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Research paper

Smart maintenance strategies in combined cycle power plant

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Abstract

This research investigates the effectiveness of various vibration data acquisition techniques coupled with different machine learning models for detecting anomalies and classifying them. To this end, synthetic vibration data was generated for techniques such as eddy current proximity transducers (ECPT), accelerometer sensor, blade tip timing, laser doppler vibrometer (LDV), and strain gauge. Afterward, the data was pre-processed and used to train gradient boosting machine, support vector machine, and random forest models. Performance evaluation metrics, including accuracy, recall, F1-score, receiver operating characteristic, and area Under curve were employed to assess the models, revealing varying degrees of success across combining techniques and models. Notable achievements were observed for the random forest model coupled with the eddy current proximity transducers technique, underscoring the significance of informed technical selection and model optimization in enhancing vibration anomaly detection systems in combined cycle power plants. The results showed that the LDV technique has a significant increase in accuracy from about 0.49 to approximately 0.52, while the ECPT technique has improved from about 0.9 to close 1.0. These advances highlight the growing accuracy of the methods and enable the development of more efficient and reliable learning machines.

1. Introduction

Vibration analysis plays an important role in various engineering applications in industry, such as structural health assessment and fault diagnostics, through the identification and analysis of vibration patterns [1]. One of these influential industries in the economy of countries is petrochemicals and power plants. In this regard, combined cycle Power Plants (CCPPs) utilize the gas turbine and Rankine cycle to generate electricity efficiently and eco-friendly [2]. The most important components of CCPP are gas and steam turbines, condensers, cooling towers, Heat Recovery Steam Generators (HRSGs), and electric generators [3]. Among them, gas turbine is a vital part of this system as it provides the primary energy source. Therefore, regular maintenance and correct operation of this part, for example, gas turbine, is necessary for the optimal performance of the system [4]. In other words, any unbalance or malfunction in the gas turbine can lead to reduced efficiency, production, and unscheduled shutdowns that affect the overall performance of the CCPP [5, 6]. Fig. 1 demonstrates some of the serious damages caused to the gas turbine of the Kirkuk power plant in Iraq.

The main objective of this study is to investigate the potential of machine learning models, particularly the random forest classifier, in analyzing synthetic vibration data obtained from various measurement techniques, including eddy current proximity transducers (ECPT), accelerometer sensor (AS), blade tip timing (BTT), laser doppler vibrometer (LDV), and strain gauge (SG). Such a comprehensive study was conducted for the first time in a CCPP. For this purpose, vibration data was gathered for each technique, machine learning models were trained, and finally evaluated using performance metrics such as accuracy, recall, F1-score, receiver operating characteristic (ROC), and area under curve (AUC). In the following, first, a detailed overview of the current state of the mentioned industry in monitoring and measuring gas turbine vibration, as well as the introduction of numerous industrial approaches for this purpose, will be discussed. Beyond that, the article will go into the pros and cons of each method.

1.1. Causes of vibration in gas turbine

Internal faults, natural disasters, and human error are the primary factors contributing to the catastrophic failure of gas turbines in CCPPs. Understanding vibration and its root causes is critical to gas turbine design and maintenance, ensuring reliable electricity generation and averting failures. In the following, a brief description of the causes will be given.

1.1.1. Shaft unbalancing

In rotating machines such as CCPP machines, two common sources of vibration are unbalanced and misalignment, which lead to excessive vibration, noise, and wear.

Unbalance and misalignment can damage bearings, shafts, couplings, and other components, increase maintenance costs and downtime, and thus reduce system efficiency by increasing power consumption and reducing output. Sudhakar and Sekhar extensively studied coupling misalignment and its effects, focusing on detection methods using motor current signs, noise, thermography, and machine learning [7]. Their findings emphasize the importance of minimizing vibrations by addressing misalignment and unbalance, potentially reducing machine power consumption by 10–15% [8]. Furthermore, bearing misalignment significantly affects the thickness of the protective film; even a slight misalignment leads to a 40% reduction in bearing load capacity [9]. A visual representation of bearing damage due to misalignment in a CCPP turbine is shown in Fig. 2.

