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A COMBINATION OF SIGNAL PROCESSING AND CLASSIFICATION TECHNIQUES FOR EVALUATING HEALTH CONDITIONS IN GEARED SYSTEMS - A SIMULATION-BASED APPROACH

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Abstract. *Within the current industrial sector, the demand for equipment maintenance has increased, underscoring the need for higher reliability and predictability. Failures in geared systems can imply significant financial, operational, and safety losses, hindering the attainment of organizational goals. Despite the importance of early and precise diagnosis in preventing equipment failures, implementing recently developed techniques—emerging from extensive research in monitoring and prognosis methodologies—imposes challenges due to their multidisciplinary and technical complexity. Streamlining this process could add substantial value. Accordingly, this study deals with fault detection in rotating machinery by assessing the effectiveness of classical diagnostic and optimization techniques through a simulated case study. A geared pair with tooth and transmission errors was simulated, embodying models of gear stiffness and transmission errors. A signal filter was employed to focus on relevant fault frequencies. Following this, the most appropriate optimization technique was selected to identify the faulty system's parameters and classify the degradation level corresponding to each failure mode.*

Keywords: *Signal processing, vibration, gearbox, parameter estimation, fault diagnosis.*

1. INTRODUCTION

The industrial sector, a vital component of the global economy, depends heavily on the efficiency and reliability of various machinery and equipment. Among these, geared systems play a crucial role in numerous industrial applications, ranging from manufacturing and processing to transportation and logistics. Consequently, the reliable operation of these geared systems is a critical factor in ensuring the uninterrupted flow of industrial processes. Failures in geared systems can imply significant financial, operational, and safety losses, hindering the attainment of organizational goals and causing substantial disruptions in the industrial workflow. The financial implications of equipment failure are often severe, with costs associated not only with the repair or replacement of the faulty machinery but also with the loss of productivity during downtime. Operational challenges include the need to reorganize work schedules, reallocate resources, and potentially miss deadlines, all of which can negatively impact an organization's reputation and customer relationships. Safety is another critical concern, as equipment failures can lead to accidents, endangering the well-being of personnel and potentially leading to costly legal implications.

In this study, a model-based approach is used, combining signal processing and classification techniques for diagnosing faults. Models of gear stiffness and transmission errors are incorporated into the simulation, which represent common faults in geared systems that can significantly impact their performance. The signal process uses FFT and relevant bands extractions in the frequency domain to filter the signal. The classification method used is based on assigning specific physics parameters to each fault on the model and comparing the simulated signal with the reference signal. The error between the two filtered signals is calculated using an error function developed for this work. The optimization then finds the parameters for each type of fault by minimizing the error, thus classifying the fault (Wu and Lee, 2015). The existing body of literature on fault detection in rotating machinery, including geared systems, is extensive and diverse. Various diagnostic techniques have been proposed and developed, which can be broadly categorized into model-based, data-based or data-driven methods (Liang et al., 2018). Model-based methods rely on a mathematical or physical model of the system to detect and diagnose faults while the data-driven methods lean on the data patterns taking little or no information about the system (Tsui et al., 2015). Model-based methods often involve the use of signal processing techniques to extract useful information from the raw signals produced by a machine. Signal processing techniques such as Fast Fourier Transform (FFT) to convert the time-domain signals into frequency-domain for easier analysis and there are also the time-frequency domain ones such as Short-Time Fourrier Transform (STFT) and Wavelet Transform (WT), which can capture better the non-stationary behaviors (Wu and Lee, 2015). These techniques can help to isolate specific features in the signal that are indicative of a fault, thereby improving the accuracy of the diagnosis. The signal processing is often carried out via application of band filters in all domains, focusing on the relevant fault information, thereby reducing the complexity of the signal.

Classification methods are a fundamental aspect of failure diagnosis in rotating machinery. These methods utilize mathematical models, signal processing techniques, and machine learning algorithms to categorize and classify different types of faults based on extracted features from the signals. The classification process involves training a model with labeled data, where the features extracted from healthy and faulty signals are used as input. Various classification algorithms, such as support vector machines (SVM), neural networks, decision trees, and random forests, can be employed to build the classification model. The model is then used to predict the fault type of new, unlabeled signals based on the learned patterns. Classification methods play a crucial role in accurately identifying and differentiating between various fault conditions, enabling timely intervention and maintenance actions to mitigate potential failures. A good method to classify the faults is the parameter estimation using optimization for curve fitting, when using physical parameter, this method provides also valuable information for maintenance actions. These methods involve constructing a mathematical model of the system and using optimization algorithms to estimate the parameters of the model that best fit the observed data. For example, the Grasshopper Optimization Algorithm (GOA) has been used to search for the optimal shape control parameter in an improved Empirical Mode Decomposition (EMD) method for fault diagnosis in rolling bearings (Ye et al., 2020). Similarly, a particle-swarm optimization method has been used to estimate the q-axis inductance of a faulty permanent magnet synchronous motor (PMSM) (Li et al., 2021). Other optimization algorithms such as the pattern search algorithm and genetic algorithm have also been used for efficient search of characteristic parameters that indicate stator short-circuit faults in induction motors (Duan and Živanović, 2016).

