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Review article

A review of vibration analysis and its applications

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ABSTRACT

Vibration Analysis (VA) is the most commonly used technique in predictive maintenance. It allows the diagnosis of faults, especially those in the early stages. The use of VA is important for maintenance costs and downtime savings, making decisions about repair and total replacement. The method has been applied in many industries and proven to be effective. It is applicable to rotating, non-rotating equipment, continuous processes or even construction structure. In this paper, vibration analysis fundamentals as well as many studies on the method's application are reviewed. The purpose is to give an overview of how vibration analysis is used in many industries including petroleum to show its potential in petroleum industry. VA has been used in many areas from transportation, refinery to drilling and production. However, there are still rooms for improvement and implementation. One potential application is detecting faults in Electric Submersible Pump (ESP) system. ESP is located downhole making it susceptible to faults and defects that could be difficult to detect using conventional methods. These faults and defects could lead to reduced pump performance or even complete failure that require replacement. Thus, it is important to monitor and analyze vibration of ESP components, specifically pump and motor. Different studies on the topic are also reviewed and discussed. Some studies have been conducted showing that analyzing ESP vibration data helps predict early problems and identifying the causes. Vibration data were also used in principal component analysis models to predict and identify problems as presented in some works. However, principal component analysis could discharge the data models to be unable to correctly predict and determine the faults. VA is a practical technique to monitor and diagnose machine's health. It is important to research VA further and apply it more in petroleum industry, especially in production system. Applications of VA could increase machine's lifespan, reduce maintenance cost and would be useful in optimization.

1. Introduction

Non-intrusive maintenance and early diagnosis of faults in machines as well as construction structure are important for maintenance cost and downtime savings. They also play important roles in making decision about repairing and total replacement of the machine or construction. Machine faults can be roughly divided into four groups: bearing faults, stator-related faults, rotor-related faults, and other faults [1]. In construction structure, faults are usually related to structure stability and strength (e.g., cracks).

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Failure to detect faults could lead to premature failure of a machine or construction or even a more catastrophic consequence. Among predictive maintenance methods, Vibration Analysis (VA) is the most common one.

VA has been around for decades and applied in many industries and areas such as power generation [2], cement plant [3], aircraft [4], civil construction engineering [5,6] to maintain the best efficiency and operating conditions. VA is applicable to rotating, non-rotating equipment, continuous processes or even construction structure. Some applications of VA are acceptance testing, quality control, loose or foreign part detection, leak detection, aircraft engine analysis, machine design and engineering [7]. VA is the most effective way to detect mechanical defects in rotating machinery [8].

Some applications involve pipeline or refining system, while others are in drilling and production area to optimize operations or identify faults in production systems (e.g., ESP system). Minette et al. [9] stated that VA is the most precise method to detect and prevent faults in ESP and it is the main method used to quantify ESPs' mechanical quality.

Electric Submersible Pump (ESP) is a widely used artificial lift method for lifting large volume of fluids from wellbores. The ESP components consist of surface and subsurface equipment (electric motor, protector, pump and cable) as shown in Fig. 1. Because most of the ESP system are located downhole, it is prone to faults and defects. Mubarak et al. [10] presented that motor and pump failures are very common (Fig. 2). Because of considerable lengths and small axial diameter, ESP system is prone to vibration problems. According to Regres et al. [11], vibration is the leading cause of failure in ESP systems. Faults in the systems could cause significant loss in production rate and eventually require intervention or installation of new pump. Hence it is useful to monitor and analyze vibration of ESP components, specifically pump and motor.

In this paper, a review of VA and its application in many industries including petroleum are presented. The purpose is to give an overview of VA fundamentals and how it has been applied in real applications to show the potential of using VA in petroleum industry.

2. Vibration analysis fundamentals

A predictive maintenance uses data analysis tools and techniques to detect possible failures in advance. Among various predictive maintenance methods, vibration monitoring is the most powerful tool [7]. Vibration data reflect conditions of mechanical equipment. Analyzing them helps detect abnormal operating conditions and early faults that can gradually become severe and affect performance of a machine. Maintenance plans could be made in advance to reduce downtime when the machine is shutdown for maintenance or replacement.

Vibration is a movement relative to a reference position caused by a force. It can be random or periodic. Machines produce some oscillatory motion during their normal operation. These are benign vibrations (e.g., blade passing frequency, gear mesh frequencies, broadband turbulence from fluid-handling machines). The amplitudes of the vibrations vary from machine to machine and depend on load condition. If the amplitudes are above normal levels, these vibrations will cause accelerated wear or premature failure and should be taken care of. In addition, each mechanical fault generates a specific vibration pattern depending on the geometry of the machine and operating condition. Hence, VA plays an important role in monitoring machine health, identifying failing elements and predicting

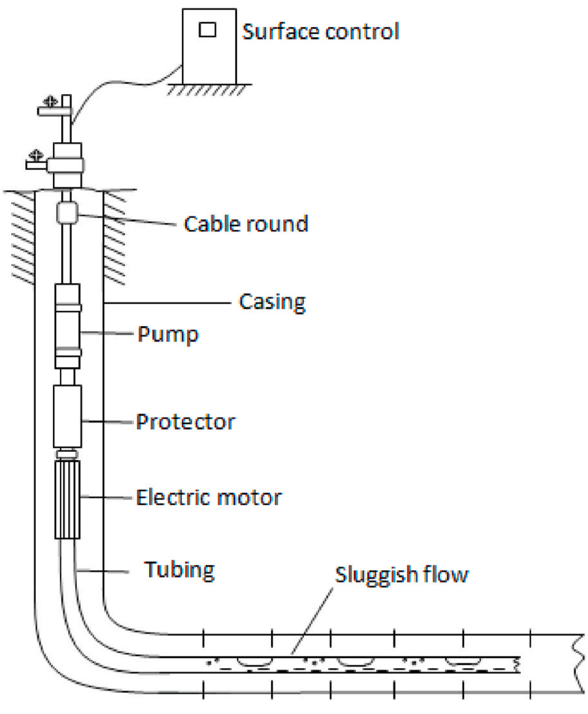

Fig. 1. Schematic of an ESP system [12].

