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PHYSICS–BASED, DATA–DRIVEN, AND PHYSICS–BASED DATA–DRIVEN METHODS FOR DIAGNOSTICS OF ROTATING MACHINERY – STATE OF THE ART

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Abstract: As the level of complexity of modern rotating machinery grows, the need for an effective and efficient maintenance process increases as well. In the last decade, researchers all over the world have shown strong aspiration to optimize the diagnostics phase in rotating machinery. This paper highlights some of the latest research on the detection of typical faults in rotating machinery such as mass rotor imbalance, misalignment, rub and looseness, bearing and gear faults. Various techniques for condition monitoring have been researched, and in this paper, they have been classified into three groups: physics–based, data–driven, and physics–based data–driven methods. Although most of the research falls into the first two prior mentioned groups, an intent to introduce a novel method, their symbiosis, has emerged in the last few years. The great potential for future work on physics–based data–driven methods in the field of rotating machinery has been briefly discussed.
Keywords: physics–based, data–driven, physics–based data–driven, diagnostics, rotating machinery

1. INTRODUCTION

Dynamical systems are systems that evolve and change their state with time over a state space according to a fixed rule. In order to ensure a safe and efficient operation of the dynamical system, a variety of tasks have to be successfully completed. First, the modeling phase has to provide a suitable model for the dynamical system, allowing a better understanding of its behaviour. Next, the control of the dynamical system has to manage, command, direct, or regulate its behaviour using control loops in order to achieve certain tasks. The diagnostic phase identifies the dynamical system's present and potential faults, and the prognostics phase predicts the remaining useful life of the system. An example of widely used dynamical systems is the group of rotating machines or i.e. rotating machinery. The performance requirements that modern rotating machinery must satisfy have introduced a trend toward higher speeds and productivity and more stringent vibration levels [1]. Consequently, as the complexity of the performance requirements of the machinery grows, its maintenance becomes more demanding and its costs significantly start to grow. For instance, in production systems composed of rotating machinery, 15 to 40% [2] of the total costs for the production of the product are due to maintenance costs. In order to fulfill the above–mentioned objectives while simultaneously reducing maintenance costs, an optimization of the maintenance strategy has to be developed. Condition maintenance of machinery includes monitoring its state based on parameters that are considered to be sufficiently sensitive to the change in its mechanical state, that is, to the occurrence of faults. The best indicator of the overall current state of the machine, which is sensitive to the appearance and development of a certain defect at the earliest stages is vibration, Table I [2].

There are various instruments for vibration measurement, which have noticed rapid technological development in recent years. In order to accurately monitor and determine the current state of the machinery by measuring its vibrations, a large amount of data has to be obtained. That one might minimize the time for processing and analysis of these data, automation of the process of monitoring the condition and identification of possible faults is in order. Empowered by the learning capability, big databases and model computing, artificial intelligence (AI) has achieved tremendous success in many different fields. A great interest and advancement in optimizing traditional maintenance strategies have been noted in the past 10 years [3]. By using the benefits of AI, the subjective opinion and possible human error of the operator would be eliminated or minimized. This is especially important in situations when a large number of faults are simultaneously present in a machine.

Table I. Indicators and most common problems in rotating machinery

	Temperature	Pressure	Flow	Lubricant Analysis	Vibrations
Imbalance					X
Misalignment	X				X
A damaged rolling bearing element	X				X
A damaged journal bearing element	X	X	X	X	X
A damaged gear					X
Looseness					X
Noise					X
Cracking					X

Intelligent autonomous systems using AI with their powerful learning ability to discover hidden trends and patterns from data enable a better understanding of the machine's behaviour. However, there are a lot of challenges in creating an intelligent system for diagnostics of rotating machinery. One of the major challenges

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is that AI requires big databases for training, which could not be always obtained. The other major challenge is the poor generalization ability or i.e. the extrapolation characteristic of the purely data–driven method. Data–driven models do not consider the underlying physics of dynamical systems or in this case the machinery and its components. Consequently, it is anticipated that it would eventually fail at generalizing unknown data due to the lack of physical understanding. In order to overcome these challenges, recently researchers are starting to take great interest in a physics–guided machine learning method. The physics–guided machine learning method elaborates the existing physics knowledge of the dynamical system in order to enhance the performance of data–driven machine learning.

