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REVIEW

A review: multiplicative faults and model-based condition monitoring strategies for fault diagnosis in rotary machines

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Abstract
In the present review article, the research findings in the field of investigating the vibrational nature of the rotating machineries under the influence of multiplicative faults and their identification in various dynamic models are well succinct. Multiplicative faults are the faults in which the process is influenced with the products of the process variables. In other words, the multiplicative faults can be stated as the simultaneous occurrence of various faults due to their interdependency nature such as unbalance and bow, bow and crack, bow and rub, crack and rub, misalignment and crack, misalignment and rub, rub and looseness as well as crack and internal damping. The causes for occurrence of multiplicative faults and the different model-based techniques for identifying them are described for the case of rigid as well as flexible rotors with conventional and smart supports. This paper also includes studies available in compound faults, fault diagnosis using artificial intelligence techniques and fault diagnosis in rotary machines utilized in underwater vehicles. Accordingly, the key points of the previous literature, general remarks as well as some perspectives for future work have been given at the end of this paper.

Keywords Condition monitoring · Multiplicative faults · Rotor-bearing systems · Vibration · Faults diagnosis

1 Introduction

Many industries in the world utilize rotating machines for the manufacturing and production of different kinds of goods. The rotating machines may have high-speed and low-speed applications. The pump, compressor, aerospace engines, gas turbines, generator come under the category of high-speed applications. Slow speed rotor applications are generally seen in the paper and steel mills, rotating biological contractor (RBC) systems, windmills, etc. The rotating members in these machines are usually supported by bearings. However, the rotors with low-speed operations are incorporated with conventional bearings, i.e. fluid-film bearings and rolling element bearings. For high-speed machines, the recent trend is to utilize smart bearings such as foil bearing with piezoelectric actuators [1, 2], and active magnetic bearings [3–5]. While the machine components are in slow-speed or high-speed operation or during their manufacturing process or long period of downtime, they may get affected due to various faults individually or simultaneously [6]. The faults are termed as synonym for failures, errors, mistakes or disturbances in the functional units which induce unwanted or intolerable vibrations of the rotating machines. The serious faults include the rotor unbalance, bow in shaft, cracks in rotor, rotor–stator rub and misalignment in the coupled rotor, the supported bearings misalignment, internal damping and mechanical looseness. In case one fault causes for the occurrence of another fault due to their interdependence nature, then these kinds of faults are known as multiplicative faults. Isermann and Balle [7] have also described two types of malfunctions in the fault detection method, in which one category was additive faults and another was multiplicative faults. The faults in which the process is influenced by the addition of process variables are known as additive faults. However, when the process in the faults is influenced by product of process variables, then

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they are called multiplicative faults. Various research works have been reported to examine the effect of one fault over another fault, such as the unbalance causing bow in the shaft [8], rotor–stator rub due to shaft crack [9], residual shaft bow resulting from shaft crack [10], mechanical looseness arising misalignment in bearings [11], rubbing of rotating components (internal damping) as a result of a crack in shaft [12] and unbalance causing misalignment [13–20].

Researchers have come through different health monitoring strategies for detection as well as diagnosis of faults in rotary machines. Fault diagnosis is the process of finding faults in a system by observing the faults symptoms and signatures, as well as based on prior knowledge. Through the fault diagnosis, the type, size and location of a fault can be determined, depending on the available measurements of the rotating machine. Nowadays, the deep learning-based intelligent fault diagnosis techniques have been also utilized by researchers. Tang et al. [21] summarized distinct papers describing about deep learning techniques used in bearings, gears, spacecraft, gearboxes and heat pump systems. They have also elaborated the current challenges faced during fault diagnosis and possible scopes of future research. Among various kinds of condition monitoring techniques, the model-based condition monitoring is also an effective and efficient technique, which benefits the analysis of system's input along with the output [22]. This approach is more sensitive to early defects as compared to the routine predictive maintenance approach. Model-based condition monitoring helps in reducing machine downtime and increasing productivity of an industry. These model-based techniques of fault detection are evolved on the basis of parameter evaluation, parity equations or state estimators, which have been utilized in diagnosing the single and multiple faults, simultaneously, in a quantitative basis through numerical and experimental investigations [23–25]. The models for numerous faults, viz. unbalance, crack, misalignment, rotor rub with stator, pedestal looseness, fluid-induced oil whirl and whip instabilities in the mathematical form, were briefly outlined by Muszynska [26] in his review paper. A survey on model-based fault diagnosis technique in an automated system was given for the detection of faults in both the plant as well as control units [27]. The main attention was focussed on the analytical approach and knowledge-based approach. The first approach utilizes quantitative mathematical models and the later approach makes use of qualitative models together with qualitative and heuristic reasoning. Further, an overview of model-based fault diagnosis techniques was also presented by Simani et al. [28], in which they discussed that the change in residuals shows appearance of fault. The process of fault detection relies on development of an accurate mathematical model without uncertainty. The structure of model-based FDI (i.e. fault detection, isolation as well as identification) of faults in rotor systems can be seen from Fig. 1.

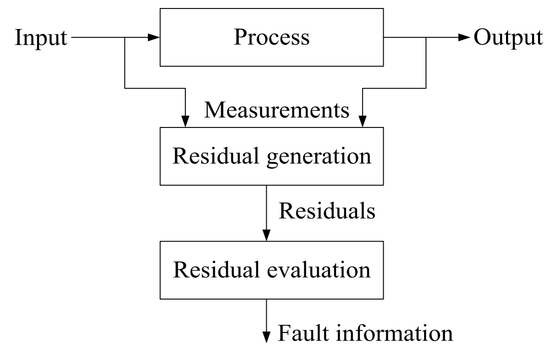


Fig. 1 Flow diagram for model-based FDI technique [28]

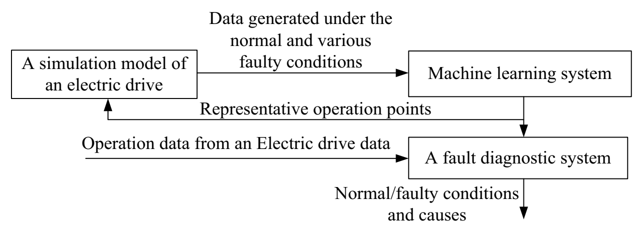


Fig. 2 Flow diagram for the combined technology of machine learning and model-based fault diagnostic technique in electric drive machines [29]

Isermann [24] presented a summary on the model-based fault detection methods along with their applicability in some practical units such as a cabin pressure outflow valve actuator of a passenger aircraft and combustion engines. They have elaborately discussed the process modelling, fault's parameter estimation and detection of faults with parity equations, state as well as output observers, and lastly, fault detection with signal models. Later, Murphey et al. [29] utilized the combined technology of machine learning and model-based fault diagnosis approach (refer Fig. 2) to identify and localize various faults in electric drives such as electric motor and power electronics-based inverters. They have conducted two sets of experiments on an electric drive machine which consisted of an induction motor, a three-phase transformer, invertor, hall sensors, etc., and found that the combined technique could detect multiple class of faults with a very high accuracy.

A model-based fault diagnosis scheme was proposed by Jalan and Mohanty [30] for the simultaneous estimation of unbalance as well as misalignment malfunctions in a simple rotating system (disc at the shaft's middle position) under the steady-state condition. Using the model-based technique, the residual forces due to faults (through experimental works) were correlated with the theoretical forces resulting from faults. With this, they were able to successfully detect the rotor-bearing health condition and their locations. At the end of this paper, it was suggested to utilize this technique for large systems such as turbine shafts and gearboxes. In the same year, Changyou et al. [31] utilized the model-based approach for estimating the degrees of unbalance as well as misalignment in a flexible rotating machine. Based on the difference in the dynamical responses for the normal and the faulty cases, the equivalent external loads were calculated. For reducing the effect of environmental noise signal on the accuracy in estimation, the denoising technique relying on a bandpass filter was utilized by them. Later, a review of model-based fault diagnosis for aerospace systems was presented by Marzat et al. [32]. The detection of sensor fault, actuator fault and process fault in a flight or aircraft system was elaborately explained with large collection of published papers.

Researchers have been also working on the fault diagnosis technique as well as isolation of multiplicative faults in rotor dynamic systems, manipulators and structural systems [33–37]. Abdelghani and Friswell [35] discussed that multiple number of sensors and actuators are required for active vibration control and finding the location of damage in structural systems. If errors are available in the sensors, then it would be difficult to get correct responses and the performance of the system may get decreased. They proposed an evaluation technique and correlation index to isolate the sensors incorporated with multiplicative faults using experimental data from a subframe structure. Afterwards, an energetic approach was utilized by Behzad et al. [36] for estimating the multiplicative component faults in the sensor and actuator. The system was considered to be a discrete-time and linear variant. For future work, they advised exploring the developed technique for nonlinear systems. Further, the dynamic model of a manipulator was constructed for fault diagnosis of actuator multiplicative fault [37]. In this paper, a nonlinear observer relying on radial basis function (RBF) neural network was proposed for analysing the fault effects and signal information. This overcame the weakness of traditional adaptive observers. In a recent research article, Zhu et al. [34] utilized the combined scheme of data-driven kappa-gap metric technique and kernel nearest-neighbour algorithm for detecting as well as isolating multiplicative faults in a dynamic system. The system was consisting of three water tanks interlinked through pipes and two centrifugal pumps for delivering input flows.

On following various studies, it is found that research articles have been already published in the area of different fault detection and diagnosis techniques for faults identification in the rotary machines [21–34], out of which the model-based identification technique is observed to be more reliable and efficient in finding the kind and location of faults individually or simultaneously. The faults in rotor systems may fall under the category of additive faults as well as multiplicative faults (as dependency may exist among two or more faults). Interdependency of faults results in developing fault chains more complex and complicated. However, there was no publication available in the field of summarizing the research done on the analysis of different multiplicative faults and model-based identification approaches for their identification. Therefore, a review has been made in this paper on multiplicative faults in the rotor systems with the main focus on the system modelling, vibration mechanism, fault effect analysis and identification.

2 Literature review on multiplicative faults

This section outlines the literature survey done on multiplicative faults in which one fault affects another fault, such as the misalignment causing bow and rub effects, crack arising due to internal damping and bow, unbalance causing bow fault and rub between stator and rotor due to looseness fault.

2.1 Interdependency of unbalance and bow faults

There are various reasons for the development of bow fault in rotor systems. This may be as a consequence of creep phenomenon, non-uniform temperature variation along the shaft, high magnitude of unbalance force for a long time. The vibration responses due to bowed shaft are independent of the shaft speed, whereas the fault resulting from unbalance force depends proportionally on the square of rotating speed. The bow in the shaft results in distinct amplitude as well as phase angle relationships than the unbalance force. In the rotor bow fault, the magnitude of the exciting force is dependent upon the magnitude of bow along the rotor. In the same line, Nicholas et al. [38] did not only investigate the unbalanced response but also explained the changes in phase due to a bowed shaft. In a real rotor system, there are several causes for the bow in rotor. This includes wheels shrinking fit in vehicles, thermal bows arising from localized rubbing or temperature variations. Generally, the local rubbing of a seal induces the thermal bow during operation. The shaft in phase angle shift is observed during the occurrence of the rotor bow. They described that if the phase angle varies quite slow while rotating at uniform speed, this can be as a result of thermal bow being induced into the shaft through a localized rub. They also presented three methods of rotor balancing in the presence of bow in the rotor. Out of these methods, the first and second methods were found to balance the total shaft amplitude to zero and the elastic deflection of the shaft to zero at the balance speed, respectively. Further, the third technique balanced the amplitude to zero at the system's critical speed without rotating at the critical speed [39]. The shortcoming of their work is that their studies did not involve the gyroscopic effect coming from the tilting disc.

Shiau and Lee [40] presented the dynamic influence of shaft bow on an unbalanced rotor-offset disc model with two rigid bearings support. They also explored the influence on the response due to different positioning of disc considering thin and thick, one by one. The residual bow was found to be 180° out of phase with the disc unbalance when the disc was attached in middle of the bearings. The pitching vibration at higher speed was observed to be more serious in comparison to the translating vibration at lower speed. Gyroscopic moment arising from offset disc affected the second peak response amplitude of both the translational as well as pitch for residual bowed shaft in forward synchronous precession. Ehrich [41] also discussed the influence of warping on the dynamics of rotor. Later, an extended transfer matrix method was utilized for acquiring the vibrational response of a two-spool aero-engine–dual-rotor system [42]. They considered the bow effect arising from unbalance fault and observed that the dynamic response was in the bow phase and out of phase on the left side and right side of the critical speed, respectively. The two shafts in the dual rotor were considered solid in the developed test rig. However, in a real case (i.e. aero-engine) the outer shaft is hollow cylindrical type and the inner shaft passes through it.