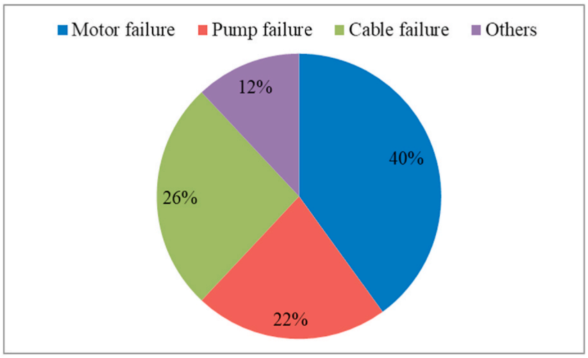

Fig. 2. Common ESP failures in Mubarak et al. [11] case study.

potential failures. The fundamentals of vibration have been thoroughly discussed [7,8].

2.1. Vibration profile

Motion can be divided in to harmonic motion and nonharmonic motion. Harmonic motions repeat themselves every complete cycle. On the other hand, nonharmonic motions represent superposition of motions from numerous sources with different frequencies. Given X_1 and X_2 are two vibration displacements with different frequencies:

$$X_1 = \mathrm{asin}\ (\omega_1 t) \tag{1}$$

$$X_2 = \mathrm{bsin}\ (\omega_2 t) \tag{2}$$

where a and b are maximum displacements or amplitudes, ω_1 and ω_2 are circular frequencies and t is time.

The total vibration, which is the sum of the two vibrations above is as follows:

$$X = X_1 + X_2 = \mathrm{asin}(\omega_1 t) + \mathrm{bsin}\ (\omega_2 t) \tag{3}$$

Any vibration can be shown as a series of sine functions with the circular frequencies (i.e., ω_1, ω_2) are referred to as the harmonics of the primary frequency ω. The equation is also known as a Fourier Series. A_1, A_2, etc. are the amplitudes if the various discrete vibrations and Φ_1, Φ_2, etc. are their corresponding phase angles. The terms 2ω, 3ω etc. reflect the harmonics of the primary frequency ω.

$$f(t) = A_0 + A_1\ \sin(\omega t + \Phi_1) + A_2\ \sin(2\omega t + \Phi_2) + A_3\ \sin(3\omega t + \Phi_3) + \ldots \tag{4}$$

A vibration profile can be displayed in time domain and frequency domain. A time domain profile (or waveform) shows amplitude versus time (Fig. 3). The sum of vibration signal is used to represent total displacement at any given time. Hence it is hard to identify a particular source of vibration. However, time domain data are still useful in overall analysis. A frequency domain profile (or spectrum), on the other hand, shows amplitude versus frequency (Fig. 4). It is obtained by converting a time-domain profile using Fast Fourier Transform (FFT) algorithm. FFT allows vibration signals to be shown as discrete frequency peaks. Identifying these frequency peaks is very crucial in VA.

FFT is the most common processing technique. Some steps in processing signals using FFT algorithm are analog signal input, anti-alias filter, analog to digital converter, windows, FFT and averaging. Sampling is generated based on recorded vibration signature at given instants. The rule is to sample at a frequency rate of at least twice the highest frequency component of interest to avoid losing any information in a sampled signal. Undersampling results in vibration signature of a lower frequency instead of one that could represent

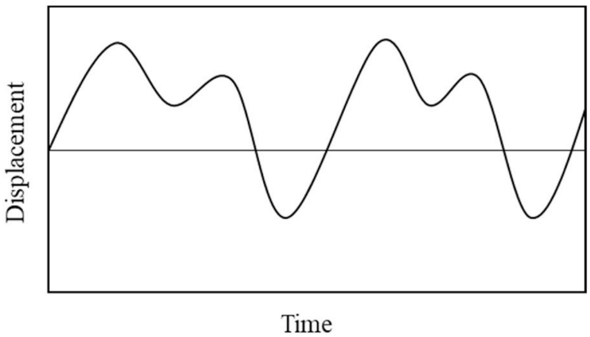

Fig. 3. An example of time domain vibration signature.