Numerous papers study and analyze various methods that enhance the capability to diagnose eventual faults and determine the health state of rotating machinery. All methods can be divided into the three above–mentioned groups: purely physics–based, purely data–driven, and physics–based data–driven method. In the next two chapters, existing literature for the two types of models, physics–based models and data–driven models of the rotating machinery, is studied in detail. The greatest part of the existing literature in the field of diagnostics of rotating machinery focuses on these two methods [4]. Nevertheless, in the last few years, an idea to combine both methods into a physics–guided machine learning method for fault diagnostics has emerged. In the fourth chapter of this paper, the existing literature for physics–guided machine learning models is reviewed. The selected faults of rotating machinery whose existing literature has been analyzed are imbalance, misalignment, rub and looseness, bearing faults, and defects in gears. These faults have been chosen due to the fact that they are some of the most common problems which occur in most types of rotating machinery, and the interlinking nature between them, Table II [2].

Table II. Typical vibration problems and their approximate percentage of occurrence

Imbalance	40%	Fan and duct turbulence	5%
Misalignment	30%	Gears	2%
Resonance	20%	Rub and looseness	5%
Bearings	10%	Torsional vibrations	3%
Motor vibrations	8%	Radial throw	2%
Cavitation in pumps	2%	Belts and Pulleys	4%

2. PHYSICS–BASED MODELS OF ROTATING MACHINERY

Physics–based models are constructed using the underlying physics of the given system. Depending on the specific application a high–fidelity or low–fidelity model can be defined. Recently, a number of authors have been exploring various methodologies for using physics–based models of rotating machinery for prognostic health management (PHM) [3], Appendix I. These types of models assess the health of the system by solving a set of equations derived from physics, engineering, and science knowledge, and can find application in diagnostics [5].

During the diagnostics phase, a fault is detected by comparison between the obtained outputs from the physics–based models and the measurements from the real system [6]. Han, T. et al. [7] simulate imbalance fault and dynamic balancing by virtual prototyping technology based on the imbalance mechanism and balancing theory. The vibration signal is acquired by virtual sensors, and motion and dynamic analysis are carried out using ADAMS software. Oppenheimer, C.H. and Loparo, K.A. [8] propose a physics–based approach for diagnostics of rotor imbalance using filters i.e., observers based on physical models of various machine–fault combinations. The model for generated vibration by an imbalance of a rotor captures two rotor modes, namely the first bending mode excited by static imbalance and the second bending mode excited by dynamic imbalance. Sudhakar, G.N.D.S. and Sekhar, A.S. [9] perform a physics–based simulation of imbalance as a fault by describing a model–based method. Two different approaches, equivalent loads minimization and vibration minimization methods are applied for the identification and localization of an imbalance fault in a rotor system. Ogbonnaya, E.A. [10] creates a software based on the underlying physics of a gas turbine rotor shaft and its most frequent faults. The "MICE" software which is an acronym for misalignment, imbalance, crack and eccentricity of a rotor shaft, identifies and differentiates these faults. Bahaloo, H. et al. [11] derive a model for coupling misalignment considering the presence of both the angular and parallel misalignments in the coupling location. Sekhar, A.A. and Prabhu, B.S. [12] study the effects of coupling misalignment on vibrations of rotating machinery by using FEM analysis. Various papers [13,14] have provided vibration identification charts that indicate that the coupling misalignment, generally, produces a frequency that is twice the speed frequency of the shaft. Rub and looseness create complex vibration signals which are difficult to diagnose using traditional methods. Nonetheless, these frequently present faults have been attractive for scientific research and have been studied in detail. Chen, G. [15] outlines a dynamic system model of a rotor–bearing–stator system embedded with a rubbing fault. Han, Q. et al. [16] develop a finite element (FE) model of a rotor system with two discs and consequently conduct numerical simulations. Transverse vibrations of the rotor system under three typical

