Compound Defect Diagnostics of Swind Turbine Gearboxes Via Variational Mode Decomposition, Hjorth Parameters and Machine Learning

INTURI VAMSI and SABAREESH GEETHA RAJASEKHARAN

ABSTRACT

This study aims to develop a robust and automated diagnostic framework for identifying and classifying compound defects in WT gearboxes. The proposed methodology adopts a multi-phase approach. Vibration signals corresponding to various compound defect scenarios across multiple gearbox stages are initially collected from a WT gearbox system. From these signals, Hjorth parameters (activity, mobility, complexity), representing time-domain features, are computed for all gearbox health conditions. Simultaneously, the signals undergo variational mode decomposition (VMD) processing to extract intrinsic mode functions (IMFs). A comprehensive set of statistical features encapsulating time-frequency domain characteristics is subsequently derived from these IMFs. Data augmentation is employed to enhance the robustness and discriminatory power of the dataset, leading to the formulation of an enriched feature set by integrating the Hjorth parameters (time-domain features) with the statistical features (time-frequency domain features). The feature set is subjected to machine-learning-based multi-class classification to diagnose compound gearbox faults. The study systematically evaluates the diagnostic performance of the augmented feature dataset and benchmarks it against individual feature sets. The findings underscore the effectiveness of the proposed methodology in accurately diagnosing compound faults with reduced dependency on complex signal post-processing techniques, thereby advancing the state of fault diagnostics in WT gearboxes.

BACKGROUND & MOTIVATION

A crucial part of the wind turbine (WT), the gearbox transfers power between the shafts to alter the torque based on the input wind speed. Gearboxes frequently operate at complex speeds and heavy loads, making them prone to breakdown under challenging working conditions [1]. Over time, the gearbox's subsystems (gear and bearings) also experience an accumulated deterioration imposed by wear and fluctuating operating

Inturi Vamsi, Assistant Professor, Email: vamsismilebox@gmail.com Department of Mechanical Engineering, Chaitanya Bharathi Institute of Technology (A), Hyderabad, India
*Sabareesh Geetha Rajasekharan, Associate Professor, Email: sabareesh@hyderabad.bits-pilani.ac.in Department of Mechanical Engineering, BITS Pilani-Hyderabad Campus, Hyderabad, India

conditions. Unexpected gearbox failure could result in unscheduled maintenance costs, which account for around 30% of the WT's total life cycle costs [2]. Therefore, lowering the gearbox failure rate is crucial for improving availability and reliability. Defects in the gearbox might be either compound or single component. The single component defects (mono-defects) of the gearbox include the defects that exist on the individual component of the gearbox, such as an inner race defect alone on the bearing [3]. Conversely, compound defects of the gearbox include additive defects on individual components (multi-component defects simultaneously) and multiplicative defects (multiple types of defects on a single component). Compared with single-component defects, multi-component defects pose a significant challenge in fault diagnosis, complicating the identification process by concealing crucial information [4]. Condition monitoring can identify incipient damage, which is very helpful in situations to avoid catastrophic failures of the WT gearboxes [5]. Although many incipient defects can be diagnosed using vibration analysis-based CM approach, some failures exhibit associated vibration characteristics that make it challenging to detect and differentiate.

However, the WT gearbox's intricate structure, numerous sub-systems, high background noise, and fluctuating operating conditions all necessitate employing sophisticated signal processing methods to extract reliable defect-specific descriptors from raw signals [6]. Extracting relevant defect-sensitive information from the raw signals involves analysing them in various domains, including time, frequency alone or joint time-frequency domain. Characteristic frequency identification based signal post-processing methods have been used in the conventional WT gearbox diagnosis and prognosis [7]. The characteristic frequency and its harmonics, which are essential for determining the sub-systems of the WT gearbox, can be identified through this method. However, the vibrations produced by various meshing sub-systems overlap, making it challenging to detect faults in WT gearboxes using vibration-based CM analysis, especially at intermediate and low-speed stages. Furthermore, compound defects involving gears and bearings introduce distributed and localised defect characteristics. These compound faults manifest as overlapping modulation phenomena in vibration signals, compromising the efficacy of traditional methods [8]. Therefore, choosing an appropriate defect-sensitive health indicator is essential to diagnosing gearbox defects. Hjorth's parameters – Activity, Mobility and Complexity – are statistical time-domain parameters, which are instrumental in analysing EEG signals [9]. Besides, being an adaptive multi-domain technique, the variational mode decomposition (VMD) demonstrated superior performance in dealing with non-stationary, aperiodic, and multi-component signals [6, 10]. Various researchers have implemented VMD and decomposed the vibration signals into band-limited intrinsic mode functions (IMFs) and computed features from the IMFs followed by data-driven fault diagnosis [10, 11].