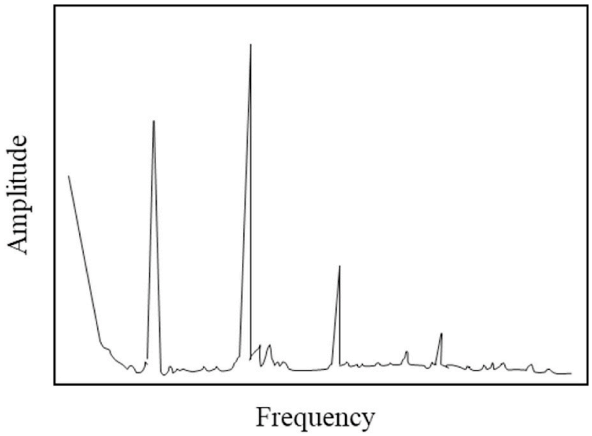

Fig. 4. An example of frequency domain vibration signature.

the actual wave. This phenomenon is called aliasing. Anti-alias filter removes all vibrations that have frequencies higher than half of the sampling rate. The signal, which is in analog, is then converted to digital values for further processing. Because sampling is done in fixed time intervals, actual wave could be truncated at its start and end leading to discontinuities in the waveform. To avoid that, windowing is applied. Windowing is the process of multiplying the signal sample by a window function of the same length. Averaging helps interpreting noisy and complex vibration signature easier. Some types of averaging are linear averaging, peak hold, exponential, synchronous time averaging.

There are many other techniques to process vibration signals for analysis. Depending on certain vibration signals and monitored targets, different techniques can be used to achieve good vibration profile with less noise while retaining useful information for analysis. Some of them are discrete Fourier transform, short time Fourier transform, Wigner-Ville distribution, envelope analysis, wavelet transform, empirical mode decomposition, time synchronous averaging methods, filtered based methods, stochastic methods, continuous wavelet transform, discrete wavelet transform, time-frequency scale domain etc. The techniques were reviewed in many works [8,13–15].

Time-frequency domain is commonly used in VA. It has been looked into thoroughly and improved over the decades in many works [16,17]. Different processing techniques (discrete Fourier transform, moving window auto-regressive, harmonic wavelet transform, Wigner Ville and windowed Wigner-Ville) were applied to real experimental vibration data to determine methods that can reduce noises while retaining useful information for analysis. For the particular data, moving window auto-regressive method was not as good as the others.

2.2. Measurable parameters

Time-domain or frequency-domain vibration profile plots are based on measurable parameters. It is important to understand the definitions and applications of these parameters to properly analyze vibration profiles. There are common elements in vibration amplitude curves that can be used to describe a function. They are peak-to-peak, zero-to-peak, and root-mean-square. Peak-to-peak value is the total amplitude of vibrations generated by a machine or a group of components. It reflects the total displacement or maximum energy produced. Zero-to-peak or peak value is half of the peak-to-peak value. Root-mean-square (RMS) is the statistical average value of the amplitude generated by a machine or a group of components. Generally, RMS is equal to 0.707 of the zero-to-peak value.

Three main vibration properties are as follows.

- Amplitude: the maximum value of vibration indicating the severity of vibration in terms of displacement, velocity or acceleration.
  - o Displacement is the change in position of an object relative to a reference point. It is usually expressed in units of mils (0.001 inch) and in terms of peak-to-peak or peak. Typically, displacement is used for motion below 10 Hz.
  - o Velocity is the time rate of change of displacement. It is usually expressed as inches per second (ips) and in terms of or peak or RMS. Typically, velocity is used for motion between 10 Hz and 1000 Hz.
  - o Acceleration is the time rate of change of velocity. It is expressed in units of inches per second squared (in/sec^2) or gravitational constant g and in terms of or peak or RMS. Vibration frequencies above 1000 Hz should always be expressed as acceleration.
- Frequency: the number of cycles of vibration of the contributing source or sources that occur in a specific period of time. Frequency can be expressed as cycles per minute (CPM) or revolution per minute (RPM) where CPM = RPM, Hz = CPM/60 or a multiple of turning speed (TS). In machines, vibrations are related to rotating or moving motions. Hence vibration activities occur at some multiple of TS (in rotating equipment) or change a running speed.

- Phase is the measure of time difference between two events occurring at the same frequency. Comparative phase readings can provide valuable information the pinpoint the specific problem when developing problems are found, given the structure of the equipment is well understood.

Three common classifications of amplitude measurements used in VA are broadband, narrowband, and component. Broadband or overall represents the total energy of all vibrations generated by a machine. Narrowband represents the energy generated by a group of vibration frequencies of choice which can be a filtered band of vibration components, failure mode, or forcing functions. Component represents the energy generated by a unique machine component, motion, or other forcing function can yield its own amplitude measurement.

2.3. *Vibration measurement and formats*

Vibration can be measured by a transducer or a portable vibration analyzer. A transducer can be an accelerometer, velocity pickup or a displacement probe. Each of them has a specific sensitivity and frequency ranges, as well as typical useable conditions. Theory of operation, ranges, advantages and disadvantages of the vibration transducers were discussed thoroughly [8]. A portable vibration analyzer is a device that is capable of mathematically converting electrical signal to acceleration per unit time, store and display the data as well as generate alarms when programmed. Vibration measuring devices should be chosen accordingly depending on the measuring conditions as shown in Table 1.

Vibration data can be acquired and analyzed in static or dynamic, single channel or multichannel format. Steady state vibration data assumes that a machine operates in a steady state condition. These data can be used to determine the relative operating condition of simple machine but do not reflect the machine's dynamic or its vibration profile. Because of that, steady-state data analysis totally neglects vibrations from transient events such as changing running speed. This weakness can be overcome by using real-time data. Single-channel data are acquired in series or one channel at a time. This method assumes that a machine's dynamics and its vibration profile are constant throughout the entire measurement process. It limits the ability to evaluate measurement point relationships on a machine in real-time and changes in operating conditions. This disadvantage can be solved by using multichannel data, in which data are measured simultaneously from all measurement points on a machine.

