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Review

A Review on Vibration-Based Condition Monitoring of Rotating Machinery

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Abstract: Monitoring vibrations in rotating machinery allows effective diagnostics, as abnormal functioning states are related to specific patterns that can be extracted from vibration signals. Extensively studied issues concern the different methodologies used for carrying out the main phases (signal measurements, pre-processing and processing, feature selection, and fault diagnosis) of a malfunction automatic diagnosis. In addition, vibration-based condition monitoring has been applied to a number of different mechanical systems or components. In this review, a systematic study of the works related to the topic was carried out. A preliminary phase involved the analysis of the publication distribution, to understand what was the interest in studying the application of the method to the various rotating machineries, to identify the interest in the investigation of the main phases of the diagnostic process, and to identify the techniques mainly used for each single phase of the process. Subsequently, the different techniques of signal processing, feature selection, and diagnosis are analyzed in detail, highlighting their effectiveness as a function of the investigated aspects and of the results obtained in the various studies. The most significant research trends, as well as the main innovations related to the various phases of vibration-based condition monitoring, emerge from the review, and the conclusions provide hints for future ideas.

Keywords: condition monitoring; vibrations; rotary machines; diagnostics; predictive maintenance

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1. Introduction

As of the past fifty years, highly technological methodologies have made it possible to monitor operating conditions, allowing for intelligent decisions about the maintenance interventions of plants or components, in any kind of industry, in order to achieve an effective maintenance. These are the well-known condition monitoring or predictive maintenance techniques, which significantly improve productivity, reliability, efficiency, and operating safety [1].

These techniques, based on measurements continuously carried out on the machinery (online condition monitoring) or performed at fixed time intervals (offline condition monitoring), aim to detect changes in the signals caused by damaged components with a clear distinction between anomalous alterations and changes caused by normal variations in the operating conditions of a system. Diagnostics are based on two spaces, the measurement space and the fault space; the mapping of the first space into the second makes it effective [2].

Regarding rotating machines—with rotor-type mechanisms, there are various industrial components in which condition monitoring research focuses on, such as rolling [3,4] and journal bearings [5], gearboxes [6], shafts [7], blades [8], entire devices [9], wind turbines [10,11], reciprocating machines [12], electric motors [13], pumps [14], helicopters [15–17], fans [15], cam mechanisms [18,19], generators [20], and compressors [20].

Different diagnostic parameters (conditions) can be monitored. In an overall view, we may include vibrations, acoustic emissions, currents, flow, speed, pressure, temperature, lubricant conditions, strain, wear, rotor-to-stator rubbing, etc. Among these, vibration is the condition that is most widely and effectively used in the industry for rotary machines. As reported by Malla and Panigrahi in their work in 2019 [3], vibration based condition monitoring allows detecting 90% of faults or failure in machines, since each system/device component has its own vibration signature, closely related with the machine operating conditions. Faults or damages in components generate additional dynamic forces (periodic or stochastic by nature), which generate vibrations in specific frequency ranges. The faults that can be detected through vibration-based condition monitoring techniques in rotary machines are manifold; among them, looseness, eccentricity, unbalance, blade defects, misalignment, defective bearings, damaged gears, and cracked or bent shafts are some of the most investigated phenomena.

In the most general case, the method of implementation requires four main phases: (i) vibration measurement and pre-processing [21]; (ii) signal processing [22]; (iii) features extraction and selection [23]; and (iv) diagnostics [23,24].

An initial bibliographic analysis of the main review works in the literature concerning the condition monitoring of rotating machinery revealed interesting insights. Table 1 collects the analyzed documents, sorted in descending order, based on the date of publication.

Table 1. Main review publication closer to the condition monitoring in a rotating machinery theme.

Ref.	First Author	Year	General	Focused	Vibrations	Phase	Main Topic
[25]	V. Sharma	2021		x		Diagnostics	Wind turbine gearboxes operating under non-stationary conditions
[26]	Z. Liu	2020		x		All	Wind turbine bearings
[3]	C. Malla	2019		x	x	All	Rolling bearings
[2]	T. Haj Mohamad	2019		x	x	Diagnostics	Non-linear systems
[27]	A. Stetco	2019		x		Diagnostics	Wind turbine condition monitoring
[28]	T. Wang	2019		x	x	All	Wind turbine planetary gearbox
[29]	W. Caesarendra	2017		x		Feature extraction	Low-speed slew bearings
[30]	M. Vishwakarma	2017	x		x	Feature extraction	
[31]	P. Jayaswal	2015	x			Diagnostics	
[5]	T. N. Babu	2015		x	x	Features extraction and selection	Journal bearings
[32]	S.S. Kumar	2014	x			All	
[33]	Samuel P. D.	2004		x	x	All	Helicopter transmission
[34]	Tandon N.	1999		x	x	All	Rolling bearings

Although all reviews in Table 1 concern the condition monitoring of rotating machines, only some of them specifically refer to vibration analysis. Analyzing the object of the condition monitoring works, referring to a specific component or machine, can be classified as "focused papers". The other works that deal with methodologies at a general level can be classified within a general class. Table 1 also presents the main investigated topic for the focused papers, and for each article, indicates whether it focuses on a specific phase of the condition monitoring process or on the whole procedure.

As it can be seen, in proportion, the number of works produced in the last five years represents the majority. The focused ones prevail over the general ones; among these, bearings and wind turbines are the most recurring themes. A good number of works deal with all phases of condition monitoring, and among those that refer to a single phase, features extraction and diagnostics are the most considered.

Besides these considerations, the preliminary analysis of the current literature reveals the lack of review works on condition monitoring based on vibration analysis, in rotating machines, not focused, and not referring to a specific phase. These—not even the paper "Vibration Analysis & Condition Monitoring for Rotating Machines: A Review" by Vishwakarma et al. [30], which, by title, would appear to be the best candidate—mainly focus on feature extraction methods.

According to the results of this analysis, the proposed review aims to fill the highlighted research gap, outlining the current state-of-the-art on the subject of condition monitoring of rotating machines, based on vibrations, in a comprehensive way.

In more detail, the proposed literature review presents two different analysis levels:

i. A prospective review, or an observational study of the distribution of published documents over time, by phase, and by intervention level;
ii. An analytical review, consisting of an in-depth study of the most used and most recently introduced methodologies, for the main phases of the condition monitoring process.

The current work, in addition to providing an up-to-date review, also aims to support the researcher, as it is suitable for application in everyday practice. For this reason, the paper analyzes the literature with a systematic approach and presents the results in a schematic layout.

The paper is organized as follows: Section 2 describes the research method in terms of a data selection protocol, prospective, and analytical review. Section 3 reports the results of the prospective review; Section 4 presents the results of the analytical review, declined for phases. Section 5 (conclusion) summarizes the review work and future ideas.

2. Research Method

2.1. Data Selection Protocol

The bibliographic research was conducted on the Scopus database. For the query definition, the following conceptual roadmap was identified: (a) the paper title must include, in exact form or variations, the words *diagnostics* or *condition monitoring*, and *vibrations*, whereas (b) the title, abstract, or keywords must appear in at least one of the variations of the substrings *rotating machinery*, *wind turbine*, *bearings*, *electric motors* or *actuators*, *gearboxes*. The search string designed to combine possible variations of the desired keywords was therefore: "(TITLE (diagnos* OR (condition AND monitor*) AND vibrat*) AND TITLE-ABS-KEY ((rotat* AND machin*) OR (wind AND turbine*) OR bearings OR (electric AND (motor* OR (actuat*))) OR gearbox*))".

The following inclusion criteria were applied to filter the results: (i) English language, (ii) document classified among at least one of the subject areas, *Engineering*, *Computer Science*, *Decision Sciences*, or *Multidisciplinary*.

The query, updated for the last time on 4 November, 2021, provided 957 documents. Figure 1 describes the results by the type of document, whereas Figure 2 depicts, in a black line, the evolution of the products by year, detailing in stacked form the trend of the two main subsets: conference paper plus book chapters on one side, and articles plus reviews on the other.

Since data revealed that the higher number of published papers occurred in the last decades, and given the purpose of providing the reader with an up-to-date review, suitable for everyday practice, the research string was further refined. In more detail, two additional criteria were included: (iii) publication year from 2000, and (iv) document type, detected as *article* or *review*.

Among the 422 identified products, papers still not consistent with the inclusion criteria (e.g., presenting only the abstract in the English language or a misclassified type of document), as well as those works considered unrelated to the topic of interest, were excluded by the set. In conclusion, 401 products passed the selection process and they were assembled in the final dataset for further analysis.

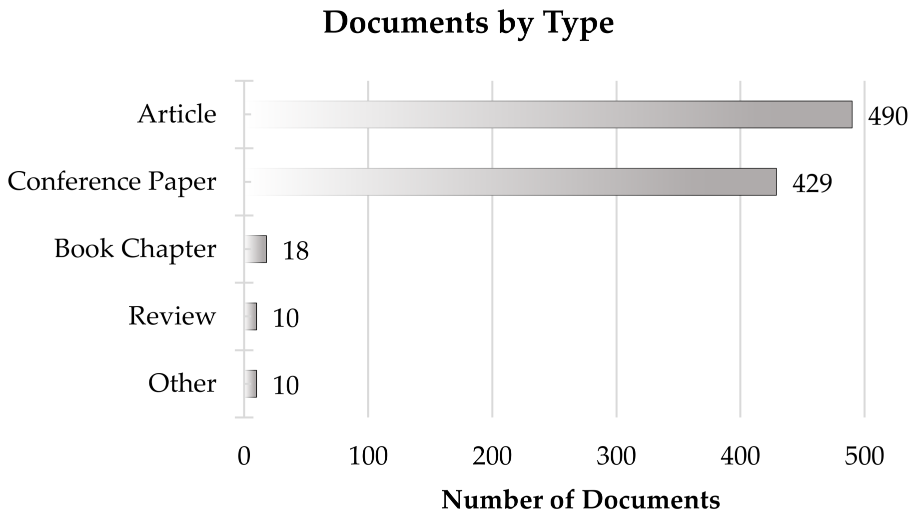

Figure 1. Distribution of the identified products by type of document. The category "Other" combines four results for "Errata", three for "Books", and one product for "Editorial", "Note", and "Retracted", respectively.

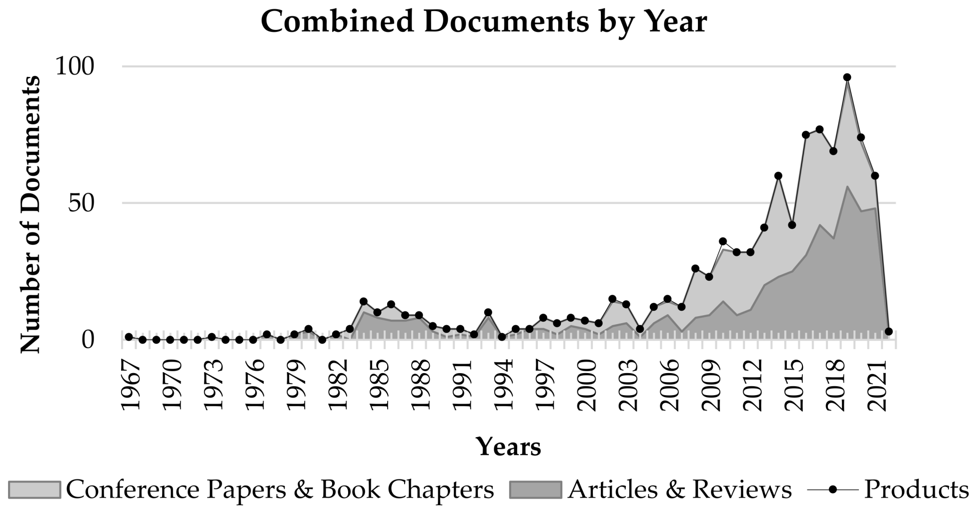

Figure 2. Distribution of the identified products by publication year. For the two subsets "Conference Papers and Book Chapters" and "Articles and Reviews"; results are presented in stacked form. The black line depicts the cumulative number of published documents each year.

2.2. Taxonomy

The dataset of 401 documents was investigated with respect to two different analysis levels, enabling the synthesis of a prospective and an analytical review.

2.2.1. Prospective Review

For the prospective review, the papers are classified according to a double taxonomy:

- The **phases** of the condition monitoring process mainly involved by the paper topic;
- The **components** of the machinery, mainly interested in the depicted monitoring techniques.

In the classification by phases, five categories were identified:

(p1) Signal type, sensors, pre-processing.

