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Barbosa de Santis, Rodrigo and Silveira Gontijo, Tiago and Azevedo Costa, Marcelo

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Condition-based maintenance in hydroelectric plants: A systematic literature review

Rodrigo Barbosa de Santis, Tiago Silveira Gontijo and Marcelo Azevedo Costa

Abstract

Industrial maintenance has become an essential strategic factor for profit and productivity in industrial systems. In the modern industrial context, condition-based maintenance guides the interventions and repairs according to the machine's health status, calculated from monitoring variables and using statistical and computational techniques. Although several literature reviews address condition-based maintenance, no study discusses the application of these techniques in the hydroelectric sector, a fundamental source of renewable energy. We conducted a systematic literature review of articles published in the area of condition-based maintenance in the last 10 years. This was followed by quantitative and thematic analyses of the most relevant categories that compose the phases of condition-based maintenance. We identified a research trend in the application of machine learning techniques, both in the diagnosis and the prognosis of the generating unit's assets, being vibration the most frequently discussed monitoring variable. Finally, there is a vast field to be explored regarding the application of statistical models to estimate the useful life, and hybrid models based on physical models and specialists' knowledge, of turbine-generators.

Keywords

Condition based maintenance, hydroelectric, fault diagnostics, fault isolation, fault monitoring, fault prognostics, system health management

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Introduction

From time to time, new technologies emerge and revolutionize entire industries, as we know them. Just as the steam engine and weaving loom transformed production in the 18th century, bringing significant productivity gains to the mass industry sectors, today we witness the fourth wave of this revolution with the digitization of processes. New buzz-words such as the internet of things (IoT), cyber-physical systems, cloud solutions, and augmented reality have been gaining popularity in academic and business environments. The industrial maintenance, which is a key strategic factor and profit contributor, have been benefiting from these new technologies as a means of guaranteeing the productivity of industrial systems.[1]

Maintenance 4.0 includes a set of advanced data analysis techniques for processing the enormous amount of data produced by shop floor processes. It seeks to detect the occurrence of disturbances in the behavior of assets. As a result, maintenance managers can develop more effective action plans, maximizing the availability of assets at a lower operating cost.[2] In the context of maintenance 4.0, a particular trend topic is the condition-based maintenance (CBM). In this paper, we adopted the definition of CBM as "a maintenance program that recommends actions based on the information collected through condition monitoring," as defined by Jardine et al.[3] and used by Bousdekis et al.[4]

There is a range of reviews in the literature in this area that deal with CBM techniques and their applications in the industry. One of the pioneer reviews to address the topic divided the CBM techniques into

Universidade Federal de Minas Gerais, Belo Horizonte, Minas Gerais, Brazil

Corresponding author:
Rodrigo Barbosa de Santis, Graduate Program in Industrial Engineering, Universidade Federal de Minas Gerais, Av. Antônio Carlos 6627, Belo Horizonte, Minas Gerais 31270-901, Brazil.
Email: rsantis@ufmg.br

Table 1. List of relevant keywords adopted in searching journal databases.

Keywords
Condition-based maintenance keywords: condition-based maintenance OR predictive maintenance OR fault detection OR diagnosis OR remaining useful life OR health monitoring AND *Hydroelectric keywords*: hydroelectric OR hydropower OR hydro generator OR hydro turbine

three main groups: data acquisition, data processing, and maintenance decision making.[3] More recently, another review presented a full view of prognosis,[5] which is the data processing phase related to estimating remaining useful life. Also, a more recent review has restricted analysis to statistical approaches for prognosis.[6] An update review that includes all stages of a CBM system, from data acquisition to estimating remaining useful life, has been presented recently.[7] Yet another review relates the CBM process to maintenance and company management, supporting decision-makers' actions.[4] Finally, a review focused on deep-learning methods applied to monitoring machine health is presented.[8] However, to date, no review has been found specifically addressing the application of these methods in the hydroelectric sector, which has specific characteristics and complexities. Thus, the present article provides a systematic review in an area not yet comprehensively reviewed.

The remainder of the present article is organized as follows. Section 2 describes the study methodology and the systematic literature review process, and presents a qualitative summary of the articles sampled. Section 3 presents the failure modes found most frequently in hydroelectric systems (HS). Section 4 summarizes the monitored variables in CBM applications, associating them with the recurrent failure modes. Sections 5 and 6 discuss the models proposed so far for dealing with the diagnosis and prognosis of HS and their components. Finally, Section 7 presents the conclusions and recommendations for future work.

Materials and methods

Review methodology

A systematic literature review (SLR) is a technique that identifies current studies, collects and analyses facts, analyzes and synthesizes contributions, and reports the data in such a way that it is possible to draw fairly clear conclusions about what is and is not known on a specific topic.[9,10] The present study aims to answer the following question: "What are the advances in the CBM area for hydroelectric systems reported in the literature in the last decade?." The research question comprises three sub-questions:

- Sub-Question 1: What are the main input variables of the reported CBM systems and what failure modes/failure mechanisms are associated with each?
- Sub-Question 2: Which attribute extraction tools have been used to enhance CBM systems?
- Sub-Question 3: What statistical and computational methods have been applied to the diagnosis and prognosis of HS?

The methodology adopted for conducting the SLR consists of a three-step procedure.[11,12] The first step is to define the list of relevant keywords that will be used to search peer-reviewed journals in online literature databases. Table 1 summarizes the keywords adopted in the present paper. The first set of keywords relates to the context of CBM; the second set refers to hydroelectric plants and components. The keyword list has been iteratively expanded to include synonyms and frequently used terms. We searched the scholarly databases *Scopus* and *Web of Science* for peer-reviewed articles featuring these keywords, either in their titles, abstracts, or lists of keywords. Only articles published in the English language during the period between 2010 and 2019 were considered. After removing duplicates, the total number of articles is 118.

The second step is to check the articles' relevance by screening their abstracts. If the abstract indicates that the paper might be relevant for this review, a detailed analysis of the entire article is carried out. Articles that do not deal effectively with the topic are removed from the sample at this stage. The third step is to conduct a backward and forward snowball search, examining relevant articles cited in our sample. At this stage, we have exceptionally included two articles published in early 2020 for presenting essential contributions in the discussion of the topics of structural health[13] and multi-source monitoring.[14]

This review is strictly limited to scientific publications. However, we note that there is an extensive development of services and solutions commercially offered by service providers and equipment manufacturers. Because these knowledge is disseminated in non-scientific ways (i.e. technical reports, documentation) and mainly privately owned techniques, they were left out of the scope of the work.