Despite numerous investigations, there exists a dearth of literature related to compound defect diagnostics of the WT gearbox in existing studies. The compound defects are frequently only considered in one gearbox sub-system, either the gear tooth or the bearing race. The defects on two different sub-systems of the WT gearbox with the same severity level are considered a compound defect scenario. When two or more defects co-occur in the gearbox, the characteristics of the fault are more likely to be strongly associated with the more severe defect than the minor severe defect. This study aims to develop a robust and automated diagnostic framework for identifying and classifying compound defects in WT gearboxes. The proposed methodology adopts a multi-phase approach. Initially, the vibration signals corresponding to various health scenarios (healthy and compound defects) are collected from the WT gearbox system. For each health scenario of the gearbox, the time-domain parameter set is achieved by computing the Hjorth's parameters from the raw vibration signals. Simultaneously, VMD is applied, and the raw vibration signals pertaining to all health scenarios are decomposed into various IMFS individually. A comprehensive set of statistical features encapsulating time-frequency domain characteristics is subsequently derived from these IMFs for every health scenario. Further, an enriched feature set is formulated by combining the statistical features (time-frequency domain features) with the Hjorth parameters (time-domain features). The formulated feature set is channelled as input to various machine-learning classifiers (decision tree, random forest, XGBoost and support vector machine) to accomplish the multi-class classification, followed by compound defect diagnosis of a WT gearbox.

EXPERIMENTATION & DATA ACQUISITION

The primary sub-systems of the laboratory-scale experimental rig are an induction motor, a flexible coupling, and a three-stage gearbox. The induction motor is connected to the variable frequency drive, and drives the whole gearbox system at a rotational speed of 750 rpm. The motor shaft and the gearbox's input shaft are connected via a flexible coupling. The WT gearbox considered in this study comprises three shafts: an input (high-speed) shaft, an idler (intermediate-speed) shaft and an output (low-speed) shaft. It also contains eight deep-grove ball bearings. The output shaft pinion and gear have 20 and 60 teeth, respectively. On the input and idler shaft, the pinion and gear have 20 and 80 teeth, respectively [12, 13]. Five uniaxial accelerometers (PCB make, sensitivity 98.4 mV/g) are mounted on the bearing housings, as illustrated in Figure 1. All the accelerometers are interfaced with a data acquisition system for synchronized vibration signal acquisition. The vibration signals are sampled at a frequency of 12 kHz. Ten distinct operational scenarios representing compound defect conditions within the WT gearbox are examined, refer Table I. The compound defects considered in this study consist of a localized crack (length 30 mm, width 0.25 mm, depth 2.2 mm) on the inner race of bearing (CIB), a crack (length 14 mm, width 0.25 mm, depth 1.4 mm) on the outer race of bearing (COB), and a root crack (length 30 mm, width 0.25 mm, depth 3 mm) at the pinion (RCP), refer Figure 2. Experiments are performed for each health scenario individually, and the components containing the defects are installed while the rest of the gearbox components are normal (defect-free). For each health scenario of the gearbox, the acquired data comprises five channels of vibration signals (Acc 1, Acc 2, Acc 3, Acc 4 & Acc5), 100 observations are recorded per vibration channel, with each observation consisting of 1,31,072 data points.