2.4. *Vibration analysis technique*

Overall velocity is a summation of low frequency vibration. Overall velocity measurement can be used to identify fault conditions (e.g., imbalance, misalignment, looseness, late-stage bearing problem). Analysis of the vibration spectrum can be divided into three areas: sub-synchronous, synchronous and non-synchronous. Vibration signal in each area may reflect a particular vibration source. Spectrum can be divided into frequency bands based on the types of mechanical faults that might appear on the machine as shown in Fig. 5. This practice is useful to recognize different fault types.

- Sub-synchronous energy is less than 1x turning speed (TS) of the shaft and can be used to identify problems with belt frequency, cage frequency, oil whirl, loose roller bearing in housing etc.
- Synchronous energy is related to TS. In other words, synchronous energy is exact multiple integers of TS (e.g., 1x TS, 2x TS, 3x TS). It can be used to identify problems with imbalance, misalignment, gear mesh, looseness, bent shaft, vane pass frequency, resonance etc.
- Non-synchronous energy is not related to TS. It is not equal to any exact multiple of TS of the shaft. It can be used to identify problems with bearings, rolling element defects, electrical, cavitation, pipe, other machine speeds or system resonances etc.

A technique of VA that is extensively used to detect faults in bearings and gearboxes is enveloping and demodulation. The technique focuses on high frequency section of the spectrum by using a high-pass filter which allows capturing peaks that could be lost in the noise floor. There are four primary methods of enveloping and demodulation: PeakVue, Spike Energy, Spectral Emission Energy and Shock Pulse Method. PeakVue is a technique that detects high frequency stress waves generated from metal-to-metal contact. In PeakVue measurement, rotational energy is filtered out to focus on impacting energy. This is useful in identifying mechanical problems such as bearing faults like inner and outer race defects, gear defects, ball defects and under-lubrication. PeakVue is especially useful for detecting rolling-element bearing problems. In PeakVue processing, two types of filters (band pass filter and high pass filter) are used to remove unwanted noise. Band pass filter removes all the data above and below the filter corner value while high pass filter removes all

Table 1
Preferred usage of vibration transducer.

Vibration transducer	Preferred usage
Velocity pickup	General purpose monitoring
Accelerometer	Machines with rolling element bearings or gear sets that generate high vibration frequencies when defective
Displacement probe	Rotating machinery with journal bearing, high speed turbomachinery

Machine's dynamic tends to generate unbalanced forces in one or more directions causing vibrations (whether normal or abnormal behaviors). Hence, vibrations should be measured in radial and axial orientations for accurate determining causes of vibration in a machine.

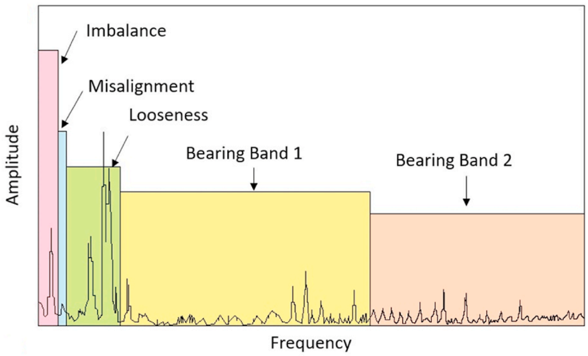

Fig. 5. An example of frequency bands in spectrum.

data lower in frequency to that of the filter selection. Band pass filter can be used when the event of interest is the excitation of a structural resonance, or the modulation of known frequencies such as gear mesh. High pass filter can be used when the goal is to detect stress waves which are emitted by metal impacting. The frequency of choice depends on highest defect frequency emitted from a machine. Note that because conventional vibration signals are filtered from PeakVue signal, all low frequency faults such as imbalance, misalignment, looseness are not indicated in PeakVue [18]. On the other hand, Spike Energy uses a rectifier, signal is enveloped and true peak acceleration values are not presented. Spectral Emission Energy applies enveloping techniques on high-frequency acoustic measurements to diagnose bearing condition. Only high frequency signals remain after the vibration signal is filtered. Shock pulse method measures the shock pulse signal upon the impact of a roller with a race defect. The transducer reacts with a large amplitude oscillation to the weak shock pulses meaning only its natural frequency at 32 kHz is recorded while lower frequencies are filtered out [8].

There are different techniques to analyze vibration profiles including trending, comparative analysis and signature analysis [19, 20]. To accurately and efficiently analyze vibration profile, a combination of the techniques is essential. Trending technique is applicable when vibration data are normalized to avoid the impact of changes in different variables (e.g., load or running speed). Trend data reflects changes of a machine over time. A change in amplitude could indicate a corresponding change in operating condition.

Trending technique can be used with broadband or narrowband data. In broadband data is useful for establishing alert limits to monitor the overall condition of a machine. However, the data type does not indicate specific frequency components, limiting its value in isolating and identifying problems. On the other hand, narrowband data can reflect vibration data of specific frequency components making them more useful in detecting problems, especially in early stages.

Comparative analysis is comparing two or more data sets to identify changes in the operating condition. This technique is only applicable on time-domain or frequency-domain data and cannot reflect a machine's dynamics. To conduct comparative analysis, a baseline data must be acquired when a machine is in normal condition to monitor it. The data need to be updated every time the machine is repaired. Baseline data is used as a reference to compare future data sets. Occasionally, a vibration profile from the monitored machine can be compared to that from another similar machine with known operating condition and problem. This practice allows determination of problems if the vibration profiles are similar. Future data can also be compared to industrial standards (Tables 2–4) or reference values.