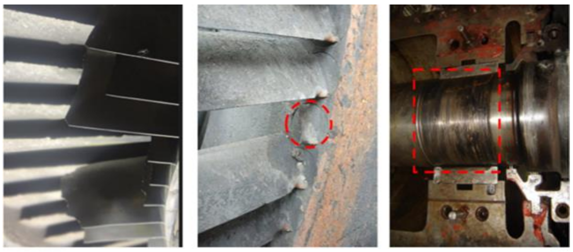
1.1.2. Critical speed

Critical speed is a significant threat to CCPPs, causing vibration, system inefficiency, and potential failure. Operating machinery above critical speeds can lead to component failure, increased maintenance costs, and reliability issues.

Sinha *et al.* [10] identified the critical speeds using the Short-Time Fourier Transform (STFT) on vibration data from rundown and start-up operations.

1.1.3. Rubbing

Rubbing occurs when rotating components rub against each other, resulting in friction and wear, eventually damaging machine parts such as bearings and seals.



(a) (b) (c)

Fig. 1. Damages to a gas turbine in Kirkuk power plant due to the occurrence of vibrations caused by (a) and (b) steam flow fluctuations, and (c) rubbing.

Fig. 2. Bearing damage due to the misalignment in a gas turbine located in Kirkuk power plant.

This leads to increased vibration, wear, and the risk of sudden failure. Edwards *et al.* [11] investigated the rubbing effect of rotor torsional vibration, and the results showed the adverse effect on rotor systems and highlighted the need to consider torsion in models of the rubbing phenomenon. The heat generated by rubbing intensifies rotor dynamics and emphasizes the importance of minimizing spin by maintaining distinct natural frequencies and considering dry friction in the stator and rotor dynamics [12]. Experimental studies by Dayi *et al.* [13] showed how sudden blade loss and rubbing impacts affect the dynamics of the rotor system, especially when the angular velocities exceed the critical velocities. Fig. 3 demonstrates an image of the effects of the rubbing phenomenon observed in a CCPP. In addition, the wear and tear of the turbine caused by the fluctuations of the steam flow is illustrated in Fig. 4.

1.1.4. Shorted turns

Shorted-turn conditions in generators or motors lead to increased current, temperature, vibration, and reduced efficiency in CCPPs. Factors contributing to shorted-turn rotors include rotor unbalance, vibration induced by unbalanced magnetic forces, and stop-start cycles.
Current and temperature monitoring, along with visual inspections and Non-Destructive Testing (NDT), help to detect and prevent short turns early. Lee *et al.* [14] conducted a shorted-turn detection test in a CCPP generator using an online detection device and a continuous flux probe for accurate and reliable results. In this regard, it is very important to monitor the flux probe signals under various load conditions to maximize shorted-turn sensitivity in rotor slots [15].

1.2. Vibration detection technologies in industry

The process of measuring vibration to perform predictive and preventive repairs in rotating machines can be divided into two general parts. The first step is to collect raw vibration data using various sensors such as optical sensors, accelerometers, proximity probes, etc. The data is then analyzed using signal processing tools in the second step of the process. Below is a brief description of some well-known practical methods in the industry:

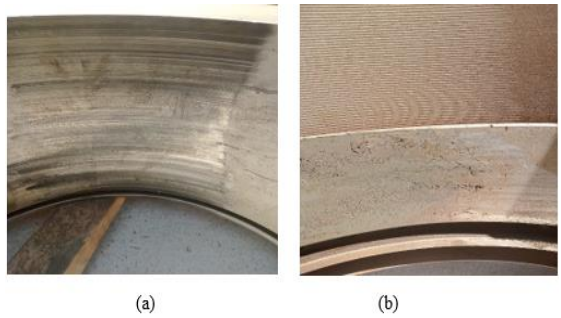


Fig. 3. Gas turbine damage in Kirkuk power plant due to the occurrence of vibrations caused by the rubbing phenomenon.