Quantitative analysis

Table 2 presents the review protocol adopted, with the number of articles at each stage of the SLR process. In

Table 2. Review protocol and sample sizes by stages.

Phase	Description	Total
Identification	Records identified through database searching	176
Screening	Records after duplicates removed	118
Eligibility	Full-text articles assessed for eligibility	88
Included	Studies included in quantitative analysis	80
	Studies included in qualitative synthesis	71

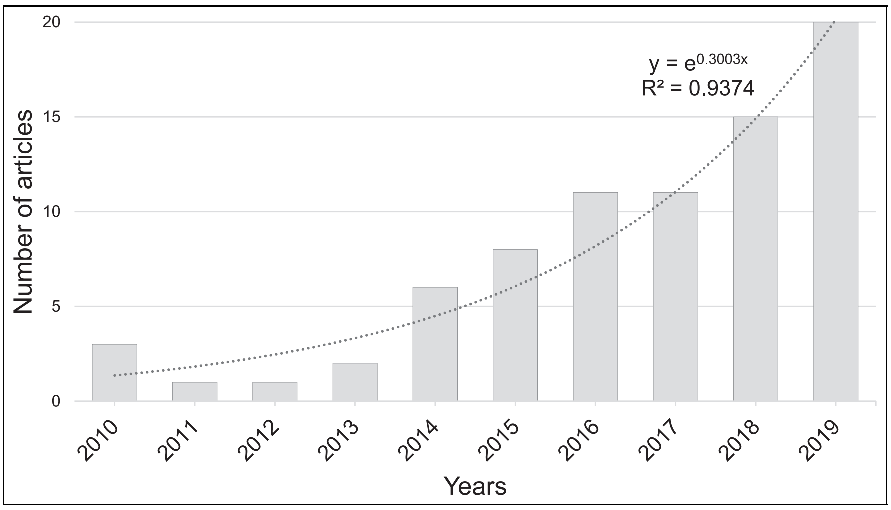

Figure 1. Number of articles published annually.

the end, the study sample consists of 80 articles. Figure 1 shows how the number of publications has been developing over time. There is a significant increase in the number of publications in the sector during the last decade, increasing from fewer than 5–20 published articles per year in 2019.

Figure 2 presents the total number of publications per journal, grouped by categories.[15] The categories were grouped into three major clusters, according to their area: the first cluster related to computer science and engineering journals; the second to energy; the third to materials science, mathematics, and physics. In general, the publications are scattered among several journals, with no single journal publishing more than three articles on the subject.

Due to the large number of articles in our literature sample, the present review adopted a strategy of associating the articles with categories belonging to a conceptual framework. This framework was adapted from other literature reviews focused on CBM,[3–5,16] in which the categories are consolidated according to the stage of the maintenance process, from data acquisition to useful life estimation. The sampled articles were assigned to the categories of the phases of the condition-based maintenance.

Figure 3 presents a temporal word cloud generated from the titles and abstracts of all articles sampled using the VOSviewer 1.6.15 software.[17] We considered the top 60% of the most relevant terms present in the articles. The circle sizes represent the frequency of occurrence of the terms, the arcs denote the strength of the associations between them, and the color shows the average year of occurrence of the terms. This representation presents a general idea of the categories addressed in the next sections, providing a global view of the study sample. Note that the average year of occurrence of the selected terms is higher than 2016, as the number of publications are concentrated at the last years of the sampled period.

It is noticed that vibration signal monitoring, applied to feature extraction techniques and computational intelligence models, has been appearing with increasing frequency in the latest publications in the area. On the other hand, mathematical formulation and the finite element method call attention to an additional cluster of publications. In the thematic analysis, we seek to illustrate all these categories in an organized and systematic way.

Common failure modes and failure mechanisms in hydroelectric plants

Failure modes differ from plant to plant, related to environmental and design factors, plant requirements, type of turbine, and operation. However, in general, some types of failure are more commonly subject to condition monitoring in all hydroelectric plants. Below,

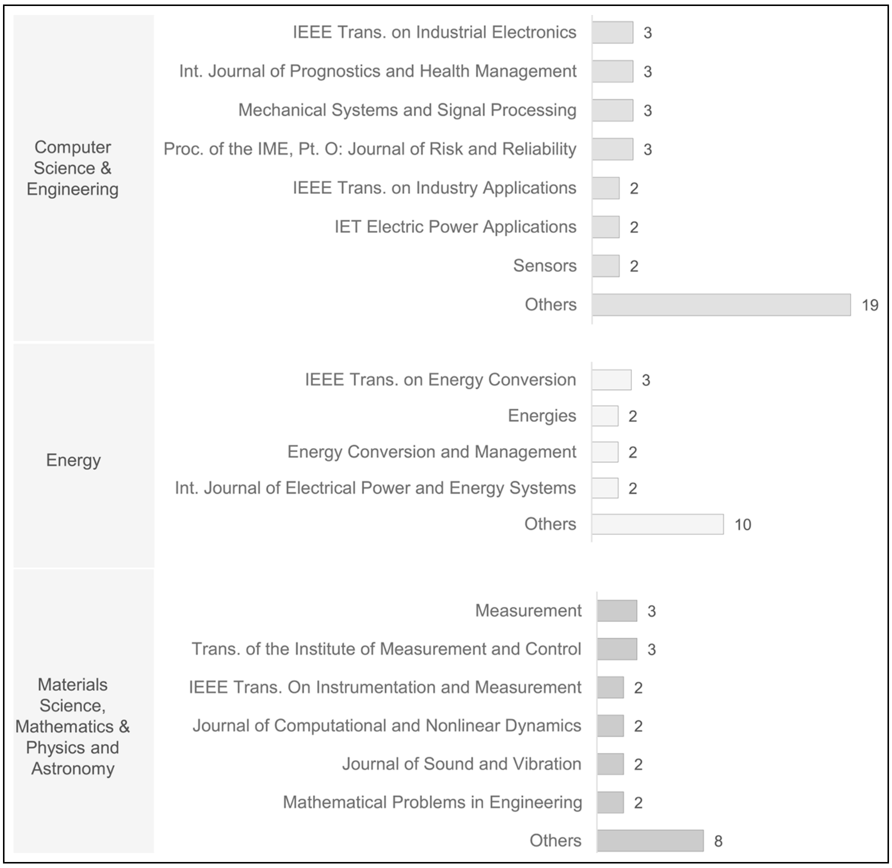

Figure 2. Journals with more publications on the topic, grouped into categories defined by SCImago.[15] Journals with only one publication have been omitted.