The choice of a simulation-based approach is motivated by several factors. Simulations provide a controlled environment where the impact of various faults on the system's performance can be systematically studied. This allows for the isolation and understanding of the effects of each fault, thereby providing valuable insights that can aid in the development of more effective diagnostic tools. Also, simulations can be easily replicated and modified, enabling the exploration of a wide range of scenarios and the testing of different diagnostic techniques under consistent conditions. Besides, it is acknowledged that simulations may not capture all the complexities and uncertainties of real-world operations it’s important to make sure that the technique can keep good precision in real cases. The value of this study lies in its potential to contribute to the field of fault detection in rotating machinery. By evaluating the effectiveness of classical diagnostic and optimization techniques in a simulated environment, this study can provide practical insights that can help improve the reliability and predictability of equipment maintenance in the industrial sector. The findings of this study can help future research aimed at developing more effective diagnostic tools for geared systems. Ultimately, this research seeks to bridge the gap between the theoretical advancements in fault detection techniques and their practical implementation in the industrial sector.

2. MODELLING THE MECHANICAL SYSTEM

In the field of fault diagnosis, model-based methods can be broadly categorized into two main groups: analytical (or quantitative) model-based methods and knowledge (or qualitative) model-based methods. Analytical model-based methods rely on mathematical models derived from the underlying physical laws governing the system. These models can take various forms, such as linear or nonlinear, deterministic or stochastic, and time-invariant or time-varying. The parameters of the model are typically estimated using data obtained from the system's normal operation. Any significant deviation between the actual behavior of the system and the predicted behavior from the model is considered an indication of a fault. Examples of analytical model-based methods include state-space models, transfer function models, and differential equation models. In contrast, knowledge model-based methods employ models that capture the qualitative behavior of the system, often expressed in the form of rules or logic statements. These models are usually constructed based on expert knowledge rather than physical laws. Fault diagnosis using knowledge model-based methods involves reasoning about the observed behavior of the system and comparing it with the behavior predicted by the model. Examples of knowledge model-based methods include rule-based systems, fuzzy logic systems, and expert systems.

Analytical model-based methods encompass a variety of models, each with its strengths and weaknesses. Among the simplest are the Single Degree of Freedom (SDOF) models, which focus on a single element's motion, often rotational, providing an efficient starting point for preliminary analyses. These models are particularly suitable for analyzing rotational dynamics in geared systems. Within the category of SDOF models, a distinction can be made between linear and nonlinear types. Linear SDOF models assume linear system properties and offer computational efficiency. However, they may not fully capture the dynamics of systems with significant nonlinearities. Conversely, nonlinear SDOF models incorporate elements such as gear backlash or bearing clearance to capture more complex behaviors, although with increased computational complexity. For systems with multiple interacting components, Multiple Degrees of Freedom (MDOF) models are often more appropriate. MDOF models consider multiple motions, including translational and rotational, resulting in a more accurate representation of the system's dynamics and enhancing the quality of the analysis. Linear MDOF models effectively capture the interactions between different system components but may fall short when significant nonlinearities are present. Nonlinear MDOF models, however, incorporate nonlinear terms in the system matrices or as additional forces, enabling a more accurate representation of the system's dynamics, especially when dealing with complex faults. Another category of analytical model-based method is numerical computation, such as Finite Element Models (FEM) and Boundary Element Models (BEM). FEM is a numerical technique used to approximate solutions to boundary value problems for partial differential equations. It subdivides a large system into smaller, simpler parts known as finite elements, enabling the simulation of complex deformations and stresses. While powerful for analyzing the structural behavior of geared systems, FEM requires significant computational resources and can be complex to implement. BEM, alternatively, is used for solving linear partial differential equations formulated as integral equations, finding applications in various fields, including fluid mechanics, acoustics, electromagnetics, and fracture mechanics.

Lumped Parameter Models assume that physical properties like mass, charge, and energy are concentrated at a single point, while Distributed Parameter Models represent systems where physical properties are distributed throughout the system, often involving partial differential equations. State-Space Models offer a different approach, representing a physical system as a set of interconnected input, output, and state variables governed by first-order differential equations. They find wide utilization in control systems design. The selection of an appropriate model depends on the specific characteristics of the system under study and the type of analysis required. For detailed stress analysis, a finite element model is typically suitable due to its ability to handle complex geometries, non-uniform material properties, and intricate boundary conditions. Meanwhile, for high-level dynamic response analysis, a lumped parameter model or a state-space model may be sufficient. The choice of the right model depends on the specifics of the system and the faults being studied. More complex models are generally more accurate but also require more computational resources and more detailed information about the system. The translational single degree of freedom (SDOF) model with time-varying stiffness is used in the study and is an example of an analytical nonlinear lumped parameter model-based method. It is derived from the physical laws of motion and incorporates the effects of gear mesh stiffness and tooth root faults on the system's dynamics. This model stands out due to its balance between simplicity and the ability to capture essential system dynamics and is particularly suitable for analyzing systems where the main concern is rotational dynamics, such as in many geared systems. This model is computationally efficient, making it ideal for applications where real-time or near-real-time fault detection is essential.

2.1 Geared pair model

The translational SDOF model with time-varying stiffness is widely used and robust and can well represent faults on the geared pair through the variation of stiffness as saw in (Harris, 1958). The Eq. (1) defines the model:

$$m\ddot{x} + c\dot{x} + k(t)x = F(t), \tag{1}$$

where x, $\dot{x}$ and $\ddot{x}$ are the displacement, velocity and acceleration in the translational direction respectively. The m, c and k are equivalent mass, dumping and time-varying stiffness, respectively and $F(t) = \frac{T}{r_p} + \sum k(t)e_i(t)$ is the force compound for the constant load force and the forces caused by transmission error. T is the torque applied by the drive system, r_p is the primitive radius of the gear and e_i is each type of time-varying transmission errors that can be considered in the model. Transmission errors will be discussed in the next topics. The dynamic behavior of geared systems is significantly influenced by gear mesh stiffness, particularly in the presence of faults. Adequate modelling of gear stiffness is therefore crucial for effective fault diagnosis and prognosis. The simplest model for gear stiffness is the Constant Stiffness Model, which assumes a constant stiffness throughout operation. While useful for initial design and analysis, this model may not accurately capture the dynamic behavior of the system under varying operating conditions, particularly in the presence of faults. More sophisticated models consider time-varying stiffness. Linear and Nonlinear Time-Varying Stiffness Models represent stiffness as a function of time, with the latter accounting for nonlinearity. These models can capture changes in stiffness due to progressive faults, such as wear or tooth breakage.