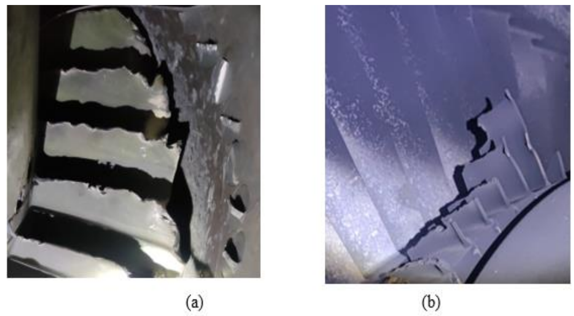


Fig. 4. Gas turbine damage in Kirkuk power plant due to the wear and tear caused by steam flow fluctuation.

1.2.1. Eddy current proximity transducers

Eddy current proximity transducers are used to monitor the displacement of rotating machines such as turbines and generators in power plants [16, 17]. A probe made of a non-magnetic metal and a coil made of copper wire with a ferrite core material constitute the transducer as shown in Fig. 5. The probe detects changes in the magnetic field caused by the proximity of the target object, while the coil creates an alternating magnetic field that induces eddy currents in an object. These currents generate a magnetic field that opposes the coil's field, and the probe detects the resulting changes and converts them into an electrical signal [18].
Some of the advantages of eddy current sensors for vibration monitoring in CCPPs are:

- High accuracy to detect small displacement changes.
- Reliability in harsh environments.
- Suitability for high-speed machinery.
- No moving parts, reducing the risk of failure.

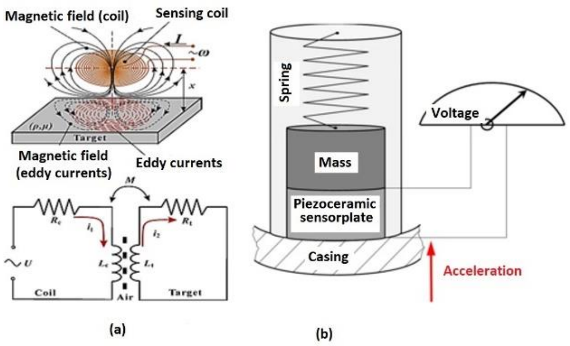


Fig. 5. Vibration detection sensors: (a) working principle of an eddy current displacement sensor, and a comparable model (reproduced from [16]) and (b) principle of an accelerometer (reproduced from [17]).

However, the sensor has some limitations, like:

- Limited sensing ranges.
- Unidirectional detection (radial).
- The need for calibration to make correct measurements is time-consuming and requires specialized equipment [16].

1.2.2. Accelerometer sensor

Accelerometers are sensors commonly used in power plants to monitor vibration. These instruments are usually small and lightweight and can detect vibration over a wide range of frequency. An accelerometer typically consists of a mass connected to a spring and a piezoelectric or capacitive element that converts the mass's motion into an electrical signal. The working principle of an accelerometer is based on the physical characteristics of the mass-spring system [17]. When a vibrating force is applied to the accelerometer, the mass connected to the spring also vibrates. Mass displacement is converted into an electrical signal by a piezoelectric element or a capacitive element [19]. Accelerometers are typically installed directly on the machine being monitored, either with adhesive or mechanically (Fig. 6).
A data acquisition system then processes the acceleration signal, which may include signal conditioning, filtering, and analysis. The output signal of an accelerometer can be measured in the time or frequency domain, providing information about amplitude, frequency, and other vibration characteristics.

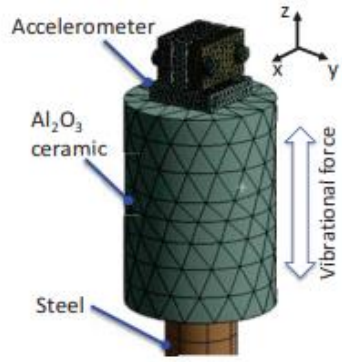


Fig. 6. Accelerometer vibration probe [19].

Accelerometers can be used in a variety of vibration monitoring applications in power plants, including monitoring of rotating machinery such as turbines and generators, as well as structural components like pipelines and support structures. Accelerometers are strategically installed on the machine, for example, near the bearings or shaft, and measure the acceleration caused by machine vibration, which can indicate issues such as unbalance, misalignment, or bearing wear.
Accelerometers offer advantages for vibration monitoring in power plants, such as:

- High accuracy in a wide range of frequencies.
- Ability to detect high and low levels of vibration.
- Easy installation in both laboratory and field measurement areas.