Table 2
Published vibration severity standards [21].

Machine			Class I	Class II	Class III	Class IV
	in/s	mm/s	small machines	medium machines	large rigid foundation	large soft foundation
Vibration Velocity Vrms	0.01	0.28	good	good	good	good
	0.02	0.45	good	good	good	good
	0.03	0.71	good	good	good	good
	0.04	1.12	satisfactory	good	good	good
	0.07	1.80	satisfactory	satisfactory	good	good
	0.11	2.80	unsatisfactory	satisfactory	satisfactory	good
	0.18	4.50	unsatisfactory	unsatisfactory	satisfactory	satisfactory
	0.28	7.10	unacceptable	unsatisfactory	unsatisfactory	satisfactory
	0.44	11.2	unacceptable	unacceptable	unsatisfactory	unsatisfactory
	0.70	18.0	unacceptable	unacceptable	unacceptable	unsatisfactory
	0.71	28.0	unacceptable	unacceptable	unacceptable	unacceptable
	1.10	45.0	unacceptable	unacceptable	unacceptable	unacceptable

Table 3
Advisory levels in overall velocity [18].

Alert level	Velocity (in RMS)
Advise	0.14 in/s
Maintenance	0.35 in/s
Failed	1.0 in/s

Table 4
Advisory levels in PeakVue [18].

Level in g's	Interpretation
0	Machine is in good condition
10	Some problem is developing on the machine
20	The problem has become serious
40	Problem is critical

Signature analysis involve analyzing FFT vibration spectrum. The spectrum reflects the characteristics pattern of vibration that a machine generates under a specific operating condition. This technique can be applied on broadband, full signature or narrowband. Broadband data generally have low resolution making it ineffective to diagnose early problems. Full-signature data require massive data acquisition and storage but they are necessary to diagnose root-cause. On the other hand, narrowband data that allow high resolution windows at specific frequency range are very useful to diagnose problems, especially during early stages. Some of common machinery faults that can be detected using overall velocity are summarized in Table 5.

3. Vibration analysis studies

Many studies have been conducted on monitoring construction structure or machine health using vibration data. Approaches used

Table 5
Common machinery faults (after [22]).

Faults	Frequency	Amplitude
Less than 1x TS		
Beats	Different frequency	Comes and goes, caused by two machines running at similar speed. Applicable to high-speed machines with plain bearings.
Oil whirl	Approx. 45% of 1× TS	Decrease with load.
Looseness	½, 1½, 2 ½, etc.	Note: Strobe light helps to see the defect.
Belts	π(TS) (pitch dia.)	A serious condition with very high amplitudes.
Resonance	Discrete peaks	
At 1x TS		
Unbalance	1 × TS	Mostly radial; a common fault
Misalignment	1 × TS + harmonics	High 2× and 3×; high axial; a common fault
Eccentricity	1 × TS	Looks like unbalance; cannot be corrected with weights
Bent Shaft	1 × TS	Looks like unbalance; can be corrected with massive balance weights near the center.
Soft Foot	1 × TS	Dramatically decreases by loosening one hold down bolt
Reciprocating	1 × TS + harmonics	More than 0.005 inches indicates misfiring.
Medium Frequencies		
Misalignment	2×, 3×, + harmonics	High axial; changes with temperature; a common fault
Motor	120 Hz + harmonics	Stops immediately upon disconnecting power. Also causes
		120 Hz sidebands at higher frequencies. Not usually destructive; an indication of the quality of construction. Present on all motors and transformers to some degree.
Looseness	½, 1½, 2 ½, etc.	Decreases with load
Bearings	FTF = 0.4 × TS BPFO = 0.4 × TS x N_B BPFI = 0.6 × TS x N_B	High frequency shock pulses in time domain
Blades	N_B = # of balls	Benign
High Frequencies		
Gears	TS x (no of teeth)	Sidebands at gear mesh frequency; 2x gear mesh usually larger
Cavitation	3–5 kHz broadband	Usually benign; pressurizing inlet helps
Bearing	Broadband	High frequency shock pulses in time domain

are various range from conventional VA techniques to modeling and neural network.

3.1. VA studies in construction structure

Some VA studies in construction structure are summarized in Table 6. Jassim et al. [6] reviewed thoroughly on detection and assessment of damage on cantilever beams. Many approaches were used and proved to be feasible and viable to achieve the goal. It was shown that it is necessary to combine different VA methods with computational models to accurately and efficiently determining location and magnitude of a crack on a cantilever beam. Frequency analysis, different mode shape vectors and indexes were used together to assess a damage occurrence. Khan et al. [23] conducted experimental and numerical studies on a steel column and steel frame structure using free VA. The results shown that it is feasible to monitor the health of structures by analyzing changes in natural frequencies and mode shapes. When cracks increment near the restrained end of the column structure or when damages appear in the frame structure, the modal frequencies of the structure decrease. When crack gets deeper, there is also a reduction in vibration frequencies. Various studies on application of VA in detection, identification and assessment of damages and cracks in structures such as beam or bridge were conducted [5,24–33]. The results shown that VA could be used to detect damage in construction structure.