This category collects methods and procedures that involve the early stages of the monitoring process, such as the definition of the most proper experimental setup, or the signal processing techniques required to read the raw data and prepare them for the application of feature extraction procedures. This class includes the choice or the development of sensors, their positioning strategies on the machine, and pre-filtering techniques on the acquired signals.

(p2) Features, signal processing.

This category includes the methods for feature identification, extraction, and selection that are used in the second step of the monitoring process. Besides the most proper feature-related techniques, signal-processing methods can fall within this class, depending on the purpose of the user. For instance, statistical and frequency analysis techniques are classified in this category when used as a mean to highlight signal characteristics or compute quantities necessary for the following analysis steps.

(p3) Diagnostics.

This category gathers algorithms and techniques used to actually discriminate whether or not the investigated system presents a healthy state. This class includes optimization strategies, techniques typical of the artificial intelligence field, as well as genetic algorithms-based solvers.

(p4) Modeling.

This category collects the models developed or applied to study the investigated system from a methodological perspective. Those models could describe the physics of the overall system, for instance, presenting the equations that describe its dynamics, or focus on more detailed aspects of the process, such as models based on the finite element method (FEM) used to simulate vibration responses. The modeling category can therefore be considered associated to a preliminary phase of the pure condition monitoring process, since it provides the framework for the analysis, and the rationale for the interpretation of data and results.

(p5) Overview.

This category includes comprehensive procedures that embrace more steps of the condition monitoring process, which compare more techniques and operative strategies, or that, in general, allow outlining an overview of the process or some phases. Therefore, unlike the previous classes, the overview category does not match a priori a single specific phase of the condition monitoring process.

Condition monitoring techniques and methodologies are chosen and developed, depending on the characteristics and on the functioning of a specific component, more than on the final application field. According to this consideration, this review does not primarily focus on application fields, but the analysis grounds instead on the different machine components to which the condition monitoring is addressed, which are transversely widespread in different application fields. Eight categories were identified in the classification by components, representative of the intervention level, which is focused on the presented methods:

(c1) Bearings, also presenting the two subclasses:
  - c1.a Journal bearings;
  - c1.b Rolling bearings.

(c2) Shafts.
(c3) Gears/Gearboxes.
(c4) Electric Motors, with the subclasses:
  - c4.a Induction;
  - c4.b Brushless;
  - c4.c Engine.

(c5) Pumps.
(c6) Wind Turbines, presenting three subclasses:

c6.a Blade;
c6.b Drivetrain;
c6.c Generator.

(c7) General/rotating machineries, indicating the application to the machine in general, as a whole.
(c8) Others, depicting specific applications not included in the previous classes.

During the analysis, particular attention was also devoted to a cross dimension of investigation, i.e., the detection of contributes especially related to three specific *topics*:

(t1) Non-stationary, or the analysis of systems presenting conditions of non-stationary vibrations;
(t2) Low-speed, or the investigation of systems with low-speed dynamics;
(t3) Test rig, or the presence of a test bench or systems for the experimental validation of the proposed findings.

In the classification by phases, the presented final categories coincide with the set of classes initially designed, whereas the classification by components evolved dynamically during the analysis, around a stable core of categories. In particular, some of the proposed classes were initially combined within the "Others" category. This custom tailoring of the taxonomy would basically introduce a dependency of the categories definition from the considered dataset; nevertheless, this strategy also allows enhancing at best the peculiarities of the documents that constitute the current state-of-the-art, precisely because the final taxonomy reflects the main features of the current dataset.

For the topics, a similar approach was used for the selection of the categories, although the initial choice of (t1) non-stationary, (t2) low-speed, and (t3) test rig was confirmed by the end of the literature review process. Moreover, the selection of these specific topics is motivated by the relevance of the subjects themselves more than by a pure rating factor.

2.2.2. Analytical Review

The analytical review analyzes, in more detail, the subsets of documents that were classified within the categories (p1) signal type, sensors, pre-processing, (p2) features, signal processing, and (p3) diagnostics. Those classes are in fact associated with the phases of the condition monitoring process most traditionally recognized, and over 70% of the total documents in the current dataset are classified within at least one of them.

In particular, the analysis aims at: (a1) identifying the methods applied in each of the classes (p1), (p2), and (p3), and (a2) investigating their relations with the categories of the classification, by components and by topics.

2.3. Data Analysis

For both taxonomies, by phases and by components of the perspective analysis, the classification has been considered not exclusive, i.e., a paper can be assigned to one or more classes, depending on its content. The classification procedure was realized in two iterative steps: a first assignation of the categories was performed analyzing the abstract content, and the classification was then checked or integrated where needed, with further analyses of the papers full-texts.

Similarly to what was described for phases and components, the investigation about the topics was performed with a non-exclusive approach, and with the same two-step procedure previously depicted, thus, with a first attempt evaluation by abstract and a cross-validation by full-text.

For the analytical review, a two-step procedure was adopted, although different in substance: in the first stage, the documents were evaluated to capture the set of presented methods; then, in the second stage, the works of each class were mapped by method and components, and by method and topics.

In the following sections, the results of the perspective and analytical reviews will be presented with a schematic approach.

3. Prospective Review

The analysis of the documents by phase and by component, as well as the investigation by topic, generated the literature mapping depicted in Table A1 of Appendix A.

For documents classified in more than one category of the taxonomy by phases, a main class was selected, as the dominant category of the work, or the most significant in terms of novelty. This aspect was evaluated independently for each document, attempting to capture the essence of the work: in fact, papers can deal with different phases of the vibration-based condition monitoring process, but the innovative contribution of the work generally concerns only one of them. Figure 3 presents, in a combined view, the results of the distribution by phases, considering the clustering of all the occurrences (dark grey bars) and of the values of the main class only (light grey bars). Evaluating the extended classification, data reveal that the category p2 "Features, Signal Processing" covers alone more than the 32.1% of all the assignments, whereas p1 and p3, i.e., "Signal Type, Sensors, Pre-processing" and "Diagnostics", respectively, share each 20.2%; category p5 "Overview" follows with 18.4% of the assignments, and finally class p4 "Modeling" collects the remaining 9.1%. The relation among percentage rates remains quite similar, also considering the classification of the main classes, although in this case, the differences among categories p1, p2, and p5 decrease (19.7% for p1, 19.5% for p2, and p5).

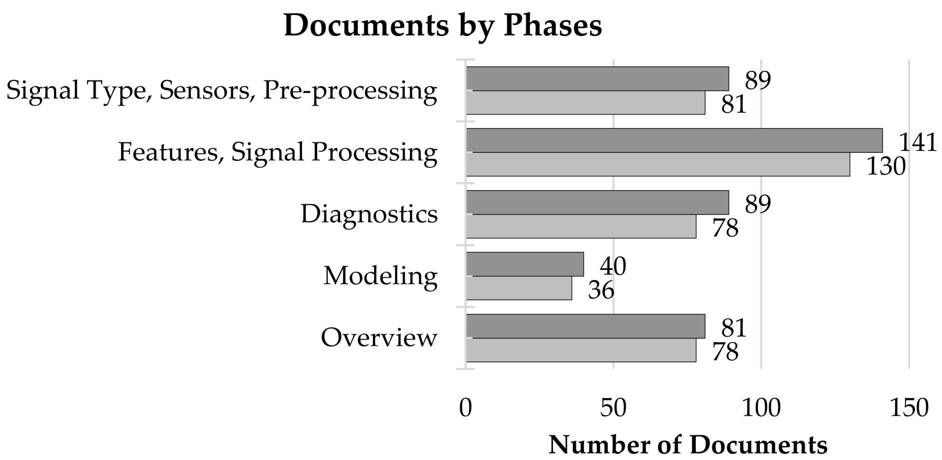

Figure 3. Distribution of the documents by phases. In dark grey, data including multiple classifications among categories, and in light gray, the clustering for the main class only.

An alternative evaluation can be performed, focusing on the evolution in time of the distribution among classes. Figure 4 depicts the trend of each category, in terms of document amount by year, in a stacked format. In the figure, the values corresponding to the extended classification (allowing multiple class assignments for the same document) were considered for the categories, whereas the black line describes the total amount of documents by year. According to the data, the number of documents regarding more than one phase increased in the last years.

For the taxonomy by components, Figure 5 synthesizes, at a glance, the clustering of data among categories and sub-categories. Most of the documents focus on the category c1 Bearings, with particular attention to rolling bearings, with journal bearings following at a remarkable distance. The second category for number of occurrences is c3 Gears/Gearboxes: an affinity with class c1 can also be detected, as the presence of documents classified in both categories proves. Although highly spaced from the first two classes, wind turbines and motors are addressed by a significant number of papers. The class c7, General/Rotating machineries, achieves third place. Sub-categories were selected in those cases presenting an explicit reference to the sub-class itself: the referring category collects instead the documents correlated to the subject, but not especially devoted to a given sub-category.

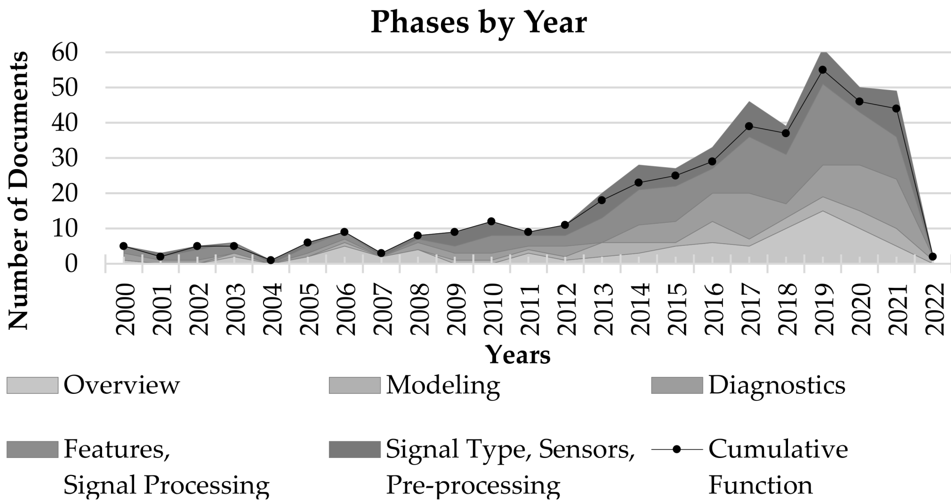

Figure 4. Distribution of the documents by year, among categories of the classification by phases. Data are presented in stacked format, and include all occurrences (extended classification). Black line—the total amount of documents by year.

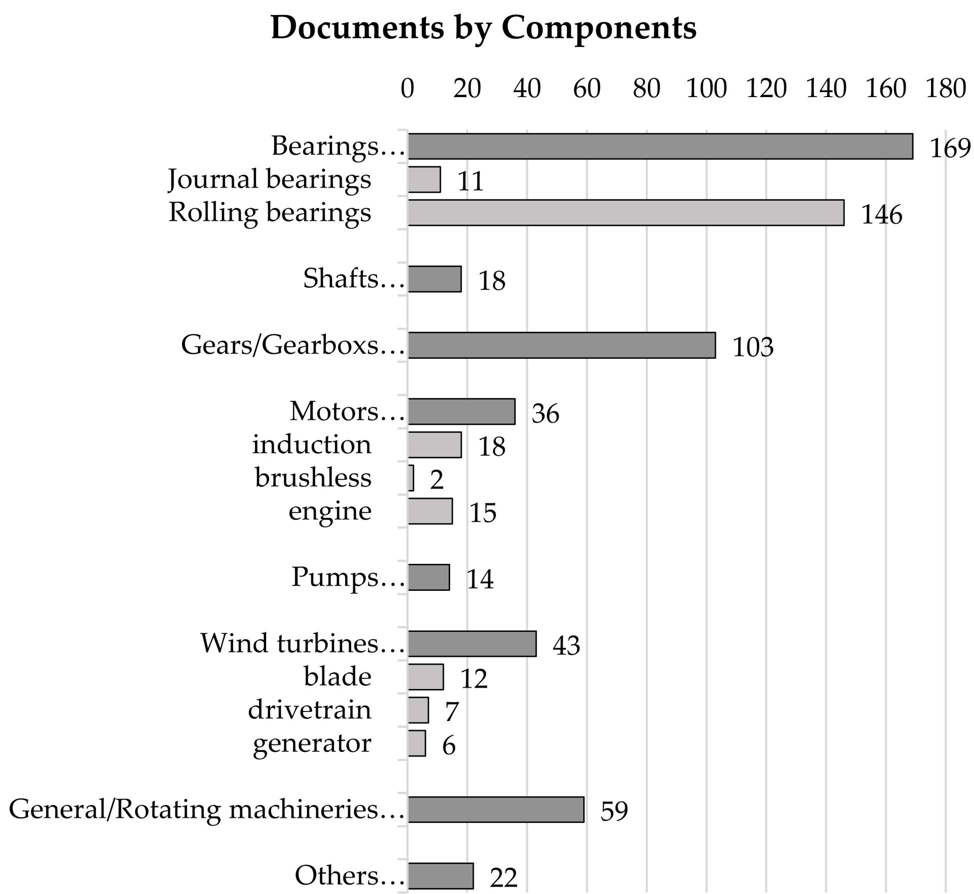

Figure 5. Distribution of the documents by components. In dark grey, data referring to the first level categories, and in light gray, the details of the clustering for the sub-categories.