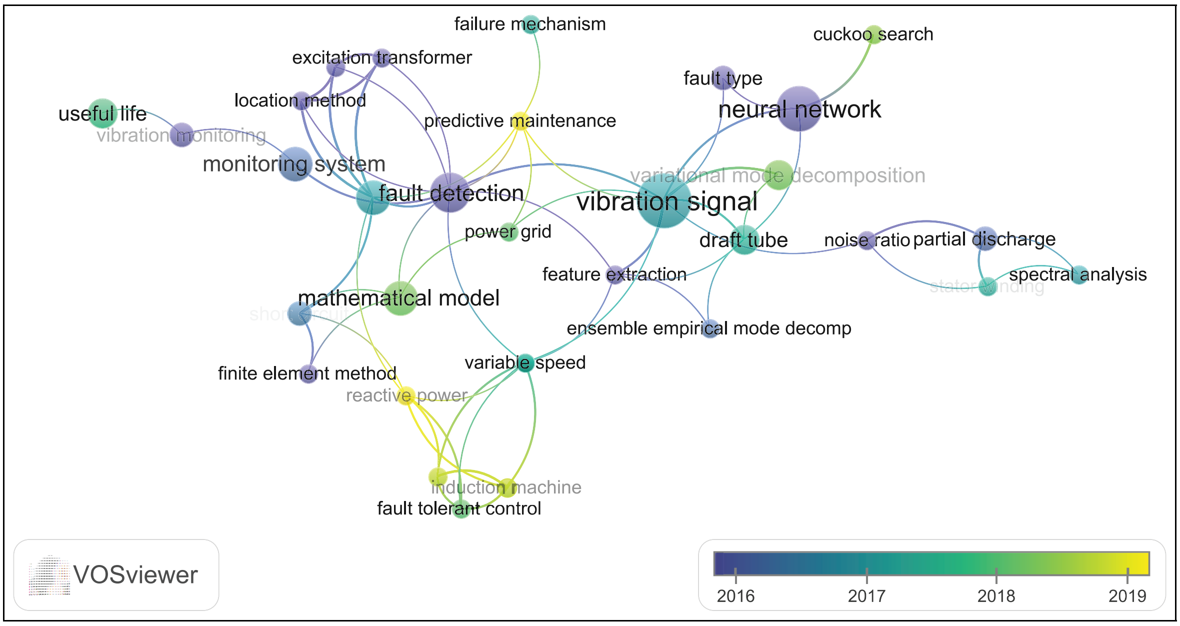

Figure 3. Temporal word cloud created from the titles and abstracts of the sampled articles. The color scales shows the terms average year of occurrence.

we present the types discussed most frequently in the sampled literature.

Cavitation

Cavitation is a complex and harmful phenomenon for hydraulic machinery such as turbines, pumps, and valves. Sudden changes in the local pressure of the liquid form bubbles that collapse, radiating acoustic energy waves, and causing the erosion of nearby surfaces.[18] Sand erosion increases the likelihood of cavitation, since eroded surfaces increase wall turbulence and, consequently, reduce the local pressure.[19]

Cavitation is more likely in Francis turbines and reversible pump turbines than in Kaplan turbines.[20] There are several types of cavitation such as leading-edge, traveling bubbles, draft tube swirl, inter-blade vortex, Karman vortex, and tip vortex (only Kaplan turbines).[20]

Loss of excitation

Loss of excitation is widespread in synchronous machines and, alone, accounts for 70% of all generator failures.[21–23] The loss of excitation is caused by short circuits of the field winding, unexpected field breakers, or relay failures. It can increase rotor speed, causing excessive vibration and bearing overheating. Additionally, as the generator operates as an induction machine, the loss of excitation of one generating unit can impact the whole power system, decreasing active power and increasing reactive power output, which may even result in the collapse of the entire interconnected system.[21]

Loss of excitation is usually enhanced by short-circuit faults of the rotor winding of the synchronous generator, which can also lead to the rotor grounding and shaft magnetization. While short-circuit failures are frequent and occur in most hydro-generators, in the long run, this type of failure causes an increase of the excitation current and, consequently, of the rotor temperature. These effects cause an unbalanced thermal distribution of the rotor magnetic poles that increase the incidence of short-circuit failures and compromise the reliable operation of the generator.[24]

Partial discharge

Partial discharge is the name given to electrical micro-discharges generated in the insulating structure when subjected to high-intensity electric fields. The diagnosis of partial discharge allows accurate assessment of the degree of insulation degradation of the generating system.[25] These discharges can partially or entirely break down the insulation between conductors. The partial discharges produce physical indicators such as light flashes, acoustic noise, temperature gradients, chemical reactions, and electromagnetic pulses.[26]

The partial discharges originate from aging deterioration, moisture pollution, or inadequate design. In generators, partial discharges can occur due to gaps in the ground-wall insulation or to degradation of the corona shielding. The identification and source separation of the partial discharges are complex tasks, and require intense adoption of pulse shape analysis and statistical/artificial intelligence techniques.[27]

Shaft, bearing, and other components' failure modes

Shaft misalignment is a significant problem in hydropower systems as it may lead to a series of vibration patterns that are adverse to steady and safe operation, contributing to accelerated wear of the components, shaft deformation, and deflection of the shaft coupling.[28] Misalignment is not an exclusive fault of the shaft; it can also be present in guide vanes, runner blades, or rotors.[29]

Each turbine-generator auxiliary system presents specific failure modes and specific monitoring variables such as the cooling and lubrication system,[30] turbine governor,[31] power converter,[32] servo-valve,[33] and pressure tubes.[34] All these failures detrimentally impact the hydroelectric operation.

Some studies model failure modes by sub-systems, and present them in an organized and interconnected way through hierarchical models.[35–37] While we highlight the phenomena recurring the most frequently in the literature, we recommend consulting these studies to comprehend the failure modes by sub-systems and their interactions.

