiting specific damage forms. Essentially, Y acts as a categorical indicator linked to the configuration of the solved MBD model, distinguishing between healthy and compromised states. The simulated FFT response data is then organized into a complete labeled dataset, expressed as:

$$Train\_set = \{(FFT_1, Y_1), (FFT_2, Y_2) \cdots (FFT_n, Y_n)\}, \text{ with } FFT_n = [FFT_n^X, FFT_n^Y] \tag{5}$$

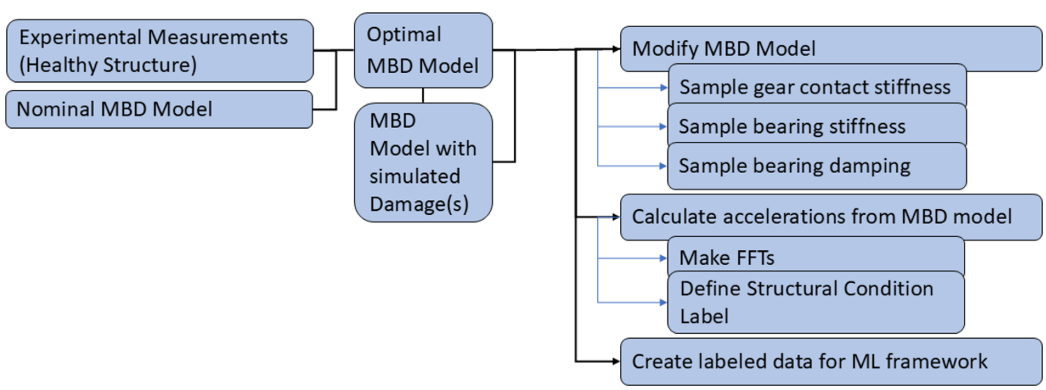

Fig. 1 Numerical data generation framework.

The simulated dataset for supervised damage detection and identification in the drivetrain system is processed using a Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel [20]. SVM is a robust classification algorithm that works by transforming the input data into a higher-dimensional space, allowing it to handle complex decision boundaries. The classification problem is expressed as:

$$y(x) = w^T \varphi(x) + b \tag{6}$$

where $\varphi(x)$ is the feature-space transformation function, and b is the bias term. The RBF kernel provides flexibility through hyperparameters and is defined as:

$$K(\boldsymbol{x}, \boldsymbol{y}) = e^{-\gamma \|\boldsymbol{x} - \boldsymbol{y}\|^2} \tag{7}$$

Where $K(\boldsymbol{x}, \boldsymbol{y})$ represents the kernel function applied to input vectors **x** and $\boldsymbol{y}$, and γ is a hyperparameter controlling the decision boundary's smoothness. The training dataset $T = \{x_i \in \mathbb{R}^n, \quad i = 1, \ldots, N\}$ and labels from two classes $y_i \in \{-1, 1\}$ are used to optimize the model.

During training, the SVM seeks to maximize the margin between classes by solving the optimization problem:

$$Maximize : W(a) = \sum_{i=1}^{N} a_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} (a_i \cdot a_j \cdot y_i \cdot y_j \cdot K(x_i, x_j)) \tag{8}$$

subject to $0 \leq a_i \leq C$, where C is a regularization parameter, and $a_i$are the Lagrange multipliers. The decision function is then used for classification:

$$f(\boldsymbol{x}) = sign\left(\sum\left(a_i \cdot y_i \cdot K(\boldsymbol{x}, \boldsymbol{x}_i)\right) + b\right) \tag{9}$$

Where, $f(x)$ is the predicted class label for input vector x and b is a constant value. This SVM-RBF model, trained using the scikit-learn Python library, can accurately classify new data and identify health states in real-time, making it suitable for condition monitoring in non-linear systems characterized by complex patterns.