The evolution of the component categories in time, depicted in Figure 6, once again highlights an increasing trend, especially for bearings, gearboxes, and wind turbines. For the latter class, the start of the significant growth trend in interest is around the year 2012, whereas it is around 2008 for the other two. In general, for all classes, the behavior reflects the rising number of publications in the last years on one side, and confirms on the other the proportional ratio among sub-categories.

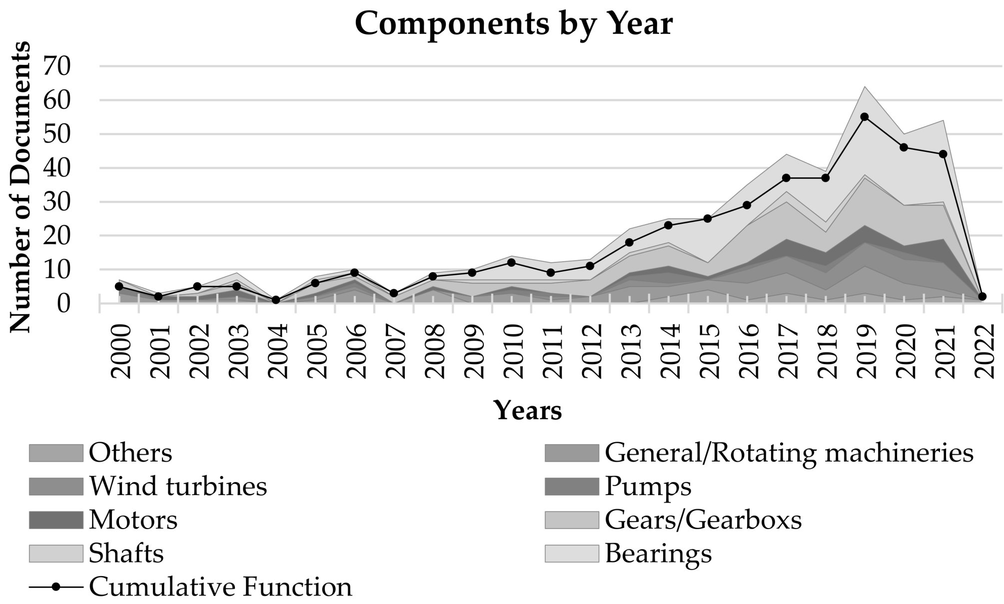

Figure 6. Distribution of the documents by year, among categories of the classification by components. Data are presented in stacked format, and include the occurrences clustered at the first level of the taxonomy (e.g., category c1 Bearings, without distinction for c1.a or c1.b, i.e., journal, and rolling bearings, respectively). Black line—the total amount of documents by year.

Finally, Figures 7 and 8 describe the results for the investigation on the topics t1 non-stationary, t2 low-speed and t3 test rig. The figures outline an overview of the interest of the scientific literature on these specific subjects: the evaluation of the total amount of occurrences (Figure 7) reveals significant lower values for the t2 class. Moreover, the evolution in time (Figure 8) presents an increasing trend, especially for the test rig category.

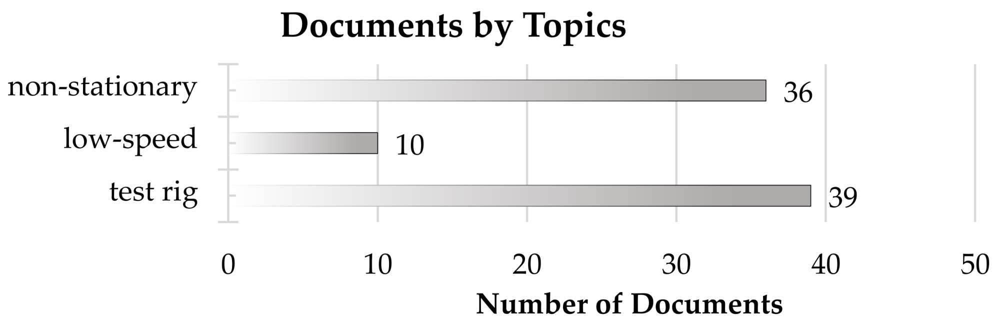

Figure 7. Distribution of the documents by topics, as the total amount of occurrences for each category.

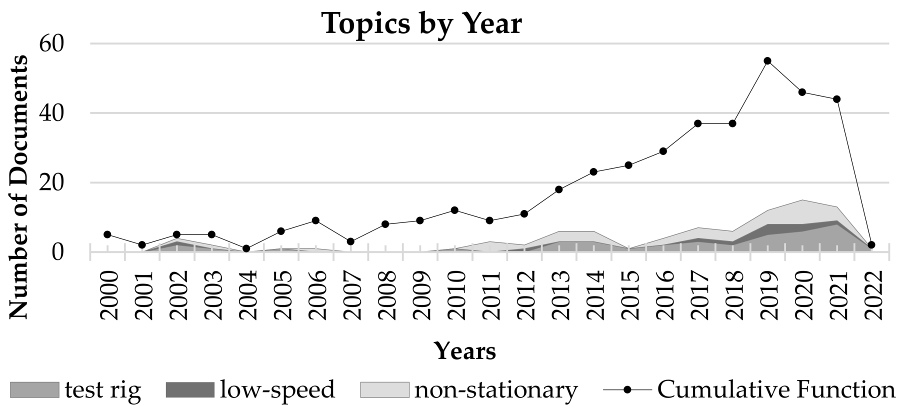

Figure 8. Evolution in time of the documents referring to the categories in the taxonomy by topics. Data are presented in stacked format. Black line—the total amount of documents by year.

4. Analytical Review

4.1. Category p1: Signal Type, Sensors, Pre-Processing

For the three investigated aspects (signal analysis, sensors, and pre-processing techniques), based on the analysis of the papers, sub-classes related to the mainly investigated themes were identified. Bearings and Gears/gearboxes are the most common topics for the signal aspect, which is in accordance with prospective review results.

Three subsections of the signal type aspect refer to the use of a different signal with respect to the vibrations or a combined use. Many articles compare the results obtained by Acoustic Emissions CM (AE-CM) vs. Vibrations-Based CM (VB-CM). For bearings, Hou in 2021 [35] found that AE-CM overcomes VB-CM in terms of fault signal-to-noise ratio, early fault diagnosis, and compound fault diagnosis capabilities; furthermore, due to a high sampling rate, a lower computational efficiency distinguishes AE-CM. Amini et al. in 2017 [36] noted that AE are sensitive to defect size and to rotating speed, otherwise the amplitude of vibrations has no significant changes as the defect size increases and vibration has a poor sensitivity to speed changes. For gearboxes, Qu et al. [37] found through their experimentations—and in agreement with [35]—that sampling rates required by AE-CM are much higher than those required by VB-CM. Furthermore, damage levels can be detected through the AE-CM and not with VB-CM, and AE signals show a stable performance, whereas mechanical resonance easily affects vibration signals (VS).

The comparison between vibrations and stator currents-based approaches for CM was investigated in systems with electric motors. As visible in Table 2, some papers related to this issue are not focused on electric motors, because a different component was the object of CM, but the system is based on an electric motor. Jin et al. in 2018 [38] presented the results for a drive train gearbox fault diagnosis and concluded that in vibration signals ghost frequencies are fault sensitive, VS are modulated by shaft rotating frequencies, the fundamental frequency component is dominant in current signals and, at the fundamental frequency, they are modulated by gearbox characteristic frequencies when gear faults appear. Yang in 2015 [39] deduced from the experiments of an automatic condition monitoring for rolling-element bearings—based on vibrations as well as stator current analysis—that vibration analysis had powerful capability in the bearing point and fault severity diagnosis, whereas current analysis showed a moderate capability. Immovilli et al. in [40] presented a comparison between current and vibration signals for the diagnosis of bearing faults in induction machines and concluded that current signal-based methods are suitable to detect only faults with quite low critical frequency rate, whereas vibration signals are robust indicators for bearing defects. Wang et al., in [41], developed and validated a current-aided vibration order tracking method adopted in variable-speed wind turbine bearing fault diagnosis.

Table 2. p1 class products classification based on investigated aspect and main topic.

Investigated Aspect / *Sub-Class*	Bearings	Gears/Gearboxes	Motors	Wind Turbines	Pumps	General	Non-Stationary
Signal type							
Vibrations and Acoustic Emissions (AE) comparison	Hou_2021 [35] Ibarra-Zarate_2019 [42] Amini_2017 [36] Yoshioka_2010 [43] Yoshioka_2009 [44]	Khan_2019 [45] Qu_2014 [37]	Othman_2016 [46]			Yi-Cheng_2016 [47] Bánlaki_2010 [48] Wu_2005 [49]	
Vibrations and current signals	Yang_2015 [39]	Jin_2018 [38]	Immovilli_2010 [40]				Wang_2016 [41]
Combined vibration and thermal analysis	Nembhard_2014 [50] Widodo_2012 [51] Nembhard_2013 [52]						
Torsional vibrations		Chen_2017b [53] Li_2017 [54] Henao_2011 [55]			Marticorena_2020 [56]		
Point of measurements		Al-Arbi_2009 [57]		Castellani_2020 [58]			
Sensor type							
Unconventional vibration sensor	Meng_2021 [59] Goyal_2021 [60] Prashanth_2018 [61]			Barusu_2021 [62]		Ghemari_2019 [63] Feldman_2015 [64]	
Low-cost solutions	Soto-Ocampo_2020 [65]		Papathanasopoulos_2021 [66]			Dos Santos Pedotti_2020 [67]	
Multi-sensor-based approach				Sharma_2021 [25] *			
Wireless sensor network (WSN)	Lu_2018 [68]					Dos Santos Pedotti_2020 [67] Bengherbia_2017 [69]	
Pre-processing							
Denoising	Sahoo_2018 [70] He_2013 [71] Yan_2012 [72] Kalista_2021 [73] Dovhan_2018 [74]						
Amplitude modulation and Frequency modulation (AM-FM) process		Yu_2021 [75] Li_2017 [54]					
Demodulation transform	Laval_2021 [76] Zhao_2021 [77] Cai_2018 [78] Sheen_2004 [79]	Laval_2021 [76]					
Continuous vibration separation (CVS)		Shen_2020 [80] Zhang_2019 [81]					
Blind spectral preprocessing	Peeters_2020 [82]	Peeters_2020 [82]					Fong_2020 [83]
Decomposition	Ren_2019 [84] Yan_2009 [85] Zarour_2019 [86]	Buzzoni_2017 [87]					Gałka_2015 [88] Wu_2009 [89]
Multiple sources	Haile_2016 [91] Hasan_2018 [93]						Wu_2019 [90] Tse_2007 [92]
Others	Wu_2021 [94] Tiwari_2021 [95]						

Thermal analysis combined with vibration signals were considered by Nembhard et al. [50,52] and by Widodo et al. [51] for bearing diagnostics. Nembhard obtained that temperature measurements addicted to the VB-CM model improved fault diagnosis. Widodo concluded that using vibrations together with source thermography featuring a good accuracy can be achieved and that plausible diagnostics results may be obtained with the thermography method.

Lateral vibration-based measurements and fault diagnosis are highly studied, but both developed and standardized wheatear torsional vibrations-based ones are unusual. In fact, despite the fact that they describe the shaft transmitting torque function, they are free from the extra AM effect due to time-varying transmission paths and have simpler frequency contents. Marticorena et al. in 2020 [56] presented a study on the torsional vibrations analysis of the shaft of the centrifugal pump in a nuclear research reactor. They found pump shaft torsional vibrations close to rotor's first torsional mode and concluded that torsional vibrations reveal important signs related to the operating condition, not highlighted by lateral vibrations. Chen and Feng's lab experimental tests, based on torsional vibrations, diagnosed sun, planet and ring gears local faults, despite the running conditions time-variability [96]. In [54], instead, amplitude modulation and frequency modulation (AM-FM) processes were used to model induced faults by torsional vibrations in resonance region.