Edwards et al. [43] proposed a method for the detection of bend in a rotor. The unbalance and flexible support parameters (as depicted in Fig. 3) were also identified numerically as well as experimentally. They were capable of distinguish among the unbalance and shaft bow by looking into the system's vibrational nature for a certain speed range especially during rundown of the machine. There was no need of any information regarding the supporting structure for the purpose of identification. However, in the concluding remark, it was suggested to perform experiments on more complex machines and power station turbogenerator for identification of the unbalance and bow faults. Later, Rao [44] considered a warped Jeffcott rotor and developed the EOMs of the system. Thereafter, the numerical simulation was performed to explore and analyse the different conditions of bow in rotor, such as the same and opposite directions of bow location with respect to the mass unbalance, and phase angle at resonance. He observed decrement in the whirl amplitude when the unbalance and bow locations oppose each other as well as increment in the whirl amplitude for their locations in the same direction. The analysis was executed in a very simple rotor, so this can be extended for a practical rotor system with different complex conditions. Meagher et al. [45] performed both the analytical and experimental approaches to investigate the rotor behaviour for different magnitudes of bow and its location relative to the unbalance. A rotor model comprising of a flexible shaft, a central disc and a disc at one of the fluid-bearing support was considered, in which the other support was rigid support. They used a rotor kit for experimental investigation for the speed range between 250 and 3500 rpm. From the analysis, it was observed that the bow factor increases with decrement in unbalance eccentricity and removing the unbalance masses.

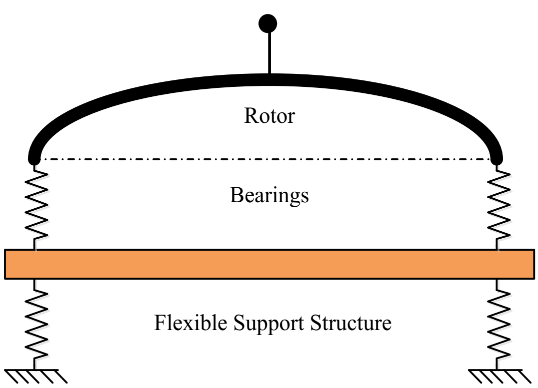
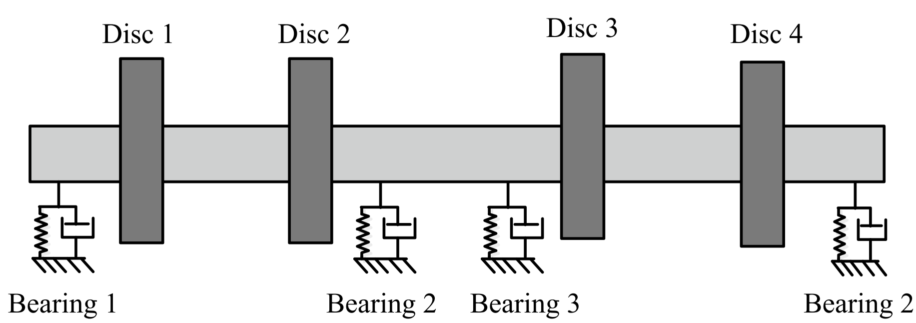


Fig. 3 Schematic diagram of a bent rotor-bearings-flexible support structure system [43]

An efficient fault diagnosis finite element-based method was presented by Yang and Hsu [46] for identification of unbalance and bow faults by their locations and amounts without their prior knowledge in a rotor-bearing system (refer Fig. 4). The gyroscopic effect and the external forces coming from shaft bow (first type fault) as well as residual unbalance (second type fault) were considered in the developed equations of motion. However, while the mathematical modelling of the bow in shaft, the deflection of the shaft was assumed to be evaluated completely through lateral forces only, not using external moments. One of the main conclusions was that the technique can accurately detect the faults, which may be either discrete or continuously distributed

Fig. 4 System configuration of the rotor system proposed by Yang and Hsu [46]



nature, or in the presence of both kinds of faults existing on the same nodes. Further, Galka and Tabaszewski [47] studied a case of an unbalance caused due to long-term rotor bow in a large steam turbine. They described that the symptom severity is influenced with object condition parameters and other several factors. Model-based method in combination with energy processor model was used for the measurement of symptom value fluctuations. Finally, they claimed that they were unable to remove the effect of factors apart from technical condition variables on measured symptom values.

A model-based identification technique was proposed for the identification of unbalance fault and bow in the shaft. Identification equation along with EOMs was derived utilizing Lyapunov matrix equation. This equation consisted of only measured DOFs and the characteristics of faults were estimated from the least-squares fitting technique. Apart from estimation of the parameters associated with faults, the bearing and coupling physical properties and rotor damping were identified from the differential evolution optimization method. The proposed technique was capable of identifying and distinguishing both faults, simultaneously, although they had similar symptoms. Experiments were also performed and validated with theoretical investigations [48–50]. However, they used the Guyan reduction method to eliminate rotational degrees of freedom as it was extremely difficult to measure all the degrees of freedom available in the system model. Chen [51] explored the vibrational nature of a double-stage geared rotor system (refer Fig. 5) in the presence of unbalance and bow faults. The axial translational vibration in the geared rotor system was assumed to be negligible. Unlike the other models, the contact ratio, as well as pressure angle of the gear pair, was considered time-varying parameters. The Lagrangian method was utilized for developing the system's equations. The response was generated using the Runge–Kutta method, and it was found that the

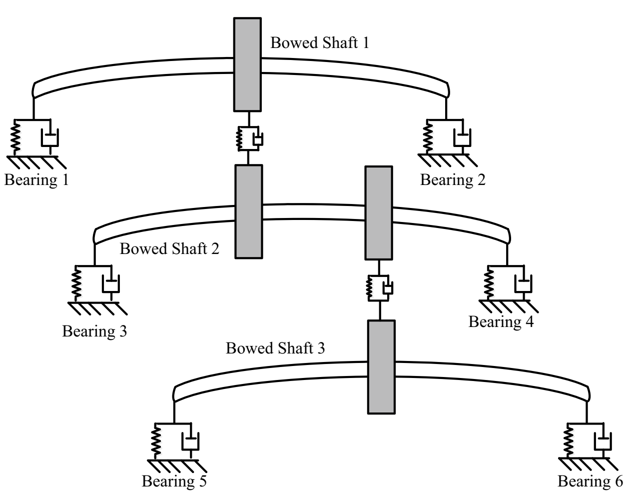


Fig. 5 A geared rotor system with bow in the shafts [51]

bow fault raised the translational displacement amplitudes, values of contact ratio as well as phase angle of paired gears in the geared rotor system. Experimental validation of the proposed technique for examining the vibrational nature of the faulty double-stage bowed rotor-gear-bearing system will be a good scope of future work.

In a recent publication, Sarmah and Tiwari [52] performed experimental and numerical investigations for identifying the unbalance and residual bow of shaft along with the crack and internal damping faults in a two DOFs Jeffcott rotor system. The system was comprised of a disc in the middle and an active magnetic bearing near the disc position for controlling vibrational motion. Apart from estimating the multiple fault parameters, the stiffness constants of AMB were also estimated through the developed algorithm. The sensitivity and robustness of the method were also checked against random noise and bias errors in the system model. This model-based multiple fault detection technique provided explicit vision to identify the various faults and their behaviours simultaneously on a quantitative basis during the machine's operation. They suggested at the conclusion that the developed technique and analysis can be explored for a more practical and realistic model with a flexible shaft and anisotropic bearings system based on finite element method.

In this section, the literature review has been discussed in the field of interdependency of unbalance and bow faults. Mostly, the works were related to exploration of the fault's effect in rotor systems associated with the assumption of various factors, such as a disc in the shaft mid-span, ignorance of gyroscopic effects and neglecting the axial and torsional vibrations. Experiments were also performed in simple rotor systems, not in actual and feasible applications-based rotating machinery. Therefore, for future work, the numerical model can be established for flexible rotor systems incorporated with nonlinearities from bearings, anisotropic nature of bearings, gyroscopic effects and multiple discs. The experimental investigations can be executed on real aero-engines, double-stage bowed rotor-gear-bearing system and power station turbogenerator for studying the dynamic analysis and identification of unbalance as well as bow faults.

Further, the listing of several pieces of the literature on interdependency of unbalance and bow faults with their defective nature and effect, identification as well as shortcomings is given in Table 1.

2.2 Interdependency of bow and rub faults

In the initial time, the dynamics of the rotor system considering rub-induced thermal bow was explored by Smalley [57] while accelerating and decelerating of a steam turbine rotor. They observed that the fault severity and vibration amplitude are very less for rapid acceleration through a critical speed than for slow acceleration. The result analysis had

Table 1 A chronological summary of research articles on interdependency of unbalance and bow faults with their identification approaches and shortcomings

Year	Refs.	Identification technique/Dynamic analysis	Nature of work	Main conclusion	Shortcoming
1976	[38, 39]	D'Alembert's principle	Num.	Exciting force depends upon the magnitude of bow. Presented three methods of balancing with residual shaft bow	Gyroscopic effect due to disc was neglected
1993	[42]	Extended TMM	Num. and Exp.	Dynamic response is in phase with bow on the left of critical and out of phase on the right of critical	Both the shafts in dual-rotor system were taken as solid in the test rig
1998	[53]	Moore–Penrose pseudo-inverse technique	Num.	Identified bend of shaft and unbalance acting concurrently and the method was robust to noise	Bearing stiffnesses were taken constant over the speed range
2008	[45]	D'Alembert's principle	Num. and Exp.	Diagnosed and balanced shaft bow from probes located at the bearings	Very simple rotor-bearing model was considered
2009	[46]	FEM and least square technique	Num.	Identified the locations and amounts of unbalance and bow faults from responses	Assumption of bow in the shaft due to the lateral forces only and not by external moments
2011	[47]	Statistical symptom determination method	Num.	Illustrated a case of an unbalance caused by permanent rotor bow in a steam turbine	Could not eliminate the influence of factors other than technical parameters
2013, 2014	[54, 55]	FEM and TMM	Num. and Exp.	Identified bow and distributed unbalance in flexible rotor as well as estimated correction mass in a single trial run and using a single balancing plane	Assumption of Euler–Bernoulli beam theory and limitations due to recursive multiplication of matrices in transfer matrix method
2016, 2018	[50, 56]	FEM, System Equivalent Reduction Expansion Process model reduction technique	Num. and Exp.	Identified unbalance and bow simultaneously in a Laval rotor and two-disc rotor systems	Assumption of Guyan reduction method to eliminate the rotational degrees of freedom
2019	[51]	FEM	Num.	Investigated dynamic response of a double-stage geared bowed and unbalanced rotor system	Axial translational vibration in the system was neglected; No experiments

Ref. reference, *Num.* numerical, *Exp.* Experimental, *FEM* finite element method, *TMM* transfer matrix method also shown that the damaging vibration could occur during shutdown, if there is rubbing as the rotor decelerates through the critical. In the concluding remark, they suggested for analysing the vibration with inclusion of axial variation of the seal excitation function. Laboratory experimentations for investigating the acceleration and deceleration effects can be done in the future. Later, Goldman et al. [58] explored the thermal or mechanical effect of rotor-to-stator rub in an isotropic long rotor. As a consequence, the shaft thermal bow was remained in the mechanical equations as a constant parameter. With these considerations, they observed from vibrational analysis that a spiral lateral motion was present with an increase in amplitude and variation in the system stiffness due to inelastic impact. The rotary inertia and shear stresses were considered to be negligible in the system model.

Pennacchi and Vania [59] obtained the experimental results from a turbine-generator unit having rotor–stator rubs and bow in the shaft. It was also discussed that the time- and temperature-dependent thermal bow can be produced due to the friction force between the rotor and stator contact. The model-based identification method based on frequency-domain response data was utilized to estimate the equivalent bending moments causing the bow effect. The causes of the rubs were also identified from the analysis of the experimental response (i.e. displacement orbit plots) and the developed identification strategy. An initial permanent bow was considered in a model of a rotor-bearing system having rub impact between rotor and stator. Governing equation of the system was developed based on nonlinear forces resulting from oil-film bearing [8]. To study the fault effect in the numerical analysis, the controlling parameters were shaft rotating speed, bow magnitude and phase between the eccentricity and bow. From the results of the displacement spectrum in frequency domain, bifurcation diagrams and orbital plots, it was found that the rotational speed changed significantly in the presence of rub due to initial permanent bow. However, the rotor model used by them for studying the vibrational nature was quite simple even though there was no involvement of gyroscopic couple effects. Yang et al. [60] presented the dynamic behaviour of a rotor-bearing system with coupled faults of unbalance, bow and rub. They did not consider the thermal effect caused by rub in the system. Because of high amplitude of whirling motion, the nonlinearity effect coming from bearings became very significant, which displayed nonlinear phenomena in the bifurcation diagrams, Poincaré maps, time histories and frequency spectra. One of the prime observations from this work was that the nature of response was greatly affected from the bow magnitudes due to coexistence of bow and nonlinearity in the model. There was also an increment in the amplitude of whiling motion of the rotor.

Here, the interdependency of residual shaft bow and rotor-to-stator rub in rotor systems has been explored through previous research papers. It is observed that very less work is available in the analysis of combined form of these faults in four decades. Analysis and identification of the bow and rub faults can be done in the practical rotating machines with consideration of thermal effect arising from the rub, shaft damping and gyroscopic effects, through numerical investigations and experiments.

The summary of the literature published in the field of bow and rub faults with their identification method, nature of work and shortcomings are given in Table 2.