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cases with different rotating speeds, rub–impact clearances, rub–impact rod stiffness, and rub frictions have been studied. Luo, Y. et al. [17] develop a dynamic model of the nonlinear elastics rotor–bearing system with coupling faults of pedestal looseness and rub impact. Liu, Y. et al. [18] define a mechanical model and finite element model of a dual–disc rotor system with looseness–rubbing coupling fault. McFadden, P.D. and Smith, J.D. [19] develop a model to describe the vibration produced by a single point defect on the inner race of a rolling element bearing under constant radial load. The model analyses the effects of the bearing geometry, shaft speed, bearing load distribution, transfer function, and the exponential decay of vibration. Patel, V.N. et al. [20,21] develop a model for the generated vibrations by deep groove ball bearings having multiple defects on the races. Sopanen, J. and Mikkola, A. [22] propose a dynamic model of a deep–groove ball bearing with six degrees of freedom. The geometry, material properties, and diametral clearance of the bearing are given as the input to the proposed model. In an additional paper, the same authors [23] implement, analyze and validate the proposed model using a commercial multi–body system software application (MSC. ADAMS). Kiral, Z. and Karagülle, H. [24] model the dynamic loading of a rolling element bearing structure by a computer program developed in Visual Basic programming language. Wang, J. et al. [25] present a new model–based approach to integrated fault diagnosis and prognosis for wind turbine bearings. Wang, C. et al. [26] develop a mathematical model for bearing fault detection based on a modified winding function approach (MWFA). Yan, R. and Gao, R.X. [27] present an energy–based approach for defect diagnosis of rolling bearings, which enhances the ability of the continuous wavelet transform in feature extraction from vibration signals. Additionally, an experimental validation using data collected from two defect–seeded ball bearings has been presented. Ruan, D. et al. [28] develop a Modelica model for the whole bearing test rig, including the test bearing, driving motor and load. First, a five degree–of–freedom (5–DoF) model was proposed for the test bearing to identify the normal bearing dynamics. Next, a fault model was applied to characterize the defect position, size and shape of multiple defects. Cubillo, A. et al. [29] identify the most important failure modes and the models available to represent the degradation mechanisms of rotating machinery. More precisely, they consider three typical components of rotating machinery: gears, rolling bearings, and hydrodynamic bearings. Apart from the physics–based models which have already been applied for rotating machinery, they propose models that can potentially be used in the future. Diehl, E.J. et al. [30] develop dynamic gearbox models (DGM) in order to replicate dynamic transmission error (DTE), dynamic stresses, stability, noise, and vibration motion of the system. Dadon, I. et al. [31] propose a new reliable dynamic model that predicts the vibrations of faulty gear transmission. Hence, the effects of the fault could be recognized, the severity of the fault could be identified, and methods for characterizing its type could be developed. Eyk, L.V. et al. [32] develop an accurate physical model of the gearboxes and their failure modes obtained from the potential energy method (PEM).

3. DATA–DRIVEN MODELS OF ROTATING MACHINERY

Nonetheless, there are limitations of physics–based models concerning the costs and accuracy of the obtained output. The first limitation of physics–based models for complex systems is the potentially high computational costs. Additionally, there is often a necessity to repetitively run the physics–based model in order to perform a stochastic analysis. The other limitation refers to the assumptions and simplifications of the physics–based model that would have to be made. The accuracy of the model decreases when it operates in a field that was not covered as a result of its simplification. The effects of these limitations can be reduced by implementing the second type of model, data–driven models.