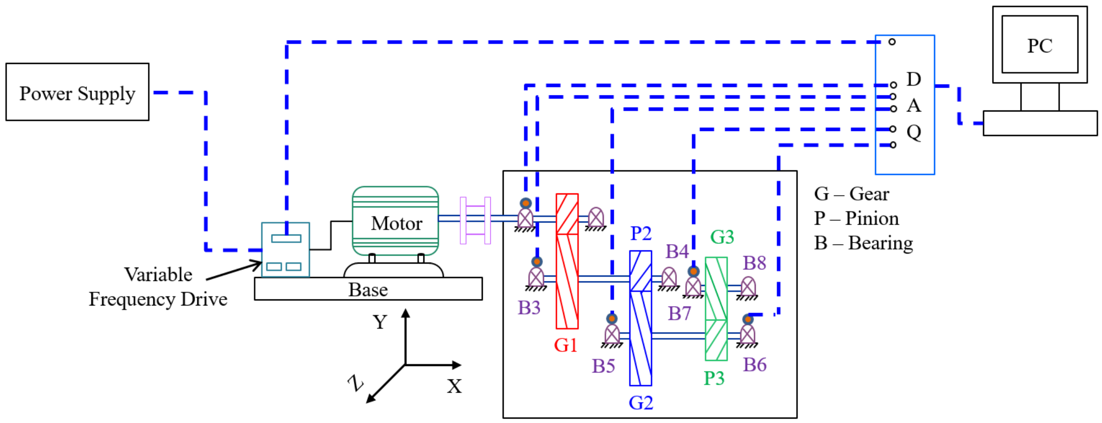

Figure 1. Schematic representation of the laboratory-scale WT gearbox experimental rig.

Figure 2. A glimpse of compound defects seeded – (left) Localized crack on bearing inner race, (middle) Localized crack on bearing outer race and (right) Localized root crack at pinion tooth.

TABLE I. Health scenarios of the WT gearbox considered in this study and the size of dataset.

Health scenario	Speed stage contributing to compound defect scenario	Size of dataset	Label
Healthy	—	100 * 131072	CD0
RCP (at pinion 1, pinion 2, pinion 3) + CIB (for bearing 2) + COB (for bearing 6)	Input + Idler + Output	100 * 131072	CD1
RCP (at pinion 1, pinion 2, pinion 3) + CIB (for bearing 2)	Input + Idler + Output	100 * 131072	CD2
RCP (at pinion 1, pinion 2, pinion 3) + COB (for bearing 6)	Input + Idler + Output	100 * 131072	CD3
RCP (at pinion 2) + CIB (for bearing 2)	Idler + Input	100 * 131072	CD4
RCP (at pinion 2) + COB (for bearing 6)	Idler + Output	100 * 131072	CD5
RCP (at pinion 1) + CIB (for bearing 2)	Input	100 * 131072	CD6
RCP (at pinion 1) + COB (for bearing 6)	Input + Output	100 * 131072	CD7
RCP (at pinion 3) + CIB (for bearing 2)	Output + Input	100 * 131072	CD8
RCP (at pinion 3) + COB (for bearing 6)	Output	100 * 131072	CD9

METHODOLOGY

The WT gearbox system is operated at 750 RPM, and the raw, time-domain vibration signals corresponding to various health scenarios (healthy and compound defects) are collected. The time-domain feature set is achieved by computing the Hjorth parameters (Activity, Mobility, and Complexity) for each health scenario of the gearbox individually. Simultaneously, VMD is applied, and the raw, time-domain vibration signals are decomposed into various IMFs. The time-frequency feature set is achieved by extracting thirteen statistical features (mean, maximum, standard deviation, entropy, etc.) from the selected IMF (IMF 10) for every health scenario. Further, feature-level fusion is implemented, and the time-domain feature set (Hjorth parameters) and time-domain feature set (statistical features) are combined to devise an enriched input feature dataset. Thus, the dataset comprises sixteen columns (13 statistical features + 3 Hjorth features) and 1000 rows (100 observations * 10 health scenarios). The formulated feature dataset is channelled as input to ML classifiers (decision tree, random forest, XGBoost and support vector machine) to accomplish the multi-class classification. The performance of the ML classifiers yielding to favourable health state classification is evaluated, refer Figure 3.

RESULTS AND DISCUSSION

HJORTH PARAMETERS

The time-domain Hjorth parameters (activity, mobility, and complexity) define the characteristics of the input vibration signal. The power, slope, and gradient of the slope of the raw, time-domain input signal are described by the activity, mobility, and complexity parameters, respectively. The activity parameter indicates the power that the input vibration signal contains, which can be computed through the variance (σ_v^2) of the signal, refer Eqs. 1a and 1b. The mobility parameter represents the mean frequency of the signal and can be obtained by computing the slope of the signal, i.e., the ratio of standard deviation of the first-order derivative (σ_v') to input signal (σ_v), refer Eq. 2 [9]. The complexity parameter indicates the similarity of input signal with a sinusoidal signal, and can be calculated by computing the change of slope of the vibration signal, refer Eq. 3 [14]. The lower value of complexity corresponds to a complex, non-stationary signal, which is challenging to extract defect-sensitive characteristics [15]. The Hjorth parameters (Activity, Mobility, and Complexity) are computed for each health scenario of the gearbox and for each vibration channel individually.