2.3 Interdependency of crack and rub faults

The rub between the rotor and stator is considered a secondary phenomenon, which may result from various primary causes such as the high amplitude of vibration due to crack, unbalance, misalignment, etc., and gravity as well as thermal effects [41]. Under the combined effect of multiple faults, the behaviour of a machine can be disturbed up to a great extent. Therefore, several kinds of the literature are

Table 2 Chronological summary of published literature in the interdependency of bow and rub faults

Year	Refs.	Identification technique/dynamic analysis	Nature of work	Main conclusion	Shortcoming
1989	[57]	Extrapolated Crank–Nicholson formulation	Num.	Examined rub-induced thermal bow vibration during acceleration and deceleration of a steam turbine rotor	Variation of temperature in axial direction and heat loss from the rotor were neglected
2000	[58]	Lagrange's principle	Num.	Studied thermal bending of the rotor due to rotor-to-stator rub	Rotary inertia and shear stresses were not considered
2008	[8]	D'Alembert's principle and Runge–Kutta method	Num.	Observed very rich forms of periodic, quasi-periodic and chaotic vibrations due to bow and rub	Gyroscopic effects due to disc tilting were neglected
2019	[60]	Lagrange's principle and Runge–Kutta method	Num.	Response seriously affected by the initial bow's degree, rub and geometrical nonlinearity	Thermal effect caused by rub was not considered

available for studying the rub impact under the influence of crack fault.

Due to high level of vibrations in a cracked rotor system, the rotor generally makes contact with the stator for less clearance situations and causing the rotor–stator rub fault. A dynamic rotor model comprised of a transverse crack in the mid location of the rotating shaft and rub-impact fault was considered by Luo et al. [61]. During modelling of the rotor system, the torsional vibration and gyroscopic moment were ignored by putting a disc at mid-span of the shaft. A continuation shooting approach was utilized for computing the periodic solution of nonlinear system. Floquet theory was also utilized to study the stability of system periodic motion and unsteady law. Later, Patel and Darpe [9] demonstrated the vibrational nature of a cracked rotor along with presence of unbalance and rotor–stator rub faults. The steady-state vibration analysis was examined using numerical and experimental investigations. They explored the analysis considering three cases, i.e. the rub without crack, crack in rotor without rub and combination of rub and crack. Unbalance was present in all three cases. It was found that the first case excited more or less equally the backward and forward whirling frequencies, whereas the second case showed mainly forward whirl vibration. However, the last case (combined rub and crack faults) revealed the vibrational signature of 2× as well as higher harmonics at corresponding subharmonic resonances. In the presented analysis, the tilting effect and gyro moment due to the disc were neglected in modelling of the rotor system.

A rotor–stator-bearing system as exhibited in Fig. 6 with time-dependent crack stiffness, force due to rotor–stator rub and bearing forces from oil film in nonlinear form (through short bearing theory) were considered to analyse the dynamic vibrational phenomena utilizing orbital plots, responses in frequency spectra, bifurcation diagrams and Poincaré maps [62]. The depth of crack and stator stiffness had an appreciable effect on the system's motion and its instability for different values of rotational speed. Moreover, the system was found to have high level of nonlinearity as well as instability at higher speeds. However, for the sake of emphasizing on oil-film force

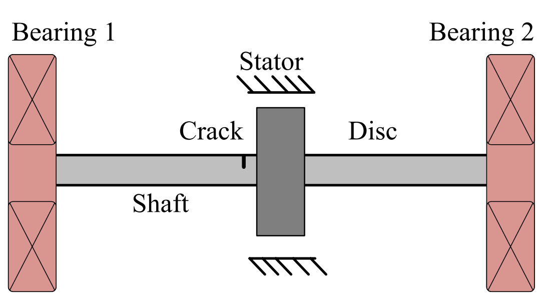


Fig. 6 A cracked rotor system with rub impact [62]

effect in the rotor system, the impact of shear deformation, gyroscopic moment and vibration in torsional mode were ignored. They asserted that the experimental works on the test rig will be a good approach to explore the effects of several parameters on the system response and verifying the numerically obtained results. Considering the same faulty rotor model, Huang [63] investigated the effect of the crack depth as well as crack angle on the response of the coupling faults of crack and rub. The numerical results showed that for small values of crack depth, the rotor system was found to be unstable using the Hopf bifurcation phenomenon. However, the analysis was presented for a very simple rotor with a disc at mid-span and without consideration of the gyroscopic effect.

Chang-Jian et al. [64] presented vibrational behaviour of cracked rotor system associated with rub between the rotor and stator. For illustration of the analysis, a flexible rotor influenced by crack fault and supported on two oil-film journal bearings was considered. Afterwards, the nonlinear equations of the model were acquired and a Runge–Kutta technique was used to evaluate the derived equations with π/300 time steps. Bifurcation diagrams were plotted using various non-dimensional parameters (i.e. damping coefficient, unbalance eccentricity and rotational speed) as control parameters. The numerically generated responses were found to have quasi-periodic, subharmonic, periodic and chaotic behaviours. Although they explored good work, the torsional vibration of the rotor and gyroscopic couple were neglected in the system. Hu et al. [65] utilized Hilbert–Huang transform for analysing instantaneous frequency signatures of the rub, crack and rub–crack combined faults in an experimental rig. The set-up consisted of a Jeffcott rotor with a middle disc and mounted on two rolling element bearings. During the development of the mathematical model, they also did not consider the nonlinear effect from bearings and gyroscopic moment. Through the response of the considered faulty model, the intrawave frequency modulation at spin speed of the rotor was observed. They discussed that the difference in the modulation frequency at the rotor spin speed can be a characteristic to differentiate these faults. In future work, they suggested more experimental investigations taking the different depths of the crack.

In the previous studies, only lateral motion was analysed under the influence of shaft-stator rub and cracks on rotors. However, Hajnayeb et al. [66] explored the combined form of torsional as well as lateral vibrations, and the removal of chaotic characteristics from these vibrations for detecting cracks and rubs as well as monitoring the faulty rotor vibration. They developed a laboratory test rig set-up (refer Fig. 7) for acquiring the system's vibrations with crack and rub faults. The phase space reconstruction (PSR) technique was utilized for examining the chaotic time series analysis of the system.

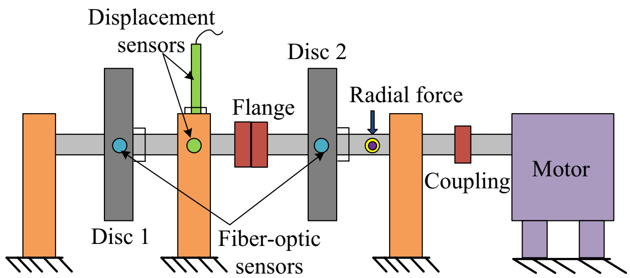


Fig. 7 Pictorial representation of a test rig set-up built by Hajnayeb et al. [66]

Research is mostly done in the area of vibrational analysis as well as identification of crack and rub impact including simple rotor systems with a disc in the middle and neglecting the gyroscopic effects. Moreover, very less experimental work has been performed for validating the numerical results and understanding the exact phenomena without consideration of various assumptions. Accordingly, research works can be further explored towards complex rotor systems with the inclusion of several necessary aspects and factors to make highly efficient and productive research.

Table 3 presents the chronological summary of the literature available in the area of crack and rub faults in the rotating machines with their identification techniques, and concluding remarks.

2.4 Interdependency of misalignment and crack faults

Sinha [69] analysed the appearance of crack in the welded section of two shafts during operation due to misalignment between the motor shaft and rotor. Misalignment in the vertical and horizontal directions was created between two supported bearings by providing some necessary arrangements at the bearing pedestal near the flexible coupling. He utilized higher-order spectra (HOS) technique to identify misalignment and crack in a rotor-coupling-bearing system through higher harmonics. The bi- and tri-spectrums were applied for condition monitoring of the rotating systems. Further, in the concluding remark, it was suggested to utilize higher-order spectra tool (i.e. bi-spectrum, tri-spectrum, etc.) for detecting the other types of faults individually or their interdependency form.

The long-time occurrence of misalignment preload can grow a fatigue crack in the rotating shaft [70]. They investigated the steady-state vibrational responses of coupled rotors associated with misalignment and unbalance faults as well as a crack in only one shaft as depicted in Fig. 8a. The bearings were considered rigid supports for avoiding any kind of masking effect. Further, the rotor system was modelled with six DOFs Timoshenko beam elements. The coupled axial–lateral–torsional vibrations were analysed at the position of the discs. To show the complete whirl responses, i.e. the forward as well as backward whirls, full-spectrum analysis was presented. Moreover, they also explored effect of the magnitude of misalignment, size of crack and its location on the responses of the system utilizing two whirling parameters δ_1 and δ_2. The parameter δ_1 was the difference of amplitudes of forward (+1×) and backward (−1×) whirls, whereas the parameter δ_2 was the difference of amplitudes of forward (+2×) and backward (−2×) whirls. The parameter δ_1 was found to be decreased when the parallel misalignment existed in the system. However, the increment was observed to be in parameter δ_2 for the case of angular misalignment and increment in the parallel misalignment level. As the cracked and misaligned rotors can both induce super-harmonic components in vibration signatures, it was a challenging task to differentiate them precisely depending on only the vibration signals in frequency domain. Apart from this, the coupled crack and misalignment faults in rotating machines can develop complex nonlinear vibrational dynamics and substantially enhance troubles in the identification of faults. The shortcoming of their presented work is that they considered the coupled rotor system with discs in middle of the shaft and neglected the gyroscopic effects of discs. Apart from this, the study can be also focused on the simultaneous occurrence of multiple faults, such as propagation of fatigue crack, bearing dynamic effects, internal damping and bow in the shaft.

Cal and Fraga [72] considered a real application of underwater tidal turbine and focused on early detection of misalignment and crack faults. They analysed the vibrational response generated by the turbine due to misalignment between the turbine shaft and electric generator shaft as well as the advent of cracks in the shafts. For propagation of cracks, a radial load was introduced and increased in progressive values to simulate the load that was produced by the misalignment. They observed that there was adequate mitigation in the stiffness of shaft and resonance frequency of the system due to crack. The orbital responses were found to have more circular patterns with internal loops corresponding to simultaneous 1× and 2× responses. For visualizing the vibrations from faulty and complex underwater tidal turbine, they have considered a very simple rotor system with disc in middle and support on isotropic and identical elastic bearings. Therefore, it is better to work on a complex rotor system with multiple discs in the presence of other malfunctions in the system.

Upon going through the literature in the fault dependency of misalignment and crack, it is found that there is more requirement of research in these areas. The simultaneous identification of the crack and misalignment faults becomes difficult as they exhibit almost the same nature of vibration spectrum. Model-based identification can be developed

Table 3 Summary of research papers published in the area of crack and rub faults

Year	Refs.	Identification technique/dynamic analysis	Nature of work	Main conclusion	Shortcoming
2007	[61]	Lumped-mass model and continuation shooting algorithm	Num.	Studied stability of periodic motion of the rotor with coupling faults of crack and rub impact	The torsion vibration and gyro moment were ignored
2008	[9]	D'Alembert's principle and full-spectrum analysis	Num. and Exp.	The responses at 2× and higher harmonics obtained due to crack and rotor–stator rub	Disc was at middle of shaft, and gyroscopic effect was not considered
2009	[67]	FEM and Newmark-β method	Num.	Investigated steady-state coupled lateral–torsional vibration response for crack and rub faults	Simple rotor system without considering titling effect of the disc
2014	[68]	D'Alembert's principle	Num.	Vibrational nature of initial bend deformation played a great role in case of shallow cracks	Disc was at middle of shaft and gyroscopic effect was not considered
2016	[62]	Lumped-mass model and Runge–Kutta method	Num.	Crack depth and stator stiffness had influences on instability of system	Impact of shear deformation, torsional vibration and gyroscopic couple were all neglected
2016	[63]	Lumped-mass model and Runge–Kutta method	Num.	Unstable nature of faults is found to be complex with increase in speed	Gyroscopic effect due to disc was not considered
2018	[64]	D'Alembert's principle and Runge–Kutta method	Num.	Various responses, i.e. periodic, chaotic natures, were observed under the effect of rub–crack fault	Torsional vibration and gyroscopic effect due to disc was neglected
2019	[65]	D'Alembert's principle and Runge–Kutta method	Num. and Exp.	Comparing to the single crack or rub fault, there were less modulation frequency harmonics in the crack–rub fault	Nonlinear effect from bearing and gyro moment were not considered
2020	[66]	Largest Lyapunov exponent theory and approximate entropy (ApEn)	Exp.	Proposed a method for examining lateral and torsional vibrations caused by rotor–stator rub and crack faults	Need to explore the proposed method for identification of other faults

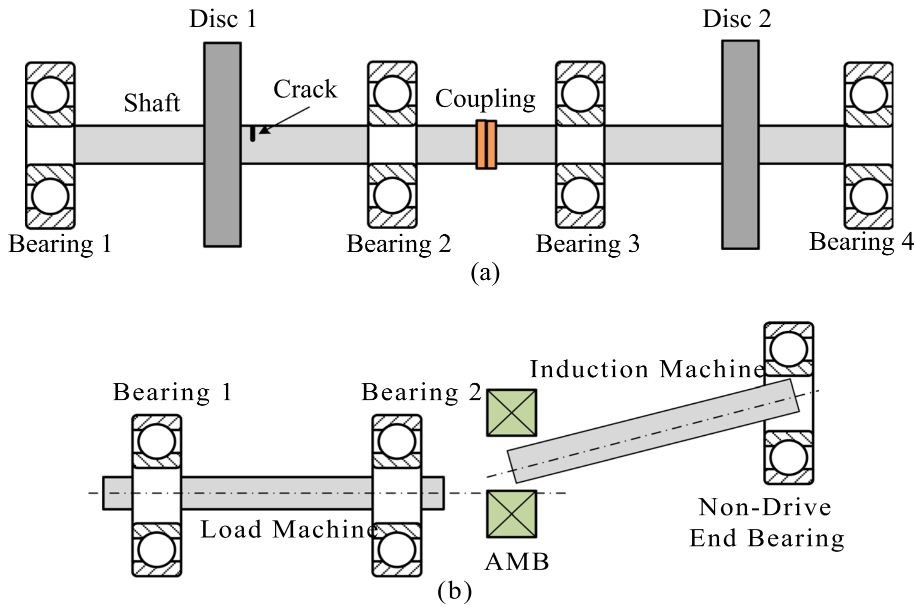


Fig. 8 **a** A coupled rotor system influenced by transverse crack [70]. **b** Schematic diagram of induction machine test rig incorporated with AMB [71]

further for the misaligned and cracked flexible rotor–multi-disc rotor system to identify these faults and study the vibrational effect on the rotating elements and supported bearings. Active magnetic bearings can be also incorporated in the dual-rotor system, turbogenerator, underwater tidal turbine and other systems for controlling the vibration and high-speed applications.