Vibration signals collected from a rotating machine using vibration transducers are often in the time domain [33]. Generally, the signals consist of a large collection of responses from several sources in the rotating machine and some background noise. Therefore, preprocessing of the signal, filtering, and extraction of certain attributes of the signal that describe its essence, have to be performed. In the machine learning community, these attributes are also called characteristics, signatures, or features [33]. There are numerous techniques for manual feature extraction in the time domain using statistical parameters, in the frequency domain as spectrum features or in the time–frequency domain. Nevertheless, extracting useful features from a large, noisy dataset of vibration signals is a highly demanding task. Therefore, techniques that perform automated feature extraction such as deep learning (DL) are attracting great attention in the scientific world. Deep learning technique uses specialized algorithms and deep neural networks which can automatically extract features from vibration signals. Once the vibration data analysis has been performed, diagnostics of the rotary machinery is in order. This phase involves fault detection and identification by using a classifying algorithm to categorize the data signals into different classes of faults, by employing their extracted features.

Most of the data–driven models determine and identify certain faults in rotating machinery in scenarios when multiple faults are simultaneously present. Firstly, a review of existing literature in the field of several machine

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learning classifying algorithms used for diagnostics of previously mentioned faults in rotating machinery is performed, Appendix II. The reviewed classifying algorithms include neural networks (NN), k–nearest neighbours (k–NN), support vector machine (SVM) and random forest (RF). For instance, Hoffman, A.J. and Van Der Merwe [34] use a combination of three different neural network classification techniques: Kohonen Network (KNN), nearest neighbour rule (NNR), and radial basis function neural network (RBFNN) to classify faults. During the manual feature extraction phase, six time domain and four frequency domain features have been extracted and various combinations of features have been tested. The conclusion from this paper states that bearing defect makes it impossible to determine the degree of imbalance based on a single vibration feature. Furthermore, Hang, J. et al. [35] present an approach for fault diagnosis in a wind turbine based on a multi–class fuzzy support vector machine (FSVM) classifier. Empirical mode decomposition (EMD) is applied in order to extract time–frequency domain features from the signal. The acquired vibration signals are a representation of four health conditions of the machine: normal, shaft imbalance, shaft misalignment, and shaft imbalance and misalignment. There are numerous authors who use SVM in order to classify faults and compare various feature extraction techniques [36–42]. Baccarini, L.M.R. et al. [36] studied the application of independent component analysis (ICA) and SVM to detect and diagnose induction motor faults. The used data–set consists of acquired vibration signals which represent a no–fault condition and three types of mechanical faults including radial and angular shaft misalignment, looseness, and rotor imbalance, and their combination. Yuan, S.F. and Chu, F.L. [37] propose a new multi–class classification of SVM named 'one to others' algorithm which is designed for solving multi–class recognition problems. Acquired vibration signals in the time domain are transformed into the frequency domain using fast Fourier transformation (FFT) and the obtained frequencies are divided in nine bands. Using principal component analysis (PCA) the nine–dimensional fault feature vectors are transformed into two–dimensional fault feature vectors. Wu, T.Y. et al. [41] differentiated between broken, worn, chipping or healthy teeth of a gear by using SVM technique. Yang, D. et al. [42] measured vibration acceleration signals of normal gear, chipped tooth gear, and missing tooth gear and extracted fault features based on the EMD and the kernel function.