$$Activity = \sigma_v^2 \tag{1a}$$

$$SD\ of\ input\ signal = \sigma_v = \sqrt{\frac{1}{M-1}\sum_{m-1}^{M}\left[v\left(m\right) - \frac{1}{M}\sum_{m=1}^{M} v\left(m\right)\right]^2} \tag{1b}$$

$$Mobility = \frac{\sigma_v\prime}{\sigma_v} \tag{2}$$

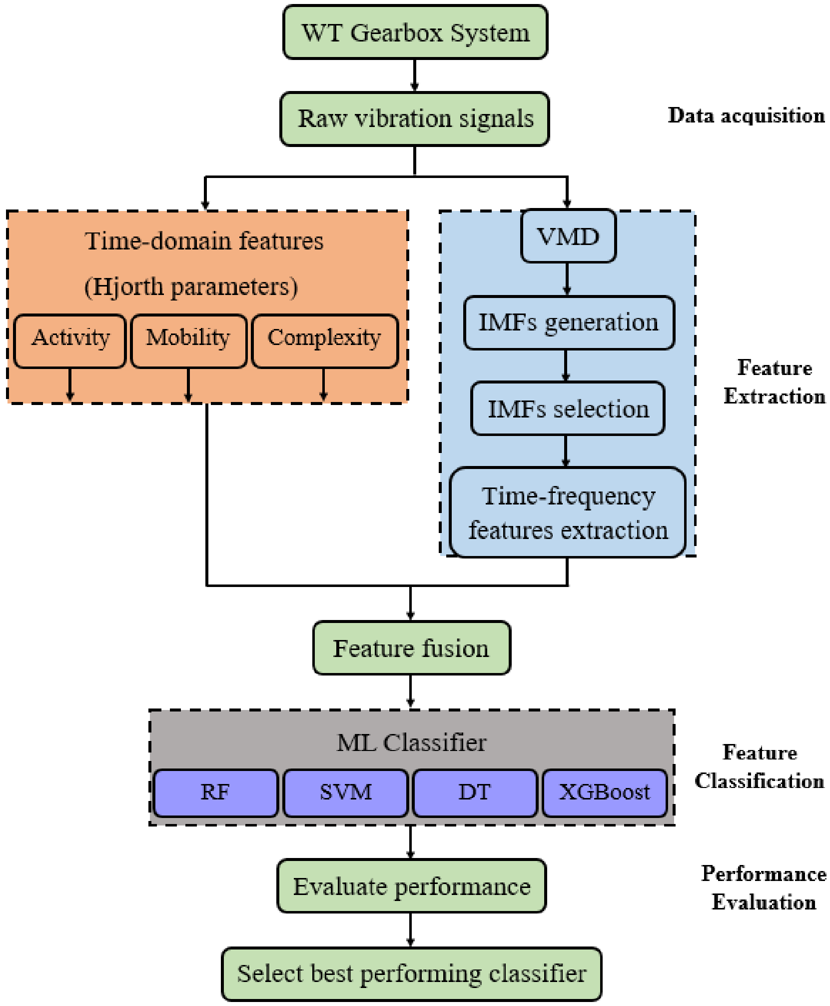

Figure 3. Scheme of the methodology employed for the compound defect diagnostics of a WT gearbox system.

$$Complexity = \sqrt{\frac{\frac{\sigma_{v}''}{\sigma_{v}'}}{\frac{\sigma_{v}'}{\sigma_{v}}}} \tag{3}$$

VARIATIONAL MODE DECOMPOSITION

As the acquired vibration signals pertaining to compound faults are aperiodic, non-stationary, and exhibit overlapping modulation phenomena, it is challenging to extract and interpret the defect-sensitive characteristics. Being an adaptive and non-recursive method, VMD is able to decompose the non-stationary and multi-component signals [6]. VMD decomposes the input signal 'v(m)' into a set of IMFs with non-overlapping frequency bands. The modes generated by VMD are band-limited around a central frequency and have the ability to collectively reconstruct the input signal, refer Eq. 4 [16]. The unit impulse is denoted by $\delta(t)$, the set of IMFs generated are represented by $IMF_i = IMF_1, IMF_2 \ldots, IMF_n$, the central frequencies of respective IMFs are rep-