Literature survey done in the area of identification and analysis of misalignment and crack faults are chronologically summarized in Table 4.

2.5 Interdependency of misalignment and rub faults

Depending upon the fault issues of the rotor-generator local rub originating from the unbalance eccentricity and lateral misalignment, a dynamical model of the two rigid rotors system (refer Fig. 9a) was proposed by Huang et al. [73]. They explored the nonlinear vibrational phenomena and observed that with the increase in stiffness and a decrease in unbalance eccentricity, the stable-state region of the system gets increased. Through this, they could avoid the appearance of unwanted vibration. After some time, they did the same investigation by considering the combined misalignment, i.e. both parallel and angular misalignment instead of only parallel misalignment [74]. Further, they suggested for diagnosing the coupled faults, reducing the consequences of failure, improving the system's characteristics as well as optimizing the design and fabrication of hydraulic generator machine as further research in future.

Later, Zhang et al. [76] considered a flexible misaligned coupled rotor with rub-impact fault supported on ball bearings and utilized finite element method for its mathematical modelling. A fourth-order Runge–Kutta technique was exploited to generate the nonlinear displacement of the system. The 2× and 4× vibrational components were found to

Table 4 Summary of research accomplished in the rotor dynamic field of interdependency of misalignment and crack faults in rotating machines

Year	Refs.	Identification technique/dynamic analysis	Nature of work	Main conclusion	Shortcoming
2007	[69]	FEM and power spectrum density	Both Num. and Exp.	Utilized higher-order spectra (HOS) tool for identification of crack and misalignment faults	HOS tool can be used for detection of other types of faults
2011	[70]	FEM and full-spectrum analysis	Num.	Analysed steady-state, coupled lateral–axial–torsional vibrations at the disc locations under the combined effect of faults	Gyroscopic effects due to discs were not considered as both discs were at middle of coupled shaft
2018	[72]	D'Alembert's principle and orbital plots	Num.	Focused on the early failure prediction of underwater tidal turbines subjected to misalignment and cracks in the shaft	Isotropic and same bearings at both ends and no gyroscopic effect coming shaft and disc

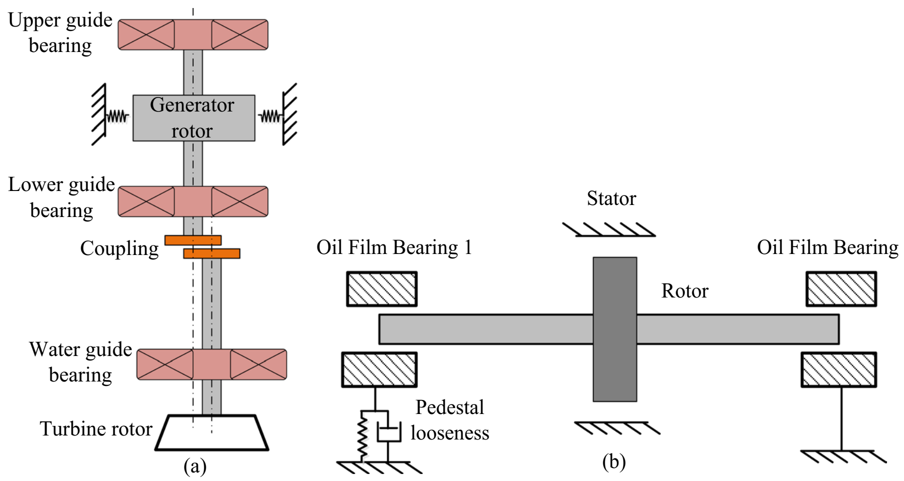


Fig. 9 **a** A rotor system with lateral misalignment and rotor-to-stator rub [73]. **b** Rotor-oil-film bearing system with rub-impact and single pedestal looseness [75]

produce high amplitude responses due to coupling faults of misalignment and rub. However, while modelling the rotor system, the gyroscopic effects of rotor were not included. Further, Ma et al. [77] explored the vibration characteristic analysis of a flexible rotor–two-disc system under the impact of rub and rotor–stator misalignment faults. They assumed the same unbalance on both discs and linearized bearings. Under asymmetrical rotor–stator clearance conditions, the effects of rubbing stiffness and rotating speeds on normal rubbing forces were also described by them. Rubbing stiffness was found to have the greatest effects on the rubbing force; however, the misalignment amount affected mostly the transient impact force and did not affect the rubbing force at the stable rubbing stage. The misalignment can be a cause to produce a secondary fault, i.e. the rub-impact fault in a rotor-bearing system. Lu et al. [78] established a rotor-coupling-bearing model, which was consisting of two discs, two shafts, one gear coupling as well as three ball bearings. EOMs of the system included the inertia force, gear coupling misalignment force, rub-impact force and force due to supported ball bearings. A Runge–Kutta technique of fourth order was utilized to obtain the nonlinear solutions of the equations. From the analysis, they concluded that the displacement with time and in the orbital form as well as the rub-impact force was very sensitive to the variation in misalignment. However, they did not consider the axial and torsional vibration of the rotor.

De Cal [79] developed a laboratory test rig of a tidal turbine to analyse the vibration due to frequent faults, i.e. the shaft misalignment and partial rub among the stator and rotor. The parallel misalignment was assumed between the supports, and axial as well as torsional vibration in the rotor was neglected for analysis of the system. The health monitoring in two planes was necessary to detect the reasons for the failure of the system. The misalignment fault was identified from elliptical or eight-shaped orbit plots and increments of 1× and 2× response, whereas the increase in the dynamic stiffness that occurred in the misaligned plane was the indication of rub-impact fault.

This section described the summary of research available on the interdependency of misalignment and rub faults. Although there is little literature available in the field of this interdependency, all are related to coupling misalignment and rotor–stator rub. Therefore, future research can be done in the areas of rotor systems with bearing misalignment and rub impact, in which the misalignment may be in conventional bearings or active magnetic bearings. Along with this, the work done by Huang [74] can be extended to optimize the design of hydraulic generator unit under the coupled faults of misalignment and rub. More experimental investigations can be explored in this field for advancement of the research in rotor dynamics.

The chronological summary of research done in the field of misalignment and rub faults is given in Table 5. This table also presents the year of publication, nature of work (numerical or experimental or both together), main conclusion and their shortcomings.

2.6 Interdependency of rub and looseness faults

The impact and rubbing of rotor–stator may be caused by looseness in the bearing seat or bases due to initial setting errors or long-time operation of rotating machinery. Lu et al. [80] exploited FEM to model a vertical rotor system consisting of two discs and mounted on elastic bearings at both ends. The system was influenced by combined faults of looseness and rub impact. However, the influence of thrust bearing was considered to be negligible. Thereafter, they investigated the system dynamics using the nonlinear contact theory and observed that the rotor-to-stator rub can mitigate the low-frequency vibration originating from the looseness fault.

The performance of rotating machinery can be enhanced with a small clearance among the rotor and the stator in

Table 5 Summary of published works in the field of misalignment and rub faults

Year	Refs.	Identification technique/dynamic analysis	Nature of work	Main conclusion	Shortcoming
2011	[73]	Lagrange principle and Runge–Kutta method	Num.	Studied vibration nature of a hydraulic generator unit rotor system under parallel misalignment and rub-impact faults	Axial and torsional vibration is negligible; only parallel misalignment was taken
2012	[76]	FEM and Runge–Kutta method	Num.	Support force of shafting presented high frequency responses under unbalance–rub-misalignment faults	Gyroscopic effects of rotor were not taken in to consideration while system modelling
2012	[77]	FEM and Runge–Kutta method	Num.	Rubbing force is mainly affected by rubbing stiffness, not by rotor–stator misalignment	Assumption of same unbalance on both discs and linearized bearings
2017	[74]	Lagrange principle and Runge–Kutta method	Num.	Studied vibration nature of a dual-rotor system under parallel and angular misalignment and rub-impact faults	Axial and torsional vibration is negligible; shaft was considered massless
2017	[78]	D'Alembert's principle and Runge Kutta method	Num.	Misalignment of gear coupling could strongly affect the stability of the rub-impact rotor system at high rotating speed	Axial and torsional vibration is negligible; only parallel misalignment was considered
2019	[79]	D'Alembert's principle and Runge–Kutta method	Num. and Exp.	Utilized vibration monitoring for early detecting the rub and misalignment failures in a tidal turbine	No gyroscopic moment and only parallel misalignment between supports

journal bearings. However, the rotor can touch the stator during whirling of the shaft as a consequence of misalignment or unbalance of the rotor. This causes frequent faults, such as partial rub and looseness, which create severe vibrations coming from impact and friction. Lee and Choi [81] applied the time–frequency analysis technique, i.e. Hilbert–Huang transform (HHT), to the faulty signals obtained from rotor kit for diagnosing the partial rub and looseness faults. This method was found to be effective when compared with conventional signal processing schemes, i.e. FFT, CWT and STFT. One of the observations was made from the result that in the presence of partial rub in the system, there was a regular generation of impact signals and an irregular generation of intermittent impact and friction signals due to the occurrence of mechanical looseness. Lastly, they suggested that there can be more improvement in the results by assigning the mean values at the ends to remove the end effects. Further, the frequency of interest should be sampled more than 12.5 times.

Jiang et al. [75] proposed a nonlinearity evolution for identifying the rub and pedestal looseness in a rotor system (refer Fig. 9b). For defining the force due to the pedestal looseness fault, the damping and stiffness coefficients concept were utilized, whereas the Coulomb type of frictional relationship was used for evaluating the force due to radial rub-impact fault. They conducted several experiments on the rotor system without rub and with pedestal looseness as well as in the presence of rub along with pedestal looseness. However, a very simple rotor system consisting of a rigid disc and massless as well as elastic shaft was considered for the analysis. The disc was assumed to be fixed at the mid-span of the shaft, where the gyroscopic effect due to the disc was neglected. They have also neglected the thermal effect of friction and considered pedestal looseness at one of the supported bearings only. After developing EOMs of this system, they generated the vibration signals on different looseness clearances and analysed them to understand their effect on the system. The nonlinearity degree was found to have a larger value for the case of coupled rub-impact and pedestal looseness fault as compared to rotor systems having pedestal looseness only. Experiments were also carried out by them for verifying the accuracy of the proposed approach.

Later, the combined faults such as blade-casing rub and pedestal looseness were considered in an aero-engine and the nonlinear vibration amplitude due to these faults was mitigated using a vibration absorber [82]. The initial gap between blade as well as casing was considered to have uneven distribution due to non-homogeneity in the coating. Further, the vibration mitigation of the rotor-bearing-blade-casing system was analysed for various values of spin speed and eccentricity of the disc. They observed that the nonlinearity of the rub and looseness entirely affected the resonance features of the system. Moreover, the amplitude of the shaft whirling was strongly enhanced due to the pedestal looseness. They also performed a similar investigation for a dual-rotor–double casing system with pedestal looseness in the high-pressure rotor. The rub was considered between the casings and the blades [83]. However, several assumptions were made by them for mathematical modelling of the dual-rotor-bearing system, such as the lumped mass blocks model for both the inner and outer casings, negligible elastic deformations of the blades and same unbalance eccentricity of the low-pressure and high-pressure turbine discs. The thermal effects and frictional torque in the rotor–stator rub fault were also ignored.