An investigation on the points of measurement is the last significant aspect that emerged from the analytical review at signal level [97,98]. Castellani in 2020 [58] studied the solution to measure vibrations at the tower instead of at the gearbox in a wind turbine and achieved positive outcomes in the bearing diagnostics without impacting the wind turbine operation. Al-Arbi in 2009 [57] treated the distortions suppression for the remote measurements issue and it emerged that the results of the different signal processing techniques were highly influenced by the signal attenuation and interference. Among the tested SP methods, time synchronous average (TSA) proved to be less sensitive to the problem.

For the sensor type aspect, various unconventional vibration sensors are the objects of investigation. In [59], Meng et al. consider a fiber-optic based vibration sensor characterized by low-cost, compact size, easy-to-fabricate, and excellent anti-interference ability. The adopted Sagnac interferometer and fiber ring laser (FRL) obtained an accurate frequency of the vibration signal within a relative error of 1.0%. Goyal et al. in [60] developed and tested a non-contact laser based vibration sensor for bearing condition monitoring and concluded that such a methodology may be effectively used for machine CM. Barasu et al., in [62], propose a microwave sensor (handheld ultra-wide band (UWB) radar) to non-invasively achieve vibrations for the CM of bearings in an induction motor, by projecting the microwave on the squirrel cage induction motor (SCIM) and by capturing the reflected signal. A new conception of piezoelectric accelerometer (the most frequently used type in industry) is presented by Ghemari et al. in [63], with the aim of obtaining more accurate results. The use of vibrations signals obtained with sensors conceived with the microelectromechanical system (MEMS) technology is discussed by Prashant et al. in [61] and Feldman et al. in [64], due to their size, cost, portability, and flexibility.

Low-cost solution is another sub-class of the sensor type [99]. Papathanasopoulos et al. in [66] use successfully low-cost piezoelectric sensors for fault diagnosis in brushless dc motor drives, concluding that these smart IoT sensors could be used for an inexpensive CM of electric motors. A low-cost data acquisition system based on Raspberry-Pi is moreover presented by Soto-Ocampo et al. in [65]. Compared to other commercial units, the proposed solution has a double recording capacity, any connection to an external computer is required, since storage is carried out directly in its memory, remote capture control is enabled, has a compact size that allows the positioning in difficult access areas and costs less than half the price of comparable devices. Furthermore, Dos Santos Pedotti et al. in [67] present a wireless sensor network (WSN) with low-cost nodes formed by microelectromechanical system (MEMS) accelerometers and a highly integrated microcontroller with built-in antenna for Wi-Fi and Bluetooth low-energy (BLE).

Another interesting issue is related to the adoption of wireless sensor networks (WSNs). Lu et al. in [68] investigate the under-sampled vibration signals acquisition from a WSN for motor bearings CM. The proposed solution is particularly suitable for installations in remote areas, such as wind farms and offshore platforms. A further work related to WSNs is presented by Bengherbia et al. in [69]. A FPGA-based wireless sensor node was developed, based on Xilinx Artix-7 XC7A35T FPGA circuit, which obtained minimal synchronization error of 60 ns.

A significant number of papers deal with pre-processing methods. The denoising is a common problem due to the fact that vibration signals are noisy in nature.

Sahoo and Das in [70] compare three adaptive noise cancellation (ANC) techniques on the vibration signal acquired from the experimental set-up; He et al. in [71] present data denoising by synthesizing the time-frequency manifold (TFM), using time-frequency synthesis and phase space reconstruction (PSR) synthesis; Kalista et al. in [73], introduce a novel modified generalized notch filter, used for harmonic vibration generation with an algorithm that automatically gets the rotor desired harmonic vibration; Dovhan et al. in [74] use a tracking notch filters based on N-channel structures, using the iterative-integrating converters for early diagnosis of bearings under adverse application conditions.

Yu et al. in [75] propose a method to detect gear fault by considering the sideband symmetry features around resonance, obtained through the frequency amplitude modulation and frequency modulation (AM-FM) process and the explicit time-varying Fourier spectra under non-stationary conditions obtaining.

The demodulation issue is addressed by Laval et al. in [76], who discuss the impact of a limited spectral bandwidth filtering with Hilbert demodulation, evaluating the interactions between the amplitude and phase estimations. Zhao et al. in [77] propose an optimization-based demodulation transform based on an optimal demodulation operator (DO), which allows to transform the time-varying frequency component into a constant one so that the largest peak can be detected in the spectrum of the demodulated signal. This method is used for the rolling bearing fault characteristic frequency (FCF) estimation for diagnostic aims.

Zhang and Hu in [81], similar to Shen et al. [80], presented a method based on continuous vibration separation (CVS), to separate dynamic responses of planet gear from overall vibration responses of planetary gearboxes, and a minimum entropy deconvolution (MED), to enhance the detection of fault-related impulses.

A non-parametric blind spectral processing is treated by Fong et al. in [83] for simultaneously denoising and extracting the harmonic content from non-stationary vibration signals. The time signals related to the extracted time-varying harmonic and residual components can be reconstructed; thus, it is a fully invertible technique. Peeters et al., in [82], derive blind filter formulations to obtain the most sparse envelope spectrum when filtering a signal, without knowing the characteristic fault frequencies of the mechanical components, and demonstrated the method effectiveness in tracking faults with a cyclostationary signature.

The decomposition issue was studied by several researchers and for different components diagnostics; e.g., Ren et al. in [84] present an iterated SVD (ISVD)-based in-band noise reduction method combined with envelope order spectrum analysis, which can extract the fault characteristic order under variable speed conditions. Wu et al., in [90], developed a new method, called the improved variational mode decomposition (VMD), based on a generalized demodulation technology (GDT) and a zero-phase shift filter (ZPSF). This hybrid approach can effectively be applied to fault diagnosis, as it allows to extract all the useful vibration components from the rotor system during start-up. The multiple source issue is treated by Haile and Dykas in [91], who implemented a blind source separation (BSS) method to demix sensor signals into correctly identifiable vibration source signals without knowing the sensor layout. Using higher-order statistics of the signals, it is possible to isolate vibration sources.

To conclude, some works deal with particular themes, such as the discrete orthonormal Stockwell transform (DOST) [93], which is a pre-processing CM step for invariant rotational speed and load scenarios, reconstruction algorithms based on the multiple side information signal (RAMSI) [94], to separate noise from signal components in non-stationary conditions, or lastly, the concealed component decomposition (CCD) [95], which is a self-adaptive signal decomposition technique that isolates the intrinsic instantaneous amplitude in balance with other essential configuration features.

4.2. Category p2: Features, Signal Processing

The analysis of the condition of a machine is a complex activity often aimed at a specific purpose. Therefore, there is a wide range of methods for signal processing and features extraction that can be classified into three broad categories: time domain; frequency domain; time-frequency domain.

In the time domain analysis, the waveform of the signal is used, i.e., its evolution over time, and from this we derive statistic quantities such as mean, peak, peak-to-peak interval, variance, crest factor, as well as high-order statistics like root mean square (RMS), skewness, and kurtosis. However, it may be useful to directly identify certain components of the signal, known as related to the phenomenon being investigated. In this case, frequency domain analysis is necessary, and different order methods have been developed for this purpose. Yet, frequency domain methods of analysis cannot handle non-stationary waveform signals, as normally occurs in presence of deterioration or faults. Based on the stationarity assumption and, therefore, providing statistical averages, they are not suitable for fully describing signals whose statistics vary over time. It is necessary to describe these signals, not only in frequency, but in time as well, and this requires specific methods capable of revealing the local features in both time and frequency domains simultaneously, as in the time-frequency analysis.

Moreover, when it comes to extracting information from a signal, signal pre-processing and/or processing is often required to make that extraction faster and more accurate by, for example, filtration, denoising, and/or demodulation. In class p1, documents specifically oriented to signal pre-processing techniques were evaluated, whereas in class p2, examined in this paragraph, works dealing with signal processing and features were considered, with all limitations deriving from the fact that the boundaries between pre-processing and processing are sometimes blurry.

A taxonomy of the main studied and applied methods for signal processing and features extraction is proposed in Figure 9; the classification drew inspiration from a previous work by Riaz et al. [100], but freely evolved according the needs revealed by the current dataset of documents.

Table 3 reports the classification of the articles of class p2, according to the proposed taxonomy. In the adopted classification, the three fundamental domains (time, frequency, time-frequency) have been preserved, including not only the methods used to extract the features, but also those that treat the signal in order to make it suitable, or more suitable, for the extraction of features. In addition to the classes of the three fundamental domains, two more categories account for specific cases that do not fall within, or hardly fall within, the canonical ones: hybrid includes cases where methods belonging to more than one domain are used; unique, on the other hand, includes cases in which new or specially developed methods are used for the specificity of the object of study; comparison collects instead works specifically oriented to the comparison between different methods.

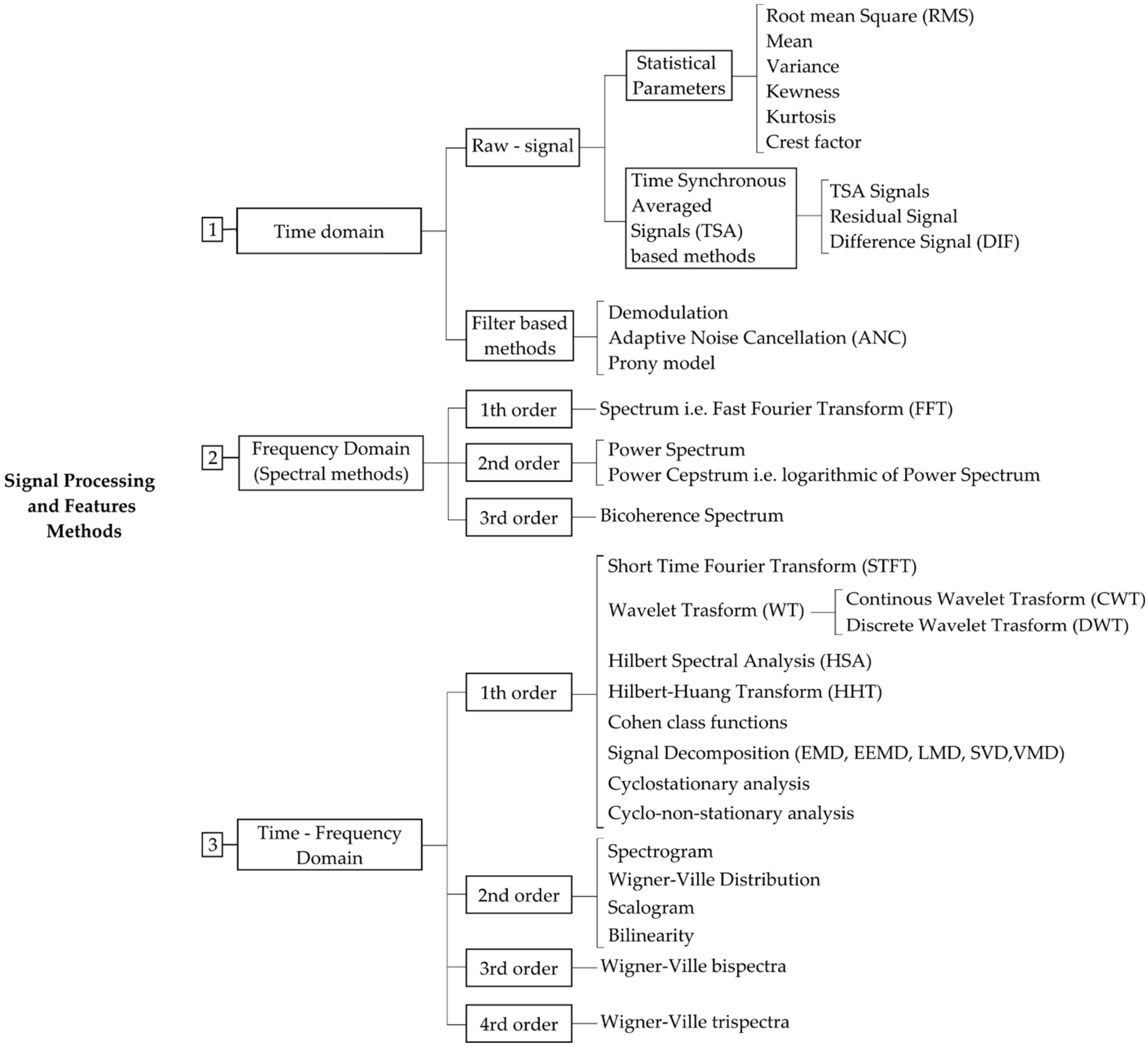

Figure 9. Taxonomy of the most common signal processing and feature extraction methods.