3.2. VA studies in machine health

Some VA studies in machine components are summarized in Table 7. Renwick & Babson [3] diagnosed gear and bearing defects in different case studies using vibration data acquired by three different levels of vibration instrumentation (basic meters, general-purpose analyzers and advanced signal analyzers). The work shown data obtained by advanced instrumentation allows early detection of component degradation in machines and identification of a problem's root cause. However, depending on the scale of a project, vibration instrumentation should be chosen carefully to efficiently monitor machine's health with a reasonable level of investment. Noureddine et al. [34] diagnosed bearing fault in a cement mill. The study involves analyzing overall level of vibration, comparing vibration behavior over time and spectral to identify defects in early stages and determine root-cause precisely. Experimental vibration data were obtained in both axial and radial (vertical and horizontal) orientations. The work was the foundation for automating diagnostic process by neural networks in further studies. Bianchini et al. [1] used VA to detect faults in linear bearings in brushless AC linear motors. Multiple approaches were applied including statistical methods, frequency-domain analysis, time-frequency-domain analysis and quefrency-domain analysis. Various analytical fault models were also developed for different faults (recirculation channel plugging, on a rolling element, on the rail, on the moving cage) in linear bearings. Expected vibration profiles were presented for each scenario. The results shown that statistical methods were unreliable in detecting the faults. FFT spectral analysis could be used to identify moving carriage fault characteristics frequency. Time-frequency analysis is more suitable to detect damage to a rolling element. In terms of recirculation channel plugging, the fault was heavily dependent on installation, mounting and load conditions causing fault index to be unreliable in real applications Many signal processing techniques were used (FFT, short-time Fourier transform, Welch periodogram, ceptrum analysis and envelope analysis). However, none of them were determinant to detect fault bearing. Among the techniques, FFT and envelope analysis provide the most relevant results. The study also pointed out that the topic was not well understood and need further investigation. Boudiaf et al. [35] did a comparative study of different processing methods (short time Fourier transform, Wigner-Ville distribution, envelope analysis, wavelet transform and empirical mode decomposition) in diagnosis of bearing fault. It is shown that the methods, except frequency analysis, could be used to identify bearing faults. Each method has different advantages and disadvantages in the particular application. Djaidir et al. [36] applied VA and statistical methods on vibration data to monitor a gas turbine's health. Experimental data were collected to validate the approach and enable further research on the dynamic behavior of components of the gas turbine to detect and locate certain defects. Abdelkrim et al. [37] combined VA with a soft computing approach involving the extraction of statistical indicators from vibration signals and a trained adaptive neuro-fuz inference system to monitor bearing health in industrial geared motors. Experimental results were used to confirm the viability of the proposed approach in real industrial applications with a very high accuracy. Li et al. and Perez et al. [38,39] tried to detect and identify multiple mechanical faults in motors. Various studies were conducted to monitor and

Table 6
Various VA studies in construction structure.

Study	Content	Approach
[24]	Analysis of a cantilever beam with a closing crack	Harmonic analysis
[25]	Vibration analysis of a building during earthquakes	Joint time-frequency analysis
[5]	Damage detection in concrete bridge	Non-linear vibration techniques
[26]	Crack identification in beams	Wavelet analysis
[27]	Crack detection in beams	Frequency response function
[28]	Crack detection in beams	Experimental modal data and finite element model
[29]	Damage detection on simple bridge superstructures	Vibration based method
[30]	Identification of multiple cracks in beams	Vibration amplitude
[31]	Structural damage assessment in a cantilever beam with breathing crack	Higher order frequency response functions
[32]	Damage detection in beams	Wavelet transform on higher vibration modes
[33]	Damage detection of beam structures	Wavelet transform
[23]	Damage and undamaged steel cantilever column and frame	Free vibration analysis

Table 7
Various vibration analysis studies in machine components.

Study	Content	Approach
[40]	Detection of rolling element bearing damage	Statistical method
[41]	Monitoring rolling element bearing conditions	Time domain methods
[3]	Identifying gear and bearing defects	Waveform and spectral analyses
[38]	Detection of common motor bearing faults	Frequency-domain method, neural network-based approach
[39]	Identification of multiple combined faults in induction motors	High-resolution spectral analysis
[1]	Fault detection of linear bearings in brushless AC linear motors	Statistical methods, frequency-domain analysis, time-frequency-domain analysis, quefrency-domain analysis
[34]	Fault diagnosis of bearings	Spectral and trending analysss
[42]	Gear faults detection and diagnosis	Statistical modeling of vibration signal
[45]	Fault detection and diagnosis in bearing fault in an induction motor	Frequency analysis, envelope analysis, short-time Fourier transform, empirical mode decomposition
[44]	Bearing fault identification and classification	Neural network
[36]	Detection of component defects in gas turbine	Statistical method, waveform and spectral analyses
[37]	Bearing faults detection and classifying in industrial geared motors	Temporal features and adaptive neuro-fuzzy inference system

diagnosis machine health related to mechanical problems (e.g., bearing and gear faults) [13,40–44]. The results show that VA is an effective method to identify these problems. In addition, VA was also used to study and detect leaks in pipeline [4].

4. Vibration data analysis applications in oil and gas industry

VA has been used in petroleum industry for many years. However, it was not common to perform VA on drilling and production operations (e.g., ESP system) until recent years.