The overall process of the proposed methodology is summarized in the flowchart presented in Figure 2. This flowchart outlines the key steps, starting from the development of a high-fidelity MBD model of the drivetrain system, including the CFRP shafts and 3D-printed gears. Numerical simulations are then performed using this model to generate data for various health states. The data is processed through FFT to capture the frequency domain responses at the bearing positions. Following this, a SVM model with RBF kernel is trained using the simulated dataset to classify different health states. The SVM-RBF is optimized by tuning its hyperparameters, such as the kernel parameter γ and regularization parameter C. Once trained, the model is capable of performing real-time condition monitoring by accurately detecting and identifying damage based on new input data.

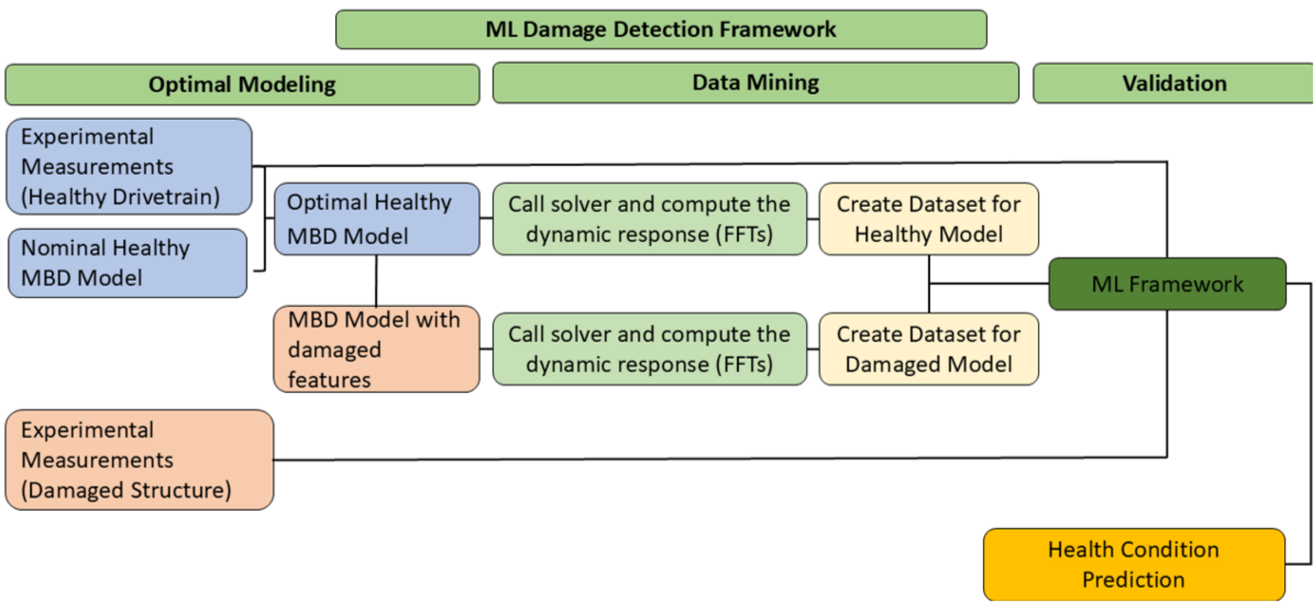

Fig. 2 Flowchart of the proposed framework.

Analysis

The experimental setup used to conduct dynamic testing of the drivetrain with Carbon Fiber Reinforced Polymer (CFRP) gears and shafts is illustrated in Figure 3. The system consists of two main components: the drive motor (1) and the load motor (2), both of which are three-phase electric motors. Additionally, it includes two shafts (3), four shaft mounting ball bearings (4), a pair of gears (5) and (6), and a mounting frame (7). To monitor the system's dynamic response, four tri-axial accelerometers are mounted on the bearings (4), allowing for measurement of acceleration in the radial direction. A torque meter is also placed on the input shaft, positioned directly after the electric drive motor, to capture the input torque of the drivetrain. The tests are conducted over a rotational speed range from 450 RPM to 1100 RPM, with increments of 250 RPM between each test. Data is recorded at a sampling rate of 5120 Hz to capture the detailed dynamic behavior of the system. The corresponding MBD model, which accurately represents the experimental drivetrain system, is illustrated in Figure 4. Table 2 summarizes the material properties of CFRP used in the MBD model for both the CFRP gears and shaft.