Data acquisition

Data acquisition is the capturing and storing of monitoring data from several sensors installed in the monitored asset. Below, we list the sensors and variables monitored in the hydroelectric sector, associating them with the types of failure modes.

Table 3 presents a detailed overview of CBM systems. The publications were grouped by monitored objects and variables, listing the failure modes that the systems can identify. The systems were assigned to one of the following contexts, depending on the nature of the monitored variables: air gap eccentricity, electrical signature analysis, multi-source, structural health, or vibration monitoring. The following subsections detail the main ways of monitoring and acquiring data in CBM systems in the hydroelectric sector.

Vibration signal

Vibration monitoring was the most frequent technique in the literature, representing 15 (39.5%) of the 38 CBM models identified in the hydroelectric context – see Table 3. It is estimated that more than 80% of failures and accidents in generating units are detected through vibration monitoring, making the vibration an essential variable of interest for identifying errors and damage to equipment.[62,73]

Vibration monitoring has a broad range of applications in the generator system, since it can detect anomalies associated with mechanical, hydraulic, and electrical failures.[62,69] Examples of failure modes usually detected using this technique are cavitation,[20] rotor unbalance,[51,62,70] rotor misalignment,[69] vortex draft tube,[69] and Karman vortices.[74] Nevertheless, the broad range of vibration monitoring applications can be a notable drawback, as it does not clearly inform what type of problem is occurring. For this reason, it is common for other forms of monitoring to be used in conjunction with vibration monitoring, as seen in magnetic flux density,[41] bearing voltage,[75] and multiple sources monitoring[35] systems.

To measure vibration, accelerometers and acoustic emission sensors are placed in different parts of the machine such as the guide vanes, turbine bearings, draft tubes, or shafts. Each location presents advantages and drawbacks in detecting different types of cavitation: (1) accelerometers in the guide vanes are useful for monitoring entrance cavitation, however accelerometers are not helpful for discriminating erosive from non-erosive cavitation; (2) sensors installed in the turbine bearing can detect erosive cavitation, but filters out transmission characteristics from the runner to the bearing; (3) sensors placed in the draft tube can only detect draft tube swirl cavitation; and (4) sensors positioned on the shaft are able to record the runner's path, but they can still be affected by the excitation of the generator.[20]

Another form of imbalance analysis is shaft orbit monitoring, in which two sensors are placed 90° apart. This arrangement allows description of the movement of the shaft center, extracting geometric, time-domain, frequency-domain, moment, and angle characteristics. This type of vibration monitoring is usually adopted to identify shaft misalignment, mass imbalance, and degradation, as found in several studies.[28,64,65]

When a unit runs under part-load conditions, the turbine cannot achieve optimum flow of the runner inlet and outlet, thus creating a vertex rope in the shaft system. During these unstable operating conditions, the vibration signals are very complex, and damage is more likely to occur to the runner and draft tube system.[70] From laboratory testing, it was estimated that each start and stop procedure causes fatigue damage equal to 15–20 h of stationary operation.[76–78] To better understand the vibration behavior during different operating states, operating conditions are often adopted, using linear models. Operating conditions are key factors that affect the dynamic response of the generating system.[79] Examples of these conditions are active and reactive power, distributor opening, and bearing temperature.[80] An example of an operating condition in vibration analysis is the rotation speed for diagnosing different failure modes.[81]

Air gap eccentricity

Air gap eccentricity is another object of interest in hydro-power generation. It allows the identification of several causes of failures like unbalanced inner forces, stator core shifts, rotor ovality, defects of stator lamination. This variable measures the space between the spinning rotor and the stationary stator in a generator unit, through the application of contacting probes or proximity sensors.[39]

The air gap monitoring system assesses rotor eccentricity and can identify shorted turns on the rotor pole winding. Static eccentricity is associated with the wrong positioning of the rotor or stator during operation or assembly. In contrast, dynamic eccentricity is associated with thermal expansion, bearings wear, shaft line bend, and rotor displacement by higher magnetic forces. Before air gap analysis, the standard way to determine the existence of shorted turns was the pole drop test. This test required stopping and partially disassembling the generator unit, and measuring the voltage drop across each pole.[40] With the recent developments of measuring systems, air gap online monitoring is now possible through the introduction of flux sensors on the stator core teeth.

The main types of measuring systems use: (1) contacting probes in no-load mode which, although precise, is not suitable for continuous monitoring since it requires stopping the generator and running the tests manually; (2) non-contacting capacitive proximity sensors, widely adopted and commercially available; and, (3) non-invasive measuring systems, which present enormous potential but are still in development. Recent experiments with slow-speed generators indicate that the non-contacting capacity proximity sensors provide measurements almost as precise as the ones measured by invasive contacting probe sensors.[39]

Air gap monitoring is not proposed as a stand-alone application, but as a complementary source of information in integrated, multi-parameter CBM systems. The similarities in the spectra of the variables evidence the connection between the air gap and vibration variables.[39] The study has shown that the results for air gap and vibration spectra should be analyzed together for more accurate evaluation of hydropower generator condition. However, further investigation in future studies and the definition of reliable evaluation criteria of the air gap spectrum is required.

Electrical signature analysis

Electrical signature analysis evaluates the current and voltage profiles of a generator in the frequency domain. It is a non-invasive technique that has been applied increasingly to CBM in hydro-electrics, to detect inter-turn short-circuit, air gap eccentricity and rotating diode failures. As it depends only on electrical measurements, the method has high technical and economic feasibility.[48]

Table 3. Summary of CBM models applied to the hydroelectric context, including monitored object, variables, and type of application – (D) Diagnosis, (P) Prognosis.