4.1. VA studies in rod pump

VA has been applied on rod pumps to detect problems and enhance run life. Bullard [46] presented an application of preventive maintenance involving analyzing vibration data for beam pumping equipment to extent equipment's lifetime. A program with inspection procedures and schedule was described. Multiple mechanical faults (e.g., misalignment, damage bearing and loosen bolts) were detected and corrected in time, resulting in lower repair and maintenance costs. Xu [45] developed a program to diagnose sucker rod string performance in straight inclined wells using vibration data. An analytical approach using Fourier series was used to evaluate the motion of the sucker rod while taking into account the Coulomb and viscous frictions. Nelson [47] proposed using VA to detect rod pump condition, whether a well was pumped off or a well had fluid over the pump. Test results shown that the vibration behavior was very different between the two cases. The median of acceleration measurements in pumped off conditions were lower than the mean. The two were similar for wells with fluid over the pump. Chen et al. [48] predicted sucker rod pumping system health in vertical oil wells by analyzing the displacement and load of any point on a rod string. In this study, Fourier series method was used to process prescribed pump cards for prediction. Sinusoidal polished-rod displacement and load could be recovered. The method was able to predict pumping conditions better than existing programs. Xing and Dong [49] studied the vibration characteristics of a sucker rod string which was used to optimize sucker-rod pumping system [50] and diagnose sucker-rod pumping systems based on the polished-rod load vibration in vertical wells [51]. The pump displacement and pump load versus time function were deduced using 1D wave equation based on known polished rod versus time function. The method was used to determine pump dynamometer card and polished-rod dynamometer card, which could be used to diagnose the system and identify problems. Hicks [52] developed a machine learning software to monitor machine health and improve runtime of jet pump with a focus on power fluid pump. The model could detect mechanical faults such as misalignment, imbalance, bearing defects, …using vibration data. It could also assess pump failure risk and alert based on advisory levels from ISO. Vibration data were collected from pumps at a trial location. The data was also analyzed by a vibration expert who found developing bearing wear on different components of a pump based on the collected data.

4.2. VA in ESP system

VA has been applied on ESP systems to identify failures. Durham et al. [53] collected vibration data from a surface configuration ESP, a downhole ESP and field data to investigate the effects of vibration on ESP's failures. Their results shown that failures and defects (specifically bearing failure, imbalance and shaft defections) cause excessive vibrations. These vibrations in turn contribute to failures in seal assembly and thrust chamber. Minette et al. [9] conducted experiments on ESPs installed in a test well used for integration tests. VA was used to identify possible natural frequencies within the operating range of the ESPs which could lead to the operation in a resonance condition resulting in high vibration amplitude. The issue could cause premature failures in ESP. Beck et al. [54] investigated ESP vibration characteristics under wear conditions (e.g., abrasive solids) using a test system that involves six ESPs pumping high abrasive solid concentration fluid. Their test results indicated that mechanical wear causes growth in vibration peak magnitude, which corresponded to observed wear patterns. The frequencies of the peaks could reflect causes, either related to pump impeller, diffuser, bearing or flange sleeves. Zhu et al. [55] investigated sand erosion in ESP experimentally by observing performance degradation, wear and vibration. Vibration signal was measured in four stages in both vertical and horizontal orientations. FFT was used to process the data. The results shown that vibration amplitude was high in the middle of the pump and lower in the last stage. The authors concluded that the changes in vibration amplitude and abrasion rate were faster at the beginning of the test and became more stable after. Regres et al. [11] analyzed ESP vibration signal under different operational conditions (e.g., fluid viscosity, pump speed and operating point) to achieve ESP vibration differential diagnosis by analyzing relations between orders of the synchronous frequency. Experiments were conducted with two ESPs in a facility that can reproduce the petroleum well field environment in a laboratory. Based on the analysis, their fault prediction results agree with recommended practice. Exploratory analysis was also performed showing that there was a high correlation between temperature difference between pump intake and discharge and turning speed frequency vibration peak amplitude.

4.3. VA studies in drilling

VA has been used to predict damage in bottomhole assemblies and optimize drilling operations. Samuel et al. [56] used and validated a model by Apostal et al. [57] to predict severe damaging vibrations in drilling. Forced frequency response were used to identify resonance frequencies. Critical speed that could cause large displacements and stresses at some points in the bottomhole assemblies, which may lead to structural instability, was determined. The study showed that the VA model could be used to minimize downhole equipment failures by providing a vibrational window to avoid undesirable rotational speeds. Samuel and Yao [58] applied the model on hole-enlarging tools. It could determine stress distribution is along the string and how the drill string components are deforming. Samuel [59] applied the model to design bottomhole assembly efficiently in riserless drilling based on strain energy and its effects on wellbore profile energy. The study also gave insights on the effects of open waters to shallow depth drilling and the intensity of wellhead-side loading at different depths. Samuel [60] used the model to predict damaging vibrations under backreaming condition. Insights into the downhole issues while backreaming were provided. The critical speeds were higher than that under normal conditions; tension and bending were the cause of increased spring force in the system. In addition, the study evaluated the capabilities and limitations of existing models that predict resonant frequencies. Ledgerwood III et al. [61] monitored downhole vibration with a in-bit vibration sensor. Tests were conducted in research wells to define stability maps for different polycrystalline diamond compact bit. Field data were gathered showing stick-slip was the primary cause of polycrystalline diamond compact bit damage. Milian [62] proposed a machine learning program that can recognize drill string stick-slip and lateral shocks phenomena based on vibration measurements at the surface. It allows downhole dynamics to be classified in severity levels, equivalent drilling time and downhole tool lifetime to be estimated. Singh et al. [63] tried to optimize real-time drilling operation by increasing rate of penetration and reducing non-productive time using vibration monitoring tools. Peak shock and average vibration data were recorded to determine whether current drilling parameters are causing high vibrations so mitigation procedure could be followed. A machine learning model was developed for rate of penetration prediction with the mean absolute percent error of less than 15%.