The recognition rates of gearbox faults have been improved by using the SVM classification model which has been optimized by the bee colony algorithm. Numerous authors investigate the possibility to develop new classifying algorithms by combining SVM and various machine learning algorithms [43–46]. Widodo, A. et al. [43] perform fault diagnosis of low–speed bearing using multi–class relevance vector machine (RVM) and SVM. The classification for fault diagnosis was conducted using prior linear feature extraction using ICA and PCA techniques and without prior feature extraction. The accuracy of the results significantly increases when prior linear feature extraction techniques have been used. Zhang, Y. et al. [44] propose a novel fault diagnosis approach based on the non–linear dimensionality reduction method of isometric feature mapping (ISOMAP). Only one parameter i.e., the number of neighbors k needs to be set for ISOMAP and its value has been empirically determined in a way that provides the best classification result. Two vibration datasets containing signals of a rotor with mass imbalance, misalignment, and rub impact faults; and rolling bearing data, with a normal condition, IR fault, and OR fault – are used to verify the fault–classification performance of the proposed method. Three classifying techniques have been used: minimum–distance classifier, k–NN, and SVM with a radial basis function (RBF) kernel. Saravanan, N. et al. [45] deal with the effectiveness of wavelet–based time features for fault diagnosis of a gearbox using artificial neural network (ANN) and proximal support vector machines (PSVM). Han, T. et al. [46] show that feature selection is critical to the success of machine fault intelligent diagnosis. In order to present a comprehensive comparison, three classes of popular features have been extracted for further model training: time–domain statistical features (TDF), frequency–domain statistical features (FDF), and multiple scale features (MCF). Additionally, the authors perform a comparison of the accuracy for classifying bearing and gear faults of RF, ANN, and SVM. It can be concluded that different feature extraction methods lead to different overall diagnostic results and accuracy. Without human intervention, the complexity of feature selection and diagnostic uncertainty of traditional feature extraction methods could be depressed [47]. Similarly, numerous papers try to investigate ANN classifying algorithms and its variations [48–53]. Vyas, N.S. and Satishkumar, D. [48] discuss an artificial neural network (ANN) simulator built for the identification of faults in rotating machinery. Five different primary faults and their combinations are introduced in the experimental set–up: rotor with no fault, rotor with mass imbalance, rotor with bearing cap loose, rotor with misalignment, and rotor with both mass imbalance and misalignment. Kaewkongka, T. et al. [49] propose a method for rotor dynamic machine condition monitoring using continuous wavelet transform (CWT) as a feature extraction technique and ANN as a classification algorithm. Combinations of four types of machine fault conditions are investigated: balanced shaft, imbalanced shaft, shaft with a misalignment, and faulty bearing.

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Additionally, combinations of four health conditions of the bearings – normal, cage fault, inner race fault, and outer race fault are analyzed in this paper. Ngolah, C.F. et al. [50] concentrate on identifying rub and looseness faults based on a three–layer ANN. Acquired signals are processed by a signal processor to extract characteristic vibration signals of ten key performance indicators. Lei, Y. et al. [51] propose a new empirical model decomposition (EMD)–based method for fault diagnosis of rotating machinery. The method is used for the diagnosis of rub–impact of a power generator and early rub–impact of a heavy oil catalytic cracking machine set. Bin, G.F. et al. [52] propose a method that combines CWT and EMD for extraction of fault feature frequency and neural network for rotating machinery early fault diagnosis. Rajeswari, C. et al. [53] use exact feature selection technique and back propagation neural network (BPNN) for gear fault classification algorithm.

Moreover, state–of–the–art deep neural network learning classifying algorithms that have been used in machine fault diagnosis is also performed, Appendix II. More precisely, existing literature in the field of machine fault diagnosis using autoencoder–based deep neural networks (DNN) [55–60], convolutional neural networks (CNN) [54,61–64], and deep belief networks (DBN) [47,59,65], is reviewed. Guo, S. et al. [54] propose a novel diagnosis method that uses a convolutional neural network (CNN) to directly classify the continuous wavelet transform (CWT). CWT is a time–frequency domain transform of the original signal and can contain most of the information of the vibration signals. The acquired vibration signals for the experiment are rotor imbalance, rotor misalignment, bearing block looseness, and contact rubbing. Sun, W. et al. [61] distinguish four types of gear faults by introducing a method based on a dual–tree complex wavelet transform (DTCWT) and CNN. Chen, Z. et al. [47] and Shao, H. et al. [66] explore the possibilities of a DBN–based fault classifier, which performs an automated feature extraction. Guo, X. et al. [60] complement the idea of extracting features automatically without significantly increasing the demand for machinery expertise. They manage to maximize accuracy without overcomplicating machine structure by developing an adaptive DNN for bearing fault identification. Sohaib, M. and Kim, J.M. [55] share a similar goal but develop a different technique that uses autoencoder–based DNN for bearing fault classification.