Table 3. p2 class products classification based on signal processing and the feature extraction method and main topic.

Investigated Aspect ***Sub-Class***	**Bearings**	**Shafts**	**Gears/Gearboxes**	**Motors**	**Pumps**	**Wind Turbines**	**General**	**Others**
Time domain	He_2020 [101] Ayaz_2014 [102] Utpat_2011 [103]		Devendiran_2015 [104] Hong_2014 [105] Rzeszucinski_2012a [106] Heyns_2012 [107] Zhan_2006 [108]		Rapur_2018 [109]	Yang_2021 [110] Pang_2018 [111] Joshuva_2017a [112]	Daga_2019 [113] Indira_2010 [114]	
Spectral methods								
FFT, *Order domain,* *Envelope spectrum and envelope order spectrum,* *cepstrum*	Huang_2021 [115] Attoui_2020 [116] Wang_2019b [28] Klausen_2019 [117] Dybała_2018 [118] Qiu_2018 [119] Li_2016d [120] Dolenc_2016 [121] Harmouche_2015 [122] Hafeez_2003 [123]	Zakhezin_2010 [124]	Wang_2019c [125] Feng_2017 [126] Guoji_2014 [127] Gelman_2005 [128]				Elbhbah_2013 [129]	Cardona-Morales_2014 [130]
Time-frequency-based methods								
STFT, *wavelet,* *Wigner-Ville (WV) distribution,* *Hilbert-Huang transform,* *Cohen class functions*	Pham_2020 [131] Ambika_2019 [132] Nissila_2019 [133] Tong_2018 [134] Jayakumar_2017 [135] Huo_2017 [136] Li_2016c [137] Hua_2015 [138] Gelman_2015 [139] Gelman_2014 [140] Tse_2013a [141] Li_2013a [142] Luo_2003 [143]	He_2017 [144] Kawada_2003 [145]	Gelman_2020 [146] Hartono_2019 [147] Puchalski_2019 [148] Gelman_2017a [149] Gelman_2017b [150] Stander_2002 [151]	Shu_2020 [152] Liu_2019b [153] Jayakumar_2017 [135] Antoni_2002 [154]		Xiao_2020 [11]	Liu_2019a [155] You_2019 [156] Antoni_2006 [157]	
Signal decomposition (EMD, EEMD, LMD, SVD, VMD)	Shao_2021 [158] Jiao_2020 [159] Chen_2019b [160] Yang_2017 [161]		Isham_2019 [162] Amarnath_2013 [163]	Mao_2018 [164] Chen_2015 [165]		Rafiq_2021 [166]	Isham_2018 [167]	Jegadeeshwaran_2014 [168]
Cyclostationary and cyclo-non-stationary analysis	Mauricio_2019 [169]		Mauricio_2020 [170]	Toyota_2000 [171]				

Table 3. *Cont.*

Investigated Aspect *Sub-Class*	Bearings	Shafts	Gears/Gearboxes	Motors	Pumps	Wind Turbines	General	Others
Hybrid	Ahmed_2021 [172] Saucedo-Dorantes_2021 [173] Sun_2020 [174] Jeon_2020 [175] Fan_2020 [176] Youcef_2020 [177] Yang_2019 [178] Xin_2018 [179] Hamadache_2018 [180] Song_2018 [181] Golbaghi_2017 [182] Li_2016c [137] Raj_2015 [183] Ocak_2001 [184]	Oh_2018 [185]	Tarek_2020 [186] Li_2018 [187] Hong_2017 [188] Cerrada_2015 [189] Fan_2015 [190]	Yang_2018 [191] Qiang_2014 [192]		Moghadam_2021 [193]	He_2016 [194]	Gierlak_2017 [195] Zhao_2019b [196]
Unique	Jablon_2021 [197] Gu_2021 [198] Mohamad_2020 [2] Yan_2019 [199] Barbini_2018 [200] Khan_2016 [201] Biswas_2013 [202]	Bai_2021a [203]	Mohamad_2020 [2] Hizarci_2019 [204] Medina_2019 [205]				Chen_2002 [206] Chen_2002	
Comparison	Tarek_2020 [186]				Sakthivel_2014 [207]			

From the classification of the p2 papers of Table 3, iy emerged that frequency domain (spectral methods) and time-frequency domain methods are the more applied ones, while the techniques based only on time domain have a limited application. The largest number of works refers to time-frequency domain methods.

In [103], Utpat et al. compare the time domain features peak-to-peak amplitude, peak amplitude, and RMS amplitude for the CM of rolling bearings, considering different loads and speeds. From the study, it emerged that peak-to-peak amplitude gives better results, followed by peak amplitude and RMS amplitude, and, in all considered conditions, any defect type is best detected by adopting peak-to-peak amplitude as the feature. Hong and Dhupia, in [105], present a time-domain diagnostic algorithm, to address the issue of the difficult modulated sideband extraction through spectral analyses techniques. The proposed method combines the fast dynamic time warping (fast DTW) as well as the correlated kurtosis (CK) techniques to characterize the local gear fault, and to identify the corresponding faulty gear and its position. This technique is beneficial in a practical analysis to highlight sideband patterns in situations where data are often contaminated by process/measurement noises and small fluctuations in operating speeds that occur, even at otherwise presumed steady-state conditions. The temporal collocation of the papers classified in the class of time-based methods, compared with those of the works that are placed in the other classes, reveals a reduction of research interest in recent years regarding these techniques.

Spectral methods are mainly used for diagnostics of bearings and gearboxes, but this trend also applies to the other methods. With reference to first order spectral methods, Hafeez et al. in [123] adopt the frequency and phase spectral analysis to diagnose the bearings vibrations root cause and found that phases are useful to detect misalignments, being related to relative motion between parts. Dybala, in [118], presents a method based on spectral analysis to automatically identify the amplitude level for signal decomposition, obtaining results in identifying bearing damages at the early stage of development better than with the classic vibration analysis. Klausen and Robbersmyr in [117] developed the whitened cross-correlation spectrum (WCCS) method based on the cross-correlation between the whitened vibration signal and its envelope, with good performances in the bearings damages early detection. In [119], Qiu et al. generate two-dimensional (2D) images, starting from the signal FFT-based spectrum, reduce the images dimension through the two-dimensional principal component analysis (2DPCA), and finally apply a k-nearest neighbor method to classify bearing faults. Dolenc et al., in [121], verified that localized and distributed faults could be distinguished by comparing envelope spectra of vibration signals. Wang et al., in [125], developed a vibration waveform frequency spectrum analysis method to get the fault severity, and to analyze the cause of the problem for wind turbine gearboxes. Zakhezin and Malysheva, in [124], proposed cepstral analysis to detect fatigue cracks in machines through analysis the autocorrelation function of a filtrated cepstrum, which enables detecting the initiation of a fatigue crack. The depth of the fatigue crack can be easily determined with the help of the number and amplitude of harmonics in the autocorrelation function, and their relative distance. In [129], Elbhbah and Sinha presented a new method to construct a single composite spectrum using all the measured vibration data set, whose performances were verified on data achieved on a laboratory test rig. Results of the method applied with the spectrum, with and without the coherence, have been investigated for the simulated faults in the rig, demonstrating that the coherent composite spectrum provides a much better diagnosis compared to the non-coherent composite spectrum. Furthermore, the composite spectrum represents the dynamics of the complete machine assembly and can make the fault diagnosis process relatively easier and more straightforward.

Time-Frequency methods are widely investigated and adopted for bearings and gears and some applications to motors have been found. For bearings diagnostics, Pham et al. in [131] use short-time Fourier transform (STFT) for features extraction, whereas health status classification is performed by a convolutional neural network (CNN) and verified that the proposed method achieves very high accuracy and robustness for bearing fault diagnosis even under noisy environments. In [135], Jayakumar and Thangavel present a method based on frequency patterns obtained using the decomposition of wavelet packets as features, applied to induction motor bearings diagnostics. In the context of methods based on spectral images used as features, Hua et al., in [138], propose the combination of a quaternion invariant moment feature extraction method and a gray level-gradient co-occurrence matrix feature extraction method, through a probabilistic neural network algorithm and a geometric learning algorithm. The features were obtained through the processing of vibration signals with the pseudo Wigner-Ville distribution, and the approach was applied to rolling bearing faults recognition, obtaining good results. Gelman et al. in [146] discuss a new method for feature extraction based on the higher order wavelet spectral cross-correlation (WSC), and provide the results of the comparison vs. HOS technologies (wavelet bicoherence and wavelet tricoherence) when applied to a gearbox fault detection. The experimental comparison revealed the clear superiority of the WSC technologies. Xiao et al. in [11] present the results of a characterization of the vibrations of a wind turbine by spectrogram, scalogram, and bi-spectrum analyses. Non-stationary and non-Gaussian stochastic properties, mode-coupling instability of the wind turbine tower were found.

A significant number of articles address hybrid solutions applied to bearings CM. Among them, Youcef et al. in [175], consider, for a convolutional neural network classifier, spectral images features obtained through a normalized amplitude of the spectral content, extracted from segmented temporal vibratory signals using a time-moving segmentation window. Tarek et al., in [186], compare cyclostationary analysis, empirical mode decomposition (EMD), and complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) applied to rolling bearing and gear defects diagnostics. For a laboratory test-rig all three methods proved to be efficient, but the authors conclude that for the industrial field, further improvements are needed for a successful application.

4.3. Category p3: Diagnostics

In the CM process, after having collected the signals and carried out all the necessary operations on them, including the extraction and selection of the features, the diagnostic phase must be performed, i.e., the recognition of the component or system fault conditions. As emerged in the preliminary analysis of the review works and in the further literature prospective review, the research activity related to the methodologies to carry out the diagnostic phase is very intense, mainly regarding the methods used to realize it automatically, such as machine learning (ML) techniques. Multiple ML techniques have been developed in recent years, in the most varied application contexts. The analysis of the papers classified in the diagnostic category allowed to derive a taxonomy of the main classes of ML methods used for this purpose, as shown in Figure 10. Based on the presence or absence of target values associated with the inputs (i.e., supervised or unsupervised learning) and on the characteristics of the assigned output variables (numerical or categorical), three main classes are identified: (i) supervised learning with numerical output variables, which performs a regression task; (ii) supervised learning with categorical output variables, which performs a classification task; (iii) unsupervised learning, which performs a clustering task [27]. Although in the proposed taxonomy the hybrid cases are not considered, and the method classes reported are not intended to be exhaustive of those present in literature, they represent the most investigated ones in the last two decades for vibration-based diagnostics in rotating machinery.

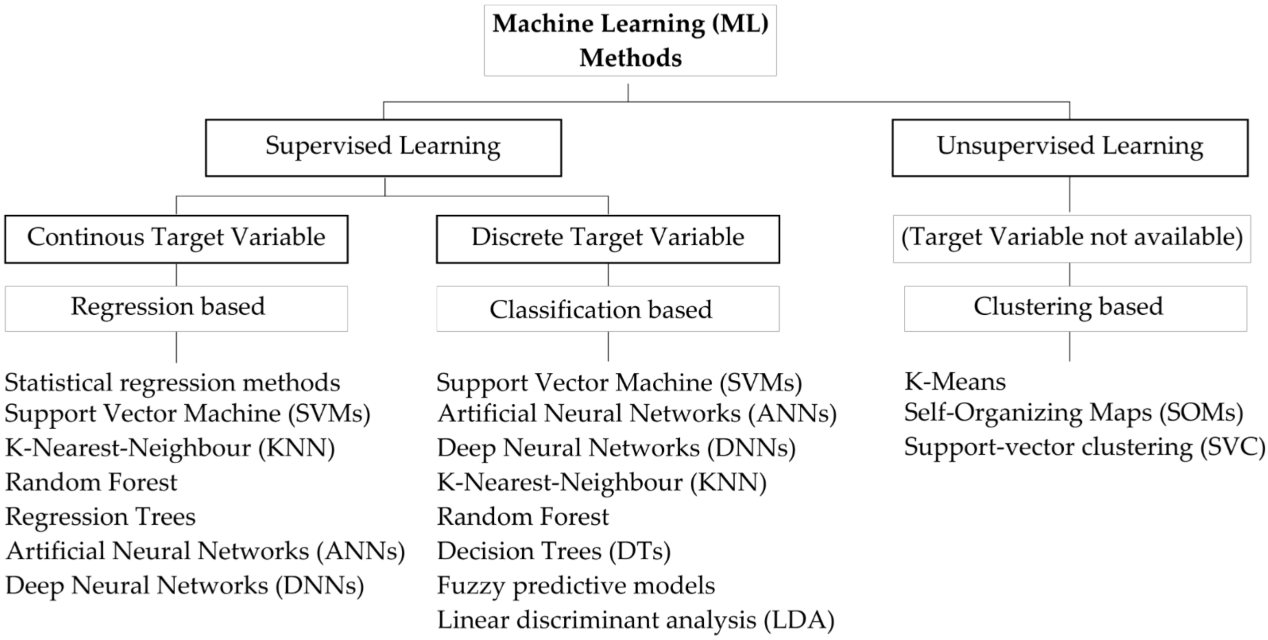

Figure 10. Taxonomy of the most investigated ML diagnostic methods.