4.4. VA studies in piping and plant

VA has been used in some studies relating to piping systems, platforms, plants, etc. Beek et al. [64] evaluated the vibration performance of a subsea pump module by numerical model and testing. Frequency response function approach was used in this study. Vibration signal was measured on pipe systems, which can be damaged when vibration amplitude gets too high resulting in excessive fatigue stresses. The model was validated with testing results. Results of the study shown that the different influence of surrounding water on small-bore piping or main piping should be considered in subsea designs. Ahmed et al. [65] used vibration/stress analysis to identify root cause of excessive vibrations in piping system in a plant. By successfully determining the cause, which is inadequate pipe supports, a solution was proposed and piping vibration were reduced significantly after modifications. Teh et al. [66] studied structural vibration of an offshore platform to analyze its structural dynamics. The research was necessary to ensure the integrity of the platform as new compressors were to be installed. Possible vibration scenarios were assessed and two solutions were proposed. However, they only met stress requirement and did not satisfy vibration criteria because of schedule constraints. Only skid vibration integrity was considered in the study while the supporting structure was not included. Khoujah et al. [67] explored production expansion opportunities of an oil and gas facility by analyzing vibration measurement of four units in the plant. The results were used to develop solutions to mitigate vibration and reinforce the existing structure. Remaining life of the units were also estimated. The study shown that the method could be applied to increase plant production and predict failure scenarios.

4.5. VA with data driven model

Some data driven models were built with the application of VA. Esmaeili et al. [68] tried to predict formation characteristics based on drillstring vibration measurements using artificial neural networks. The results shown that formation characteristics strongly affect vibrations and there are linear relations between some drilling parameters, vibrations data and formation characteristics. Yin et al. [69] proposed a directional wells anti-collision technology using drill bit vibration signal. The data were analyzed in time domain and frequency domain to realize the approach of the drill bit to a risky well.

Even though vibration data are usually collected in real-time in recent artificial lift applications, they are not really used or tend to be overlooked in system health monitoring models. Some studies proposed the used of vibration data for predictive approach using data driven models [70–72]. In these studies, many parameters are available such as vibration data, ESP discharge pressure, intake pressure, discharge temperature, motor temperature, motor current, leakage current. Principal component analysis was conducted to perform ESP fault detection. However, this method may fail to capture vibration signal because it tries to reduce the dimension of the dataset. When the importance of vibration is not dominating compared to other features', the technique will not take the vibration into account, leading to disregard for the use vibration data. Evidently, the results only focused on the first two or three principal components, meaning vibration data were most likely discharged, to find the relation to the available data. Because of that, the models are only able to detect anomalies related to motor temperature variations and high current reading and cannot predict mechanical failures such as pump broken shaft. In the studies, the models could only explain up to around 70% of the data for validation. Many other studies also failed to utilize available vibration data [73–75].

It should be noted very few works use enveloping/demodulation methods (e.g., PeakVue). Provided that the methods were implemented in the studies, mechanical faults such as bearing problems could be predicted or identified earlier and more clearly.

5. Summary and conclusion

Mechanical equipment in motion generates vibrations. These vibrations could be analyzed for predictive maintenance purposes. The technique has been proved efficient in many industries and applications. Many techniques could be applied on vibration data such as statistical methods, frequency-domain analysis, time-frequency-domain analysis, quefrency-domain analysis. VA can be used to diagnose faults, especially in early stages, in machines and construction structure.

From the presented literature review, it can be seen that VA has been applied in the petroleum industry (e.g., in transportation and refining systems, drilling and artificial lifts), yet there is plenty of room for further research and improvement. The application and thorough understanding of VA in these areas would improve the safety, efficiency and longevity of the operations. Hence, VA should be considered more in planning, management and monitoring facilities and equipment health. One of the applications is the diagnosis of faults in artificial lift system, particularly ESP. The importance of VA on ESP system has been discussed. Studies have been conducted showing that analyzing ESP vibration data helps predict early problems. In addition, it also helps to determine causes of faults or defects. This is crucial because pump failure can lead to production loss or even a complete shutdown that requires pump replacement. Aside from predictive maintenance VA, vibration data were also used in data-driven models such as principal component analysis to predict and identify problems. Because the vibration signal that reflects fault behaviors of the pump is usually ignored, the models would be unable to correctly predict and determine mechanical faults such as broken shaft. The application of enveloping/demodulation methods is not common in petroleum industry. These methods could play critical roles in optimizing operations, predicting and identifying mechanical faults or defects.

VA is a feasible technique to monitor and diagnose a machine's health. It is important to research VA further and apply it more in the petroleum industry, especially in the production system. Applications of VA could increase a machine's lifespan, reduce maintenance costs and be useful in optimization.

Data availability statement

No data was used for the research described in the article.

CRediT authorship contribution statement

Thuy Chu: Writing – review & editing. **Tan Nguyen:** Supervision, Funding acquisition. **Hyunsang Yoo:** Validation, Supervision. **Jihoon Wang:** Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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