4. PHYSICS–BASED DATA–DRIVEN MODELS OF ROTATING MACHINERY

Nonetheless, data–driven method or purely–data driven machine learning also faces many limitations for example, intensive training data and poor generalization ability. In order to overcome these limitations and take advantage of both the physics–based model and data–driven model, in the past few years [70, 71] a novel methodology in the field of rotating machinery diagnostics is proposed, the physics–based data–driven method. In spite of the fact that recently machine learning models have been greatly studied and implemented in the field of machinery diagnostics, a limited research effort has been devoted to incorporating physical knowledge into these models [72].

Sadoughi, M. and Hu, C. et al. [73] are the first researchers who propose a novel physics–based convolutional neural network (PCNN), for fault diagnosis of rotating machinery. Furthermore, the same authors [74] concentrate their research using PCNN on fault diagnosis of rolling element bearings. A deep CNN model with a physics–based convolutional layer as the first layer for bearing fault identification has been created. Additionally, Lu et al. [75] present a novel physics–based feature weighting (PFW) technique that leverages the fault characteristic frequencies of a bearing to weigh the vibration features based on the amount of fault–related information that they are expected to carry. Shen, S. et al. [76] prove the ability to increase the identification accuracy of the model by using test data from 18 bearings on an agricultural machine operating in the field, and data from bearings on a laboratory test stand. The results considering the identification accuracy of the PCNN are compared to the accuracy of SVM, RF, and CNN and show a great improvement in bearing fault detection accuracy which results in reducing the likelihood of false alarms. Additionally, fault characteristic frequencies are learned as part of the hyperparameters, as opposed to the previous paper [74] which pre–computed them and fed them into a PCNN model as pre–defined inputs.

5. CONCLUSIONS

Maintenance of rotating machinery is the essential part and the core of every production process and directly affects its productivity and quality. As the capabilities and complexity of rotating machinery grow, its maintenance becomes more demanding, and its costs significantly start to grow. Therefore, automation of the diagnostics phase of rotating machinery, i.e. monitoring of its condition and identification of possible faults is crucial for a well–organized production plant. Physics–based models which are based on the physics of the given system, are used for the diagnostics of rotating machinery by comparing the obtained outputs from the physics–based models and the measurements from the real system. In order to reduce the effects of the limitations of physics–based models concerning the complexity, costs, and accuracy of the obtained output, data–driven models have been intensively used in the field of rotating machinery diagnostics. However, this

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method has its own limitations concerning the need for large databases and intensive training data, and poor generalization ability. In an effort to get the most out of the two methods, a physics–based data–driven method which is gained as a combination of the prior mentioned methods has been studied in the past few years. Physics–based data–driven methods have already been intensively studied and used for the automation of feature extraction and detection in civil engineering [77]. Nevertheless, evidently, only a few authors research the use of physics–based data–driven methods in the field of rotary machinery diagnostics, and only in the last few years. A wide area of research awaits to investigate the applicability of various proposed physics–based machine–learning methods identification of various other rotary machinery faults.