The main interest, for the purposes of diagnostics, is aimed at classification methods, for fault classification.

In Table 4 the selected papers for the review, previously inserted in the diagnostic class, are further classified, depending on the considered method. Classical statistical methods allow a regression task, but to be used for automatic diagnostic, threshold values need to be identified, in order to decide when an error magnitude is sufficient to be of concern. This is a major challenge: an inadequate alarm triggering may cause false alarms or, even more critical, do not report an alarm when necessary. Due to this criticality of the threshold-based methods, often classification methods are preferred. As emerges through the analyses and as confirmed in other literature reviews [27], ANNs [208], DNNS, and SVMs are the most investigated methods, and among them DNNs have been dominant in the last years.

Table 4. p3 class products classification based on the investigated aspect and main topic. The star symbol identifies review papers.

Investigated Aspect ***Sub-Class***	**Bearings**	**Gears/Gearboxes**	**Motors**	**Wind Turbines**	**General**	**Non-Stationary**	**Low Speed**
Statistical methods		Samuel_2005 * [33]					
Regression-based models	Hu_2015 [209]		Dhandapani_2018 [210]		Ruiz-Cárcel_2016 [211]		
Naïve Bayes	Kumar_2014 [212]			Joshuva_2017b [213]			
Statistical hypothesis					Toyota_2000 [171]		
Cointegration method						Sharma_2021 * [25]	
Support Vector Machine (SVMs)	Moosavian_2012 [214]			Stetco_2019 *[27]	Fei_2014 [215]	Sharma_2021 * [25]	
Linear kernel	Vives_2020 [216] Agrawal_2019 [217] Hwang_2015 [218]		Hwang_2015 [218]				
Radial basis function kernel	Rauber_2021 [219]						
Gaussian kernel				Stetco_2019 *[27]			
Hypersphere SVM				Wu_2017 [220]			
MSLA-SVM					You_2019 [156]		
Artificial Neural Networks (ANNs)	Malla_2019 * [3]			Stetco_2019 *[27]	Hoffman_2002 [221]		
MultiLayer Perceptron (MLP)	Jayaswalt_2009 * [31] Golbaghi_2017 [182]	Tao_2019 [222] Khazaee_2013 [223]	Khoualdia_2021 [224]	Wu_2016 [225]	Espinoza_2021 [226] Sepulveda_2020 [227] Gierlak_2017 [195]		
Hidden Markov Models	Ocak_2001 [184] Mubaraali_2020 [228]						
Neuro-Fuzzy NN	Djamila_2018 [229] Dewangan_2012 [230]				Jayaswal_2010 [231] Jayaswalt_2009 * [31]		
Radial Basis Function (RBF)	Jayaswalt_2009 * [31]						
Probabilistic Neural Network (PNN)	Jayaswalt_2009 * [31]						
Deep Neural Networks (DNNs)		Chen_2017b [53]			Zhao_2017 [232] Li_2016c [137]		
Convolutional Neural Network (CNN)	Wang_2021 [233] Rauber_2021 [219] Fan_2021 [234] Qian_2020 [235] Zhao_2020a [236] Chen_2020 [237] Li_2020 [238] Xin_2020 [239] Li_2019 [240] Hoang_2019 [241] Qian_2018 [242]	Qian_2018 [242]			Bai_2021b [243]	Sharma_2021 * [25]	

Table 4. *Cont.*

Investigated Aspect ***Sub-Class***	**Bearings**	**Gears/Gearboxes**	**Motors**	**Wind Turbines**	**General**	**Non-Stationary**	**Low Speed**
Deep Morphological Convolutional Network (DMCNet)		Ye_2021a [244]					
Multiscale Convoluted Neural Network (MSCNN)	Ye_2021b [245]	Ye_2021b [245]		Stetco_2019*[27]			
Multi-Channels Deep Convolutional Neural Network (MC-DCNN)					Kolar_2020 [246]		
Generative adversarial network + Stacked Denoising Auto-Encoder (GAN-SDAE)	Fu_2020 [247]						
Deep Capsule Network (DCN)	Chen_2019b [160]						
Stacked Sparse Autoencoder (SSAE)	Saufi_2019 [248]						
K-Nearest-Neighbor (KNN)	Rauber_2021 [219] Samuel_2005 * [33] Vives_2020 [216]						
Random Forest	Rauber_2021 [219]	Li_2016b [249]					
Fuzzy predictive model	Hadroug_2021 [250] Malla_2019 * [3] Strączkiewicz_2015 [251]	Saravanan_2009 [252]			Da Silva_2017 [253]	Sharma_2021 * [25]	
Decision Trees (DTs)		Lipinski_2020 [254]		Joshuva_2017a [112]	Tabaszewski_2020 [255] Yang_2005 [256] Yang_2000 [257]		Song_2018 [181]
Dempster-Shafer (D-S) evidence theory		Khazaee_2014 [258] Khazaee_2012 [259]					
Multi-Sensor Data fusion	Safizadeh_2014 [260]	Khazaee_2012 [259]	Stief_2017 [261]			Sharma_2021 * [25]	
Hybrid classifier based on SVM and ANN						Sharma_2021 * [25]	
Hybrid classifier based on Principal Component Analysis (PCA) and ANN		Liu_2008 [262] Devendiran_2015 [104] De Moura_2011 [263]			Bendjama_2010 [264]		
Others	Stefanoiu_2019 [265] Yan_2019 [199] Liu_2014 [266] Zhang_2021b [267]			Avendaño-Valencia_2017 [268]			

Jayaswal and Wadhwani, in 2009 [31], reviewed the techniques successfully implemented for the automated fault diagnosis of bearings until that time, and refer to expert systems developed with multilayer perceptron (MLP), radial basis function (RBF) and probabilistic neural network (PNN). More recently, Tao et al., in 2019 [222], adopted a multilayer gated recurrent unit (MGRU) method for gear fault diagnosis; a comparison with long short-term memory (LSTM), multilayer LSTM (MLSTM), and support vector machine (SVM) LSTM, MLSTM, GRU, and SVM models, based on an experimental analysis, revealed improved accuracy with the MGRU network. Mubaraali et al., in 2020 [228], present the positive results obtained with a neuro-fuzzy intelligent diagnostic system in the time and frequency domain, with fuzzy rules of the IF-THEN form. Khoualdia et al. in 2021 [224] present an ANN, with the Levenberg–Marquardt learning algorithm, capable of detecting faults in an induction motor under different operating conditions. Sepulveda and Sinha in 2020 [227] present a vibration-based ML model (VML), with a multi-layered perceptron (MLP) network, four hidden layers and each of them with a variable quantity of nonlinear neuron, applied to the fault diagnosis of a test rig, demonstrating the robustness in the prediction capabilities of the method, even when blindly applied to machine data from the different operating condition.

ANNs have shown, in a varied number of works in the past and even today, their effectiveness for carrying out classification tasks aimed at diagnostics; however, recently, the attention has shifted more towards DNNs techniques, as the performed analysis (Table 4) demonstrated. It is also noted that the work relating to DNNs is mainly concentrated in the last three years and principally applied to rolling bearings diagnostics. A more flexible structure, better adaptability, and stronger learning ability are the main advantages of DNNs compared with ANNs, and the high number of hidden layers with non-linear transformation allows a powerful ability in vibration signals features learning. A variety of models are proposed for fault diagnosis and, among these, convolutional models (CNNs) have become one of the most popular deep learning methods because they support diverse input data, not only vectors, e.g., images. Some examples applied to rolling bearing diagnostics are: MIMTNet, a CNN with multi-dimensional signal inputs and multi-dimensional task outputs, proposed by Wang et al. in 2021 [233]; the CNN and transfer learning (TL) based fault diagnosis method proposed by Fan et al. in 2021 [234]; a one-dimensional-CNN and a dilated CNN, obtained through the combination between a CNN and an automatic hyper-parametric optimization, proposed by Li et al. in 2020 [238]. The deep morphological CNN (DMCNet), where a morphological filter is used to implement noise reduction and impulsive component extraction, and the multiscale CNN (MSCNN), with a novel morphological layer is smoothly embedded in DNN as a signal processing layer to extract impulses and filter out the noise, were presented by Ye and Yu in 2021, in [244,245], respectively; a multi-channels DCNN (MC-DCNN) was described by Kolar et al. [246], with a high definition 1D image of raw three axes accelerometer signals as input, and the deep capsule network with stochastic delta rule (DCN-SDR) was presented by Chen et al. in 2019 [269].

Support vector machines (SVMs) form another significant class of ML methods often used in fault detection, to perform regression or classification, based on the identification of support vectors, which maximize the distance between decision hyperplanes and closest data points [27]. They can be used even in presence of data that cannot be linearly separated; in these cases, SVMs use kernel transformations to make data linearly separable. Different kernels can be used, such as linear, polynomial, and Gaussian kernels. The hypersphere support vector machine, used in the case of linear indivisibility, is based on a nonlinear mapping of training samples from the original space to a high-dimension feature space [220].

In addition to the models that fall into these three main classes, there are ML models based on the methods K-nearest-neighbor (KNN), decision trees (DTs), fuzzy predictive models, random forest. Hybrid solutions, e.g., classifier based on SVMs and ANNs [25] or neuro-fuzzy models have been investigated. Furthermore, in some studies, multi-sensor-based approaches are used (for example by combining vibration and sound measurements), using data fusion methods. Khazaee et al. in [259] examine the fusion of the SVMs, ANNs, and D-S evidence theory classifiers.

A classification accuracy comparison among four different models afferent to the classes ANNs, KNN, DTs and SVMs was developed by Agraval and Jayaswal in 2019 [217], and SVM reports the best classification outcomes. SVMs exhibit high classification precision, but similar to ANNs and DNNs, do not provide a physical interpretation of the classification; conversely, DTs, KNN, and fuzzy predictive models provide an interpretation, which is based on a set of rules.

Moosavian et al. in 2012 [214] compared three classifiers for the fault diagnosis of a journal bearing based on vibration: Fisher linear discriminant (FLD), K-nearest neighbor (KNN), and support vector machine (SVM). The results demonstrated that the performance of SVM was significantly better in comparison to FLD and KNN.

A key issue in using supervised ML methods is the need of labels, namely to assign a specific category to each training instance. To create labeled vectors is time-consuming, error prone, and may result in an unbalanced number of classes [270]. Different solutions have been studied to address the unbalanced classes problem [27], e.g., by removing instances belonging to the majority class (under-sampling) or by sampling more instances from minority class (oversampling), or by removing points in the majority class that are considered borderline, noise or redundant [271].

In the class “Others”, in Table 4, some particular methods, which do not belong to the other classes, are collected. With reference to the problem of labels, Zhang et al. in [267] propose a method that combines self-supervised learning with supervised learning, making full use of unlabeled data to learn fault features, and transforms the data into three-channel vibration images. Stefanoiu et al., in [265], present a method based on the matching pursuit algorithm (MPA), a new finding in signal processing, which proves the possibility of performing fault diagnosis of bearings, even in case of multiple defects. Yan et al. in [199] show the results of the application of the AdaBoost algorithm (which belongs to fusion algorithms class) to diagnose faults of bearings. In the paper, the performances of a two-layer AdaBoost, SVM and a KNN, are compared under different numbers of kinds of features, and AdaBoost performed best, but for a few kinds of features.