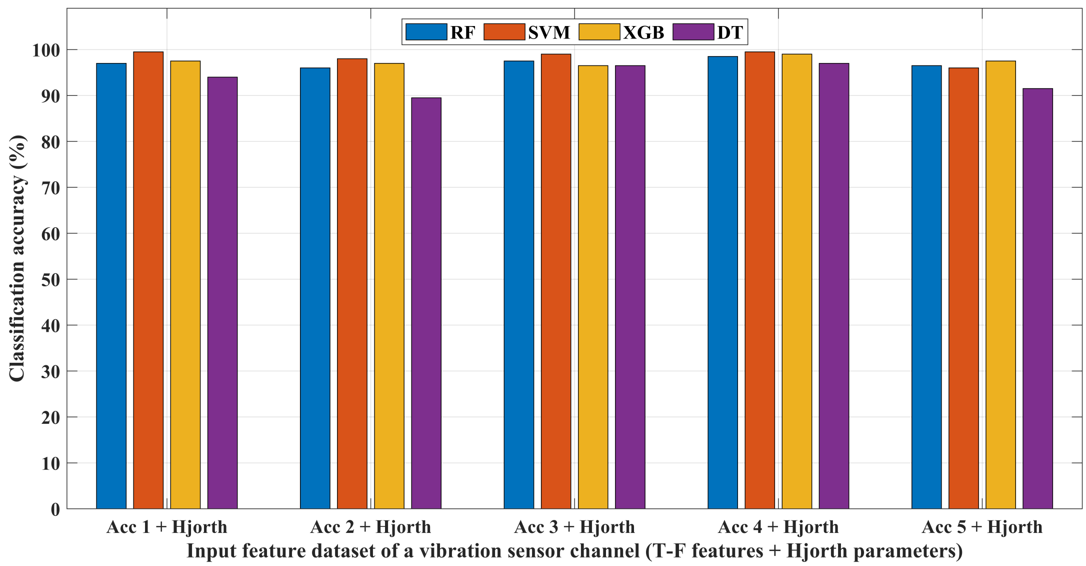

Figure 4. Classification accuracies for various ML classifiers during the multi-class classification of WT gearbox system.

resented by $f_i = f_1, f_2....., f_n$ and the convoluted Hilbert transform for each of the IMF is indicated by $(\delta(t) + j/\pi t) * IMF_i(t)$.

$$min\ (IMF_i, f_i) \left\{ \sum_{i}^{N} \parallel \partial t \left[\left(\delta\left(t\right) + \frac{j}{\pi t} \right) * IMF_i\left(t\right) \right] e^{j f_i t} \parallel_2^2 \right\} \tag{4}$$

MACHINE-LEARNING CLASSIFICATION

Owing to its ability to handle non-linear, multi-class and high-dimensional datasets, implementing ML classifiers is extensive in defect classification [13]. Support Vector Machine (SVM) initially identifies a separating hyperplane across the various classes and tries to maximize the distance between the created hyperplane and each classes nearest data points (support vectors) [17, 18]. The data points are optimally separated into distinct classes upon creating a successful boundary. By using appropriate kernel functions, SVM can transform the non-linearly separable data [12]. The random forest (RF) classifier builds several decision trees, and each tree is trained using a random subset of the input dataset. The RF classifier used in this study is based on bootstrap aggregating, in which a random selection of data and features is used to train each tree [19]. The individual outputs of all these generated trees are combined to get the final classification result. On the other hand, the extreme gradient boosting (XGBoost) classifier sequentially constructs decision trees, with each new tree attempting to correct the errors of the one before it. Thus, for each iteration, the total prediction error gets reduced, and the performance of weak learners gets boosted [20]. In this paper, to solve the multi-categorical classification problem, each ML classifier is given the input feature dataset individually. Training utilizes 70% of the data, and the validation is done by reserving 10%. Each ML classifier is configured with a fixed set of hyperparameters to ensure a fair performance comparison. The output structure of the evaluation is designed to support multi-class classification comparison.