The Periodic Time-Varying Stiffness Model is particularly relevant for gear systems, as it models the periodic variation in stiffness due to the changing number of teeth in contact and the position of the contact point along the tooth profile. This model can represent the effects of periodic faults, such as pitting or tooth cracking. The Potential Energy Method, as described in (Wu, 2007), provides a more detailed model of gear mesh stiffness. This method calculates the potential energy of the gear pair system considering the bending deformation energy, the shear deformation energy, and the compressive deformation energy of the gear teeth. The gear mesh stiffness is then obtained by differentiating the potential energy with respect to the gear mesh displacement. This method can accurately model the effects of faults that alter the deformation behavior of the gear teeth, such as cracks or material defects. Other models mentioned in (Wu, 2007) work include the Contact Mechanics Method and the Finite Element Method. The Contact Mechanics Method models the contact mechanics between gear teeth, while the Finite Element Method uses a numerical approach to solve the equations of motion for the gear pair system. These methods provide detailed representations of the gear mesh stiffness and can capture the effects of complex faults. For the purpose of this work, it will be used a Periodic Time-Varying Stiffness Model comparing to literature FEM models. An equation model can be seen at Eq. (3), where we have the amplitude of variation of the stiffness and the respective variation function given respectively by a and $\sigma(t)$ and the K as the constant stiffness component, which can be given by

$$k(t) = K + a\,\sigma(t). \tag{2}$$

As the faults advance, each gear tooth can have a different stiffness behavior and amplitudes, so we can have different values of parameter a for each tooth. For this model, it was considered a single faulty tooth represented by the amplitude parameter a_f, and, for the other tooth, a common amplitude parameter a_0. The stiffness variation can be modeled using many different functions, such as cosines, square waves and other most advanced shapes. Some FEM models according to (Brauer, 2004) shows that the stiffness is a merge of a square and cosine wave, so for this work it was developed a parametric wave that can became a cosine, a square or something between then as the parameter, that we will call form factor f_f, varies from zero to one as can be seen in Figure 1.

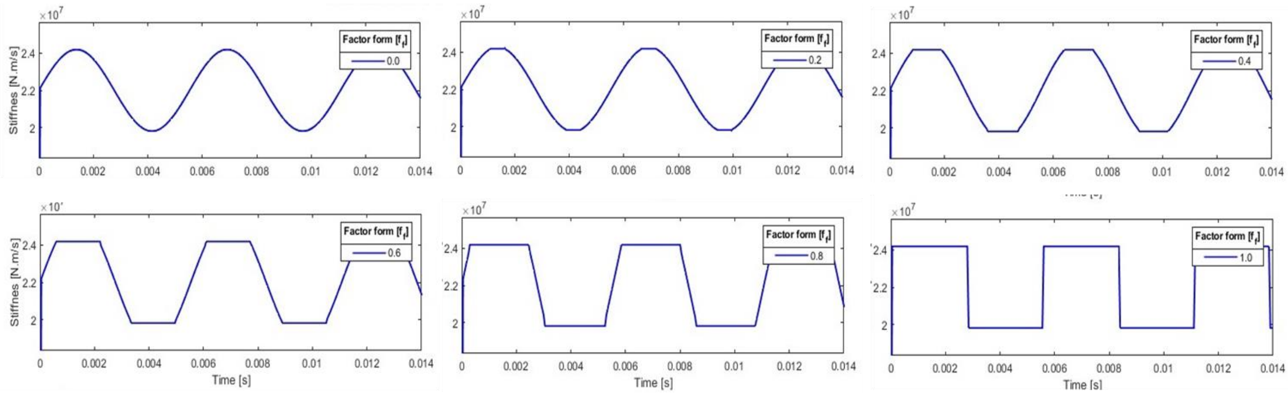

Figure 1. Influence of form factor on stiffness.

2.2 Transmission errors

Transmission errors (TE) is defined as the deviation between the ideal and actual position between the geared pair (Arato, 2006). This discrepancy is directly associated with the generation of vibrations and noise during the operation of the gearbox (Harris, 1995). Recent research, such as (Zhu et al., 2021), has further explored the impact of factors like time-varying meshing stiffness and transmission error amplitude on the system's vibration response, underscoring the importance of TE in the study of mechanical systems. Transmission errors can be attributed to a variety of factors, including but not limited to, manufacturing and assembly errors, thermal deformation, tooth surface deviations, and even wear and tear over time. Specifically, manufacturing errors might include inaccuracies in the tooth geometry due to limitations in the manufacturing process. Assembly errors can result from improper alignment, spacing of the gears in a gear pair and eccentricity, while thermal deformation can occur due to temperature changes during operation. Additionally, the tooth surface deviations, which might occur due to wear or manufacturing inaccuracies, can also contribute to TE. All these factors can result in non-uniform transmission of motion, fluctuations in gear mesh stiffness, vibration, and noise. The prediction and analysis of TE incorporate a variety of modeling techniques, including analytical methods, finite element methods (FEM), and experimental procedures. This work focuses on the analytical model used in (Arato, 2006) and many other references. The model used is divided in two error components, the first one relates to assembling problems (Almeida et al, 2017) and is given for the pinion and driven gear by