Reference	Context	Object	Failure mode/failure mechanism	Monitored variables	T
Valavi et al.[38]	Air gap	Rotor winding	Inter-turn short circuit	Air gap flux density, phase voltage	D
Griscenko and Elmanis-Helmanis[39], Babić et al.,[40] and Dirani et al.[41]	Air gap	Stator winding	Magnetic unbalance	Magnetic flux and vibration spectrum	D
Ramírez-Niño et al.[42]	Electrical	Generator	Impendence asymmetry between phases, mechanical defects	Neutral current	D
Abdel Aziz et al.[21] and Joseph et al.[32]	Electrical	Generator	Loss of excitation, power converter failure	Terminal voltage and stator current	D
Blanquez et al.43,44 and Pardo et al.45	Electrical	Rotor winding	Ground fault	Field-winding voltage and grounding voltage	D
Oliveira et al.[26], Dallas et al.[46], Carvalho et al.,[47] and Salomon et al.[48]	Electrical	Stator winding	Partial discharge	Voltage from different phases and points of measurement	D
Guo et al.[31]	Electrical	Turbine governor	Defective components	Current, frequency, gate displacement	D
Xu[49]	Multi-source	Generator	Winding, electromagnetic, structure, oil cooling failures	Current, voltage, power (active, reactive), insulation resistance, temperature, temperature oil, vibration, sound	D
Blancke et al.[50]	Multi-source	Generator stator	Partial discharge, erosion, insulation degradation, etc.	Expert knowledge and diagnostic data	P
Wu et al.[29]	Multi-source	Turbine	Cavitation, mass unbalance of the rotor, oil whirl, vortex in draft tube, rotor misalignment, guide vane uneven, and runner blade uneven	Governor, excitation, vibration, ground current, pressure, voltage	D
Cheng et al.[35] and Xu et al.[51]	Multi-source	Turbine	Several	Several	D
Selak et al.[30]	Multi-source	Thrust bearing	Overheating, lubrification consumption, cooling system failure, degradation	Output power, rotation frequency, temperature, oil level, oil temperature, velocity	D
Mateja et al.[13] and Klun et al.[52]	Structural	Dam and bearing structure	Hydraulic faults, fatigue	Vibration signal	D
Mazzocchi et al.[34]	Structural	Pressure tunnels and shafts	Wall stiffness drop	Pressure wave reflections	D
Milic et al.[53]	Temperature	Rotor poles	Overheating	Temperature by infrared radiation	D
Kanegami et al.[25]	Temperature	Stator winding	Partial discharge	Resistance-temperature sensor readings	D
Lu et al.[54] and Wang et al.[55]	Vibration	Draft tube	Vortex strip	Upper/lower guide bearing vibration, turbine guide vibration	D
Peng et al.[56], Cheng et al.[57], Zhu et al.[58], Xia et al.[59], Xia and Ni[60], Xia et al.[61], Cheng et al.,[62] and Fu et al.[63]	Vibration	Generator	Rotor unbalance, rotor misalignment, rubbing, movement collision, and vortex draft tube, Karman vortice	Vibration spectrum	D
Xu et al.[28] and Luo et al.[64]	Vibration	Generator	Shaft misalignment, mass unbalance	Displacement (orbit), water head, turbine flow, guide vane opening, rotation speed, generator rotor	D

(continued)

Table 3. Continued

Reference	Context	Object	Failure mode/failure mechanism	Monitored variables	T
Pino et al.[65]	Vibration	Guide bearing	Degradation	Vibration displacement (orbit)	D
An et al.[66]	Vibration	Generator	Degradation	Upper bracket horizontal vibration, active power, working head	P
Gregg et al.[18] and Valentín et al.[20]	Vibration	Turbine	Cavitation	Vibration and acoustic emissions	D/P
Xue et al.[67] and Qiao and Chen[68]	Vibration	Turbine	Mechanical faults	Lower bearing vibration and draft tube pressure	D/P
Zhang et al.[69]	Vibration	Turbine	Several (mechanical, electrical, hydraulic)	Vibration from upper/lower guide bearing, water pilot bearing, upper bracket	D
An et al.[70,71] and Zhou et al.[72]	Vibration	Turbine	Vortex	Shaft vibration, lower guide vibration	D

Partial discharge was one of the first failure modes associated with electrical monitoring. The voltage spectrum of different phases undergoes cross talk interference, that can be overcome by clustering the partial discharge pulses according to shape similarity.[27] Using signal decomposition techniques, partial discharge pulses can be automatically decomposed and the denoising can be evaluated from the time shift difference and noise threshold levels.[47] These approaches can better filter out wide-band noise and significantly reduce background interference with the partial discharge measurement of hydro-generators.

The inter-turn short-circuit diagnosis also benefits from the development of systems based on the electrical signature. The spectral analysis of stator voltage and current can be applied to detect early stage, rotor inter-turn faults.[38] This is possible since some of the signal harmonics amplitudes increase only when this kind of fault develops.

Several factors such as over speeding, vibration, excessive field currents, reduced cooling, and temperature rise expose the field winding to abnormal mechanical and thermal stresses. These stresses lead to breakdown of the insulation of the field winding and the rotor iron at points where stress is maximum, thereby generating a ground fault. While a single ground fault does not represent any immediate danger, high currents and mechanical imbalances can severely harm or even melt the rotor if a second fault arises.[44]

Temperature

Temperature sensors, such as the resistance temperature detectors, are commonly found in power generation systems, presenting significant advantages such as stability, repeatability, and accuracy.[82] Temperature variations are excellent indicators of impending failure conditions. In generator systems, temperature monitoring is usually associated with bearing monitoring: the bearing being the machine component that supports shaft rotation. In the event of failure of the lubrication system or defect in the shaft (i.e. misalignment, vibration overload, or speed), the bearings absorb the thermal overload and prevent damage to vital components of the system.

In the design of a generating unit, the maximum operating temperatures are defined from technical test simulations. Generation is stopped as soon as the limit is reached. However, temperature monitoring has low latency, which makes it reactive. Frequently, once the temperature trip alarm is triggered, the fault (or set of faults) has already occurred. A recent solution adopted contactless infrared detector measurements for online monitoring of the surfaces of water-cooled rotors poles.[53] From the time-frequency analysis of the resistance-temperature sensor, the stator winding discharge detection can be improved, as the phase angle can aid in distinguishing signals from noise.[25]