5. Conclusions

This paper investigated the current state-of-the-art on the subject of condition monitoring of rotating machines, based on vibrations, in a comprehensive way, i.e., with a review not focused on a specific component of the system, and not referring to a given phase of the condition monitoring process.

The analysis was performed on 401 documents, journal articles, and reviews, published since the year 2000. The study was performed thanks to a dual level investigation:

i. The prospective review, which generated the classification of the documents by phase and components, and allowed the observational study of the literature evolution over time, by process stage and by intervention level.
ii. The analytical review, which generated, for each of the main process phases, a mapping of the documents, by the implemented methods and involved components.

The tables, obtained as outputs of both analyses, were conceived for the purpose of providing the reader with “handy support” in regard to the interpretation of the best practices currently adopted in each scenario. Nevertheless, the taxonomy by components was designed to capture, at best, the peculiar features of the current dataset; for this reason, the same dataset could be better described by alternative categories and taxonomies, if analyzed with a different scope. Moreover, other evaluations on the topic could be performed considering a different dataset. For instance, one very interesting aspect that future revision works could investigate is the relation between vibrations and component materials [272–275], and how condition-monitoring techniques can be influenced by them.

The results of the review suggest an ever-growing trend in the research issues related to signal processing, selection of features, and diagnostic techniques, revealing the research world's great interest in these topics. New procedures will certainly emerge in these areas, and given the growing general interest in artificial intelligence techniques, it is very likely that innovative diagnostic methods based on machine learning will be developed in the near future.

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Appendix A

Table A1 presents the analysis of the documents by phase and component at the basis of the perspective review. In the table, the nomenclature for categories and sub-categories of phases, components, and topics reflect the previously introduced legend.

Table A1. Classification of the analyzed papers by phases, components, and topics.

ID	Phases					Main Class	Components																Topics		
	p1	p2	p3	p4	p5		c1	c1.a	c1.b	c2	c3	c4	c4.a	c4.b	c4.c	c5	c6	c6.a	c6.b	c6.c	c7	c8	t1	t2	t3
Bajaj_2022 [276]			x			p3																x			
Xu_2022 [277]				x		p4	x																		x
Ye_2021a [244]			x			p3					x														
Ahmed_2021 [172]		x	x			p2	x		x																
Mufazzal_2021 [278]				x		p4	x																		
Yang_2021 [110]		x				p2	x		x		x						x		x						
Moghadam_2021 [193]		x				p2											x		x						
Saucedo-Dorantes_2021 [173]		x				p2	x		x			x	x												
Espinoza-Sepulveda_2021 [279]				x		p4															x				x
Kalista_2021 [73]	x					p1	x		x																x
Zhang_2021a [280]				x		p4	x	x																	
Zhang_2021b [267]			x			p3	x		x																
Meng_2021 [59]	x					p1	x		x																
Tiwari_2021 [95]	x					p1	x		x																
Tatsis_2021 [281]				x		p4											x	x							
Leaman_2021 [282]					x	p5					x													x	
Ou_2021 [283]					x	p5											x	x							
Espinoza_2021 [226]			x		x	p3															x				x
Wang_2021 [233]			x			p3	x		x																x
Goyal_2021 [60]	x					p1	x		x																
Bai_2021a [203]		x				p2				x												x			x
Yu_2021 [75]	x					p1					x												x		
Papathanasopoulos_2021 [66]	x					p1						x		x											
Sharma_2021 [25]	x					p1					x						x						x		
Rauber_2021 [219]			x			p3	x		x																
Laval_2021 [76]	x					p1	x		x		x														x
Shao_2021 [158]		x	x			p2	x		x																
Rafiq_2021 [166]		x				p2					x						x		x				x		
Zhao_2021 [77]	x					p1	x		x																
Gómez_2021 [284]	x					p1											x		x						
Jablon_2021 [197]		x				p2	x		x																
Barusu_2021 [62]	x					p1	x		x			x	x												
Hadroug_2021 [250]			x			p3																x			
Hou_2021 [35]	x		x			p1	x		x																
Yuan_2021 [285]					x	p5						x													
Ye_2021b [245]			x			p3	x		x		x														
Tingarikar_2021 [286]				x		p4	x																		
Ribeiro_2021 [287]		x				p2						x													
Peng_2021 [288]		x	x			p2					x						x		x						
Gu_2021 [198]		x				p2	x		x																
Fan_2021 [234]			x			p3	x		x																
Bai_2021b [243]			x			p3						x													x
Khoualdia_2021 [224]			x			p3						x	x												x
Wu_2021 [94]	x					p1	x		x																
Huang_2021 [115]		x				p2	x		x														x		
Hosseinpour-Zarnaq_2021 [289]					x	p5					x														
Krot_2020 [290]				x		p4					x												x		
Sepulveda_2020 [227]			x			p3															x				
Shen_2020 [80]	x					p1					x														
Lipinski_2020 [254]			x			p3					x												x		
Bengherbia_2020 [291]		x				p2															x				
Dos Santos Pedotti_2020 [67]	x					p1																x			
Gelman_2020 [146]		x				p2					x														
Pham_2020 [131]		x				p2	x		x																
Fu_2020 [247]			x			p3	x		x																
Tarek_2020 [186]		x				p2	x		x		x										x				x

Table A1. *Cont.*

ID	Phases					Main Class	Components																Topics		
	p1	p2	p3	p4	p5		c1	c1.a	c1.b	c2	c3	c4	c4.a	c4.b	c4.c	c5	c6	c6.a	c6.b	c6.c	c7	c8	t1	t2	t3
Vives_2020 [216]			x			p3											x								
He_2020 [101]		x	x			p2	x		x																x
Kolar_2020 [246]			x			p3															x				
Xu_2020 [292]				x		p4	x		x								x								
Fong_2020 [83]	x					p1					x												x	x	
Mubaraali_2020 [228]			x			p3											x			x				x	
Soto-Ocampo_2020 [65]	x					p1	x		x																
Sun_2020a [174]		x				p2	x		x																
Mohamad_2020 [2]		x				p2	x		x		x														
Ranjan_2020 [293]					x	p5	x	x																	
Pichler_2020 [294]					x	p5	x																		
Singh_2020 [295]					x	p5	x		x																x
Qian_2020 [235]			x		x	p3	x		x																
Sun_2020b [296]				x		p4					x														
Vekteris_2020 [297]					x	p5	x																		
Jeon_2020 [175]		x				p2	x		x																
Peeters_2020 [82]	x					p1					x										x				
Mauricio_2020 [170]		x				p2					x														
Xiao_2020 [11]		x		x		p2											x	x					x		
Zhao_2020a [236]			x			p3	x		x																
Zhao_2020b [298]					x	p5											x								
Attoui_2020 [116]		x				p2	x		x																
Joshuva_2020 [8]					x	p5											x	x							
Nasef_2020 [299]					x	p5										x									
Marticorena_2020 [56]	x			x		p1										x									
Jiao_2020 [159]		x				p2	x		x																
Fan_2020 [176]		x				p2	x		x																
Chen_2020 [237]			x			p3	x		x																
Xin_2020 [239]			x			p3					x														
Tabaszewski_2020 [255]			x			p3									x										
Shifat_2020 [300]					x	p5						x		x									x		
KN_2020 [301]					x	p5					x				x										
Castellani_2020 [58]	x					p1											x						x		
Shu_2020 [152]		x				p2						x	x												x
Youcef_2020 [177]		x				p2	x		x																x
Li_2020 [238]			x			p3	x		x														x		x
Li_2019 [240]			x			p3	x		x																
Caldero_2019 [302]		x				p2				x		x	x												
Hizarci_2019 [204]		x				p2					x														
Xue_2019 [303]				x		p4	x																		
Chen_2019a [269]			x			p3	x		x																
Jablonski_2019 [304]					x	p5					x														
Sinutin_2019 [305]				x		p4	x																		
Ibarra-Zarate_2019 [42]	x					p1	x		x																
Medina_2019 [205]		x				p2					x														
Khan_2019 [45]	x					p1					x														
Aralikatti_2019 [306]					x	p5																x			
Joshuva_2019a [307]					x	p5											x	x							
Joshuva_2019b [308]					x	p5											x	x							
Gangsar_2019 [309]					x	p5						x	x												
Stefanoiu_2019 [265]	x		x			p3	x		x																
Chandra_2019 [310]					x	p5						x	x												
Ghemari_2019 [63]	x			x		p1																x			
Malla_2019 [3]					x	p5	x		x															x	
Wu_2019 [90]	x					p1															x				
Yang_2019 [178]		x				p2	x		x		x														x
Ambika_2019 [132]		x				p2	x		x																
Zhang_2019 [199]	x					p1					x														
Wang_2019a [28]					x	p5					x						x								
Joshi_2019 [311]					x	p5															x				
Daga_2019 [113]		x				p2	x		x												x				x
Xie_2019 [312]				x		p4						x	x												
Chen_2019b [160]		x				p2	x		x								x						x		
Zhao_2019a [313]		x				p2	x		x																
Wang_2019b [314]		x				p2	x		x																
Isham_2019 [162]		x				p2					x														
Hartono_2019 [147]	x	x				p2					x														
Mauricio_2019 [169]		x				p2	x		x		x						x						x		
Klausen_2019 [117]		x				p2	x		x															x	
Yan_2019 [199]		x	x			p3	x																		
Elisabeth_2019 [315]					x	p5					x														
Joshuva_2019c [316]					x	p5											x	x							
Puchalski_2019 [148]		x				p2					x														
Liu_2019a [155]		x				p2	x		x												x				
Kamran_2019 [317]					x	p5															x				
Silahuddin_2019 [318]					x	p5															x				x
Liu_2019b [153]		x				p2						x	x												
Zarour_2019 [86]	x					p1	x		x																
Zhao_2019b [196]		x				p2																x			
Liu_2019c [319]					x	p5															x				
Ooijevaar_2019 [320]	x				x	p5	x		x																
Tao_2019 [222]			x			p3					x														x
Saufi_2019 [248]			x			p3	x		x															x	x
Ren_2019 [84]	x					p1	x		x														x		
Nissila_2019 [133]		x				p2	x		x																
Arun_2019 [321]		x				p2	x		x																
Agrawal_2019 [217]			x			p3	x		x																
You_2019 [156]		x	x			p3															x				
Wang_2019c [125]		x				p2					x						x						x		
Gao_2019 [322]		x				p2	x		x																
Hoang_2019 [241]			x			p3	x		x																
Hasan_2018 [93]	x					p1	x		x																
Rapur_2018 [109]		x				p2										x									
Jin_2018 [38]	x					p1					x														
Xin_2018 [179]		x				p2	x		x																x
Dybała_2018 [118]		x				p2	x		x																
Tong_2018 [134]		x				p2	x		x																
Shah_2018 [323]					x	p5				x															
Hamadache_2018 [180]		x				p2	x		x																
Qian_2018 [242]			x			p3					x														
Trumpa_2018 [324]	x					p1	x		x																
Mao_2018 [164]		x		x		p4									x										
Mokhtar_2018 [325]				x		p4						x													
Li_2018a [326]		x				p2					x												x		