$$e_j(t) = \xi_j \sin(w_j t), \tag{3}$$

where $\xi_j = \frac{e}{r_g}\sqrt{\frac{{r_g}^2\, e}{r_g + e} - \left(\frac{r_g\, e}{r_g + e}\right)^2}$, r_g is the pitch radius, e is eccentricity e w_j is the angular rotation of the shaft. The j notation is used to represent the pinion or the gear. In order to define the assembling transmission error as a function of a normalized parameter f_{ate} that ranges nearly from zero to one, a ξ_{max} is calculated using the max eccentricity admissible for the system, and then the assembling transmission error becomes:

$$e_j(t) = f_{ate}\, \xi_{max}\, sin\,(w_j t). \tag{4}$$

The other component is about the geometrical problems, here we consider the total deviation used by (Lopez et al, 2003) and defined as

$$e_g(t) = \gamma_j \sin(w_{fe} t), \tag{5}$$

where γ_j is the precision class of the gear, normally between 4μm and 7μm, $w_{fe} = w_g/N_{ap}$, w_g is the gear mesh angular speed and $N_{ap} = lcm\ (N_p, N_d)/N_p$ is the assembling phases number, which is the number of cycles of the pinion to coincide two gear tooths, $lcm\ (N_p, N_d)$ is the least common multiple between the number of teeth of pinion and driven gear. In order to define the geometrical transmission error as a function of a normalized parameter f_{dte} that ranges nearly from zero to one, a γ_{max} is calculated using the max precision class expected for the system, and then the geometrical transmission error becomes $e_g(t) = \ f_{dte}\, \gamma_{max} \sin{(w_{fe}t)}$. Finally, Eq. (1) can be adjusted to become the geared pair fault equation defined below, considering the error in the pinion only (subscript p):

$$m\ddot{x} + c\dot{x} + k\big(t, a_f, a_0, f_f\big)x = \frac{T}{r_p} + k\big(t, a_f, a_0, f_f\big)\left[f_{ate}\, \xi_{max} \sin\big(w_p t\big) + f_{dte}\, \gamma_{max} \sin{(w_{fe}t)}\right]. \quad (6)$$

3. SIMULATION

Numerical resolution of differential equations is essential for simulating systems and diagnosing faults, particularly in the realm of engineering and physics. These equations, which describe the dynamic behavior of systems, often cannot be solved analytically, especially when dealing with complex, non-linear, or time-varying systems. In such cases, numerical methods provide a powerful tool to approximate the solutions and understand the system's behavior over time. These methods, including but not limited to Euler's method, Runge-Kutta methods, and finite difference methods, discretize the continuous problem into a set of discrete points, and then solve the equations at these points. In the context of fault diagnosis, the numerical resolution of differential equations enables the simulation of a system under various conditions, including the presence of faults. By comparing the simulated behavior with the actual behavior, it is possible to identify and diagnose faults in the system. For instance, an unexpected deviation in the system's response could indicate a fault. Furthermore, by analyzing how the system's behavior changes over time, it is possible to predict the progression of faults and take preventive measures. However, the accuracy of the fault diagnosis depends on the accuracy of the numerical method used, which in turn depends on factors such as the size of the time step and the numerical stability of the method. Therefore, careful consideration must be given to the choice of numerical method and its parameters. For this work it was used the Runge-Kutta method in Matlab. Eight cases will be shown in Table 1 and Figure 3 to demonstrate the simulator.

First investigated casa is the good condition one, the second, third and fourth cases are a gear tooth fault different levels represented by an increase in the form factor f_f and in the amplitude stiffness of one tooth a_f as can be seen in Figure 2. It is well known that the gear tooth fault causes a decrease in stiffness, represented by a_f, also the impacts became higher and it is represented by f_f which that shapes the stiffness to a square wave as it gets nearest to 1. The fifth, sixth and seventh cases are increasing levels of both transmission errors, represented by the factors f_{ate} and f_{dte}, assembling and dimensional errors respectively. The eighth is a combination of all the faults in the medium severity. Finally, a Gaussian-noise with signal-to-noise ratio (SNR) of 10 was added to all the signals. The Figure 3 show all the eight simulated cases.

Table 1. Eight simulated cases and parameters

	Cases	a_0	a_f	f_f	f_{ate}	f_{dte}
1	Good condition	0.1	0.1	0.1	0.0	0.0
2	Gear tooth fault (early stage)	0.1	0.2	0.4	0.0	0.0
3	Gear tooth fault (medium stage)	0.1	0.3	0.6	0.0	0.0
4	Gear tooth fault (advanced stage)	0.1	0.6	0.9	0.0	0.0
5	Transmission error fault (early stage)	0.1	0.1	0.1	0.1	0.1
6	Transmission error fault (medium stage)	0.1	0.1	0.1	0.2	0.2
7	Transmission error fault (advanced stage)	0.1	0.1	0.1	0.4	0.4
8	All faults (medium stage)	0.1	0.3	0.6	0.2	0.2

The gear tooth fault is represented by the stiffness signal and can be seen in the figure below:

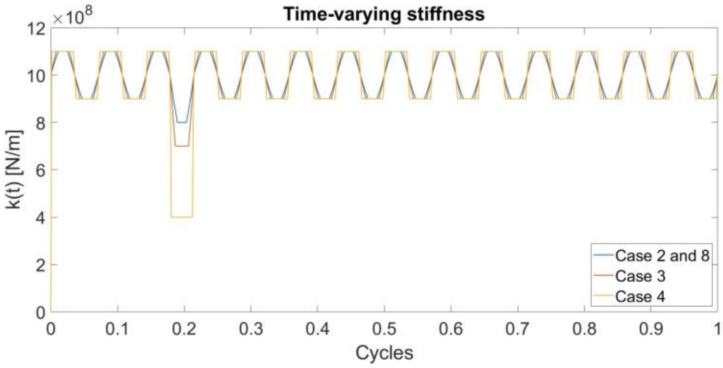

Figure 2. Stiffness signal for a gear tooth fault – cases 2, 3, 4 and 8.