But it has limitations such as:

- Limited dynamic range and sensitivity.
- Susceptibility to interference from external vibrations or electromagnetic noise.
- Requiring calibration and regular maintenance to ensure accuracy.
- Unsuitability for measuring certain types of vibration, such as low-frequency or high-amplitude vibrations [20].

1.2.3. Blade Tip Timing (BTT)

BTT is common in the CCPPs to monitor the vibration of gas turbine blades. A BTT system usually consists of a series of sensors that are installed around the periphery of the turbine rotor and measure the passage time of the blade tips as they rotate past the sensors [21]. Fig. 7 depicts a schematic of the BTT technique.

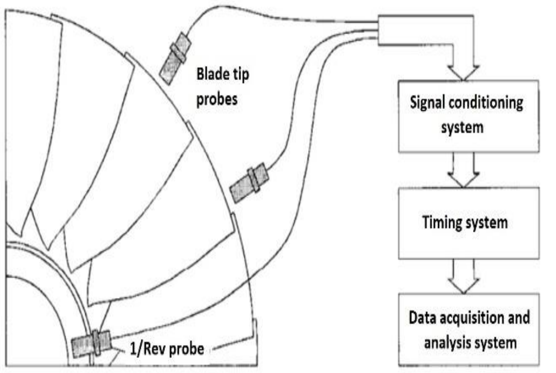


Fig. 7. A simple schematic of blade tip timing system (reproduced from [21]).

Each blade has a unique vibration sign that is determined by the shape and stiffness of the blade as well as the rotational speed. Optical sensors installed on the stator or casing surrounding the rotor are commonly used in BTT systems. The passing blade tip interrupts the light beam emitted by these sensors. A microwave sensor-based approach for the BTT system was reported by Zhang *et al.* [22], in which a patch antenna probe was used to transmit and receive microwave signals from the reflective surface of the turbine blades [23]. An overview of the microwave tip timing system used to monitor the turbine blades is illustrated in Fig. 8.

BTT can also be used to monitor rotor balance and detect any unbalance that could cause excessive vibration. Some of the advantages of BTT can be regarded as follows:

- BTT can provide very accurate measurements of blade vibration.
- They are non-intrusive and do not require changes to turbine blades or rotors.
- BTT can detect both high and low vibration frequencies.
- BTT can monitor blade vibration in real-time.

However, BTT has some limitations of:

- It can only measure the vibration of the blade tip and cannot provide information about the vibration of the rest of the blade or rotor.
- Calibration is required for BTT systems to ensure accurate measurements [24].

1.2.4. Laser doppler vibrometer

Laser doppler vibrometer (LDV) is a non-contact vibration measurement technique used in power plants for vibration monitoring. LDV is a high-precision instrument capable of detecting extremely small vibrations with high accuracy [24]. An LDV system typically consists of a laser source, an optical beam splitter, and a photodetector. The laser emits a light beam, which is split into two parts by the optical splitter. One beam is aimed at the vibrating surface, while the other is focused on the reference surface. As shown in Fig. 9, the two beams are reflected to the photodetector, where they interfere, resulting in an interference pattern.

The LDV operates by measuring the frequency shift in the interference pattern caused by surface vibration. The photodetector detects variations in the frequency of the reflected light when the surface vibrates. The LDV measures vibration amplitude and frequency and enables real-time monitoring of rotating machines.

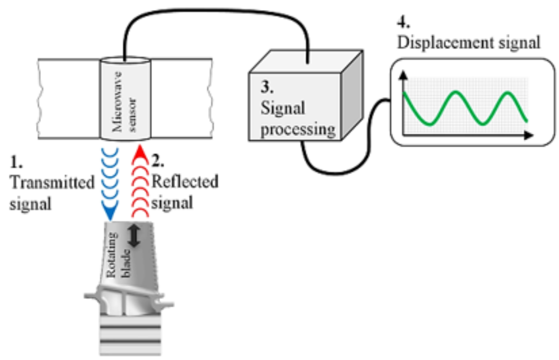


Fig. 8. Microwave tip timing system used for turbine blade monitoring (reproduced from [23]).