Youfeng et al. [84] studied a flywheel energy storage system under the coupled faults of the rub and mechanical looseness. The Runge–Kutta fourth-order technique was utilized to evaluate the differential EOMs of the dynamic model consisting of nonlinear force from the oil-film sliding bearing. They explored the effects of several parameters, i.e. the unbalance eccentricity, mass of the supported bearings, the shaft rotational speed and stator stiffness on the flywheel system. Based on the analysis, it was found that the rotor system started to be lifted with a rise in speed and the vibration of the loose end gradually intensified. Moreover, the increase in bearing support mass converted the chaotic motion behaviour into periodic motion. In the speed range of 2000–2500 rad/s, the quasi-periodic motion interval was consistently found to be increased under the effect of stator stiffness. The analysis was performed in a simple rotor model by considering looseness at one of the supported bearings only. Therefore, the work can be extended further for the rotor system with a gyroscopic effect and looseness at both bearings.

This section covers the research explored in the coupled faults of rotor-to-stator rub and mechanical looseness faults. Observations were made by studying most of the published papers that the mathematical models in the presence of rub and looseness have been developed with various assumptions, such as neglecting the gyroscopic effect as well as elastic deformations of the blades and ignoring the friction torque and thermal effect in rub impact. Moreover, the pedestal looseness was considered mostly at one bearing position only. Therefore, there is a scope for developing complex and practical rotor models, considering the temperature variations and their effects on the rub fault and looseness at both or more supported bearings. Almost all investigations were done at low speeds, which can be further explored for the rotor systems in the range of higher spin speeds.

The summary of research papers published in the area of rub and looseness faults is chronologically provided in Table 6, which includes the publication year, nature of work, etc.

2.7 Interdependency of crack and internal damping faults

The internal damping of material can affect the flexural modes of the cracked shaft. Sekhar and Dey [85] proposed a finite element modelling of a rotor system having crack fault, viscous as well as hysteretic internal damping to investigate the stability threshold of the system. It was found that the

Table 6 A chronological summary of the literature in the field of rub and looseness faults

Year	Refs.	Identification technique/dynamic analysis	Nature of work	Main conclusion	Shortcoming
2007	[80]	FEM and contact theory	Num.	Impact-rub of rotor and stator can reduce low-frequency vibration caused by looseness	Influence of thrust bearing was considered to be negligible
2008	[81]	FEM and Runge–Kutta method	Num. and Exp.	Impact-rub of rotor and stator can reduce low-frequency vibration caused by looseness	Frequency of interest should be sampled more than 12.5 times
2018	[75]	D'Alembert's principle and Runge–Kutta method	Num. and Exp.	Proposed a nonlinearity evaluation to identify the rub impact in rotor systems with pedestal looseness	Thermal effect of friction was neglected and considered single pedestal looseness at one of the bearing
2020	[82]	Lagrange principle and Runge–Kutta method	Num.	Utilized a nonlinear vibration absorber for vibration mitigation due to imbalance looseness-rub coupled faults	Shaft was modelled as a massless and flexible Euler beam; casing was treated as lumped mass
2020	[83]	FEM and Runge–Kutta method	Num. and Exp.	Studied the dynamics of dual-rotor system under pedestal looseness and rotor–stator rub faults	Effects of thermal and friction torque in rub impact were ignored
2021	[84]	D'Alembert's principle and Runge–Kutta method	Num.	With the increase of bearing support mass, the chaotic motion gets into periodic motion	Looseness was assumed to be in one bearing only; no gyroscopic term

speed for the instability region gets significantly lowered with enhancement in crack depth. Moreover, the system stability is comparatively more affected by hysteretic damping than viscous damping. They also presented the stability of the system for two cracks (remains open during rotation) in the rotor and perceived the effect of one crack over another for threshold speed limits.

Afterwards, Chasalevris and Papadopoulos [86] proposed a rotor shaft model using the Rayleigh equation mounted on nonlinear fluid-film bearings. Crack was introduced based on the strain energy release rate method and internal damping was also incorporated into the current model. Continuous wavelet transform was used to confine the influence of breathing crack and determine the identification parameter. However, the proposed technique was applicable for identifying cracks of almost 5% of the rotor radius only. Peng and He [87] considered the internal damping along with crack and investigated the consequence of crack position on both the stiffness as well as whirl motion of a heavy and large turbomachine using the root locus technique. The stiffness calculation result showed that the crack position did not have much effect on the parameter α_1 (which was the ratio of reduced amount of shaft stiffness directed towards the crack front direction to the stiffness of intact or uncracked shaft), but significantly affected the parameter α_2 (which was the ratio of reduced amount of shaft stiffness directed towards the normal of crack front to the stiffness of intact shaft). The observation was made that the super-critical instability of the system in the crack position at $2l/L=0.75$ was most affected by the internal damping fault. They analysed the effect of crack and internal damping in a simple Jeffcott rotor without consideration of tilting effect of disc and gyroscopic moment.

Murugan et al. [88] developed FEM modelling for a flexible rotor-conventional bearings system influenced by an open crack in the transverse direction. In the modelling, they accounted for several crack depths as well as shaft internal damping. Apart from this, the internal damping effect can be significantly intensified as a consequence of the rubbing of crack faces in a cracked rotor system [12, 89]. They assumed the concept of discrete unbalance at the disc position and neglected the gyroscopic moment due to the rotating shaft and disc. Instability regions were obtained under the effect of these faults and noticed that with increase in the crack depth, the natural whirl speeds get reduced. The stability behaviour of the system was also studied at different speeds and for distinct values of disc eccentricities using the time integration scheme.

Here, the identification procedures of the crack and internal damping faults and their vibrational analysis were summarized based on works performed by distinct researchers. However, there is more requirement of research in these areas in both the experimental and theoretical domain. From the literature, it has been found that the proposed mathematical models of the rotor systems (associated with crack and internal damping) involved various assumptions, such as the consideration of discrete unbalance concept, ignoring the gyroscopic effect due to shaft and disc and neglecting the nonlinearity of the supported oil-film bearings. Future work can be done for the analysis and identification of these combined faults in complex and real high-speed rotating machines supported by active magnetic bearings.

Table 7 displays the summary of research done in the rotor dynamic field of dynamic analysis and identification of interdependency of crack and internal damping faults. The year of publication, main conclusion and shortcoming of these papers are also given in this table.

2.8 Interdependency of crack and bow faults

Bachschmid et al. [94] explored the effect of crack and bow on a two-rigidly coupled rotor system with four oil-film bearings support. Dynamic equations of the system were developed with inclusion of force due to the inertia, damping and stiffness parameters of bearings, unbalance and bow effect, crack force. They neglected the nonlinear oil-film effects in the supported bearings. Although the nonlinear vibrations are generally caused by the crack fault, the equations were made linear with the assumptions of overcoming nature of self-weight of the horizontal heavy rotor over the crack behaviour. They identified the crack location and equivalent bending moments due to crack utilizing the frequency-based identification method and least square technique. Afterwards, the ratio of equivalent bending moment to the static bending moment in the cracked element as a result of the shaft's self-weight and bearing alignment states was used to compute the relative crack depth. The proposed method was validated with experimental investigations.

Darpe et al. [95] considered crack along with shaft bow and developed EOMs of a rotor system. They analysed steady-state as well as transient responses of the system with and without the influence of gravity. They neglected the effect of gyroscopic couple as the disc was present in the middle position. The prime intention of this investigation was to acknowledge the influence of bow (for distinct values of bow intensity) on the rotor vibrational dynamics as well as the stiffness characteristics of the cracked rotating shaft. It was observed that gravity dominated the switching nature of the cracked shaft for normal values of residual bow. Moreover, there was no change in the amplitude of higher harmonics and their directional nature in the cracked rotor resulting from the shaft bow effect. However, a significant change was found in the rotational frequency component.

Pennacchi and Vania [96] established a model-based diagnostic methodology to identify the crack in a load coupling in gas turbine. They also simulated vibrations coming

Table 7 A chronological summary of the literature available in the area of crack and internal damping faults

Year	Refs.	Identification technique/dynamic analysis	Nature of work	Main conclusion	Shortcoming
2008	[86]	Continuous wavelet transform and Newton–Raphson	Num.	Identified the crack and internal damping in a rotor system supported by fluid-film bearings	Applicable for identifying cracks of almost 5% of the rotor radius only
2018, 2019	[89, 90]	Least square fitting technique and Runge–Kutta method	Num.	Identified crack and internal damping faults in a rotor–AMB system without and with gyroscopic couple effect	Isotropic AMB; discrete unbalance at disc; rotational DOFs were removed during modelling
2019	[87]	Root locus method and FEM	Num.	Analysed whirl motion of a breathing cracked rotor with rotational damping	The gyroscopic effect was not taken into the consideration
2019, 2020	[12, 91]	Least square fitting technique and Runge–Kutta method	Num.	Identified crack and internal damping faults in a rotor system without and with gyroscopic couple effect	Discrete unbalance at disc; rotational DOFs were removed during modelling
2019, 2020	[92, 93]	Least square fitting technique and Runge–Kutta method	Exp.	Estimated parameters of unbalance, crack and internal damping faults in a two and four DOFs rotor-bearing system	The shaft bow effect was not considered and the analysis was applicable for slow rotor speeds

from the shaft bow as a result of crack developed in the stub shaft of the load coupling. This investigation showed the technique for managing the health monitoring and vibrational data for online and offline diagnostics of the faults in the rotating machine. Moreover, this study also showed that although there was negligible change in the 2× vibrations, crack propagation can be detected in the stub shaft of the load coupling. Bowing of the shaft in steam turbine can make the rotor blades strike the casing of turbine, which causes crack in the blade due to fatigue loading [97]. Bow in the shaft occurs in the case of faster shut down of turbine and improper cooling time of the shaft. They investigated that the bowing effect will be different depending upon the rotor blade stage and location. The crack propagation occurs either at leading edge or trailing edge or any location along the chord of blade, which causes high stress at different locations of the blade root. Due to this high stress in blade, its fatigue life will be very less and may cause the turbine to fail.

In a recent publication, Sarmah and Tiwari [10] presented a model-based estimation strategy for determining the parameters assisted with additive and multiplicative faults in a rotor–active magnetic bearing system. In their work, the AMB was used as a vibration controller. During modelling of the system, the rotor unbalance fault was examined as an additive fault, while the interdependency of bow and the fatigue crack was taken as a multiplicative fault. The vibration of shaft was surveyed under the influence of transverse switching crack, an initial shaft bow, disc unbalance and internal as well as external damping faults. The PID controller strategy was used for the mitigation of the vibrational amplitudes. To examine the sensitiveness and robustness of the proposed strategy, it was also checked against various random noises and system modelling errors and found to be suitable in fault identification. However, they considered isotropic AMB and assumed discrete unbalance at disc location. The rotational DOFs were also removed during the development of system's model.

The present section covers the survey done in the vibrational analysis and identification of crack and residual bow in rotating machinery. Almost all the literature discusses the interdependency of transverse crack and bow. Therefore, the numerical investigations can be explored for understanding the effect of slant crack or longitudinal crack on the bent shaft and validated through experimental works. Moreover, experimental investigations can also be done in future work for detection of crack and bow in the turbine blades. Further, the nonlinearities from the supported oil-film bearings, the shaft residual unbalances and anisotropic AMB–rotor supports can be considered while theoretically developing the complex rotor models.

A summary of published works in the field of interdependency of crack and bow faults in the rotating machines (including publication year, identification method, analysis, concluding remark and drawback) is presented in Table 8.

3 Fault diagnosis of other multiplicative faults and compound faults

Gibbons [98] explained that the bend in the shaft can occur due to restoring moments in the torsionally loaded misaligned couplings. The severity of the residual shaft bow and machinery vibration can increase with enhancement in the torque and rotational speed. Two model-based techniques were presented by Höfling and Pfeufer [99] for the detection of additive as well as multiplicative faults. They have also illustrated the techniques in a direct current (DC) motor. An offset in the sensor (or actuator) and amplifier may be the cause for additive faults, which are generally modelled using the superposition of signals on the inputs, states as well as outputs of the process, while the changes in the parameters of the process, like changes in resistances, inductances, inertia constants or damping coefficients fall into the category of multiplicative faults. Out of the proposed techniques, the first technique was the continuous-time parity space approach with adaptive thresholds, whereas the second technique was the parameter estimation method. The combination of both methods was found to be effective and provided optimal fault detection.

Shiau et al. [100] explored the dynamic influences of the eccentricity and transmission error of the rotating gear as well as the shaft bow on a gear-rotor system supported on bearings, which were modelled as flexible elements with stiffness and damping constants. However, they ignored the axial translational vibration and gyroscopic effects due to discs in the gear-rotor system. Later, Bachschmid et al. [101] utilized commercial software to examine the thermal behaviour of the cracked circular beam through a three-dimensional nonlinear finite element model. They found that the temperature distribution was unaffected by a crack in the beam. However, the crack significantly affected the stress and strain distributions, which resulted in bow of the rounded beam. They also presented a one-dimensional model for computation of the thermal and axial stress distributions in an infinite cylinder and validated with the finite element model.