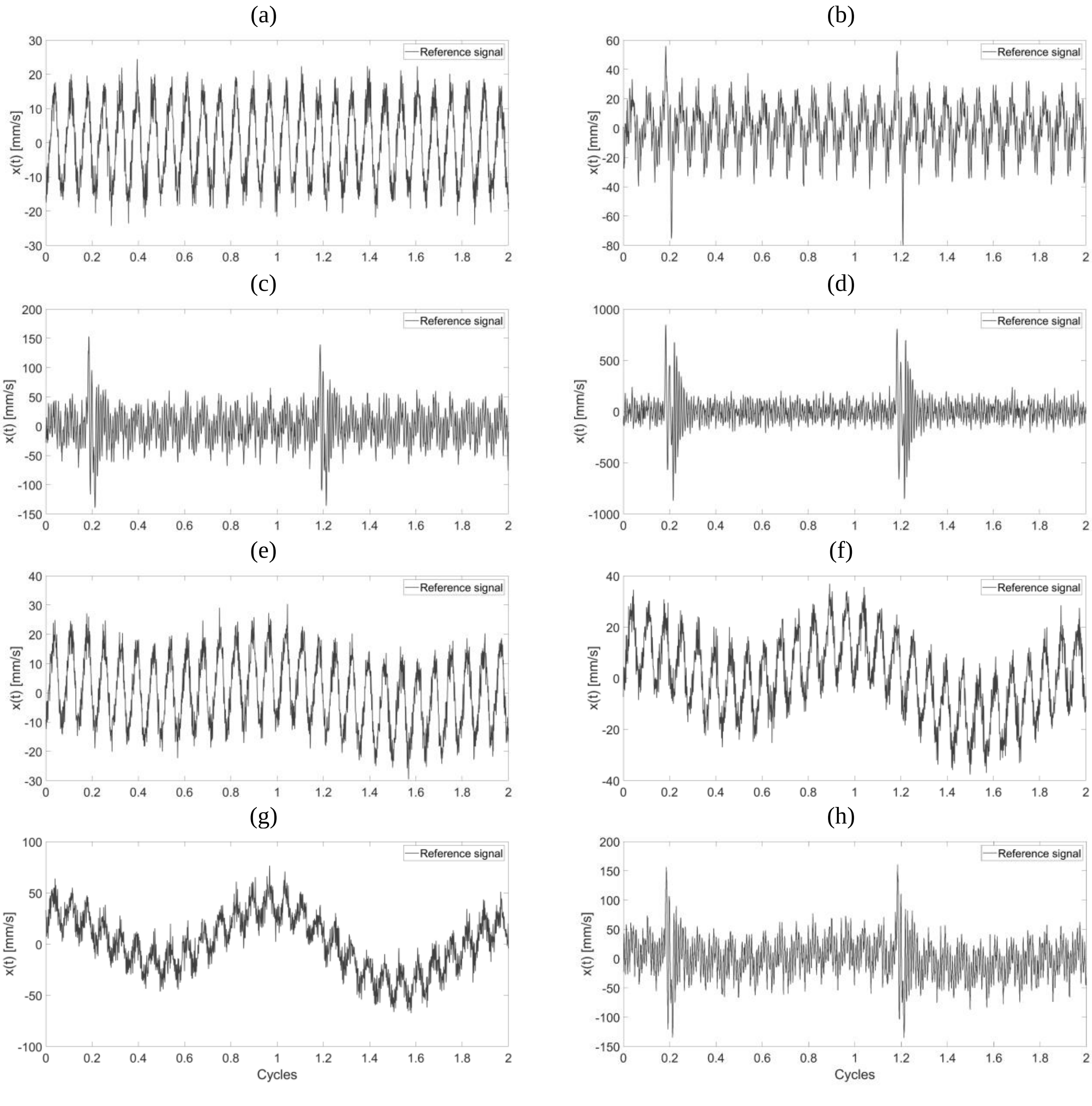

Figure 3. Time domain simulated signal of all cases: (a) case1; (b) case 2; (c) case 3; (d) case 4; (e) case 5; (f) case 6; (g) case 7; (h) case 8.

4. SIGNAL PROCESSING

Signal processing involves the analysis and manipulation of signals - such as sound, electromagnetic waves, or sensor readings - to extract meaningful information, which can be used to identify and diagnose faults in a system. The signals, which are often time-varying and may contain noise, provide a wealth of data about the system's behavior under various operating conditions. By analyzing these signals, it is possible to detect anomalies that may indicate a fault, and to track changes in the signals over time that may suggest the progression of a fault.