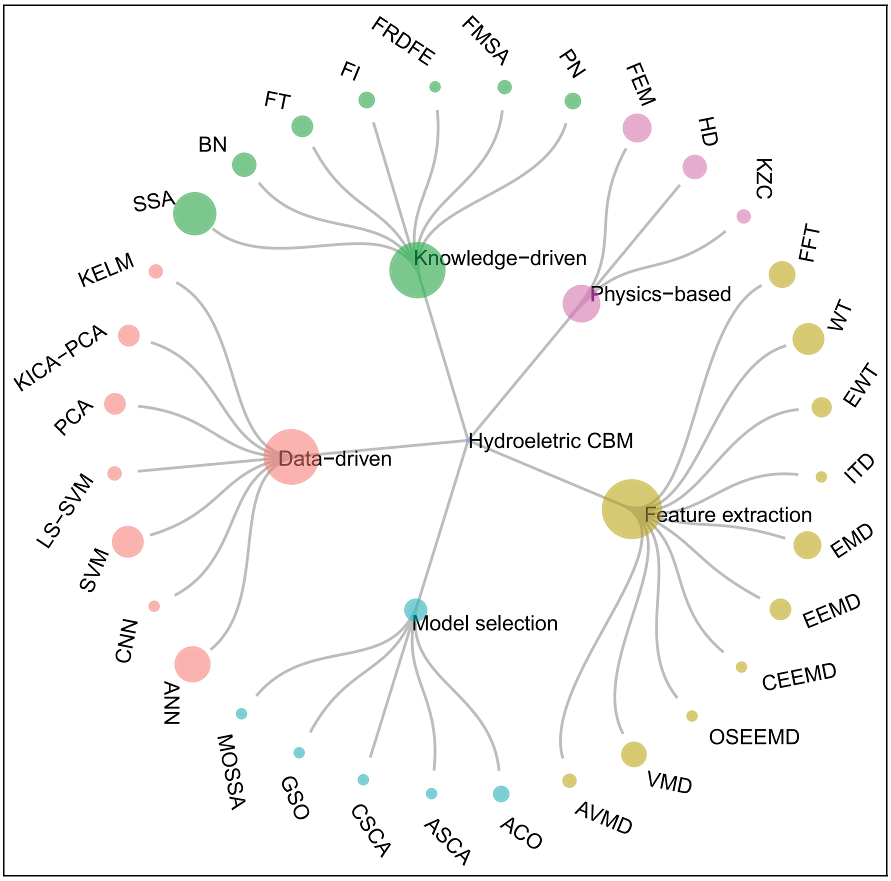

Figure 4 Dendrogram with the most used techniques in CBM models for HS. The size of the nodes represents the number of articles associated with each term.

Temperature is also adopted as a condition parameter for estimating other variables. A three-dimensional mathematical model relates the temperature, thermal deformation, and thermal stress of magnetic poles fields, in the rotor winding inter-turn short circuits. The shorted turns decrease the temperature of magnetic poles, indicating that diagnosis can be obtained by monitoring the temperature change of the rotor.[24]

Structural health monitoring

Structural health monitoring assesses the health of the structures that constitute a hydroelectric generation system, such as the powerhouse or the dam. This is vital for preventing structural damage that could collapse the entire system. The effects of dam failure, for instance, have substantial social and environmental costs, which makes structural monitoring so critical and necessary.

Vibration monitoring is commonly associated with structural assessment. In hydroelectric structures, vibration is also applied to diagnose critical structural components. A two-step model can identify the modal order and the characteristic of dams under operation, with the dynamic response of the hydraulic structure excited by fluctuations in flow load.[83] Through modeling the interaction between the unit shaft system and the powerhouse structure during transient, sudden load increasing process, it is concluded that the generator floor structure is more susceptible to the transient process and to excessive vertical vibration.[84]

The laser Doppler vibrometer (LDV) is a non-contact sensor. It was developed to measure the amplitude and frequency of surface vibration by analyzing the reflected laser beam frequency applied to the surface of interest. The use of LDV, under transient conditions within the concrete dam monitoring context, can contribute to the elimination of pseudo-vibrations and noise from measures inherent in the non-stationary process.[52] A low-level reading of instrument noise is obtained by placing the sensor inside the powerhouse, as regular accelerometers are sensitive to magnetic field excitation. Some solutions such as the use of reflective tapes, adoption of standing points that are more rigid than the observation point, and instrument visor shading are proposed to minimize ambient noise.[13]

Multi-source

While most of the work in the CBM area is related to monitoring a specific type of variable, there is a tendency to develop models that simultaneously monitor variables of different natures. This monitoring process, taking input from multi-modal sensors, is known as sensor fusion. It seeks to develop collaborative distributed systems.[85]

Some studies have been successful in applying multivariate monitoring systems in the context of hydroelectric maintenance. An example is the control system based on the combine input of 12 different types of sensors, such as accelerometers, inductive displacement sensors, inductive switches, pressure sensors. In total, 108 attributes were extracted and used to create a classification model of approximately 97% accuracy.[30] Other applications have applied nineteen variables such as tank level, rotor and bearing temperature and vibration, excitation current and voltage, runner speed, among others. The model diagnoses 17 failure modes, hierarchically grouped in the bearing, rotor, and stator sub-systems, and sequentially grouped in two root nodes: dynamo system and hydro turbine.[35]

In the context of structural health monitoring, several factors can influence the behavior of the system. Hydro-power dam dislodging, for instance, is affected by different elements such as dam maturing, store water level, air, water, and stable temperature, which cause complicated, nonlinear behavior that is hard to foresee. Additionally, natural external factors such as earthquakes and ice pressure interfere with the structural monitoring models and reduce their accuracy. A multivariate approach considered a set of these external variables: air temperature, water temperature, concrete temperature, displacements between dam blocks, inclination of dam blocks, uplift water pressure, and underground water pressure.[14] The model presented accuracy in the short term; however, the biggest limiter for the long term was the climatic forecast, especially concerning precipitation and air temperature, which directly influence the water level and the concrete temperature.

Feature extraction

Among the feature extraction techniques found in the sampled literature, the fast Fourier transformation (FFT) and the wavelet transform (WT) were the most used for feature extraction. They are useful for transforming signals from the time domain to the time-frequency domain. The magnitude and phase signal decomposition of each frequency component can contribute to a set of fault patterns for machine diagnosis: a detection system can promptly identify faults by monitoring the increase of the values of certain higher harmonics in the signal spectrum. Examples of applications that have adopted FFT for feature extraction can be found in the literature.[40,52,59,60,86] Figure 4 presents a dendrogram with the most used techniques in CBM models for HS.