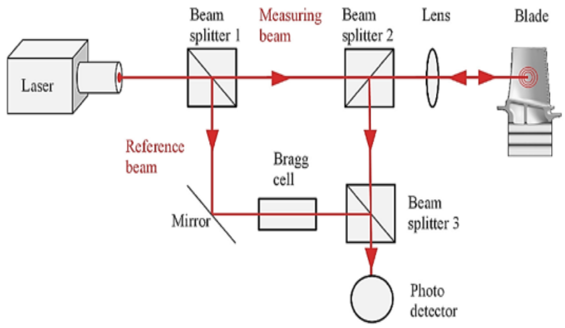


Fig. 9. Simplified structure of LDV [21].

The benefits of LDV include:

- Non-contact measurement.
- High sensitivity to small vibrations.
- Detection of high and low frequencies.
- Real-time monitoring of rotating machinery.

But the limitations of this method are:

- Limited measurement ranges.
- High cost of purchase and maintenance.
- A complex setup and specialized expertise are required to operate in some applications [22].

1.2.5. Strain gauge

A strain gauge is a type of sensor commonly used in power plants to monitor vibration. It is based on the measurement of strains due to vibration or deformation caused by vibration [25]. The sensing element of a strain gauge is typically a small metal strip or wire that is bonded to the surface of the object being measured. The sensing element deforms when the object vibrates and causes a change in its electrical resistance. The Wheatstone bridge circuit connected to the strain gauge measures these changes in resistance. Strain gauges are commonly used in power plants to monitor the vibration of large structures such as buildings, foundations, and support structures for large equipment. They are installed on strategic locations in the structure and measure the changes in strain caused by the structure's vibration [26]. Engineers can detect changes in the vibrational characteristics of the structure by analyzing strain data over time, which can indicate various issues such as structural fatigue, foundation settling, or improper support.
Strain gauges have several advantages when it comes to vibration monitoring in power plants, including:

- Strain gauge sensors are extremely sensitive and can detect very small strain changes.
- These sensors can detect both high and low vibration frequencies.
- Since strain gauge sensors have no moving parts, the risk of failure or wear and tear is reduced.
- Installation of these sensors is relatively simple and can be installed in various locations throughout the structure.

However, strain gauge sensors have some limitations, including:

- Changes in temperature can affect the accuracy of the sensor.
- These sensors can only measure strain in their mounting direction.
- Calibration of these sensors is required to ensure accurate measurements.
- Strain gauge sensors have a limited sensing range, which usually ranges from a few millimeters to a few centimeters.

The current research introduces a new approach by examining the effectiveness of different vibration data acquisition techniques in CCPPs for anomaly detection and classification tasks. Unlike previous studies that often focused on individual techniques, this research provides a comprehensive comparative analysis of five common techniques, including ECPT, AS, BTT, LDV, and SG, coupled with advanced machine learning models such as RF, GBM, and SVM. Therefore, combining different modes of measurement techniques and machine learning models for industrial data is done for the first time with this comprehensive scope, which is the innovation of this research to obtain the most accurate combination for use in large industries.

2. Methodology

Synthetic vibration data generation, data preparation, machine learning model training, and performance evaluation using several metrics are all detailed in this section. The goal is to test how well machine learning models work in simulating different vibration measurement techniques and identifying typical and non-standard vibration patterns.

2.1. Data generation

To perform these tests, synthetic vibration data is generated to simulate various measurement techniques commonly used in condition monitoring. For each technique, parameters such as frequency, amplitude, and noise level are carefully selected to mimic real-world scenarios. A custom function is implemented to simulate the vibration data for each technique, ensuring that the generated data closely resembles the actual sensor readings. The physical concept behind the generation of synthetic vibration data is to create realistic simulations of the vibration signals that would be measured by various sensors in a real power plant environment. This allows full testing and optimization of the machine learning models without the constraints and limitations of real-world data collection.

2.2. Preprocessing

Before training the model, synthetic data were preprocessed to guarantee the quality and appropriateness of the analysis. This involved labeling the data as "normal" or "abnormal" based on predefined criteria. Additionally, outliers in the data were identified and removed using a clipping technique, which restricted the data to a specified amplitude range. The purpose of these preliminary procedures is to make the data more usable and accurate for subsequent modeling.