The optimal contact force model, along with its corresponding parameters as estimated through the optimal selection using the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) algorithm, is presented in Table 3. In addition to this, the table summarizes the stiffness and damping values for the bushings used in the system.

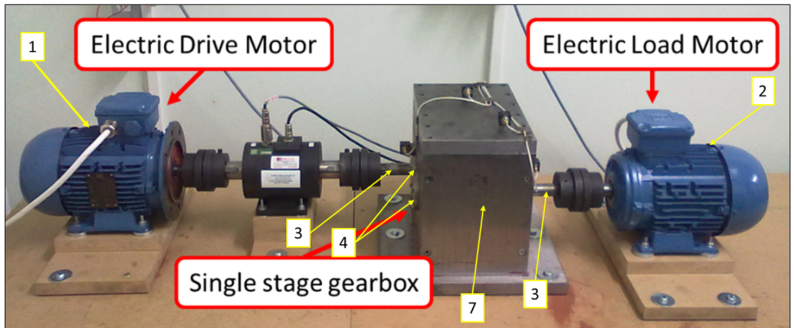

Fig. 3 Experimental drivetrain system and measuring equipment.

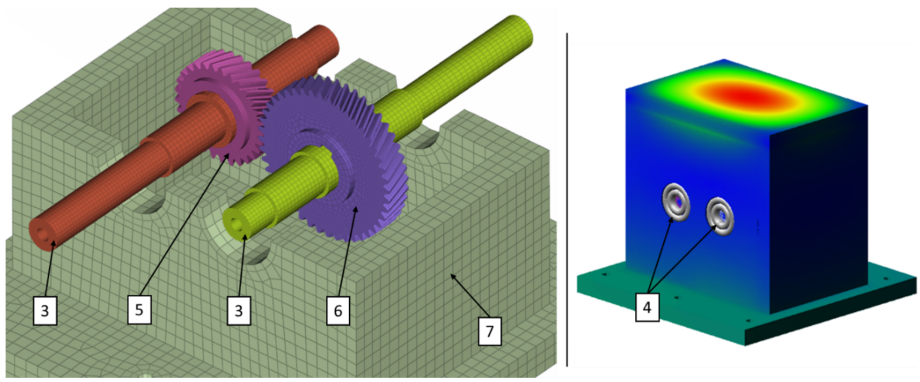

Fig. 4 Drivetrain system numerical model (MBD).

Table 2 CFRP material properties.

Property		
Modulus of Elasticity in X	E_1[GPa]	138.945
Modulus of Elasticity in Y	E_2[GPa]	6.6154
In-plane Shear Modulus & Transverse Shear Modulus 1-Z plane	$G_{12} = G_{1z}$ [GPa]	3.387
Transverse Shear Modulus 2-Z plane	G_{2z} [GPa]	2.2864
Density	ρ[kg/m^3]	1560

Table 3 Optimal force model and parameters.

Contact force model	$K\ [\frac{N}{mm^2}]$	$c_r[-]$	$n\ [-]$
Flores et al.	3.25e5	0.96	1.2
Bushing force model	$K\ [\frac{N}{mm^2}]$	$C\ [\frac{N*s}{mm}]$	
$F = -K*\delta - C*\dot{\delta}$	1.825e5	12.3	