Appendix I – State of the art – Physics–based models for diagnostics of faults of rotating machinery

Research papers	Fault	Fault identification method	Theoretical background	Validation stage
Han, T. et al. [7]	Mass imbalance of Rotor	Virtual prototyping – ADAMS software	Imbalance mechanism and balancing theory	experiment
Oppenheimer, C.H. and Loparo, K.A. [8]	Mass imbalance of Rotor	Integrated filter–based method (observers) and life models	Physical relationships between fault severity and machine signatures	–
Sudhakar, G.N.D.S. and Sekhar, A.S. [9]	Mass imbalance of Rotor	Equivalent loads minimization method	FEM for flexural vibrations	experiment
Ogbonnaya, E.A. [10]	Misalignment, imbalance, crack and eccentricity of rotor shafts	Numerical simulation using MICE software	Newton's Second law (beam theory), Inagaki equations	ANN
Bahaloo, H. et al. [11]	Coupling misalignment	Ritz series method	Harmonic Balance Method (HBM)	–
Sekhar, A.A. and Prabhu, B.S. [12]	Coupling misalignment	Higher order finite element model	FEM analysis for flexible structures	–
Chen, G. [15]	Rubbing of a rotor–bearing–stator system	Rotor–Ball Bearing–Stator Coupling Dynamics Model	Euler free beam model of equal–section, Hertz nonlinear contact force, Zhai method	experiment
Han, Q. et al. [16]	Rubbing on a dual–disc rotor system	FEM model, Hilbert–Huang transform (HHT) method	Euler–Bernuli beam model, Empirical mode decomposition (EMD), Hilbert analysis	experiment
Luo, Y. et al. [17]	Rubbing and looseness on rotor–bearing system	Dynamic model of the nonlinear elastics rotor–bearing system	Reynolds equation, rub–impact equation, motion differential equation	–
Liu, Y. et al. [18]	Rubbing and looseness in rotor–sliding bearing system	Nonlinear finite element method, Lagrange method	Nonlinear oil film force, looseness stiffness model, Hertz contact theory	–
McFadden, P.D. and Smith, J.D. [19]	Inner race of rolling bearing	Model for Single point defect on inner race	Effects of bearing geometry, shaft speed, bearing load distribution, transfer function and the exponential decay of vibration	experiment
Patel, V.N. et al. [20,21]	Inner and outer race of rolling bearings	Model for multiple defects on inner and outer race	Equations of motion, Runge–Kutta method, time and frequency domain analysis	experiment
Sopanen, J. and Mikkola, A. [22,23]	Inner and outer race of rolling bearings	Dynamic model of localized and distributed defects	Non–linear Hertzian contact deformation and elastohydrodynamic (EHL) lubrication	ADAMS sim.
Kiral, Z. and Karagülle, H. [24]	Ball–fault of ball bearings	Numerical simulation using package I–DEAS	FEM analysis, time and frequency domain analysis	–
Wang, J. et al. [25]	Bearing of wind turbine	Model based method of integrated fault diagnosis and prognosis	Paris law	experiment
Wang, C. et al. [26]	Rolling bearing	Model based on numerical simulation in MATLAB	Modified winding function approach (MWFA)	–
Yan, R. and Gao, R.X. [27]	Inner and outer race of rolling bearings	Quantitative energy–based feature extraction method	Wavelet transform, envelope extraction, Fourier transform	experiment
Ruan, D. et al. [28]	Rolling bearing	Nonlinear 5–DoF Model of a bearing, Bearing Defect Model	Newton's second law, Hertz contact theory	CNN
Diehl, E.J. et al. [30]	Gear fault	Dynamic gearbox models, harmonic wavelet transforms (HWT)	Dynamic transmission error, dynamic stresses, stability, noise, vibration motion	–
Dadon, I. et al. [31]	Gear fault	Generic dynamic model	Equations of motion, gear mesh stiffness, damping	experiment
Bankert, R.J. et al. [36]	Mass imbalance and misalignment	Finite Element rotor dynamics model	Timoshenko beam element, Reynold's equation, FEM analysis	experiment

Appendix II – State of the art – Data–Driven models for diagnostics of faults of rotating machinery