Table A1. *Cont.*

ID	Phases					Main Class	Components																Topics		
	p1	p2	p3	p4	p5		c1	c1.a	c1.b	c2	c3	c4	c4.a	c4.b	c4.c	c5	c6	c6.a	c6.b	c6.c	c7	c8	t1	t2	t3
Cai_2018 [327]	x					p1	x		x																
Song_2018 [181]		x	x			p3	x		x															x	
Pang_2018 [111]		x				p2											x			x					
Panda_2018 [328]					x	p5	x																		
Anand_2018 [329]					x	p5																x			
Artigao_2018 [330]					x	p5											x								
Oh_2018 [185]		x				p2	x	x		x		x													
Barbini_2018 [200]		x				p2	x		x																
Djamila_2018 [229]			x			p3						x	x												
Lu_2018 [68]	x					p1	x		x																
Isham_2018 [167]		x				p2					x		x								x		x		
Kondo_2018 [331]					x	p5				x					x										
Yang_2018 [191]		x				p2						x													x
Xue_2018 [332]				x		p4					x														
Prashanth_2018 [61]	x					p1	x		x																
Dovhan_2018 [74]	x					p1										x									
Sogoba_2018 [333]					x	p5											x			x					
Qiu_2018 [119]		x				p2	x		x																
Li_2018b [187]					x	p5															x				
Joshuva_2018 [334]					x	p5											x	x							
Kotulski_2018 [335]					x	p5											x								
Sahoo_2018 [67]	x					p1	x		x																
Dhandapani_2018 [210]			x			p3															x		x		
Praveenkumar_2018 [336]					x	p5					x														
Olejarova_2017 [337]	x					p1															x				
Caesarendra_2017 [29]		x				p2	x		x															x	
Antoni_2017 [338]					x	p5									x								x		
Mollasalehi_2017 [339]					x	p5											x			x					
Wu_2017 [220]			x			p3					x						x								
Chen_2017a [96]	x					p1					x														
Abboud_2017 [340]	x					p1	x		x																
He_2017 [144]		x				p2				x	x										x				
Seimert_2017 [341]					x	p5	x																		x
Hong_2017 [188]		x				p2					x												x		
Gelman_2017a [149]		x	x			p2					x														
Gelman_2017b [150]		x				p2					x														
Guan_2017 [342]				x		p4	x		x	x															
Jayakumar_2017 [135]		x				p2	x		x			x	x								x				
Hashish_2017 [343]		x				p2						x													
Avendaño-Valencia_2017 [268]			x			p3											x	x							
Gierlak_2017 [195]		x	x			p2																x			
Amini_2017 [36]	x					p1	x		x													x			
Bengherbia_2017 [69]	x					p1															x	x			x
Bovsunovsky_2017 [344]	x					p1				x															
Joshuva_2017a [112]		x	x			p3											x	x							
Tse_2017 [345]		x	x			p2	x		x																
Feng_2017 [126]		x				p2					x												x		
Buzzoni_2017 [87]	x					p1					x														
Li_2017 [54]	x	x				p1					x														
Stief_2017 [261]			x			p3						x	x												
Joshuva_2017b [213]			x			p3											x	x							
Da Silva_2017 [253]			x			p3															x				x
Brito_2017 [346]					x	p5	x	x																	
Yunusa-Kaltungo_2017 [347]					x	p5															x				
Chen_2017b [53]			x			p3					x														
Zhao_2017 [232]			x			p3																x			
Huo_2017 [136]		x				p2	x		x																
Golbaghi_2017 [182]		x	x			p3	x		x																
San'Ko_2017 [348]				x		p4					x														
Yang_2017 [161]		x	x			p2	x		x			x													
Anil_2017 [349]		x				p2						x	x												
Lipus_2016 [350]					x	p5															x				
Randall_2016 [351]					x	p5					x						x								
Jiang_2016 [352]		x				p2															x				
Haile_2016 [91]	x					p1	x		x																
Wang_2016 [41]	x					p1	x		x								x								
Chen_2016 [353]				x		p4									x										
Yong_2016 [354]			x	x		p4					x														
Li_2016a [355]					x	p5					x														
Li_2016b [249]	x		x			p3					x														
Keshtan_2016 [356]			x			p3	x		x																
Zachar_2016 [357]	x					p1															x				
He_2016 [194]		x				p2															x		x		
Li_2016c [137]		x	x			p3	x		x		x														
Feng_2016 [358]				x		p4	x		x		x														
Lei_2016 [359]				x		p4					x														x
Devendiran_2016 [360]					x	p5					x														
Li_2016d [120]		x				p2	x		x																
Noroozi_2016 [361]			x			p3					x	x													
Khan_2016 [201]		x				p2	x		x														x		
Li_2016e [362]		x				p2	x		x																
Hong_2016 [363]			x	x		p4					x														
Othman_2016 [46]	x					p1	x		x																
Romero_2016 [364]					x	p5	x		x		x						x								
Yi-Cheng_2016 [47]	x					p1																x			
Aleksandrov_2016 [365]					x	p4										x									
Wu_2016 [225]			x			p3											x								
Ruiz-Cárcel_2016 [211]			x			p3															x				x
Dolenc_2016 [121]		x				p2	x		x																
Desavale_2016 [366]				x		p4	x		x																
Kutalek_2015 [367]		x				p2	x		x																
Budik_2015 [368]					x	p5																x			
Cerrada_2015 [189]		x				p2					x														
Zhang_2015a [369]	x					p1	x		x																
Hwang_2015a [218]			x			p3	x		x																
Feldman_2015 [64]	x					p1																x			
Ng_2015 [370]					x	p5	x		x																
Hu_2015 [371]			x			p3	x		x																
Harmouche_2015 [122]		x				p2	x		x																
Raj_2015 [183]		x				p2	x		x																
Gałka_2015 [88]	x					p1															x				
Miao_2015 [372]				x		p4					x														
Yang_2015 [39]	x					p1	x		x																
Strączkiewicz_2015 [251]			x			p3	x		x																
Hua_2015 [138]		x				p2	x		x												x				

Table A1. *Cont.*

ID	Phases					Main Class	Components																Topics		
	p1	p2	p3	p4	p5		c1	c1.a	c1.b	c2	c3	c4	c4.a	c4.b	c4.c	c5	c6	c6.a	c6.b	c6.c	c7	c8	t1	t2	t3
Zhang_2015b [373]			x			p3															x				
Narendiranath_2015 [5]					x	p5	x	x																	
Chen_2015 [165]		x				p2						x	x												
Lee_2015 [374]					x	p5																x			
Hwang_2015b [218]			x			p3	x		x																
Senthilkumar_2015 [375]		x				p2																x			
Devendiran_2015 [104]		x	x			p3					x														
Mohamed_2015 [376]					x	p2									x										
Gelman_2015 [139]		x				p2	x		x																
Fan_2015 [190]	x	x				p2					x														x
Gelman_2014 [140]		x				p2	x		x														x		
Liu_2014 [266]			x			p3	x		x																
Hong_2014 [105]		x				p2					x														
Sakthivel_2014 [207]		x				p2										x									
Cardona-Morales_2014 [130]	x	x				p2											x		x			x	x		
Guoji_2014 [127]		x				p2					x														
Qu_2014 [37]	x					p1					x														x
Khazaee_2014 [258]	x		x			p3					x														
Prasad_2014 [377]	x					p1										x									
Ayaz_2014 [102]		x				p2	x		x																
Łukasiewicz_2014 [378]				x		p4					x														
Qadir_2014 [379]		x				p2						x				x									
Jegadeeshwaran_2014 [168]		x				p2																x	x		
Mironov_2014 [380]	x					p1	x		x																
Majumdar_2014 [381]				x		p4															x				
Nembhard_2014 [50]	x					p1	x		x																x
Sendhil_2014 [32]					x	p5															x				
Fei_2014 [215]			x			p3				x											x				
Qiang_2014 [192]		x		x		p2									x						x				
Kumar_2014 [212]		x	x			p3	x		x																
Safizadeh_2014 [260]	x		x			p3	x		x																
Assaad_2014 [382]					x	p5					x														x
Seshadrinath_2014 [383]					x	p5						x	x												
He_2013 [71]	x					p1	x		x														x		
Tse_2013a [141]		x				p2	x		x																
Tse_2013b [384]	x					p1	x		x																
Kawahito_2013 [385]	x					p1										x									
Jablonski_2013 [386]		x				p2											x								
Biswas_2013 [202]		x				p2	x	x									x			x					
Gautier_2013 [387]				x		p4															x				
Li_2013a [142]		x				p2	x		x			x											x		
Zhang_2013 [388]					x	p5															x				
Elbhbah_2013 [129]		x				p2				x											x				x
Cong_2013 [389]				x		p4	x		x																x
Feng_2013 [390]	x			x		p4					x														
Komorska_2013 [391]				x		p4					x														
Amarnath_2013 [163]		x				p2					x														
Khazaee_2013 [223]	x	x				p2					x														
Nembhard_2013 [52]	x					p1															x				x
Sinha_2013 [392]	x					p1	x	x													x				
Li_2013b [393]					x	p5					x												x		
Widodo_2012 [51]	x					p1	x		x												x				
Dewangan_2012 [230]			x			p3	x		x																
Rzeszucinski_2012a [106]		x				p2					x														
Feng_2012 [394]				x		p4					x														
Heyns_2012 [107]		x				p2					x												x		
Moosavian_2012 [214]			x			p3	x	x	x						x										
Akechi_2012 [395]	x					p1	x	x													x			x	
Yan_2012 [72]	x					p1	x		x																
Rzeszucinski_2012b [396]		x				p2					x														
Khazaee_2012 [259]			x			p3					x														
Kankar_2012 [397]					x	p5	x																		
Zamanian_2011 [398]		x				p5					x												x		
Yavors'kyi_2011 [399]					x	p5	x																x		
De Moura_2011 [263]			x			p3	x		x																
Utpat_2011 [103]		x				p2	x	x								x									
Henao_2011 [55]	x					p1					x												x		
Loutas_2011 [400]					x	p5					x										x				
Botsaris_2011 [401]		x				p2	x		x																
Chebil_2011 [402]					x	p5	x																		
Anegawa_2011 [403]				x		p4				x							x	x							
Ahmadi_2010 [404]		x				p2										x									
Jovančić_2010 [405]				x		p4					x				x										
He_2010 [406]	x					p1	x		x																
Bendjama_2010 [264]			x			p3															x				
Immovilli_2010 [40]	x					p1	x		x																
Wu_2010 [407]		x				p2															x				
Zakhezin_2010 [124]		x				p2	x		x	x		x													
Yoshioka_2010 [43]	x					p1	x		x																
Bánlaki_2010 [48]	x					p1									x										
Indira_2010 [114]		x				p2	x		x												x				
Jayaswal_2010 [231]			x			p3	x		x																
Sadoughi_2010 [408]		x				p2	x		x																x
Hassan_2009 [409]		x				p2					x														
Ahmadi_2009 [410]		x				p2	x		x																
Wu_2009 [98]	x					p1				x											x				
Yoshioka_2009 [44]	x					p1	x		x																
Yan_2009 [85]	x					p1	x		x																
Jayaswalt_2009 [31]			x			p3															x				
Al-Arbi_2009 [57]	x					p1					x														
Saravanan_2009 [252]			x			p3					x														
Bartelmus_2009 [411]				x		p4					x														
Janjarasjitt_2008 [412]					x	p5	x		x																
Su_2008 [413]					x	p5																x			
Kulikov_2008 [414]		x				p2																x			
Pennacchi_2008 [415]			x			p3																x			
Dragomir_2008 [416]	x					p1																x			
Bartelmus_2008 [417]					x	p5	x		x		x														
Monavar_2008 [418]					x	p5						x													

Table A1. *Cont.*

ID	Phases					Main Class	Components																Topics		
	p1	p2	p3	p4	p5		c1	c1.a	c1.b	c2	c3	c4	c4.a	c4.b	c4.c	c5	c6	c6.a	c6.b	c6.c	c7	c8	t1	t2	t3
Liu_2008 [262]			x			p3					x														
Tse_2007 [92]	x					p1	x		x																
Fan_2007 [419]					x	p5					x														
Tan_2007 [420]					x	p5					x														
Sinha_2006a [421]			x			p3										x									
Pennacchi_2006 [422]					x	p5															x				
Al-Bedoor_2006 [423]				x		p4				x							x								
Sinha_2006b [424]					x	p5															x				
Orhan_2006 [425]					x	p5	x		x																
Sinha_2006c [426]					x	p5															x				
Zhan_2006 [108]		x				p2					x														
Antoni_2006 [157]		x				p2															x		x		
Wadhwani_2006 [427]					x	p5						x	x												
Wu_2005 [49]	x					p1				x					x										
Gelman_2005 [128]		x				p2					x														
Peng_2005 [428]		x				p2					x	x													x
Yang_2005 [256]			x			p3															x				
Samuel_2005 [33]					x	p5					x						x		x						
Yu_2005 [429]					x	p5	x	x							x										
Sheen_2004 [79]	x					p1	x		x																
Luo_2003 [143]		x				p2	x		x																
Hafeez_2003 [123]		x				p2	x		x			x													
Kawada_2003 [145]		x				p2				x	x						x			x	x				
Geng_2003 [430]				x	x	p5									x								x		
Peng_2003 [431]					x	p5					x	x													x
Betta_2002 [432]	x					p1						x													x
Hoffman_2002 [221]			x			p3	x		x																
Antoni_2002 [154]		x				p2									x								x		
Stander_2002 [151]		x				p2					x														x
Chen_2002 [206]		x				p2	x		x												x			x	
Ocak_2001 [184]		x	x			p3	x		x			x	x												
Zheng_2001 [433]	x					p1															x				
Jack_2000 [434]		x				p2															x				
Wang_2000 [435]					x	p5				x						x									
Yang_2000 [257]			x			p3															x				
Koo_2000 [436]		x				p2				x						x									
Toyota_2000 [171]			x			p3															x				

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