To accurately replicate the damage scenarios and develop a machine learning (ML)-based model capable of identifying the health state of the drivetrain, two new MBD models were created, each representing specific damage conditions. These models, combined with the existing healthy state model, enable a comprehensive analysis of the system's behavior across different health conditions. In this study, three distinct health states of the drivetrain were analyzed. The first is the baseline "healthy" state, where no faults or damage are present. The second state represents a surface fault, characterized by wear or degradation on the pinion gear teeth surface. This condition was simulated by reducing the contact stiffness of the gears by 15%, mirroring the reduction in stiffness typically observed in real-world surface damage scenarios. The third state represents a more severe fault, a missing tooth on the pinion gear, which drastically alters the dynamic behavior of the drivetrain due to the abrupt change in contact mechanics. Figure 5 illustrates the gear models used for each of these health states. By incorporating these different damage conditions into the MBD framework, the study provides a robust dataset for training the ML-based damage detection system, which is designed to classify the health states based on the system's dynamic responses under varying operational conditions.

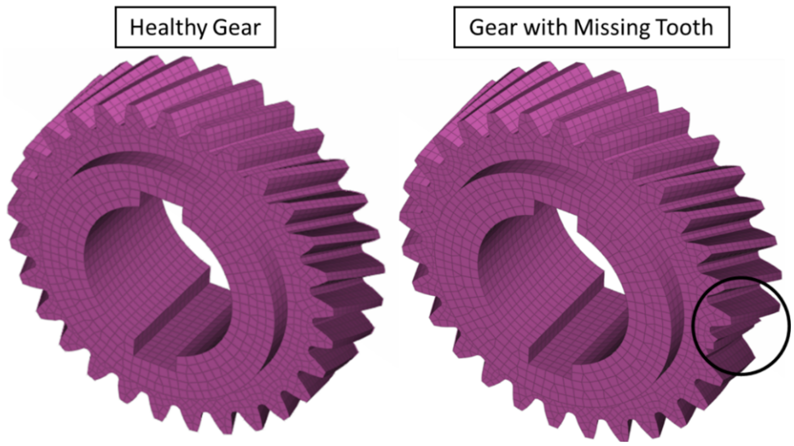

Fig. 5 Gear geometry for different health states.

Figure 6 presents the acceleration responses in the frequency domain for the optimal MBD models at rotational speed of 450RPM. The responses are shown for the first nine harmonics of the Gear Mesh Frequency (GMF) of the gear pair, providing insight into the system's dynamic behavior at various speeds. Figure 7 compares the simulated responses of the drivetrain system in both its healthy and damaged states. This comparison highlights the differences in dynamic behavior and helps in identifying damage by observing the variations between the healthy and faulty conditions.