Wei et al. [102] discussed that the sensor faults in a wind turbine can be considered additive faults or multiplicative faults. They built a wind turbine model relying on a closed-loop identification approach, in which both the additive and multiplicative faults were investigated from the residual generated by Kalman filter. By detecting the variation in the mean value of the residual as well as the generalized likelihood ratio test, the identification of the additive fault case was made possible, while the multiplicative fault was

Table 8 A chronological summary of literature survey in the field of crack and bow faults

Year	Refs.	Identification technique/dynamic analysis	Nature of work	Main conclusion	Shortcoming
2000	[94]	Least square identification method	Num. and Exp.	Identified both the location and the depth of a crack in a rotor considering bow effect	Nonlinear oil-film effects in bearings were neglected
2006	[95]	D'Alembert's principle and Runge–Kutta method	Num.	Explored bow effect on the breathing nature of the cracked rotor for various bow magnitudes	Gyroscopic effect due to middle disc at shaft position was neglected
2008	[96]	Least square identification method	Num. and Exp.	Simulated vibrations caused by the shaft bow due to the propagation of a crack in the stub shaft of the coupling	Technique can be used for identification of other severe faults also
2018	[97]	Finite element simulation and stress analysis	Num.	Initiated crack on the blade of rotor by bowing of the shaft of a typical steam turbine	Experimental work needs to be explored for crack and bow in turbine blades
2020	[10]	Least square fitting technique and Runge–Kutta method	Num.	Identified various faults such as unbalance, bow and crack in a rotor–AMB system without and with gyroscopic couple effect	Isotropic AMB; discrete unbalance at disc; rotational DOFs were removed during modelling of the system

explored as a result of the variance change detection of the residuals. Simulation results manifested that the proposed technique was appropriate for the underlying sensor fault detection issue. Heredia et al. [103] presented an actuator and sensor fault identification method for small size of autonomous helicopters. Detection and diagnostics of faults is required to avoid hazardous accidents. Comparison between faulty behaviour of the rotor with fault-free behaviour was utilized to identify faults in the rotating machines in a helicopter. Both the simulations and experimental results were demonstrated by them to check the robustness and efficacy of the developed technique. Experiments were conducted to accumulate input and output data in various test conditions, which included five different kinds of sensor failure. The five types of sensor failure included total sensor failure, constant bias sensor failure, additive type sensor failure, multiplicative type sensor failure and outlier data sensor failure. Moreover, the actuator fault detection was implemented for the stuck actuator type failure. They further suggested that the outlier data sensor failures can be combined with global positioning system signal quality measures for improvement in the reliability of faulty position estimations.

El-Shafei et al. [104] explored the effect of plain journal bearing misalignment on the oil whip and oil whirl characteristics in a test rig comprised of a flexible rotor having two cylindrical-shaped fluid-film bearings supports. A misalignment fault was introduced between the main shaft and the drive end or both bearings. They performed five different runs in experiments, where the degree of misalignment was varied. One of the observations was made from the analysis that the overall rotor operation was quite stable for the case of parallel misalignment between the two supported bearings as compared to angular misalignment. The period of instability was also less for the parallel misalignment state. Wei et al. [105] developed an identification algorithm to establish a state-space linearized model in a three-blade horizontal axis wind turbine. They also proposed a Kalman filter-based diagnosis algorithm to detect the additive and multiplicative sensor faults. The variation in mean value of the residuals as well as the generalized likelihood ratio test was exploited for the detection of additive faults, while the multiplicative faults were identified through the variance change of the residuals. Using numerical simulation, they found that the proposed approach was successfully implemented to identify the blade root moment sensor fault. In the concluding remarks, it was proposed to include the modelling errors in the wind turbine system and perform the fault diagnosis.

Oil whip originated from fluid-induced instability is one of critical issue, whereas dry whip generated due to rub is other issue. However, the rub is always a secondary effect originating from fluid-induced instability which utilizes the rotor-to-stator gap. Moreover, the variation in the bearing dynamic features and frictional impact are the extensive physical phenomena, which occur due to oil whip and dry whip. Fan et al. [106] utilized the combination of Hilbert transform and full spectrum, i.e. the full Hilbert spectrum for detecting the fluid-induced instability as well as the rub fault. They plotted a variety of plots, such as the time base plot and shaft centreline orbit plot, which were helpful in understanding the features and consequences of the fluid-induced instability. For further research, the discussed approach can be extensively explored in developing advanced control means of the supported bearings. Boulkroune et al. [107] proposed a residual generator-based model for detecting and isolating the additive as well as multiplicative faults in the current measuring sensors of a doubly-fed induction generator. This generator is widely used in wind turbines, pumped storage plants, and flywheel energy storage system. However, they are extremely sensitive to current sensor faults. A mixed H-minus and H-infinity ($\mathcal{H}_{-}/\mathcal{H}_{\infty}$) fault detection method followed by a Kalman filter was utilized in this model to attenuate the modelling uncertainties on the residuals. The whole fault detection and isolation process was achieved within the imposed time slot when tested through simulations on a controlled doubly-fed induction generator.

De Oca et al. [108] discussed a fault-tolerant control scheme for the linear parameter varying system. They used a virtual sensor for the implementation of this strategy. The prime reason for developing this approach was to reform the control loop, which would help in utilizing the nominal controller without its retuning. Moreover, they developed a fault estimation technique employing the least-squares approach to identify additive and multiplicative sensor faults. A two-degrees-of-freedom helicopter simulator was exploited to demonstrate the performance of the presented approach. Kaliappan et al. [109] considered a helicopter and described the different faults that existed in it. The faults include additive faults, i.e. the component faults and multiplicative faults, such as the sensor faults and actuator faults. Component faults occur when there is some change in the internal component. However, the partial or complete loss of the controlling act is related to actuator faults and the incorrect readings from the sensor or failure of the sensor itself represent for sensor faults. Afterwards, they proposed a fault-tolerant control approach using parameter estimation method and pseudo-inverse method for detecting and isolating the faults. The approach was found to be robust and efficient when tested with numerical simulation.

Wan et al. [110] explored the dynamic effect of coupling misalignment fault on a multidisc rotor system mounted on oil-lubricated journal bearings using both theoretical as well as experimental works. Misalignment is an extremely serious and frequent malfunction in the rotatory machine, which can give rise to various other faults; however, limited attention was paid to the misalignment problem in comparison to crack, unbalance, rotor–stator rub, and fluid-induced vibrations. Reddy and Sekhar [111] focussed on utilizing torque measurements as a convenient and effective technique for the detection of coupling misalignment and health monitoring of the machine. They also discussed that the high levels of shaft misalignment may lead to fatigue cracks or rotor-to-stator rubbing. Later, Ma et al. [112] elaborated on the interplay between oil whip phenomena, unbalance and parallel as well as angular misalignments in an overhung rotor-conventional bearing-coupling system with FEM modelling. They examined and studied the effects of combined coupling misalignment as well as angular acceleration on the oil-film instability during the run-up and run-down speed phenomena.

The shafting of a large and massive rotating machine, i.e. steam turbine-generator model is a multi-bearing rotor system, in which a different number of rotors are fastened using various couplings. Extensive vibration in the system can be created due to additional bearing loads from an unreasonable elevation of the bearings [113]. Further, Mobarak and Wu [114] developed an analytical model for exploring the effect of unbalance fault over the crack location and its breathing behaviour during operation. They concluded that a crack in an unbalanced rotor has extra breathing patterns as compared to a crack in a balanced rotor. Corne et al. [71] incorporated an AMB at the driving-end side of 11 kW induction machine test rig (refer Fig. 8b). The relation between the current fault signatures, misalignment severity and unbalance were explored by them. Misalignment fault between the induction machine shaft and load machine shaft was caused from the looseness of bolts at the non-driving end of bearing pedestal in the induction machine. The method was utilized for investigating the vibration from the unbalance and misalignment faults (caused by looseness) in a very simple and small motor shaft system. Afterwards, Antonino-Daviu and Popaleny [11] considered the motor misalignment caused due to mechanical looseness fault by loosened bolts and soft foot. They focussed on analysing the transient motor currents in the time–frequency data for detecting certain faults, which included unbalance and misalignment. Experiments were performed to illustrate the developed method relying on the starting current. The transient currents can also be used for identifying various rotors as well as bearing faults. Moreover, in the direction of other multiplicative faults, the effect of profile and index errors as well as variable load torque on the transmission error was analysed in a two-stage spur gear system [115]. The nonlinear gear model was considered to have 14 degrees of freedom including 6 DOFs in the direction of torsional vibration and 8 DOFs in the direction of radial displacement vibration. The time-varying damping and stiffness parameters were present in the gear model. The difference in the positive peak and negative peak of the optimized load transmission error was found to be decreased by 60.7%. This enhanced the efficacy and accuracy of transmission as well as minimized the disturbance occurrence. In the coming future, the effectiveness of the optimization technique can be validated using experimental works. More recently developed signal processing approaches can be considered for analysing the faults in the gearboxes.

Niemann et al. [116] proposed a method without using a model for fault diagnosis as well as health monitoring of rotating components in wind turbines. The method was relying on measurements from standard sensors, which include moment sensors and rotor angle sensors. The amplitude, as well as phase information of the signals, was utilized to identify faults in rotor systems. Relying on the signatures, they were able to isolate the faulty components, such as the sensor fault, actuator fault and internal blade fault in wind turbines. Two types of perturbations were included in the periodic input vector of multiblade coordinate transformation, i.e. an additive perturbation and multiplicative perturbation. Utilizing this transformation, it was feasible to detect the rotor's asymmetry fault in the system. An actuator fault was found to be yielding a change in the pitch for one of the turbine blades, which caused variation in the flap-wise moment together with the edge-wise moment. Moreover, the effect of these moments was measured by sensors. However, for further investigations, they suggested to implement the discussed diagnosis technique for simultaneously existing multiple faults in practical wind turbines. Yue et al. [117] explored the dynamic nature of several malfunctions in momentum exchange devices, which were modelled similar to cascade motor and variable speed drive system. Various kinds of additive and multiplicative faults were incorporated into this system. For the electric motor, the potential faults belonging to multiplicative faults were classified as rotor faults, stator faults, bearing faults, eccentricity faults and gear faults. While the additive faults, such as the sensor faults and actuator faults were associated with the variable speed drive. Visualization of the possible outputs influenced by these faults was done to demonstrate the fault severities. Based on the standpoint of accuracy in controlling performances, the additive fault was found to be more severe than the multiplicative fault. After going through this paper, it is found that the future scope of work can be on verifying the proposed fault model using reaction wheel and control moment gyro testbed. Moreover, to accommodate the actuator fault and recover the nominal control performance, analysis and design of fault detection, diagnosis and control can also be addressed by leveraging the developed fault model.

Yang et al. [118] presented a novel fault-tolerant compensation control technique for simultaneously detecting the additive as well as multiplicative actuator faults in Markov jump systems. This technique was able to entirely reduce the unfavourable effects due to the simultaneous presence of additive and multiplicative actuator faults as well as inconsistent nonlinearity phenomena. To illustrate the effectiveness and validity of the proposed approach, a practical wheeled mobile manipulator system was utilized. However, the transition probabilities of some practical applications were unknown. Hence, how to design the fault-tolerant controller based on the proposed method can be done in future work. Under the simultaneous influence of multiplicative actuator faults and additive sensor faults, Ma et al. [119] developed a virtual actuator-based active fault-tolerant tracking control strategy for the turbofan engine. This scheme was developed to reconfigure the system so that it can have a similar kind of vibration nature to the fault-free system without modifying the nominal controller. In addition to handling the actuator fault by the virtual actuator, the reconfigured controller adopted a feedforward control signal to compensate for the sensor fault. Future research work can be explored in extending the virtual actuator-based fault-tolerant control to some types of nonlinear system. Li and Wang [120] proposed a passive fault-tolerant pitch control technique for actuator faults. Depending on this scheme, a dual multiple-input multiple-output system consisting of a multivariable model-free adaptive controller with differential characteristics was developed. Faults in the actuator were classified as the multiplicative fault (effectiveness reduction) and additive fault. For the multiplicative fault, its intuitive performance is that the actuator cannot respond to the control command, which lowers the effectiveness of the actuator. The additive fault is that the actuator always has a certain offset output, which makes the desired output unattainable. In the future research, the hardware in the loop or field experiments can be explored for checking the accuracy, robustness and practicability of the discussed dual multiple-input multiple-output system.

Apart from multiplicative faults, various researchers are also focussing on compound fault diagnosis of rotating machinery. Compound faults are different from multiplicative faults. In the compound faults, two or more types of faults occur at the same time in a system or its components. These faults may also have unequal severity, and distinct faults feature can be coupled together and hidden in the measured signals. However, it is not necessary that one fault is the cause of another fault or interdependency existing between them. Dibaj et al. [121] utilized an integrated technique of fine-tuned variational mode decomposition (VMD) and convolutional neural network (CNN) to identify the compound faults of unequal severity in an automobile gearbox system. The developed hybrid method shows great performance in fault features extraction and classifying the minor fault (i.e. bearing fault) from the fault of higher severity (i.e. gear fault).

After 1 year, a novel fault diagnosis method based on fault feature region (FFR) was proposed by Tang et al. [122] to detect compound faults in rolling element bearings. Using the new fault extraction strategy, they investigated the combined fault pattern between single fault as well as compound faults. It was observed to have more than 80% accuracy in fault diagnosis of various faults in rolling bearings (i.e. inner race fault, ball fault, outer race fault) as compared to traditional approaches. At the last for future work, they suggested to do improvements in the proposed technique by optimizing the compound fault discrimination terms. This will provide more refinements in the diagnosis of compound faults. It was also proposed to build models of less weight and utilize the method for industrial applications.