Research papers	Fault	Pre–processing technique	Classification algorithm
Hoffman, A.J. and Van Der Merwe [34]	Mass imbalance of rotor, bearing fault	Time domain and frequency domain analysis	Kohonen Network (KNN), nearest neighbour rule (NNR), and radial basis function neural network (RBFNN)
Hang, J. et al. [35]	Shaft imbalance and misalignment	Empirical mode decomposition (EMD)	multi–class fuzzy support vector machine (FSVM)
Baccarini, L.M.R. et al. [36]	Rotor imbalance and sshaft misalignment, looseness	Independent component analysis (ICA)	Support vector machine (SVM)
Yuan, S.F. and Chu, F.L. [37]	Rotor imbalance and misalignment, rub and looseness, bearing and gear fault	Fourier transformation (FFT), principal component analysis (PCA)	SVM

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Kang, M. et al. [38]	Bearing fault	Kernel feature analysis	SVM
Liu, Z. et al. [39]	Rolling bearing fault	empirical model decomposition (EMD)	SVM
Shen, C. et al. [40]	Rolling bearing fault	time–domain and frequency–domain statistical features	SVM
Wu, T.Y. et al. [41]	Gear fault	time–domain and frequency–domain analysis	SVM
Yang, D. et al. [42]	Gear fault	EMD and the kernel function	SVM
Widodo, A. et al. [43]	Bearing fault	ICA and PCA	Relevance vector machine (RVM) and SVM
Zhang, Y. et al. [44]	Mass imbalance, misalignment, rub, rolling bearing	Isometric feature mapping (ISOMAP)	Minimum–distance classifier, k–NN, and SVM with a radial basis function (RBF) kernel
Saravanan, N. et al. [45]	Gear fault	wavelet–based time (WT)	Artificial neural network (ANN) and proximal support vector machines (PSVM)
Han, T. et al. [46]	Rolling bearing, gear fault	Time–domain statistical features (TDF), frequency–domain statistical features (FDF) and multiple scale features (MCF)	RF, ANN and SVM
Chen, Z. et al. [47]	Bearing fault	–	DBN
Vyas, N.S. and Satishkumar, D. [48]	Mass imbalance of Rotor, bearing fault, shaft misalignment	Time domain and frequency domain analysis	Artificial neural network (ANN)
Kaewkongka, T. et al. [49]	Mass imbalance of Rotor, bearing fault, shaft misalignment	Continuous wavelet transform (CWT)	ANN
Ngolah, C.F. et al. [50]	Rub and looseness	Time domain and frequency domain analysis	ANN
Lei, Y. et al. [51]	Rub	EMD	ANN
Bin, G.F. et al. [52]	Rotor imbalance and misalignment, rub and looseness	CWT and EMD	ANN
Rajeswari, C. et al. [53]	Gear fault	WT	Back propagation neural network (BPNN)
Guo, S. et al. [54]	Rotor imbalance, rotor misalignment, bearing block looseness, and contact rubbing	WT	Convolutional neural network (CNN)
Sohaib, M. and Kim, J.M. [55]	Bearing fault	–	Autoencoder–based DNN
Zhou, F. et al. [56]	Rolling bearing fault	FFT	DNN
Mao, W. et al. [57]	Rolling bearing fault	FFT	DNN
Qi, Y. et al. [58]	Rolling bearing and gear fault	EEMD, AR	DNN
Shao, H. et al. [59]	Rolling bearing fault	–	DBN
Guo, X. et al. [60]	Bearing fault	–	Adaptive deep neural networks (DNN)
Sun, W. et al. [61]	Gear fault	dual–tree complex wavelet transform (DTCWT)	CNN
Verstraete, D. et al. [62]	Bearing fault	STFT,WT, and HHT	CNN
Jing, L. et al. [63]	Gear fault	FFT	CNN
Wang, P. et al. [64]	Gear fault	WT	CNN
Tao, J. et al. [65]	Bearing fault	–	Deep belief network (DBN)

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