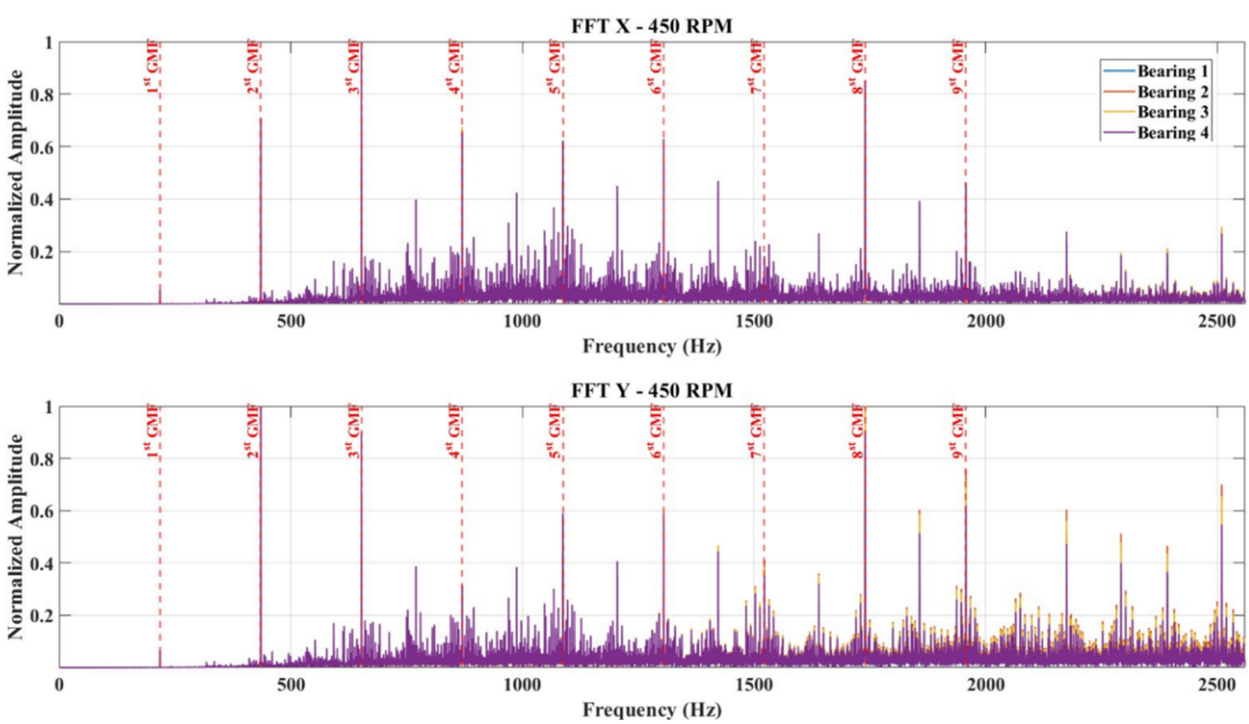

Fig. 6 Frequency response comparison of the optimal MBD system in its healthy state at 450 RPM.

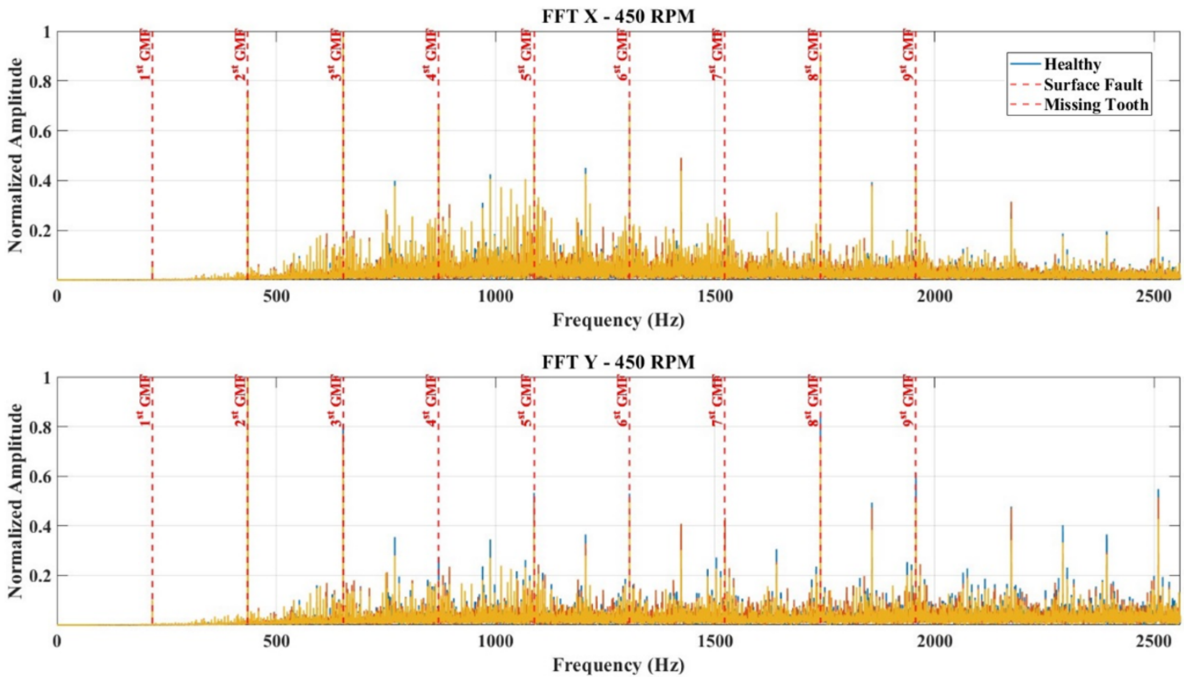

Fig. 7 Frequency response comparison between the healthy and damaged MBD models at 450 RPM.