The process of signal processing for fault diagnosis typically involves several steps. First, the raw signals are collected from the system, often using sensors or other data acquisition devices. These signals are then pre-processed to remove noise and other irrelevant information, and to normalize the signals for further analysis. Various techniques can be used for this purpose, including filtering, normalization, and spectral analysis. Once the signals have been pre-processed, they are analyzed to extract features that are indicative of the system's behavior. This can involve techniques such as Fourier analysis, wavelet analysis, and time-frequency analysis, among others. The extracted features are then used to diagnose faults in the system, often using machine learning or statistical methods.

For this work the reference and reconstructed signal are generated through simulation, so the signal process here intent to isolate the interest fault frequencies and to be fast as it will be called many times in parameter estimation. So, for now, it is interesting to keep it simple. It is used the FFT and a band filter in frequency domain, the bands used consists of harmonics of the shaft rotation in a way to take four meshing gear harmonics plus five shaft rotation harmonics and the assembling phase frequency. For each band it is considered the maximum value inside the band, Figure 4 shows the bands over the signals.

5. PARAMETER ESTIMATION FOR FAULT DIAGNOSIS

Parameter estimation is a fundamental technique in the field of fault diagnosis, providing a systematic approach to identify the key characteristics of a system. It involves the use of mathematical models and observed data to estimate the parameters that define the system's behavior. These parameters, which may include physical properties such as mass, stiffness, and damping, or operational conditions such as speed and load, can provide valuable insights into the system's health and performance. Any significant deviation in these parameters from their expected values can indicate a potential fault, making parameter estimation a critical tool for fault diagnosis. The process of parameter estimation typically involves several steps. Initially, a mathematical model of the system is developed, which describes the relationship between the system's parameters and its behavior. This model can be derived from physical laws, empirical relationships, or data-driven methods. Subsequently, observed data from the system is collected or simulated, which may include measurements of the system's response to certain inputs or operating conditions. This data is then used to estimate the parameters of the model, often using optimization techniques that minimize the difference between the observed data and the model's predictions.

The selection and application of an appropriate optimization technique depends on the nature of the problem, the characteristics of the mathematical model, and the quality of the observed data. Gradient-based methods like Newton's method and the method of steepest descent are commonly used, leveraging the objective function's derivative for optimal parameter search. However, these methods may struggle with non-differentiable, discontinuous objective functions or problems with multiple local minima. For problems where the derivative is difficult to compute or non-existent, derivative-free or direct search methods are employed. These include the Nelder-Mead method and genetic algorithms. These methods are robust to non-differentiable, discontinuous, or multi-modal objective functions. Particle swarm optimization, a population-based optimization method, is particularly noteworthy. Inspired by the social behavior of bird flocking or fish schooling, it represents each potential solution as a particle in the swarm. The particles move in the search space based on their own and their neighbors' best positions, converging towards the optimal solution. This method has proven effective in handling complex optimization problems, including those with multiple local optima.

Simulated annealing and differential evolution are other derivative-free methods known for their effectiveness in handling complex optimization problems. Surrogate optimization is useful when the objective function is expensive to evaluate or lacks a derivative. Surrogate models approximate the objective function, providing a derivative estimate and allowing optimization on the surrogate model instead of the actual objective function. Pattern search methods, a type of direct search method, explore the search space following a specific pattern, guiding the optimal parameter search. Direct search methods, a broad class of optimization methods, directly search the parameter space for optimal parameters, making them suitable for problems with non-differentiable, discontinuous, or multi-modal objective functions. Lastly, the Grasshopper Optimization Algorithm (GOA) is another derivative-free method that has been briefly applied in fault diagnosis, showing potential in handling complex, multi-modal optimization problems. After investigating some methods like direct search, pattern search and surrogate optimization the best precision method found was Particle swarm optimization. The objective function is an error function between the two filtered signals, the reference and the parameter estimated signals. A specific error function found in Eq. (12) was developed for this purpose to improve the results as it gives more importance to greater pikes and also keeps the algorithm less susceptible to noise.

$$E = \sqrt{\left(\left|\frac{S(f)}{max\,[S(f)]}\right| + 1\right)^2 (S(f) - R(f))^2}, \tag{12}$$

where $S(f)$ is the filtered estimated signal and $R(f)$ is the filtered reference signal.

6. RESULTS

The eight cases were conducted to check the parameter estimation using the technique related before and the results are summarized in Figure 4 in the frequency domain analysis.