The vibration signals produced by hydro-power plants in unstable operation situations are extremely complicated.[70] The FFT signal analysis method is ineffective for dealing with the non-stationary signals nature of these signals. WT offers a better time-frequency analysis function.[70] However, since WT is also based on the FFT with an adjustable window, there will be energy leakage inevitably.[70]

For overcoming this limitation, other feature extraction techniques have been proposed and applied in the hydroelectric CBM context. Intrinsic time-scale decomposition (ITD), empirical mode decomposition (EMD), and the ensemble of empirical mode decomposition (EEMD) are all self-adaptive signal decomposition methods proposed for analysing nonlinear signals. The application of ITD with a classification algorithm has shown better results than the application of the classification algorithm.[66] The analysis results indicate that this method has good performance in eliminating the residue noise and reducing the costing time, which also provides more accurate decomposition results than the original ensemble empirical mode decomposition.

Several versions of EEMD, such as the noise-assisted method complementary ensemble empirical mode decomposition (CEEMD) and the over-sampling ensemble empirical mode decomposition (OSEEMD), have been proposed for feature extraction in hydroelectric generator, to obtain more accurate decomposition sets while keeping computational costs at a minimum.[67] The adaptive local iterative filtering (ALIF) method uses an iterative filtering strategy with an adaptive, data-driven filter length selection to decompose the signal, inhibiting the mixing mode inherent in EMD.[70] More recently, empirical wavelet transform (EWT) was adopted to decompose the signal in multiple components. EWT presents higher accuracy mode estimation at significantly reduced computation time, compared to EEMD and EMD.[87]

Finally, variational mode decomposition[71] (VMD) and adaptive variational mode decomposition[63] (AVMD) are pre-processing methods used to decompose the signal into a set of intrinsic mode components with limited bandwidth. The AVMD automatically determines the mode number, based on the characteristic of intrinsic functions, using a set of indexes: entropy, extreme value, kurtosis criterion, and energy loss coefficient.

Diagnosis

Data-driven

In fault diagnosis applications using supervised learning algorithms, the data is labeled by specialists as either healthy or faulty. The labels can also be obtained using technical tests in which specialists design specific failure situations that seek to differentiate the algorithms. The algorithms can adopt a multi-class approach, seeking to determine not only if there is a failure, but also what type of failure it is such as misalignment, vortex with eccentricity, or shaft imbalance.

The learning algorithm most frequently found in our literature sample is the artificial neural network (ANN). This is a nonlinear model, widely used in the area of machine learning, that is capable of mapping fault symptoms to a set of source failures. A more elaborate architecture, that considers temporal dependency between observations, the application of one-dimension convolutional neural networks (CNN), has been proposed.[88]

However, there are some limitations to the application of ANN: the low speed of convergence and the high sensitivity to initial parameters. To circumvent these, some authors propose applying heuristic optimization algorithms such as the ant colony optimization[74] (ACO) and the cuckoo search[62,89,90] (CS). The aim is to decrease the training instability and increase the generalizability and convergence speed of the model. Other data-driven methods found in the literature are the support vector machine[60,81] (SVM) and the principal component analysis[18] (PCA).

Failure diagnosis in hydroelectric plants can also be seen as a nonlinear, multivariate process. Conditions are monitored and faults are detected online if the process deviates from normal operating conditions. The kernel independent component analysis and principal component analysis (KICA-PCA) method is used for this, to extract and reduce the dimensionality of independent components. These are combined with the confidence limits of the Hotelling's T^2 and SPE statistics to evaluate the normal condition.[58]

Among the stability models of hydroelectric units, the application of computational intelligence methods for regression of the vibration and pressure variables, such as ANN and the least square support vector machine[68] (LS-SVM), is becoming more commonplace. The main advantage of these models is their ability to generate nonlinear mapping of the stabilization parameters, providing more accurate models for predicting the output parameters.

Knowledge-driven

Knowledge-based models are built from the input of experts and technicians, and seek to consolidate tacit knowledge in intelligent decision-making systems.

Spectral signal analysis (SSA) is one of the techniques most frequently applied by specialists to detect anomalies. This technique consists of analyzing the harmonics that make up the signal. From their observations, the experts formulate basic operating conditions to be met. The latest developments in the area seek precisely to enable intelligent algorithms to learn to define them, with or without human intervention. The spectral analysis is applicable to vibration signals,[70,71] neutral current,[42] air gap,[39] and partial discharge.[26]

Fuzzy inference (FI) systems are capable of assigning a set of reference rules to represent the relationship between the fault phenomenon and the fault reason, in a concise and interpretable way. They can be applied either alone[49] or together with machine learning models like, for instance, SVM[69,81] or ANN.[21] Fuzzy theory is widely applied in the industrial sector, adding artificial intelligence agents to the regulation and control of resource activities with the adoption of the fuzzy recursive decision feedback extension[91] (FRDFE) models.

Another knowledge-based approach to multi-fault diagnosis is the construction of system fault trees (FT) and their components. Failure probabilities are interrelated using logical AND and logical OR conditions in a tree hierarchy. The FT starts with the failure mechanism and is grouped into components, sub-systems, and, finally, the whole system. Subsequently, the calculated probabilities feed a Bayesian network (BN) in which the model receives input from maintenance experts.[36] In this framework, current advances seek to construct the BN model from the perspective of machine learning and the experience of specialists, into a model capable of expanding or reducing according to the size of the hydroelectric station and the requirements of maintenance personnel.[35]

Physics-based

Physics-based approaches are generally mathematical models built from the premise that there are underlying, deterministic phenomena that influence the generation system. The modeling is focused on a specific component (or group of components). The adoption of simplified models, such as the influence of bearing stiffness[92] and hydraulic dynamics[84] on the monitored vibration, can generate satisfactory results when the operating condition is appropriately determined.