2.3. Model training and testing

Three distinct machine learning classifiers were employed in this study: random forest (RF), gradient boosting machine (GBM), and support vector machine (SVM). Each classifier was trained and evaluated using the pre-processed synthetic data for each technique. Thus, to ensure an impartial evaluation of the model's performance, the data is partitioned into two sets: training and testing [27-29]. For each model, various evaluation criteria such as accuracy, recall, F1-score, receiver operating characteristic (ROC), and area under curve (AUC) were used and calculations aimed at determining how well it could differentiate between standard and non-standard vibration patterns. In general, a schematic diagram of the work steps in each model is given in Fig. 10. In addition, the working steps of different machine learning algorithms, including RF, GBM, and SVM are as follows:

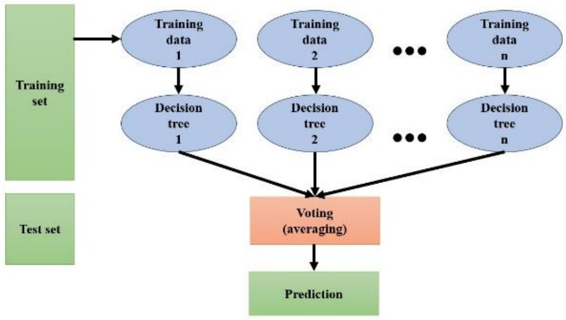


Fig. 10. A visual schematic of the working steps in the machine learning models used in this research.

Algorithm for RF:

Input (synthetic data parameters);
Output (evaluation results for random forest;
1. Precondition: import necessary libraries including numpy, matplotlib. pyplot;
2. Define a function generate_vibration_data;
3. Loop through technique_parameters and generate synthetic vibration data;
4. Preprocessing (label and clean);
5. Label the synthetic data as "normal" and "abnormal";
6. Define a function train_and_evaluate_model (x, y) to train and evaluate the random forest;
7. Split the data into training and testing sets;
8. Initialize and train the random forest classifier model;
9. Make predictions on the test set and evaluate the model;
10. Print the evaluation results for each technique;
11. Functions;
12. Generate_vibration_data;
13. Train_and_evaluate_model (x, y);
14. Return random forest score;

Algorithm for GBM:

Input (synthetic data parameters);
Output (evaluation results for gradient boosting machine);
1. Process;
2. Import libraries;
3. Generate synthetic data;
4. Preprocess data (label and clean);
5. Train and evaluate GBM models;
6. Print evaluation results for GBM;
7. Visualize GBM performance comparison;
8. Functions;

9. Generate_vibration_data (technique, frequency, amplitude, noise_level);
10. Train_and_evaluate_model_with_gbm (x, y);
11. Return;
12. Evaluation results for GBM;
13. Visualization of GBM performance comparison;

Algorithm for SVM:

Input (synthetic data parameters);
Output (evaluation results for support vector machine);
1. Procedure;
2. Import libraries;
3. Generate synthetic data;
4. Preprocess data (label and clean);
5. Train and evaluate SVM models;
6. Print evaluation results for SVM;
7. Visualize SVM performance comparison;
8. Functions;
9. Generate_vibration_data (technique, frequency, amplitude, noise_level);
10. Train_and_evaluate_model_with_svm (x, y);
11. Return;
12. Evaluation results for SVM;
13. Visualization of SVM performance comparison

2.4. Performance comparison of different algorithms

In this section, the evaluation results obtained from the trained models are compared to identify the most suitable classifier for condition monitoring applications. Bar graphs are used to visualize the performance measures of the different techniques for each classifier, which allows a comprehensive comparison of their performance. Key insights and observations derived from the performance comparison are analyzed into the strengths and limitations of each model.