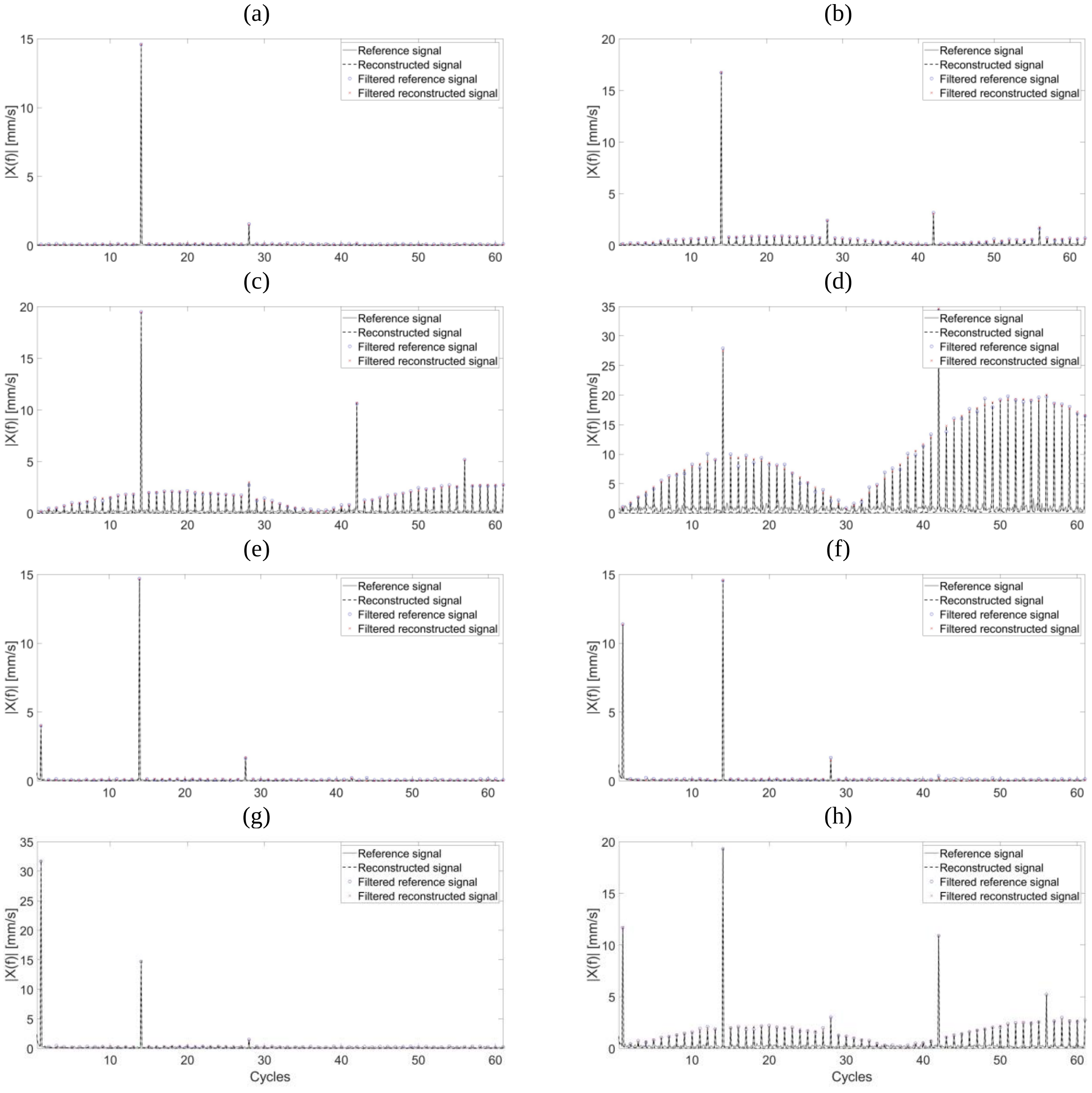

Figure 4. Frequency domain reference and reconstructed full and filtered signals for all the eight cases: (a) case1; (b) case 2; (c) case 3; (d) case 4; (e) case 5; (f) case 6; (g) case 7; (h) case 8.

As expected, the good condition signal had the mesh frequency1in 4 cycles ($N_p = 14$) and its harmonics, as the gear teeth fault got worse the sidebands spaced by the shaft rotation frequency increased around gear mesh frequency and its harmonics. The transmission errors cases present a shaft rotation peak and a sub-harmonic also, that is the assembling phase frequency, it's had not a relevant influence in gear mesh. The method was very precise even with noise as shown in Table 3 and 4, the worst absolute errors was the 4 and 7 with 0.0255 and 0.0285, which is a very small error. A possible cause is because the amplitude difference between the fault types were bigger, and as the error function gives more importance to the highest peaks the lowest one has their error worsen. The absolute error was selected because all parameters are normalized to fall between 0 and 1. Relative errors for small parameter values can increase significantly even with low absolute errors, which typically is not a problem. Figure 5 depicts the results for the 8 cases investigated. The estimated parameter and the percentage error are shown for convenience.