The stability modeling of a generator system is obtained from the vibration of the unit and conversion efficiency. It seeks to establish bases for the safe and stable operation of hydroelectric stations during the transient processes. A unified mathematical model for the sensitive analysis of turbines is approached from three aspects: hydraulic, mechanical, and electrical. The confidence interval of the variable is estimated from computational simulations. The new observations are monitored using the mathematical model and, if the confidence limit is exceeded, it is considered an anomaly.[28,93,94]

The Kutta-Zhoukowski conditions (KZC) can be applied to the input and output velocity vectors and unbalanced forces to estimate the normality curves of the vibration and efficiency variables.[95] In this type of model, a challenge arises from the sensitivity influence of the initial conditions on its performance. The Hamiltonian dynamic (HD) can also be used to describe the dynamic evolution of the energy produced, dissipated, and supplied in an operating, multi-generator system.[96] Finally, a three-dimensional mathematical formulation of the temperature and thermal stress fields of the magnetic poles of the rotor can be used for stability estimation. The model is based on the theory of heat transfer and its resolution is obtained using the finite element method (FEM). Unlike previous models that acted generically, this one is specific to the type of rotor winding inter-turn short circuit failure.[24]

Prognosis

Prognosis seeks to estimate the useful life of an asset and establish a confidence interval for that estimate. In the hydroelectric context, prognosis consists of forecasting a given variable of interest, such as vibration, pressure, or the calculated health index, within a timeframe feasible for interventions in the system. An example of a prognosis system is based on the application of Shepard's interpolation of three variables, bearing vibration, apparent power, and working head, to construct the health index of the generator unit. Applying ITD, the signal is decomposed into a finite number of rotating components. An ANN is trained for each of the temporal components intrinsic to the signal, while the first order gray model predicts the trend of the series. Finally, the individual forecasts of each temporal component are summed together into a single forecast for the original series.[66]

Later models present a similar framework, with varied individual methods. Signal decomposition can be obtained through the VMD, optimizing the meta-parameters using the least-square error index. The LS-SVM regression model can substitute for the ANN, and the model is fine-tuned using either the chaotic sine cosine algorithm (CSCA) or the adaptive sine cosine algorithm (ASCA).[63,97] The signal pre-processing, feature selection, and prediction steps can also be condensed into a single, multi-objective optimization framework. The EWT to decompose the signal into several modes, along with an entropy-based sample reconstruction strategy, refactor the modes. Variables are selected using the Gram-Schmidt orthogonal (GSO) process, and each series is extrapolated using the kernel extreme learning machine (KELM) method. A multi-objective salp swarm algorithm (MOSSA) adjusts the hyper-parameters of both the GSO and KELM models from the bias-variance indices.[72]

Other forms of prognosis can be developed from hybrid models involving knowledge- and data-driven methods. An example is the application of failure mechanism and symptoms analysis (FMSA) and Petri nets (PN) to predict the occurrence of degenerative states. This approach predicts the applicable time interval for maintenance tasks, based on the occurrence and propagation of known failure modes.[50]

Discussion and conclusions

The present paper has provided a systematic overview of the state-of-art of CBM models for the hydroelectric sector. The discussion is summarized according to five categories: common failure modes, data acquisition, feature extraction, diagnosis, and prognosis. Machine learning algorithms associated with time-frequency decomposition have been playing an important part in publications in this area in the last decade. The advantage of these models is that they do not require extensive human work or specialist knowledge, since the end-to-end structure is capable of mapping raw data with the associated failure classes. In addition, some research trends and potential future directions are given, as follows:

- *Multi-source data acquisition*: Vibration monitoring clearly predominates in the models proposed in recent years. Nevertheless, combining other variables such as temperature, electrical signature, pressure, and acoustic emission in multi-source systems is a trend in the research, given the capacity of these other variables not only to identify other failure modes that vibration does not capture, but also to help in classifying the type of failure. Studies associating the feature importance of monitored variables with the types of failure, like cavitation[18] and partial discharge,[98] can guide the design of new hydroelectric CBM systems.
- *Hybrid models*: The explainability of data-driven models, or machine explainability, offers the potential to provide insights into model behavior using various methods such as visualization, feature importance scores, counterfactual explanation, or influential data.[99] This type of approach requires continuous interaction with specialists who have expertise in the knowledge domain, from the discrimination of attributes to the continuous feedback of the system, to articulate new anomalies as they arise. From the adoption of simple mathematical models and expert judgment, the model shows great improvement in its accuracy.[36,92]
- *Deep learning techniques*: Machine learning models currently predominate in the hydroelectric CBM models. In the next decade, it is expected that the application of deep learning techniques will become more common in the area.[8] These techniques may include auto-encoders, restricted Boltzmann machines, convolutional neural networks, and recurrent neural networks. In recent years, due to their high accuracy in large-scale machinery datasets,[6] these techniques have been widely applied in the context of asset health management.
- *Health management and prognosis*: Reports on the prognosis of hydroelectric generating units are still scarce in the literature. Most studies present a very restricted framework for estimating the useful life of the generating unit. For example, there is a range of statistical methods such as the Wiener and Gamma process, also the stochastic filtering-based, hidden Markov models, that are used in prognosis and could be applied to this specific problem. Another important challenge in the area is to propose approaches that consider the interaction among faults between different generating units and auxiliary systems interconnected in the same generation system.

In conclusion, development of CBM technical applications in the energy sector is a trend that has been evident in recent years. It is gradually transforming the entire sector in the Industry 4.0 context. With the maturing of the different monitoring types, that is, electrical signature and structural monitoring, it is natural for diagnostic systems to take the next step toward prognosis. The next step in the development of maintenance systems does not depend on the adoption of a single technology but on the interactions between intelligent systems and human specialists, complementing each other's strengths in striving toward a common goal.

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ORCID iD

Rodrigo Barbosa de Santis https://orcid.org/0000-0001-8454-4512

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Appendix

Abbreviations

The following abbreviations are used in this manuscript:

ACO	ant colony optimization
ANN	artificial Neural Network
ASCA	adaptive sine cosine algorithm
AVMD	adaptive VMD
BN	Bayesian network
CBM	condition-based maintenance
CEEMD	complementary EEMD
CNN	convolutional neural network
CS	cuckoo search
CSCA	chaotic sine cosine algorithm
EEMD	ensemble of EMD
EMD	empirical mode decomposition
EWT	empirical WT
FFT	fast Fourier transform
FI	fuzzy inference
FMSA	failure mechanism symptoms analysis
FRDFE	fuzzy recursive decision feedback extension
FT	fault tree
GSO	Gram-Schmidt orthogonal
HD	Hamiltonian dynamic
HS	hydroelectric systems
IoT	internet of things
ITD	intrinsic time-scale decomposition
KELM	kernel extreme learning machine
KICA-PCA	kernel independent component PCA
KZC	Kutta-Zhoukowski conditions
LDV	laser Doppler vibrometer
LS-SVM	least square SVM
MOSSA	multi-objective salp swarm algorithm
OSEEMD	over-sampling EEMD
PN	Petri net
PCA	principal component analysis
SLR	systematic literature review
SSA	spectral signal analysis
SVM	support vector machine
VMD	variational mode decomposition
WT	wavelet transform