The training data for this study was generated from optimal healthy and damaged MBD models, comprising 500 examples for the healthy state and 500 samples for each damage scenario, resulting in a total dataset of 1,500 cases. To introduce realism into the models, the optimal hyperparameters (θ) were perturbed by $\pm 3\%$ using a Gaussian distribution. This stochastic variation helps to replicate uncertainties present in experimental scenarios. The computational efficiency of this approach was significant, with the MBD problem solving completed in approximately 20 seconds. Overall, the data generation process was completed in under 30 seconds per example, a marked improvement compared to traditional methods.

The numerical data was organized into labeled datasets corresponding to specific structural health conditions, adhering to guidelines outlined in Background Chapter and forming the training set as defined in Equation (5). Table 4 summarizes the labels used to describe the numerical data. The generated datasets show close proximity among different health states, underscoring the challenge of accurately detecting structural changes within the system.

Table 4 Dataset used labels.

Health State	Healthy	Surface Fault	Missing Tooth
Label Y	0	1	2

The next phase in the machine learning framework involves training the SVM-RBF model for robust classification of the experimental structure's health state using this numerical dataset. Seventy percent of the dataset is allocated for training, allowing the model to learn underlying patterns, while the remaining 30% serves as a validation set for unbiased performance assessment. Prior to training, data scaling standardizes the input features to have zero mean and unit variance, ensuring balanced contributions from all features. Key hyperparameters 'C' and 'gamma' are finely tuned, with 'C' set to 1.2 for balance between decision boundary optimization and error reduction, and 'gamma' assigned the value 'scale' to enhance model performance.

The model's accuracy was thoroughly assessed on the validation set using experimental measurements across the three health states studied, yielding remarkable results: 99.4% accuracy at 450 RPM, 91.8% at 775 RPM, and 98.2% at 1100 RPM. Confusion matrices (Figure 8) provide a comprehensive overview of the model's performance, detailing the rates of true positives, true negatives, false positives, and false negatives for each health state. Overall, the model demonstrates a strong capacity for accurately classifying both healthy and damaged states of the drivetrain, achieving an average efficiency of 95%. Additionally, Figure 9 highlights the model's prediction percentages at various rotating speeds, further underscoring its reliability and effectiveness in real-world applications.

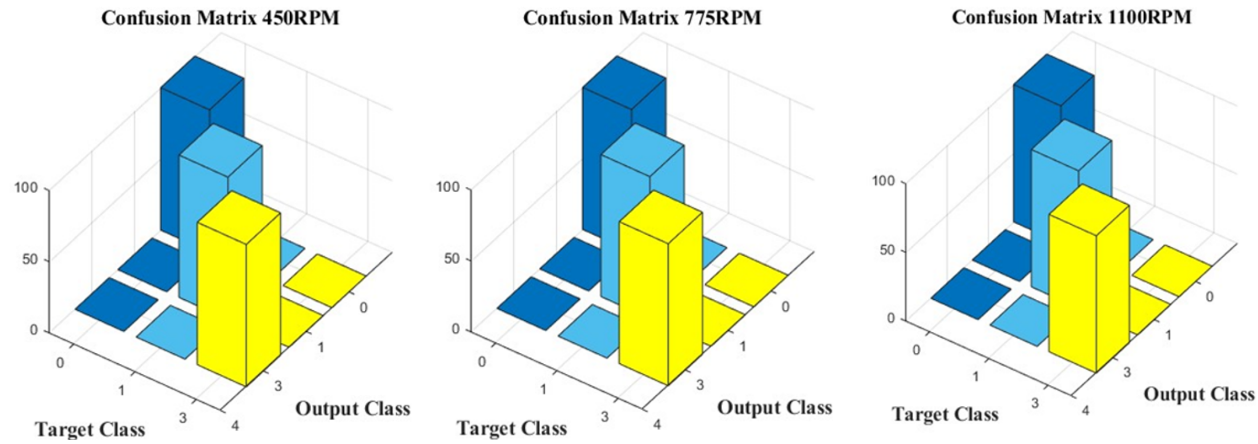

Fig. 8 Confusion matrices for different rotating speeds.