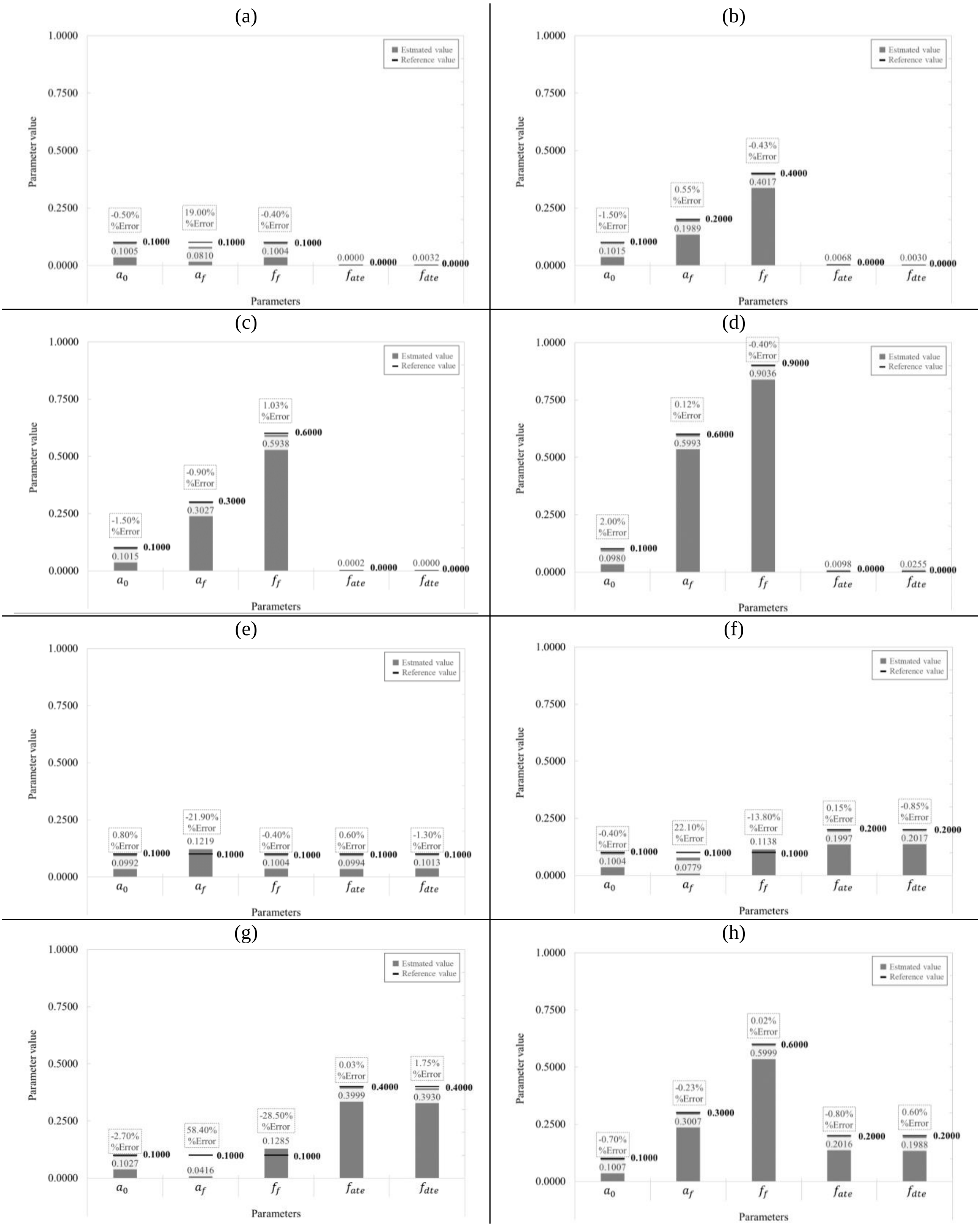

Figure 5. The estimated parameter values and their respective errors for all the eight cases evaluated: (a) case1; (b) case 2; (c) case 3; (d) case 4; (e) case 5; (f) case 6; (g) case 7; (h) case 8.

7. CONCLUSION

The system analyzed can be very challenging to diagnose as we saw for example in time domain signals, it is not easy to differentiate between some faults and its severity. Frequency domains signals was also challenging as it became very complex as the peaks increase. A good diagnosis method is that one which can gather information from these complex signals, classify and quantify the faults. The proposed method achieved with good precision all this goals by find the parameter values that represents the failure mode and its degradation level. The simulator represented very well the faults behaviors and the error was very low in all the cases showing that the method works very well and is promising for real signal analyses. When the difference between the fault types were bigger the absolute error was the worse but still under 0.0285 as the factors are normalized. The method showed very promising in diagnosing geared pairs faults and worth investing efforts to improve the model used, incorporate other faults and testing in real signals.

8. REFERENCES

Almeida, F.C.L., Gonçalves, A.C., Brennan, M.J., Paschoalini, A.T., Arato Junior, A., Silva, E.F.M., 2017. "An Illustration of Some Methods to Detect Faults in Geared Systems Using a Simple Model of Two Meshed Gears". In *Ekwaro-Osire, S., Gonçalves, A., Alemayehu, F. (eds) Probabilistic Prognostics and Health Management of Energy Systems*. Springer.

Arato, A.J., 2006. *Análise de Vibrações em Transmissão de Engrenagens com Foco na Manutenção Preditiva e Diagnóstico de Defeitos*. Technical Report, UNESP, Ilha Solteira, Brazil.

Barnes, J.W., 1994. *Statistical Analysis for Engineers and Scientists: A Computer-Based Approach*. McGraw Hill, Singapore.

Duan, F. and Živanović, R., 2016. "Induction Motor Stator Fault Detection by a Condition Monitoring Scheme Based on Parameter Estimation Algorithms". *Electric Power Components and Systems*, Vol. 44:10, p. 1138-1148.

Harris, S.L., 1958. "Dynamic Loads on the Teeth of Spur Gears". *Proceedings of the Institution of Mechanical Engineers*, Vol. 172, pp. 87-112.

Li, Z., Chen, D., Chen, Y., Lei, H. and Zhu H., 2021. "PMSM parameter identification based on improved PSO". *Journal of Physics*, Conference Series 1754 012235.

Liang, X., Zuo, M.J., Feng, Z., 2018. "Dynamic Modeling of Gearbox Faults: A Review". *Mechanical Systems and Signal Processing*, Vol. 98, p. 852-876.

Tsui, K.L., Chen, N., Zhou, Q., Hai, Y., Wang, W., 2015. "Prognostics and Health Management: A Review on Data Driven Approaches". *Mathematical Problems in Engineering*, Vol. 2015, Article ID 793161, p. 17.

Wu, F., Lee, J., 2015. "Information Reconstruction Method for Improved Clustering and Diagnosis of Generic Gearbox Signals". *International Journal of Prognostics and Health Management*, ISSN 2153-2648, 2011 004.

Wu, S., 2007. *Gearbox Dynamic Simulation and Estimation of Fault Growth*. Master dissertation, Faculty of Graduate Studies and Research, University of Alberta, Alberta, Canada.

Ye, X., Hu, Y., Shen, J., Feng R. and Zhai, G., 2020. "An Improved Empirical Mode Decomposition Based on Adaptive Weighted Rational Quartic Spline for Rolling Bearing Fault Diagnosis". *IEEE Access*, vol. 8, pp. 123813-123827.

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