Later, Xu et al. [123] claimed that it would be very difficult to detect unknown compound faults in an industry by employing the model trained on single fault samples. Therefore, they proposed a zero-shot learning method for the purpose of diagnosis of coupling of various faults in the supported bearings. In this method, firstly the two-layer convolutional neural network was utilized to extract the time–frequency characteristics of the compound faults signal data, and then, the semantic feature of the faults was used to exhibit the knowledge about type of fault. Their study in fault diagnosis of the compound fault in bearings consisted of three types of fault only, i.e. the inner ring fault, outer ring fault and rolling body fault. Therefore, they suggested for exploration of more number of complicated faults in bearings and distinct network structures of convolutional neural network for improvement in the performance.

Lin et al. [124] explored the analysis of compound faults in photovoltaic systems, occurring due to deposition of dust on the photovoltaic array. The timely detection of faults is extremely important in order to improve the solar panel's operating efficiency and human safety. In this paper, they have proposed a fault diagnosis scheme based on integrated techniques of multi-scale squeeze and excitation residual neural network (SE-ResNet) as well as multi-scale receptive field fusion module (MRFF). The field fusion module was able to do improvement in the working of fault diagnosis method. The single faults, partial shading conditions and compound faults were successfully diagnosed for different amounts of dust spread at the bottom of photovoltaic panels. The proposed method was tested on both the numerical and experimental platforms and found to be providing good results as compared to other approaches such as shallow neural network and deep neural network.

In this section, the other kinds of multiplicative faults, i.e. the sensor fault, actuator fault, fault in gear system and oil whirl phenomena, occurring in the helicopter, gearbox, wind turbine, steam turbine-generator system and compound faults, have been elaborated through previous research papers. Various studies were also summarized in the field of interdependency of misalignment and bow, unbalance and crack, misalignment and looseness, misalignment and oil whirl, bow and gear transmission error, combination of faults in gears, rolling bearings and gearbox systems. The outcome, shortcomings and future scope of the works discussed in the research articles were also addressed in detail.

4 Review on model-based fault detection and diagnosis techniques

About four decades ago, Patton et al. [125] elaborated on model-based fault diagnosis methods by going through various articles. They have discussed traditional fault detection approaches such as frequency spectrum analysis, parallel redundancy and fault dictionary technique. Two primary stages are considered in model-based fault diagnosis system which is the residual generation and residual evaluation. They discussed that one of the practical applicability of model-based methods relies on the detection and isolation of faults in actuators and sensors. In this paper, an integrated knowledge-based fault diagnosis system (refer Fig. 10) was discussed by them, which included both analytical and heuristic knowledge. These knowledge are to be processed with regard to residual generation as well as feature extraction. Within 1 year of duration, a short review on applications of model-based method was published by Isermann and Balle [126]. In this paper, they discussed various types of fault that can be diagnosed using the model-based technique, which include sensor fault, actuator fault, process fault and controller fault. At last, it was suggested to explore the technique in the field of chemical processes as well as thermal and fluid dynamic processes. Later, several case studies and investigations on utilizing the model-based method for the detection of faults were explored in a review paper [127]. The case

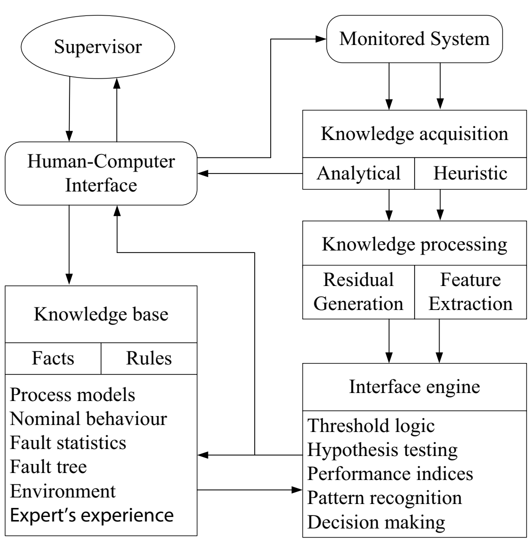


Fig. 10 A flow chart describing the process involved in the integrated fault diagnosis technique [125]

studies include a cabin pressure outflow valve actuator of a passenger aircraft, lateral behaviour of faulty passenger cars and combustion engines.

Trave-Massuyes and Milne [128] explored the combined use of model-based diagnosis technique and artificial intelligence technology for monitoring the condition of gas turbines in industries. They mainly focussed on Tiger system (which is a trademark of Intelligent Applications Ltd.), which can predict the fault conditions and identify faults in a proper time. Tiger could exhibit short as well as long-term parameter trends and enable condition monitoring with higher accuracy. Further, a review on the quantitative model-based approach was presented by Venkatasubramanian et al. [129] for fault detection as well as diagnosis in process engineering. In this review paper, the introduction of the analytical redundancy approach was outlined along with various fault detection and isolation approaches such as diagnostic observers, parity equations, Kalman filters and parameter estimation. In future work, it was assured to survey qualitative model-based as well as process history-based methods. These three types of method can also be compared at the last.

Charles et al. [130] utilized model-based condition monitoring at the interface between the railway track and wheel. The change in vehicle response may occur due to any kind of changes in the shape of the track–wheel profile or the contact adhesion conditions. Model-based condition monitoring utilizes the complete system knowledge in the mathematical equation form as well as the measured vehicle dynamic response for estimating the vital system parameters. They have identified separately two tasks, i.e. wheel–rail profile estimation and low adhesion detection. Moreover, it was planned to investigate the combination of both tasks, i.e. the estimation of railway track–wheel parameters at controlled low adhesion states. The model-based approach was further employed for the condition monitoring of wind turbines [131]. For this purpose, they utilized supervisory control and data acquisition (SCADA) system to identify the types and characteristics of faults associated with the generator and the bearings in wind turbines.

Ogbonnaya et al. [132] used the component model structure as depicted in Fig. 11, for model-based condition monitoring of the gas turbine. The main three major components of gas turbine machine were considered in their work, i.e. compressor (axial and centrifugal compressor), turbine and combustion chamber. The examined operational parameters were temperature, pressure, net power output, efficiencies and airflow rate. From the results analysis, they could conclude that high pressure ratio as well as rise in high temperature across the compressor can be aimed at during design of gas turbine plants. Further study also involves the application of model-based approach in identifying the tool run-out in the milling process [133]. Estimation of surface

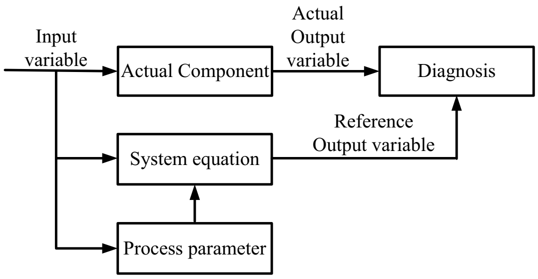


Fig. 11 Component model structure flow chart for model-based technique proposed by Ogbonnaya et al. [132]

roughness was also done using measured cutting forces. It was observed that the estimated surface topography arising from the identified run-out parameter correlated excellently with the measured roughness of the machined surface. The obtained result was also capable in demonstrating the function as well as the performance of the run-out identification method.

Cross and Ma [134] proposed a model-based approach for the identification of fault parameters in a nonlinear wind turbine system. The model parameters were varied as functions of the system variables and identified directly from the input and output data of the process. For the wind turbine simulation, it was shown that the occurrence and severity of grid faults, broken rotor bars and direct current capacitor faults can be identified using the output predicted by models of the relationships between wind speed and the root-mean-square phase current and the electrical torque output. At the end of the paper, it was claimed by them that future research will be on the development of the early warning system utilizing fuzzy logic concept which will interpret the amount by which the adaptive threshold is surpassed as well as the period of time over which this occurs. Moreover, the research will also consider the number of data necessary to be retained in the long and short-term buffers.

Fault diagnosis includes three tasks, that is, fault detection, fault isolation and fault identification. Fault detection is the most basic task of fault diagnosis, which is used to check whether there is a malfunction or fault in the system and determine the time when the fault occurs. Furthermore, fault isolation is to determine the location of the faulty component, and fault identification is to determine the type, shape and size of the fault. Gao et al. [135] presented a survey on model- and signal-based fault diagnosis techniques. The model-based fault diagnosis covers the listing of fault diagnosis approaches for deterministic systems, stochastic fault diagnosis methods, discrete-event and hybrid system diagnosis approaches and networked and distributed system diagnosis techniques. On the other hand, the signal-based fault diagnosis covers the categories of time-domain, frequency-domain and time–frequency-domain approaches. They determined to carry out the review on knowledge-based fault diagnosis and hybrid as well as active fault diagnosis along with their applicability in the coming future.

Rao and Tiwari [136] developed a model-based identification algorithm and detected asymmetric transmission error in a geared rotor system having coupled lateral vibration. Full-spectrum analysis was performed by them to grasp the forward and backward whirling motions due to asymmetry in the transmission error. The rotor system consisted of a simple spur gear pair supported on rigid bearings. The bearings were considered rigid to lessen the complexity of the system's equations of motion. The transverse as well as torsional vibrations were also considered to be uncoupled. With the developed identification equation, they have estimated various system and gear parameters. Numerical results were also validated with experimental works and found to be exhibiting a satisfactory outcome. Model-based estimation methodology and full-spectrum concept were further utilized by researchers [91–93] to identify the internal damping and external damping in a fatigue-cracked rotor system having middle disc and offset discs. The developed methodology was also observed to be executing excellent results with addition of signal noise and rotor modelling errors. Further, they suggested considering a multi-degrees-of-freedom cracked rotor system and utilizing finite element approach for the mathematical modelling. This will provide more realistic and accurate results in fault identification.

Shi and Bai [137] proposed a model-based method for monitoring the health of ceramic ball bearings associated with uneven loading states and starved lubrication. Both numerical and experimental investigations were performed by them for different sizes of the balls. The developed method was found to be excellently matching with the experimental works. It was revealed from the results that with an increase in the maximum difference of adjacent ball diameter, the uneven loading condition became more obvious which can be evaluated using the amplitudes of the peak frequencies. The model-based identification scheme was also used by Majumder and Tiwari [138] for the identification of system and fault parameters in a geared-coupled rotor–AMB system. Two AMBs were employed in the system to control vibrational amplitude and estimation of various parameters. One AMB was located at the input shaft, and another AMB was positioned at the output shaft. This research article was an extension of the paper [136] in which AMB was incorporated in the geared system and gear run-out was considered along with asymmetric dynamic transmission error. However, the spur gear pair was located in the middle of the shafts. Later, the same methodology and procedure were utilized with consideration of offset spur gear pair at higher speeds and gyroscopic couple effects [139]. Further, they performed an experimental investigation for vibration control of the same geared rotor system using an electromagnetic actuator and PID controller [140]. They have presented various plots showing the transverse and torsional displacement responses with and without AMB, with respect to time and frequency domains. The maximum attenuation that could be attained was nearly 50% after fine-tuning of the controller gains under constant loading conditions.

Song and He [141] collected various research papers and presented a survey on model-based fault diagnosis of networked systems which includes sensor, actuator, controller and auxiliary signal generator components. There are many applications of fault diagnosis technology for networked systems such as wireless sensor networks in wind turbines, distributed heating, ventilation and air conditioning systems and train control systems. In the conclusion section, they advised that as the complexity in network systems is rapidly increasing day by day, fault diagnosis should not be ignored and more diagnosis technologies can be developed to ensure the reliability and security of networked systems. In a recent publication, Zhao et al. [142] explored a survey on model-based fault diagnosis techniques of stochastic dynamic machines. The method utilizes the input–output relationship of the system. They have also presented various applications of the model-based method in industrial plants such as battery management systems and wind turbine systems.

This section completed with exploration of model-based identification technique for detecting and diagnosing of various faults in rotating machines. To understand the basic concept of model-based technique, a flow chart was given at the initial part of the section. Moreover, the short descriptions, drawbacks and scope of future works of various papers were also discussed through technical papers and review papers.

5 Artificial intelligence (AI)-based fault diagnosis of rotating machines

Recently, various researchers are also focussing on artificial intelligence (AI) techniques for the purpose of an effective fault detection and diagnosis in different kinds of rotating machines. The artificial intelligence methods include deep learning techniques (i.e. convolutional neural networks, deep neural networks, recurrent neural networks, etc.), machine learning techniques (i.e. support vector machines, k-nearest neighbours, etc.), evolutionary computation techniques (i.e. genetic programming, particle swarm optimization, differential evolution, etc.), fuzzy logic techniques, and more. These methods can intelligently detect faults through processes such as data collection and processing, feature extraction and selection, feature construction and classification. These techniques assist in time consumption for fault detection and provide higher accuracy.