2.5. Sensitivity analysis

In the synthetic vibration data generation process outlined above, various technical parameters are crucial to accurately simulate real-world conditions and facilitate effective machine learning analysis. For instance, in representing the behavior of an accelerometer sensor, a frequency of 25600 Hz, an amplitude of 2, and a noise level of 3 are considered. These values are chosen based on typical operating frequencies, expected signal strength, and the ambient noise level typically encountered in the sensor readings. Similarly, for the BTT technique, parameters such as a frequency of 100 Hz, an amplitude of 2, and a noise level of 0.3 are used, reflecting the unique characteristics of this vibration measurement method. Such careful selection and calibration of technique parameters ensure that the synthetic data accurately mimics real-world scenarios and enables robust machine learning model training and testing [30-32].
The reason for using machine learning algorithms such as RF, GBM, and SVM is to analyze synthetic vibration data generated to simulate various vibration measurement techniques used in power plant condition monitoring. These algorithms are usually employed to identify typical and non-standard vibration patterns, evaluate the performance of different vibration measurement techniques, and distinguish between standard and non-standard vibration patterns.

3. Results and discussion

In this section, the efficiency of the aforementioned sensors in detecting vibrations in a rotating system is presented. Each sensor is modeled using an equivalent circuit. The output of these models is fed into a machine-learning algorithm. The rotating system is modeled with different vibration modes. Also, vibrational modes are applied randomly. Additionally, a noise source was added along with the vibration modes. The power of the noise source is varied across various vibration modes. Finally, a machine learning algorithm was used to process the output of each sensor in different vibration modes. The algorithm can predict system vibrations using different aforementioned sensors. Each sensor node is verified for accuracy in detecting vibration modes. Vibration modes such as axial, longitudinal, short-circuit, strain-based, etc. are modeled using various waveforms collected from an industrial data acquisition system. The vibration data measured using different techniques are shown in Fig. 11. This image only presents the collected vibration data, which indicates that by using different techniques, vibration data were collected within a certain range and acceptable changes, and further, it is the nature of the learning machine and also the training process that has a significant impact on the accuracy of the evaluation. Also, the following section presents a summary of the simulation results obtained using the machine learning algorithms.

A comparison of five techniques of ECPT, AS, BTT, LDV, and SG is demonstrated in Fig. 12. The eddy current proximity transducers technique exhibited the lowest performance in all metrics with accuracy, recall, F1-score, ROC, and AUC of approximately 0.12. However, there is a significant performance improvement to progress through the techniques. The accelerometer sensor showed moderate gains in all metrics, with values ranging from 0.47 to 0.48.

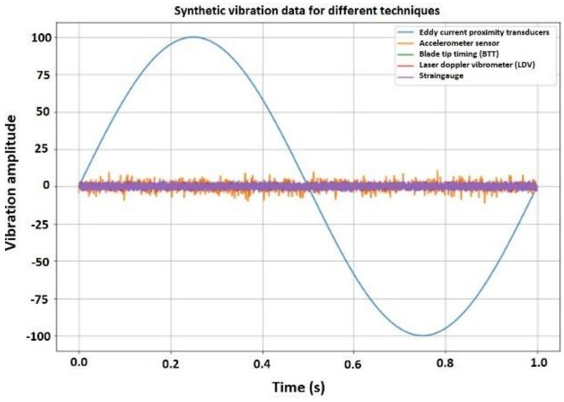


Fig. 11. Vibration data measured using different techniques.

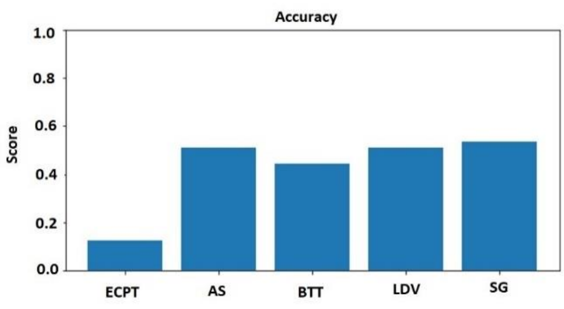


Fig. 12. Comparison plot of all five vibration measurement techniques.

Moving further, the blade tip timing technique showed a slight improvement, achieving scores of around 0.53 to 0.54 across all metrics. The laser doppler vibrometer demonstrated further enhancement, exceeding 0.55 for accuracy, recall, and F1-score. Finally, the strain gauge technique showed similar performance metrics to the accelerometer sensor with slightly higher scores ranging from 0.49 to 0.50. Overall, this comparison emphasizes the gradual increase in performance from the ECPT to the LDV, indicating that the latter may be the most effective technique among the evaluated options for the specified task.