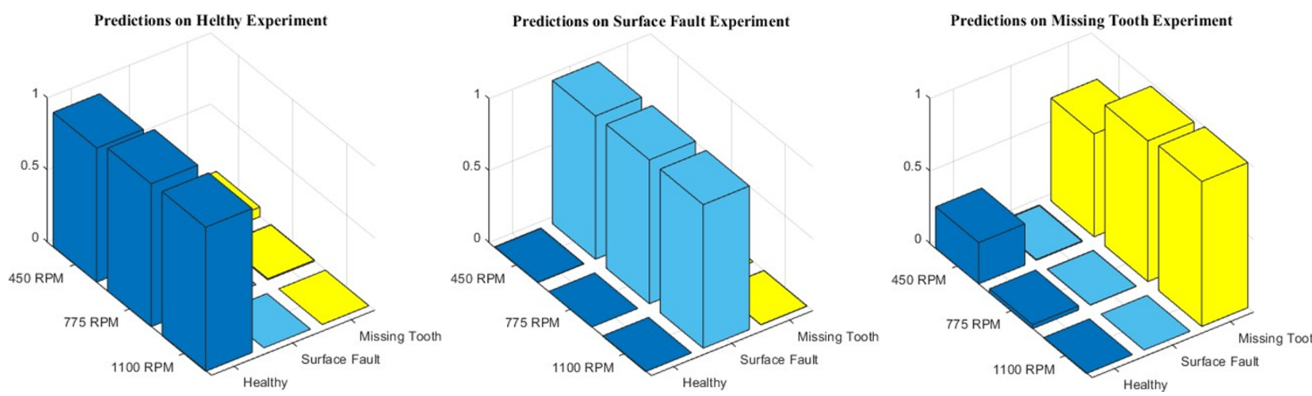

Fig. 9 SVM-RBF prediction percentages on experimental datasets.

Conclusion

This study presents a comprehensive approach to developing a machine learning framework aimed at effectively classifying the health states of a drivetrain system using CFRP gears and shafts. The primary objective was achieved through a combination of advanced simulation techniques and machine learning algorithms, resulting in significant findings and contributions to the field of condition monitoring. First and foremost, the development of the optimal Multibody Dynamics model allowed for the generation of a substantial dataset comprising 1,500 instances, representing various health states of the drivetrain. This dataset was instrumental in training the machine learning model and showcased the effectiveness of simulating different operational conditions, including healthy and damaged states. The use of a Support Vector Machine with a Radial Basis Function kernel demonstrated impressive classification performance, achieving accuracy rates of 99.4% at 450 RPM, 91.8% at 775 RPM, and 98.2% at 1100 RPM on the validation set. This high level of accuracy underscores the potential of the proposed framework for real-time health state classification in practical applications. Furthermore, the integration of Gaussian perturbations into the model's hyperparameters effectively introduced a realistic element of uncertainty, closely mimicking real-world experimental scenarios. This approach not only improved the robustness of the model but also ensured its applicability to varying operating conditions. In conclusion, this study not only demonstrates the efficacy of using advanced simulation techniques and machine learning for health state classification but also provides a valuable framework for future research in the field of condition monitoring and fault detection in mechanical systems. Further investigation into the optimization of the model and expansion of the training dataset will be essential for improving classification performance across all health states, ultimately contributing to more reliable and effective monitoring of drivetrain systems.

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