During the multi-categorical classification, it can be seen that the enriched input feature dataset devised by combining the time-domain feature set (statistical features) and time-domain feature set (Hjorth parameter) resulted in favourable classification accuracies, refer to Figure 4. This input feature dataset holds the advantage of statistical variation of the individual vibration signals, where vibrations signals are adept at incipient level defects (such as bearing race defects), and the activity parameter is sensitive towards the changes in the sparsity of the vibration signal [1, 14]. Notably, the SVM classifier has provided favourable classification accuracies across most scenarios, as the SVM algorithm demonstrates superior generalization property while dealing with smaller/limited and non-linear datasets [17, 18]. The classification accuracies are 99.5%, 98%, 99%, 99.5% and 96% for the feature dataset derived from vibration channel (accelerometer) 1, 2, 3, 4 and 5, respectively. It is worth noting that the feature dataset that is derived from the accelerometer (ACC 4) mounted at the bearing housing (B7) of the outer shaft of the WT gearbox has provided the highest classification accuracies (99.5%) among the other feature datasets derived from other vibration channels, refer Figure 4. Additionally, for each ML classifier, three significant performance indices, such as precision, recall, and F1-score, are calculated using the weighted average approach and analyzed to demonstrate the performance of each of the ML classifier. Weighted metrics ensure that the evaluation reflects the contribution of each class proportionally, which is especially valuable in compound defect diagnostics of a WT gearbox system. A glimpse of the evaluation metrics achieved for the ML classifier is shown in Table II, which also confirms that the SVM classifier has yielded better classification. Hence, the input feature dataset formulated by combining the time-domain feature set (statistical features) and time-domain feature set (Hjorth parameter) can effectively accomplish the compound defect diagnostics of the WT gearbox.

TABLE II. Evaluation indices of various ML classifiers – Precision (Pr), Recall (Re), F1-Score (F1).

Classifier	Acc 1 + Hjorth			Acc 2 + Hjorth			Acc 3 + Hjorth			Acc 4 + Hjorth			Acc 5 + Hjorth		
	Pr	Re	F1	Pr	Re	F1	Pr	Re	F1	Pr	Re	F1	Pr	Re	F1
RF	0.975	<u>0.975</u>	0.974	0.970	0.970	0.969	0.966	0.965	0.964	0.990	0.990	0.989	<u>0.975</u>	<u>0.975</u>	<u>0.974</u>
SVM	<u>0.995</u>	0.970	<u>0.994</u>	0.980	<u>0.980</u>	<u>0.979</u>	<u>0.990</u>	<u>0.990</u>	<u>0.989</u>	<u>**0.995**</u>	<u>**0.995**</u>	<u>**0.994**</u>	0.962	0.960	0.959
GB	0.970	0.970	0.969	0.959	0.960	0.959	0.975	0.975	0.974	0.985	0.985	0.984	0.966	0.965	0.964
DT	0.940	0.940	0.939	<u>0.989</u>	0.895	0.891	0.966	0.965	0.965	0.973	0.970	0.970	0.918	0.915	0.913

CONCLUDING REMARKS

This study proposed an automated compound defects diagnostic framework for a WT gearbox. The vibration signals corresponding to various compound defect scenarios across the multiple stages of the WT gearbox are collected using five vibration channels/accelerometers. The time-domain feature set is achieved by individually computing the Hjorth parameters (Activity, Mobility, and Complexity) from each vibration channel. Simultaneously, VMD is applied, and the raw, time-domain vibration signals from each vibration channel are decomposed into various IMFs. The time-frequency feature set is achieved by extracting thirteen statistical features from the selected IMF. An enriched feature set for each vibration channel is formulated by integrating the Hjorth parameters (time-domain features) with the statistical features (time-frequency domain features). The formulated feature dataset for each vibration channel is channelled as input to ML classifiers (decision tree, random forest, XGBoost and support vector machine) to accomplish the multi-class classification. It is observed that the SVM classifier has provided favourable classification accuracies with the classification accuracies of 99.5%, 98%, 99%, 99.5% and 96% for the feature dataset derived from vibration channel (accelerometer) 1, 2, 3, 4 and 5, respectively. The findings underscore the effectiveness of the proposed methodology in accurately diagnosing compound faults with reduced dependency on complex signal post-processing techniques, thereby advancing the state of fault diagnostics in WT gearboxes.

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