Over time, many measurement techniques become more accurate. Factors contributing to this trend include rising demand for more accurate measurements, new technologies becoming more available, and increasing accuracy of instruments. Therefore, recent achievements show that the accuracy of the methods mentioned above has increased over the years. For instance, the accuracy of the LDV technique has increased from about 0.4 to about 0.9, while the accuracy of the ECPT technique has increased from about 0.2 to about 0.8. Because of this, engineers can create learning machines that are more efficient and reliable than ever before. Also, here are some specific ways that improved precision is making a difference in daily: new and more accurate sensors increase engine performance and fuel efficiency in the automotive industry. The medical industry uses more precise sensors to detect diseases such as cancer and heart disease, leading to more accurate diagnoses.

Finally, Tables 1-3 present the comparison between the RF, SVM, and GBM machine learning algorithms and distinguish the best algorithm that has high accuracy.

The comparison results among various techniques and models indicate different levels of performance across different evaluation criteria. For instance, when considering the gradient boosting machine model, the accelerometer sensor technique exhibited the highest accuracy of 0.52, and an ROC AUC of 0.53, indicating relatively better overall performance compared to other techniques. In contrast, the strain gauge technique showed the lowest performance metrics across all evaluated models, with accuracy, recall, F1-score, and ROC AUC at 0.44. Notably, the eddy current proximity transducers technique achieved perfect scores across all metrics when utilizing the random forest model, indicating exceptional performance with accuracy, recall, F1-score, and ROC AUC at 1.00.

Table 1. Overall performance of the vibration measurement techniques coupled with the RF as machine learning algorithm.

Technique	Accuracy	Recall	F1-score	ROC AUC
Eddy current proximity transducers	1.00	1.00	1.00	1.00
Accelerometer sensor	0.49	0.49	0.49	0.49
Blade Tip Timing (BTT)	0.52	0.52	0.52	0.51
Laser Doppler Vibrometer (LDV)	0.52	0.52	0.52	0.52
Strain gauge	0.49	0.49	0.49	0.49

Table 2. Overall performance of the vibration measurement techniques coupled with the SVM as machine learning algorithm.

Technique	Accuracy	Recall	F1-score	ROC AUC
Eddy current proximity transducers	0.48	0.48	0.48	0.48
Accelerometer sensor	0.49	0.49	0.49	0.49
Blade Tip Timing (BTT)	0.48	0.48	0.31	0.50
Laser Doppler Vibrometer (LDV)	0.44	0.44	0.44	0.44
Strain gauge	0.48	0.48	0.31	0.50

Table 3. Overall performance of the vibration measurement techniques coupled with the GBM as machine learning algorithm.

Technique	Accuracy	Recall	F1-score	ROC AUC
Eddy current proximity transducers	0.46	0.46	0.46	0.46
Accelerometer sensor	0.52	0.52	0.50	0.53
Blade Tip Timing (BTT)	0.49	0.49	0.49	0.50
Laser Doppler Vibrometer (LDV)	0.48	0.48	0.49	0.49
Strain gauge	0.44	0.44	0.44	0.44

Overall, these results highlight the importance of selecting both technique and model employed in achieving optimal performance in vibration data analysis tasks.

4. Conclusions

In the present study, the authors tried to conduct a thorough analysis of vibration measurement techniques in combined cycle power plants, utilizing synthetic data and machine learning models like RF, GBM, and SVM. It is noteworthy that the ECPT combined with RF achieves high performance, consistently scoring 1.0 across various metrics, while the LDV also shows strong results of over 0.55. Progressively, from ECPT to LDV, performance improves, with the AC increasing from 0.47 to 0.48 and the BTT technique enhancing from 0.53 to 0.54. However, the SG technique performed similarly to the AS with slightly higher scores ranging from 0.49 to 0.51. The SVM model with the AS excels and scores 0.49 for accuracy, recall, and F1-score, while the LDV technique exhibits the weakest performance with a score of 0.44. Overall, the LDV emerges as the most effective technique for vibration anomaly detection, with the RF model consistently outperforming other classifiers.

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