Chen et al. [143] proposed a new convolutional neural network method which was transferable in nature. This method was developed to overcome the performance restrictions of deep neural networks, where there was lack of adequate training data and high computing power. In the proposed method, firstly one-dimensional convolutional neural network was created and pre-trained. After that, a transfer learning approach was utilized to train a deep model on target tasks with the help of pre-trained network. In order to check and verify the performance of developed method, experimental works were executed on bearing and gearbox test set-up. Four different cases were considered according to shaft rotational speeds. In the first case, the vibration signal data were captured at a speed of 1250 rpm. For the second case, the vibration data were collected at the combined speeds of 1000 rpm and 1250 rpm. Vibration data captured at a uniform speed of 1100 rpm were the third case, and data collected at the combined speeds of 800 rpm and 1100 rpm were the fourth and last case. The method was found to be robust and having good stability for all cases. At last, they suggested to utilize the discussed method along with machine learning methods, i.e. unsupervised or semi-supervised learning for more improvement in the fault detection.

Liang et al. [144] utilized combined methods of wavelet transform, generative adversarial nets (GANs) and convolutional neural networks for fault detection in the rotating systems. The vibration data in the time–frequency domain were extracted and converted to feature images using wavelet transform technique, and then, further the high trained image samples were developed by generative adversarial nets. Lastly, the convolutional neural networks (CNNs) had been exploited for detecting the fault in machines. CNN strategy required the original generated image samples and trained image data. For checking effectiveness of the combined methods, experimental works were done on bearing and gearbox systems. High accuracy was noticed in the method, which was depending on the size of training samples. However, the trained image samples were similar to original image samples. There were no new image samples. In future work, the generative adversarial nets can be utilized for developing compound fault image samples using various single fault image samples.

After 1 year, a thermal image-based technique was employed by Choudhary et al. [145] for fault diagnosis in one of the crucial components (i.e. bearing) in rotor systems. They have created thermal images of the bearing for six number of cases, in which one case was for healthy bearing and other five cases with faults such as defect in outer race, defect in inner race, ball defect, cage defect and insufficiency of lubrication. Further, the artificial neural network method (ANN) and convolutional neural network method (CNN) were used for the purpose of classification and comparative study among these cases. They have performed experimental investigations on a test rig set-up consisting of a simple rotor system with two fluid-film bearings and a constant load. A thermal imaging camera was available to capture the infrared images of the bearing for different conditions. One of the main observation was made that the results output coming from CNN was more accurate than ANN. However, the temporal information from time series signals is neglected by CNN method.

Later, in order to overcome the deficiencies of CNN-based method, a novel technique based on recurrent neural network (RNN) was utilized by Zhang et al. [146] to determine the types of faults in the rotating machines. In the proposed method, one-dimensional time series vibration signal data were transformed into two-dimensional images in the first step. Further, in the second step, a gating mechanism was incorporated to utilize temporal details of time series data and study illustrative characteristics from generated images. Robustness of the method was also checked in presence of noise signal. The method was found to be quite robust even in the noisy working environment as compared to other intelligent methods. However, the RNN method was also able to generate limited number of data. Therefore, it was proposed to utilize generative adversarial network (GAN) method, which can develop higher number of vibration data with more quality.

A supervised model of generative adversarial network (i.e. modified auxiliary classifier GAN) was proposed by Li et al. [147] for fault diagnosis of bearing and gear. This method was able to overcome the shortcomings of traditional GAN in terms of mode collapse and gradient vanishing. Moreover, the unsupervised GAN could not generate multi-mode fault samples at the same time. However, the modified GAN technique generated efficiently multi-mode fault samples having higher qualities. The results derived from the novel technique were also observed to be highly accurate and stable in the presence of noise signal. Finally, for future work, they suggested to create high-quality and multi-source fusion fault samples as well as develop an efficient fault diagnosis model for minimization of noise effect.

Recently, Ning et al. [148] utilized a graph neutral network (GNN) method and visibility algorithm to identify the inner race fault, outer race fault and ball defect in a bearing. The visibility algorithm was employed to convert the time series data into non-Euclidean space graph structure data. Further, these data were given as input in GNN-based method for classification of faults. They also performed experiments on a test rig set-up consisting of motor, dynamometer and torque sensor to check the robustness of the method. The defective bearings with distinct fault diameters were manufactured by electric discharge machining and tested under different values of constant load. The results have shown higher accuracy in the proposed method. Moreover, the visibility algorithm provided a more comprehensive expression and knowledge of the local vibration data as compared to traditional composition techniques. For future work, they have given suggestion to simplify the graph data structure and optimize the computational time and complexity of the discussed method.

Similarly, in the recent publication, a discrete wavelet transform was used for an intelligent fault diagnosis of the rotating systems [149]. This paper also investigates the effect of mother wavelet, sensor selection and machine learning models. Two different approaches were used by researchers which included single-step fault monitoring (SSFM) and two-step fault monitoring (TSFM). In the first approach, the machine learning models detected the type of fault using faulty and healthy signals, whereas in the second approach, the built models are used to determine whether the machine is faulty or not. Further, if there is any fault in the system, then it is detected by the models. While making comparison between the first approach and second approach, it was observed that TSFM approach was more appropriate than SSFM, because it crucially enhanced the accuracy of SMFM models in the identification of faulty and healthy machines. At last, it was recommended for considering multiple number of faults such as stator, rotor, electrical supply and gear faults in a system and identify them using the proposed approaches.

In this section, the brief induction about artificial intelligence techniques and their classification have been given at the starting point. Its advantages over other fault detection and diagnosis techniques were also given. Various studies were found as the published works, which used either single intelligence technique or in the combined way for fault identification in the rotating machines such as bearing and gearbox system. For future work, more number of rotating systems with multiple faults can be considered and analysed using artificial intelligence techniques.

6 Fault diagnosis of rotary machines used in underwater vehicles

In order to make the present article more interesting and knowledgeable to the readers, some research papers have been also reviewed and discussed in this section. The section includes the survey done in the field of fault diagnosis in the rotating components utilized in underwater vehicles.

Alessandri et al. [150] proposed a model-based method for identification of actuator fault in an unmanned underwater vehicle. They have created an approximate model of the vehicle to study the system's dynamics. Any changes occurred during vehicle motion was captured and analysed to determine the faults. Due to nonlinearity in the system, an extended Kalman filter estimator was used to find the type of fault in the actuator. Experimental works were also performed to check the efficacy of the proposed approach. However, there was availability of only one sensor type, i.e. KVH DGC 100 compass to measure the responses. Therefore, it was suggested to take more number of measuring instruments and analyse more effectively the dynamics of the underwater vehicle (UV). This would help in excellent performance of the fault diagnosis technique.

Later, Omerdic and Roberts [151] utilized the combined concepts of fault diagnosis and fault accommodation subsystems to detect thruster fault in underwater vehicles. However, in this paper, they did not consider the fault in control surfaces type actuator. Hence, the future work can be towards utilizing the developed combined techniques in the fault diagnosis of actuator fault along with the fault in thruster.

Inzartsev et al. [152] applied artificial intelligence (AI) strategies for fault diagnosis in autonomous underwater vehicles. In general, the vehicles utilize monitoring and emergency systems for enhancing their working performance and safety in the water. However, the intelligent-type monitoring and emergency systems consisting of three main block subsystems were employed by them. The first block was denoting for collecting knowledge-based information through parameters measured by sensors, the second block was a translator for converting the knowledge into program codes, and the third was monitoring and emergency system itself.

The recurrent neural networks (one of the type of AI) were exploited by researchers [153] for modelling and diagnosis of thruster fault in UVs. The method provided good accuracy in the fault identification through time-dependent signals collected from sensors installed at vehicles. However, they applied this method in a laboratory by developing a simple test model. Hence, they suggested to apply the proposed approach in a real UV machine as a scope of future work.

Further, Tsai et al. [154] employed the deep learning method (i.e. convolutional neural network) for fault diagnosis in thruster propeller of underwater vehicles. The Hall effect sensor was utilized for collecting current signal from thruster, and the hydrophone was used for obtaining sound signal in water. The collected time-domain signals were transformed into frequency-domain data using a fast Fourier transform technique. Then, the frequency-domain signals were given as input to the convolutional neural network. The output of the network was to show health conditions of the thruster propeller. They used the techniques of combined signals (i.e. current, voltage and vibration signals) and single signal to demonstrate the characteristics of propeller fault. From the results, it was observed that the combined signals input was providing greater accuracy as compared to single signal input. Distinct types of propeller fault conditions can be considered in the future work, and the method can be utilized in the actual sea platform.

Recently, a transferrable thruster fault diagnosis technique was proposed by Yin et al. [155] for identifying time as well as frequency boundaries of the local region in the time–frequency power spectrum resulting from thruster fault. They also utilized transferrable support vector machine (TSVM) algorithm for the purpose of classifying thruster faults, which gave an effective and accurate results as compared to conventional SVM algorithm.

In this section, the different fault detection and diagnosis methods used in the underwater vehicles were described by going through various published papers. It is found that the authors have used generally artificial intelligence techniques for the fault diagnosis in actuator and thruster faults in autonomous water vehicles. Researchers suggested for utilizing the proposed fault detection techniques in the real conditions when the robot vehicles are on some missions in the ocean.

7 General remarks and scopes of future work

A review on the dynamic effects of multiplicative faults and their identification through distinct traditional and recent approaches has been nobly described in the present paper. Out of the several techniques, the main emphasis is given on model-based fault detection and diagnosis approach which can provide better results in both the qualitative and quantitative aspects. In this article, various review papers on models of numerous faults in the rotor, bearing, sensor, actuator, etc., model-based fault detection and identification scheme and their applicability in industrial plants, aircraft and combustion engines are also summarized. The multiplicative faults included the interdependency of unbalance and bow faults, the interdependency of bow and rub faults, crack and rub faults, misalignment and crack faults, misalignment and rub faults, rub and mechanical looseness faults, crack and internal damping faults as well as interdependency of crack and bow faults. Researchers have performed both experimental and numerical works in these areas. However, there were some assumptions to make the rotor-bearing models simpler and easy to solve the mathematical equations. These assumptions have been also highlighted in this paper. The summary of works executed by different researchers is also described in each section of the article. Experimental validation is necessary for any kind of rotor system mathematical models and numerically obtained results. This will show that the proposed method works properly and gives truthful outcomes as well as acceptable in a laboratory or industry. Some of the important concluding points of the present review are given as follows:

7.1 General remarks

1. It is well established that multiplicative faults are extremely unsafe and prone to catastrophic failure in machine components and unwanted hazardous accidents. It is due to the complexity involved in multiplicative faults, as the process is affected by the products of the process variables in these faults.
2. Very less work has been performed in the areas of the interdependency of bearing misalignment especially active magnetic bearing misalignment, interdependency of misalignment and looseness faults, interdependency of misalignment and crack as well as interdependency of misalignment and oil whirl.
3. Dynamic influence of a dual-rotor system with unbalance and bow effects was experimentally studied by considering both the inner and outer shafts as solid. However, in an actual aero-engine system, the outer shaft is hollow and the inner shaft passes through it.
4. Although there was little literature available in the field of the interdependency of misalignment and rub, all were related to coupling misalignment and rotor-to-stator rub. Good literature survey has been done in the field of fault detection and diagnosis of wind turbine system.
5. Experimental investigations were not executed on actual aero-engines, double-stage bowed rotor-gear-bearing system and power station turbogenerators for identification of unbalance and bow faults.
6. There was a lack of work in the laboratory experimentation to analyse the acceleration and deceleration effects in a steam turbine rotor under the influence of shaft bow and rotor-to-stator rub effect.
7. During the development of several mathematical models in the faulty cracked rotor-bearing-rub system, the nonlinear effects from the supported bearings, the impact of shear deformation, vibration in torsional mode and gyroscopic moment were not considered.
8. Experimental investigations were not performed for the detection of cracks and bows in the turbine blades of gas turbine, hydraulic turbine and steam turbine.

7.2 Some perspectives for future work

After going through vast literature surveys in the field of multiplicative faults and model-based fault detection, isolation and identification approach, it is found that numerous works can be performed as a scope of the future. Some of the key areas are given as follows:

1. Model-based identification algorithm can be proposed for the misaligned and cracked flexible rotor–multidisc rotor system to identify these faults and study the vibrational effect on the rotating elements and supported bearings.
2. Active magnetic bearings can be also incorporated in the dual-rotor system, turbogenerator, underwater tidal turbine and other systems for controlling the vibration and high-speed applications.
3. Future work can be done on utilizing the model-based fault diagnostic approach to identify the simultaneous occurrence of multiple faults, such as propagation of fatigue crack, bearing dynamic effects, internal damping and bow in the shaft.
4. Researchers can also focus on works involving the interdependency of two or more faults together, i.e. interdependency of bow, crack and misalignment, interdependency of crack, rub and looseness, etc. Then, it will be interesting to analyse the rotor vibrational signature and other faulty effects.
5. Experiments can be executed on more complex machines and power station turbogenerator for identification of the unbalance and bow faults.
6. Optimization technique can be performed for the ideal design of hydraulic generator unit under the coupled faults of misalignment and rub.
7. Complex rotor systems with multiple discs and anisotropic as well as flexible bearings can be modelled to visualize the vibrations from faulty and actual underwater tidal turbine.
8. Nonlinearities from the supported oil-film bearings, the shaft residual unbalances, anisotropic AMB–rotor supports can be considered in the future while theoretically developing the complex rotor models.

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